Some Help on the Way: Opportunistic Routing under Uncertainty

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ABSTRACT

We investigate *opportunistic routing*, centering on the recommendation of ideal diversions on trips to a primary destination when an unplanned waypoint, such as a rest stop or a refueling station, is desired. In the general case, an automated routing assistant may not know the driver's final destination and may need to consider probabilities over destinations in identifying the ideal waypoint along with the revised route that includes the waypoint. We consider general principles of opportunistic routing and present the results of several studies with a corpus of real-world trips. Then, we describe how we can compute the expected value of asking a user about the primary destination so as to remove uncertainty about the goal and show how this measure can guide an automated system's engagements with users when making recommendations for navigation and analogous settings in ubiquitous computing.

Author Keywords

Opportunistic routing, mixed-initiative, information value.

ACM Classification Keywords

H5.m. Information interfaces and presentation: Miscellaneous.

General Terms

Experimentation, Human Factors, Theory.

INTRODUCTION

We explore the challenge of providing drivers of cars with efficient diversions to waypoints that may address an acute or standing interest or need on the way to a primary destination. As examples, a driver may issue a voice search in pursuit of an entity or service, such as a rest stop or a refueling or recharging station while driving to a target destination. Alternatively, an automated recommender system, embedded in an onboard device or communicating through a cloud service, might know or speculate about a driver's or passenger's rising needs or background interests, understand about a user's time availability, and recognize when opportunities for modifying a trip in progress might be desired. The system could then alert the driver about the possibilities, and share information about the ideal routing and time required for the divergence. We investigate such *opportunistic routing*. We extend prior work on opportunistic routing by considering methods for selecting among candidate unplanned waypoints and formulating efficient revised routes *given uncertainty about the primary destination*. In the general case, an automated routing assistant may not know a final destination and may need to consider the uncertainty in the destination of the driver in identifying the best waypoint and revised route to the primary destination. In fact, drivers specify their destination to their vehicle's navigation system for only about 1% of their trips, making uncertainty almost inevitable [1]. We shall first consider principles of opportunistic routing under

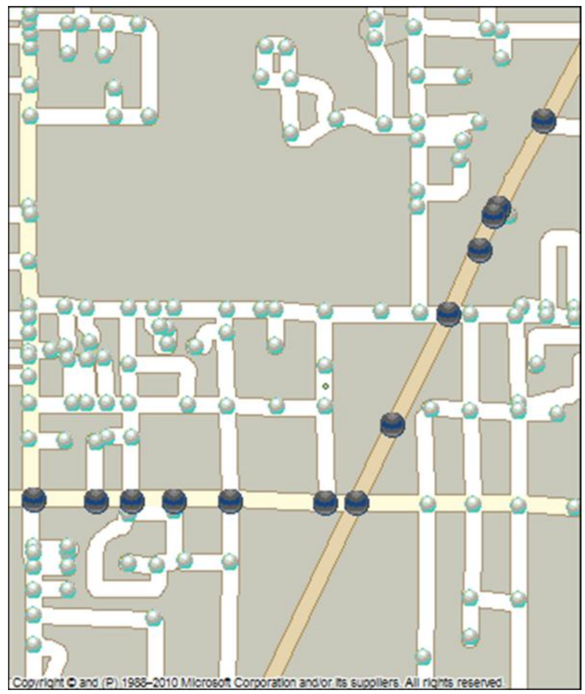


Figure 1: Candidate destinations are at road intersections (light dots). Trips are represented as a sequence of intersections (black dots).

UbiComp' 12, Sep 5 – Sep 8, 2012, Pittsburgh, USA.

uncertainty. Then we introduce methods for computing the expected value of gaining additional information about the primary destination. We discuss how this computation can be harnessed to guide decisions about the value of asking drivers to resolve a system's uncertainty about the ultimate destinations—versus providing recommendations on waypoint candidates in an autonomous manner.

RELATED WORK

The problem of mobile opportunistic routing was introduced by Horvitz, Koch, and Subramani in [2]. The work presents methods for opportunistic routing and describes a prototype named *Mobile Commodities*. The system receives queries or automatically identifies needs for accessing goods or services during a trip to primary destination. Standing goals, such as "search for a gas station when fuel tank is less than 10 percent full," can be encoded in the system. The prototype continues to perform cost-benefit analyses as it speculates about potentially valuable waypoints and the time associated with investing time in a diversion. While the project mentions the challenge of handling uncertainty in destinations, the effort focuses largely on cases where a known destination is input to the system, and considers detailed modeling of the uncertainty in the availability of a driver and the cost of taking additional time to divert to and engage in an opportunistic task, using Bayesian user models of the context-sensitive cost of time (drawing upon information from an online calendar and traffic). Inferences about the cost of elapsed time are used in considerations of introducing new waypoints or finding ideal solutions to needs such as refueling a car based on a consideration of the pricing and distance of fueling stations. Later related work by Kamar, Horvitz, and Meek [3] explored multiple challenges with electronic commerce in an opportunistic routing setting and introduced an auction-centric system named MC-Market. The prototype provides decisions about offers and pricing for various goods and services based on drivers' locations, destination, and preferences, and can initiate context-sensitive auctions on pricing of services. Like the work before it, efforts on MC-Market center largely on opportunistic routing in situations where the primary destinations of drivers are known.

In this paper, we focus on opportunistic routing under *uncertain destinations.* The work leverages prior work on probabilistic predictions of a driver's destination. The problem of predicting destinations has been addressed by other researchers. Marmasse and Schmandt [4] presented experiments with a Bayes classifier, histogram matching, and a hidden Markov model to match a partial route with stored routes. Ashbrook and Starner [5] clustered GPS data to find a person's significant locations like home and work, and then trained a Markov model to predict transitions between these locations. Hariharan and Toyama present a means of clustering GPS points and then use a Markov model to characterize transitions [6]. Liao *et al.* [7] and Patterson *et al.* [8] describe probabilistic models for route prediction, trained from observations on individuals. Besides routes, their techniques can infer the person's mode of transportation. The *Predestination* algorithm by Krumm and Horvitz predicts destinations based partially on past behavior, but also allows for predictions at previously unvisited locations [9]. Ziebart *et al.* train a location prediction algorithm from GPS observations of 25 taxi drivers [10]. Their algorithm reasons about route decisions in context and gives predictions for the driver's next turn, their route to a given destination, and their next destination given a partially observed trip. The NextPlace system not only predicts destinations, but arrival times [11]. Filev *et al.* present a fuzzy Markov model for predicting previously visited destinations based on the previous destination, the day of the week, and the time of day [12].

While our technique recommends slight modifications to a driver's existing route, other work has concentrated on recommending entire routes, such as the T-Drive system by Yuan *et al.* [13]. The same group has looked at helping taxi drivers find their next passenger [14] and travel recommendations based on GPS traces [15]. Also related is the work of Zhang *et al.* who learn a user's important locations and routes [16].

DESTINATION PREDICTION

Identifying the optimal waypoint, and associated diversion introduced to a trip, requires knowledge of the driver's destination. Although a driver may sometimes provide a destination to a vehicle's navigation system, this happens rarely. Thus, we take as a central focus the identification of ideal waypoints under uncertainty in a driver's destination. To compute probabilities over destinations, we employ a destination prediction algorithm derived as a modification of the methodology described in [17]. The technique is based on the observation and expectation that drivers drive efficiently toward their destination. The method computes destination probabilities $p(D)$ for destinations D contained in a set of candidate destinations D_s, *i.e.* $D \in D_s$. In the version of the algorithm we shall use in studies, the candidate destinations consist of all road intersections within 60 minutes driving time from the start of the trip.

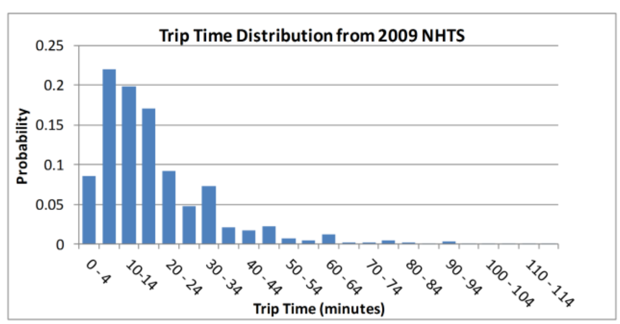


Figure 2: Distribution of trip durations. Durations of trips from U.S. National Household Travel Survey used to limit geographic extent of destination predictions and serve as a prior probability on candidate destinations.

Figure 1 shows some candidate destinations on a map.

We represent the driver's current partial trip as a sequence of intersections, as shown in Figure 1. The sequence is derived from GPS data via a map matching algorithm described in [18]. As the driver moves to new intersections, we compute the driving time to all candidate destinations using the RPHAST route computation algorithm described in [19]. RPHAST is an algorithm for efficiently solving the one-to-many shortest path problem. When the driver reaches a new intersection, we identify, for each candidate destination, whether the driving time to that candidate has increased or decreased as compared to the state at the previous intersection. Decreased times are evidence that the driver may be driving to the candidate destination, and we multiply its probability by $p = 0.932$. Looking at transitions between pairs of intersections along a trip, this number gives the fraction of times that a driver will decrease the apparent driving time to his or her ultimate destination. This value of p is derived from training on 20 recorded driving trips. If the driving time to the candidate has increased, we multiply its probability by $1 - p$. Then, we normalize the probabilities, so $\sum_{D \in D_s} p(D) = 1$. Since p is relatively large, the $1 - p$ term tends to quickly reduce the probability of destinations that the vehicle is driving away from.

In order to bound the geographic extent of the candidate destinations and to increase accuracy, we consider prior probabilities of each destination and update the likelihoods of candidates based on the likelihoods of the durations of trips, where times are marked from the trips' beginnings. We use a distribution of driving times drawn from the U.S. 2009 National Household Travel Survey (http://nhts.ornl.gov/). The distribution of trip times is shown in Figure 2, and details of how this was derived from the NHTS data are provided in [20].

Figure 5 shows how $p(D)$ changes over the course of an example trip. As the trip progresses, the candidate destinations with the largest probabilities tend to cluster near the trip's end.

IDEAL OPPORTUNISTIC DIVERSION

We now explore methods for identifying the optimal waypoint of a set of candidate waypoints (*e.g.*, fueling stations) and associated diversion in light of uncertainty about the driver's destination. Let us assume that a predictive system continues to compute destination probabilities, $p(D)$, $D \in D_s$ during a trip. At some time during the trip, assume that the driver requests a recommendation for the best stop to make for refueling. In the general case, we need to consider waypoints and the diversion that each introduces in terms of adding distance and travel time to the route to the primary destination. As the destinations are uncertain to the system, it must consider *expected diversions* under uncertainty. We refer to Figure 3 as a simple example to motivate expected diversion analyses. In this case, the driver is currently located at point L. Assume that the inferred destinations are either points A and B, and that each destination has equal likelihood, $p(A) = p(B) = 1/2$. We also consider location X, which is not a destination of the driver, *i.e.* $p(X) = 0$. We assume that the driver has an urgent need to stop for fuel somewhere soon, and there are fueling stations at points A and X. Our task is to identify the best fueling stop to recommend to the driver.

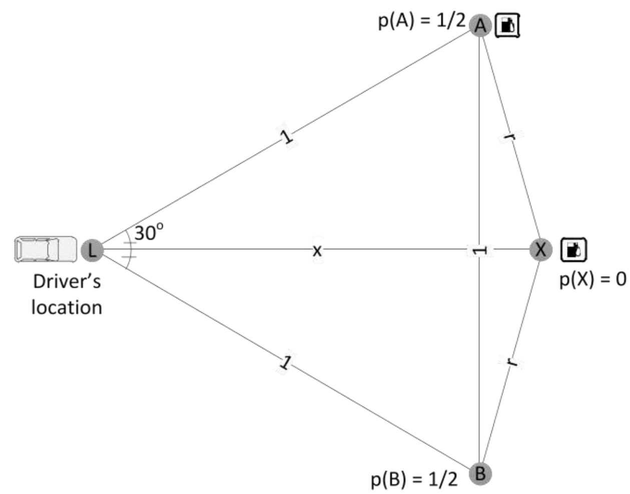


Figure 3: Illustrative diversion analysis. Driver's current location and points A and B form an equilateral triangle, with fueling stations at points A and X. Assume predictions show equal probability of driver heading to destinations A or B. If waypoint X is close enough, it may be preferred for fueling as that stop minimizes the expected total driving distance under current uncertainty in the final destination.

If we recommend to the driver to choose the fueling station at A, but the driver is actually driving to point B, the diversion cost will be one unit. This is because driving directly to B is a distance of one, but the distance from L to A to B is a distance of two. We use the more general notion of a driving cost function, which could be distance or time, and compute the divergence as the extra driving cost introduced by the waypoint. Referring to Figure 3, the divergence for point A is $C(L \to A \to B) - C(L \to B) = 2 - 1 = 1$. Similarly, if we tell the driver to choose the gas station at X when the driver is actually going to point B, the cost of the diversion is $C(L \to X \to B) - C(L \to B) = x + r - 1$, where r is the shortest distance between X and B, $C(X \to B) = \sqrt{x^2 - \sqrt{3}x + 1}$.

Since our onboard predictive system has access to destination probabilities, we can compute the *expected* costs of choosing the fueling station at A versus at X. The expected cost for any waypoint sums the products of the probability of incurring a diversion cost based on the likelihood of each destination and the cost (diversion cost) associated with that destination. Turning back to the

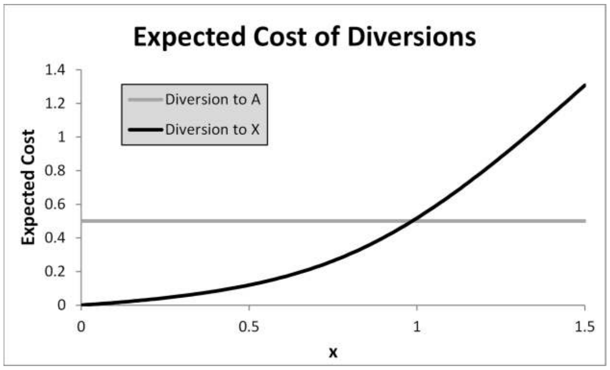


Figure 4: Exercising example (from Figure 3). Expected cost of diverting to X grows with x and eventually exceeds expected cost of diverting to A.

illustrative example, the expected cost of choosing the gas station at A is thus,

$$\begin{aligned} c_A &= p(A)[C(L \to A \to A) - C(L \to A)] + \\ &\quad p(B)[C(L \to A \to B) - C(L \to B)] + \\ &\quad p(X)[C(L \to A \to X) - C(L \to X)] \\ &= 0.5[1-1] + \\ &\quad 0.5[2-1] + \\ &\quad 0.0[1+r-x] \\ &= 0.5 \end{aligned}$$

We can compute the expected cost of choosing the gas station at X in a similar way:

$$\begin{aligned} c_X &= p(A)[C(L \to X \to A) - C(L \to A)] + \\ &\quad p(B)[C(L \to X \to B) - C(L \to B)] + \\ &\quad p(X)[C(L \to X \to X) - C(L \to X)] \\ &= 0.5[x+r-1] + \\ &\quad 0.5[x+r-1] + \\ &\quad 0.0[x-x] \\ &= x+r-1 \end{aligned}$$

We would recommend the fueling stop that associated with the smallest expected cost of diversion. In the example, the expected cost of diverting to the gas station at X, c_X, varies with x. The expected cost of choosing A is invariant with x. The plot in Figure 4 shows the values of c_A and c_X as a function of x, where we see that the gas station at X becomes a worse choice when $x > 0.986$, which is approximately where we have drawn X in Figure 3.

We note that, in the general case, the ideal waypoints are sensitive to the probabilities of destinations, the locations of candidate waypoints, and the topology of the road network, which rarely provides cases with the simplicity represented in the illustrative example. Also, we typically have many candidate destinations to consider in the real world. From the previous section, each candidate destination D is part of a set of destinations, D_S. The expected cost of diverting to point Z when the driver is currently at point L is

$$c_Z = \sum_{D \in D_S} p(D)[C(L \to Z \to D) - C(L \to D)] \tag{1}$$

The destination probabilities $p(D)$ come from the inferences about destinations as described above. These probabilities are recomputed as the trip progresses. In practice, we use Equation (1) to compute the best waypoint Z^*associated with the minimum expected cost of diversion, by substituting in each waypoint candidate Z, computing the expected cost of divergence for each, and seeking the ideal waypoint as follows,

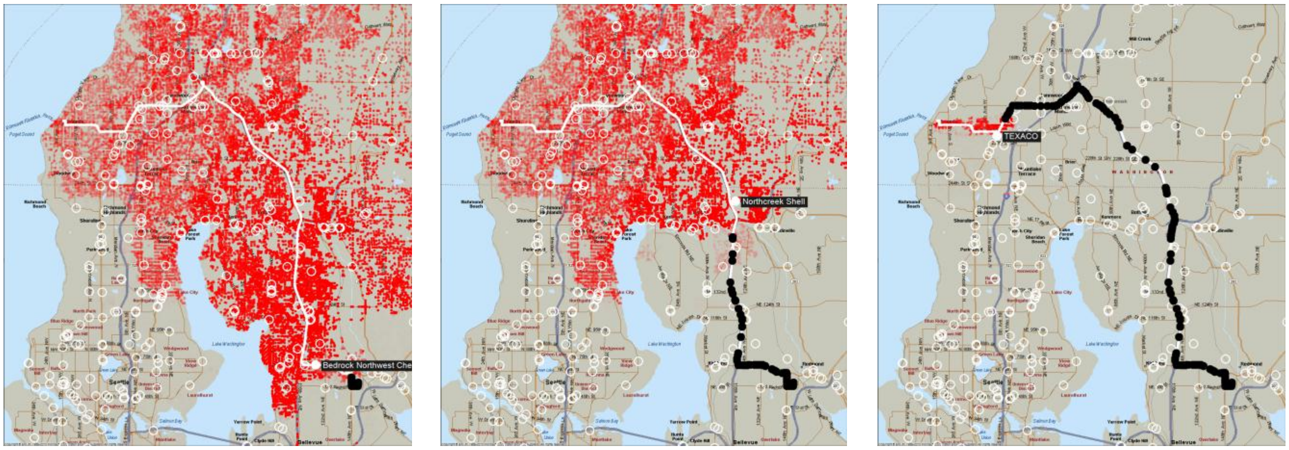
$$Z^* = \underset{Z \in Z_S}{\arg\min}\, Z \sum_{D \in D_S} p(D)[C(L \to Z \to D) - C(L \to D)] \tag{2}$$

Equation (2) represents computations at the heart of the opportunistic routing procedure.

Although we used Euclidian distance in the example, it is more realistic to express cost as driving time. This is convenient, because we are already computing driving times to each candidate destination for the purposes of destination prediction. Also, we can employ real-time and forecasted traffic flows in computing expected divergences that are measured in additional expected driving times. We further note that Equation (2) could be modified to consider both the cost of transportation and the cost of goods or services in a broader cost-benefit analysis that might trade off the distance of travel for gaining access to less expensive goods, *e.g.*, traveling to a more distant fueling station that provides less expensive gasoline. Such a cost-benefit analysis is considered in prior work on the Mobile Commodities prototype, which performed waypoint analysis for known destinations [2]. For now, however, we use simple driving time as the cost function, ignoring traffic.

In the analysis in this study, we move each candidate diversion to the nearest road intersection. Thus, all locations in the algorithm are at intersections. In addition to the raw driving times, we also impose a U-turn penalty of 120 seconds, which matches the value used by a major Web-based provider of driving directions.

We implemented and tested an algorithm for computing Equation 2. We note that this analysis is typically costly for real-world opportunistic routing: For each waypoint and for each destination under consideration the algorithm calls for the generation of an ideal route from the current location to the destination that passes through the candidate waypoint. Thus, the complexity of the analysis scales the cost of generating routes with the product of the number of waypoints and the number of destinations. Thus, realistic implementations of the methodology require very efficient methods for rapid route generation. We employed a fast routing methodology call RPHAST as described by Delling *et al.* [19, 21]. RPHAST is in a class of fast routing algorithms called “contraction hierarchies”. In such an



(a) (b) (c)

Figure 5: Predictions and diversions at three points along a trip. White line shows the actual trip, from beginning to end, starting at the lower right. Black dots show the intersections up to the current point of the trip. Cloud of small dots in the background shows the destination predictions, which tend to cluster more tightly together as trip progresses. White circles are candidate diversions (actual fueling stations), and filled white circle shows the optimal diversion with the name of the station.

algorithm, the graph representing the road network is augmented by short, precomputed shortest paths that the online part of the algorithm can use to more quickly compute long shortest paths. RPHAST is particularly aimed at the one-to-many shortest paths problem that computes driving times and routes from a single location (*i.e.* intersection) to many other locations (*i.e.* candidate destinations). RPHAST is orders of magnitude faster than the Dijkstra algorithm, and it runs in a few tens of milliseconds for each one-to-many problem on our regular PC (four cores at 2.67 GHz with 12 GB RAM).

Figure 5 shows an example run of the algorithm for one trip. The figure shows a separate map for each of three points along the trip. The white line shows the full trip, and the black dots show the progression of the trip from its start in the lower right. The small dots show the candidate destinations, where the dots with small destination probabilities are more faded. The white circles show candidate diversions, which are fueling stations in this case. At each intersection encountered along the trip, the opportunistic routing algorithm computes the diversion with the minimum expected diversion cost. In Figure 5, these optimal diversions are shown as filled white dots with a rectangular label. In the three instances shown, the optimal diversion is ahead of the vehicle's current location and close to the future route.

TEST DATA

We tested our algorithm using recorded GPS data and a database of candidate diversions maintained by our organization for business applications. Candidate diversions could be convenience stores, coffee shops, restaurants, or any type of business. For testing, we considered fueling stations as candidate waypoints, envisioning the common scenario where a driver attempts to refuel at a gas station that will not add significant driving time to a trip. Some of the fueling stations are shown on a map as white circles in Figure 5.

The GPS test in our study consists of 100 trips recorded in a region around Seattle, WA, USA. These trips were carefully recorded by turning on the GPS logger at the trip's start, waiting for a lock with the GPS satellites, and then turning off the GPS at the end of the trip. This approach to collecting trip information is more tedious than recording continuously, but it helps to ensure complete coverage and proper segmentation of the trips. The GPS data was sampled at 1 Hz. The 100 test trips did not include any of the 20 trips we had used earlier to compute p for the destination prediction procedure. A map of the 100 test trips is shown in Figure 6. We considered destinations within 60 minutes of the trip's start as candidates, averaging 205,594

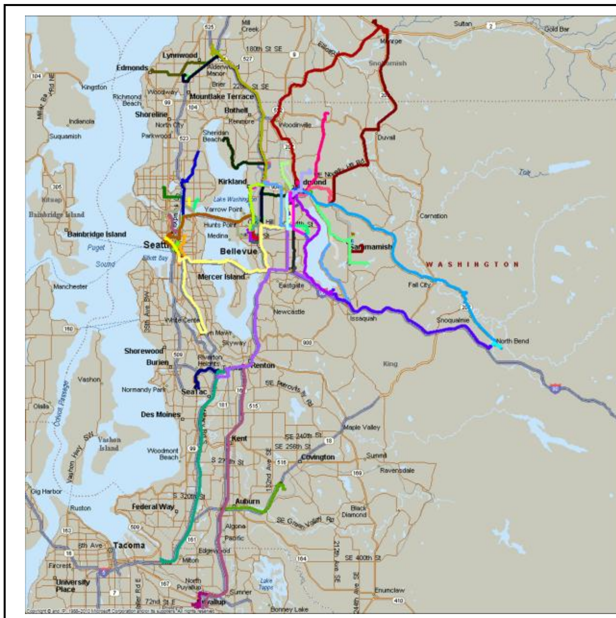


Figure 6: Corpus of trips for testing. 100 recorded trips we used for testing are displayed as separately colored paths.

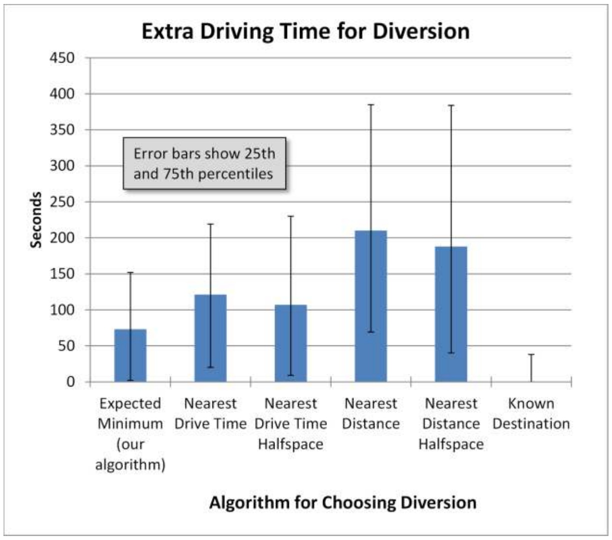


Figure 7: Given uncertainty about the destination, the opportunistic routing algorithm chooses diversions that minimize extra driving time, compared to other algorithms. The bars show the median extra driving time.

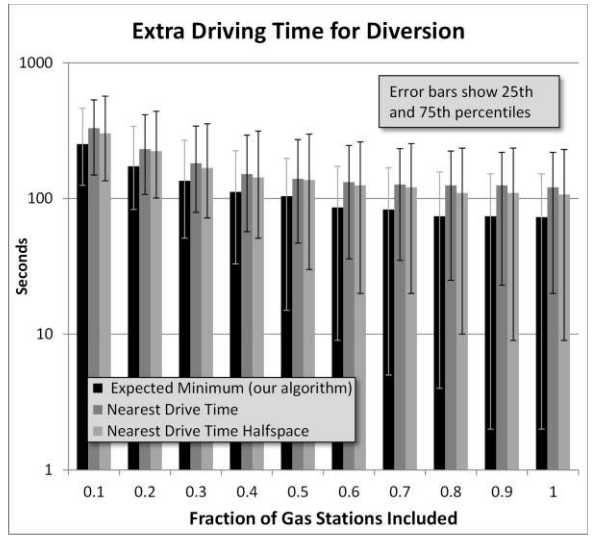


Figure 8: Exploration of varying density. When candidate waypoins are less dense, the relative performance of opportunistic routing improves. Note that vertical axis is on a log scale.

over the 100 trips in the test set. We evaluated our algorithm at each intersection encountered along each test trip, resulting in a total of 10,726 evaluations. In the next section, we describe the results of our evaluations with the opportunistic routing algorithm and some alternative procedures.

TEST RESULTS

For all 100 of the test trips, we computed the best diversion whenever the vehicle reached a new intersection along its trip. Prior to picking the best diversion, we recomputed and updated the destination probabilities for use in selection of an ideal waypoint. (For the first intersection, before we could do any predictions, we simply chose the nearest diversion by driving time.) As shown in Figure 7, the median extra diversion time is 73 seconds. This is an estimate of the extra time it would take to drive to the selected diversion and then on to the original destination over driving directly to the destination. It does not include the time stopped at the diversion, as this would be approximately the same for all diversions.

We compared our algorithm to five other algorithms whose results are also given in Figure 7 (times are reported as medians):

Nearest Drive Time. Select the diversion that is nearest to the driver in terms of driving time: 121 seconds.

Nearest Drive Time Half-Space. Same as above, but limit diversion candidates to the half-space ahead of the driver's current heading. This helps eliminate U-turns: 107 seconds.

Nearest Distance. Select the diversion that is nearest to the driver in terms of Euclidian distance. This is what most current local search engines recommend: 210 seconds.

Nearest Distance Half-Space. Same as Nearest Distance, but limit diversion candidates to the forward half-space: 188 seconds.

Known Destination. Assume driver explicitly tells the system their destination. This requires the possibly tedious and distracting entry of a destination: 0 seconds (mean was 44 seconds).

Except for the "Known Destination" case, our algorithm gives the smallest median diversion times. The median for "Known Destination" was zero, due to the fact that most routes in our test set passed at least one fueling station.

We note that fueling stations in our test area are relatively dense. Other types of diversion candidates, like coffee shops or electric charging stations, may be less common. We evaluated our algorithm on reduced sets of gas stations, where we randomly deleted gas stations to achieve lower densities. The results of this experiment are shown in Figure 8. Here we compare our algorithm to the two best alternatives, Nearest Drive Time and Nearest Drive Time Half-Space. In all cases, our algorithm performs better than its competitors, and its relative savings improve as the diversion candidates become less dense. (Note the log scale on the vertical axis in Figure 8.)

In looking for a diversion, drivers may prefer to specify approximately when they would want to stop. For instance, the driver may want to stop in the next 20-30 minutes for fuel while on a highway trip. The diversion suggested by the opportunistic routing algorithm may be immediately ahead or much farther away. The four alternative algorithms we tested (not including Known Destination) cannot make an intelligent suggestion for a diversion that is, say, 20 minutes away, because they have little or no idea of where the driver is going. Since our algorithm uses

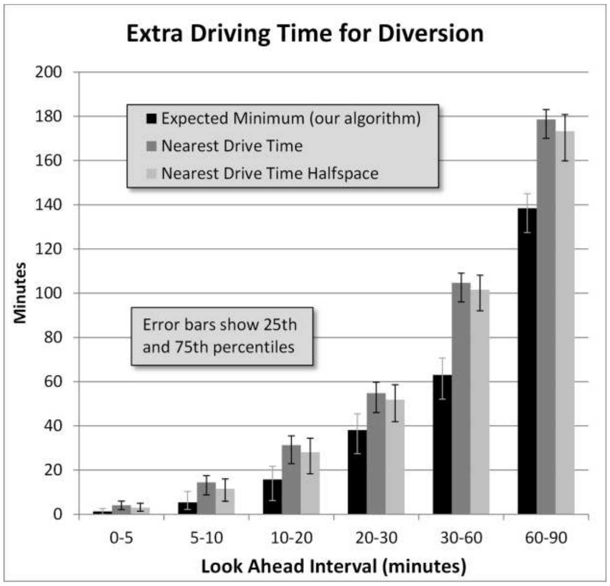


Figure 10: Opportunistic routing algorithm performs significantly better than other procedures in a comparative analysis in situations where waypoint is desired at some pre-specified time interval in the future.

reasonable predictions of where the driver is going, it works much better for suggesting diversions at some given time ahead. We tested our algorithm against the two best alternatives, Nearest Drive Time and Nearest Drive Time Half-Space. For these two alternatives, given a pre-specified future time interval, we chose the diversion that was closest to the middle of the interval, in the absence of other criteria for making the choice. For the opportunistic routing algorithm, we chose the diversion with the minimum expected diversion cost anywhere within the pre-specified interval.

The results of imposing a pre-specified look-ahead are displayed in Figure 10. In contrast to the previous results, the vertical axis is reported in minutes rather than seconds. Our algorithm does much better than the best alternatives. For instance, when the look-ahead time is 10-20 minutes, our algorithm saves over 12 minutes when comparing the medians. This savings is made more explicit in Figure 9, where we show the amount of time the opportunistic routing algorithm saves over the next best algorithm when comparing the medians from each experiment.

EXPECTED VALUE OF ASKING

As we saw in Figure 7, we can pick the best diversion if we know the driver destination, which we can get by explicitly asking. However, asking is at best bothersome and, at worst, a dangerous distraction. The expected value of asking incurs a definite cost of interruption for the uncertain benefit of providing a better waypoint. However, the net value of asking may be low as the system may already be confident of the driver's destination or because there are few choices of candidate waypoints to recommend. We explore the value of asking from a decision-theoretic perspective similar to prior work on the use of decision

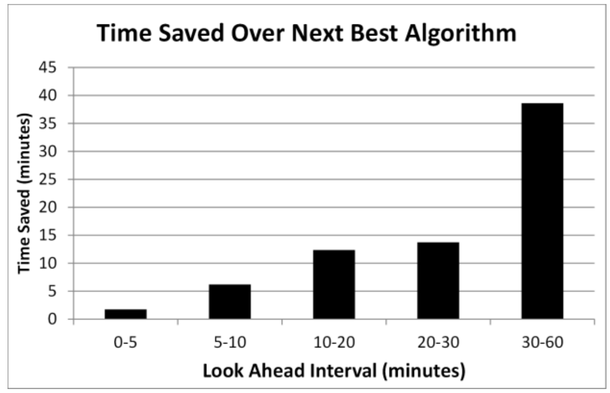


Figure 9: For identifying desired waypoint at some time interval in the future, the opportunistic routing algorithm significantly reduces total driving time.

theory to guide decisions about engaging users in human-computer interaction [22]. We consider specifically the expected value of asking a driver about the current destination. The expected value of asking (VOA) is computed as the following:

$$\begin{aligned}\mathrm{VOA} = {} & \min_{Z \in Z_s} Z \sum_{D \in D_s} p(D)[C(L \to Z \to D) - C(L \to D)] \\ & - \sum_{D \in D_s} p(D) \min_{Z \in Z_s} Z\,[C(L \to Z \to D) - C(L \to D)] \\ & - C(A) \qquad \textbf{(3)}\end{aligned}$$

The first term is just the expected cost of diverting to the waypoint (Z^*) with minimal expected cost under uncertainty in the destination, as computed by Equation (2). The second term is the expected minimal cost of divergence with learning the destination. The core idea is that we will know the true destination after asking, but we are currently uncertain about the answer we will hear. We can assume that the likelihood of hearing each answer is just the current inferred probability of each destination. For computing the current value of knowing the destination after asking, we select the minimal cost waypoint for each destination, and sum the costs of diverting to each of these waypoints as weighted by the probability that each destination is indeed the actual destination. Finally, we must consider the cost of asking, $C(A)$, which is scaled to be measured in units of additional driving time that a user is willing to incur so as to avoid a distracting or annoying inquiry from the system. In summary, the VOA is the difference in the cost of the best waypoint to select under uncertainty, as computed by Equation (2), and the reduced cost associated with picking the best waypoint for each destination and weighting these costs by the likelihood of each destination, with consideration of the additional cost incurred with asking. When VOA is positive, it is worth asking the user about the destination. Else, it is better to identify the single waypoint with lowest expected cost.

We note that over a trip the point-wise VOA can be changing as the value of each term can shift based on changes in the probabilities inferred about different ultimate destinations, and the changing details of the geospatial structure of waypoints and the topology of the road network relative to the current location of the car. Also, beyond a driver's preferences about being asked about destinations, the cost of such an interaction can change based on several contextual factors, including whether a driver is currently speaking with a passenger and the complexity of driving. Studies in driving simulators have demonstrated the existence of a task-dependent microstructure of the interaction of human cognition and driving complexity, and the influence of different mixes of road complexity and cognitive tasks (*e.g.*, introduced in phone conversations) on driving safety [23]. In practice a proactive system might monitor the value of asking and if positive defer engaging the user until a better time. Other studies of bounded deferral of notifications and engagement are relevant to this task [24].

We performed a study with the same test corpus of 100 recorded GPS trips aimed at exploring the expected value of asking using Equation (3) to compute the value of asking. We set $C(A) = 0$ here for simplicity. We found that the median cost saved by asking is 16 seconds. The 75^{th} percentile of savings is 99 seconds, and maximum savings is about 23 minutes. The relatively low median shows that our algorithm is doing a good job recommending a waypoint, based on predictions. However, the value of asking can be high, so it can be valuable to ask about the destination.

The VOA over the course of the trip from Figure 5 trip is displayed in Figure 11. We display both the expected value of asking and the actual value of asking, computed by taking the difference of the driving time for the best waypoint under uncertainty and the driving time for a waypoint optimized for the actual destination. We also set $C(A) = 0$ here. We note how well the VOA tracks the actual value of knowing the destination. Also, we note that both the expected value and the actual value of knowing the destination vary over the trip, rising and falling. In use, a threshold could be set on the value of asking, and a question about the destination could be asked of the driver should a need for a waypoint (*e.g.*, for fueling) arise or requested and a threshold in the expected value of asking exceeded.

CONCLUSION AND FUTURE WORK

We presented principles and studies of opportunistic routing for the general case where there is uncertainty about a driver's destination. The methods are aimed at identifying ideal waypoints on the way to primary destinations, as candidates associated with minimal expected additional cost of driving. We introduced an opportunistic routing algorithm and demonstrated its performance in comparative studies with other methods with a test corpus of GPS data of 100 trips. Finally, we presented a formulation of the expected value of asking and discuss how this measure can be used to guide a system's pursuit of additional knowledge about the primary destination. The methods and studies extend prior work on opportunistic routing to the case of uncertain destinations, and highlight the value of harnessing ongoing predictions about destinations to help with routing, and to guide decisions about resolving uncertainty by engaging people about their goals.

In ongoing research, we seek to better understand how methods for opportunistic routing under uncertainty might be leveraged in different settings and applications. For example, we are interested in the application of the methods for enhancing the quality of results provided in mobile search in cases where people search for goods and services by location. Given a search in a mobile setting, it may be most appropriate to rank results with a function that takes as arguments the relevance of results and the location of goods and services linked to those results. However, there are questions about the best results to provide in mobile settings. For example, if someone searches on "coffee shop" or "movie theater," is it most appropriate to rank results by how near they are to the user's current location, or how close they are to the predicted destinations? As a third alternative, the results might best be ranked by the expected divergence associated with going to each of the locations of the goods or services and then on to a likely destination, per the focus of this paper. The most appropriate ordering over recommended locations depends on the *transportation context*. Using methods of opportunistic routing as an input to ranking search results is most applicable when the user is headed to a specific destination, and would wish to see relevant results that would make for efficient waypoints on the way to that

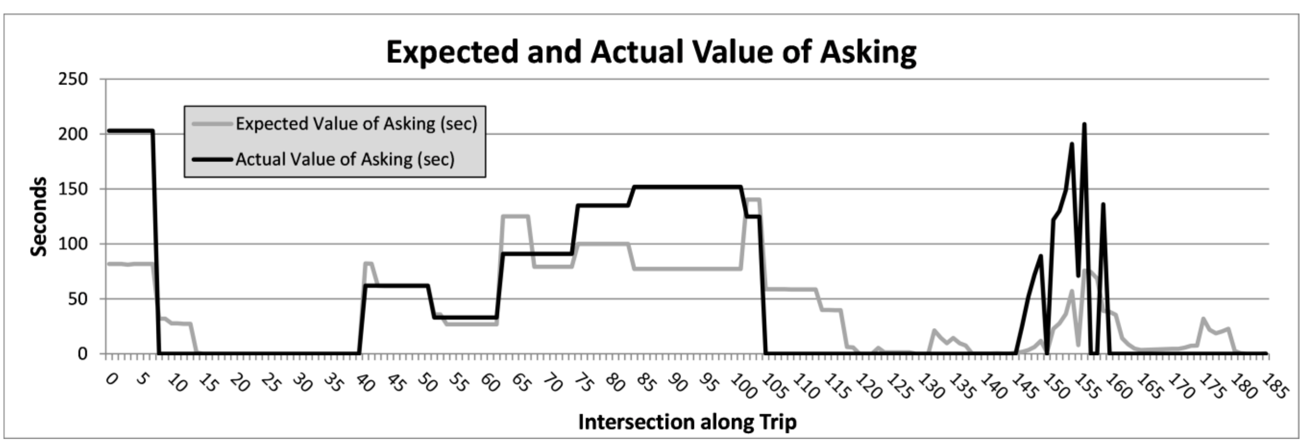


Figure 11: Computation of expected value of asking driver about destination. For a trip, we graph the expected value of asking the user and compare this with the actual value of resolving uncertainty about the destination.

destination. Proximity-based ranking may be best for the transportation contexts where driver and passengers are either casually exploring a city or are leaving or planning to leave their homes and offices to head directly to the specific location before returning back. Inferences about users' transportation contexts may be feasible based on such rich attributes as location and velocity data, and streams of queries over time.

ACKNOWLEDGMENTS

We thank Daniel Delling for his assistance with using efficient routing routines.

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