How can we improve bus ETAs?

Using real-time position data to estimate road state

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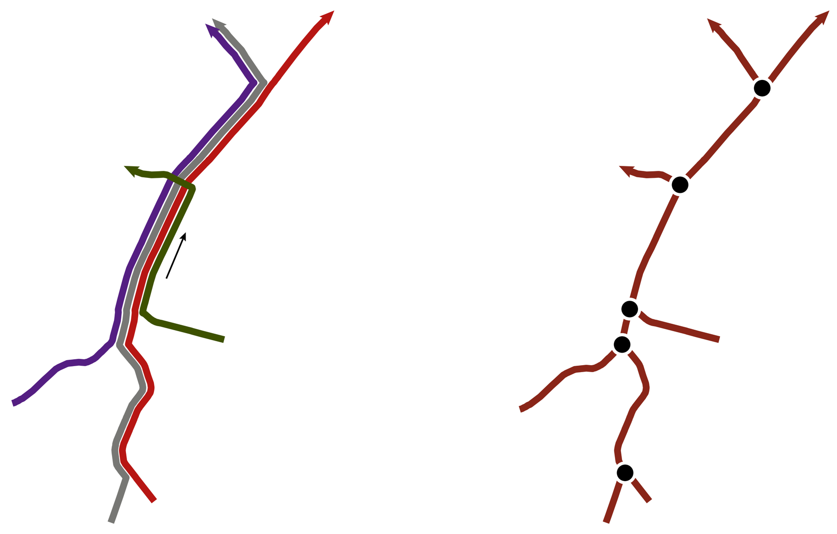
1. Introduction

- **real time information (RTI)**: estimated arrival time (ETA), delays, cancellations
- helps commuters **plan journeys** and **improves their experience** [1] . . . but **only if the information is reliable!**
- generating ETAs involves 1. a **real-time vehicle tracking** system (e.g., GPS), 2. a **vehicle state model** to process real-time noisy observations (e.g., Kalman filter [2–4], particle filter [5]), and 3. **travel time predictions**
- predictions often based on scheduled inter-stop travel times, occasionally historical data; however **real-time travel times** along intermediate roads would seem to be the best predictor

- **proposal**: a generalised approach to modeling transit vehicles and network congestion to obtain reliable ETAs
- **test location**: Auckland, New Zealand, where Auckland Transport provides a publically accessibly vehicle locations API

2. GTFS transit network

- **GTFS**: API specification for transit data [6], 500+ locations worldwide
  - static: routes, **shapes**, stops, scheduled arrival/departure times
  - real-time: **vehicle locations**, arrival/departure delays
- **transit network** consists of intersections (nodes) and connecting road segments (edges)
- general method for constructing network from raw GTFS data
  1. Import raw GTFS shape data
  2. generate network of intersections (nodes) and road segments (edges) using adaptation of [7]
  3. express each route as a sequence of road segments
- Implementation in progress: `gtfsnetwork` R package



3. Vehicle state model

- estimate vehicle state $\boldsymbol{X}_k$ from a sequence of real-time GPS observations $\boldsymbol{Y}_k$
- **transition function** f describes behaviour of a bus: acceleration/deceleration and wait times at bus stops/intersections, where Q_{k-1} is system noise (in vehicle speed)

$$\boldsymbol{X}_k = f(\boldsymbol{X}_{k-1}, w_k), \quad w_k \sim N(0, Q_{k-1})$$

- **measurement function** h determines GPS coordinates for a known state using GTFS shape and distance traveled, so measurement model is

$$\boldsymbol{Y}_k = h(\boldsymbol{X}_k)$$

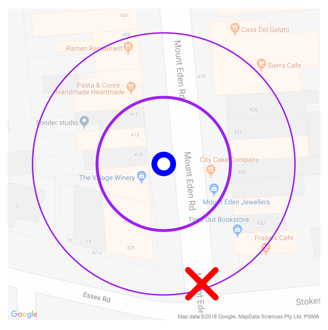
(we use an equirectangular projection g to work with geographic coordinates)

- **likelihood**: given $\hat{\boldsymbol{X}}_k$, define distance between $h(\hat{\boldsymbol{X}}_k)$ and $\boldsymbol{Y}_k$

$$\delta_k = d(h(\hat{\boldsymbol{X}}_k), \boldsymbol{Y}_k)$$

then δ_k^2 is the sum of two independent normal random variables with variance σ_y^2

$$\left(\delta_k^2/\sigma_y^2\right) \sim \chi^2(2) \sim \text{Exp}(0.5)$$



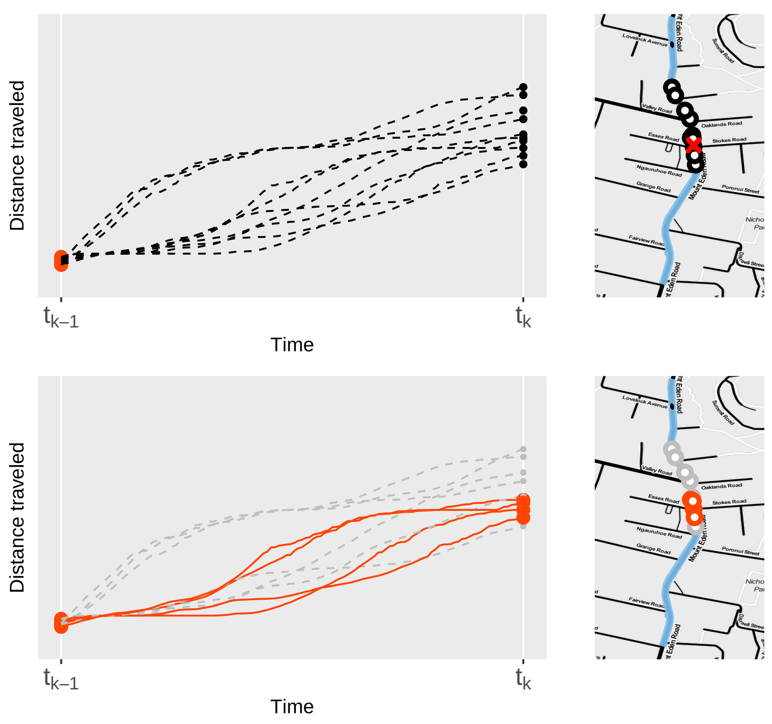
- **particle filter**: flexible estimation method approximating $\boldsymbol{X}_k$ using particles $(\boldsymbol{X}_k^{(i)})_{i=1}^N$

1. **predict new state** by transitioning particles up to time t_k
2. **evaluate likelihood** of each particle

$$p(\boldsymbol{Y}_k | \boldsymbol{X}_k^{(i)}) = 0.5e^{-(\delta_k^{(i)})^2/2\sigma_y^2}$$

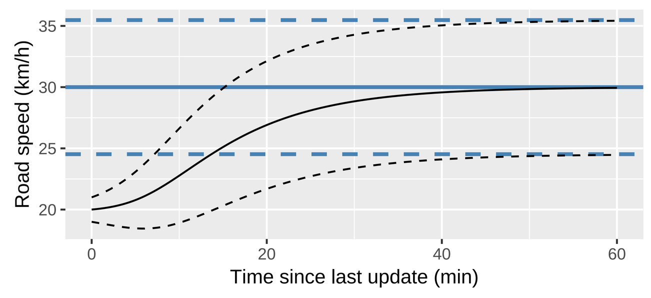
3. **weighted resample with replacement**

$$w^{(i)} = \frac{p(\boldsymbol{Y}_k | \boldsymbol{X}_k^{(i)})}{\sum_{j=1}^N p(\boldsymbol{Y}_k | \boldsymbol{X}_k^{(j)})}$$

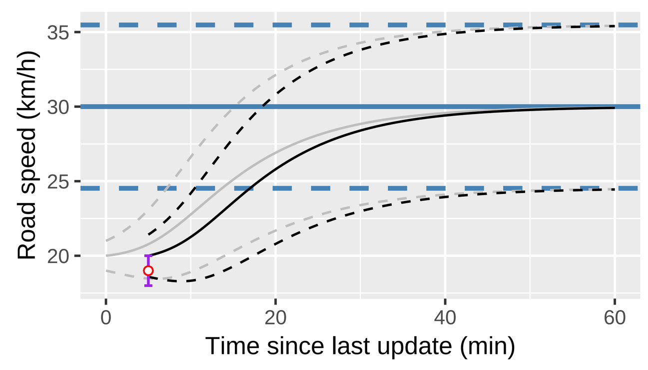


4. Network state model

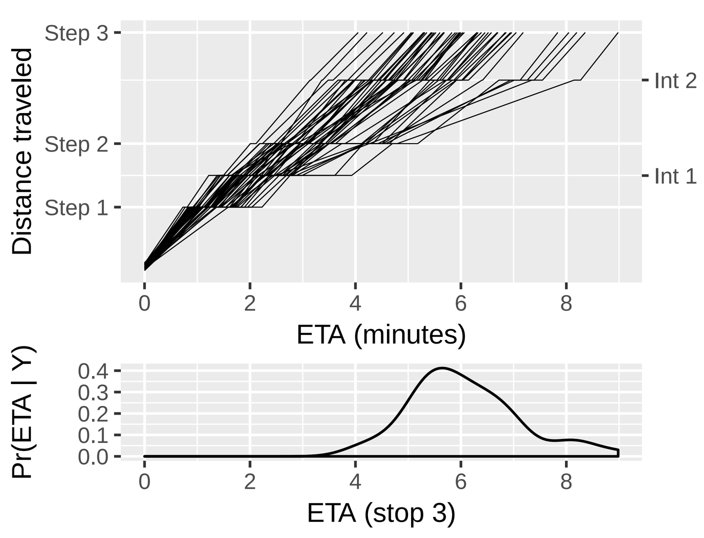
- estimate **real-time network state** from vehicle speeds, and forecast future states for ETAs
- β_r^j is average **speed of buses** along road segment j at time t_r
- forecasted state converges towards **historical mean** (i.e., the prior)



- update as vehicles traverse network using extended Kalman filter algorithm
  - observation $\hat{s}_t$ is mean speed of particles along segment
  - measurement error r_t^2 is variance of particle speeds



5. Predicting arrival time



- **simulate particle trajectories**, using forecasted segment speeds
- obtain **distribution of arrival times**, $(A_j^i)_{i=1}^N$ for each stop j
- provide commuters with summary statistics of distribution, for example
  - a **point estimate** of 5 minutes
  - a **prediction interval** of 4–8 minutes
- we want ETAs that **decrease with time** while also **minimising** $\Pr(A_j < \hat{A}_j | \boldsymbol{X}_k)$

6. Conclusion

- segmenting routes allows vehicles to share travel times with others using the same roads
- real-time vehicle and network state models combine real-time and historical data to predict arrival time
- current real-time C++ implementation takes up to 20 seconds on an 8-core Virtual Machine with 5000 particles per vehicle

7. Future work

- improve network state model:
  - **non-constant segment speed**: speed varies by time and distance along road
  - **additional covariates**: adjacent segments, yesterday's traffic, weather, etc.
- stop- and intersection-wait time models to estimate and quantify wait time uncertainty
- find optimal point and interval estimates for ETAs

References

[1] Transit Cooperative Research Program. Real-time bus arrival information systems. TCRP synthesis 48, Transportation Research Board, Washington, DC, 2003.

[2] Z. Wall and D.J. Dailey. An algorithm for predicting the arrival time of mass transit vehicles using automatic vehicle location data. In *Proceedings of the Transportation Research Board Annual Meeting*, 1999.

[3] D. Dailey, S. Maclean, F. Cathey, and Z. Wall. Transit vehicle arrival prediction: Algorithm and large-scale implementation. *Transportation Research Record: Journal of the Transportation Research Board*, 1771:46–51, jan 2001.

[4] F. W. Cathey and D. J. Dailey. A prescription for transit arrival/departure prediction using automatic vehicle location data. *Transportation Research Part C: Emerging Technologies*, 11(3-4):241–264, jun 2003.

[5] Etienne Hans, Nicolas Chiabaut, Ludovic Leclercq, and Robert L. Bertini. Real-time bus route state forecasting using particle filter and mesoscopic modeling. *Transportation Research Part C: Emerging Technologies*, 61:121–140, dec 2015.

[6] Google Developers. What is GTFS? https://developers.google.com/transit/gtfs/, 2006.

[7] Yongchuan Zhang, Jiping Liu, Xinlin Qian, Agen Qiu, and Fuhao Zhang. An automatic road network construction method using massive gps trajectory data. *ISPRS International Journal of Geo-Information*, 6(12), 2017.

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