REPRESENTATION OF E-COMMERCE INTERACTIONS BY MEANS OF A GAME THEORY MODEL
Adoption of the Trust

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Abstract: In this paper, we investigated the application of trust in an e-Commerce system. In a B2C scenario of an e-Commerce system, a game model is proposed in order to investigate the best strategies for merchants and customers. Preliminary investigation outlines the benefits of trust information in the proposed game and preliminary results, conducted on a transactional database, shows an increased value of sensitivity of provided recommendations to the customers, entailing an higher customer loyalty. Future works are aimed at validating this findings by means of a larger real dataset.

1 INTRODUCTION

The concept of trust is related to the research in many fields, including computer science, cognitive science, economics, sociology and psychology. Trust is a complex concept, and different definitions of trust there exist.

In general, trust is a directional relationship between two parties that can be called trustor and trustee. In the e-Commerce domain, trust is applied to a specific purpose, such as mutual trust between the customers and the sellers or in a customer-based perspective if the seller is trustworthy. In particular, according to the customer's point of view, it is possible to distinguish two scenarios: (i) if the customer can rely on the seller suggestions when he does not know exactly what product to buy or (ii) if the customer can consider seller trustworthy when he wants to buy a specific item.

Webs of trust are networks through which a trust-aware system can ask a user to evaluate other users already known. For example, Epinions suggests to put in a user's web of trust "those reviewers whose reviews and ratings resulted to be extremely useful". Online interpersonal relations are becoming one of the major characteristics of the Web 2.0, and are also useful for social aspects (MySpace, Msn, Facebook), working connections (LinkedIn) and information (Slashdot.org, Epinions.com) besides, obviously, commercial purposes (eBay.com, Amazon.Com).

This paper proposes a game theoretic trust-based recommendation system. The proposed approach is based on the adoption of trust information in recommendation system in order to improve the quality of suggestions, entailing a more faith on the e-Commerce platform.

Game theory provides a formal mathematical framework for modeling and defining strategies for a set of common problems and has been proposed by different recent studies as a foundation for quantitative and theoretical analysis of different problems (Oza, 2006; Shiva et al., 2010).

The remainder of this paper is organized as follows: Section 2 introduces trust and social norms, Section 3 describes the strategy for suggesting products to the customers, Section 4 models the problem by means of game theory, Section 5 describes the proposed strategy, Section 6 provides preliminary results, and Section 7 outlines conclusions and future directions.

2 TRUST AND SOCIAL NORMS

Do online trust systems contribute to trade goods? This question is answered by several research analysis of existing systems. Among the different studies, Resnick and Zeckhauser (Resnick and Zeckhauser, 2002) have analyzed the feedback rating system used in eBay as a reputation system. They defined that a trust system must meet three challenges: (i) provide

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information that allows buyers to distinguish between trustworthy and non-trustworthy sellers (ii) encourage sellers to be trustworthy, and (iii) discourage participation of those who are not.

According to Liu (Liu and Shi, 2010) trust and reputation management research is highly interdisciplinary, involving researchers from networking and communication, data management and information systems, e-commerce and service computing, artificial intelligence, and game theory, as well as the social sciences and evolutionary biology.

2.1 Social NBorms

According to a common definition: "a norm exists in a given social setting to the extent that individuals usually act in a certain way and are often punished when seen not to be acting in this way" (Lim et al., 2008).

Recent studies have proven how homogeneous social norms may arise in heterogeneous societies consisting of groups with competing interests.

An important norm that has been found to pervade human societies for repeated interactions is *reciprocity norm*. Indeed, people use reciprocity norms even in very short time-horizon interactions (Mui et al., 2002). Reciprocity norms refer to social strategies consisting in reacting to the positive actions of others with positives responses and in reacting to the negative actions of others with negative responses.

Several reciprocity strategies have been proposed in literature, the most famous of which is the tit-for-tat strategy which has been studied within the Prisonerss Dilemma game. This strategy entails a cooperation if the other participants have cooperated and a defection if the other players have defected. To sum up, reciprocity is viewed as a social norm shared by agents in a society.

This social norm could be very useful in the e-Commerce domain where among different elements that characterize customer-behavior, past actions of other customers and feedback of stranger users are also taken into account.

In an environment such as Web, where individuals "regularly" perform reciprocity norms, there is an incentive to acquire a reputation for repeated actions.

3 RECOMMENDATION SYSTEM

Recommendation systems are aimed at helping users in the search of interesting items among a large set of items within a specific domain by using knowledge about user's preferences in the domain.

So that, based on users interests, preferences, hobbies and online behaviors, recommender systems model the relationship between users and items and help customers to select items from a set of choices, deciding what products to buy, in order to fit their tastes. Typically recommendations can be generated on the basis of user interaction history or on the history of related users.

In other words, Recommendation System is a way for improving personalization by giving personalized suggestions.

Recently, recommendation systems have largely been adopted in different domains: almost every e-Commerce site (e.g., Amazon) has its own recommendation engine; different Web site are focusing on suggesting a personalized content such as a movie (e.g., *MovieLens* and *Netflix*) or a song (*Yahoo!Music*). Therefore, different kinds of recommender systems are implemented, from simple ones, that only recommend items according to statistics, to complex ones, that use several different approaches and recommendation techniques.

Recommendation systems were introduced in 1992 by means of the Tapestry project (Goldberg et al., 1992). Several different approaches have recently been proposed in order to increase the accuracy of the predicted values, thus minimizing the prediction error and improving the quality of the recommendation while taking into account performance issues. However, some issues related to the quality of recommendations and to computational aspects still arise because collaborative systems rely solely on users preferences to make recommendations. Among recommendation techniques, Collaborative Filtering has gained great success in the practical application of e-Commerce (Adomavicius and Tuzhilin, 2005) and has been proven to be one of the most successful techniques. CF algorithms are divided into two categories: Memory-Based Collaborative Filtering and Model-Based Collaborative Filtering. In general, Memory-based algorithms are aimed at finding a group of users with similar tastes and producing a prediction for the active user by means of the entire user-item database. In contrast, model-based algorithms use the user-item database to infer a model which is then applied for predictions.

Model-based CF algorithms, such as Clustering CF, address this problem by providing more accurate predictions for sparse data as confirmed by (Huang and Yin, 2010) and by (Birtolo et al., 2011) who proved with their experimentation the benefits of clustering-based CF algorithms.

Once it is defined what items to consider, a prediction $p_i(u)$ for the active user u is generally evaluated by:

$$p_i(u) = \overline{r_i} + \frac{\sum_{j \in W_i} sim(i,j) \cdot (r_j(u) - \overline{r_j})}{\sum_{j \in W_i} |sim(i,j)|} \quad (1)$$

where $r_j(u)$ is the rating given to item j by the user u, $\overline{r_i}$ is the average rating given to item i, $sim(i,j)$ is a similarity function between item i and item j, and W_i is the set of items belonging to the same cluster of item i.

Recent works proved some benefits in terms of an increased quality of suggestions, by including trust information in recommendation systems (Liu and Yuan, 2010). These arising systems are called *Trust-based Recommendation Systems* (TRS) (Massa and Avesani, 2007; Zarghami et al., 2009) and combine the potentialities of a traditional recommendation system with a trust-aware system. The major problems of a TRS are the time necessary to explicitly define the online relations among users and, first and foremost, the small number of social links defined by users themselves, aspect that leads to a scarce quality of recommendations. The second problem, instead, is currently investigated and enhancing user trust seems to be a challenging task. Different cultures, different habits and different preferences complicate this problem and data are often unavailable (Huberman et al., 2005).

4 MODELING E-COMMERCE INTERACTIONS BY MEANS OF GAME THEORY

In this paper, in order to study the trust in the e-Commerce system, a model of relationship between a customer and a merchant is proposed.

Observing the dynamics of user behavior when he interacts with e-Commerce platform or when he looks for an item to buy, a model of this problem according to game theory is outlined.

The studied game is depicted in Fig.1. At the beginning of the game, the merchant M selects an item i within a given catalogue and he proposes this item to the customer C.

If the customer decides not to buy the proposed item, the game ends. In this case, the merchants payoff is 0 and the customers payoff is a.

On the other hand, if the customer chooses to buy the product, this choice yields a merchants payoff equals to a, while the customers payoff b can range within the interval $b_1..b_n$, assuming b_1 as the

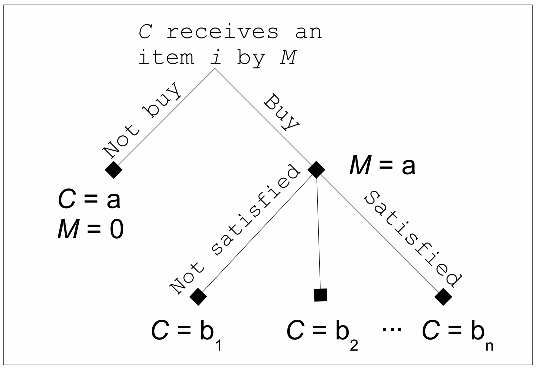

Figure 1: The game model.

worst case (i.e., the item does not satisfy the customer), while b_n as the best case (i.e., the item satisfies the customer). Throughout we shall assume $1 \le b_1 \le a \le b_n$.

Assuming a 1-to-5 scale of user feedback ($n = 5$), we have 5 different payoffs for a customer who buys the proposed item. Tab.1 illustrates the payoff matrix for the different possible outcomes, the couple (x,y) represents the payoff of customer and merchant respectively, while $e_1..e_m$ are the customer's possible strategies (e_1: "the customer buy the proposed item" and e_2: "the customer do not buy the proposed item") and $f_1..f_n$ are the merchant's possible strategies (f_1: "the merchant proposes an item which the customer consider strongly unsatisfactory"... f_5: "the merchant proposes an item which the customer consider strongly satisfactory").

Table 1: The payoff matrix of the proposed game model.

	Merchant				
Customer	f_1	f_2	f_3	f_4	f_5
e_1	(b_1,a)	(b_2,a)	(b_3,a)	(b_4,a)	(b_5,a)
e_2	$(a,0)$	$(a,0)$	$(a,0)$	$(a,0)$	$(a,0)$

The proposed game is non-cooperative because each player chooses a strategy independently and non-zero-sum (see Tab.1), indeed a merchant's gain does not necessarily imply customer's loss.

The best strategy for both customer and merchant is investigated above, proving the benefits if trust is taken into account.

4.1 Parameters of the Proposed Model

The merchant's payoff a, according to cost of the suggested item ranges from 1 ("very low cost") to 5 ("very high cost"). While the customer's payoff b is equal to r, which is the rating expressed by the customer after his evaluation of the purchased item.

The ratings r are integer numbers on a 1("bad")-to-5("excellent") scale. In other words, the customer's payoff ranges from $[1,5]$, 1 being the worst result and 5 the best.

Extending this model, it is possible to consider also a different definition of the customer's payoff. For instance, b could be defined as a convex combination of a and r, in order to take into account the intrinsical value of item that decreases its initial value once it is bought; so that the customer's payoff is defined as:

$$b = \sigma \cdot a/2 + (1-\sigma) \cdot r \tag{2}$$

where $\sigma \in [0,1]$, while a is divided by 2 because we assume that an item decreases its initial value of 50% once it was bought. In this study, we assume $b = r$.

4.2 Best Strategies

Values of a and b influence the best strategies. In any case, the best strategy for merchant is to sell his item (obtaining a payoff a), while for customer is to buy if $a = b_1$ and not to buy if $a = b_n$. In other cases, two main factors influence customer's decision: (i) value of a, (ii) expectation to obtain an item which complies with his preferences.

Assuming that a user has a positive payoff if the bought goods satisfy his taste, we have $0 < b_1 < b_2 < b_3 < a < b_4 < b_5$. Looking at the payoff matrix (see Tab.1), the strategy profiles (e_1, f_4) and (e_1, f_5) are Nash Equilibrium pairs and (e_1, f_5) is Pareto-dominant.

If the game is played once, the merchant can select an item without taking into account customer's preferences, while repeating the game different times, different strategies occur. Customer can change his strategy according to his past experience. For instance he can adopt a reciprocity strategy. While merchant must take into account user feedback in order to ensure a positive interaction and to increase the customer loyalty.

5 ASSISTING THE SELECTION OF THE STRATEGY BY MEANS OF TRUST MEASURE

Best strategies are based on the products' sale and on user satisfaction, so that two main problems have to be addressed:

- Improving the quality of merchants' suggestions by taking into account user preferences
- Enhancing user trust on the willingness of a particular merchant and on the quality of personalized suggestions

In literature, the selection of personalized item in order to guarantee user satisfaction is addressed by means of recommendation systems. Even if these systems are widely adopted on the web, some issues related to the quality of recommendation and to computational aspects still arise, so that in the last ten years several approaches have been proposed.

Trust can considered as a remarkable element influencing a user's decision making. It represents the level of trust that a user has toward the recommendation source. The concept of trust includes both the cognitive and the emotional dimensions. Trust-based Recommendation System uses the social ties established among online users. Even though these online ties are not established with the explicit aim of favoring the advice taking, recommender systems can use them to connect a user with a source of relevant information. In order to take into account trust information in suggestions, we proposed the following approaches:

1. Defining an *index of homophily* [1] between users in order to promote some suggestions and penalize other ones.
2. Promoting suggestion by analyzing experience of users close to the active one, not only by taking into account similar rating but also considering their demographical information such as cultural background and nationality (*customer closeness metric*). This information is useful in order to take into account similar habits.

The first proposed approach introduce and index of homophily $h(u,v)$ between item u and item v in order to emphasize trustworthy information which come from a subset of trusted users. This index is calculated according to the Eq. 3.

$$h(u,v) = \frac{\max(\alpha,k)}{\alpha} \cdot \frac{\min(\beta,k)}{\beta} \cdot t \tag{3}$$

where t is the trust component and α and β are two parameters ($\alpha < \beta$), so that when $k > \beta$, $h(u,v) = k/\alpha$ greater than 1 (*positive homophily*) and when $k < \alpha$, $h(u,v) = k/\beta$ lesser than 1 (penalty of correlation between items or a *negative homophily* because few users have evaluated in the same way the two items). For instance assuming $\alpha = 2$ and $\beta = 5$, when $k < 2$ we have:

$$h(u,v) = \frac{\max(2,k)}{2} \cdot \frac{\min(5,k)}{5} = \frac{k}{5} \cdot t < t$$

[1]Homophily can be defined as similarity in knowledge and preferences between two users

when $k > 5$ we have:

$$h(u,v) = \frac{\max(2,k)}{2} \cdot \frac{\min(5,k)}{5} = \frac{k}{2} \cdot t > t$$

Adopting the index of homophily means to modify prediction function of a standard recommender system, so that the prediction of a rating p of item i for the user u is expressed by Eq. 4.

$$p_i(u) = \overline{r}(u) + \frac{\sum_{v=1}^{V} h(u,v) \cdot sim(u,v) \cdot (r_i(v) - \overline{r}(v))}{\sum_{v=1}^{V} |h(u,v) \cdot sim(u,v)|} \quad (4)$$

where $r_i(u)$ is the rating given to item i by the user u, $\overline{r}(u)$ is the average rating given by the user u, $sim(u,v)$ is a similarity function between user u and user v, V is the set of users with profile of interest similar to the target user u.

While according to the second approach, closeness information is adopted, this means to restrict the cluster of user to those very close to the active one, so that prediction of a rating p of item i for the active user u expressed by Eq. 1 is updated by:

$$p_i(u) = \overline{r_i} + \frac{\sum_{j \in T_i} sim(i,j) \cdot (r_j(u) - \overline{r}_j)}{\sum_{j \in T_i} |sim(i,j)|} \quad (5)$$

where $T_i \subseteq W_i$ because T_i is a selection of users according to the customer closeness metric.

From merchant point of view, by adopting trust-based recommendation system the quality of recommendation should increase, while from customer point of view, by understanding the motivation of suggestion and by incorporating trustworthy information the customer loyalty should increase and so the buying or a repeated buying of items should be encouraged.

6 EXPERIMENTAL RESULTS

In our experimentation we consider a transactional database of a real e-Commerce platform of Poste Italiane. The dataset consists of 2,406 ratings for 477 items rated by 1,878 users; we assume equals to 5 the rating of a repeat customer purchase, while equals to 4 a single purchase. According to related literature (Herlocker et al., 2004) we consider as interesting item $\hat{i}$ for the user u , an item which user u have rated by 4 or 5, while not interesting the other ones.

For the experimentation we consider a subset ensuring at least a fixed number s of ratings per user ($s = 5$). The resulting subset is made of 107 items and is randomly divided into a training set (80% of the ratings per user) and a testing set (20% of the ratings per user). Starting with the training set recommendation algorithms predict unknown ratings, while the testing set is used to evaluate the accuracy of the predictions.

Different methods can be adopted to calculate the similarity of items or users. Generally, $sim(i, j) = 1$ when $i = j$, while in other cases $sim(i, j)$ indicates the similarity between item i and item j. According to the literature (Birtolo et al., 2011; Jeong et al., 2010), we adopt Pearson correlation similarity between items i and j defined as:

$$sim(i,j) = \frac{\sum_{u \in U_{ij}} (r_i(u) - \overline{r}_i)(r_j(u) - \overline{r}_j)}{\sqrt{\sum_{u \in U_{ij}} (r_i(u) - \overline{r}_i)^2} \sqrt{\sum_{u \in U_{ij}} (r_j(u) - \overline{r}_j)^2}} \quad (6)$$

where $\overline{r_i}$ is the average rating of item i (m is the number of users):

$$\overline{r_i} = \frac{1}{m} \cdot \sum_{l=1}^{m} r_i(l)$$

In order to evaluate the predicted rating we consider the Eq.5. We measure the true positive rate or *sensitivity* defined as the probability that an item will be interesting for users when he wishes to buy it.

The adoption of trust in recommendation system rather than the standard recommendation system (memory-based collaborative filtering) improve the number of predicted interesting items. Sensitivity of the proposed trust-based recommendation system is equals to $77,876\%$, while for a traditional item-based collaborative filtering is equals to 43.363%. The values are justified by the cold-start issues related to the low number of users who rated a significative number of products. Indeed, in order to make accurate recommendations, the system must first learn the users preferences from their ratings, so that if the users rated few items the recommendation could be unsuitable. Moreover, new items or items not rated by a substantial number of users (*cold-start items*) could rarely or never be recommended.

7 CONCLUSIONS AND FUTURE WORKS

Trust as a multidisciplinary field can benefit from careful integration and exploitation of advances in artificial intelligence, game theory, distributed computing, information systems, knowledge discovery, knowledge modeling, engineering, social sciences, and economics. The more Internet applications increase the more trust systems could play an important role in establishing effective cooperation among distributed Internet application participants.

In this paper we presented a game theoretic trust-based recommendation system. Our approach is based on the adoption of trust information in recommendation system in order to improve the quality of suggestions, thus identifying the best strategy for the game model proposed. To sum up, the main contributions of this paper are: (i) the representation of e-Commerce interactions by means of a game theory model, (ii) the proposal of the best strategy by means of the adoption of trust information, and (iii) the modeling of a trust-aware recommendation system by means of an integration between similarity, which is evaluated according the customer profile of interest, and the proposed trust metrics.

In future, we aim at investigating two main directions. The first is to extend the approach presented here in order to find the experimental evidence that the proposed model can provide benefits (e.g., increased profits for merchants or increase customer surplus) in a large real dataset of Poste Italiane. Furthermore, user information regarding age, sex, occupation, and geographical information with the provided feedback related to some products are available so that experimenting deeper the different trust model could confirm the benefits of the proposed approach.

The second direction will examine how to find out multi-player scenario, indeed in e-Commerce domain online shopping is becoming more and more widespread and represents an everyday activity for many. In this actual scenario, we will analyze the proposed game model when it is executed with different players, several customers and several merchants at the same time. Moreover, we will highlight new arising issues and investigate the best strategy.

REFERENCES

Adomavicius, G. and Tuzhilin, A. (2005). Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *Knowledge and Data Engineering, IEEE Transactions on*, 17(6):734–749.

Birtolo, C., Ronca, D., Armenise, R., and Ascione, M. (2011). Personalized suggestions by means of collaborative filtering: A comparison of two different model-based techniques. In *NaBIC*, pages 444–450. IEEE.

Goldberg, D., Nichols, D., Oki, B. M., and Terry, D. (1992). Using collaborative filtering to weave an information tapestry. *Commun. ACM*, 35:61–70.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., and Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Trans. Inf. Syst.*, 22:5–53.

Huang, C. and Yin, J. (2010). Effective association clusters filtering to cold-start recommendations. In *Fuzzy Systems and Knowledge Discovery (FSKD), 2010 Seventh Int. Conf. on*, volume 5, pages 2461–2464.

Huberman, B. A., Adar, E., and Fine, L. R. (2005). Valuating privacy. *IEEE Security and Privacy*, 3:22–25.

Jeong, B., Lee, J., and Cho, H. (2010). Improving memory-based collaborative filtering via similarity updating and prediction modulation. *Information Sciences*, 180(5):602 – 612.

Lim, H. C., Stocker, R., and Larkin, H. (2008). Ethical trust and social moral norms simulation: A bio-inspired agent-based modelling approach. *Web Intelligence and Intelligent Agent Technology, IEEE/WIC/ACM International Conference on*, 2:245–251.

Liu, B. and Yuan, Z. (2010). Incorporating social networks and user opinions for collaborative recommendation: local trust network based method. In *Proc. of the Workshop on Context-Aware Movie Recommendation*, CAMRa10, pages 53–56, New York, NY, USA. ACM.

Liu, L. and Shi, W. (2010). Trust and reputation management. *Internet Computing, IEEE*, 14(5):10 –13.

Massa, P. and Avesani, P. (2007). Trust-aware recommender systems. In *Proceedings of the 2007 ACM conference on Recommender systems*, RecSys '07, pages 17–24, New York, NY, USA. ACM.

Mui, L., Mohtashemi, M., and Halberstadt, A. (2002). A computational model of trust and reputation. In *System Sciences, 2002. HICSS. Proceedings of the 35th Annual Hawaii International Conference on*, pages 2431 – 2439.

Oza, N. V. (2006). Game theory perspectives on client: vendor relationships in offshore software outsourcing. In *Proceedings of the 2006 international workshop on Economics driven software engineering research*, EDSER '06, pages 49–54, New York, NY, USA. ACM.

Resnick, P. and Zeckhauser, R. (2002). Trust among strangers in Internet transactions: Empirical analysis of eBay's reputation system. In Baye, M. R., editor, *The Economics of the Internet and E-Commerce*, volume 11 of *Advances in Applied Microeconomics*, pages 127–157. Elsevier Science.

Shiva, S., Roy, S., and Dasgupta, D. (2010). Game theory for cyber security. In *Proceedings of the Sixth Annual Workshop on Cyber Security and Information Intelligence Research*, CSIIRW '10, pages 34:1–34:4, New York, NY, USA. ACM.

Zarghami, A., Fazeli, S., Dokoohaki, N., and Matskin, M. (2009). Social trust-aware recommendation system: A t-index approach. In *Web Intelligence and Intelligent Agent Technologies, 2009. WI-IAT '09. IEEE/WIC/ACM International Joint Conferences on*, volume 3, pages 85 –90.