ABSTRACT

In recent years, a vast amount of research has been conducted on learning people’s interests from their actions. Yet their collective actions also allow us to learn something about the world, in particular, infer attributes of places people visit or interact with. Imagine classifying whether a hotel has a gym or a swimming pool without ever talking to the people who stayed there. Or imagine predicting whether a restaurant has a happy hour or a romantic atmosphere without asking its patrons. Algorithms we present can do just that.

Many web applications rely on knowing attributes of places, for instance, whether a particular restaurant has WiFi or offers outdoor seating. Such data can be used to support a range of user experiences, from explicit query-driven search to proactively recommending places the user might like. However, obtaining these attributes is generally difficult, with existing approaches relying on crowdsourcing or parsing online reviews, both of which are noisy, biased, and have limited coverage. Here we present a novel approach to classifying place attributes, which learns from patrons’ visit patterns based on anonymous observational data.

Our method, STEPS, learns from aggregated sequences of place visits. For example, if many people visit the restaurant on a Saturday evening, coming from a luxury hotel or theater, and stay for a long time, then this restaurant is more likely to have a romantic atmosphere. On the other hand, if most people visit the restaurant on weekdays, coming from work or a grocery store, then the restaurant is less likely to be romantic. We show that such transition features are highly predictive of place attributes. We also introduce a variant of our method, STEPS-E, which builds a high-dimensional embedding model trained on co-visitiation data, and completely eliminates the need for feature engineering. In an extensive empirical evaluation, STEPS nearly doubled the coverage of a state of the art approach thanks to learning from observational location data, which allowed our method to reason about many more places.

1. INTRODUCTION

“You know my method. It is founded upon the observation of trifles.”
– Sherlock Holmes.

In recent years, numerous web services and applications have been built to facilitate access to information about brick-and-mortar businesses and places such as restaurants, hotels, parks, or tourist sites. These include review sites and recommendation apps (TripAdvisor, Yelp, Zagat), online business directories (Urbanspoon, Yellowpages), mapping services (Google Maps), travel sites (Hotels.com, Expedia), and even web search. Many of these services rely on knowing attributes of places to help users narrow down their search. For example, recommendation web sites often categorize restaurants using a variety of attributes, such as whether a restaurant is a fine-dining or casual place, whether it offers free WiFi or outdoor seating, whether it takes reservations or offers take-out. Similarly, travel sites allow users to search for hotels based on attributes such as whether the hotel is frequented by business customers or leisure travellers, and whether it has amenities such as a gym or swimming pool. Therefore, identifying these attributes is a critical component in many user-facing applications.

However, obtaining these attributes of places in a scalable manner is challenging. Existing approaches have traditionally taken one of two routes: (a) Crowdsourcing the task, or (b) Inferring attributes from text analysis of online reviews about the place. The former approach explicitly asks visitors to manually specify attributes of the place. We also introduce a variant of our method, STEPS-E, which builds a high-dimensional embedding model trained on co-visitiation data, and completely eliminates the need for feature engineering. In an extensive empirical evaluation, STEPS nearly doubled the coverage of a state of the art approach thanks to learning from observational location data, which allowed our method to reason about many more places.
rant reviews talk about the cuisine type, prices or ambience, but only a few (if at all) may explicitly mention whether the restaurant requires reservations, offers take-out, or has outdoor seating (see Table 2 for the long list of attributes we predict). Finally, reviews are biased because only a handful of people choose to write them, and usually they were either extremely happy or unhappy with the service.

We take a fundamentally different approach, and study the movement of people to infer attributes of places they visit. As a motivating example, imagine you stumbled upon a coffee shop you have never visited before. Over two dozen people are waiting in line. The coffee must be good, you say to yourself, because all those people waiting patiently must know what they are doing. At that very moment you have inferred an attribute of a physical place by observing how people act around it. In this paper, we present algorithms that do just that.

We introduce STEPS, Spatio-TEmporal analysis of Place attributes, which learns from trajectory patterns of patrons’ visits to the place. STEPS derives spatial and temporal features from anonymous aggregated Location History data that our users have proactively chosen to share with us. The data comes in the form of aggregated visit sequences (before/after visiting a given place), along with place categories (e.g., restaurant or grocery store), binned arrival time, and duration. Similar data is available in the form of place check-ins on Foursquare, Facebook or Yelp, or geo-coded tweets on Twitter. However, the anonymous visit data has much higher coverage (as it does not require explicit check-in) and temporal resolution (we can compute visit durations and arrival times). It is also much less biased than reviews because no effort is required from the visitor. In this paper, we show how this micro-scale visit data allows us to learn new macro-scale facts about the world (place attributes).

STEPS uses features based on sequences of other places visited by patrons of a given place, which are often predictive of place attributes. For example, if many people visit a particular restaurant soon after visiting a park or a beach, then the restaurant is more likely to have outdoor seating because it appeals to patrons who like to be outdoors. If a restaurant is often visited for short periods of time in the afternoon, after visiting another restaurant and before going home, then it is likely to offer good desserts. On the other hand, if many people go to a restaurant directly from home or work and stay there for a long time, it is probably good for meals rather than desserts. (See Section 5 for additional examples of visit patterns we use as prediction signals.) One might think that many of these patterns are only weakly correlated with the attribute we are trying to predict. A key insight of this paper is that when we aggregate multiple weak signals over a large population, we can classify many place attributes with high accuracy and coverage.

We formulate the problem of attribute classification in a supervised learning setting, and use manually labeled training data. STEPS employs a semi-automatic approach to feature generation, which constructs a large number of features based on several simple (hand-chosen) properties of co-visited places, for example, their categories (e.g., grocery store or park) and the durations of visits. We then use these features to train a binary classifier for each attribute.

We also introduce a variant of STEPS called STEPS-E, which completely automates feature construction and learn features directly from the data. STEPS-E performs collaborative filtering on the co-visitation patterns of people and places to create a high-dimensional embedding (hence “-E”) of each place in an underlying latent space. The dimensions of the latent space are then treated as automatically-constructed features for training binary classifiers for each attribute. STEPS-E uses low-rank matrix factorization to automatically create 1000-dimensional feature vectors for each place. The latent features in STEPS-E are much fewer than the fine-grained features created in STEPS. However, as evident from the experiments in Section 4, they are rich enough to capture many of the spatio-temporal visit patterns useful for attribute classification.

The contributions of this paper are threefold. First, we proposed a novel approach to classifying attributes of a place based on other places frequently visited by its patrons. Second, we employed the richness of aggregated anonymous location data to automatically construct features that characterize nearby locations visited and the time spent there. It should be emphasized that this data is entirely observational, hence no extra effort is required to collect it. Third, we performed a comprehensive evaluation of our approach using real world data spanning several dozen different attributes of thousands of places (restaurants and hotels). We compared our results to a state of the art baseline that mines the text of online reviews to infer attributes. We showed that our approach significantly increases the coverage of the baseline method, while exhibiting competitive classification accuracy. Since reviews are not always available and may not mention all the relevant attributes, relying on reviews is a major limitation, which our proposed approach alleviates and nearly doubles the classifier coverage. We also note that the nature of the location data is orthogonal to that of the review text. As a result, when we combine features from the two data sources (reviews + place visits), we observe a further improvement in classification performance. Finally, we present a qualitative study that explains in depth how our method works on several attributes.

2. BACKGROUND

With the rapid increase in location-aware applications, there has been a large body of work on location data mining and its various use-cases. Several papers have focused on collecting and modeling location data for personalized Point-of-Interest (POI) recommendation. Ye et al. [19] modeled users’ check-in behavior in location based social networks, and proposed a collaborative POI recommendation algorithm using Naïve Bayes methods. Lian et al. [11] proposed a matrix-factorization approach for POI recommendation, by jointly modeling users’ geographic preferences and their place-visit data from location based social networks. Zheng et al. [21] mined a large scale GPS dataset to extract correlations between user locations for personalized recommendations. Zheng et al. [20] used GPS data along with user text comments to create a location-activity matrix for collaborative location and activity recommendations. Cheng et al. [1] considered temporal and sequence information to predict a user’s next-POI by incorporating personalized Markov Chain information during matrix factorization.

Another direction in location data mining deals with modeling user trajectories and visit distribution patterns to pre-

1 Users can switch it off at any time via My Account. This is essentially the same data we use in Google Now to notify users about the best time to visit their favorite museum.

8 We could then use these features directly for the data.
dict a user’s next destination or activity. Li et al. [10] predicted user trajectories using a probabilistic motion model trained on anonymized GPS-snippets. Cheng et al. [2] used check-in data from location based social networks, and learnt a Hidden Markov Model to predict a user’s activity and location at the next step. Lichman et al. [13] modelled a user’s spatial distribution using a mixture of Kernel Density Estimators. Kirmse et al. [7] used location histories obtained from GPS and WiFi signals to infer users’ frequently visit places and commute patterns. Laio et al. [12] modeled raw GPS traces using relational Markov networks to simultaneously infer a user’s significant locations and activities.

Somewhat related to our work is the recent paper by Zhong et al. [22] who used location check-in records to create spatial and temporal location features of users for predicting various user demographics such as age, gender, educational background, etc. However, the focus of our paper is different from [22] (and indeed, from most of the above papers on inference using location data) in that we model location data not to predict user attributes, but rather place attributes, and hence our location features are aggregate, population level features, instead of per-user features.

While we are not aware of prior work on using location data for extracting place attributes, there has been a large body of work on inferring attributes of products, places and other entities from text mining of online content. In particular, there exists a rich line of work in the area of opinion mining [14], which performs text analysis of documents, customer reviews or online discussion forums to identify attributes of an entity and extract customer opinions and sentiments for these attributes. Several of these papers use a notion of frequent noun phrases to identify important attributes from reviews [9,6,4,16,15]. Another class of opinion mining papers involves leveraging relationships between potential attributes and sentiment-bearing words (usually adjectives) to discover relevant attributes, and their sentiment scores. Hu et al. [3] extracted low-frequency attributes by identifying the nearest noun phrases to sentiment-bearing words. Qui et al. [17] used a double propagation method to jointly extract attributes and sentiment words. Zhuang et al. [23] mined relationships between attributes and sentiment words using a dependency grammer graph, and extracted valid attribute-sentiment pairs for movie reviews. Jakob et al. [6] proposed a supervised CRF-based sequence modeling approach to extract attributes, using features such as the part of speech tags, string tokens, dependency-parse-tree distances, and distance to sentiment words. Wang et al. [18] addressed the problem of teasing out users’ latent ratings on different topical attributes of hotel reviews from users’ overall review scores and their review text.

The key intuition here is that the sequence of places people visited before and after a given place, can reveal patterns that are correlated with attributes of the place. Admittedly, this correlation might be quite weak for any individual pattern. However, our experimental results suggest that aggregating such patterns over a large population of place visitors leads to surprisingly strong prediction of place attributes.

We construct a large set of spatio-temporal features using aggregated data for an entire population of visitors to a place. The features can be logically grouped as follows.

- **Duration features**: These features capture the distribution of time people stay at a place. Intuitively, such features are useful for predicting attributes of restaurants such as availability of WiFi, or whether it has fast service. For example, patrons may stay longer in a cafe with WiFi available, and they may stay less in a fast-food restaurant.

- **Arrival time features**: These features capture the distribution of people’s arrival times to a place. Specifically, we create a set of real-valued features for each hour of the week, where the feature value corresponds to the fraction of people that visit the place at that hour. There are several attributes for which this temporal signal is useful. For example, if a restaurant is frequented by patrons in the afternoon, it is more likely to offer good desserts. Similarly, if a restaurant is popular on Sunday mornings, it is likely that it serves a good brunch menu.

- **Occupancy features**: These features capture the occupancy distribution of a place (measured in terms of the fraction of people who visit the place at different hours of the week). For example, a restaurant offering brunch menu may be crowded between breakfast and lunch hours on Sundays. Note that while the arrival and duration features characterize people’s visits, the occupancy features characterize the busyness of a place. Occupancy features essentially define the occupancy histogram of a place, by the hour of the week.

- **Transition features (previous visit)**: Place attributes are correlated with previous visits. Our features capture temporal signal of people’s visits to other places within a time window (1, 4, 8, 16 and 24 hours). To ensure that such features generalize well, this distribution is computed not over the specific places people visit, but over place categories (e.g., restaurant, grocery store, hotel). The value of each feature reflects the fraction of people who visited that place category in a given time window before the target place visit (e.g., 2% of visitors to the given restaurant have visited a grocery store in the previous hour). Several place attributes can be predicted better using such features. For example, if a cafe is frequented by people who visit another restaurant beforehand, then this cafe is more likely to offer good desserts. If a restaurant is popular among patrons who visit parks or beaches prior to it, then the restaurant is likely to have outdoor seating (as it appeals to people who like to be outdoors).

- **Transition features (next visit)**: Analogous to the previous-visit features described above, we also compute the distribution of people’s visits (to other places) after visiting a given place, within a particular time window. For example, if many people visit surf shops after a hotel, then the hotel is likely to have beach access. If many people visit a cafe in the morning after staying at a hotel, then it is likely that the hotel does not provide breakfast.

The above groups of features are instantiated for different place categories and time intervals, hence the total number
of features we generate for each place is quite large (about \( \sim 100K \)). This process is semi-automatic, because the only manual part is compiling the lexicon of place categories and the choice of time intervals. Cf. Section 3 for examples of features we use for predicting different attributes.

We use supervised learning to train models for predicting individual place attributes. We have a multi-labeled setting whereas each restaurant (or hotel) has multiple attributes, and we predict each one independently by training a dedicated binary classifier. Note that our feature set is comprehensive enough to be predictive of all attributes, and is not specific to any particular attribute. We perform per-attribute feature selection (using a standard Mutual Information-based method), and retain up to 10,000 features per attribute. All the attributes we predict are binary, hence we use binary classification models (however, STEPS is applicable to predicting multi-class attributes too).

Specifically, for each attribute we collect a ground-truth set of positive and negative labels corresponding to places that have this attribute and places that do not have it. The labels are obtained from third-party aggregator sites as well as via crowdsourcing, as described in Section 4. In the experiments described in Section 4 we used linear Support Vector Machines for classification, however, our STEPS method can work with any binary classifier.

Automating feature generation with embeddings

The STEPS method described in the previous section relies on human engineered features. We now propose a variant of STEPS called STEPS-E, which performs automated feature generation for attribute classification, with only a small penalty in accuracy compared to using manual feature engineering. At a high level, STEPS-E generates a feature vector for each place using collaborative filtering on the (anonymous) person-place visit data. We use low-rank matrix factorization [8] on the person-place co-visit matrix (normalized to factor out location bias [11], as described below) to compute an embedding vector for each place in a latent low-dimensional space. The dimensions of this vector are then used as features for representing the place.

Specifically, we first construct a person-place matrix \( L \) with rows representing people and columns representing places. Note that the data in this matrix is completely anonymous. Every cell in the matrix contains a boolean value representing whether the person has visited the place or not, and has an associated weight corresponding to the number of times the person visits the place, capped by a maximum threshold. The weight represents a confidence score, and captures the relative contribution of the cell to the matrix-factorization objective function. A well-known issue in geographical matrix factorization (see [11]) is the tendency of people to have location bias. For example, people are more likely to visit restaurants in a small set of locations they are familiar with, and less likely to visit restaurants in unfamiliar areas. Thus, not visiting a restaurant in a familiar area should carry a stronger negative signal, and visiting a restaurant in new areas should carry stronger positive reinforcement. Several approaches have been proposed to correct this location bias [11]. We used a simple yet effective normalization heuristic, which divides the weight of each cell in the matrix (counting the person’s visits to a place) by the number of other places this person has visited in a 2 km radius. Given this weighted co-visit matrix, we use standard low-rank matrix factorization to compute a low dimensional person embedding \( U \) and place embedding \( V \), by optimizing the following loss function (using Weighted Alternate Least Squares [8]):

\[
\min_{U,V} \sum_{i,j} W_{ij} \left( L_{ij} - U_i^T V_j \right)^2 + \lambda \left( \sum_i ||U_i||_2 + \sum_j ||V_j||_2 \right),
\]

where \( W \) is the weighting matrix, and \( \lambda \) is the L2-norm regularization constant.

Each place embedding is then used as a feature vector of the place to train binary classifiers for various attributes, as described in the previous section. Since we use low-rank matrix factorization, the number of embedding dimensions is small enough that we do not need to use feature selection.

4. EMPIRICAL EVALUATION

We describe the datasets and the baseline, and then report the performance of our methods. We also present ablation studies that explore the utility of the different feature groups. All the results were obtained via 10-fold cross-validation. We evaluated the performance of place attribute predictions using the area under the ROC curve (AUC).

4.1 Datasets

We evaluated our methodology on 2 large datasets with labeled data about attributes of restaurants and hotels.

The restaurant dataset included 29 restaurant attributes (all binary) listed in Table 1. Admittedly, these attributes are somewhat subjective (e.g., whether the restaurant is inexpensive), and are partly overlapping (e.g., cozy / quiet / romantic atmosphere). However, from a user perspective, these attributes are deemed useful for making restaurant recommendations, and we had ample human-labeled data for them, hence we used them to evaluate our method. Labeled examples corresponded to actual restaurants that had or did not have a given attribute (positive / negative, respectively). The human labels were obtained from third-party aggregator sites, such that each label was confirmed by at least two sites (there were no label contradictions, resulting in essentially 100\% inter-rater agreement). Owing to lack of space, we do not show the exact numbers of examples for each attribute, but the average number of positive examples per attribute was 34K (median 24K) and the average number of negative examples was 54K (median 34K). These examples represent a sample of restaurants across several countries.

The second dataset included 16 binary hotel attributes such as whether the hotel has a golf course, airport shuttle, beach access, free breakfast, laundry service, fitness center (the full list of attributes is given in the first column of Table 2). Labeled examples corresponded to hotels that had or did not have a given attribute. We obtained the labels from an in-house crowdsourcing project, using at least two raters per hotel. The average number of positive examples per attribute was 65K (median 65K) and the average number of negative examples was 91K (median 87K). These examples represent a sample of hotels across several countries.

4.2 Baseline

We compared the performance of our method, STEPS, with that of a baseline classifier trained on a corpus of text reviews. The reviews were crawled from public Google+ web pages for the respective restaurants and hotels. We pooled
### Table 1: Restaurant attributes.

| Attribute      | Attrib type | Description                          |
|----------------|-------------|--------------------------------------|
| Wine           | Notable     | Good for wine                        |
| Takeout        | Meal type   | Food takeout available               |
| Brunch         | Meal type   | Serves brunch                        |
| Happy hour     | Meal type   | Has happy hour                       |
| Upscale        | Formality   | Formal attire                        |
| Hip            | Crowd       | Attracts hip crowd                   |
| WiFi           | Features    | WiFi available                       |
| Romantic       | Atmosphere  | Romantic atmosphere                  |
| Outdoor seating| Features    | Has outdoor seating                  |
| Breakfast      | Meal type   | Serves breakfast                     |
| Lunch          | Meal type   | Serves lunch                         |
| Dinner         | Meal type   | Serves dinner                        |
| Food           | Intent      | Mainly visited for food              |
| Drink          | Intent      | Main visit: drinks                   |
| Low price      | Price       | Inexpensive                          |
| Cozy           | Atmosphere  | Cozy atmosphere                      |
| Lively         | Atmosphere  | Lively atmosphere                    |
| Quiet          | Atmosphere  | Quiet atmosphere                     |
| Groups         | Company     | Good for groups                      |
| No reservations| Ease of entry| Reserv. not required              |
| Usually a wait | Ease of entry| Longer wait time                    |
| Live music     | Entertainment| Has live music                     |
| Fast food      | Restaur. type| Serves fast food                    |
| Delivery       | Features    | Delivers food                       |
| Casual         | Formality   | Casual attire                        |
| Dessert        | Notable     | Good for desserts                   |
| Tea            | Notable     | Good for tea                        |
| Healthy        | Food type   | Serves healthy food                  |
| Vegetarian     | Food type   | Good veg. selection                 |

As we can readily see, STEPS shows superior results on average, and demonstrates slightly inferior performance for only 6 out of 29 attributes.

However, the true importance of these results stems from the dramatically increased classification coverage due to our method. Of all the restaurants in our database, reviews are only available for 30.4% of restaurants, but STEPS features can be computed for 59.6% of restaurants — a relative coverage gain of 95.8%! This happens because online reviews are not available for all businesses (especially for the newer ones), and even when they are available, they might not mention the attributes we are interested in. People often write reviews to express a strong opinion (positive or negative) about the restaurant, but do not mention all the numerous applicable attributes of the business. Therefore, the coverage of the review-based (baseline) classifier is limited. However, simply using observational data about how people get in and out of the restaurant, allows us to substantially increase the classification coverage, and reliably predict attributes for almost twice as many restaurants.

4.4 The effect of different groups of features

Our STEPS method uses several groups of spatio-temporal features defined in Section 3. We now explore the relative utility of these different groups (owing to lack of space, we combined the previous-visit and next-visit features into one group of transition features). We show the ablation results in the four rightmost columns of Tables 2 and 3, where each column corresponds to using a different group of features.

For restaurants (Table 2), each of the 3 temporal groups of features performs fairly well by itself, resulting in 11%–12% lower AUC than the full STEPS model. The combination of the 3 groups of temporal features yields macro-averaged AUC of 0.833 (6% lower than STEPS; not shown in the table for lack of space). Interestingly, the spatial features alone

To maintain the anonymous aggregated nature of the data, we computed STEPS features only for restaurants (hotels) that have been visited by at least 10 people.
| Attribute           | Reviews | STEPS  | Gain   | Reviews + STEPS | Gain   |
|---------------------|---------|--------|--------|-----------------|--------|
| Wine                | 0.941   | 0.945  | 0.4%   | 0.968           | 2.9%   |
| Takeout             | 0.831   | 0.916  | 10.2%  | 0.929           | 11.8%  |
| Brunch              | 0.875   | 0.887  | 1.4%   | 0.921           | 5.3%   |
| Happy hour          | 0.928   | 0.891  | -4%    | 0.943           | 1.6%   |
| Upscale             | 0.916   | 0.95   | 3.7%   | 0.963           | 5.1%   |
| Hip                 | 0.921   | 0.869  | -5.6%  | 0.939           | 2%     |
| WiFi                | 0.812   | 0.923  | 13.7%  | 0.931           | 14.7%  |
| Romantic            | 0.79    | 0.891  | 12.8%  | 0.892           | 12.9%  |
| Outdoor seating     | 0.846   | 0.845  | -0.1%  | 0.912           | 7.8%   |
| Breakfast           | 0.909   | 0.961  | 5.7%   | 0.972           | 6.9%   |
| Lunch               | 0.849   | 0.906  | 6.7%   | 0.926           | 9.1%   |
| Dinner              | 0.904   | 0.953  | 5.4%   | 0.967           | 7%     |
| Food                | 0.884   | 0.928  | 5%     | 0.946           | 7%     |
| Drink               | 0.916   | 0.946  | 3.3%   | 0.967           | 5.6%   |
| Low price           | 0.968   | 0.969  | 0.1%   | 0.992           | 2.5%   |
| Cozy                | 0.75    | 0.805  | 7.3%   | 0.84            | 12%    |
| Lively              | 0.737   | 0.829  | -0.5%  | 0.796           | 8%     |
| Quiet               | 0.755   | 0.817  | 8.2%   | 0.855           | 13.2%  |
| Groups              | 0.728   | 0.817  | 12.2%  | 0.841           | 15.5%  |
| No reservations     | 0.917   | 0.946  | 3.2%   | 0.968           | 5.6%   |
| Usually a wait      | 0.702   | 0.734  | 4.6%   | 0.798           | 13.7%  |
| Live music          | 0.723   | 0.863  | 19.4%  | 0.902           | 24.8%  |
| Fast food           | 0.918   | 0.945  | 2.9%   | 0.976           | 6.3%   |
| Delivery            | 0.891   | 0.888  | -0.3%  | 0.93            | 4.4%   |
| Casual              | 0.844   | 0.839  | -0.6%  | 0.89            | 5.5%   |
| Dessert             | 0.818   | 0.912  | 11.5%  | 0.942           | 15.2%  |
| Tea                 | 0.896   | 0.938  | 4.7%   | 0.959           | 7%     |
| Healthy             | 0.764   | 0.801  | 4.8%   | 0.837           | 9.6%   |
| Vegetarian          | 0.852   | 0.861  | 1.1%   | 0.914           | 7.3%   |
| Macro-average       | 0.848   | 0.885  | 4.4%   | 0.918           | 8.3%   |

Table 2: Classifying restaurant attributes. Performance is reported as Area Under the Curve (AUC). Note that STEPS increases the coverage by 95.8% compared to only using Reviews (cf. Section 4.3).
15%-18% lower performance than features are less powerful. Individually, each group exhibits of these kinds of meals have characteristic hours. breakfast, lunch, dinner, and tea attributes, because each groups of features are (individually) highly predictive of attributes, the performance of duration features is within 5% of STEPS). Similarly, both the Arrival time and Occupancy groups of features are (individually) highly predictive of breakfast, lunch, dinner, and tea attributes, because each of these kinds of meals have characteristic hours.

Interestingly, for hotels (Table 3), the 3 groups of temporal features are less powerful. Individually, each group exhibits 15%-18% lower performance than STEPS, and even taken together their performance is 11% lower. Thus, most of the STEPS performance is due to the spatial features (Transition), whose performance is on average within 2% of the full STEPS feature set. We hypothesize this happens because people stay much longer in hotels than in restaurants (on the scale of days as opposed to hours), hence the variability in their temporal patterns is greater, and it is more difficult to find consistently predictive patterns. On the other hand, there are stronger patterns in the kinds of places that are co-visited with hotels, which explains the predictive power of the Transition features. For example, if hotel guests visit sports or recreational facilities (such as hiking trails or yoga studios), then the hotel likely appeals to fitness enthusiasts and therefore likely has a fitness center.

4.5 The evaluation of place embeddings
In this section, we report the performance of the embeddings-based method, STEPS-E, introduced in Section 3. The results were computed using 1000 embedding dimensions (we used grid search to determine the optimal number of dimensions that maximized cross-validated performance). Due to lack of space, we only report aggregate results across all the restaurant attributes and do not show per-result attributes. The classification performance of the embedding-based STEPS-E method is 6.2% lower than the baseline, but completely eliminates the need for manual feature construction required for STEPS. At the same time, the improvement in classifier coverage of the STEPS-E method is 94.8%, the same as for STEPS, as reported in Section 4.3. We believe that in most practical situations, sacrificing 6.2% in prediction accuracy is a reasonable tradeoff for doubling the coverage and eliminating the need to craft features manually.

5. QUALITATIVE STUDY
To get a more intuitive understanding of the classification models obtained using STEPS, we now study the top positive and negative spatio-temporal features learned by the trained STEPS model for some of the restaurant and hotel attributes. We also plot the actual distribution of these feature values for the positive and negative classes of the attributes (owing to lack of space, we show distribution plots for only some of the attributes).

For identifying “romantic” restaurants, the top positive features are those corresponding to people’s visiting the restaurant on weekends, arriving at the restaurant between 8–10PM, staying for more than 90 minutes, and coming to the restaurant from a luxury hotel, museum, or performing arts theater. The top negative features correspond to people’s visiting the restaurant on Mondays and Tuesdays, staying for less than 60 minutes, and arriving at the restaurant before or after visiting a grocery store or gas station. These features capture our intuition about romantic restaurants as places that people often go to for a long, leisurely meal on a weekend, often preceded by a visit to a museum, theater or concert (but presumably not often preceded by a grocery store or gas station visit).

To understand these features better, in Figures 1(a) and 1(b) we show the distributions of visit time duration and days of week of people’s visits to romantic restaurants, and to restaurants not labeled as “romantic”. The duration time distributions are clearly discriminative — the positive class has a peak at 80 minutes, compared to the negative class that peaks at around 60 minutes. The differences in the day-of-week distribution between the positive and negative classes are less pronounced, but one can still see that this difference is largest on Saturdays (positive difference) and Mondays (negative difference). These small differences in the distributions are significant enough for the model to use as discriminative features. Figure 1(c) plots the percentage of restaurant patrons visiting the above mentioned characteristic places before the restaurant, and confirms the utility of transition features in the model. The figure clearly shows that patrons of romantic restaurants are much more likely to have previously visited museums, theaters and luxury hotels, compared to gas stations and supermarkets.

For identifying restaurants offering “breakfast”, temporal features are, not surprisingly, the most informative features in the classification model. The top positive features include arriving at the restaurant between 8–11AM, and staying at the restaurant (occupancy) from 9–11AM. The top negative features include arrival times between 12–2PM, indicating that the restaurant is more likely to be popular for lunch than for breakfast. Figures 2(a) and 2(b) plot the distribution of these features for the “breakfast” attribute, and highlight the slightly earlier arrival and occupancy times for the positive class that are picked up by the model.

For identifying restaurants or cafes that offer WiFi, the top positive features correspond to people staying at the place between 4–7PM or between 10–11PM, visiting the place on weekdays, and visit duration times between 30 to 80 minutes. Other positive features include visiting a work location shortly before or after the cafe. Indeed, these features match our expectations of cafes that offer WiFi — they are usually busy late afternoons and late evenings on weekdays, and are frequented by people who use WiFi to work and therefore stay longer at the place. The top negative features include those corresponding to people’s visiting the place on Fridays and Saturdays, and staying at the place for less than 30 minutes.

For predicting restaurants that offer “takeout”, the top positive features are again related to duration — a large fraction of people stay at such places for less than 20 minutes. However, some of the top features are not so obvious, such as visiting a work location immediately before or after
the restaurant (positive feature), and visiting a shopping center or bar after the restaurant (negative feature).

Another attribute where the predictive power of STEPS is, at first glance, rather unexpected is “healthy” restaurants. The top positive features correspond to visiting the restaurant in the middle of the week (Tuesdays, Wednesdays and Thursdays) and going to work immediately after the restaurant. The top negative features correspond to visits on weekends, and visiting a bar immediately before or afterwards. This hints at some interesting sociocultural trends; for example, people are more likely to frequent healthier restaurants in the middle of the week than during the weekend, and people visiting healthy restaurants are less likely to visit bars before or afterwards.

We also observe interesting trends when studying the top positive and negative features for some of the hotel attributes. In contrast to predicting restaurant attributes, duration and occupancy features are less important here than transition features, which capture the types of places visited by the hotel guests. For example, to identify hotels with “beach access”, the top features correspond to visits to surf shops, swimwear stores and beaches, while the top negative features include visits to water parks and ski resorts. Figure 3 shows the proportion of hotel guests visiting these places from the hotel. On average, guests at hotels with beach-access are 10 times more likely to visit surf shops, swimwear stores and beaches, 3 times less likely to visit ski resorts, and 2 times less likely to visit department stores.

6. CONCLUSIONS

Many online services recommend brick-and-mortar businesses such as restaurants or hotels based on their attributes. These attributes are often difficult to obtain, and previous approaches based on crowdsourcing and mining review text were challenging to scale, and hence had limited coverage. We presented an approach to predict numerous place attributes using spatio-temporal features, which characterize how large populations of people go in and out of these places. Our method, STEPS, uses several groups of spatial and temporal features, and its variant, STEPS-E, uses embeddings to completely eliminate the need for manual feature construction. The key idea is to derive signals from anonymous aggregated observational data. This allows us to reliably predict dozens of attributes of businesses without ever visiting them or talking to people who did.
In an extensive empirical evaluation, we compared our methods to a baseline that uses web reviews for restaurants and hotels. Our STEPS method was able to reliably classify numerous place attributes while nearly doubling the coverage of the baseline (review-based) classifier, and offered comparable or superior performance. In our future work, we plan to explore joint modeling of attributes, as well as experiment with cross-products of STEPS features.

Acknowledgments
We would like to thank John Giannandrea and Chandu Thota for making this work possible. We would also like to thank Ravi Kumar, Bo Pang, Finnegan Southey, Mukund Sundararajan, and Andrew Tomkins for stimulating discussions that helped greatly improve this paper.

7. REFERENCES

[1] Cheng, C., Yang, H., Lyu, M. R., and King, I. Where you like to go next: Successive point-of-interest recommendation. In IJCAI (2013).
[2] Cheng, H., Ye, J., and Zhu, Z. What’s your next move: User activity prediction in location-based social networks. In SIAM (2013).
[3] Eland, A. Tackling urban mobility with technology, http://googlepolicies.weurope.blogspot.com/2015/11/tackling-urban-mobility-with-technology.html Google Europe Blog, 2015. Visited on January 29, 2016.
[4] Hu, M., and Liu, B. Mining and summarizing customer reviews. In KDD (2004).
[5] Hu, M., and Liu, B. Mining opinion features in customer reviews. In AAAI (2004).
[6] Jakob, N., and Gurevych, I. Extracting opinion targets in a single-and cross-domain setting with conditional random fields. In EMNLP (2010).
[7] Kirmse, A., Udeshi, T., Bellver, P., and Shuma, J. Extracting patterns from location history. In GIS (2011).
[8] Koren, Y., Bell, R., and Volinsky, C. Matrix factorization techniques for recommender systems. IEEE Computer 42, 8 (Aug. 2009), 30–37.
[9] Ku, L.-W., Liang, Y.-T., and Chen, C.-H. Opinion extraction, summarization and tracking in news and blog corpora. In AAAI Spring Symp.: Computational Approaches to Analyzing Weblogs (2006).
[10] Li, M., Ahmed, A., and Smola, A. J. Inferring movement trajectories from gsp snippets. In WSDM (2015).
[11] Lian, D., Zhao, C., Xie, X., Sun, G., Chen, E., and Rui, Y. GeoCMF: Joint geographical modeling and matrix factorization for point-of-interest recommendation. In KDD (2014).
[12] Liao, L., Fox, D., and Kautz, H. Location-based activity recognition. In NIPS (2005).
[13] Lichman, M., and Smyth, P. Modeling human location data with mixtures of kernel densities. In KDD (2014).
[14] Liu, B. Sentiment analysis and opinion mining, vol. 5 of Synthesis Lectures on Human Language Technologies. Morgan & Claypool Publishers, 2012.
[15] Long, C., Zhang, J., and Zhut, X. A review selection approach for accurate feature rating estimation. In COLING (2010).
[16] Popescu, A.-M., and Etzioni, O. Extracting product features and opinions from reviews. In Natural language processing and text mining. Springer, 2007, pp. 9–28.
[17] Qiu, G., Liu, B., Bu, J., and Chen, C. Opinion word expansion and target extraction through double propagation. Comput. Linguist. 37, 1 (Mar. 2011).
[18] Wang, H., Lu, Y., and Zhai, C. Latent aspect rating analysis on review text data: A rating regression approach. In KDD (2010).
[19] Ye, M., Yin, P., Lee, W.-C., and Lee, D.-L. Exploiting geographical influence for collaborative point-of-interest recommendation. In SIGIR (2011).
[20] Zheng, V. W., Zheng, Y., Xie, X., and Yang, Q. Collaborative location and activity recommendations with gsp history data. In WWW (2010).
[21] Zheng, Y., Zhang, L., Xie, X., and Ma, W.-Y. Mining correlation between locations using human location history. In GIS (2009).
[22] Zhong, Y., Yuan, N. J., Zhong, W., Zhang, F., and Xie, X. You are where you go: Inferring demographic attributes from location check-ins. In WSDM (2015).
[23] Zhuang, L., Jing, F., and Zhu, X.-Y. Movie review mining and summarization. In CIKM (2006).