Modeling User Intrinsic Characteristic on Social Media for Identity Linkage

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11

Most users on social media have intrinsic characteristics, such as interests and political views, that can be exploited to identify and track them, thus raising privacy and identity concerns in online communities. In this article, we investigate the problem of user identity linkage on two behavior datasets collected from different experiments. Specifically, we focus on user linkage based on users' interaction behaviors with respect to content topics. We propose an embedding method to model a topic as a vector in a latent space to interpret its deep semantics. Then a user is modeled as a vector based on his or her interactions with topics. The embedding representations of topics are learned by optimizing the joint-objective: the compatibility between topics with similar semantics, the discriminative abilities of topics to distinguish identities, and the consistency of the same user's characteristics from two datasets. The effectiveness of our method is verified on real-life datasets and the results show that it outperforms related methods. We also analyze failure cases in the application of our identity linkage method. Our analysis shows that factors such as the visibility and variance of user behaviors and users' group psychology can result in mis-linkages. We also analyze the details of the behaviors of some representative users to understand the essential reasons for their identity being mis-linked. We find that these users have high variance level in their behaviors. According to the above experimental results, we introduce a confidence score into identity linkage to provide information about the accuracy of the method results.

CCS Concepts: • **Human-centered computing** → **Social media**; • **Security and privacy** → *Privacy protections*;

Additional Key Words and Phrases: Social media, privacy issue, identity linkage, intrinsic characteristic, embedding method

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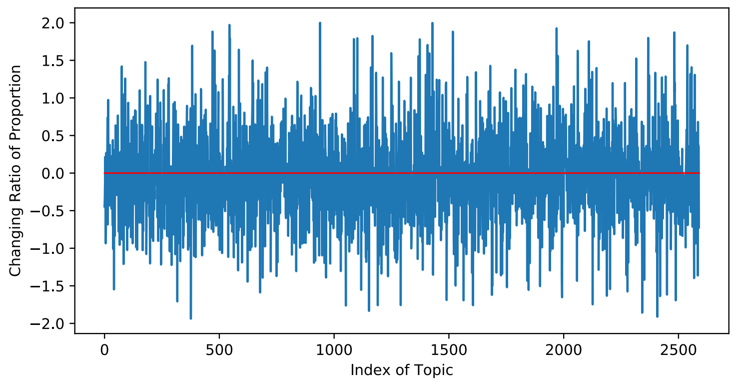
1 INTRODUCTION

The User Identity Linkage (UIL) problem refers to the problem of recognizing that two user identities from two different data sources actually refer to the same individual in real life [25]. The problem has recently received increasing attention from both academia and industry. It is of special concern for social communities because of privacy issues. It is also of critical importance for service providers to obtain deeper understanding of their customers from multiple perspectives to profile users on social media for better promotions or services.

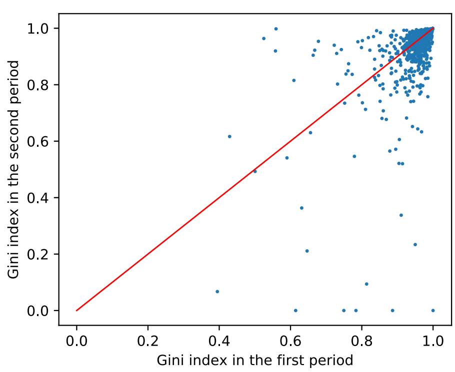
In this article, we focus on a setting in which we are given user behaviors collected during two time periods on the same social media platform. It is a common setting in UIL approaches that link identities via behavior data [8, 9, 27, 30]. It assumes that, in the first period, user identities are known, and in the second period, their identities are anonymized [22]. For example, user identities might be anonymized by using some privacy-preserving techniques for protection against identity linkage attacks [10]. A user's web behaviors may include activities such as browsing a piece of news on CNN, rating a film on MovieLens, or answering a question on Quora. Generally, such behaviors are relevant to some topics. For example, a user answered the question *How to evaluate Donald J. Trump be elected the 45th president of the United States* on Quora, and tags *Political* and *President Election* associated with this question can be included as topics of this user behavior. We refer to interactive activities with respect to a set of topics as *interactions*. Then a user behavior is thus characterized by all topics in the interactions of the user. Our goal is to answer whether users can be identified only by their interactions with respect to topics.

The identification of users based on their interactions with respect to topics requires addressing two challenges. One is the dynamic evolution of popular topics. As the popularity of topics changes with time, so do the user interactions. We collected some statistics on topic frequency among all user behaviors in two time periods and obtained two probability distributions over topics. Figure 1(a) shows the difference between the two probability distributions. The X-axis represents topics and the Y-axis represents the changing ratio of topic proportion, which is calculated as their difference divided by the average of topic proportions in the two periods. The red line can be seen as a reference for the case in which the popularity of topics does not change between the two periods. The results show that most topics have obvious changes, either in an increasing trend or in a decreasing trend. Thus, it is clear that popular topics vary a lot in different periods. As our problem is to distinguish user identities based on their behaviors, we also evaluate the discriminative abilities of topics. Considering the fact that many users pay almost the same attention to some specific topics, it is difficult to distinguish them against these topics. However, if a topic is of concern to only a few users, this topic would be helpful in identifying them. So, we adopt the Gini index to evaluate the discriminative abilities of topics, which is calculated as $1 - \sum_{i=1}^{m} p_i^2$, where p_i denotes the probability of the ith topic. It is often used as a measure of the impurity of data [12]. Figure 1(b) shows the Gini indexes of topics in two periods, where the X-axis represents the Gini index in the first period and the Y-axis represents the Gini index in the second period. Each point represents a topic. The red line is a reference for the case in which the Gini index of the topic does not change between the two periods. Most of the points are at some distance from the red line. The great difference between the two periods indicates that for most topics the discriminative ability on user identities has changed over time.

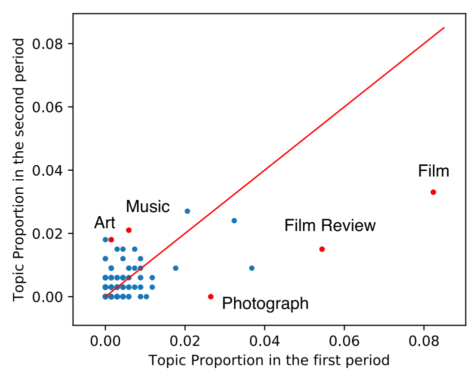
Another observation is the change of topics of interest for each user. Figure 1(c) shows the proportions of topics in a user's behaviors. The X-axis represents the topic proportion in the first period and the Y-axis represents the topic proportion in the second period. Each point represents a topic. The red line is a reference for the case in which the topic proportion does not change between the two periods. We can see that many points are at some distance from the red line, especially the points that have high proportions. It is easy to understand that the statistics over topics in the



(a) Changing ratios of topic proportions over two periods



(b) Gini indexes of topics in two periods



(c) Topic proportions in two periods from an user's behaviors

Fig. 1. The data are collected from the Zhihu website. The data consist of users' behavior data in a whole year period. Figure(a) shows the changing ratios of topic proportions in two periods. Figure(b) shows the Gini indexes of topics in two periods. Figure(c) shows, in a selected user's behavior records, the proportions of topics in two periods.

two periods are quite different and thus two identities cannot be linked by the similarity on the statistics over topics of interests.

To address the above challenges, this article introduces the concept of user intrinsic characteristic to identify the inner motivations implied in user behaviors. Consider the example in Figure 1(c). Note that, although the topics of interest for the user seem different, it does not mean that the user's interests have changed. We mark some topics in red to denote topics that have a high proportion in at least one period and the proportion has changed considerably. These topics are *film review*, *film*, *photograph*, *art*, *music*. From the point of view of an art lover, the characteristics of this user remain the same in these topics. Thus, our approach is to investigate the implicit semantics of topics by embedding each topic as a vector in a latent space and model users' intrinsic characteristics based on their interactions with topics. A topic representation is denoted by a d-dimensional vector, which can be learned from the training data. A user vector is the statistics on topics and then is mapped to the same latent space as topics. To learn the embedding representations of both topics and user characteristics, we apply a joint-objective optimization. The first optimization objective is to maximize the compatibility between topics with similar semantics and their discriminative ability with respect to identity recognition. We define the semantic relevance between a pair of topics as their compatibility. Topics co-occurring in a behavior share a higher compatibility score, and thus their representations should be close in the latent space. The discriminative abilities of topics reflect the differences of user interactions on topics. We take the correlation between topics as a regularization in vector compatibility learning. The second optimization objective is to maximize the consistency of two characteristics in different time periods for each seed user, which reflects the fact that the intrinsic characteristics of an individual often remain stable over time. Then, we adopt the learned embedding vectors to solve the task of identity linkage. We conduct experiments on two real-life datasets, and the results show that our method outperforms related methods.

We further investigate which factors negatively affect the ability of our model in recognizing some users. The most important element we found is the visibility of a user interaction trace. From the personal aspect, a user with fewer behavior records cannot be clearly profiled and thus this user may be mis-linked to another identity. From the perspective of crowds, a user who has a group psychology is more likely interested in hot topics and thus her profile tends to be confused with the profiles of a group of similar people, which may lead users in such group to be mis-linked to each other. Another important factor is the variance of user behaviors. We found that most of the unrecognized users have a higher variance in behaviors than the correctly recognized users. It is easy to understand that if a user's topics of interest change frequently, the statistics about his interaction behaviors cannot well reflect his intrinsic characteristics. Finally according to our findings, we introduce a confidence score to judge whether a given identity linkage is trustworthy, which is obtained by training a neural network using the above factors as features. The experiment results show that the accuracy of our method can be further improved.

The rest of the article is organized as follows. Section 2 discusses related works. Sections 3 and 4 present the formal definition of the UIL problem and the model of user intrinsic characteristics, respectively. We discuss in Section 5 the learning process of embedding representations. Section 6 presents the experimental results, and Section 7 discusses the failure cases in user identity linkage and our enhanced solution. Finally, Section 8 concludes the article.

2 RELATED WORKS

Our work is related to several areas, which we discuss in what follows.

2.1 Privacy and Identity Issues in Online Communities

Privacy and identity issues in online communities have attracted increasing attention upon the emergence of de-anonymization techniques, which match users in an anonymous datasets to real individuals. In recent years, organizations have been releasing more and more datasets obtained from online communities for use in different applications, such as business promotion and epidemic diseases prediction. These datasets often contain sensitive individual information, such as health histories and shopping transactions. Although these datasets are anonymized by techniques such as k-anonymization [6], recent research has shown that an adversary can use auxiliary information to de-anonymize users' records from correlated and publicly available datasets [23, 24]. Narayanan et al. first introduced this problem [23] and used film reviews in IMDB as auxiliary information to successfully re-identify a number of specific users in an anonymous Netflix dataset by comparing user activities in the two datasets. They also proposed a de-anonymization algorithm for a dataset of user relation networks, which is able to effectively re-identify users in the anonymized graphs with only a few auxiliary information [24]. All these methods are based on the the presence of overlapping information between the anonymous and auxiliary datasets. Unlike such work, our work focuses on the setting in which users' data are collected from two non-overlapping time periods. We present a method to model users' intrinsic characteristics to solve the de-anonymization problem.

2.2 Behavior-Based Identity Linkage

Behavior-based identity linkage has recently become an active research area in the field of social computing. Several papers report results of analyses based on statistical methods for user linkage based on behavior. Zang et al. analyzed a nationwide call-data record dataset and demonstrated that the most frequently visited locations can act as quasi-identifiers to re-identify users [30]. Gambs et al. introduced a Markov model to analyze the temporal evolution of mobility patterns of users [8, 9]. These data are collected from user mobile intelligent devices and thus reflect users' physical movements or real contacts. In comparison, in our context, that is, social media, user behaviors are more noisy and random, which make those previous analysis methods inapplicable. Unnikrishnan et al. proposed a statistical method for matching user identity based on browsing history [22, 27]. They preprocess item data as categorical types and model user behavior as statistics on these categories, where each user is formalized as a distinguished probability distribution pattern. The assumption behind such an approach is that each dimension of a random vector is independent from the others and each behavior follows an independent and identical distribution. However, in practice, such assumption does not always hold. For example, suppose that some news are related to the following topics: *Presidential Election*, *Trump* and *Political*. These topics are regarded as categorical data in the probability distribution but they are semantically related. Moreover, the behavior of reading a news about *Presidential Election* is probably followed by the behavior of reading a news about *Trump's Speech*, which is not an independent and identically distributed event. Understanding semantics of people's behaviors on social media sites is a complex task, requiring a series of systematic studies. Bakhshi et al. examine the relationship between social signals and the emotional valence of users' reviews on the online recommendation community Yelp [2]. Some methods in collaborative recommendation systems model users' preference on the Web as a latent semantic vector by matrix factorization [4, 15]. In our work, we also model users' intrinsic characteristics in a latent vector space. However, unlike previous work, we learn the latent representations of users by a quite different objective function.

2.3 User Linkage Across Social Media Platforms

A lot of research has focused on the problem of user linkage across social networks, which is highly related to our work. In social networks, information about user attributes and user relation networks can be used to link user identity across different social platforms. Some researchers have shown that it is possible to recognize user identities by the structure of their social networks. Korula and Lattanzi introduced a many-to-many mapping algorithm based on the degrees of unmapped users and the number of common neighbors with the help of anchor users [16]. Bartunov et al. proposed an approach based on the conditional random fields, referred to as Joint Link-Attribute (JLA) [3], which considers both profile attributes and network properties. Liu et at. proposed a heterogeneous behavior modeling method [18]. They combine user attributes, topic distribution (obtained by LDA [5], which is a generative probabilistic model for collections of discrete data such as text corpora), graph topology, and other information, and learn the mapping function by a multi-objective optimization to match user accounts from different social networks. Although these approaches show that jointly using user attributes and network structures can lead to better performance, such information is often unavailable in many online communities. So they are not appropriate for solving our problem. Amitay et al. investigated the problem of author detection over a collection of blog pages originating from different sources and written to serve different online functions [1]. They proposed a compression-based method to solve the problem.

Unlike their method that analyzes user generated content(UGC), we aim at analyzing the impact that the topics in users' web behaviors have in revealing their identities. We propose an embedding method that focuses on interpreting the semantics of user behaviors. Based on such semantics interpretation, we are then able to model users' intrinsic characteristics and identify users.

This article is an extended version of our conference paper [29]. With respect to the conference version, we add the analysis of factors that negatively affect the ability of our model to recognize some users. We developed the analysis with respect to both the personal aspect and the crowd aspect. The results of our analysis indicate that the visibility of user behaviors and user's group psychology are important factors. We also analyze details about some representative users' behaviors and find that a high variance level in user's behaviors is the essential reason for some users being mis-linked. We introduce a confidence score by which our method can determine whether to accept an identified linkage. The score is calculated by a neural network. The input features of neural network are based on the factors that we have found. The experiment results show that this method can further improve the accuracy of our model. Finally, we discuss the limitation of our model and some related social issues.

3 PROBLEM DEFINITION

Let U denote the user set in a given setting. For any user $u \in U$, his or her behaviors on social media are given as a sequence of topic interactions. Let $T = \{t_1, t_2, \ldots, t_{|T|}\}$ represent the set of all topics on a platform. The behavior sequence of u is denoted as $B_u = [\mathbf{b}_1, \ldots, \mathbf{b}_{|B_u|}]$, where each behavior $\mathbf{b}_i$ is a vector of size $|T|$, $\mathbf{b}_i \in \{0,1\}^{|T|}$. For each behavior $\mathbf{b}_i$, $\mathbf{b}_i(k) = 1$ indicates that $\mathbf{b}_i$ interacts with topic t_k; and $\mathbf{b}_i(k) = 0$ otherwise. Let $\mathbb{B}_1 = \{B_1, B_2, \ldots, B_{|\mathbb{B}_1|}\}$ and $\mathbb{B}_2 = \{B_1, B_2, \ldots, B_{|\mathbb{B}_2|}\}$ denote two sets of behavior sequences collected from two separate time periods. The UIL problem is defined as follows.

Definition 3.1 (User Identity Linkage (UIL)). Given a set of users U, and their behavior sequences from two time periods—the identity-labeled $\mathbb{B}_1$ and the anonymized $\mathbb{B}_2$, the UIL problem is to label behavior sequences in $\mathbb{B}_2$ with user identities in $\mathbb{B}_1$.

We summarize the notations used in the article in Table 1.

4 INTRINSIC CHARACTERISTIC MODELING

As we discussed in the Introduction, the challenges in addressing the UIL problem are topic popularity evolution and variations of similar topics. To address these challenges, we propose a user intrinsic characteristics model based on topic embedding (see in Figure 2). The model includes two parts: learning topic representation in latent space according to a joint-objective optimization and modeling user intrinsic characteristic against behavior related topics. Based on the intrinsic characteristics, we then verify user identity mapping relationships based on user vectors in the latent space.

To model the user intrinsic characteristics, we first learn the user behaviors by using some statistics over topics. For a user's behavior sequence B_u, let $\mathbf{d}_u \in R^{|T|}$ denote the probability distribution over topics, where the kth element of $\mathbf{d}_u$ is given by

$$\mathbf{d}_u(k) = \frac{\sum_{i=1}^{|B_u|} \mathbf{b}_i(k)}{\sum_{i=1}^{|B_u|} \sum_{j=1}^{|T|} \mathbf{b}_i(j)}, \ k = 1, 2, \ldots, |T|. \tag{1}$$

To interpret the semantics of topics, we embed them into a latent space. Each topic is represented as a d-dimensional vector representing some intrinsic characteristics. Let matrix $\mathbf{V} \in R^{|T| \times d}$ denote

Table 1. Notations in This Article

SYMBOL	DESCRIPTION
u	user
U	set of users
T	set of topics
t_i	the ith topic in T
B_u	behavior sequence of user u
$\mathbf{b}_i$	the ith behavior in B_u
$\mathbb{B}$	set of behavior sequences of users
$\mathbf{d}_u$	probability distribution over topics for user u
$\mathbf{v}_i$	embedding representation of topic t_i
$\mathbf{V}$	embedding matrix of topics in T
$\mathbf{p}_u$	intrinsic characteristic vector for user u
e	event of topic co-occurrence
c	normalization parameter for soft-max probability function
θ	parameters to be learned, including $\mathbf{V}$ and c
λ	weight parameter of regularization term
γ	preference parameter in joint objective optimization function

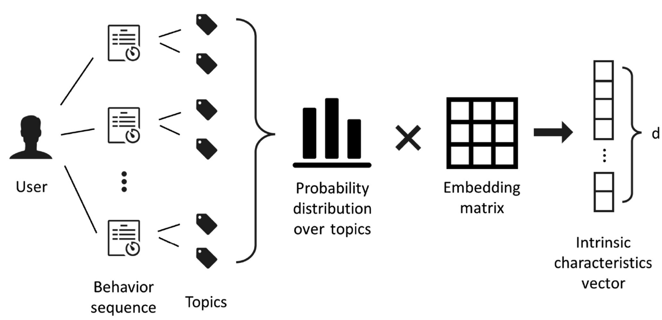


Fig. 2. Modeling user intrinsic characteristic based on topic embedding.

the embedding representations of topics,

$$\mathbf{V} = \begin{bmatrix} \mathbf{v}_1^\top \\ \mathbf{v}_2^\top \\ \vdots \\ \mathbf{v}_{|T|}^\top \end{bmatrix}, \tag{2}$$

where $\mathbf{v}_i$ is the embedding representation of topic t_i. Then a user's intrinsic characteristic is modeled as a linear transformation of the topic distribution $\mathbf{d}_u$, namely, $\mathbf{p}_u = \mathbf{V} \cdot \mathbf{d}_u$. Here, the topic embedding matrix $\mathbf{V}$ is called the transformation matrix. Modeling user intrinsic characteristics has two benefits. From the perspective of a single user, it helps in finding the common semantics in the dynamics of the topics of interest to the user and so to keep the consistency of one's traces in different time periods. From the global perspective, it helps interpreting the semantics of a newly emerged topic. Besides, since many topics are created by users, they might be noisy and sparse. The embedding method can reduce the dimension of topic space in user behaviors.

Based on the topic vectors, the UIL problem can be solved by three steps: Step (1) It models the intrinsic characteristics of each user behavior sequence in both $\mathbb{B}_1$ and $\mathbb{B}_2$. Step (2) It quantifies the similarity between two user vectors $\mathbf{p}_u$ from $\mathbb{B}_1$ and $\mathbf{p}'_u$ from $\mathbb{B}_2$. Step (3) For a target anonymized user $\mathbf{p}'_u$, it uses the nearest neighbor method to find the top k similar users in $\mathbb{B}_1$. There are many candidate distance functions, such as Euclidean distance and Cosine distance. We discuss in detail which distance function is the most appropriate for the UIL problem in the experiments section.

5 EMBEDDING LEARNING

In this section, we first discuss the joint-objective of the topic embedding learning process and then present the learning algorithm.

5.1 Joint-Objective

The embedding representations are learned by jointly optimizing two objectives. The first objective is to maximize the compatibility between topics. This is motivated by the fact that topics associated with the same content are often related. For example, on the Q&A website Quora, a user answered the question *How to learn deep learning*. The tags marked by users on the question are regarded as topics, such as *Machine Learning* and *Deep Learning*. Although they are different words, they are actually highly related with respect to semantics. That is, topics co-occurring in a behavior always have high compatibility. Consequently, their embedding representations should be close in the latent space. So, we introduce the compatibility score between a pair of topics as their semantic relevance. The co-occurrence of topics t_i and t_j is defined as an event e_{ij}. The compatibility score of e_{ij} is given by

$$S_\theta(e_{ij}) = \mathbf{v}_i \cdot \mathbf{v}_j, \tag{3}$$

where $\theta = \{\mathbf{V}\}$ denotes the set of model parameters.

When we consider the topic compatibility with respect to semantics, at the same time, we also take into account the discriminating ability on identity linkage, that is, how much a pair of topics contribute in distinguishing identities. We thus introduce the correlation coefficient between two topics as an adjustment parameter, which is learned from the statistics on these topics against all user behaviors. There are many correlation function candidates. For example, the Pearson correlation coefficient (PCC)[1] can be chosen as a measure, which is the linear correlation between two variables and ranges from −1 to 1, where value 1 indicates that they are totally positive linearly correlated, and value −1 indicates they are totally negative linearly correlated. Let PCC_{ij} denote the PCC between topic t_i and t_j. We refine the compatibility score between topics t_i and t_j as

$$S_\theta(e_{ij}) = \frac{\mathbf{v}_i \cdot \mathbf{v}_j}{\sigma(\text{PCC}_{ij})}, \tag{4}$$

where $\sigma(x) = \frac{1}{1+\exp(-x)}$. The introduction of the sigmoid function $\sigma(x)$ is to prevent the denominator from being zero.

Here is an example to illustrate why PPC is helpful for the discriminative ability of a pair of topics. Consider the pair of topics *Dota* and *LOL*, two popular computer games of the same type. They are occasionally mentioned together for comparison and discussion purposes. But in a more general case, they appear independently. Based on general knowledge about games, we know for example that a *Dota* game player seldom plays game *LOL*, and vice versa. If we learn their representations only by their co-occurrences, then they would be very close to each other and it would be difficult to distinguish two types of players. Since these two topics share a low PCC, based on their correlation parameter, their compatibility score can also reach a high value without their representations being too close.

[1] https://en.wikipedia.org/wiki/Pearson_correlation_coefficient.

Let $\mathbf{E}$ be the set of events, namely, all topic pairs, $|\mathbf{E}| = \frac{|T|(|T|-1)}{2}$. We adopt the soft-max function to model the occurrence probability of such an event:

$$P_\theta(e) = \frac{\exp(S_\theta(e))}{\sum_{x \in \mathbf{E}} \exp(S_\theta(x))}. \tag{5}$$

Let E_p denote the event dataset of all pair-wise topic co-occurrences extracted from the training data. The loss function of topic compatibility is defined as follows:

$$J_T(\theta) = -\sum_{e \in E_p} \log P_\theta(e). \tag{6}$$

The second objective is to maximize the consistency of the intrinsic characteristics of the same user. Recall the notions of user behavior sequences in two periods, $B_u \in \mathbb{B}_1$ and $B'_u \in \mathbb{B}_2$, respectively. For any two sequences B_u and B'_u belonging to the same user u, the corresponding latent vectors are $\mathbf{p}_u$ and $\mathbf{p}'_u$. Let $\mathrm{Dist}(\mathbf{p}_u, \mathbf{p}'_u) = -\mathbf{p}_u \cdot \mathbf{p}'_u$ be the expression for evaluating the distance between them. Given a set of seed users labeled in both periods, denoted as $U_{\mathrm{seed}} \subset U$, and B_u and B'_u from two periods belonging to the same user $u \in U_{\mathrm{seed}}$, our goal is to maximize the consistency of the same user and the difference between different users. The objective function for minimization is defined as follows:

$$J_C(\theta) = \sum_{u \in U_{\mathrm{seed}}, v \in U, u \neq v} \Big(\mathrm{Dist}(\mathbf{p}_u, \mathbf{p}'_u) - \mathrm{Dist}(\mathbf{p}_u, \mathbf{p}'_v)\Big). \tag{7}$$

We transform the function into the form of hinge loss and add a regularization term:

$$J_C(\theta) = \sum_{u \in U_{\mathrm{seed}}, v \in U, u \neq v} \Big(\max(0, \mathrm{Dist}(\mathbf{p}_u, \mathbf{p}'_u) - \mathrm{Dist}(\mathbf{p}_u, \mathbf{p}'_v) + \epsilon)\Big) + \lambda ||\mathbf{V}||_2^2. \tag{8}$$

Based on the above two objectives, we formulate the learning process of topic embedding as a joint-objective optimization. We model the objective function as a linear combination of the above two objective functions,

$$J_U(\theta) = \gamma \cdot J_T(\theta) + (1 - \gamma) \cdot J_C(\theta), \tag{9}$$

where $\gamma \in [0, 1]$ is a preference parameter. The optimal solution of parameters is

$$\theta^* = \arg\min_\theta J_U(\theta). \tag{10}$$

Since the size of $\mathbf{E}$ in Equation (5) is $\frac{|T|(|T|-1)}{2}$, calculating the normalization part is quite time consuming. To address this challenge, we use the Noise Contrastive Estimation (NCE) [11] to estimate the parameters in our objective function. NCE provides a principle for unnormalized statistical models, which has been applied in estimating language models, word embedding, and anomaly detection [7, 20, 21]. NCE considers the normalization constant as an additional parameter of the model. We first consider the normalization constant as a parameter c. The probability in Equation (5) is thus re-written as

$$P_\theta(e) = \exp(S_{\theta_0}(e) + c), \tag{11}$$

where $\theta = \{\theta_0, c\}$ represents the new parameters to be learned. In NCE, artificially generated noise data is added to the training data, and both parameters in probability density function and normalization constant can be estimated by discriminating the original data and noise data. The artificial noise distribution, denoted by $P_n(e)$, is the probability of an event e to be a noise sample. For each observed event e, we sample k noise samples $\{e'\}$ according to P_n. As for the chosen P_n, it can be some factorized distribution on the event space, which can be specified uniformly or computed by counting the frequency of topics in the dataset. In this article, we use the strategy of counting the frequency as it has been reported to be better [7]. We use $D = 1$ to indicate the event e in the observed data set $\mathbf{E}$ and $D = 0$ to indicate an event from the noise sample. The posterior probability is

$$P(D = 1|e, \theta) = \frac{P_\theta(e)}{P_\theta(e) + kP_n(e)} = \sigma(\log P_\theta(e) - \log kP_n(e)), \tag{12}$$

$$P(D = 0|e, \theta) = \frac{kP_n(e)}{P_\theta(e) + kP_n(e)} = 1 - \sigma(\log P_\theta(e) - \log kP_n(e)), \tag{13}$$

where $\sigma(x) = \frac{1}{1+\exp(-x)}$ is the sigmoid function. Now, we fit the model by maximizing the expectation of log-posterior probability over the mixture of observed samples and noise samples. The expectation is formulated as follows:

$$\begin{aligned} &E_{P_\theta}[\log P(D = 1|e, \theta)] + kE_{P_n}[\log P(D = 0|e, \theta)] \\ &= E_{P_\theta}[\log \sigma(\log P_\theta(e) - \log kP_n(e))] + kE_{P_n}[\log(1 - \sigma(\log P_\theta(e) - \log kP_n(e)))]. \end{aligned} \tag{14}$$

Then, the loss function of an event and its noise samples are formulated as

$$J_T(\theta) = -\log \sigma(\log P_\theta(e) - \log kP_n(e)) - \sum_{e'} \log\Big(1 - \sigma\Big(\log P_\theta(e') - \log kP_n(e')\Big)\Big). \tag{15}$$

The gradient function for $\mathbf{V}$ in $J_T(\theta)$ is

$$\begin{aligned} \frac{\partial J_T(\theta)}{\partial \mathbf{V}} =& [\sigma(\log P_\theta(e) - \log kP_n(e)) - 1]\frac{\partial S_\theta(e)}{\partial \mathbf{V}} \\ &+ \sum_{e'}\Big[\sigma\Big(\log P_\theta(e') - \log kP_n(e')\Big)\Big]\frac{\partial S_\theta(e')}{\partial \mathbf{V}}. \end{aligned} \tag{16}$$

Since the gradient function for c is similar to $\mathbf{V}$, for presentation simplification, we do not present it in this article. The gradient function for the other objective function $J_C(\theta)$ is formulated as follows:

$$\frac{\partial J_C(\theta)}{\partial \mathbf{V}} = \sum_{u \in U_{\text{seed}}, v \in U, u \neq v} \Big[\mathbf{d}_u\Big(\mathbf{d}_u'^\top - \mathbf{d}_v'^\top\Big) + \Big(\mathbf{d}_u' - \mathbf{d}_v'\Big)\mathbf{d}_u^\top\Big]\mathbf{V}. \tag{17}$$

5.2 Learning Algorithm

In our approach, we adopt the stochastic gradient descent (SGD) method for learning the parameters. To speed up the learning procedure, we propose a weighted joint-objective optimization algorithm based on Adam [14].

The Adam algorithm has been shown to work well in practice and to favorably compare to other adaptive learning methods. To make this article self-contained, we present the Adam steps in Algorithm 1. Our algorithm is summarized in Algorithm 2. In each iteration, to increase the efficiency of the computation, we randomly select an objective to update parameters $\mathbf{V}$ based on γ. And we sample a mini-batch of topic co-occurrences for objective J_T and sample a user from the seed user set for objective J_C. All parameters in Adam, except for $\mathbf{V}$, are independent from each other in the optimization process of the two objectives.

6 EXPERIMENTS

6.1 Datasets

We use two real datasets, *MovieLens* and *Zhihu*, to experimentally evaluate the proposed method. The statistics of the two datasets are listed in Table 2. Details are given below.

MovieLens Dataset. The *MovieLens 20M* dataset released by Grouplens [13] contains user rating and free-text tagging activities on *MovieLens*, a popular movie recommendation platform. It contains data created by 138,493 users between January 09, 1995 and March 31, 2015. Since most

Table 2. Statistics of Experiment Datasets

Datasets	# users	# topics	# events	# records
Zhihu	1,861	2,590	2,710,804	2,935,482
MovieLens	1,857	1,100	2,396,979	831,106

ALGORITHM 1: Adam SGD Algorithm

Require: α: Stepsize
Require: $\beta_1, \beta_2 \in [0, 1)$: Exponential decay rates for the moment estimates
Require: $f(\theta)$: Stochastic objective function with parameters θ
Require: θ_0: Initial parameter vector
$m_0 \leftarrow 0, v_0 \leftarrow 0, t \leftarrow 0$
while θ_t *not converged* **do**
    $t \leftarrow t + 1$
    $g_t \leftarrow \nabla_\theta f_t(\theta_{t-1})$(Get gradients w.r.t stochastic objective at timestep t)
    $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$
    $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2$
    $\widehat{m}_t \leftarrow m_t / (1 - \beta_1^t)$
    $\widehat{v}_t \leftarrow v_t / (1 - \beta_2^t)$
    $\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t / (\sqrt{\widehat{v}_t} + \epsilon)$
end
return θ_t (Resulting parameters)

ALGORITHM 2: Adam-based Joint-objective SGD Algorithm

Input: Size of mini-batch n; Preference weight γ; Training samples of topic co-occurrences **E**; Users set U and seed user set U_{seed}
Output: Embedding matrix V
Initialize V randomly
while $J_U(\theta)$ *not convergenced* **do**
    $x = random(0, 1)$ //generate a real number $x \in [0, 1)$
    if $x < \gamma$ **then**
        Sample n topic co-occurrence events e and $k * n$ noise events e' randomly
        Select $J_T(\theta)$ as objective function, perform an iteration in Adam to update **V**
    end
    else
        Sample a user u_i randomly
        Select $J_C(\theta)$ as the objective function, perform an iteration in Adam to update **V**
    end
end
return V

users remain active across 20 years, we select a part of the dataset that was created from April 2009 to March 2015, in which enough active users exist. Users' ratings on movies are considered as user behavior records. Each pair of movie and tag is associated with a relevance score ranging from 0 to 1, using the Tag Genome approach [28]. Considering the semantic correlation between tags and a movie, only tags with relevance scores higher than 0.7 are selected as topics on the movie. To evaluate our method for solving the UIL problem, we partition the selected dataset into two parts according to time period: the first part, $\mathbb{B}_1$, covers ratings from April 2009 to April 2012, and second part, $\mathbb{B}_2$, covers ratings from April 2012 to April 2015.

Zhihu Dataset. *Zhihu* is a Chinese Q&A website where questions are created, answered, edited, and organized by the platform audience. We crawled user behavior records of around 8,000 users from October 2015 to September 2016, such as answering questions, voting up answers, and so on. The tags marked on questions are selected as topics. The dataset is also partitioned into two parts: the first part, $\mathbb{B}_1$, covers behaviors from October 2015 to March 2016, and second part, $\mathbb{B}_2$, covers behaviors from April 2016 to September 2016.

6.2 Evaluation Metrics and Distance Metrics

For the UIL problem, a widely adopted evaluation metric is to calculate the top-k similar candidates for a target user and verify whether the true identity is within the results. In our setting, for each user $u \in \mathbb{B}_2$, we calculate its distances with users in $\mathbb{B}_1$ and rank them in an ascending order. The index function $hit(u)$ is used to verify whether user u is correctly mapped to the same identity in $\mathbb{B}_1$ within the top-k users. $hit(u) = 1$ indicates that u has been correctly linked, $hit(u) = 0$ otherwise. Let U_{test} denote the set of test users, the accuracy for identity linkage is defined as follows:

$$acc = \frac{\sum_{u \in U_{test}} hit(u)}{|U_{test}|}. \tag{18}$$

There are many candidate distance functions. Considering the semantics of user vectors, we adopt the Cosine distance and Euclidean distance in most experiments. Since some comparison methods adopt probability distributions as user vectors, we also adopt the balanced KL divergence as the distance metrics in this method. For example, Naini et al. adopt the balanced KL divergence for user matching problem. It performs well in their statistics method [22, 27]. We adopt their best results for the comparison. However, this metric is not suitable for the intrinsic characteristic vectors that we use in our approach. So this metric is only used in the comparison methods.

Another evaluation strategy is matching all users simultaneously, which can be seen as the problem of minimum-weight perfect matching on a bipartite graph. We do not choose this strategy for two reasons. One is the complexity of the problem. The well-known Hungarian algorithm can solve the perfect matching problem with complexity $O(n^3)$ [17] where n represents the number of users. As n increases, the computation cost becomes high. Another reason is that the *perfect matching* definition is not common in practice.

6.3 Comparison Methods and Settings

We compare the following state-of-art methods for UIL.

Statistics. In this method, the probability distribution over topics is seen as a user characteristic vector [22, 27], which is directly applied to the distance between users.

NMF. We also consider the topic model NMF [26], because it is similar to our method from the point of view of discovering latent characteristics. We define hyper-topic (or latent factor) as a higher level generalization among topics. We use the user-topic probability distribution matrix as the input to NMF. NMF outputs the relevance between user and hyper-topics, which is used as the user vectors for identity linkage.

E-T (Embedding with Topic compatibility). This method is a specific form of our proposed method, which learns the embedding using only the objective of topic compatibility and ability to distinguish users, namely, γ is equal to 1.

Table 3. Accuracy of Identity Linkage Compared with Different Methods

	Top-1			Top-5			Top-10		
Distance Metric	cos	Euc	KL	cos	Euc	KL	cos	Euc	KL
Zhihu Dataset									
Statistics	0.366	0.302	0.354	0.528	0.435	0.493	0.586	0.489	0.564
NMF	0.379	0.344		0.576	0.520		0.651	0.584	
E-T	0.419	0.441		0.603	0.623		0.672	0.695	
E-C	0.372	0.372		0.607	0.602		0.693	0.687	
E-TC	**0.497**	**0.469**		**0.695**	**0.664**		**0.762**	**0.730**	
MovieLens Dataset									
Statistics	0.059	0.055	0.043	0.162	0.142	0.113	0.229	0.209	0.153
NMF	0.065	0.058		0.156	0.143		0.248	0.219	
E-T	0.090	0.088		0.210	0.208		0.280	0.277	
E-C	0.104	0.100		0.246	0.237		0.336	0.322	
E-TC	**0.129**	**0.126**		**0.279**	**0.270**		**0.366**	**0.355**	

E-C (Embedding with Characteristic consistency). This method is the second form of our proposed method, which learns the embedding using only the objective of user intrinsic characteristic consistency. It means that γ is set to 0.

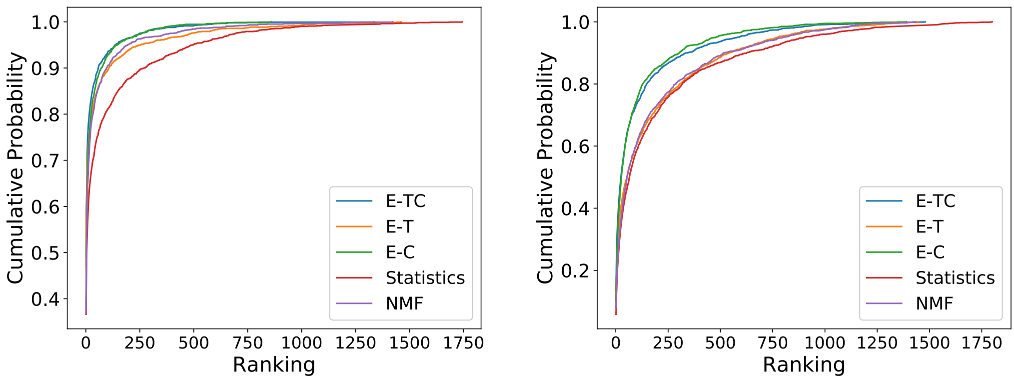
E-TC (Embedding with Topic compatibility and Characteristic consistency). This is the general form of our proposed method, which learns the embedding using a joint-objective optimization.

The dimension of the latent space in our methods and the numbers of hyper-topics in NMF are set to 50. All parameters to be learned are initialized randomly. For each observed topic co-occurrence, we draw one negative sample. To speed up the computation of the stochastic gradient descent, we set a mini-batch of 1024 for sampling topic co-occurrence events. For the experiments on the *Zhihu* dataset, we set a behavior threshold of 100, which means we choose users who have more than 100 behavior records in both periods. We explore how this threshold influences identity linkage in the experiments. We also filter out topics that occur less than 200 times. Other parameters are set as follows: $\epsilon = 10^{-1}, \gamma = 0.5, \lambda = 0$. In the *MovieLens* dataset, we set the behavior threshold to 50 and $\epsilon = 10^{-2}, \gamma = 0.1, \lambda = 10^{-5}$. We adopt a fivefold cross-validation in our experiments.

6.4 Results for Identity Linkage

We first verify the accuracy of our methods and other comparison methods. The results, reported in Table 3, show that method **E-TC** largely outperforms other methods. On top-1 identity linkage, the accuracy of **E-TC** reaches nearly 50% in *Zhihu* dataset and nearly 13% in *MovieLens* dataset, respectively, which is 12% and 6% higher than the NMF method. On top-5 and top-10 linkage, the accuracy of the **E-TC** methods outperforms on both datasets. Furthermore, in the *MovieLens* dataset, an increasing value for k enhances the accuracy of the **E-TC** method compared with the other methods. This good performance shows that although the learned characteristics of users cannot guarantee an exact identity matching, they are able to provide good approximations for recognizing a user.

When we use only a single objective to learn the embedding, namely, methods **E-T** or **E-C**, the accuracy is still higher than the accuracy of baseline methods on both datasets. It is interesting to



(a) CDF of ranking in Zhihu (b) CDF of ranking in MovieLens

Fig. 3. The CDF of ranking of users with themselves in different methods. The X-axis corresponds to the ranking of true identity linkage. The Y-axis represents the cumulative distribution of users, which means the proportion of users whose ranking is less than the value in the X-axis. Both figures indicate that introducing seed users (E-TC, E-C) improves the learning of the embedded user behavior semantics.

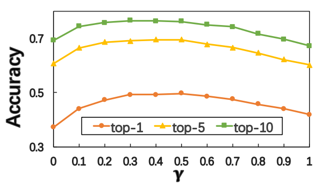
notice that in the *Zhihu* dataset under the Cosine distance, the **E-T** method outperforms the **E-C** method in the case of top-1 linkage. But as k increases, the **E-C** method gradually outperforms the **E-T** method. Such a result indicates that the objective of topic compatibility is quite helpful when performing accurate identity linkage, and the objective of characteristic consistency makes a user's trace more identical from the global perspective.

When comparing different distance metrics, there is no obvious difference between Cosine and Euclidean distances. In most cases, the Cosine distance performs slightly better than the Euclidean distance except in the *Zhihu* dataset by the **E-T** method. So, we adopt the Cosine distance metric in the rest of the experiments.

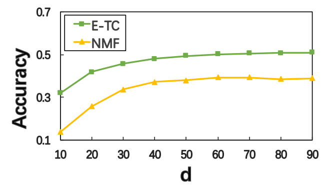
Although our methods cannot exactly link every user identity, they do reduce the difficulty in recognizing a specific user from a large user set. To have a clear explanation of such a result, for each anonymized user $u \in \mathbb{B}_2$, we calculate the distance between u and every user $v \in \mathbb{B}_1$, and count the ranking of his or her true identity. The smaller the ranking, the better the linkage performance. Figure 3 shows the Cumulative Distribution Function(CDF) curve on the rankings for the whole test dataset. We can see that, in both datasets, the **E-TC** method performs the best, shown as the fast rising curve, followed tightly by the **E-C** method. Such results show that introducing seed users provides more background knowledge; thus the embedding method can learn more comprehensive semantics from user behaviors. Since the **E-T** method does not introduce such background knowledge, it performs worse than the other two.

6.5 Influence of Parameters and Settings

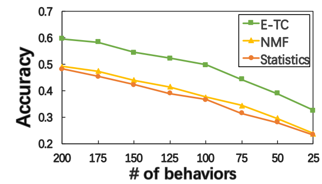
We first analyze the preference parameter γ, which is the trade-off term for the two learning objectives. Figure 4(a) shows the performance for different values of γ on the *Zhihu* dataset, where $\gamma = 0$ indicates using only the characteristic consistency objective, and $\gamma = 1$ indicates using only the topic compatibility objective. We can see that when γ is around 0.3–0.4, our method performs best. Figure 4(d) shows the performance for different values of γ in the *MovieLens* dataset. Our method performs best when $\gamma = 0.1$. Such results show that, in the *MovieLens* dataset, tags are not so semantically relevant as in the *Zhihu* dataset. Consequently, the results show the small importance of topic compatibility in optimization.



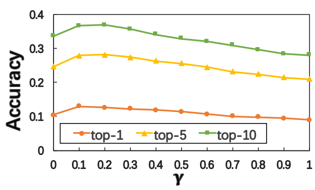
(a) Influence of γ in Zhihu



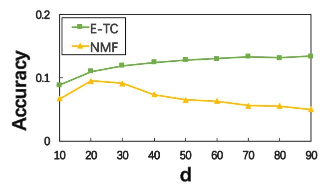
(b) Influence of d in Zhihu



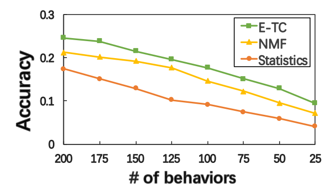
(c) Influence of behavior threshold in Zhihu



(d) Influence of γ in MovieLens



(e) Influence of d in MovieLens



(f) Influence of behavior threshold in MovieLens

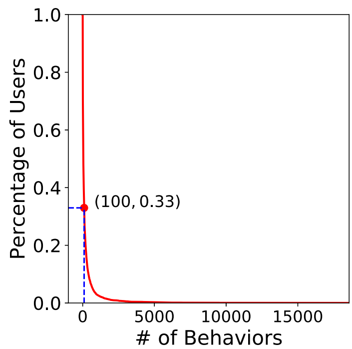
Fig. 4. Influence of parameters and settings and comparison with other methods on the two datasets. Figures (a, d) show the performance with respect to γ. Figures (b, e) show the performance with respect to d. Figures (c, f) show the performance with respect to behavior threshold. The optimal value that leads to the best performance is dependent on the dataset for all parameters. Our E-TC method outperforms the other methods consistently.

Then, we analyze the impact of the embedding dimension parameter d. As a comparison, we choose the same dimension as the number of hyper-topics in the NMF method. Figures 4(d) and 4(e) show the performance with respect to d for the two datasets. We can see that for the *Zhihu* dataset, the accuracy increases fast for both methods when d is less than 50 and becomes stable after d reaches 50. In the *MovieLens* dataset, the accuracy of the **E-TC** method increases fast when d is smaller than 40. But for the NMF method, the peak accuracy is at about $d = 20$. Since a larger d means more computation, in practice, we should take into account both accuracy and computation cost. In most of the experiments reported in this article, we choose d as 50 and 40 for the two datasets.

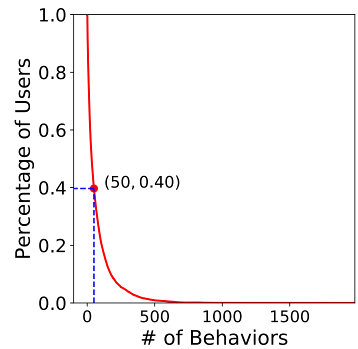
We also analyze how the number of user behaviors influences identity linkage. Figures 5(a) and 5(b) show the statistics about the number of behaviors in the two datasets, where the X-axis represents the number of behaviors, and the Y-axis represents the proportion of users whose number of behaviors is higher than a given threshold in both periods. We can see that the number of user behaviors in both datasets follows a long-tail distribution. A large amount of users have only a small amount of behaviors. We conduct our experiments on different settings for the behavior threshold; the results are shown in Figures 4(c) and 4(f). As the behavior threshold decreases, the accuracy decreases, since a large amount of users with a small amount of behaviors are taken into account. This makes it difficult to learn user intrinsic characteristics from a small quantity of behaviors. However, our **E-TC** method outperforms the other methods consistently.

6.6 Understanding Semantics of Topic Embedding

To provide more understandable results for other applications, we evaluate the semantics of embedding from two perspectives: topic relevance and user intrinsic characteristics. To give an intuitive view on the meanings of topic embedding, we first use the t-Distributed Stochastic Neighbor Embedding (t-SNE) technique [19] to find 2d coordinates of the original topic embedding in the *Zhihu* dataset. t-SNE is a technique for dimensionality reduction particularly well suited for the



(a) # of behaviors in Zhihu



(b) # of behaviors in MovieLens

Fig. 5. Statistics on the user behavior quantity. The X-axis represents the number of behaviors, and the Y-axis represents the proportion of users whose number of behaviors is higher than a given threshold in both periods. We can see that users in both datasets follow a long-tail distribution. The selected behavior threshold in this article is marked by the red point.

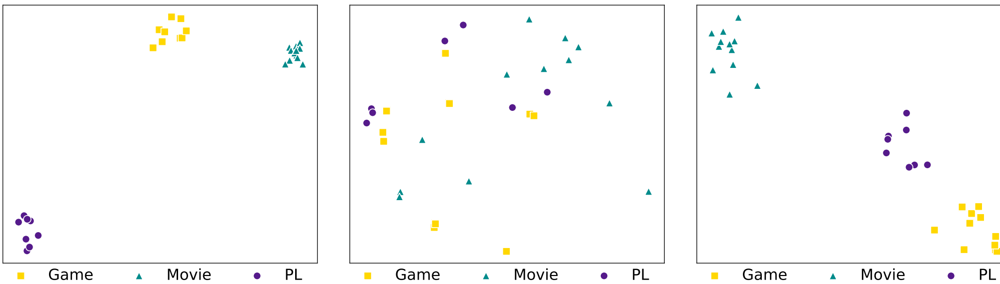
Table 4. Selected Topics in Three Themes

Theme	Topics
Game	Overwatch, LOL, Dota2, Hearthstone, Dota, MOBA, Clash of Clans, Steam Minecraft, iOS Game, Game Design
Movie	Hongkong film, micro film, Douban film, Chinese film, American film, horror film Japanese film, film, Hollywood film, Korea film, science fiction film
Programming Language	c/c++, JavaScript, JAVA, Python, PHP, C#, Node.js, C

visualization of high-dimensional datasets. We select topics from three themes, which are *Game*, *Movie*, and *Programming Language(PL)*, respectively. Details about the selected topics are reported in Table 4. We color topics according to their themes. We expect points with the same color to be clustered together, and each point is be distinguished from others.

Figure 6(a) shows the embedding learned by the **E-T** method. We can see that the majority of topics in the same theme are clustered quite closely. There are clear boundaries between clusters of different themes. But topics in the same theme cannot be distinguished from each other. The reason is that when using method **E-T**, we learn semantics of topics based on their compatibility, which is modeled based on the co-occurrences of topics. Our objective is to let the embedding of co-occurred topics be as close as possible. However, each topic has its own semantic, which is not exactly the same of similar topics. Using only the information about topic co-occurrence seems not enough to comprehensively learn topic semantics. Figure 6(b) shows the topic embedding learned by the **E-C** method. We can see that topics are roughly clustered together without clear boundaries between them. The reason is that the **E-C** method considers user characteristic consistency. The topics of interest to the same user are learned to be close in their vectors. Since this method uses the seed users rather than the platform population, it may lead to classify irrelevant topics as close due to some users' occasional activities.

The semantics learned by the **E-TC** method overcomes the shortcomings of methods **E-T** and **E-C**. Figure 6(c) shows the topic embedding learned by the **E-TC** method. We can see that topics in the same theme are clustered together and the boundaries between clusters are obvious. It is



(a) Embedding by E-T (b) Embedding by E-C (c) Embedding by E-TC

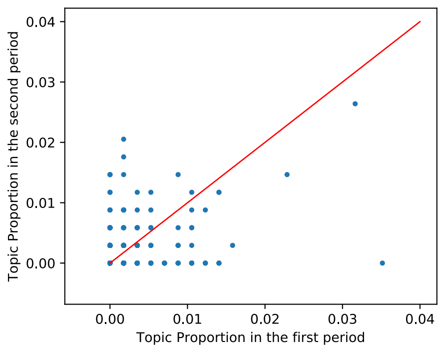
Fig. 6. The 2d coordinates representations of the embedding of selected topics for three methods. Topics selected from the theme of *Game*, *Movie*, and *Programming Language* are labeled by yellow square, green triangle, purple solid circle, respectively. We can see that the results of dimensionality reduction of the three methods are quite different.

Table 5. Top 10 Topics Concerned by Three Users in Two Time Periods

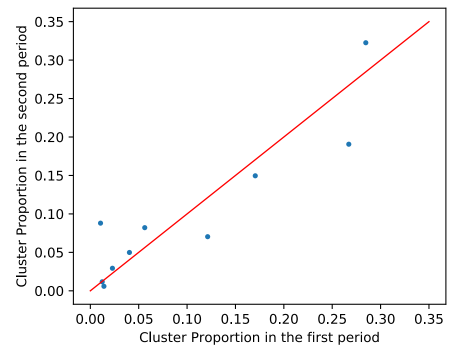
	In the first time period	In the second time period	Ranking promotion
User 1	Living, Internet, History **Artificial Intelligence**, Society Experience, **Deep Learning** **Google**, **Computer**, **Baidu**	Internet, **Math**, Health **Alibaba**, **Technology** **Didi Travel(online hailed car)** Law, History, **Google**, **Travel O2O**	1,200
User 2	Living, Literature, Experience Psychology, Film, Novel Interpersonal communication **Programmer**, society, survey question	**Python**, **Program**, Living Medical Science, Health, **Programmer** **Crawler(Computer Networks)** Life, Life history, Internet	912
User 3	Living, **Psychology**, Experience Homosexual, Variety Show, **Art** **Photograph**, **Mentality**, Film survey question	**Design**, Japan, Living **Drawing**, **Art**, **Graphic Design** **Psychology**, **Photoshop** **Photograph**, Film	652

worth noting that clusters for *Game* and *Programming Language* are closer than the cluster *movie* when the **E-TC** method is applied. Such a result reflects the fact that the background knowledge about seed users reveals that programmers are more likely to enjoy games, which is not shown by results obtained by the **E-T** method.

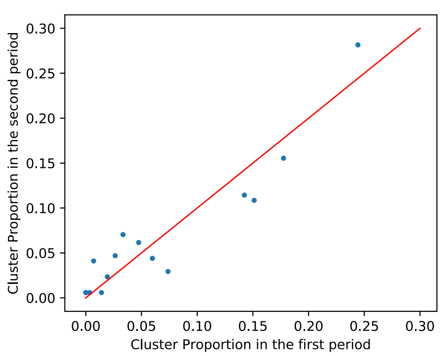
We now discuss how the semantics solve the UIL problem compared to other methods. We analyze the representative users who are well recognized with great ranking promotion by our method than the statistics method. We choose three such users from the *Zhihu* dataset and list the top-10 topics of interest for each one in Table 5. Although some common topics such as *Living*, *Experience*, *Life*, and *Internet* are the same, most topics of interest for the same user in the two periods vary a lot. That is why the statistics method cannot recognize them correctly. But we can identify some intrinsic characteristics from the semantics related topics (highlighted by colors in the table). For example, the first user is probably employed in an Internet company according to the topics in red, and the blue topics show his/her interests in the domain of artificial intelligence. The second user is probably a network programmer according to the topics colored in blue. For the third user, the blue topics indicate that he or she is a graphic designer, and red topics indicate the interests in psychology.



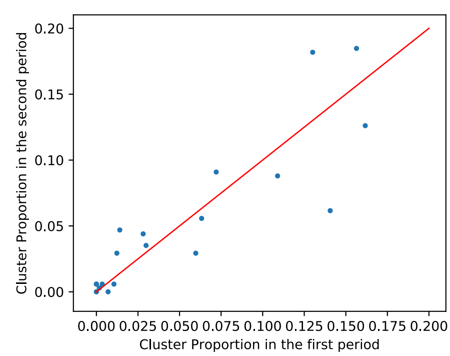
(a) original topics



(b) 10 clusters



(c) 15 clusters



(d) 20 clusters

Fig. 7. A user's behaviors in two time periods are described in four forms of probability distributions over: (a) original topics; (b) 10 clusters; (c) 15 clusters; and (d) 20 clusters. The X-axis represents proportion in the first period and the Y-axis represents proportion in the second period. The red line is a reference for the case in which proportion does not change between two periods.

To further understand how the semantics of embedding help in recognizing a user, we compare a user's behavior pattern in different modes. First, we cluster all topics into k classes based on their embedding representations and then represent each user as a probability distributions over these classes. An example is given in Figure 7. For the above first user, his or her behaviors are modeled as the probability distributions over topics and clusters, for $k = 10$, $k = 15$, and $k = 20$, respectively. The X-axis represents the proportion in the first period and the Y-axis represents the proportion in the second period. The red line is a reference for the case in which the proportion does not change between two periods. In Figure 7(a), each point is a topic. In Figures 7(b)–7(d), each point represents a cluster. We can see that points representing clusters are closer to the red line than points representing topics. The results show that the variants on user's topics of interest between two periods have been highly reduced under the learned embedding representation, and they are similarly consistent on different k settings. As we expected, it indicates that the embedding method learned the consistent intrinsic characteristics implied in user behaviors.

7 DISCUSSION

In this section, we first discuss the factors that negatively affect the correct linkage of users. Then, we select some representative users who are mis-linked and analyze their fine-grained behaviors

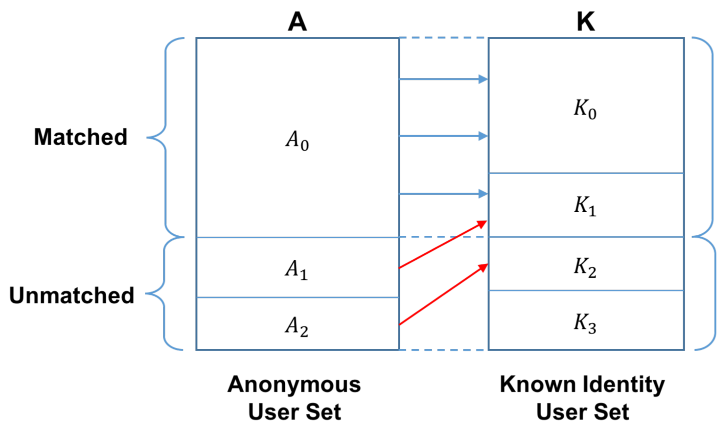


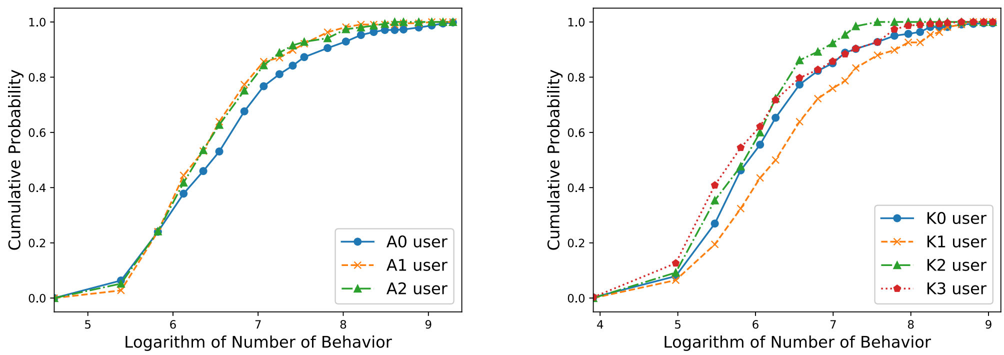
Fig. 8. All users in two sources are divided into seven types.

to better understand the specific semantics leading to these failures. Finally, we introduce a model for assessing the trustworthiness of linkages.

7.1 Factors Leading to Linkage Failures

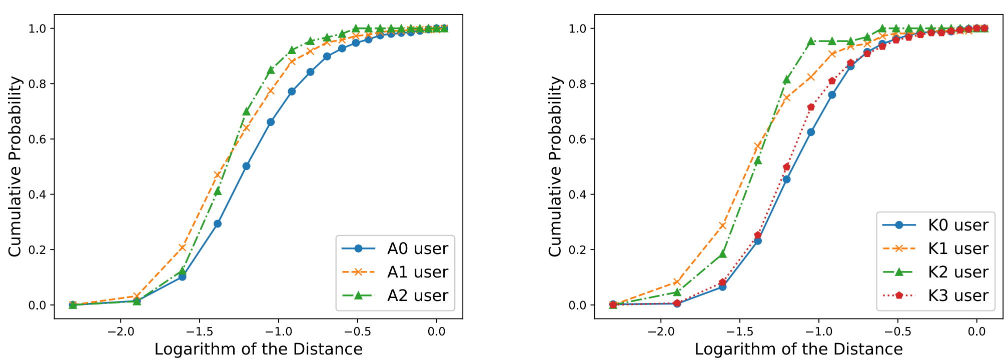
Although our method improves the performance of UIL compared to some baseline methods, there are still users that are not correctly linked. These users are called *unmatched users*. To understand the reasons for such failures, we have analyzed a set of users in the Zhihu dataset; each such user has more than 200 behavior records. We first classify the users from two sources into seven types, as shown in Figure 8. Let **A** denote the source dataset with anonymous users and **K** denote the source dataset where users' identities are known. **A** is classified into three partitions according to whether the users can be recognized. The users who are correctly linked are called matched users, denoted by A_0. The other users in **A** are called unmatched users; these users are further partitioned into two categories denoted by A_1 and A_2. Users in A_1 are incorrectly matched to known users who are already correctly matched by the users in A_0. Such subset of **K** is denoted by K_1. The users in A_2 are mismatched to the identities in **K** for which no correct linkage is found by our method, denoted by K_2. The subset K_0 of **K** consists of the correctly matched users except for users in K_1. K_3 denotes the set of unmatched users who are not associated with any linkage. Blue arrows in the figure denote the correct linkages and red arrows denote false linkages. We then investigate the reasons for failures in solving the UIL problem from both the personal perspective and the crowd perspective and compare these different types of users.

The first factor we consider is the "behavior visibility" of users. It is easy to understand that a user with less behavior records cannot be clearly profiled. To verify how much the number of records in a user behaviors influences the correct identity linkage for the user, we calculate the cumulative distribution function (CDF) of users against the number of behaviors. The results are shown in Figure 9, where seven CDF curves denote the different types of users, the X-axis denotes the number of behaviors and the Y-axis denotes the proportion of users whose number of behaviors is larger than the value on the X-axis. The faster the curve rises, the more users have few behavior records. Figure 9(a) shows the CDF curves for users in the source dataset **A**. We can see that the unmatched users in either A_1 or A_2 tend to have a lower number of behavior records than the matched users in A_0. Figure 9(b) shows the CDF curves for users in source **K**, where we can see that the unmatched users(K_2, K_3) tend to have less behavior records. It is worth noting that many users in K_1 have much more behaviors, which is the opposite conclusion. So, we need to mine the semantics behind the K_1 phenomenon.



(a) CDF of Number of behaviors for Users in Source A (b) CDF of Number of behaviors for Users in Source K

Fig. 9. The CDF curve of the number of behaviors for users of different types. Figure (a) is for users in source **A**. Figure (b) is for users in Source **K**. The X-axis denotes the number of behaviors. The Y-axis denotes the proportion of users whose number of behaviors is larger than the value on the X-axis.



(a) CDF of Distance to Centroid for Users in Source A (b) CDF of Distance to Centroid for Users in Source K

Fig. 10. The CDF curve of the distance to the cluster centroid for users of different types. Figure (a) is for users in source **A**. Figure (b) is for users in Source **K**. The X-axis denotes the distance to the cluster centroid. The Y-axis denotes the proportion of users whose number of behaviors is larger than the value on the X-axis.

We thus analyze the group psychology of users. Generally, data in the behavior datasets we have used indicate that there are users that have a wide range of interest. As a result, users are clustered. A reason for explaining linkage failures is thus that a user within a cluster is more likely to be confused with others in the same cluster, which might explain why users in A_1 are linked to users in K_1. So, we introduce a measurement of the distance for a given user to the nearest cluster centroid. We adopt the K-MEANS method to cluster users into k classes based on their intrinsic characteristics vectors and calculate the distance between each user and the centroid of the class the user belongs to. Figure 10 shows the CDF curve of the distance for users of different types, where the X-axis denotes the distance to cluster centroid and the Y-axis denotes the proportion of users whose distance is larger than the value in X-axis. The setting in this experiment is $k = 30$. The faster the curve rises, the more are the users close to the center of clusters. Figure 10(a) shows the CDF curve for users in source **A**. We can see that the unmatched users(A_1, A_2) are closer to cluster centroids than matched users(A_0). Such results indicate that users who have a group psychology are more likely to be mis-linked. Figure 10(b) shows the CDF curve for users in source **K**. We find

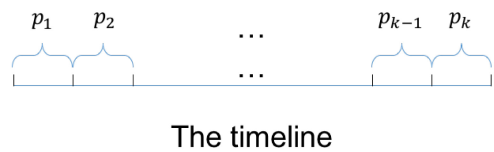


Fig. 11. User's continuous temporal behavior patterns.

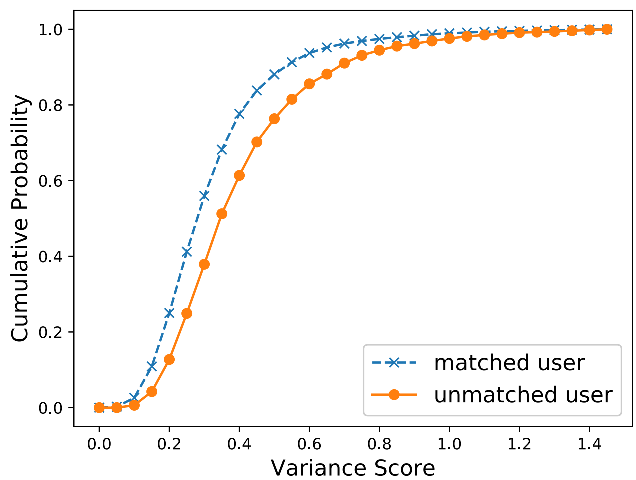


Fig. 12. The CDF curve of behavior variance score for matched users and unmatched users. The X-axis denotes the variance score and the Y-axis denotes the cumulative distribution probability.

that users in K_1 and K_2 are closer to the center of clusters. Such result explains why unmatched users are mis-linked to those clusters.

Another important factor that highly influences the correct linkage of an identity is the variance of users' behaviors. If a user's topics of interest change frequently, then it is difficult to model the user's identity as statistics against topics, as our method does. The inconsistency of the user's interactions with respect to topics makes it hard to correctly link the user. To verify the impact of this factor, we analyze the fine-grained periods of user behaviors, as shown in Figure 11. In the experiments, we adopt $k = 6$ periods, each of which maps to about one month.

The temporal vector of a user for each period is computed against the topics and mapped to the latent space, denoted by $\mathbf{p_i}$. Let $\bar{\mathbf{p}}$ denote the average of k vectors. We introduce the variance score as the metric for user behaviors. Formally,

$$variance\_score = \frac{\sum_{i=0}^{k} ||\mathbf{p_i} - \bar{\mathbf{p}}||_2^2}{k}. \tag{19}$$

The CDF curves of the variance score for both matched users and unmatched users are shown in Figure 12, where the X-axis denotes the variance score and the Y-axis denotes the cumulative probability. We can see that the behaviors of unmatched users vary more than the behaviors of matched users. Such results show that uncertainty in users' behavior can lead to linkage failures.

7.2 Identification of Trustworthy Linkages

To better assess user identity linkages, we introduce the problem of identity linkage trustworthiness determination. This problem is formalized as follows:

Table 6. Features Used in the Neural Network for the Trustworthiness Assessment of Identity Linkages

Notation	Feature
n_u, n_v	Numbers of Behaviors of Users
var_u, var_v	Variance Scores of Users
std_var_u, std_var_v	Standard Deviation of the Variance Sequence of Users
$center\_dist_u, center\_dist_v$	Distances to Cluster Centroid of Users
$cosine\_dist(\mathbf{p}_u, \mathbf{p}_v)$	Cosine Distance between Users
$euclidean\_dist(\mathbf{p}_u, \mathbf{p}_v)$	Euclidean Distance between Users

Definition 7.1 (The Trustworthiness Determination (TDP)). Let u and v be two users selected from some datasets. Let B_u and B_v denote the behavior sequences of u and v, respectively. The TDP problem is to determine the trustworthiness of the linkage between B_u and B_v.

The idea is that once we find a linkage for an anonymous user, we can decide whether to accept or discard it by checking its trustworthiness. The hardness of this problem is the same as the UIL problem, since once we have such comparable scores for all linkages, we can choose the ones with the highest score from all candidates. To make the verification practical, we perform a post-processing of the results produced by our method to compute a confidence score for each linkage by using a neural network. The linkage features used in the neural network are listed in Table 6. The neural network has two hidden layers and each hidden layer has 10 nodes. We adopt the ReLU function as the activation function for the hidden layers and sigmoid function for the output layer. If the output confidence score is equal or larger than 0.5, then the linkage is considered trustworthy. Otherwise it is rejected. We randomly select 20% linkages for training the neural network. When using the confidence score, the accuracy increases to 87%. Here, the accuracy indicates the proportion of the correct linkages we accept as trustworthy. It is a great improvement compared with the accuracy of 62% obtained when the confidence score is not used.

7.3 Limitation of Our Method

Although the introduction of the user intrinsic semantics helps in understanding user behaviors, our behavior model has still some limitations. The assumption of our model is the consistency of the intrinsic characteristics embedded in user behaviors over time, so that we can match user identities by the statistics on topics that relate to user behaviors. But in practice, not every user keeps a consistent behavioral semantic pattern. To show this, we analyze users' behaviors in fine-grained periods, as we have done in the previous section, to obtain the temporal patterns in the series of periods, denoted by $\mathbf{p_1}, \mathbf{p_2}, \ldots, \mathbf{p_k}$, respectively. Here, we set $k = 12$. The change δ_i of the behavioral semantic pattern between $\mathbf{p_i}$ and $\mathbf{p_{i+1}}$, called variance, is calculated as

$$\delta_i = Distance(\mathbf{p}_i, \mathbf{p}_{i+1}). \tag{20}$$

For a given series of periods, the variance sequence of a user is denoted as $[\delta_1, \delta_2, \ldots, \delta_{k-1}]$.

We select three representative users, one matched user and two unmatched users, and plot their variance sequences in Figure 13. We can see that the variances of the matched user are stable, while for unmatched users, the curves skew a lot. For example, consider the unmatched user 1; for this user, the variances in the first three periods are very high, but in the other periods, they remain relatively stable. The reason could be that the user was not sure about his/her specific topics of interest and thus it took a while for the user to stabilize his/her behavior. Perhaps this was a user who had just joined the networks and thus at the beginning just started exploring the discussions

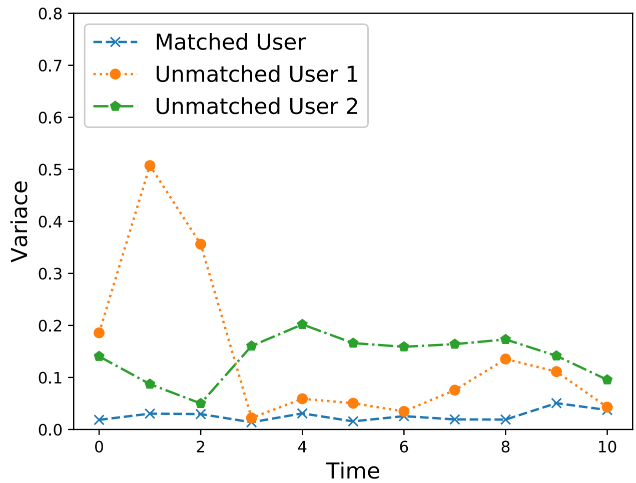


Fig. 13. The variance sequence of three representative users. The X-axis denotes the time and the Y-axis denotes the variance of behavior.

and topics. Now consider unmatched user 2; for this user there are consistently high variances of behaviors over time. Such behavior may be due to interest changes that are so frequent that make it difficult to trace the user only by analyzing the user's interaction behaviors. Since the core of our method is linking a user based on the consistence of behavior semantics, it does work on either of the above two cases.

7.4 Social Issues

Privacy Issue. The effectiveness of our method highlights the privacy and identity issues in online communities. It proves that users have be careful about their behaviors to avoid being deanonymized. From another perspective, for online service providers, they should provide more protection on users' private information.

Economic Issue. As discussed early in this article, the introduction of seed users brings a lot of background knowledge that helps us in better understanding the intrinsic characteristics of users. But keeping track of a user requires not only recording the user's behaviors but also more details on the user' identity, such as IP address, timestamp, MAC address of mobile devices, and so on. This results in high costs. Therefore an important issue is how to select seed users to improve the performance under a given computation and seeding budget.

8 CONCLUSION

In this article, we have proposed an approach to the problem of user identity linkage on social media by discovering user intrinsic characteristics. We propose an embedding method to understand the semantics of topics related to user behaviors. The embedding representations of topics are learned by a joint-objective optimization, which tries to maximize the topic compatibility, discriminating ability, and characteristic consistency of the seed user. Experimental results on two real social media datasets show that our method outperforms other related methods. We also analyze the semantics of embedding representations from both topic view and user behavior perspective to provide an interpretation for our methods. To better understand which factors influence the recognition of an identity, we further analyze the failure cases. Our analysis shows that factors that negatively affect our method include the visibility and variance of user behaviors, as well as the group psychology. We also propose a function for assessing the trustworthiness of identity linkages to improve the accuracy. Finally, we discuss the limitation of our model and some related social issues. As a future work, we plan to investigate the identity linkage problem on different social media platforms. Since users may have different interests and behave differently on different platforms, understanding topics from different sources and embedding them into the same latent space will be more complex and challenging.

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