Word of Mouth, Viral Marketing & Open Data: a Large Scale Simulation for Predicting Opinion Diffusion on Ethical Food Consumption

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Abstract

This paper presents the first results of a large scale-Agent Based Simulation devoted to simulate individual behaviour inside a medium size city (600.000 Inhabitants). Humans are simulated as Intelligent Individual entities characterized by several attributes created from Open Data available by means of a Agent Based multi-layer approach.

The work presented is divided into two main parts: the first part aims to extend the multilayer approach with the social network layer in order to capture how social networks can be correlated with human activities and how “Individual Opinion” changes based on social interactions. The second part is devoted to present a case study for simulating the propagation dynamics of ethical value based on social interactions. Finally it is presented a food choice model based on three parameters: accessibility of ethical shops, price difference with standard products, and ethical value propagation.

Key Words: ***Agent Based, Simulation, Green Products Consumption Simulation, Social Networks Simulation, Opinion Simulation***

1) Introduction

The web of global economic connection is growing deeper (Manika et al., 2016) and the number of web-connected population is rising fast, in particular in emerging countries. It is interesting to note that mobile Industry declared that in 2017 number of people connected to mobile services surpassed 5 billion globally (GSMA, 2018). Several authors uses the new world “Digital Globalization” that underlines the new step of globalization era that is moving from the globalization of “goods” up to the globalization of human digital connections. For example, a recent research (Perrin, 2015), proved that in 20015 nearly (65%) of American adults use social networking sites while ten years before, in 2005, the media usage was only at 7%. In addition, it is important to consider how much time is spent on the web: indeed, according to recent surveys, 51% of USA adults spend in average 5,6 hours connected by Smartphone, laptop and other internet services (Meeker, 2015). Humans are constantly (at least potentially) connected to the web. This process lead to radical changes in modern societies in a very quick time since social interactions have become faster and more frequent by means of the internet. Indeed each individual with an internet access is daily bombarded by several information from friends, media, social networks and web advertising. In addition, each individual receive information and also “emit” information about his opinion and the same time by publishing pictures, likes, post etc… Such process generates viral loops of reading-publishing the popular web content.

Reproducing the information exchange within a network is pretty challenging but it can be extremely interesting in many areas like Social Engineering, Viral Marketing, Social Science, Transport, Government and Politics as well as Safety and (Cyber) Security. The aim of this paper is double: the first goal is to describe a multi-layer simulation devoted to recreate individual behaviour in urban context by making use of the open data available. The second goal of the paper is to define and test an Opinion Function in the marketing domain in the form of "Ethical Value" for capturing the individual behaviour on ethical food choices. Such function is incorporated into a binary choice model with two possible options: a) buy standard food b) buy ethical food. The choice is assumed dependent on three parameters: Price, Accessibility and Ethical Value.

2) **Opinion Propagation, Word-of-Mouth and Multi Layer Approach**

The propagation phenomena in a social network was study at first in medicine for analysing and predicting dynamics of epidemic evolution of infectious diseases (Teng, 1985). Basically such models are based on a simple logic: when an infected agent i approach to an healthy agent j, the healthy agent have a given probability to shift in different possible states (i.e. become infected, become immediately immune, became immune after a certain time etc..). Nowadays, this models that was borne for simulating "physical contact" are interesting for simulating result of social interactions in particular considering the web-based social interactions.

The communication among social network is extremely powerful and the importance of the "propagation phenomena" is recognised in several disciplines as social science, politics, communication, marketing as well as security. The following keywords "digitalization of Word-of-mouth phenomena", "Opinion Propagation", "Innovation Propagation", "Public Consensus Formation" as well as the "Panic Propagation" due to misinformation are basically correlated to the same "physical phenomena" that is the propagation over a social network. (Dellarocas, 2003; LIU, C. Y et al, 2006; Watts and Dodds, 2007). Modelling and Simulating such behaviour is interesting for many scopes, and it is often correlated to "influence maximization problem" (Mossel and Roch, 2007).

Here in the following, the authors try to provide some insight about propagation phenomena inside social networks:

- Propagation/Opinion Exchange is based on social interactions
- Social networks are depicted as node and edges
- A social interaction happens when two nodes are connected
- A social interaction is a new stimulus received from a other node
- A social interaction is a mix of face-to-face and web-based interactions
- Face-to-face interactions are more influent but less frequent compared to web-interactions
- There are social interactions that have more influence than others
- Each individual has a personal opinion and changes his opinion when he receive a new stimulus
- Each node is both a receiver and an "emitter" since each individual can publish something in the network to other nodes in form of picture, likes, comments on blogs etc.. ".

The work presented aims to answer to the following questions:

RQ1: How can we use simulation for reproducing humans and their interaction considering both face-to-face and web interactions?

RQ2: How can we correlate daily individual activity for reproducing social interactions?

RQ3: How can we simulate the Individual Opinion Dynamics resulting from Social Interactions?

RQ4: How can we match the Individual Opinion to the probability to buy Ethical Food or Standard Food according to the social interaction dynamics?

The author's opinion is that Simulation can be helpful to reproduce such phenomena since web network are complex network and there are many aspects that can be captured and evaluated only by making use of big data and simulation tools.

3) The Potential of the open data for simulating Large Scale Agent Based Intelligent Social systems

The work presented aims to extend the previous researches carried out from the authors for simulating individual behaviour in large scale systems by means of Intelligent Agents. Indeed, Simulation Team, Genova University have several years of experience in reproducing Human Behaviour by means of Intelligent Agents Computer Generated Forces (IA-CGF) for simulating the dynamic evolution of different individual parameters like stress, fear, aggressiveness as result of social interactions. These libraries have been fruitfully applied in urban disorders during country reconstruction (Bruzzone and Massei, 2010; Bruzzone et. al, 2011), Disaster Management (Bruzzone et. al., 2016), homeland security (Bruzzone et. al, 2015), epidemic evolution (Bruzzone at al, 2012) and Social influence in Obesity diffusion (Bruzzone et.al, 2012)

Modelling and Simulating Individual behaviour is really challenging: humans have at least two level of complexity: individual and social complexity. Individual complexity is often driven by mental models that are not known, partially hidden and irrational. Social Complexity is the result of humans inside the society that creates infinite interactions among the multitude of agents.

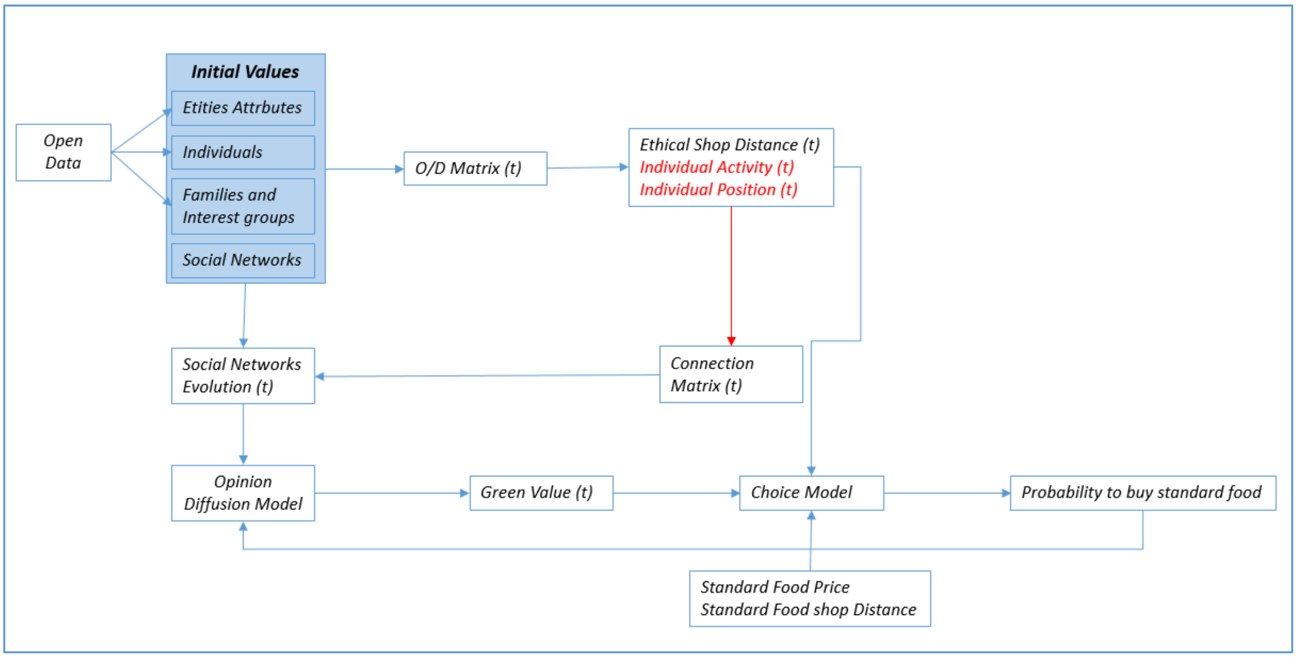
Internet is making cultural exchanges faster and faster; this process have a similar influence to the invention of the press, radio and television; indeed interaction among people can happen not only physically, not only with one-direction instruments like television, radio and newspapers, nut now people can be also active in the process of information production. The result are complex, instant and frequent interactions among a complex network at a worldwide scale. (Fuchs, 2007).

In this context Agent Based Social Simulation (ABSS) can be helpful to capture the different phenomena inside a social network; ABSS is often described as the intersection of three scientific areas (Davidsson, 2002): Agent-based computing, Social sciences, and Computer simulation.

Obviously, simulating social systems requires a big amount of data for the Verification and Validation of the model; in this context, a new opportunity is provided by "open data". Currently, several studies, prove that there is an increasing number Countries where "open data" are being placed on the political and administrative agenda (Huijboom and Van den Broek, 2011; Bauer and Kaltenböck, 2011). This results in an exponential growth of the quantity of "open information" available in several countries both from public and from private sources; this adds a new dimension to big data analytics giving rise to future data-driven innovation (Manyika et. al, 2013).

4) Method

The authors makes use of IA-CGF (Intelligent Agent Computer Generated Force) Libraries developed in the course of the year by Simulation Team for reproducing population behaviour in Genova, a middle size city of 600.000 inhabitants.



4.1) Multi Layer Approach

In the following, the authors propose a multi-layer approach for simulating a social system inside the city of Genova, a medium size city (600.000 inhabitants). The simulation makes use of several sources of Open Data from Genova Municipality, Regione Liguria coupled with National, European and Worldwide Datasets.

The layer considered are the following:

- Layer 1: Entities and Objects
- Layer 2: Individual People
- Layer 3: Interest Group and Social Networks

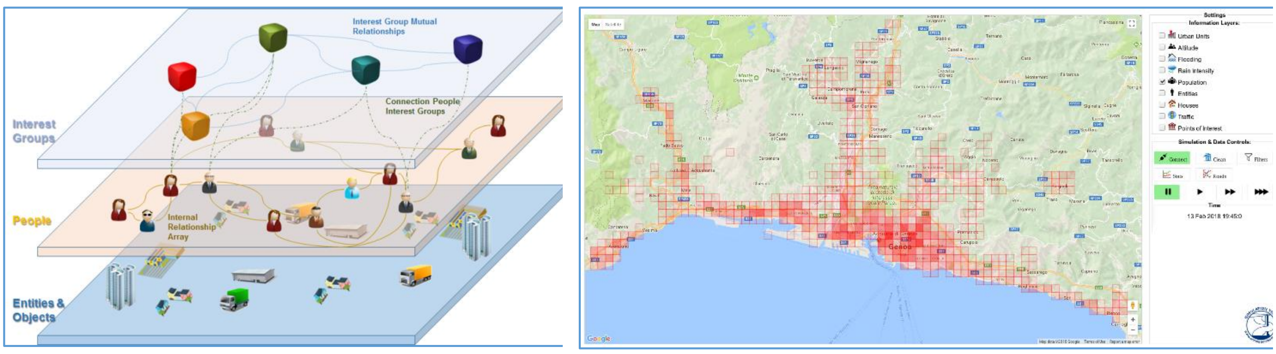


Figure 1: Multi Layer Approach for simulating Individual in Daily Activity

4.2) Layer1: Entities & Objects

This layer allow to geo-localize punctual elements in a map. Such points are generator/attractor points and are used for determine the daily individual behaviour of each single inhabitant. In the following table are reported the different categories that have been used for the simulation.

This layer include ore that 1.000 real point of interest have been inserted and geo-localized in the map. In addition, more than 3.000 of smallest point of interest have been created statistically based on urban density, and other economical indexes in order to reproduce a more realistic individual behaviour.

Point of Interest	**Icon**	**# jobs**	**# max people attracted**	**Opening Hour**	**Type**
Commercial Centres					Based on real data
Hospital					Based on real data
Fire Fighters					Based on real data
Police Stations					Based on real data
Small Shops					Generated
Parking Areas					Based on real data/Generated
Stadium					Based on real data
Cinema					Based on real data
Theatre					Based on real data
Museums					Based on real data/generated
Bar					Generated
Households					Based on real data
Parks					Based on real data
Schools/Universities					Based on real data

The whole Genova Municipality is subdivided into 71 statistical units which can be aggregated into the 9 Genova Municipalities that represent the smallest political unit and the smallest level of disaggregation of data available.

Name	Total Surface [ha]	Urban Area [ha]
Genova Centro Est	707,74	495,64
Genova Centro Ovest	485,2	423,35
Genova Bassa Val Bisagno	789,74	435,11
Genova Media Val Bisagno	4.179,17	1.077,68
Genova Val Polcevera	3.327,11	1.182,33
Genova Medio Ponente	1.885,13	723,6
Genova Ponente	7.507,78	751,2
Genova Medio Levante	571,35	478,76

Genova Levante	3.659,29	873,63
Porto	845,48	234,97
Total	**23957,99**	**6676,27**

4.3) Layer 2: Generation of individual entities

In this second layer people are created as single entities by using open data available. Hereafter is described the process for generating individual the simulation start. The simulator generates single individuals, at first, and then it aggregates each one into families and social network, based on a weighted graph in the following step.

- Individual Generation
- Families and Interest Groups

Each individual is characterized by the following parameters, assumed to be known, based on statistical distribution derived from the open data that have been analysed. The 9 parameter that have been considered for generating individual are: **Age, Sex, Level of Education, Area of the city where he lives, Area of the city where he works/go to school, Income, Occupation Type, Political Orientation, Ethnic Group, Religion.**

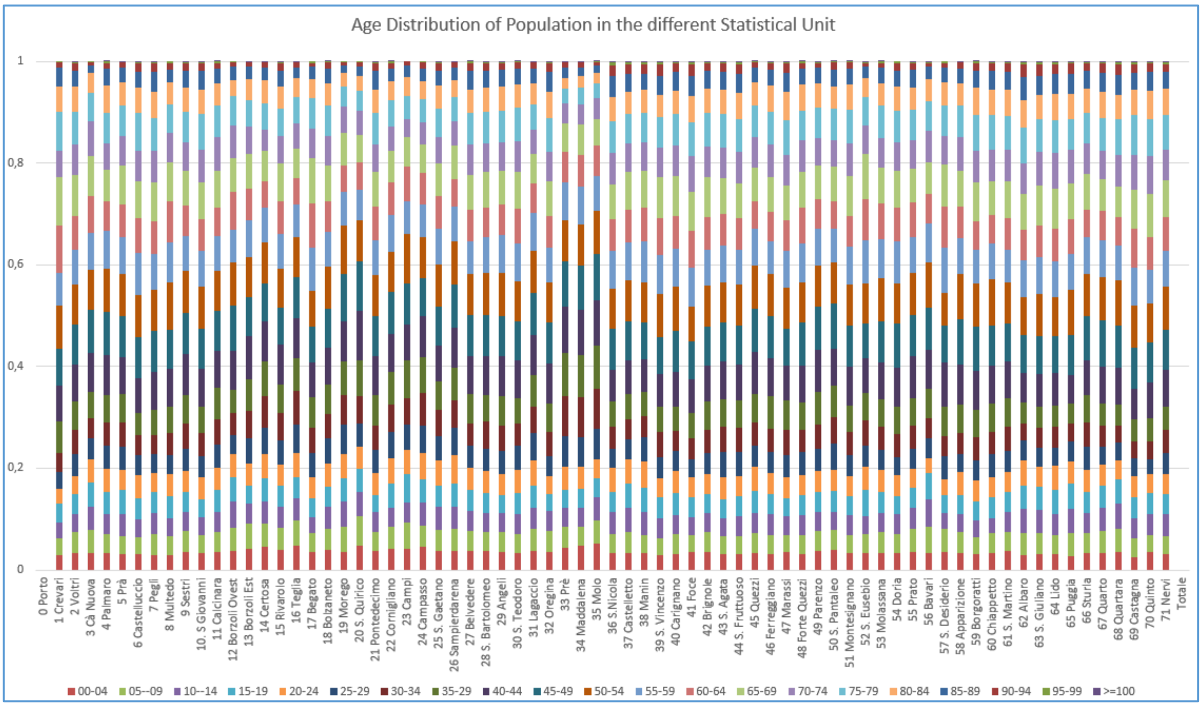


Figure 2: Age distribution in the statistical units

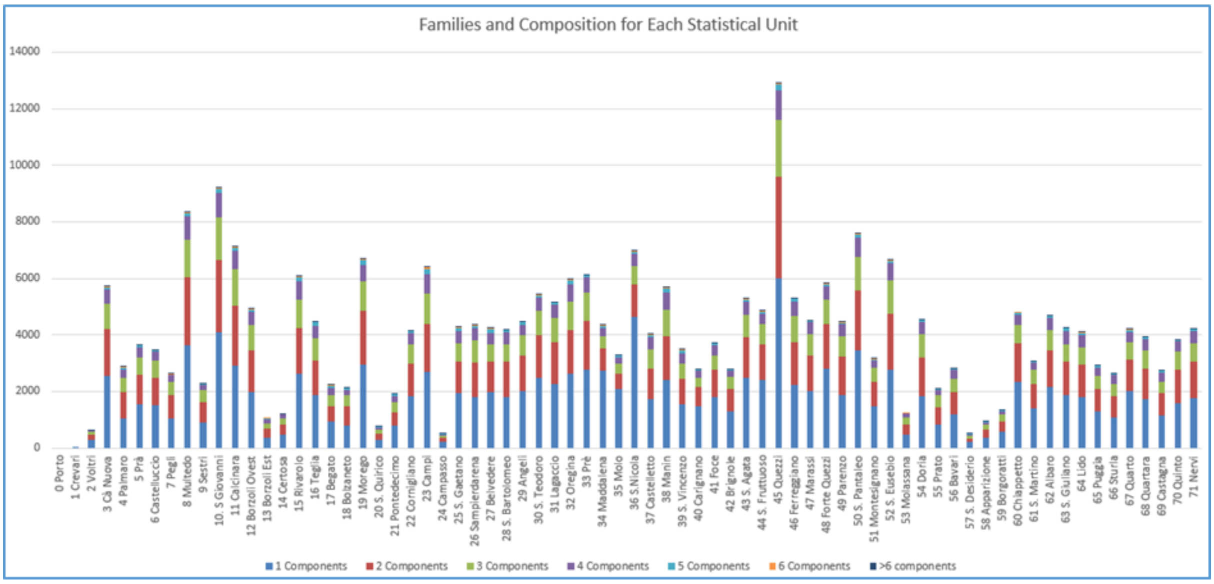


Figure 3: Families and their Composition for Each Statistical Unit

4.4) Layer 3: Generation of the Families and Interest Groups

In this phase the individuals are aggregated with a compatibility algorithm with the other individuals for the generation of families and Interest Group.

4.5) Generation of quasi-realistic Social Network

This step formally recreates a quasi-realistic social network based on the artificial association to each individual inside families, interest groups and other nodes of the network.

One of the most effective way to simulate social systems is by making use of graph theory and modelling the individuals by means of nodes and their connections by means of links. This layer aims to recreate single individual connections during the day. The basic idea is to recreate the social structure by making use of Social Network Theory and calculate the initial connection of each node based on the individual parameters. In particular:

- ✓ Nodes: have a double nature (Virtual and Physical). They represent Individuals, websites, social networks, Television, Radio and other main source of information
- ✓ Links: have a double nature (face-to-face connection and web connections) They represent the connections among the different node of the network

Indeed in order to reproduce social interaction we need to consider both face-to-face and virtual interactions. In addition, the author propose to make use of weighted graph in order to capture the different influence each different social interaction.

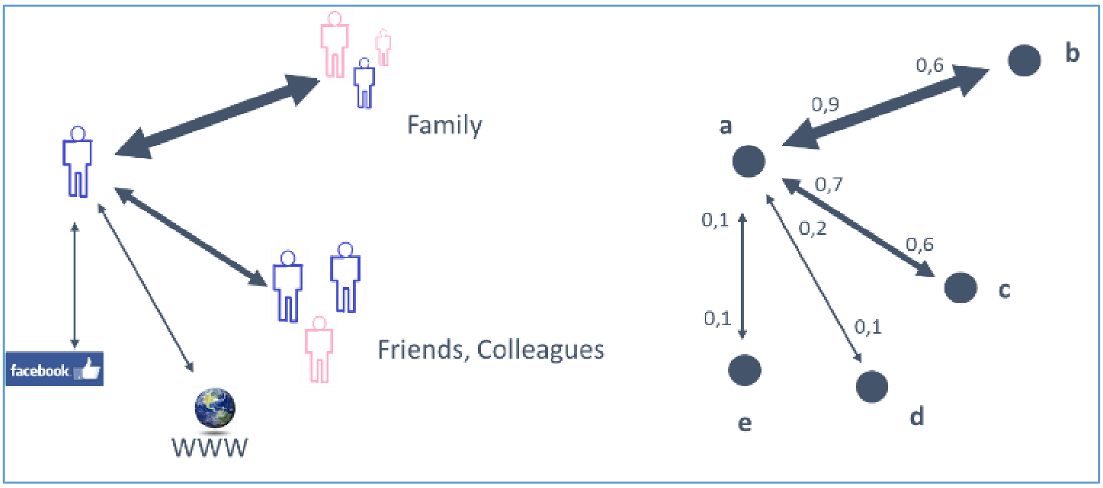
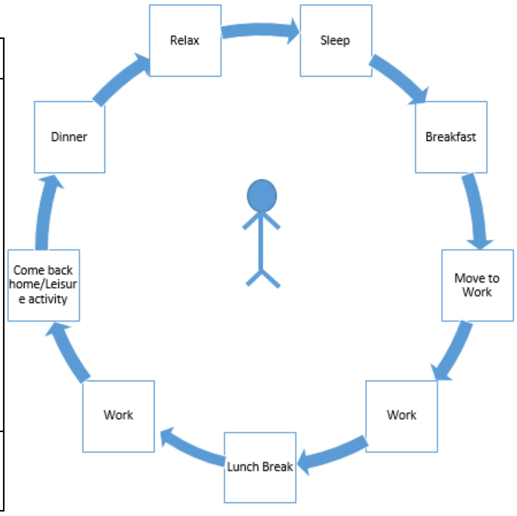


Figure 4: Weighted Network for simulating Influence in Social Interactions

4.6 Generation of Daily Activities and O/D Matrix calculation

At this step each single people according to the parameters that have been considered have an assigned a set of activities, that are performed daily. In the following table is reported an example of the activities on a "standard week" of seven days and 24 hours for a generic individual.

ID=223512	Parameters	Value
Individual Parameters	Age	25-30
	Sex	M
	Level of Education	Middle School
	Living Statistical Unit	65
	Working Statistical Unit	43
	Occupation Type	White Collar
	Income	25.000$
	Religion	Catholics
	Politic Orientation	Neutral
Family Parameters	Number of Family Member	3
	Family Income	40.000$



Daily activity is used for calculating people movement around the city during the simulated time in term of O/D Matrix. The simulator is equipped also of a transport choice model witch allow to reproduce the main segments of rail and transport network in the city. Based on the cost of the different possibilities and based on its parameters (i.e. car owner or not) he choose the best path maximising its utility.

By this approach the population is simulated as composition of single intelligent individuals living in a simulated town or region, represented by people objects interacting with their interested group (e.g. green movement, youth, universities students etc.) as well as to entities and objects that operate on the field (e.g. radio station, supermarket, etc.). Each agent is characterized by an intelligent behavior that make him moving inside the town and perform other activities (i.e. buy food, going to work, move in the free time etc).

In the following picture is reported the car traffic flow over the network in the morning peak hour resulting from simulation run.

Car flows h 6,00 a.m.

Car flows h 9,15 a.m.

Car flows h 9,45 a.m.

4.7 Layer 3: Simulating Social Interactions and Opinion Dynamics

Simulating Social Interactions and Opinion dynamic requires several assumptions:

Assumptions:

a) Two node types are considered: “virtual nodes” and “physical nodes”,. Virtual nodes are website, blog, television, radio etc..) physical node represent people
b) Nodes interact I two ways: Face-to-face and virtually (by web)
c) Virtual node are connected (potentially) to all the nodes
d) Television and Radio are one-way: the other user cannot influence the content
e) All virtual nodes (except radio and television) can receive opinion from the other nodes
f) Each node is equipped by an opinion function
g) The flow on the network is mono-thematic
h) When two agents get in contact they exchange they mutually exchange the opinion
i) All the agents are receivers and emitters of information in the network
j) All the agents receive and emit with the same intensity
k) All the people in the network are potentially connected
l) Connections in time are determined by the Connection Matrix that is calculated by the simulator
m) Connection Matrix provide the intensity of the social interaction in time
n) Each agent can connect only to one node for each time step (excluded the virtual nodes)
o) Each individual >13 years old is connected to the network so is connected to Virtual Nodes
p) Each individual always active in the network: he receive from the other nodes and provide to the other nodes information about his feeling
q) Only “one topic” exchange is considered: when there is a connection the two agent exchange information about that topic
r) When two agent get in contact they exchange their opinion and they modify their personal status with a given rule
s) Not all the people have the same influence, familiar, friends and colleague are more influent compared to other nodes (for example virtual nodes)
t) When two entities are in connections, they exchange opinion immediately

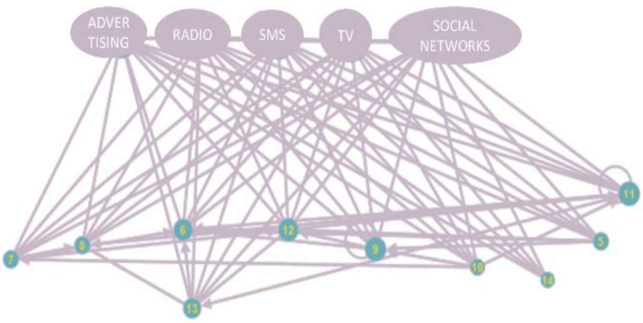
u) Each individual is described by an “Opinion Function” that chance every time the individual get in touch with a other entity with certain rules

The social interactions are calculated by the simulator by means of a Connection Matrix C(t) that is time dependent and it is updated each time step with the following rule:

If (i,j)>0 then individual i is connected to individual j
If I,j =0 then individual i is not connected to individual j

Matrix C is the result of individual activity; more precisely each i-individual during his daily activity have a probability to get in touch with a other agent according to his daily routine. For example if he is driving he will have more probability to listen the radio compared to the probability to read a post. Such matric include both face-to-face and web interaction in a whole single matrix.

ID	TV	RAI	WE	FAC	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	
TV	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
RADIO	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
WEB	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
FACEBOOK	1	1	1	1	1					1							1						
1					0																		
2						0							1										
3							0											1	1	1			
4								0														1	
5									0														
6										0													
7											0								1	1			



Each cell of C(i,j) has a value [0:1] in order to consider the different weight of each interaction; in particular family member and friends are weighted more since are more influent compared to other nodes. Weighted network, have been used firstly in system biology application and then adapted in large scale social systems (Can, Özyer, & Polat, 2014; Bruzzone 2013).
Finally it is necessary to set up some rules for opinion formation. Indeed each individual is supposed to be equipped with an “Individual Opinion Function”.
In the following a possible opinion function is presented: Opinion Function O is assumed to be a function defined as O_i(t)= $O_i(t = 0) + \alpha * \Delta O_{i,j}$
Where:

$\Delta O_{i,j} = O_i - O_j$
α_i: [0:1] inertia coefficient

O_i $can\ assume\ the\ following\ integer\ values$: $[-10{:}\ 10]$ $with$:

O_i=0 neutral

$O_i = 10\ strongly\ agree$

$O_i = -10\ strongly\ disagree$

5 Case Study: Ethical Food - Introduction to Consumer Driver Demand – Factors Affecting Food

5.1 Motivation

Many hypotheses exist about the modern drivers of consumer demand and the growing influence of ethical and environmental issues since over 20 years (Strong 1996; Crane 2001; Peloza et al. 2013); indeed the food industry is even further sensitive to these elements and there are interests in investigating these aspects to develop new models (Jensen et al. 2011). The complexity of this context touches many different issues, from operational ones (e.g. logistics and production processes) to marketing and promotion often dealing with human factors (Schröder et al. 2004; Siro et al. 2008; Bruzzone et al. 2009a). It is evident that the complexity of each of these elements and their mutual interactions with human factors create many challenges in the development of quantitative analysis on this framework. Therefore, the importance to create models and simulators dealing with these issues results to be a strategic advantage for planner and decision makers (Bredahl et al. 1998; Vermeir & Verbeke 2006; Bruzzone et al. 2009b). Due to these reasons, the authors propose the development of an agent based simulation able to capture **how consumers affect and are affected from an opinion inside the communication network.**

4.2 Ethical and food Consumption

Hereafter, different researchers and models, developed along the years, are summarized in order to identify the most promizing approaches to be used in a modern simulation tool for simulating food consumption choices based on the correlation of different factors, and perform further analyis. These empirical findings raise a question for investigation *"what are the main parameter affecting food choice and how social influence can be reproduced?"*,

- **First Two main drivers: Price and Accessibility**

Despite the widespread attention in ethical consumption is receiving, consumers show little interests in actually purchasing ethical products, such as organic or fair-trade produces. For instance, Futerra (2005) found that whilst 30% of consumers claims themselves to be ethical consumers whereas only 3% of them actually put into practices. Such intention-behavior gap reflects the situation that the benefit of product ethicality is at a lower hand against the practical concerns, such as price, accessibility, and quality issues, in the decision-making process (Devinney, Auger, & Eckhardt, 2010).

- **Third Driver: Social Network Position**

Yet, there is an increasing evidence suggesting impression management reasons as main key factors to promote ethical consumption. For instance, Griskevicius, Tybur, and Van den Bergh (2010) demonstrated that eliciting consumers' status motives increase their desire for green products. The use of social norms (e.g., joining fellow citizens to save waters) increase also the likelihood for pro-social choices (Goldstein, Cialdini, & Griskevicius, 2008; White & Simpson, 2013). Extent researches demonstrate these lay beliefs drive, unconsciously, people's ethical product choices. For instance, Griskevicius et al. (2010) demonstrated that by motivating consumers attaining a high social status, the likelihood for them to choose green products over the regular counterparts increase as the former helps signal a positive social image.

Consumer's social network position is defined as the relationship between himself/herself and other individuals or groups within the network. In terms of analysing the consumer's network position involves two main types of centrality in this research. The first of which is betweenness centrality that is defined as the least number of times that an actor needs to take in order to approach another agent (Freeman, 1979). More precisely, betweenness centrality captures the extent to which an actor facilitates the information flow within the network, not sheer number of connections he/she possess. Consequentially, when a high betweenness-centrality actor leaves the network, the efficiency of the network itself suffers in terms of information flow (Kratzer, 2009). The second type is the closeness centrality which is defined as the number of connections that a person possesses (Borgatti, 1995). Consequentially, when a consumer is in a high degree of betweenness and/or closeness centrality position, he, or she, will be involved in frequent social interactions in everyday life. Such situation requires a person to present a positive image in front of others, so that the authors argue that these types of consumers have a high need for impression management in their everyday life (Goffman, 1967). Impression management, corresponding to maintaining a good image in front of others, is found as a key factor that motivates consumer's ethical product choices. This pattern reflects the instrumental altruism facet in people's altruistic behaviour (Andreoni, 1990; Kahneman & Knetsch, 1992; Zahavi, 1975). More specifically, purchasing an ethical product, though implicitly, signals the buyer a positive pro-social or moral image (Semmann, Krambeck, & Milinski,2005; Wedekind & Braithwaite, 2002; Catlin & Wang, 2013; Mazar & Zhong, 2010). Such symbols, in people's beliefs, would have positive effects on people's social life, such as being reckoned as a trustworthy member of the group.

Based upon an instrumental altruism perspective, the authors conjecture is that consumer's social network position (e.g., how many connections they have and how central and active they are in the network) affects to what extent they will appreciate the social values of ethical products (Andreoni, 1990; Kahneman & Knetsch, 1992; Zahavi, 1975). Firstly, people who are at the central positions within their social network generally play as the roles of opinion leaders or lead users, which involve them having frequent social interactions with other members within their social node (Kratzer & Lettl, 2009). So, these types of consumers would have a higher need for impression management whereas the engagement in ethical consumption results to be one of major means that consumers do frequently (Crane & Matten, 2016). In facts agent based modeling has been applied in different area of marking to capture the aggregate dynamics originated from interactions among individual consumer (Delre et al. 2007; Goldenberg, Libai, and Muller 2010) as well as to examine these impacts on consumer's choice (Haenlein & Libai, 2013).

5.3 Human Behavior Modelling Applied to Ethical Consumption

Here the authors focus their attention in simulating individual functions that are influencing an Opinion Function and its correlation with the ethical food choice compared to the standard food.

To capture how consumer's social network, influence their ethical food consumption, the authors used agent driven simulation paradigm based on IA-CGF libraries. The following weight have been assigned for determine the influence of each social connection in opinion function:

	Family Member	Friends	Colleagues	Other individuals	Facebook	Radio	Other Social Networks	Television
Individual i Receiving Opinion	0.9	0,8	0,7	06	0,2	0,5	0,25	0,6
From Individual	0.9	0,8	0,7	06	0,2	0	0,25	0

All these parameters are assumed in both the direction, from a generic node to individual i and from individual i to the generic node. The only difference is that we assume that individual cannot influence Radio and television, so such coefficient is set to zero.

In order to capture "Individual Opinion" and its variation due to relationship with other nodes, the function Opinion O previously described it is used in order to simulate the "Ethical Value" for each individual.

5.4 From Ethical Function to a Mode Choice

In this step, the author aim to link the Ethical Value to the food choice; Discrete Choice Models are useful to analyze and predict the individual choices when the set of choice is constituted by a finite number of alternatives. Such Models make use conventionally by Random Utility Model (RUM) that have been proposed for the first time by (Block & Marschak, 1960). These disaggregate models have been widely used for the simulation of individual choices in particular for what concern transportation and travel choices. (Ben Akiva & Lerman, 1985); choices are based on a finite number of transport alternatives such as: start a trip or not, choose the departure time, choose the mode of transport, choose the route. Each individual has a set of different choices that depend on personal parameters, for example: age, income, availability of a private car, individual value of time, type of the trip. For an extensive description of these model is possible to take in account interesting previous models developed in this field since decades(Ben-Akiva & Lerman, 1985; Ben Akiva & Biedlare, 2003).

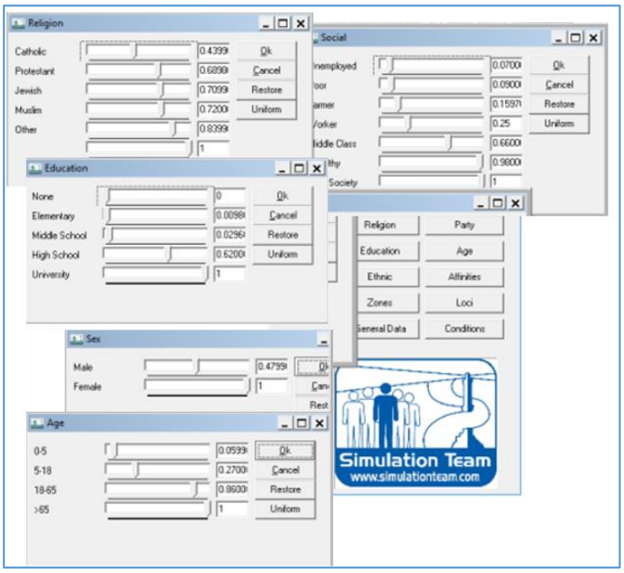


Figure 5: IA-CGF Individual People Characteristics

Considering the consumer choice, such models have been widely applied, also considering the Behavioral Decision Theory (BDT). (Swait & Adamowicz, 2001). In general discrete choice model Discrete are derived from utility theory and in this case is applied a simple binary Logit is applied (Matejka et al.2014); the common requirements for discrete choice models are:

- The set of alternatives must be collectively exhaustive; this imply that each individual and group of similar individuals have its own set of alternatives from where to choose
- The alternatives must be mutually exclusive
- The set must contain a finite number of alternatives

Each individual is expected to maximise its *utility* derived from the different options that are available among the possible choices in set C. In this case each individual i has option among 2 choices:

a: Standard Food

b: Ethical Food

Each of these options provide to the single individual the *utility* from the two options: U_a and U_b with:

$$U_a = V_a + \mathcal{E}$$
$$U_b = V_b + \mathcal{E}$$

V_n = Systematic Utility of each n-option

Ɛ = Error Term (Assumed to have a logistic distribution) for simulating the error on perception of each single individual and irrational behaviour.

So the probability of choosing an alternative n for each individual i is given by:

$P_{i,n} = \mathrm{G}(\, x_{i,a,} x_{i,b,} \underset{*}{\gamma}_{i,}, \beta_i)$

$x_{i,a}$ is a vector of attribute of alternative a

$x_{i,b}$ is a vector of attribute of alternative b

$\underset{*}{\gamma}_{i,}$ is a vector of characteristic of person i

β_i [0:1] is a parameters

$$U_{i,n} = \beta_{i,n} \cdot \underset{*}{\gamma}_{i,n} + \mathcal{E}$$

$$V_{i,n} = \beta_{i,n} + \underset{*}{U}_{i,n}$$

So, the probability of choosing a green product a, and/or a standard product b, for each individual i is defined by:

$$P_{a,i} = \Pr\left(-V_{a,i} + \mathcal{E}_{a,i}\right) > \Pr(-V_{b,i} + \mathcal{E}_{b,i})$$
$$P_{b,1} = \Pr\left(-V_{a,i} + \mathcal{E}_{a,i}\right) < \Pr(-V_{b,i} + \mathcal{E}_{b,i})$$
$$P_{a,i} = \frac{1}{1 + \exp(-\beta_i \cdot V_{a,i})}$$
$$P_{b,i} = \frac{1}{1 + \exp(-\beta_i \cdot V_{b,i})}$$

For modelling customer green choices, the authors have considered the following additional parameters that have been correlated to each single individual.

$U_{i,n}$ = $\beta_1 *$ (Green – Standard Product Cost) + $\beta_2 *$ Ethical Value of individual i+ $\beta_3 *$ (Accessibility of the Ethical Shops)

These parameters have been hypothesized considering specific assumptions and the choice manipulation is based on the following parameter:

- Price sensitiveness (Ethical food and Standard Food) (Lichtenstein, Ridgway, & Netemeyer, 1993)
- Ethical Value Function
- Accessibility of the ethical food based on the daily minimum distance from ethical shop in individual routine

5.5 Simulation Results

For this first experiment have been performed a simulation with real data from the city of Genova, in particular have been considered 71 zones and 600.000 Individuals. Each individual has been defined by its own parameters generated stochastically based on aggregated open data available from Genoa databases. A first simulation run was performed with one year-simulated time

Obviously a very critical aspect in developing this model is to finalize the VV&A (Verification, Validation and Accreditation) processes. Due to these reasons the author are actually conducting dynamic virtual experimental campaigns on numerical case to achieve preliminary validation of the proposed approach; ANOVA technique and experimental error temporal evolution analysis are the methods to be used to check consistency of the stochastic factors included in the models (Montgomery 2008).

6 Conclusions

This paper proposes a preliminary investigation devoted to match intelligent agents with social network simulation in real cases respect green food product consumption. It is evident the complexity of the phenomena related to this context as well as the uncertainty affecting the human factors and, consequently, the efforts required to fine tuning the model parameters. Therefore it is important to outline that the adopting of agent driven simulation based on stochastic discrete event approach enables to model these complex scenarios and could result an interesting support to improve the understanding of this context. As anticipated the authors are working on VV&A and it is expected that these new models, as soon as validated, could result as a strategic advantage in supporting decisions in this application areas. Currently the authors are working on finalizing the certification of numerical data sets for the proposed scenario based on examples inspired by real historical case studies; these data will be used to complete dynamic and statistical VV&A of the proposed simulator with support of SME.

This approach is able to reproduce how a consumer's social network position influences the ethical food choices considering stochastic factors as well as human behavior modifiers (Bruzzone et al. 2011). The contribution of this paper is mainly twofold: firstly, it is devoted to contribute to the ethical marketing literature regarding the moderation role of social network position and other communication channels on consumer's perception about the social values of ethical products.

Second goal is to analyze and demonstrate the potential of M&S (Modeling & Simulation) as support for marketing scientist in testing and validating their hypothesis within a synthetic environment. Indeed, social systems, communication channels and time are proved to be, at least, three of the four main key drivers required to analyze the diffusion of new product in marketing science (Mahajan, Muller & Bass, 1991).

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