Cognitive Inference of Demographic Data by User Ratings

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Abstract—Cognitive inference of user demographics, such as gender and age, plays an important role in creating user profiles for adjusting marketing strategies and generating personalized recommendations because user demographic data is usually not available due to data privacy concerns. At present, users can readily express feedback regarding products or services that they have purchased. For example, users often rate mobile apps, restaurants, and movies, and this process has generated a large amount of user ratings data. During this process, user demographics are concealed, but the data has never yet been successfully utilized to contribute to the cognitive inference of user demographics. In this paper, we investigate the inference power of user ratings data, and propose a simple yet general cognitive inference model, called rating to profile (R2P), to infer user demographics from user provided ratings. In particular, the proposed R2P model can achieve the following: 1) Correctly integrate user ratings into model training. 2) Infer multiple demographic attributes of users simultaneously, capturing the underlying relevance between different demographic attributes. 3) Train its two components, i.e. feature extractor and classifier, in an integrated manner under a supervised learning paradigm, which effectively helps to discover useful hidden patterns from highly sparse ratings data. We introduce the motivation and objectives in incorporating user ratings data into the research field of cognitive inference of user demographic data, and detail the model development and optimization process for the proposed R2P. Extensive experiments are conducted on two real-world ratings datasets against various compared state-of-the-art methods, and the results from multiple aspects demonstrate that our proposed R2P model can significantly improve on the cognitive inference performance of user demographic data.

Index Terms—User demographics, cognitive inference, rating data, feature extractor, classifier, relevance, representation learning.

1 INTRODUCTION

User demographics, such as information regarding the genders and ages of users, play an important role in areas such as marketing strategy adjustment [1] and personalized recommendations [2]. However, it is usually not available due to data privacy concerns. As a result, the cognitive inference of user demographics has emerged as it can utilize kinds of public available user data to infer user demographics statistically. For instance, a major US retail network employed customer shopping records to infer pregnancies in its female customers and send them well-timed and well-targeted offers [3]. Furthermore, in academia some recent studies suggest that user demographics are predictable from various behavioral records of users, such as web browsing [4], social media [3], [5], and mobile data [6].

With the development of mobile internet and E-commerce, as well as deciding whether or not purchase a product or service, users may also readily express feedback regarding these, such as book reviews or movie ratings. Taking rating data as an example, it is known that users often rate services such as mobile apps, restaurants, and movies, and this process generates a significant amount of user ratings data. The collected user ratings data may conceal user demographics that remain to be extracted. This is expected to provide a new direction of study for improving on the performance of user demographic inference. For example, the provision of a high rating for the movie The BFG

movies, and this process generates a significant amount of user ratings data. The collected user ratings data may conceal user demographics that remain to be extracted. This is expected to provide a new direction of study for improving on the performance of user demographic inference. For example, the provision of a high rating for the movie The BFG

1. http://play.google.com/store/apps
2. https://bj.nuomi.com/
3. http://www.imdb.com/
4. http://www.imdb.com/title/tt3691740/
from a user suggests that this user is more likely to be relatively young or young parent with small children, because The BFG is a typical child-oriented fantasy adventure movie. In our previous work [7], we have mentioned the potential that users’ rating data has in performance improvement of service recommendation. To confirm this assumption, we visualize user ratings data regarding movies by using a heat map in Figure 1. This shows the mean values of ratings data regarding 250 movies, provided by eight gender-age groups of audiences (note that we infer a user’s gender attribute as a binary classification task, i.e., female or male, and age attribute as a four-class classification task, by dividing user ages into four age groups according to the age partition scheme adopted in [6], [8], [9]: young (15-24), adult (25-34), middle-age (35-49), and old (≥ 50). So the number of gender-age groups is eight by multiplying two with four). Note that the integer values of the vertical ordinate (i.e. 1, 2, · · · , 250) means the number of movie orders, which is not an important consideration here. From Figure 1, we find that there exist significant differences relative to different gender and age groups of users. Although this difference appears to be uninterpretable and chaotic in Figure 1, it may contain informative and useful hidden patterns for improving demographic inference for audiences.

Although there is a huge volume of work showing that user demographics can be inferred from all kinds of data [4], [10], [11], [12], [3], [6], [13], to our best knowledge no proper model has been successfully developed so far for inferring user demographics by utilizing user feedback (e.g., ratings data) for purchased products or services. For example, Wang et al. [13] attempted to infer the gender, age, and marital status of users based on their purchasing behavior (e.g., whether or not users purchased a certain product). Seneviratne et al. [14] inferred user demographics by considering the mobile apps installed on their personal smartphones. However, neither of these methods [13], [14] exploit user feedback, much less the utilization of user ratings data. Otterbacher et al. [15] attempted to extract features regarding writing style, content, and metadata from user reviews regarding movies, and to employ these features to train a logistic regression (LR) classifier for user demographic inference. However, this approach cannot deal with ratings data. Kosinski and Stillwell et al. [3] employed Facebook likes to infer user demographics. Specifically, they first adopted a singular-value decomposition (SVD) reduction as the feature extractor to extract features from a sparse binary matrix, then trained a classifier using the method in [15]. One of the drawbacks of the methods in [14], [15], [3] is that they train the two vital components of a classification system, the feature extractor and classifier, independently, which may impair the cognitive inference performance of user demographic data [16], [17]. Based on existing research findings, we state that the challenging aspects in inferring user demographics from ratings data are as follows: 1) How to exploit the rating values properly into a user demographic inference model. 2) How to capture the underlying relevance between different demographic attributes for better inference performance, as cognitive inference of user demographic can be considered as a multi-task (i.e., gender and age) classification problem [6], [18]. 3) How to design a cognitive inference model in which feature extractor and classifier are trained in an integrated manner in support of discovering informative and useful hidden patterns from highly sparse ratings data.

In this paper, to tackle the above problems we investigate the inference power of user ratings data for inferring user demographics, and propose a simple yet general rating to profile (R2P) model for inferring multiple user demographic attributes simultaneously from ratings. More specifically: 1) Following the idea that a higher rating value indicates a higher probability that the corresponding user likes the service or product, we appeal to probability theory to incorporate ratings values into R2P development. 2) R2P is able to train its two components, i.e. feature extractor and classifier, in an integrated manner under a supervised learning paradigm. More specifically, R2P can automatically learn the representation of each movie and encode informative and useful learned patterns. 3) R2P models multiple user demographics into the designed joint representation, which can automatically leverage the relevance between different demographic attributes. Overall, the major contributions of our work are as follows:

- We make the first attempt to investigate the inference power of user ratings data for the cognitive inference of user demographic data.
- We propose a novel R2P model for multiple user demographic inference, which can learn representation of each movie automatically, train the feature extractor and classifier in an integrated manner, and capture the relevance between different demographic attributes.
- We have conducted extensive experiments on two real-world ratings dataset against various compared state-of-the-art methods, and the results show from multiple aspects that our proposed R2P model can enhance significantly the performance of user demographic inference.

The remainder of this paper is organized as follows. We provide a review of related work in Section 2. In Section 3, we detail the model development and optimization process of the proposed R2P. In Section 4, we present experiments to demonstrate that our R2P model can significantly enhance the performance of user demographic inference compared with compared state-of-the-art methods. Finally, our conclusions and directions for future work are laid out in Section 5.

2 RELATED WORK

In this section, we briefly review three areas of research relevant to our work: demographic inference, feature extraction and classification, and multi-task prediction.

2.1 User Demographic Inference

User demographic inference based on various cues has been studied in various scenarios. Early studies regarding demographic inference attempted to infer demographic attributes based on samples of written text or answers in a psychometric test. For example, Schler et al. [19] found that there are significant differences in both writing style and content among authors of different genders or ages.

Later, human migration to digital environments, such as electronic communications and the Internet, rendered it
possible to base such inference on digital records of human behavior. It has been shown that age, gender, occupation, education level, and even personality can be inferred from a person’s website browsing logs [4, 20]. Torres [10] determined that the clicked pages were correlated with the demographics of users. Hu et al. [4] discovered demographic tendencies from web pages, and inferred user demographics through a discriminative model. Bi et al. [11] inferred the demographics of users performing searches based on independent social datasets. These works demonstrated that by leveraging social and search data in a common representation, a better demographic inference performance can be achieved.

Recently, the rapid development of online social networks and mobile computing technologies has generated large quantities of valuable user data, making it possible to infer user demographics in these scenarios. Some studies have proposed supervised learning frameworks for inferring user demographics based on properties of Facebook or Twitter profiles, such as numbers of friends or the densities of friendship networks [12], [3]. Mislove [21] found that users with common profiles are more likely to be friends, and often form a dense community. Dong et al. [6] focused on the micro level analysis of mobile communication networks to infer user demographics. Culotta et al. [22] trained a LR model to infer user demographics using information regarding followers of each user on Twitter.

To our knowledge, the majority of existing studies have focused on designing and then selecting from many manually defined features for the cognitive inference of user demographics, rather than learning features automatically from raw data [23], [4], [3], [15]. Here, considering a fairly different research problem, we focus on how to improve the performance of user demographic inference by utilizing user feedback (more concretely, user ratings data) on products or services that they have purchased, which has never previously been explored. For example, Wang et al. [13] attempted to infer the gender, age, and marital status of users based on their purchasing behaviors. Similar methods in [14] inferred user demographics by considering the apps installed on their personal smartphones. However, these methods do not consider user feedback, let alone utilize user ratings data. Otterbach et al. [15] attempted to extract features regarding writing style, content, and metadata from user reviews on movies, and to employ these features to train a LR classifier for the cognitive inference of user demographics. However, this approach cannot deal with ratings data.

2.2 Feature Extractor & Classifier
A general classification system consists of two components, namely a feature extractor and classifier. The main function of a feature extractor is to generate informative and useful features from raw data, while the classifier, taking these generated features as input, attempts to provide the best classification [17], [4], [3], [6]. For instance, Kosinski et al. [3] specified SVD and LR as the feature extractor and classifier, respectively.

Among the various feature extractors (e.g., SVD), representation learning [24] functions effectively in removing irrelevant and redundant data, increasing learning accuracy, and improving the comprehensibility of results. Furthermore, representation learning can generate features automatically, without relying on expensive and tedious domain-specific knowledge to manually define features. This property has attracted ever increasing attention, making this an important issue in the present machine learning community. For example, in object recognition, Doersch et al. [25] proposed employing representation learning as the feature extractor for discovering objects within images. In addition, Wang et al. [26] studied representation learning experimentally in the visual, speech, and language domains.

It is worth noting that feature extractor and classifier can be trained either independently or in an integrated manner. For example, Kosinski et al. [3] trained these (SVD and LR) independently, while [24], [13] trained the two components in an integrated manner. The former option has an advantage in implementation, because the feature extractor only must be trained once for employment with any classifier, whereas the latter has the advantage that it can be used to minimize classification errors directly [17].

In this study, we propose the use of representation learning to automatically learn representations in the user ratings scenario, and train feature extractor and classifier in an integrated manner to achieve high performance in user demographic inference.

2.3 Multi-task Prediction
The idea behind multi-task prediction is to improve the generalization performance by leveraging the possible relevance between a set of tasks, which has proven to be reasonably successful in practice [27], [6], [13]. To this end, a typical method involves training several tasks simultaneously, while using a shared representation [6], [28], [18]. Many methods have been presented for solving multi-task learning with various regularizers or kernels, to exploit and utilize the relevance among tasks. For example, Evgeniou et al. [29] proposed an approach to predicting multiple tasks by minimizing the values of regularization functions. Michelli et al. [30] demonstrated that different kernels can be used to model relevance.

In this paper, we formalize the cognitive inference of user demographics from ratings data as a multi-task prediction problem. Inspired by relevant methods in [6], [13], we propose the concept of demographic joint representation (Section 3), and incorporate this into the building process of our proposed inference model, which can explicitly encode the relevance among different tasks and improve the general performance of user demographic inference.

3 PROPOSED R2P MODEL
In this section, we introduce the proposed R2P model. First, we describe some basic notations that will be frequently employed, and then we detail the model development of R2P. Finally, we describe how to train the R2P and employ it to infer user demographics.

3.1 Notations and Preliminaries
3.1.1 Demographic Joint Representation
The concept and process of constructing of the demographic joint representation will be described in this paragraph.
As mentioned in Section 1, in this paper we consider the cognitive inference of user demographics as a multi-task classification problem. Specifically, we consider gender inference as a binary classification task, and age inference as a four-class classification task. To obtain the joint demographic representation, we first encode both labels of the two corresponding classification tasks (e.g., male/female and age) using one-hot encoding [24], and then concatenate them together to form a joint representation of user demographics. Here, the one-hot encoding trick is employed to transform the label of an \( l \)-class task into a bit vector of size \( l \), where only one bit takes value 1 with 0 values for the rest. As a result, in this paper gender is encoded using a bit vector of size two, which corresponds to male (10) and female (01), respectively. Furthermore, age is encoded with a bit vector of size four, which corresponds to four age groups, namely young (1000), adult (0100), middle age (0010), and old (0001). Then, by concatenating gender and age together, we obtain a bit vector of size six, which we call the demographic joint representation. Clearly, a user’s demographic joint representation contains their gender and age information. An example of the construction of the demographic joint representation (010010) for the gender-age group <female, middle age> is presented in Figure 2.

```
Gender:<female> Age:<middle age>
0 1
0 0 1 0
0 1 0 0 1 0
```

**Fig. 2:** An example of one-hot encoding and joint representation of user demographics.

The benefit of the demographic joint representation is obvious, because the relevance among different tasks can now be explicitly encoded, e.g., the joint representation that refers to male and adult is much more popular than that referring to male and old. Therefore, to some extent the demographic joint representation can capture the relevance between different demographic attributes.

Henceforth, we denote the demographic joint representation of all users by \( Y = \{ y_n \in \{0, 1\}^C | n = 1, 2, \cdots, N \} \), where \( y_n \) is a bit vector of size six that denotes the demographic joint representation of the \( n \)-th user \( u_n \), and \( N \) denotes the total number of users. Note that \( C = 6 \) in this paper, which indicates the bit vector size of the demographic joint representation.

### 3.1.2 Representation Vectors of Items

In this paper, we use term *item* to uniformly represent a product or service, such as a movie enjoyed in a cinema or a kind of telecommunication package provided by telecom operators.

Let \( V = \{ v_m \in \mathbb{R}^D | m = 1, 2, \cdots, M \} \) denote the representation vectors of all items in a \( D \)-dimensional continuous space, where the vector \( v_m \) represents the \( m \)-th item \( b_m \), and \( M \) denotes the total number of items. The representation vectors of all items (i.e., \( V \)) are shared across all users, and should be obtained from the item ratings data. Note the presence of the dimensional variable \( D \in \mathbb{Z}^+ \). The value of \( D \) is determined by the subsequent experimental results in Section 4.

Note that in the model training process mentioned later, our proposed R2P model can automatically learn the parameter \( V \) from the item ratings data. This means that R2P automatically learns representations of all items for demographic inference, without the need for manually defined features. This mechanism is analogous to the learning of representations of supermarket products in [13] and words of a corpus in [31]. What distinguishes our work is that there exist continuous numerical ratings relative to each item in our scenario.

#### 3.1.3 Item List & Rating Data

Let \( S_n \) denote the list of items that \( u_n \) has previously rated. Then, the relation \( b_m \in S_n \) indicates that the user \( u_n \) has rated the item \( b_m \). The length of \( S_n \) (i.e., the number of ratings by \( u_n \)) and its elements may vary for different users \( u_n \). This makes sense, because people’s preferences for different item genres or leisure periods during the day for enjoying this kind of service or product differ from each other.

Then, we denote the user ratings data by \( R = \{ r_{n,m} | n = 1, 2, \cdots, N, m \in S_n \} \), where \( r_{n,m} \) denotes the rating value by the user \( u_n \) for the item \( b_m \), if \( m \in S_n \). Note that our proposed R2P model can deal with both discrete-valued and continuous-valued ratings data, which is represented by the value taken by the variable \( r_{n,m} \).

#### 3.1.4 Workflow of R2P

Based on the above-mentioned notations and preliminaries, the workflow of the proposed R2P is as shown in Figure 3. Given a user’s rating data, we can get the list of items (i.e. item list) that the user has rated. With the item list, we can get the representation vector of each item (i.e. representation vector of items) that the user has rated from the representation vectors of all items. Taking the user’s rating data and the representation vectors of items that the user has rated, Inference is used to obtain the best demographic joint representation for this user. Based on the best demographic joint representation, we can obtain user’s demographic attributes, such as the gender and age information by employing the method of obtaining the demographic joint representation in reverse.

```
User's Rating Data → Inference → Demographic Joint Representation

Item List → Representation Vectors of Items

User Demographics Attributes
```

**Fig. 3:** Workflow of R2P to infer user demographics from user ratings data.
3.2 Development of R2P Model

First, regardless of user ratings, if the user $u_n$ has bought the item $b_m$, then we define the probability that $u_n$ likes $b_m$ via a softmax function, which is frequently employed in various probabilistic multi-task classification methods [31]:

$$p_r(v_m|y_n) = \frac{\exp(v_m^T W y_n)}{\sum_{m \in S_n} \exp(v_m^T W y_n)}. \quad (1)$$

In the formulation of this function, because the user $u_n$’s joint demographic representation $y_n$ is a $C$ dimensional vector and the representation vector of the item $b_m$ is a $D$ dimensional vector, $W$ denotes a $D \times C$ matrix, which we call the interaction matrix. Note that the value of each entry of the interaction matrix $W$ is automatically learned from user ratings data, which is the same as for the representation vector of the item $b_m$.

Next, we discuss why Eq. 1 is not sufficient for capturing users’ real preferences, and why user ratings should be taken into account. Taking movie as an example, it is known that a user watching a movie does not necessarily indicate that they like it. The user may just wish to investigate whether they find the movie interesting. Therefore, if for instance a user $u_n$ has not only watched a movie $b_m$, but has also provided a high rating for it, then we are more convinced that the probability that they like the movie is high, and vice versa. As a result, by adding the corresponding rating value $r_{m,n}$ as a scaling factor of Eq. 1, we can obtain a more suitable function to represent the probability that the user $u_n$ likes item $b_m$ as follows:

$$p(v_m|y_n) = \left( p_r(v_m|y_n) \right)^{r_{m,n}} = \frac{\exp(r_{m,n} v_m^T W y_n)}{\sum_{m \in S_n} \exp(r_{m,n} v_m^T W y_n)}. \quad (2)$$

Then, according to the product rule in probability theory, we can obtain the general probability that user $u_n$ likes all of his rated items $S_n$ as follows:

$$p(S_n|y_n) = \prod_{m \in S_n} p(v_m|y_n) = \frac{\exp \left( \sum_{m \in S_n} r_{m,n} v_m^T W y_n \right)}{\prod_{m \in S_n} \exp(v_m^T W y_n)^{r_{m,n}}} \quad (3)$$

In this equation, the vector $\sum_{m \in S_n} r_{m,n} v_m$ is the weighted sum of all of the items’ representation vectors in the user’s ratings history, with the corresponding rating values as weights of all of the items’ representation vectors. In addition, to some extent the vector $\sum_{m \in S_n} r_{m,n} v_m$ can be considered as the representation vector of user $u_n$, which makes sense, because the representation vector of a user must be associated with the items they have bought and the user’s ratings regarding these.

Suppose that given $S_n$, from the modern Bayesian perspective, we can write down the probability of assigning demographics $y_n$ to the user $u_n$ as follows:

$$p(y_n|S_n) \propto \tilde{p}(y_n)p(S_n|y_n), \quad (4)$$

where $\tilde{p}(y_n)$ is the empirical distribution of the demographic joint representation $\tilde{y}_n$, given by the dataset.

Finally, we obtain the objective function of R2P as the log likelihood over all of the users, as follows:

$$\ell_{R2P} = \sum_{n=1}^{N} \log p(y_n|S_n) - \lambda ||\Theta||^2, \quad (5)$$

where $\lambda$ is the regularization constant to prevent overfitting, and $\Theta$ represents parameters of the model ($\Theta = \{W, V\}$).

Then, as we review the above formulations, we will find that the proposed R2P model can suitably integrate user ratings into the model construction, and user ratings data plays an important role in the model construction process.

3.3 Model Training and Inference of R2P

Training. Direct optimization using Eq. 6 is expensive, owing to the high computational cost. Therefore, we appeal to the negative sampling technique [31] for an efficient optimization, which approximates the original objective $\ell_{R2P}$ using the following objective function:

$$\Theta^* = \arg\max_{W,V} \sum_{n=1}^{N} \left\{ \left( \sum_{m \in S_n} r_{m,n} v_m^T W y_n \right)^T W y_n - \sum_{m \in S_n} r_{m,n} \log \sum_{m \in S_n} \exp(v_m^T W y_n) \right\} - \lambda ||\Theta||^2 \quad (6)$$

Training. Direct optimization using Eq. 6 is expensive, owing to the high computational cost. Therefore, we appeal to the negative sampling technique [31] for an efficient optimization, which approximates the original objective $\ell_{R2P}$ using the following objective function:

$$\ell_{neg} = \sum_{n=1}^{N} \left\{ \log \sigma \left( \sum_{m \in S_n} r_{m,n} v_m^T W y_n \right)^T W y_n - \sum_{i=1}^{k} E_{\tilde{y}_n \sim P_n} \log \sigma \left( - \left( \sum_{m \in S_n} r_{m,n} v_m^T W \tilde{y}_n \right)^T \right) \right\} + \lambda ||\Theta||^2 \quad (7)$$

where $\sigma(x)$ is the logistic function $\sigma(x) = 1/(1 + e^{-x})$. Here, for each joint demographic representation there are $k$ negative samples drawn according to the noise distribution $P_n$, which is modeled by an empirical distribution over all possible joint demographic representations. We observe that the objective of R2P with negative sampling aims to differentiate the ground truth from noise by increasing the probability of the correct joint demographic representations and decreasing that of any incorrect ones, given the user input.

We then apply the stochastic gradient descent algorithm to maximize the new objective function for the model training. The training process of R2P is detailed in Algorithm 1. Specifically, Line 7 updates the interaction matrix $W$, Lines 8-10 update the item representation vectors $V$, and Lines 11-17 illustrate the negative sampling process.

Inference. With the trained interaction matrix $W$ and item vectors $V$ prepared, we can proceed to infer user demographics. Specifically, for any new user, if we only know their ratings data, then we can infer their user demographics
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Algorithm 1: Learning algorithm of R2P

Input: ratings \( R \), joint demographic representations \( Y \), learning rate \( \eta \), maximum iterative number \( \text{maxIter} \), negative sampling number \( k \); 
Output: interaction matrix \( W \), item vectors \( V \);
Initialize \( W \), \( V \) randomly;
1. Initialize \( W \), \( V \) randomly;
2. For convenience, define \( \varphi_n = \sum_{m \in S_n} r_{m,n} \bar{v}_m \);
3. while not converged or \( t > \text{maxIter} \) do
4. \( t = t+1; \)
5. for \( n = 1; n \leq N; n = n + + \) do
6. \( W = W + \eta(1 - \sigma(\varphi^T W \bar{y}_n)) \varphi_n \bar{y}_n^T; \)
7. for \( m \in S_n \) do
8. \( \bar{v}_m = \bar{v}_m + (1 - \sigma(\varphi^T W \bar{y}_n)) r_{m,n} W \bar{y}_n; \)
9. end
10. for \( i = 1; i \leq k; i = i + + \) do
11. sample negative sample \( \bar{y}_i \) from \( P_n; \)
12. \( W = W - \eta(1 - \sigma(\varphi^T W \bar{y}_n)) \varphi_n \bar{y}_n^T; \)
13. for \( m \in S_n \) do
14. \( \bar{v}_m = \bar{v}_m - (1 - \sigma(\varphi^T W \bar{y}_n)) r_{m,n} W \bar{y}_n; \)
15. end
16. end
17. end
18. \( W = W - 2 \lambda \theta W; \)
19. \( V = V - 2 \lambda \theta V; \)
20. end
21. return \( W, V; \)

by looking for the best joint demographic representation \( \bar{y}_i^* \) that maximizes the following objective function:

\[
\bar{y}_i^* = \arg \max_{\bar{y}_i \in Y} \sum_{m \in S_i} r_{m,i} \bar{v}_m^T W \bar{y}_i - \left( \sum_{m \in S_i} r_{m,i} \right) \log \left( \sum_{m \in S_i} \exp \left( \bar{v}_m^T W \bar{y}_i \right) \right) \]

(8)

With \( \bar{y}_i^* \), we can obtain the gender and age information of this user by employing the method of obtaining the demographic joint representation in reverse.

Now, we further analyze Eq. 8 from the following two aspects: 1) For all candidate vectors \( \bar{y} \) of all given users, the terms \( \left( \sum_{m \in S_i} r_{m,i} \bar{v}_m \right)^T W \), \( \sum_{m \in S_i} r_{m,i} \) and \( \bar{v}_m^T W \) only need to be computed once. Therefore, the process of obtaining the best joint demographic representation \( \bar{y}_i^* \) does not require too many computing resources. 2) From the modern Bayesian perspective, the best inference is determined by two components. The first is the empirical distribution \( \hat{p}(\bar{y}) \), which can be considered as the prior probability of the candidate vector \( \bar{y} \) and the second component \( p(S_i|\bar{y}_i) \) is closely relevant to the likelihood function in Bayes theorem.

As a result, R2P can make use of prior knowledge, and give the maximum a posteriori probability estimate as a more intuitive and meaningful inference. No existing approaches, at least in this area, has been able to achieve this so far [3], [6], [13].

As we can see, under the supervised learning paradigm, R2P combines the ground truth and the output of the classifier together to update the representations of items generated by the feature extractor, and then uses the updated representations to train a better classifier. Thus, R2P can train its two components, i.e. the feature extractor and classifier in an integrated manner.

4 Experimental Evaluation

In this section, we describe experiments conducted on a real-world movie ratings dataset to evaluate our proposed R2P model, and explore the extent to which it can improve on the inference performance of user demographic data.

4.1 Dataset

Here we describe in detail the datasets used in the experiments. Because no specified off-the-shelf benchmark ratings dataset exists yet (e.g., neither TripAdvisor nor Yelp contains user demographics), we constructed two datasets, namely MovieRatings and MobilePackageRatings, from different domains to evaluate the effectiveness of our proposed R2P model. In addition, we made one of our datasets—MovieRatings’—available for download from the Internet for research use.

4.1.1 MovieRatings

To construct MovieRatings, we implemented a Scrapy framework based web-crawler to collect users’ self-reported demographics and their movie ratings from Douban. After filtering out users with no or only partial gender and age information, we finally obtained only 243,000 ratings expressed by 1,452 distinct users with complete gender and age information, relating to 2,300 movies. To make the data easier to use, the ratings are linearly normalized as continuous numerical numbers in the range [0, 1] with Min-Max scaling method by the following:

\[
r' = \frac{r - r_{min}}{r_{max} - r_{min}},
\]

(9)

where \( r' \) is the rating value after normalized, \( r \) is the original rating value, \( r_{max} \) and \( r_{min} \) are respectively the maximum and minimum rating value of all ratings.

The users’ self-reported demographic information can be considered trustworthy, because this is in line with users’ interests as they can obtain well-targeted friends and movies recommendations through their information. Therefore, this can serve as the ground truth in the subsequent model training and testing process. In addition, this way of handling ground truth has been successfully adopted in different domains [6], [8], [9], [13]. With the inferred demographic data of users with no or only partial gender and age information, Douban can recommend movies to them according to their user demographics.

5. http://times.cs.uiuc.edu/~wang296/Data/
6. https://www.yelp.com/dataset
7. http://www.dropbox.com/s/ok1tzyzwlxapd8/MovieRatings.csv?dl=0
8. http://scrapy.org/
9. http://www.douban.com
TABLE 1: Distribution of demographic attributes in the two datasets.

| attributes    | value  | MovieRatings | MobilePackageRatings |
|---------------|--------|--------------|----------------------|
| gender        | male   | 0.4178       | 0.7433               |
|               | female | 0.5822       | 0.2567               |
| age           | young  | 0.2368       | 0.0423               |
|               | adult  | 0.3589       | 0.3528               |
|               | middle age | 0.2516   | 0.3734               |
|               | old    | 0.1527       | 0.2313               |

4.1.2 MobilePackageRatings

MobilePackageRatings is constructed based on a real-world mobile data bundle dataset collected by a local mobile operator in Shanghai of China in six successive months. This dataset contains 3,519,777 pieces of mobile users’ data traffic records, one of which consists of a user, the user’s gender and age information, the name of the mobile data bundle that the user is using, and the time slot. In this dataset, there are a total 4,418 users (each is denoted by a unique user ID) and 4 kinds of mobile data bundles (denoted by 0, 1, 2, 3 respectively).

In MobilePackageRatings, users’ ratings on mobile data bundles are obtained as follows. For each pair of user and mobile data bundle, we calculate the total time of this mobile data bundle by this user in the six months period. It make sense as if a user prefers a mobile data bundle, he will spend more time on it. We normalize the total time by Min-Max scaling method in Eq. 9 as users’ ratings for the mobile data bundles, and we get the MobilePackageRatings dataset. With the inferred demographic data of users with no or only partial gender and age information, the local mobile operator can recommend them with accurate telecommunication services relative to user demographic data.

4.1.3 Analysis of Two Datasets

The basic statistical characteristics of the two datasets are as follows. The demographic distribution over all users in the dataset is shown in Table 1. The sex ratio in MobilePackageRatings is more imbalanced than in MovieRatings, which is the inherent property of the datasets and beyond the scope of this paper.

The two datasets are complementary and quite different with each other. In MobilePackageRatings, every one only has used one mobile data bundle. Figure 4 shows the distribution of numbers of the four mobile data bundles in different gender-age groups in MobilePackageRatings dataset. While in MovieRatings, most users have rated more than one movies. On average, each user has ratings records for less than 17 movies (approximately 7.3% of the total movies), so the ratings data is sparse. The ratings data is also highly imbalanced. Figure 5 illustrates the cumulative percentages of the numbers of users’ that have rated different numbers of movies. We find that most users have rated fewer than 300 movies (> 94.4%), and users that have rated more than 500 movies account for a relatively small fraction (< 0.53%).

4.2 Experimental Setup

First we present four state-of-art relative compared methods, and then we list three evaluation metrics that are commonly employed in multiple task classification problems.

4.2.1 Compared Methods

We evaluate R2P in comparison with the following four compared state-of-the-art methods for the cognitive inference of user demographic data. Note that owing to space limitations, we cannot describe each of these in detail here, so we refer the reader to [3], [13] for additional implementation details.

- SVD-Single: In the SVD-Single method, SVD is first conducted over the user-item matrix to obtain low dimensional representations of users. Then, an LR model is learned over the low dimensional representation to infer separately each demographic attribute [3], [13].
- SVD-Multiple: The only difference compared to SVD-Single is that SVD-multiple employs a log-bilinear model to infer multiple demographic attributes, and
thus it can leverage the possible relevance between multiple tasks for a better performance [13].

- JNE: In the joint neural embedding (JNE) model, all of the tasks are assumed to share the same representation vector as the user, and a joint model is employed to infer multiple attributes separately [13].
- SNE: The structured neural embedding (SNE) model can automatically learn the representations of users, and use these to infer multiple demographic attributes simultaneously. Unlike our proposed R2P model, SNE cannot make further use of user ratings data to improve the inference performance [13].

All these compared methods are applied in the field of user demographics inference to deal with users’ ratings data for purchased products or services. In [3], the input data of SVD-Single is whether a user commented on a Facebook post or not instead of the degree of his likes and dislikes. In [13], the input data only contains whether a customer has bought a product from a market or not, instead of his feedbacks on it. SVD-Single and SVD-Multiple can take users’ ratings data as model input, however, the inference performance of user demographics is inferior to the proposed R2P, which will be shown in the experimental results.

4.2.2 Evaluation Metrics

We employ three widely used evaluation metrics, namely Hamming Loss, Micro F1, and 0/1 Loss (respectively denoted by h-loss, micro-F1 and 0/1-loss in the remaining parts) [32], [33], to evaluate the performance of the proposed R2P model against the compared methods. The three evaluation metrics are defined as follows:

- **h-loss**: i.e. Hamming Loss, which calculates the fraction of misclassified instance-label pairs:
  \[
  h\text{-loss} = \frac{1}{NC} \sum_{n=1}^{N} |\tilde{y}_n^* \triangle \hat{y}_n^*|,
  \]
  where \( \triangle \) denotes the symmetric difference of two sets, and \( |\tilde{y}| \) returns the number of 1 values in the bit vector \( \tilde{y} \). The smaller the Hamming Loss value, the better the performance [32], [33].

- **micro-F1**: i.e. Micro F1, which evaluates the micro average of both Precision and Recall with equal importance:
  \[
  \text{micro-F1} = \frac{2 \sum_{n=1}^{N} |\tilde{y}_n^* \cap \hat{y}_n^*|}{\sum_{n=1}^{N} |\tilde{y}_n^*| + \sum_{n=1}^{N} |\hat{y}_n^*|},
  \]
  where \( \cap \) denotes the intersection of two sets. The bigger the value, the better the performance [32].

- **0/1-loss**: i.e. 0/1 Loss, which evaluates the 0/1 Loss over the inference of labels:
  \[
  0/1\text{-loss} = \frac{1}{N} \sum_{n=1}^{N} \mathbb{I}(\tilde{y}_n^* \neq \hat{y}_n^*),
  \]
  where \( \mathbb{I}(\cdot) \) denotes the indicator function, i.e., \( \mathbb{I}(\pi) = 1 \) if and only if \( \pi \) holds, and otherwise \( \mathbb{I}(\pi) = 0 \). The smaller the value, the better the performance [33].

Note that the 0/1-loss is more strict than h-loss or micro-F1, in that the inference for a user is correct only when all attributes are correctly inferred. Therefore, the combination of these complementary metrics can help to provide a more comprehensive and credible evaluation.

4.2.3 Hardware and Software

We implemented the experiments via Python 2.7, Numpy 1.12 and Anaconda 4.2.0 on an IBM server with Inter Xeon E5-2670 eight-core 2.60 GHz CPU and 32G RAM.

4.3 Experiment Results

In this section, four experimental results to validate our proposed R2P from multiple aspects are presented.

4.3.1 Performance Comparison with Compared Methods

Now, we compare the cognitive inference of user demographic data of our proposed R2P model with the compared state-of-the-art methods, including SVD-Single, SVD-Multiple, JNE, and SNE.

The four parameters are discussed in detail in section 4.3.2 and 4.3.3, which include Training Ratio (i.e. the portion of training data), Dimension of the Representation Vectors, Negative Sampling Number and Regularization Constant. Specifically, the training ratio is set as 90% by adopting 10-fold cross-validation method. As to dimension of the representation vectors, the best values on the two datasets, i.e. MovieRatings and MobilePackageRatings, are quite different. On MovieRatings, we set the parameter representing the dimension of movies’ representation vectors in R2P (i.e., \( D \)) to 70. In the implementations of SVD-Single and SVD-Multiple, only the top 70 SVD components are used, in line with work in [3]. The dimensions of the items’ representation vectors in JNE and SNE are also set to 70. It should be noted that we also conducted experiments with \( D \) set as 30, 50, and 90, where R2P still outperform the compared methods, although achieving an inferior absolute performance than with \( D = 70 \). While on MobilePackageRatings, the dimension of dimension of the representation vectors is set as \( D = 14 \).

The results are presented in Figure 6, which illustrates the average values and standard deviations of the three metrics for each method, through a 10-fold cross-validation method. Figure 6a shows the performance on MovieRatings dataset, where we can extract the following observations:

1) SVD-Multiple performs better than SVD-Single, and SNE performs better than JNE. Because SVD-Multiple and SNE can utilize the possible relevance among a set of prediction tasks to improve the inference performance, the experimental comparison confirms the relation between prediction tasks. 2) It is evident that JNE and SNE perform better than SVD-Single and SVD-Multiple. To our knowledge, JNE and SNE train the feature extractor and classifier in an integrated manner, while SVD-Single and SVD-Multiple train the feature extractor and classifier separately. As a result, this experimental comparison validates the assumption that a classification system can improve its performance by training the feature extractor and classifier in an integrated manner. 3) Our proposed R2P model performs significantly better than all of the compared methods. For example, the relative improvement of R2P over the best compared method, SNE, is 21.2% in terms of the micro-F1. This result is made possible because R2P can train the feature...
extraction extractor and classifier in an integrated manner, capture the relevance among different prediction tasks, and utilize user ratings data. Thus, although the absolute performance shown in Table 2 may seem poor, the enhancement achieved by R2P could bring about significant revenue growths for companies such as Douban, IMDb, or Netflix [34]. Figure 6b shows the performance on MobilePackageRatings dataset. It demonstrates the similar trends as shown in Figure 6a. That is to say, R2P still maintains the dominant position against the compared methods in Figure 6a, but the overall performance is a little weaker.

So, the performance comparison on the two user ratings datasets validates the advantages of the proposed R2P model in the cognitive inference of user demographic data.

4.3.2 Effects of the Training Ratio and Dimension of the Representation Vectors

Table 2 shows the inference performance of the proposed R2P model with two relevant variables, namely the training ratio (the percentage of data used for the model training) and the dimension D of the representation vectors. Clearly, we can observe the trend of better performances as the training ratio increases, for any combination of evaluation metrics and values of D. This demonstrates the positive effects of an increased training data size on inferring user demographics from ratings data. Furthermore, the positive effects increase more slowly as the training ratio increases, which reveals the limited contributions of the training ratio on inferring user demographics.

As in section 4.3.1, we conduct experiments on the two datasets respectively, namely MovieRatings (Table 2(a)) and MobilePackageRatings (Table 2(b)). In Table 2(a), we can observe that for a fixed training ratio, the best performance with each metric (three boldface digits per line, of which each corresponds to one metric) is in most cases obtained when we set the dimension as D = 70. Because each dimension in a movie representation vector represents one latent pattern for the corresponding movie, the dimension D = 70 indicates that the proposed R2P can automatically learn 70 pieces of informative patterns from the ratings data. When the value of D is smaller than 70, not all informative patterns are extracted; while when D takes a larger value than 70 this will introduce noisy patterns. Both of these cases will have a bad influence on the generalization ability of the inference model and weaken the subsequent inference performance on test data. While in Table 2(b), the best value of dimension of the representation vectors is taken when D = 14.

As a result, in the experiments of section 4.3.1, 4.3.3 and 4.3.4, we set D = 70 on MovieRatings and D = 14 on MobilePackageRatings, and apply 10-fold cross-validation to assess the average performances of different methods.

4.3.3 Impacts of Negative Sampling Number and the Regularization Constant

We have performed parameter analysis on the negative sampling number and the regularization constant. The experiments here are conducted on the MovieRatings dataset. The results are similar to experimental results on MobilePackageRatings dataset.

In the development of the R2P model, in order to avoid overfitting we introduce the variable λ as a regularization constant. Then, in the training of the R2P model, we employ a negative sampling technique for optimization. One of the parameters in this technique is the negative sampling number, denoted by k. Here, we investigate the impacts of the negative sampling number k and the regularization constant λ on the performance of user demographic inference. Specifically, we test k ∈ {1, 2, 4, 6, 8, 10} and λ ∈ {0.001, 0.01, 0.1}, and illustrate the test performance of R2P in terms of micro-F1 with different combinations of negative sampling numbers and regularization constants in Figure 7.

It can be seen that for a fixed negative sampling number, a large value of λ results in a low micro-F1 value. If λ is sufficiently small (less than 0.1), then micro-F1 does not vary significantly as λ changes. In addition, the value of micro-F1 is reasonably stable as the negative sampling number increases if k ≥ 2. Therefore, we set the negative sampling number to k = 2 in our learning procedure, for efficiency, and set the regularization constant as λ = 0.01.

4.3.4 Effects of User Activeness

Experiments on the MovieRatings dataset also validated the assumption that user activeness (e.g. the number of items the user has rated) also has a significant influence on the performance of demographic inference. We do not adopt the MobilePackageRatings dataset here for the fact that every user only has used one mobile data bundle in history.

Now, we split the users in the MovieRatings dataset into three categories of activeness (i.e., inactive, medium, and active), based on their numbers of movie ratings, and further investigate the performance of our proposed R2P model in the different categories. We consider a user to be inactive if they have rated fewer than 100 movies, and active if they have rated more than 300 movies. The remainder are considered as medium. The inactive, medium, and active categories defined in this manner account for 61.7%, 32.7%, and 5.6% of total number of users, respectively. As is shown in Table 3, the performance of demographic inference in the active category is significantly better than in the other categories. This implies that if we can take proper measures to guide users to provide more ratings, we can infer user demographics more accurately in practical applications.

4.4 Limitations and Analysis of R2P model

- Although service recommendation system will benefit from user demographic inference, this paper only focuses on how to improve user demographic inference performance using users’ rating data, regardless of the subsequent service recommendation.
- The proposed R2P model has very poor performance with the sparsity of data or the cold start problem, where a user has not rated even one movie. User demographic inference in this scenario would depend on prior knowledge or other side information about users, such as the writing style of a user’s comments on a service.
- The proposed R2P model can only utilize users’ rating data for better user demographic inference, and cannot
combine users' comments with the rating data together for better performance.

- Currently there is no a specified off-the-shelf benchmark that can be properly used to test the proposed R2P model. As a result, we experimented with only two datasets that we by ourselves constructed, and thus it is hard to know how it will work on different domains.

However, we have conducted a series of experiments to prove the effectiveness of the proposed R2P model in improving on the performance of user demographics inference. In the next, we will open the constructed datasets for public research use and construct more datasets to perform experiments to validate the proposed R2P model.

---

**TABLE 2:** Performance of R2P with different training ratios and dimension numbers for representation vectors.

(a) Performance on MovieRatings dataset.

| ratio | $D = 30$       |       |       | $D = 50$       |       |       | $D = 70$       |       |       | $D = 90$       |       |       |
|-------|----------------|-------|-------|----------------|-------|-------|----------------|-------|-------|----------------|-------|-------|
|       | h-loss | micro-F1 | 0/1-loss | h-loss | micro-F1 | 0/1-loss | h-loss | micro-F1 | 0/1-loss | h-loss | micro-F1 | 0/1-loss |
| 20%   | 0.522  | 0.102   | 0.619  | 0.485  | 0.181   | 0.601  | 0.484  | 0.208   | 0.577  | 0.483  | 0.200   | 0.575   |
| 40%   | 0.513  | 0.157   | 0.617  | 0.481  | 0.244   | 0.573  | 0.473  | 0.311   | 0.574  | 0.481  | 0.308   | 0.577   |
| 60%   | 0.517  | 0.194   | 0.602  | 0.481  | 0.315   | 0.574  | 0.467  | 0.405   | 0.561  | 0.472  | 0.466   | 0.574   |
| 80%   | 0.508  | 0.222   | 0.588  | 0.478  | 0.398   | 0.569  | 0.443  | 0.576   | 0.559  | 0.456  | 0.497   | 0.568   |
| 90%   | 0.504  | 0.271   | 0.575  | 0.479  | 0.423   | 0.566  | 0.442  | 0.582   | 0.548  | 0.459  | 0.512   | 0.565   |

(b) Performance on MobilePackageRatings dataset.

| ratio | $D = 10$       |       |       | $D = 14$       |       |       | $D = 16$       |
|-------|----------------|-------|-------|----------------|-------|-------|----------------|
|       | h-loss | micro-F1 | 0/1-loss | h-loss | micro-F1 | 0/1-loss | h-loss | micro-F1 | 0/1-loss |
| 70%   | 0.582  | 0.426   | 0.612  | 0.581  | 0.419   | 0.604  | 0.572  | 0.413   | 0.561   |
| 80%   | 0.497  | 0.468   | 0.598  | 0.479  | 0.475   | 0.589  | 0.488  | 0.469   | 0.594   |
| 90%   | 0.483  | 0.470   | 0.585  | 0.472  | 0.482   | 0.578  | 0.479  | 0.480   | 0.588   |

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Fig. 6: Performance comparison of user demographic inference for different compared methods in terms of the $h$-loss, $\text{micro-F1}$, and $0/1$-loss.

(a) Performance on MovieRatings dataset.

(b) Performance on MobilePackageRatings dataset.
We should go one step further to evaluate how the inferred user demographics can be exploited to improve the user modeling and recommendation tasks, by evaluating for example the contribution of this data to solve or alleviate the cold start problem.

5 Conclusion

This paper demonstrates the degree to which relatively basic user feedback (e.g., ratings data) on products or services can be used to automatically and accurately infer user demographics. More specifically, we have investigated the inference power of ratings of movies and mobile data bundles, and proposed a simple yet general inference model, called rating to profile (R2P), to automatically learn the representations of the rated items and infer multiple user demographic attributes simultaneously from the user ratings datasets. To validate our proposed R2P, we constructed two real-world ratings datasets, namely MovieRatings and MobilePackageRatings, and the experimental results showed that R2P can make better user demographic inference against the compared methods from multiple aspects.

Our future work will include, but not be limited to, the following: 1) Because the embedding of texts has been widely studied, it would be interesting to also map the content of comments into the space of users and items, and then study whether content and ratings information can be complementary to each other in the cognitive inference of user demographic data. 2) The wide variety of demographic attributes studied in this area (e.g., marital status, political tendencies, education level) indicates that given appropriate training data, it may be possible to also reveal additional attributes.

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References

[1] K. Kalyanam and D. S. Putler, “Incorporating demographic variables in brand choice models: An indivisible alternatives framework,” Marketing Science, vol. 16, no. 2, pp. 166–181, 1997.
[2] X. W. Zhao, Y. Guo, Y. He, H. Jiang, Y. Wu, and X. Li, “We know what you want to buy: a demographic-based system for product recommendation on microblogs,” in Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1935–1944, ACM, 2014.
[3] M. Kosinski, D. Stillwell, and T. Graepel, “Private traits and attributes are predictable from digital records of human behavior,” Proceedings of the National Academy of Sciences, vol. 110, no. 15, pp. 5802–5805, 2013.
[4] J. Hu, H.-J. Zeng, H. Li, C. Niu, and Z. Chen, “Demographic prediction based on user’s browsing behavior,” in Proceedings of the 16th International Conference on World Wide Web (WWW), pp. 151–160, ACM, 2007.
[5] Y. Zhong, N. J. Yuan, W. Zhong, F. Zhang, and X. Xie, “You are where you go: Inferring demographic attributes from location check-ins,” in Proceedings of the 8th ACM International Conference on Web Search and Data Mining (WSDM), pp. 295–304, ACM, 2015.
[6] Y. Dong, Y. Yang, J. Tang, and Y. Yang, “Inferring user demographics and social strategies in mobile social networks,” in Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 15–24, ACM, 2014.
[7] S. Wang, Z. Zheng, Z. Wu, M. R. Lyu, and F. Yang, “Reputation measurement and malicious feedback rating prevention in web service recommendation systems,” IEEE Transactions on Services Computing, vol. 8, no. 5, pp. 755–767, 2015.
[8] C. Sarrate, P. Blanc, and J. Burroni, “A study of age and gender seen through mobile phone usage patterns in mexico,” in Advances in Social Networks Analysis and Mining (ASONAM), 2014 IEEE/ACM International Conference on, pp. 836–843, IEEE, 2014.
[9] J. Brea, J. Burroni, M. Minnón, and C. Sarrate, “Harnessing mobile phone social network topology to infer users demographic attributes,” in Proceedings of the 8th Workshop on Social Network Mining and Analysis, p. 1, ACM, 2014.
[10] S. Duarte Torres and I. Weber, “What and how children search on the web,” in Proceedings of the 20th ACM international Conference on Information and Knowledge Management (CIKM), pp. 393–402, ACM, 2011.
[11] B. Bi, M. Shokouhi, M. Kosinski, and T. Graepel, “Inferring the demographics of search users: social data meets search queries,” in Proceedings of the 22nd international conference on World Wide Web (WWW), pp. 131–140, ACM, 2013.
[12] D. Lazer, A. Pentland, L. Adamic, S. Aral, A.-L. Barabási, D. Brewer, N. Christakis, N. Contractor, J. Fowler, M. Gutmann, T. Jebra, G. King, M. Macy, D. Roy, and M. Van Alstyne, “Computational social science,” Science, vol. 323, no. 5915, pp. 721–723, 2009.
[13] P. Wang, J. Guo, Y. Lan, J. X. and X. Cheng, “Your cart tells you: Inferring demographic attributes from purchase data,” in Proceedings of the 9th ACM International Conference on Web Search and Data Mining (WSDM), pp. 251–260, ACM, 2016.
[14] S. Seneviratne, A. Seneviratne, P. Mohapatra, and A. Mahanti, “Your installed apps reveal your gender and more!,” ACM SIGMOBILE Mobile Computing and Communications Review, vol. 18, no. 3, pp. 55–61, 2013.
[15] J. Otterbacher, “Inferring gender of movie reviewers: exploiting writing style, content and metadata,” in Proceedings of the 19th ACM International Conference on Information and Knowledge Management (CIKM), pp. 369–378, ACM, 2010.
[16] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.
[17] K. E. Hild, D. Erdogmus, K. Torkkola, and J. C. Príncipe, “Feature extraction using information-theoretic learning,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 9, pp. 1385–1392, 2006.
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[18] E. Zhong, B. Tan, K. Mo, and Q. Yang, “User demographics prediction based on mobile data,” Pervasive and Mobile Computing, vol. 9, no. 6, pp. 823–837, 2013.

[19] J. Schler, M. Koppel, S. Argamon, and J. W. Pennebaker, “Effects of age and gender on blogging,” in AAAI Spring Symposium, vol. 6, pp. 199–205, 2016.

[20] D. Murray and K. Durrell, “Inferring demographic attributes of anonymous internet users,” in Web Usage Analysis and User Profiling: International WEBKDD’99 Workshop San Diego, CA, USA, August 15, 1999 Revised Papers, pp. 7–20, Springer, 2000.

[21] A. Mislove, B. Viswanath, K. P. Gummadi, and P. Druschel, “You are who you know: inferring user profiles in online social networks,” in Proceedings of the 3rd ACM International Conference on Web Search and Data Mining (WSDM), pp. 251–260, ACM, 2010.

[22] A. Culotta, N. R. Kumar, and J. Cutler, “Predicting the demographics of twitter users from website traffic data,” in Proceedings of the 29th AAAI Conference on Artificial Intelligence, pp. 72–78, AAAI, 2015.

[23] C. Boulis and M. Ostendorf, “A quantitative analysis of lexical differences between genders in telephone conversations,” in Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics (ACL), pp. 435–442, Association for Computational Linguistics, 2005.

[24] Y. Bengio, A. Courville, and P. Vincent, “Representation learning: A review and new perspectives,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 8, pp. 1798–1828, 2013.

[25] C. Doersch, A. Gupta, and A. A. Efros, “Unsupervised visual representation learning by context prediction,” in Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp. 1422–1430, 2015.

[26] W. Wang, R. Anora, K. Livescu, and J. Bilmes, “On deep multi-view representation learning,” in Proceedings of the 32st International Conference of Machine Learning (ICML), pp. 1083–1092, 2015.

[27] S. Ben-David and R. Schuller, “Exploiting task relatedness for multiple task learning,” in Learning Theory and Kernel Machines, pp. 567–580, Springer, 2003.

[28] Y. Ji and S. Sun, “Multitask multiclass support vector machines: model and experiments,” Pattern Recognition, vol. 46, no. 3, pp. 914–924, 2013.

[29] T. Evgeniou and M. Pontil, “Regularized multi–task learning,” in Multiple task learning, in Proceedings of Advances in Neural Information Processing Systems (NIPS), pp. 921–928, 2004.

[30] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” in Proceedings of Advances in Neural Information Processing Systems (NIPS), pp. 3111–3119, 2013.

[31] X. Kong, M. K. Ng, and Z.-H. Zhou, “Transductive multilabel learning via label set propagation,” IEEE Transactions on Knowledge and Data Engineering, vol. 25, no. 3, pp. 704–719, 2013.

[32] X. Kong, B. Cao, and P. S. Yu, “Multi-label classification by mining label and instance correlations from heterogeneous information networks,” in Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data mining, pp. 614–622, ACM, 2013.

[33] C. A. Gomez-Uribe and N. Hunt, “The netflix recommender system: Algorithms, business value, and innovation,” ACM Transactions on Management Information Systems, vol. 6, no. 4, p. 13, 2016.