A Review of Trust-Aware Recommender Systems Based on Graph Theory

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ABSTRACT

The Web is currently characterised by user contribution. As a result, content is generated in an uncontrolled way leading to the so-called "information overload". The role of information filtering techniques and recommender systems is to give a solution to this problem by taking into account user preferences, and/or other context of information to present the content. Furthermore, word-of-mouth and trust plays a key role in the decision-making process of a person, while ratings, comments, opinions and tags are increasingly gaining popularity in social networks. The aim of this paper is to study the current approaches of trust-aware recommender systems with a focus on graph based models and to identify possible gaps for providing insights and directions for future researches. In the beginning there is an introduction with presentation of traditional recommendation approaches along with their limitations. Then there is a review of trust definitions and properties. It follows a review of current trust-aware approaches which are classified in five major categories according the technique they use. In the last section there is a focus on graph models of trust-aware recommender systems which are compared according four categorisation criteria. Finally the study identifies the gaps in the current literature of graph based models and proposes areas for future research.

KEYWORDS

Recommender systems, trust, trust-aware recommender systems, graph based trust recommender systems

1 INTRODUCTION

During the last decade the rapid evolution in Information and Communications Technologies has brought tremendous changes in all sectors of modern society. Information sharing in the Web is getting enormous, while Web 2.0 applications allow millions of users to publish and edit content as well as to share and tag data in an uncontrolled way. Hence the explosive growth of information has led to the "information overload" problem - that is, the inability to cope with and manage all the available information in an efficient way. As stated in [1] this means that traditional information retrieval systems face tremendous difficulties in retrieving information from "a mess".

All this constantly growing information, as well as the advent of new businesses and services, led users to a labyrinth of choices making the final decision difficult and many times with limited confidence [2]. Difficulties in decision-making process are usually increased due to the user's limited knowledge about a topic, or the time spent on dealing with the volume of the available information. This process is even more complicated when there are too many alternatives, intensified by information overload, as it then becomes too time-consuming to acquire deep knowledge of all the different alternatives. Considering the case of a travel plan, the task is even more complicated as the user has to find information in different topics, regarding accommodation, attractions, destinations etc. A typical solution

ISBN: 978-1-941968-04-8 ©2014 SDIWC

to this is to seek advice and suggestions from friends and/or experts. In practice, users need information filtering and recommendations to support their decisions and to avoid waste of time.

The purpose of a recommender system is to assist the user to cope with the vast amount of information which is available on the Internet and, moreover, to function as a supporting tool to the decision-making process. Recommender systems are tools that deal with the information overload by filtering information through various techniques and make suggestions for information items that are probably of interest to the user. One of the first studies in recommender systems was Tapestry [3] that also introduced the “collaborative filtering” technique. Recommender systems based on collaborative filtering take into account the preferences of a multitude of users. The main concept of this technique is that common preferences and choices between two or more users in the past tend to be the same in the future. The other main technique in recommender systems is content-based filtering where the items are recommended according to their similarity of their characteristics. All the other approaches are based on one or even both of these filtering techniques.

Despite the continuous research and variety of approaches, recommender systems still face limitations, as presented later in section 2.1, and need further improvements to be more effective and applicable to a broader range of real-life applications [4].

2 RECOMMENDATION APPROACHES

Recommender systems initially relied in the research area of information filtering and retrieval where techniques are mainly based on document content and item description without considering user preferences or context.

The two major methods for producing recommendations are the content-based based filtering technique which relies on item attributes and/or historical data of the user, and the collaborative filtering technique which is based on the opinions and preferences of other users. Whilst there are hybrid techniques combining both of the above, collaborative filtering is the most successful and widely-used technique [5]. One of the first commercial recommender systems, as previously mentioned, was Tapestry [3] which was purely based on collaborative filtering.

Generally, recommender systems build and exploit user model to generate recommendations which is the improvement over the traditional information retrieval approaches. In demographic recommender systems, for example, the user model contains demographic information like age, gender, education, etc. while in collaborative filtering user is modelled by his ratings to the items [1]. There are two main methods for collecting information about the user: Explicitly, where the information is provisioned explicitly by the user by asking the user to do a check list of his interests or by collecting from the user previous ranking information. Implicitly, where information is extracted from user’s browsing history through automated reasoning mechanism.

The aforementioned approaches and techniques are static, whereas user preferences and attributes change over time. However, there is a need [6] for constant updates of the user profile for producing better recommendations.

Recently, research has focused on the semantic description of user model enriching user profiles with metadata, moving on from the conventional vector representation of user model. Many approaches try to semantically describe the user model [7], [8], [9], [10]. In a recent study [11], the user model is based on the semantic representation of the user’s activity taking also into account the structure of visited web sites. Lately, research in Social Network Analysis [12], [13], [14] and Natural Language Processing [15] has offered a new perspective and solutions in the semantic description of user model.

However the emergence and the widespread of the Social Networks has given opportunities in developing new approaches for recommender systems exploiting not only the comments and tags created by users but also the relationships. Friends in a social network are a kind of trusted network which has given a boost to the newcomer trust-aware approach.

2.1 Limitations of typical recommender systems

One of the constant pursuits of researchers is to find out how to recommend the “best for the user”. The reason for these continuous research efforts in this area is that there are certain limitations on the current systems which are presented here:

The cold start problem. It is generally encountered in all approaches where a new user or a user with low activity does not provide enough knowledge about his preferences to the system. Similarly, a new item needs a kick start rating.

Sparsity. It is a problem encountered in collaborative recommender systems and refers to the user ratings matrix which is typically sparse as most users do not usually rate most items.

Malicious ratings, fraud. One of the drawbacks of the collaborative recommender systems is that they are prone to malicious attacks. A typical example of this is fake profiles and pseudo-ratings to particular products.

Lack of transparency. Another basic drawback of recommender systems is the lack or absence of explanations. If there is not enough explanation of the way recommendations emerged, the user does not trust the source enough.

A solution to overcome the limitations presented above is to enhance recommender systems with trust relationships which already exist in social networks and build the so-called trust-based or trust-aware recommender systems.

3 ABOUT TRUST

Trust as a notion can be found in many disciplines and is extensively explored in social sciences, social psychology, cognitive psychology, economics, political sciences, organisation science and computer science among many others. In social sciences trust is a factor that impacts human decisions. In economics trust enables people to do business with each other which in turn affects the economy of a country [16]. Especially in computer science trust is broadly used in IT security as identity verification and authentication for network access control or as a metric for reliability of a source.

There are many different definitions of the trust concept according its science origin and the application domain. Most researches refer to trust as a belief [17]: the trustor believes that the trustee can be trusted for a specific goal in a specific context.

One of the first definitions is that of Gambetta [18] where trust is defined as a subjective probability with which an agent will perform a particular action in a context in which it affects his own actions. Mui [19] define trust as “a subjective expectation an agent has about another’s future behaviour based on the history of their encounters”, while Falcone and Castelfranchi [20] give a socio-cognitive model of trust. The definition of [21] refers to “the willingness or intention of a person to depend on the other person generally and not in a specific situation, even though they were aware of potential problems in their relationship”. Moreover authors in [22] refer to trust as the extent to which one is willing to depend on somebody in a given situation.

Especially in computer science Marsh [23] introduced trust as a computational concept. He stated that trust is a measurable level of risk, through which an agent X assesses the likelihood that another agent Y will successfully perform a particular action, both before X can monitor such action and in a context in which it affects its own actions.

Marsh also introduced the distrust as the negative trust which later was considered by many researchers [13], [21], [24], [25], [26]. In this paper we will focus on computer science aspect of trust and particularly on how it is used and computed in intelligent systems.

Hence trust is a relationship between two agents namely the trustor and the trustee where the trustor trusts the trustee in a specific context. For example Alice trusts Bob for fixing her car. The role of context in a trust relationship is of major importance e.g. Bob trusts John as a dentist but does not trust him as a driver. Moreover trust in a person is different than trust in a person's recommendation; for compatibility with the traditional way users participate in social networks both of these ideas are represented as a single value, as is common in computer science [27].

3.1 Computational properties of trust

Trust as a concept has properties which computational processes exploit for inferring trust relationships. This section presents the functional properties of trust that computational trust models are based on for trust dissemination:

Asymmetry. Trust is personal and subjective. Such as Alice trusts Bob to fix her car but Bob doesn't trust Alice to fix his car, while Alice and Bob may fully trust each other for recommending a restaurant. Hence, trust as a rule is directed and asymmetric although sometimes can be symmetric.

Propagation. In real life if we trust a friend we also tend to trust the friend of our friend. For example if Alice trusts Bob and Bob trusts Frank then Alice can derive some conclusion about the degree of trust she can have about Frank based on the degree of her trust for Bob and the degree of Bob's trust for Frank. So in a social network, trust information can be propagated and create trust chains. By propagating trust on a social network we can infer more trusted persons and hence improve the predictive performance of recommender systems by building a bigger trust network.

No-Transitivity. Generally trust is not transitive [28]. Suppose Alice trusts Bob and Bob trusts Frank this does not necessarily imply that Alice will trust Frank. Although trust is propagative, as stated before, this does not imply that is also transitive. In the literature many times transitivity and propagation are confused though the propagative property is really concerned and extensively researched as a computational property of trust.

Composability. When there is not direct trust for an agent and trust information is propagated from more than one source, then there is a need to compose all the propagated trust information in one trust score. Let's say Alice does not know anything about Frank and she receives information from her friends Bob and Jenny about Frank's trustworthiness. Alice has to combine the suggestions from her friends to make a conclusion about his trustworthiness based on her own degree of trust for each of her friends. Of course information from different sources can be contradictory. The mechanism that exploits the composability property is the trust aggregation.

Context dependency. Trust is context and time dependent [17]. Preferences change over time and are also location dependent. Moreover trust degree may decrease or increase due to negative or positive evidences respectively and it is commonplace that it is more easily to crash than to build a trust relationship. For instance Bob used to trust Alice to cook a meal but after the last time which was "disappointing", his trust was dramatically decreased!

3.2 Trust metrics

A lot of effort has been put within different disciplines for computing trust and several approaches have been proposed. A socio-cognitive model of trust is built in [29] by using Fuzzy Logic to compute the value of the trustfulness starting from belief sources that refer to trust features. Authors in [30] propose an ontology integration tool that uses suggestions for dynamically changing trust of a document author. Historical data in peer-to-peer networks and Genetic Algorithm where used in [31]. Authors in [32] build a trust network in the Semantic Web by extending FOAF profiles to include trust relationships. Appleseed [33] is a local and group trust metric for ranking all the nodes in the network.

Reputation is another notion often used but also confused with trust. The key distinction is that reputation of an agent is a factor that affects his trustworthiness. Trustworthiness is based on previous experience with the agent while reputation is based on measures that this agent (node) has within a social network. Mui et. al in [19] state that reputation is the perception that an agent creates through past actions about its intentions and norms.

The term “global trust” is sometimes used instead of reputation and “local trust” is respectively used for defining trustworthiness. PageRank [34] is a very popular global trust metric for measuring the importance of a website. Similarly authors in [35] proposed the EigenTrust algorithm which is a global trust metric for peer-to-peer networks. These two algorithms are very widely used in the literature as global metrics.

3.3 Trust-Aware Recommender Systems

It is common in real life to seek advice for topics we are not expert in or have no experience on. Friends can be a valuable information source but the Internet can also play an important role in information seeking. Nowadays, with the explosive growth of Web 2.0 technologies, the two sources, friends and the Internet, are combined in services called Social Networks. Recommender systems that take advantage of these technologies are called social recommender systems and exploit not only opinions and ratings about items but also the relationships between users. The emergence of Web 2.0 and the ability of the user to express himself and be heard all over the world, changed not only the way of communication but also business and marketing. The expression of personal opinion is “more likely to be believed by today's sceptical consumer than advertisements or professional input” [36]. Social networks are characterised by relations between “friends” or “followers” with similar interests. As O’ Connor [37] points out, “consumers are no longer dependent on web site owners to publish the information they seek, as they can increasingly rely on unfiltered, dynamic and topical information provided by their own peers”. For example, in a usual shopping day, just like a friend’s opinion counts more than the seller’s, in the same way word-of-mouth “is perceived as being more vivid, easier to use and more trustworthy than marketer-provided information”.

Hence, research in recommender systems, has turned to the exploitation of trust relationships to improve predictions. Golbeck in [38] proposed Filmtrust, which is a movie recommender system based on FOAF vocabulary for creating a social network of trust with trust values given by the users. Massa & Avesani [39] computed similarity between users using trust metrics based on trust networks. In a more recent study [40], trust-aware recommendations are enhanced with ontologies for creating annotated content for the Semantic Web. In a recent study [41] shuffled frog leaping algorithm was applied for clustering the users different social contexts. Generally, trust-aware systems proved [5], [42] to be more accurate than traditional recommender systems and overcome known limitations as the cold start problem, frauds and attacks.

Both collaborative and content-based filtering recommendation approaches are based on similarity measures either between users or between items respectively. Euclidean distance, cosine based similarity and Pearson correlation coefficient are some of the most popular methods used in calculating similarity measures. Trust aware systems use the weight of a trust relationship to measure the similarity between users. Trust relationships are weighted and can be expressed in various scales for stating trust or distrust or even intermediate degrees of trust.

4 TRUST MODELS

Various approaches exist in the literature for modeling trust but this paper concentrates in trust models for recommender systems and classifies them based on the technique they use. Another classification of trust-aware recommender system is that of Victor in [13] where she adopts a classification of probabilistic versus gradual approaches while examines which of the trust/distrust concepts are represented. In the former trust is computed as the probability of trusting someone or not while in the latter trust is gradually expressed, as in everyday life, using a scale to represent the degree of trust in another user. But this is a very general classification and does not examine in depth which technique is based on.

Here we classify trust models in five major categories based on the techniques the use: (i) statistical technique, (ii) heuristics-based, (iii) graph based, (iv) semantic based and (v) fuzzy logic. In some of them we distinguish their subcategories.

Table 1. Classification of trust models

<table>
<tr><th>Statistical techniques</th><th>Heuristics-based solutions</th></tr>
<tr><td rowspan="7">• Probabilistic techniques
○ Bayesian systems
Mui et al. [19]
Josang & Lo [22]
○ Belief models
Falcone et al. [29]
Barber & Kim [43]
Guha et al. [44]
■ Dempster-Shafer theory
Yu & Singh [45]
■ Subjective logic
Jøsang [46]
Jøsang et al. [47]
○ Markov Models
Fouss et al. [48]
Dong & Frossard [49]
ElSalamouny [50]
Song et al [51]
• Machine learning
○ Artificial Neural Networks
Bedi & Kaur [52]
○ Bayesian classifiers
Hooijmaijers & Stumptner [30]
Guanfeng et al. [53]
Patel et al. [54]
Guanfeng et al. [55]
○ Decision trees
Zolfaghar & Aghaie [56]</td><td>• Genetic algorithms
Serlvaraj & Anand [31]
• Ant colony
Bedi & Sharma [57]</td></tr>
<tr><td>Graph theory</td></tr>
<tr><td>Golbeck [27]
Golbeck [38]
Zhang et al [58]
Walter et al [42]
Li et al [59]
Yang et al [60]
Victor et al [13]
Ziegler & Lausen [33]
Golbeck & Hendler [61]</td></tr>
<tr><td>Semantic based</td></tr>
<tr><td>Golbeck [62]
Heath et al. [63]
Kim & Kwon [64]
Oufaida [65]
Gao & Systems [66]
Martin-Vicente et al. [67]
Golbeck et al. [32]
Bedi et al.[40]</td></tr>
<tr><td>Fuzzy logic</td></tr>
<tr><td>Aberer et al. [68]
Bedi & Kaur [52]
Capuruco & Capretz [69]
Chen et al. [70]
Li & Kao [71]</td></tr>
</table>

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As it is shown in Table 1, statistical techniques are very popular within which probabilistic techniques have the majority of variants. Probabilistic techniques are also very popular in predicting user ratings in traditional collaborative filtering recommender systems. However, graph-based trust models introduce a new philosophy and treat the concept of trust as a relationship between users within a social network. The technique is consistent with every day's social interactions and exploits the properties of the existing web based social networks through Social Network Analysis, for discovering similarities between users.

4.1 Graph Based Recommendation Models.

Essentially a trust network is a social network which can be represented as directed graph in which nodes are the users and edges are the trust relationships. When trust weights follow a gradual scale then this graph is a labelled directed graph with the degree of trust as labels. Therefore, graph theory and propagation property of trust can be exploited to infer not only existing trust relationships but also to cluster users and create groups of users with common preferences for improving performance of recommender systems, however trust models that exploit graph theory are in infancy.

Hence it is meaningful to study recommender systems based on graph theory and identify possible gaps and improvements. Consequently these models were examined for the computational properties of trust, they take into account, the trust metrics as also the trust establishment.

<u>Categorisation criteria</u>

Accordingly the literature about graph based trust-aware recommender systems can be categorized based in four major categories regarding (i) propagation, (ii) network perspective (iii) trust establishment and (iv) context dependency.

Propagation.

As mentioned before, propagation is a property of trust that benefits the process of predicting the trust score through known trust paths. Direct trust relations in a user's trust network build a path through which new indirect connections can be established with other users, not known. There are various strategies for computing trust propagation. One very common is the random walk approach which assigns a transition probability to each edge by walking from one node to another. It is a method used also in PageRank [34] and EigenTrust [35] for computing the global trust of a node. Appleseed [33] is another method that propagates by spreading "trust energy" based on the strength of the edge. A graph based popular method is that of Golbeck's TidalTrust [27] where propagation is based not only on shortest path but also on strongest path. An extension of TidalTrust is the MoleTrust [72] which uses a fixed parameter, horizon, as maximum path length and a trust threshold for participating in the process.

Network perspective: Global versus Local trust.

As already mentioned trust can be inferred through global or local trust measures. Local trust is the subjective measure of a user for the trustworthiness of another user. In other words it is the degree of a trust relationship between two users that is stated explicitly. Global trust, on the other hand, is the average opinion of the whole community about the trustworthiness of a user. Namely it is the reputation that a user has in the network. In trust aware recommender systems literature local trust metric is generally preferred [13], [40], [41], [52], [72], [73], [74], [75] although there are systems that adopt both local and global trust [60], [76], [77].

Comparing the two strategies, local trust metrics are computationally more expensive than global metrics, as it has to be calculated for all pair of users, while they are proved [78] to be more accurate solution in case of controversial topics. Moreover, they are more resistant against attacks due to relationships explicitly stated although in global trust fake user profiles can impact the reputation of a user.

Trust establishment.

Trust establishment can be based on explicit or implicit trust networks. Explicit networks are built with explicit trust statements whereas implicit are inferred from user behaviours. Implicit trust relationships can be computed through user similarity and other trust metrics.

Explicit and implicit trust can be either bivalent or expressed in a gradual scale. Several studies [13], [27], [72], [73], [74], [76] use explicit trust however several other [40], [41], [52], [57], [60], [75] infer trust relationships to build the implicit trust.

Context dependency.

Context dependency is a property of trust as discussed in section 3.1 which plays an important role in trust establishment between two users. Usually context is considered in general models of trust and sometimes with alternative names such as "domain" [17], "topic" [32], [79] or "category" [60]. Whatever the name is used the meaning is the same: context is a factor that impacts trust relationship [80] and has to be regarded in the computational process of trust. However in the majority of graph-based models, context is predefined or is omitted in the computational process either for "the sake of simplicity" [13] or due to no availability of appropriate data [27].

Table 2 illustrates briefly the main literature which use graph models in their trust-aware recommender systems based on the categorisation criteria defined previously in this section. It becomes immediately apparent that the focus of these models is in computing trust values through propagation by exploiting various techniques in the trust network based on graph theory while context has not been taken into account or not studied experimentally [27]. In all these models trust networks are explicit whereas in the majority of these only local metrics of trust have been considered.

Table 2. Comparison of main literature in graph-based trust-aware recommender systems

	Algorithm approach	**Propagation**	**Network perspective**	**Trust establishment**	**Context dependency**
Golbeck [27]	TidalTrust (breadth-first search)	Shortest path + strongest path	Local	explicit	Yes but not studied
Massa & Avesani [72]	MoleTrust Collaborative+trust	Shortest path with horizon+ strongest path with threshold	Local	explicit	No
Victor et al. [13]	EnsebleTrust trust as a weight	Yes	Local	explicit	No
Hess [74]	Multilayer network trust network+ document reference network	Yes	Local	explicit	No
Hang & Singh [77]	Graph similarity	Graph propagation	Local + global	explicit	No

5 DISCUSSION

Although propagation is extensively addressed in all of the models of Table 2 it can be clearly identified that there is a lack on dealing with the last computational property of trust presented in section 3.1 which refers to the context dependency. In all these models, context dependency is either not taken into

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account at all or omitted for simplicity reasons [13]. Usually in the literature trust-aware recommendation systems are domain specific thus context is not considered in their model although it is a factor that impacts trust relationships. Golbeck in [27] has taken into account the factor of context as “topic” in the FOAF profile, however she did not included it in her experiments. Moreover Hess [74] computes trust aware recommendations by building multilayer network for a specific domain namely document reference. In the other two studies [72], [77] scholars did not considered at all the factor of context dependency.

Hence it is obvious that context is a notion that needs to be incorporated in the computational process as it is admittedly a property that impacts [80] trust relationships while global metrics need more attention.

In final consideration, it is apparent that a novel approach is needed that exploit all the benefits of the graph based technique while takes into account the context and furthermore incorporates it in the model.

In a recent research [60] authors take into account the context dependency by inferring category-specific social “trust circles”. However their approach is not a graph based model consequently does not use propagation property to infer more trust relationships. Inspiring from this approach and combining it with the notion of multilayers that Hess [74] adopts we propose a novel approach that incorporates the context property of trust.

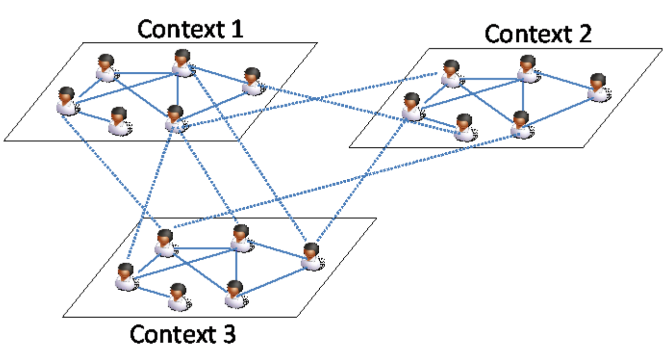

Figure 1. A multi-layer trust network approach

Our proposal is to build a multi-layer trust network where each layer will represent a different context. Trust can then be propagated in each layer separately and recommendations can be produced for each context independently. Of course this is an initial proposal which in the future we intend to implement and evaluate with experiments.

6 CONCLUSION

This study presented a review of current approaches in trust aware recommender systems with a focus on graph based models. The study also reviewed the definitions of trust along with computational properties of trust and trust metrics. Afterwards the examined trust-aware approaches were classified in five major categories according the technique they use and was identified that the majority of them are based on probability techniques while the emerging graph based techniques are gaining attention. In the last section, graph models of trust-aware recommender systems were compared according five categorisation criteria From the categorisation table it was identified that context-dependency have not received enough attention through the examined models and therefore new approaches are needed for incorporating the context property of trust in the graph based models.

Findings of this paper indicate that the property of trust which refers to the context-dependency has to be incorporated in the current graph models of trust-aware recommenders and extensively researched.

REFERENCES

[1] F. Ricci, L. Rokach, B. Shapira and P.B. Kantor, "Recommender Systems Handbook,"2011.

[2] B. Schwartz, '"The paradox of choice: why more is less", 2004.

[3] D. Goldberg, D. Nichols, B.M. Oki and D. Terry, '"Using collaborative filtering to weave an

information tapestry," *Commun ACM*, vol. 35, no. 12, December, pp. 61-70.

[4] M. Gao, K. Liu and Z. Wu, "'Personalisation in web computing and informatics: Theories, techniques, applications, and future research," *Inf.Syst.Front.*, vol. 12, no. 5, November, pp. 607-629.

[5] S. Ray and A. Mahanti, "Improving Prediction Accuracy in Trust-Aware Recommender Systems,"Washington, DC, USA2010 pp. 1-9.

[6] N. Nanas, A. De Roeck and M. Vavalis, "What Happened to Content-Based Information Filtering?" vol. 5766,2009 pp. 249-256.

[7] H. Kim, I. Ha, J. Jung and G. Jo, "User Preference Modeling from Positive Contents for Personalized Recommendation," vol. 4755,2007 pp. 116-126.

[8] E. Kang, H. Kim and J. Cho, "Personalization Method for Tourist Point of Interest (POI) Recommendation," vol. 4251,2006 pp. 392-400.

[9] D. Heckmann, T. Schwartz, B. Brandherm and A. Kr, "Decentralized User Modeling with UserML and GUMO,"2005 pp. 61-64.

[10] D. Heckmann, T. Schwartz, B. Brandherm, M. Schmitz and M. von Wilamowitz-Moellendorff, "Gumo – The General User Model Ontology," vol. 3538,2005 pp. 149-149.

[11] H. Zhang, Y. Song and H. Song, "Construction of Ontology-Based User Model for Web Personalization,"Berlin, Heidelberg2007 pp. 67-76.

[12] M. McGrath, "Employing 'Social Network Analysis' to Influence Tourism Events Decision-Making: A Pilot Study,"2008 pp. 556-567.

[13] P. Victor, C. Chris and d.C. Martine, "'Trust Networks for Recommender Systems", 2011.

[14] G. Erétéo, F. Gandon, M. Buffa and O. Corby, "Semantic Social Network Analysis - Web Science Repository," vol. 2010, no. 12/20/2010,2009.

[15] Y. Wilks and C. Brewster, "'Natural Language Processing as a Foundation of the Semantic Web," *Found.Trends Web Sci.*, vol. 1, no. 3-4, March, pp. 199-327.

[16] T. Harford, "The Economics Of Trust,"2010.

[17] S. Adali, "'Modeling Trust Context in Networks", 2013.

[18] D. Gambetta, "Can We Trust Trust?"1988 pp. 213-237.

[19] L. Mui, M. Mohtashemi and A. Halberstadt, "A Computational Model of Trust and Reputation for E-businesses,"Washington, DC, USA2002 pp. 188.

[20] R. Falcone and C. Castelfranchi, "Trust and Deception in Virtual Societies," no. Social Trust: A Cognitive Approach,Norwell, MA, USA2001 pp. 55-90.

[21] D. Harrison McKnight and N. Chervany, "Trust and Distrust Definitions: One Bite at a Time," vol. 2246,2001 pp. 27-54.

[22] A. Jøsang and S. Lo Presti, "Analysing the Relationship between Risk and Trust," *Trust Management* vol. 2995,2004 pp. 135-145.

[23] S.P. Marsh, "Formalising trust as a computational concept,"1994.

[24] R.J. Lewicki, D.J. Mcallister and R.J. Bies, "Trust and Distrust: New Relationships and Realities,"1998.

[25] W. Yuan, L. Shu, H.C. Chao, D. Guan, Y. Lee and S. Lee, "'iTARS: trust-aware recommender system using implicit trust networks," *Communications, IET*, vol. 4, no. 14, pp. 1709-1721.

[26] D. O'Doherty, S. Jouili and P.V. Roy, "Trust-based recommendation: an empirical analysis,"2012.

[27] J.A. Golbeck. , Computing and Applying Trust in Web-based Social Networks, University of Maryland at College Park, 2005.

[28] W. Sherchan, S. Nepal and C. Paris, "'A Survey of Trust in Social Networks," *ACM Comput.Surv.*, vol. 45, no. 4, aug, pp. 47:1-47:33.

[29] R. Falcone, G. Pezzulo and C. Castelfranchi, "A Fuzzy Approach to a Belief-based Trust Computation,"Berlin, Heidelberg2003 pp. 73-86.

[30] D. Hooijmaijers and M. Stumptner, "'Trust Calculation,", vol. 228, pp. 111-121.

[31] C. Selvaraj and S. Anand, "'Peer profile based trust model for P2P systems using genetic algorithm,"

Peer-to-Peer Networking and Applications, vol. 5, no. 1, pp. 92-103.

[32] J.A. Golbeck, B. Parsia and J. Hendler, "Trust Networks on the Semantic Web," vol. 2782,2003 pp. 238-249.

[33] C. Ziegler and G. Lausen, "Spreading activation models for trust propagation,"2004 pp. 83-97.

[34] S. Brin and L. Page, "The Anatomy of a Large-scale Hypertextual Web Search Engine,"Amsterdam, The Netherlands, The Netherlands1998 pp. 107-117.

[35] S.D. Kamvar, M.T. Schlosser and H. Garcia-Molina, "The Eigentrust Algorithm for Reputation Management in P2P Networks,"New York, NY, USA2003 pp. 640-651.

[36] D. Smith, S. Menon and K. Sivakumar, "'Online peer and editorial recommendations, trust, and choice in virtual markets," *Journal of Interactive Marketing*, vol. 19, no. 3, pp. 15-37.

[37] P. O'Connor, "'Information and Communication Technologies in Tourism 2008; User-Generated Content and Travel: A Case Study on Tripadvisor.Com,", pp. 47-58.

[38] J.A. Golbeck, "Generating Predictive Movie Recommendations from Trust in Social Networks," vol. 3986,2006 pp. 93-104.

[39] P. Massa and P. Avesani, "Trust-Aware Collaborative Filtering for Recommender Systems," vol. 3290,2004 pp. 492-508.

[40] P. Bedi, H. Kaur and S. Marwaha, "Trust based recommender system for the semantic web,"San Francisco, CA, USA2007 pp. 2677-2682.

[41] S. Mehta and H. Banati, "Trust aware social context filtering using Shuffled frog leaping algorithm,"2012 pp. 342-347.

[42] F. Walter, S. Battiston and F. Schweitzer, "'A model of a trust-based recommendation system on a social network," *Auton.Agents Multi-Agent Syst.*, vol. 16, no. 1, pp. 57-74.

[43] K.S. Barber and J. Kim, "Belief Revision Process Based on Trust: Agents Evaluating Reputation of Information Sources," *Trust in Cyber-societies* vol. 2246,2001 pp. 73-82.

[44] R. Guha, R. Kumar, P. Raghavan and A. Tomkins, "Propagation of Trust and Distrust,"New York, NY, USA2004 pp. 403-412.

[45] B. Yu and M.P. Singh, "An Evidential Model of Distributed Reputation Management,"New York, NY, USA2002 pp. 294-301.

[46] A. Jøsang, "'A Logic for Uncertain Probabilities," *Int.J.Uncertain.Fuzziness Knowl.-Based Syst.*, vol. 9, no. 3, jun, pp. 279-311.

[47] A. Jøsang, R. Hayward and S. Pope, "Trust Network Analysis with Subjective Logic,"Darlinghurst, Australia, Australia2006 pp. 85-94.

[48] F. Fouss, A. Pirotte, J. Renders and M. Saerens, "'Random-Walk Computation of Similarities Between Nodes of a Graph with Application to Collaborative Recommendation," *IEEE Trans.on Knowl.and Data Eng.*, vol. 19, no. 3, mar, pp. 355-369.

[49] X. Dong and P. Frossard, "'Clustering with multi-layer graphs: A spectral perspective," *â€¦ IEEE Transactions on*, vol. 60, no. 11, pp. 5820-5831.

[50] E. ElSalamouny, V. Sassone and M. Nielsen, "'HMM-Based Trust Model,", vol. 5983, pp. 21-35.

[51] W. Song, V.V. Phoha and X. Xu, "The HMM-Based Model for Evaluating Recommender's Reputation,"Washington, DC, USA2004 pp. 209-215.

[52] P. Bedi and H. Kaur, "'Trust based Personalized Recommender System," *INFOCOM Journal of Computer Science*.

[53] L. Guanfeng, W. Yan, M.A. Orgun and L. Ee-Peng, "A Heuristic Algorithm for Trust-Oriented Service Provider Selection in Complex Social Networks,"2010 pp. 130-137.

[54] J. Patel, W.T.L. Teacy, N. Jennings and M. Luck, "'A Probabilistic Trust Model for Handling Inaccurate Reputation Sources,", vol. 3477, pp. 193-209.

[55] L. Guanfeng, W. Yan and M.A. Orgun, "Trust Inference in Complex Trust-Oriented Social Networks," vol. 4,2009 pp. 996-1001.

[56] K. Zolfaghar and A. Aghaie, "'A syntactical approach for interpersonal trust prediction in social web applications: Combining contextual and

structural data," *Knowledge-Based Syst.*, vol. 26, feb, pp. 93-102.

[57] P. Bedi and R. Sharma, "'Trust based recommender system using ant colony for trust computation," *Expert Syst.Appl.*, vol. 39, no. 1, 1, pp. 1183-1190.

[58] F. Zhang, L. Bai and F. Gao, "'A User Trust-Based Collaborative Filtering,", no. 2005, pp. 411-424.

[59] C. Li, J. Luo, J.Z. Huang and J. Fan, "'Multi-Layer network for influence propagation over microblog," *Intelligence and Security Informatics*, pp. 60-72.

[60] X. Yang, H. Steck and Y. Liu, "'Circle-based recommendation in online social networks," *Proceedings of the 18th ACM SIGKDD â€¦*, pp. 1267-1275.

[61] J.A. Golbeck and J. Hendler, "'Inferring binary trust relationships in Web-based social networks," *ACM Transactions on Internet Technology*, vol. 6, no. 4, nov, pp. 497-529.

[62] J.A. Golbeck, "'Combining provenance with trust in social networks for semantic web content filtering," *Provenance and Annotation of Data*.

[63] T. Heath, E. Motta and M. Petre, "'Computing word-of-mouth trust relationships in social networks from semantic web and web 2.0 data sources,", pp. 44-56.

[64] S. Kim and J. Kwon, "'Effective Context-aware Recommendation on the Semantic Web," *IJCSNS*, vol. 7, no. 8, pp. 154-159.

[65] H. Oufaida, "Exploiting Semantic Web Technologies for Recommender Systems: A Multi View Recommendation Engine (Short Paper),"2009.

[66] Q. Gao and W.I. Systems, "'Towards Trust in Web Content Using Semantic Web,", pp. 457-461.

[67] M. Martín-Vicente, A. Gil-Solla and M. Ramos-Cabrer, "'Implicit Trust Networks: A Semantic Approach to Improve Collaborative Recommendations,", vol. 32, pp. 107-119.

[68] K. Aberer, Z. Despotovic, W. Galuba and W. Kellerer, "'The Complex Facets of Reputation and Trust,", vol. 38, pp. 281-294.

[69] R.A.C. Capuruço and L.F. Capretz, "A fuzzy-based inference mechanism of trust for improved social recommenders." vol. 872,2012.

[70] G. Chen, Z. Li, Z. Cheng, Z. Zhao and H. Yan, "'A Fuzzy Trust Model for Multi-agent System,", vol. 3612, pp. 444-448.

[71] Y. Li and C. Kao, "'TREPPS: A Trust-based Recommender System for Peer Production Services," *Expert Syst.Appl.*, vol. 36, no. 2, Part 2, 3, pp. 3263-3277.

[72] P. Massa and P. Avesani, "Trust-aware Recommender Systems,"New York, NY, USA2007 pp. 17-24.

[73] P. Massa and P. Avesani, "'Trust metrics in recommender systems," *Computing with social trust*, pp. 1-27.

[74] C. Hess. , Trust-based recommendations in multi-layer networks, 2007.

[75] A. Zarghami, S. Fazeli, N. Dokoohaki and M. Matskin, "'Social Trust-Aware Recommendation System: A T-Index Approach," *2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology*, pp. 85-90.

[76] R. Andersen, C. Borgs, J. Chayes, U. Feige, A. Flaxman, A. Kalai, V. Mirrokni and M. Tennenholtz, "Trust-based recommendation systems: an axiomatic approach,"2008 pp. 199-208.

[77] C. Hang and M.P. Singh, "Trust-based recommendation based on graph similarity,"2010.

[78] P. Massa and P. Avesani, "Controversial Users Demand Local Trust Metrics: An Experimental Study on Epinions.Com Community,"2005 pp. 121-126.

[79] S. Toivonen and G. Denker, "'The Impact of Context on the Trustworthiness of Communication: An Ontological Approach." *\ldots , Security, and Reputation on the \ldots*, pp. 1-10.

[80] C. Castelfranchi and R. Falcone, "'Trust Theory: A Socio-Cognitive and Computational Model" ed. 1st, 2010.