A Framework for Scalable Data Analysis and Model Aggregation for Public Bus Systems

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Introduction

Efficient urban mobility

- Individual Transport?
  - Cars, Uber, taxis
  - Congestion at peak hours
- Rail transport systems?
  - Efficient but high cost
- Bus transport systems?
  - Reasonable cost
  - Delays

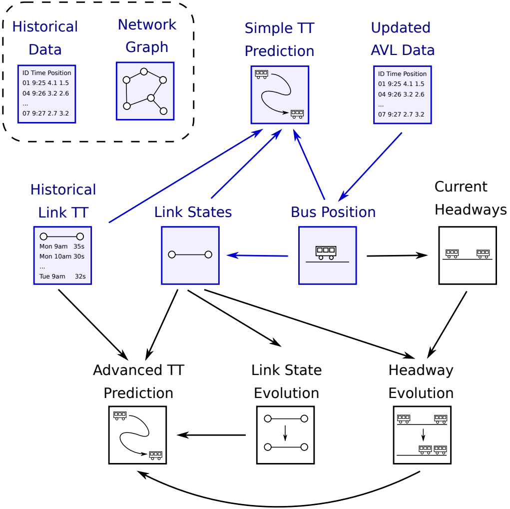
Better understand the behavior of bus system

- Many aspects of the bus system
- Only a few efforts using those aspects together

Proposal of a framework to:

- Maintain the state of the network
- Predict the travel time between arbitrary points in a bus route
- Understand the evolution of the link states during the day
- Model the occurrence of bus bunching

Framework for Modeling the Bus Network

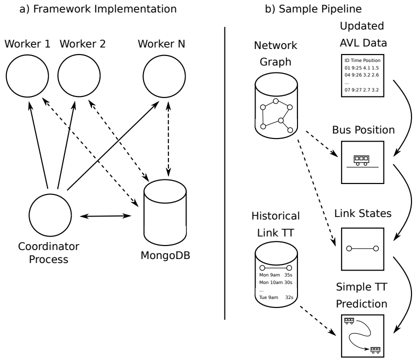

Historical Data
ID Time Position
01 9:25 4.1 1.5
04 9:26 3.2 2.6
...
07 9:27 2.7 3.2
Network Graph
Simple TT Prediction
Updated AVL Data
ID Time Position
01 9:25 4.1 1.5
04 9:26 3.2 2.6
...
07 9:27 2.7 3.2
Historical Link TT
Mon 9am 35s
Mon 10am 30s
...
Tue 9am 32s
Link States
Bus Position
Current Headways
Advanced TT Prediction
Link State Evolution
Headway Evolution

Dask: framework for distributed computing in Python

- Creation of tasks for execution on different machines
- Integrated with Python frameworks, such as Pandas and Scikit-learn

MongoDB: storage of non-relational data, providing more flexibility

- Permits information sharing between models
- Can be replicated if required



Estimation Models

- Bus Position Model
  - Travelled distance on the bus route
- Graph Model
  - Based on GTFS (General Transit Feed Specification) data

Prediction Models

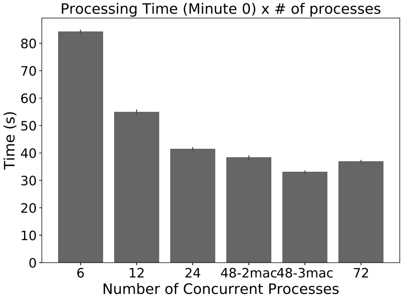
- Mean Travel Time Model: (1 per hour)
  - Historical average for each link (1977 links)
  - 7 Months data, restricted on Weekday and Hour
- K Travel Time Model (1 per 10 minutes):
  - Average from the Latest $K (= 3)$ travels on each link
- Combined Model:
  - Weighted Average from MTT $(wgt = 1)$ and KTT $(wgt = 2)$ Models

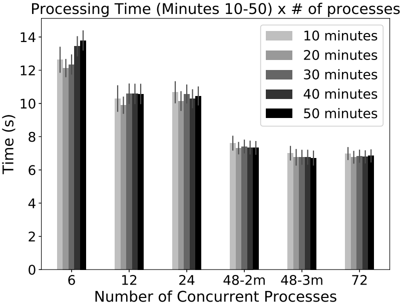
Experiments

We considered scenarios with 6 to 72 workers

- First experiment: Execution time
- Second Experiment: total travel time prediction accuracy

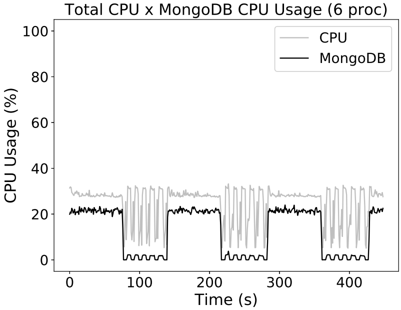
Processing Time

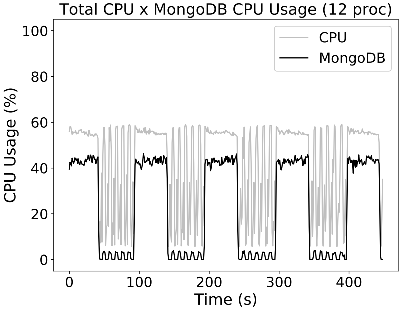




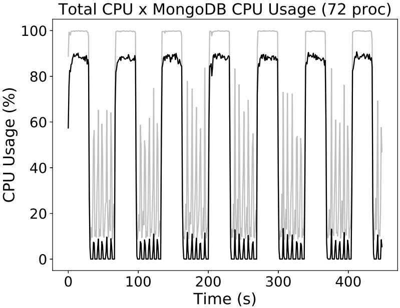
- Increasing # of workers reduces total processing time up to a certain point

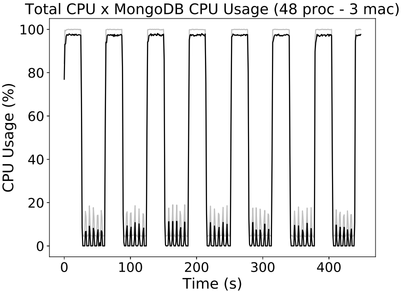
CPU Usage


Total CPU x MongoDB CPU Usage (6 proc)
CPU
MongoDB
CPU Usage (%)
Time (s)
0
20
40
60
80
100
0
100
200
300
400


Total CPU x MongoDB CPU Usage (12 proc)
CPU
MongoDB
CPU Usage (%)
Time (s)
0
20
40
60
80
100
0
100
200
300
400

CPU Usage





- Since each worker access the DB concurrently, it becomes the bottleneck

Algorithm	RMSE (min.)	MAE (min.)	MAPE (%)
MTT	9.21	6.70	11.12
KTT	12.05	8.37	13.95
Combined	8.97	6.68	11.22

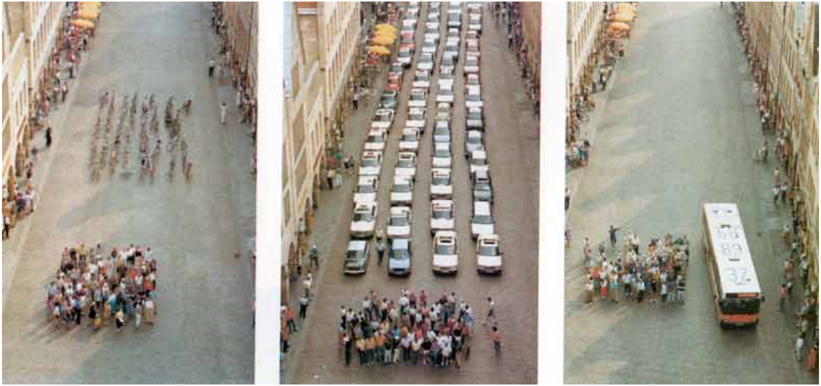
Table: Errors for full travel time predictions

KTT uses less data and is faster, but it is more sensitive to data errors and travel deviations

Conclusions

- Public bus systems are difficult to model and predict
- Important to combine different models in the prediction
  - Historical travel times, link state status and evolution, bus headways, etc.
- Proposed framework combines those models
- Bottleneck on the shared database
- Next steps

Obrigada



Fonte: State University of NY (2000)