Tackling the Challenges of Big Data
Introduction and Use Cases

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Tackling the Challenges of Big Data
Introduction and Use Cases
Case Study: Transportation

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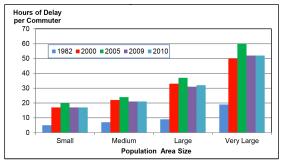
Big Data Meets the Big City

[Image Source: T-mobile]

Transportation: A Crisis in the Making



[2011 Urban Mobility Report, Texas Transportation Institute]

Cost
- Time
- Fuel
- Air pollution
- Frustration, etc.

Challenges
- Uncertainty
- Congestion
- Estimation
- Computational cost

Future Urban Mobility

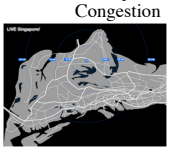
- Data-Driven Transportation
  - Improve Level of Service
  - Enhance sustainability
  - Modeling, Predicting, Controlling
  - Personalization
  - Optimization

[Future of Urban Mobility, SMART]

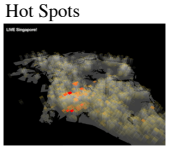
Data-Driven Transportation Goals

- Algorithmic and policy solutions for improving traffic
  - Visualizing traffic
  - Analysis of travel patterns
  - Congestion-aware routing
  - Urban planning
  - Road pricing

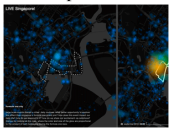
Congestion



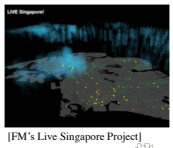
Hot Spots



Special Events

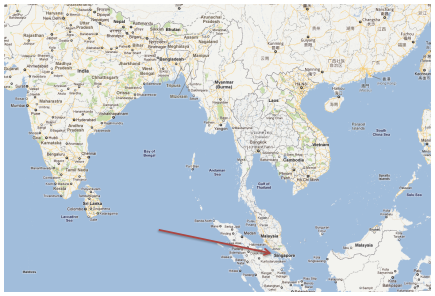


Weather



[FM's Live Singapore Project]

Case Study in Singapore



Singapore

30 x 16 miles, 5M people, high GDP per capita, *lots of taxis*…

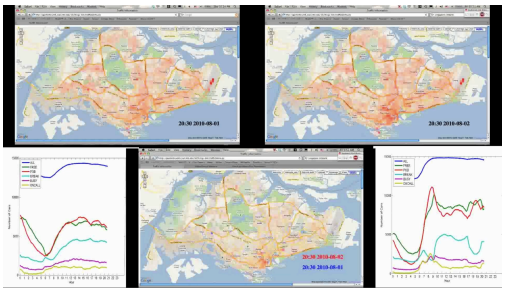
Singapore Taxi Data

- 16k unique taxis
- ID, GPS location, speed, status, timestamp
- ≈ 0.5-1 min intervals
- One month: 512M data points, 33 GB of data

In-car Data Device

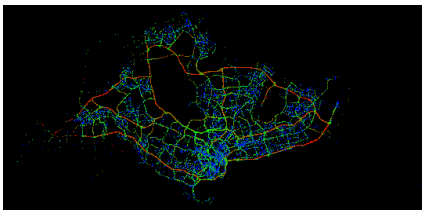
- Data cleaning, map matching, …

Traffic Visualization: Volume



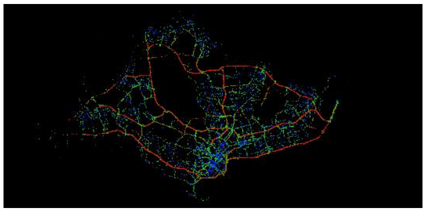
Traffic Visualization Example

Traffic Visualization: Speed/ Congestion



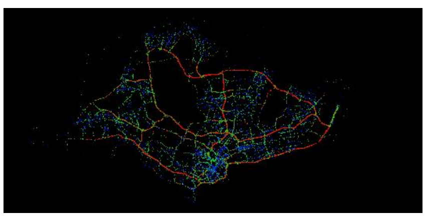
Slow Medium Fast

Traffic Visualization: Congestion Sweep



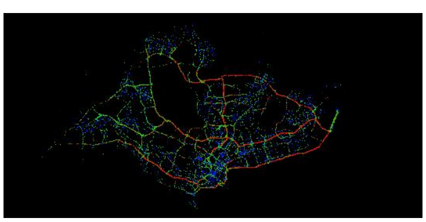
Slow Medium Fast

Traffic Visualization: Congestion Sweep



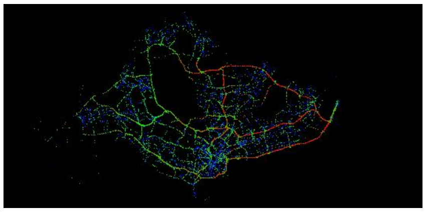
Slow Medium Fast

Traffic Visualization: Congestion Sweep



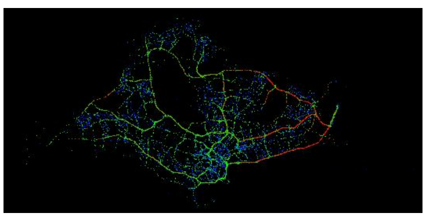
Slow Medium Fast

Traffic Visualization: Congestion Sweep



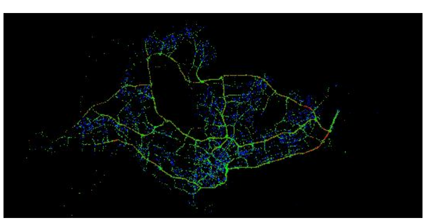
Slow Medium Fast

Traffic Visualization: Congestion Sweep



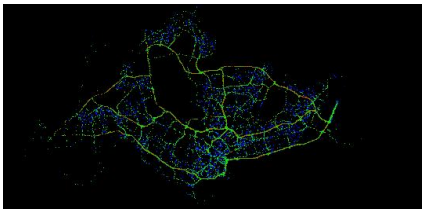
Slow Medium Fast

Traffic Visualization: Congestion Sweep



Slow Medium Fast

Traffic Visualization: Congestion Sweep



Slow Medium Fast

Case Study: Transportation in Singapore

Source: Live Singapore, Future of Urban Mobility, Singapore-MIT Alliance for Research and Technology

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Outline

- The traffic problem
- Using taxi probes to analyze traffic
- Why are taxis good probes?
- Applications

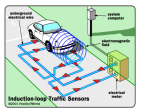
Travel Pattern Analysis

- How does traffic flow ?
  - workdays / non-workdays
  - rush hour / non- rush hour
- Where does traffic originate?
- What is its destination?
- What routes are taken?
- How does this affect planning, resource allocation, etc.?

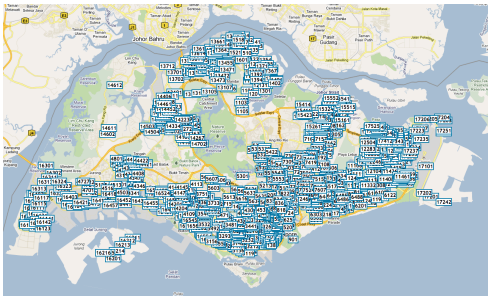
Data-Driven Traffic Modeling

- GPS sensors on vehicles
  - Measures traffic speed or delay
  - Easy to deploy
- Inductive loop detectors
  - Measures traffic flow
  - Costly to install

CarTel sensor node:
[Hull, Madden, Balakrishnan 2006]



Full Study

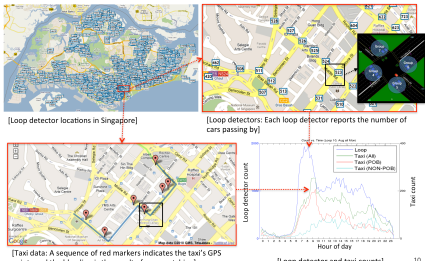


How Representative is Taxi Traffic?

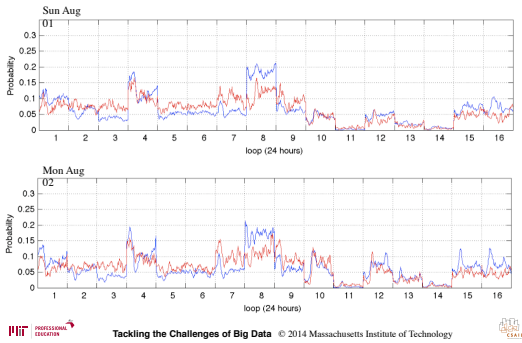
- Taxis are a *sample* of overall traffic…
- Is it an *unbiased* sample?
  - If not, can we systematically *correct* for the bias?

Do Taxis Measure General Traffic?

loop detector count per 15 minutes: ground-truth of traffic flow
taxi count per 15 minutes: sampled version of general traffic flow

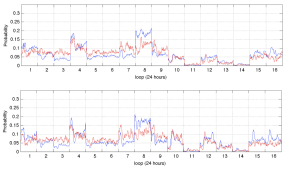


Taxis vs. Loop Distribution

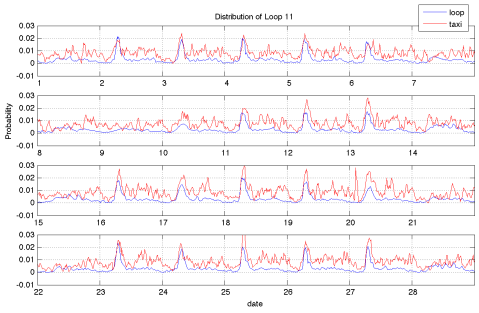


Biased Sample

- Conclusion…
  - taxi sample is biased,
  - but is it consistently biased and thus correctable?



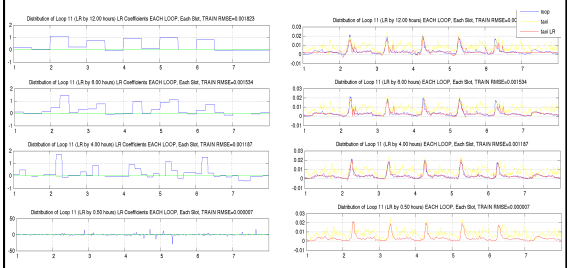
One Month, Loop 11



Traffic Flow Estimation

- Goal:
  - Predict the general traffic flow using taxi data and available set of loop detector data
- Approach:
  - Learn linear regression coefficients
    - trafficFlow= **m** * taxiFlow + **b**
  - Different time models for linear regression:
    - Day category
    - Hour category
  - Find the best time model with the most predictive power

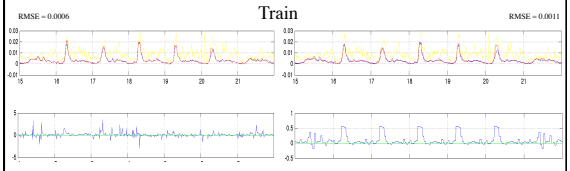
Correction Factors: Regression



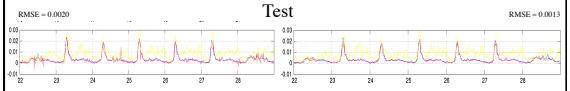
Cross-validation: Regression

Day-of-week, 15 minutes | Workday/Non-workday, 1 hour

Train

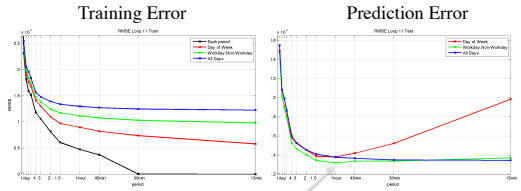


Test



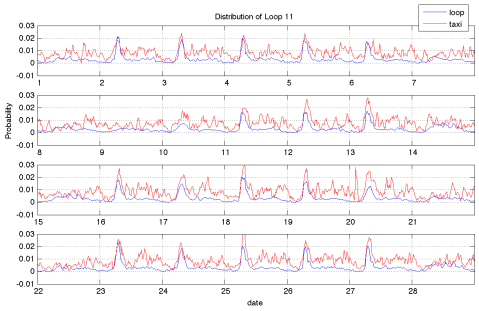
Cross Validation, Model Selection

Training Error | Prediction Error

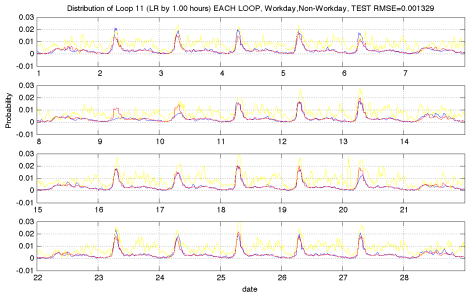


Workday/Non-workday, 1 hour

Before…

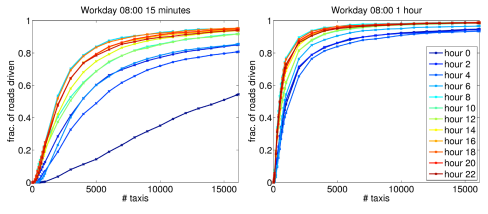


… After Regression



How Many Taxis are Needed?

- What fraction of roads are covered at least 30 times within 15 minutes / 1 hour?

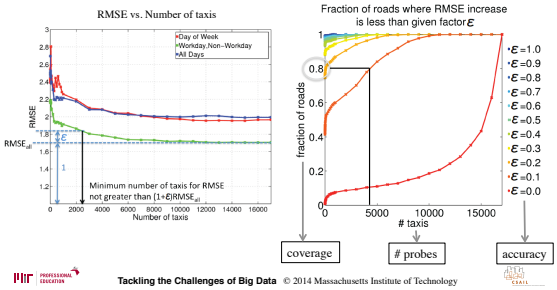


Taxi Traffic Conclusions

- Taxi traffic is a biased sample of overall traffic
- Bias is consistent and easily correctable
  - even at the granularity of individual intersections
  - using just workday/non-workday + hour of sample
- Can infer overall traffic from taxi traffic…
  - but why does this work?

Number of Probe Vehicles Needed

- Identify the number of probe vehicles required to predict the general traffic flow with defined accuracy and coverage



Travel Analysis from Personal Phones

- Slide was removed due to copyright restrictions.
- We are sorry for any inconvenience this may cause.

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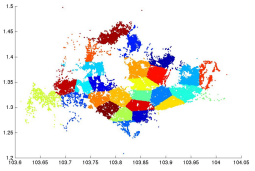
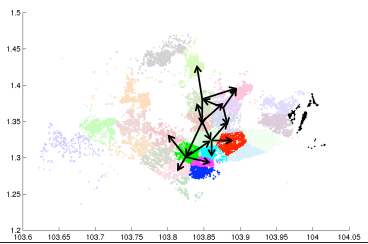
Bias Assessment Methodology

- Election forecasting analogy:
  - distribution of sample vs. distribution of voters
  - different distributions imply biased sample
  - need *ground truth* to compare against
  - loop detectors…



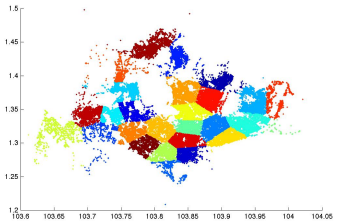
Why Are Taxis Good Probes?

- Stochastic taxi movement due to randomness of passenger
-



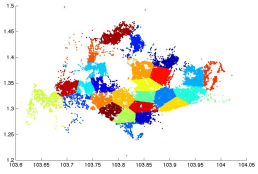
Traffic Analysis Setup

- What are origins/destinations?
  - GPS coordinates, street addresses, *regions*…

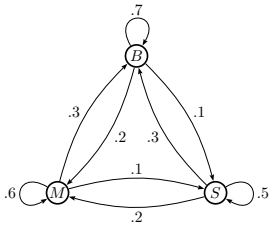


Traffic Analysis Setup

- Analysis criteria?
  - Micro-level: o/d prob, cond prob, …
  - Macro-level: uniformity, randomness
- Macro-level uniformity measures:
  - entropy (bits)
  - *perplexity* (regions)

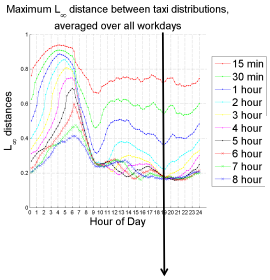


Markov Chains

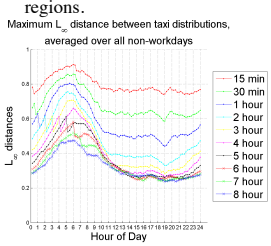


Pr[B] = 1/2, Pr[M] = 1/3, Pr[S] = 1/6

Rapidly Mixing Taxi Distributions



Upper bound on divergence between distributions of taxis starting from different regions.



Distributions converge quickly.
Taxi probes provide good coverage regardless of initial distribution.

RMMC Summary

- At a *coarse* granularity, taxis behave like a rapidly mixing Markov chain.
- Consequence: taxis are good for *sampling*
- *Future work:*
  - granularity vs. fleet size vs. mixing time vs. coverage probability
  - sensing and monitoring applications
    - road conditions, air quality, noise pollution, potholes…

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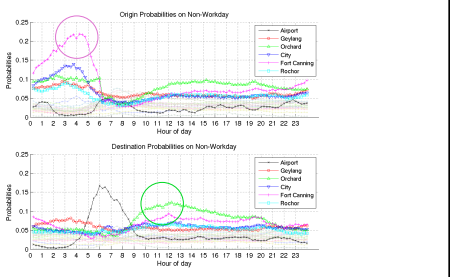
Application: Hotspots

- Detect regions of high traffic volume and potential congestion

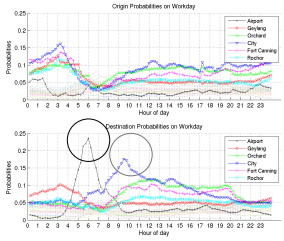
Application: Hotspots

- Detect regions of high traffic volume and potential congestion

Application: Origin-Destination Analysis

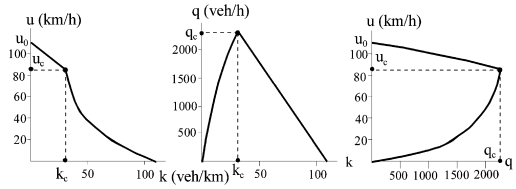


Application: Origin-Destination Analysis



Fundamental Traffic Flow Diagram

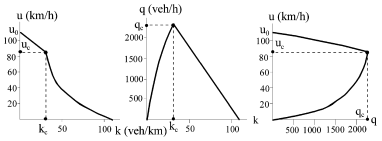
- Road performance: speed vs. flow vs. density



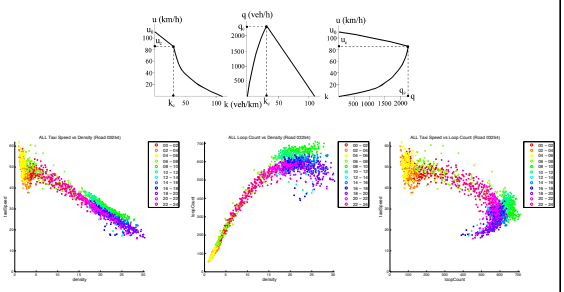
flow (veh/hr) = speed (km/hr) * density (veh/km)

Fundamental Traffic Flow Diagram

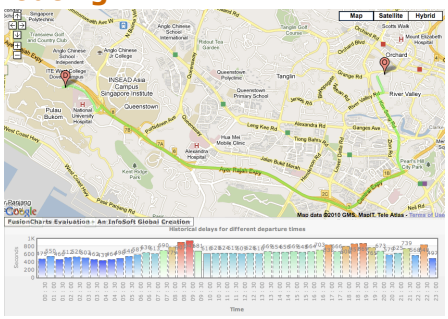
- Can be inferred from taxi and loop data
- Given earlier results…
  - diagrams can be inferred from taxi data alone
  - performance can be inferred in *real time*



Church Street



Application: Congestion-Aware Routing



Wrapping Up

- Roving sensor network of taxi probes
- Predict general traffic flow using taxi flow
- Intuition: Rapidly mixing taxi distributions
- Identify the number of probe vehicles required to predict the general traffic flow
- Demonstrate use of dynamic traffic probes at city scale

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