A real-time particle filter for bus arrival prediction with discrete CDFs for journey planning

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Summary. The prediction of transit vehicle arrival time is a complex problem with the added difficulty of its real-time nature. Reliable predictions require the combination of both vehicle and network states, implying that real-time traffic congestion information is incorporated into the predictions. Inevitably, however, there is a lot of uncertainty around arrival times: road speeds fluctuate, particularly around peak time, and multimodality is added with every stop passed (which may or may not cause the bus to stop depending on passenger demand). Therefore, not only do we need to predict arrival time, but also assess and report the uncertainties involved. We present a method of using a particle filter to combine the states of both vehicle and network to obtain arrival time distributions. These are then discretised in such a way that allows real-time calculation of event probabilities for use in journey planning applications.

Keywords: particle filter, transport, real-time, GTFS, transit networks, journey planning

1. Introduction

- the problem of predicting bus arrival - it needs to use real-time traffic information Citation Needed (2020)
- however, many deployed methods are either specific to a provider/city, or don't make use of real-time data (only vehicle position and/or arrival delays, e.g., in Auckland)
- since the only logical source of "traffic data" in this setting is the transit vehicles themselves, makes sense to develop framework that uses them to estimate real-time network state Elliott and Lumley (2020)

- in this example, particle filter is used to obtain a sample of points from the arrival time distribution - many many points, which cannot possibly be distributed or stored efficiently
- we propose a method of reducing this to a simple discrete CDF of arrival time (in minutes)
- we show that these results can be used to answer some common journey planning questions, in real-time, which outperform current "method"

Some of the references include:

- Cathey and Dailey (2003)
- Yu et al. (2006, 2010, 2011)
- Hans et al. (2015)

2. Background

Before describing the process of obtaining arrival time distributions, we must first define the framework with which we obtain vehicle and network state estimates. Elliott and Lumley (2020) present a process for constructing a transit road network from raw GTFS data.

2.1. A transit road network

- information about GTFS
- the concept of converting it into a network (as per Elliott and Lumley (2020))
- end product is real-time estimates of traffic state

2.2. Estimating network and vehicle state using particle filtering

- particle filter on vehicle state
- used to estimate vehicle speed, position
- obtain distribution of travel times for each vehicle along each road

3. Predicting arrival time

Accurate, reliable prediction of bus arrival time requires knowledge of both vehicle and network states, represented by $\boldsymbol{x}_k$ and β_c, respectively. Since there is a high degree in the uncertainty of these, particularly when forecasting future network states around peak times, it is crucial to incorporate this uncertainty into the arrival time distribution and, ultimately, decision making processes.

The particle filter presents a robust method of sampling all of the possible trajectories the vehicle might take (Hans et al., 2015).

- initial state incoporates uncertainty (shape, multimodality) of vehicle state
- trajectory of each particle = one possible path the bus might take
- accounts for uncertainty in (forecasted) road speed, correlations, etc
- result makes no assumptions about shape of distribution

The main downside of the particle filter is the computational demand of it, often requiring 5000-10000 particles per bus.

- Elliott and Lumley (2020) showed the pf is feasible in real-time for modelling
- need to also show predicions can be done quickly and usefully
- reduce number of particles where possible

Our implementation is described in section 3.1. To examine the effectiveness of our approach, we run our method on a full day and compared the predictions with the actual arrivals, as well as the currently used "GTFS" predictions. These are discussed in section 3.2.

3.1. Particle filter ETAs

In our application, the vehicle state is already represented by a set of N particles,

$$p(\boldsymbol{x}_{k|k} \mid \boldsymbol{y}_k) \approx \sum_{i=1}^{N} w_k^{(i)} \delta_{\boldsymbol{x}_k^{(i)}}(\boldsymbol{x}_k)$$

which we use directly. However, were vehicle states available in some other form, one would simply take a sample from the posterior state estimate $p(\boldsymbol{x}_{k|k} \mid \boldsymbol{y}_k)$. This gives us a sample of plausible bus states for which we can predict individual arrival times at upcoming stops.

As with the vehicle model described by Elliott and Lumley (2020), we can iteratively forecast each particle's arrival at all upcoming stops. This involves incorporating network state (vehicle speeds along roads) as well as bus stopping behaviour. These two aspects are described individually below, and each particle simply iterates between them until it reaches the end of the route.

[introduce trip state]

3.1.1. *Road segment travel times*

[mostly copy 5-step process from thesis section 5.2.1]

Each particle begins having travelled $x_k^{(i)}$ meters along the route, with a current speed of $\dot{x}_k^{(i)}$. The first travel time required is, therefore, the time to reach the end of the current road segment, $\ell^{(i)}$, assuming the bus maintains its current speed. From the transit network construction, we know that segment $\ell^{(i)}$ starts $\mathcal{D}_{\ell^{(i)}}$ meters along the route and has a length of $\mathcal{L}_{\ell^{(i)}}$ meters, so the distance remaining is

$$\bar{z}^{(i)} = \mathcal{D}_{\ell^{(i)}} + \mathcal{L}_{\ell^{(i)}} - x_k^{(i)}$$

which will take the particle

$$z^{(i)} = \frac{\bar{z}^{(i)}}{\dot{x}_k^{(i)}} \text{ seconds}$$

to complete.

[once trip state introduced, the above becomes:]

... particle has completed $100 p_\ell^{(i)}\%$ of the segment. If the vehicle is nearing the end of the segment (less than 200 meters remaining), we keep the particle's initial speed $\dot{x}_k^{(i)}$. Otherwise, we simulate a speed from the network state with mean β_ℓ, uncertainty $\mathbf{P}_\ell$, and between-vehicle variability $\boldsymbol{\psi}_\ell$, as follows:

$$\dot{x}_\ell{}^{(i)\star} = \begin{cases} \dot{x}_k^{(i)} & (1 - \hat{p}_k)\mathcal{L}_\ell < 200, \\ v_\ell{}^{(i)} \sim \mathcal{N}_T\left(\beta_\ell,\, \mathbf{P}_\ell^2 + \boldsymbol{\psi}_\ell^2,\, 0,\, \mathbb{V}_\ell\right), & \text{otherwise.} \end{cases}$$

Now the travel time to the end of the current segment can simply be obtained as

$$\tilde{z}^{(i)} = \frac{(1 - \hat{p}_k^{(i)})\mathcal{L}_\ell}{\dot{x}_\ell{}^{(i)\star}}.$$

We now store an iterative variable *travel-time-so-far* with the time taken to reach the end of the current segment, $\eta^{(i)} = \tilde{z}^{(i)}$.

3.1.2. Bus stops

3.1.3. Arrival time distribution

3.2. Results

4. A discretized CDF approximation for journey planning

- CDF makes it possible to answer many (often complex) jouney planning questions
- P(catch)
- P(arrive on time)
- P(transfer)
- this is a simple computation - can be done client side (i.e., on a user's phone) by passing CDF (small size, as e.g., JSON)

4.1. Simplified ETA CDF

- round to minutes
- compute the CDF by definition "number of particles arriving within x minutes"

5. Discussion

- what this means
- how this makes JP more accessible

5.1. Future Work

- automated route selection
- improved particle filter
- improved network construction
- improved network state forecasts

5.2. Conclusion

- simple conclusion of the paper

References

Cathey, F. W. and Dailey, D. J. (2003) A prescription for transit arrival/departure prediction using automatic vehicle location data. *Transportation Research Part C: Emerging Technologies*, **11**, 241–264.

Citation Needed (2020) *Missing citations.*

Elliott, T. and Lumley, T. (2020) Modelling the travel time of transit vehicles in real-time through a GTFS-based road network using GPS vehicle locations. *Australian & New Zealand Journal of Statistics*, **62**.

Hans, E., Chiabaut, N., Leclercq, L. and Bertini, R. L. (2015) Real-time bus route state forecasting using particle filter and mesoscopic modeling. *Transportation Research Part C: Emerging Technologies*, **61**, 121–140.

Yu, B., Lam, W. H. K. and Tam, M. L. (2011) Bus arrival time prediction at bus stop with multiple routes. *Transportation Research Part C: Emerging Technologies*, **19**, 1157–1170.

Yu, B., Yang, Z.-Z., Chen, K. and Yu, B. (2010) Hybrid model for prediction of bus arrival times at next station. *Journal of Advanced Transportation*, **44**, 193–204.

Yu, B., Yang, Z.-Z. and Yao, B. (2006) Bus arrival time prediction using support vector machines. *Journal of Intelligent Transportation Systems*, **10**, 151–158.