Improving the travel time prediction by using the real-time floating car data

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Abstract

In this paper we consider the problem of travel time prediction for a car navigation system. Given a static black box prediction model based on historical data, the aim of the research is to improve the performance of this model by a dynamic counterpart utilizing real-time GPS floating car data generated by the users of the car navigation system. The prediction is computed for each single segment of the road network by using the Gaussian process model or the exponential smoothing. We consider also two extensions that take into account the dependencies between different segments. In the first one, the prediction of the travel time is additionally based on data from the most correlated segments. In the second one, the travel times are smoothed over segments constituting the longer paths of the main roads. Exhaustive experiments on real data were conducted that show high accuracy of the proposed models and significant improvement over the static black-box model.

1 Introduction

The travel time estimation has always been an important part of intelligent transportation systems (ITS) research domain. An accurate real-time prediction of travel times can be a crucial part of the driver information or the traffic management system.

The travel time estimation based on the real-time floating car data is also especially important for personal car navigation or route guidance systems. The aim of these systems is to guide their users with an optimal route to a chosen destination. Such a system can help, for example, in avoiding the traffic jams. The further consequence can be a reduction of traffic congestion in general, which itself is related to lowering fuel costs and air pollution, etc..

The benefits mentioned above are not the hypothetical ones, since the personal navigation systems are becoming more popular, particularly those that use mobile phones equipped with built-in GPS. These kinds of devices can guide the drivers by using the real-time data from the traffic network.

Travel time estimation in the above context is the main concern of this paper.

2 Research purpose

Given a static black box prediction model based on historical data, the aim of the research is to improve the performance of this model by a dynamic counterpart utilizing real-time GPS floating car data generated by the users of the car navigation system. The system also needed to be simple and efficient for easy practical implementation and deployment.

The predictions of the model are then to be used in an algorithm for searching the shortest path between any two points in the network. Therefore the prediction must be done separately for a very large number of short segments of the roads.

3 Related Work

The analyzed problem belongs to the field of travel time prediction based on data (as opposed to flow simulation methods or similar). Studies based on similar input exist in the literature [5], but our problem has a few specific features that make it different from most other research in the area.

The scope of the predication covers the entire road network. Some similar global approaches can be found [2], however, the majority of the methods focus on single paths [4, 5], freeways [3, 4], or consider some urban arterial roads only [5]. In these cases, information is usually provided by the loop detectors [4] or other stationary sensors [1].

The introduced model predicts the travel time for each of the segments of the road network. Similar approaches can be found [1], however, the prediction for longer paths is considered more often.

4 Applied methods

Formally, the problem can be defined as learning of a function $f(\mathbf{x})$ to be a good prediction of the unknown value y_{it}. In this case, y_{it} is the travel time on the i-th segment at the time t. Thus, the estimate of y_{it} is:

$$\hat{y}_{it} = f(\mathbf{x}),$$

where $\mathbf{x}$ is a set of features being travel times collected from the entire road network. These can be considered as time series for each of the segments. The goal is to fit $f(\mathbf{x})$ in order to reduce the square-error loss:

$$L(y_{it}, \hat{y}_{it}) = (y_{it} - \hat{y}_{it})^2.$$

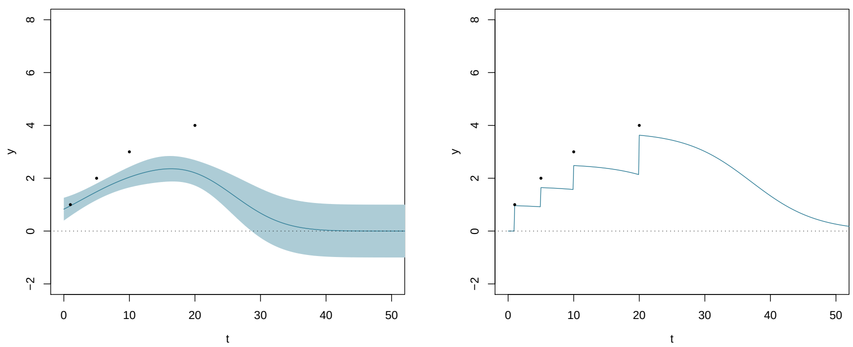

Figure 1: Visualization of an Gaussian process (left) and exponential smoothing (right) based on 4 data points

We considered the Gaussian process model and the exponential smoothing applied independently to each of the road segments. One can extend this simple model by assuming dependencies between different segments. We applied two such extensions. The first one is based on the data, and relies on computing correlations. The second one is based on domain-knowledge — the travel times are smoothed by averaging over the segment constituting the longer paths of the main roads.

4.1 Gaussian process model and exponential smoothing

Gaussian process model and exponential smoothing belong to the field of stochastic process modeling and time series analysis. They try to predict the travel time on a road segment based on previous values of the same type.

Gaussian process model is based on the assumption that the time series is a Gaussian process with known covariance function, observed at the points of the series. The prediction is then made by calculating the expectation of the conditional distribution given the previous data at the point for which value needs to be predicted.

An example of a Gaussian process is shown in Figure 1. The blue line denotes the mean value of the process and the light blue background shows the range of one standard deviation around the mean. It should also be noted that the actual prediction is done after the last data point. The part before the last data point shows the effect of interpolation (which is not really useful for our purpose).

Exponential smoothing performs a prediction which is a weighted average of previous observations, with weights decaying at exponential rate with respect to the time difference between the prediction and observation times. This can be formally expressed as follows:

$$\hat{y}(t_0) = \frac{\sum_{t_i<t_0} w(t_0 - t_i) y(t_i)}{\sum_{t_i<t_0} w(t_0 - t_i) + R}$$

where:

$$w(t) = e^{-t/T}$$

The T is the time constant determining the speed of exponential decay and R is the regularizing constant pushing the prediction value towards 0. An example visualization of the exponential smoothing is given in Figure 1. The *stair-like* form of the function before the last data point is the result of adding data points during prediction (there is no interpolation, as opposed to the Gaussian process).

Of the two methods, the exponential smoothing can be considered the simpler and computationally more efficient one, but potentially yielding inferior (less accurate) results.

4.2 Linear correlations

The linear correlation is used for modeling the relations between different segments. It becomes a measure of similarity of simultaneous (in a defined time window) travel time changes — e.g. showing a tendency for some road parts to be congested at the same time. The time series methods are then extended by using observations from the most correlated segments.

The correlations are calculated between directed road segments (basic small road parts). This is possible due to the already map-matched floating car data, which is described in detail in section 5.1. The correlated variables values are the passage time differences between the actual data and the given base black-box model predictions. The algorithm used to calculate the correlations can be described as follows:

1. for a given pair of directed road segments s_1 and s_2 take all passage sets $P_1(s_1)$ and $P_2(s_2)$
2. take all pairs of passages $(p_1 \in P_1, p_2 \in P_2)$, such that: p_1 and p_2 are no more distant than:
   (a) 5 km spatially
   (b) 15 min temporally
3. calculate the correlation over pairs $(\Delta t(p_1), \Delta t(p_2))$, where $\Delta t(p)$ is a time difference for passage p between the actual time and the black-box model prediction.

4.3 Smoothing by road segments aggregation

Smoothing by road segments aggregation uses the expert rules (based on the digital road network map) to determine longer parts of main roads — passable sequences of basic short road segments with the road category indicating a main road that are not intersected with road of the same or higher category.

The resulting paths are then used to smooth the input data — vehicles passing the path are treated as having a constant velocity along the segments.

The above method should be equivalent to a prediction based on longer road parts. This can lead to a slightly more complicated routing process, but potentially reduces the prediction noise.

5 Experiments

5.1 Data and methodology

The data was delivered by a Polish company, *NaviExpert*, that provides a commercial on-line navigation system. We obtained the *GPS floating car data* that had already been map-matched, i.e. it had a form of velocity and event time bound to a passage of a specific road segment in a given direction. The data was also quite sparse and unevenly distributed among time and space. It covered two large Polish cities with broad surroundings over a few months in 2008. A digital roads network map matching the traffic data was also made available for the research. It provided data such as road categories, specific road segment lengths and other.

The data was divided into two parts for the sake of evaluating the results of the prediction methods. The learning set covered the passages from 15th October to 15th November, while the test set ranged from 15th November to 15th December.

After some preliminary experiments the basic predicted variable was decided to be the passage time difference between the actual data and the given base black-box model predictions. The chosen model evaluation measure was root mean square error (RMSE), which is in conformance with the problem definition given in section 4.

5.2 Results

In the initial experiments, the Gaussian process model and the exponential smoothing methods were applied. While both have shown a slight improvement over the black box model, there was virtually no difference between the two approaches. Thus it was concluded, that the exponential smoothing method can be an accurate and fast approximation of the much more computationally intensive Gaussian processes and later experiments were focused exclusively on the former method.

Table 1 shows the results of applying exponential smoothing and correlations. The error measure is the root mean square error expressed as a percentage of the error of the black-box model. The improvement is noticeable, although not extremely high.

Next, the dependence of the model quality on the density of data was investigated. The denser data was simulated by filtering the input — only the data

Model	**RMSE[%]**
Base black-box	100.0
Exponential smoothing	**99.0**
Exponential smoothing + correlations	**98.6**

Table 1: Results of the exponential smoothing with and without correlations

$\boldsymbol{N}$	**RMSE[%]**	**%obs**
0	99.0	100.0
1	96.7	40.7
2	94.7	17.8
3	93.1	8.1
5	**89.0**	1.4

Table 2: Results of the exponential smoothing on dense data obtained by filtering the input data

points which had at least $\boldsymbol{N}$ previous observations in the last three hours were considered as subjects for prediction and error calculation.

The results of this phase of experiments can be seen in Table 2. The percentage of observations that match the above mentioned filter is also noted. There is a clear improvement in the prediction accuracy along with the increasing density of data.

Next, the smoothing by road segments aggregation was applied, as described in Section 4.3, along with exponential smoothing and correlations. This resulted in a larger improvement as can be seen in Table 3.

More dense data simulation was also conducted in conjunction with roads aggregation, yielding an even larger improvement. The results can be seen in Table 4.

6 Conclusions

The main conclusion arising from the obtained results can be summarized in the following points:

- it is possible to create a simple, yet meaningful system for improving the travel time prediction covering the whole roads network, using possibly sparse floating car data,
- the exponential smoothing is a good and fast substitute of the Gaussian process model for the above purpose,
- the quality of the time prediction depends strongly on the density of the available data — denser input yields a better prediction,

Model	RMSE[%]
Exponential smoothing	**94.4**
Exponential smoothing + correlations	**93.9**

Table 3: Results of the exponential smoothing with road segments aggregation

N	RMSE[%]	%obs
0	94.4	100.0
1	**84.8**	40.1
2	80.8	17.8
3	79.7	8.1
4	77.2	3.5
5	76.4	1.4
6	75.9	0.5

Table 4: Results of the exponential smoothing with road segments aggregation on dense data

- where possible — prediction on longer paths (as opposed to short road segments) may be desirable, due to less noise and better prediction quality,
- the linear correlations that indicate the dependencies between different segments of the road network, can also be used for improving the prediction.

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