Measuring the relevance of different-typed objects in weighted signed heterogeneous information networks

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Measuring the Relevance of Different-typed Objects in Weighted Signed Heterogeneous Information Networks

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***Abstract*—Relevance measure in both homogeneous and heterogeneous networks has been extensively studied. However, how to measure the relevance among different-typed objects in weighted signed heterogeneous information networks remains an open problem. It is challenging to incorporate both positive and negative multi-typed relationships simultaneously in signed heterogeneous networks due to the opposite opinions implied by them. To this end, this paper proposes a random walk based approach for relevance measure by utilizing and modeling the rich semantic information in weighted signed heterogeneous networks. Particularly, we first transform a signed network into a non-signed network according to the different semantic meanings represented by positive and negative relationships. This paves the way to properly utilize negative relationships. Next, we conduct random walk from the source object to the target object based on a bunch of single meta-paths separately. Finally, we combine multiple meta-paths together to obtain a more comprehensive relatedness between the source object and the target object. Extensive experiments on real datasets demonstrate the superior performance of the proposed approach.**

***Index Terms*—relevance measure, meta-path, weighted signed heterogeneous network.**

I. Introduction

In recent years, heterogeneous information network has attracted extensive research interests in data mining community[1,2,3]. Many interesting and practically important research issues can be conducted on heterogeneous information networks, of which relevance measure is a fundamental work. There are a few good studies leveraging link information in networks for relevance measure, such as personalized PageRank[4], SimRank[5], PathSim[6] and HeteSim[7]. However, conventional researches mainly focus on measuring similarity of same-typed objects in non-signed homogeneous information networks or relatedness of objects of different types in non-signed heterogeneous information networks. In real world, there are many signed networks with both negative and positive links, where positive links represent positive relationships, while negative links represent negative relationships. For example, users in Wikipedia can vote for or against the nomination of others to adminship; users in Epinions can express trust or distrust on others; and participants in Slashdot can declare others to be either "friends" or "foes"[8,9].

We define the sign of a link to be positive or negative based on whether it expresses a positive or negative attitude from the generator of the link to the recipient. Therefore, signed networks can be regarded as preference networks. Moreover, we not only define signs to each link, but also assign it a weight denoting the degree of likeness or dislikeness. For example, in a movie review network as shown in Fig. 1, we can transform the rating score of a user on a movie into the weight of the corresponding link between them. In Fig. 1, the weight of the link from the user *Marry* to the movie *Forrest Gump* is 2.3 while the weight of the link from *Marry* to the movie *Mrs. Winterbourne* is only 0.13. This means that *Marry* prefers *Forrest Gump* to *Mrs. Winterbourne* although both links are positive.

Although measuring the relevance between objects of different types in a signed heterogeneous information network is particularly important in many applications, it is still not fully explored due to the following challenges. First, existing approaches for non-signed information networks cannot be directly applied to signed information network. It is an open challenge to effectively incorporate both positive and negative relationships in model-based methods for relevance measure. Second, it is also challenging to fully utilize and fuse the heterogeneous and rich relationships in a weighted signed heterogeneous information network. For a specific pair of objects, we may get totally different relevance measures following the different search paths that connect two objects through a sequence of relations. Therefore, a general relevance measure model for weighted signed heterogeneous information networks is necessary.

In this paper, we propose a novel meta-path based methodology called WsRel (***W****eighted* ***S****igned* ***Rel****evance Measure*)

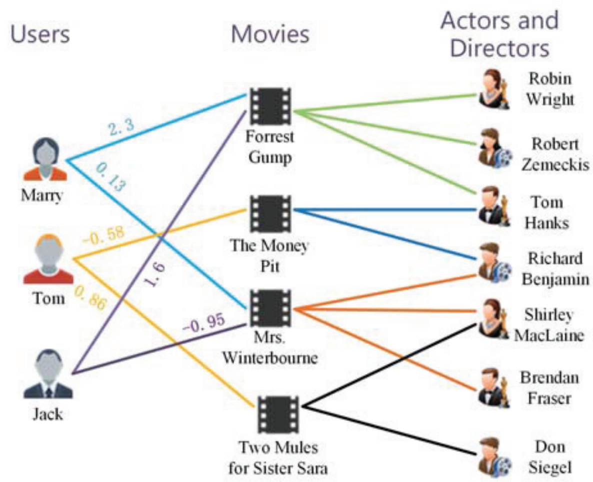


Fig. 1: The IMDB network can be organized as a signed weighted heterogeneous information network.

to calculate the relevance between two objects of different types effectively. The meta-path connects two objects through a sequence of different types of relations, which can be used to exploit rich semantic information in heterogeneous information network. Specifically, we first transform a weighted signed heterogeneous information network into a weighted non-signed heterogeneous information network due to the different semantic meanings represented by positive and negative relationships. Next, a random walk is conducted surfing from the source object to the target object along a meta-path. As there may be multiple meta-paths between two objects, a linear combination strategy is finally provided to obtain the comprehensive relatedness between the source object and the target object.

The major contributions of this paper are summarized as below.

- We study the relevance measure problem among different-typed objects in weighted signed heterogeneous information networks for the first time.
- A novel meta-path based approach called WsRel is proposed to calculate the relevance of different-typed objects in weighted signed heterogeneous networks.
- We evaluate the proposed approach on real-world datasets. The results show the effectiveness of the proposed approach by comparing with other relevance measure methods.

II. Related Work

SimRank[5] is a representative method for computing the similarity between two nodes of the same type by the similarities of their neighbors in a network. Panther[10] is a sampling method to quickly estimate top-k similarity search in large networks, the algorithm is based on the idea of random path.

PathSim[6] is a similarity search method to measure the similarity of same-typed objects in heterogeneous networks. SemRec[11] used PathSim to measure the similarity of users in IMDB network by considering the attribute values on links to perform more accurate recommendation. However, PathSim cannot measure the relatedness of objects with different types. PCRW[12] estimates the relevance between different types of nodes following the random walk framework, which can be applied in a heterogeneous information network. HeteSim extends SimRank to heterogeneous network, which computes the probability of source object and target object meeting at the middle of a meta-path. A major limitation of above studies is that they assume the network edges are all positive.

However, signed networks widely exist in real world, in which the links can be positive or negative. There have been many researches in signed networks[13]. Guha et al.[14] studied the propagation of trust and distrust in a network for the first time. Song et al.[15] developed a efficient latent link recommendation algorithm to recommend links in signed networks. However, none of them studies relatedness measure in signed networks. SignSim[16] is an pioneering work to study the relevance search problem in signed heterogeneous networks. However, SignSim can be only applied in some specific scenarios, and it does not consider the weights of links.

III. Preliminary

In this section, we introduce some definitions and notations to help us state the studied problem.

Definition 1. ***Weighted Signed Heterogeneous Information Network.*** *A weighted signed heterogeneous information network is defined as such a directed graph $G = (V, E, W)$ with the object type mapping function τ: $V \to \mathcal{A}$ and the link type mapping function ϕ: $E \to \mathcal{R}$ subject to $|\mathcal{A}| > 1$ and $|\mathcal{R}| > 1$. Each object $v \in V$ belongs to a particular object type $\tau(v) \in \mathcal{A}$, and each link $e \in E$ belongs to a particular relation type $\phi(e) \in \mathcal{R}$. Each link weight $w \in W$ can be negative, 0 or positive.*

We explicitly distinguish object types and relationship types in the network. Note that, a *weighted signed heterogeneous information network* has various types of objects and relationships. The weight associates with a link is not merely -1 or +1, it can be continuous values, which denotes the degree of like or dislike in a fine-grained manner. Furthermore, the weight of the link connecting node a and node b can be zero, representing we can not judge the preference from a to b. This is quite different from the case that there is no link from node a to node b. Next, we give an example of the weighted signed heterogeneous information network.

Example 1. *The IMDB network shown in Fig. 1 is a typical weighted signed heterogeneous information network. It contains five types of objects: $users(U)$, $movies(M)$, $directors(D)$, $actors(A)$, and $genres(G)$. For each movie $m \in M$, it has links to a set of actors, a $director$, a set of $users$, and some of $genres$. We use continous values to represent how $users$ treat $movies$.*

Given a complex heterogeneous information network, it is necessary to provide its meta level($i.e.$, schema-level) description for better understanding. Therefore, we introduce the network schema to describe the meta structure of a network.

Definition 2. ***Network Schema.*** *The network schema is a meta template for a weighted signed heterogeneous network $G = (V, E, W)$ with the object type mapping function τ: $V \rightarrow \mathcal{A}$ and the link type mapping function ϕ: $E \rightarrow \mathcal{R}$, which can be represented as a directed graph with vertex set $\mathcal{A}$ and edge set $\mathcal{R}$, denoted as $T_G = (\mathcal{A}, \mathcal{R})$.*

For a relation R between two objects of type A and type B, we denote such a relation as $A \xrightarrow{R} B$, and we name A as the ***source type*** and B as the ***target type*** of relation R. The inverse relation R^{-1} holds naturally for $B \xrightarrow{R^{-1}} A$. For most times, R and its inverse R^{-1} are not equal, unless the two types are the same and R is symmetric.

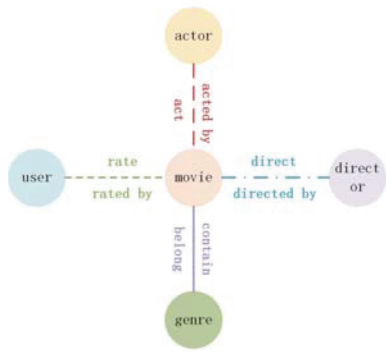


Fig. 2: Schema of IMDB network.

Example 2. *The schema of IMDB network is shown in Fig. 2. The links between $users$ and $movies$ denote the $rate$ or $rated$-by relations, the links between $actors$ and $movies$ denote the act and $acted$-by relations, the links between $directors$ and $movies$ denote the $direct$ and $directed$-by relations and the links between $genres$ and $movies$ denote the $belong$ and $contain$ relations.*

In heterogeneous information network, different paths imply different relatedness. Meta-path as a tool to exploit rich semantic information in heterogeneous information networks is introduced as follows.

Definition 3. ***Meta-Path.*** *A meta-path M of length l is a sequence of nodes in the form of $A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \cdots \xrightarrow{R_l} A_{l+1}$, which is a meta-level description of a path instance from node type A_1 to A_{l+1}.*

For simplicity, we also use the names of node type to denote the meta-path if there is no ambiguity. For example, in the IMDB network, the relation *"users rate movies acted by actors"* can be described as $U \xrightarrow{rate} M \xrightarrow{acted\, by} A$, or UMA for short.

We say a path $p = (a_1 a_2 \cdots a_l)$ from a_1 to a_l in network G follows the meta-path $\mathcal{P} = (A_1 A_2 \cdots A_l)$, if $\forall a_i$, $\tau(a_i) = A_i$ and $\forall e_i = \langle a_i, a_{i+1} \rangle$, $\phi(e_i) = R_i$. p is a ***path instance*** of $\mathcal{P}$, which is denoted as $p \in \mathcal{P}$.

Problem Statement. ***Relevance Measure in Weighted Signed Heterogeneous Information Networks.*** *In a weighted signed heterogeneous information network $G = (V, E, W)$, given a source object s, $\tau(s) \in A_s$, target object t, $\tau(t) \in A_t$, where $A_s \neq A_t$, the problem is how to evaluate the relatedness of s and t.*

IV. WsRel: A Relevance Measure

In this section, we propose a relevance measure method built on a weighted signed heterogeneous information network called **WsRel** to evaluate the relatedness of two objects with different types. Specifically, WsRel first transforms a signed network to a non-signed network, and then calculates relatedness of source object and target object based on various single meta-paths. On different meta-paths, the object pair can obtain different relatedness results. Finally, WsRel combines these relatedness together.

A. Transform Signed Network to Non-signed Network

As we have discussed above, the values of links denote the degree of like or dislike in weighted signed heterogeneous information networks. For example, $s \xrightarrow{3.8} t$ may represent that s likes t very much, while $s \xrightarrow{0.2} t$ may represent s likes t a little bit. Specifically, $s \xrightarrow{0.0} t$ represents that we can not judge whether s likes t or s dislikes t.

Based on the above cognition, we regard that the more s likes t, the more relevant they are. That is, the weight value between s and t can be considered as the probability of s relevant to t. A user more likes a item, they are more likely to be related. For example, the probability of s relevant to $t(s.t.,\ s \xrightarrow{3.8} t)$ is larger than that of s relevant to $t^{'}(s.t.,\ s \xrightarrow{0.2} t^{'})$ intuitively.

Based on above analysis, we need a mapping function $f(w)$ to map the link weight values into a new metric space, and the function should satisfy the following conditions:

- The domain of f is $(-\infty, +\infty)$.
- The range of f is $(0, 1)$.
- The function f is monotonic non-decreasing.

Sigmoid function $f(x) = \frac{1}{1+e^{-x}}$ is an alternative function, because it meets all the conditions and very concise. Thus in this paper we choose it as the mapping function.

After transforming the signed network to non-signed network, the distribution of reassigned weighted values is as follows:

$$\begin{cases} f(w) < 0.5, & if\ w < 0 \\ f(w) = 0.5, & if\ w = 0 \\ f(w) > 0.5, & if\ w > 0 \end{cases} \tag{1}$$

where w is the original link weight.

Note that, when $w = 0$, $f(w) = 0.5$. That is to say, when we cannot distinguish the attitude of s towards t, the probabilities of relevance and irrelevance of s and t are equal. As we discussed before, *zero* and *null* are quite different. A $zero$ weighted value of a link between s and t denotes that s holds neutral attitude towards t. However, $null$ denotes that there exits no connection between s and t. An advantage of the mapping function $f(\cdot)$ is that it can eliminate the ambiguity by tranfromed $w(e) = 0$ to $f(w(e)) = 0.5$ when the original weighted value of link e is $zero$.

B. Meta-path Based Relevance Measure

As we have mentioned above, the semantic meanings implied by different meta-paths are completely different. For this reason, a meta-path based approach is necessary. We propose a novel meta-path based relevance measure model, which can capture the subtle semantic of source object and target object implied in the meta-path.

Definition 4. ***WsRel.*** *Given a meta-path $\mathcal{P} = A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \cdots \xrightarrow{R_l} A_{l+1}$, the relatedness of source object s and target object t following the meta-path $\mathcal{P}$ is:*

$$WsRel(s,t|R_1R_2\cdots R_l) = \frac{1}{|O(s|R_1)|}\sum_{s'\in O(s|R_1)} w(s,s')\cdot WsRel(s',t|R_2R_3\cdots R_l) \tag{2}$$

where $O(s|R_1)$ is the out-neighbors of s based on relation R_1 and $w(s,s')$ is the reassigned weight value of the link between s and s'.

When s has no out-neighbors following the meta-path $\mathcal{P}$ ($i.e.$, $O(s|R_1) = \emptyset$), we cannot infer the relatedness between s and t based on formula (2). In such a case, we define their relatedness value to be 0. When $l = 1$, the relatedness between s and t following the meta-path $\mathcal{P}$ is:

$$WsRel(s,t|R) = \frac{1}{|O(s|R_1)|}w(s,t) \tag{3}$$

According to the above analysis, a pair of different-typed objects will have high relevance score if: (1) they are strongly mutual connected to each other following selected meta-paths; or (2) they are connected by paths with high weights following the selected meta-paths. WsRel obeys the property of non-negativity, specifically, *WsRel*$(s,t|\mathcal{P}) \in [0,1]$. Since WsRel is a path-based measure, it does not obey the triangle inequality. WsRel is not a semi-metric measure, since it does not obey the symmetry property. However, we think asymmetry is meaningful. For example, for a fan of *Matt Damon*, *Matt Damon* is very relevant to him, but for *Matt Damon*, he is basically irrelevant.

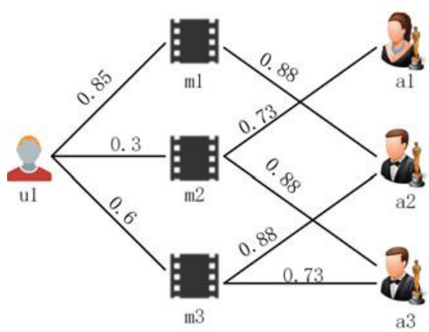


Fig. 3: A toy IMDB network after transformed.

Example 3. *Taking Fig. 3 as an example, we want to know the relatedness of u_1 and a_2 following the meta-path $\mathcal{P} = U \xrightarrow{R_1} M \xrightarrow{R_2} A$.*

$$WsRel(u_1,a_2|R_1R_2) = \frac{1}{|O(s|R_1)|}\sum_{s'\in O(s|R_1)} w(s,s')\cdot WsRel(s',t|R_2)$$

where $O(s|R_1) = \{m1, m2, m3\}$. $WsRel(u_1,a_2|R_1R_2) = \frac{1}{3}\times 0.85\times\frac{1}{1}\times 0.88+\frac{1}{3}\times 0.3\times\frac{1}{2}\times 0+\frac{1}{3}\times 0.6\times\frac{1}{2}\times 0.88 = 0.34$.

C. Combining Multiple Meta-paths

There may be several meta-paths connecting the source object and the target object, so the relevance between them should be comprehensively considered by combining the possible multiple meta-paths $\mathcal{P}_1, \cdots, \mathcal{P}_n$ together.

The simplest method is linearly combining the relevance scores over each meta-path $\mathcal{P}_i$,

$$r(s,t) = \sum_{i=1}^{n}\theta_i\cdot WsRel(s,t|\mathcal{P}_i) \tag{4}$$

where θ_i is the appropriate weight for meta-path $\mathcal{P}_i$.

The problem is that how to determine the weight θ_i for $\mathcal{P}_i$. Lao and Cohen[12] demonstrated that supervised learning method can be used to estimate these parameters. They proposed to optimize a regularized objective function for the given training data. However, the training process of such supervised learning method is usually time-consuming. Furthermore, we need to label those learning instances, which is subjective. Thus, a heuristic weight learning method is needed. Shi et al.[17] proposed a heuristic weight learning method, which can be applied in our work.

The importance $\mathcal{I}$ of a path $\mathcal{P} = A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \cdots \xrightarrow{R_k} A_{k+1}$ is determined by its strength $\mathcal{S}$ and length k. The path strength is decided by the strength of relations constructing the path that can be defined as follows:

$$\mathcal{S}(\mathcal{P}) = \prod_{i=1}^{k}\mathcal{S}(R_i) \tag{5}$$

The strength of a relation $A \xrightarrow{R} B$ is related to the degree of A and B based on R. Intuitively, the less out-degree of A or in-degree of B, the more important they are to each other. The relation strength is defined as follows:

$$\mathcal{S}(R) = \frac{1}{\sqrt{|O(A|R)|\cdot|I(B|R)|}} \tag{6}$$

where $|O(A|R)|$ is the average out-degree of type A following relation R and $|I(B|R)|$ is the average in-degree of type B based on relation R.

The importance $\mathcal{I}$ of the path $\mathcal{P}$ is positively correlated to the path strength $\mathcal{S}$ and negatively correlated to the path length k.

$$\mathcal{I}(\mathcal{P}) = \mathcal{S}\cdot k^{-1} \tag{7}$$

Thus the weight θ_i of path $\mathcal{P}_i$ is

$$\theta_i = \frac{\mathcal{I}(\mathcal{P}_i)}{\sum_{i=1}^{n}\mathcal{I}(\mathcal{P}_i)} \tag{8}$$

With the θ_i, we can take meta-paths for linear combination.

V. EXPERIMENTS

In this section, we validate the effectiveness of the proposed approach with comparison to existing relevance measure algorithms on the real dataset.

A. Data Set

We use hetrec2011-movielens[18] dataset for evaluation. It contains 2K users, 10K movies, 4K directors, and 11K actors. We extract the first five main actors from the original dataset according to the orders of actors in the cast. On average, there are 5 actors and 1 director per movie.

The rating scores range from 0.5 to 5.0 on the links between users and movies, where a higher score means a stronger preference. However, because of the existence of individual differences, if we directly define that raw scores larger than some values, such as 3.0, means users like movies, it is not very reasonable. So we need to normalize the rating scores, such that it can be compared directly between different distributions of raw scores.

The standard score z_u of user u's raw score r_u can be calculated by

$$z_u = \frac{r_u - \mu_u}{\sigma_u}$$

where μ_u is the mean of the rating scores of user u, σ_u is the standard deviation of the rating scores of user u. z_u is negative when the raw score is below the mean μ_u, and positive otherwise.

Thus a weighted signed heterogeneous information network can be built on this dataset which contains four types of objects: $users$, $movies$, $directors$ and $actors$.

B. Metrics

To evaluate our approach, we sort all the rating records in the dataset according to the timestamps firstly. Then we select the latest 30% records as the testing data and the remaining as the training data. Given a user, we generate a list of K movies named R_u that are not in the user's training movie set. If the movie in R_u is also in the user's testing movie set T_u, we call it a hit. We use standard *precision*, F_1*-measure* and *MAP* as metrics to evaluate the results.

C. Baselines

In order to validate the effectiveness of our approach in weighted signed heterogeneous networks, we compare our model with the following methods.

PathSim measures the similarity of same-typed objects based on symmetric paths in heterogeneous networks. We extend PathSim to ExPathSim, so that it can be applied to a pair of different-typed nodes.

ExPathSim counts the number of paths between a pair of nodes in the network. Given a meta-path $\mathcal{P}$, source object s and target object t,

$$ExPathSim(s,t|\mathcal{P}) = \frac{2 \times c(s,t|\mathcal{P})}{c(s,\cdot|\mathcal{P}) + c(\cdot,t|\mathcal{P})}$$

where $c(s,t|\mathcal{P})$ means the number of path instances along $\mathcal{P}$ starting from s to t, $c(s,\cdot|\mathcal{P})$ means the number of path instances starting from s, $c(\cdot,t|\mathcal{P})$ means the number of path instances ending at t.

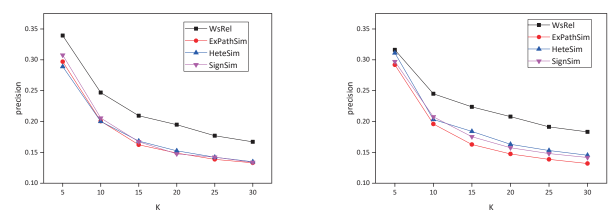
HeteSim[7] computes the probability of source object and target object meeting at the middle of a given meta-path $\mathcal{P} = R_1R_2\cdots R_k$.

SignSim[16] computes the relatedness for each pair of nodes by splitting meta-path into several atomic meta-paths, and using collaborative filtering to get the relevance of source object and target object.

D. Experimental Results

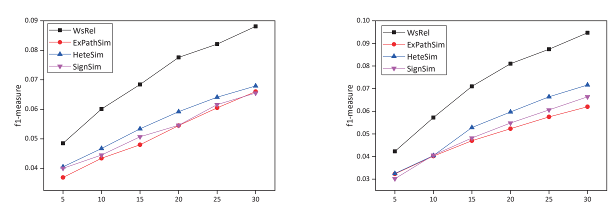
1) Study of Single Meta-path: In this section, we quantitatively compare our proposed method with three baselines based on a single meta-path. We first select two main meta-paths UMAM and UMDM. The following experimental results are based on these two meta-paths.

Fig. 4 shows the precision of different approaches with various K. Fig. 5 shows the F_1-measure of different approaches with various K. Horizontal axis represents the numbers of movie recommended to a user. It is clear that WsRel achieves better performance than baselines on almost all metrics.



(a) UMAM (b) UMDM

Fig. 4: Compare WsRel to baselines in precision based on different meta-paths.

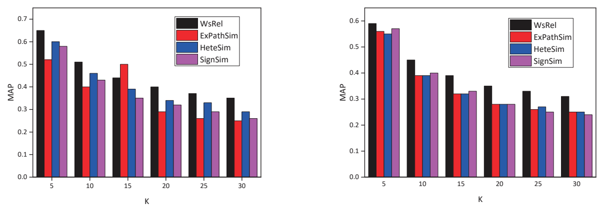


(a) UMAM (b) UMDM

Fig. 5: Compare WsRel to baselines in F_1-measure based on different meta-paths.

However, comparing the performance of WsRel on UMAM and UMDM, we can find that WsRel performs better on meta-path UMDM in most of times. The reason is the different importance of the meta-paths. Previous researches have demonstrated that the length of meta-path can significantly affect the relevance measure performance. However, when the lengths are the same, the strengths of different-typed meta-paths are also very important. The relation strength between movie and director is much stronger than that between movie and actor. So the performance of WsRel on UMDM is better.

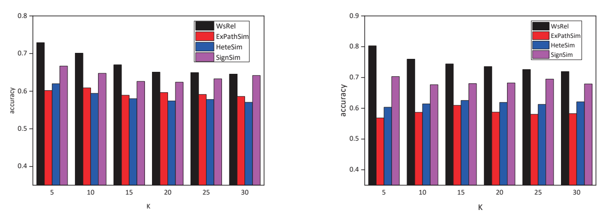
In most cases, it is better to submit more certain recommendations first. Thus we use MAP metric to compare WsRel with baselines. Fig. 6 shows the MAP of several methods following UMAM and UMDM. As we can see from the Fig. 6, WsRel can obtain better results in the vast majority of cases.



(a) UMAM (b) UMDM

Fig. 6: Compare WsRel to baselines in MAP based on different meta-paths.

In order to further validate the significance of the link weights in signed weighted heterogeneous information networks, Fig. 7 shows the accuracy of WsRel compared with other methods following UMAM and UMDM. The accuracy refers to the proportion of films that the user definitely likes among predicted hit movies. It is clear that our method achieves better performance than other approaches.



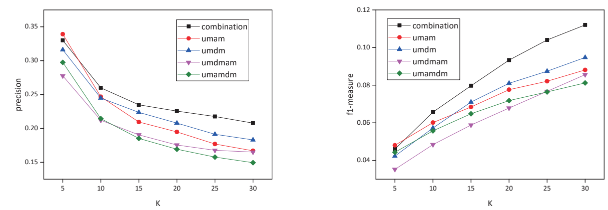
(a) UMAM (b) UMDM

Fig. 7: Compare WsRel to baselines in accuracy based on different meta-paths.

2) Study of Combining Multiple Meta-paths: In this section, we compare the performance of individual meta-paths with their combination. We show the precision and F_1-measure curves of UMAM, UMDM, UMDMAM, UMAMDM and their combination in Fig. 8. The weight values of these four meta-paths are 0.1505, 0.7773, 0.0361 and 0.0361 respectively. In Fig. 8, we can see that the combination of these four meta-paths performs better than any single meta-path.

VI. Conclusion

In this paper, we study the relevance measure problem in weighted signed heterogeneous information networks. We propose a novel method called WsRel to measure the relatedness of objects with different types in weighted signed heterogeneous information networks. WsRel can utilize information provided by negative links to subtly depict the semantics. Extensive evaluations demonstrate the effectiveness of WsRel.



(a) precision (b) F_1-measure

Fig. 8: Compare different meta-paths and their combination in precision and F_1-measure.

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