Influence of Personality on Information Diffusion in E-Learning Networks

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Abstract: *This paper is the first of a series describing elemental parts of a project on modelling information diffusion in social networks. The projects objective is to develop methodological starting points and a prototype of an Agent-Based Simulation for simulating the spread of information in a social network. In this paper we describe the need for and application of measures to determinate the probability of information absorption and transmission of an individual actor in a social network.*

Key words: *e-Learning, Social Network Analysis, Agent-based Simulation, Personality Traits.*

INTRODUCTION

The diffusion of information between individuals and in groups, or even populations, can be considered a mayor stimulation for learning. While an information transmission from 1-to-1 or 1-to-n is a common method for initiating learning processes, e.g. teacher-to-class in school, the transmission from n-to-m in social networks may be assumed to be at least equally important. This is even more the case for e-learning, where participants activities are not bound by space or time, and/or in situations which focus more on knowledge generation than transmission. In both cases information diffusion is not only important for stimulating learning but for inter- and intra-group coordination and administration. Furthermore the simulation of information diffusion may help to identify and select individuals for e-learning courses who will additionally spread the acquired knowledge in their social network vicinity. Thus reducing the number of required training courses for an enterprise or organization. But not only does the simulation of information diffusion may reap benefits for the customer´s side, it provides mayor advantages for the organizations or enterprises that offer e-learning courses, too. When considering and optimizing information flow, the learning and group experience of all customers can be improved. Thus creating a good reputation and increasing the probability of future customer contacts.

SOCIAL NETWORKS AND GRAPH THEORY

One could define a network as a number of connected elements or entities. When these connections resemble interactions or relations (e.g. kin- or friendships) such networks might be called social networks. While the literature on social networks goes back at least to the work of Harary, Rapoport and others in the 1940s and 1950s [1], a typical analysis technique, the graph theory, even goes back to Leonhard Euler who described in 1735 the problem of „The Seven Bridges of Koenigsberg" [2,3]. In graph theory entities are called „nodes" or „vertices" and the connections „edges" [4]. These edges may have a certain weight attached, e.g. specifying the intensity of the relationship or the probability of an information transmission. Furthermore edges may be either directed or undirected. Directed edges contain information from a certain perspective, e.g. who phoned or loves whom. Whereas undirected edges simply imply a relationship that is equal to both sides, e.g. kinships. The decision how to model the relationships between the entities depends on the objective of the network analysis. Coming back on the "who phoned whom" example, one might be inclined to model this with directed edges. While this is intuitive, it might not be required. This can be showcased with the analysis objective of modelling the possibility of an information diffusion over synchronous communication channels in a social network. Here it might be suitable to model the edges as undirected relationships, as it can assumed that no matter who initiated the communication, both participants may utter information.

Considering the nodes themselves in information diffusion models there has been a certain lack of researching the effect of individual attributes. Exemplary for this is the simulation of innovation diffusion, which we consider as a special case of information diffusion. Here it is common to propose that the acceptance of an information and afterwards its propagation is sufficiently modelled by assuming that the nodes only possess a certain threshold value [5]. When the ratio of connected nodes that propagate the information exceeds this threshold the node accepts the information and from now on transmits it, too. In more sophisticated models the individual threshold values may vary belonging to one class, e.g. early adopter or laggard. Furthermore an additional value for individual versus social preferences is introduced and the modelling of nodes in a regular lattice has been abandoned in favour of a scale-free network [6]. In such networks, the number of connections per node may vary. In another publication where the spreading of information in a mobile phone network is considered, the nodes do not even possess a threshold [7].

The absence of further consideration of the nodes attributes in information diffusion models may be explained by the respective network research objective of basic statistical network properties. In contrast to that, recent publications researching positive and adversarial network effects on individual and group performance have started considering the influence of personality traits [8], too.

THE FIVE-FACTORS OF PERSONALITY

Some personality attributes can be considered more or less stable over a long period of time and are thus called personality traits [9]. One approach describes five factors or dimensions where each encompasses a large number of attributes. A model using this approach is the "five-factor model of personality" [10] another is often referred to as the "Big Five" [11]. Although both approaches have distinct origins, one being derived from questionnaires the other lexically, they yield "largely consonant models" [12]. The results propose categories or domains that cover the personality of individuals. These domains are commonly called: "extraversion", "agreeableness", "conscientiousness", "emotional stability" and "openness to experience". Following we will introduce the five factors, mainly following [8,10,11,12], and propose how these may influence the information diffusion in social networks.

OPENNESS TO EXPERIENCE

The domain "openness" encompasses personality traits like active imagination, preference for variety, intellectual curiosity, but also non-conformity and autonomy. Thus it may be assumed that people scoring high on questionnaires referring to openness would have a lower acceptance barrier for new information and thus will accept those with a higher probability(I). The lowering of the acceptance barrier does not necessarily mean accepting the new information as the information will very probable be only one of many, possibly contradicting, information available to this person. In equation (I) "p" represents the maximum influence of the openness trait on the message acceptance barrier. The parameter "N" models the scale of the openness trait and "x" the participants score. Commonly the scale of the five-factors questionnaires reach from 0 to 100, but this is not mandatory thus we modelled the scale as the parameter N. In contrast to people scoring high on openness, people scoring low prefer familiarity over novelty. Thus they probably resist information that does not match their view of the world and may even hinder the flow of information that contradicts and foster the flow of information that corresponds to their own world view(II).

$$y = p \cdot \cos\left(\left(\frac{\pi}{N}\right) \cdot x\right) \quad \text{(I)}$$

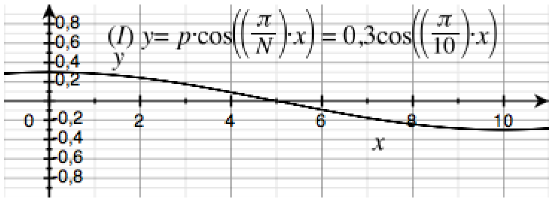

Fig.1: Eq. (I) with exemplary values for parameters.

In equation (II) we again use the parameter p that signifies the maximum influence but this time of the influence on the probability of information propagation. The parameter x denotes the degree of accordance of an information to the world view of the participant. While d denotes the distance of positive and negative boundary values to the midpoint, in scales with an equal number of positive and negative options. When considering the accordance of an information item to the world view of a node ranging between absolutely non-conform to absolutely conform and having additionally one option for moderately (non-)conform the value for the distance d would be 2. The parameter "s" represents the percentage score on a personality trait in the questionnaire. Thus (1-s) signifies the fact that the influence on fostering or hindering the flow of information is stronger for individuals scoring low on openness to experience.

$$y = \frac{(1-s)p}{d^3} \cdot x^3 \quad \text{(II)}$$

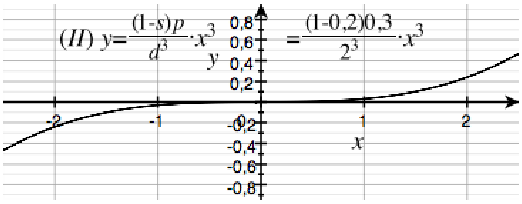

Fig.2: Eq. (II) with exemplary values for parameters.

AGREEABLENESS

The domain "agreeableness" encompasses personality traits like being generous, help- and trustful, cooperative and striving for social harmony. Thus people scoring high on agreeableness will probably not hinder information diffusion. Quite contrary they might even invest by actively querying information from their many connections when asked by another person, thus increasing the potential value of the propagated information(III). In equation (III) we describe this value increase in relation to the maximum influence p, the scale of the questionnaire N and x the score of the individual in the agreeableness domain.

$$y = \frac{p}{N^6} \cdot x^6 \quad \text{(III)}$$

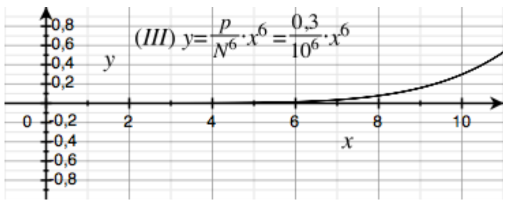

Fig.3: Eq. (III) with exemplary values for parameters.

Furthermore one can assume that information will be less scrutinized and thus more easily accepted. This can be modelled by reusing equation (I). Whereas people scoring low on agreeableness, are said to be manipulative in using their social relationships thus they might try to influence the flow of information to their own advantage. For example they might exaggerate (IV) or understate (V) the importance of an information item to the receiver hoping either to retain or gain such an advantage.

$$y=\frac{p}{N^{10}}\cdot(x-N)^{10} \qquad \text{(IV)}$$

$$y=\frac{-p}{N^{10}}\cdot(x-N)^{10} \qquad \text{(V)}$$

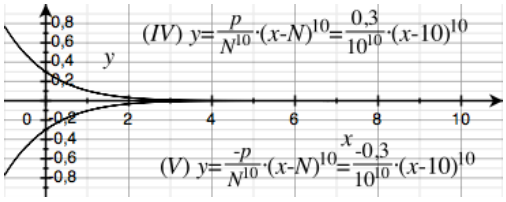

Fig.4: Eqs. (IV) and (V) with exemplary values for parameters.

CONSCIENTIOUSNESS

The domain of conscientiousness encompasses personality traits like being careful, self-disciplined, meticulous, organized, reliable and goal oriented. Thus it can be assumed that people scoring high on conscientiousness might inhibit the flow of information that might be considered rumour/unreliable or just because an information item is deemed insignificant by them. People scoring low on conscientiousness in contrast might inhibit the flow of information unintended due to being less organized, thus being prone to simply forget to tell somebody else. These two facts are described by equation (VI).

$$y=\frac{-p}{\left(\frac{N}{2}\right)^4}\cdot\left(x-\left(\frac{N}{2}\right)\right)^4 \qquad \text{(VI)}$$

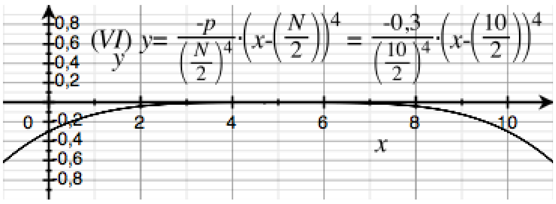

Fig.5: Eq. (VI) with exemplary values for parameters.

The being seen as meticulous and reliable may have the additional effect, that in case of publishing information connected nodes will value those to a greater extent than from other, less conscientious nodes. As these, less conscientious, nodes will be seen as unreliable the information from individuals scoring low will be devalued. The valuation of messages in relation to the level of conscientiousness of the sender is specified by equation (VII).

$$y=\frac{p}{\left(\frac{N}{2}\right)^3}\cdot\left(x-\left(\frac{N}{2}\right)\right)^3 \qquad \text{(VII)}$$

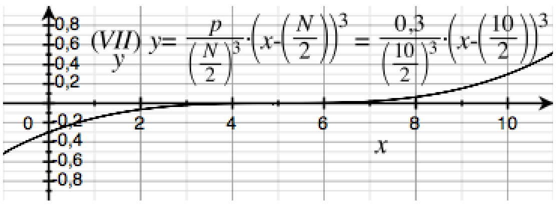

Fig.6: Eq. (VII) with exemplary values for parameters.

EXTRAVERSION

The domain of conscientiousness encompasses personality traits like being sociable, gregarious, assertive, attention seeking, taking pleasure in extensive social activities while seeking less time to spent alone. People scoring high in extraversion will foster the information flow due to their talkativeness and their many connections, increasing the possibility of a given message to be sent. To describe this fact we modify equation (I) to (VIII). Furthermore when combined with a high agreeableness individuals may invest even more time and resources in providing good information to nurture their many relationships. Nonetheless, in cases scoring extremely high, the talkativeness might result in a decrease of the perceived value or importance by receiving nodes, as these may suspect that the sender only talks, probably making things up, to be in the spotlight(VIII).

$$y = -p \cdot \cos\left(\left(\frac{\pi}{N}\right) \cdot x\right) \qquad \text{(VIII)}$$

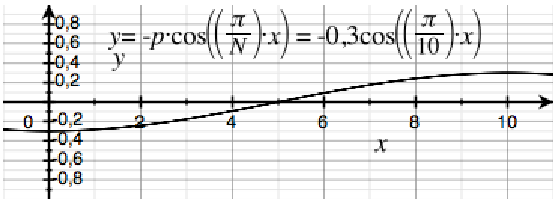

Fig.7: Eq. (VIII) with exemplary values for parameters.

Contrary to that, information sent by extreme introvert people might be perceived as more reliable or of particular importance. We therefore modify equation (VII) to (VIIII) by negation and increasing the exponent, thus accounting for the constraint on extremely high and low scores.

$$y = \frac{-p}{\left(\frac{N}{2}\right)^7} \cdot \left(x - \left(\frac{N}{2}\right)\right)^7 \qquad \text{(IX)}$$

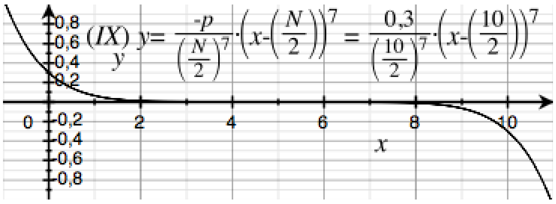

Fig8: Eq. (IX) with exemplary values for parameters

EMOTIONAL STABILITY

This domain is also inversely referred to as neuroticism and then encompasses personality traits like being moody, tense, anxious and emotionally reactive. While when being referred to as emotional stability it covers traits like being even-tempered. We will focus in this work on emotional stability as people scoring low being easily brought out of their equilibrium by both bad and good news, while people scoring high are less excitable. Following this line of thought we can assume that low scoring people tend to increase the flow of information that concerns themselves, of new things/ideas or experience made. An good example for the latter would be an unsatisfactory contact with a group member or e-learning tutor, where high scoring people might think nothing of it but people scoring low might boil with rage for days. Thus they can be assumed to spread a negative word-of-mouth for days, reducing group moral and performance. In contrast to that emotionally stable individuals actually may inhibit the flow of information as they might not get overly excited and thus find the information less interesting and assume that others share this opinion.

CONCLUSIONS AND FUTURE WORK

The diffusion of information between individuals and in groups, or even populations, can be considered a mayor stimulation for learning and influences important aspects of e-learning like administration and individual/group performance. The simulations of such diffusion processes will render important insights and thus may enable significant enhancements in a wide variety of e-learning concerns. We found that in simulations the modelling set-ups for attributes of nodes and edges are commonly rather simplistic and may thus influence the results negatively.

In this paper we focused on the attributes of nodes and discussed the implications of the five-factors of personality traits on information flow and message valuation. The five factor approach was selected due to its general acceptance as a promising (though not undisputed) approach [8,12] and as a compromise between modelling overly simplistic and trying to model every single personality trait. Furthermore the five factors are referred to as the "psychology of the stranger" as they describe traits that are easily perceivable but exclude non-public or context dependent aspects [13]. While this sounds like a disadvantage, for our project rather the opposite is true. As these traits can be checked relatively easy using standard questionnaires it can be assumed that real instead of stochastic values can be used. While discussing the domains one may have thought that some aspects of personalities are modelled implicitly even in simplistic approaches. When thinking about agreeableness and extraversion one may argue that these are implicitly modelled by the number or weight of edges a node possess, however this does not enable any prediction about the evaluation of message importance or selectiveness of nodes and neglects the other three dimensions. Thus we think it important to model the nodes closer to reality. Needless to say further research will be necessary to analyse the prediction improvement when contrasted with simplistic or more complex set-ups.

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