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Hybrid microblog recommendation with heterogeneous features using deep neural network

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ABSTRACT

With the development of mobile Internet, microblog has become one of the most popular social platforms. The enormous user-generated microblogs have caused the problem of information overload, which makes users difficult to find the microblogs they actually need. Hence, how to provide users with accurate microblogs has become a hot and urgent issue. In this paper, we propose an approach of hybrid microblog recommendation, which is developed on a framework of deep neural network with a group of heterogeneous features as its input. Specifically, two new recommendation strategies are first constructed in terms of the extended user-interest tags and user interest topics, respectively. These two strategies additionally with the collaborative filtering are employed together to obtain the candidate microblogs for final recommendation. Then, we propose the heterogeneous features related to personal interests of users, interest in authors and microblog quality to describe the candidate microblogs. Finally, a deep neural network with multiple hidden layers is designed to predict and rank the microblogs. Extensive experiments conducted on the datasets of Sina Weibo and Twitter indicate that our proposed approach significantly outperforms the state-of-the-art methods. The code and the two datasets of this paper are publicly available at GitHub.

1. Introduction

The development of the mobile Internet brings out the boost of various mobile social applications such as Facebook, Twitter and Sina Weibo. Lots of social applications have deeply affected people's life. People can use social platforms to communicate with each other and realize instant sharing of information such as texts, pictures and videos. For example, many celebrities use social platforms to post their latest developments and communicate with fans so as to improve their popularity. Merchants post advertisements on social platforms to attract customers. In addition, ordinary users can use microblogs to post their recent life and catch up with life of friends and family. They can also follow the latest and hottest news, and associate with people who share similar interests. Especially, microblog platforms attract a large number of users due to their rich content and real-time capability. According to the 2018 Sina Weibo User Development Report (Weibo, 2018), monthly active users in Sina Weibo totaled about 462 million, daily active users reached about 200 million, and microblog content stock exceeded 100 billion. Accordingly, the problem of information overload caused by the huge user-generated content makes it difficult for users to obtain their interested microblogs from mass information. Thus, microblog recommendation approaches are urgently needed to solve this problem.

Most existing works about microblog recommendation mainly adopt the methods of content-based recommendation and collaborative filtering recommendation. Technically, the content-based recommendation principally focuses on how to use topic mining approaches to enhance the performance, such as the Latent Dirichlet Allocation (LDA) (Blei et al., 2003), the modeling about the co-occurrence of words due to data sparsity (Yan et al., 2013), and the usage of the external databases for feature representation (Tang et al., 2012), and so on. Collaborative filtering recommendation mainly focuses on finding the similar users and then recommending microblogs that the similar users like. However, that approach overlooks the content that users interested in. In addition, the approaches in these two families utilize only one or two influencing features such as microblog content or social relationships. Actually, there are many factors affecting the interests of users in microblogs. These factors could include users' familiarity with microblog authors, richness and attractiveness of microblogs, and so on. However, seldom works do consider their usage for microblog recommendation.

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In this paper, we propose a hybrid microblog recommendation based on deep neural network with heterogeneous features (DNN-HF). The task of hybrid microblog recommendation is to combine the content-based and user-based collaborative filtering recommendations and improve the precision and recall of recommendation. Our approach includes three stages. First, two recommendation strategies are proposed to obtain candidate recommended microblogs. One recommendation strategy is to design a tag extension algorithm with using association rules to extend user interest tags, and another recommendation strategy is to identify the links between users and interest topics in microblogs, called the topic links. Here, the topic links indicate the hashtag and super topics in microblogs. These two strategies additionally with the collaborative filtering strategy based on interactive behaviors are jointly employed together to obtain the candidate microblogs for final recommendation. Second, a group of heterogeneous features are extracted to represent the candidate microblogs, which are related to personal interests of users, interest in authors, and microblog quality. Third, a deep neural network by taking these heterogeneous features as its input is constructed and trained to rank the microblogs to be recommended. Extensive experiments conducted on the datasets, including Sina Weibo and Twitter indicate that our proposed approach significantly outperforms the state-of-the-art methods.

The contributions of this paper are summarized as follows:

- We propose a hybrid microblog recommendation with heterogeneous features using deep neural network. Our framework includes three stages: (a) building candidate recommended microblogs based on the extended user interest tags, user interest topics, and user-based collaborative filtering, (b) generating the heterogeneous feature vectors, (c) using the deep neural network to identify recommended microblogs. Upon this framework, the content and behavior factors influencing users' recommendation of microblog can be integrated together into a deep neural network, which provides a unified model to rank recommended microblogs.
- Two new recommendation strategies are proposed to generate candidate recommended microblogs in this paper. One is developed based on the information of the extended user interest tags, which helps to improve the inaccuracy problem of user interest tags. Another is constructed on the information of user interest topics, which helps to identify user's interests by using explicit semantic tags, that is, the topic links. By contrast, the commonly-used strategy of collaborative filtering uses interactive behaviors to calculate user similarity for microblog recommendation. Technically, in this paper we combine these three strategies together to improve the variousness as well as the accuracy of the candidate microblogs to be recommended by considering the microblog content, the interactive behaviors and social relationships between users.
- A group of heterogeneous features are proposed to represent microblogs, which include those related to personal interests of users, interest in authors and microblog quality. Technically, such heterogeneous features offer a uniform representation approach for mining the interests, hobbies and behavior habits of users from the microblog content and interactive behaviors of users. It is noted that those eight features are involved in texts, pictures and videos in microblogs.
- Extensively comparative experiments conducted on the datasets of Sina Weibo and Twitter indicate that our proposed approach significantly outperforms the state-of-the-art methods.

The code[1] and the two datasets[2] of this paper are publicly available at GitHub.

[1] https://github.com/gjm827/DNN-HF.

[2] https://github.com/gjm827/MicroblogRecommendationDatasets.

The remainder of this paper is organized as follows. In Section 2, we discuss the related works. Section 3 presents our proposed approach for hybrid microblog recommendation with heterogeneous features using deep neural network. The experimental results are reported in Section 4. Finally, we conclude this paper in Section 5.

2. Related works

Facing the information overload problem, more and more works have been launched to investigate personalized recommendation methods in order to provide accurate knowledge services. Present works about social platforms recommendation can be mainly classified into three categories: content-based recommendations, collaborative filtering recommendations and hybrid recommendations.

2.1. Content-based recommendations

The contend-based recommendations obtain users' interests via their generated content and further recommend users the items with similar content. Many existing content-based recommendation methods on social platforms have been developed to utilize text to identify user interest tags or topics.

The user interest tags are extracted by keywords mining algorithms. Typically, Tu and Huang combined the term frequency-inverse document frequency (TF-IDF) with TextRank to better mine user interest tags (Mihalcea & Tarau, 2004; Tu & Huang, 2016). Marujo et al. (2015) proposed a method to automatically extract keywords for twitter. Zhou et al. (2014) presented a real-time customized microblog recommendation approach, which utilizes users' tags to construct tag-user graphs, in order to measure the similarities between microblogs and users. Comparatively, Zhang et al. (2016) introduced the probability correlation between tags for microblog recommendation. Ma et al. (2015) improved the user-tag matrix by introducing multi-tag correlation. They investigated the relations between tags and employed inner and outer correlation for the purpose of solving the user-tag matrix sparsity problem. Ma et al. (2017) integrated tag correlation with users' social relations. They designed an iterative updating method to acquire the final tag-user matrix. Latter, Ma et al. (2018) further used microblog content to generate hypergraph and performed random walk on it to obtain user tags.

In parallel, some researches focused on recommendation based on topic model (Deng et al., 2018; Godin et al., 2013; Li et al., 2016a, 2016b; She & Chen, 2014; Wang et al., 2014; Zhao et al., 2016). However, text in social platforms are often short in length, thus can bring challenges to topic mining. Many works are conducted for short text topic modeling (Bicalho et al., 2017; Das et al., 2015; Li et al., 2017; Zuo et al., 2016). In addition, there are some works which fused topic mining with semantic information to capture users' interests more accurately. Liang et al. (2012) employed the social relationships and the temporal information of microblogs to recognize relevant topics of each topic in terms of their semantics and temporality. Moreover, He and Tan (2015) utilized the k-cores analysis to obtain user interest topics, and built a real-time Sina microblogs recommendation model founded on semantic network.

Furthermore, some efforts have been paid on extracting multiple influencing factors from the content to better perform recommendation. For instance, Gurini et al. (2018) extracted the semantic attitudes, including sentiment, volume and objectivity, from user-generated content and then built a three-dimensional matrix factorization. Recently, Amato et al. (2019) presented a user-centered recommendation approach for social platforms, which introduces the preferences, opinions and behaviors of users, and integrates user features, features of items and context information.

2.2. Collaborative filtering recommendations

The collaborative filtering recommendation methods mainly include user-based and item-based ones. The user-based approaches first find a group of people who share the same interests with the target user and then recommend the items they like. Comparatively, the item-based approaches first compute the similarity between items via users' behaviors and then recommend items which are most similar to the items that the target user likes. Typically, Kim and Shim (2011) proposed a Twitter recommendation strategy based on collaborative filtering, and that method can recommend the top-k users for a user to follow and the top-k tweets to browse. Liao and Lee (2016) introduced an item-based approach which implements a self-constructing clustering algorithm to group similar products, in order to reduce the dimensionality of the number of products. Moreover, Zhao et al. (2017) presented a friends recommendation model, and it can recommend friends who possess the similar interests with users in terms of location features.

2.3. Hybrid recommendations

The hybrid recommendations combine more than one recommendation methods to improve the recommendation accuracy and solve the data sparsity problem. Most present approaches of hybrid recommendations aggregate together the content-based and collaborative filtering recommendation (Chen et al., 2016, 2017; Kaššák et al., 2016; Lu et al., 2015; Wang et al., 2015, 2017; Wei et al., 2016). In the literature, there are mainly two families of aggregation methods. In the first family, two algorithms are separately developed, and then their predictions are fused. In the second family, the idea or characteristics of one method is integrated into another to predict the recommended microblogs. As an illustration, the content information is usually introduced to build the similarity matrix for collaborative filtering.

Kaššák et al. (2016) proposed a mixed hybrid group recommend model which integrates the content-based and collaborative recommendation approaches. Wei et al. (2016) used the hybrid recommendation model to solve the cold start problem, which employs a deep neural network to obtain the item content features and utilizes those features to the timeSVD++ collaborative filtering model. Moreover, Wang et al. (2017) combined incremental update item-based collaborative filtering and latent semantic analysis based relative term frequency method. That method can dynamically adjust recommendation results meanwhile guaranteeing the relevance of recommendation articles.

There are also some works made use of multiple sources of information to provide more accurate hybrid recommendation. Typically, Zhang et al. (2015) utilized social graph, user-generated content and the company's organizational chart to conduct enterprise social link recommendation. Kazai et al. (2016) employed users' location, Facebook and Twitter user profiles to conduct news and blog recommendation and Kou et al. (2018) built multi-features about user, hashtag and text information of microblogs for hashtag recommendation.

3. Hybrid microblog recommendation with heterogeneous features using deep neural network

The traditional microblog recommendation methods, including content-based and collaborative filtering recommendations, only utilize one or two influencing features such as microblog content or social relationships of users. Actually, there are many factors affecting users' interests in microblogs. More usually, those factors comprise users' interests in microblog content, users' familiarity with microblog authors, users' preference for authors, richness and attractiveness of microblogs.

In this section, we present a hybrid microblog recommendation based on deep neural network with heterogeneous features (DNN-HF). Fig. 1 shows the proposed framework. The steps are given in Algorithm 1. This framework first employs three recommendation strategies to obtain candidate recommended microblogs based on extended user interest tags, user interest topics, and user-based collaborative filtering. For clarity, they are collected respectively into the sets A, B and C. By removing the duplicated ones, the set R of candidate microblogs in Algorithm 1 is organized as their union, namely, $R = A \cup B \cup C$. Then, the heterogeneous feature vectors are generated with personal interests of users, interest in authors and microblog quality. Finally, in order to sort the candidate microblogs, we develop a deep neural network (DNN), which is widely used to solve lot of problems such as disease prediction and intrusion detection (Ali et al., 2019; Kim et al., 2017; Snyder et al., 2017). We use the trained DNN model to rank the microblogs and recommend the top-N microblogs for users. Technically, here we address the task of microblog ranking as a classification problem.

Algorithm 1 The DNN-HF algorithm for hybrid microblog recommendation.

Input: The target user u, the followed user set S of u, the training set T, the test set M, the sample set S_d, the number N of microblogs to be recommended.
Output: The set M_r of recommended microblogs.

```
Build A = Recommendation_based_on_extended_user_interest_tags(u, S, T, M);
Construct B = Recommendation_based_on_user_interest_topics(u, S, T, M);
Build C = Recommendation_based_on_collaborative_filtering(u, S, T, M);
Merge the candidate recommended microblog sets, and build R = A ∪ B ∪ C;
Generate the heterogeneous feature vector for samples in S_d;
Split the sample set S_d into the train set and the dev set;
Train the deep neural network model on the train set and measure F1-score on the dev set;
for each microblog m ∈ R do
    Generate the heterogeneous feature vector of m about personal interests of users, interest in authors and microblog quality;
    Use the trained deep neural network model to predict Score(m);
end for
Sort microblogs in M by Score(m) and get the set M_r of top-N microblogs;
Output M_r.
```

3.1. Microblog recommendation based on the extended user interest tags

User tags in microblog platforms are personalized information that describe users' personal interests. They are greatly helpful to design the recommendation method when building user profiles. However, very few users actually add interest tags themselves. User profiles in microblog platforms are often short in length, thus severe data sparseness makes it difficult to achieve interest tag-based recommendations. In this paper, we extract keywords from users' microblogs and then propose a user interest tag extension algorithm based on association rules to improve the inaccuracy problem of user interest tags.

3.1.1. User interest tag extension algorithm

The present user tag mining algorithm, such as TF-IDF, TextRank and TextRank with TF-IDF factor (Tu & Huang, 2016), can only generate single words, and some proper nouns have been inaccurately segmented. This fact causes the problem of user tag inaccuracy. Here we illustrate an example to illustrate that fact. For a microblog user u, for example, suppose that we are given ten user interest tags by using TextRank with TF-IDF factor method: {'Oscar', 'lottery', 'sophie', 'funko', 'thrones', 'game', 'fans', 'marvel', 'phoenix', 'turner'}. It is seen that 'sophie' and 'turner' together refer to a British actress '*Sophie Turner*', and 'thrones' and 'game' together means a famous American TV series '*Game of Thrones*'. These two proper nouns are wrongly split.

Furthermore, there is another problem that the same word may have different meanings in different contexts, that is, the polysemy problem.

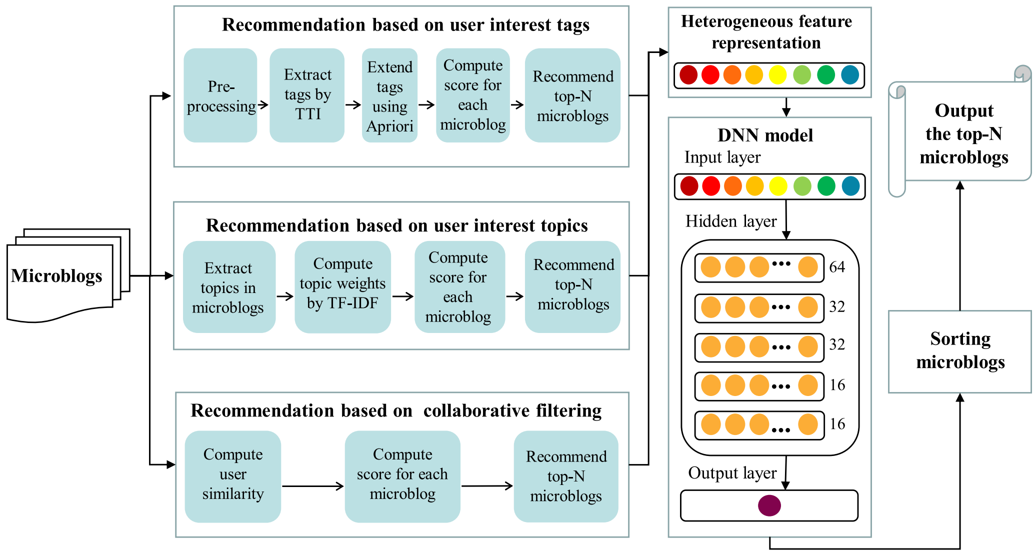

Fig. 1. The hybrid microblog recommendation framework with heterogeneous features using deep neural network.

For instance, the meaning of 'apple' when it appears together with 'banana' is different from the meaning when it occurs together with 'product'. Therefore, in the present works, we can find that (a) user interest tags are ambiguous and are difficult to describe user interests accurately; (b) user interest tags cannot fully cover users' interests.

Here we propose an effective approach to solve the above two problems, that is, using the association rules to extend user interest tags. The details of the proposed approach are given as following:

(a) The TextRank with TF-IDF factor (TTI) strategy (Tu & Huang, 2016) is employed to generate keywords and their weights. The TTI strategy helps improve the performance of the TextRank (Mihalcea & Tarau, 2004) by introducing the TF-IDF factor in the iterative calculation. We take the set T_a of these keywords as the item set.

(b) For each microblog, a transaction is constructed by extracting the keywords appearing in the microblog.

(c) The Apriori algorithm is employed to generate frequent item sets and association rules. For convenience, we record all association rules in the form of $X \rightarrow Y$, where X is a set including one keyword and Y is a set of keywords. Here, we set the minimum support α and the minimum confidence β.

(d) For each association rule, Y is used to extend X. By adding the keywords in Y to X, a set X' of the extended tags is obtained. For clarity, we use X' to replace X in T_a and sort T_a by their weights. Finally, the top-10 tags in T_a are selected as the extended user interest tags.

To help understand the above operations, an example is given to demonstrate the extension process of user interest tags.

(a) For user u, the twenty keywords, for example, are first extracted from his or her microblogs as the item set: {'oscar', 'lottery', 'sophie', 'funko', 'thrones', 'game', 'fans', 'marvel', 'phoenix', 'turner', 'sister', 'x-men', 'jordyn', 'olsen', 'kim', 'eminem', 'money', 'khloe', 'brand', 'lounge'}.

(b) For the following microblog of the user u: " *Excellent//[GoT will launch beauty makeup]The famous beauty brand urban decay announced today that it will cooperate with Game of Thrones to launch a new beauty product in April. #Game of Thrones##For The Throne#* ", the approach will generate a transaction: ['brand', 'game', 'thrones']. It is noted that these three words are contained in the item set of u and they also occur in this microblog.

(c) The following association rules are then obtained by Apriori algorithm:

{{'turner'}→{'sophie'}, {'sophie'}→{'turner'}, {'phoenix'}→{'x-men', 'marvel'}, {'game'}→{'thrones'}, {'thrones}'→{'game'}}

(d) The extended interest tag set for user u is finally constructed as: {"game, throne", "sophie, turner", "phoenix, x-men, marvel", "oscar", "lottery", "funko", "fans", "marvel", "sister", "jordyn"}.

Therefore, it is seen that our approach obtains the extended user interest tags, which can accurately describe users' interests.

3.1.2. Microblog recommendation based on extended user interest tags

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For a microblog user u, let his or her extended interest tags be $t = \{t_1, t_2, \ldots, t_{10}\}$. Given a microblog m, the interestingness score $TagScore(u, m)$ of u to m is then defined as:

$$TagScore(u, m) = \sum_{i=1}^{10} In(t_i, m) * Weight(u, t_i) \tag{1}$$

where $In(t_i, m)$ denotes whether tag t_i appears in microblog m or not, and $Weight(u, t_i)$ represents the weight of tag t_i for user u. Note that for a tag that consists of multiple words, $In(t_i, m)$ equals 1 only when every word in the tag appears in the microblog m. The proposed microblog recommendation algorithm based on the extended user interest tags is given in Algorithm 2.

3.2. Microblog recommendation based on user interest topics

Present microblog recommendations only use the text in microblogs, but ignore the rich link information. A lot of microblogs contain topic links that can depict the main idea of a microblog. For example, topic links in Sina microblog include hashtag and super topics. Hashtag are also widely used in other social platforms such as Facebook and Twitter. Fig. 2 shows an example of topic links in Sina Weibo. In this microblog, the first topic link "elizabetholsen" is a super topic and the second topic link "sorryforyourloss" is a hashtag.

Recently, many users like to add relevant topics when posting microblogs. On the one hand, they can clearly identify the topic of microblogs. On the other hand, adding topics can improve the popularity of microblogs. For recommendation systems, topics can indicate user interests and are helpful to build user personas. In addition, topics in microblogs have the same structure. In this paper, we propose a recommendation founded on user interest topics, which can accurately discover the microblogs that users are interested in.

For every topic link in user u's microblogs, the TF-IDF is used to calculate its weight. Then ten topics with the highest weights are selected

Algorithm 2 Microblog recommendation based on the extended user interest tags.

Input: The target user u, the followed user set S of u, the training set T, the test set M, the number N of microblogs to be recommended.
Output: The set A of candidate recommended microblogs.

for each user $i \in S$ **do**
  Integrate the microblogs of user i into one document D_i;
  Segment D_i to get the word set W_i;
  Remove stop words and non-nouns in W_i;
end for
for each word $j \in u$'s word set W_u **do**
  Compute TF-IDF score of j;
  Calculate the word j's weight $Weight(u, j)$ by TextRank with TF-IDF factor;
end for
Sort W_u by word weights and get the set T_a of top-20 keywords;
Adopt the Apriori algorithm to get the frequent item set F;
for each rule $\{X \rightarrow Y\} \in F$ **do**
  Obtain extended tag set X' by adding Y to X;
  Use X' to replace X in T_a;
end for
Sort T_a by weights and select top-10 tags as extended user interest tags;
for each microblog $m \in M$ **do**
  Use Eq. (1) to calculate $TagScore(u, m)$;
end for
Sort M by $TagScore(u, m)$ and get the set A of the top-N microblogs;
return Output A.

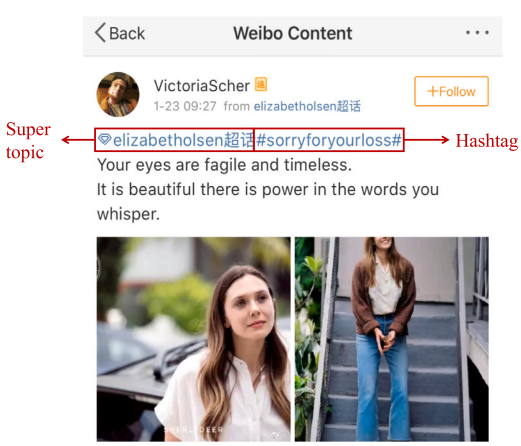


Fig. 2. A microblog from Sina Weibo, which contains super topic and hashtag.

as user interest topics $tp = \{tp_1, tp_2, \ldots, tp_{10}\}$. Given a microblog m, the interestingness score of u to m is defined as:

$$TopicScore(u, m) = \sum_{i=1}^{10} In(tp_i, m) * Weight(u, tp_i) \tag{2}$$

where $In(tp_i, m)$ denotes whether the topic tp_i appears in the microblog m or not, and $Weight(u, tp_i)$ stands for the weight of topic tp_i for user u. The proposed microblog recommendation algorithm based on user interest topics is shown in Algorithm 3.

Algorithm 3 Microblog recommendation based on user interest topics.

Input: The target user u, the followed user set S of u, the training set T, the test set M, the number N of microblogs to be recommended.
Output: The candidate recommended microblogs B;

for each user $i \in S$ **do**
  Extract topic links in user i's microblogs to get topic set Tp_i;
end for
for each topic $t \in u$'s topic set Tp_u **do**
  Calculate its weight $Weight(u, t)$ by TF-IDF;
end for
Sort Tp_u by topic weights and select top-10 topics as user interest topics;
for each microblog $m \in M$ **do**
  Use Eq. (2) to calculate $TopicScore(u, m)$;
end for
Sort M by $TopicScore(u, m)$ and get the set B of the top-N microblogs;
return B.

3.3. Microblog recommendation using user-based collaborative filtering

Recommendation based on collaborative filtering is the most widely used method in personalized recommendations, and is also one of the most effective algorithms. The main idea of user-based collaborative filtering is to find a set of users who share similar interests with the target user, and recommend the items they like to the target user. In this section, we investigate three methods measuring the similarity between users, and then use them to implement user-based collaborative filtering. Those three methods include ones based on user content, interactive behaviors and social relationship, respectively.

3.3.1. User content

User content (UC) means the microblog content published by the users, which directly reflects the interests of users. Users with similar microblog content usually share similar interests and therefore have high similarity. Present works often use the word bag model to represent users' microblog content, calculate the weights of words by TF-IDF to generate word vectors, and then compute the similarity of two users by cosine similarity. But this kind of method suffers from severe data sparsity and high computational complexity. In this section, we use the extended user interest tags to compute user content similarity.

For a target user u_1 and a given user u_2, let u_1's extended interest tags be $t = \{t_1, t_2, \ldots, t_{10}\}$, u_2's microblog set be $M(u_2)$, the user content similarity $UC(u_1, u_2)$ between u_1 and u_2 can be calculated using the following formula:

$$UC(u_1, u_2) = \frac{\sum_{m \in M(u_2)} \sum_{i=1}^{10} In(t_i, m) * Weight(u_1, t_i)}{\sqrt{|M(u_2)|}} \tag{3}$$

where $In(t_i, m)$ denotes whether tag t_i appears in microblog m, $Weight(u_1, t_i)$ represents the weight of tag t_i for the user u_1, and $|M(u_2)|$ denotes the number of microblogs of user u_2. Typically, the user content similarity represents the matching degree between the user u_2's microblogs and the target user u_1's interest tags.

3.3.2. Interactive behaviors

Interactive Behaviors (IB) refers to the users' behaviors of posting and forwarding microblogs. On the one hand, user interactive behaviors reflect users' interests: a user will post or forward the microblog he or she is interested in. On the other hand, it can reflect the users' social preferences and relationship. As an illustration, a user may forward the microblog of his or her favorite authors. Here the interactive behavior similarity is calculated by counting the number of microblogs that the target user and other users jointly forward.

For the target user u_1 and a given user u_2, let u_1's microblog set be $M(u_1)$, u_2's microblog set be $M(u_2)$, the interactive behavior similarity $IB(u_1, u_2)$ between u_1 and u_2 can be calculated using the following formula:

$$IB(u_1, u_2) = \frac{|M(u_1) \cap M(u_2)| + \sum_{m \in M(u_1) \cap M(u_2)} isOriginal(u_2, m)}{\sqrt{|M(u_2)|}} \tag{4}$$

where the intersection of $M(u_1)$ and $M(u_2)$ indicates the microblog set that user u_1 and user u_2 both forward, $isOriginal(u_2, m)$ represents whether or not the user u_2 is the original author of the microblog m, whose value is 1 or 0. In Eq. (4), the similarity is normalized by the square root of the size of $M(u_2)$ to reduce the affect in the case that u_2 has a large set of microblogs.

3.3.3. Social relationship

Social Relationship (SR) are the following and follower relationships, which can reveal the familiarity between two users. We use two formulas to calculate the social relationship similarity.

Formally, for a target user u_1, given a user u_2, the first social similarity $SR(u_1, u_2)$ between u_1 and u_2 is defined as follows:

$$SR(u_1, u_2) = \begin{cases} 1, & \text{if } u_1 \text{ and } u_2 \text{ follow each other} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

The second formula investigates the following relationship between users, which utilizes Jaccard similarity coefficient to calculate the similarity between users' followed user sets. For a target user u_1, given a user u_2, $Follow(u_1)$ indicates the user set that u_1 follows, the social similarity $SR_1(u_1, u_2)$ between u_1 and u_2 is:

$$SR_1(u_1, u_2) = \frac{|Follow(u_1) \cap |Follow(u_2)|}{|Follow(u_1) \cup |Follow(u_2)|} \tag{6}$$

3.3.4. Recommendation based on collaborative filtering

Here the user similarities in Eqs. (3), (4), (5) and (6) are used to recommend microblogs based on collaborative filtering. For a target user u_1, given a microblog m, the collaborative filtering score $CFScore(u_1, m)$ of u_1 to m is defined as:

$$CFScore(u_1, m) = \sum_{u_2 \in userSet(m)} Sim(u_1, u_2), \tag{7}$$

where $userSet(m)$ represents the user set that have posted or forwarded microblog m, and $Sim(u_1, u_2)$ denotes the similarity between user u_1 and user u_2.

3.4. Heterogeneous features to train the DNN model

After obtaining candidate recommended microblogs using the above three strategies, heterogeneous features are generated from those microblogs, which are then fed into the deep neural network.

Specifically, we propose to extract three major user interest influencing factors: personal interests of users, interest in authors, and microblog quality. Totally, eight heterogeneous features about those three factors are constructed, as shown in Table 1. Accordingly, the dimension of the feature vectors is eight. It is noted that (1) those eight features are involved in texts, pictures and videos in microblogs. (2) they are extracted from the microblog content, social relationships, and user behaviors; (3) users interest tags, user interest topics and user similarity are utilized to extract those features. Finally, a DNN model is constructed to rank the microblogs. Its architecture is given in Fig. 1. It consists of an input layer, several hidden layers and an output layer. The output layer has one node, which is designed to predict the ranking score for recommendation.

To train the deep neural network model, we use microblogs in the training set as samples. For each sample, the class label is 1 or 0, where 1 stands for the target user like that microblog, and 0 shows the target user does not like that microblog. When predicting the microblogs, the DNN model outputs a probability for each microblog as its score. Finally, we sort the microblogs by their scores and recommend top-N ones.

4. Experimental results

4.1. Datasets

The experimental datasets were collected from Sina Weibo (weibo.com) and Twitter (twitter.com). Both datasets include not only microblogs, but also the social network. For a target user u, the social network is built based on the user set A that u follows. In the social network, a node denotes a user, the relation between two nodes represent the follow relationship between two users. Each microblog is composed of text, links, timestamps, etc. The Sina Weibo dataset contains 2792 users with 216,176 microblogs from January to February, 2019. We divide that dataset into the training set S_t and the test set S_e, as shown in Table 2. The training set S_t includes 146,908 microblogs and the test set S_e comprises 69,268 microblogs. In addition, the Twitter dataset includes 1267 users with 265,033 microblogs, and it is segmented into the training set T_t with 212,567 microblogs and the test set T_e with 52,466 microblogs, as shown in Table 2.

4.2. Experimental settings

In our experiments, the microblog recommendation methods we used include DNN-HF, ones based on extended user interest tags, user interest topics, and user-based collaborative filtering in this paper, and the methods in the related works (Ma et al., 2015, 2017; Tu & Huang, 2016).

To train the DNN model, we construct the set S_d of samples which is obtained from the training set S_t of Sina Weibo, and the set T_d of samples extracted from the training set T_t of Twitter.

It is noted that the training set S_t of Sina Weibo and training set T_t of Twitter are utilized to train the three recommendation strategies of obtaining candidate recommended microblogs based on the extended user interest tags, user interest topics, and user-based collaborative filtering, while the set S_d and the set T_d are only used to train the DNN model. The target users' microblogs in S_t are chosen as positive samples which are added into the set S_d. Here, the target users means the users for whom we recommend. For each target user, if a microblog in S_t was forwarded more than three times by his or her followed users but the target user did not forward it, then this microblog is selected as a negative sample which is added into the set S_d. Further, the set S_d of Sina Weibo dataset is composed of 6280 samples which contain 3160 positive samples and 3120 negative samples. Here, 80% of samples (5024 samples) in S_d are taken as the train set and the remaining 20% samples (1256 samples) are used as the dev set, as shown in Table 2. Analogously, the set T_d of Twitter comprises 5445 samples with 2899 positive samples and 2546 negative samples. We use the 80% of samples (4356 samples) in T_d as the train set and the remaining 20% samples (1089) as the dev set, as shown in Table 2.

In the construction method of candidate recommended microblogs based on extended user interest tags, α represents the minimum support of association rules and β denotes the minimum confidence. We use the occurrence times of the item as the minimum support. Our experiment sets different values for α and β and compares their recommendation performances. The ranges of α and β are {1, 2, 3, 4, 5, 6} and {0.5, 0.6, 0.7, 0.8, 0.9}, respectively. Fig. 3 shows the precision of microblogs recommendation based on extended user interest tags on two datasets.

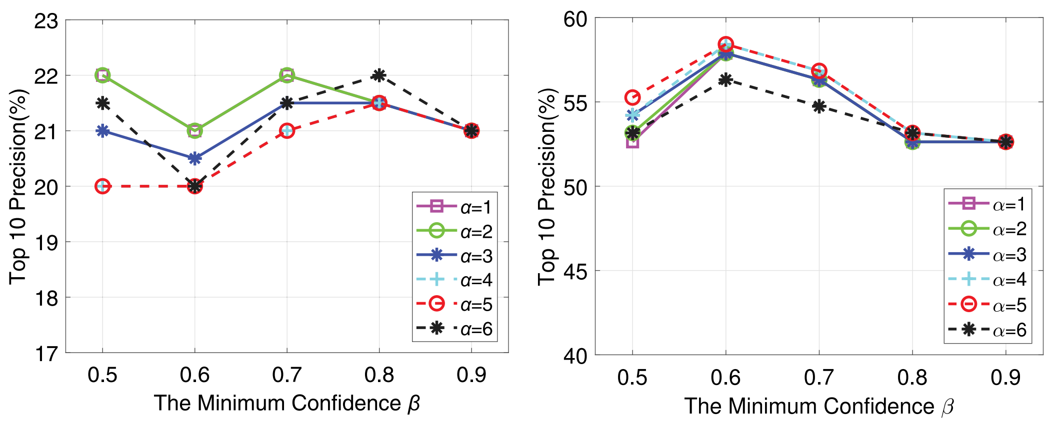
From Fig. 3, it is seen that our approach achieves better performance for Sina Weibo dataset when α equals to 2. The recommendation precision decreases when the value of α increases. The reason for this fact lies in that less tags can be extended when the minimum support increases. In addition, it can be observed from Fig. 3(a) that when α equals to 2 and β equals to 0.7, that approach obtains the best performance. In the experiments of recommendation, α is set to be 2 and β is taken as 0.7 for Sina Weibo dataset. As for Twitter dataset, the precision reaches its highest value when β equals to 0.6 and α equals to 4 or 5 in Fig. 3(b). We take α as 4 and β as 0.6 for Twitter dataset for the experiments in Section 4.3.

Table 1
The heterogeneous features of the deep neural network model.

Factors	Feature name	Meaning
Personal interest	Tag_score	The similarity between the microblog and the target user's extended interest tags, can be calculated by Eq. (1)
	Topic_score	The similarity between the microblog and the target user's interest topics, can be calculated by Eq. (2).
Interest in authors	Interactive_score	The interactive behavior similarity between the microblog's author and the target user, can be calculated by Eq. (4).
	Social_score	The social relationship similarity between the microblog's author and the target user, can be calculated by Eq. (5).
Microblog quality	Has_pic	Whether the microblog contains pictures.
	Has_video	Whether the microblog contains videos.
	Text_length	The length of the microblog text.
	Topic_num	The number of topic links in the microblog.

Table 2
The statistics of Sina Weibo dataset and Twitter dataset.

Dataset	Users	Train for DNN-HF	Test for DNN-HF	Train for DNN	Dev for DNN
Sina Weibo	2792	146,908	69,268	5024	1256
Twitter	1267	212,567	52,466	4356	1089



(a) Sina Weibo Dataset   (b) Twitter Dataset

Fig. 3. The precision of microblog recommendation based on extended user interest tags with different minimum support α and minimum confidence β.

4.3. Experimental results and analysis

The following experiments have been conducted to evaluate the validation of our proposed approach.

(a) Comparison between the extended user interest tags and other works.

(b) Comparison of user similarity calculation methods for collaborative filtering recommendation. Those methods include ones based on user content, interactive behaviors and social relationships.

(c) Hyper parameter sensitivity analysis.

(d) Comparison of the DNN-HF model with three single recommendation strategies based on extended user interest tags, user interest topics, and collaborative filtering.

(e) Comparison between the DNN-HF model and other related works.

(f) Ablation experiments of the DNN-HF model.

4.3.1. Comparison between the extended user interest tags and other works

To demonstrate the effectiveness of our proposed microblog recommendation based on extended user interest tags ($EUIT$), we compared our method against the following three methods: TextRank with TF-IDF factor (TTI) (Tu & Huang, 2016) and Tag Correlation (TC) (Ma et al., 2015), and the variant of TC: TC-TFIDF, which uses TF-IDF for user tag retrieval.

For clarity, let N denote the number of microblogs to be recommended. In addition, the scores of precision and recall are employed to evaluate the performance. Furthermore, let "P@N" and 'R@N" indicate the precision and the recall for the top-N recommendation, respectively. The comparative experimental results are shown in Table 3.

Table 3 shows that our EUIT approach achieves the best performance than those of TTI, TC and TC-TFIDF in most cases for microblog recommendation. Specifically, for Sina Weibo dataset, TC-TFIDF gets the best scores when recommending 10 and 20 microblogs, while our method obtains the best performance when recommending 30, 40 and 50 microblogs. For Twitter dataset, our EUIT significantly improves the precision and recall score when recommending 10, 20 and 30 microblogs. However, as N increases, TC-TFIDF achieves higher results in the cases of top-40 and top-50 recommended microblogs.

To further demonstrate the performance, two users are randomly selected from Sina Weibo platform to mine their interest tags by TC-TFIDF, TTI and our EUIT. The top-5 tags are shown in Table 4. According to the extended user interest tags, it is seen that user A is interested in American TV series *Game of Thrones* and movie *X-men*, and user A also likes actress *Sophie Turner*. User B is interested in that movie *Fantastic Beast and Where to Find Them* since tag 1 ('grindelwald') and tag 2 ('grindelwald, dumbledore') are characters in that movie. Compared with TC-TFIDF and TTI, we can learn that our EUIT method can more accurately describe user interests. This observation demonstrates the effectiveness of our algorithm.

4.3.2. Comparison of user similarity calculation methods for collaborative filtering recommendation

In Section 3.3, different methods are developed to compute the user similarity based on user content (UC), interactive behaviors (IB), the first social relationship(SR), and the second social relationship(SR_1), based on Eqs. (3), (4), (5) and (6). The curves in Figs. 4 and 5 shows that the precision and recall of IB are superior to those of UC, SR and SR_1 in both datasets. The reason for this fact lies in that user

Table 3
The precision and recall of TC, TC-TFIDF, TTI and our EUIT on two datasets.

Dataset	Sina Weibo					Twitter				
Top-N	P@10	P@20	P@30	P@40	P@50	P@10	P@20	P@30	P@40	P@50
TTI	0.185	0.165	0.140	0.129	0.124	0.421	0.321	0.282	0.234	0.200
TC	0.145	0.155	0.157	0.129	0.108	0.353	0.316	0.272	0.254	0.224
TC-TFIDF	**0.255**	**0.198**	0.172	0.150	0.131	0.411	0.382	0.328	**0.280**	**0.239**
Our EUIT	0.220	0.195	**0.187**	**0.160**	**0.135**	**0.584**	**0.434**	**0.333**	0.268	0.215
Top-N	R@10	R@20	R@30	R@40	R@50	R@10	R@20	R@30	R@40	R@50
TTI	0.046	0.083	0.105	0.129	0.155	0.105	0.161	0.212	0.234	0.250
TC	0.036	0.078	0.118	0.129	0.135	0.088	0.158	0.204	0.254	0.280
TC-TFIDF	**0.064**	**0.099**	0.129	0.150	0.164	0.103	0.191	0.246	**0.280**	**0.299**
Our EUIT	0.055	0.098	**0.140**	**0.160**	**0.169**	**0.146**	**0.217**	**0.250**	0.268	0.268

Table 4
The user interest tags obtained by TC-TFIDF, TTI and our EUIT from Sina Weibo Dataset.

Rank	User A(TC-TFIDF)	User A(TTI)	User A(our EUIT)	User B(TC-TFIDF)	User B(TTI)	User B(our EUIT)
1	Behatiprinsloo	Oscar	Game, thrones	Ggad	Grindelwald	Grindelwald
2	Funko	Lottery	Sophie, turner	Jude	Geric	Grindelwald, dumbledore
3	Game	Sophie	Phoenix, x-men, marvel	Geric	Ggad	Geric
4	Sophie	Game	Oscar	Rowling	Beast	Ggad, beast
5	Turner	Throne	Lottery	Dumbledore	Fan	Marvel, fan

interactive behaviors can reflect not only the users' interests, but also social preferences. The performance of SR and SR_1 on the Twitter dataset is worse than those of UC and IB. The reason may be that many users like to follow VIP users and celebrities, and user similarity cannot be accurately reflected by the social relationships.

4.3.3. Hyper parameter sensitivity analysis

In this section, a series of experiments are conducted to analyze the hyper parameters sensitivity for our DNN model, including the structure of hidden layers, solver, initial learning rate, activation function and maximum iteration. The sample set S_d is used for DNN model training. The set S_d is made up of positive and negative samples, hence we conduct binary classification to train the model. Considering both precision and recall score of the classification, we use F1-score on dev set for model comparison and hyper parameter analysis.

First, a group of experiments have been conducted to analyze the structure of hidden layers. For both datasets, we set the solver, activation function, initial learning rate and maximum iteration as adam, relu, 0.0005 and 300, respectively. Then, five different models with different structures of hidden layers are trained, which are compared with F1-scores on dev set. Those five DNN structures are (64), (64, 32, 16), (64, 32, 32, 16, 16), (128, 64, 64, 32, 32), and (128, 64, 64, 32, 32, 16, 16), respectively. Here "(64, 32, 16)" means that there are three hidden layers with 64, 32, 16 nodes, respectively. Other structures can be constructed accordingly. As can be observed from Fig. 6(a), both datasets achieve best performance on the model with hidden layers of (64, 32, 16).

Second, the DNN model is trained by using three different solvers: Adam, SGD, and LBFGS. Fig. 6(b) shows that Adam significantly outperforms other two solvers on the two datasets.

Third, we set the initial learning rate as {0.0001, 0.0005, 0.001, 0.01, 0.05} to analyze the sensitivity of that hyper parameter. Fig. 7(a) shows their performances. For Sina Weibo dataset, the F1-score reaches its highest value when the learning rate is equal to 0.0005. In addition, the F1-score drops when the learning rate increases. As for Twitter dataset, the best learning rate is 0.001.

Fourth, the activation function of the DNN model is taken as {Relu, Tanh, Logistics, Identity} to investigate the sensitivity of that hyper parameter, shown in Fig. 7(b). It is seen that Relu outperforms the other three activation functions for Sina Weibo dataset, while the performance of Tanh is superior to those of the other three activation functions for Twitter dataset.

Finally, the DNN model is trained on five values of maximum iteration: {100, 200, 300, 400, 500}. Fig. 8 shows that the F1-score achieves the highest performance on two datasets when the maximum iteration is 200. The F1-score drops as the times of iteration increase, since more iterations may lead to over-fitting. The values of hyper parameters in the DNN model for both datasets are summarized in Table 5.

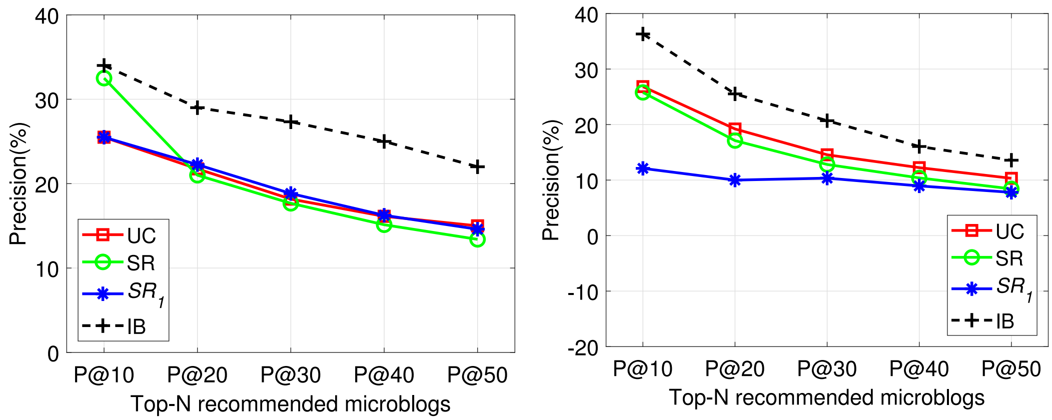
Table 5
The hyper parameters setting of deep neural network model.

Parameters	Sina Weibo dataset	Twitter dataset
The structure of hidden layers	(64, 32, 16)	(64, 32, 16)
Activation function	Relu	Tanh
Solver	Adam	Adam
Initial learning rate	0.0005	0.001
Maximum iteration	200	200

4.3.4. Comparison of the DNN-HF model with three single recommendation strategies

We implemented microblog recommendation based on extended user interest tags (EUIT), user interest topics(UT), user-based collaborative filtering (CF), and our proposed hybrid microblog recommendation based on deep neural network with heterogeneous features (DNN-HF). It is noted that the collaborative filtering approach with interactive behaviors is used in DNN-HF. The precision and recall on the Sina Weibo dataset and Twitter dataset are reported in Table 6.

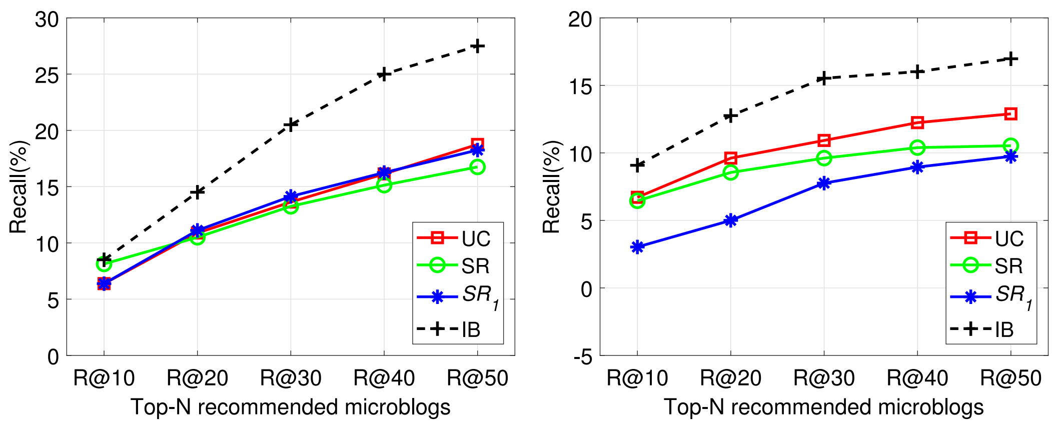
As shown in Table 6, our DNN-HF model achieves the best performances than those of three single recommendation methods EUIT, UT and CF on both datasets. That fact indicates that our algorithm can fuse the advantages of three single methods, and is able to assign high probabilities to the microblogs that user are actually interested in. Moreover, for Sina Weibo dataset, CF obtains better performances than those of EUIT and UT, while EUIT achieves best performances than those of CF and UT in Twitter dataset. In most cases, the precision and recall of UT are the lowest among three single recommendation strategies, the reason of which is that only some microblogs contain topic links, and the actual number of recommended microblogs of UT approach does not reach N. After analyzing the recommendation results, we find that recommendation based on user interest topics is able to recommend microblogs that the other two single algorithms cannot do and those recommended microblogs contain the topic links that users are interested in. That fact shows the advantage of UT approach.



(a) Sina Weibo Dataset

(b) Twitter Dataset

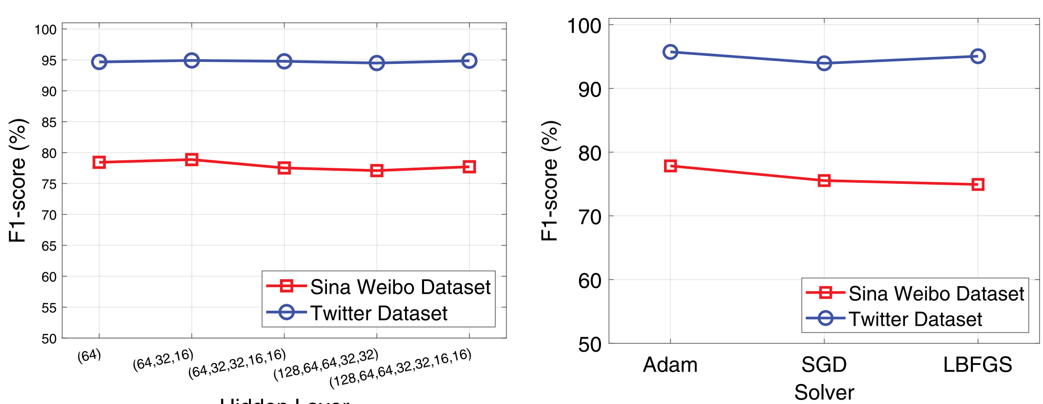
Fig. 4. The precision comparison of microblog recommendation methods: (1) the collaborative filtering based on user content(UC), (2) the collaborative filtering based on interactive behaviors(IB), (3) the collaborative filtering based on the first social relationship(SR), (4) the collaborative filtering based on the second social relationship(SR_1).



(a) Sina Weibo Dataset

(b) Twitter Dataset

Fig. 5. The recall comparison of microblog recommendation methods: (1) the collaborative filtering based on user content (UC), (2) the collaborative filtering based on interactive behaviors(IB), (3) the collaborative filtering based on the first social relationship(SR), (4) the collaborative filtering based on the second social relationship(SR_1).



(a) Influence of the deep neural network model structure

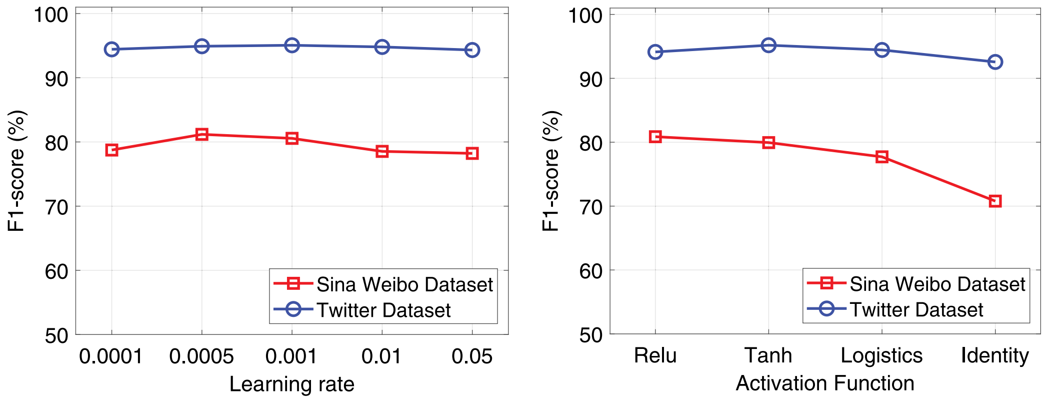
(b) Influence of the solver

Fig. 6. Hyper parameter experiments of the DNN model about DNN structure and solver.

4.3.5. Comparison between the DNN-HF model and other related works

To further demonstrate the effectiveness of our proposed approach, our method (DNN-HF) has been compared against the following five methods: TextRank with TF-IDF factor (TTI) (Tu & Huang, 2016), Tag Correlation (TC) (Ma et al., 2015), Iterative Tag Correlation and User Social Relation (ITCAUSR) (Ma et al., 2017) and the variants of TC and ITCAUSR: TC-TFIDF and ITCAUSR-TFIDF, which use TF-IDF for user tag retrieval. The comparative experimental results are given in Table 7. It is seen that our DNN-HF approach achieves the highest performance compared with other five methods on both datasets, indicating the validation of the proposed DNN-HF.

The superiorities of the DNN-HF can be summarized as follows. (a) We extend user interest tags based on association rules to address the inaccuracy problem of user interest tags. (b) Utilizing the topic links



(a) Influence of the learning rate (b) Influence of the activation function

Fig. 7. Hyper parameter experiments of the DNN model about the learning rate and the activation function.

Table 6
The precision and recall of EUIT, UT, CF and DNN-HF on two datasets.

Dataset	Sina Weibo					Twitter				
Top-N	P@10	P@20	P@30	P@40	P@50	P@10	P@20	P@30	P@40	P@50
EUIT	0.220	0.195	0.187	0.160	0.135	0.584	0.434	0.333	0.268	0.215
UT	0.270	0.158	0.123	0.111	0.093	0.237	0.195	0.154	0.117	0.096
CF	0.340	0.290	0.273	0.250	0.220	0.363	0.255	0.207	0.161	0.136
DNN-HF	**0.520**	**0.370**	**0.298**	**0.275**	**0.260**	**0.705**	**0.529**	**0.418**	**0.343**	**0.301**
Top-N	R@10	R@20	R@30	R@40	R@50	R@10	R@20	R@30	R@40	R@50
EUIT	0.055	0.098	0.140	0.160	0.169	0.146	0.217	0.250	0.268	0.268
UT	0.068	0.079	0.093	0.111	0.116	0.059	0.097	0.116	0.117	0.120
CF	0.085	0.145	0.205	0.250	0.275	0.091	0.128	0.155	0.161	0.170
DNN-HF	**0.130**	**0.185**	**0.224**	**0.275**	**0.325**	**0.176**	**0.264**	**0.313**	**0.343**	**0.376**

Table 7
The precision and recall of TTI, TC, TC-TFIDF, ITCAUSR, ITCAUSR-TFIDF and DNN-HF on two datasets.

Dataset	Sina Weibo					Twitter				
Top-N	P@10	P@20	P@30	P@40	P@50	P@10	P@20	P@30	P@40	P@50
TTI	0.185	0.165	0.140	0.129	0.124	0.421	0.321	0.282	0.234	0.200
TC	0.145	0.155	0.157	0.129	0.108	0.353	0.316	0.272	0.254	0.224
TC-TFIDF	0.255	0.198	0.172	0.150	0.131	0.411	0.382	0.328	0.280	0.239
ITCAUSR	0.195	0.200	0.158	0.138	0.126	0.500	0.426	0.349	0.289	0.252
ITCAUSR-TFIDF	0.350	0.270	0.223	0.184	0.165	0.421	0.355	0.353	0.292	0.264
DNN-HF	**0.520**	**0.370**	**0.298**	**0.275**	**0.260**	**0.705**	**0.529**	**0.418**	**0.343**	**0.301**
Top-N	R@10	R@20	R@30	R@40	R@50	R@10	R@20	R@30	R@40	R@50
TTI	0.046	0.083	0.105	0.129	0.155	0.105	0.161	0.212	0.234	0.250
TC	0.036	0.078	0.118	0.129	0.135	0.088	0.158	0.204	0.254	0.280
TC-TFIDF	0.064	0.099	0.129	0.150	0.164	0.103	0.191	0.246	0.280	0.299
ITCAUSR	0.049	0.100	0.119	0.138	0.158	0.125	0.213	0.262	0.289	0.314
ITCAUSR-TFIDF	0.088	0.135	0.168	0.184	0.206	0.105	0.178	0.264	0.292	0.330
DNN-HF	**0.130**	**0.185**	**0.224**	**0.275**	**0.325**	**0.176**	**0.264**	**0.313**	**0.343**	**0.376**

in the microblogs to mine user interests and recommend microblogs. (c) User interactive behaviors are utilized to compute user similarities, which are used to fulfill microblog recommendation based on collaborative filtering. (d) Heterogeneous features about personal interests of users, interest in authors and microblog quality are introduced to represent candidate microblogs, and the deep neural network is employed to rank microblogs.

4.3.6. Ablation experiments of the DNN-HF model

In this section, we report the ablation experiments to demonstrate how each feature, each factor and each strategy of our DNN-HF model contributes to the microblog recommendation result. First, we evaluate the impact of each heterogeneous feature by removing one feature at a time. The results are showed in Table 8. Here, Diff@10 means the difference with DNN-HF in terms of the precision of top-10 recommendation.

From the results of No. 2 to No. 9 in Table 8, it is seen that for the Sina Weibo dataset, social_score plays the most important role, since the precision drops most significantly after removing this feature. Social_score reflects the familiarity between users and the authors, and microblogs with higher social_score will ranks higher. As for Twitter dataset, interactive_score is the most influential feature, for it reflects not only the users' interests, but also social preferences. Other features like tag_score and topic_score also attribute a lot to the DNN-HF model. From No. 10 to No. 12 in Table 8, we remove each factor in Table 1 in at a time. The results indicate that interest in author is most crucial for Sina Weibo dataset and personal interest for Twitter dataset.

Second, the impact of three microblog recommendation strategies are evaluated: EUIT, UT, and CF by removing one strategy at a time. The result of Sina Weibo is summarized in Table 9 and the result of Twitter is showed in Table 10. Table 9 shows that CF is the most valuable strategy, and the precision of our model drop a lot in five cases after removing CF. This conclusion is consistent with the results of

Table 8
The impact of heterogeneous features on two datasets.

Dataset No.	Method	Sina Weibo P@10	Sina Weibo Diff@10	Twitter P@10	Twitter Diff@10
1	DNN-HF(all features)	0.520	0.000	0.705	0.000
2	w/o Tag_score	0.445	−0.075	0.637	−0.068
3	w/o Topic_score	0.450	−0.070	0.647	−0.058
4	w/o Interactive_score	0.425	−0.095	0.632	**−0.073**
5	w/o Social_score	0.400	**−0.120**	0.674	−0.031
6	w/o Has_pic	0.455	−0.065	0.679	−0.026
7	w/o Has_video	0.460	−0.060	0.674	−0.031
8	w/o Text_length	0.435	−0.085	0.679	−0.026
9	w/o Topic_num	0.445	−0.075	0.674	−0.031
10	w/o Personal interest	0.415	−0.105	0.616	**−0.089**
11	w/o Interest in author	0.365	**−0.155**	0.632	−0.073
12	w/o Microblog quality	0.410	−0.110	0.653	−0.052

Table 9
The impact of three candidate microblog recommendation methods on Sina Weibo dataset.

Method	P@10	Diff@10	P@20	Diff@20	P@30	Diff@30	P@40	Diff@40	P@50	Diff@50
w/o EUIT	0.535	+0.015	0.355	−0.015	0.307	+0.009	0.290	+0.015	0.254	−0.006
w/o UT	0.430	−0.090	0.340	−0.030	0.303	+0.005	0.294	+0.019	0.258	−0.002
w/o CF	0.370	**−0.150**	0.283	**−0.087**	0.250	**−0.048**	0.213	**−0.062**	0.176	**−0.084**
DNN-HF	0.520	0.000	0.370	0.000	0.298	0.000	0.275	0.000	0.260	0.000

Table 10
The impact of three candidate microblog recommendation methods on Twitter dataset.

Method	P@10	Diff@10	P@20	Diff@20	P@30	Diff@30	P@40	Diff@40	P@50	Diff@50
w/o EUIT	0.516	**−0.189**	0.384	**−0.145**	0.311	**−0.107**	0.257	**−0.086**	0.221	**−0.080**
w/o UT	0.726	+0.021	0.511	−0.018	0.405	−0.013	0.339	−0.004	0.293	−0.008
w/o CF	0.647	−0.058	0.521	−0.008	0.396	−0.022	0.308	−0.035	0.261	−0.040
DNN-HF	0.705	0.000	0.529	0.000	0.418	0.000	0.343	0.000	0.301	0.000

Table 11
The precision and recall of SVM-HF and DNN-HF on two datasets.

Dataset	Sina Weibo					Twitter				
Top-N	P@10	P@20	P@30	P@40	P@50	P@10	P@20	P@30	P@40	P@50
SVM-HF	0.420	0.330	0.283	0.263	0.241	0.679	0.492	0.391	0.342	0.297
DNN-HF	**0.520**	**0.370**	**0.298**	**0.275**	**0.260**	**0.705**	**0.529**	**0.418**	**0.343**	**0.301**
Top-N	R@10	R@20	R@30	R@40	R@50	R@10	R@20	R@30	R@40	R@50
SVM-HF	0.105	0.165	0.213	0.263	0.301	0.170	0.246	0.293	0.342	0.371
DNN-HF	**0.130**	**0.185**	**0.224**	**0.275**	**0.325**	**0.176**	**0.264**	**0.313**	**0.343**	**0.376**

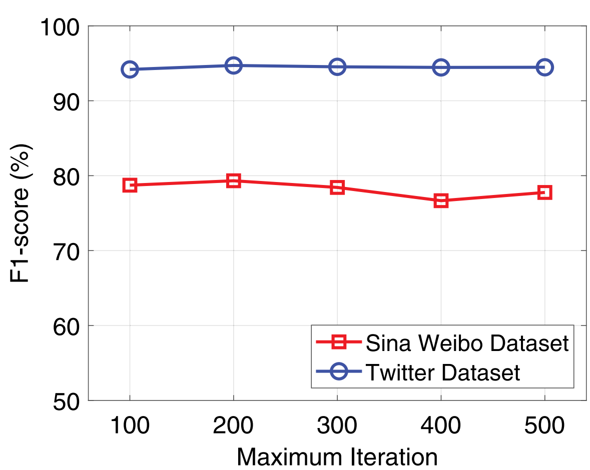


Fig. 8. Hyper parameter experiments of the DNN model about the maximum iteration.

Table 6, as CF achieves the highest performance among three strategies. Analogously, EUIT plays the most crucial roles for Twitter dataset, since it obtains highest precision and recall scores among three strategies in Table 6.

Finally, in order to demonstrate the effectiveness of DNN-HF model, we compare it with a Learning to Rank method for microblog sorting. Learning to Rank is widely used for information retrieval and academic expert ranking and so on (Liu, 2009; Moreira, 2011; Moreira et al., 2015). In experiments, we replace DNN with support vector machine (SVM) and use SVM for microblog ranking. This approach is named as SVM-HF for convenience. Table 11 summarized the results on two datasets. It is seen that DNN outperforms SVM on both datasets. Actually, DNNs are more powerful in modeling large-scale and complex data, and thus more suitable for microblog sorting.

5. Conclusion

In this paper, we propose a hybrid microblog recommendation with heterogeneous features using deep neural network. (1) Two recommendation strategies have been proposed to obtain candidate recommended microblogs. The first recommendation strategy based on extended user interest tags obtains tags through users' microblog content and uses association rules for extending tags. The second recommendation strategy founded on user interest topics utilizes the topics links in microblogs to discover the interests of users. (2) The heterogeneous features are extracted from candidate microblogs to represent those microblogs. (3) The deep neural network framework is used to sort microblogs as recommended microblogs. Two datasets of the Sina Weibo and Twitter have been employed to conduct the experiments, and experimental results demonstrate that our algorithm achieves the state-of-the-art results. In the future, we plan to address the issue of microblog recommendation according to multi-modal information contained in the microblogs. In other words, deep features within the audios, the videos and the pictures are extracted to recommend microblogs.

CRediT authorship contribution statement

Jiameng Gao: Conceptualization, Methodology, Software, Investigation, Data curation, Writing - original draft. **Chunxia Zhang:** Conceptualization, Validation, Formal analysis, Resources, Review & editing, Visualization, Supervision. **Yanyan Xu:** Conceptualization, Validation, Resources, Review & editing, Supervision. **Meiqiu Luo:** Writing - review & editing. **Zhendong Niu:** Resources, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eswa.2020.114191.

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