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Making Explainable Friend Recommendations Based on Concept Similarity Measurements via a Knowledge Graph

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ABSTRACT Studying the similarities between the concepts in a knowledge graph can be useful in making friend recommendations on various microblogging platforms. Most existing approaches that only focus on accurate friend recommendation and can not give a reasoning explaining. In addition, existing similarity measurements are too costly and ineffective to be used in practical applications. To solve these problems, we purposed the shortest path-guide reasoning path, we perform explicit reasoning with knowledge for decision making so that the friend recommendation are supported by an interpretable causal inference. Then we designed a novel Weighted Euclidean-Shortest Path (WESP) method for measuring concept similarity in a knowledge graph and applied it to friend recommendations on a microblogging platform. First we took the shortest path as an example to measure concepts similarity. Although it was easy to use the shortest path to measure the similarity between concept pairs, the results of the measurements via the shortest path were affected by local structural imbalance in the knowledge graph. The imbalance had a significant impact on measuring concepts similarity; the more balanced the local structure, the greater similarity between the concept pairs. Then, we applied the WESP method to friend recommendations on the microblogging platform. We use the optimization similarity measurement (OSM) model that calculated the similarity between corresponding concept pairs. Our experimental results showed that the OSM method achieved better performance than the baseline methods in making friend recommendations.

INDEX TERMS Knowledge graph, similarity measurement, semantic similarity, the shortest path, Euclidean-shortest path, imbalance structure.

I. INTRODUCTION

In recent years, the development of artificial intelligence has given rise to a large number of intelligence applications that have fine-tuned machine cognition to the point that many machines can think or behave like humans [1], [34]–[36]. Since knowledge representation is particularly important, the machine first acquires human language expressions. However, knowledge must be represented in a way that

computers can handle it. The computer can handle only data that have a logical rule and appropriate structure. Therefore, expressing knowledge in a way that it can be recognized by computer is a key focus in the development branch of artificial intelligence. A knowledge graph is an important expression technique including various entities/concepts with rich semantic relations. The semantic relation between entities/concepts provides a powerful background corpus for the machine, and its friendly structure can help machines understand language. At present, knowledge graphs are widely applied in artificial intelligence [3], [37], [38] areas such as

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question answer frameworks [4], [8]–[10] and recommender systems [11]–[14]. However, although the graphs are used widely, using them to measure the similarities between concept pairs effectively in friend recommendations remains a challenge. By the same token, the Internet has revolutionized the ways in which people socialize. For example, instead of venturing to traditional social spheres such as bars and cafes to meet a date, people now use online dating platforms. Moreover, Twitter and China's Sina microblogging platforms have been embraced as digital hangouts for those looking to make friends. Users can get a lot of valuable information on from these social platforms, but they have to spend a lot of time to select useful information or interesting topics from the huge information source. Faced with the problem of information overload, users often find it hard to find interesting people. To find like-minded people on these microblogging platforms, a more accurate friend recommendation method must be adopted. As for existing microblogging platforms, their friend recommendation algorithms are efficient but impractical; friend recommendation requests on these platforms often yield narrow results that lack diversity.

Considering the aforementioned problems, we found it necessary to introduce the concept of a knowledge graph into friend recommendation platforms. In this study, we first measured concepts similarity in a knowledge graph, and then we used the shortest path as an example to measure the similarity between concepts. According to concepts feature, we incorporating rich semantic information into the friend recommendation system to interpret the reasoning process, we give a explicitly the shortest path-guide reasoning path from user to candidate friends. Although the shortest path would have effectively measured the semantic similarity between concepts, a knowledge graph with seriously imbalanced local structures would have had a significant impact on the measurement of semantic similarity. We found that the more balanced the local structure, the higher the similarity between the concept pairs. Therefore, to reduce the influence of local structural imbalance on semantic similarity, we proposed new semantic similarity measurement method: the Weighted Euclidean- Shortest Path (WESP). The WESP method could alleviate structural imbalance in semantic similarity measurement. When we compared the results of the WESP method with that of WordSimilarity-353 [29]. The results showed that the two had a strong correlation. This proved that the WESP method is a credible way to measure semantic similarity between concepts in a knowledge graph. We applied the semantic similarity calculation of concept pairs to the friend recommendation system on microblogging platforms. We proposed a generalized computing similarity (GCS) model for friend recommendation. Although this model contained all of the path information of all of the concepts, it would have been too tedious for users to calculate. Specifically, the set of concepts contained N concepts, which needed to be added N^2 times. Therefore, we further proposed an optimization similarity measurement (OSM).

It calculated only the similarity value for the corresponding concept pairs of the two sets of concepts. In other words, if there were N concepts and only N results were added, the calculation would be simpler yet more accurate than the GCS model.

The key contributions of this paper are summarized as follows:

- We highlight the significance of incorporating rich semantic information into the recommendation system, and proposed the shortest path-guide reasoning path for explaining friend recommendation.
- We used the shortest path as an example to measure concept similarity, and we found using the shortest path to measure similarity led to structural imbalance in the knowledge graph.
- We proposed an improved semantic similarity measurement method known as WESP; to help reduce local structural imbalance, to improve the similarity accuracy of concept pairs, and to compare similar values with WordSimilarity-353.
- A more effective method known as OSM was applied, which simplified the calculation process and yielded more accurate similarity values than the GCS model did.

The rest of the paper is organized as follows. Section 2 provides background information. Section 3 discusses the similarity measurement using the shortest path on the knowledge graph. The similarity calculation using WESP between the concept pairs is represented in Section 4. Section 5 presents two models for computing similarity values for friend recommendations. Experimental results are discussed in Section 6, and related works are briefly reviewed in Section 7. Section 8 provides our conclusion.

II. PRELIMINARY

A. WIKIPEDIA

Wikipedia is an online encyclopedia with more than 40 million documents covering computer science, history, medicine, and places, people, sports events, art, and other fields. The topics are linked together via hyperlinks throughout documents [15], and the site is available in 291 languages. Wikipedia's documents consist of entities, concepts, and the relationships between them, all of which are widely used in natural language processing, information retrieval, artificial intelligence, and concept management.

B. CONCEPTS

Wikipedia comprises a set of isolated documents, which are called concepts in a knowledge graph. Wikipedia employs a category system on similar topics. According to Wikipedia standards, contributors to Wikipedia documents are manually assigned to categories using makeup language, and every document has at least one category. Categories represent a set of concepts in Wikipedia. A set of concepts is denoted as $C = \{c_1, \dots, c_n\}$.

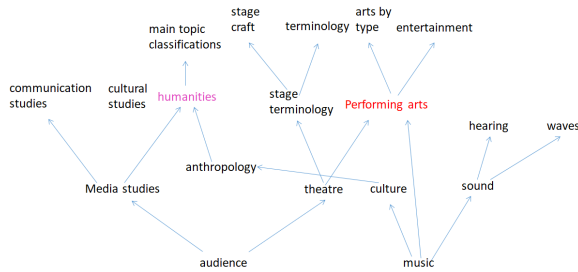


FIGURE 1. Knowledge graph of Wikipedia.

C. THE CONCEPT GRAPH

Semantic relation in Wikipedia heavily relies on hyperlinks graph and categories. The semantic relation feature can be directly measured by concepts. Ma *et al.* [16] demonstrated Wikipedia category' usefulness for entity searches, and many studies have shown that a category plays a key role in related concepts [17], [18]. In Wikipedia, one concept is the subclass of another concept, as shown in Fig. 1. In the figure, *Media studies* and *anthropology* are subclass of *humanities*. Therefore, the concept graph has inherent natural characteristics that can be used to measure semantic relevance.

III. THE SHORTEST PATH METHOD FOR MEASURING CONCEPT SIMILARITY IN A KNOWLEDGE GRAPH

Semantic similarity is widely used to measure correlations between concepts in knowledge graphs [14] and nodes in network [31], [32]. Although concepts similarity has been applied extensively to knowledge graphs, few studies have analyzed whether knowledge graphs are appropriate for measuring the semantic similarity between concepts. Therefore, we measured and analyzed concepts similarity in a knowledge graph. When a knowledge graph is rootless (e.g., Wikipedia), and the loop between concepts is removed, the knowledge graph is treated as a directed network, shown in FIGURE 1. In this paper, knowledge graphs were directed knowledge graphs belongs to subsets of semantic networks that was defined formally as follows.

Definition 1: Where V was a set of nodes and E was a set of edges, a knowledge graph was defined as $G = (V, E)$. v_1, v_2 were concepts in the graph, and E was the subclass relation of a concept.

As is conventional, the distance between two concepts to the superclass was the number of edges from two concepts to the common superclass. There was more than one superclass between any two concepts in the knowledge graph, and the superclass with the shortest distance from two concepts to the superclass was called the *least common superclass*. If two concepts had one common superclass, there was a semantic association between the two concepts, so we used the shortest path to measure the semantic correlation between the two concepts.

Definition 2: Where c_1 and c_2 were two concepts represented by the nodes a and b , respectively, in the knowledge graph a measure of the distance between a and b was given

by

$Dist(a, b) =$ the shortest path from superclass to a and b

For example, the paths of the concept pair $\langle audience, music \rangle$ are shown in FIGURE 1. They share two superclass *performing arts* and *humanities*, with the paths from *performing arts* and *humanities* are 3 and 5 respectively. These distances were represented as follows:

$$Dist(audience, music)_{performingarts} = 3$$

$$\text{and } Dist(audience, music)_{humanities} = 5.$$

Although there were two paths from the superclass to concept pairs, the best choice was the shortest path from the concept pairs to the superclass *performing arts*, represented as follows:

$$Dist(audience, music)_{performingarts} = 3.$$

We used the shortest path as an example for measuring the semantic similarity between concepts. We measured 100 concept pairs with the shortest path is 2. We selected some concept pairs with the shortest path is 2 and other concept pairs with the shortest path ranging from 3 to 20, as shown in Table 1. Semantic relevance refers to the degree of correlation between two concepts. There may be no similar relationship between two concepts, but they can be related through some other relationships. Semantic similarity of two concepts is the semantic proximity of two concepts. As can be seen in Table 1, intuitively, most of the concept pairs were semantically similarity. For example, the concept pairs of $\langle girl, boy \rangle$, $\langle wife, husband \rangle$, and $\langle tiger, cat \rangle$ were similar. In addition to the semantic similarity between concepts, a small number of concepts were semantically relevant, such as the concept pairs $\langle happiness, loneliness \rangle$, although the shortest path was also 2 in these cases. In total, we computed the shortest path of 5000 concept pairs. Semantic similarity was observed in 85% of these concept pairs, while semantic association was observed in 15% of the pairs. The shorter the shortest path of concept pairs, the more similar the semantics.

In Table 1, x represents the shortest path from the first concept to the superclass, and y represents the shortest path from the second concept to the superclass. $Dist(x, y)$ represents the shortest path from concept pairs to the superclass. Some x, y points in Table 1 are represented in the coordinate axis, as shown in FIGURE 2. The closer to the axis, the more similar the value.

IV. THE SHORTEST PATH-GUIDED REASONING AND THE WEIGHTED EUCLIDEAN-SHORTEST PATH

A. THE SHORTEST PATH-GUIDED REASONING

In general, a knowledge graph with concept set C and relation set R is defined as $G = (h, r, t) | h, t \in E, r \in R$, where each triplet (h, r, t) represents a fact of the relation r from head concept h to tail concept t . Let U represents the user set and F represents the candidate friends set. We consider using the shortest path for reasoning friend recommendation,

TABLE 1. The shortest path of concept pairs.

Concept pair	x	y	$Dist(x, y)$
$\langle girl, boy \rangle$	1	1	2
$\langle wife, husband \rangle$	1	1	2
$\langle television, film \rangle$	1	1	2
$\langle woman, man \rangle$	1	1	2
$\langle tiger, cat \rangle$	1	1	2
$\langle woman, man \rangle$	1	1	2
$\langle sun, star \rangle$	1	1	2
$\langle happiness, love \rangle$	1	1	2
$\langle happiness, loneliness \rangle$	1	1	2
$\langle wood, forest \rangle$	1	1	2
$\langle galss, metal \rangle$	1	1	2
$\langle seafood, lobster \rangle$	1	2	3
$\langle information, economy \rangle$	2	2	4
$\langle beauty, happiness \rangle$	2	3	5
$\langle art, beauty \rangle$	2	4	6
$\langle culture, beauty \rangle$	3	4	7
$\langle female, learning \rangle$	4	4	8
$\langle beauty, goddess \rangle$	3	6	9
$\langle travel, feeling \rangle$	4	6	10
$\langle fashion, man \rangle$	3	8	11
$\langle travel, poem \rangle$	4	8	12
$\langle travel, coffee \rangle$	10	3	13
$\langle travel, physician \rangle$	13	1	14
$\langle goddess, life \rangle$	14	1	15
$\langle animal, goddess \rangle$	2	14	16
$\langle television, female \rangle$	1	16	17
$\langle cash, woman \rangle$	4	14	18
$\langle actor, female \rangle$	14	6	20

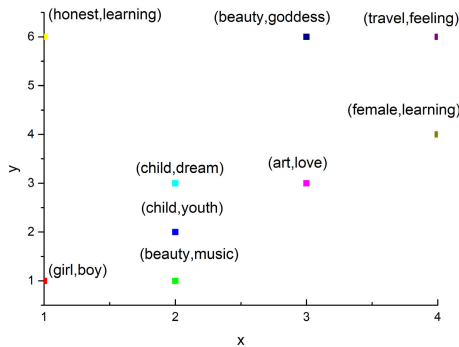


FIGURE 2. The shortest path comparisons between concept pairs.

friend recommendation on micro-blogging platform detailed in . Given a user u , the goal is to find a set of candidate friends f_n and the corresponding reasoning paths $p_n(u, f_n)$. One straightforward way is to sample n paths for each user u according to the connecting concepts over knowledge graph. However, this method cannot guarantee the performance of recommendation. Therefore, we propose to employ the shortest path guided reasoning path over knowledge graph. We give a relaxed definition of the multiple-hop shortest path over the knowledge graph as follows.

Definition 3: A multiple-hop the shortest path from concept c_1 to concept c_k is defined as a $k + 1$ concepts connected by k relations, denoted by $p_k(c_1, c_k) = (c_1 \xrightarrow{r_1} c_2 \xrightarrow{r_2} \dots \xrightarrow{r_k} c_k)$.

For the acquired candidate friends, there may exist multiple paths between the user u and friend f_n . Thus, each pair of

(u, f_n) in the candidate list, from the initial user u to the candidate friends, we select the shortest path p_k as the one to interpret the reasoning process of why friend f_n is recommended to u . Finally, we rank the selected interpretable the shortest path and recommend the corresponding friends to the user.

B. THE WEIGHTED EUCLIDEAN-SHORTEST PATH BETWEEN CONCEPT PAIRS

However, although it was easy to use the shortest path to recommend friends and measure the similarity between concept pairs, we observed that the shortest path in the knowledge graph had a serious imbalance, and the imbalance had a significant effect on the similarity values between the concept pairs, as we will detail in section IV-B2.

1) NORMALIZATION OF SEMANTIC DISTANCE

As discussed in section III, semantic similarity was closely related to the path to the superclass among the concept pairs. The shorter the path from the concept pair to the superclass, the more similar the concept pair. The semantic similarity between concept pairs decreased as the path increased. We let d be the shortest path to the superclass between the concept pairs a_i and b_j , and we let e be the decay factor indicating that the path had an inverse relationship with similar values. After introducing the decay factor e , we redefined the similarity between two concepts to $e^{-d_{a_i}} \times e^{-d_{b_j}}$. The similarity of the concept pairs was between $[0,1]$. If the two concepts were identical, the similarity value was 1 and the difference value was 0.

2) IMBALANCE STRUCTURE OF A KNOWLEDGE GRAPH

Statistics characteristic of a knowledge graph such as the distribution of degrees, distribution of hops and distribution of clustering coefficients, have been studied [22]. However, the same shortest path from concept pairs to *LCS* has different local structures, and the local structure imbalance can lead to different similarity values of semantic. The local structural differences we observed are shown in Table 2. In Table 2, part of the shortest path from the concept to the superclass was counted as $Dist(x, y) = 4, 6, 7, 8, 9, 10$. For instance, for $\langle youth, child \rangle$, the shortest path to the superclass was 4, and the shortest path to the superclass was 2 and 2 for both concepts, whereas the shortest path to the superclass was 4 for $\langle studio, film \rangle$, and the shortest path to the superclass was 1 and 3 for each concept. $Dist = 4$, for example, could be divided into $Dist = (2, 2), (1, 3)$, and $Dist = 5$ could be divided into $Dist = (2, 3), (1, 4)$. For each different local structure, there were different classifications. The imbalance in the local structure of knowledge graph is shown in Table 2, and FIGURE 3 and 4. In FIGURE 3 and 4, we show only the shortest path as $Dist = 4, Dist = 6, Dist = 7$, and $Dist = 8$. For example, in FIGURE 3(b), the shortest path to the superclass was $Dist = 6$, the local structure could be divided into $(3,3), (2,4), (1,5)$, and the balance of

TABLE 2. The shortest path of concept pair.

Concept pair	(x,y)	Dist(x,y)
<i><youth, child></i>	(2,2)	4
<i><studio, film></i>	(1,3)	4
<i><affection, actor></i>	(3,3)	6
<i><animal, love></i>	(2,4)	6
<i><biology, love></i>	(1,5)	6
<i><art, audience></i>	(3,4)	7
<i><culture, country></i>	(2,5)	7
<i><life, tourist></i>	(6,1)	7
<i><study, man></i>	(4,4)	8
<i><goddess, loneliness></i>	(5,3)	8
<i><goddess, learning></i>	(2,6)	8
<i><commodity, nation></i>	(1,7)	8
<i><literature, female></i>	(5,4)	9
<i><culture, health></i>	(3,6)	9
<i><culture, actor></i>	(2,7)	9
<i><audience, actor></i>	(1,8)	9
<i><man, evidence></i>	(5,5)	10
<i><travel, emotion></i>	(4,6)	10
<i><stock, policy></i>	(3,7)	10
<i><poem, culture></i>	(2,8)	10
<i><policy, investment></i>	(1,9)	10

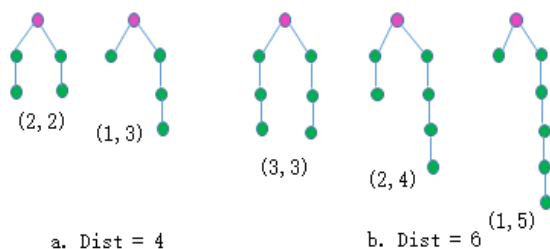


FIGURE 3. Difference local structure of Dist = 4 and Dist = 6.

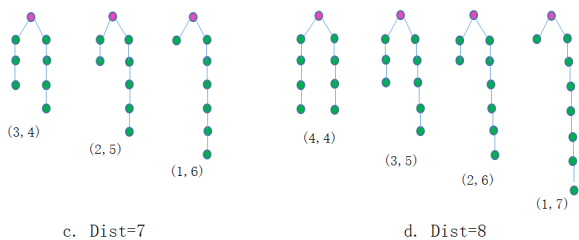


FIGURE 4. Difference local structure of Dist = 7 and Dist = 8.

local structure $(3, 3) > (2, 4) > (1, 5)$. In Fig. 4(a), where $Dist = 7$, the local structure could be divided into $(3,4)$, $(2,5)$ and $(1,6)$, and the balance of local structure $(3, 4) > (2, 5) > (1, 6)$. Similarity, in FIGURE 4(b), where $Dist = 8$, the local structure could be divided into $(4,4)$, $(3,5)$, $(2,6)$, and $(1,7)$ and the balance of the local structure was $(4, 4) > (3, 5) > (2, 6) > (1, 7)$.

3) THE WEIGHTED EUCLIDEAN-SHORTEST PATH SIMILARITY MEASUREMENT METHOD

The imbalance of the local structure of the knowledge graph had the greatest influence on similarity. The structures between any concept pairs were more balanced, and the similarity between concepts was higher. The shortest path between concepts could not directly represent the

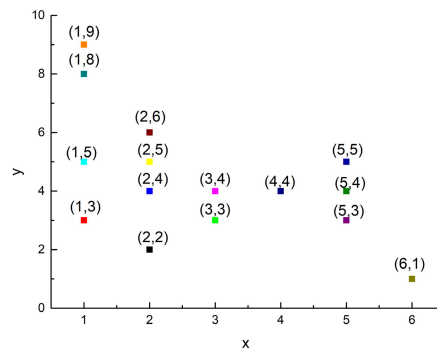


FIGURE 5. Euclidean-Shortest path of concept pairs.

difference in the structural imbalance, whereas the Euclidean distance could help to decrease effect of structural imbalance on semantic similarity. We let d_1 be the shortest path to the superclass of concept a_i , and d_2 be the shortest path to the superclass of concept b_j . We let ρ be the Euclidean metric, and the similarity between the concept pair a_i, b_j was $\rho = \sqrt{d_1^2 + d_2^2}$. The smaller the Euclidean distance, the more similar the concept. In FIGURE 5, $Dist = 4$, the Euclidean metric $(2, 2) < (1, 3)$, and the similarity value between concepts was $(2, 2) > (1, 3)$. When $Dist = 6$, the Euclidean metric was $(3, 3) < (2, 4) < (1, 5)$, and the semantic similarity was $(3, 3) > (2, 4) > (1, 5)$. When $Dist = 7$, the Euclidean metric was $(3, 4) < (2, 5) < (1, 6)$, and the semantic similarity was $(3, 4) > (2, 5) > (1, 6)$. When $Dist = 8$, the Euclidean metric was $(4, 4) < (5, 3) < (2, 6) < (1, 7)$, and the semantic similarity was $(4, 4) > (5, 3) > (2, 6) > (1, 7)$. This indicated that the better the balance between concepts, the greater the similarity between them.

Therefore, we used the semantic distance combined with Euclidean distance to improve the similarity between concept pairs, which resulted in the Weighted Euclidean-Shortest Path(WESP) method. The model is represented as follows:

$$\alpha \times e^{-a_i} \times e^{-b_j} + (1 - \alpha) \times \rho, \tag{1}$$

where $\alpha \in (0, 1)$, α is the adjust parameter between the semantic distance and the Euclidean distance.

V. FRIEND RECOMMENDATION ON MICROBLOGGING PLATFORMS

Microblogging platforms serve as an important tool for information dissemination; hundreds of millions of people use these platforms to spread and share texts, photos, and information [25], [26]. But it is not easy to find like-minded users on these platforms. Friend recommendation features can solve this problems. Friend recommendation are largely based on whether two users have the same interests. In this study, when users forwarded another user’s tweets, we regarded the two users as homogenous [27], and we regarded the users who forwarded other user’s tweets as candidates for friend recommended.

A. GENERALIZED COMPUTING SIMILARITY

Here, S was the set of all source seed users, and T was the set of forwarding users $T = \{t_1, t_2, \dots, t_m\}$, with each t_m also containing the *top* – 20 forwarding users of the source seed user. We also let SM be the set of tweets of the seed users, and let TM be the set of forwarding users of each seed user. We used the splitting tool to divide SM and TM , and put the results after word splitting into SM_W and TM_W . Here, tf represented the c_i frequency of occurrence in tweet set SM_W or TM_W , idf was the inverse frequency, $idf = \log \frac{N}{n_i+1}$, N represented all of the concepts, and n_i represented all of the tweets in the tweet set $SM_W \cup TM_W$ containing concept c_i . The weight of the concept c_i in the tweets was denoted as $TF - IDF = tf \times idf$.

On the microblogging platform, we recommended friends according to the tweets posted by users. Therefore, we extracted and selected the concept c_i with the highest frequency (i.e., $TF - IDF$) from the crawled tweets. We chose high-frequency concepts from tweets that could express the user's interest, such as *woman*, *goddess*, *child*. These concepts contained the main content of the tweets. Then we translated these concepts into English and then mapped these concepts to the knowledge graph. The detail process of knowledge distillation as following: first, to distinguish concepts in micro-blogging content, we utilize the technique of entity linking [30], [31] to disambiguate mentions in tweets by associating these concepts with predefined entities in a knowledge graph (e.g., Wikipedia). Based on these identified concepts, we construct a sub-graph and extract all relational links among concepts from the original knowledge graph.

Formally, we selected N concepts from SM_W of user A and N concepts from TM_W of user B . To obtain all of the conceptual information, we considered all of the path information of the concept comprehensively, and calculated and compared the shortest path between the concepts. For example, we selected four concepts for user A and user B . Each concept in user A was then compared with each concept in user B , and similar values were calculated.

We let $tfidf_{a_i}$ be the weight of concepts a_i of user A , and $tfidf_{b_j}$ be the weight of concepts user B . Let $W_A = tfidf_{a_i} e^{-d_{a_i}}$, and $W_B = tfidf_{b_j} e^{-d_{b_j}}$. Then, the similarity of candidate user and target user calculated was as follows:

$$Sim(A, B) = \frac{\sum_{i=1}^N \sum_{j=1}^N (W_A \times W_B) \times \alpha + (1 - \alpha) \times \rho}{N^2} \quad (2)$$

where N is the total number of concepts, $i \neq j$, $e^{-d_{a_i}}$ represents semantic distance of concept, a_i , $e^{-d_{b_j}}$ represents semantic distance of concept, b_j , and ρ is the Euclidean metric. We called this measure as the GSM.

B. OPTIMIZATION SIMILARITY MEASUREMENT

We let $h_{ij} \in H$, and $h_{ij} = Dist(a_i, b_j)$, H was a matrix. If we used GSM to calculate the similarity between users,

the calculation would have been $\sum_{i=1}^N \sum_{j=1}^N h_{ij}$. However, if we had N concepts and had to add N^2 times, it would have been difficult and tedious to calculate. Therefore, when the minimum value of these concept pairs in each row was $\min_j(h_{iN})$, we only calculated $\sum_{i=1}^N \min_j(h_{iN})$, which greatly reduced the amount of calculation required. In addition to considering the shortest path, we also had to consider the optimal value between concept pairs. For example, suppose A and B extracted four concepts as follows:

$A = \{woman, goddess, children, fashion\}$

$B = \{life, film, happiness, beauty\}$

$$\begin{cases} Dist(woman, life) = 3, \\ Dist(woman, happiness) = 6, \\ Dist(woman, beauty) = 17, \\ Dist(goddess, life) = 15, \\ Dist(goddess, film) = 6, \\ Dist(goddess, happiness) = 6, \\ Dist(goddess, beauty) = 9, \\ Dist(children, happiness) = 4, \\ Dist(children, beauty) = 3, \\ Dist(fashion, beauty) = 3. \end{cases}$$

The shortest path of these concepts were marked on the line, as shown in FIGURE 6. In the knowledge graph, there was no superclass in some concept pairs such as $\langle fashion, life \rangle$, $\langle fashion, film \rangle$, and $\langle fashion, life \rangle$. Clearly, the concept *woman* matched other concepts, such that $Dist(woman, life) = 3$. The concept *goddess* matched other concepts, such that $Dist(goddess, film) = 6$, $Dist(goddess, happiness) = 6$. We used one of the two values. In fact, we had to use the minimum value for *children* to match it with other concepts, such that $\langle children, beauty \rangle = 3$. However, only one concept matched for the concept of *fashion*, such that $Dist(fashion, beauty) = 3$. Therefore, to get the maximum similarity value, we had to represent $Dist(children, happiness) = 4$, and the result was as follows:

$$\begin{cases} Dist(woman, life) = 3, \\ Dist(goddess, film) = 6, \\ Dist(children, happiness) = 4, \\ Dist(fashion, beauty) = 3. \end{cases}$$

We adjusted the formula again to calculate the similarity value between users A and B as follows:

$$Sim(A, B) = \frac{\sum_{i=1}^N \sum_{j=1}^N (W_A \times W_B) \times \alpha + (1 - \alpha) \times \rho}{\sqrt{W_A^2} \times \sqrt{W_B^2}} \quad (3)$$

We called this measurement as the OSM.

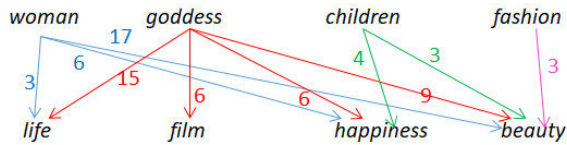


FIGURE 6. Concept matching.

TABLE 3. Comparisons of WESP with WordSimilarity-353.

Concept pair	WESP	Wordsimilar353
<i><tiger, jaguar></i>	1.54	8.00
<i><murder, manslaughter></i>	1.54	8.53
<i><psychonoly, psychiatry></i>	1.54	8.08
<i><planet, sun></i>	1.54	8.02
<i><planet, star></i>	1.54	8.05
<i><death, life></i>	2.94	7.88
<i><tiger, organism></i>	3.73	4.77
<i><psychology, discipline></i>	5.13	5.58
<i><peace, plan></i>	5.78	4.75
<i><stock, love></i>	6.64	3.73
<i><Wednesday, news></i>	7.94	2.22

VI. EXPERIMENT

A. EVALUATION SIMILARITY ACCURACY

To assess the accuracy of the semantics, we compared the semantic similarity measured by the WESP method with the gold standard dataset WordSimilarity-353 [29]. WordSimilarity-353 consists of 353 pairs of English words whose similar values are between 0 (unrelated words) and 10 (extremely relevant words/identical words), and each pair had a unique semantic similarity value. In the experiment, we mapped each concept pair in WordSimilarity-353 to the knowledge graph and calculated their similarity. In total the similarity value of 353 concept pairs was calculated. For the sake of simplicity, we selected only some concept pairs for comparison, which are shown in Table 3. The similarity of concepts was measured by the WESP method; the shorter the distance between concepts according to the WESP method, the more similar. While WordSimilarity-353 is the larger the similarity values, the more the similarity between the concepts. For example, the semantic similarity of the concept pairs *<tiger, jaguar>* in the knowledge graph was 1.54, and it was 8.00 in WordSimilarity-353. The similarity value of the concept pairs *<Wednesday, news>* was 7.94 in the knowledge graph and 2.22 in WordSimilarity-353. We simulated only the correlation between some concept pairs, as shown in Table 3. WordSimilarity-353 was strongly correlated with the semantic similarity measured through the WESP method, and the correlation coefficient was $R^2 = 0.905$, $R \in [0, 1]$, as shown in FIGURE 7. Therefore, we concluded that it is feasible and convenient to use the WESP method to measure the semantic similarity of concepts. That said, because WordSimilarity-353 contains only 353 pairs of concepts, and the knowledge graph contained millions of concepts, we also concluded that the knowledge graph is more suitable for similarity comparisons between concept pairs, the result will be better.

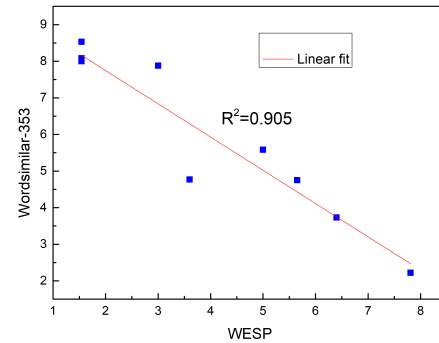


FIGURE 7. The correlation coefficient of WESP and WordSimilarity-353.

B. DATASET DESCRIPTION

The microblogging topics used in the study included education, politics, military, schools, celebrities, and sports. Two-hundred source seed users originated new tweets on the microblogging platforms, and we randomly selected topics from user's tweets. First, we crawled the users who forwarded the source seed users' tweets, and then we calculated the number of times that each forwarding user forwarded the source seed's tweets. The more times the tweets were forwarded, the more interested the users were in the source seed user. In the process of data collection, 2.2 million users were captured as ground truth and the number of forwarding users was ranked from high to low. After calculation, we ranked recommendation candidate friends list and took the top 20 as evaluation. Second, 1000 tweets from each source seed and each forwarding user were extracted, and a total of about 200 million tweets were extracted.

C. RECOMMENDATION EVALUATION MEASURES

- Spearman correlation coefficients: We let X be the rank order of the ground truth. After GSM calculation, we reordered the candidates' friends rank. We let Y be the rank order of the candidates' friends after reordering. We then used the Spearman correlation coefficients for evaluation, calculated as Equation follows:

$$\theta = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}, \quad (4)$$

where d is the rank difference between the rank X , Y .

- Precision@k [28]: Precision at k was calculated as Eq. 5, where k is the size of recommendation list, and r is the number of recommend friends in top- k recommended items.

$$\text{Precision@}k = \frac{r}{k}. \quad (5)$$

D. COMPARISONS OF GSM AND PARAMETERS

In this section, we compared the Spearman correlation coefficient and precision of GSM with the parameter tfidf, WESP, and Path. We briefly described the implementation of the schemes.

In the experiment, we calculated the Spearman correlation coefficient of different methods. We ranked the candidate

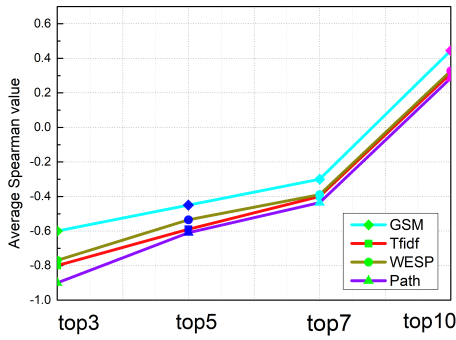


FIGURE 8. Average Spearman values of GSM and parameters of the top 3, top 5, top 7, and top 10.

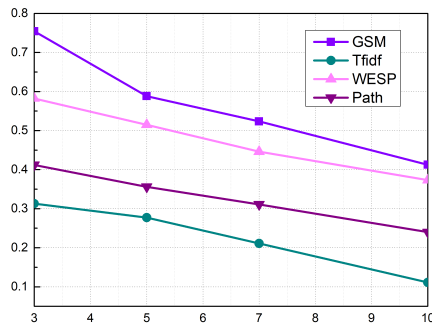


FIGURE 9. Precision of GSM and parameters.

friends list and took top 20, but we found that the top 10 have better results, so we compared only the different methods in the top 10. The average Spearman value of the GSM and several parameters were compared, as shown as FIGURE 8. In FIGURE 8 shows the average results of the correlation coefficients in the top k , where $k(k = 3, 5, 7, 10)$ is the number of recommendation friends, and path is the shortest path of concept pair. It can be seen from the figure that the user similarity value of path was the lowest; noticeably, only the path could not fully measure the similarity between the users. The similarity of *Tfidf* was better than the path. *Tfidf* focused on the contribution of the documents and the correlation between documents, but it did not consider the semantic distance. WESP performed better than *Tfidf* and Path because it incorporated the features of the shortest path and Euclidean distance. The precision result is shown in FIGURE 9. The precision of the GSM method outperformed that of the other parameters.

As shown in FIGURE 8 and 9, the GSM method greatly increased the precision and correlation coefficient. The results showed that it was necessary to calculate the user’s similarity with several parameters.

E. COMPARISONS OF OSM AND GSM

We compared the Spearman correlation coefficient of the GSM and OSM for the top 3, top 5, top 7 and top 10, as shown in FIGURE 10. The results showed that the Spearman value of the OSM for top 3, top 5, top 7 and top 10 was better than that of GSM. In FIGURE 10, illustrates a comparison between the two friend recommendation models GSM and OSM for the

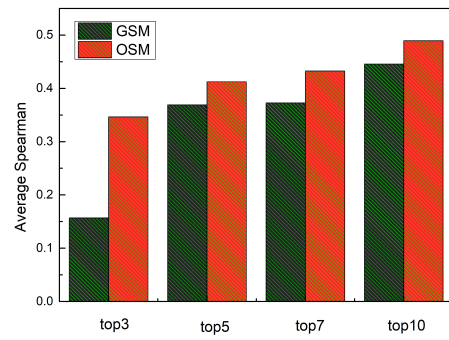


FIGURE 10. Spearman comparisons of GSM and OSM for the top 3, top 5, top 7, and top 10.

average values of top 10, OSM performed better than GSM. Moreover, the OSM method also reduced the computational complexity. Therefore, we utilized the OSM model for friend recommendation.

F. OSM AND BASELINE METHODS

In this section, we compare our method, OSM, with several existing schemes, including PageRank, Latent Dirichlet Allocation (LDA), Twixonomy, and Twittermender. We also briefly describe the implementation of the baseline schemes.

- PageRank, the importance of a page is measured by the hyperlink relationship; the greater the in-degree of a page, the higher the level; otherwise, it is lower. In our experiment, PageRank (PR) was used to measure the influence of microblogging users. The influence of users was mainly determined by the number of followers. The more followers a user had, the wider his or her reach on the microblogging platform, and the stronger his or her influence.

- LDA [19], a document and topic generation model, also known as the three-level Bayesian probability model, contains three layers of words, topics and documents. This model can be used to identify the latent topic information in a large set of documents or corpus. We can use the bag-of-word to sample a topic from the topic distribution of the document, and then sample a word in the distribution of the corresponding word in this topic, repeating it until all documents complete the process. In the experiment, the tweets posted by users were used as documents, and an LDA model was formed from the tweets.

- Jaccard, Jaccard coefficient is a similarity metric, and used to measure the intersection of two set of concepts.

- Twixonomy [20] was first performed by Stefano Faralli et al. It involves a large-scale homophily analysis on Twitter using user’s interests. To build a hierarchical graph based on Wikipedia categories, the researchers first associated users’ lists of interesting topics with Wikipedia categories. Starting from topical interest lists on wikipages, all paths connecting these pages were extracted and then used to efficiently build a direct acyclic graph G .

- Twittermender [24] proposed by Hannon and consisting of two recommendation method, was used to extract the high-frequency keywords from users’ tweets and then to indexing

TABLE 4. Comparison results of Spearman and Precision.

Measures	Spea.@3	Spea.@5	Spea.@10	Prec.@3	Prec.@5	Prec.@10
PageRank	-0.8211	-0.8520	0.1124	0.2512	0.1986	0.1188
LDA	-0.7561	-0.7122	0.1238	0.2912	0.2977	0.1989
Jaccard	-0.7426	-0.6912	0.1745	0.1788	0.4023	0.2579
TwitterMender	-0.7393	-0.5987	0.1899	0.4211	0.4123	0.2918
FRPCP	-0.6198	-0.5887	0.3320	0.4611	0.4828	0.3781
Twixonomy	-0.5881	-0.5667	0.3542	0.5811	0.5128	0.4388
CKE	-0.5235	-0.4966	0.4188	0.6273	0.5534	0.4721
OSM	-0.4383	-0.3014	0.4393	0.6653	0.6256	0.4997

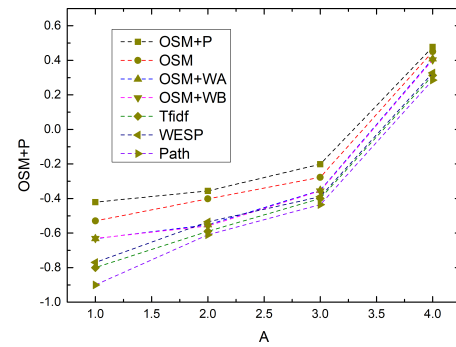
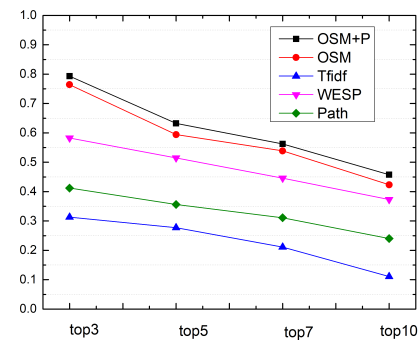
users' IDs with their neighbors' interests. We used the first method based on tweet content.

- FRPCP [6], friend recommendation considering preference coverage problem (FRPCP) was proposed by Fu Yu *et al.* and provide a friend recommendation problem based on location-based social networks. They consider preference coverage problem, which is also one NP-hard problem.

- CKE [12] proposed knowledge-base embeddings for recommendation. Knowledge-based embedding makes it possible to learn entity representation while preserving the structure of knowledge graph.

Table 4 show the results of the Spearman correlation coefficient and precision at the top 3, top 5, and top 10. The results show that the average correlation coefficient and precision of the PageRank was the lowest among all baselines. The result suggested that PageRank is not an efficient way to recommend friends for users, as it considers only the follower/followee. The LDA model had slightly better than the PageRank method did. This suggested that the LDA model is also not a wise choice for friend recommendation. TwitterMender method is higher than Jaccard method, because Jaccard only compare the concept of two sets, if the data is sparse, then it has bad performance. FRPCP is a NP-hard problem, and it is impractical in real world. KGE performs the best among the baseline methods. The result shows that the embedding of KG has a key importance for user recommendation.

OSM method greatly improves the top-k correlation coefficient. The more key concepts extracted from twitter, the more relevant the profile describing the user. The results further indicate that the knowledge graph contains a variety of semantic relations, which provides different semantic connections for measuring concept similarity. Deep pair learning does not reveal the deep semantic relationship of the information content [7]. KGE only preserve the structures of knowledge graph, and can not provide the link between entities, while uses the shortest path over knowledge graph, discover the rich semantic relationship between entities. The rich semantic relations of the knowledge graph can discover the diversified interests of users and improve the satisfaction and acceptance of users' recommendation results. Therefore, the knowledge graph can make friends recommendation more accurate and enhance users' trust in the recommendation system. As expected, OSM outperform all the

**FIGURE 11.** Average Spearman values of GSM and parameters of the top 3, top 5, top 7, and top 10.**FIGURE 12.** Precision of GSM and parameters.

baseline methods. This is because OSM can better recommend friends for users.

G. COMPARISONS OF OSM AND PARAMETERS

In this section, we compared the Spearman correlation coefficient and precision of OSM with the parameter α , tfidf, WESP, and Path. We denote the OSM add parameter α as OSM + P, the parameter W_A as OSM + WA, the parameter W_B as OSM + WB. We briefly described the implementation of the schemes.

In the experiment, we calculated the Spearman correlation coefficient of different methods. Same to GSM method, we compared only the different methods in the top 10. The average Spearman value of the OSM and several parameters were compared, as shown as FIGURE 11. In FIGURE 11 shows the average results of the correlation coefficients in the top k , where k ($k = 3, 5, 7, 10$) is the number of recommendation friends. Similar to the conclusion in GSM, it can be seen from the figure that the path was the lowest. The similarity of Tfidf was better than the path. WESP performed better than Tfidf. OSM + WA and OSM + WB almost coincide. OSM method performs better than OSM + WA and OSM + WB. While OSM + P performs better than OSM because parameter α balances the local structure of the knowledge graph and helps improve recommendation performance. The precision result is shown in FIGURE 12. The precision of the OSM method outperformed that of the other parameters. Similarly, OSM + P performs better than OSM and better than other metrics.

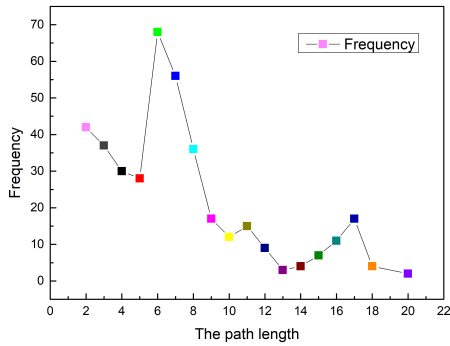


FIGURE 13. Path length analysis for friend recommendation.

H. THE MULTIPLE-HOP OF THE PATH

In this experiment, we studied how the path length influences the recommendation performance of our OSM model over knowledge graph.

This experiment reveals how many hops from the initial user in the knowledge graph can reach the recommended friends, and also verifies the influence of path balance on the the performance of recommended friends. We ran the experiments on the micro-blogging dataset using the parameter settings given previously. The results for the dataset are plotted in FIGURE 13.

We make several observations about these results. First, considering the micro-blogging friend recommendation dataset, the path length ranging between 2 to 68. According to our statistics in the experiment, path lengths of 2 to 8 accounted for 74%, indicating that the shorter paths improved the friend recommendation performance. Second, From the initial user to the friend candidate list, the path with length 6 appears most frequently and has the best recommendation performance, which also indicates that the more balance of the local structure of the knowledge graph is, the better the recommendation performance will be. Third, In friend recommendation, the path from the initial user to the candidate recommended user is short, which also proves that knowledge graph has rich semantic information and context connection between concepts. Compared with traditional friend recommendation, knowledge graph has strong friend recommendation performance.

I. CASE STUDY

To demonstrate the performance of friend recommendation over knowledge graph, we randomly sampled a user on results generated in the previous experiments. Using the source user Yuehong Zhao as an example, we rank the candidate friends and concepts in Table 5. The source user has ten candidate friends, and compare the similarity with rank friends. We select five concepts from the user and the candidate friend, respectively. The source user was described by five feature concepts (yuchunli, video, youth, studio, beautiful). The first candidate friend YiQing was described by five concepts (yumi, video, youth, film, happiness), the semantic of concept yuchun li is same to yumi, so the the semantics of the

TABLE 5. Source user and candidate friends list.

No.	Source User	Concepts
1	Yuehong Zhao	yuchun li,video,youth,studio,beautiful
No.	Candidate Friends	Concepts
1	YiQing	yumi,video,youth,film,happiness
2	Jianxia Lee	yuchun li,concert,youth,music,fashion
3	Mo Ruo	yuchun li,studio,concert,fashion,child
4	Sun	yuchun li;concert;film;fashion;music
5	Sister8	yuchun li,studio,child,fashion,beautiful
6	Qiao	yuchun li,youth,concert,film,fashion
7	ThreeTree	yuchun li,concert,film,graceful,child
8	Heart Qing	studio,video,beautiful,child,life
9	Spring Onions	yuchun li,beautiful,fashion,film,child
10	Smile Youth	studio,youth,child,happiness,film

TABLE 6. Friend recommendation.

No.	Candidate Friends	SpearNo.	Candidate Friends	Ground truth
1	YiQing	2	Sister8	YiQing
2	Jianxia Lee	5	YiQing	Mo Ruo
3	Mo Ruo	6	Sun	Jianxia Lee
4	Sun	3	Qiao	Sun
5	Sister8	1	Jianxia Lee	Litou
6	Qiao	4	Mo Ruo	Three007
7	ThreeTree	8	Heart Qing	Flyya
8	Heart Qing	7	ThreeTree	Flyflower
9	Spring Onions	9	Spring Onions	ThreeTree
10	Smile Youth	10	Smile Youth	Water1993

first three concepts are the same, then we match the shortest path values of the last two concepts. We get a reasoning path with {user → c₁ → c₂ → c₃ → c₄ → c₅ → friend}. We conclude that the shortest path-guide reasoning path is able to find efficiently reasoning paths for the friend recommendations.

According to OSM method, we calculate the similarity value between the source user and each candidate friend. We calculate the Spearman correlation coefficient and rearrange the list of friend candidates, shown in Table 6. We find that the candidate friends **YiQing**, **Jianxia Lee**, **Mo Ruo** and **ThreeTree** in the ground truth. Therefore, the validity of our method is verified.

VII. RELATED WORK

Friend recommendations in social networks have been widely studied. Bagci et al. [21] proposed a friend recommendation algorithm using a random-walk-based contextual awareness by considering the current context of the user to provide personalized friend recommendation. In addition, Wan et al. [23] proposed information-based friend recommendations according to the extent to which is a friend satisfied the target user’s unfulfilled information needs. Moreover, Hannon et al. [24] proposed content similarity for recommending friends by using the bag-of-word model to profile the users based on profile similarity between the candidate users and the target users. Yu et al. [6] proposed location-based social networks for friend recommendation. Dimitrios and Fabio et al. [7]

proposed location-based social network for friend recommendation via deep pair wise.

The knowledge graph has become an important representation of knowledge in the age of artificial intelligence. It can provide a powerful background knowledge base for machines. The usage of the knowledge graph for recommender systems are attracting increasing attention in recent years. For example, the hierarchical knowledge graph [5] derived from the pruned DBpedia knowledge base to identify personalized entities as products recommendation for users. The major difference between prior studies and ours was that we used a knowledge graph to explore the deep logic semantic connections among users to provide more precise and useful friend recommendations. To the best of our knowledge, this study was the first work that considered and analyzing the imbalance in the knowledge graph structure.

VIII. CONCLUSION

We verified the reliability of the knowledge graph structure in measuring concept similarity, and we compared the semantic similarity of the WESP method with that of WordSimilarity-353. We propose the shortest path-guide reasoning over knowledge graph for recommendation with interpretation. On the other hand, we observed that the structure of the knowledge graph was seriously unbalanced, which had a great impact on the semantic similarity measurement. Therefore, the WESP method was proposed to mitigate the impact of the imbalance in the knowledge graph structure in measuring semantic similarity. We put forward the GSM model to recommend friends for users. This method took into account the information of all of the cross-comparison concepts, which made the calculation tedious. Therefore, to simplify the calculation, we used the OSM method for friend recommendation, which yielded better performance than the GSM method did. The Spearman and precision characteristics were used to compare the OSM with the baseline method, and the experimental results showed that OSM model recommended friends for users more accurately. This suggested that our work can be used to improve the precision of existing recommendation systems.

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