Evidential Multi-relational Link Prediction Based on Social Content

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Abstract. A novel framework to address the link prediction problem in multiplex social networks is introduced. In this framework, uncertainty found in social data due to noise, missing information and observation errors is handled by the belief function theory. Despite the numerous published studies on link prediction, few research are concerned with social data imperfections issues which cause distortions in social networks structures and probably inaccurate results. In addition, most works focus on similarity scores based on network topology whereas social networks include rich content which may add semantic to the analysis and enhance results. To this end, we develop a link prediction method that combine network topology and social content to predict new links existence along with their types in multiplex social networks. Structural and social neighbors information are gathered and pooled using belief function theory combination rules. It is subsequently revised according to global information about the multiplex. Experiments performed on real world social data show that our approach works well and enhances the prediction accuracy.

Keywords: link prediction, multiplex social networks, belief function theory, uncertainty, social content

1 Introduction

Recent years have witnessed the huge growth of the World Wide Web, enabling access to rich social content. Personalized recommendations [7] are effective tools to alleviate the massive data. Recommendation in social networks [5] comes to a vogue in fields such as network science and computer science (i.e., data mining and machine learning). In particular, potential connections recommendation is generally performed by evaluating similarities between social entities. Such task is handled by link prediction. Classical works use network topology to perform predictions, discarding valuable social content. Various social networks include information about the entities. For example, personal information such as age, gender and address, behavioral information like smoking and sporting activities and beliefs and opinions such as political preferences and favorite sports team. Obviously, considering such patterns adds semantic to prediction and allows personalized recommendations in multiplex social networks where nodes connect via multiple relationships types simultaneously.

Social networks structure highly depends on the accurate nature of data. Yet, such data are usually missing and incorporate erroneous labels due to noise and observation errors [2, 14]. This induces uncertainties regarding the network structure. As pointed out in [29], one can encounter two kinds of uncertainty in social networks (i) whether a specific node is distinct or not (ii) or whether a link actually exists between two nodes. Furthermore, multiplex social networks are more affected with such uncertainties. According to [27], inaccuracies concerning multiplex social networks components are very common due to unreliable experimental settings and technical issues. To avoid data imperfections, one may discard some of the data risking the loss of useful information or use all uncertain data [14]. In both cases, this will inadequately affect the analysis.

To cope with uncertainty problems, we embrace the belief function theory [8, 26]. Such theory enables us not only to present and manage data imperfections but it also allows tools to update, pool evidence and make decisions. We develop a fruitful link prediction framework that takes both topological features and social content in multiplex social network into account. Furthermore, our framework considers the worthwhile information given by relationships mixture and use it properly to study social linkage.

The rest of the paper is organized as follows. Section 2 gives some related works on link prediction. In section 3, belief function basic concepts are re-called. Section 4 details our proposals for evidential link prediction in multiplex social networks. Section 5 reports the experimental results and section 6 concludes the paper.

2 Link prediction Related Work

Let $G(V, E)$ be a social network graph where V is the set of nodes and E is the set of edges. Link prediction is the problem of determining the potential existence of a link between unconnected nodes (u, v) given an observed state of the network. Many link prediction methods have been proposed that can be classified into three families: structural similarity based methods, supervised methods and latent models based methods.

Structural similarity approaches Generally, similarity based methods use two types of topological information: local information and global information. Local methods explore node neighborhoods where popular measures include Common Neighbors [23], Adamic/Adar [1], the Jaccard Coefficient [11], Preferential Attachment [23] and Resource Allocation [37]. For instance, the common neighbors method, denoted by CN, computes the number of common neighbors between (u, v). By contrast, global methods use structural topology of the global network. Well known scores include the shortest path, Katz score [13] and SimRank [12]. Even though global methods give generally better results than local based methods [15], they have limited use. Actually, computing global score require information of the whole network which can be time consuming. Furthermore, global topological information is not always accessible. Above all, the additional complexity, by comparison with local methods, does not certainly pay off since the latter methods are very able to give great performance results. Meanwhile, other works use alternative information for link prediction. The authors in [34] combine network proximity to node attributes to predict links in weighted social networks by promoting associations between nodes with similar features. Yet, the approach only applies to weighted networks. In [10], link prediction is performed using authors features to predict co-authorships. However, some attributes are not convenient to assess similarities between authors.

Supervised learning based approaches Link prediction can be reformulated into a binary classification problem where the objective is to predict the classes of query links. For the most part, topological scores are employed as predicator attributes and the existence of links represent class labels [10, 4]. Some other works use other features, for example the authors in [3] used network motifs as features for supervised learning link prediction. In [25], community information, connectivity, interaction and trust information are were used as features for supervised link prediction. In [24], co-participation in events over time are predicted using both network and entity features under supervised learning. Although, link prediction under supvised learning benefits from all the advantages of classification, some issues need to be handled such as the convenient classification model, the appropriate combination of features and class imbalance.

Latent models based approaches Such methods assume a particular organizing principles of the network structure, with some rules and parameters captured by maximizing the likelihood of the observed structure. Predicted links are determined on the basis of their probabilities computed according to these rules and parameters. Many methods combine matrix factorization and latent features to predict new links [21]. Others use Markov Random Field [30, 35], Bayesian nonparametric models [31] or stochastic relational models [33]. Yet, this family of methods suffer from high computational costs due to matrix decomposition, factor matrices and latent features learning which limits their application to large networks.

Challenges Obviously, using social content enhances link prediction as it adds semantic to the task. In online social networks, users information is generally undisclosed for legal, ethical or practical concerns. Furthermore, information about the social entities cannot be considered fully accurate i.e., when collecting social data from surveys, the asked people can lie to some questions, when gathering data from online social networks, users can put wrong and misleading information or even invent fake profiles. Link prediction algorithms are sensitive to such noisy and missing data especially in complex networks such as social networks [36] and biological networks [6]. To handle such ambiguity, we take uncertainty into account in link prediction by embracing the belief function theory which provides effective tools to manage imperfect knowledge. We draw on local methods and consider social content of node attributes to enhance predictions and add semantic.

Actually, we tackled the link problem under the belief function theory framework in previous works. In [18] and [19], two link prediction approaches are proposed based on network topology solely in uniplex and multiplex social networks. In [20], a link predicator is presented which handles uncertainty in social data and uses node attributes. Yet, the latter method operates only on uniplex social networks. It can obviously be applied to multiplex networks by considering links types' separately however relevant information concerning the multiplex will be neglected. This motivated us to develop a new link prediction framework for multiplex social networks that considers uncertainty and social content and takes into account worthwhile information of the multiplex structure.

3 Belief Function Theory Basic Concepts

The belief function theory [8, 26] has well-defined mathematical concepts managing uncertain knowledge. A problem is represented by a finite set of exhaustive and mutually exclusive events called the frame of discernment denoted by Θ. Evidence in the belief function theory is quantified through a mass function $m : 2^{\Theta} \to [0, 1]$, called basic belief assignment (*bba*), which satisfies:

$$\sum_{A \subseteq \Theta} m(A) = 1. \tag{1}$$

Evidence induced from two reliable and distinct sources of information is pooled using the conjunctive rule of combination [28] denoted by $\bigcirc\!\!\!\!\cap$. It is applied as follows:

$$m_1 \bigcirc\!\!\!\!\cap m_2(A) = \sum_{B,C \subseteq \Theta : B \cap C = A} m_1(B) \cdot m_2(C). \tag{2}$$

Sometimes one needs to combine two bba's m_1 and m_2 defined on two disjoint frames Θ and Ω. To do this, the vacuous extension is applied. First, the bba's are extended to the product space $\Theta \times \Omega = \{(\theta_i, \omega_k), \forall i \in \{1, \ldots, |\Theta|\}, \forall k \in \{1, \ldots, |\Omega|\}\}$. Then, the vacuous extension, denoted by $\uparrow$, is applied as follows:

$$m^{\Theta \uparrow \Theta \times \Omega}(C) = \begin{cases} m^{\Theta}(A) & \text{si } C = A \times \Omega, \\ & A \subseteq \Theta, C \subseteq \Theta \times \Omega \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

When the source of information is not completely trustworthy, a discounting operation [26] can be applied to m using a discounting rate $\alpha \in [0, 1]$. The discounting operator is defined as following where ${}^{\alpha}m$ is the discounted bba:

$$\begin{cases} {}^{\alpha}m(A) = (1 - \alpha) \cdot m(A), \forall A \subset \Theta \\ {}^{\alpha}m(\Theta) = \alpha + (1 - \alpha) \cdot m(\Theta). \end{cases} \tag{4}$$

On the other hand, in some cases, a bba m may be revised by reinforcing the evidence committed to an element A of the frame. The belief function theory offers a mechanism of reinforcement [22] which operates according to a reinforcement rate $\beta \in [0, 1]$. It is defined by:

$$\begin{cases} {}^{\beta}m(A) = (1 - \beta) \cdot m(A) + \beta \\ {}^{\beta}m(B) = (1 - \beta) \cdot m(B), \forall B \subseteq \Theta \text{ and } B \neq A. \end{cases} \tag{5}$$

To specify the relation between two different frames of discernment Θ and Ω, the multi-valued mapping mechanism [8] is applied. It is function, denoted by τ, which assigns the subsets $B \subseteq \Omega$ that may correspond to a subset $A \subseteq \Theta$ as follows:

$$m_{\tau}(A) = \sum_{\tau(B) = A} m(B). \tag{6}$$

Decision in the belief function framework can be made according to the pignistic probability denoted by $BetP$. It is computed on the basis of the *bba* m as follows [28]:

$$BetP(A) = \sum_{B \subseteq \Theta} \frac{|A \cap B|}{|B|} \frac{m(B)}{(1 - m(\emptyset))}, \forall A \in \Theta. \quad (7)$$

4 Evidential link prediction in multiplex social networks

We introduce our proposals for evidential multi-relational link prediction using social contents. The novel method draws on local information approaches from literature. We consider a multiplex social network graph with uncertainties encapsulated at the links structure presented in Fig. 1. A multiplex social network is given by a graph $G(V, E_1, \ldots, E_n)$ where $V = \{v_1, \ldots, v_{|V|}\}$ is the set of nodes, and $E_1, \ldots, E_n$ are the sets of links where n is the number of connection types. Each link $uv \in E_i$ has assigned a bba defined on the frame of discernment $\Theta_i^{uv} = \{E_{uv}, \neg E_{uv}\}$ denoted by m_i^{uv}. The elements E_{uv} and $\neg E_{uv}$ mean respectively that uv exists or is absent. The mass function m_i^{uv} represents the degree of evidence about the existence of a link of type i between (u, v).

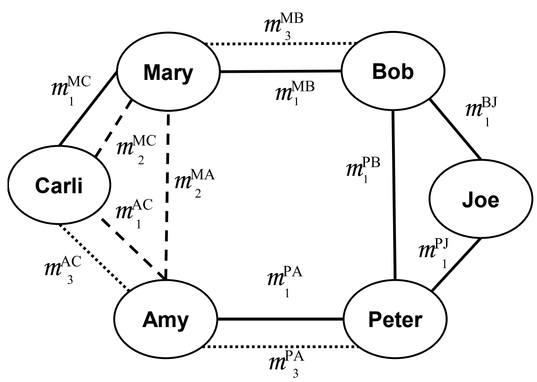

Fig. 1. Evidential multiplex social network

In the following, we present our framework to predict the existence of a link uv of type i in the detailed five steps below.

4.1 Step 1: Evaluating similarity

Our proposals are based on local information methods. To evaluate the likelihood of existence of uv_i, we use social content of node attributes and structural information. The sets of neighbors $\tau(u)$ and $\tau(v)$ linked to u and v according to at least a link of type i are extracted. Then, we match the features of u to those of the nodes in $\tau(v)$, and those of v to $\tau(u)$. Consequently, both semantic and structural information are used by the predicator. Accordingly, the similarity between $node_1$ and $node_2$ is assessed as follows:

$$S_{node_1,node_2} = \frac{\#\textit{matched attributes}}{\#\textit{total attributes}} \tag{8}$$

According to assessed similarities, we detect the most similar node $u' \in \tau(u)$ and $v' \in \tau(v)$ to respectively v and u. This is motivated by the idea that social entities with similar connections are likely to connect. For instance, when the characteristics or behavior of a person is very similar to another one's friend i.e., same hometown, same college and same work, then they are more likely to be friends.

4.2 Step 2: Reliability evaluation

When the neighbors are not common neighbors or not completely similar, they are not considered fully trustworthy. Thus, their evidence is revised using a discounting operation. The bba's $m_i^{uu'}$ and $m_i^{vv'}$ are discounted respectively using $\alpha' = 1 - S_{uv'}$ and $\alpha'' = 1 - S_{vu'}$. For instance, for $m_i^{uu'}$, discounting is computed as follows:

$$\begin{cases} {}^{\alpha'}m_i^{uu'}(\{E_{uu'}\}) = (1-\alpha') \cdot m_i^{uu'}(\{E_{uu'}\}) \\ {}^{\alpha'}m_i^{uu'}(\{\neg E_{uu'}\}) = (1-\alpha') \cdot m_i^{uu'}(\{\neg E_{uu'}\}) \\ {}^{\alpha'}m_i^{uu'}(\Theta_i^{uu'}) = \alpha' + (1-\alpha') \cdot m_i^{uu'}(\Theta_i^{uu'}) \end{cases} \tag{9}$$

4.3 Step 3: Information pooling

In order to pool evidence given by similar neighbors, we need to unify our referential, for that a vacuous extension (Equation 3) is performed on the product space $\mathcal{PS} = \Theta^{uu'} \times \Theta^{vv'}$. The obtained masses are fused using the conjunctive rule (Equation 2). We get the overall bba $m_{\bigcirc\!\!\!\!\cap}^{\mathcal{PS}}$ as follows:

$$m_{\bigcirc\!\!\!\!\cap}^{\mathcal{PS}} = m^{uu'_i \uparrow \mathcal{PS}} \bigcirc\!\!\!\!\!\cap\, m^{vv'_i \uparrow \mathcal{PS}} \tag{10}$$

Next, the obtained bba's are transfered to the frame Θ_i^{uv} by applying a multi-valued mapping mechanism (Equation 6) according to the procedure presented in [19].

4.4 Step 4: Evidence update

The next step is to take into account the multiplex structure. When u and v already have common neighbors, we evaluate the rate of common neighbors connected by the links of type i denotes by CN^{uv_i} according to the total number of common neighbors denotes by CN_{tot}^{uv}, we get: $\delta^{uv_i} = \frac{|CN^{uv_i}|}{|CN_{tot}^{uv}|}$. Then, m^{uv_i} is discounted using $\beta = 1 - \delta^{uv_i}$. We obtain ${}^{\beta}m^{uv_i}$.

On the other hand, when u and v already connect via m link(s) ($m \in [1, \gamma - 1]$) (γ is the number of link types), the rate S_{*i}^{m+1} of simultaneous links of more than two types in the multiplex is computed, where $* = \{1, \ldots, m\}$ are the types of the shared links. If $S_{*j}^{m+1} \neq 0$, the bba is reinforced on the element "exists" using $\phi = \frac{S_{*j}^{m}}{S_{G}^{m}}$ as a reinforcement rate. Finally, we obtain the mass ${}^{\gamma}m_i^{uv}$.

4.5 Step 5: Link selection

Decision about the link existence is made according to the score $BetP^{uv_i}(E)$. Local information approaches from literature rank similarity scores according to a decreasing order and predict links with highest score values. In the same way, link selection is made by ranking query links according to pignistic probabilities on the element “exists” where the top k ones are predicted.

4.6 Complexity

Our link prediction framework is based on local information approaches as we only consider neighboring nodes for prediction. However, unlike these methods, our framework handles uncertainty found in social data. Link prediction methods based on local information are known to have the lowest computational complexity among existing methods from literature [32] especially compared to global methods. Actually, local similarity scores are easy and simple to compute. As our method builds upon local methods, the theoretical complexity would be approximately the same. For the most part, it is based on the common neighbors method. The theoretical complexity of the latter is $\mathcal{O}(N.k^2)$ [9], where N denotes the number of nodes and k is the average degree of all nodes in the network. The additional computational costs for manipulating and pooling evidence are minor since we consider frames of discernment with only two elements. Indeed, the multiplex structure adds a layer of complexity as we count simultaneous links which costs $\mathcal{O}(N)$. Thus, the overall theoretical complexity is $\mathcal{O}(N^2.k^2)$.

5 Experimental study

To evaluate the performance of our novel framework, we perform tests on the relationships network collected from the social evolution dataset [16]. It contains 21K links connecting 84 persons according to 5 link types. Data include information regarding the social entities collected through sociometric surveys such as political opinions, diet attitudes, favorite music genres or smoking behavior.

Data are pre-processed to construct the evidential multiplex social network by simulating bba’s according to the procedure presented in [17]. The technique is based on graph sampling and simulation methods popular in literature. We conduct a comparative study of our novel method, denoted by mLPNA, with three other link prediction in evidential social networks. The first method, denoted uLPLI, is an evidential link prediction approach based on local information for uniplex social networks [18]. It is inspired from the Common Neighbors method and uses solely structural properties. uLPLI is applied to each layer of the multiplex apart then overall performance is averaged over layers. The second method, denoted mLPLI, is the multiplex version of the uLPLI approach [19]. The third baseline method is the uniplex version of our proposed approach [20], denoted by uLPNA. All methods apply to evidential networks. What we are mainly concerned about here, is to evaluate the contribution of considering social content of node attributes and handling multiplex structure in the prediction task. Precision and recall results are reported in Fig. 2.

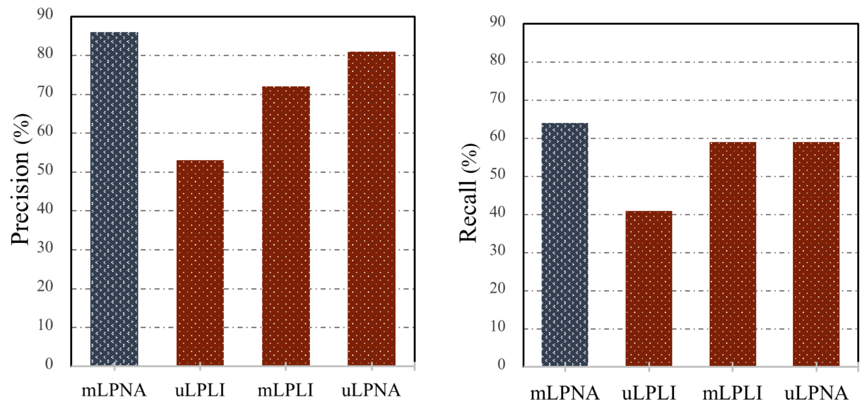

Fig. 2. Precision and recall results measured on the Relationships network

As illustrated in Fig. 2, we notice that mLPNA reaches the highest precision and recall results i.e., 86% precision and 64% recall. On the other hand, it outperforms its uniplex version i.e., 59% for uLPNA. mLPLI and uLPLI have lowest results which proves that considering node attributes information enhances performances. The same observation is made for recall results. That is, performance results in terms of both precision and recall are highest when social content and multiplex structure are considered in prediction.

The results are consistent with our assumptions. Social content combined to network topology add a semantic meaning to the link predicator. That is to say, the novel framework is more effective and accurate for predicting new links between social entities across layers. It improves the prediction quality. Furthermore, it is more suitable to multiplex social networks as it tackles social data uncertainty issues and handles such complex structure. The empirical results demonstrate that our approach has better predictive power than other methods that do not take social content and/or multiplex structure information into account. In addition to social content, our work opens up another dimension for addressing the link prediction problem.

6 Conclusion

In this paper, we have developed a framework to address the link prediction problem in multiplex social networks by combining topological properties and social content. Social data imperfections are handled thanks to the belief function theory. Similarities are assessed by matching nodes features where common neighbors are endorsed as trustworthy sources of information. Overall evidence is revised according to the global multiplex structure and potential links are predicted through a fusion procedures. The results of our framework confirm that semantic information based on nodes attributes promotes link prediction results and permits to understand relevant clues and better discern social entities linkage.

A straightforward direction for future work would be to study the case where there are missing attribute values which may be due to hidden profile information or to noise generated from anonymization. Therefore, we get uncertain node attributes and links structures in the network.

References

[1] Adamic, L., Adar, E.: Friends and neighbors on the web. Social Networks 25(3), 211–230 (2003)

[2] Adar, E., Ré, C.: Managing uncertainty in social networks. Data Engineering Bulletin 30(2), 23–31 (2007)

[3] Aghabozorgi, F., Khayyambashi, M.R.: A new similarity measure for link prediction based on local structures in social networks. Physica A: Statistical Mechanics and its Applications 501, 12–23 (2018)

[4] Ahmed, N.M., Chen, L.: An efficient algorithm for link prediction in temporal uncertain social networks. Information Sciences 331, 120 – 136 (2016)

[5] Bao, J., Zheng, Y., Wilkie, D., Mokbel, M.: Recommendations in location-based social networks: a survey. GeoInformatica 19(3), 525–565 (2015)

[6] Ceci, M., Pio, G., Kuzmanovski, V., Deroski, S.: Semi-supervised multi-view learning for gene network reconstruction. PLOS ONE 10(12), 1–27 (2015)

[7] Chen, L., Zhang, Z., Liu, J., Gao, J., Zhou, T.: A novel similarity index for better personalized recommendation. CoRR abs/1510.02348 (2016)

[8] Dempster, A.P.: Upper and lower probabilities induced by a multivalued mapping. Annals of Mathematical Statistics 38, 325–339 (1967)

[9] Gao, F., Musial, K., Cooper, C., Tsoka, S.: Link prediction methods and their accuracy for different social networks and network metrics. Scientific Programming 2015, 1–13 (2015)

[10] Hasan, M.A., Chaoji, V., Salem, S., Zaki, M.J.: Link prediction using supervised learning. In: Proceedings of the 6th workshop on Link Analysis, Counter terrorism and Security. pp. 1–10 (2006)

[11] Jaccard, P.: Étude comparative de la distribution florale dans une portion des Alpes et du Jura. Bulletin de la Société Vaudoise des Sciences Naturelles 37, 547–579 (1901)

[12] Jeh, G., Widom, J.: Simrank: A measure of structural-context similarity. In: Proceedings of the Eighth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. pp. 538–543. KDD '02 (2002)

[13] Katz, L.: A new status index derived from sociometric analysis. Psychometrika 18(1), 39–43 (1953)

[14] Kossinets, G.: Effects of missing data in social networks. Social Networks 28, 247–268 (2003)

[15] Liben-Nowell, D., Kleinberg, J.: The link prediction problem for social networks. In: Proceedings of the Twelfth Annual ACM International Conference on Information and Knowledge Management. pp. 556–559 (2003)

[16] Madan, A., Cebrian, M., Moturu, S., Farrahi, K., Pentland, A.: Sensing the health state of a community. Pervasive Computing 11(4), 36–45 (2012)

[17] Mallek, S., Boukhris, I., Elouedi, Z., Lefevre, E.: Evidential link prediction based on group information. In: Proceedings of the 3rd International Conference on Mining Intelligence and Knowledge Exploration. Lecture Notes in Computer Science, vol. 9468, pp. 482–492 (2015)

[18] Mallek, S., Boukhris, I., Elouedi, Z., Lefevre, E.: The link prediction problem under a belief function framework. In: Proceedings of the IEEE 27th International Conference on the Tools with Artificial Intelligence. pp. 1013–1020 (2015)

[19] Mallek, S., Boukhris, I., Elouedi, Z., Lefevre, E.: An evidential method for multi-relational link prediction in uncertain social networks. In: Proceedings of the 5th International Symposium on Integrated Uncertainty in Knowledge Modelling and Decision Making. pp. 280–292 (2016)
[20] Mallek, S., Boukhris, I., Elouedi, Z., Lefevre, E.: Evidential link prediction in uncertain social networks based on node attributes. In: Proceedings of the 30th International Conference on Industrial Engineering and Other Applications of Applied Intelligent Systems, Proceedings, Part I. pp. 595–601 (2017)
[21] Menon, A.K., Elkan, C.: Link prediction via matrix factorization. In: Proceedings of the 2011 European Conference on Machine Learning and Knowledge Discovery in Databases. pp. 437–452 (2011)
[22] Mercier, D., Denœux, T., Masson, M.H.: Belief Function Correction Mechanisms, vol. 249, pp. 203–222 (2010)
[23] Newman, M.E.J.: Clustering and preferential attachment in growing networks. Physical Review E 64, 025102 (2001)
[24] O'Madadhain, J., Hutchins, J., Smyth, P.: Prediction and ranking algorithms for event-based network data. SIGKDD Explor. Newsl. 7(2), 23–30 (2005)
[25] de Sa, H.R., Prudêncio, R.B.C.: Supervised link prediction in weighted networks. The 2011 International Joint Conference on Neural Networks pp. 2281–2288 (2011)
[26] Shafer, G.R.: A Mathematical Theory of Evidence. Princeton University Press (1976)
[27] Sharma, R., Magnani, M., Montesi, D.: Missing data in multiplex networks: A preliminary study. In: Signal-Image Technology and Internet-Based Systems (SITIS), 2014 Tenth International Conference on. pp. 401–407 (2014)
[28] Smets, P.: Application of the transferable belief model to diagnostic problems. International Journal of Intelligent Systems 13(2-3), 127–157 (1998)
[29] Svenson, P.: Social network analysis of uncertain networks. In: Proceedings of the 2nd Skövde workshop on information fusion topics (2008)
[30] Wang, C., Satuluri, V., Parthasarathy, S.: Local probabilistic models for link prediction. In: Proceedings of the 2007 Seventh IEEE International Conference on Data Mining. pp. 322–331. ICDM'07 (2007)
[31] Williamson, S.A.: Nonparametric network models for link prediction. Journal of Machine Learning Research 17(202), 1–21 (2016)
[32] Yang, J., Yang, L., Zhang, P.: A new link prediction algorithm based on local links. In: Proceedings of the 2015 International Workshops on Web-Age Information Management. pp. 16–28 (2015)
[33] Yu, K., Chu, W.: Gaussian Process Models for Link Analysis and Transfer Learning, pp. 1657–1664. Curran Associates Inc. (2008)
[34] Yu, Z., Kening, G., Feng, L., Ge, Y.: A new method for link prediction using various features in social networks. In: Proceedings of the 11th Web Information System and Application Conference. pp. 144–147. WISA'14 (2014)
[35] Zalaghi, Z.: Link prediction in social networks using markov random field. Ciłncia e Natura 37 (2015)
[36] Zhang, P., Wang, X., Wang, F., Zeng, A., Xiao, J.: Measuring the robustness of link prediction algorithms under noisy environment. Scientific reports 6, 18881 (2016)
[37] Zhou, T., Lü, L., Zhang, Y.C.: Predicting missing links via local information. The European Physical Journal B-Condensed Matter and Complex Systems 71(4), 623–630 (2009)