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TESI DI LAUREA

A SIMULATION OF CONSUMER BEHAVIOUR WITH INFORMATION ASYMMETRY

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Introduction

The consumer market has been analysed extensively by innumerable disciplines, due to its heterogeneous framework. Consumer market is, in fact, a combination of several areas: sociology, psychology, marketing and economics. For this reason, the fact that it is constituted by countless and heterogeneous phenomena, all merged together, it has been approached as one complex system. The present work introduces an economic model grounded on consumers behaviour under asymmetric information, and it is focused on the study and analysis of the interwoven dynamics that generate the purchasing process. Starting from single individuals, with heterogeneous preferences and needs, we exploited the potentials of Agent-Based modelling (ABM) to simulate what can be intended as a target market and its decision-making process. Consumers' consumption on the marketplace depends upon innumerable variables, but our analysis mainly focused on the exchange of influences among autonomous actors. Fundamental attention was placed on creating the appropriate framework in which we could analyse differences in the purchasing process when consumers have different levels of information at disposal. One of the aims of the study is to strengthen the importance of the concept of asymmetric information in consumer behavioural studies. This concept, mainly used in financial applications, does not find, in our opinion, an adequate development in this field. In order to accomplish the desired results, we needed several reproductions of social structures characterized by particular settings. Therefore, a good amount of time has been spent on the creation of the model, using a series of techniques derived from network science. We found this discipline relatively useful to give exact measurement of intrinsic properties generated by each setting. According to our experience, the will of extrapolating insights from a system needs to be followed by the will of understanding the system itself. Results obtained in a setting with unknown properties are, in fact, bound to produce unworkable information. In addition, if we approach a setting with unknown properties it is possible to consequently reproduce a social environment not in compliance with our interests. The use of network analysis has been boldly extended to allow the study of advertisement from a perspective of particular interest, in fact data provided by centrality measures have a significant relevance in the diffusion of information. The analysis of every context in which two or more agents interact can be facilitated by the findings of network science, which helps in the retrieving process of valuable data. In the implemented simulation, information shared by agents can be of two types, i.e. business-to-consumer and consumer-to-consumer. Doing so, we were able to construct and evaluate integrated marketing communications that render the exchange of influence the pivotal aspect, which has to be considered in accordance with preference satisfaction. We also made use of the marketing mix, which is the tool employed by firms to try and develop their business.

To follow, a brief outline of the structure of the present work, which has

been divided into three main sections. One focuses on the analysis of the literature on the matter. The second section is devoted to the developing of the model itself and the last section analyses and discusses all the simulations that have been done in order to obtain valuable information from the model.

Chapter 1 is dedicated to a broad overview of the most interesting concepts regarding some of the central aspects constituting the theoretical framework of our study. The discussion starts in section 1.0.1, where we broached the agent-based modelling technique as the ideal tool to accomplish our study. Computer simulation pave the way for the creation and study of several bottom-up approaches. We reviewed the paper summarizing the reasons that lead us to such extensive use of this technique. Using a particular agent-based programming language named NetLogo, we are capable of developing our market simulation. In section 1.0.2 we presented an interesting real world application of an agent-based model. The model was created from the collaboration of Unilver and LeShop.ch, where the latter constitute the first online grocery shop in Switzerland. The paper also introduces two notably common top-down approaches, often used by Unilever. The fist one is the Bass diffusion model, which, by means of simple equations explains how the adoption of new goods could be understood just dividing consumers into pioneers and followers, and determining the coefficients of innovation and imitation. The Independent Cascade Model, is the second model under analysis, it is a theoretical structure quite close to the Bass model and we analysed how the two differ from each other. We carefully showed the main differences between the top-down and the bottom-up approaches and explained further reasons that lead our work to be constructed on an agent-based model. In section 1.0.3 we introduced other real world applications of agent-based modelling, focusing, this time, on urgent diffusion scenarios using data collected from Twitter. Although, the topic of this ABM is not directly related to the study of the market, we were able to exploit the many similarities that exist whenever a diffusion of information takes place. In fact, as a proof of this, even the work on urgent scenario has been grounded on the Bass diffusion model. The paper reviewed in section 1.0.4 sheds some light on a theoretical and fundamental concept, namely, uncertainty. The author of this paper, Armen Alchian, intended to spread the fundamental predominance that imperfect foresight has in daily decision processes. His ideas against the rational agent and his analysis of adaption versus adoption, gave us several theoretical insights that where applied all along the simulation. In Subsection 1.0.5 we briefly introduced to the reader the reasons that lead the present work not to consider the utility functions. The full study of network analysis is discussed in section 1.0.6. After a little introduction to this science, made through the explanation of basic notions, we made a specific review of the terminology used in this field and presented theoretical and practical examples of several networks. To conclude we highlighted the use made of this discipline in our work and we offered a precise explanation of all the various coefficients and metrics of our interest. Section 1.0.7 of the literature review inspects an interesting analysis made on seller's reputation. This work has been developed within the economic discipline of trust and reputation and is focused on the effects that changes in the sellers' reputation, expressed by consumer through the use of reviews, have on both consumers and sellers

behaviour. Another important aspect of this study in centred on the quality of different reputation mechanisms that assist consumers in achieving satisfactory purchases. This analysis has been considered because of the existing similarities that consumers' responses show in situations where there are changes in sellers' reputation or in products reviews. The last section of the literature review (1.0.8) proposes an inspection of the concept of big data. Modern technologies allow the possibility to aggregate enormous amount of information, which, corporations may use. A suggested new way for using these consumers' related data foresees an evolution towards more sophisticated methods of analysis. The various insights gathered from the theory on the matter have been implemented in the model object of this study.

Chapter 2 is devoted to the explanation of our simulation. Our work starts with a basic reproduction of the market and in the first version of the model we introduced consumers and goods. After giving to all agents heterogeneous preferences/attributes, we created the basic trade mechanism. The second version of the model has been based on the creation of firms and shops, and we gave a predominant role to firms that are bound to set the supply. We developed the idea that there is a distance between consumers and goods, and that the purchase will solely be possible when the distance is inferior to a prior determined value. We also started to incorporate the idea of uncertainty within the trade making process. In the third version we introduce links and advertisers and we developed the purchasing process depending on the level and quality of advertising. In the fourth version we augmented the possibility of consumers relations introducing the word of mouth effect, in accordance to which we extended the possibility of consumers to establish a network of information given their starting similarities and differences. In this version we decided to introduce a third firm and also a customised absolute income hypothesis, were we led the marginal propensity to consumption to be dependent upon advertising. In the fifth and last version of the model we augmented the advertising possibilities, we extended the possibility that consumers have to communicate with each other and we introduced decisions made according to a knowledge level. Another introduction inserted in this version is the feedback effect, seen as the possibility of consumers to leave reviews and subsequently to study them before purchasing. We then worked in the standardization of the various influences in order to be able to combine them together avoiding, undesired preponderances. The last supplement implemented in the model regarded blending all the influences depending on the desired probability of occurrence of the effect itself. Even if information asymmetry has not been mentioned in any of the model versions, this does not mean that it has not been considered. In fact, due to its predominant role, information asymmetry has been fully integrated in every aspect of the simulation. We want to stress that the simulation has been made trying to settle as little constraints as possible. We created an interface that gives to the user the possibility of changing a great amount of fundamental variables and processes. Doing so, we paved the way for simulating many different scenarios in order to find valuable insights. One of our purposes was understanding the communication process. We wanted to measure how information can

ripple through the network, and investigate the role of information asymmetry in consumers behaviour approaching the marketplace. From a marketing point of view, we analysed the effects of different communication patterns in the determination of their market share.

Chapter 3 puts into practice all the theoretical and practical elements analysed and developed in chapter 1 and 2. After a brief overview of the variables of the model, the chapter continuous with the presentation and discussion of four different experiments scenario. Each of the four scenario has been developed with a different background structure aimed at emphasizing specific aspects that wanted to be inspected.

Chapter 1

Literature review

1.0.1 Multiscale agent-based consumer market modelling

Consumer markets have been analysed with several methods, due to the constant need of extrapolating interesting and valuable information able to project the results of a given marketing campaign in the future and thus leading managers to consistent and profitable decisions. Many techniques such as regression-based models, logit models, and theoretical market-level models have been used to achieve this latter goal. These techniques belong to the traditional modelling techniques group. Some of the general issues pertaining to these models according to by North et al., 2010 are:

1 Number of factors they can incorporate

2 Level of detail on each factor they can accommodate

3 Behavioral complexity they can account for

The lack in the number of factors may produce a result based on incomplete models. Indeed not incorporating all the factors could lead to exclude some of the main players of a system. Neglecting details of some factors is another aspect which can make a model incomplete. In fact, the reduction and extrapolation of fundamental data in a context in which there is a multitude of worthless information is a key aspect of any model. Finally, in order to comprehend the complexity of the market in depth we need a tool able to represent the interdependencies of the decisions made by consumers, retailers, and manufacturers. In short, we can say that the sequence of interlocking leading to complex interactions, side effects, and repercussions of decisions can cause overestimation of the quality of a model, which is something that should be avoided. The analysis of these interdependencies through agent-based modelling becomes an interesting and intriguing journey. This analysis is possible, because ABM uses business-driven rules that are applicable to each type of individual within the simulation. Moreover, this type of model, considers each agent as an autonomous decision-maker entity, able to take into account other agents' reactions, even in case of non-linear behaviour[1]. As North et al., 2010 state:

> Traditional methods are typically not able to fully account for the fact that each market participant's subsequent decisions are intimately and sensitively dependent on all previous decisions by every market participant, including itself.

[1]The term "non-linear" in this case means that changes in system outputs are not directly proportional to changes in system inputs.

This can be applied to a manager's perspective starting a new marketing campaign. The campaign will engage the competitors' reactions. These will then lead to a succession of reactions from all the market's participants, such as consumer and retailer, which, in turn, will create a loop of actions-reactions from each of the market's participants. In this case, the manager in question needs to project the marketing campaign to estimate, or just have an insight in, the reactions of the marketplace. Doing so, i.e. using a consistent model, or a set of insights taken from different models, can be of valuable help to decrease the level of uncertainty that is inevitably part of reality. One of the most successful examples arose from the efforts of Argonne and PG. A result of this collaboration has been the developing of the virtual marketing learning lab. The model is an ABM of consumer markets, in which the structure represents interactions among retail store, retail chain, and manufacturer. The model aims to an evaluation of both the shopping behaviour of consumer households[2] and the business behaviour of manufactures and retailers in a simulated national consumer market. In this model, all the interdependencies among agents are taken into account. This entails the evaluation of a high level of information, considering it is necessary to include in the analysis the above mentioned complex system of interactions and feedbacks. The implementation of the virtual marketing learning lab has been done by using the Recursive porous agent simulation toolkit (repast)[3].

1.0.2 How to capture consumer interactions and geographical effects

On March 26th 2014 the Unilever research group, leaded by Dr. M.Iqbal Adjali, introduced their conceived model of an online grocery store. Unilever is one of the widest multinational consumer goods industries. Its model is an ABM created thanks to the collaboration between Unilever and LeShop.ch, the first online grocery store in Switzerland. The multinational decided to extend its marketing research using agent-based modelling, but was unable to collect direct information of its customers. In the trading process, Unilever sells all its goods to retail corporations, and has no direct contact with the final purchasers. LeShop was a well-timed partner since its activities started in the same period of Uniliver marketing activity, and the agreement involved providing data in exchange of insights. Unilever group has always made marketing activities, but using another type of approach. The traditional (top-down) approach is the one implemented by Bass, 1969 with its diffusion model. Generally speaking, the top-down approach, consists in the break down of a system into many sub-systems, the breaking down process goes forth till reaching an adequate level of comprehensibility of the sub-systems obtained. Whereas, the bottom-up approach is defined as:

[2]The people of a house collectively which, to some degree, coordinate their shopping.

[3]The recursive porous agent simulation toolkit (repast) is one of several agent modelling toolkits that are available for researcher. Repast has multiple pure implementations in several languages and built-in adaptive features such as genetic algorithms and regression. `http://repast.sourceforge.net/repast_3/`

> The piecing together of systems to give rise to more complex systems, thus making the original systems sub-system of the emergent system.[4]

The Bass diffusion model has been successful in predicting many market takes-up by innovators producing consumer durables[5]. The model computes the rate of adoption as the sum of two parts, the spontaneous take-up and the imitation take-up, as shown in 1.1. 1.2, instead shows the evolution of the sum, i.e. the total number of adopters.

The main issue of this model comes from the needs of restrictive assumption such as:

- homogeneous population
- perfect mixing: people are free to talk with each other (situation of perfect information)

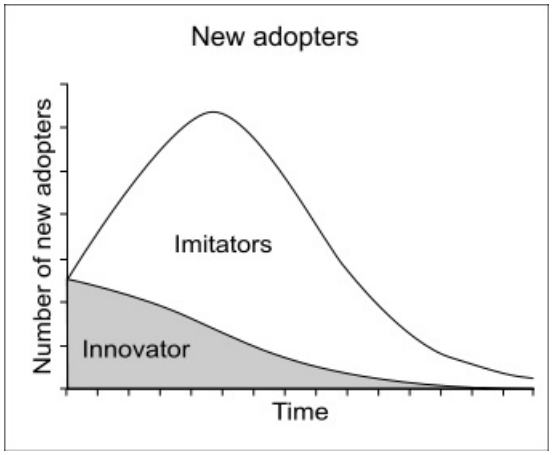

FIGURE 1.1: New adopters as the sum of innovators and imitators.

Given these two main assumptions, the model becomes difficult to generalise. This prompted researchers to better evaluate the possibilities deriving from the top-down approach and led them to take into consideration different methods.

The ABM is perfectly structured to study an environment such as the market. Using the bottom-up approach, the sub-systems are the agents, not homogeneous anymore, and the aggregation of all sub-systems establishes the market itself. Thus, studying the single interactions between agents, we try to get useful insights. The first step made by Iqbal Adjali's team was examining and analysing customers' data. They dealt with the available registrations in order to extrapolate all possible information. The dataset obtained contained largely demographic data and transaction data. It is

[4] `http://en.wikipedia.org/wiki/Top-down_and_bottom-up_design`

[5] Consumer durables involve any type of products purchased by consumers that are manufactured for long-term use. As opposed to many goods that are intended for consumption in the short term, consumer durables are intended to endure regular usage for several years or longer before replacement of the consumer product is required.

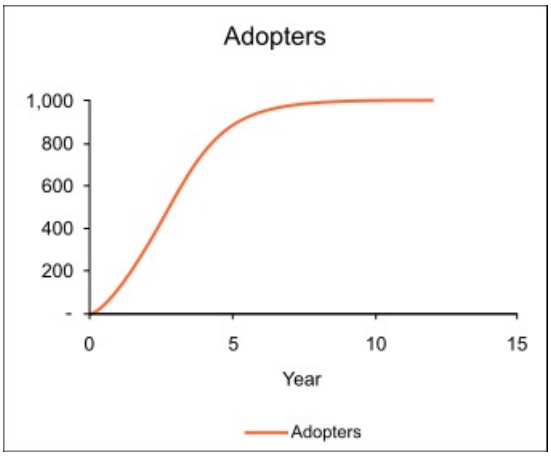

FIGURE 1.2: Evolution of the total number of adopters.

worth of attention how the Swiss environment is an heterogeneous framework, due to the coexistence of three main languages in a total population of only 8 millions people. The simulation platform implemented focuses on:

- History of customers' transaction data
- GIS (geographic information system) and demographical data owned by the office of national statistics
- Quality and advertising data obtained by marketing agencies

The second step, after collecting the data, is called data mining. In "Principles of data mining" by Hand, Mannila, and Smyth, 2001, the authors define this technique as:

> The analysis of observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner.

The demographic variables were connected with the information of recommendation gathered from Leshop. The project envisage the retailer implementing a sale promotion using a system of coupons. The first customer was prompted to foster as many peers as possible to buy in the online shop and when purchasing they had to upload the coupon code of the first one. The coupon gave a trade discount to both the first and the second customer. This type of promotions presents many strong points, and of them is the network effect, [6] because it starts a shop chain in which all customers benefit in spreading the coupon. Another point of strength of this type of promotion, is the natural low cost of this marketing activity in which the customer becomes promoter. Last but not least, is the possibility to monitor those recommendation data. Researchers connected all the data,

[6] In economics and business, a network effect (also called network externality or demand-side economies of scale) is the effect that one user of a good or service has on the value of that product to other people. When a network effect is present, the value of a product or service is dependent on the number of others using it (Shapiro and Varian, 2013).

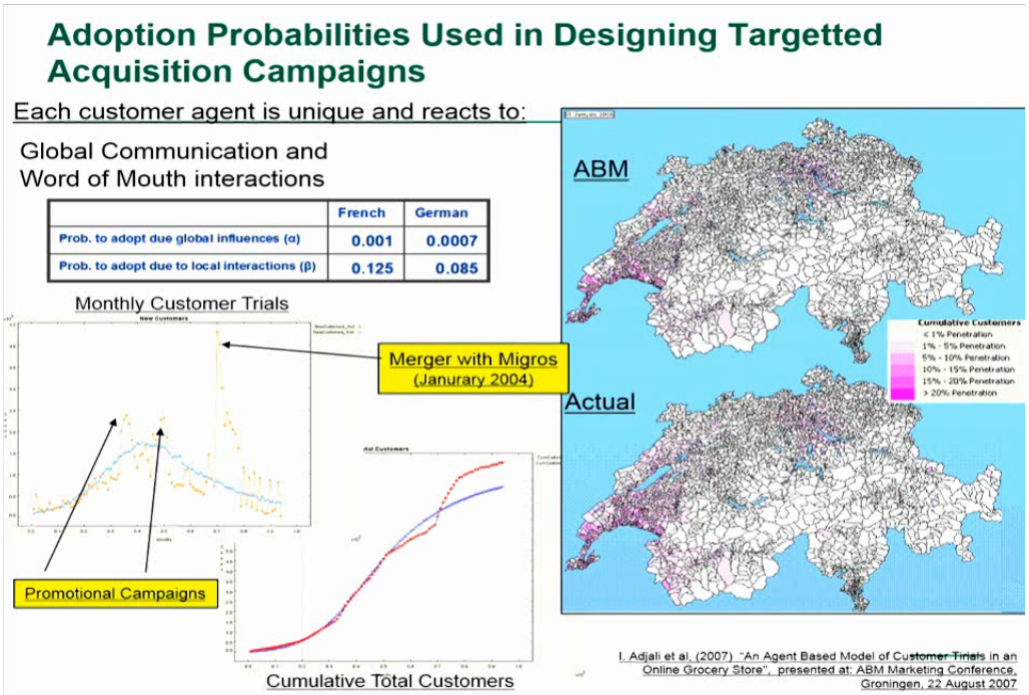

FIGURE 1.3: Similarities between unfolding of real events and developed ABM.

extracted both from a demographic side (i.e. postcode and native language) and from a behavioural side (communicating and purchasing inclination) and, as a consequence, were able to understand how the purchasing niches were evolving, both in number and in space, with extreme precision. Results have then been shown using Switzerland national map. Figure 1.3 represents the comparison between actual realization and their forecast. It is not difficult to understand how close they have been to reality just by looking at the clouds of points in both maps.

The figure also highlights an important difference, namely, French and German different types of reaction to external influences. This path was included in the model by accurately weighting global communication and word of mount effects. The meaningfulness of this model is embodied in its final result.

1.0.3 An Agent-Based Model of Urgent Diffusion in Social Media

Social media have been analyses by scholars according to numerous and different points of view. Many are the interesting ideas which can be derived by the literature on the matter, mostly those focused on understanding the diffusion of information in large-scale networks. One recent contribution by Herrmann et al., 2013 aims to achieve a better understanding within the context of urgent scenarios, which are identified as events in which the diffusion of information flows is slower than the realization of the external dynamics, so that the most recent news enters in the system compromising the diffusion of the previous information. Nowadays, great progress has been made in understanding how people spread meaningful data, even though the majority of the literature has focused on non-urgent

diffusion events. Two famous and traditional models, the Bass, 1969 model and the Cascade model, have been built to respectively explain: (I) The adoption of durable consumer appliances and (II) How information diffuse in a network.

Both models are therefore able to dissect different contents. The decision of Herrmann et al. was to fit these models with real data extrapolated from the following four famous events: (1) the capture of Osama Bin Laden, (2) Hurricane Irene, (3) Hurricane Sandy, and (4) U.S. Election night of 2012.

In order to understand the importance of this work with relation to our simulation, we need to explain some crucial connections. First of all, urgent diffusion in social media is a small subset in the analysis of human behaviour. Connections are grounded on the study of psychological, social and emotional factors, and these factors need to be analysed in a marketing context as well. Other useful reasons that relate the two models to our simulation are: the possibility to extend this research to brand crisis, the use of the Bass diffusion model (created to understand consumer behaviour, and due to its robustness one of the most cited model in Marketing) and the similarities in the use of clusters.

For the sake of clarity, a brief explanation of the two models is needed. The fist model to be analysed will be the Bass model. We already introduced this top-down approach providing some insights (see pages 3-4), and now we need a detailed explanation of its procedure together with some formulae.

Models

The Bass model relies its main assumption on the simple idea that people gather their information from two sources: advertising and word of mouth. The model formulation is identified as follows:

$$\frac{F'(t)}{1 - F(t)} = p + qF(t) \tag{1.1}$$

$$F(0) = 0 \tag{1.2}$$

$F(t)$ is the subset of the population aware at time t, p is the innovation or advertising coefficient, q is the imitation or word-of-mouth coefficient, and $\frac{F'(t)}{1-F(t)}$ is the hazard rate. The hazard rate can be seen as the probability that if the subject is not aware at time t, he/she will be aware in the next instant. Precisely in this case, the hazard rate is the sum of the innovation coefficient and of the imitation coefficient multiplied by the fraction of population aware. Usually in the Bass model q is greater than p. This reveals how social communication is the most important force with respect to the advertising effect. The original Bass model is not an agent-based model. Nonetheless, it is possible to translate the model and this has actually been done already by Herrmann et al., that explain the procedure used as follows:

> First, we discretize the problem, giving unaware agents an opportunity to become aware of the information at each time step. Then, instead of determining a deterministic translation of some

> portion of the population, we update each agents state probabilistically. If every agent observes the actions of every other agents in the model, then this becomes equivalent to the hazard rate Bass model limited by discretization.

The above mentioned process is worth of attention, mostly because of the numerous similarity with the ABM being here formulated. The first similarity is that our consumers' purchase decision can be influenced both by advertisers and by neighbours, as in the Bass Model. Another important similarity relies on the possibility of consumers to be: either (1) unaware or (2) aware. In spite of the above mentioned similarities, it must be said that our simulation has some important differences with respect to the Bass Model. The aware state is necessary for an agent to become a possible consumer, because in the unaware state agents are not able to buy products. This awareness though can still be improved by advertisers. A real life explanation can be useful in order to better understand this difference. Let us suppose the existence of two different brands, A and B, both of them selling a similar product in the same location. If we were to ask a sample of randomly chosen people if they knew each one of the products, we could then mark on a scale of 1 to 10 their aware and unaware state. It becomes a little different when we are dealing with an aware person and we want to dig up deeper in his/her memory, in order to understand which one of the two products affected him/her more. In this circumstance, there is the need to establish a different evaluation system.

This concept is identified in the marketing idea of *brand awareness*, defined as:

> The extent to which a brand is recognized by potential customers, and is correctly associated with a particular product[7].

Our model presents other differences with respect to the Bass model. For example, it does not settle on a unique and constant probability of the consumer being influenced by the advertising. Therefore, the invariable p is not present. This is extremely important, because our simulation focuses on the role of advertising. Therefore, considering our model aims to dissect different advertising methods and their effects, a wider set of "marketing possibilities" is required.

The second model that is going to be analysed is a diffusion model named the **Independent Cascade Model** (ICM). The model was developed to understand how information diffuses in a network. Pal, Kundu, and Murthy, 2014 describe the ICM as a stochastic information diffusion model, where information flows over the network through Cascade. It works similarly to the Bass model since there is a small probability that external news events can update the agents. And there is a higher probability that agents become aware of the news when a given fraction of their neighbours have become aware. To understand the main difference between the ICM and the Bass model we can refer to Herrmann et al., 2013:

> The basic intuition behind the cascade model is that information and adoption decisions ripple through a social network in

[7] `http://www.businessdictionary.com/definition/brand-awareness.html`

cascades, rather than in long-term exposures such as the Bass model denotes.

The ICM proposes same parameters as the Bass model, where p is the coefficient of innovation and q is the coefficient of imitation. To follow, a comparison of the two presented models with the application of real data.

Data and conclusions

The developers of this work selected the above-mentioned four real cases in order to construct the comparison, and they collected all the data from Twitter. Twitter provides two APIs [8] for the collection of data, i.e. (I) Streaming API and (II) RESTful API. Considering that (I) empowers the programmer to collect all the tweets on a particular topic, the streaming API becomes the appropriate tool to achieve Herrmann et al. idea[9].

Afterwards it was important to pick data from a focal sub-sample of Twitter users, so they collected information about 15,000 users. The sub-group excluded celebrity and non-active users. Having all the data and connections among agents, and assuming that an agent becomes aware of the event when he/she tweets about a specific topic, it is then possible to identify the first time that each agent becomes aware of the event. Having all the connections, allowed researchers to have a deeper insight and users could be categorized as innovators or imitators. To have a graphical insight of this network, Herrmann et al. used a software named Gephi[10], see figures 1.4, 1.5, 1.6 and 1.7. In these figures we can visualize nodes and edges that represent respectively Twitter users and the relationships among them. As we can see from the shape of the cluster, each user has really different influencing power. The nodes floating without any edge represent a situation in which of two users only one has influenced the other.

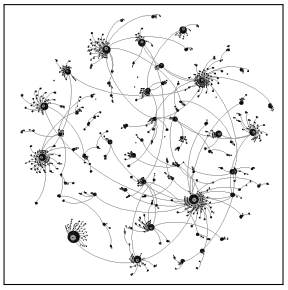

FIGURE 1.4: Visualization of Hurricane Irene Diffusion.

A remarkable job has been done to realize these graphical networks, but the aim of the research is the realization of standard adoption curves. Herrmann et al. were able to build an adoption curve from each of the events,

[8] An application programming interface (API) is a particular set of rules ("code") and specifications that software programs can follow to communicate with each other. It serves as an interface between different software programs and facilitates their interaction, similar to the way the user interface facilitates interaction between humans and computers.

[9] In order to have an appropriate MySQL database the streaming API was used with TwEater (short for Twitter Eater) is a tool designed to help programmers archive long-term Twitter search queries. `https://github.com/dmonner/tweater`.

[10] Gephi is an open-source network analysis and visualization software package.

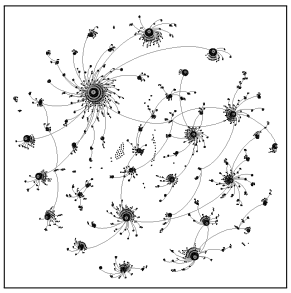

FIGURE 1.5: Visualization of Osama Bin Laden Diffusion.

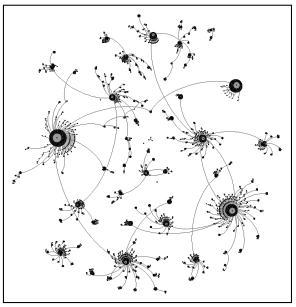

FIGURE 1.6: Visualization of Hurricane Sandy Diffusion.

and thereafter it began the investigation to find the most fitting parameters in order to compare the model with the data. The investigation of these parameters was done by implementing a grid search and employed a "guess and check" method in which a software tries all the combinations of the parameters in the grid, and then the results are compared with the real data. The comparison is done using the Mean Absolute Percentage Error (MAPE)[11].

Table 1.1 contains all the innovation and imitation parameters and the values $(\hat{p}^*, \hat{q}^*)$ that minimize the average MAPE. Once discovered the most accurate parameters, it is useful to provide a graphical representation of the models compared to the data. Since all the comparisons have a similar result, we prefer to underscore the most accurate for both the Cascade model and the Bass model.

As we can see from figures 1.8 and 1.9, the models well approximate real data. And in this particular case, the hurricane events fit the model better than the other events do. Accordingly to Herrmann et al. this happens because "The hurricane cases have longer time horizon and, we hypothesize, numerous subevents". This is an important concept because it asserts the possibility that both the Bass model and the Cascade model are better fitting situations with numerous influences from the external environment. From a marketing point of view, this means that an advertising campaign should establish numerous contacts in order to realize a forecasted event.

[11] MAPE is also known as mean absolute percentage deviation (MAPD), is a measure of accuracy of a method for constructing fitted time series values in statistics, specifically in trend estimation. It usually expresses accuracy as a percentage, and is defined by the formula: $MAPE = 1/n \sum_{t=0}^{n} \frac{|true_t - simulated_t|}{true_t}$.
`http://en.wikipedia.org/wiki/Mean_absolute_percentage_error`.

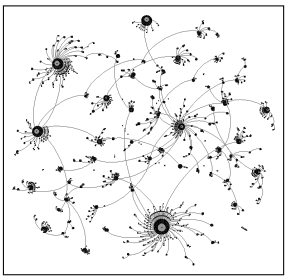

FIGURE 1.7: Visualization of US 2012 Presidential Election Diffusion.

model	dataset	$\hat{p}$ range		$\hat{q}$ range		$\hat{p}^*$	$\hat{q}^*$
cascade	bin laden	0.045	0.080	0.040	0.080	0.065	0.060
cascade	irene	0.001	0.034	0.014	0.054	0.014	0.034
cascade	sandy	0.001	0.027	0	0.020	0.007	0
cascade	election	0.014	0.054	0	0.028	0.034	0.008
bass	bin laden	0.079	0.119	0	0.021	0.099	0.001
bass	irene	0.005	0.045	0	0.020	0.025	0
bass	sandy	0.001	0.024	0	0.029	0.004	0.009
bass	election	0.015	0.055	0	0.023	0.035	0.003

TABLE 1.1: Range of parameter values and optimum values as determined by lowest MAPE.

There is another result of this research that deserves to be highlighted. The authors explored the sensitivity of the model to different parameters doing a comparison among all the MAPE values which are close to the identified optimal one. Then using the heat-map, they showed how different minimal MAPE were fitting the data.

Figure 1.10 shows the sensitivity of the Hurricane Sandy data. In this heat map, minimal errors are represented by the dark blue areas, while red areas represent higher MAPE. All the blue area represents the range of values that produces similar results to the best fitting set of values. This

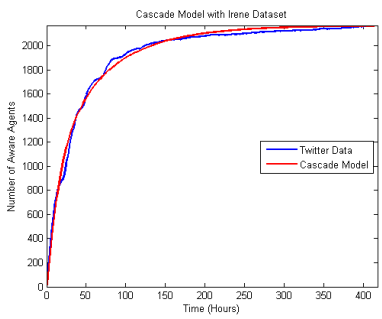

FIGURE 1.8: Cascade model with Irene dataset.

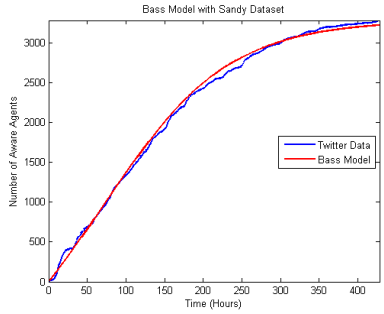

FIGURE 1.9: Bass model with Sandy dataset.

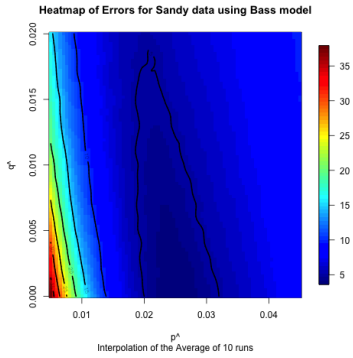

FIGURE 1.10: Heat map illustrating the sensitivity of the Bass model on the Hurricane Sandy data.

outcome shows us how it is possible to find a set of values able to reach a decent predictive result.

1.0.4 Uncertainty, Evolution and Economic Theory

In the 1950's an American economist named Armen Alchian published one of his most famous works. The paper in question is related to the importance of uncertainty in each economic scope. His critiques led to a series of valuable questions, prompting researchers to search for alternative solutions while focusing on the analysis of any dynamic system. Here we will inspect some of his insights and try to understand why some of them are considered interesting for the purpose of marketing research. His position contrasts the rationality assumption drawn by mainstream economics. Alchian states that: "In the presence of uncertainty - a necessary condition for the existence of profits - there is no meaningful criterion for selecting the decision that will *maximize profit*". His idea is that uncertainty leads inevitably to imperfect foresight, therefore the profit maximization criterion loses its substance. In spite of that, he states how uncertainty should not lead to random decision making. Economist should search alternative efficient strategies to achieve success, even if this means that the objective has to be modified. With respect to this different perspective, Alchian, 1950 posit that:

> In an economic system the realization of profits is the criterion according to which successful and surviving firms are selected [...] Realized positive profits are the mark of success and viability.

Once we have accepted this position, we can start wondering how important is for a firm that hypothetically has decennial plans to distinguish between present profits and future expected profits. And also to consider the importance of potential profits accruing due to present expenses. We can definitely state that positive profit is a benchmark of success. In the development of this simulation we will consider a successful marketing campaign as the one able to accomplish the best result delivered by the minimum effort. Considering the tremendous competition firms must face, there is little or no space for mistakes and waste. One of the most important ideas - that arises directly from patterns of evolution observed in the study of biology - is the concept of adaptation versus adoption. The latter evaluates success deriving from two different chances: (i) the firm that adapt his feature to the markets, trying to achieve the best match possible or (ii) the market that adopt the firm due to the necessity of its presence in the environment. We believe both possibilities have their share of importance which can change according to different situations. This idea though, contains a subtle truth, namely that sometimes efforts to adapt a certain product can vanish if the market decides to adopt a competitor brand. We can grasp another important insight that relies in the necessary commitment of a firm to dig up in the dynamics of the market. We will implement distinctive situations trying to face different realities. Firms will have different degrees of similarities to the market and we will try to see what happens when the firm that has been less consistent with the preferences tries to beat the competition following alternatives routes, i.e. marketing expenditure in various characterization. Another important insight grasped from Alchian theory concerns a double viability to achieve success. The theory states that firms achieve success by adapting via imitation and trial and error. We believe reality can unfold in a similar way. Therefore, a simulation should include both opportunities. While competing to enhance their profits, firms will continuously study the position of competitors and all the previously developed steps. To achieve a greater result, any step should be classifiable as a success or as a failure, allowing the firm to decide whether the implementation of the strategy is consistent or not. For this reason the implementation of each strategy will consider the possibility of adapting via imitation if affordable and considered profitable. Firms will analyse their present competitors and the information available in the market from competitors' blueprint. The aim of this simulation is to understand how different marketing strategies are rewarded. From this theory of uncertainty we improved the importance of considering the environment as a proactive element able to modify at each step its characteristics and being influenced by firms. The latter idea constitutes the possibility of having some degree of endogeneity into the system. We believe that in the real world, as the firms modifies its behaviour following consumption, consumers adapt their behaviour following producers incentives. An example can be made considering pervasive advertising relying on the importance

of word-of-mouth. Due to this effect, the input of the first advertisers unfolds into uncontrolled patterns of communication via social media able to enhance the brand awareness. This leads to consumers affecting the decision of other consumers and, as a consequence, the market modifies its features. This applies in particular when communication is established adopting *Integrated Advertising* that belongs to the world of integrated marketing communications[12]. We conclude asserting that our model will include the just mentioned modern and pervasive attempts to make advertising and we will then analyse in which situations expenses are concretely rewarded.

1.0.5 Agent-based simulation and utility function

The modern concept of modelling uses autonomous agents that are endowed with different traits and preferences that make each operational unit able to fully interact with the environment. For all the elements to be matched a double requirement needs to be fulfilled. The first requirement is the intrinsic capacity of each agent to elaborate information. Information that comes from two different paths:

- the changing environment that offers different products and data at each time step,
- the agent itself that changes its preferences following a set of metarule establishing a behavioural structure in continuous mutation.

The second requirement is the agent-based model with its computational power, able to make these autonomous agents interact simultaneously in a changing network. The possibility to combine the first and the second requirement originates a framework in which the autonomous decision making process fulfil all the requirements needed to simulate the real world. A more classical approach that follows the consumer theory, is based on the maximization of the utility function. Negahban and Yilmaz, 2014 identified six main types of decision-making processes and one of these is the utility-based, which they envisioned as a utility function used to evaluate product choices and choose the product with the maximum utility value. The utility function approach is based on the concept of instrumental rationality. According to this concept, individuals know the utility coming from each panel of goods and therefore they are able to compare all of them and understand which one better satisfies their needs. In the simulation model proposed in this work, utility has a different connotation because it comes from the realization of the match between the attributes of the goods and the personal preferences of the agent. There is no need for a numerical value representing an ideal satisfaction deriving from a good. In the establishment of the utility values from the agents to the goods, the utility value is meaningless with respect to the effective complexity of reality. Since agents are able to measure the satisfaction they get from each purchase, they do not need to pre-emptively establish an ideal utility numerical value. Therefore, the aim of this model is to infer how firms can manipulate attributes and increase the incisiveness of the communication to increase the perceived

[12]Integrated Marketing Communication is the application of consistent brand messaging across both traditional and non-traditional marketing channels and using different promotional methods to reinforce each other.

satisfaction of consumers. By using AMBs it will be possible to extend the concept of instrumental rationality to get closer to the idea of expressive rationality by which individuals are able to choose by themselves without any mathematical imposition. This would only be possible if agents had the ability of discerning different situations and choosing the goal of their own actions, given the information set they dispose of. The present work will thus aim to construct the most suitable framework to allow autonomous decision making.

1.0.6 Network Analysis

The Network Analysis (NA) is part of a wider discipline named graph theory. The aim of the latter is the study of graphs, which are mathematical structures used to model pairwise relations between objects[13]. In turn, the methodology of NA has been interwoven with sociology, and from this combination, has been develop another important branch, namely Social Network Analysis (SNA), which is in fact, the one mostly exploited in our study. According to Wasserman and Faust, 1994 :

> Social network analysis examines the structure of relationships between social entities.

These entities can have different features, they can represent human beings, groups of people organized both formally and informally, legal entities, nations and so on. The connection of SNA with marketing analysis is more than obvious, each individual is seen as a future buyer with different preferences and tastes that let him/her be part of a different interest group. This interest group could be the desired segment of the market of a given firm, transforming them into a desired target. Or it can be too distant in terms of matching interests, if so the firm will avoid to target them as potential buyers. Once established the preferred interest group (one or more than one), the firm needs to decide how to spend its resources in order to maximize the quality and quantity of the communication with its target. SNA interwoven with other disciplines will give us answers about the efficiency of the communication obtained following different strategies. Nonetheless, even considering only the marketing field, the role of SNA does not terminate here. SNA can be exploited to verify whether a campaign was successful or not, and can be used to understand which strategy has been better in terms of performance. These two different results, albeit important, do not provide a clear explanation of the full power of network theory and social network analysis. The study needs to be decomposed in *ex-ante* and *ex-post* analysis. Before deepening the discussion, it will be better to introduce some basic elements and then suggest some of the achievable possibilities.

The first thing that has to be done is specifying the terminology used in Network Analysis (NA). Each actor of the analysis, referred as entity until now, is defined *node*, and the relationship between two or more nodes is called *edge* or *link*.

In order to ground our knowledge of NA, we need to start from the smallest network existing, composed by two nodes. The concern is on the existence of an edge between them. When the edge exists we call this network a dyad, and according to the characteristics of this network, the edge

[13] https://en.wikipedia.org/wiki/Graph_theory

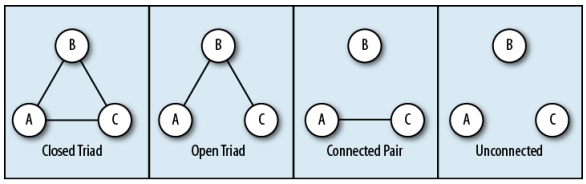

FIGURE 1.11: Types of undirected triads.

can have different features. Each edge can be directed or undirected. The undirected is seen as a mutual relationship, A knows B and B knows A. The directed edge can be explained as, A knows B and B knows A and other two combination A knows B and B does not know A and vice-versa. The easiest explanation of these 2 types of link is done referring to the two biggest social network of this period, Facebook and Twitter. In the former two people establish a connection when both of them accept to do so, which means that they accept to be mutual friends. Instead, Twitter allows asymmetric relationships, one person can follow another person and in the majority of the cases the relation is unidirectional. The only fact that the relation is unidirectional already implies the need of a more complete tool, which is, in fact, represented by the directed links.

Speaking in terms of network size, the next step lies in the analysis of networks composed by three nodes. These are called triads. This case presents a much wider set of different combinations. Even more, if we consider the case in which the network allows asymmetric information. Starting from the symmetric case, we can visualize the combinations. A summary of the possibilities is available in fig. 1.11, in which each of the four opportunities presents interesting traits. If we imagine this three nodes to be people, and we insert into the frame the existence of mutual interest on a given information, we can see that: in the closed triads case, each person will have at disposal the same communication possibilities, in fact each node *knows* the other two. The connected pair case has a single unconnected node that is not reachable from the other two. These two, instead, present the same set of possibilities again. The unconnected case is interesting, but there is not much to achieve, there are no edges and, therefore, if we give the information to one of them, it will remain stuck (the only idea could be trying to make a new connection or more). The last case and also the most interesting one is the open triad. It has a node that can exploit the fact that the other two do not know each other. In Social Network Analysis this lack of edge is called structural hole. In many real situations the information have value, and the discrimination power of the use of this information makes this value even higher. This is also the reason that leads agents in being directly interested in keeping and strengthening an information asymmetry within the network. From the dyad with its two possibilities (nodes connected or not), in the triad we find ourself with four different possibilities. Looking instead at figure 1.12 we see the case of a triad in which there are directed links, in this situation we have 16 possibilities given by 3 nodes only. Imagining to increase the number of nodes the possibilities increase more than linearly.

Now we need to move to a much larger network, the one in fig 1.13,

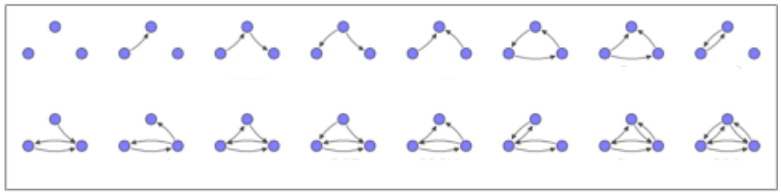

FIGURE 1.12: Types of directed triads.

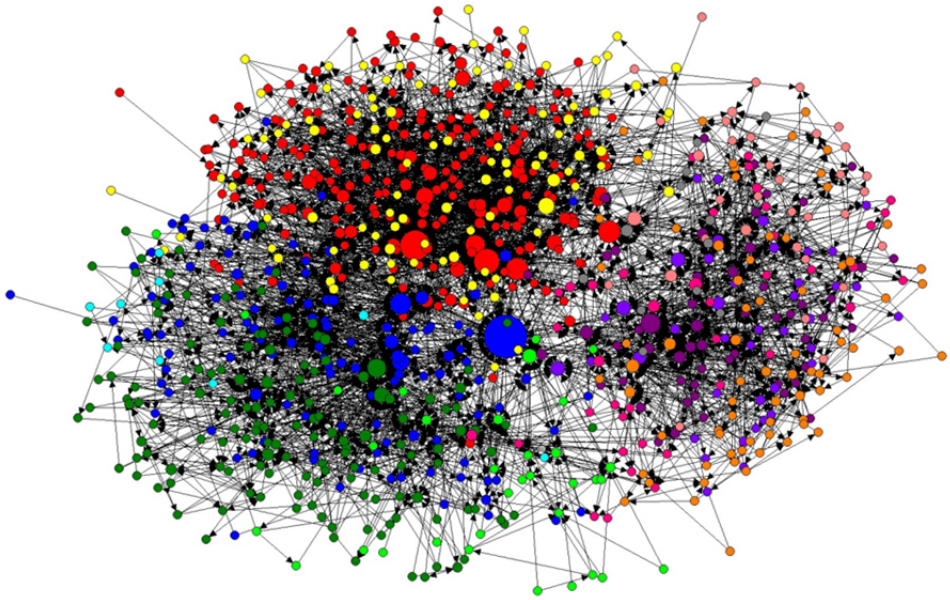

FIGURE 1.13: Graph example.

where we can see different coloured small circles, each of those is a particular node. Colours can be selected in order to represent visually key attributes of each node. They can for example, stand for: nationality, salary range, last product purchased, and so on. The big difference in this network is not the colour, but the fact that different nodes have different sizes. In this case, the size of the node expresses the number of directed links that point towards the node. If we imagine it from the point of view of a Twitter user, the biggest nodes are those that have more followers, they are more important than the others, given the fact that when publishing a tweet more people will be able to see them. Another example could be done by thinking about phone calls in a little town, in which each node is a person and some people have more telephone contacts with each other than others. Looking at fig. 1.13 we can start to see how complex reality can be when we have a good number of individuals to take into account. Going back to the idea that SNA could give us *ex-ante* and *ex-post* information about the network, we now explain its potential.

The *ex-ante* power of Network Analysis relies in the deep understanding of the role of each node that, in turn, characterizes the whole frame. We should highlight that the topic of interest in SNA is not the node itself, but its interdependencies with the whole. We understand different features of the network exploiting different metrics, algorithms and network

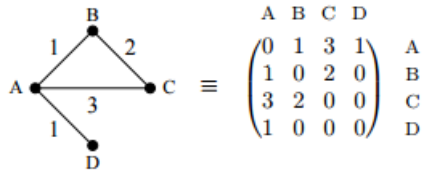

FIGURE 1.14: Example of an adjacency matrix.

topologies. Each of the previous topics gives us coefficients and quantitative information. Still thinking about fig. 1.13 we could let the dimension of the nodes be related to a coefficient selected according to a given necessity, having thus the best visualization to describe our interests. Different software give us different possibilities such as: changing colour and size of the nodes and of the links, providing the possibility to write the coefficient just above the node, and others. Therefore, using SNA metrics we can describe intrinsic communication dynamics of different nodes, and in aggregate of different networks. The *ex-post* power on the other hand, lies in the possibility to subsequently study the evolution caused by an input. Different structures will react differently to new inputs, some structures could present unconventional outputs, thus worthy to be studied. According to a preferred outcome we can adopt the best strategy.

The possibilities of the network are not limited to directed and undirected links, allowing networks to be either symmetric or asymmetric. Both directed and undirected networks can include the possibility to differentiate links from each other. Therefore, we need to introduce the definition of weighted network as the one that accounts the possibility that different relationships do have different properties. In fact, this kind of network presents links related to weights. How to evaluate the weights depends on the set up, we can consider weights as distance between points or as the perceived importance of a friendship. These two cases show how great values of the weights need to be related to each context. The effects of including weights are enormous, leading different researchers to apply network analysis.

As Newman, 2004 states:

> A weighted network can be represented mathematically by an adjacency matrix with entries that are not simply zero or one, but are equal instead to the weights on the edges.

The adjacency matrix, in fig. 1.14, in an example taken from Newman, 2004.

We also need to point out that this discipline is evolving incredibly fast. New insights, algorithms and metrics are developed continuously. The next session presents a deeper understanding of the above mentioned algorithms and metrics.

Network properties

In this section we want to present the algorithms and metrics used in the graph theory. Due to the size of the topic, we focus on those used while

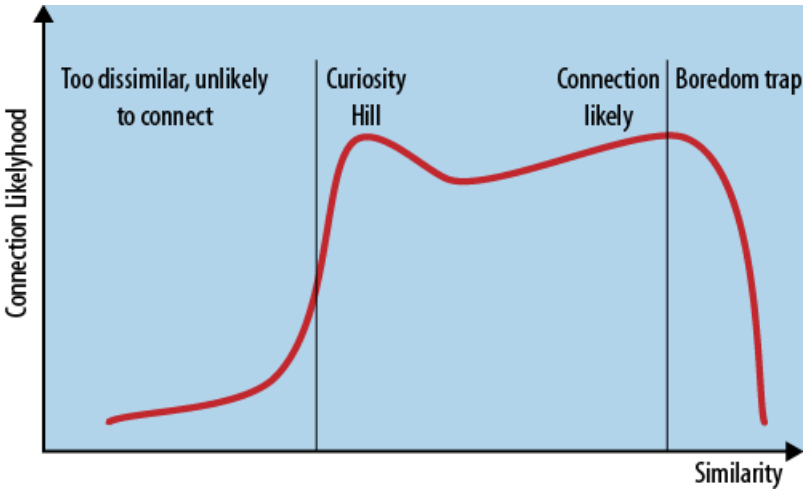

FIGURE 1.15: A relation between homophily and curiosity.

achieving the present research. We start by introducing some general concepts that help the understanding of the more detailed metrics that we are going to use.

The first concept is that of homophily, which is the tendency of individuals to connect to similar ones. The saying "birds of a feather flock together" is often used to explain this concept, it let us understand how homophily comes from our inner nature, which cannot deviate easily. Humans are social animals and act following schemes and patterns that often repeat themselves. Lazarsfeld, 1954 distinguished: status homophily and value homophily. "Status homophily means that individuals of a similar social class, wealth, and status are more likely to associate with each other than by chance. Value homophily means a tendency to associate with others who think in a similar way or like similar things, regardless of class and status." In figure 1.15 we see how sociologists related two important forces, homophily and curiosity. The idea is that each of us is curious for some degree, this curiosity fosters our connection to others. Each of us is unable to connect to those too dissimilar, but when the dissimilarities are present, but below the level of curiosity, then there is a new connection. In figure 1.15 we see a curiosity hill, that all humans have even though at a personal level. As it is shown, curiosity is the input that fosters a conversation between people. The boredom trap takes place when two people are exactly the same, in this case the connection in not able to endure since the minimum level of curiosity is not satisfied. All the idea is much more understandable if we intend curiosity as information seeking, doing so finding the reason that leads two identical people to be uninterested of each other is trivial.

Another important concept is the one of Propinquity. It is the seed from which many metrics arise. It is the tendency for agents to establish more ties with geographically close others. In the case of electronic communication this is not directly true, since the electronic word-of-mouth (eWOM) breaks down geographical distances. We anyway face a slightly different kind of propinquity, the one of psychological proximity. We will see metrics that try to evaluate the distance between members of a network and how the

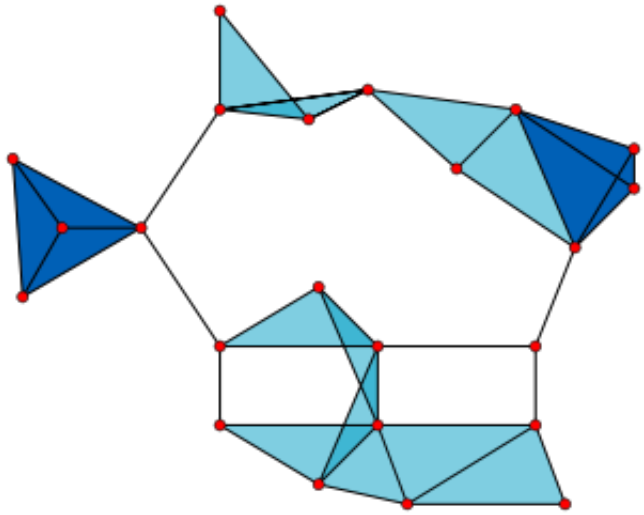

FIGURE 1.16: A network in which subnetworks are cliques.

network forms aggregations.

We need also an introduction to the concept of clique. Tsvetovat and Kouznetsov, 2011 state:

> A clique is defined as a maximal complete subgraph of a complete graph- i.e. a group of people where everybody is connected directly to everyone else.

An example of clique is provided in 1.16, in which we can see that each subgraph is a complete network.

Before describing the metrics, we need to recall that ties have different forces, we have ties of different nature (in short, weaker and stronger ties). We need metrics that establish quantitative information, as the number of connections and how these are distributed. It is also of our interest to have some indications about the quality of this relations.

- Density: Is the portion of established connection to the number of possible connection. Algebraically is computed as:

$$\frac{actual\ connection}{potential\ connection}$$

  Its value can change between 0 and 1. Zero if in the whole network there is not a single edge between nodes. One is the full density case, it happens whenever a network has a node for each pair of nodes. Generally, the larger a network is, the easiest will be to find a lower density. This is why many online social network have density 0.1% or less. To illustrate this we can make an example, which shows how straightforward this implication is. Imagining a network composed by 10 people that know each other, thus we have 10 nodes and full density. Suppose a new node is added into the frame, to keep the density at its full value the new entrant must establish a singular connection with each of the separated node. As the number of nodes increases, the number of links required to the entrant follows. As previously mentioned, the density is not sufficient since it does not take

into consideration the strength of the ties that link these nodes. It anyway provides meaningful information.

- clustering coefficient: is the fraction of all possible pairs of friends that are friends with each other. This metric is slightly more complicated and provides an information that can be really important when we want to analyse the position hold by a single individual. When using its average we instead have information about patterns of the whole network. "Evidence suggests that in most real-world networks, and in particular social networks, nodes tend to create tightly knit groups characterised by a relatively high density of ties; this likelihood tends to be greater than the average probability of a tie randomly established between two nodes" (Watts and Strogatz, 1998; Holland and Leinhardt, 1971).

  Following Watts and Strogatz, 1998 we give a measure of the node's clustering coefficient. It is determined as:

  $$C_i = \frac{Number\ of\ triangles\ connected\ to\ node\ i}{Number\ of\ triples\ centered\ around\ node\ i}$$

  In our analysis we used the average clustering coefficient and the global clustering coefficient. The average clustering coefficient is simply the average of the clustering coefficient, it is computed as:

  $$C = \frac{1}{n}\sum_{i=0}^{n} C_i,$$

  The global clustering coefficient is computed as:

  $$\frac{Number\ of\ closed\ triplets}{Number\ of\ connected\ triplets\ of\ vertices}$$

  Instead, the average clustering coefficient is an alternative way to measure how nodes tend to cluster. It is based on the local clustering coefficient of a vertex, that quantifies how close its neighbours are to being a clique. And is computed as the average of the local clustering coefficient. The latter metric differs from the global clustering coefficient since it gives more weight to low degree nodes. Therefore a network with many clique except some will have a lower average clustering coefficient than a global clustering coefficient.

- Average path length: the average number of steps along the shortest paths for all possible pairs of network nodes. The properties based on network topology are quite intuitive and useful. While the path length is the distance (in terms of nodes) between two selected nodes. When we measure the average, we take into account the whole network with all its nodes. When we find a lower average path length we encounter a network that presents better level of efficiency of information.

Another set of metrics is based on the idea that people situated in a communication bottleneck may gain power from this situation. Measure

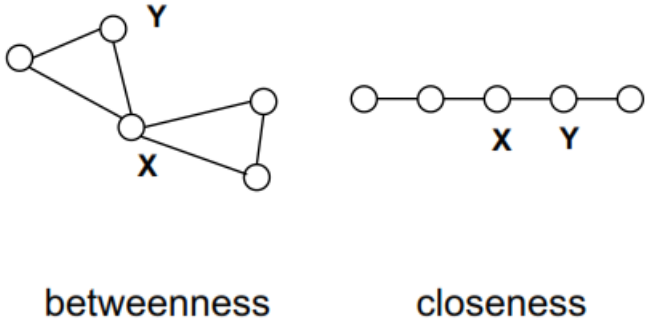

FIGURE 1.17: Betweenness and closeness centrality.

of centrality try to identify the most important vertices in a graph, that are indeed those having a position of privilege in the diffusion of a given information. In figure 1.17 we see two networks, in each of these the node X has higher centrality than Y according to a particular measure.

Measures of centrality utilized in the actual work:

- Betweenness centrality: "It is equal to the number of shortest paths from all vertices to all others that pass through that node[14]". A node with high betweenness centrality has an influential role in the diffusion of information across the network, under the assumption that the information spreads following the shortest path.

- Weighted closeness centrality: In a connected network nodes have a particular distance between each other, defined by the length of their shortest paths. Contucci, 2014 state: "The farness of a node is defined as the sum of its distances from all other nodes and its closeness is defined as the inverse of the farness".

- Eigenvector centrality: "The assumption is that each node's centrality is the sum of the centrality values of the nodes that it is connected to[15]."

Since the eigenvector centrality is less utilized in this work we will concentrate on the other two metrics, and the difference between the first two above cited metrics can be explained as follow. Betweeneess helps to answer the question: how many nodes would the information need to go through in order to reach another node with the minimum number of steps? While closeness emphasize another aspect of the network, what if the perfect position for a node is not the one that is in between many relations, but instead is the one that is closest to the middle of all relations? Usually this first two measures are highly correlated, but it can happen that a node has high closeness and low betweeneess. In this case it means that the node is close to many others but at the same time, the same happens for many other nodes. While the opposite case, instead, high betweeness and low centrality, is a much rare circumstance. It happens for a node that monopolizes all

[14] https://en.wikipedia.org/wiki/Betweenness_centrality
[15] http://demonstrations.wolfram.com/NetworkCentralityUsingEigenvectors/

the ties for a small subsection of the network while being distant from the main aggregation of nodes.

After the introduction of these metrics it is essential to introduce the small-world network of Watts and Strogatz, 1998. This concept is largely used in social network analysis, since it found the properties that real life network have. In sum "a small-world network is a type of mathematical graph in which most nodes are not neighbour of one another, but most nodes can be reached from every other by a small number of hops or steps.[16]". This concept is explained in different ways and the conventional wisdom goes as follow: in the real world there are maximum 6 degrees of separation between any two nodes. This means that whoever in this world can reach another randomly unknown person with a friend-of-friend chain of maximum six people. This idea is still a myth, but it shows off an important characteristic of real world societies. Communities are characterized by the formation of strict sub-groups, and the possibility to reach any other sub-group following the right connections. Therefore each member of the group will have many friends that are connected to each other, while it is possible to contact a member of another group following the shortest friend-of-friend chain. The small world network can be defined as the one that has lower average distance between nodes, but higher clustering. We believe the word of mouth must be based on a network displaying small world properties. Whereas the electronic world of mouth must be based on a network with different features.

1.0.7 The dynamics of seller reputation

An interesting paper of Cabral and Hortacsu, 2010 examines the dynamics of sellers' reputation on buyers and on sellers' behaviour. We are mainly interested in the buyers' reaction to different sellers' reputation. This work is framed on a wider field named economic of trust and reputation. Discipline that sees the author of this paper, Luis Cabral, as one of the major exponent. The main line is whether or not consumers are interested in the reputation of the seller and, this process is particularly relevant in any online context. It is important to stress that this work and its findings are based on real world evidence, derived using econometric techniques on a panel data of transactions occurred on Ebay. This leads to a major concern, the negative feedbacks do not only occur due to differences between expectation and perception of the product, but they often happen for a lack of the shipping service and for other problems that can happen while buying on an online website. We will not take into consideration the reason that led this negative feedbacks, since we are mainly interested in the impact that this negative and positive feedback have on different sellers. Therefore, while conducting this analysis, we move our interest on the seller's reputation and not only on the good reputation. As real world evidence from the impact of different scandals showed us, a product is inevitably correlated to its manufacturer. We can just take into consideration the drop of sells following the Nike shoe plant scandal of the 1997 and the corresponding high expenditure in promoting its reputation in 1998.

In table 1.2 we see the impact of the first three negative feedbacks on the average weekly growth rate. As shown in the table, the first negative

[16] https://en.wikipedia.org/wiki/Small-world_network

TABLE III
IMPACT OF NEGATIVES ON SALES GROWTH (%)

Avg. Week.		Object			
	Growth R.	Thinkpad	Eagle	Silver	Teddy
First Negat.	Before	5.17	6.88	5.07	12.06
	After	− 7.56	− 4.67	− 8.25	− 5.28
	Difference	− 12.74 ***	− 11.56 ***	− 13.32 ***	− 17.34 ***
	Std. Error	4.89	3.56	3.44	3.69
	N	66	95	130	136
Second Negat.	Before	2.57	− 1.67	3.41	6.41
	After	9.53	9.00	7.61	7.51
	Difference	+ 6.96	+ 10.67 ***	+ 4.20	+ 1.10
	Std. Error	5.03	4.82	5.96	6.12
	N	37	70	78	83
Third Negat.	Before	8.14	2.75	2.81	1.00
	After	4.91	− 2.53	2.13	9.70
	Difference	− 3.23	− 5.28	− 0.68	+ 8.70
	Std. Error	6.14	7.47	3.21	6.22
	N	28	52	57	64

Notes:
1. Standard errors in parentheses. Significance levels 10, 5, 1 per cent (one to three stars).
2. Weekly detrended growth rates are based on the number of sales-related feedbacks received by the seller.
3. Growth rate in week t = ln(no. feedbacks in week t) − ln(no. feedbacks in week $t - 1$).
4. Weekly growth rates are averaged over 4 week periods taken before and after the reception of a negative.

TABLE 1.2: Impact of negative feedbacks on sales.

feedback leads from a positive growth rate to a negative one. The difference is statistically significant in statistical terms. Whereas the second and third difference, even if are not of the expected sign are not troublesome since are not statistically significant therefore are not to take into account.

The possibility that the negative average growth rate was not caused by the first negative has meticulously been controlled. The result is that even though the exact difference may be different, the arrival of a negative feedback is inevitably correlated with some negative effect in the sale growth rate. Another important section of this research lies in the empirical result obtained studying the behaviour that proceed the exit from the market. As figure 1.18 shows, an increase in the positive feedback reduces the likelihood of the actor to leave the market. In this analysis an increase from 3 positives to 55 positives reduces the exit probability of about 40% shows that the probability of leaving the market. As already mentioned these effects occur because consumers prefer to purchase products considered more trustworthy. For the same reason, firms could see a reduction in their market share if their products receive negative reviews. The above mentioned study is really interesting in terms of methodology applied. The same set of experiments could be developed to study how goods modify the reputation of the firm after being introduced into the market. We believe that by using big amounts of data, firms could deepen their understanding of what led them to generate different results. This being done, a firm can opt for those decisions that led to greater results even though it is not visible in the short term.

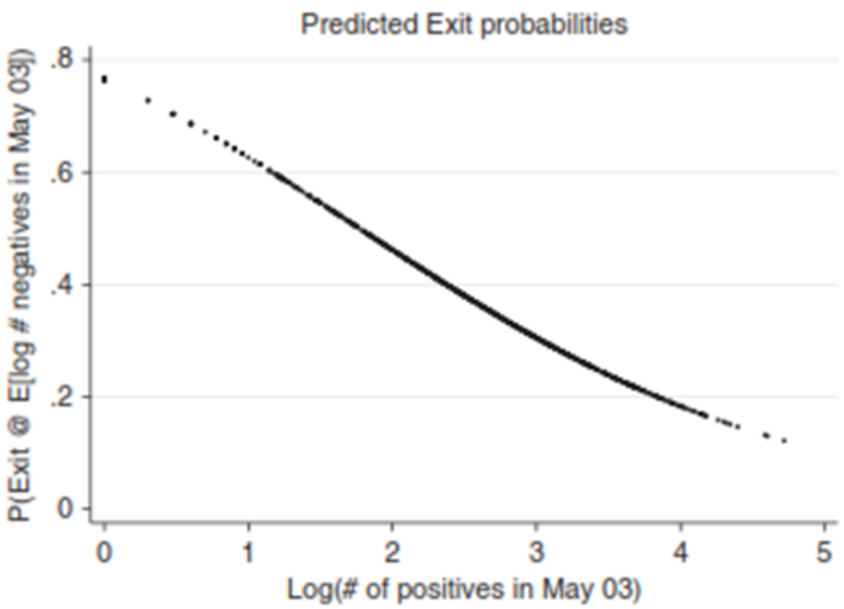

FIGURE 1.18: Positive feedback and exit.

1.0.8 The importance of big data

The importance and relevance of big data for the actual work is of indisputable evidence. It is intrinsic in the way we analyse consumers and their relationship that we expect future developments made with real market generated data. First of all we need to define the concept of big data as it is understood in the scientific sector. One of the most famous definition of big data is the one proposed by the Gartner group[17]:

> Big data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation.

Another interesting definition is proposed instead by Snijders, Matzat, and Reips, 2012:

> Big Data is a loosely defined term used to describe data sets so large and complex that they become awkward to work with using standard statistical software.

What lead us to speak about big data? The discussion starts with the understanding of the simulation itself. We generates heterogeneous consumers, in terms of preferences, that possess unique desired characteristics in the goods they are looking for. We let this preferences originate randomly in a bounded interval, reproducing how consumer characteristics are usually shaped in real life. A firm that is able to improve its customers preferences by extrapolating real data (for example as Amazon does), is surely

[17]Gartner, Inc. is a research and advisory firm providing information technology related insight headquartered in Stamford, Connecticut, United States. `https://en.wikipedia.org/wiki/Gartner`

bound to create a better target market. At the same time, knowing its segment, the firm can develop a product tailed to generate higher client satisfaction. This process could represent a possible and entangling evolution in the way firms approach the market. In real world, the unfolding of events shows us that firms - at least those able to - are gathering bigger amounts of data containing relevant and non-relevant information. The crucial point becomes the analysis of this enormous amount of data. Approaching big data is considered an evolution of the classical data analysis, were the two present from three to five major differences, namely: volume, variety and velocity,machine learning and digital footprint. Volume, is of course, a by-product of the new high-tech levels that our society has reached, when we use our smartphone and we check which restaurants is closer to our position, then we extend the research to our favourite type of cuisine, all these steps are just adding new data about our personality and tastes. The second difference is in the variety, and this change is due to the previous impossibility of adding so many different information about each single person. The last development is in the velocity. Thanks to modern levels of technology, both the small devices in our possession and the big servers owned by corporations, are able to process bigger amounts of data in a faster way, which previously was inconceivable. The importance of this aspect is clear when we think of websites that help us in finding the product of our interest. Even if we just started to look at the category, the company possess particular algorithms that improve fast what we are looking for and guide us in our process of information. By machine learning is intended the gathering and analysis of data by computers. Therefore, computer analysis of data differs from the human analysis because machines do not investigate reasons, they only chase trends. The last important aspect is the digital footprint, where this term indicates the big amount of data that we leave for free each time we make a digital interaction. We really believe that the ongoing processing of those information is changing our day by day behaviour and, considering how technology is evolving, we truly foresee a future in which companies will improve how to make the most economic advantages from this analysis. The debate about how firms should behave is already open, we want to cite the interesting point of view of McAfee et al., 2012, that state

> Businesses are collecting more data than they know what to do with. To turn all this information into competitive gold, they'll need new skills and a new management style.

and continues

> Simply put, because of big data, managers can measure, and hence know, radically more about their businesses, and directly translate that knowledge into improved decision making and performance.

In the work of McAfee et al., 2012 they speak of a work they led at the MIT Center for digital business, in which they investigate the relationship between data driven decisions and performances. Results were strongly in favour of those firms already developing decisions based on real data, and the higher performance was measured both in terms of productivity and profitability.

Another important point in the discussion, in which all the literature seems to agree, is that we still need a good share of human wisdom in order to extract real valuable information from all these big data. Software are not able to analyse underlays of combined events and make accurate evaluation of the interrelation between variables. In fact, if the analysis shifts to sociological aspects, it is even more important the human role in the analysis. The point is that not all data are equivalent and the selection of the variables of interest must be carefully made by humans. We want to conclude with one of the six provocations of big data presented in the work of Crawford et al., 2011 that state:

> Just because it is accessible doesn't make it ethical.

The author, along with a huge segment of the population, stands by the side of the community that sees its information being gathered and used for commercial purposes. Often this process is at the borderline of the legality, but more often researchers exploited the lack of legislation on the matter. This strong ethical debate cannot be unheeded easily and consumers' privacy must be always protected from the interest of private corporations. In fact, our position is that there is a good amount of ethical data available that is able to increase both the profits of the firms and consumers experience that the unethical data could be left untouched.

Chapter 2

Development of the model

2.0.1 First Version of the Agent-Based Model

Netlogo is an agent-based programming language that offers the programmer the possibility to set up all the structure in which the agents will interact; in order to achieve this result it is necessary to think accurately about the code design. The purpose of the initial version of the program is to establish the basic framework of the model, that is shaping the behaviour of agents in a competitive market. The starting point is generating the agents, the products and then establishing the principal interaction between them. The virtual world is populated by two breeds of agents: consumers and goods. The first thought has been that of creating only consumers as a unique breed of agents. Though the final decision of treating goods as agents as well, and not as lists, comes from the need of providing them with essential features that enable a more realistic representation of the market and basically allow the code to be less chaotic and better understandable. The set-up button includes the creation of these two categories of agents, the user then is able to choose their number just by using the slider positioned on the interface of the program. This possibility derives from the need of making different experiments in which the initial quantity of potential buyers and products may be an interesting variable. In the process of creating consumers, by the use of the "ask" command it is possible to diffuse consumers in the world and endow them with some important traits, among which the possibility of buying products, initially set as the opportunity of buying one product only. A similar command then spreads the goods, sets their colour (white), names a variable "purchased" and sets its value to zero. This last trait has the role of identifying when a product is no longer available because another agent has already decided to acquire it.

The following code represents the set-up structure just mentioned above:

```
to setup
clear-all
reset-ticks
creationOfConsumers
CreationOfGoods
ask consumers [ setxy random-xcor random-ycor
set color red set availability 1]
ask goods [ setxy random-xcor random-ycor
set color white set purchased 0]
defineAttributesAndPreferences
end
```

The last step of the set-up is giving a numerical value in a range from one to five to the attributes of the goods, which constitutes a quality index, and to the preferences of the potential buyers, which represents the level of the minimum required quality. This implementation casts the foundation for a momentous change from many other marketing models. We posit a model where consumers and goods are heterogeneous. Consumers differ in their preferences while goods exhibit varied attributes. Assessing the behaviour of heterogeneous consumers overcome an important hurdle of many theories buttressed on models focused on identical customers, therefore lacking of an autonomous decision-making process. To follow a part of the code representing the creation of heterogeneous attributes and preferences.

```
to defineAttributesAndPreferences
ask consumers
[set preferences n-values characteristicN [random-float 5 ]]
ask goods
[set attributes n-values characteristicN [random-float 5 ]]
end
```

After the creation of the world and the agents, the purpose of the simulator is to reproduce how consumers act in a trading process, matching the desire of the potential buyers with the characteristics of the goods. In the world there are plenty of goods, so constraints of the real society, such as the inability to grasp any available information, prevent consumers to evaluate all the deals; to include this feature each agent has been set to see only products that are close to him. As in the actual business system, that is crowded with different goods and diverse consumers' tastes, the ABM simulates the market as the system in which the potential customers' desires meet the characteristics of the goods and the first decides whether to buy or not the latter. As mentioned above this matching process is based on the comparison between products quality level and the standards required by the potential buyer. It is possible to see how the first procedure named *tryToBuy* calls another one named *compare*. This procedure uses two variable g and p that stand respectively for products attributes and consumer's features. Its aim is to provide the exact number of characteristics able to overcome the desires of the consumer. A final control of this procedure can at this point be done. Each consumer in fact is tolerant to a threshold level which is defined by the user through a slider on the interface, this means that to buy a product is not necessary for all the characteristics of the good to meet the required quality, but is enough that a sufficient number of them does. To follow the tryToBuy and compare structures.

```
to tryToBuy
while [possibility > 0 and any? goods in-radius 10]
[let tempGood one-of goods in-radius 10
let tempAttributes [attributes] of tempGood
let matchingCharacteristics
compare tempAttributes preferences
if  matchingCharacteristics >= acceptationThreshold
[set possibility possibility - 1
ask tempGood [die]]]
```

```
end

to-report compare [g p]
let aN 0
let i 0
while [i < characteristicN]
[if item i g >= item i p [set aN aN + 1]
set i i + 1]
report aN
end
```

To better explain this concept, if in the real life a person has to buy a good that is endowed, in the example provided, of four characteristics such as taste, texture, ingredients and packaging, it could be sufficient for the buyer that the good presents at least two of the just mentioned characteristics for purchasing it. The fact that each feature of the product has the same importance as the others is a limit of the code, but this will be overcome in successive versions by weighting each characteristic of the good.

2.0.2 Second Version of the Agent-Based Model

During the creation of the first version of the program emerged the need to extend and enlarge the basic framework previously devised. The aim of the simulation is to understand the marketing dynamics and to construct a model of the real world, or precisely a model of the market, therefore many improvements are still required. To better understand the path that will be followed, a brief digression into the concept of market is required. As Browning, 1983 state:

> Markets [...] refer to the interplay of all potential buyers and sellers involved in the production, sale, or purchase of a particular commodity or service.

Nowadays the sale-purchase process is being studied at a deep level. This fact implies the existence of a tremendous quantity of data to take into account, therefore the virtual set of interaction representing the market should emphasize some of the key aspects that subsequently are going to be studied. It is essential to focus on a limited amount of objects that are worthy of attention. Another aspect of this citation deserving an explanation is the use of the word interplay with its broad sense. Literally, it means action and reaction, therefore interaction among agents. This aspect is one of the main reasons that makes the market a complex phenomenon and makes it hard for researchers and economists dealing with it. In the first version of the model the interplay was created between consumers and goods, but it was not enough for a sufficient representation of the market. Therefore one main step has been achieved, which is the involvement in the simulation of firms and shops. Firms create products, endow them with the attributes needed and then spread these goods all around the world. Goods may be

located in a specific shop or they can just be scattered around, this decision represents the will of including the E-commerce[1] into the model. This creation process is coded as follows:

```
to creationOfGoods

ask firms [
let goodAttributes definingAttributes
hatch-goods (NumberOfGoods / 2)
[set size 1 set color white set shape "box"
set attributes Goodattributes
set brand [firmBrand] of myself
ifelse random-float 1 > 0.3
[move-to shop brand]
[ setxy random-xcor random-ycor ]]
set producedProducts  producedProducts + (NumberOfGoods / 2)]
end
```

Since reality is divided into offline and online trading, the model too includes both these possibilities. That of buying in shops and that of choosing goods disperse in the space. In fact just like the virtual reality allows us to shop whenever and wherever we want, our consumers are able to purchase when close enough to one of the two stores or when they are close to some of the disperse goods.

The further development of the simulation has been extended also to goods. Starting with the creation of two types of goods, that are distributed in different stores. This initial phase of diversification of the products, with continuous implementation, is going to re-create the frame needed, in order to study the competition among companies. The necessity of rivalry, intrinsically included in the use of the word competition, can be achieved by studying the evolution of a single product in the market or by contrasting two or more products. To achieve this goal a further diversification of products has been implemented. The attributes of the products are not anymore a string of random values. The user, indeed, is able to choose three out of five numeric attributes, which are represented by the variables x,y, and z in the interface of Netlogo. Albeit the user is able to choose the values, they will not be the exact values used by the simulation. In fact these inputs will be randomly modified in a range of one unit, therefore they can be increased or decreased of 0.5 maximum. The reason behind this random modification lies in the necessity of having differentiated products and also because the reality often proves the impossibility of possessing absolute control over the decision process, this is why we often prefer to include some degree of uncertainty embedded in the formation of random shocks. The necessity of having this stochastic effect on one or more inputs, in some circumstances can lead to a misleading by-product. When the user opts for small amounts of one or more inputs, the design of the code could change some of the x,y and z signs, and this hypothesis should be prevented. The first and second attributes need to be always negative or maximum zero,

[1]Electronic commerce, commonly known as E-commerce or e-Commerce, is a type of industry where the buying and selling of products or services is conducted over electronic systems such as the Internet and other computer networks.

and the third should be nonnegative. In order to guarantee the sign of the first 3 values of the attributes list a further control has been made. The first and second inputs will be set equal to zero if the random choice of the program will lead to an higher value and therefore positive sign, whereas the third value will be set equal to zero if the random choice will be negative. The implementation of this procedure is coded as follows.

```
to-report definingAttributes
let goodAttributes  n-values characteristicN
[((random-float (10)) - 5)]
set goodAttributes replace-item 0 goodAttributes
(x - 0.5 + random-float 1)
set goodAttributes replace-item 1 goodAttributes
(y - 0.5 + random-float 1)
set goodAttributes replace-item 2 goodAttributes
(z - 0.5 + random-float 1)
if item 0 goodAttributes > 0
[set goodAttributes replace-item 0 goodAttributes  0]
if item 1 goodAttributes > 0
[set goodAttributes replace-item 1 goodAttributes  0]
if item 2 goodAttributes < 0
[set goodAttributes replace-item 2 goodAttributes  0]
report goodAttributes
end
```

One of the main roles of the company in this simulation is the accumulation of information extrapolated from the market, but in this version of the model the companies are just born and this they are endowed with little ability. Firms effectively understand when a product was unsold and is still available in the market, therefore they try to increase the attractiveness of the latter by improving some characteristics. This cycle increases the first and third value of the unsold products' attributes:

```
if remainder ticks 10 = 0
[ ask goods
[ set timeInTheMarket timeInTheMarket + 1 ]
creationOfGoods ]
(...)
ask goods with [timeInTheMarket != 0]
[ let i 0
while [i < 3]
[ ifelse i != 2
[ let momentary item i attributes
set attributes replace-item i attributes
(momentary + random-float 0.5)
set i i + 1]
[set i i + 1]]
if timeInTheMarket = 5 [set GoodsWasted GoodsWasted + 1
die]]
```

An easy example of the above mentioned idea can be the decision of decreasing the price of the unsold product and/or increasing the product

visibility. The second variable is consciously being unaffected because is not possible to subsequently modify the pollution made in the production phase. The role of the shops will evolve in the future since presently it is limited to a local space, where products are available without any organizational criterion.

The model is starting to overcome an important limit of its first version. As previously explained the attributes of each good represents something in real life, therefore our attributes are: price, estimated pollution level, weight, colour, rate of alleged quality and so on. The attributes need to own a broader meaning and starting by setting them with specific values will lead to non-random behaviour in the creation of the goods. This idea can be seen as the pricing process decision of a firm or, taking into account all the frames, in the design and making process.

All the simulation is working within a timing path. Products are not anymore generated at each time step but at every ten ticks. This means that in an environment equipped with a fixed number of products consumers have ten units of time before firms decide to produce more and then spread new goods. This path better meets the reality where products are in continuous evolution but with some time lapse. Future developments will consider more variables before firms start to produce new goods. The last step of this command is evaluating unsold goods. When their variable *timeInTheMarket* is equal to 5 they will disappear from the market (since products are agents the command used to make them disappear is "Die") and as a consequence a specific variable named *goodsWasted* will increase. This variable works as a counter for the whole market, holding important information for the firms. In fact when *goodsWasted* increases it unveils different possibilities, such as (i) the population of the market is not enough to satisfy the supply of goods, (ii) the products presently available are not matching the desires and/or the economic possibility of the target. It is important to specify that *timeInTheMarket* increases of one unit each ten time ticks. The codification implies goods will "Die" when their variable *timeInTheMarket* is equal to 5 ; therefore goods start to disappearing from the fiftieth tick. This trick is made to soften the calculation that the software has to do at each step, in fact by doing so we are able to provide the same outcome but decreasing the amount of variable changing in each tick.

The last difference that is placed into the program and visible into the interface regards the consumers view radius. Consumers are able to see only a circumscribed number of products, and this delimitation represents the inability of each person to know all the products in the market. In this simulation agents are endowed with a tool that may represent the sense of sight or, with a broader meaning, the ability to know what surrounds them. This ability can be enlarged or decreased by the user, through the employment of a slider. In real life searching and keeping information from the market relies on an enormous sphere of variables. For this reason only the most influential variable will be considered, for example the will and skills of each individual to grasp information about the products. Another important variable that can not be forgotten is the luckiness bias, because it influences all decisions. In order to achieve reliable results we need to take into consideration how uncertainty affects each singular force. We deal with this problem implementing in many ways the possibility of deviation from an alleged standard behaviour. The code is able to represent

random choices and we include this possibility in many steps. This is really important, because many endeavours in marketing lie their chance of success upon nonrational behaviour[2]. In any case including the possibility that some agents may have more information even because of accidental reasons and including more complexities due to uncertainty in the decision process is not going to influence the outcome of the research. A further challenge will concerns the creation of a more affordable use of the sight ability.

2.0.3 Third version of the Agent-Based Model

The communication between agents, an essential and complex trait, reaches its first development in this version of the model. This step includes a pillar of the code, i.e. how we decide to store information about series of events affecting the agents. There are different ways to save data using an ABMs, and in particular NetLogo. Since our virtual world is populated by a *variable* number of consumers and goods, both continuously changing, the need of a mutable and flexible tool became compulsory. This tool should be capable of becoming real when needed and it should also be able to store and provide the information accumulated, then vanish when is not useful anymore. Although the variety of ways provided by the program, there is not a tool focused on solving this strong necessity. Therefore we decided to use the links, in that they suit well our cause. According to the dictionary of NetLogo:

> A link is an agent that connects two turtles. These turtles are sometimes also called nodes.

Given their nature of agents, links are able to store as many information as requested. And given their role of connectors they intrinsically own the identification numbers of the nodes, that are in particular the consumer and the good. To better explain how their memory works we can have a look at Figure 7.1.

At the top of the figure, in bold type, we find the name of the agent, that in this case is Brand-links 4 2. This is a defined breed of link, made to store information about a particular brand of a defined product. As we can see from the first two rows the chart, the link connects the consumer with the id number four (end 1) and with the good number two (end 2). This connection, thanks to the property of the links, is endowed by standard information. All information are included in the chart, for example colour, label, shape and so on. Whereas brand, radius and *influenceAccumulated* are extra variables that we added using the following instruction:

```
links-own [brandL radius influenceAccumulated ]
```

Indeed, by including new variables we can fulfil the necessity of storing as many information as we desire. In this version each consumer is affected by advertising. To make this happen we created the advertiser, a known position that makes the communication. He is able to influence the consumers

[2]The decision about whether to base marketing communication on rational logic or emotional appeal is at the centre of a perennial debate within the marketing community. http://www.orwig.net/articles/rational_emotl/rational_emotl.html

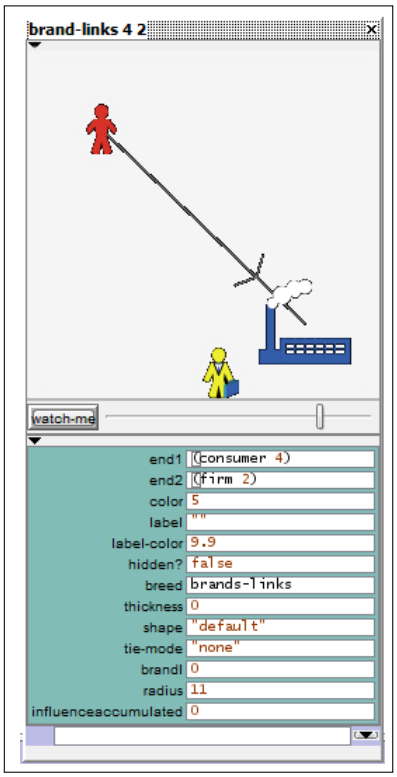

FIGURE 2.1: Representation of the link and its monitor.

when close enough. Consumers understand which is the advertised brand and modify their preferences. Then they modify their ability to "see" that particular good. As in the real world people are not able of knowing all the existing goods, in this simulation we use the distance between a consumer and a good as a informational tool. Advertisers inform consumers about the existence of the advertised product. They can also increase the consumers' space view, this relies on the possibility of a person to be conscious or not about the existence of a product. In future developments of the model advertisers will affect more variables, e.g. the possibility to modify the desire of buying the product, either positively or negatively.

Below it is possible to observe an important command of the simulation, from which we can have some insight regarding the purchasing phase.

```
to tryToBuy
ask consumers with [cash > 0]
[let ConsumptionT 0
let brandControl 0
let radiusP 0

if any? out-link-neighbors[
ask item 0 FavouriteBrAd
[set brandControl brandL set radiusP radius]
set ConsumptionT absoluteIncomeHyp
if any? goods with [brand = brandControl]
in-radius (radiusP) and (consumptionT > 0.5)
[set goodsUnderChoice goods
```

```
with [brand = brandControl] in-radius radiusP
creationOfGoodsListAndThresholdControl]
if any? goods in-radius (Viewradius) and cash > 0
[set goodsUnderChoice goods in-radius ViewRadius
creationOfGoodsListAndThresholdControl]]
]
end
```

In the first step of the command we establish the local variables, then we set them equal to zero and by doing so each consumer will subsequently modify his values according to his own necessities. At this point consumers begin the decision process. In order to proceed with the purchasing process consumers are required to know at least one product, i.e. they should have at least one active link, otherwise they will not perform any purchase at all. As above-mentioned, the possibility that a consumer is aware of a product depends on the realization of the communication process that should be made by the advertiser. If this condition is satisfied, consumers proceed in the calculation of their propensity to buy, taking into account the influence accumulated by the most advertised brand. If consumers are able to see the most advertised brand and their propensity to buy is high enough (higher than 0.5 over 1), they proceed with the control of the threshold level of the most advertised good. In the following procedure we can see how the code creates the variable *FavouriteBrAd*. The first step is creating a list of all the brand links owned by consumers. These links in turn are endowed of information about the goods, at this point the crucial variable of interest becomes the level of advertising to which consumers have been affected with regard to each good. In this way consumers are able to recall which good is the best advertised one and the creation of the list continues sorting all the other goods which are organized in decreasing order. The variable that allows this control is named *InfluenceAccumulated*.

```
to CreationOfPreferitBrandAd
ask consumers with [any? my-out-Brands-links]
[let linksConsumer my-out-Brands-links
set FavouriteBrAd sort-by [[influenceAccumulated]
of ?1 > [InfluenceAccumulated] of ?2] linksConsumer
ifelse [end2] of item 0 FavouriteBrAd = firm 2
[ set color blue]
[set  color red]]
end
```

The closing part of the command sets the colour of the consumers according to their favourite brand. By doing so we can have a glance to consumers advertising preferences.

If the just mentioned advertised good is able to overcome the threshold level the consumers will purchases it and by doing so they will not be able to purchase any other product, because of the budget constraint. Consumers will never know if another good was able to satisfy them more. On the other hand consumers that are not able to see the most advertised product (because it is too distant) will proceed with the second phase. They will

create a list of the goods around them and purchase the one which best match their requirements.

Nonetheless the *tryToBuy* procedure includes another important piece of code. As we can see in the following extract of the code:

```
to creationOfGoodsListAndThresholdControl
let a 0
ask goodsUnderchoice
[set NofCharacteristicsOvercome
compare attributes [preferences] of myself]
set goodsUnderChoiceSorted
sort-on [(- NofCharacteristicsOvercome)]
goodsUnderchoice
set tempBestGood item 0 goodsUnderChoiceSorted
set a totalGoodsSOld
ask tempBestGood
[if NofCharacteristicsOvercome >= acceptationThreshold
[set a totalGoodsSold
set totalGoodsSold totalGoodsSold + 1
ask firms with[ firmBrand = [brand] of myself]
[ set soldProduct soldProduct + 1] die]]
if a != totalGoodsSold
[set cash cash - 1 set NproductPurchased NproductPurchased + 1]
end
```

The code can be divided in two main segments. The first segment has already been explained when dealing with the first version of the program. In this procedure however this first segment has been enlarged and enriched with important changes. On the basis of these developments each consumer entering in this procedure is asked to create a list of goods sorted in descending order according to attributes able to overcome the consumer's desires. This list will be one of the fulcra of the model. By turning the idea behind the code into reality we created the wish-list of each consumer. This wish-list includes only "visible" goods, and gives us the possibility to be compared with the complete wish-list made in a market where consumers have access to complete information. A further improvement is due to the fact that the list we created is a list of goods and at the same time a list of agents. This helps us in making the comparison between lists, because it allows us to use a useful tool, which is the momentous ask command. This tool is immediately utilized to check whether one or more products are effectively above the acceptance threshold level. If so the consumer purchases as much products as possible considering his budget constraint. When a product is sold the firm selling the good stores the information while the consumer utilizes a unit of money and stores the information about occurred purchase.

Another procedure called by the *tryToBuy* is the *AbsoluteIncomeHyp*, which we can see in the code below.

```
to absoluteIncomeHyp
set MarPropConsum influenceP / 5
set ConsT MarPropConsum * cash
end
```

The title of this procedure derives from the absolute income hypothesis theory of consumption proposed by the well-known English economist John Maynard Keynes. The model is the following:

$$C_t = \lambda Y_t \tag{2.1}$$

where:

- C_t is consumption at time t.
- λ is the marginal propensity to consume $(0 < \lambda < 1)$
- Y_t is income at time t.

Consumers in the simulation must be able to spread their income over time. With this procedure they start to estimate when it is worthy or not to use their money. Not only considering whether they accept the features of the products, but adding into the general frame the evaluation of other variables. For example, some agents are more inclined to save money than others. The Marginal propensity to consume can be a useful tool. It will be developed in the future version in the much endogenous way possible. This variable will be able to summarize different aspects of the consumers.

The last implementation concerns consumers' preferences and the features of the goods. Previously these where only positive values. But in the real world some characteristics can be considered negative by consumers, e.g. a higher price usually affects negatively the consumption of a given product, except within the luxury environment. The same occurs when a brand has a bad reputation which is capable of decreasing sales. For this reason we decided to include this aspect in our simulation, setting up two negative characteristics.

To conclude we can consider Radas, 2005:

> [...] Everyday experience teaches us that markets are never constant for long stretches of time. Different levels of competitive activity, changes in advertising level and changes in price elasticity, among other factors, all have a significant impact on diffusion and its parameters. Allowing parameters to vary with time would permit diffusion models to better match real data.

An agent-based model allows the programmer to decide if he/she wants the parameters to rely upon mutating data or not. By connecting these parameters to the changing environment we are able to build our evolving market. In this third version the consumer is still unable to provide feedback related to a brand and has little information about the total environment. The basic communication framework and the role of the advertiser are going to be extended. Continuous progresses in market trends cause in all the agents the need to better improve their previous activity, in order to satisfy their evolving goals. Future developments regarding this matter are going to be implemented later on.

2.0.4 Fourth version of the Agent-Based Model

The implementation of the basic structure required refinements, to some extent, and plenty of new procedures to enlarge the set of forces affecting

consumers. In order to achieve an acceptable representation of the market, we need to include some important aspects in the set of real life interactions. Each person, voluntarily or not, is forced to receive influences by the environment. For this reason, we decided to include various types of interactions between agents. The explanation will begin from one of the most important types, that is the word of mouth effect. As already pointed out, consumers are possibly divided into two groups, i.e. innovators and imitators. The first kind constitute the original niche that tries the new product. When the experience is positive they will spontaneously spread information to other people, either voluntarily or by side effect. When the communication is direct, therefore achieved by a spontaneous decision, it will constitute the word of mouth effect. Examples of the latter are: private talking between people and suggestions given by the employee without any form of personal interest. The word of mouth effect can be done even through the feedback system implemented by websites companies providing reviews. In this particular case and when consumers share in various way information via internet, we speak of electronic word of mouth (eWoM). It is worth understanding also the paid version of this process that is explained as:

> When the sender of word-of-mouth communication is rewarded than this process is referred to as word-of-mouth marketing, which relies on the added credibility of person-to-person communication. [3]

The simulation already includes some of the above mentioned types of advertising. With the following procedure we begin the communication of the best advertised good.

```
to wordOfMouthEffect

CreationOfPreferitBrandAd

ask consumers with
[any? consumers in-radius viewRadius with
[[who] of myself != who and FavouriteBrAd != []]]
[ let i 0 let ListClose []
let c consumers in-radius viewRadius with
[[who] of myself != who and FavouriteBrAd != []]
ask c [set ListClose lput self ListClose]
let temporaryGoodCons2End2 0
let temporaryGoodCons2Influence 0
let temporaryGoodCons2Brand 0
while [ListClose != []]
[ask first listClose [
set temporaryGoodCons2End2 [end2] of item 0 FavouriteBrAd
set temporaryGoodCons2Influence [InfluenceAccumulated]
of item 0 FavouriteBrAd
set temporaryGoodCons2Brand [brandL] of
item 0 FavouriteBrAd]
ifelse FavouriteBrad != []
[ifelse
```

[3] http://www.entrepreneur.com/encyclopedia/word-of-mouth-advertising

```
[end2] of item 0 FavouriteBrAd = temporaryGoodCons2End2
[ask my-links with [end2 = temporaryGoodCons2End2]
[set influenceAccumulated influenceAccumulated
+ temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1]]
[while [i < length FavouriteBrAd]
[ ifelse [end2] of item i FavouriteBrAd
= temporaryGoodCons2End2
[ask my-links with [end2 = temporaryGoodCons2End2]
[set influenceAccumulated influenceAccumulated
+ temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1
set i 100]]
[set i i + 1]]
if i = length FavouriteBrAD [ifelse
[influenceAccumulated] of item 0 FavouriteBrAD
< temporaryGoodCons2Influence
[ if InformationAsymmetry <= random-float 0.99
[create-brand-links-to temporaryGoodCons2end2
[set brandL temporaryGoodCons2Brand
set radius viewRadius + 1
set influenceAccumulated influenceAccumulated
+ temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1
set hidden? not show-brand-links ]]]
[if InformationAsymmetry <= random-float 0.99
[create-brand-links-to temporaryGoodCons2end2
[set brandL temporaryGoodCons2Brand
set radius viewRadius + 1
set influenceAccumulated influenceAccumulated
+ temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1
set hidden? not show-brand-links]]]]]]
[if InformationAsymmetry <= random-float 0.99
[create-brand-links-to temporaryGoodCons2end2
[set brandL temporaryGoodCons2Brand
set radius viewRadius + 1
set influenceAccumulated temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1
set hidden? not show-brand-links ]]]
set ListClose but-first listclose]]

CreationOfPreferitBrandAd

end
```

The first step of the procedure is to recall the already known CreationOf-PreferitBrandAd in order to have updated data about which good is the one preferred by the consumer. We should highlight that here we are considering the favourite brand in terms of advertising experienced. While the best

good is the one that has more characteristic above the consumer needs, the nomenclature preferred good is here used to indicate the advertising process affecting the will of purchasing a given product even before a closer inspection of the product characteristics. Before the procedure starts, the list is made considering the direct influence undergone by the consumer from the advertiser. Whereas at the end of the procedure the list is made again, but this time it will include the opinion of other closer consumers - in terms of distance - trying to share their opinion to the one developing his knowledge. The design of the code demands that the consumer should ask others what they think about goods. Nonetheless the direction of the communication in the real world does not work always in this way. In fact the information that we possess reaches us in several ways, both voluntarily or involuntarily. Sometimes it is possible that we listen to strangers speaking about a good, or that we ask to a friend about his/her experience before purchasing a product that he/she already possess but it is also possible that said friend shares his/her ideas without any direct demand. We often find ourselves involved in a conversation about a particular brand just because the interlocutor wants to talk about his/her own experience. In each of the above mentioned cases we end up always with the same outcome, i.e. an individual increasing his thoughts about a brand. So the code is written to allow this outcome independent of the direction or motivation of the communication. Before entering in the core of the procedure, the actual consumer is asked to create a list of the closest people in his sight range, this list contains all the agents able to influence our consumer. Each of them, once at the time will set some local variables with its own features, paving the way to the process of comparison between information of the actual consumer and information of the others. Indeed each agent, once at the time, will be compared with the actual agent. The actual agent can face several different paths depending on his own knowledge. The procedures hits its first juncture depending on whether the agent knows any product or not, i.e. *ifelse FavouriteBrAd != []*. Recalling the Netlogo dictionary:

> Ifelse reporter [commands1] [commands2] Reporter must report a boolean (true or false) value. If reporter reports true, runs commands1. If reporter reports false, runs commands2.

Therefore when the consumer has the list *FavouriteBrAd* - that is the abbreviation of favourite brand advertised - it means that consumers informed of the existence of at least one brand will run the command1. Whereas command2 will be executed. Command1, in turn, is divided in order to include the different options that can occur while the two different agents are confronting their knowledge:

- Do they have the same favourite brand?
- Do they have different favourite brand? Does the other know the one I want to advertise?

The first case is simple, the logical conclusion is that the two are going to enforce their opinion about the good that both deem as the better advertised. The second case discloses more options. Such as:

- The other consumer does not prefer the same brand as mine, but at least he/she is informed about his existence.

- The other consumer does not know my brand at all.

As before, in the first case the consumer is going to increase the idea about the good that his friend suggests, whether or not it will become his favorite depends solely on his experienced influence. The second case leads again to another juncture:

- The consumer does not know the other brand but the influence about his own brand his higher than the other one.
- The consumer does not know the other brand and the influence about his own brand his lower than the other brand. Therefore he/she will prefer the suggested one.

In both latter cases the consumer will be informed about the existence of the other good whereas $InformationAsymmetry <= random - float0.99$. This means that the consumer wants to know the good, but it depends on the likelihood that that market has in letting information easily accessible to all its members. This concept will be examined afterwards. However we still need to understand when command2 is executed. If the reported reports false it means that the actual agent has an empty list *FavouriteBrAd*, and does not know any product at all. This lead to the simpler case in which the actual agent will grasp the information about the favourite advertised brand of his/her influencer. The only difference in this case is: when creating the new connection with the unknown brand the actual agent needs to store the variables that, when lacking, prevent him to see the good. Thereafter he/she has all the means to purchase the good. Anyway this case too, as the above one, can happen solely whether $InformationAsymmetry <= random - float0.99$, i.e when the variable *informationAsymmetry* that is chosen through a slider by the user is lower than a random quantity chosen by the software, having as possible maximum 0.99. We decided to set 0.99 as Max in order to protect the possibility of the user to stop all the information between agents. If the user selects *informationAsymmetry* equal to 1 there is no way that feedbacks - involving the awareness of the existence of a different product not known yet - are going to be released.

Meanwhile it is worth remembering that, in the simulation, an agent that wants to know another good, implies the necessity that he/she have to establish a new brand-link with the firm producing it. In the advertising phase it was the advertiser contacting the agents, whereas here is a "close" person. This difference entails an important contribution that leads to the study of different influences hitting the actual agent. We have already developed a variable that remembers how many times the consumer is influenced by the advertiser, this variable is stored in the link connecting the advertised firm and the agent, and it is called *timesContacted*. Now we developed a variable that stores the number of times each consumer is influenced by another agent, we called it *timescontactedfriends*. The last implementation we can see in the code, refers to *set hidden? not show-brand-links*. Since the quantity of links is continuously increasing, the user is able to enable or disable the possibility of viewing the links connecting consumers and firms. He can make it through the use of the switch in figure 2.2.

The procedure ends with *CreationOfPreferitBrandAd* that is, as already said, the creation of the up to date list of favourite goods.

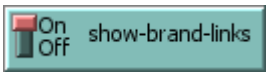

FIGURE 2.2: Representation of the switcher that enables the user to make visible links connecting consumers and firms.

During the creation of the *WordOfMouthEffect* command we have understood the need for a series of developments. One of them regards the creation of the decomposition of the original *ViewRadius* into two different variables. The original slider influenced the ability of all the agents, both consumers and advertisers referred to it in order to know the radius of distance they could inspect. In the real world each person has different and personal spectra of opportunities therefore is a subjective value. But the likelihood that consumers and advertisers have different means is really high. In fact the two types of character have completely different means and goals. We developed the *viewRadiusAdvertisers*, and the original *viewRadius* become instead the solely consumers view radius. In this way advertisers that are professional agents trying to enhance their ability to sell products are not confused with consumers. We should not forget that consumers are normal people living their life while companies try to develop new products - so new advertising campaigns - to enhance their life in order to make positive profit. Consumers share information with their group, more often with subgroups of interest. This first development allows a glimpse to the idea that buttress the next procedure. Agents in the model have already a feedback system, but we could not let agents spread their information with a bunch of random people situated close to them. The idea that consumers are more familiar with some subgroups than others leads to the necessity of achieving a command able to create different networks. In the real world - excluding the professional agents with different interest such as selling - we are normally exchanging information with: members of our family, friends, colleagues of different sort (school, work and other groups of interest). As already seen in the *Network analysis* chapter, we had to include the possibility of having different types of relationship between our agents. We decided to call this command Friendship for the prevalent importance of this world in the mainstream social network in usage nowadays. There are long discussions about the usage of this word; in some context it implies a strong bond between two members, in others it implies a really little knowledge of one another. We use it to claim both possibilities depending on the couple of reference. Our network analysis is indeed built on links having different weight, reproducing therefore the enormous quantity of different connections that agents have within the real world. We decided to develop a command able to let the user being free in choosing which type of connections he/she wants to develop. The best way to do so was to insert the chooser in figure 2.3 in the interface. It allows the choice among five options. Four of them create a network following a set of instructions based on different necessities, whereas the fifth option called *reset* deletes the existing network, that has been possibly created before.

The other types are now going to be explained in detail. All the four possibilities are subject to the user's decision of the *viewRadius*, that now is consumers only. It is of equal importance in the creation of all the types of

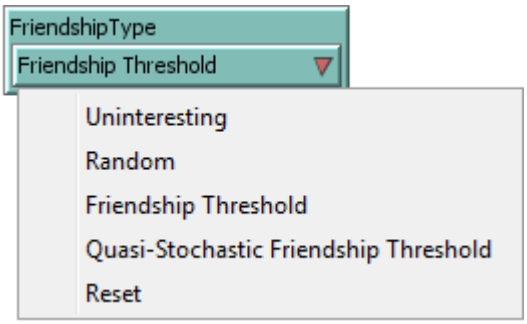

FIGURE 2.3: Representation of the Friendship chooser.

network because it constitutes a preliminary decision about the size of the area that consumers must control. Another common point of these possibilities relies in the usage of a new type of link. This link is dedicated to the establishment of the consumer's friendship relation. It Belong to the realm of undirected links, meaning that both agents connected by the link have the same importance and features. Both agents have an equal and identical connection, because the link is bidirectional. To better understand this concept the NetLogo dictionary provides an helpful explanation:

> There are two flavours of links, undirected and directed. A directed link is out of, or from, one node and into, or to, another node. The relationship of a parent to a child could be modeled as a directed link. An undirected link appears the same to both nodes, each node has a link with another node. The relationship between spouses, or siblings, could be modeled as an undirected link.

Once decided the surrounding area of interest, we can modify the instruction by which each agents decide the members of its own network, i.e. he/she decides with who to have a bond. It depends on the user selection, if the selection is:

- *Uninteresting*: consumers will establish new links with whoever is in the range of visualization. All the links are going to weight equally, precisely 0.01.

If the selection is:

- *Random*: Consumers will establish links randomly with other surrounding agents. To let the random process more meaningful the user will be requested to answer the following question: "Which is the probability of consumers to establish a friendship? Give a value between 0 and 100". This probability will be stored in a variable called Randomness. Afterwards each agent, once at time, is requested to check the random process *if* $(Randomness > random100.1)$ with all the members in a visible range. If positive, the consumer will create a new link with his new "friend", if negative he/she will check the same control with all the members in his surrounding. It is important to highlight that the agent inspecting his surroundings will check whether the variable chosen by the user is higher of a random

quantity that changes for each different agent under control. This allows the creation of links with a random subgroup. Whereas in the other option - when an agent makes the random control only once - the agent could have either all or none of the closer agents as friends.

Only with the following two types of instructions in the creation of the network we have specifically developed a personal and more interesting type of friendship relationship.

- *Friendship Threshold*: When the user selects this option, he/she should also set the slider *FriendshipThreshold*. As already explained, each agent has a set of personal characteristics that represent his own preferences. These preferences are letting to heterogeneous consumers and they are the key variables in the creation of non-identical agents. We decided to use this personal characteristic in the creation of the network of each agent. Starting from the idea that we are interested in reproducing the word of mouth network - i.e. the network of people that are going to influence us in a subsequent purchasing phase - we implemented a code in which each agent check how "close" the preferences of the other people are, and if a certain number of them overcome the threshold of acceptance, than they will institute a weighted link. The idea of enough close is constituted in this way: each of the preferences should be included in a range of +/- 0.5 with respect to the one of the other agent. This means that if consumer A has his first preferences equal to 2, we will take the range 1.5-2.5 and we will check whether consumer B first preference is within this range. If positive, consumers have 1 out of N preferences enough close to constitute the link. Supposing an amount of 5 preferences, if the user selects a *FriendshipThreshold* equal to 3, each pair of friends will need to have at least 3 out of 5 preferences in a close range. A further development giving substance to this way of computing the interpersonal relationship, is that we can measure the importance of a relationship. In our example we have links that are created when at least 3 out of 5 preferences are similar; in this way we can distinguish stronger bounds from weaker ones. The weight is agreed upon the total number of preferences enough close to be considered successful in a friendship relation of this kind. Continuing with our example we will say that couple of consumers having 5 out of 5 close preferences have a stronger bound with respect to other couple with 4 out of 5 or less. The code already allows links to set their weight on the basis of the number of close preferences following the above relation:

$$Weight = \frac{CharacteristicN - NofCharacteristicsOvercomeToFriendship}{characteristicN} + 0.01 \quad (2.2)$$

The weight has a value included in a range between 0 and 1. It is closer to 1 when the number of characteristics enough close with each other is inclined to zero, i.e. they have less in common. On the other hand it is close to zero if they have all their characteristics really similar. We want to recall the concept already explained in the network analysis chapter: the reason why the weight is closer to zero when

characteristics are more similar is because in the network analysis world, the weight can be seen as the distance between agents: higher distance mean lower bond, whereas a lower distance means a much more important connection. The last element of the equation is the sum of 0.01 for each weight. This is a necessary step due to a calculus problem. Whether two consumers satisfy the maximum bond as possible (e.g. 5 out of 5 common characteristics) their weight will be equal to 0. In the computation of some index the weight goes in the denominator, but as we already know recalling our calculus knowledge, it is impossible to divide by zero. Another detail prominent in the design of the code is in the necessity of allowing the user set, as maximum value of the *FriendshipThreshold*, the variable *characteristicN* that is selected through another slider by the user. We can see in figure 2.4 how the slider is coded.

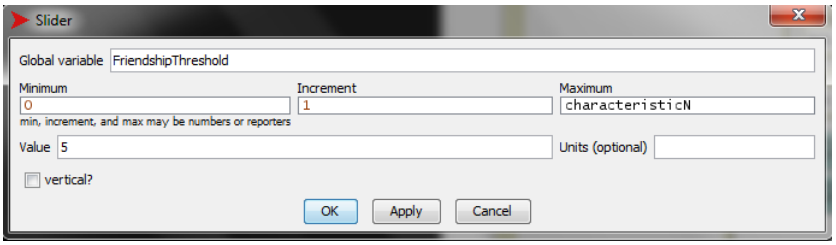

FIGURE 2.4: Set up of the friendshipthreshold slider.

- *Quasi-Stochastic Friendship Threshold*: This is the last option in the creation of the friendship network. And probably is the one that mostly leads us close to a meaningful network. The definition is here created because the process followed is not completely stochastic, but it follows determinate instructions augmented by a random process that include some degree of uncertainty. The first part is completely equal to the *Friendship Threshold* process. But this time each agent will be subject to a possibly different *FriendshipThreshold*. The difference lie in the possibility of the threshold of being changed for each couple of agents. Therefore when the user sets the *FriendshipThreshold* it may be changed by the software. The value can be modified following different paths according to a random process, three events have the same probability of occurrence, i.e. 1/3. If the first event occurs the value will be lessen by one unit. If the second occurs the input will not be modified. In conclusion, if the last option occurs the value will be augmented by one unit. To make it more clear we prefer to provide an easy example, when the user decides the *FriendshipThreshold* that two agents trying to be friend should overcome, as example equal to 2. Than the software will randomly choose, as new threshold of reference, among the options: 1,2 or 3. This random process will provide a new network each time being run, even though the community is unmodified. Therefore when the user wants to delete the network made with the *Friendship Threshold* process, he/she will have the same network each time he/she tries to re-establish it (of course whether the community members are in the same position). The structure of the

weight of the various links follows the same procedure as the previous command.

Below we posit the extract of the code just mentioned:

```
to FriendShip

If (friendshipType = "Uninteresting")
[ ask consumers
[ let Id who
ask consumers in-radius ViewRadius with [who != id]
[ ifelse link-neighbor? consumer Id []
[create-Consumer-links-with consumer id
[set weight 0.01
set hidden? not show-consumer-links
]]]]]

If (friendshipType = "Random")
[ let Randomness read-from-string
user-input "Which is the probability of consumers
to establish a friendship? Give a value between 0 and 100."
ask consumers
[let Id who
ask consumers in-radius ViewRadius with [who != id]
[ ifelse link-neighbor? consumer Id  []
[ if (Randomness > random 100.1)
[create-Consumer-links-with consumer id
[ set weight 0.01 set hidden? not show-consumer-links
]]]]]]

If (friendshipType = "Friendship Threshold")
[ ask consumers
[let Id who let temporaryPref preferences
ask consumers in-radius ViewRadius with [who != id]
[ifelse link-neighbor? consumer Id []
[let NofCharacteristicsOvercomeToFriendship
compareConsumersChar preferences temporaryPref
let tempWeight
(((characteristicN - NofCharacteristicsOvercomeToFriendship)
/ characteristicN) + 0.01)
if (NofCharacteristicsOvercomeToFriendship
>= FriendshipThreshold)
[create-Consumer-links-with consumer id
[set weight tempWeight
set hidden? not show-consumer-links
]]]]]]


If (friendshipType =
"Quasi-Stochastic Friendship Threshold")
[ask consumers
```

```
[ let Id who let temporaryPref preferences
ask consumers in-radius ViewRadius with [who != id]
[ ifelse link-neighbor? consumer Id []
[  let NofCharacteristicsOvercomeToFriendship
compareConsumersChar preferences temporaryPref
let w random-float 1
if w < 0.33
[set NofCharacteristicsOvercomeToFriendship
NofCharacteristicsOvercomeToFriendship - 1]
if w >= 0.33 and w <= 0.66 []
if w > 0.66
[set NofCharacteristicsOvercomeToFriendship
NofCharacteristicsOvercomeToFriendship + 1]
let tempWeight
(((characteristicN - NofCharacteristicsOvercomeToFriendship)
/ characteristicN) + 0.01)
if (NofCharacteristicsOvercomeToFriendship
>= FriendshipThreshold)
[create-Consumer-links-with consumer id
[ set weight tempWeight
set hidden? not show-consumer-links]]]]]]

if (friendshipType = "Reset")
[ask consumers [ ask consumers-links [die]]]

centralityConsumers
end
```

As above mentioned the code ends by calling *centralityConsumers*. This procedure makes use of the network extension provided by NetLogo. This extension will be used from now on in order to make a significant implementation in the study of consumers' dynamics. After the creation of the network we begin to use the information it provides. Below the segment of the code referring to the network extension:

```
to centralityConsumers
nw:with-context consumers Consumers-links
[ ask consumers
[ set centrality nw:betweenness-centrality
set centrality precision centrality 2]]
nw:with-context consumers Consumers-links
[ ask consumers [
set WeightedClosenessCentrality
precision nw:weighted-closeness-centrality "weight" 2 ]]
ifelse Show-Weighted-Closeness-Centrality
[ ask consumers
[ set label WeightedClosenessCentrality]]
[ ask consumers [ set label ""]]
end
```

With the procedure above we developed useful indicators, such us the betweenness-centrality and the Weighted Closeness Centrality. In this version we implemented some other indices. All of them are precisely explained in the Network Analysis chapter. Here we just list them in order to highlight that the following indices find their initialization in the actual version of the model. These are: average-local-clustering-coefficient, Full-Average-Local-Clustering-Coefficient, Full-global-clustering-coefficient, density, Average-weighted-path-length. The user, visualizing the monitors in figure 2.5, will be able to grasp different insights about two networks, the first composed of consumers only and the second composed of both consumers and firms.

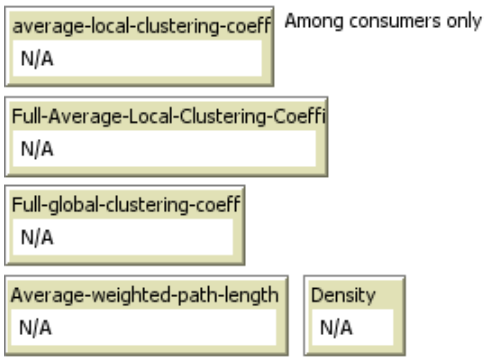

FIGURE 2.5: Monitors showing the structure of the networks.

The last part of the procedure, starting precisely from *ifelse Show-Weighted-Closeness-Centrality* , allows to the user the choice to visualize a different important index. Each agent compute and remember his/her own amount of weighted closeness centrality, this is a unique index for each member of the network. The user has the possibility to modify a switch that allows to visualize consumers' weighted closeness centrality values. In fact, when the switch is in *On* mode, each agent sets his own label equal to his/her weighted closeness centrality. If the switch is in *Off* agents will set their label as " " that leads to an empty label.

It is worth to have a look at the procedure that enables consumers compute the amount of "close" characteristics. Since consumers' characteristics are stored in a list, we had to compare each value with the one in the same position of the confronted list. Furthermore we do not want to use the precise value of the other list. But, as previously explained, we have to take a range of + 0.5 from each value. The best solution was in creating two new lists, the first containing all the characteristic lessened by 0.5, the second containing the augmented values by 0.5. Once the list had been created, we had to make the code control each element one by one. This checks if the original value is in between the minimum and the maximum values of the same position, if so this characteristic can be considered enough close. When all the values have been subject to the control, than the two consumers will report the non-negative number coming from the comparison, and decide whether or not a friendship relation is possible. In the code design we used the *while* cycle twice, since it is the best instrument that can

help us in achieving the scan of all the values in the lists. The following code represents the mentioned procedure:

```
to-report compareConsumersChar [g p] ;
let aN 0
let i 0
let j 0
let UpperP []
let lowerP  []

while [ i < characteristicN ]
[set upperP lput (item i p + 0.5) upperP
set lowerP lput (item i p - 0.5) lowerP
set i i + 1]
set i 0
while [i < characteristicN]
[if item i g >= item i lowerP and
item i g <= item i upperP
[set aN aN + 1]
set i i + 1]
report aN
end
```

The creation of a network among consumers is easily apparent when the user let consumer-links visible. For convenience, considering that we are going to use this nomenclature, we recall the concept according to which consumers in a network are called nodes, while links are called edges. In order to avoid confusion in the understanding of the network, caused by overlapping edges, we decided to include another possible way of visualizing a pre-established network. The user has two new buttons at his/her disposition. By pressing the button *set-up circle* the user is able arrange all the nodes in circle, as an example we can have a look at figure 2.6. This allows a fast understanding of the total amount of nodes and edges. This kind of view is also worthwhile when we want to visualize the weighted closeness centrality as label. When the user has no more need to understand the visual structure of the network, by clicking the button *originalPosition* the nodes will be rearranged in the previous position.

This first implementation of network analysis tools will be interwoven with the needs of our simulation. The first need is that of working with a communication structure of our interest. We understood that without means provided from the network theory we would strive to achieve satisfying information about the various set of interactions in place in our simulation. In fact, due to the random positioning process, the user faces each time a different structure of agents. Moreover the choice of variables such as:*NumberOfConsumers*, *viewRadious*, *friendshipThreshold* and *InformationAsymmetry*, is going to radically modify the structure of communication within the simulation. These possibilities are intentionally exposed to the will of the user. The motivation is clear, we want to have the closest framework possible to the real world, and we know that different situations need different structures. An in-depth analysis regarding these concepts is provided in the Network analysis chapter. Meanwhile, we here disclose the

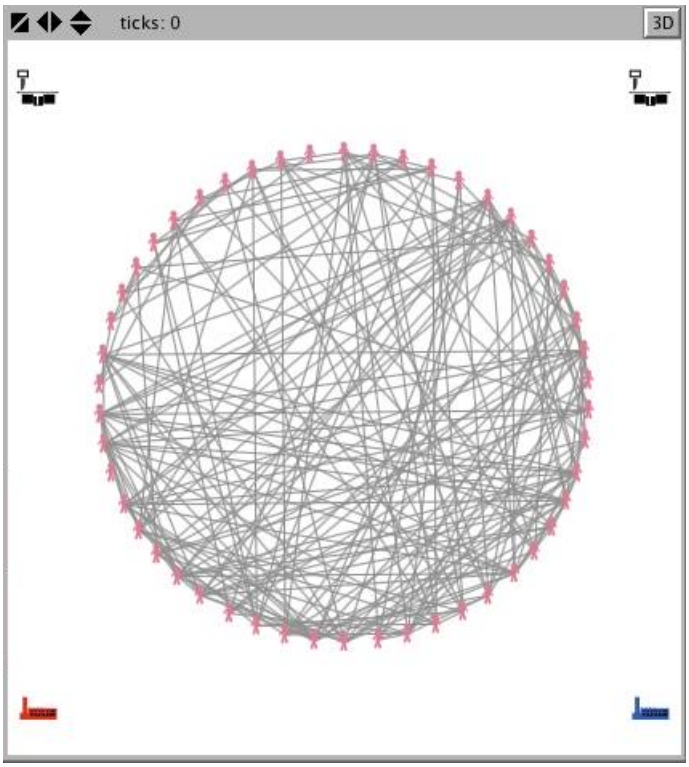

FIGURE 2.6: Example of a network arranged in a circle.

necessity of linking this procedure with the previously developed *wordOf-Mounth* effect.

Even though we are directly interested in advertising, we already discovered the need to extend the constraints that characterize consumers within this model. In the third version of the model we have included the *absoluteIncomeHyp* command, that allows the agents to consume only if their marginal propensity to consume is sufficiently high. In this model we let this variable being more endogenous. The construction in the *tryToBuy* procedure, allows consumers to evaluate products only when these are "visible" and when (*consumptionT* > 0.5), but we have to explain how this *consumptionT* is computed. Below is possible to see the code of reference:

```
to-report absoluteIncomeHyp
let ConsT 0
let TempMarPropConsum 0
ask item 0 FavouriteBrAd
[ ifelse InfluenceAccumulated >= 0
[ set TempMarPropConsum
(0.5 + ((InfluenceAccumulated) /
((5 * timesContacted + timesContactedFriends) * 2
)))]
[set TempMarPropConsum
0.5 - (((- InfluenceAccumulated) /
((5 * timesContacted + TimesContactedFriends) * 2
)))]]
set MarPropConsum TempMarPropConsum
```

```
set ConsT MarPropConsum * cash
report ConsT
end
```

After the establishment of some local variables we begin with the computation. Each agent calls his best advertised good stored in *FavouriteBrAd* and he/she will need to remember to which amount of influence has being subject to. This quantity is really important since it unveils the results of the numerous efforts made by each advertiser, and in particular by the one that has done the greatest job. If this quantity is positive the marginal propensity to consumption will be greater than 0.5 and lower than 1; if this quantity is negative it will be in a range from 0 to 0.5. The exact value will precisely depend on the amount of influence received in comparison to a standard of alleged perfect undergone influence. This can only be possible if the advertiser is always able to perform advertising at his best. Logically the term best hypothesis is from the advertisers point of view, because it is the situation in which he/she is able to keep the maximum interest toward his/her brand. Therefore, the marginal propensity to consumption increases with the minimization of the difference among the observed and the potential influence accumulated. The below equations are respectively assessing the value of *ConsumptionT* in the case of positive and negative *influenceAccumulated*.

$$0.5 + ((InfluenceAccumulated)/((5 * timesContacted + timesContactedFriends) * 2)) \quad (2.3)$$

$$0.5 - ((-InfluenceAccumulated)/((5 * timesContacted + TimesContactedFriends) * 2)) \quad (2.4)$$

When *InfluenceAccumulated* is positive, 0.5 will be augmented by another component. This last component should be equal to 0.5 if the influence accumulated on the alleged maximum influence accumulated is equal to 1. The nominator of this component is the influence accumulated itself. The denominator is the total times of contact received - computed as the sum of the time a consumer is contacted both by advertisers or by friends - multiplied by the maximum influence that in each occasion can be actuated, e.g. 5 in our model. When nominator and denominator are equal the result will be equal to 1. Since we need the half of this quantity, we multiply the denominator by 2. Whereas, if the influence undergone by the consumer is negative, he/she will compute *ConsumptionT* using the second expression. The consumer is going to have a marginal propensity to consumption included between 0 and 0.5. The formula works similarly to the preceding one. But this time we have to subtract the second component as the negative influence accumulated increases. The last step of the procedure is to multiply the consumption just computed by the cash owned by the consumer. This guarantees that richer consumers have the willingness to spend more.

The last procedure that is going to be exterminated is *advertising*. It must be highlighted how important this procedure is, in fact it is directly called by the *start* procedure. How it is possible to notice by looking at its last

row, this is the procedure that triggers the *wordOfMouthEffect* previously explained. Within this procedure the advertisers set casually their personal influence. This process will be developed in future versions of the model. Than they create a list in which they arrange all the consumers in decreasing order of *WeightedClosenessCentrality*. This list is particularly important because it inform the advertiser about the most influential consumers that they can contact. In this way we can develop some experiment trying to understand if contacting the most influential person really increases the selling of the product. We can already forecast that an advertiser performing the best job will not have a good result if its brand is not able to overcome the threshold level. But we do not know the exact impact of an advertising process based on a repetitive way of contacting the market members, with respect to a random process. This list has not been used yet, but the future version will include this possibility. Then the advertiser starts his/her real work. He/She controls a range based on the advertiser radius and contact the reachable consumers. And he/she is able to increase/decrease the opinion of consumers that are already aware of the existence of his/her brand. On the other hand, other consumers get to know it for the first time. Below the code of *advertising*:

```
to advertising
ask advertisers [ set heading random 360 fd random 2
set influence ((random-float (10)) - 5)
let B brand
let c sort-on [( - WeightedClosenessCentrality )]
consumers in-radius viewRadiusADV
let in influence
let ViewRadiusAD viewRadiusADV
if any? consumers in-radius viewRadiusADV
[ask consumers in-radius viewRadiusADV [
if any? out-link-neighbors
[ask my-out-Brands-links with [brandL = B]
[set influenceAccumulated (influenceAccumulated + in)
set timesContacted timesContacted + 1 ]]
ask consumers in-radius viewRadiusAD
[create-brands-links-to firms with [firmBrand = B]
[set brandL B
set radius viewRadius + 1
set influenceAccumulated in
set timescontacted timesContacted + 1
set hidden? not show-brand-links]]]]]
wordOfMouthEffect
end
```

The last development made concerns the number of firms within the market. Until now the market was set as a duopoly, each firm was producing a single brand having, in turn, a single product. In short we have constructed a mono-product brand market. The need to compare different strategies leaves an hard commitment, we need no confusion in the necessity of knowing what firms are offering to the final consumer, thus we can understand whether a particular product was successful and the communication was well made. Through the interface the user will be able to

set manually many parameters regarding the production of the goods and also regarding both the way communication is made by advertisers and the ability of the market to be fully efficient in letting information flow through peers. The idea of extending the number of goods though, was evident since the beginning of the model. The study of a single firm compared with another is not satisfactory. The market is a complex system and is composed by many different products and consumers, both subject to different influences. The issue is to reproduce the maximum complexity needed, and we want to achieve it with the smallest number of elements possible. The solution was to create a third firm producing different goods and thus a different brand. This first multi-product firm will behave as if many different firms are separately introducing their product in the market. Each brand will have its own feature. The creation of this third firm is going to reproduce a proper and therefore more natural number of actors competing in selling their product. We are reproducing a competitive market in which firms compete with one another to grasp some profit. They need to be better of their actual competitors in order to sell their products. Naturally the total number of sells is subject to the number of consumers in the market, when this number is high enough all the products are going to be sold, reproducing the case of excess of demand. Studying the behaviour of a firm in competition with its main rival, the third firm is going to reproduce the noise in background under which both are subject. To better explain this idea we can do a practical example. In a market in which two firms display the higher market share and compete with each other every day to avoid losing it, they will be followed by several competitors. These competitors are not able to independently sustain a sufficiently high market share, but if combined they can come across enough strong and having a good slice of the market. Moreover there are no doubts that when the time goes by everything can happen, thus the market could permit a substitution in the main leader dominating the market. Our third firm has no constraint in being worse, when selling more of the other two it can lead to a situation in which all the business exhibit same sells or even that the challenger have become more important of the firm under scrutiny.

2.0.5 Fifth and last version of the Agent-Based Model

The implementation of the environment, while introducing new procedures and variables, continuously unveils complex and interesting new necessities and opportunities. The elaboration of this last version implied the completion of many important tasks, since this edition represents the implementation of the final simulator. Firstly we have been perfectioning the system of influences as long discussed in the previous chapters. We have strongly improven the old procedure *Advertsing*, created a new procedure called *ProconsumerWordOfMouth* and made a particular commitment to blend and combine all these influences together. The second development we made is strictly focused on matching the simulator with the real world, where we do not know exactly how the real processes work. Thus, we have created choosers, inputs and sliders to let the user interact with the simulator. Our main concern, indeed, is not forcing the code to have unique solutions for real life situations, as various different options are available. A third development needed, was the creation of a variable for

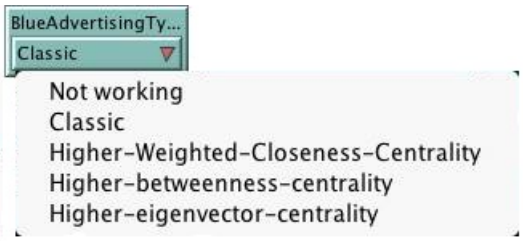

FIGURE 2.7: Firm chooser for the advertising type.

representing the knowledge of consumers. Finally, the last important task has been checking the code and revising the the procedures that behaved discordantly to our intentions. This long process entails a deep study of the code in its details. The inspection of specific and customised outputs while functioning with different settings has been of particular relevance. In this chapter we are going to introduce the whole concept that backs up these new variables and their implementation along with an explanation of the developments one by one. The influence system requires advertisers able to act differently, exploiting information that a deep study of the market could hypothetically provide. We need to highlight that some of the settings we are going to test use information that are really difficult to gather nowadays, but that will not be unlikely to be seen in a closer future given the present growth of technological means. We have created a new *advertising* procedure that, according to the chooser in figure 2.7, selects the type of strategy that each firm wants its advertisers to promote. The first option is not working. This possibility is included when we want to keep our advertisers not operative, as if they had never being created. The second hypothesis is called *classic*. It is the only possibility that does not exploit information obtained making use of network analysis techniques. It works as follows, all consumers are indiscriminately contacted if they are in a given distance from the advertisers. The distance is chosen from the slider named *ViewRadiusAdvertisers* and the selection is made by the user from the interface. This value represents the power of advertisers in terms of how far their can get advertising their products.

The classic option is more expensive in terms of time spent in order to accomplish it, and it has a negligible cost in terms of intellectual work to be developed. As a perfect example of real life situation of this strategy we identify flyering and television advertisement. We will not dig too much details up, but knowing that both advertisement types can be made by focusing on a given target (outside schools rather than in congested streets) or randomly (leaving flyers on cars, buildings) makes these examples a perfect match for the just mentioned advertising strategy. This strategy is called classic given its similarities with some of the most common advertising strategies. The further options are *higher-weighted-closeness-Centrality*, *higher-betweenness-centrality* and *higher-eigenvector-centrality*. All these make use of specific measurements in order to find the most appealing target to specialize the communication. For a detailed explanation of the metrics used we suggest to revise chapter 1.0.6 that copiously explains properties of networks and centrality measures. Here we are going to explain the use

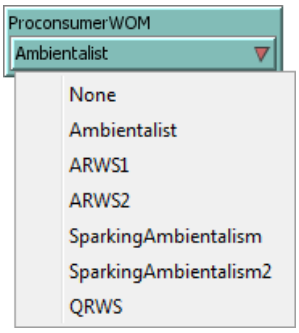

FIGURE 2.8: Chooser selecting the Proconsumer word of mouth type.

of these metrics. Advertisers collect a particular information about consumers in a distance decided through the variable () . The information that they gather is consistent with the advertising strategy that they use, and it informs advertisers with regards to who is the most important consumers in his/her surroundings, in terms of the metrics they want to exploit. As explained in chapter 1.0.6, not all consumers are equal in terms of their position in the network. Due to their difference in visibility, some consumer could be a more valuable target than others. The reason that makes him/her special is that through his/her position this consumer can use his/her influence to generate positive word of mouth between other possible customers. In the previous development, we have introduced an elaborated procedure that allows consumers to interact by word of mouth. We are now going to count all the contacts made between advertisers and consumers and between consumers and other consumers. In practice we can see the effects of these different strategies on sales and, by considering the number of contacts made by advertisers, we can broadly determine which strategy is better given its cost. We can also see how the strategy triggers the word of mouth, which is further translated in positive profits. The code allows the user to have the possibility of modifying strategies within a single simulation. For particular reasons, it could be more profitable to begin with a classic advertising strategy and, only later, to switch to another one. One last detail, important to highlight, is that in case of the three advertising strategies exploiting network information, these strategies concentrate the focus on a single consumer rather than on all the possible reachable consumers. Since all the attention is on a single consumer, the effect that the advertiser has on him/her has been doubled in comparison to the classic strategy. To be more clear, if in the classic case the advertisers' influence equals 5, the other advertiser that focuses on this single consumer affects it by 10. These values, as previously explained, are going to directly affect the consumer's choice. If we imagine two advertisers focusing on the same customer, we want to be sure that if the attention of one of the two advertisers was focused on a single customer that advertisers had much more impact on him/her.

Another important procedure implemented during the development of the simulator is inspired by the concept of Proconsumer word of mouth. This name was coined for the word of mouth activities that contrast the commercially motivated WoM.

As it is possible to see in figure 2.8 the user is able to choose among six different options. We made many possibilities, and sometimes they present little differences between each other. The reason why we prefer this solution is that we want to test how two similar influence strategies evolve in the same environment. Since all the options are really similar, except for the last, we are going to explain their general behaviour and we will conclude highlighting the differences. When the chooser selects one of the first five options, the following process starts. Consumers that are above the expected value in terms of the average environmental preference, spread the information about the worst firm in terms of polluting levels. The number of consumers able to do so is strongly limited, since in real life this occurs if various conditions hold. Influent consumers must be really interested in ecological issues and they are required to possess a knowledge level that should overcome the impediments created by the information asymmetry. they also need to overcome a variable called *thresholdKnowledge* that is set by the user. We have not introduced yet the variable knowledge and we are going to do so along this chapter. The creation of this Proconsumer WoM is one of the main reasons that lead us to the development of the variable knowledge. Consumers able to overcome this threshold directly influence their friends by an amount that depends on the strategy itself. They will not pick a random friend, they will opt for the one with whom he/she has the best friendship relation and has a lower knowledge level than him/her. We decided to implement this procedure in order to avoid information to be stuck among a small niche of consumers that will inform their best friends and expect the information to come back. But, what are the differences between these options? First of all, they differ in the way the influence is set and, secondly, in its diffusion. In the creation of the list of firms by pollution, we decided to envisage the possibility that the consumer could have wrong information according to their knowledge level. As a consequence, higher knowledge level is equal to higher probability of diffusing the correct information. The choices present the below unique settings:

- Environmentalist: the threshold of ecological interest is set to be 2.5 on 5 in terms of acceptance of the pollution level, therefore we expect almost half of the population to overcome this threshold. When this option is selected, the environmentalist is informed about his/her best friend's favourite product. If this good corresponds to the one that he/she knows being the most polluting, he/she decreases his/her friends willingness to buy it by an amount that depends on the friend's acceptance of pollution.

- Sparking Environmentalist: the difference from the previous one is that in this case the reduction of the best friend willingness to buy depends on the acceptance of pollution of the actor spreading the message.

- Sparking Environmentalist2: this is the same as the previous one, but there is one strong difference. The sparking environmentalist 2 influences his/her friend even though the good under attack is not the favourite of his/her friend.

- ERWS 1 and 2: this is an acronym that stands for environmentalist real world sensitive. There are two major differences with respect to the

previous ones. The first is that the threshold level needs to be much higher for information to be spread. In fact, the threshold of ecological interest is set to be 4 on 5 in terms of acceptance of the pollution level. The second difference is that the environmentalist is able to know the worst firm pollution level, and the influence is directly proportional to its amount. The more the firm pollutes, the more the agent will promote against the firm. The difference between type 1 and 2 is that, in the first type the consumer informs his/her friend solely when the worst firm in terms of pollution is the friends' favourite producer. The second type influences the friend even though he/she prefers another firm to the most polluting one.

The last option is called QRWS and is not related to the environment, but to another important dynamic that is slowly progressing. The acronym stands for quality real world sensitive, it works similarly to the ERWS, but the focus is concentrated on the quality of the product rather than on the pollution level produced by the firm. The diffusion of internet engendered the spread of blogs related to product quality. This dynamic is strongly evolved for hotels, technological products, restaurants and so on. Following this line of reasoning, we could not forget to take into account that consumers want to spread this type of proconsumer word of mouth, that is strongly in contrast with the will of producers, who would prefer to diffuse solely the virtues of their products. When this option is selected, a small fraction of acknowledgeable agents spreads the information he/she knows to his/her best and less informed friend. We believe that reality does not follow exactly this route, but doing so the code ripples the information across consumers in a way that closely resembles to a real dynamics. In the age of information, the influence system affecting consumers could not lack a feedback system. The idea that agents have the possibility to use reviews from previous purchasers, constitutes an important reality in almost all societies nowadays. When we spoke about electronic word of mouth we already gave a hint of this process but, even though the command *WordOfMouthEffect* could approximately resemble this process, we prefer to implement one feedback system that works by itself. The necessity to create a separate command was disclosed when we became conscious of the usefulness of comparing two processes that can work in two directions; they can supplement each other in the making of the same choice, or each can work against the other supporting contrasting options. For example, the latter case happens when the WoM supports the purchasing of product A if the reviews strongly show the collective preferences of product B. We also decided to implement this process creating an extremely important difference between the WoM/EWom and the feedback system. Trying to reproduce real dynamics, we let the former procedure come out in favour of the products that better push their promotions, while the feedbacks effect is much closer to a subjective evaluation made by consumers once the product has been purchased. The difference between the two procedures is strongly evident. After a long study of the feedback system, we understood that consumers often had betrayed expectations and understood it solely once the product was purchased and used. This can be considered the difference between the expected value of an object and its real value. Satisfied and

unsatisfied consumers, in a small percentage, decide to share their product experiences. These thoughts are produced once the product is received and this is how we differentiated this real world dynamic from all previous procedures developed. The ratings are structured from zero to five, in a really similar way to major e-commerce and website providers' reviews like Amazon, TripAdvisor and many others. The feedback is submitted by a percentage of buyers that depends on the probability that the feedback effect is used. This probability is set by the user through the interface and will be better discussed later when we will inspect the use of the various dynamics. The application of feedbacks follows this idea: buyers that have bought a product are able to be fully informed of the real attributes of the products, so they will evaluate whether the good satisfies their expectations. As in real life, the subjective expectations can be betrayed or overcome. If the user decides to submit his/her evaluation, the feedback is updated online and the firms will show an average of all these reviews. The simulation differs from real life, where we have intermediaries telling us the average, like the previously cited sites, but this aspect has no effects on the results. Consumers, then, have another valuable source from which they can grasp insights about the products. How the information is generated in the *CreationOfFeedback* command, is going to be analysed when we will introduce the new command that blends all these influences together.

When activated, the above procedures strongly influence the choice of the favourite good. Still, we needed to blend all the influences in a unique variable and we decided to standardize all the word of mouth communications between 0 and 5 in terms of influence spread to other consumers. The standardization was an inevitable step that we made thinking to the final choice that the consumer has to make. When we buy a product, we are not conscious of all the information we gathered in our mind, but we have some beliefs that incorporate all the different influences received. We tried to reproduce this general process that affects us all when purchasing a product. In real life, the environmental aspect is not as much debated as it should be. The creation of this procedure has, in fact, been done to verify how a network would hypothetically behave if some portion of its population paid enough attention to this dynamic. It is interesting to note that the proconsumer word of mouth works solely between friends, we recall that two agents set a friendship solely when their background is similar. This would imply that for all options of the Proconsumer WoM procedure the information originates from some focal agent and slowly diffuses across all consumers. Other important introductions we have made are referred to different topics. One awaited development consisted in creating an environment that allowed agents to have a different background in terms of importance bestowed to each product feature. The user is able to decide if a given population weights more an attribute compared to others. As an example, consumers may consider much important the price of the product compared to the quality level. We inserted three inputs for the first three product attributes. When evaluating if any good overcomes the selected threshold, consumers will weight each attribute according to the selected importance. Another difference previously mentioned was the introduction of consumers' knowledge level. We do not need to relate this variable to the school level. In fact, the best interpretation that this variable has in

the model is to consider that people have different willingness to gather information about what they are going to purchase. Experts and collectors, for example, have a huge culture about a given segment of products. People can be easily differentiated in terms of hours spent gathering valuable information about goods. If we consider knowledge as the willingness to gather information before a purchase, we comprehend also those with a low school educational level, who are the most informed about a particular category of products. Therefore knowledge has a strong impact in the pro-consumer word of mouth and in the ability of buyers to make a desirable purchase on their own.

As previously mentioned, in this version of the model we had to implement a command able to blend all the influences in a unique decision. The main challenge we had to overcome is the generation of a setting able to allow the user to reproduce different possibilities. To achieve this result we had to write again the *TrytoBuy* procedure, firstly shown in chapter 2.0.3. This time, on the one hand we have both the word of mouth and the pro-consumer word of mouth that affect a variable that stores the influences for any given brand. On the other hand, we have the feedback system, that is based on post-purchasing subjective evaluation. The framework of each simulation is decided by the user. How many consumers in a given market niche are influenced by the feedback system in the phone market, or in the car market? Does the food market work primarily with word of mouth and classic advertising, since the feedback system does not affect it at all? All the different possibilities should be correctly implemented. Those are the reasons that lead us to the creation of two variables that correspond respectively to the probability value that word of mouth is present and/or the feedback system is at work. The probabilities pave the way to four different scenarios:

- Scenario 1: Both probabilities are set equal to zero or their amount is too small to overcome the threshold.
- Scenario 2: The feedback system is at work since its probability is high enough, the influence effect does not overcome the threshold.
- Scenario 3: The influence effect is at work, the feedback system does not overcome the threshold.
- Scenario 4: Both effects influence the agents.

We reproduced these four different scenarios and we analysed them one by one. When the probabilities are small or zero, it means agents are not able to be affected by neither of the effects. All the advertising, WoM and ProWom, is groundless as well as the feedback system, that does not operate at all. Consumers buy products almost randomly, in fact the agent does not have any preference. The agent sees products in its surroundings and tries to buy the one that is closer to its taste. If the good overcomes the threshold of accepted characteristics the agent purchases it. If this threshold is set to zero, the consumer, each day, buys the best good in its view, although it might even be the worst in the market. In the second scenario the feedback system is the main or unique system at work. When the probability of the feedback effect is set between [0,1), agents, singularly, in accordance

to a unique threshold, may follow two different paths, either they use the feedback effect or they end up in Scenario 1. The number of people that will adopt the feedback system is proportional to the probability chosen on the interface. In this case consumers start to purchase randomly since no feedbacks are present. Slowly each firm finds an almost stable level of feedbacks in terms of ratings and this level is directly correlated to the attributes of the good produced by the firm. Consumers with higher level of knowledge have an higher probability of using the feedback system, since, as it was explained, knowledge is proportional to the amount of time spent in order to grasp valuable information about the products. Once the agent has decided which firm is the favourite one, he/she will purchase solely from that one firm, if the product is able to overcome the acceptance threshold, otherwise the consumer will inspect the other goods. The third scenario depends on the probability of the influence system to be at work. As before, when the probability is set to 1 all consumers will adopt it, if it is set between 0 and 1, the number of agents adopting this system is proportional to the probability chosen in the interface. When the probability for a given consumer of overcoming the threshold to access the system is high enough, consumers follow the steps to come. All the advertising forces start to act in order to promote their brand to every consumer. Once per week word of mouth acts if present consumers are also affected by the proconsumer WoM. All these forces let the consumer aware of the existence of the products promoted, and buyers elaborate a favourite list. Naturally a consumer will try to buy the product with better image in terms of brand identity, which is the first in his/her favourite list, if the number of accepted characteristics is enough high enough to overcome the threshold. If not, the consumer will try to purchase the second good in the favourites list. The last option is when both probabilities are positive. If these probabilities are not exactly equal to one, consumers, in proportion to the probabilities chosen, are directed to use one of the three explained possibilities. But when both probabilities are high enough to overcome both thresholds, consumers adopt the fourth case, in which we combined all the effects. For the sake of comprehension, we make some examples. If the probabilities are set to be 0.7 for the influence effect and 0.8 for the feedback effect, we will have a really small segment of agents ending up in Scenario 1, a good amount of consumers ending up in Scenario 2 or 3 and the largest slice ending up in the scenario 4. If, instead, we set set both probabilities equal to 1, all consumers will have to use unanimously scenario 4, because the probability cannot be overcome by any threshold level. The fourth scenario works as follows. Consumers, always proportionally to their knowledge, start to gather information from the feedback system, they are also continuously influenced by advertising, world of mouth and proconsumer word of mouth. Due to the influences, agents have a list of favourite products. Also, they are conscious of the reviews that these goods display. The buying decision works as follow: if the difference, in feedback terms, between the favourite good and the good of the firm having the best reviews is smaller than a given amount, the consumer buys the good that strongly influenced him. When the favourite good has a review that is below the best review by a value that overcomes the threshold amount, than the consumer opts for the good showing the best review. As noticed, the user is again in control of all the dynamics. The two probabilities in accordance to which is considered

the maximum acceptable distance in terms of reviews are the variables that control all the purchasing flows. The rest of the decision is obviously up to consumers.

While making the first trial experiment we decided to implement the model with some switches, able to regulate different dynamics. The user is now able to:

- Sets all the firms to have advertisers promoting their products with a non-random power and all with an equal force. This way we can confront different strategies knowing that the advertisers level of commitment is equal for all three firms.

- Sets all the firms to be continuously producing in an identical way. Previous versions of the model let the product have some attributes evolving over time, this is now decided by the user and we strongly believe that goods should not evolve over time if additional developments are not made. This idea can be intended as a desirable advancement.

- We modified all the fixed time patterns in order to let the simulator run as if each tick corresponds to a day. Goods are wasted after a month and the word of mouth takes place once a week. The purchases are made once per day if consumers are able to find a product overcoming the specific threshold.

We conclude the chapter introducing the last development made in order to facilitate our research through the simulator. The code entails a statistic procedure, which, at the end of the desired time span, provides us some summarizing values for the variables we are studying. The values investigated by statistics are the sales of each firm, their market share, the amount of products wasted, the number of goods sold with no profit, we study how much sales are correlated with the amount of advertising and of all kinds of word of mouth separately, finally we research the unsatisfied demand. With all this statistics we can understand *a posteriori* how consumers behaved and if the received influence was misleading, pushing them to buy the worse products. Also, we study how environmentalism diffuses and the threshold of consumers that must push its dynamics in order to let it be effective. Studying the case of the proconsumer word of mouth we can see how the qualitative thoughts of consumers spread around the network.

Chapter 3

Simulations

3.0.1 General understanding and the interface

In this section we provide some useful tools to let the reader knowledgeable about all the key aspects we will encounter during the simulations. Variables have been named using a self explanatory way, but sometimes they can have tricky effects. Therefore, we suggest to the reader to complement the general understanding provided in this section with the detailed description made in chapter 2.

In order to allow a feasible comprehension of the experiments that are going to follow, we want to briefly review the meaning and functioning of the variables created. To follow the complete list:

NumberOfGoods: total amount of goods that the user wants the firm to produce at the beginning of each day. This value can only be set to be a multiple of three, because the total amount will be equally shared by the three firms competing in the marketplace.

CharacteristicN: total amount of characteristics that establishes both numbers of the consumers' preferences and of the attributes of each goods. We recall that the user will be asked to decide the first three attributes of the goods of firms A and B, whereas the general firm will automatically generate its attributes on the basis of the average of its competitors.

AcceptanceThreshold: defines the minimum amount of attributes that each consumer needs to accept in order to proceed with the buying process. The result derives from a subjective evaluation of the visible attributes of the good.

NumerOfConsumers: establishes the total number of consumers that originate in each simulation.

ViewRadius: represents the imaginary consumers' ability to see products in their surroundings.

ViewRadiusFriendship: controls the consumers' ability to communicate with other peers in a defined distance.

ViewRadiusAdvertisers: set the advertisers' ability to contact customers in a defined distance.

Weights: define the importance that the market gives to a given attribute. The user is able to define the first three attributes only.

PowerWom: probability that word of mouth takes place in these setting in which its effect is included.

PowerProconsumerWom: probability that the proconsumer word of mouth takes place in these setting in which its effect is included.

UniqueProduct: when the “switch" is set in the “on" mode, each firm does not change attributes of its product during the course of the simulation.

Blue And Red Advertising type: defines the type of advertising that we want the firm to develop during the course of the simulations. The general firm does not have a button since it will always operate in the “classical" mode.

ProconsumerWom: this is a “chooser" that enables the user to decide which type of dynamics consumers should follow in their proconsumer behaviour.

Adv.Equal.Influence: when the “switch" is set in the “on" mode, each singular contact made from all the advertisers possess an identical power.

FriendshipThreshold: defines the minimum amount of similar preferences that two consumers must have in order to establish a friendship relation.

Information Asymmetry: defines the probability that population may have less or inaccurate information.

FriendshipType: this “chooser" allows the user able to decide which process wants the simulator to run in order to make consumers establish a friendship relation.

ConsumerStep: defines the consumers’ virtual step. They point each day towards a random direction and are able to move their position of this given amount. When this variable is set to be low, consumers move randomly in the space, but they will almost keep their position unchanged.

Max.difference: defines the consumer maximal difference, in terms of reviews, accepted between the selected good and the one best evaluated in the marketplace. This control occurs when consumers rely on feedbacks to purchase a product.

ThresholdKnowledge: represents the threshold of the knowledge variable, consumers in particular settings will be able to exploit information or sharing them when this threshold is overcome.

CommunicationType: allows the user the possibility to decide which communication process consumers can unfold.

Prob.Influence.effect: is the probability for pre-defined types of influences to affect consumers.

Prob.FeedBack.Effect: is the probability that population may take as a reference the feedback system.

The reader should also be able to interpret the graphs that come across with the simulations, we can see the ones used in figure 3.1.

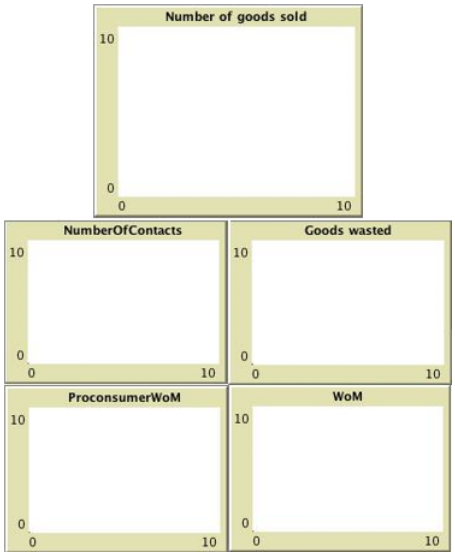

FIGURE 3.1: Graphics within the simulator.

Our intention was to give self-explanatory names but, for the sake of clarity, we prefer to briefly disclose the information provided by each of them. Graphs in the list below have in common the fact that they reproduce each firm level separately.

Number Of goods: total number of goods sold by each firm.

Number Of contacts: business-to-consumer communication, it shows advertising levels attained by each firm. The amounts proposed in this graph are particularly important to evaluate the effects of a given marketing campaign.

Goods Wasted: total amount of goods that consumers have not purchased in the 30 days of life of the products.

Wom: reports the levels of the consumers-to-consumer communication made through the word of mouth communication process. In the actual work it is considered always as a positive by-product of advertising.

ProconsumerWom: reports other levels of the consumer-to-consumer communication. This is a different type of word of mouth, where we have included information left from consumers that do not rely on advertising, but on a subjective knowledge of the firms. It can be either positive or negative, according to the strategy selected from the user.

In these graphs, firms A, B and general have respectively blue,red and magenta colours.

During this simulation we will deal with changes in goods attributes from the consumers point of view. Each good attribute is linked to a consumer preference, when a positive attribute increases its value, the likelihood that consumers will accept it increases as well, the opposite happens for negative attributes. Consumers' preferences and goods attributes are set to be between 0 and 5 for positives and 0 and -5 for negatives. The consequences of these settings are many. First of all the expected value of consumers preferences is equal to 2.5, this is a fundamental information when we compare two attributes of two firms. By means of an example, if firm A and B present quality levels equal to 5 and 2.5 respectively we understand that: firm A will be accepted by all the consumers in terms of its quality level, firm B will be accepted by an average of 50 % of consumers. Proceeding with this line of reasoning as the quality increases of 1 unit, we will expect a difference of consumers accepting it of precisely 20% of the total amount of consumers. This happens not only for the quality, but also for all the positive variables. On the other hand, negative variables will work in the opposite direction. During the course of these experiments we will often be making comparisons based on these differences.

3.0.2 First set of experiments: no feedback no influence

In order to understand the functioning of our model it was straightforward to begin with agents making their choice free from any restrains or indications. We run a series of simulations in which almost all the setting parameters are set equal to zero or null. A few exceptions are: a positive number of goods and consumers in the market, the consumer step and the consumer ability to see the world around him/her. We selected 51 consumers and goods for this first experiment, the reason that lead to choosing a non-round number is due to the necessity of firms to produce the same number of goods at each time step, therefore a multiple of 3 was required. Among other variables set as positive, there are the consumers' *viewRadius* and their steps. For this first experiment, the *viewRadius* variable is set equal to 5, leading to an impossibility for consumers to see everything that is present in the whole space. The variable storing the step has instead been set equal to 0.1, meaning that we decided to strongly restraint their ability to move across the world. The idea behind the first experiment is to study the behaviour of agents when their shopping routine depends solely on their ability to see available products around them. In this simulation, consumers have the possibility to buy maximum one product a day. During this experiment the products do not have to overcome any threshold level, meaning that a consumer will buy any good he/she is able to. Since the number of consumers equals the number of goods, we firstly expected all goods to be sold at the end of each day, but the limited capability to see the space around each consumer let many goods unsold. The reason why this happens is that consumers and goods are randomly distributed around the world and, as mentioned, consumers are not able to move much from their original position. Therefore, in a random setting, we have some part of the world much more densely populated than others. Goods create the same phenomena, they are allocated randomly in the space creating natural agglomerations, this happens many times and in different positions. It may happen that goods and consumers create situations in which both are

more densely populated in a certain part of the world but not in coordinates close enough to start a purchase. Since goods are wasted if after 30 days they are not sold, and in the position in which they are allocated there are not enough consumers to purchase them all, we can conclude that with the actual setting, all the unsold goods could have been purchased if they just were positioned in the right spot of the world. This experiment has been made 15 times, in mean we have seen a number of wasted goods approximately equal to 2800 with a standard deviation of 950 products. The total production is always equal to 51000 products since we let the simulator run 1000 days and at each day each firm produces 51 products. The percentage mean of wasted goods corresponds to 5.5% of the total production, with a maximum of 9% and a minimum of 2.8% products wasted. The inspection of the market share shows that at almost every simulation the three firms displayed an almost equal market share corresponding to the 33% of the total production. We expected this result, which appears recursively, and that originates from the unconcern of consumers while deciding which product is better for them. In fig. 3.2 we can analyse some plot originated from this experiment. The first plot represents the number of goods sold for each firm. In the plot there are three functions respectively drawn with colours red, blue and magenta. Each one keeps the information about the number of goods that each firm has sold during the experiment. We can notice that the three functions are represented by a single line that is created by overlapping the three separate functions. All firms, then, sell the same amount of products in the experiment time. Nonetheless, there were situations in which there was not a perfect overlapping and it was possible to notice that a firm had more luck in the random allocation of its goods. From the other plot we notice that Number of contacts is always equal to zero. That happens because this plot counts the contacts implemented by advertisers in order to increase brand awareness. In this experiment, though, we did not let advertisers operate. From goods wasted we can see that the actual setting of the model lets some goods being wasted, the slope of the function is almost constant and higher than 1. This shows us that for each day there is at least one wasted product. In some circumstances the function reached coefficient 5, meaning that 5 products were being wasted per day. The last two graphs show how many times consumers interact by word of mouth and Proconsumer word of mouth. Both display a flat and equal to zero graph-line, the functions show that the intention of the experiment holds, we therefore have a setting clear of any influence.

To assess the truthfulness of our assumption,namely that the percentage of unsold goods is directly correlated with the sight of consumers, we run different experiments. Here we show plots originated with an experiment having same setting except for *viewRadius* that has been set equal to 24, that corresponds to the minimum amount needed in order to have a complete view of all the goods in the world. As shown in figure 3.3 we get zero goods wasted along the 1000 days of trade.

We can say that when consumers have full information about the products position and are able to buy a product independently of the distance that separate them, we face a full sold-out at each day. In such a situation there are no wasted goods, all the agents satisfy their maximum necessity given their possibility.

A different approach to increase the *viewRadius* is the incrementation of

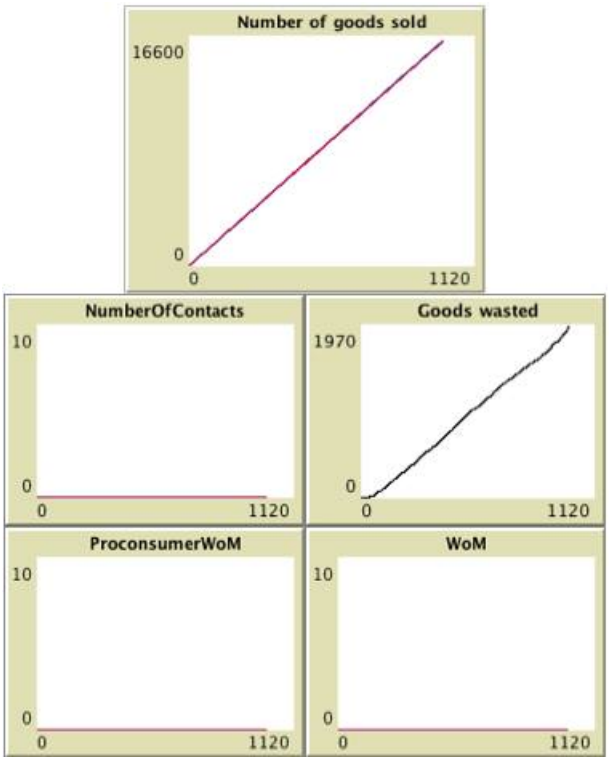

FIGURE 3.2: Graphics in the first example.

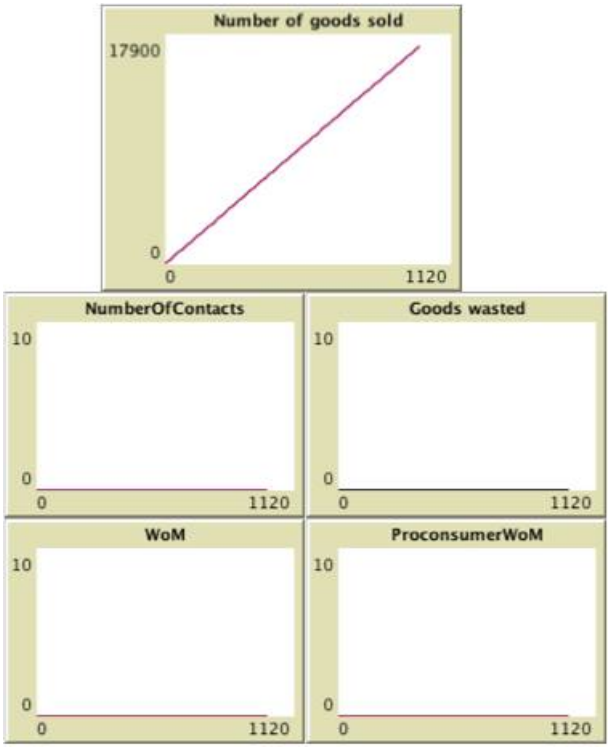

FIGURE 3.3: Graphics in the second example, no wasted goods in the market.

the consumer step. We have goods that last 30 days in the market, therefore making the agents move could be a good way to shorten the distance between unsold products and consumers in need. The problem is that with the actual setting, consumers move at the end of the day while at the beginning of the next day the same amount of good is again supplied. If in a certain day the movement of consumers create an aggregation that is far enough from the aggregation of goods, some of the latter will not be purchased. The next day consumers move toward a different position, even if we assume them in a better place in relation to the goods supply, they will now make their shopping choice on an amount of goods that is higher than the number of consumers itself. This let the mobility of consumers being not enough if the supply per day exactly equals the demand, but no enough importance is attributed on the place in which the supply is distributed. Although this is true, we notice that the mean of goods wasted drastically drops. This happens because the unsold goods will keep their position increasing the density of products in the marketplace, even though their position is not accurate consumers will move exploiting them. When the new supply is not on the best side of the space some of the old goods will cover the present demand. The proportion of the change is described by the new percentage of goods wasted that in mean corresponds to 1.5% of the whole production. We conclude that when supply equals demand the simulation highlights the importance of the place in which goods are sold. These phenomena have a particular behaviour, we analysed the percentage number of goods wasted with the usual limited sight and with a different number of consumers and goods. In percentage terms, goods wasted increases when we increase both consumers and goods, this happens up to a certain threshold of consumers. In fact, by increasing consumers we also increase their density and the probability of consumers and goods to be close each other. We see that conspicuously increasing the number of both consumers and goods, the rate of goods wasted on the total production drastically decreases.

The previous group of experiments is based on the idea that consumers do not really evaluate what they are purchasing. This happens due to the zero value selected in the *acceptationThreshold* level, that is a variable affecting the buying process of each consumers. As previously mentioned in chapter 2.0.1 consumers are able to compare the features of the goods under choice with their preferences, since they have not purchased the good yet they can just make a general comparison, in fact consumers are not conscious of the exact properties of the product, they just know if the latter broadly overcome their minimum requirements. When all consumers have a threshold of zero, they check their surroundings and select the most appealing product available, even though this best product does not overcome any requirement, they buy it. When the threshold raise to one, they do the same process but if the best good picked in their surroundings does not overcome at least one preferences, the consumer is not going to purchase any product, given that he/she knows that the one picked up was already the best offer available. For further detail an example of this concept is provided in chapter 2.0.1. Changing this variable is an important difference that we applied to the simulation. We decided to modify the characteristics of the firms as well. All 3 firms are equal but their properties have

	Characteristics		
Firm A	-3	-2	3
Firm B	-1	-2	1
Firm General	-2	-2	2

TABLE 3.1: Firms attributes.

been changed. All firms now represent the average firm in terms of produced goods, the number of characteristics is again 3 but this time all the values are set equal to 2.5 on 5. From now on we will keep this setting when we want to analyse how consumers interact in a marketplace with 3 identical firms. We begin a series of experiments, as mentioned the number of characteristics is equal to 3, so we checked how consumers behaved when the *acceptationThreshold* was gradually raised from 0 to 3. Naturally the percentage of goods wasted on the total considerably increases when we make a positive unit change in the threshold. At the first unit change, from 0 to 1, the percentage of goods wasted increases from 0.05% to 0.10%. A marked difference appears when the threshold is set equal to 2, in this case the amount of goods wasted reaches the 43% of the total production, while a threshold equal to 3 let percentage raise to 86%. This setting where run many times with different *viewRadius* and we can conclude that the different *acceptationThreshold* has a considerable impact on consumers choice. We decided to continue making the same sort of experiment with nonidentical firms. When the two main firms have different characteristics, the third general firm is going to position its product exactly between the other two. Firms attributes are shown in table 3.1. With *acceptationThreshold* equal to 1 and 2 we did not observed significant differences. While when the threshold was set equal to 3, different experiment showed quite different results. All firms gained the higher market share in at least 1 simulation. This result is in line with our theoretical belief since consumers in different simulation have different tastes, even tough the expectation for the average of preferences does not change. It is important to highlight that the general firm never end up in the last position in terms of market share, the reason why this happens is going to be analysed in the course of these experiments. Another experiment has been made confronting an high vs low cost firms with values shown in table 3.2. We need to note that in this case the two vectors of attributes of the goods produced from the firm A and B have first and third element symmetric to the expected value of consumer's preferences, leading the third firm to produce goods with the first and third attributes exactly equal to the expected value of consumer's preferences. For the law of large numbers with this set of assumptions and with many trials run, we believe that firm A and B should tend to the same market share. From our results we see that neither of the two firms performs continuously better than the other, and this is consistent with our assumption. While we see that the general firm performs really continuously well, never ending up in the third position in terms of market share. We can conclude saying that for the general firm it is easier to overcome the threshold, even when its level is set to be 3 out of 3. The values of the goods sold by the general firm are

	Characteristics		
Firm A	-4	-2	4
Firm B	-1	-2	1
Firm General	-2.5	-2	2.5

TABLE 3.2: Goods attributes in a low vs high cost situation.

	Characteristics		
Optimal vector	0	0	5

TABLE 3.3: An example of an optimal attributes vector of a product.

closer to the consumer's preferences expected values. This is not a preferable condition since the best attributes are the one far away from the mean but closer to zero for the negative attributes and to five for the positive one. The optimal vector is shown in table 3.3. The straightforward conclusion is that, in this settings, being closer to the expected value for all 3 characteristics is a better position in comparison to having some attributes closer to the extremes. This lead to an higher probability of finding agents able to overcome with their preferences the vector of attributes altogether. In fact when 1 attributes out of 3 is particularly high it is much more rare to have agents able to overcome it.

An example that can help us in understanding this concept can be made by thinking about two different products. They differs in their price and quality. The first good has both price and quality equal to 5 on a maximum of 10 and, the other has the price equal to 8 out of 10, and the quality equal to 10 out of 10. If we imagine a random population that has the expected value of the willingness to buy a product to 5 out of 10 and they also have an expected value of the requirement for the quality equal to 5. It is straightforward that even though consumers will prefer the higher quality product that has an extra quality per unit of money spent, they will not be able to afford it. This simple example summarize dynamics that happen often in our everyday buying process and that is reproduced in the simulation.

Other experiments within the same framework are run with more consumers than goods and more goods than consumers. Both situation behave as forecasted. When goods are more than consumers, we see an higher number of goods wasted, but also an higher number of products sold. Products wasted are not linearly increasing with the higher amount of production due to the compensation that takes place between the necessity of those consumers that could not satisfy their needs and the overproduction. To make this happen we need enough goods to cover a good portion of the market surface. This happens till a certain point, when the overproduction is enough high to compensate the lack of product positioning, an additional

amount of goods in the market is directly going to make an equal amount of wasted goods. In such circumstances no consumers end the day with unsatisfied demand but, in order to achieve this result, the amount of product wasted grows dramatically.

When the number of consumers is higher than the number of goods something similar happens. Total number of goods sold increases with the increasing of the number of consumers, as well as the total demand unsatisfied. We run different experiments always setting 51 products produced per day. We studied the dynamics happening with: 51,60,70,80,90,100,150 and 200 consumers, running the experiment many times for each quantity. It is noticeable that the random disposition of consumers let each simulation have different results. The number of unsold goods clearly decreases in mean, increasing the number of agents, but its standard deviation remains still high. This is due to the fact that it is not difficult to have, even with more than 60 and consumers up to 100, a situation in which they aggregate leaving some empty spot that will provoke the waste of some products that has been positioned in that particular point. With 150 and 200 consumers we have run 5 simulations and all of them showed exactly zero goods wasted. We therefore understood that between 100 and 150 consumers there is a threshold that let the percentage of goods wasted be much frequently closer to zero than with smaller quantities. We run the experiment many times with different quantities finding that with 51 goods there is the need to have 120 consumers in order to have an almost equal to zero mean of goods wasted. For the sake of accuracy we want to highlight that the dynamics of the random distribution of agents let the space for a positive number of goods wasted even with 200 agents or more, but since they will be spread around the world it is very unlikely that some space will remain uncovered of demand. Improving that the best and sometimes unique solution for having all the demand interacting with all the supply is to have a *viewRadius* equal to 24 is the practical insight we needed in order to better reproduce the best environment for the future and more complex experiments. Future experiments will see many other variables in action. Therefore, in some circumstances, we need to isolate the effects that lead to products being not sold, in situations in which it is appropriate to not interfere with the results we can just let all the demand be conscious of all the supply as an assumption.

3.0.3 Second set of experiments: influences case

This groups of experiments are characterized by a setting in which the probability of being influenced is equal to 1, i.e. maximal. And the probability of using the feedback systems is equal to 0, therefore, consumers will not weight their purchasing process on information provided by reviews. The consequences in the purchasing process are extended. Doing so we let all consumers purchase through the *Influence.effect* command that grounds all the autonomous decision processes on two main factors: the amount of influence received for every product and the number of features appreciated. As mentioned in chapter 2.0.5 , were we introduced the last version of the model, consumers try to buy the first product to which they consciously attribute much importance in terms of brand identity and brand awareness. Once the customer has decided which is the *a priori* favourite brand he/she

tries to purchase it if, from the information available, he/she believes will to be satisfied from this product.

The experiment phase starts assessing the validity and congruence of the procedure. We run a series of straightforward cases to assess whether or not the behaviour of consumers leaded to foreseeable results. In all the experiments we set *FriendshipType* to be equal to *Quasi-Stochastic FriendShip Threshol*, and this is so because among the other possibilities developed this one structures the network in a almost realistic frame. For a deeper understanding of our reasoning we suggest to review chapter 2.0.4. When we set *acceptationThreshold* equal to zero, a supply equal to the demand and the full possibility of buying products in every part of the world, all firms present equal market shares, corresponding to the 33% of the total, and this result does not depend on the attributes given to the goods. The fact that *acceptationThreshold* equals to zero lead consumers to buy whatever product in supplied to them. The first change we have made was rightly in the number of consumers within the market, decreasing it to 30 and setting each firm to produces 30 goods per day for a total amount of 90 goods produced. This implies that all consumers would be able to purchase from a single producer if its brand identity is the one perceived as the best in all the market. In this setting and with all three firms producing identical goods, it is straightforward to keep the attention on the relations between goods sold and amount of contacts per advertisers. We expected the firm producing higher levels of influence to control the market, but by making many times the same simulation we have seen that this is not the always the case. In the majority of the simulations an higher level of influence leads to higher market share. In some circumstances the firm that spent more in advertising, producing in this context higher levels of influence, did not ended up as the one selling more products. After a cautious verification of the reasons we discovered two leading possibilities. In the first case, the higher amount of influence was predominantly focused within a sub-group of the population, and was not properly disperse all around the world. Even though this is not a completely unsuccessful strategy - since dispersing too much the influence lead to same or worse market share low values - we know that the advertising could have been better realized. An example of how this dynamic evolved is shown in figure 3.4 , where the Firm A (with blue line) has an evident higher number of contacts for the whole period, as it is easily evident the number of goods sold from the same firm is not compared with the general firm (with magenta line) that has an higher level of product sold from the beginning of the period to the end. In fact, firms conclude the 3 years simulation with the following market shares: Firm A: 0.26 Firm B: 0.29 General Firm: 0.45. In this example we also see that firm A cannot reach the word of mouth levels of the other two firms. This happens because the sub-group influenced by the firm was too small to be spread around by the word of mouth effect.

The same high budget campaign with low returns unveils, many times, depending on completely different reason. In another example we also see that the firm A could not reach the word of mouth levels to contrast the other firms. Knowing that consumers suggest by word of mouth process the product that they consider the best in terms of influence accumulated, and that even in this case firm A was the leading firm in terms of consumers contacted, we made a punctual verification of what could have

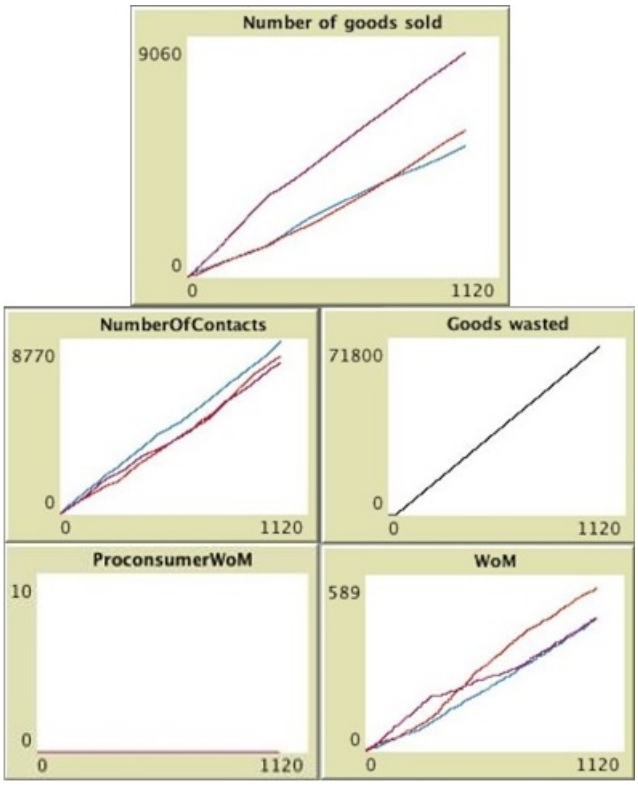

FIGURE 3.4: High advertising budget with low purchases.

	Characteristics		
Firm A	0	0	5
Firm B	-5	-5	0
Firm General	-2.5	-2.5	2.5

TABLE 3.4: Goods attributes in the Best vs worst firm scenario.

happened. The firm's advertiser dispersed too much the advertising budget, and was unfortunately hitting the sub-groups more influenced by the other two firms with not enough power. Faithful consumers did not crack under his/her promotion. Of course, if the advertiser's total efforts reduced the target market, he/she could have generated much higher returns. From this set of simulations many insights unfolded and we understood how setting a good market target is important in order to obtain higher returns. In addition, the advertisers in the simulation do not collude trying to slit the market, this leads to many unexpected results.

Other interesting experiments are run with firms producing non-identical products. In fact, with this set of experiments we can test how consumers are incited in buying the worse products and what conditions lead this strategy to be successful. Firms generate goods that have attributes as in figure 3.4. Leading, therefore, firm A to be the best possibility a consumer can choose.

	Characteristics		
Firm A	-5	-1	4
Firm B	-2	-3	2
Firm General	-3.5	-2	3

TABLE 3.5: Goods attributes in the high vs low quality scenario.

It was peculiar understanding what the simulations presented. The first note is that when consumers try to buy firstly the goods that are strongly advertised, and no information are spread in order to help consumer to make the real best choice, the number of goods sold per firm depends solely on the budget and on how picky consumers are. In this context *acceptationThreshold* is the variable that changes completely the final market shares. It is useless to say that when this variable is zero, all consumers buy all the products, and the worst firm ends up with the 33% as well. Firm B, producing an expensive and polluting product with low quality, makes of the lack of information its better fortune. When *acceptationThreshold* is set to be equal to 2 on 3, none of the consumers accept the worst product, since it is too distant from their preferences, even thought the advertising was successful, whereas when *acceptationThreshold* is equal to 1, a small amount of unfortunate consumers buy the worst product, just because it was advertised to them.

We did not studied the role of information asymmetry yet. The reason is that with the actual settings we are generating environments where information asymmetry is still ineffective. Its role will be verified when consumers will be able to communicate information that generate a feedback that is unrelated to the advertising but is centred in their subjective evaluation of the good. In this case, the worst firm would see a negative feedback that could undercut its sells.

We continued with other simulations of the influence effects case, we want to recall that all these simulations present equal weights for all the single attributes, which means that consumers evaluate the importance of price equally as the one of quality and, in this contexts, pollution. It was interestingly run a case in which firm A is the high price/quality producer with a low pollution level, and it is compared against firm B, a low price/quality producer with high polluting levels. All firms developed an advertising method that we called classic, leading final influences to vary solely on the amount of reachable consumers that advertisers are able to contact at the end of each day. In this setting, the general firm will automatically set its goods'attributes to: medium price/quality and medium pollution as well. The firms attributes are shown in figure 3.5 With the high vs low quality firms settings we have run many simulations, modifying structural variables as the *acceptationThreshold* and the weights of each attribute. We have always seen, in at least 30 trials, the low price firm in strong disadvantage compared to the other two. Of course, this effect was more relevant when *acceptationThreshold* was equal or higher to 2, and this is the case because consumers start to be more picky about their purchases. The reason

that lead agents in making this preferences is again straightforward, and is strictly related to the way preferences are weighted up. In fact, we have the low price firm that, on 3 attributes, makes of its good price their leading strong point to incite purchases, meanwhile its quality and its pollution levels are bad. The high quality firm has instead two strong points, clearly the quality, and also the amount of pollution produced per product made. In a context in which all the variables weight identically in terms of importance, it is normal that two strong points are better than one. An interesting challenge instead, is the one happening between the high quality and the general firms. That is the case since the general firm has a lower price, lower quality and higher pollution level per product made. As already explained, we can deal to differences in attributes looking at it from the consumer's point of view. We know that the lower price of general firm attracts 30% more consumers, and both the lower quality and higher pollution levels diminish of the 20% each the likelihood of consumers accepting the product. We should therefore end up with the high quality firm having a much higher market share compared to the one producing the medium quality good. But this is not the case. This happens because of two main reasons. The influence generated by the advertiser of the general firm has often defeated the influence levels of other advertisers. Advertising is therefore one of the two leading reasons that keep the sells of the general firm higher compared to its rivals. The advertising triggers properly the word of mouth. We are able to see from the data analysis that the higher amount of money spent in advertising equals higher word of mouth levels. We are not able to assess if there are rules in the percentage changes of money spent in advertising in order to generate higher word of mouth, and we have already seen that the relationship is not always straightforward. We just want to recall that in this context all three firms make advertising in the same classical way, and that, given the exclusion of the proconsumer word of mouth, the word of mouth generated by consumers is uniquely positive and supports the firm that better developed its advertising. Since all firms use the same advertising strategy, it will be interesting to see how the levels of word of mouth develop when firms change their approach using metrics based on centrality measures. The second important aspect triggering sells of the general firm, is a dynamic that we can deduce from a detailed combination of settings. The general firm is able to overcome the high threshold that consumers require in order to purchase the product, and it is able to do so more times than the higher quality producer. This happens because the higher price imposed from the higher quality firm drives many consumers off. This happens due to the fact that when the price is that high all consumers will surely have their threshold overruled by the price. When *acceptationThreshold* is equal to 1, it leaves consumers with the need of accepting the other characteristic, otherwise the good will be rejected altogether. When *acceptationThreshold* is equal to 3, it is essential that the consumers buying the higher quality product are also higher budget consumers. This lead the setting with *acceptationThreshold* equal to 3, to show an average of goods wasted on the total production equal to 0.70%. This high value let us foresee that the amount of products waiting to be purchased in their month of existence is really high, leading to the possibility of consumers to make their choice having at disposal all the different products. However, for many consumers is it not convenient to

purchase any products since no one is close or cheap enough to meet their desires. To get this setting closer to reality we decided to make the same set of experiments changing how consumers evaluate different attributes. We run the case in which price, quality and pollution are respectively weighted 2,1 and 0.1. Another important aspect of this context is that the supply of each producer is able to satisfy the whole demand by itself. In this context, with a threshold equal to 2 all the agents must overcome price if they want to purchase the product. Running many experiments, we see that the relationship between market share and marketing decreases in terms of relevance, but still holds. The product of the firm with the low quality/price firm is much closer to the needs of the consumers that leaves no chance for the high price/quality firm to make, on average, market share higher than the 10%, whereas the low price/quality producer makes, in average, the 60% of the market share. The average has been computed running 5 experiments with the same settings. Still, a 30% of the market is available and it is earned by the general firm. This is again a successful result for this producer, it constitute a third way that has a discrete quality and not so cheap price, and assess the possibility of generating positive profits given two circumstances, its product is anyway well positioned and advertising needs to be made properly. It is evident that the general firm is not able to compete with the low cost firm, but this is so just in terms of market share, since in terms of profit, in this simulation, we cannot assess a result even though we know the challenge is open. In this context, where price is two times more important than quality and the fact that a firm has lower pollution is considered the 0.05% as important as a low price, the result obtained from the general firm is remarkable. In these experiments, when it happens that the inexpensive producer has a low and ineffective advertising strategy, it is really interesting to see that consumers do not talk about the cheapest and most purchased good. This happens because the word of mouth is concentrated on the advertising levels, and this process is the only one that keeps the more expensive firms to have sales, in fact, otherwise, their market share combined would be nearly close to zero. We can see the unfolding of this dynamics in figure 3.5.

We wanted to test how information asymmetry modifies the final market share in a context in which consumers should be able to notice that the final goods are completely different, and one is better than the others. We also need to recall that we let the feedback effect and, partly, the proconsumer word of mouth as the instruments able to generate valuable information in a consumer-to-consumer communication, whereas the WoM that is here tested is not of any help in suggesting the good that most deserves to be sold. A really interesting phenomena happens when *ceteris paribus*, *acceptationThreshold* is set to be equal to 3. We foresee an increase of the percentage of goods wasted on the total production, but the three firms market share follow a similar unexpected behaviour during 5 trials made. We expected the market share of the low cost firm to increase even more since the other firms could not satisfy the high acceptance threshold, but, even though the low cost firm has a better advertising strategy, the other two firms are able to gain together around the 50% of the market share. This happens due to an interesting combination of effects. When *acceptationThreshold* was equal to 2, the low cost firm could see its product being purchased from agents satisfied uniquely from the price, since it is weighted is

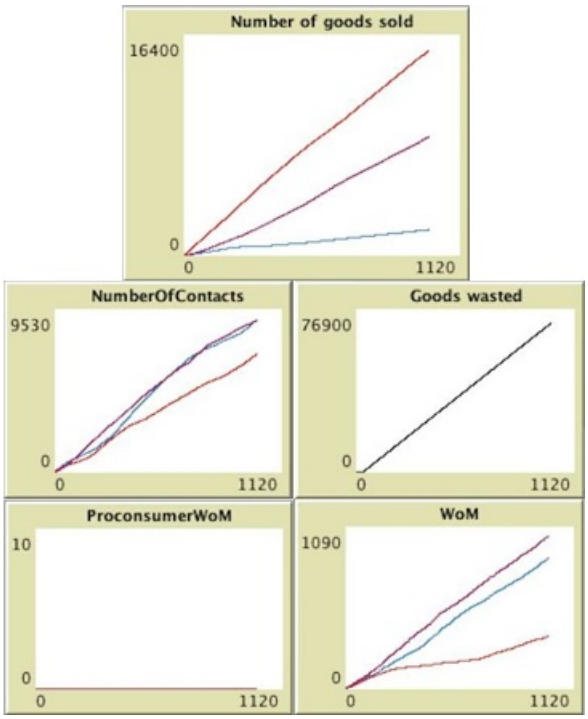

FIGURE 3.5: Goods attributes in the high vs low quality scenario with price strongly weighted.

enough to overcome the threshold. When *acceptationThreshold* is instead set to 3, the total number of products sold inevitably decreases to the 10% of the production. The remaining group of consumers buying the product must accept both the price and quality of it. In this situation, the low cost firm looses the extra purchases of all the consumers accepting only the price, and the market tends to split in two, in fact we have run the experiment many times and firm A plus the general firm always end up sharing the 50% of the market. One interesting case, framed in the same background, unfolds its dynamics in figure 3.6. In this situation we can clearly see that the number of goods sold follows the number of contacts.

3.0.4 Third set of experiments: feedback case

This group of experiments is characterized by a setting in which the probability of using the feedback system is equal to 1, i.e. maximal. The probability of being influenced is instead equal to 0, therefore, consumers will make decisions basing their purchase process solely on the reviews system. We run this case in order to assess the dynamics that consumers can unfold when the whole decision making process is based on a subjective evaluation of the products. The first set of experiments made was achieved by setting all the firms with equal values. In figure 3.7 we can see the values chosen.

When the supply is equal to the demand and all consumers have full information about the product locations, with *acceptationThreshold* equal to zero, we see all firms selling all the products. When *acceptationThreshold* is

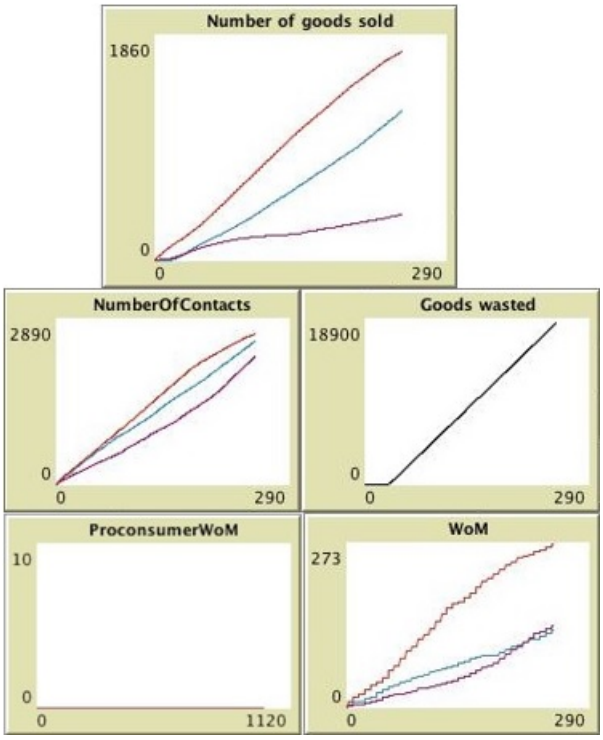

FIGURE 3.6: Goods attributes in the high vs low quality scenario with price strongly weighted, relevant result.

	Characteristics		
Firm A	-2.5	-2.5	2.5
Firm B	-2.5	-2.5	2.5
Firm General	-2.5	-2.5	2.5

FIGURE 3.7: Equal attributes.

raised, firms tend to slowly lose their proximity from an equal division of the market.

There is a major effect that unfolds during the course of this experiment; firms with equal attributes do not always end up having same reviews. Running the experiment 30 times we see that feedback averages change from firm to firm and from experiment to experiment, even though standard deviation of changing attributes is not high. The maximum difference from the total mean is of $+/-0.4$ with a standard deviation of 0.17. We believe that reality can unfold in a similar way. This difference happens because consumers, both in the simulations and in real life, have different tastes, and when the evaluation is made it depends not solely on the real attributes of the product. Another important aspect that we need to take into consideration is that when *acceptationThreshold* is raised, the average feedback increases considerably (of about the 8% for each unit increase in the threshold). This phenomenon happens because of the very formulation of feedback itself and also because of the absence of any information asymmetry. When consumers have an higher *acceptationThreshold* they will also be more picky in their purchases. More picky consumers do not purchase any product at all if they are not really close to be satisfied by it. It is therefore obvious that, with the absence of information asymmetry, those who purchase the product will surely leave a positive feedback afterwards. However, even if an increasing *acceptationThreshold* produces an increase in the average rating of the reviews, running many experiments with different attributes values, we have seen a strong correlation between attributes and reviews. Therefore, the average rating of the reviews depends on the attributes levels. Results obtained in the previous simulations are consistent with the hypothesis on which the simulator has been based. Nonetheless, an interesting phenomenon that unfolded was the continuous strengthening of the products feedback. A higher *AcceptanceThreshold* originates smaller consumers niches and, as a consequence, makes the average feedback raise. A smaller amount of consumers self promotes the purchased product that only similar peers have the possibility to buy. This process stops if the system takes into considerations positive levels of information asymmetry. In the real world, in fact, consumers have less information about the real attributes of products, for this reason we will investigate contexts with a positive value of information asymmetry.

We then changed the attribute of each good as in table 3.4, since this is the basic framework in which we want to understand how higher levels of information asymmetry generate undesirable results. Keeping all the variables unchanged, we run plenty simulations with a raised level of information asymmetry. With *InformationAsymmetry* equal to 0.5, the difference of worst with respect to the market share, compared to the case with no asymmetric information, was not as high as expected. The worst firm, in fact, has an average of 0.10% product sold with complete information and it increases of around 0.02% with a probability that the market asymmetry is set to the 50% of its complete probability of occurrence. Nonetheless, there is a major effect that we are able to notice, even though the market share does not differ in percentage level, there is a considerable increase in absolute values. This is reinforced by the fact that the market has a whole, shows a higher total number of goods sold. The reasons that generated this effect

are not obvious and we decided to run other simulations with different values in order to understand if this is a true relation and why the simulator underlined it. Since *InformationAsymmetry* is a probability value, the obvious thing to do is to raise its value considerably. We decided, in fact, to set it first to 0.7% and then to its maximal level, level in which consumers act according to random decisions. We see that the market share of the firms changes considerably. We compute the mean between 15 experiments and the worst firm presents a 17% level of the whole market sells. This is the maximal level that the firm could obtain in this scenario even with none feedback system at work, and the level is this low because it is established in accordance with the *acceptationThreshold* equal to 2, that does not allow many consumers to purchase the product. We also continue to see that the simulator presents a relationship between goods wasted and information asymmetry and, after a cautious analysis of consumers behaviour, we discovered a peculiar by-product effect. When high budget purchasers could prefer to buy the best good and the information of the market where useless in understanding which one was truly the best, they could have been redirected to purchasing the worst good. We, therefore, see that the higher number of product sold depends on the fact that the purchasing process is randomly generated. Obviously, the fact that goods wasted decrease, is a negative effect in this scenario. The reason is that consumers continuously support the worst producer and by doing so the production will not be stopped. In terms of compared damages it is better to have an higher level of wasted goods for a relatively not high time span, than a continuously high level of pollution created in order to sell more products.

3.0.5 Fourth set of experiments: combinations of influences and feedback

The whole simulator has been constructed following the belief that real world consumers do get influences by advertising campaigns, friends, blogs, online reviews and all other types of information sharing. Therefore, the aim of the simulation was to achieve experiments combining both the effects of the influence system and of the feedback system. The question: to which extent? we believe different product have different market niches with unique characteristics. The producer of a highly expensive product will target its customers exploiting a basic background that they can have in common. Advertisers will, therefore, expect to be dealing with high budget clients, possessing an average medium/high level of education, quite picky on their search for quality/visibility/prestige and so on. The background just mentioned strongly differs from product to product, even in the same category. We tried to generate a simulator that, working on relative terms, is able to develop many different consumers behaviours, according to the category we want to analyse. Due to the high number of variables developed, we decided to analyse in this work only the most considerable experiments.

We want to start from a situation in which consumers have the 3.4 scenario, supply equals demand. There is a probability of 50% of being influenced, and of receiving word of mouth communications. The proconsumer WoM is not included. The *FriendshipType* is again set to be equal to

Quasi-Stochastic FriendShip Threshol and it will be so for the rest of all experiments. We begin with *acceptationThreshold* equal to 1 and *InformationAsymmetry* equal to zero. The levels that we are going to refer from now one are averages computed between simulations run a minimum of 10 times each. Consumers, obviously, prefer the high quality firm and the general firm, but this is not proportional to the advertising budgets. Consumers, in fact, purchase firstly the favourite products, the high and medium price/quality products are sold out at each tick and the 23% of goods wasted on the total production belongs solely to the worst firm. This is a quite interesting result, because the introduction of the two influences effects with no asymmetry of information leave the market to avoid purchasing from the worst firm. This happens much more commonly than in the case of no influences, showing how the feedback system, even with a low probability of occurrence, helps consumers in making a better purchasing process. This goods wasted level is also strongly correlated to the *acceptationThreshold*, but it is positive to notice, that the feedback system helps in reducing the market share of the worst firm. It is important to highlight that attribute setting is mainly develop in order to assess the effects of the procedure. In fact, the worst firm has a major competitor, a firm that produces a good considered 100% better than its own in terms of quality, and asks no profits for it. We begin to raise the *InformationAsymmetry* and we notice that the market share does change and this difference in levels is strongly correlated to the *acceptationThreshold*. In fact, when the *acceptationThreshold* is equal to 1, the information asymmetry has a higher power in changing the market shares. When instead is set to be 2 or 3, consumers are less influenced by asymmetry of information, because they refuse the product altogether.

Another interesting application has been made in the 3.5 scenario. This simulation is very far from reality due to the fact that consumers weight equally price, pollution and quality. Nonetheless, results obtained with this weights will help our understanding of similar settings with more entangling inputs. Once again we begin with a supply equal to the demand, there is a probability of 50% of being influenced, and of receiving word of mouth communications. The proconsumer WoM is not included. We begin with *InformationAsymmetry* equal to zero and we let *acceptationThreshold* raise by 1 in each 5 simulations. Results behave as our expectations, from simulation to simulation consumers may be closer to a given firm, therefore we do not have a consistent behaviour toward firm A or firm B. It is possible, instead, to see a trend is in the high purchases of the general firm. Again, the fact that this producer is perfectly in between the other two firms in terms of goods attributes, leads it to be in a good position closer to consumers' desires. An objective evaluation of the happiness of consumers can be done by looking at the reviews levels. We can assess that in this scenario consumers are not at the best of their possibilities.

To make things more interesting we implemented the scenario with the following weights: the price is weighted 2 times more than the quality and the importance bestowed to pollution is the 0.05% of the price. In this setting only high budget consumers are allowed to purchase the high quality product. Results highlight how advertising is important for the high quality firm in order to keep its customers, its rating is higher than the one of the other firms and this happens because of the presents of an interesting dynamic, similar to the one experienced in the feedback effect case (refer

to 3.0.4 for a better understanding). The first important dynamic that we want to study is the effect that the proconsumer WoM has on this setting, we let *ProconsumerWom* be equal to QRWS that allows consumers with a good knowledge level to spread information about the quality of products (a full description of this procedure has done in chapter 2.0.5). We have seen that the high quality firm has an higher market share of the 3%-4%, the amount of influence generated by the advertiser of the high quality firm is helped by these proconsumer WoM dynamics. Another important result is that the low cost firm, ruling the market due to its point of strength, losses market share also in favour of the general firm, that performs better than without proconsumer WoM. Another important development has been made including different levels of information asymmetry. With its probability level equal to 0.5 we did not see much differences. We therefore decided to set *ThresholdKnowledge* equal to 2.5 on 5. The effects are clear. When the number of consumers leaving their comments about the products decreases, only those more able in understanding the real attributes of the products have the possibility to share their opinion, the performance of the high quality firm increases. Therefore this can be considered as an increase in the quality of the information in spite of the quantity. We need to explain this result by making some connections with the network analysis and the general understanding. The *FriendshipType* is again set to be equal to *Quasi-Stochastic FriendShip Threshol*. First of all, we experienced how this effect starts to lose of importance when we set *ThresholdKnowledge* to be higher than 3.5, this happens because the number of informed consumers drastically drops. We need to recall that consumers form many subgroups. With this setting the network analysis coefficients can be interpreted as follow: the density of the network, in this setting, has an average equal to 0.06, with a standard deviation close to 0.005. It informs us that, on average, the network presents a 6% of connections on the total connections possibilities. This amount is directly proportional to the *ViewRadius-Friendship* variable, and it is consistent with the general understanding of what a density measure should be like in order to reproduce real world dynamics. We also see a really low *average-weighted-path-length* that is below 0.01, and an *average-local-clustering-coefficient* almost equal to 0.5. We believe that these values are consistent with the network and therefore we keep the *ViewRadiusFriendship* unchanged. This is important while understanding the fact that when *ThresholdKnowledge* increases of more than 3.5, a really small amount of people can start to inform their friends about the existence of a better product. When, instead, *ThresholdKnowledge* is below 3.5 and above 1.5, a good amount of consumers medium and high informed is able to ripple the information through the whole network. We tried another combination of effects. *ProconsumerWom* has been set to be equal to ERWS2 (Environmentalist real world sensitive), a process that let consumers achieve a proconsumer word of mouth against polluting firm. With this setting the simulator provided results really similar to the QRWS process, this is so because the best firm in terms of quality is also the best in terms of low levels of pollution, and the general firm that has a medium level of price/quality and pollution, enhance its position in contrast of the low price/quality firm as well. These similar results are so even though the QRWS process is really different from the ERWS2. In fact, the ERWS2, as introduced in chapter 2.0.5, produce a negative word of mouth effect for the

firm with high levels of pollution.

Conclusions

The complex and different nature of the topics included in this analysis, as well as the many sociological and physiological aspects related to the consumer's behaviour, did not render this work easy to conduct. Our endeavours mainly concerned the understanding of consumers and consumption. We delved into the study of countless disciplines and concepts often very similar, only divided by subtle layers. Developing a bottom-up approach that tried to fit as many interesting real world dynamics as possible, has been a fairly complicated task. Our journey can be divided into both a theoretical and a practical challenge.

From the theoretical point of view, the challenge has been dealing with the study of a great deal of material. Scientific papers, real world applications and many e-commerce studies, have all been used to extrapolate real world dynamics useful for the enhancement of the project. The theoretical part of the analysis began with an introduction on the agent based simulation technique. We introduced its characteristics and the reasons that lead this technique to be a valuable tool in the achievement of the analysis of the consumer market. We moved forward into examining real world applications of agent based modelling, centred respectively on a promotional campaign and on urgent diffusion scenarios. To follow, we explained why an agent based simulation as the one implemented in this work, does not need to consider the concept of utility function. The reason is that the simulator is able to compute the singular satisfaction experienced by each consumer by itself.

The comprehension of the market through the realization of simulated models required a full understanding of the dynamics unfolding between singular agents. This is the reason why a sizeable amount of work has been centred on the discipline of network analysis. Concepts as homophily and propinquity, that characterize the actions made by all human beings, found a wide application during the achievement of the simulation. The discipline offered a good amount of extremely useful tools, that were necessary for the realization of a market in compliance with the desired aspirations. A different but related concept, is the one of big data. It is in fact postulated that, through their usage, the future will unfold towards new methods of analysis. The scientific sector is already developing the potentials of computer simulations in sociological and economical sciences and we believe that a combination of computer simulations and real data can nurture the general understanding of consumers in their decision-making processes. Notwithstanding that a data-driven approach can lead to deeper understanding of many dynamics, we assert how important it is to ground decisions evaluating the future as continuously mutating and not perfectly foreseeable. The relativity present in this work comes from our belief that each human being is inevitably unique. Many economical forecasts based on human behaviour, adopt conclusions derived from the past. Considering the very nature of a human being, these forecasts may produce unworkable results.

Some of this thoughts are the result of the study of the scientific method, others come from the analysis of Armen Alchian's work on uncertainty and evolution. Nonetheless, even though social behaviour easily differs in time, this does not mean that random decision making is the appropriate choice.

From the practical point of view, in line with our line of reasoning, we developed the code trying to engender a flexible simulator. We generated different versions, and by using the trial-and-error method we continuously improved the previous versions in the quality and variety of dynamics considered. The final result, enhanced by all the various integrated experiences, has been carefully verified and its validation brought to the accomplishment of its predominant role. Once the simulator had been considered operationally valid, we began to investigate the results presented. A number of different scenarios has been implemented in the proposed model, all grounded on an oligopoly competition. Given the large amount of variables able to be processed by the simulator, experiments have been done in the most appropriated setting, according to the topic that wanted to be inspected. The first scenario inspected considers the contrast between three different firms, the first one producing the best possible goods, the second producing the most uncompetitive product and the third producing a product in between. We analysed how information asymmetry was able to affect consumers' decisions. In the context, in which this information asymmetry was high, consumers were really far form making the best purchase decision. This allowed uncompetitive products, produced with high level of pollution, to be purchased in a quantity that solely depends on the average consumer's rigidity towards their preferences. The contrast exemplified in the second scenario sees a high price/quality firm against a medium and a low price/quality firm. In this context, as foresaw, we have very often seen the medium quality firm achieving the best results. During this inspection, focused on the Proconsumer Word/of/mouth, we discovered the existence of an optimal knowledge range in the diffusion of the quality information related to the goods. While increasing the requested knowledge, in order to be able to diffuse known information about the quality, we have seen an increase in the quality of the total market behaviour up to a threshold level. From the moment in which the requested knowledge let smaller amounts of consumers, below the 30% of the most prepared consumers, to exchange information between each other, the general knowledge of the quality began to decrease. This is a consequence of the fact that when a system spreads too much information it is possible that some if this information will not improve the system structure anymore. On the other hand, we can see that when the communications is done by a fewer number of people that do not have a strong diffusion mechanism, information remain stuck. Another development has been done in a context in which all firms were equal, so that we could analyse how advertising affected purchases. we observed how big amounts of advertising did not always achieve the best performance. The main reasons that led to this circumstance is related to how advertising was spread. Even though a firm achieved higher numbers of contacts to the market, obtaining the best level of advertising among it competitors, situations in which the advertiser tries to persuade too many consumers, led often to vain effort. At the same time, when the advertising made by a firm does not wider its target to enough consumers, the influences provided do not trigger word of mouth mechanisms leading to the best performance.

Other simulations, that tried to estimate the quality of an influence system generated on centrality metrics did not provide useful results.

To conclude, our efforts were concentrated on the development of a market system and we believe that the result obtained can easily be implemented. The model here implemented can be customizable according to different necessities. Future developments of the model have already been conceived. For example it will be extremely interesting to add relativity to the life span of the products and develop the firm capacity to manage the information provided by the market. As a consequence of this study, we can assert the usefulness of an agent-based simulation approach, along with an understanding of the network analysis discipline, for an investigation of the consumer market.

Appendix A

Netlogo Code

```
extensions [nw]
globals [ tempBestGood goodsUnderChoice
goodsUnderChoiceSorted totalGoodsSold
GoodsWasted layoutcircle
totalContaction attributesImportance ]
breed [ goods good ]
breed [ consumers consumer ]
breed [ shops shop ]
breed [ firms firm ]
breed [ advertisers advertiser ]
consumers-own [xcor0 ycor0 cash preferences
NproductPurchased FavouriteBrAd knowledge
worseFirmBP ListByQuality
betweennessCentrality WeightedClosenessCentrality
eigenvectorCentrality]
goods-own [ brand attributes
NofCharacteristicsOvercome timeInTheMarket ]
shops-own [name ]
firms-own [name firmBrand producedProducts soldProduct
FirmgoodsWasted ZeroProfitSoldProduct
advertisingType myX myY myZ
MyGoodattributes Reviews NofReviews ]
advertisers-own [ brand influence
viewRadiusADV advertisingTypeAd Owncolor ]
directed-link-breed [Brands-links brand-links ]
undirected-link-breed [Consumers-links Consumer-links ]
Brands-links-own [ brandL radius
influenceAccumulated influenceAccumulatedPRO
MarPropConsum timesContacted
timesContactedFriends timesContactedProWOM ]
Consumers-links-own [ weight ]


to setup

clear-all
reset-ticks
ask patches [ set pcolor white]
creationOfShops
creationOfFirms
```

```
creationOfConsumers
set totalGoodsSOld 0
set goodsWasted 0
set layoutCircle "off"
set attributesImportance n-values (characteristicN - 3) [ 1 ]
set attributesImportance fput z.weight attributesImportance
set attributesImportance fput y.weight attributesImportance
set attributesImportance fput x.weight attributesImportance

end


to creationOfShops

create-shops 2
ask shops
[ set shape "Building store"
set size 2  set color white ]
ask shop 0
[ set name "shopGoods0" set xcor 15 set ycor 15 ]
ask shop 1
[ set name "shopGoods1" set xcor -15 set ycor 15 ]

end


to creationOfFirms

create-firms 3
ask firms
[ set shape "factory" set size 2
set Reviews 0 set NofReviews 0 set label-color black ]
ask firm 2 [ set name "FirmBlue" set firmBrand 0
set xcor 15 set ycor -15 set color blue ]
ask firm 3 [ set name "FirmRed" set firmBrand 1
set xcor -15 set ycor -15 set color red ]
ask firm 4 [ set name "generalFirm" set firmBrand 2
hide-turtle set advertisingType "Classic" set xcor 0 set ycor -15 ]
ReadADVtype

end


to ReadADVtype

If (RedAdvertisingType = "Classic") [ ask firm 3
[ set advertisingType "Classic"]]
If (RedAdvertisingType = "Higher-Weighted-Closeness-Centrality")
[ ask firm 3
[ set advertisingType "Higher-Weighted-Closeness-Centrality"]]
If (RedAdvertisingType = "Higher-betweenness-centrality")
```

```
[ ask firm 3
[ set advertisingType "Higher-betweenness-centrality"]]
If (RedAdvertisingType = "Higher-eigenvector-centrality")
[ ask firm 3
[ set advertisingType "Higher-eigenvector-centrality"]]

If (BlueAdvertisingType = "Classic")
[ ask firm 2
[ set advertisingType "Classic"]]
If (BlueAdvertisingType = "Higher-Weighted-Closeness-Centrality")
[ ask firm 2
[set advertisingType "Higher-Weighted-Closeness-Centrality"]]
If (BlueAdvertisingType = "Higher-betweenness-centrality")
[ ask firm 2
[set advertisingType "Higher-betweenness-centrality"]]
If (BlueAdvertisingType = "Higher-eigenvector-centrality")
[ ask firm 2
[set advertisingType "Higher-eigenvector-centrality"]]

end


to creationOfConsumers

create-consumers NumberOfConsumers
ask consumers
[ setxy random-xcor random-ycor set xcor0 xcor set ycor0 ycor
set worseFirmBP [] set ListByQuality []
set color pink set cash 1 set shape "person" set FavouriteBrAd []
set knowledge random 6
set preferences n-values (characteristicN - 2 )
[ precision random-float 5 3 ]
while [length preferences < characteristicN]
[ set preferences fput
precision ((random-float(5)) - 5) 3 preferences ]]

end


to creationOfAdvertisers

let tempinflu 0
ask firms
[ hatch-advertisers 1 [ set size 1 set color yellow
set Owncolor [color] of myself set shape "person business"
set label "" set brand [firmBrand] of myself
set label [name] of myself
set viewRadiusADV viewRadiusAdvertisers
set advertisingTypeAd [advertisingType] of myself ]]
ifelse Adv.Equal.Influence [ask advertisers
[set influence 5]] []
```

```
end


to start

if (ticks = 1001) [ stop statistics ]
if (ticks = 0 or remainder ticks 1000 = 0)
[ creationOfAdvertisers ]
creationOfGoods
advertising
ProconsumerWordOfMouth
tryToBuy
ask goods with
[ timeIntheMarket = 15 or
timeInTheMarket = 20 or timeIntheMarket = 25 ]
[ let i 0
while [ i < 4 ] [
if i = 0 [ let momentary item i attributes
set attributes replace-item i attributes
(momentary + precision random-float 0.5 3)
if item i attributes > 0
[ set attributes replace-item i attributes 0 ]
set i i + 1 ]
if i = 1 [ set i i + 1 ]
if i = 2 [ set i i + 1 ]
ifelse characteristicN > 3 and i = 3
[ let momentary item i attributes
set attributes replace-item i attributes
( momentary + precision random-float 0.5 3)
if item i attributes > 5
[ set attributes replace-item i attributes 5 ]
set i i + 1 ]
[set i i + 1 ]]]
ask consumers [ if cash <= 0 [ set cash cash + 1 ]
set heading random 360 fd random-float consumerStep ]
ReadADVtype
ask advertisers
[ set advertisingTypeAd item 0 [ advertisingType ]
of firms with [ firmBrand = [brand] of myself ]]
ask goods [ set timeInTheMarket timeInTheMarket + 1
if timeInTheMarket = 30
[ ask firms with [ firmBrand = [ brand ] of myself ]
[ set FirmGoodsWasted FirmGoodsWasted + 1 ]
set GoodsWasted GoodsWasted + 1 die ]]
tick
wait 0.05

end
```

```
to creationOfGoods

let goodattributes []
ask firms[
ifelse UniqueProduct [ ifelse ticks < 1
[ set goodAttributes definingAttributes ]
[ set goodAttributes MyGoodAttributes  ]]
[ set goodAttributes definingAttributes ]
hatch-goods (NumberOfGoods / 3)
[ set size 1 set color black
set shape "box" set label ""
set attributes Goodattributes
set brand [ firmBrand ] of myself
ifelse stores
[ ifelse brand < 2
[ ifelse random-float 1 > 0.3
[ move-to shop brand ]
[ setxy random-xcor random-ycor ]]
[ setxy random-xcor random-ycor ]]
[ setxy random-xcor random-ycor]]
set producedProducts  producedProducts +
(NumberOfGoods / 3) ]

end


to-report definingAttributes

if name = "FirmBlue" [ set myX (- x.blue)
set myY (- y.blue) set myZ z.blue ]
if name = "FirmRed" [ set myX (- x.red)
set myY (- y.red) set myZ z.red ]
if name = "generalFirm"
[ set myX (precision (((- x.blue) + (- x.red) ) / 2) 3)
set myY (precision (((- y.blue) + (- y.red)) / 2) 3)
set myZ (precision ((z.blue + z.red) / 2) 3) ]
let goodAttributes  n-values characteristicN
[ precision random-float 5 3 ]
set goodAttributes replace-item 0 goodAttributes  ( myX )
set goodAttributes replace-item 1 goodAttributes  ( myY )
set goodAttributes replace-item 2 goodAttributes  ( myZ )
set MygoodAttributes goodAttributes
report goodAttributes
end


to tryToBuy
ask consumers with [ cash > 0 ]
[ let thresholdFeedback precision random-float 1 2
let thresholdInfluence precision random-float 1 2
if  Prob.FeedBack.Effect <= thresholdFeedback and
```

```
Prob.Influence.Effect <= thresholdInfluence
[ .zeroeffect ]
if  Prob.FeedBack.Effect <= thresholdFeedback and
Prob.Influence.Effect >= thresholdInfluence
[ .Influence.Effect ]
if  Prob.FeedBack.Effect >= thresholdFeedback and
Prob.Influence.Effect <= thresholdInfluence
[ .FeedBack.Effect ]
if  Prob.FeedBack.Effect >= thresholdFeedback and
Prob.Influence.Effect >= thresholdInfluence
[ .Influence.EffectPlusFeedBack.Effect ]]

end


to .Zeroeffect

if any? goods in-radius (ViewRadius)
[ set goodsUnderChoice goods in-radius ViewRadius
creationOfGoodsListAndThresholdControl
]
end

to .FeedBack.Effect

let MaxReviews []
let MaxreviewsSorted []
let tempfirm []
set MaxreviewsSorted sort-on [ reviews ] firms
if knowledge < thresholdKnowledge or
informationAsymmetry > random-float 1
[ set MaxreviewsSorted sort-on [ random 3  ] firms ]
let brandControl 0
let flowi 0


while [ flowi < 3 and cash > 0 ]
[ ask item flowi MaxreviewsSorted
[ set brandControl firmbrand ]
if any? goods with [ brand = brandControl ]
in-radius (Viewradius + knowledge)
[set goodsUnderChoice goods with [ brand = brandControl ]
in-radius (Viewradius + knowledge)
creationOfGoodsListAndThresholdControl ]
set flowi flowi + 1 ]

end


to  .Influence.Effect
```

```
let ConsumptionT 0
let brandControl 0
let radiusP 0
let flowi 0
let NumKnownBrand length FavouriteBrad
while [ flowi < NumKnownBrand and cash > 0 ]
[ ask item flowi FavouriteBrAd
[ set brandControl brandL set radiusP radius ]
set ConsumptionT absoluteIncomeHyp flowi
if any? goods with [brand = brandControl]
in-radius (radiusP) and (consumptionT > 0.5)
[ set goodsUnderChoice goods with
[ brand = brandControl ] in-radius radiusP
creationOfGoodsListAndThresholdControl ]
set flowi flowi + 1 ]

end


to .Influence.EffectPlusFeedBack.Effect

let ConsumptionT 0
let brandControl 0
let BestFeedBackbrandControl 0
let radiusP 0
let flowi 0
let MaxReviews []
let MaxreviewsSorted []
let tempfirm []
set MaxreviewsSorted sort-on [ reviews ] firms
if knowledge < random-float thresholdKnowledge or
informationAsymmetry > random-float 1
[ set MaxreviewsSorted sort-on [ random 3 ] firms ]
ask item 0 MaxreviewsSorted
[ set BestFeedBackbrandControl firmbrand ]
let NumKnownBrand length FavouriteBrad
while [ flowi < NumKnownBrand and cash > 0 ]
[ ask item flowi FavouriteBrAd
[set brandControl brandL set radiusP radius ]
ifelse item 0 [ reviews ] of firms with
[ firmBrand = brandcontrol]  -
item 0 [reviews] of firms with
[ firmbrand = Bestfeedbackbrandcontrol]
>= ( - Maxdifference )
[ set ConsumptionT absoluteIncomeHyp flowi
if any? goods with [brand = brandControl] in-radius
(radiusP) and (consumptionT > 0.5)
[ set goodsUnderChoice goods with
[ brand = brandControl ] in-radius radiusP
creationOfGoodsListAndThresholdControl ]
set flowi flowi + 1]
```

```
[ if any? brands-links with
[ brandl = BestFeedBackbrandControl ]
[ ask one-of brands-links with
[ brandl = BestFeedBackbrandControl ]
[ set radiusP radius ]]
if any? goods with
[ brand = BestFeedbackBrandControl ] in-radius (radiusP)
[ set goodsUnderChoice goods with
[ brand = Bestfeedbackbrandcontrol ] in-radius radiusP
creationOfGoodsListAndThresholdControl ]
set flowi 5 ]]

end


to-report absoluteIncomeHyp [ flowi ]

let consT 0
ask item flowi FavouriteBrAd [ ifelse InfluenceAccumulated >= 0
[ set MarPropConsum
(0.5 + ((InfluenceAccumulated) /
(10 * (timesContacted + timesContactedFriends))))]
[ set MarPropConsum
(0.5 - (((- InfluenceAccumulated) /
(10 * (timesContacted + TimesContactedFriends) ))))]]
set consT [MarPropConsum] of item flowi FavouriteBrAd * cash
report consT

end


to creationOfGoodsListAndThresholdControl

let a 0
ask goodsUnderchoice
[ set NofCharacteristicsOvercome compare
attributes [ preferences ] of myself ]
set goodsUnderChoiceSorted sort-on
[ (- NofCharacteristicsOvercome) ] goodsUnderchoice
set tempBestGood item 0 goodsUnderChoiceSorted
set a totalGoodsSold
ask tempBestGood
[ if NofCharacteristicsOvercome >= acceptationThreshold
[ CreationOffeedback
if item 0 attributes > ( - 0.02 )
[ ask firms with
[ firmbrand = [ brand ] of myself ]
[ set ZeroProfitSoldProduct ZeroProfitSoldProduct + 1 ]]
set a totalGoodsSold
set totalGoodsSold totalGoodsSold + 1
ask firms with[ firmBrand = [ brand ] of myself ]
```

```
[ set soldProduct soldProduct + 1 ]  die ]]
if a != totalGoodsSold
[ set cash cash - 1
set NproductPurchased NproductPurchased + 1 ]

end


to-report compare [g p]

let aN 0
let i 0
while [ i < characteristicN ]
[ if item i g >= item i p
[ set aN aN + (1 * item i attributesImportance) ]
set i i + 1 ]
report aN

end

to CreationOffeedback

If (CommunicationType ="Feedback" or
CommunicationType = "WOM + Feedback")
[let maxPossDifference 0
let minPossDifference 0
let i 0
let myReview 0
while [ i < characteristicN]
[ set maxPossDifference maxPossDifference +
(5 * item i attributesImportance)
set i i + 1]
let myDifference compareFeedback attributes
[preferences] of myself
let depuratedDifference myDifference / maxPossDifference

if depuratedDifference >= -1 and depuratedDifference < -0.4
[ set myReview 1 ]
if depuratedDifference >= -0.4 and depuratedDifference < -0.2
[ set myReview 2 ]
if depuratedDifference >= -0.2 and depuratedDifference < 0
[ set myReview 3 ]
if depuratedDifference >= 0 and depuratedDifference < 0.5
[ set myReview 4 ]
if depuratedDifference >= 0.5 and depuratedDifference <= 1
[ set myReview 5 ]

ask firms with [ firmBrand = [ brand ] of myself ]
[let totalReviews reviews * NofReviews
set NofReviews NofReviews + 1
set Reviews precision
```

```
((totalReviews + myReview) / NofReviews) 1
set label Reviews  ]]

end


to-report compareFeedback [ g p ]

let valuation 0
let i 0
let V 0
while [ i < characteristicN]
[ ifelse i < 1
[ set V V - ((item i p - (item i g )) *
item i attributesImportance)
set i i + 1 ]
[set V V - ((item i p - item i g) *
item i attributesImportance)
set i i + 1 ]]
set valuation v
report valuation

end


to advertising

friendship
ask advertisers with [ advertisingTypeAd ="Classic" ]
[ set heading random 360 fd random 2
ifelse Adv.Equal.Influence [ ]
[ set influence (precision ((random-float (10)) - 5) 3) ]
let B brand
let in influence
let ViewRadiusAD viewRadiusADV
if any? consumers in-radius viewRadiusADV
[ ask consumers in-radius viewRadiusADV
[ if any? out-link-neighbors
[ ask my-out-Brands-links with [brandL = B]
[ set influenceAccumulated (influenceAccumulated + in)
set timesContacted timesContacted + 1 ]]
ask consumers in-radius viewRadiusAD
[ create-brands-links-to firms with [ firmBrand = B ]
[set brandL B  set radius viewRadius + 1
set influenceAccumulated in
set timescontacted timesContacted + 1
set hidden? not show-brand-links ]]]]]

ask advertisers with
[ advertisingTypeAd = "Higher-Weighted-Closeness-Centrality" ]
[ set heading random 360 fd random 2
```

```
ifelse Adv.Equal.Influence [ ]
[ set influence ( precision ((random-float (10)) - 5) 3) ]
let B brand
let cList sort-on
[ ( - WeightedClosenessCentrality ) ] consumers with
[ WeightedClosenessCentrality >= 0 and
color != [ Owncolor ] of myself ] in-radius viewRadiusADV
let in influence * 2
let ViewRadiusAD viewRadiusADV
if length cList != 0
[ ask item 0 cList [ if any? out-link-neighbors
[ ask my-out-Brands-links
[ ifelse any? Brands-links with [ brandL = B ]
[ set influenceAccumulated (influenceAccumulated + in)
set timesContacted timesContacted + 2 ]
[ ask item 0 cList
[ create-brands-links-to firms with [ firmBrand = B ]
[ set brandL B set radius viewRadius + 1
set influenceAccumulated in
set timescontacted timesContacted + 2
set hidden? not show-brand-links ]]]]
if not any? out-link-neighbors
[ create-brands-links-to firms with [ firmBrand = B ]
[set brandL B  set radius viewRadius + 1
set influenceAccumulated in
set timescontacted timesContacted + 1
set hidden? not show-brand-links ]]]]]]

ask advertisers with
[ advertisingTypeAd ="Higher-betweenness-centrality" ]
[ set heading random 360 fd random 2
ifelse Adv.Equal.Influence [ ]
[ set influence ( precision ((random-float (10)) - 5) 3) ]
let B brand
let cList sort-on
[( - betweennessCentrality )] consumers with
[ betweennessCentrality >= 0 and
color != [ Owncolor ] of myself ] in-radius viewRadiusADV
let in influence * 2
let ViewRadiusAD viewRadiusADV
if length cList != 0
[ ask item 0 cList
[ if any? out-link-neighbors
[ ask my-out-Brands-links
[ ifelse any? Brands-links with [brandL = B]
[ set influenceAccumulated (influenceAccumulated + in)
set timesContacted timesContacted + 2 ]
[ ask item 0 cList
[ create-brands-links-to firms with [firmBrand = B]
[ set brandL B set radius viewRadius + 1
set influenceAccumulated in
```

```
set timescontacted timesContacted + 2
set hidden? not show-brand-links ]]]]
if not any? out-link-neighbors
[ create-brands-links-to firms with [ firmBrand = B ]
[set brandL B set radius viewRadius + 1
set influenceAccumulated in
set timescontacted timesContacted + 1
set hidden? not show-brand-links ]]]]]]

ask advertisers with
[ advertisingTypeAd ="Higher-eigenvector-centrality" ]
[ set heading random 360 fd random 2
ifelse Adv.Equal.Influence [ ]
[ set influence ( precision ((random-float (10)) - 5) 3) ]
let B brand
let cList sort-on
[( - eigenvectorCentrality )] consumers with
[ eigenvectorCentrality != FALSE and
color != [ Owncolor ] of myself ] in-radius viewRadiusADV
let in influence * 2
let ViewRadiusAD viewRadiusADV
if length cList != 0
[ ask item 0 cList [ if any? out-link-neighbors
[ ask my-out-Brands-links
[ ifelse any? Brands-links with [ brandL = B ]
[ set influenceAccumulated (influenceAccumulated + in)
set timesContacted timesContacted + 2 ]
[ ask item 0 cList
[ create-brands-links-to firms with [f irmBrand = B ]
[ set brandL B set radius viewRadius + 1
set influenceAccumulated in
set timescontacted timesContacted + 2
set hidden? not show-brand-links ]]]]
if not any? out-link-neighbors
[ create-brands-links-to firms with [firmBrand = B]
[ set brandL B set timescontacted timesContacted + 1
set hidden? not show-brand-links ]]]]]]

CreationOfPreferitBrandAd
if remainder ticks 7 = 0  [wordofMouthEffect]

end


to wordOfMouthEffect

If (CommunicationType = "Word Of mouth" or
CommunicationType = "WOM + Feedback"  )
[cask consumers with
[ any? Consumer-links-neighbors in-radius viewRadius with
[ FavouriteBrAd != []]]
```

```
[cif powerWOM > random-float 0.99
[clet me who
let i 0 let ListClose []
let cLinkA Consumer-links-neighbors in-radius viewRadius with
[ FavouriteBrAd != []]
set listclose sort-by [[[ weight ]
of link-with turtle me] of ?1 >
[[ weight ] of link-with turtle me] of ?2] cLinka
let temporaryGoodCons2End2 0
let temporaryGoodCons2Influence 0
let temporaryGoodCons2Brand 0
if ListClose != []
[ ask first listClose
[ set temporaryGoodCons2End2 [ end2 ] of item 0 FavouriteBrAd
ifelse [timesContacted] of item 0 FavouriteBrAd  != 0 or
[ timesContactedFriends ] of item 0 FavouriteBrAd != 0
[ set temporaryGoodCons2Influence
(([ InfluenceAccumulated ] of item 0 FavouriteBrAd)
/ (([ timesContacted ] of item 0 FavouriteBrAd ) +
( [ timesContactedFriends ] of item 0 FavouriteBrAd))) ]
[ set temporaryGoodCons2Influence [ InfluenceAccumulated ]
of item 0 FavouriteBrAd ]
set temporaryGoodCons2Brand [ brandL ]
of item 0 FavouriteBrAd ]]
ifelse FavouriteBrAd != []
[ ifelse
[ end2 ] of item 0 FavouriteBrAd = temporaryGoodCons2End2
[ ask my-links with [ end2 = temporaryGoodCons2End2 ]
[ set influenceAccumulated
influenceAccumulated + temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1 ]]
[ while [ i < length FavouriteBrAd  ]
[ ifelse
[ end2 ] of item i FavouriteBrAd = temporaryGoodCons2End2
[ ask my-links with
[ end2 = temporaryGoodCons2End2 ]
[ set influenceAccumulated
influenceAccumulated + temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1
set i 100 ]]
[ set i i + 1 ]]
if i = length FavouriteBrAD
[ ifelse [influenceAccumulated] of item 0 FavouriteBrAD <
temporaryGoodCons2Influence
[ create-brand-links-to temporaryGoodCons2end2
[set brandL temporaryGoodCons2Brand
set radius viewRadius + 1
set influenceAccumulated
influenceAccumulated + temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1
set hidden? not show-brand-links ]]
```

```
[ create-brand-links-to temporaryGoodCons2end2
[set brandL temporaryGoodCons2Brand
set radius viewRadius + 1
set influenceAccumulated
influenceAccumulated + temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1
set hidden? not show-brand-links ]]]]]
[ create-brand-links-to temporaryGoodCons2end2
[ set brandL temporaryGoodCons2Brand
set radius viewRadius + 1
set influenceAccumulated temporaryGoodCons2Influence
set timescontactedfriends timesContactedFriends + 1
set hidden? not show-brand-links ]]
set ListClose but-first listclose]]
CreationOfPreferitBrandAd ]

end


to ProconsumerWordOfMouth

let temporaryPollutionThreshold 0
let temporaryQualityThreshold 0
let temporaryBrand 0
If (proconsumerWOM = "Environmentalism")
[ If (CommunicationType = "Word Of mouth" or
CommunicationType = "WOM + Feedback"  )
[ ask consumers with [ length FavouriteBrAd > 1 ]
[ if knowledge >= (informationAsymmetry * 5) and
knowledge > thresholdKnowledge and
item 1 preferences > (- 2.5)
[ set WorseFirmBP FirmPreferencebyPollution ]]
ask consumers with
[ any? Consumer-links-neighbors in-radius viewRadius
with [FavouriteBrAd != [] and
knowledge < [ knowledge ] of myself ]]
[ if PowerProconsumerWOM > random-float 0.99 and
InformationAsymmetry <= random-float 0.99
[ let me who
let i 0 let ListClose []
let cLinkA Consumer-links-neighbors in-radius viewRadius
with [FavouriteBrAd != [] and
knowledge < [ knowledge ] of myself ]
set listclose sort-by
[[[ weight ] of link-with consumer me] of ?1 >
[[ weight ] of link-with consumer me ] of ?2] cLinka
if worsefirmBP != []
[ set temporaryPollutionThreshold
( - (5 + item 1 preferences)) ]
if ListClose != [] and [FavouriteBrAd] of
first ListCLose != [] and length WorsefirmBP > 1
```

```
[ ask first listClose
[ if [end2] of item 0 FavouriteBrAd =
[ item 0 WorsefirmBP ] of myself
[ ask my-links with
[ end2 = [[ end2 ] of item 0 FavouriteBrAd] of myself ]
[ set influenceAccumulatedPRO
influenceAccumulatedPRO + temporaryPollutionThreshold
set timesContactedProWOM timesContactedProWOM + 1
]]]]]]]]


If (proconsumerWOM = "SparkingEnvironmentalism")
[ If (CommunicationType = "Word Of mouth" or
CommunicationType = "WOM + Feedback"  )
[ ask consumers with [ length FavouriteBrAd > 1 ]
[ if knowledge >= (informationAsymmetry * 5) and
knowledge > thresholdKnowledge and
item 1 preferences > (- 2.5)
[ set WorseFirmBP FirmPreferencebyPollution ]]
ask consumers with [
any? Consumer-links-neighbors in-radius viewRadius
with [ FavouriteBrAd != [] and
knowledge < [knowledge] of myself ]]
[ if PowerProconsumerWOM > random-float 0.99 and
InformationAsymmetry <= random-float 0.99
[ let me who
let ListClose []
let cLinkA Consumer-links-neighbors in-radius viewRadius
with [FavouriteBrAd != [] and
knowledge < [knowledge] of myself ]
set listclose sort-by
[[[ weight ] of link-with consumer me] of ?1 >
[[ weight ] of link-with consumer me] of ?2] cLinka
if ListClose != [] and [ FavouriteBrAd ]
of first ListCLose != [] and length WorsefirmBP > 1
[ ask first listClose
[ if [ end2 ] of item 0 FavouriteBrAd =
[ item 0 WorsefirmBP ] of myself
[ ask my-links with
[ end2 = [[ end2 ] of item 0 FavouriteBrAd ] of myself ]
[  set influenceAccumulatedPRO influenceAccumulatedPRO +
( - (5 + ([item 1 preferences] of myself)))
set timesContactedProWOM timesContactedProWOM + 1
]]]]]]]]


If (proconsumerWOM = "SparkingEnvironmentalism2")
[If (CommunicationType = "Word Of mouth" or
CommunicationType = "WOM + Feedback"  )
[ ask consumers with [ length FavouriteBrAd > 1 ]
[ if knowledge >= (informationAsymmetry * 5) and
```

```
knowledge > thresholdKnowledge and
item 1 preferences > (- 2.5)
[ set WorseFirmBP FirmPreferencebyPollution ]]
ask consumers with
[ any? Consumer-links-neighbors in-radius viewRadius
with [FavouriteBrAd != [] and
knowledge < [ knowledge ] of myself ]]
[ if PowerProconsumerWOM > random-float 0.99 and
InformationAsymmetry <= random-float 0.99
[ let me who
let i 0 let ListClose []
let cLinkA Consumer-links-neighbors in-radius viewRadius with
[ FavouriteBrAd != [] and  knowledge < [ knowledge ] of myself ]
set listclose sort-by
[[[ weight ] of link-with consumer me ] of ?1 >
[[ weight ] of link-with consumer me ] of ?2 ] cLinka
if worsefirmBP != []
[ set temporaryBrand [ who ] of item 0 worseFirmBP ]
if ListClose != [] and [ FavouriteBrAd ] of
first ListCLose != [] and length WorsefirmBP > 1
[ ask first listClose
[ ask my-links with [ end2 = firm temporaryBrand ]
[ set influenceAccumulatedPRO influenceAccumulatedPRO +
( - (5 + ([ item 1 preferences ] of myself)))
set timesContactedProWOM timesContactedProWOM + 1
]]]]]]]

If (proconsumerWOM = "ERWS1")
[ If (CommunicationType = "Word Of mouth" or
CommunicationType = "WOM + Feedback"  )
[ ask consumers with [ length FavouriteBrAd > 1]
[ if knowledge >= (informationAsymmetry * 5) and knowledge >
thresholdKnowledge and item 1 preferences > (- 1)
[ set WorseFirmBP FirmPreferencebyPollution ]]
ask consumers with
[ any? Consumer-links-neighbors in-radius viewRadius with
[FavouriteBrAd != []
and knowledge < [ knowledge ] of myself ]]
[if PowerProconsumerWOM > random-float 0.99 and
InformationAsymmetry <= random-float 0.99
[ let me who
let i 0 let ListClose []
let cLinkA Consumer-links-neighbors
in-radius viewRadius with [FavouriteBrAd != []
and knowledge < [ knowledge ] of myself ]
set listclose sort-by
[[[ weight ] of link-with consumer me ] of ?1 >
[[ weight ] of link-with consumer me ] of ?2 ] cLinka
if worsefirmBP != []
[ set temporaryPollutionThreshold  item 1 preferences -
[ myY ] of item 0 worseFirmBP
```

```
set temporaryBrand [ who ] of item 0 worseFirmBP ]
if ListClose != [] and
[ FavouriteBrAd ] of first ListCLose != [] and
length WorsefirmBP > 1 and
temporaryPollutionThreshold > 0
[ ask first listClose [ ask my-links with
[ end2 = firm temporaryBrand ]
[ set influenceAccumulatedPRO
influenceAccumulatedPRO - temporaryPollutionThreshold
set timesContactedProWOM timesContactedProWOM + 1
]]]]]]]

If (proconsumerWOM = "ERWS2")
[ If (CommunicationType = "Word Of mouth" or
CommunicationType = "WOM + Feedback"  )
[ask consumers with [ length FavouriteBrAd > 1 ]
[ if knowledge >= (informationAsymmetry * 5) and
knowledge > thresholdKnowledge and
item 1 preferences > (- 1)
[ set WorseFirmBP FirmPreferencebyPollution ]]
ask consumers with
[ any? Consumer-links-neighbors
in-radius viewRadius  with [ FavouriteBrAd != [] and
knowledge < [ knowledge ] of myself ]]
[ if PowerProconsumerWOM > random-float 0.99 and
InformationAsymmetry <= random-float 0.99
[ let me who
let i 0 let ListClose []
let cLinkA Consumer-links-neighbors
in-radius viewRadius with [ FavouriteBrAd != [] and
knowledge < [ knowledge ] of myself ]
set listclose sort-by
[[[ weight ] of link-with consumer me] of ?1 >
[[ weight ] of link-with consumer me] of ?2] cLinka
if worsefirmBP != []
[ set temporaryPollutionThreshold  item 1 preferences -
[ myY ] of item 0 worseFirmBP ]
if ListClose != [] and
[ FavouriteBrAd ] of first ListCLose != [] and
length WorsefirmBP > 1 and
temporaryPollutionThreshold > 0
[ask first listClose
[ if [ end2 ] of item 0 FavouriteBrAd =
[ item 0 WorsefirmBP ] of myself
[ ask my-links with
[ end2 = [[ end2 ] of item 0 FavouriteBrAd ] of myself ]
[ set influenceAccumulatedPRO
influenceAccumulatedPRO - temporaryPollutionThreshold
set timesContactedProWOM timesContactedProWOM + 1
]]]]]]]]
```

```
If (proconsumerWOM = "QRWS ")
[ If (CommunicationType = "Word Of mouth" or
CommunicationType = "WOM + Feedback"  )
[ ask consumers with [ length FavouriteBrAd > 1 ]
[ if knowledge >= (informationAsymmetry * 5) and
knowledge > thresholdKnowledge and
item 2 preferences > (4)
[ set ListByQuality FirmPreferencebyQuality ]]
ask consumers with
[ any? Consumer-links-neighbors in-radius viewRadius with
[FavouriteBrAd != [] and
knowledge < [ knowledge ] of myself]]
[if powerWOM > random-float 0.99 and
InformationAsymmetry <= random-float 0.99
[let me who
let i 0 let ListClose []
let cLinkA Consumer-links-neighbors
in-radius viewRadius with
[FavouriteBrAd != [] and
knowledge < [ knowledge ] of myself ]
set listclose sort-by
[[[ weight ] of link-with consumer me ] of ?1 >
[[ weight ] of link-with consumer me ] of ?2 ] cLinka
if ListByQuality != []
[ set TemporaryBrand [ who ] of item 0 ListByQuality
set temporaryQualityThreshold
(5 - (item 2 preferences -
[ myZ ] of item 0 ListByQuality))]
if ListClose != [] and
[ FavouriteBrAd ] of first ListCLose != [] and
length ListByQuality > 1 and temporaryQualityThreshold > 0
[ ask first listClose
[ ask my-links with [ end2 = firm temporaryBrand ]
[ set influenceAccumulatedPRO
influenceAccumulatedPRO + temporaryQualityThreshold
set timesContactedProWOM timesContactedProWOM + 1
]]]]]]]

end


to-report FirmPreferencebyPollution

let g 0
let pollutionlist []
let knownFirms []
while [ g < length FavouriteBrAd ]
[ set knownFirms fput [end2]
of item g FavouriteBrAd knownFirms
set g g + 1  ]
ifelse informationAsymmetry != 0 and knowledge <= random 5
```

```
[ set pollutionList sort-on
[ ( myy + myy *
(( 1 + ( random-float (5 - [knowledge] of myself) / 5  )) *
random-float ( 1 + informationAsymmetry))) ]
turtle-set KnownFirms ]
[ set pollutionList sort-on
[ (myy * ( 1 + random-float informationAsymmetry)) ]
turtle-set KnownFirms ]
report pollutionList

end


to-report FirmPreferencebyQuality
let g 0
let QualityList []
let knownFirms []
while [ g < length FavouriteBrAd ]
[ set knownFirms fput [ end2 ] of
item g FavouriteBrAd knownFirms
set g g + 1 ]
ifelse informationAsymmetry != 0 and knowledge < random 5
[ set QualityList sort-on
[( - ( myz + myz * (( 1 +
( random-float (5 - [ knowledge ] of myself) / 5  )) *
random-float ( 1 + informationAsymmetry)))))]
turtle-set KnownFirms ]
[ set QualityList sort-on
[( - (myz * ( 1 + random-float informationAsymmetry))) ]
turtle-set KnownFirms ]
report QualityList

end


to CreationOfPreferitBrandAd

ask consumers with [ any? my-out-Brands-links ]
[ let linksConsumer my-out-Brands-links
set FavouriteBrAd sort-by
[[ influenceAccumulated + influenceAccumulatedPRO ]
of ?1 >
[ InfluenceAccumulated + influenceAccumulatedPRO ]
of ?2 ]  linksConsumer
ifelse [ end2 ] of item 0 FavouriteBrAd = firm 2
[ set color blue ]
[ set  color red ]
if [ end2 ] of item 0 FavouriteBrad = firm 4
[ set color magenta ]]
end
```

```
to FriendShip

If (friendshipType = "Uninteresting" )
[ ask consumers
[ let Id who ask consumers in-radius
ViewRadiusFriendship with [ who != id ]
[ ifelse link-neighbor? consumer Id []
[ create-Consumer-links-with consumer id
[ set weight 0.01 set hidden? not show-consumer-links
]]]]]

If (friendshipType = "Random" )
[ let Randomness read-from-string
user-input  "Which is the probability of consumers
to establish a friendship? Give a value between 0 and 100."
ask consumers [ let Id who
ask consumers in-radius ViewRadiusFriendship with
[ who != id ]
[ ifelse link-neighbor? consumer Id  []
[if (Randomness > random 100.1)
[ create-Consumer-links-with consumer id
[ set weight 0.01 set hidden? not show-consumer-links
]]]]]]

If (friendshipType = "Friendship Threshold" )
[ ask consumers
[ let Id who let temporaryPref preferences
ask consumers in-radius ViewRadiusFriendship with [ who != id ]
[ ifelse link-neighbor? consumer Id []
[ let NofCharacteristicsOvercomeToFriendship
compareConsumersChar preferences temporaryPref
let tempWeight
(((characteristicN - NofCharacteristicsOvercomeToFriendship) /
characteristicN) + 0.01)
if (NofCharacteristicsOvercomeToFriendship >= FriendshipThreshold)
[ create-Consumer-links-with
consumer id [ set weight tempWeight
set hidden? not show-consumer-links ]]]]]]


If (friendshipType = "Quasi-Stochastic Friendship Threshold" )
[ ask consumers
[ let Id who let temporaryPref preferences
ask consumers in-radius ViewRadiusFriendship
with [ who != id ]
[ ifelse link-neighbor? consumer Id
[ ask Consumer-links-with consumer id
[ if weight < 0.8
[ if random-float 10 > random-float 100 [ die ]]]]
[ let NofCharacteristicsOvercomeToFriendship
```

```
compare ConsumersChar preferences temporaryPref
let w random-float 1
if w < 0.33
[ set NofCharacteristicsOvercomeToFriendship
NofCharacteristicsOvercomeToFriendship - 1 ]
if w >= 0.33 and w <= 0.66 []
if w > 0.66
[ if NofCharacteristicsOvercomeToFriendship
< characteristicN
[ set NofCharacteristicsOvercomeToFriendship
NofCharacteristicsOvercomeToFriendship + 1 ]]
let tempWeight
(((characteristicN -
NofCharacteristicsOvercomeToFriendship) /
characteristicN) + 0.01)
if (NofCharacteristicsOvercomeToFriendship
>= FriendshipThreshold)
[ create-Consumer-links-with consumer id
[ set weight tempWeight
set hidden? not show-consumer-links
]]]]]]

if (friendshipType = "Reset")
[ ask consumers [ ask consumers-links [ die ]]]
centralityConsumers

end


to-report compareConsumersChar [g p]

let aN 0
let i 0
let j 0
let UpperP []
let lowerP  []
while [ i < characteristicN ]
[ set upperP lput (item i p + 0.5) upperP
set lowerP lput ( item i p - 0.5 ) lowerP
set i i + 1 ]
set i 0
while [ i < characteristicN ]
[ if item i g >= item i lowerP and
item i g <= item i upperP [ set aN aN + 1 ]
set i i + 1 ]
report aN

end


to setup-Circle
```

```
if layoutcircle = "off"
[ ask consumers
[ set xcor0 xcor set ycor0 ycor ]
set layoutcircle "on" ]
layout-circle consumers ( 12 )

end


to originalPosition

ask consumers
[ set xcor xcor0
set ycor ycor0 ]
set layoutcircle "off"

end


to-report average-local-clustering-coefficient

report precision (mean [ cluster ] of Consumers) 2

end


to-report cluster

let neighborhood Consumer-links-neighbors
let numberLinks link-set
[ my-links with [ member? other-end neighborhood ]]
of Consumer-links-neighbors
let k count neighborhood
ifelse k < 2 [ report 0 ]
[ report (2 * count numberLinks) / (k * (k - 1)) ]

end


to-report Full-Average-Local-Clustering-Coefficient

report precision mean
[ nw:clustering-coefficient ]  of consumers 2

end


to-report Full-global-clustering-coefficient

let closed-triplets sum
```

```
[ nw:clustering-coefficient * count my-links  *
(count Consumer-links-neighbors - 1) ] of turtles
let triplets sum
[ count my-links *
(count Consumer-links-neighbors - 1) ] of turtles
report precision (closed-triplets / triplets) 2

end


to centralityConsumers

nw:with-context consumers Consumers-links
[ ask consumers
[ set betweennessCentrality nw:betweenness-centrality
set betweennessCentrality
precision betweennessCentrality 2 ]]
nw:with-context consumers Consumers-links
[ ask consumers
[ set WeightedClosenessCentrality precision
nw:weighted-closeness-centrality "weight" 2 ]]
nw:with-context consumers Consumers-links
[ ask consumers
[ set eigenvectorCentrality nw:eigenvector-centrality ]]
ifelse Show-Weighted-Closeness-Centrality
[ ask consumers
[ set label WeightedClosenessCentrality ]]
[ ask consumers [ set label "" ]]

end


to-report density

report precision
(mean
[ count Consumer-links-neighbors
/ (count consumers - 1) ]
of Consumers) 2

end


to-report Average-weighted-path-length

let avWe 0
nw:with-context consumers Consumers-links
[ set avWe nw:mean-weighted-path-length "weight" ]
report precision AvWe 2

end
```

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