Travel times in Dynamic Demand Responsive Transportation

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1 Context

Travel time management is a core topic within the transportation field [1]. More precisely, both the way to mathematically model [3] and the way to estimate [4] the travel times used in a transportation system have been widely discussed in the literature. However, it is actually rare to study both of them together and it is even rarer to also consider the impact of a selected travel times model on the operational quality and efficiency of a service.

In particular, Dynamic Demand Responsive Transport systems are required to communicate and to commit on a pick-up time as well as a drop-off time to each passenger, whether it be for a booking that is made days in advance or just a few minutes before departure. To do so, a robust but reasonable definition of the travel times must be determined by the operator.

This work reviews the operational impact of the travel times design in a Dynamic Demand Responsive Transport service and how we tackle this issue at Padam Mobility. In short, we ran theoretical experiments to evaluate the potential impact of both underestimation and overestimation of the travel times. We then developed a framework able to provide a better estimation of the travel times using the geolocation history of the operating vehicles.

2 Operational Impact

An overestimation of the travel times leads to a faster saturation of the drivers' schedules. By solving the Selective Dial-a-Ride Problem (SDaRP) on a variety of real-world situations with varying travel times, we can quantify this loss of effectiveness within our services.

An underestimation of the travel times leads to delays that can snowball from the first shift of the day to the very last one. By finding the closest feasible schedule that respects the actual travel times to a schedule built on underestimated travel times, we can quantify the delays experienced by our passengers. For instance, even a relative error as small as 15%, that is 1min30 in a 10min trip, can lead to significant lateness at the end of the day.

3 Travel history processing

The trajectories retrieved from the mobile devices of the drivers during their shifts suffer from several ills. Not only the geolocation data that makes up the trajectories is inherently uncertain, but it also contains many stops, given the nature of our services. For a given trajectory segment, we want to calculate the theoretical travel time and the realized travel time.

Two difficulties then arise: we must ensure the consistency of the trajectory and the division of these segments. Due to the imprecision of the data, a segment composed of two geolocations can lead to large variations in the distance traveled. Furthermore, at the time of sending a geolocation, the driver can be at full speed, accelerating, decelerating or stopped, impacting the travel time even more as the sampling frequency is low.

We therefore applied two concepts: *stop detection* [2] to identify homogeneous "moving" segments followed by *map matching* to project those segments onto the underlying graph.

4 Travel time estimation

Our objective is to adapt the weights of the edges of the graph that represents the underlying road network to reduce the error between the theoretical travel times and the real travel times. Real travel times come from our processed historical data while the initial weights of the graph are provided by external sources.

In the literature, there are two main paradigms used to tackle this problem: segment-based and route-based approaches. The first one considers each pair of geolocations as independent and associates them with the closest edge of the underlying graph. The second one considers a list of geolocations that form a complete trip between two stops and associates them with the corresponding list of traversed edges.

We use a segment-based approach in our work but directly rely on the pairs of successive geolocations instead of the underlying edges. First, we fit a boosting regression model that predicts for each pair of observations the ratio $\frac{\text{Experienced Travel Time}}{\text{Theoretical Travel Time}}$ based on geographical features, such as the average coordinates of the pair of geolocations, on temporal features, such as the hour of the day or the day of the week of those geolocations, but also derived features, such as the estimated speed of the vehicle $\frac{\text{Distance between geolocations}}{\text{Experienced Travel Time}}$ on this segment

We use this fitted model to estimate the ratios for all our samples. We then divide the map into a grid of cells, associate each pair of geolocation observations to the cell it is contained in, and obtain a ratio for the cell by averaging the predicted ratios of the samples contained in the cell. The cells of the map that are not covered by any data are given a global ratio which is defined as the average of all the ratios of our samples.

Using the following methodology, we were able to improve our planned travel times by a significant margin. The error used to compute the following metrics is the difference between the planned travel time and the real travel time in seconds of a trip, which is the golden metric from a business logic perspective.

	Relative error	Absolute error	Standard deviation
Initial map	−15.24 %	51.31 s	77.57 s
Calibrated map	3.58 %	42.53 s	72.17 s

TAB. 1: Estimated travel times - Results analysis

The absolute error has been reduced by 17.1%, the distribution is now almost centered on 0 and, more importantly, the standard deviation of the error has been reduced by 7%.

References

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