Predictive Modelling Approaches for Bus Travel Time Prediction

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Bus Arrival Time Prediction (BATP)

Intro

- *BATP* - old problem, relatively well solved in developed countries.
- challenging problem in developing economies.
- *Traffic Conditions* - excess vehicles, lack of lane discipline, diverse modes of transport, poor adherence to schedule.
- (a)minimize waiting time at bus stops (b)plan arrival at bus-stops.
- efficient, smarter public transportation $\implies$ lesser no. of vehicles.

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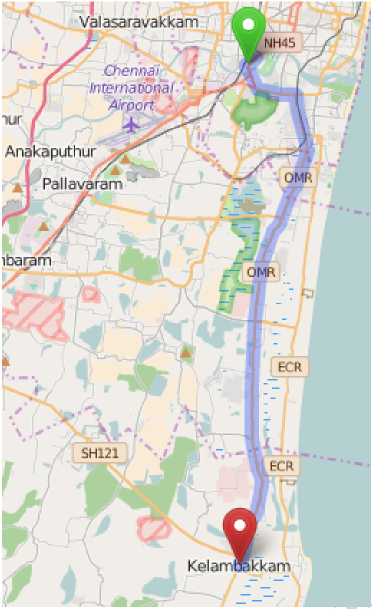
Data Input and Setting

- GPS data from all trips across a day.
- Route segmented into uniform length sections (min distance b/w busstops).
- Section Travel time (from GPS traces) includes dwell time + Running time.

Bus Route (Chennai)



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Exploiting Temporal Correlations

Data pre-processing and motivation

- bin the time axis into intervals (uniform or otherwise).
  - obtain a travel time measurement for each bin from data (use imputation if necessary).
- each segment - have a sequence (or time-series) of travel-time measurements along a day, across days.

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Lognormality of the Data

- Sample histograms were found to be right-skewed.
- *lognormal distribution* gave the best goodness of fit.
- *exploit* to achieve statistically optimal predictions under both temporal models.

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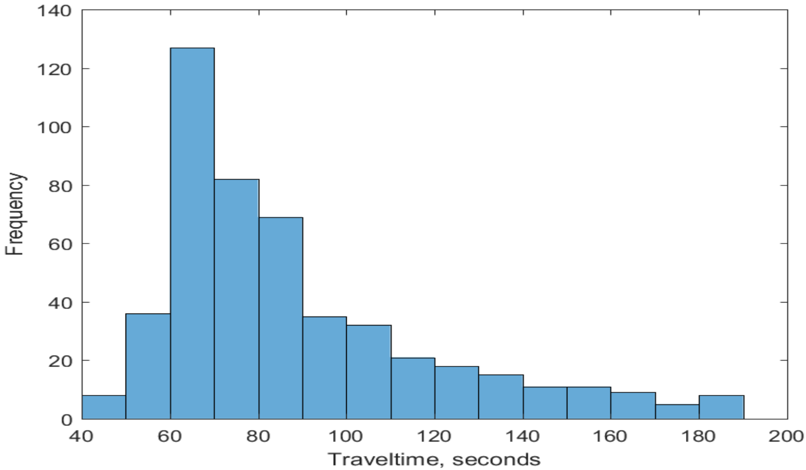
Sample (Travel time) Histogram



First Approach for Temporal Prediction

- classical time-series approach of fitting a seasonal AR model.
  - tackle non-stationarity by assuming a classical decomposition
  - trend + periodic component + integrating type non-stationarities.

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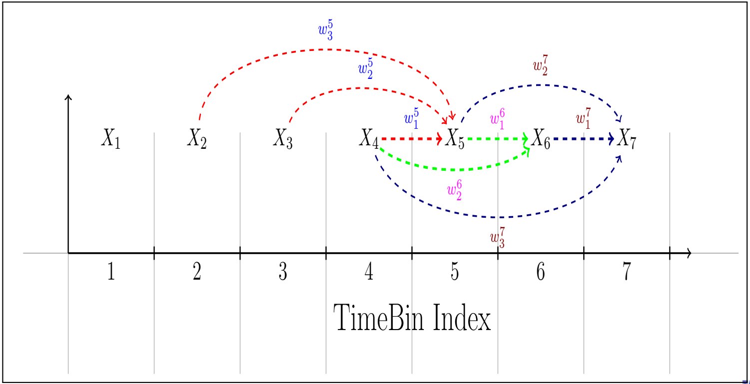
non-stationary auto-regressive (AR) approach

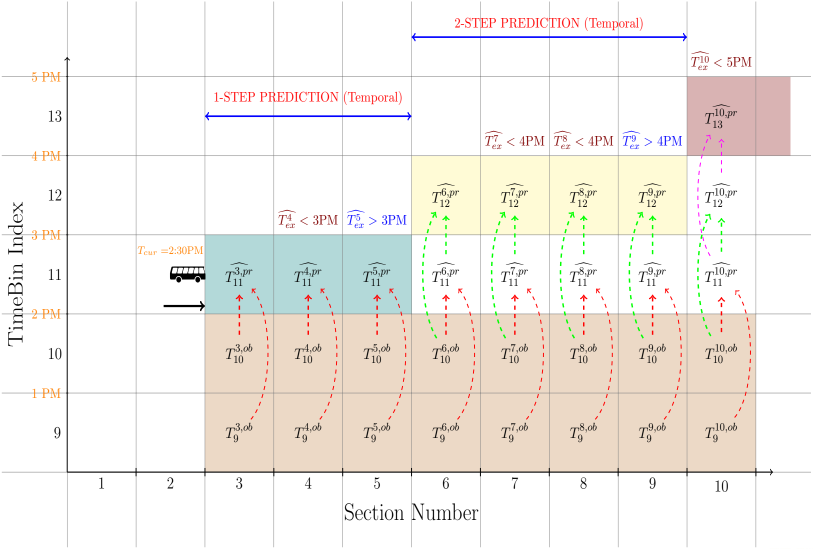
- model travel time vector over a day as Gaussian/lognormal random vector.
  - travel time vectors across days are i.i.d. realizations.
- conditional distributions are linear gaussian
  - auto-regressive model fitting.
- the no. of preceding travel-time measurements (that can influence) can be position dependent.
- essentialy need to figure out the cond. independence structure.
- partial correlation comes to our aid.

Non-Stationary Correlations

- Are X_n and $X_{n-(k+1)}$ cond. independent given $X_{n-1}, \ldots X_{n-k}$.
- least k for which the above is true.
- equivalent to asking if PC is zero (Gaussian)



Spatial Multi-Step Prediction



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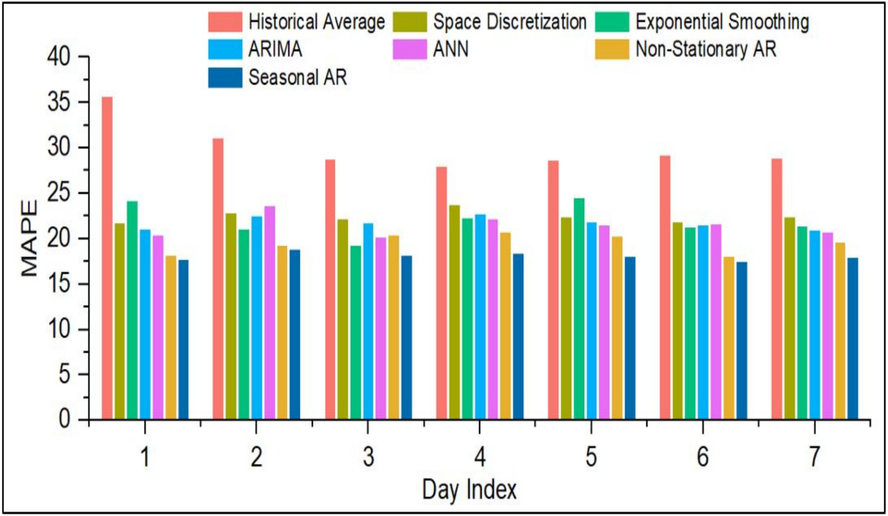
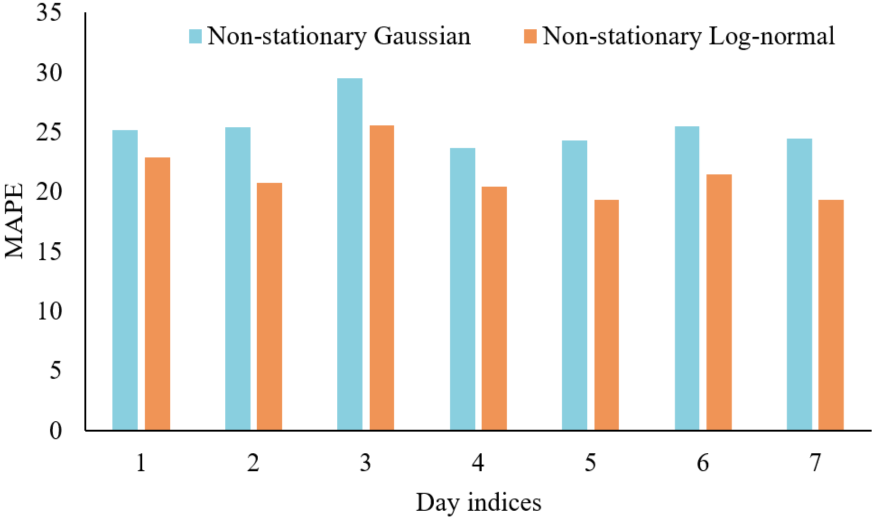
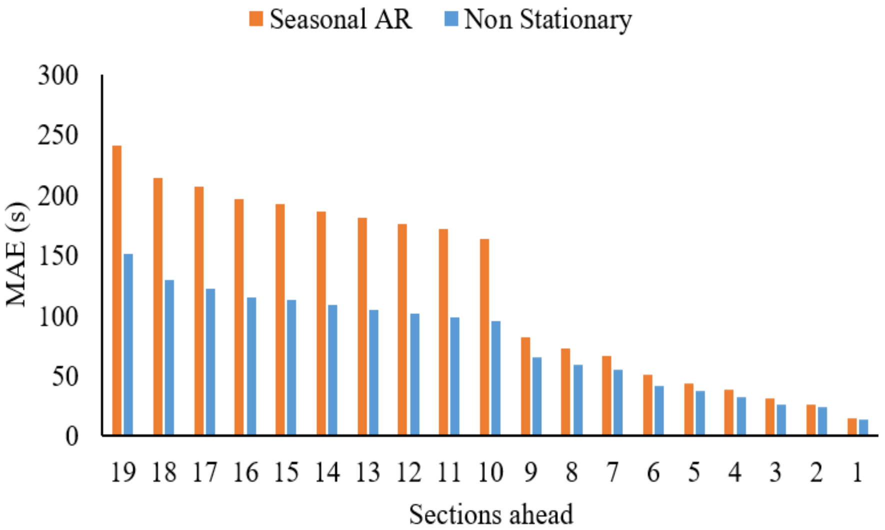
Comparison One-Step MAPE



Lognormal vs Gaussian



Multi-step results



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Spatio-Temporal Correlations

Spatial Correlations

- build a non-stationary auto-regressive model in the spatial dimension.
- order of auto-regression Q is constant.

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Temporal Correlations

- influence of previous bus, depends on the time-difference T_d.
- $Z_n = e^{-a_n * T^d} * Z_n^{pv} + (1 - e^{-a_n * T^d})\mu_n + \eta(n)$
- Learn a_n, μ_n from data using non-linear least squares.

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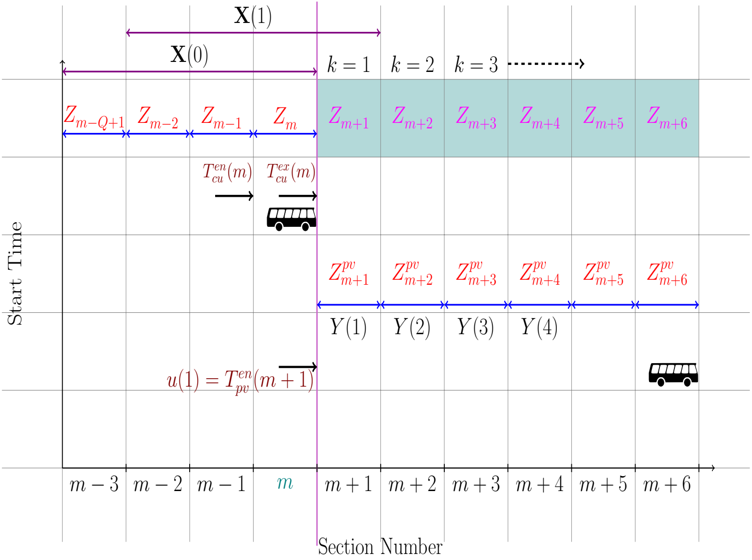
Predictive Model

- Combine above two dependencies into *linear* dynamical system model.
- cast prediction as an inference (hidden state estimation).
  - *State* - Q consec. section travel times
  - *observations* - previous bus measurements.
  - Linear Kalman filter (with some care) for optimal estimation.

Prediction Setting



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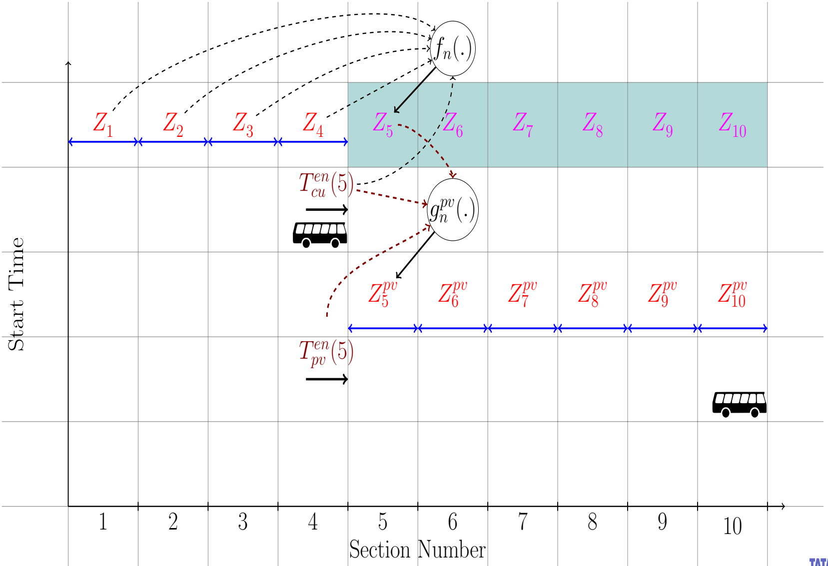
Nonlinear correlations



Non-linear Correlations

- non-linear extension of previous model
  - allow smooth non-linear function approximators (regressors)
  - incorporate *current time* into the model
- Combined predictive model (non-linear dynamical system)

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State-Space Form:

$$\begin{aligned} \mathbf{X}(k) &= F_k\left(\mathbf{X}(k-1)\right) + \mathbf{w}(k) \quad \text{(State Eqn.)} \\ Y(k) &= G_k\left(\mathbf{X}(k), u(k)\right) + \mathbf{v}(k) \quad \text{(Observation Eqn.)} \end{aligned} \tag{1}$$

- *State* - Q consec. section travel times, exit & entry time at last section.
- $Y(k)$ - prev bus section travel time, $u(k)$ - prev bus entry time.

Prediction

- non-linear dynamical system (NLDS) model: exact inference is intractable.
- choose Extended Kalman Filter (EKF) for approx. inference (low computational complexity) compared to PFs(for instance).
- recursive computation which proceeds sequentially in space.
- EKF involves Jacobian computation of F_k and G_k maps.
- Both Jacobians are sparse (structure of F_k and G_k).
- computation of the partial derivatives is online during prediction.
- SVR: partial derivatives in closed form is possible.

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One-Step Comparison

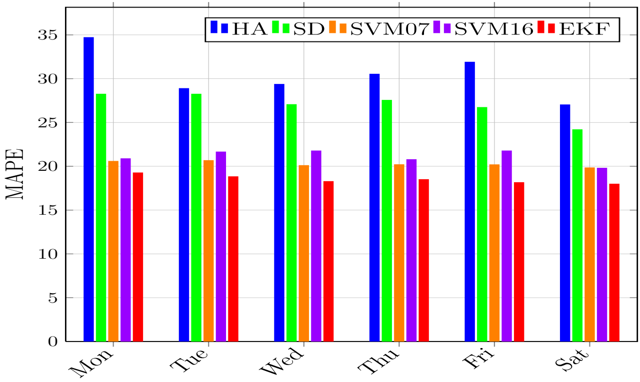
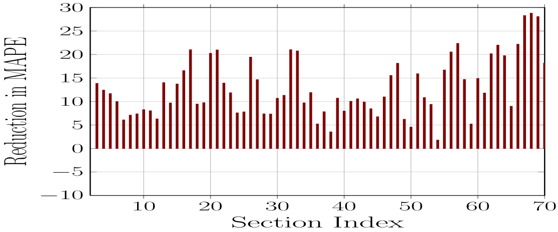
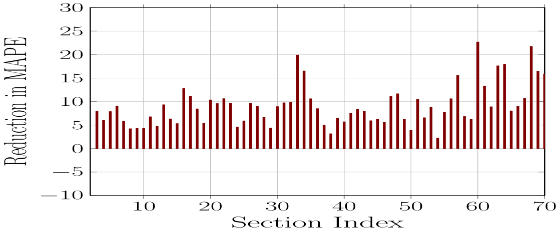


Figure: 12-week data.

Sectionwise Comparison



(a) HA



(b) SD

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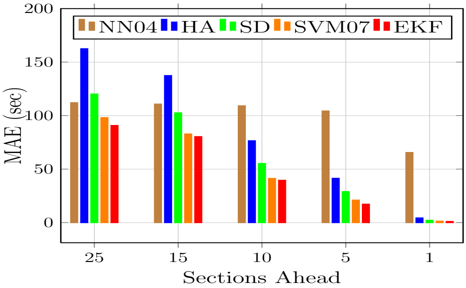
Multistep Comparison



(c) 12 week data

Figure: Multi-Step Comparison at a Sample Bus-stop.

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Conclusions

- purely temporal approach (statistical)
- spatio-temporal approach (statistical and an ML flavor)
- fuse other data sources like speed, volumes, weather etc.

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Publications

- Bus Travel Time Prediction: A log-normal Auto-Regressive (AR) Modeling Approach - accepted in Transportmetrica A: transport science.
- Dynamic bus travel time prediction: A Spatial kalman filter approach - IEEE Transactions on Intelligent Transportation Systems.
- Bus Travel Time prediction using Nonlinear correlations - IEEE International joint conference on Neural Networks (IJCNN) 2019.

Collaborators

- Dhivyabharathi, Anil Kumar, Lelitha Devi Vanajakshi - IITM.
- Rohith Regikumar, Akshaya Natarajan - TCS.

Thank You!