A Probabilistic Framework for Location Inference from Social Media

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ABSTRACT
We study the extent to which we can infer users’ geographical locations from social media. Location inference from social media can benefit many applications, such as disaster management, targeted advertising, and news content tailoring. In recent years, a number of algorithms have been proposed for identifying user locations on social media platforms such as Twitter and Facebook from message contents, friend networks, and interactions between users. In this paper, we propose a novel probabilistic model based on factor graphs for location inference that offers several unique advantages for this task. First, the model generalizes previous methods by incorporating content, network, and deep features learned from social context. The model is also flexible enough to support both supervised learning and semi-supervised learning. Second, we explore several learning algorithms for the proposed model, and present a Two-chain Metropolis-Hastings (MH+) algorithm, which improves the inference accuracy. Third, we validate the proposed model on three different genres of data – Twitter, Weibo, and Facebook – and demonstrate that the proposed model can substantially improve the inference accuracy (+3.3-18.5% by F1-score) over that of several state-of-the-art methods.

KEYWORDS
Location Inference, Factor Graph Model, Social Media

1 INTRODUCTION
In many social media platforms, such as Twitter, Facebook, and Weibo, location is a very important demographic attribute to support friend and message recommendation. For example, one observation is that the number of friends tends to decrease as distance increases [3, 27]. Another study also shows that, even on the “global” Internet, the user’s ego-network tends to stay local: the average number of friends between users from the same time zone is about 50 times higher than the number of friends between users from different time zones [15]. However, the geographical location information is usually unavailable. Statistics show that only 26% of users on Twitter input their locations [7]. Twitter, Facebook, and Weibo also have a function to allow adding per-tweet geo-tags; however, it turns out that only 0.42% of all tweets contain a geo-tag.

In this work, our goal is to design a general framework for inferring users’ geographical locations from social media data. Different from previous works [3, 7, 24] that deal with this problem in a specific scenario (e.g., determining USA cities only) or with specific data (e.g., Twitter), we aim to design a method that is general enough to be applied to different scenarios, and is also flexible enough to incorporate a variety of information—contents, user profiles, network structure, and deep representation features.

Previous work on location inference. The location inference problem has been widely studied by researchers from different communities. Roughly speaking, existing literature can be divided into two categories. The first focuses on studying content. For example, Eisenstein et al. [10] proposed the Geographic Topic Model to predict a user’s geo-location from text. Cheng et al. [7] used a probabilistic framework and illustrated how to find local words and overcome tweet sparsity. Ryoo et al. [30] applied a similar idea to a Korean Twitter dataset. Ikawa et al. [16] used a rule-based approach to predict a user’s current location based on former tweets. Wing et al. [31] used language models and information retrieval approaches for location prediction. Chen et al. [5] used topic models to determine users’ interests and mapped interests to location. The other line of research infers user locations using network structure information. For example, Backstrom et al. [3] assumed that an unknown user would be co-located with one of its friends and sought the ones with the maximum probabilities. McGee et al. [25] integrated social tie strengths between users to improve location estimation. Jurgens [17] and Davis Jr et al. [34] used the idea of label propagation to infer user locations according to their network distances from users with known locations. However, these methods do not consider content. Li et al. [24] proposed a unified discriminative influence model and utilized both the content and the social network to predict user locations. However, they focused on US users, and only considered location names in tweets. Another study using user profiles can be found in [34]. Table 1 summarizes the most closely related works on location inference. Survey and analysis of location inference techniques on Twitter can be also found in [2, 18]. Unlike the existing literature, our goal is to propose a general method that is able to deal with text in any languages by incorporating content, network, and other factors.

Problem formulation. The problem of location inference can be generally formalized as a prediction problem. For each user, we aim to predict which country/state/city the user comes from. Our input is a partially labeled network \( G = (V, E, Y_L, X) \) derived from social media data, where \( V \) denotes the set of \( |V| = N \) users with \( V_L \subset V \) indicating the subset of labeled users (with locations) and \( V^U \subset V \) the subset of unlabeled users (without locations), \( E \subseteq V \times V \) is the
Table 1: Summary of previous studies on geo-location inference in social media.

| Features | Authors            | Scope | Language | Object |
|----------|--------------------|-------|----------|--------|
| Content  | Eisenstein et al.  | US    | All      | User   |
|          | Cheng et al.       | US    | All      | User   |
|          | Ryoo et al.        | Korea | All      | User   |
|          | Ikawa et al.       | Japan | Japanese | Tweet  |
|          | Wing et al.        | US    | English  | User   |
|          | Chen et al.        | Beijing | Chinese | Tweet  |
| Network  | Backstrom et al.   | World | All      | User   |
|          | Mcgee et al.       | World | All      | User   |
|          | Jurgens et al.     | World | All      | User   |
|          | Davis Jr et al.    | World | All      | User   |
| Content+Network | Li et al.          | US    | English  | User   |
| Profile  | Zubiaga et al.     | World | All      | Tweet  |

The set of relationships between users, \( Y^L \) corresponds to the set of locations of users in \( V^L \), and \( X \) is the feature matrix associated with users in \( V \) with each row corresponding to a user, each column corresponding to a feature, and \( x_{ij} \) the value of the \( j^{th} \) feature of user \( v_i \). Given the input, we define the problem of inferring user locations as follows:

**Problem 1. Geo-location Inference.** Given a partially labeled network \( G = (V, E, Y^L, X) \), the objective is to learn a predictive function \( f \) in order to predict the locations of unlabeled users \( V^U \)

\[
f : G = (V, E, Y^L, X) \rightarrow Y^U
\]

where \( Y^U \) is the set of predicted locations for unlabeled users \( V^U \).

Without loss of generality, we assume that all predicted locations are among the locations occurring in the labeled set \( Y^L \). It worth noting that our formulation of user location inference is slightly different from the previous work we mentioned above. The problem is defined as a semi-supervised learning problem for networked data — we have a network with some labeled nodes and many unlabeled nodes. Our goal is to leverage both the local attributes \( X \) and the network structure \( E \) to learn the predictive function \( f \).

**Our solution and contributions.** In this paper, we propose a probabilistic model in factor graph model to address the location inference problem. The model seamlessly combines content information and network structure into a probabilistic graphical model. In the graphical model, labeled locations are propagated to unlabeled users. In this way, the model supports both supervised learning and semi-supervised learning. The model also supports incorporating deep representations features learned from social context. To improve the learning effectiveness and efficiency, we explore several learning algorithms. It shows that Loopy Belief Propagation (LBP) achieves good performance, but is not scalable to large networks. Softmax regression (SR) and Metropolis-Hastings (MH) algorithms have successfully addressed the efficiency problem. Moreover, we present a Two-chain Metropolis-Hastings (MH+) algorithm, which further improves the inference accuracy.

We conduct experiments on several datasets of different genres: Twitter, Weibo, and Facebook. The results show that the proposed probabilistic model significantly improves the location inference accuracy (+3.3-18.5% by F1-score), compared to several state-of-the-art methods. In terms of time cost of model training, the proposed MH+ algorithm achieves more than 100× speedup over LBP.

**Organization.** Section 2 presents the proposed methodology. Section 3 presents experimental results that validate the effectiveness of our methodology. Section 4 concludes this work.

### 2 PROBABILISTIC FRAMEWORK

In this section, we propose a general probabilistic framework based on factor graphs for geographical location inference from social media. We first give the model definition, and then introduce several learning algorithms.

#### 2.1 Proposed Model

For inferring user locations, we have three basic intuitions. First, the user’s profile may contain implicit information about the user’s location, such as time zone and the language selected by the user. Second, the tweets posted by a user may reveal the user’s location. For example, Table 2 lists the most popular “local” words in five English-speaking countries, including locations (Melbourne, Dublin), organizations (HealthSouth, UMass), sports (hockey, rugby), local idiom (Cifu, wyd, lad), etc. Third, network structure can be very helpful for geo-location inference. In Twitter, for example, users can follow each other, retweet each other’s tweets, and mention other users in their tweets. The principle of homophily [22] — “birds of a feather flock together” [26] — suggests that “connected” users may come from the same place. This tendency was observed between Twitter reciprocal friends in [15, 21]. Moreover, we found that the homophily phenomenon also exists in the mention network. Table 3 shows the statistics for USA, UK, and China Twitter users. We can see when user A mentions (@) user B, the probability that A and B come from the same country is significantly higher than that they come from different countries. Interestingly, when a USA user A mentions another user B in Twitter, the chance that user B is also from the USA is 95%, while if user A comes from UK, the probability sharply drops to 85%, and further drops to 80% for users from China. We also did the statistics at the state-level and found that there is an 82.13% chance that users A and B come from the same state if one mentions the other in her/his tweets.
SSFGM consists of two kinds of variables: observations \( \{ x \} \) and latent variables \( \{ y \} \). In our problem, each user \( v_i \) corresponds to an observation \( x_i \) and is also associated with a latent variable \( y_i \). The observation \( x_i \) represents the user’s personal attributes and the latent variable \( y_i \) represents the user’s location. We denote \( Y = \{ y_1, y_2, \ldots, y_N \} \), and \( Y \) can be divided into labeled set \( Y^L \) and unlabelled set \( Y^U \). The latent variables \( \{ y_i \} \) are correlated with each other, representing relationships between users. In SSFGM, such correlations can be defined as factor functions.

Now we explain the SSFGM in details. Given a partially labeled network as input, we define two factor functions:

- **Attribute factor**: \( f(x_i, y_i) \) represents the relationship between observation (features) \( x_i \) and the latent variable \( y_i \);
- **Correlation factor**: \( h(y_i, y_j) \) denotes the correlation between users \( v_i \) and \( v_j \).

The factor functions can be instantiated in different ways. In this paper, we define the attribute factor as an exponential-linear function

\[
f(x_i, y_i) = \exp \left( \alpha^T \Phi(x_i, y_i) \right)
\]

\[
\Phi_k(x_i, y_i) = \mathbb{I}_{(y_i = k)} x_i, \quad k \in \{1, \ldots, C\}
\]

where \( \alpha = (a_1, \ldots, a_C)^T \) is the weighting vector, \( \Phi = (\Phi_1, \ldots, \Phi_C)^T \) is the vector of feature functions, \( C \) is the number of location categories, and \( \mathbb{I}_{(y_i = k)} \) is an indicator function.

The correlation factor is defined as

\[
h(y_i, y_j) = \exp \left( \gamma^T \Omega(y_i, y_j) \right)
\]

where \( \gamma \) is also a weighting vector, and \( \Omega \) is a vector of indicator functions \( \Omega_{kl}(y_i, y_j) = \mathbb{I}_{(y_i = k, y_j = l)} \). Correlation can be directed (e.g., mention), or undirected (e.g., reciprocal follow, Facebook friend). For undirected correlation, we need to guarantee \( y_{kl} = y_{lk} \) in the model.

**Model enhancement with deep factors.** Recently, deep neural networks have achieved excellent performance in various fields including image classification and phrase representations [8, 19]. The proposed SSFGM is flexible enough to incorporate deep feature representations. To do this, we define a deep factor \( g(x_i, y_i) \) in the SSFGM model to represent the deep (non-linear) relationships between \( x_i \) and \( y_i \). The \( g(x_i, y_i) \) represents a function between the location label \( y_i \) and the latent representation learned by a deep neural network (Cf. the right side of Figure 1).

Specifically, the deep factor is defined by a two-layer neural network. The input vector \( x \) is fed into a neural network with two fully-connected layers, denoted as \( h^1(x) \) and \( h^2(x) \):

\[
h^1(x) = \text{ReLU}(W^1 x + b^1)
\]

\[
h^2(x) = \text{ReLU}(W^2 h^1(x) + b^2)
\]

where \( W^1, W^2, b^1, b^2 \) are parameters of the neural network, and we use \( \text{ReLU}(x) = \max(0, x) \) as the activation function. Similar to the definition of attribute factor, we define

\[
g(x_i, y_i) = \exp \left( \beta^T \Psi(x_i, y_i) \right)
\]

\[
\Psi_k(x_i, y_i) = \mathbb{I}_{(y_i = k)} h^2(x_i), \quad k \in \{1, \ldots, C\}
\]

where \( \beta \) is the weighting vector for the output of the neural network.
Thus, we have the following joint distribution over \( Y \):

\[
p(Y|G) = \frac{1}{Z} \prod_{v_i \in V} f(x_i, y_i) q(x_i, y_i) \prod_{(v_i, v_j) \in E} h(y_i, y_j)
\]

(6)

where \( Z \) is the normalization factor to ensure \( \sum_Y p(Y|G) = 1 \).

**Feature definition.** For the attribute factor, we define two categories of features: profile and content.

**Profile features** include information from the user profiles, such as time zone, user-selected language, gender, age, number of followers and followees, etc.

**Content features** capture the characteristics of tweet content. The easiest way to define content features is using a bag-of-words representation. But it suffers from high dimensionality, especially in Twitter, which has hundreds of languages. In our work, we employ Mutual Information (MI) [32]. We compute MI using the corpus to aggregate all the words in a user’s tweets.

**Model learning.** Learning a Semi-Supervised Factor Graph Model involves two parts: learning parameters \( W, b \) for the neural network of the deep factor, and learning parameters \( \alpha, \beta, \gamma \) for the graphical model. In this paper, we use a separate two-step learning approach. We leave the joint learning of the neural network and the graphical model as our future work.

We first introduce our approach for learning the neural network. Cheng et al. [6] suggested that joint learning of wide and deep models can gain the benefits of memorization and generalization. In our work, we combine the attribute factor and deep factor by adding a softmax layer on the top of two models to generate the output \( y \), as illustrated in Figure 1 on the right. We train the model with labeled data only, and use squared loss as the loss function. We adopt stochastic gradient descent (SGD) to perform back propagation on the neural network and update the parameters. After the neural network is trained, we can compute deep factors for all users, and then move to learn the factor graph model.

The next step is to learn the graphical model – i.e., determine a parameter configuration \( \theta = (\alpha^T, \beta^T, \gamma^T)^T \) such that the log-likelihood of the labeled data can be maximized. For simplicity, we denote \( s(y_i) = (\Phi(x_i, y_i)^T, \Psi(x_i, y_i)^T, \frac{1}{2} \sum_{j} \Omega(y_i, y_j)^T)^T \), and \( S(Y) = \sum_Y s(y_i) \). The joint probability defined in Eq. 6 can be rewritten as

\[
p(Y|G) = \frac{1}{Z} \prod_i \exp(\theta^T s(y_i)) = \frac{1}{Z} \exp(\theta^T \sum_i s(y_i))
\]

(7)

The input of SSFGM is partially labeled, which makes the model learning very challenging. The general idea here is to maximize the marginal likelihood of labeled data. We denote \( Y|Y^L \) as the label configuration that satisfies all the known labels. Then we can define the following MLE objective function \( O(\theta) \):

\[
O(\theta) = \log p(Y|G) = \log \sum_{Y|Y^L} \frac{1}{Z} \exp(\theta^T S)
\]

\[
= \log \sum_{Y|Y^L} \exp(\theta^T S) - \log \sum_{Y} \exp(\theta^T S)
\]

(8)

Now the learning problem is cast as finding the best parameter configuration that maximizes the objective function, i.e.,

\[
\hat{\theta} = \arg \max_{\theta} \log p(Y|G)
\]

(9)

We can use gradient descent to solve the above optimization problem. First, we derive the gradient of each parameter \( \theta \):

\[
\frac{\partial O(\theta)}{\partial \theta} = \frac{\partial}{\partial \theta} \left( \log \sum_{Y|Y^L} \exp(\theta^T S) - \log \sum_{Y} \exp(\theta^T S) \right)
\]

\[
= \frac{\log \sum_{Y|Y^L} \exp(\theta^T S) \cdot \sum_{Y} \exp(\theta^T S)) - \log \sum_{Y} \exp(\theta^T S)}{\sum_{Y} \exp(\theta^T S)}
\]

\[
= \frac{\sum_{Y|Y^L} \exp(\theta^T S) \cdot \sum_{Y} \exp(\theta^T S)) - \log \sum_{Y} \exp(\theta^T S)}{\sum_{Y} \exp(\theta^T S)}
\]

\[
= \sum_{Y|Y^L} \exp(\theta^T S) \cdot \sum_{Y} \exp(\theta^T S)) - \log \sum_{Y} \exp(\theta^T S)
\]

(10)

The gradient equals to the difference of two expectations of \( S \), which are under two different distributions. The first one \( p_0(Y|Y^L, G) \) is the model distribution conditioned on labeled data, and the second one \( p_0(Y|G) \) is the unconditional model distribution. Both of them are intractable and cannot be computed directly.

### 2.2 Basic Learning Algorithms

We start with two basic algorithms to tackle the learning problem in SSFGM.

**Loppy Belief Propagation (LBP).** A traditional method to estimate the gradient in graphical models is Loopy Belief Propagation (LBP) [28], which provides a way to approximately calculate marginal probabilities on factor graphs. LBP performs message passing between variables and factor nodes according to the sum-product rule [20]. In each step of gradient descent, we perform LBP twice to estimate \( p_0(Y|G) \) and \( p_0(Y|Y^L, G) \) respectively, and then calculate the gradient according to Eq. 10.

However, this LBP-based learning algorithm is computationally expensive. Its time complexity is \( O((I+I_0)(|V|+|E|+|C|)) \), where \( I \) is the number of iterations for gradient descent, \( I_0 \) is the number of iterations for belief propagation, and \( C \) is the number of the location categories (usually 30-200). This algorithm is time-consuming, and not applicable when we have millions of users and edges.

**Metropolis-Hastings (MH).** In addition to LBP, Markov Chain Monte Carlo (MCMC) methods have proved successful for estimating parameters in complex graphical models, such as SampleRank [29]. In our work, we employ Metropolis-Hastings sampling [13] to obtain a sequence of random samples from the model distribution and update the parameters. The learning algorithm is described in Algorithm 1.

We now explain Algorithm 1 in detail. At first, we initialize parameters \( \theta \) randomly. The Metropolis-Hastings algorithm simulates
Algorithm 1: Metropolis-Hastings (MH)

Input: \( G = (V, E, Y^L, X) \), learning rate \( \eta \);
Output: learned parameters \( \theta \);
1. Initialize \( \theta \) and \( Y \) randomly;

2. repeat
3. \( y_i \) uniformly at random;
4. \( \theta \) \sim \( U(0, 1) \);
5. \( \tau \leftarrow \min \left\{ \frac{p_0(Y^{*}(G)g(Y)|Y)}{p_0(Y|g(Y)|Y)} \right\} \);
6. if \( u < \tau \) then / accept
7. \( Y \leftarrow Y^{*} \);
8. else
9. \( Y \leftarrow \theta + \mathbf{N}(0, \eta) \cdot \nabla \left( \log p_0(Y^{*}) - \log p_0(Y) \right) \);
10. \( Y \leftarrow Y^{*} \);
11. \( \theta \leftarrow \theta + \mathbf{N}(0, \eta) \cdot \nabla \left( \log p_0(Y^{*}) - \log p_0(Y) \right) \);
12. \( Y \leftarrow Y^{*} \);
13. until convergence;

random samples from the model distribution \( p_0(Y|G) \). In each iteration, it generates a candidate configuration \( Y^{*} \) from a proposal distribution \( q(\cdot|Y) \), and accepts it with an acceptance ratio \( \tau \) (line 6). If the candidate \( Y^{*} \) is accepted, the algorithm continues to update the parameters \( \theta \) (line 8-11). We compare the accuracy (ACC) and likelihood of the two configurations \( Y \) and \( Y^{*} \). Ideally, if one’s accuracy is higher than the other, its likelihood should also be larger; otherwise the model should be adjusted. Thus there are two cases to update the parameters: 1) if the accuracy of \( Y^{*} \) is higher but its likelihood is smaller, update with \( \theta^{\text{new}} \leftarrow \theta^{\text{old}} + \eta \cdot \nabla \left( \log p_0(Y^{*}) - \log p_0(Y) \right) \); 2) if the accuracy of \( Y^{*} \) is lower but its likelihood is larger, update with \( \theta^{\text{new}} \leftarrow \theta^{\text{old}} - \eta \cdot \nabla \left( \log p_0(Y^{*}) - \log p_0(Y) \right) \). Note that we only have to calculate unnormalized likelihoods of \( p_0(Y^{*}) \) and \( p_0(Y) \). Thus, the gradient can be easily calculated,

\[
\nabla \left( \log p_0(Y^{*}) - \log p_0(Y) \right) = \nabla \left( \theta^T \mathbf{S}(Y) - \theta^T \mathbf{S}(Y) \right) = \mathbf{S}(Y^{*}) - \mathbf{S}(Y)
\]

(11)

This algorithm is more efficient than the previous LBP algorithm, but also has some shortcomings. The algorithm updates the model when larger likelihood leads to worse accuracy. It actually optimizes an alternative max-margin objective instead of the original maximum likelihood objective. In addition, it relies on an external metric (accuracy in our work), which could be arbitrary and engineering-oriented, since multiple metrics are often available for evaluation.

2.3 Enhanced Learning Algorithms

We now present two enhanced learning algorithms – Softmax Regression (SR) and Two-chain Metropolis Hastings (MH+) for SSFGM. SR is very efficient, much faster than the basic learning algorithms and MH+ achieves a better prediction performance.

Softmax Regression (SR). We propose a new learning algorithm based on softmax regression (also called multinomial logistic regression). Estimation of joint probability Eq. 7 is an intractable problem because of the normalization factor Z, which sums over all the possible configurations Y. Our idea here is to only consider \( \gamma_i \) and fix all other variables, its marginal can be easily calculated as a softmax function,

\[
p(y_i|G, Y - \{y_i\}) = \frac{\exp(\theta^T \mathbf{s}(y_i))}{\sum_{y_i'} \exp(\theta^T \mathbf{s}(y_i'))},
\]

(12)

where \( \mathbf{s}(y_i) = (\Phi(x_i, y_i) \mathbf{1}, \Psi(x_i, y_i), \Omega(y_i, y_i)^T) \).

Eq. 12 has the same form as softmax regression. The difference is that the neighborhood information is also contained in feature function \( \mathbf{s}(y_i) \). Softmax regression can be trained using gradient descent, and the gradient is much easier to compute than factor graph models. We then design an approximate learning algorithm based on softmax regression:

Step 1. Conduct softmax regression to learn \( \alpha \) and \( \beta \), with labeled data \( \{(x_i, y_i) \mid y_i \in Y^L\} \) only;\(^1\)

Step 2. Predict the labels \( Y_U \) for unlabeled users;

Step 3. Conduct softmax regression to learn \( \theta \) according to Eq. 12;

Step 4. Predict the labels \( Y_U \) for unlabeled users. If the prediction accuracy on validation set increases, go to Step 3; otherwise, stop.

This algorithm is an approximation method for learning SSFGM, but it is both effective and very efficient. We can use SR to initialize the model parameters for the other learning algorithms.

Two-chain Metropolis-Hastings (MH+). The classical MH algorithm does not directly maximize the log-likelihood [29] and relies on additional evaluation metrics. We introduce a new idea to directly optimize the objective function in Eq. 8 without using additional heuristic metrics. We refer to this algorithm as Two-chain Metropolis-Hastings (MH+).

Algorithm 2 illustrates the new algorithm. In Eq. 10, the gradient consists of two expectation terms. To obtain an unbiased estimation of the gradient, we sample \( Y_U \) from \( p_{data} = p_0(Y|G, Y^L) \) and sample

\(^1\)Here we use \( p(y_i|G) = softmax \left( \alpha_{\gamma_i} \Phi(x_i, y_i) + \beta_{\gamma_i} \Psi(x_i, y_i) \right) \).

Algorithm 2: Two-chain Metropolis-Hastings (MH+)

Input: \( G = (V, E, Y^L, X) \), learning rate \( \eta \) and \( \text{batch size} \);
Output: learned parameters \( \theta \);
1. Initialize \( \theta \) with SR-based learning;
2. Initialize \( Y_U \) with \( Y^L \) fixed, and \( Y_U \) randomly;
3. Initialize \( Y_2 \) randomly;
4. repeat
5. \( \theta^{*} \leftarrow \theta \);
6. for \( t = 1, 2, \ldots, \text{batch size} \) do
7. \( y_i \) uniformly at random;
8. Generate \( y_i \sim q(|Y\rangle) \);
9. Accept \( y_i \) such that \( Y_1 \sim p_0(Y|G, Y^L); \)
10. Accept \( y_i \) such that \( Y_2 \sim p_0(Y|G); \)
11. if \( y_i \) is accepted in \( Y_1 \) or \( Y_2 \) do then
12. \( \theta \leftarrow \theta + \eta \cdot (\mathbf{s}(y_i) - \mathbf{s}(y_i^*)) \)
13. until early stopping criteria satisfied;
we randomly sample an index \( i \) according to a uniform distribution, and set \( y_1 \) as a random value \( y_i^1 \) according to another uniform distribution. In each iteration, we select the same index \( i \) and propose the same \( y_i^1 \) for both chains \( Y_1 \) and \( Y_2 \) to ensure stable gradient estimation. However, the new label configurations in the two chains are accepted with different acceptance ratios \( (\tau_1 \text{ and } \tau_2) \) such that they follow the corresponding distributions, i.e.,

\[
\begin{align*}
\text{for chain } Y_1, \quad &\tau_1 = \min \left\{ 1, \frac{p_\theta(Y_1^1 | G, Y^L)}{p_\theta(Y_1 | G, Y^L)} \right\} \\
\text{for chain } Y_2, \quad &\tau_2 = \min \left\{ 1, \frac{p_\theta(Y_2^1 | G)}{p_\theta(Y_2 | G)} \right\}
\end{align*}
\]  

To further speed up the learning algorithm, we approximate the gradient by only considering a local update—i.e., \( s(Y_1^1 | Y_1) - s(y_i^1 | Y_2) \)—rather than a global update \( s(Y_1) - s(Y_2) \). If \( y_i^1 \) is rejected in both chains, we do not update the parameters. Our choice of proposal distribution has several advantages: 1) empirically the algorithm’s performance is better than changing multiple variables each time or changing different variables in two chains, and 2) it simplifies the calculation of acceptance ratio and gradient, since we only need to consider local variables and factors. We also tried other strategies such as sampling \( y_i \) with probabilities proportional to the marginal probabilities, but do not obtain further improvements.

We use several techniques to improve the stability and efficiency of the learning algorithm. The first technique is mini-batch gradient descent. We compute the gradient for a mini-batch of sampling steps, and then update the parameters with the sum of these gradients. \( batch\_size \) is a hyperparameter. The second technique is early stopping. We divide the labeled data into a training set and a validation set. During the learning process, we only use the labels in the training set. We evaluate the model after each \( \delta \) iterations, and if the prediction accuracy on the validation set does not increase for \( \epsilon \) evaluations, we stop the algorithm and return the parameter configuration \( \theta \) that achieves the best accuracy on the validation set. \( \delta \) and \( \epsilon \) are also hyperparameters. These techniques can also be used in the previous MH algorithm.

In contrast to the basic MH algorithm based on only the model distribution \( p_{model} \), our algorithm utilizes both \( p_{model} \) and \( p_{data} \) so that we can directly optimize the log likelihood. LBP also maximizes the likelihood, but it requires traversing the entire network in each iteration to compute the gradient. Instead, we leverage MH sampling to estimate the gradient efficiently. Similar ideas based on Markov chains have been adopted for training restricted Boltzmann machines [14], but those algorithms do not apply to a partially-labeled factor graph model as in our work.

### Parallel Learning

To scale up the proposed model to handle large networks, we have developed parallel learning algorithms for SSFGM. For the SR algorithm, softmax regression can be easily parallelized. The gradient is a summation over all the training examples, and the computation is independent. For MH and MH+, we parallelize the learning algorithm by dividing the batch. Each thread generates random samples and computes gradients independently, and with a smaller batch size. Then master thread gathers the gradients from different threads and updates the parameters.

### 2.4 Prediction Algorithm

We can apply the learned SSFGM to predict unknown locations—i.e., to find the most likely configuration \( \hat{Y} \) for unlabeled users based on the learned parameters \( \theta \),

\[
\hat{Y} = \arg \max_Y p_\theta(Y | G, Y^L)
\]

For prediction, we consider two algorithms. The first one is based on LBP. It uses the max-sum algorithm instead of sum-product in LBP to find the \( \hat{Y} \) that maximizes the likelihood. The second algorithm is based on Metropolis-Hastings sampling. We keep sampling with the estimated \( \theta \), and finally return the configuration \( \hat{Y} \) with the maximum likelihood.

### 3 EXPERIMENTS

We evaluate the proposed model on three different data: Twitter, Weibo, and Facebook. All datasets and codes used in this paper are available online.

#### 3.1 Experimental Setup

**Datasets.** We conduct experiments on four datasets. Table 4 shows the basic statistics of the datasets.

| Dataset      | #user | #edge | #region |
|--------------|-------|-------|---------|
| Twitter (World) | 1,516,075 | 25,867,610 | 159 (a) |
| Twitter (USA)  | 329,457  | 3,194,305  | 51 (b)  |
| Weibo (China)  | 1,073,923 | 26,849,112 | 34 (c)  |
| Facebook      | 856     | 11,789  | 10 (d)  |

* (a) 159 countries; (b) 50 states and Washington, D.C.; (c) 34 provinces; (d) 10 anonymous locations.

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1. In our work, we use LBP for prediction when the model is trained with the LBP algorithm, and use MH for prediction when the model is trained with MH/MH+.
2. `http://dev.aminer.org/thomas0809/MH`
Weibo [33]: Weibo is the most popular Chinese microblog. The dataset consists of about 1,700,000 users, with up to 1,000 most recent microblogs posted by each user. The task is to infer the user’s province. We use reciprocal following relationships as edges in this dataset.

Facebook [23]: The dataset is an ego-facebook dataset from SNAP, and does not contain content information. In our experiments, we only consider users who indicate their hometowns in their profiles. Locations are anonymized in this dataset. We use Facebook friendships as edges.

Data preprocessing. We now introduce how we preprocess the data. First, we filter out users who have fewer than 10 tweets in the dataset. Then, we tokenize the tweet content into words. In Twitter, we split the sentences by punctuations and spaces. For languages that do not use spaces to separate words (such as Chinese and Japanese), we further split each character. In the Weibo data provided by [33], the content has been tokenized into Chinese and Japanese, we further split each character. In the Weibo data, we consider this method as the classification model to predict user location. We use the same feature set as our proposed model.

Comparison methods. We compare the following methods for location inference:

- **Logistic Regression (LR):** We consider this method as the baseline method, which applies logistic regression as the classification model to predict user location. We use the same feature set as our proposed model.
- **Support Vector Machine (SVM) [34]:** Zubiaga et al. have applied SVM to classify tweet location. We choose a linear function as the kernel of SVM.
- **Graph-based Label Propagation (GLP) [9]:** It infers locations of unlabeled users by counting the most popular location among one’s friends with a simple majority voting.

Table 5: Performance comparison of different methods in user geo-location inference. ("—" indicates that the result is unavailable for the corresponding method.)

| Method              | ACC | Prec. | Rec. | F1  | ACC | Prec. | Rec. | F1  | ACC | Prec. | Rec. | F1  |
|---------------------|-----|-------|------|-----|-----|-------|------|-----|-----|-------|------|-----|
| Logistic Regression | 94.40 | 65.18 | 42.69 | 51.59 | 48.62 | 53.16 | 31.09 | 39.23 | 36.98 | 32.46 | 11.68 | 17.18 |
| SVM [34]            | 94.33 | 63.75 | 44.79 | 52.61 | 47.68 | 55.72 | 28.36 | 37.59 | 35.73 | 32.03 | 8.26 | 13.13 |
| GLP [9]             | 72.12 | 65.18 | 35.97 | 46.36 | 39.83 | 64.54 | 30.36 | 41.30 | 64.28 | 78.82 | 44.94 | 57.24 |
| FindMe [3]          | 72.29 | 69.18 | 36.30 | 47.61 | 40.03 | 63.79 | 30.92 | 41.65 | 63.54 | 79.63 | 43.71 | 56.44 |
| SSFGM (LBP)         | 95.81 | 66.40 | 45.57 | 54.05 | 59.20 | 58.27 | 42.80 | 49.35 | 70.34 | 70.41 | 57.52 | 63.31 |
| SSFGM (SR)          | 94.71 | 67.74 | 44.11 | 53.43 | 55.66 | 60.30 | 39.15 | 47.48 | 64.38 | 79.62 | 45.22 | 57.68 |
| SSFGM (MH)          | 95.17 | 61.71 | 43.19 | 51.81 | 58.56 | 54.20 | 41.70 | 47.13 | 69.45 | 66.95 | 56.40 | 61.22 |
| SSFGM (MH+)         | 95.71 | 66.31 | 46.05 | 54.35 | 59.11 | 57.18 | 42.88 | 49.01 | 70.01 | 71.84 | 56.00 | 62.94 |
| SSFGM (MH+Deep)     | 95.81 | 66.40 | 45.57 | 54.05 | 59.20 | 58.27 | 42.80 | 49.35 | 70.34 | 70.41 | 57.52 | 63.31 |

Table 6: Running time by different learning algorithms.

| Method     | Twitter (USA) | Weibo | Facebook  |
|------------|---------------|-------|-----------|
| SSFGM (LBP)| > 100 days    | > 100 days | 16.8min    |
| SSFGM (SR) | 2hr, 59min    | 2hr, 46min | 1.90sec    |
| SSFGM (MH) | 7hr, 36min    | 4hr, 12min | 5.26sec    |
| SSFGM (MH+) | 5hr, 12min | 4hr, 57min | 8.57sec    |

For baseline methods, we use the implementation of Liblinear [11]. For the proposed method, all experiment codes are implemented in C++ and Python. The deep factor in our model has been implemented using TensorFlow [1]. We empirically set up the hyperparameters as the following: for LR and SVM, we set the regularization penalty $\lambda = 1$ in MH and $\lambda = 100$ in MH+, early stopping threshold $\delta = 1000$, $c = 20$; the deep factor is set as a two-layer neural network, where the first layer has 200 hidden units and the second layer has 100 hidden units.

Evaluation metrics. In our experiments, we divide each dataset into three parts: 50% for training, 10% for validation, and 40% for testing. For the methods which do not require validation, the validation data is also used for training.

We evaluate location inference performance using the measures for multi-class classification. Specifically, we use four measures: Macro-Accuracy (percentage of the users whose locations are predicted correctly), and Macro-Precision, Recall, and F1-score (the average precision, recall and F1-score of each class).
3.2 Experiment Results

Inference performance. We compare the performance of all the methods on the datasets. Table 5 lists the performance of comparison methods for geo-location inference. SSFGM consistently outperforms all the comparison methods in terms of accuracy and F1-score on all datasets. In Twitter (World), linear models (LR and SVM) can achieve an accuracy of 94.4% for classifying users into 159 countries. Our SSFGM improves the accuracy to 95.8% by incorporating social network. In Twitter (USA), SSFGM achieves a significant improvement in terms of both accuracy and F1-score. This is because for inferring user country, the content information might be more important, as users from different countries may use different languages; while for inferring location at the state-level, the effect of network information increases. The proposed SSFGM can leverage the network structure information to help improve the inference accuracy. This can be confirmed by taking a closer look at the Weibo data, where we have a complete following network. From the Facebook data, we have another observation, it seems that the SSFGM (LBP) still achieves the best performance. The only problem to SSFGM (LBP) is its low efficiency. We cannot obtain results on the other three datasets by SSFGM (LBP). We will analyze the computational efficiency of different learning algorithms later. Finally, we can observe that in general the deep factor indeed helps to improve inference accuracy. Deep factors can incorporate non-linear, cross-dimensional representations of input features, and thus help the model to improve its performance.

Comparison of different learning algorithms. We compare the performance of four learning algorithms for SSFGM. The traditional LBP-based leaning still results in a very good inference accuracy, but its computational cost is high. Comparing softmax regression (SR) and Metropolis-Hastings (MH), they result in similar performance — SR outperforms (0.3-1.6% by F1-score) MH on Twitter (World) and Twitter (USA), but underperforms (3.3-3.6% by F1-score) on Weibo and Facebook. The proposed MH+ algorithm further improves the performance and achieves consistently better performances (0.7-5.3% by F1-score) than SR and MH.

Compared with the traditional LBP-based learning algorithm, the studied SR and MH algorithms are much more efficient. Table 6 shows the training time of SSFGM used by different learning algorithms, where each algorithm is running with a single computer core. LBP uses about 16 minutes to train SSFGM on our smallest dataset, and needs more than one hundred days on the other large datasets. SR seems to be the most efficient among the four learning algorithms. MH and MH+ take SR as parameter initialization and further improve the accuracy. Generally speaking, they are very efficient on large datasets and over 100x faster than LBP. Their running time varies a little in different datasets because of the difference in convergence speed.

Scalability performance. We have implemented parallel learning algorithms for the MH and MH+ algorithms utilizing OpenMP architecture. We now evaluate the scalability of the two learning algorithms on the Twitter (USA) dataset. Figure 2 shows the scalability performance with different numbers of cores (2-8). The speedup curve of MH is close to the perfect line at the beginning. Though the speedup inevitably decreases due to the increase of the communication cost between different computer nodes, the parallel algorithms can still achieve ~ 3.3 – 4.5x speedup with 8 cores.

Factor contribution analysis. We now evaluate how different factors (content, profile, and network) contribute to location inference in the proposed model. We use the two Twitter datasets in this study. Specifically, we remove each factor from our SSFGM and then evaluate the model performance decrease. A large decrease means more importance of the factor to the model. Figure 3 shows the results on the Twitter datasets. We see that different factors contribute differently on the two datasets. The content-based features seem to be the most useful in the proposed model for inferring location on the Twitter datasets. On the other hand, all features are helpful. This analysis confirms the necessity of the flexibility to incorporate various features in the proposed model.

Hyperparameter sensitivity. Finally, we analyze how the hyperparameters in the proposed model affect the inference performance.

Learning rate ($\eta$): Figure 4(a) shows the accuracy performance of SSFGM (MH and MH+) on Twitter (USA) dataset when varying the learning rate $\eta$ from $10^{-3}$ to $10^{1}$. Generally speaking, the performance is not sensitive to the learning rate over a wide range. However, a too large or too small learning rate will hurt the performance.
4 CONCLUSIONS

In this paper, we studied the problem of inferring user locations from social media. We proposed a general probabilistic model based on factor graphs. The model generalizes previous methods by incorporating content, network, and deep features learned from social context. The model is sufficiently flexible to support both supervised learning and semi-supervised learning. We presented several learning algorithms and proposed an Two-chain Metropolis-Hastings (MH+) algorithm, which improves the inference accuracy. Our experiments on four different datasets validate the effectiveness and the efficiency of the proposed model. We also implemented a parallel learning algorithm for the proposed model, which enables the proposed model to handle large-scale data.

Inferring user demographics from social media is a fundamental issue and represents a new and interesting research direction. As for future work, it would be intriguing to apply the proposed model to infer other demographic attributes such as gender and age. It is also interesting to connect the study to some real applications – for example, advertising and recommendation – to further evaluate how inferred location can help real applications. Finally, we also consider how to integrate social theories such as social status and structural holes to understand the underlying mechanism behind user behavior and network dynamics.

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