POIsketch: Semantic Place Labeling over User Activity Streams

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Abstract

Capturing place semantics is critical for enabling location-based applications. Techniques for assigning semantic labels (e.g., “bar” or “office”) to unlabeled places mainly resort to mining user activity logs by exploiting visiting patterns. However, existing approaches focus on inferring place labels with a static user activity dataset, and ignore the visiting pattern dynamics in user activity streams, leading to the rapid decrease of labeling accuracy over time. In this paper, we tackle the problem of semantic place labeling over user activity streams. We formulate this problem as a classification problem by characterizing each place through its fine-grained visiting patterns, which encode the visiting frequency of each user in each typical time slot. However, with the incoming activities of new users in data streams, such fine-grained visiting patterns constantly grow, leading to a continuously expanding feature space. To solve this issue, we propose an updatable sketching technique that creates and incrementally updates a set of compact and fixed-size sketches to approximate the similarity between fine-grained visiting patterns of ever-growing size. We further consider the discriminative weights of user activities in place labeling, and seamlessly incorporate them into our sketching method. Our empirical evaluation on real-world datasets demonstrates the validity of our approach and shows that sketches can be efficiently and effectively used to infer place labels over user activity streams.

1 Introduction

Semantically understanding human activity is a key ingredient when developing human-aware applications. One critical aspect of this understanding is semantic place labeling, which aims at assigning semantic labels to locations. For example, it is often more useful to know that a place is a bar rather than knowing its GPS coordinates only. By understanding the semantics of previously visited places, one can enable various location-centric applications such as personalized location based services [Yang *et al.*, 2013a; 2013b] and user activity inference [Yang *et al.*, 2015b].

The recent rise of Location Based Social Networks (LBSNs), such as Foursquare[1], made large-scale spatiotemporal user activity data become more accessible. In LBSNs, users share their real-time activities with their social circles by checking in at Points of Interest (POIs), such as a given bar or French restaurant. In practice, the semantic labels of POIs in LBSNs are not always available due to a variety of reasons, such as the users' unwillingness to label them, or some lack of information from service providers. The basic intuition behind automatically inferring POI labels is that POIs of the same type usually share similar visiting patterns, which are encoded by users' check-ins. For example, [Cheng *et al.*, 2011a] defines the traffic pattern of a POI as the aggregated check-in frequency in each time slot during a typical time period (e.g., 168 hours in a week), and uses such traffic patterns for place labeling. In that context, most of the recent contributions [Ye *et al.*, 2011; Falcone *et al.*, 2014] try to select the most representative features from a static dataset of check-ins in order to train dedicated classifiers.

However, as an intrinsically online data source, LBSNs continuously capture user activity data (7 million check-ins/day on Foursquare [Blog, 2015]), which makes the existing place labeling approaches inadequate. Specifically, user dynamics in LBSNs (e.g., check-ins from newly registered users) make features selected on static datasets become less efficient for new POIs, leading to a rapid decrease in accuracy (see for example Figure 4(b) below for an empirical evaluation of this effect). Moreover, the high computational costs of existing approaches (e.g., random walks in [Ye *et al.*, 2011]) make them ill-suited for streaming data.

Motivated by those facts, we introduce in this paper a novel approach for semantic place labeling over activity streams by leveraging data sketching techniques. Specifically, instead of using coarse-grained traffic patterns that encode temporal dynamics [Cheng *et al.*, 2011a] only, we consider fine-grained visiting patterns encoding both temporal and user dynamics, captured by the cumulative check-in frequencies of each user-time pairs during a typical time period. Our study shows that such finer-grained patterns yield more accurate labels (see Figure 4(a) for details). With large numbers of check-ins, however, the size of the resulting fine-

[1] http://foursquare.com/

grained visiting patterns makes the classification become impractical. One key idea to overcome this limitation is to apply sketching techniques [Aggarwal and Philip, 2010; Bachrach *et al.*, 2009] in order to maintain a set of compact and fixed-size sketches of the original fine-grained visiting patterns while still preserving their similarity.

However, applying sketching techniques to our problem faces two challenges. First, our approach needs to be incrementally updatable, since the visiting pattern of a POI characterized by check-ins continuously grows, which departs from classical sketching techniques that focus on sketching complete data instances. Ideally, the new sketch of a POI visiting pattern should be incrementally computed from the former sketch and the newly arrived data. Second, users' activities are not all equally important when labeling POIs. For example, check-in data showing less obvious routines are less discriminative for place labeling, and should be given a lower weight during the classification [Wettschereck *et al.*, 1997]. Considering streaming check-ins implies that such discriminative weights might have to be dynamically recomputed over time, and more importantly, to be incorporated in classification with sketches.

To address those two challenges, we propose a data sketching method that creates and incrementally updates sketches from streaming check-in data, while dynamically measuring their discriminability and seamlessly incorporating the resulting weights into the sketching process. Specifically, we resort to consistent weighted sampling techniques [Manasse *et al.*, 2010] to approximate the min-max similarity when creating the sketches, which has been proved to be an effective similarity measure for nonnegative data [Li, 2015]. For each incoming check-in at a POI, the sketch is directly updated based on the former sketch and the cumulative frequency of the newly arrived check-ins. To take into account the discriminative weight of each user-time pair, we first estimate the entropy weight for individual user-time pairs, and then dynamically incorporate such weights when creating and updating the sketches. In such a way, the discriminative weights are seamlessly propagated to the sketches (see Section 3.2 for details).

We evaluate our approach on two real-world LBSN datasets collected from Foursquare in New York City and Tokyo. Our empirical results (see Section 4) show that our approach can not only efficiently create and update sketches for the fine-grained visiting patterns of POIs, but can also effectively preserve their similarity, yielding to very accurate inferred labels.

2 Related Work

Existing work on semantic place labeling mainly leverage three types of user activity data: diary data collected though surveys, continuously sampled data from wearable sensors, and self-reported activity data from LBSNs. Diary data, such as [Krumm and Rouhana, 2013], are collected by asking participants to fill out a questionnaire covering their visits in a certain time period. Due to this labor-intensive collection process, such datasets are however hard to maintain. Continuously sampled data from wearable sensors usually consist of fine-grained activity logs from various sensor readings (e.g., GPS, accelerometer, Bluetooth, WiFi, etc.), such as [Do and Gatica-Perez, 2014]. Although wearable sensors can provide fine-grained and continuous samples of user activity, obtaining large-scale datasets is difficult due to privacy concerns [Shilton, 2009]. Finally, LBSNs have attracted millions of users reporting their daily activities by checking in at POIs. Previous work on semantic place labeling using LBSN datasets [Ye *et al.*, 2011; Falcone *et al.*, 2014] all try to manually select representative features of visiting patterns based on static datasets, which are subsequently fed into a classifier for inferring the labels. However, the streaming nature of check-in data in LBSNs makes such features become rapidly less effective over time. To the best of our knowledge, this paper is the first attempt at addressing the semantic place labeling problem over streaming activity data.

Data sketching techniques were designed to handle massive data, particularly data streams. Their basic idea is to maintain compact sketches allowing to approximate specific properties of the original data. Sketches can power a wide range of applications, including enumerating different kinds of frequency statistics of data streams [Cormode and Muthukrishnan, 2005], or approximating the similarity of high dimensional data (e.g., documents and images) [Wang *et al.*, 2014]. Sketching techniques have also been studied to approximate various similarity measures, including the Jaccard [Broder *et al.*, 1998; Mitzenmacher *et al.*, 2014], cosine [Kutzkov *et al.*, 2015], and min-max [Li, 2015] similarities. In this paper, we leverage data sketching techniques to approximate the min-max similarity between fine-grained visiting patterns from user activity streams. Different from existing sketching techniques for min-max similarity that are all applied on complete instances [Manasse *et al.*, 2010; Ioffe, 2010; Li, 2015], we focus on fine-grained POI visiting patterns that are based on continuously updated data. Therefore, we propose a new data sketching approach that creates and incrementally updates sketches from streaming check-in data, and also consider their discriminability in the sketching process.

3 Sketch-Based Semantic Place Labeling

The basic idea behind our approach is to create a concise and updatable sketch of the fine-grained POI visiting patterns over user activity streams in LBSNs, for the purpose of inferring place labels. For a specific POI, its fine-grained POI visiting pattern is represented by a vector $V \in \mathbb{N}^{|\mathcal{D}|}$, where $\mathcal{D}$ is the activity vocabulary including all user-time pairs. The size of $\mathcal{D}$ is $|\mathcal{U}| \cdot |\mathcal{T}|$, where $\mathcal{U}$ and $\mathcal{T}$ are the set of users and the set of time slots in a typical time period, respectively. Each element of V_i, $i \in \mathcal{D}$ encodes the cumulative count of the corresponding user-time pair i on that POI. In this paper, we define the time slot as hours and the typical time period as a week (i.e., 168 hours in a week), which is a widely adopted method in studying check-in patterns [Yang *et al.*, 2015a]. With the increasing number of users, the size of $\mathcal{D}$ rapidly grows. Therefore, in order to efficiently classify POIs (assigning semantic labels to POIs) based on ever-growing V, our objective is to create and efficiently maintain a compact

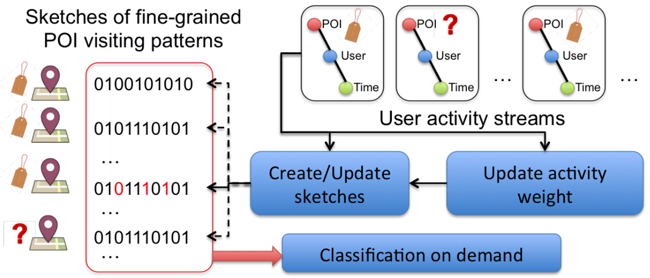


Figure 1: Overview of our approach

and fixed-size sketch S of V to effectively approximate the similarity between V of different POIs, such that the classification can be efficiently run based on S.

As illustrated in Figure 1, our approach takes user activity streams from LBSNs as input. For each check-in triplet (POI-user-time), we first update the global discriminative weights (see Section 3.2) of individual activities in $\mathcal{D}$, i.e., user-time pairs. Based on the discriminative weights, we then update the sketches for each POI. In order to infer place labels, the classical classification method can then be performed on demand. In the following, we first present our updatable sketching method for approximating the min-max similarity, and then discuss how to seamlessly incorporate the discriminative weights in the sketches.

3.1 Updatable Sketching Method

In this section, we present our updatable sketching method to approximate the min-max similarity, which is an effective measure of similarity for nonnegative data [Li, 2015]. Given two fine-grained visiting pattern vectors V^a and V^b, their min-max similarity is defined as follows:

$$Sim_{MM}(V^a, V^b) = \frac{\sum_{i \in \mathcal{D}} \min(V_i^a, V_i^b)}{\sum_{i \in \mathcal{D}} \max(V_i^a, V_i^b)} \quad (1)$$

The proposed sketching method creates sketches S^a and S^b of size K ($K \ll |\mathcal{D}|$) for V^a and V^b, respectively, with the property that their collision probability is exactly the min-max similarity between V^a and V^b:

$$Pr[S_j^a = S_j^b] = Sim_{MM}(V^a, V^b) \quad (2)$$

where $j = 1, ..., K$. The min-max similarity between V^a and V^b can then be approximated by the Hamming similarity between S^a and S^b. The computation over S, which is compact and of fixed-size, is much more efficient than that over V, which is a large, ever-growing vector.

Sketch Creation

In order to create S from V, we borrow the idea of consistent weighted sampling [Manasse *et al.*, 2010], which was originally used for approximating min-max similarity for complete data instances. Specifically, given a vector V, it applies a random hash function h_j on each (i, f), where $i \in \mathcal{D}$ and $f \in \{1, ..., V_i\}$, and obtains the corresponding hashed value $h_j(i, f)$. Note that the random hash function h_j maps (i, f) uniquely to $h_j(i, f)$, which follows a uniform distribution over $(0, 1)$, i.e., $h_j(i, f) \sim Un(0, 1)$. Then, one element of S is returned as $(i_j^*, f_j^*) = \arg\min_{i \in \mathcal{D}, f \in \{1,...,V_i\}} h_j(i, f)$. The theoretical results show that:

$$Pr[(i_j^{a*}, f_j^{a*}) = (i_j^{b*}, f_j^{b*})] = Sim_{MM}(V^a, V^b) \quad (3)$$

In order to further reduce the size of the above sketches, a recent study [Li, 2015] proposed that it is sufficient to only keep i_j^* in the above sketches, and also empirically proved the following property:

$$Pr[i_j^{a*} = i_j^{b*}] \approx Pr[(i_j^{a*}, f_j^{a*}) = (i_j^{b*}, f_j^{b*})] \quad (4)$$

Therefore, for a specific random hash function h_j, we assign $S_j = i_j^*$. By applying K independent random hash functions ($j = 1, ..., K$), we generate sketch S (with size K) from V (with arbitrary size).

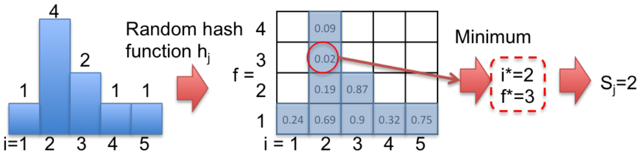


Figure 2: An example of sketch creation

Figure 2 illustrates the sketch creation process. The left-hand side of the figure shows the histogram of a fine-grained visiting pattern V with an activity vocabulary size $|\mathcal{D}| = 5$. By applying a random hash function h_j on each (i, f), we obtain the corresponding hash values (shown in the blue cells), and then select the cell whose hash value is minimum: $(i^* = 2, f^* = 3)$ with a corresponding hash value of 0.02. We hence obtain the corresponding sketch element $S_j = 2$.

Sketch Updating

As V incrementally grows with the incoming check-in data, our sketching method needs to be updatable. To achieve this goal, besides the sketch S, we also keep a vector Q (of size K) storing the corresponding minimum hash values (e.g., $Q_j = 0.02$ in the above example). For each new check-in at a POI (i.e., for a user-time pair r), the corresponding V_r is increased by 1. In case of a new activity $r \notin \mathcal{D}$, we add r in $\mathcal{D}$, and augment V to include $V_r = 1$. Then, we only need to apply the hash function h_j on (r, V_r). By comparing the new hash value $h_j(r, V_r)$ with that of the old sketch Q_j, we update $S_j = r$, iff., $h_j(r, V_r) < Q_j$. If S_j is updated, we also update Q_j to its corresponding hash value, i.e., $h_j(r, V_r)$. Figure 3 illustrates the sketch updating process following the previous example. The incoming check-in is added to V_4, resulting in a new $V_4 = 2$. We thus apply h_j only on $(4, 2)$. By selecting the minimum hash value between $Q_j = 0.02$ and $h_j(4, 2) = 0.01$, we update $S_j = 4$, and the corresponding $Q_j = 0.01$. With K random hash functions, we maintain a sketch S of size K and the corresponding minimum hash values Q for each V.

Note that the above updating process requires to access the former value of V_r. As it is continuously growing, we maintain each V in a compact count-min sketch [Cormode and Muthukrishnan, 2005], which is a fixed-size probabilistic data structure (d rows and w columns) serving as a frequency table of elements, with an estimated frequency error

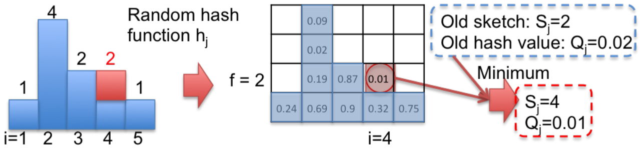


Figure 3: An example of sketch updating

of at most $\frac{2}{w}$ with probability $1-(\frac{1}{2})^d$. We set the parameters $d=10, w=50$ to guarantee an error within 4% with probability 0.999.

3.2 Discriminative Weight Consideration

All activities (user-time pairs) in $\mathcal{D}$ are not equally important to infer place labels. For example, if a user frequently goes to bars rather than other places on Friday night, we can label an unknown place he visited on a Friday night as a bar with high confidence. Traditionally, with a static dataset, we can measure such discriminability as a discriminative weight, which can be easily incorporated in the inference process. However, with user activity streams, the discriminative weight of activities might dynamically change; more importantly, the activity vocabulary $\mathcal{D}$ continuously grows. Therefore, we need to dynamically measure the discriminability of the activities and incorporate it seamlessly into the sketching process. To achieve this goal, we first define the *weighted min-max similarity* between fine-grained visiting patterns V as follows:

$$Sim_{WMM}(V^a, V^b) = \frac{\sum_{i\in\mathcal{D}} W_i \cdot \min(V_i^a, V_i^b)}{\sum_{i\in\mathcal{D}} W_i \cdot \max(V_i^a, V_i^b)} \tag{5}$$

where W_i is the weight of activity i, $i \in \mathcal{D}$. We note that the discriminative weight W_i here is a global feature weight, which is different from the "weight" of consistent weighted sampling, which represents the frequency of the data. In this section, we further discuss how to seamlessly incorporate those weights in the sketching process, such that:

$$Pr[S_j^a = S_j^b] \approx Sim_{WMM}(V^a, V^b) \tag{6}$$

where the approximate equality comes from Eq. (4). In the following, we first describe how to compute the weights before turning to their incorporation in the sketching process.

Weight Computation

We leverage a widely used weighting function, i.e., entropy weighting [Nakov *et al.*, 2001]. (We note however that our approach is not limited to any specific weighting function.) Specifically, for a given set of place labels, $\mathcal{C}$, we use entropy weighting to empirically measure the uncertainty of place labels when observing individual activities. For each activity i in $\mathcal{D}$, we compute its entropy weight W_i as follows:

$$W_i = 1 + \frac{\sum_{l\in\mathcal{C}} p_{l,i}\log p_{l,i}}{\log|\mathcal{C}|} \tag{7}$$

where $p_{l,i}$ is the probability that POIs with activity i are labeled as l, $l \in \mathcal{C}$. Higher values of W_i imply higher degrees of discriminability for the corresponding activity i. To calculate $p_{l,i}$, we maintain a vector F^l for each place label of size $|\mathcal{D}|$ to record the cumulative frequency of each activity in $\mathcal{D}$. With each incoming check-in, we update F^l accordingly. Thus, we are able to empirically compute $p_{l,i} = \frac{F_i^l}{\sum_{l'\in\mathcal{C}} F_i^{l'}}$ at any time. Particularly, for each incoming check-in i, only the corresponding W_i needs to be updated. To improve space efficiency, we also store F^l in a compact count-min sketch data structure similar as the one we used for V.

Weight Incorporation in Sketching

We further extend our previous sketching method to incorporate the discriminative weights W. Our previous sketching method samples one element (i, f) from V for each hash function h_j. The key idea of incorporating W in the sketching process is to get sample (i, f) with higher probability for larger W_i, since activity i is more discriminative in the classification. In the simple case of positive integer weight for W, for the same (i, f), it is sufficient to generate W_i different random hash values $h_j^m(i, f)$, $m = 1, ..., W_i$, and select the minimum hash value $\hat{h}_j(i, f) = \min_{m=1,...,W_i} h_j^m(i, f)$. In such a way, an activity i with larger weight will have more random hash values and thus have a higher probability to be the minimum (i.e., sampled as S_j), or vice versa. To extend the above method for positive real weights, we follow the idea of [Chum *et al.*, 2008] and design a new variable following the same cumulative distribution function (CDF) with $\hat{h}_j$. The new variable can be generated directly from one random hash value only and W_i, rather than W_i random hash values. Specifically, since $h_j^m \sim Un(0, 1)$, we compute the CDF of $\hat{h}_j$ as:

$$Pr[\hat{h}_j \le x] = 1 - (1-x)^{W_i} \tag{8}$$

for $x \in (0, 1)$. We assume another random uniformly distributed variable $z \sim Un(0, 1)$, and formulate its CDF $Pr[z \le y] = y$, $y \in (0, 1)$ as:

$$Pr[z \le 1-(1-x)^{W_i}] = 1-(1-x)^{W_i} \tag{9}$$

where $y = 1-(1-x)^{W_i}$ is an invertible continuous increasing function ($x = 1 - \sqrt[W_i]{(1-y)}$) over $(0, 1)$. By applying the change-of-variable technique on Eq. (9), we obtain:

$$Pr[1 - \sqrt[W_i]{(1-z)} \le x] = 1-(1-x)^{W_i} \tag{10}$$

Since Eqs. (10) and (8) show the same CDF, $\hat{h}_j$ can be obtained by $\hat{h}_j = 1 - \sqrt[W_i]{(1-z)}$. As $(1-z) \sim Un(0, 1)$, the computation can be simplified to $\hat{h}_j = 1 - \sqrt[W_i]{z}$. As we only care about the ordering of those hash values, we can further simplify the computations via a monotonic transformation, and obtain:

$$\hat{h}_j = \frac{-\log z}{W_i} \tag{11}$$

Using Eq. (11), we can efficiently compute the hash value $\hat{h}_j$ from one random hash value, rather than generating W_i different random hash values. More importantly, Eq. (11) can take any positive real weight.

Based on the above derivation, we only need to modify the hashing function in our previous sketching method to incorporate W. Specifically, for both sketch creation and updating,

Table 1: Dataset statistics

Dataset	New York City (NYC)	Tokyo (TKY)
Check-in number	129,774	169,033
POI number	5,823	4,228
User number	6,981	2,495

we first update the current weight W, and then compute the hash value for each (i, f) using $\hat{h}_j$ as follows:

$$\hat{h}_j(i, f) = \frac{-\log h_j(i, f)}{W_i} \tag{12}$$

where h_j is the random hash function in Section 3.1.

We note that the consistent weighted methods proposed by [Ioffe, 2010; Li, 2015] can take positive real number vectors as input, so that the sketch for Eq. (5) can be directly obtained by regarding $V \circ W$ as input, where $\circ$ represents the element-wise product. However, these sketching methods require to maintain three positive real number parameter matrices in memory, each of size $K * |\mathcal{D}|$. The ever-growing activity vocabulary $\mathcal{D}$ makes these methods impractical in our context.

4 Experimental Evaluation

In this section, we conduct a series of experiments to evaluate our approach. We first describe our experimental setting, followed by our results for assessing both the effectiveness and the efficiency of our approach.

4.1 Experimental Settings

We evaluate our approach on a check-in dataset collected by [Yang *et al.*, 2015a; 2016] for about 18 months (from April 2012 to September 2013). Without loss of generality, we select check-in data from two big cities, New York City and Tokyo, for our experiments. In our dataset, POIs are classified by Foursquare into 9 root categories (i.e., Arts & Entertainment, College & University, Food, Great Outdoors, Nightlife Spot, Professional & Other Places, Residence, Shop & Service, Travel & Transport), which are further classified into 291 sub-categories[2]. Table 4.1 summarizes the main characteristics of our dataset.

In our experiments, we consider the POIs appearing in the first 9-month check-ins as labeled training data, and the new POIs in the last 9-month data (unseen in training data) as unlabeled testing data. As inferring POI labels is intrinsically a classification problem, we decided to leverage a KNN classifier [Mitchell, 1997], which does not require building a model from training data and can always takes the most up-to-date training data for classification. Such properties fit our case of rapidly growing visiting patterns well. It is important to note that our sketching method is not bound to the KNN classifier, and can be used with any classifiers. We empirically set KNN with the five nearest neighbors, and report the classification accuracy on both the 9 root categories (Lv1) and the 291 sub-categories (Lv2). The classification is triggered when 10 check-ins are observed for each POI tested.

In order to evaluate our approach, we compare it with the following baseline methods:

- *Coarse*: We calculate the POI similarity based on their traffic patterns [Cheng *et al.*, 2011b] (coarse-grained visiting patterns), which is represented by a vector with size $|\mathcal{T}|$ where each element is the frequency of check-in in the corresponding time slot. Euclidean similarity is used as similarity measure.
- *Fine-Jaccard*: We regard fine-grained visiting patterns as binary vectors, and measure their Jaccard similarity.
- *Fine-MinMax*: We measure the min-max similarity of fine-grained visiting patterns (Eq. 1).
- *Fine-MinMax-Weighted*: We measure the weighted min-max similarity of fine-grained visiting patterns (Eq.5).
- *Sketch-Jaccard*: We use min-hash sketching [Broder *et al.*, 1998] to approximate *Fine-Jaccard*.
- *Sketch-MinMax*: Our method without discriminative weight (i.e., approximation of *Fine-MinMax*).
- *Sketch-MinMax-Weighted*: Our method with entropy weight (i.e., approximation of *Fine-MinMax-Weighted*).

4.2 Place Labeling Performance

In this section, we evaluate the effectiveness of our approach. We first compare our approach to the baselines, and then show the classification accuracy of different methods over time. Finally, we study the impact of the sketch length on the classification accuracy.

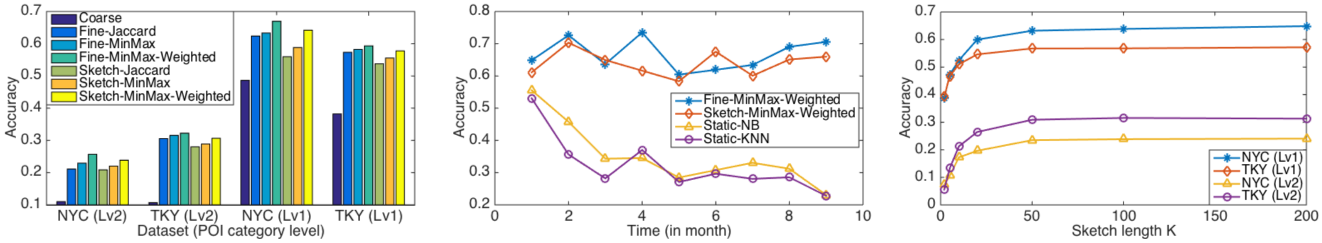
Comparison with other approaches

In this experiment, we compare our method to the baseline approaches by fixing the sketch length to 50 for all sketching methods (the impact of sketch length is studied below). Figure 4(a) plots the average accuracy for both datasets on the two level categories. We observe that coarse-grained visiting pattern yields the worst results. Based on the fine-grained visiting patterns, classification with weighted max-min similarity achieves the best results, which shows the effectiveness of this similarity measure. Our sketching method outperforms all other sketching baselines. Particularly, compared to *Fine-MinMax-Weighted*, our sketching method can effectively approximate the weighted min-max similarity with only a small loss in classification accuracy (e.g., about 3.3% on average for root POI categories).

Classification accuracy over time

We now study the classification performance of our approaches over time. Specifically, we report the place labeling accuracy for each of the 9 months, with a sketch length $K = 50$. We also implement two baseline classifiers trained only on static training data, i.e., Naive Bayes (*Static-NB*) and KNN (*Static-KNN*). All methods in this experiment use fine-grained visiting patterns. Figure 4(b) plots the results on NYC dataset and the 9 root levels of categories. (Experiments on the TKY dataset and on the 291 sub-categories show the similar results). We observe that our method consistently achieves good results by approximating the weighted min-max similarity over streaming data accurately. However, the

[2] https://developer.foursquare.com/categorytree



(a) Comparison with other approaches (b) Classification accuracy over time (c) Impact of sketching length

Figure 4: Place Labeling Performance

two classifiers based on static datasets show a rapid performance decay, which can be explained by two reasons. First, due to the high user dynamics (e.g., varying activity of users, newly registered users) in user activity streams from LBSNs, the fine-grained visiting patterns incrementally evolve. Second, with the continuously incoming user activities, the discriminability of user activities also dynamically changes. The two baselines based on a static dataset fail to capture these features, leading to rapid performance decay.

Impact of sketching length

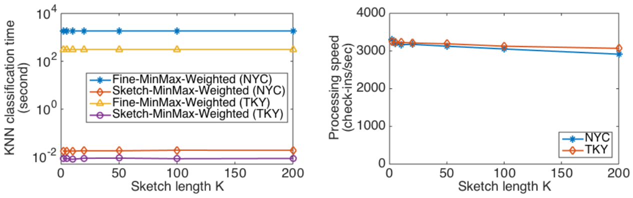
To study the impact of the sketching length K on classification accuracy, we vary K within $\{2, 5, 10, 20, 50, 100, 200\}$. Figure 4(c) reports the average accuracy of our approach. We observe that the accuracy increases with increasing values of K, which implies that longer sketches can better characterize the similarity between fine-grained visiting patterns. Moreover, there is no significant improvement when K gets higher than 50, which means that sketches with $K = 50$ are sufficient to characterize the similarity between V in practice. Therefore, we set the K to 50 in previous experiments.

4.3 Runtime Performance

To evaluate the efficiency of our approach, we investigate the execution time of both check-in data processing and place label classification, w.r.t, the sketch length K, $K = \{2, 5, 10, 20, 50, 100, 200\}$. All experiments were conducted on a commodity PC (Intel Core i7-4770HQ@2.20GHz, 16GB RAM, Mac OS X) running MATLAB[3] version 2014b.

Figure 5(a) shows the KNN classification time (on log scale). We observe that using sketches can dramatically reduce the classification time (with an order of 10,000x), since the Hamming similarity between sketches of small size can be much more efficiently computed than the weighted min-max similarity between the fine-grained visiting patterns of larger size. With short sketch lengths, we find little variance in the classification time across different K. The time differences between datasets are mainly caused by the different number of training POIs and the size of the activity vocabulary $\mathcal{D}$ in the two datasets. More training data and larger size of $\mathcal{D}$ implies longer execution times for the KNN classification.

Figure 5(b) reports the processing speed on check-in streams. We observe that the processing speed slightly decreases with increasing sketch lengths, since larger K values imply a larger number of random hash functions in the sketching process. For $K = 50$, our test PC is able to process about 3,200 check-ins/sec on both dataset, which can easily accommodate the current Foursquare check-in stream where the peak-day record shows 7 million check-ins/day [Blog, 2015] (about 81 check-ins/sec on average). Since the sketch length K controls the tradeoff between the processing rate and accuracy (see Figure 5(b) and 4(c)), in practice, one can adjust K to improve accuracy at the expense of the processing rate margin.



(a) Classification time (b) Processing speed

Figure 5: Runtime Performance

5 Conclusions

In this paper, we introduce a novel semantic place labeling approach over user activity streams in LBSNs by leveraging data sketching techniques. Specifically, by characterizing POIs through their fine-grained visiting patterns, we propose a sketching method to maintain a set of compact and fixed-size sketches to approximate their min-max similarity. Moreover, in order to consider the discriminability of user activities for place labeling, we introduce a technique to dynamically measure such weights and seamlessly incorporate them into the sketching process. Based on two real world datasets collected from Foursquare, the evaluation results show that our approach can efficiently create and update sketches of fine-grained visiting patterns for the purpose of semantic place labeling.

As future work, we plan to explore user social networks to further improve the accuracy of the labeling, and consider the concept drift problem [Li *et al.*, 2012] over time.

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