Multiple User Context Inference by Fusing Data Sources

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Abstract—Inference of user context information, including user's gender, age, marital status, location and so on, has been proven to be valuable for building context aware recommendor system. However, prevalent existing studies on user context inference have two shortcomings: 1. focusing on only a single data source (e.g. Internet browsing logs, or mobile call records), and 2. ignoring the interdependence of multiple user contexts (e.g. interdependence between age and marital status), which have led to poor inference performance. To solve this problem, in this paper, we first exploit tensor outer product to fuse multiple data sources in the feature space to obtain an extensional user feature representation. Following this, by taking this extensional user feature representation as input, we propose a multiple attribute probabilistic model called MulAProM to infer user contexts that can take advantage of the interdependence between them. Our study is based on large telecommunication datasets from the local mobile operator of Shanghai, China, and consists of two data sources, 4.6 million call detail records and 7.5 million data traffic records of 8,000 mobile users, collected in the course of six months. The experimental results show that our model can outperform other models in terms of recall, precision, and the F1-measure.

Index Terms—User context inference, fusing data sources, interdependence, maximum entropy, tensor outer product.

1 INTRODUCTION

User context information has been proven to be valuable for building context aware recommender system [1], [2], [3], [4]. The objective of incorporating user contexts, including user’s gender, age, marital status, location and so on, is to acquire and utilize information pertinent to the context of the user, the environment, or the mobile device to provide services that are tailored to a particular user, place, time, and event [5], [6]. However, a major obstacle to collecting user contexts is the unavailability of user context information or its incompleteness due to privacy concerns. From the point of view of the user, the exposure of such personal context attributes is potentially harmful. At the same time, mobile terminals like Apple’s iOS devices are equipped with protection mechanisms (e.g., rejecting third-party cookies by default), hence making it difficult to track even user behavior from log information, let alone user contexts. As a result, user context inference are critical in enabling service providers to target users with more personalized services [7], [2], [4], [5], [6].

Therefore, inference of user contexts is of considerable interest to both industry professionals and academics. For example, Nokia Research organized the 2012 Mobile Data Challenge, which involved inferring user contexts of a small group of mobile users from records of their use of mobile Apps, such as Bluetooth and GSM [8], [9], [10], [11]. Dong et al. [12] and Perozzi et al. [13] focused on mobile communication networks where each node represents a user and an edge between two nodes represents communication between the users corresponding to the nodes. However, they ignored other discriminative information of the kind provided in [8], [9], [10], [11].

Although prevalent research has yielded important insights that can be helpful in inferring user contexts, they have of drawbacks that leave room for improvement in inference performance, which is by the following two:

- First, prevalent studies focus on a single data source, such as mobile communication networks [14], [12], [13], Internet browsing logs [15], writing and speaking styles [16], [17], [18], location check-ins [19], etc. However, different data sources provide complementary information to improve the performance of learning tasks [20], [21], [22], [23], and fusing them appropriately will yield better user context inference performance. Therefore, the problem has arisen that how to fuse more than one data sources to improve user context inference. However, it is not trivial for too many uncertain factors, e.g. how to extract useful features, whether to fuse the dataset directly or fuse them in feature space and how. In fact, no proper model has been proposed to cope with this problem yet.

- Second, current work in the area either involves inferring only one user context attribute (such as gender [24] or age [13]) or separately inferring user contexts [17], which ignores the interdependence of user contexts (e.g. interdependence between age and marital status, gender and age) and leave room for improvement in inference performance [12], [25]. Done et al. [12] took this into account, but their framework is not suitable
for the situation that we consider here, where the communication network is extremely sparse. Therefore, a more general model that can deal with both of sparse and dense networks and can extract useful information from them to get better user context inference performance should be further studied. We handle features instead of an integral social network, although some features used in this paper are extracted from a network created by cell phone calls. This difference renders model training more efficient, as network training is invariably expensive. This makes our model more flexible because it can properly cater to practical scenarios.

For the first one, in this paper, unlike in prevalent studies, which invariably use only information obtained from mobile Call Detail Records (CDR), we incorporate mobile Data Traffic Records (DTR) into user context inference. That is to say, we investigate how to fuse data sources to infer user contexts. CDR and DTR can be regarded as heterogeneous data because CDR can be considered as a communication network where the connected users will influence each other, whereas DTR only depends on the corresponding user, and can be treated independently (Despite the heterogeneity of CDR and DTR, they share the same user set, which means that the same ID in CDR and DTR represents the same user. This property allows us to avoid the user matching process, which is invariably confronted when dealing with more than one data sources of data and leads to error [19]). More specifically, we first extract user features from CDR and DTR, and normalize them to alleviate the value missing and outlier problems. We then fuse two kinds of features into an extensional feature for each user by using tensor outer products. To the best of our knowledge, few studies have used different data sources to infer user contexts.

For the second, we have studied the interdependence between different user context attributes and found interdependence between gender and age from CDR and DTR. For instance, men in general tend to call more men than women, and people of different ages demonstrate explicitly different preferred age orientation in their interlocutors (interaction between same gender or similar age is greater). Based on these findings, we propose a general Multiple Attribute Probabilistic inference Model (called MulAProm) based on the Maximum Entropy Principle to capture this interdependence for better user context inference. That is to say, we investigate multiple user context inference by fusing data sources. MulAProm takes extensional features as input, and simultaneously infers a user’s gender and age. MulAProm supports the addition of useful factors (such as mobile communication networks [14], [12], [13], Internet browsing logs [15], writing, and styles of speech [16], [17], [18], location check-ins [19], etc.) to its extensional features for better inference.

Our contributions in this paper are three fold:

- To the best of our knowledge, our work is the first to study how to fuse different data sources (CDR and DTR) together to infer user contexts, and demonstrates better user context inference performance by fusing data sources.
- We consider the interdependence between different user context attributes (e.g., gender and age), and study to propose a general multiple attribute probabilistic inference model called MulAProm based on the Maximum Entropy Principle that can simultaneously infer multiple user contexts and yield better inference performance than common classification models.
- We have implemented our proposed model and experimented on a real-world large telecommunication dataset from a local mobile operator in a large city. We use two kinds of data: 4.6 million call detail records and 7.5 million data traffic records of 8,000 mobile users collected in six successive months. The experimental results have validated the proposed model.

The remainder of this paper is organized as follows: We present related work in the area in Section 2. Section 3 contains an account of the motivation underlying our proposed model, drawn from CDR and DTR. In Section 4, we detail our proposed multiple attribute probabilistic inference model. Experiments and results analysis are detailed in Section 5. We draw our conclusions and discuss our plans for future work in Section 6.

2 Related Work

Research on user context inference has attracted researchers from a wide variety of fields.

Earlier work mainly focused on writing styles, e.g., bloggers’ writing styles were used to infer their gender and age [16]. Pertaining to the music industry, [26] investigated the possibility of a computer to automatically infer personal traits from the records of the music that users had listened to in the past. As Web browsers became popular, some researchers attempted to infer user contexts from online browsing and search histories [27], [15], [28], [29]. With the development of social network sites (e.g., MSN and Facebook), more studies have been devoted to social networks. Leskovec and Horvitz [30] examined the interdependence of the MSN network and user context attributes. Tang et al. extracted and modeled user contexts in large-scale collaboration networks [31]. The correlation between Facebook’s user contexts and their posts were extensively studied [17], [18]. Moreover, patterns underlying human mobility and trajectory records in daily life have also been studied for user context inference [32], [19]. Even in modern urban management, user context inference is considered helpful in crime prevention [33].

In recent years, as mobile phone subscriptions have skyrocketed1 and the field of computational social science has matured [34], an increasing amount of research has been devoted to studying mobile phone data and mobile communication networks, and this has led to a deeper understanding of mobile users’ behavior. The differences in phone use habits between men and women were studied in [24]. Nokia Research organized the 2012 Mobile Data Challenge to infer mobile user contexts by providing communication records of 200 users without revealing their network information [8], [10], [11]. Similar attempts were made in [35], [36]. In these works, each user is studied

1. http://www.ericsson.com/res/docs/2014/ericsson-mobility-report-november-2014.pdf
independently and has nothing to do with others. As to the mobile social network composed by interactive users, due to the difference as users are not independent anymore and cannot be treated respectively, studies have been devoted to extracting features from mobile social networks, and then utilize these features to infer user context information. Pentland et al. [37] tried to infer users’ friendship networks using mobile phone data, and Dong et al. [12] revealed the usefulness of social interaction data by using these to create a probabilistic model for user context inference [12]. Perozzi et al. [13] designed a system that could learn social representations that could capture community information and considered the problem of exact age inference in social networks using a regression model. However, many social networks, like the communication network used in [12], contain sparse information [38], [39], and a model that only uses social networks for information is insufficient for accurate inference.

Although prevalent research has offered important insights that can be helpful for user context inference, they have the following two drawbacks that leave room for improved inference performance. First, most current works focus on single-data sources, such as CDR [14], [12], [13], Internet browsing logs [15], writing and speaking styles [16], [17], [18], location check-ins [19], etc. However, fusing different data sources provides complementary information to improve learning performance [20], [21], [22], [23], and fusing such information appropriately will help improve user context inference. Therefore, the problem has arisen that how to fuse different data sources to improve user context inference. However, it is not trivial for too many uncertain factors. To deal with this problem, we exploit the tensor outer product to fuse two data sources, CDR and DTR, to improve user context inference performance.

Second, current studies either infer only one user context attribute (such as gender [24] or age [13]) or separately infer different user contexts [17] by ignoring the interdependence between user contexts. To alleviate this shortcoming, we propose a multiple attribute probabilistic inference model based on the Maximum Entropy Principle to simultaneously infer users’ gender and age. Our model takes extensional user feature representation as input and exploits the interdependence between different user contexts. Done et al. [12] take this factor into account, and this is the most relevant paper to our work. However, their framework is not suitable for the situation that we consider, where the communication network is extremely sparse. Furthermore, our model can include discriminative information of the sort provided in [8], [9], [10], [11].

### 3 Analysis and Findings

In this section, we analyze the datasets CDR and DTR respectively, and find some intriguing patterns related to user context information. These correlations between mobile dataset patterns and users’ context information, enable us to obtain users’ gender and age from CDR or DTR.

Above all, we introduce details of CDR and DTR. Each item of CDR consists of the ID of the caller and the corresponding callee, and their context information. As each item of DTR contains the start time of a call (online timestamp) and the end time (offline timestamp). Therefore DTR is simpler than CDR as the users can be treated independently. Undoubtedly, CDR and DTR share the same user-id set, which means that each customer has the same ID in both datasets, and no two customers have the same ID.

For the sake of brevity, we will use the abbreviated form of the context groups or subgroups (Table 1). As we can see, in this paper, we infer user gender as a binary classification problem, i.e., Female (F) or Male (M), and user age as a four-class classification problem by splitting users’ ages into four groups: Young (Y, 18-24), Young Adult (YA, 25-34), Middle Aged (MA, 35-49), and Senior (S, > 49). Based on the two gender groups and the four age groups, we construct eight subgroups as shown in Table 1: F-Y, F-YA, F-MA, F-S, M-Y, M-YA, M-MA, and M-S. Our target is to design a system that can automatically learn to make accurate inferences, which means classifying incoming samples into one of the given sets of subgroups defined here.

| Group | Gender | Age |
|-------|--------|-----|
| M-Y   | M (Male) | Y (18-24) |
| M-YA  | M (Male) | YA (25-34) |
| M-MA  | M (Male) | MA (35-49) |
| M-S   | M (Male) | S (>49) |
| F-Y   | F (Female) | Y (18-24) |
| F-YA  | F (Female) | YA (25-34) |
| F-MA  | F (Female) | MA (35-49) |
| F-S   | F (Female) | S (>49) |

Fig. 1. Average CDR everyday from different Gender Groups.
3.1 CDR

If users can be considered nodes, each item of CDR can be viewed as a connection between the caller and the corresponding recipient of the call. Therefore, CDR can be used to form a weighted directed social network, where the directions reveal the caller-callee relation, and weight reveals the count number. We want to know to what extent user contexts are related to those of their neighbors.

We first count the average CDR record from/to different gender groups for users belonging to different subgroups. As is shown in Fig. 1, several intriguing preference patterns are revealed:

1) The most prominent pattern is strong gender homophily, which means that users prefer calling/being called by users of the same gender. Male users tend to call other males instead of female users (Fig. 1a), female users tend to call female users (Fig. 1b), male users tend to receive more calls from male users (Fig. 1c), and female users tend to receive more calls from female users (Fig. 1d).

2) The younger the user, the more calls they made. Younger people tend to not only make more calls, but also be called more frequently. Fig. 1 shows that the frequency of calls involving same-gendered users generally decrease from the Y, the YA, and the MA to the S group mentioned before.

3) We also find homophily between each user’s calling and being called patterns. This phenomenon is apparent in comparing Fig. 1a and Fig. 1c, where the trends are almost identical. The comparison between Fig. 1b and Fig. 1d also supports this.

Following this, we proceed to study the average CDR records from/to different age groups for users belonging to different subgroups. The result is shown in Fig. 2. We have some interesting findings: 1) The three preference patterns underlying average CDR records from/to different gender groups in the above analysis are also mirrored here. 2) Fig. 2d and Fig. 2h confirm that cross-generation interactions. We think this is the case because there is significantly more communication between age groups Y and S, which are separated in age by more or less a generation interval (In general we think of a generation being about 25 years, from the birth of a parent to the birth of a child.).

Hence, CDR contains statistical information related to user contexts, and we can utilize this information.

3.2 DTR

Compared to CDR, DTR is more easy to deal with because items of DTR do not interact with one another. This difference is as shown in Fig. 3. Hence, we can conduct a statistical analysis within different groups regardless of relatedness between users.

We first discuss the average DTR frequency per day and DTR duration per unit time of different groups. As shown in Fig. 4a, male and female users follows almost the same
trend, whereby the values generally decrease from the Y, the YA, the MA, to the S group. The only difference is that female frequency (which means the times of woman items around a fixed time-in-point) is a little lower than male. The average DTR duration depicted in Fig. 4b shows similar characteristics as that in Fig. 4a.

![Average DTR Frequency and Duration](image)

(4) Average DTR Frequency (b) Average DTR Duration

Fig. 4. Average DTR frequency and duration.

We now consider the different average DTR frequencies at different times of the day for different groups. The underlying patterns are shown in Fig. 5. Fig. 5a shows the DTR frequency of different gender groups, and we see that male frequency is higher than female all the time. Fig. 5b shows the DTR frequency of different age groups, and we see that the frequency values decrease from Y, YA, MA, to S. Fig. 5c shows the DTR frequency of different gender and age groups. We see a decreasing trend from M-Y, F-Y, M-YA, F-YA, M-MA, F-MA, M-S, to F-S, although there are several intersections.

From Fig. 5, we find common patterns whereby nearly all curves achieve their peak values around 12:00 and 17:00, and then decrease, with valleys around 4:00 and 14:00. In spite of the shared patterns, we can to some extent distinguish these curves in Fig. 5a, Fig. 5b, and Fig. 5c. We can make use of this to obtain user context information. Fig. 5d shows the standard deviation of the DTR frequency of different gender and age groups. There is a one-to-one correspondence between curves of the same color in Fig. 5c and Fig. 5d, which convinces us that high average DTR frequency always gives rise to high variance (The standard deviation is the square root of the variance).

Hence, DTR contains statistical information related to user contexts, and we can utilize this knowledge to obtain user contexts.

### 3.3 Summary and Clues

From the findings before, we can conclude as follows:

1) Either CDR or DTR can be utilized to get user contexts. As is known, multiple data sources provide complementary information to improve the learning performance for learning tasks [20], so fusing them appropriately will gain better user context inference.

2) All the findings above clearly show mutual interdependence between user gender and age. For example, a 20-year-old female’s behaviors are different from not only a 20-year-old male, but also from a 50-year-old female, which is explicitly shown in the above figures. So we propose a multiple attribute probabilistic inference model to capture the interdependence for better user context inference.

Our work is based on just two data, i.e. CDR and DTR, however, our work can deal with a lot of similar application problem. That is determined by the inherent property of CDR and DTR. As is shown in Fig. 3, CDR and DTR can represent two typical application scenarios. CDR can represent the application of social network, such as Twitter, Facebook, etc. [17], [13], [12], [18]; while DTR can represent all kinds of time series data [40], [41], [10], [11], [19].

### 4 User Context Inference Model

In this section, we detail the proposed user context inference model that aims to infer user gender and age information from CDR and DTR datasets. We will focus on describing how to overcome the two existing problems that are mentioned in Section 3.3. Specifically, to get the complementary information of different data sources, we apply the feature space tensor outer product to fuse data sources. Then taking the derived features as input, we propose a general multiple attribute probabilistic inference model called MulAProM based on the Maximum Entropy Principle. This model can simultaneously infer users’ gender and age, and capture the mutual interdependence between user gender and age.

### 4.1 Feature Extraction

In this section, we will introduce how to extract useful and informative features from CDR and DTR. The features in this paper mainly come from two different sources: 1) Here, the patterns revealed in the observational study of the datasets in Section 3 begin to play an important role in the feature construction process. To be specific, the extracted features reflects the discussion in Section 3 to some extent. 2) Beyond that, we also accept the lessons taught in the early works in the feature selections [8], [10], [11], [14], [35], [37], [42].

**f-CDR.** With regard to CDR, the features (called f-CDR) consist of: Mean and variance of number of calls per day; Mean and variance of calls in/calls out per day; Mean and variance of calls in/calls out with males/females per day; Mean and variance of calls in/calls out with the aforementioned four age groups per day; Mean and variance of calls in/calls out on weekdays and weekends; Number of days when the user had call activity; In/Out degree of one user in the phone call network; The number of unique users that call or are called.

Based on the above eight classes of features, we also apply tricks in feature engineering [43] to construct new features, such as the difference/ratio between numbers of calls in/calls out, etc. Unsupervised step is it, however, feature engineering here is helpful to capture more useful patterns.

**f-DTR.** For DTR, the features (called f-DTR) are as follows: Mean and variance of duration of DTR per day; Mean and variance of duration of DTR on weekdays and weekends; Mean and variance of DTR counts during several predefined timeslots: morning, afternoon, evening and midnight; and Number of days when the users had DTR.

Based on these four kinds of features, we construct additional features using the same technique as with f-CDR.
At last, we finally obtain f-CDR (including 67 total features) and f-DTR (including 26 total features) for each user, which are used to infer the corresponding user contexts.

### 4.2 Fusing Data Sources
In this section, we list the steps about how to fuse data sources. First we normalize the features to deal with various scales for different elements. Then we apply the feature space tensor outer product to fuse data sources. To alleviate the problem of dimensionality, we adopt Principal Component Analysis.

#### 4.2.1 Feature Normalization
Real-world data is dirty in general, and mobile phone datasets are no exception. As a result, the f-CDR and f-DTR features of some users may contain missing values or outliers. Analyzing data that have not been carefully screened for such problems can produce misleading results in the subsequent data mining algorithm [44]. On the other side, the features may contain elements with a mixture of scales for various quantities. In general, however, in machine learning algorithms, objective functions do not work properly without normalization. For example, in Section 4.2.2, without normalization, elements with big quantities will incline to play primary role, which is not the desired results.

We thus normalize the features with a frequently used method known as Z-scores [45]. For a feature vector \( x \), the transformation formula is as follows:

\[
z_i = \frac{x_i - \mu}{\delta},
\]

where \( x_i \) is the \( i \)-th element of vector \( x \), \( \mu \) is the mean of \( x \), and \( \delta \) is its standard deviation.

With elementary algebraic manipulations, it can be shown that a set of Z-scores has mean zero and standard deviation one. Therefore, Z-scores constitute a unit-free measure, which can be used to compare observations in different units. In addition, the feature normalization process can only change the values of the features, without changing the number of the features in CDR and DTR.

#### 4.2.2 Feature Space Tensor Outer Product
In general, different views provide complementary information to improve performance for learning tasks [20], [46], [47]. Until now, we have focused on single-data sources (CDR or DTR) and processed them separately. Specifically, in Sections 4.1 and 4.2.1, we obtain f-CDR and f-DTR. An intuitive idea is to simply concatenate features from all views to transform multi-view data into single-view data. However, this would fail to leverage the underlying correlations among views.

Tensors can be viewed as higher-order arrays that naturally generalize the notions of vector and matrix to multiple dimensions. The concept of tensor outer product is as follows:

**Definition 1.** Tensor outer product Given an \( I_1 \)-dimensional vector \( x \in \mathbb{R}^{I_1} \) and an \( I_2 \)-dimensional vector \( y \in \mathbb{R}^{I_2} \), the tensor outer product of \( x \) and \( y \), denoted by \( x \circ y \), represents an \( I_1 \times I_2 \) matrix with the elements \((x \circ y)_{i_1i_2} = x_{i_1}y_{i_2}\).

There is no difficulty in expanding the tensor outer product to an arbitrary number of dimensions. Based on the definition of the tensor outer product of two vectors in Definition 1, with an additional vector \( z \in \mathbb{R}^{I_3} \), we can express \( x \circ y \circ z \) as a third-order tensor, which makes an \( I_1 \times I_2 \times I_3 \) box. The elements are defined as \((x \circ y \circ z)_{i_1i_2i_3} = x_{i_1}y_{i_2}z_{i_3}\). It is clear that the tensor outer product forms an elegant algebraic structure for the theory of tensors. Such a structure endows the tensor outer product with the advantage of representing real-world data, which naturally enables the interaction of features from different data sources (Fig. 6). Each mode of the tensor corresponds to one feature. For this reason, we conclude that the use of the tensor outer product is a reasonable choice for adequately capturing the properties of raw multi-view features and hidden relationships in the original data.

However, as shown in Fig. 6, although the tensor outer product can capture the correlation between two features, it discards the original feature vector [48], [49], therefore losing the original information contained in the original feature vectors to some extent. The simple concatenation method [50] avoids this downside and retains the original features. Thus, we propose aggregating the best aspects of both methods. Specifically, suppose the length of f-CDR is \( I_1 \) and that of f-DTR is \( I_2 \). Then, we can get another \( I_1 \cdot I_2 \) features by the tensor outer product. Along with the original \( I_1 + I_2 \) features, we then have \( I_1 \cdot I_2 + I_1 + I_2 \) features. As the number of f-CDR is 67 and the number of f-DTR is 26, the total number of features that we finally obtain is \( 67 \times 26 + 67 + 26 = 1835 \), which is a much larger number of features than in existing user context inference works [8], [9], [10], [12], [13], [19].

In Section 4.2.1, we have mentioned the feature scaling

![Fig. 5. Average DTR frequency at different time.](image)

(a) DTR frequency of different Gender Groups (b) DTR frequency of different Age Groups (c) DTR frequency of different Gender&Age Groups (d) Variance of DTR frequency of different Gender&Age Groups
process, and here will show its necessity by using the tensor outer product as an example. Suppose two big-quantity elements \( x_1 \) and \( x_2 \), and another two small-quantity elements \( x_p \) and \( x_q \), then in the tensor outer product, the product of \( x_p \) and \( x_q \) will be much greater than the product of \( x_1 \) and \( x_2 \), which will result in unfavorable outcome later. If all elements are normalized according to Section 4.2.1, this problem will be automatically eliminated.

4.2.3 Dimension Reduction

Until now, we successfully capture the possible complementary information among multiple views of data (Section 4.2.2), but it may incur the dimensionality curse problem [51]. This means that when the feature dimensionality of each data source or the number of data sources increase, the volume of the training data and the computational cost of model training grows exponentially. Another problem is that the combination of multiple views can potentially incur redundant information, which is useless for model training. Further, from Section 3, we see that patterns of different features are similar, which indicates that redundant information needs to be minimized. Faced with this problem, we adopt Principal Component Analysis (PCA) [52] to reduce dimensionality. The reason that we turn to PCA instead of tensor decomposition to avoid curse of dimensionality problem is as follows: Tensor decomposition based methods, such as Canonical Polyadic Decomposition and Tucker Decomposition, are not suitable for our work, because the tensor in our work are rank one, which means that the tensor can be written as an outer product of several nonzero vectors. If we apply tensor decomposition to a tensor of rank one, we will get the original feature vectors.

PCA is a basic multivariate statistical method that can preserve most variation in datasets. It is originally proposed for dimension reduction of huge amounts of data [53]. To be specific, PCA can be applied to full features, and yield meaningful low-dimensional feature representations. Because of its simplicity and ability to handle large amounts of data, PCA has been widely and successfully applied to many computational areas, such as image analysis, feature extraction, pattern recognition, data compression, and time series inference [52], [53].

The core of PCA are as follows. Consider an \( M \times N \) matrix \( \mathbf{X} \), each column of which corresponds to a feature vector for a sample, and \( M \) rows correspond to \( M \) features. According to PCA, the \( k \leq M \) largest eigenvalues of matrix \( \mathbf{X} \) are to be selected, and their associated \( R \) eigenvectors form an \( k \times M \) matrix \( \mathbf{A} \) as follows:

\[
\mathbf{A} = \left[ \begin{array}{c} \nu_1^T \\ \nu_2^T \\ \vdots \\ \nu_R^T \end{array} \right].
\]  

Then, given an arbitrary original \( M \)-dimensional feature vector \( \mathbf{x} \), we can use matrix \( \mathbf{A} \) to transform it to an \( k \)-dimensional \((k \leq M)\) vector \( \tilde{\mathbf{x}} \) as follows:

\[
\tilde{\mathbf{x}} = \mathbf{A} \mathbf{x}
\]

Once we get the lower dimensional vector \( \tilde{\mathbf{x}} \), we will abandon the original feature vector \( \mathbf{x} \) and use \( \tilde{\mathbf{x}} \) in the following part. In this way, we achieve the expected goal of dimension reduction and minimize redundant information. Note that without causing any ambiguity, we still use the symbol \( \mathbf{x} \) instead of \( \tilde{\mathbf{x}} \) to denote a lower dimensional feature vector.

4.2.4 Computational Complexity of Fusing Data Sources

Consider an \( M \times N \) matrix, which represents \( N \) users, each represented with \( M \) features, then the computational complexity of PCA is \( O(\min(M^3, N^3)) \) [52]. Here we denote the number of different data sources as \( S \), and let the numbers of features from different data sources be the same number \( I \) (i.e. \( I_1 = I_2 = \cdots = I_S = I \)). Then we can denote \( M = IS + SI \). So the computational complexity of dimension reduction is \( O(\min(IS^3, N^3)) \). In addition, the computational complexities of feature normalization and feature space tensor outer product are respectively \( O(NSI) \) and \( O(NTS) \). So the total computational complexity of fusing data sources is \( O(\min(IS^3, N^3) + NT^2) \). We find that the time complexity of fusing data sources is polynomial for the number of users \( N \) and the number of features of each data sources \( I \). While the time complexity is exponential for the number of data sources \( S \). Practically, we can turn to parallel processing [54] or iterative method [55] to alleviate the high complexity by PCA.

4.3 Proposed Inference Model: MulAPrOM

In this section, we describe the proposed Multiple Attribute Probabilistic inference Model (MulAPrOM) to simultaneously infer user gender and age. We first provide an outline of the Maximum Entropy Principle, and then provide a formulation of our problem. Finally, we detail the proposed MulAPrOM and introduce the Gaussian prior to alleviate model overfitting.
4.3.1 Maximum Entropy Principle

The Maximum Entropy Principle [56] is a general technique for estimating probability distributions from data. The core of the principle is that when nothing is known, the distribution should be assumed to be as uniform as possible, i.e., it should have maximal entropy.

The model for the Maximum Entropy Principle can be formalized as follows:

$$\max_p -\sum_{x,y} \tilde{P}(x)P(y|x) \log P(y|x)$$

s.t. $\sum_{x,y} \tilde{P}(x)P(y|x)f_i(x,y) = \sum_{x,y} \tilde{P}(x,y)f_i(x,y)$, $i = 1, 2, \cdots, R$

$$\sum_y P(y|x) = 1.$$ (4)

where $x$ represents a sample from training data, $y$ is a possible output class for $x$, $\tilde{P}(x)$ is the empirical distribution of $x$, $P(y|x)$ is the empirical joint probability of $x$ and $y$, $f_i(x,y)$ is the so-called feature indicator, which is true if $x$ and $y$ satisfy property $f_i$, and $R$ is the total number of features. The first equation means that the model $P(y|x)$’s expectation of $f_i$ is constrained to match the observed expectation of $f_i$. The second guarantees $P(y|x)$ a proper probability distribution. The model’s target is to maximize model entropy.

The solution for the maximum entropy model by Eq. 4 is of the following form [56]:

$$P_\lambda(y|x) = \frac{1}{Z_\lambda(x)} \exp \left( \sum_i \lambda_i f_i(x,y) \right),$$ (5)

where $\lambda_i$ is a parameter that should be estimated and $Z_\lambda(x)$ is simply the normalizing factor to ensure a proper probability distribution, as follows:

$$Z_\lambda(x) = \sum_y \exp \left( \sum_i \lambda_i f_i(x,y) \right).$$ (6)

4.3.2 Problem Formulation

Given a dataset of labeled users, denoted by $D^L = (X^L, G^L, A^L)$, where $X^L$ is the known feature matrix of labeled users, $G^L$ and $A^L$ are gender and age of the labeled users respectively. Our target is to learn a discriminant model from $D^L$, and use it to infer gender and age $(G^U, A^U)$ of unlabeled users from their features matrices $X^U$. The problem can be formalized as follows:

$$\left( X^L, G^L, A^L \right), X^U \rightarrow \left( G^U, A^U \right),$$ (7)

where each notation is as described before.

Taking into account the interdependence between user age and gender shown in section 3, we are motivated to make use of the interdependence for better user context inference. Reflected in the problem formulation in Eq. 7, we model $P(G^U, A^U|D^L, X^U)$ and infer user gender and age (i.e. $G^U, A^U$) simultaneously.

This is different from past works, where only one user context attribute was inferred (either gender [24] or age [13]), or different user context attributes were inferred separately [17], [42], [19], both of which ignores the interdependence between different user context attributes. Our work here is also different from [12], as we handle features instead of an integral social network, although some features in this paper are extracted from a network of mobile phone calls. This difference results in an efficient model training because network training is invariably expensive. It also renders our model flexible as it can hence encompass more kinds of practical scenarios.

4.3.3 MulAProM

Thus far, we have introduced the Maximum Entropy Principle and the problem formulation of user context inference. We now aggregate them to construct our proposed MulAProM.

Model. The proposed MulAProM can be considered as a variation of the Maximum Entropy Principle to adapt to our requirement to infer gender and age simultaneously. From Eqs. 5 and 6, we replace scalar $x$ with feature vector $x$, and $y$ with pair of $g, a$, and we can directly obtain a solution by the following:

$$P_\lambda(g, a|x) = \frac{\exp \left( \sum_k \lambda_k f_k(x, g, a) \right)}{\sum_{g,a} \exp \left( \sum_k \lambda_k f_k(x, g, a) \right)},$$ (8)

where $g$ and $a$, respectively, represent the gender and age of user feature $x$, and $k \in \{1, 2, \cdots, K\}$ ($K$ represents the total number of elements of $x$). We denote parameter $\lambda = \{\lambda_k\}$ for short, and it has $K \times 2 \times 4$ elements.

We plug Eq. 8 into the objective function in Eq. 4, and take the logarithm to obtain the objective function as follows:

$$O(\lambda) = \sum_{x,g,a} \tilde{P}(x,g,a) \sum_k \lambda_k f_k(x, g, a)$$

$$- \sum_x \tilde{P}(x) \log \sum_{g,a} \exp \left( \sum_k \lambda_k f_k(x, g, a) \right).$$ (9)

According to the property of maximum entropy model, the objective function is concave, so we can guarantee that there exists only one global maximum point.

Training. The training of the model involves finding the optimal configuration for the free parameters $\lambda$, following which the log likelihood of the objective function $O(\lambda)$ can be maximized, given the training set, by the following:

$$\lambda^* = \arg \max O(\lambda).$$ (10)

To solve the optimization problem, we adopt the gradient ascent method (or the Newton-Raphson method) to find the minimum of the negative of the objective function, which is a general-purpose optimization technique in maximum entropy model training that has shown better performance than the standard iterative scaling algorithm [57]. We make this choice due to MulAProM’s strong association with the Maximum Entropy Principle shown by Eq. 5 and Eq. 8. Specifically, we take the derivative of the objective function in Eq. 9 with respect to each parameter by the following:

$$\frac{\partial O(\lambda)}{\partial \lambda_k} = \sum_{x,g,a} \tilde{P}(x,g,a) f_k(x, g, a)$$

$$- \sum_x \tilde{P}(x) \sum_{g,a} P_\lambda(g, a|x) f_k(x, g, a).$$ (11)
The model training process can then be described as an iterative algorithm. Each iteration contains two steps. First, we calculate marginal distributions of unknown variables \( P_\lambda (g, a|x) \). Second, we update \( \lambda \) with learning rate \( r (0 < r < 1) \) by Eq. 12, which shows the training process as follows:

\[
\lambda_{k,g,a}^{new} = \lambda_{k,g,a}^{old} + r \cdot \frac{\partial O(\lambda^{old})}{\partial \lambda_{k,g,a}}. \tag{12}
\]

The training process terminates when parameter \( \lambda \) reaches convergence.

**Inference.** With the estimated parameters \( \lambda \), we can now assign the value of unknown labels \( g, a \) by selecting a label configuration that maximizes the objective function as follows:

\[
(g^*, a^*) = \arg \max_{g,a} O(g, a|D, X, \lambda). \tag{13}
\]

From the above description of our model, we can see that MulAProM is very easy to extend to other user context attributes, such as activity, status, agenda, location, movement, mood, occupation, marital status, sexual orientation, etc.

### 4.3.4 Gaussian Prior against Overfitting

Like most machine learning models proposed in existing user context inference works [8], [58], [20], [36], our model may suffer from overfitting, which may lead to bad performance on the test data. The parameters are learned from labeled training data and, like other training model, when training data is sparse, overfitting can occur in the proposed MulAProM. By introducing a prior on the model, overfitting can be reduced and performance improved.

Inspired by work in [58], we use Gaussian prior for the model, with the mean at zero, and a diagonal covariance matrix. This prior favors weights closer to zero, that is, ones that are less extreme. Another reason we choose Gaussian prior lies in the fact that we have found the probability density curve of the trained parameters is very much like Gaussian function curve.

Specifically, the prior probability of the model is simply the product over the Gaussian of each feature value \( \lambda_i \) with constant variance \( \sigma^2 \) by the following:

\[
P(\lambda, \sigma^2) = \prod_{k,g,a} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-\lambda^2_{k,g,a}}{2\sigma^2}\right). \tag{14}
\]

So the derivative of Eq. 9 changes as follows:

\[
\frac{\partial O(\lambda, \sigma^2)}{\partial \lambda_{k,g,a}} = \sum_x \hat{P}(x) \sum_{g,a} P_{\lambda}(g, a|x) f_{k,g,a}(x, g, a)
- \sum_x \hat{P}(x, g, a)f_{k,g,a}(x, g, a) - \frac{\lambda_{k,g,a}}{\sigma^2}, \tag{15}
\]

and the gradient of variance \( \sigma^2 \) is by the following:

\[
\frac{\partial O(\lambda, \sigma^2)}{\partial \sigma^2} \propto \sum_{k,g,a} \left( -\frac{1}{\sigma^2} + \frac{\lambda^2_{k,g,a}}{\sigma^4} \right). \tag{16}
\]

The updating step of \( \sigma^2 \) are the same to \( \lambda \) in Eq. 12.

It is evident that the Gaussian prior will not bring about mathematical manipulation trouble or additional computational cost, since it only adds an additive term to the derivative of each feature value.

### 4.3.5 Computational Complexity of the proposed MulAProM

The computational complexity of the proposed MulAProM is referring mostly to the computational complexity of the model training step. For each iteration in updating the parameters, the computational complexity is \( O(NK(I^S + S^I)) \). So we find that the model training of MulAProM is in polynomial complexity for the number of users \( N \) and total number of elements of final feature vector \( K \), polynomial complexity for the number of features of each data sources \( I \), and exponential complexity for the number of data sources \( S \). In addition, we adopt the gradient descent method instead of the traditional standard iterative scaling algorithm, which in itself yields a great savings in computational complexity [57]. As a result, the proposed MulAProM is easy to solve in theory.

## 5 Experiments

### 5.1 Experiment Setup

#### 5.1.1 Dataset and Platform.

Our study is based on real-world telecommunication data sets from a local mobile operator in Shanghai, China. We use two kinds of data, 4.6 million Call Detail Records (CDR) and 7.5 million Data Traffic Records (DTR) of 8,000 users, collected in six successive months. The basic statistical information of CDR and DTR has been discussed in Section 3. To reduce noisy data, we discard records of users with missing context information, or those that appear fewer than 10 times in both the CDR and DTR datasets. In contrast to past work, we use the information of discarded users for feature extraction (Section 4.1) involving the other users.

The majority of the code is implemented in Python, whereas the model training procedure of the proposed MulAProM (Section 4.3) is written in C++ for the sake of training efficiency. The experiments are all performed on a server with a 16-core 2.6 GHz Intel Xeon processor with 32 GB of RAM.

#### 5.1.2 Baseline Models and Evaluation Metrics

We compare our proposed MulAProM model with a number of baseline classification models. The baseline models and their basic information are as follows:

1. kNN (k-nearest neighbors). In kNN, an item is classified by a majority vote of its neighbors.
2. LRC (Logistic Regression Classifier). LRC measures the relationship between a class label and features by estimating probabilities using a logistic function.
3. NB (Naive Bayes). NB applies Bayes’ theorem by assuming independence among features.
4. GBDT (Gradient-Boosted Decision Tree). GBDT is typically used with decision trees of a fixed size as base learners.
5. ANN (Artificial Neural Network). ANN is inspired by biological neural networks, and is used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown.
6. L-SVM (Linear form Support Vector Machine). L-SVM is a support vector machine model with a linear-form kernel function.
7) N-SVM (non-linear form Support Vector Machine). Comparisons with non-linear SVM should be added for the fact that SVM is known for its good performance when used together with Gaussian.

8) SM^2L (structure-constrained multi-source multi-task learning model). SM^2L is proposed in [22] to infer user interests from social networks. It takes source consistency and the tree-guided task relatedness into consideration. We do not construct a tree structure as in [22] to represent the relatedness of users’ demographics because there are only two attributes in our experimental datasets, i.e. gender and age.

These baseline classification models are chosen because they have their individual typical characteristics and can represent a large proportion of existing user context inference models in existing works [9], [10], [11], [19], [35], [22], [21], so the combination of them can help to give a more comprehensive and credible evaluation of the proposed MulAProM model. Especially, in works [13], [17], the LRC model are directly used to infer user contexts. For kNN, LRC, NB, and GBDT, we employ scikit-learn2, whereas for ANN, L-SVM and N-SVM, we choose Weka3. Same to the proposed MulAProM, the parameters of the competing algorithms are tuned via cross validation. It is worth noting that the implementation of L-SVM and N-SVM in Weka derives from LIBSVM4, a well-known library for the support vector machine model. The extensive use of many mature models from state-of-the-art machine learning packages as baselines guarantees a comprehensive and credible experimental evaluation. The difference between the proposed MulAProM and the baseline models lies in that the proposed model can naturally utilize the interdependence between user gender and age for better user context inference performance (Sections 3 and 4.3).

We evaluate the results using the following measurements for inference tasks: 1) Effective and common metrics for binary classification (e.g., gender contains two categories, i.e. M and F.), such as precision, recall and the F1-measure are all calculated. 2) For multi-class classification (e.g., age information here is divided into four categories: Y, YA, MA, and S.), weighted precision, weighted recall, and the weighted F1-measure are employed. Under the condition of without causing confusion, the latter weighted metrics are also referred to as precision, recall and F1-measure respectively from now on. To ensure experimental accuracy, we conduct a 10-fold cross-validation experiment, and calculate the mean and variance of each metric.

5.2 Results

In this section, we describe a series of experiments that are conducted on a real-world data to evaluate our proposed MulAProM and explore how much it can improve the inference performance of user contexts against the baselines.

5.2.1 Effects of Dimension Reduction

In Section 4.2.3, to solve the dimensionality curse problem, we adopt PCA to transform the original high dimensional feature vector to an lower dimensional vector. Here, we perform experiment to validate the effects of dimensional reduction. Specifically, we test the inference performances of the number of the transformed lower dimension (denoted by variable d) with \( d \in \{20, 40, 60, 80, 100, 120\} \). The result is as shown in Table 2. Clearly, we can see better performance trends as \( d \) increases from 20 to 80, which means that a too small \( d \) will lose useful information in data during the dimension reduction process. While when \( d \) increases from 80 to 120, the inference performances go down slightly, which means that a too large \( d \) may result in overfitting phenomena as a larger \( d \) will bring more parameters. This result shows that if the value of \( d \) is set properly, dimension reduction not only can alleviate the dimensionality curse problem, but also can improve inference performance. So, the best value of \( d \) for the proposed MulAProM is 80 and this setting will be used continuously in the subsequent experiments from now on.

5.2.2 Improvement by Data Fusion

Fig. 7 shows the strength of fusing data sources (CDR & DTR) against a single-data source (CDR or DTR, respectively). We obtain the performance statistics for CDR and DTR by directly applying the corresponding features to the proposed MulAProM model. By fusing CDR and DTR, we obtain significantly better performance and lower variance in F1-Measure, for both user gender and age inference. By contrast, using CDR by itself yield a performance loss, as expected, and using DTR by itself generated even worse results. This shows that fusing data sources improves user context inference.

| TABLE 2 |
|---|
| \( d \) | Gender | Age |
|---|---|---|
| Precision | Recall | F1-Measure | Precision | Recall | F1-Measure |
| 20 | 0.5943 | 0.5745 | 0.5892 | 0.4371 | 0.4685 | 0.4539 |
| 40 | 0.6908 | 0.7010 | 0.6994 | 0.5279 | 0.5110 | 0.5143 |
| 60 | 0.7831 | 0.7712 | 0.7648 | 0.6437 | 0.6571 | 0.6511 |
| 80 | 0.8197 | 0.8139 | 0.8146 | 0.6971 | 0.6904 | 0.6955 |
| 100 | 0.8017 | 0.8010 | 0.8094 | 0.6819 | 0.6825 | 0.6829 |
| 120 | 0.7845 | 0.7928 | 0.7900 | 0.6457 | 0.6714 | 0.6697 |

2. http://scikit-learn.org/stable/
3. http://www.cs.waikato.ac.nz/ml/weka
4. https://www.csie.ntu.edu.tw/cjlin/lbsvm/
Table 3

| Method   | Gender | Age |
|----------|--------|-----|
|          | Precision | Recall | F-Measure | Precision | Recall | F-Measure |
| kNN      | 0.7324   | 0.7388 | 0.7301   | 0.6371   | 0.4642 | 0.6568    |
| LRC      | 0.7321   | 0.7385 | 0.7323   | 0.6366   | 0.4642 | 0.6559    |
| NB       | 0.7321   | 0.7222 | 0.7311   | 0.6243   | 0.6227 | 0.6570    |
| GBDT     | 0.7654   | 0.7716 | 0.7699   | 0.6695   | 0.6684 | 0.6642    |
| ANN      | 0.7435   | 0.7517 | 0.7485   | 0.6586   | 0.6485 | 0.6425    |
| L-SVM    | 0.7667   | 0.7644 | 0.7646   | 0.6609   | 0.6607 | 0.6574    |
| N-SVM    | 0.7672   | 0.7640 | 0.7655   | 0.6609   | 0.6609 | 0.6588    |
| SM²L     | 0.7740   | 0.7693 | 0.7714   | 0.6697   | 0.6728 | 0.6718    |
| MulAProm | 0.8189   | 0.8139 | 0.8146   | 0.6971   | 0.6904 | 0.6935    |

5.2.3 Improvement by Interdependence between User Contexts

Table 3 lists the user context inference results of different models for gender and age inference in terms of precision, recall, and the F1-measure. Our proposed MulAProm yield better performance than the baseline models in the two inference tasks by leveraging the interdependence between user gender and age. The SM²L model achieves the best inference results among baseline models, but is inferior to MulAProm. Perhaps the reason is that the source consistency is not very strong, and the tree-guided relatedness structure is not adopted.

Compared to the state-of-the-art precision and recall values for these types of applications, our results are quite good. In [12], which predict users’ gender and age from users’ call records, the best of the performance of gender inference is {precision: 0.8088, recall: 0.8076, F1: 0.8063}, and the best of the performance of age inference is {precision: 0.7266, recall: 0.7140, F1: 0.7132}. In [19], which predict users’ gender from users’ Location Check-ins, the best performance of gender inference in city Beijing is {precision: 0.8211, recall: 0.8059, F1: 0.8134}, in city Shanghai is {precision: 0.8368, recall: 0.8127, F1: 0.8246}. In [11], which infers user activities recorded by mobile phones, the best performance of gender inference is {precision: 0.8750, recall: 0.8570, F1: 0.8660}. From these works’ results, we can conclude that the inference performances will be quite different with different datasets and models.

5.2.4 Effects of Training Percentage

Fig. 8 shows the inference results when varying the ratio of training set. We have the following findings: 1) We observe rising trends of the F1-measure as the training percent-
age increases from 10% in Fig. 8a and Fig. 8b. This indicates the positive effect of training data size on inferring gender and age information. 2) The curves in both subfigures begin to vary only slightly, and show a smoother trend as the percentage approximates to 90%, which results in a turning point. This shows that it is unnecessary to train as many more datasets as possible in model training to completely capture related pattern knowledge. When training percentage is past the turning point, more training data would simply have wasted computational resources in vain. 3) The curve in Fig. 8b arrives at the turning point earlier, and at a lower value, than the one in Fig. 8b. This phenomenon may suggest that it is more difficult to infer users’ age than gender. 4) In both cases, obvious improvements are obtained by our proposed MulAProm model with different percentages of training data against baselines.

6 Conclusion and Future Work

In this paper, we focus on taking advantage of fusing data sources and interdependence between different inference tasks for better performance of user context inference. We have studied real-world telecommunication datasets from two sources: call detail records and data traffic records.

As the beginning of the work, we list some intriguing patterns related to users’ gender and age. Then, based on preliminary findings, we detail the user context inference model step by step. We first extract user features from CDR and DTR, and normalize these features using Z-scores. We then use the tensor outer product to aggregate features from different data sources in a complementary manner to capture the underlying interdependence between CDR and DTR features. Following this, we adopt PCA to reduce the dimensionality of extensional features. Then taking the derived features as input, we propose our MulAProm model to simultaneously infer user gender and age by utilizing their interdependence. Our experiments validate the effectiveness and efficiency of our proposed model.

Our model may suggest lessons for the general field despite of its exclusive target for user context inference: 1) As shown in this paper, in domain-specific data mining, observational studies can help acquire useful prior knowledge of the object of research that can be applied to guide the research. 2) We use tensor outer product to aggregate features from different data sources for the purpose of capturing interdependence between two input feature vectors. 3) We propose the MulAProm model based on the Maximum Entropy Principle to capture the interdependence between two output variables.

Our future work includes, but is not limited to the following: 1) We believe that our proposed model can be used to identify profiles containing fake context information. This is because the context information provided by a mobile user on a postpaid plan while creating an account may contain inaccurate information. 2) Mobile usage records of different groups of users may contain time-dependent patterns. For example, the social circles of young people tend to change quickly, while older people tend to maintain relationships with the same people, such as their spouses and children. Hence, this time-dependency of patterns can
be used to improve user context inference. 3) In the research of user demographic inference, due to user privacy constraints and the scarcity of public datasets, more than one dataset is difficult to obtain. This is a common problem confronted by most researchers in this field, such as [11], [12], [19], in which only one dataset is used in the experiments. What we should is to perform experiments on more datasets to validate the proposed inference model and try to release part of or the whole of the dataset for public research use.

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