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Predicting link travel times from floating car data

Michael Jones[1], Yanfeng Geng[2], Daniel Nikovski[3], and Takahisa Hirata[4]

***Abstract*— We study the problem of predicting travel times for links (road segments) using floating car data. We present four different methods for predicting travel times and discuss the differences in predicting on congested and uncongested roads. We show that current travel time estimates are mainly useful for prediction on links that get congested. Then we examine the problem of predicting link travel times when no recent probe car data is available for estimating current travel times. This is a serious problem that arises when using probe car data for prediction. Our solution, which we call geospatial inference, uses floating car data from nearby links to predict travel times on the desired link. We show that geospatial inference leads to improved travel time estimates for congested links compared to standard methods.**

I. INTRODUCTION

Predicting car travel times along road segments is an increasingly important component of today's car navagation systems. We explore the problem of predicting travel times from floating car data (FCD). Floating car data are traces of GPS positions from actual cars driving on a road network. This is in contrast to the other major source of traffic data: stationary sensors such as inductive loop detectors or video cameras. These provide speed or flow estimates at regular intervals for a particular section of a road. Whereas floating car data provides speed or travel time estimates across the entire road network, stationary sensors typically only provide speed or flow estimates on highways or major roads. A major disadvantage of floating car data is that, unlike data from stationary sensors, the floating car data occur at irregular intervals and are typically much less frequent for any particular road segment. This means that, for a particular road segment, there may not be any traces for a long period of time. We propose a method for dealing with this problem called *geospatial inference*. Before presenting the idea of geospatial inference, we first present some results on predicting travel times using our floating car data when a recent estimate of travel time along a road segment is available. We look at two standard techniques for predicting travel times as well as two methods based on Support Vector Machine regression [19]. We find that the amount of congestion is the most important factor for determining which method works best.

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II. RELATED WORK

To predict travel times, real travel time data is typically measured and recorded in one of two ways: using stationary observers or moving observers. Stationary observers include loop detectors and video surveillance [7], which provide flow or speed estimates at regular and frequent intervals. Moving observers, involving floating cars or probe cars, are becoming popular travel time collection methods since they can cover almost any road segment as needed [17].

There have been numerous methods on predicting travel times. They can be categorized into three groups: regression methods (such as linear regression [14], local linear regression [16], nonliear regression [9], and Support Vector Machine regression [20], etc), time series analysis methods [1], [3], and Artificial Neural Network methods [8], [18]. Most of these methods are applied for short-term travel time prediction (15 to 30 minutes), and use stationary observer data. For example, Wu et al. [20] used Support Vector Machine regression for predicting travel times as we do, but their method relies on estimates of travel times at regular intervals in the past and thus cannot be applied to FCD.

Recently an increasing number of studies use floating car data to estimate traffic state and predict travel times [5], [12], [13]. Most of the work still assumes that frequent floating car data is available both on the link being predicted and on immediately preceding and succeeding links (e.g., in a paper by de Fabritiis et al. [6]). However, this assumption is often violated since most of FCD is irregular and sparse due to the limited number of probe cars.

To our knowledge, very few researchers have discussed the situation where no recent floating car data exists for estimation. We propose a *geospatial inference* method to deal with such scenarios, which utilizes the data from geographically nearby links to predict the travel time of the designated link. The work of Min et al. [10] also used information from nearby links (spatial information) as well as temporal information for the link to predict future travel times. Their model is a spatio-temporal autoregressive model that relies on speed and volume data for all links arriving at regular intervals (every 5 minutes in their experiments). They do not deal with the problem of predicting travel times when recent estimates are not available. A geostatistical kriging model was employed by Aultman-Hall and Du [2] to predict with sparse GPS probe data, where they assumed that roads in a small area could be traversed at almost the same speed. The geospatial inference approach we propose does not rely on this assumption. A similar kriging method is studied in [11] to also deal with sparse floating car data. In their paper, the kriging method is used to predict only long routes and not to predict travel times on short links. Their kriging method would most likely have large errors on short links.

The main characteristics of our work that differentiate it from past work are

- the use of sparse floating car data,
- the ability to predict an arbitrary amount of time into the future,
- and a method for making predictions even when no recent floating car data exists for estimating a recent travel time.

III. Predicting travel times on a link when recent floating car data is available

We have experimented with various methods for predicting travel times on road segments (also called links) using floating car data. Our floating car data is from actual vehicles driving around the Kanagawa prefecture in Japan with a GPS-based car navigation system. The data was provided by Pioneer Corporation and collected by their Smartloop system. The system records a *trace* of each trip driven in the vehicle. A trace consists of a series of time stamps, longitudes and latitudes recorded every 3 seconds. We have floating car data for the Kanagawa prefecture from about 2 million trips over a period of time from March 2008 through March 2011. From this data we can extract a set of trip segments covering a particular link that consists of the start date and time of the trip segment over the link and the time to traverse the link (the travel time). This is the raw data used to train a travel time predictor for a link.

Travel time prediction can be treated as a regression problem which attempts to map a set of input variables for a particular link to the travel time. The first question is what the set of input variables should be. Clearly the current time and current travel time estimate may be useful variables. In addition the amount of time in the future to predict is needed if we would like to control this variable when making a prediction. Thus we propose learning a regression function that takes as input the start time, t, an estimate of the travel time, τ_t, at time t, and the amount of time in the future to predict, Δt. The output is the predicted travel time at time $t + \Delta t$, denoted $\tau_{t+\Delta t}$. We choose to use Support Vector Machine regression [19] with Gaussian kernels due to its impressive accuracy on a range of regression problems. Briefly, a Support Vector Machine regression function with Gaussian kernels is a linear combination of Gaussian functions centered on a subset of the input vectors (called support vectors). The learning algorithm finds an optimal set of input vectors to use as centers (means) and an optimal set of weights for the Gaussians. The resulting regression function is

$$f(\mathbf{x}) = \sum_{i=1}^{N} a_i G(\mathbf{x}; \mathbf{c}_i, \Sigma_i) \tag{1}$$

where $\mathbf{x}$ is the input vector, a_i is the weight of the ith Gaussian, and $G()$ is a Gaussian function with mean $\mathbf{c}_i$ and covariance Σ_i. More details can be found in [15]. We refer to this method of predicting travel times as the 3-input SVM method.

We will also try using a 1-input SVM method that takes the prediction time, $t + \Delta t$, as the sole input and outputs $\tau_{t+\Delta t}$. By comparing this method with the 3-input SVM method, we can evaluate the importance of past travel time estimates (from floating car data) for predicting future travel times.

We also look at two standard methods of predicting travel times: historical profiles and the current travel time. The historical profile method creates a table of average travel times at different times of day for a particular link given historical travel time data. The table contains the average travel time for each interval of time during the day. We chose 192 bins for our table which corresponds to a bin for every 7.5 minutes during the day. One would expect this method to become less accurate during times of unexpected congestion or unusually high congestion when travel times differ from their historical values. Our experiments show that this is indeed the case.

The current travel time method simply uses the estimate of the current travel time as the prediction for future travel times on a link. One would expect this method to become less accurate the further in the future one attempts to predict.

A. Experiments on congested and uncongested links

To evaluate different methods for travel time prediction, we extracted travel time data for various links from our large set of floating car data. We manually defined 4 highway links from different areas of Kanagawa prefecture. These highway links were chosen because they tend to get congested. The four highway links are labeled Link 2, 5, 8, and 11. (The reason for this numbering will become clear when we introduce other nearby links in the experiments on geospatial inference.) We also choose two non-highway links which rarely get congested in order to test the various methods under uncongested conditions as well. These links are labeled Link 13 and 14.

1) Travel time data for the links used in our experiments: Each of the links used for testing has average travel times of around 1 or 2 minutes. The amount of data extracted for each link is about 32,000 different trips for the highway links and 11,000 different trips for the non-highway links over all three years of our data. Figures 1 through 3 show plots of time of day versus travel time for all data extracted for each link. We should note that because points in these plots overlap, an accurate picture of the density of points in different regions is lacking. Link 2 clearly shows that congestion often occurs around 8am and rarely at other times. Link 5 shows two times of frequent congestion at about 11am and 5pm. Link 8 shows congestion often occurring from about 8am all the way through 11pm or midnight. Link 11 shows some congestion occurring around 7pm and occasionally at other times. For the non-highway links, Link 13 shows very few trips with congestion although on the rare cases where congestion does occur it is most often around 8am. Link 14 shows a wide variation of travel times (mostly due to this link including a traffic light) and only occasionally more congestion in the late morning to early afternoon.

It is also interesting to look at the variations in travel times for a single day. This is shown for two links in Figure 4. These plots show that travel times can change quickly. This is often due to differences among drivers (fast drivers versus slow drivers) and not necessarily due to changes in congestion level.

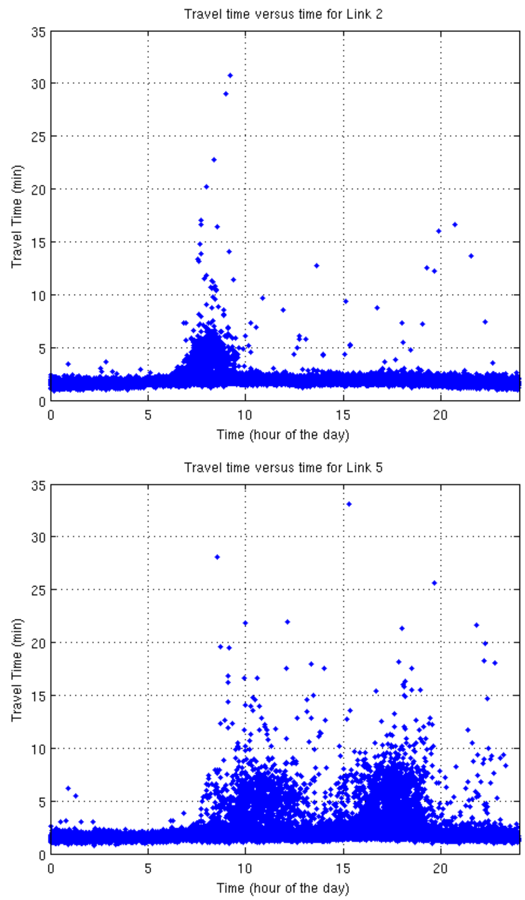

Fig. 1. Time of the day versus travel time for Links 2 and 5 across all days in the data set. Each trip in the data set that traverses the link is represented by a single dot in the graph.

2) When are recent travel time estimates useful for predicting future travel times?: If a link is congested at time t_1 then it is likely to also be congested at time t_2 where t_1 and t_2 are close in time. This implies that the travel time for a congested link at time t_1 is a good predictor of the travel time at time t_2. However, if a link is not congested, then the (relatively small) changes in travel time from one car to the next tend to be less predictable. In this case, recent travel times are not necessarily a bad predictor of future travel times, but a better predictor is the historical average travel time. An illustration helps to make this point clearer. Figure 5 shows plots of travel times at two times t_1 and t_2 where t_1 and t_2 are within 15 minutes of each other. If the travel time at t_1 is a good predictor for the travel time at t_2 then we would expect the points in this plot to fall roughly along the $\tau_1 = \tau_2$ line (where τ_1 and τ_2 are the travel times at start times t_1 and t_2, respectively). For Links 2 and 5 this is roughly true. For links 8 and 11 shown in Figure 6 there is some correlation between nearby travel times but it is not as strong. For links 13 and 14 shown in Figure 7 there is very little correlation. Link 14, especially, shows that the travel time at t_1 has no ability to predict the travel time at a nearby start time t_2. In general, we have observed that knowing the recent travel time for a link is only helpful for predicting future travel times for that link if the link has frequent congestion. This is discussed further in the description of our experiments.

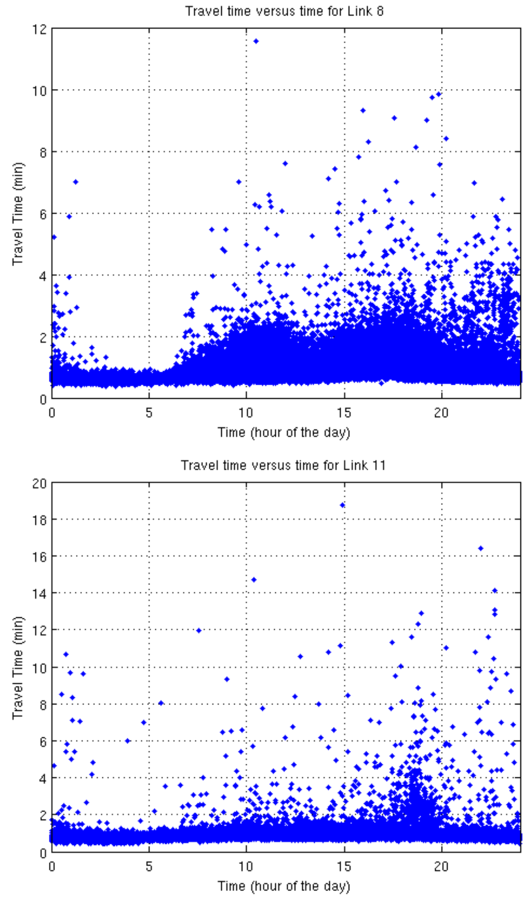

Fig. 2. Time of the day versus travel time for Links 8 and 11 across all days in the data set. Each trip in the data set that traverses the link is represented by a single dot in the graph.

B. Description of results

For each of the 6 links used for testing (4 with significant congestion and 2 without), the floating car data extracted for each link was converted into training and testing examples for travel time prediction. A training example consists of 3 inputs and 1 output as follows: $(t_i, \tau_{t_i}, \Delta t_i) \rightarrow \tau_{t_i+\Delta t_i}$ where t_i is the start time of the car entering the link, τ_{t_i} is an estimate of the travel time over the link at time t_i, Δt_i is the amount of time in the future to predict, and $\tau_{t_i+\Delta t_i}$ is the observed travel time over the link at time $t_i + \Delta t_i$.

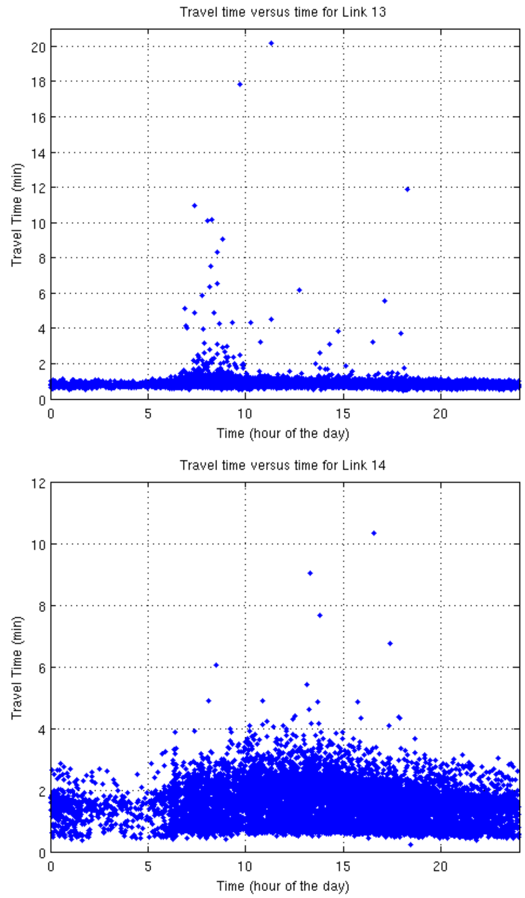

Fig. 3. Time of the day versus travel time for Links 13 and 14 across all days in the data set. Each trip in the data set that traverses the link is represented by a single dot in the graph.

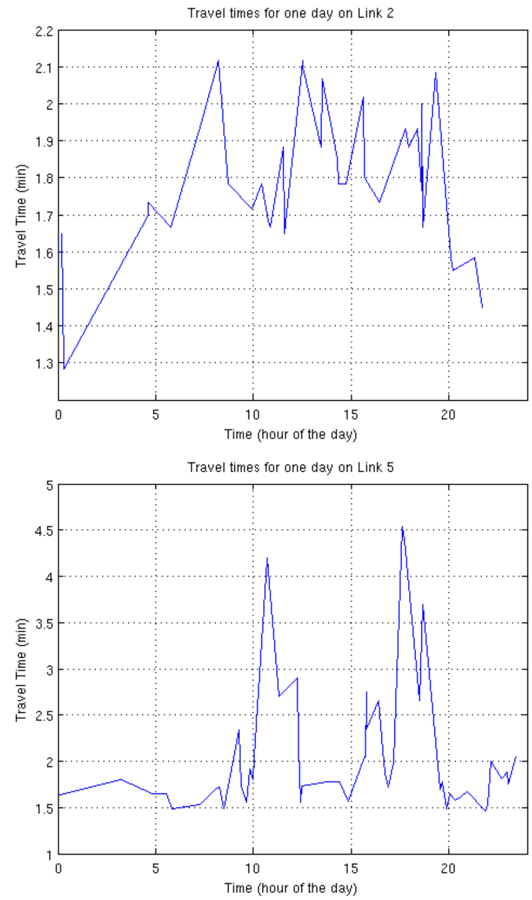

Fig. 4. Time of the day versus travel time for Links 2 and 5 for a single day. The plots show that travel times can change erratically over small periods of time.

The examples for each link were split into training and testing sets. For the testing sets, we wanted to ensure that there were plenty of examples occuring during congested periods (if congestion occurred at all). To do this we choose as testing days, only days containing at least one trip with a travel time greater than the mean travel time plus two standard deviations for that link. All trips on the chosen testing days were included in the testing data which means that plenty of uncongested trips were included as well. Using this method, about 6% of the total trips over a link were included as testing data and the remainder used as training data. While this results in a test set that is skewed toward trips during congested periods, we argue that this is the interesting and important part of the data to test on. As discussed before, our experiments showed that it is only during congested periods that estimates of current travel times are helpful for prediction. Thus, if almost all of the test data is taken from uncongested periods then prediction based solely on historical data will perform as well as any technique.

To create 3-input examples as described above, we need to decide on a range for Δt_i. How far into the future can we hope to reliably predict? This choice also influences the type of predictor that is best. The larger Δt_i is, the less the estimate of the current travel time helps to predict future travel times for congested links. To determine how large Δt_i can be before the current travel time estimate is no longer predictive of future travel times, we trained a 3-input SVM for Link 2 (which has congestion) and Link 14 (which does not have congestion). Then we plotted the error on the test set versus Δt_i to see how the error varies with Δt_i. Figure 8 shows the results. For error we are using relative mean error (RME) which is defined as

$$RME = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{(\tau_i - f(\mathbf{x}_i))}{\tau_i} \right| \qquad (2)$$

where τ_i is the ground truth travel time, $f(\mathbf{x}_i))$ is the predicted travel time given the input vector $\mathbf{x}_i$, and N is the number of testing examples.

For the sometimes congested Link 2, we see that the error increases with increasing Δt_i until Δt_i gets to around 1 hour. After that it levels off. For the rarely congested Link 14, the error does not seem to be dependent on Δt_i which confirms our earlier conclusion about uncongested links not being dependent on current travel time estimates. Given this experiment, we decided to choose Δt to be from 0 to 2 hours. For larger Δt's, the current travel time estimate will not be

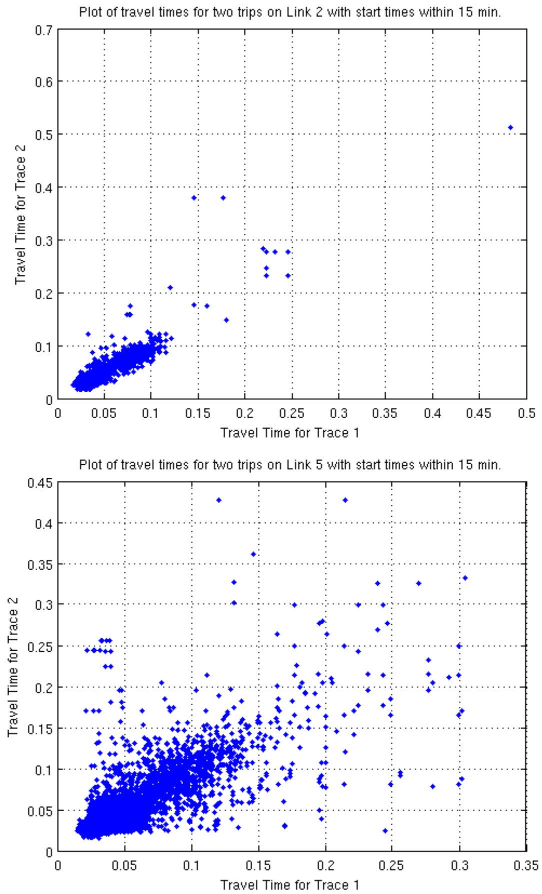

Fig. 5. Travel time at start time t1 versus travel time at start time t2 for two trips within 15 minutes of each other (i.e. $|t1 - t2| < 15$ min) for Links 2 and 5. If travel times change smoothly over time then points will be clustered around the $x = y$ line. Links that do not get congested usually display very little correlation between nearby travel times.

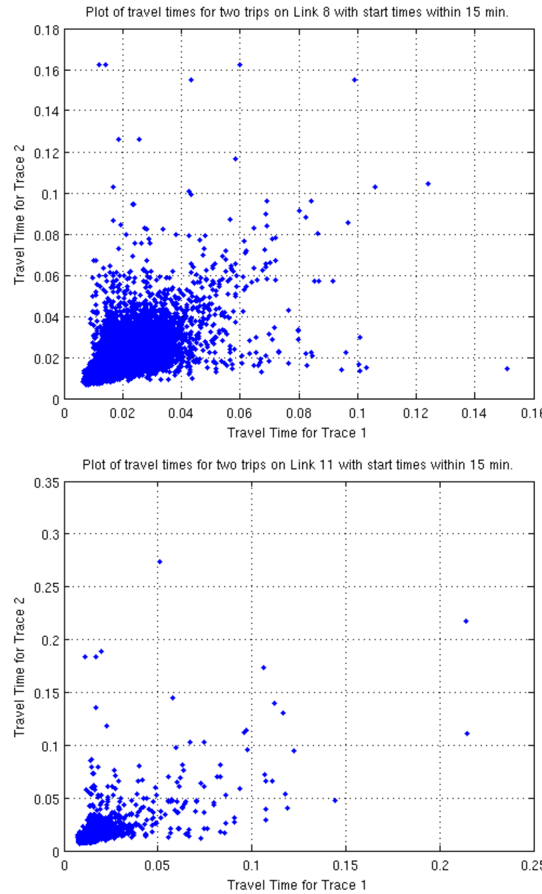

Fig. 6. Travel time versus travel time for trips that are within 15 minutes of each other on Links 8 and 11.

helpful for predicting future travel times, in which case a predictor such as historical profiles or 1-input SVM which does not use current travel time estimates for prediction should be used.

To train a 3-input SVM regression function, the training examples were exactly as specified above. The LIBSVM library [4] was used to train an SVM with Gaussian kernels.

For a 1-input SVM regression function, the training examples consisted only of start time t_i and output travel time τ_{t_i}. An SVM using Gaussian kernels was trained.

For an historical profile predictor, a table with bins for every 7.5 minutes was populated by averaging the travel times τ_{t_i} that fell into each bin according to start time t_i.

For a current travel time predictor, no training is used. This predictor predicts τ_{t_i} for a test example with target output $\tau_{t_i+\Delta t_i}$.

The results on the testing data for each of these methods is shown in Table I. The 3-input SVM has the lowest error for 4 out of 6 of the links. For the 4 links with congestion, it is best on all but Link 11. From Figures 2 (bottom) and 6 (bottom) we can see that while Link 11 does get congested occasionally, it has less congestion than Links 2, 5, and 8. As we noted before, links without a lot of congestion do not benefit from using recent travel time estimates in their prediction function. The results on Link 11 are further evidence of that.

For Links 13 and 14 in which there is very little congestion, 3-input SVM, 1-input SVM and historical profile predictors all perform fairly closely.

One might also wonder why a 1-input SVM usually performs better than the historical profile prediction. They both take only the time to predict as input. The reason is most likely that the 1-input SVM finds an optimal placement of Gaussians along the start time line. One can think of the Gaussians as equivalent to the bins of the historical profile. For the historical profile predictor, the bins are fixed. For the 1-input SVM the bins (Gaussians) are learned from the training data. This optimization of the Gaussian positions leads to an improvement over the fixed bins of the historical profile predictor.

IV. Geospatial Inference

One major problem with applying the 3-input SVM regression method for travel time prediction in a real routing system that uses continuously arriving floating car data is

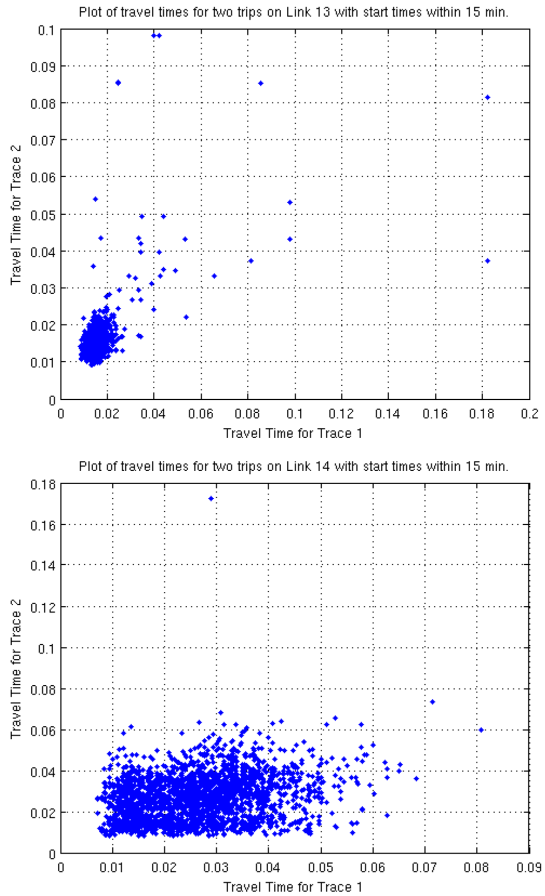

Fig. 7. Travel time versus travel time for trips that are within 15 minutes of each other on Links 13 and 14.

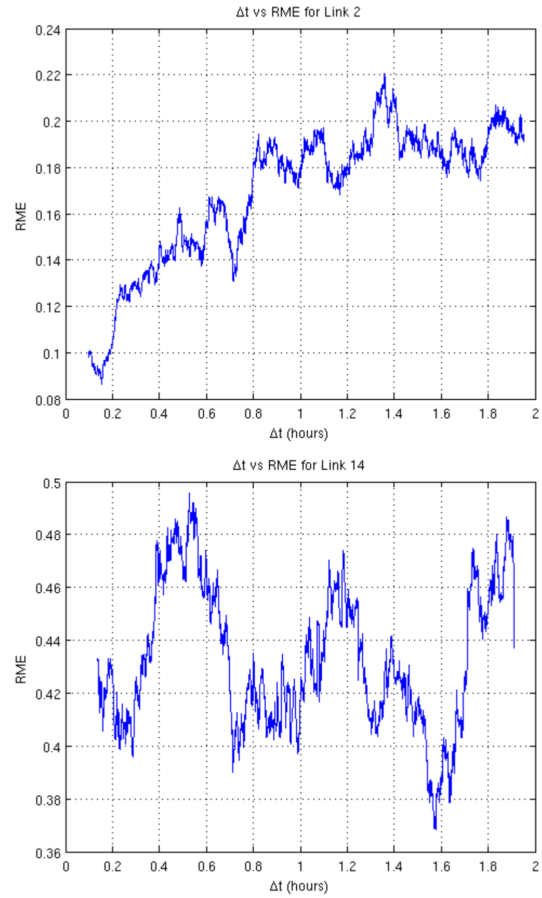

Fig. 8. RME versus Δt_i (amount of time in the future to predict) for Links 2 (top) and 14 (bottom).

Link	3-input SVM	1-input SVM	Historical profile	Current travel time
2	**16.73%**	19.62%	17.26%	28.63%
5	**18.91%**	20.79%	23.24%	30.17%
8	**20.05%**	22.16%	27.55%	32.02%
11	14.75%	**14.62%**	17.06%	27.41%
13	**24.35%**	24.67%	25.73%	55.88%
14	43.27%	42.80%	**41.92%**	56.70%

TABLE I

COMPARISON OF TRAVEL TIME PREDICTION USING VARIOUS METHODS ON DIFFERENT LINKS. RELATIVE MEAN ERRORS (RME) ARE GIVEN IN THE TABLE.

that it requires a recent estimate of the travel time for each link. This is a problem for any method that uses recent travel time as an input variable - not just SVMs. Floating car data is often sparse on a particular link especially for links on non-major roads. For many periods of the day there may not be any recent floating car data on a particular link. The severity of this problem depends on the number of probe cars in the region, but until car navigation systems that report their position saturate the market, this problem seems likely to be very serious.

We propose a solution to this problem called geospatial inference. The basic idea is to predict the travel time on a link using data from nearby links. This means the future travel time on a link is predicted using the estimated travel times (from floating car data) of nearby links when there is no recent floating car data available on the link. The assumption is that if a certain link is congested then nearby links are likely to be congested as well. It is possible to use training floating car data to learn which pairs of links are well correlated in the sense that travel times on one link are predictable from the other.

A. Details of Main Idea

We have tested the idea of geospatial inference using the four highway links used in the previous experiments along with two new highway links near each one of the four old links. The configuration of each of the four sets of three links is shown in Figures 9, 10, 11, and 12.

From our data we create a set of training examples of the form

$$(t, \tau_t^{L_j}, \Delta t) \rightarrow \tau_{t+\Delta t}^{L_i} \tag{3}$$

where t is the current time, $\tau_t^{L_j}$ is the ground truth travel time on link L_j at time t, Δt is the amount of time in the

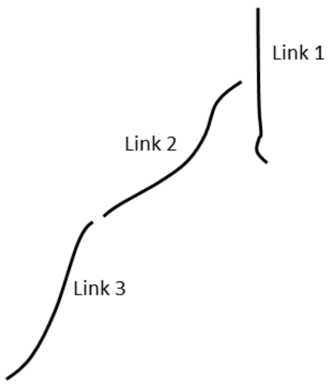

Fig. 9. First set of links used in geospatial inference experiments

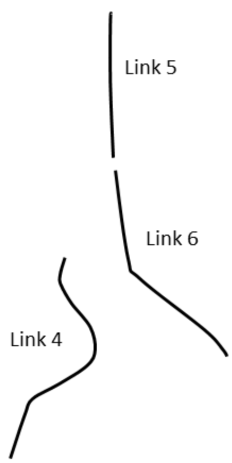

Fig. 10. Second set of links used in geospatial inference experiments

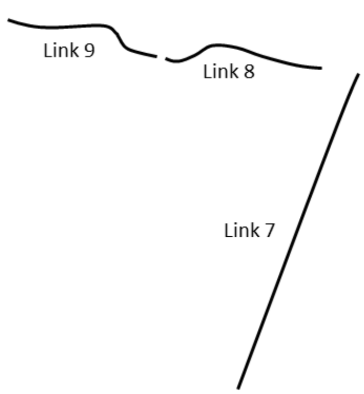

Fig. 11. Third set of links used in geospatial inference experiments

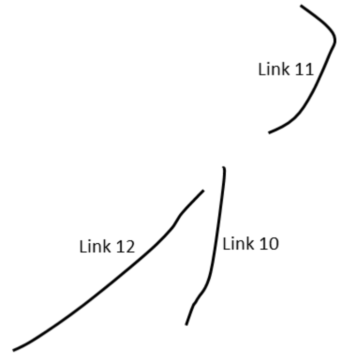

Fig. 12. Fourth set of links used in geospatial inference experiments

future to predict and $\tau_{t+\Delta t}^{L_i}$ is the ground truth travel time on link L_i at time $t + \Delta t$.

From examples of this form for links L_j near L_i, we train an SVM regression function $f_{L_i L_j}$:

$$f_{L_i L_j}(t, \tau_t^{L_j}, \Delta t) = \tau_{t+\Delta t}^{L_i}. \tag{4}$$

which predicts the travel time on link L_i from link L_j.

Given a set of such predictions from nearby links L_j, a final prediction is made using a weighted average:

$$\hat{\tau}_{t+\Delta t}^{L_i} = \sum_{j=1}^{N} w_j f_{L_i L_j}(t, \tau_t^{L_j}, \Delta t) \tag{5}$$

where $\hat{\tau}_{t+\Delta t}^{L_i}$ is the predicted travel time for link L_i at time $t + \Delta t$.

B. Experiments

This framework was used to train 3-input SVM regression functions to predict Link 2 from Links 1 and 3, to predict Link 5 from Links 4 and 6, to predict Link 8 from Links 7 and 9 and to predict Link 11 from Links 10 and 12. Training and testing examples were created by finding all trips over Link 1 (for example) that occurred up to 2 hours before a trip on Link 2. A separate set of testing examples were created for predicting Link 2 from Link 1 and for predicting Link 2 from Link 3. The two trained SVM predictors, $f_{L_2 L_1}$ and $f_{L_2 L_3}$, made predictions separately on their respective testing sets. For any pair of testing examples in the two sets which corresponded to the same target travel time and for which the start times were within 5 minutes of each other, the two output predictions were averaged together to get a final travel time prediction. All other testing examples used the prediction from just one of the SVM predictors as its final prediction. The former case corresponds to both nearby links having recent travel time estimates at about the same time so that the SVM predictors for both links can be used and averaged. The later case corresponds to only one of the nearby links having a recent travel time estimate available.

Travel time prediction using geospatial inference is compared against 1-input SVM and historical profile predictors since these do not need recent travel time estimates and so can also be used when such estimates are not available. These baseline methods were trained and tested on the same training and testing data as was used for the geospatial inference method (except the travel time estimates from neighboring links were not used). Note that the testing examples used are different from those used in our previous experiments in Section III. Although we used the same testing days as before (which all have at least one trip during a congested period), the testing examples were created based on the availability of a current travel time estimate in at least one neighboring link. This results in different examples than before. Relative mean error results are shown in Table II.

Link	Geospatial inference	1-input SVM	Historical profile
2	15.89%	17.23%	**15.43%**
5	**19.90%**	20.77%	23.18%
8	**19.79%**	22.11%	27.59%
11	**14.92%**	15.03%	17.43%

TABLE II

COMPARISON OF TRAVEL TIME PREDICTION USING GEOSPATIAL INFERENCE COMPARED AGAINST TWO OTHER METHODS. RELATIVE MEAN ERRORS (RME) ARE GIVEN IN THE TABLE.

Geospatial inference achieves the lowest overall error for Links 5, 8 and 11. The historical profile predictor is slightly better on Link 2. If we look at the plot of RME versus travel time shown in Figure 13, we see that the geospatial inference predictor has lower error for larger travel times which are times of greater congestion. These are arguably the most important times to have more accurate predictions. It is also interesting to note that the plot of RME versus travel time in Figure 13 shows that the prediction error is lowest for all methods near the mean travel time (which can be roughly approximated from Figure 1). The prediction error goes up for all methods as travel times differ from the mean.

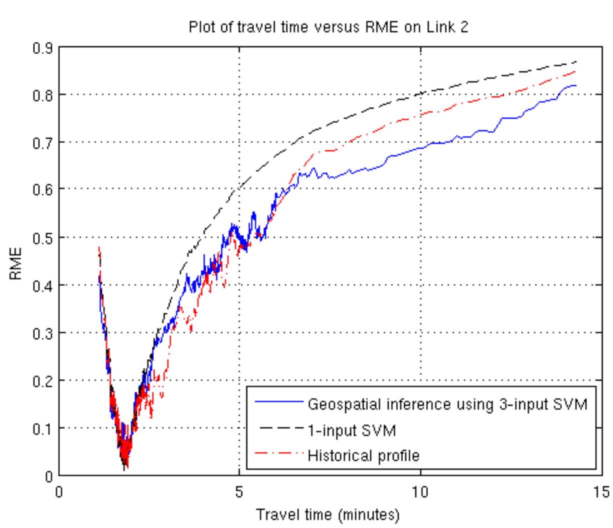

Fig. 13. RME versus τ (travel time) for travel time prediction using geospatial inference, 1-input SVM, and historical profile on Link 2. Prediction using geospatial inference has the lowest error when congestion is greatest (large travel times).

V. CONCLUSIONS

In our first set of experiments we demonstrated that estimates of the current travel time are only helpful for predicting future travel times on a link when it has congestion. For congested links, the 3-input SVM regression function with Gaussian kernels is more accurate than a 1-input SVM regression function, an historical profile predictor, or current travel time predictor. We also showed that geospatial inference can be used in the case where a recent travel time estimate is not available on the desired link but is available on at least one nearby link. Geospatial inference leads to lower error rates compared to a 1-input SVM predictor or an historical profile predictor.

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