Measuring and Recommending Time-Sensitive Routes from Location-based Data

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Location-based services allow users to perform geo-spatial recording actions, which facilitates the mining of the moving activities of human beings. This paper proposes to recommend time-sensitive trip routes, consisting of a sequence of locations with associated time stamps, based on knowledge extracted from large-scale time-stamped location sequence data (e.g. check-ins and GPS traces). We argue a good route should consider (a) the popularity of places, (b) the visiting order of places, (c) the proper visiting time of each place, and (d) the proper transit time from one place to another. By devising a statistical model, we integrate these four factors into a route goodness function which aims to measure the quality of a route. Equipped with the route goodness, we recommend time-sensitive routes for two scenarios. The first is about constructing the route based on the user-specified source location with the starting time. The second is about composing the route between the specified source location and the destination location given a starting time. To handle these queries, we propose a search method, *Guidance Search*, which consists of a novel heuristic satisfaction function which guides the search towards the destination location, and a backward checking mechanism to boost the effectiveness of the constructed route. Experiments on the Gowalla check-in datasets demonstrate the effectiveness of our model on detecting real routes and performing cloze test of routes, comparing with other baseline methods. We also develop a system *TripRouter* as a real-time demo platform.

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1. INTRODUCTION

Location-based Services (LBS), such as Foursquare[1] and Gowalla[2], allow users to perform the action of location recording that pins the geographical information of current locations and time stamps onto their personal pages. By continuously recording such actions by users, a large-scale location sequences dataset can be generated. The rapid accumulation of location sequence data can not only collectively represent the real-world human activities, but also serve as a handy resource for constructing location-based recommendation systems. Since the user-moving records implicitly reveal how people travel around an area with rich spatial and temporal information, including longitude, latitude, and recording timestamp, one reasonable application leveraging such user-generated location sequence data is to recommend the travel routes. Indeed, many of existing works recommend and construct traveling routes using GPS trajectories [Chen et al. 2011; Wei et al. 2012] or geo-tagged photos [Arase et al. 2010; Cheng et al. 2011; Yin et al. 2011].

In this paper, instead of relying on past moving trajectories to recommend traveling paths, we propose a novel time-sensitive trip route recommendation

[1] Fouresquare: https://foursquare.com/

[2] Gowalla: http://gowalla.com/

framework using the time-stamped route data. To do so, we argue that a good route recommendation system should consider the following factors when constructing a route:

— **The popularity of a place.** Popular landmarks by definition should attract more visitors.

— **The proper time to visit a place.** In general, the pleasure of visiting a place can be significantly diminished if arriving at the wrong time. Some places have a wider range of preferred visited time while others are constrained to certain particular time slots. For example, most people do not want to visit a beach during boiling hot noon, but rather arrive in the late afternoon to enjoy the sunset scene. Or certain sports game events usually take place at particular time period (e.g. in the evening). As shown in Figure 1, derived from the Gowalla check-in data described in Section 5, visitors visit some places with higher probability during certain time slots. For example, (a) people usually visit the Empire State Building from about 12:00 to the mid night (note that this place is famous for its night view), (b) people tend to visit the Madison Square Garden in the early evening for a basketball game, (c) the proper time to visit the Central Park is during daytime, and (d) Time Square is preferred from afternoon to midnight.

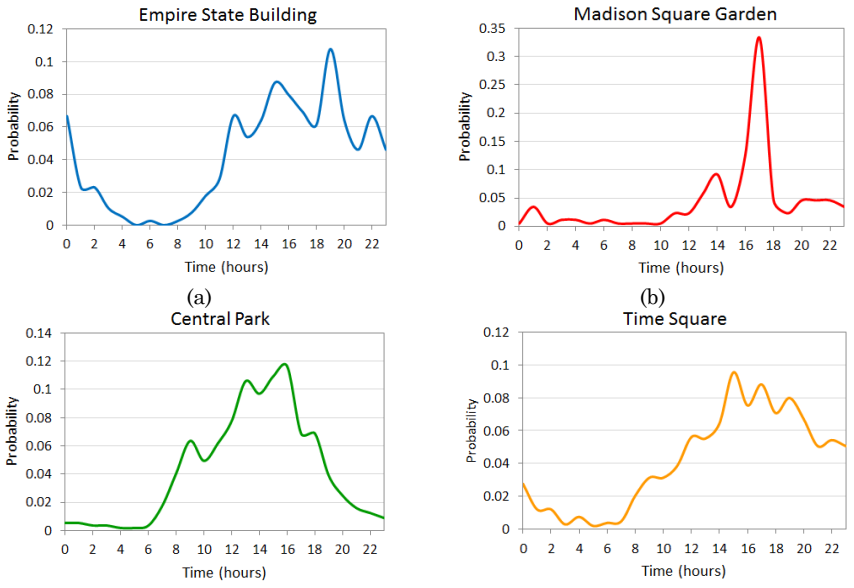


Fig. 1. The distribution of the visiting probability at each time unit (hour) for (a) Empire State Building, (b) Madison Square Garden, (c) Central Park, and (d) Time Square. These distributions are derived from the Gowalla check-in data.

— **The amount of time required to transit from one place to another.** The transit time between places is critical to the design of a suitable route. To recommend the next place to visit with the proper visiting time, we should consider the amount of time spent on traveling. For example, if one has bought tickets to a football game at a stadium 2 hours away, then he or she shall logically choose to start traveling toward the stadium 2 hours ahead of the

official kick off time instead of going to a nearby museum 30 minutes away then.

— **The visiting order of places.** The visiting order of places is highly correlated to the nature of places and human preference, and it can affect the quality of the recommended trip to the user. For example, going to the gym first then going to nearby restaurant for dinner might be a better plan than the other way around since it might not be unhealthy to exercise right after a meal.

While some places are extremely sensitive to the visiting time, the others (e.g. movie theaters) might not possess such strict constraint. An intelligent route recommendation system should consider such diversity and be able to create a route that has higher chance of satisfying users' needs. This paper argues that by exploring the time-stamped location sequence dataset, it is possible to design a statistical model to achieve such goal.

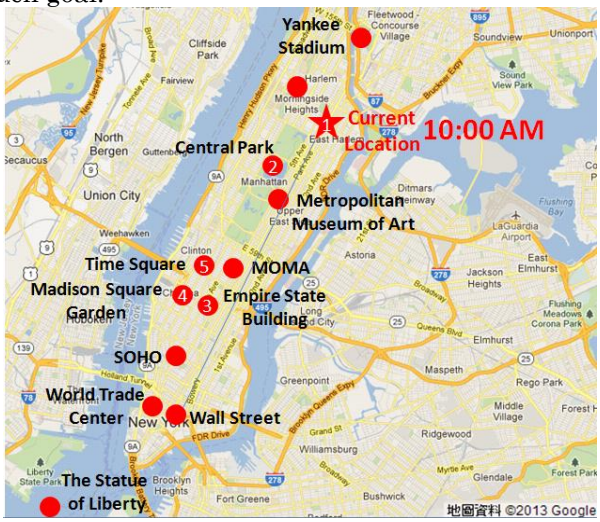


Fig. 2. An example for recommending a trip route starting from a given position at 10:00 AM, in Manhattan area, New York City.

What we employ for measuring and constructing time-sensitive routes is the time-stamped location sequence data. Currently there are two major resources that can provide such location sequence data. One is the user moving trajectories from the GPS trace recorders (with famous spots annotated) while the other is the online check-in data. Although from this point on we assume it is the check-in data that are used, our model can in fact be trained using any given time-stamped route dataset.

In our experiment we use online check-in data from location-based services (LBS) to acquire the time-stamped route information to train our model. The online check-in data provide plenty of explicit or implicit information that allows us to fulfill the abovementioned requirements for the sake of planning a proper trip route. First, we can distill from the check-in data the number of people who have visited a certain place, and thus derive the popularity of places. Second, users in LBS tend to perform check-in actions to keep track of their trips. As a result, we can obtain and consider the visiting order of places. Third, the check-in records contain the visiting time stamps of locations. Users in LBS are able to collectively reveal the proper visiting time of places. Fourth, followed by the check-in time stamps from existing routes, we

are able to hypothesize the transit time between places. Equipped with such elements, we utilize the check-in data to recommend the trip routes. Figure 2 is an example outcome of our time-sensitive trip route recommendation. Assuming a certain user starts to travel from his hotel, marked with a star in Figure 2, at 10:00 AM. According to the distribution of the locations to be visited at each time unit in Figure 1, a possible trip route consists of going to Central Park first, followed by Empire State Building, Madison Square Garden, and finally Time Square.

Formally, the goal of this paper is to construct a time-sensitive route from the time-stamped location sequence data. We propose to tackle two real-world demands of recommending time-sensitive routes. The first is to construct a route given a *source* location, and the second is to create a route given the *source-destination* pair of locations. Both queries consider the starting time of the trip. Given a query, our model finds a sequence of recommended places, in which each location can be visited at a proper time with a reasonable transit time from one place to another in the route. A time-sensitive route is supposed to be more effective than a simple route without time stamp as it allows the users to better manage their time during the trip.

We propose statistical approaches to construct the time-sensitive routes with respect to the proposed queries. In general, our model consists of two phases. In phase one, the quality of a route is measured using a goodness function, which integrates the abovementioned four requirements about a proper trip route. In phase two, given the user-specified query, we design an effective and efficient search method, the Guidance Search, to identify the places to be visited by optimizing the route goodness function.

We summarize the contributions of this paper in the following.

— We propose a novel time-sensitive trip route recommendation problem. We fulfill the idea by developing a *TripRouter* system based on the real-world Gowalla check-in data.
— Conceptually, we propose that a good route should consider four elements: (a) the popularity of a place, (b) the visiting order of places, (c) the proper visiting time of a place, and (d) the proper transit time between places.
— Technically, we devise a goodness function to measure the quality of a route. By exploiting certain statistical methods, we model the four requirements into the design of the goodness function.
— We propose two time-sensitive query scenarios about route recommendation. To deal with these queries, we develop the *Guidance Search* algorithm to construct the route by optimizing the goodness function.

This paper is organized as follows with the accompaniment of the flowchart, as shown in Figure 3. The input and output of our route recommendation are the Time-Sensitive Query and the Time-Sensitive Route respectively. After describing the related work in Section 2, we will formally describe these terms and the problem definition in Section 3.1. The main proposed method consists of two parts: Route Goodness Function and Route Construction. The former aims to measure the goodness of a given route while the latter is to construct the route satisfying the query. As the route construction algorithm proceeds, the route goodness function is exploited to intelligently determine the next location in the route. We will first describe how to design the route goodness function in Section 3 and elaborate the

proposed route construction algorithm in Section 4. We evaluate the proposed method in Section 5 and demonstrate the *TripRouter* system in Section 6. Section 7 concludes this work.

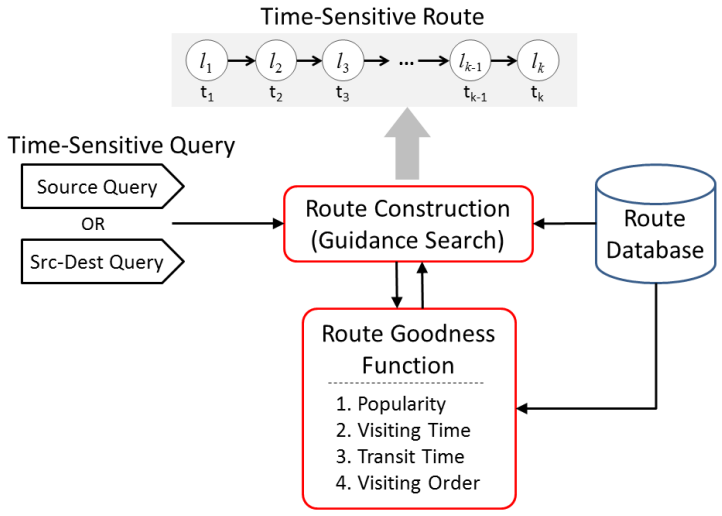


Fig. 3. The flowchart of the proposed time-sensitive route recommendation framework.

2. RELATED WORK

2.1 Route Planning by GPS Trajectory Data

There are lots of related works about route planning using the GPS trajectories. J. Yuan et al. [Yuan et al. 2011a; Yuan et al. 2011b] find the fastest routes to a destination. Z. Chen et al. [Chen et al. 2011] and L.-Y. Wei et al. [Wei et al. 2012] search for popular and attractive trajectories for recommendation. Z. Chen et al. [Chen et al. 2010] find the top-k trajectories connecting some user-given locations. H. Yoon et al. [Yoon et al. 2011] and Y. Zheng et al. [Zheng et al. 2011] propose the itinerary recommendation by considering user preference based on mined trajectory attributes. Y. Zheng et al. [Zheng et al. 2009; Zheng et al. 2011] aim to discover interesting and classical travel sequences. L.-A. Tang et al. [Tang et al. 2011] find the top-k nearest neighboring trajectories with the minimum aggregated distance to some query locations. L.-Y. Wei et al. [Wei et al. 2010] construct the top-k routes which sequentially pass through the query locations within the specified time span. Considering the travel cost (i.e., the financial cost and the time cost), Y. Ge et al. [Ge et al. 2011] provide a focused study of cost-aware tour recommendation. Q. Liu et al. [Liu et al. 2011] develop a Tourist-Area-Season Topic (TAST) model, which extract the topics conditioned on both the tourists and the intrinsic features of the landscapes, to recommend topic-dependent and/or season-based travel packages. L.-A. Tang et al. [Tang et al. 2012a; Tang et al. 2012b] investigate the problem of discovering groups that travel together from trajectory data streams. Their system can discover companions without accessing the object details. J. Bao et al. [Bao et al. 2012] consider both user preference and social opinions to develop a location recommender system that allows users to specify a set of venues within a geospatial range.

Though there are many successful proposals to solve different kinds of route planning problems, the issues of proper visiting time of places and proper transit time between places are not tackled adequately. This work proposes to soundly

measure and construct the time-sensitive trip routes using large-scale time-stamped location sequence data.

We use Table I to summarize the differences between our work and other relevant studies. Here we list some important issues about route planning, including: whether it allows the Query of certain Locations (QL), and whether it considers the following ideas: Popularity (PO), Visiting Order (VO), Visiting Time (VT), Transit Time (TT), User Preference (UP), Distance (DI), Travel Duration (TD), Top-k retrieval (TK), financial costs (CO), and group and/or social consideration (GS).

Table I. Summarization of differences between this paper and other related works.

	QL	PO	VO	VT	TT	UP	DI	TD	TK	CO	GS
[Yuan et al. 2011a; Yuan et al. 2011b]		■	■			■	■	■			
[Chen et al. 2011]	■	■	■								
[Wei et al. 2012]	■	■	■						■		
[Chen et al. 2010]	■		■						■		
[Yoon et al. 2011]	■	■	■		■	■		■	■		
[Zheng et al. 2009; Zheng et al. 2011]	■	■	■			■			■		
[Tang et al. 2011]	■						■		■		
[Wei et al. 2010]	■	■						■	■		
[Ge et al. 2011; Liu et al. 2011]		■				■		■	■	■	
[Tang et al. 2012]			■			■		■			■
[Bao et al. 2012]	■	■				■	■		■		■
This work	■	■	■	■	■		■	■			

2.2 Route Recommendation Using Social Media

The rapid rise of social media applications generates huge-volume geo-spatial data of human activities, such as geo-tagged photos in Flickr and check-in records in Foursquare. Both geo-tagged photos and check-in data can reveal how people sequentially visit places in an area. Using geo-tagged photos, Y. Arase et al. [Arase et al. 2010] mine frequent route patterns for recommendation. A.-J. Cheng et al. [Cheng et al. 2011] propose personalized travel recommendation based on personal profiles and visual attributes of geo-tagged photos. X. Lu et al. [Lu et al. 2010] and T. Kurashima et al. [Kurashima et al. 2010] construct routes based on user preference of must-go destinations, visiting time, and travel duration. Z. Yin et al. [Yin et al. 2011] mine and rank trajectory patterns from geo-tagged photos and diversify the ranking results. L.-Y. Wei et al. [Wei et al. 2012] infer the top-k routes traveling a given location sequence within a specified travel time from uncertain check-in data. Different from these works, we aim to perform knowledge discovery to construct the time-sensitive routes.

3. ROUTE GOODNESS MEASURE

3.1 Basic Definitions

Definition 3.1 (Location). A location l_i is a tuple, $l_i = (x_i, y_i)$, where x_i is the longitude, y_i is the latitude.

Definition 3.2 (Route of Time-stamped Locations). A route is a sequence of locations with the corresponding time stamps, denoted by s, $s=<(l_1,t_1), (l_2,t_2), ..., (l_n,t_n)>$, where n is the number of locations. Throughout this paper, we focus on recommending single-day route, which implies t_n-t_1 is no more than 24 hours.

Definition 3.3 (Time-sensitive Query). We define the *Time-sensitive Query* as $Q = (l_q, t_q)$, where l_q is the initial location of a user, and t_q is the starting time for this trip. Note that in the following we will further define the source query and source-destination query (in Section 4), which are two kinds of Time-sensitive query.

Definition 3.4 (Time-sensitive Route). Given a time-sensitive query, we define the *Time-sensitive Route* as a sequence of time-stamped locations $s_r = <(l_1,t_1), (l_2,t_2), ..., (l_k,t_k)>$, which can have higher score under the following defined route goodness function (in Section 3.2), where $l_1 = l_q$, $t_1 = t_q$, and k is the number of locations in the route, which can be either specified by users or be determined automatically based on the proposed algorithm (in Section 4). Note that the time-sensitive route is simply a common spatial-temporal sequence, just like a regular route. The main novelty lies in that the generation of them considers temporal information as constraints to optimize.

In the following we will describe how to measure the quality of a time-sensitive trip route. Based on the proposed goodness definition, we are able to search and recommend better time-sensitive routes given an initial time-sensitive query.

3.2 Measuring the Quality of a Trip Route

In order to construct a high-quality route for recommendation, we need to first design a proper metric to measure the quality of any given route. We propose that a good trip route should consider the following four factors: (a) the popularity of a place, (b) the proper visiting time of a location, (c) the proper transit time traveling from one location to another, and (d) the visiting order of places in the route. We attempt to model these factors into the goodness function, and utilize such function to greedily selecting locations for the construction of the final trip route.

3.2.1 Route Popularity

A popular place, by definition, should be somewhere that attracts more visitors in general. If a route contains more popular places, it has higher potential to satisfy a user. The popularity of a place can be represented by the number of recording actions performed at that place. In our goodness measure of a route, we first consider the popularity of places in the route. We define the relative popularity of a location l_i as:

$$pop(l_i) = \frac{N(l_i)}{N_{max}}$$

where $N(l_i)$ is the number of recording actions performed on location l_i, and N_{max} is the maximum number of recording actions among all the locations in the location sequence data. Given a route $s=<(l_1,t_1), (l_2,t_2), ..., (l_n,t_n)>$, we define the popularity-based goodness function $f_{pop}(s)$ as:

$$f_{pop}(s) = \left(\prod_{i=1}^{n} pop(l_i) \right)^{\frac{1}{n}}$$

3.2.2 Proper Visiting Time

The time-stamped location sequence data reveals that while some locations (e.g. park and movie theater) are popular regardless of the visiting time in a given day, other locations (e.g. stadium and beach) are more attractive during certain time period of the day. We propose to learn such time-dependent popularity of each location from the location sequence data. We begin from defining the *Temporal Visiting Distribution* as the following.

Definition 3.5 (Temporal Visiting Distribution (TVD) of a Location). We define a *Temporal Visiting Distribution* for a location l, TVD_l (t_i), as the probability distribution of a randomly picked recording action of location l occurs at time t_i. For example, in a 24-hour span, *TVD* can be a legal probability distribution shown in Figure 4. *TVD* can easily be learned from the time-stamped location sequence data, representing how popular a place is at a given time.

Using *TVD*, we can determine whether it is proper to visit a place at a given time. For example, assuming we want to know how well a decision is to visit a place at 8AM, given the location's *TVD* is represented as the green dotted line in Figure 4. To do that, we propose to first generate a thin Gaussian distribution $G(t;\mu,\sigma^2)$ whose mean value μ is 8 with a very small variance σ^2 (e.g. standard deviation is 1). And then we can transform the original task into measuring the difference between the Gaussian distribution with the learnt *TVD* of such location. Here we use the *symmetric Kullback-Leibler* (*KL*) *Divergence* between $G(t;\mu,\sigma^2)$ and $TVD_l(t)$ to represent the fitness of the assignment. The formal mathematical definition of a fitness score between a place l and a time t can be defined as:

$$D_{KL}(G(t;\mu,\sigma^2)||TVD_l(t)) = \sum_x G(x;\mu,\sigma^2)\, log\, \frac{G(x;\mu,\sigma^2)}{TVD_l(x)} + \sum_x TVD_l(x)\, log\, \frac{TVD_l(x)}{G(x;\mu,\sigma^2)}$$

Conceivably, a smaller KL value indicates better match between the assignment and the distribution learned from data. Consequently, we formally define the temporal visiting goodness function $f_{visit}(s)$ of a route s=<(l_1,t_1), (l_2,t_2), ..., (l_n,t_n)>, as a combination of the popularity of places together with the fitness of each location over time, in the following equation.

$$f_{visit}(s) = \left(\prod_{i=1}^{n} D_{KL}\left(G(t;t_i,\sigma^2)||TVD_{l_i}(t)\right) \times \frac{1}{pop(l_i)} \right)^{\frac{-1}{n}}$$

If the places in a route s are visited during the proper time period, the $f_{visit}(s)$ value would become higher.

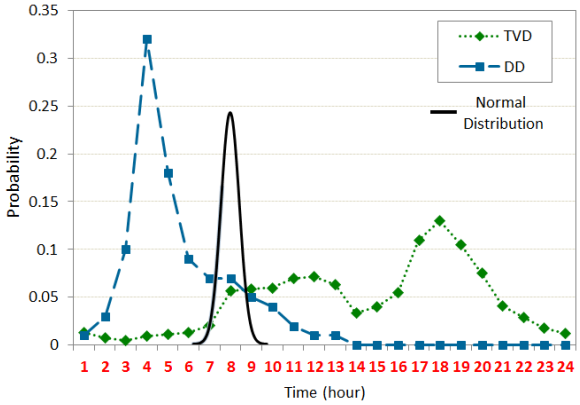


Fig. 4. Examples of the temporal visiting distribution (*TVD*) (the green dotted curve) for a certain location l_i, and the duration distribution (*DD*) (the blue dashed curve) between location l_i and l_j. The black solid curve represents a normal distribution of a particular time assignment to measure the fitness values.

3.2.3 Proper Transit Time Duration

To schedule a good trip route, another key element to be considered is the visiting time of each place as well as the transit time from one place to another. Although the

time-stamped location sequence data (user check-in data in this paper) cannot explicitly tell us the above two kinds of information, we can simply treat the duration between two checked-in places as the summation of the visiting time of the first place plus the transportation time from the first to the second place. Such duration can further be utilized to evaluate the quality of a trip. Here we propose the *Duration Distribution*, as defined in the following, to model such 'visiting plus transit time' between places.

Definition 3.6 (Duration Distribution (DD) between Two Locations). We define the *Duration Distribution (DD)* between locations l_i and l_j as the probability distribution over time duration Δ, $DD_{l_i l_j}(\Delta)$, which can be obtained from the following random experiment: randomly pick two consecutive location recording actions (l_i, t_i), (l_j,t_j) of a person, and calculate the probability that t_j-t_i=t.

Again, we consider only one-day trip, and therefore treat the outcome space of *DD* between hours 0 through 24. For example, any legal probability distribution between hours 0 through 24 can be a *DD* (e.g. the blue dashed line in Figure 4).

Similar to what we do to *TVD*, given a pair of locations l_i and l_j together with an assignment of a given time duration Δ among them, we can model Δ as a thin Gaussian distribution and compare it with $DD_{l_i l_j}(\Delta)$ using symmetric KL divergence. Consequently, for a route s=<(l_1,t_1), (l_2,t_2), ..., (l_n,t_n)>, it is possible to know how good the route is based on the durations between places by defining a goodness function of duration:

$$f_{duration}(s) = \left(\prod_{i=1}^{n-1} D_{KL}\left(g(t; \Delta_{i,i+1}; \sigma^2) || DD_{l_i l_j}(\Delta) \right) \right)^{\frac{-1}{n-1}}$$

A route s with higher value of $f_{duration}(s)$ indicates such route can be visited with proper "transit+visiting" time between places.

Here we use Figure 5 as an illustration to summarize our idea of utilizing *TVD* and *DD* to measure the goodness of a trip route. Given a route s=<(l_1,t_1), (l_2,t_2), ..., (l_n,t_n)>. We use symmetric KL divergence to measure the visiting fitness of each location l_i by calculating a $D_{KL}(l_i)$ value between TVD_{li} and a narrow Gaussian distribution. We also use KL divergence to measure the fitness of each transition $l_i \rightarrow l_j$ and derive a $D_{KL}(\Delta_{ij})$ between $DD_{l_i l_j}$ and a thin Gaussian distribution. Eventually we compute the geometric mean of such D_{KL} values to be the time-related route goodness.

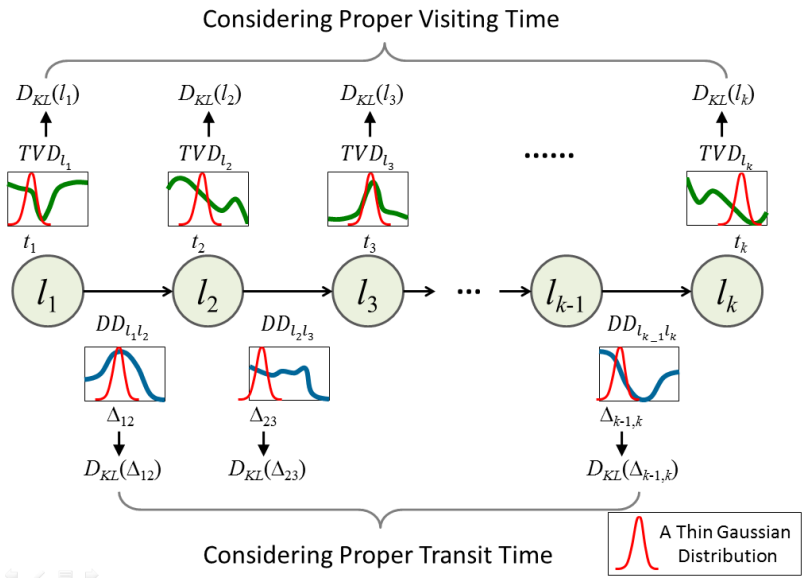


Fig. 5. For a route s=<(l_1,t_1), (l_2,t_2), ..., (l_k,t_k)>, we compute 2k-1 values of KL-divergence and then take the geometric mean of such values as the time-dependent goodness of a route.

3.2.4 Proper Visiting Order

Due to the characteristic of each place, there might be certain latent patterns about the order of the places to be visited. With the time-stamped location sequence data, we are able to learn such orders and exploit them to evaluate the quality of a route. For example, going to restaurant for dinner and then going back to hotel is better than the other way around. In this section, we propose to exploit the idea of the n-gram language model to measure the quality of the order of visits in a trip route. Using the location sequence corpus, we can first generate the n-gram probabilities of locations. Then, given a route s=<(l_1,t_1), (l_2,t_2), ..., (l_n,t_n)>, we can compute its n-gram probability. We consider such n-gram probability as the goodness of visiting order. Technically, we use the average value of the probabilities of uni-gram, bi-gram, and tri-gram to estimate the goodness of orders. Note that the uni-gram probability is corresponding to the popularity-based route goodness. We can formally write the probabilities as follows.

$$P_{uni}(s) = f_{pop}(s)$$
$$P_{bi}(s) = (P(l_1)P(l_2|l_1)P(l_3|l_2)\cdots P(l_n|l_{n-1}))^{\frac{1}{n}}$$
$$P_{tri}(s) = (P(l_1)P(l_2|l_1)P(l_3|l_1l_2)\cdots P(l_n|l_{n-2}l_{n-1}))^{\frac{1}{n}}$$

Therefore, the goodness of visiting order of a route can be defined:

$$f_{order}(s) = \frac{\left(P_{uni}(s) + P_{bi}(s) + P_{tri}(s)\right)}{3}$$

Higher $f_{order}(s)$ value represents better quality of route. Note that we utilize the add-one technique for smoothing. Also note that since the trip route would not be too long, and visiting a certain place usually depends on only the previous and the next locations, we consider only up to tri-gram.

3.2.5 Final Goodness Function

Here we integrate the goodness measures of the proper visiting time, the proper transit time duration, and the proper visiting order into the final goodness function $f(s)$. Our design of the route goodness function integrates these factors accordingly. We divide the goodness function into two parts and provide a weighting parameter for users to determine the significance and balance of such two parts. The first part is the average value of the temporal visiting goodness $f_{visit}(s)$ and the location transition goodness $f_{duration}(s)$. The second part is the visiting order goodness $f_{order}(s)$. Note that the first part $f_{visit}(s)$ is time-sensitive while the second part is not. We use a parameter $\alpha \in [0,1]$ to devise a linear combination of such two parts. This parameter provides users the flexibility to specify whether they prefer the time-sensitive routes. The final goodness function $f(s)$ is defined in the following.

$$f(s) = \alpha \times \left(\frac{f_{visit}(s) + f_{duration}(s)}{2} \right) + (1 - \alpha) \times f_{order}(s)$$

A route s with higher value of $f(s)$ will be considered as a better route. Experiments in Section 5.3 suggest $\alpha \approx 0.9$ being more effective on measuring route quality. Such result exhibits the usefulness of the proposed time-sensitive route recommendation.

4. ROUTE CONSTRUCTION ALGORITHM

In this section, we define the time-sensitive trip route recommendation problem based on the proposed route goodness measure. We design two types of queries, *source* query and *source-destination* query, which correspond to the two real-life route recommendation tasks. To solve such problems, we propose a route search algorithm, *Guidance Search*.

4.1 Problem Statement

We first provide the definitions of the source and source-destination queries in the following.

Definition 4.1 (Source Query). The input consists of (a) the source/starting location $Q_s = (l_s, t_s)$, where l_s contains the longitude and the latitude of such location, and t_s is the starting time stamp (e.g. 8AM), and (b) The number k of locations in the final route to be recommended.

Definition 4.2 (Source-Destination Query). The input consists of (a) the source/starting location $Q_d = (l_s, t_s, l_d)$, where l_s contains the longitude and the latitude of such location, t_s is the starting time stamp (e.g. 8AM), and l_d is the destination/end location, and/or (b) the number k of locations in the final route to be recommended.

Both queries are very common for real-world trip planning. For source query, people might want to know where they can visit in a city given their available starting time. For the source-destination query, people might need to arrive at a destination place starting from the current place at a certain time, but want to know along the line where they can visit.

Therefore, our trip recommendation system can be regarded as given (a) the routes extracted from the time-stamped location sequence data, and (b) either the source query $Q_s = (l_s, t_s)$ or the source-destination query $Q_d = (l_s, t_s, l_d)$, the goal is to

construct a route s_r = <(l_1=l_s,t_1=t_s), (l_2,t_2), ..., (l_k,t_k)> that optimizes $f(s_r)$. Note that l_k is required to be l_d for the source-destination query.

THEORE 4.3. The Time-sensitive Route Construction Problem with the Source-Destination Query is NP-hard.

PROOF. We prove this theorem by a reduction from the *Longest Path Problem* (LPP) [Cormen et al. 2009]. In the decision version of LPP, we are given a weighted graph $G = (V, E)$, where $V = \{v_1, \dots, v_n\}$ is the set of nodes and E is the set of edges, as well as a source node v_s and a destination node v_d. Each edge $(v_i, v_j) \in E$ is associated with a non-negative weight c_{ij}. The length of a path $p = \langle v_1 = v_s, v_2, \dots, v_k = v_d \rangle$ is defined by: $c(p) = \sum_{i=1}^{k-1} c_{i,i+1}$, $i = 1, \dots, k$. The objective is to find a simple path $LP(v_s, v_d)$ (i.e., path without any repeated nodes) with the maximum length among all paths from v_s to v_d in G.

Now we are transforming an instance of the LPP to an instance of our Time-sensitive Route Construction problem with Source-Destination query $Q_d = (l_s, t_s, l_d)$, termed by TRCSD, as follows. Based on the route database constructed from user check-in sequences (the details is given in Section 5), we can build a graph $H = (L, A)$, where L is the set of check-in locations and A is the set of edges connected by two consecutively visited locations (l_i, l_j). Let $s_{x \to y}$ be the route starting from location l_x to l_y in H. Consider a special case of TRCSD: all the locations and all the routes between locations are visited once (led to $f_{order}(s) = 1$ for any given route s), and both the temporal visiting distributions on all the locations and the duration distributions between locations are generated by any kinds of monotonically increasing functions with respect to time (led to $f_{visit}(s)$ and $f_{duration}(s)$ are non-decreasing for any given route s, i.e., $f_{visit}(s_{s \to \cdots \to i}) \leq f_{visit}(s_{s \to \cdots \to i \to j})$ and $f_{duration}(s_{s \to \cdots \to i}) \leq f_{duration}(s_{s \to \cdots \to i \to j})$). Therefore, the route goodness function $f(s)$ is monotonically increasing. Based on such special case, for every edge $(v_i, v_j) \in E$ in LPP, we use the route goodness function $f(s)$ of TRCSD to create the corresponding edge weight c_{ij}. By assigning the starting locations l_s and l_d in TRCSD to nodes v_s and v_d in LPP respectively, we compute the edge cost of edge (v_i, v_j) by $c_{ij} = f(s_{s \to \cdots \to i \to j}) - f(s_{s \to \cdots \to i})$. Hence, the graph H in TRCSD is identical to the graph G in LPP. Resulting from this mapping, we can find that there exists a path solution to the LPP problem with maximum path length if any only if there exists a route solution to the TRCSD problem with maximum route goodness. Therefore, the proof is complete. □

4.2 Route Construction Algorithm: *Guidance Search*

We develop the *Guidance Search* algorithm to deal with the route recommendation task for the source and source-destination queries. The general idea aims to find a proper time-sensitive route (whose locations possess proper visiting time, transition time, visiting order, and higher popularity), and requires the constructed route to start from the source location for the source query (and finally reach the destination location for the source-destination query). Therefore, in addition to construct the route up to length k from the source location, we further need to implement a certain guiding mechanism to direct the search algorithm to move towards the destination if the destination is specified. To fulfill such goal, we develop a novel search algorithm, *Guidance Search*, which takes advantage of the idea of *best-first search* that attempts to find a least-cost path from a given initial node to the goal. The central idea of *Guidance Search* consists of two main parts. The first is to design the *heuristic satisfaction function*, which is in charge of the guidance to determine the next most

promising location towards the destination. The second is the *backward checking mechanism* that keeps the historical search tree (all the expanded routes starting from the source location) for reconstructing the route with higher *satisfaction* score.

We first describe the deployment of the *heuristic satisfaction function* $f^*(l)$. Since our central goal is to recommend a trip route with a great time-sensitive satisfaction, we consider the time-sensitive route goodness function $f(s)$ (described in Section 3.2.5) as the fundamental to design the heuristic satisfaction function $f^*(l)$. The input of the heuristic satisfaction $f^*(l)$ is a location l. The goal of $f^*(l)$ is to measure the satisfaction of selecting location l as the next visiting location considering the sub-route from the source location l_s to the location l and from the location l to the destination location l_d. On one hand, if only the former part (i.e., from l_s to l) is considered, the source query can be tackled. On the other hand, we can address the source-destination query when both the former and the latter parts (i.e., from l to l_d) are considered.

$f^*(l)$ can be decomposed into two parts. The first is the time-sensitive route goodness function $g(l) = f(l_s \rightarrow l)$. $g(l)$ computes the goodness score of the sub-route starting from the source location l_s to the location l. The second is the *heuristic function* $h(l)$. $h(l)$ considers both the route goodness $f(l \rightarrow l_d)$ and the geographical distance $d(l \rightarrow l_d)$ of a sub-route from the location l to the destination l_d. The former part $f(l \rightarrow l_d)$ aims to estimate the route goodness of a certain sub-route from l to l_d. The latter part $d(l \rightarrow l_d)$ serves as the role of guidance. Specifically, we use the geographical distance between l and l_d as the steering force to direct the search process to move towards the destination location. When selecting next visiting location during the route construction, those locations with shorter distance to the destination has higher chance to be picked, if the rest of the criteria are equally satisfied. Moreover, because there could be many sub-routes from l to l_d in the route database, we will compute all the scores and take the best one as the final $h(l)$ value. Consequently, the heuristic function can be formally written as:

$$h(l) = max_{(l \rightarrow l_d) \in S(l \rightarrow l_d)}\{\sqrt{f(l \rightarrow l_d) \times (1 - d(l \rightarrow l_d))}\}$$

where $S(l \rightarrow l_d)$ is the set of sub-routes starting from l to l_d extracted from all the routes derived from the time-stamped location sequence data. Note that the $d(l \rightarrow l_d)$ is normalized to [0,1]. Eventually, we write down the final heuristic satisfaction function as:

$$f^*(l) = (1 - \beta) \times g(l) + \beta \times h(l)$$

where $\beta \in [0,1]$ is the weighting parameter to control the strength of the guidance to the destination. Higher β values indicate stronger guidance. When $\beta = 0$, $f^*(l)$ is considered as a greedy search with the backward checking mechanism, and can be utilized to tackle the source query (because in $g(l)$ function, no destination information is needed).

Here we give an example to elaborate the idea of the proposed *heuristic satisfaction function* $f^*(l)$ for selecting the next visiting location towards the destination location in Figure 6. Assume our search is current at location l_{cur} and has to find the next best location to expand from l_{cur}. In the route database, assuming there are some candidate locations l_1, l_5, ..., and l_7 which have ever been visited after

l_{cur}, then the satisfaction scores $f^*(l_1)$, $f^*(l_5)$, ..., and $f^*(l_7)$ can be generated. For instance, to derive $f^*(l_1)$, all the sub-routes starting from l_1 and ending at l_d (such as $< l_1, l_2, l_4, l_9, l_d >$, $< l_1, l_5, l_8, l_d >$, and $< l_1, l_5, l_3, l_{12}, l_d >$) are considered to find the one with the maximum score among them as the $h(l_1)$ value. On the other hand, we can derive $g(l_1) = f(l_s \rightarrow l_1)$. Eventually we have $f^*(l_1) = (1-\beta) \times g(l_1) + \beta \times h(l_1)$. By applying such computation process to l_1, l_5, ..., and l_7, it is possible to choose the next visiting location with the highest satisfaction.

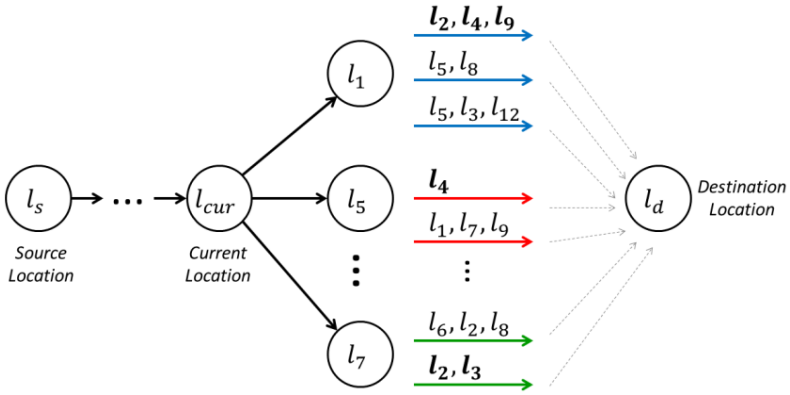


Fig. 6. An example to elaborate the idea of the proposed *heuristic satisfaction function* for tackling the source-destination query.

The *backward checking mechanism* is the key to the best-first search and can be applied to our route construction algorithm. Specifically, while exploiting the *heuristic satisfaction function* to choose the next location to visit, it is necessary to expand all neighbor locations to generate the corresponding satisfaction scores. We keep track of such scores in the expansion tree. When it is needed to select the next visiting location, not only the expanded locations from the current location, but also those had ever been expanded during the previous rounds can be considered. In other words, in addition to continue expanding the current location, the algorithm can possibly go backward to consider the previously expanded nodes for finding the ones with the highest satisfaction score.

The *Guidance Search* algorithm to construct the route for tackling either the source query or the source-destination query is given in Algorithm 1. We first construct the initial route s_0 by including the source location l_s (line 1). A *PriorityQueue* is employed for the purpose of the backward checking mechanism (line 2). Each element in the *PriorityQueue* consists of a route s and the corresponding heuristic satisfaction score. The *PriorityQueue* automatically sorts its elements according to their satisfaction scores. We add s_0 to initialize the *PriorityQueue*. After setting the final route s_r as the initial one s_0 (line 3), we perform the iterative expansion search process until the route s_r is constructed up to length k (line 4-12). For each iteration, the last location l_{last} in the route s_r with the highest satisfaction score is identified (line 5 and line 12) and each possible next visiting location l_{next} is put into a candidate set C (line 6). Then for each candidate for the next location l_c, we can derive the heuristic satisfaction score $f^*(l_c)$ (if $l_d = \emptyset$, we set the weighting parameter $\beta = 0$ for the function f^*; otherwise $0 < \beta \leq 1$). We put $f^*(l_c)$ together with the corresponding route s_{tmp} into the *PriorityQueue* (line 7-11). The *PriorityQueue*

will then pick the next best route and location to conduct the further expansions (line 12). Finally (line 13), the route s_r is reported as the result of recommendation.

ALGORITHM 1. *Guidance Search* algorithm

Input: (a) RouteDB: routes extracted from the time-stamped location sequences data;
(b) $Q_d = (l_s, t_s, l_d)$: if $l_d = \emptyset$: the source query,
if $l_d \neq \emptyset$: the source-destination query;
(c) k: the number of locations in the final route s_r.
Output: a time-sensitive route $s_r = \langle (l_1, t_1), (l_2, t_2), \dots (l_d, t_k) \rangle$.

$s_0 = \langle (l_1 = l_s, t_1 = t_s) \rangle$.
$PriorityQueue = \{(s_0, 0)\}$.
$s_r = s_0$. $l_{last} = null$.
while $|s_r| < k$ **OR** $l_{last} \neq l_d$ **do:**
    $l_{last} = s_r.EndLocation$.
    $C = \{l_{next} | l_{last} \rightarrow l_{next}$ in $RouteDB\}$.
    for *each* $l_c \in C$ **do**
        $s_{tmp} = s_r + \langle (l_c, t_c) \rangle$.
        $score = f^*(l_c)$.
        $PriorityQueue.Insert((s_{tmp}, score))$.
    end
    $s_r = PriorityQueue.Pull()$.
Return: s_r.

Time Complexity. The time complexity of *Guidance Search* mainly depends on three parts: the number of search expansion N, the number of candidates of next location $|C|$, and the operation of the $PriorityQueue$ $O(\log(|E|))$, where E is the set of elements in the $PriorityQueue$. We can simply write down the complexity as $O(N \times |C| \times \log(|E|))$. In the worst case, both the candidate set C_i of each next location and the number of search expansion could be all the locations in the route database. By denoting the set of all locations in the database as L, the complexity is $O(|L|^2 \times \log(|E|))$ for the worst case.

5. EXPERIMENTS

5.1 Dataset and Data Analysis

We utilize the Gowalla dataset [Cho et al. 2011] which has been exploited for location-based analysis in several places (such as [Scellato et al. 2010] and [Scellato et al. 2011]) to construct our time-sensitive route recommendation. The Gowalla dataset contains 6,442,890 check-in records from Feb. 2009 to Oct. 2010. The total number of check-in locations is 1,280,969. Considering a route as a sequence of check-in locations of a user within a day, we construct the route database *RouteDB* containing 1,136,737 routes whose length is more than one (the average length of them is 4.09). Figure 7(a) shows the distribution of the route length, which is highly-skew and heavily-tailed. Figure 7(a) also shows that people usually do not prefer visiting too many locations in a day, but with some exceptions. Figure 7(b) shows the distribution of the time difference between the visiting of two places. It indicates that people consider places closer to where they are while planning the next destination.

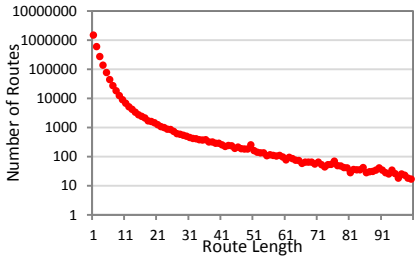
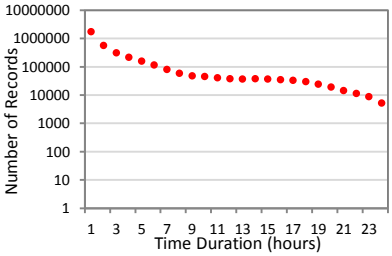


Fig. 7. (a):Distribution of route length.



(b): Distributions of time duration in *RouteDB*.

We extract three subsets of the check-in data, which corresponds to cities of New York, San Francisco, and Paris. Some statistics are reported in Table II. Figure 8 shows the distribution of route length in the three subsets of check-in data while Figure 9 shows the distribution of the time duration.

Table II. The statistics of RouteDB and the three subsets

	Total Number of Check-ins	Avg. Route Length	Variance of Route Length
RouteDB (all data)	6,442,890	4.09	48.04
New York	103,174	4.46	71.24
San Francisco	187,568	4.09	58.36
Paris	14,224	4.45	75.73

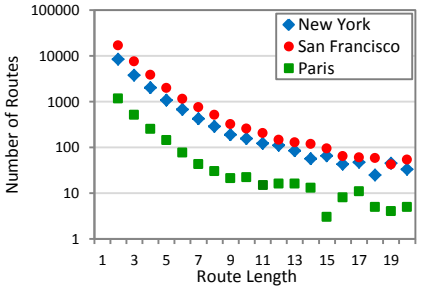


Fig. 8. Distribution of route length for 3 cities.

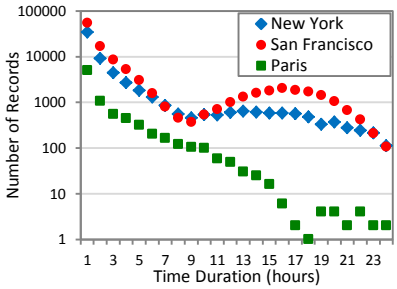


Fig. 9. Distribution of time duration for 3 cities.

5.2 Evaluation Plan

In this section, we introduce two experiments to test the effectiveness of our goodness model and demonstrate the performance of the proposed search methods. In the first experiment, we conduct the **pairwise time-sensitive route detection** to compare the quality of our goodness model with several baseline methods. In the second experiments, we design the **time-sensitive cloze test of locations in routes** to validate the quality of the recommended routes by our search algorithm, comparing to not only our previously proposed greedy method [Hsieh et al. 2012] but also a series of baseline methods. We show the results in Section 5.3 and provide some discussions in Section 5.4.

Experiment 1: **Pair-wise Time-sensitive Route Detection.** In this experiment, we would like to verify whether our goodness model can rank the existing routes higher than the non-existing ones. We first randomly choose one thousand real routes from the check-in data. Note that the time stamp is associated

with each location l. For each route, we replace a portion of the locations with other locations in the same city to generate a pseudo route. Note that each existing route will be paired with a pseudo route. To make the task non-trivial, we adopt a replacing strategy to replace a location with a 'plausible' one instead of a randomly selected one. That is, to replace a location at position i of a route, we only choose from candidate locations that have ever appear right after the location at position i-1 (e.g. the bigram probability of them is non-zero). Furthermore, after the replacement, we double-check to make sure the generated pseudo routes do not exist in the database. That is, there is no such route in the database of the same location sequences together with the same associated time stamps. As can be seen in Figure 10 to 12, the amount of replaced locations occupies from 10% to 50% of a route. That is, for each route at least half of the locations are correct. We then use our goodness model to examine each pair of the existing route and its pseudo route, and record how frequently our method ranks the correct one higher. Finally, we report the accuracy of our method and compare it with the baseline results. The accuracy is defined as the number of correctly ranked pairs (i.e. an algorithm assigns higher score to the existing route than the pseudo route) divided by the total number of pairs.

Similarly, we can generate another kind of pseudo route by perturbing the time stamps of certain locations in an existing route. For example, given an existing route s=<(l_1,t_1), (l_2,t_2),… (l_{i-1}, t_{i-1}), (l_i,t_i), (l_{i+1},t_{i+1}),..., (l_n,t_n)>, we change t_i to a different time t_j, where $t_{i-1} < t_j < t_{i+1}$. We expect a proper fitness function to assign lower score to such pseudo routes. In general, the baseline approaches cannot handle the case of time perturbation so that the identification rate is 50%.

Experiment 2: Time-sensitive Cloze Test of Locations in Routes. Given some real trip routes with time stamp in each location, through randomly removing m consecutive locations in each route, it is possible to test whether a method can successfully recover the missing locations. With the increasing of m, consecutive removal of locations does impose decent level of difficulty to this cloze test. It is because that when m increases, the information that can be utilized becomes sparse, and mistakes in the earlier position can lead to follow-up errors in the next positions to be predicted. Here we use the *Hit Rate* as the accuracy measure for this cloze test. Given there are totally N removals of locations over all routes, and assumed M places out of N is successfully predicted, the hit rate is defined as M/N. Higher hit rate indicates better quality of recommendation. For each city, we extract all the existing routes of length is larger than 6 for experiments. There are a total 3702 routes with average route length 10.26 for this experiment. Note that when there are multiple missing places in the cloze test, we only consider the fully-recovered sequences as hits. For instance, if the system fills (A X Y Z E) in a cloze route (A_ _ _ E) while the original sequence being (A B C D E), all X Y Z will be considered as missing even another sequence (A B Y D E) exists in the database.

Baseline Approaches. To evaluate the effectiveness of our method, we design the following four baseline methods.

— **Distance-based Approach.** This method chooses the closest location to the current spot as the next spot to move to. It rates a route using the goodness function $f_d(s) = (\prod_{i=1}^{n} \frac{1}{D(l_i, l_{i-1})})^{\frac{1}{n}}$, where $D(l_i, l_{i-1})$ is the geographical distance between two consecutive locations.

— **Popularity-based Approach.** This method chooses the most popular spot of a given time in that city as the next spot to move to. It rates the path using the goodness function $f_{pop}(s)$ as have been defined previously in Section 3.2.1.
— **Forward Heuristic Approach.** The forward heuristic chooses a location l_i that possesses the largest bi-gram probability with the previous location $P(l_i|l_{i-1})$ as the next location to move to. Its goodness function is $f_{forw}(s) = P_{bi}(s)$, as defined previously in section 3.2.4.
— **Backward Heuristic Approach.** The backward heuristic chooses a location l_i that possesses the largest bi-gram probability with the next location $P(l_i|l_{i+1})$ as the next location to move to. The fitness function can be described as $f_{backw}(s) = (P(l_1|l_2)P(l_2|l_3)\cdots P(l_{n-1}|l_n))^{\frac{1}{n}}$.

5.3 Experimental Results

Section 5.3.1 shows the results of pairwise route detection and Section 5.3.2 presents the outcome of cloze test. For both experiments, we implement four baseline methods to compare with. We also compare our method with the greedy search method of our previous work [Hsieh et al. 2012].

5.3.1 Pairwise Time-sensitive Route Detection

We first vary the number of replaced locations from 10% to 50% and report the accuracy of different methods. We set α of our goodness function as 0.5. Figure 10 contains the results for San Francisco City. Our fitness model achieves around 98% accuracy in distinguishing the real routes from replaced ones. The accuracy scores of the forward and backward heuristics reaches about 80%. The popular-based and distance-based methods do not do a good job as they only reach 50% or lower in accuracy. Similar trend happens in New York and Paris (Figure 11 and 12). The results are not surprising because our method does consider the location preference over time and location order.

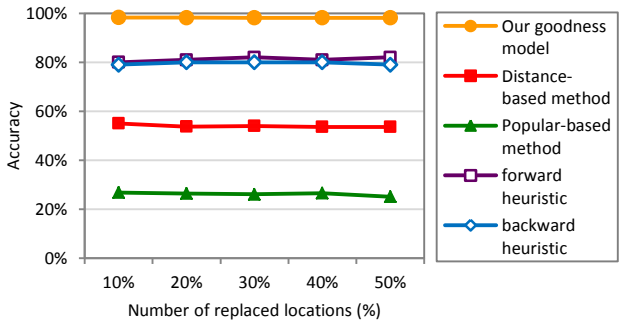


Fig. 10. Accuracy by varying the number of replaced locations in San Francisco.

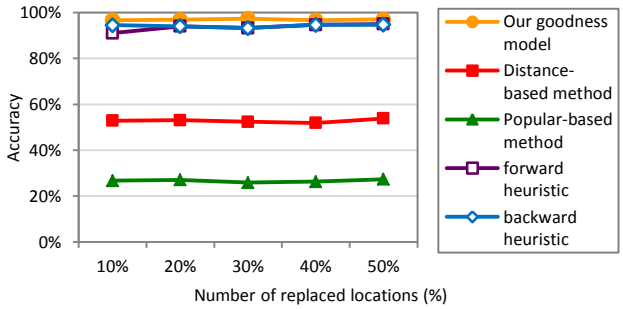


Fig. 11. Accuracy by varying the number of replaced locations in New York.

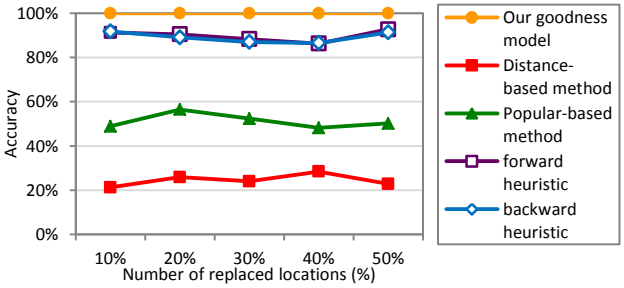
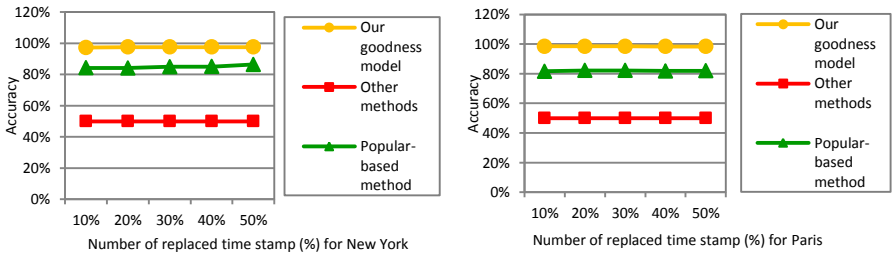
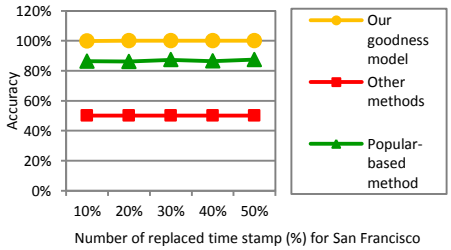


Fig. 12. Accuracy by varying the number of replaced locations in Paris.

Figure 13 shows the results of creating pseudo paths by shifting time stamps for some locations in three cities. Again we vary the ratio of change from 10% to 50%. The results show that our model can almost perfectly detect such change, better than the popularity-based method (around 15% accuracy). The other competitors, such as distance-based, forward heuristic and backward heuristic methods do not have the capability to distinguish such pairs because they do not consider time information during route generation, and therefore their can only achieve 50% for such pair of routes in Figure 13.



(a) New York (b) Paris



(c) San Francisco

Fig. 13. Accuracy by varying the number of replaced time stamp for our method in (a) New York (b) Paris, and (c) San Francisco.

5.3.2 Time-Sensitive Cloze Test in Routes

In cloze experiment of locations in routes, we first report the hit rate in three cities by varying β (i.e., the weight for $h(l)$) from 0 to 1, as shown in Figure 14 to 16. Our goal is to investigate whether the heuristic function $h(l)$ mentioned in Section 4.3 can improve the hit rate. We set the number of missing locations as 3 and α (for goodness function) as 0.5. The results indicate that increasing the weight of a heuristic function $h(l)$ provides a positive influence to the performance. When β=0.5, it can consistently produce the best (or close to the best) results. The hit rates of the four baseline models are lower than 3% in these three cities. Moreover, we compare this with a greedy-based approach proposed previously by ours [Hsieh et al. 2012], and found that our search can consistently outperform the previous method. It is not surprising because the previous greedy method does not embed a heuristic function to consider the quality of selection to the destination.

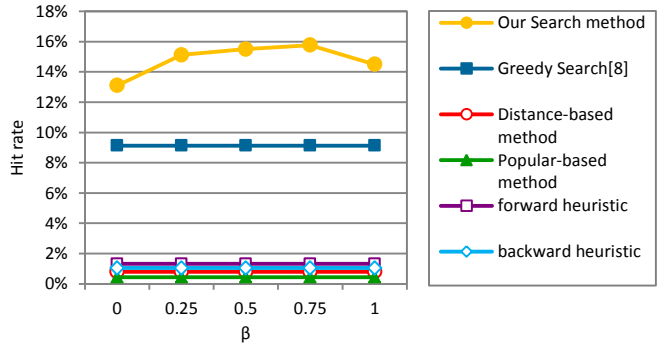


Fig. 14. Hit rate by varying the varying the weight of β in New York.

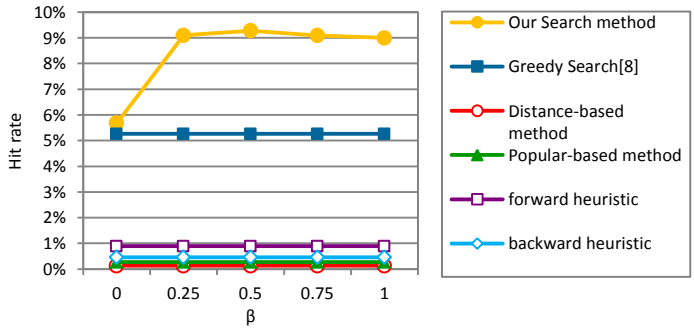


Fig. 15. Hit rate by varying the weight of β in San Francisco.

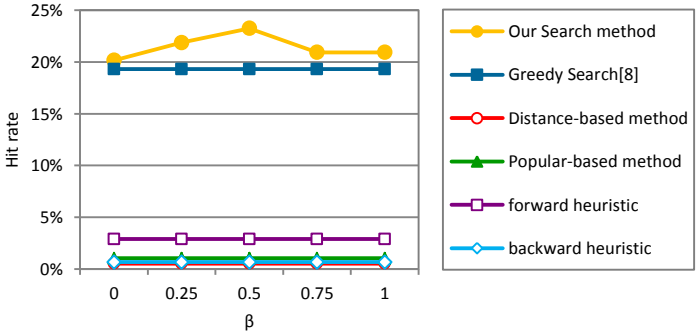


Fig. 16. Hit rate by varying the weight of β in Paris.

Next, we vary the number of missing instance per route and report the hit rate in three cities. Here, we set the weight of β as 0.5 (i.e., the $g(l)$ function and $h(l)$ function is considered as equally important). General speaking, the hit rate of each methods is decreasing while the number of missing instance increases. Our proposed method still outperforms the greedy search method [Hsieh et al. 2012] and other baselines significantly. The results in three cities are shown in Figure 17 to 19.

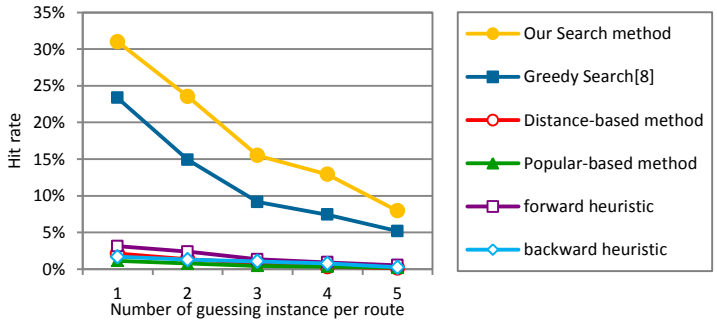


Fig. 17. Hit rate by varying the number of guessing instance per route in New York.

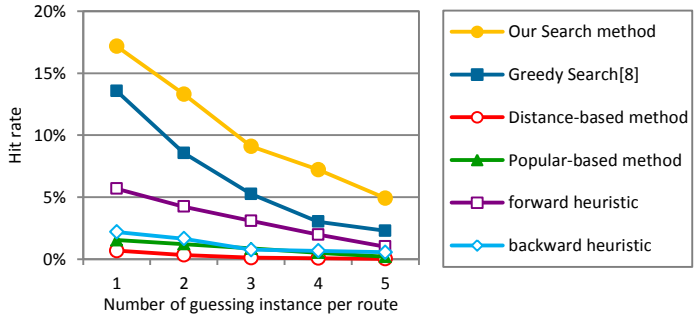


Fig. 18. Hit rate by varying the number of guessing instance per route in San Francisco.

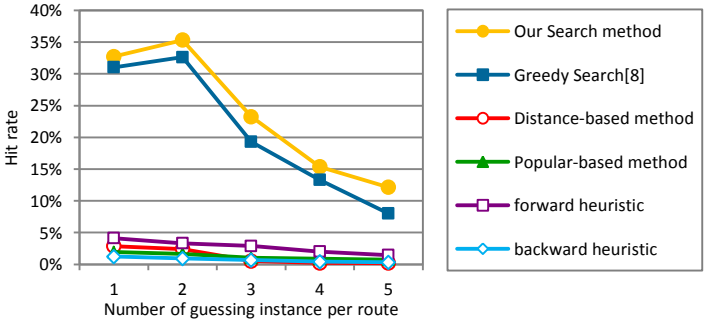


Fig. 19. Hit rate by varying the number of guessing instance per route in Paris.

5.4 Discussions

5.4.1 The relationship between $g(l)$ and $h(l)$

While sequentially recommending the route, our search model utilizes destination information $h(l)$ as heuristics. In this section, we would like to investigate the interaction between $h(l)$ and $g(l)$ of through varying β.

Given a random chosen source location, destination location and starting time, we exploit the Guidance search to recommend a route r. In this discussion, we generate a total of 1000 routes, and control the route length so that there are 200 routes each for the length from 4 to 8.

In Figure 20, we vary the parameter β for the Guidance search and examine the corresponding $g(l)$ score as well as the time needed to produce a route in New York city. Similarly, same settings are applied to San Francisco and Paris city. The results are reported in Figure 21 and 22. It shows that when β becomes larger, it considers to pay more attention to the heuristic satisfaction score $h(l)$, rather than simply optimizes $g(l)$. Therefore, $g(l)$ decreases as β increases.

Because the $h(l)$ function utilizes the destination information to guild the search, increasing β (i.e. emphasizing on h) allows us to reach the destination more quickly. However, it pays the cost of not optimizing the fitness function $g(l)$. Figure 20 to 22 demonstrates that by setting for an inferior $g(l)$ value, we can indeed improve the efficiency through increasing β.

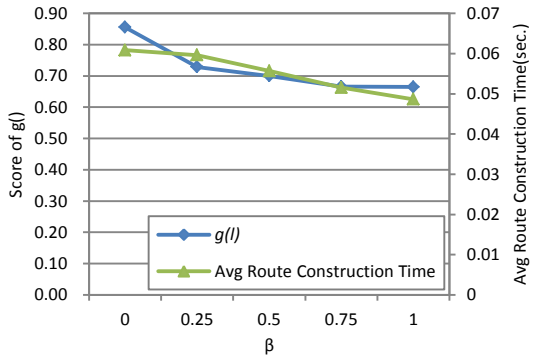


Fig. 20. Score of $g(l)$ for Guidance Search and the corresponding average construction time by varying β in New York.

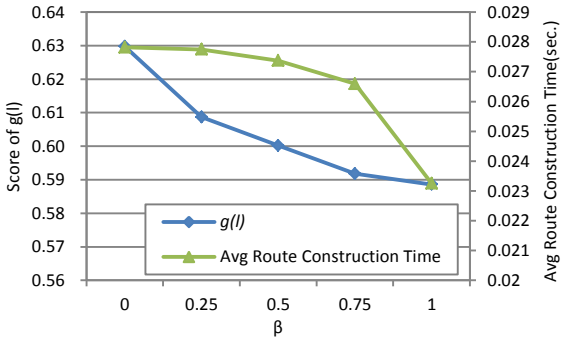


Fig. 21. Score of $g(l)$ for Guidance Search and the corresponding average construction time by varying β in San Francisco.

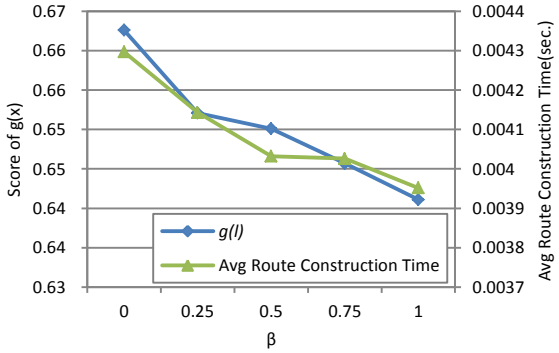


Fig. 22. Score of $g(l)$ for Guidance Search and the corresponding average construction time by varying β in Paris.

5.4.2 Impact of α for cloze experiment

We examine how sensitive the Guidance Search is to the parameter α (higher α means we pay more attentions to time-sensitive route), ranging from 0 to 1. We evaluate on the hit rate of the cloze test, and display the results in Figure 23. In New York and Paris, the best α value is around 0.9. That is, time-sensitive information is preferable than the visiting order on the cloze test task. In San Francisco City, α performs well at 0.5.

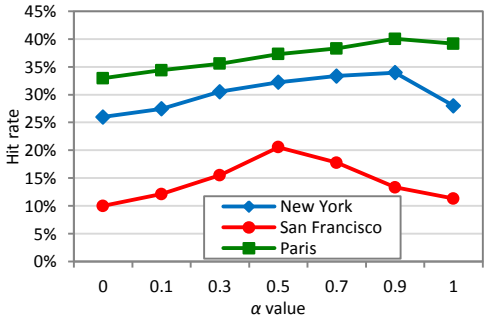


Fig. 23. The impact of α for our Guidance Search method on the time-sensitive cloze test for the three cities.

5.4.3 The approximation ratio of Guidance Search compared with Exhaustive Search

In this section, we conduct an evaluation to measure the closeness of Guidance Search and other baseline methods towards the optimal route (i.e. the route that maximize the goodness function) generated by exhaustive search. We randomly generate 1000 queries from each city and compare the goodness scores of the proposed Guidance Search, f(sGS) and other baseline methods. Since the optimization problem is NP-hard, we obtain the optimal solution relying on the exhaustive search method. We can then calculate the approximation ratio (from 0 to 1) as how close is the goodness measure of each method toward the optimal goodness value. In Figure 24, we vary the parameter β for the Guidance search and examine the corresponding approximation ratio. In general, the approximation rate for our Guardian Search outperforms the other methods when $\beta \leq 0.8$, and reaches as high as 87% optimal when β is around 0.4. In addition, the results show that the proposed Guidance Search is actually an efficient search process (average route construction time <=0.0043 second, which is 65814 times faster than Exhaustive Search which teaks on the average 283 seconds.) due to the imposition of the heuristic function $h(l)$ into the best-first search mechanism.

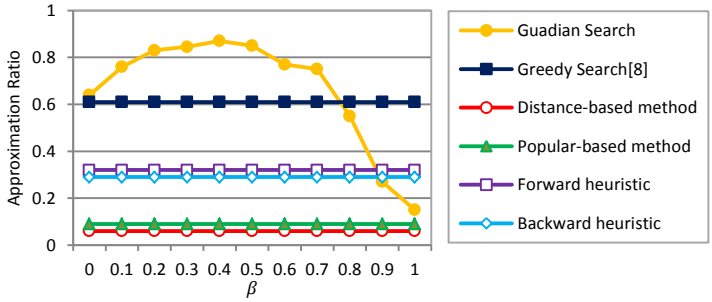


Fig. 24. The approximation ratio of all methods compared with the Exhaustive Search.

5.5 User Study

We conduct a user study to test whether the time-sensitive routes recommended by the proposed algorithm are rational, useful and acceptable to users. For each city, we randomly select two paired locations as source-destination to construct the routes for user study. The route length varies from 4 to 7. For comparison, we produce four routes for the user study. The first three routes are generated by our Guidance Search method with $\beta = 0$, $\beta = 0.5$ and $\beta = 1$. The fourth is the popularity-based route construction which sequentially selects the most popular neighbors and the corresponding most popular visiting time slots. We invite 10 people to conduct the user study. The evaluation criteria for the user study includes the location popularity, visiting order, visiting time, transition time, whether moving towards destination, and the overall acceptance of the recommended route (see Table III for details). For each user, we ask him/her to give the 0~5 score to each criterion/question for each constructed route. Higher score represents better satisfaction for such criteria. Each user will provide 6 (criteria)*3(cities)*2(routes)*4(models) =144 scores. Finally we report the average value for each criterion in Figure 25.

Table III. The criteria and the corresponding questions for user study.

Criteria	Question
Location Popularity (LP)	Do you think these recommended locations are popular ones?
Visiting Order (VO)	Is the visiting order of locations in the route suitable/acceptable?
Visiting Time (VT)	How do you feel about the visiting time of locations in the route?
Transition Time (TT)	Do you think the transition time between locations is rational?
Towards Destination (TD)	As traveling along the route, does it guide you to the destination?
Overall Acceptance (OA)	If you are a traveler, do you want to adopt this route?

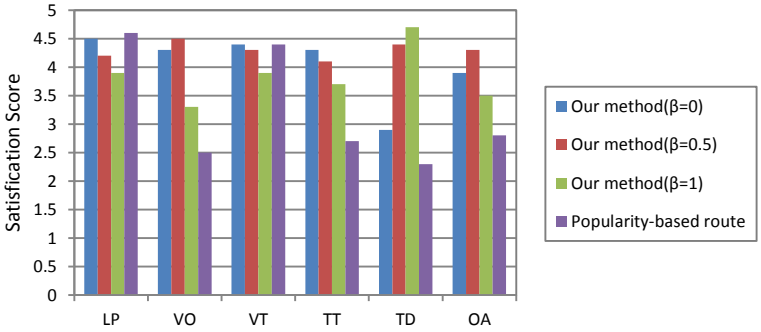


Fig. 25. Results of subjective evaluation for four methods.

In general, our method with $\beta = 0.5$ produces scores greater than 4 for all the criteria. For the case of $\beta = 0$, it also gets high score for LP, VO, VT and TT. However, it does not consider the distance between current location and destination, and therefore cannot guide users toward destination. The proposed method with $\beta = 1$ has highest score for TD since it emphasizes on the heuristics that utilize the destination information. However, its scores for other criteria are lower than those of $\beta = 0$ and $\beta = 0.5$. The baseline method, popularity-based route ensures that the visiting locations associated visiting time stamps are popular, but the scores for the remaining four criteria are significantly lower. The user study gives us a quick view that the β can be set as 0.5 to achieve a better satisfaction score.

6. SYSTEM DEMONSTRATION

Using our model, we develop an online time-sensitive trip route recommendation system, called *TripRouter*. The system snapshot is shown in Figure 26. In *TripRouter* users first determine the city they intent to travel, and then select one location as their starting location, together with the starting time. *TripRouter* allows users to specify their destination and the desired number of places to visit during a trip. We list the three major functions of *TripRouter* as below: (a) time-sensitive route recommendation, (b) displaying diverse information of locations and routes such as location attributes, route statistics, and some geo-tagged photos obtained from Flickr, and (c) recommending the transportation mode by querying Google Map API according to mined transit time duration.

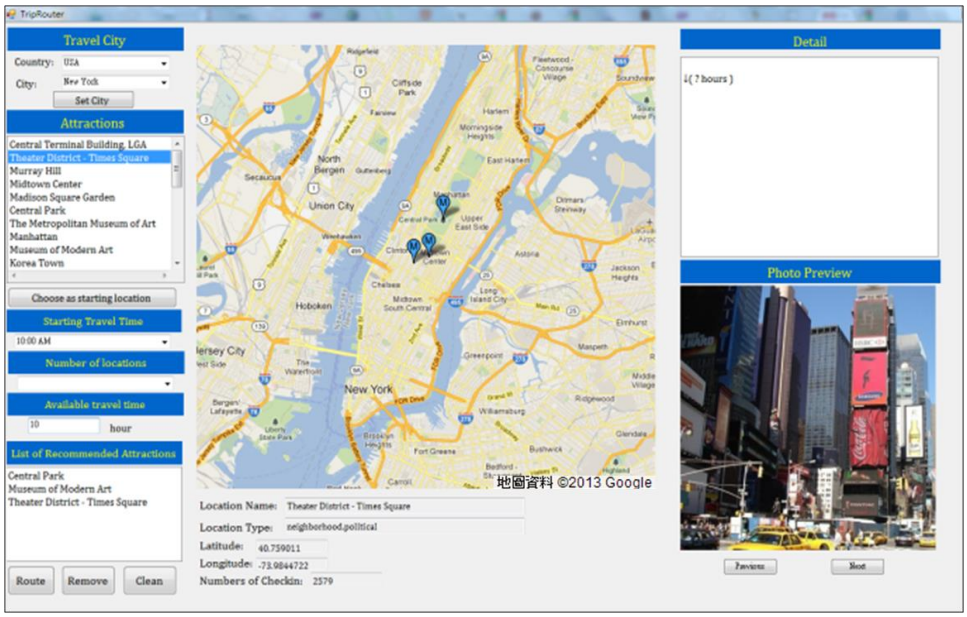


Fig. 26. The system interface of *TripRouter*.

Below we vary β as 0, 0.5 and 1 to show three recommended routes querying from Central Park to Time Square starting at 10AM using Guidance Search method , where and the route length k is set to 4. The corresponding paths are highlighted with blue and shown in Figure 27 (a)(b)(c).

Route 1. ($\beta = 0$)**:** Central Park (10AM) →Metropolitan Museum of Art (1PM) → American Museum of Natural History (4PM) → Time Square (9PM).
Route 2. ($\beta = 0.5$)**:** Central Park (10AM) → 5th Ave (1PM) → New York Public Library (5PM) → Time Square (7PM).
Route 3. ($\beta = 1$)**:** Central Park (10AM) → New York Public Library (2PM) → Bryant Park (7PM) → Time Square (9PM).

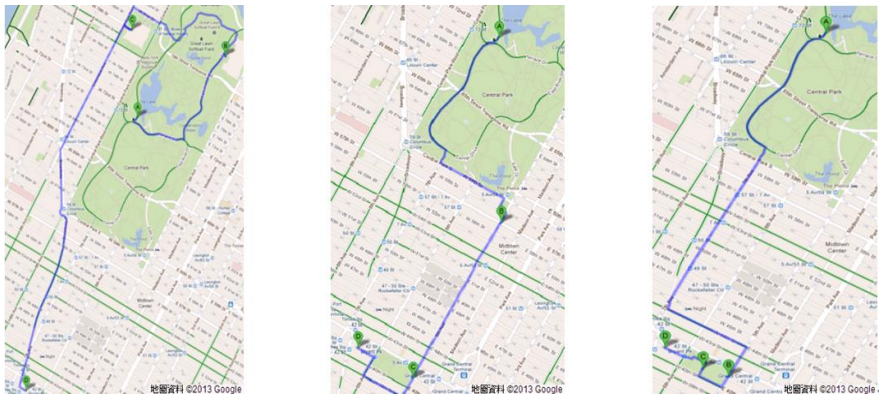


Fig. 27. Three recommended cases for varying β.
(a) $\beta = 0$ (b) $\beta = 0.5$ (c) $\beta = 1$.

For $\beta = 0$, it pays most attention to fit the time-sensitive score, $g(l)$. Therefore, for every visiting location, it will try to find a fitting score considering proper visiting time, transit time, visiting order and popularity. However, it can produce longer transit time to the final destination. The overall distance for route 1 is relatively large (3.9 miles, almost twice as much as the other cases). The $\beta = 0$ case provides routes for users who have much traveling time, and care about time-sensitivity of locations.

$\beta = 1$ finds shorter route to the destination However, the visiting time, transit time, visiting order and popularity are not considered since it does not include $g(l)$ to optimize. The overall distance for route 2 is 2.1 miles. $\beta = 1$ is moe suitable for people who prefers to go to the destination sooner than later, but still wants to visit some places along the route.

The case of $\beta = 0.5$ is suitable for general travelers because it tries to strike a balance between $g(l)$ and $h(l)$. The overall distance for route 3 is 2.6 miles and the time-sensitive factors are considered.

Moreover, our system allows users to dynamically specify where they would like to go during the journey. Such user-feedback functions can easily be achieved by combing the source and source-destination queries.

7. CONCLUSION

This paper tries to address an important research question: can we measure and construct the time-sensitive trip route that considers the visiting time of each place for trip recommendation? Note that our approach is mostly data-driven, which assures diverse results can be learned from different cities in which visiting patterns

may vary with different culture and characteristics of the city. Moreover, despite that we emphasized on the check-in data in our experiments, in fact any kinds of route data can be exploited in our framework. For example, the GPS trajectory data can be used if we can perform some pre-processing in advance to identify the main locations, to compensate some of the drawbacks from the check-in data (e.g. missing records, coarse granularity, and noise). Our future works are focusing on three directions: (a) improving the quality of the check-in routes by detecting missing-locations in routes (b) using maximum likelihood estimator to accurately model the visiting time duration of a place and transportation time between places, and (c) exploiting the collaborative filtering approaches to take advantage of the user and location similarities.

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