Exploring Traffic Dynamics in Urban Environments Using Vector-Valued Functions

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Traffic in a City

- Key component of an urban ecosystem
- Traffic patterns can help
  - Plan infrastructure development
  - Form policies
- Improve quality of life in a city!
- Urban planners need to understand traffic patterns

Understanding Traffic

- Scalar-based questions
  - Speed
  - Density
- Mobility-based questions
  - Slow moving traffic
  - Free flow of traffic
  - Direction of traffic movement

[https://www.google.com/maps]

[http://www.tibco.com/blog/wp-content/uploads/2013/07/traffic.jpg]

Challenges

- Acquiring traffic information
- Visualizing traffic flow patterns

[http://newyorknotebook.net/006-on-hailings-cabs-and-other/]

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[http://www.traffic-tech.com/]

Traffic Information

Challenges: Traffic Source

- Different times
- Over all streets
- Spread cameras, E-Zpass rea
  - coverage is very sparse
- Existing map tools
  - Along main roads
  - No historical data
- Can we obtain complete data?

[http://newyorknotebook.net/006-on-hailings-cabs-and-other/]

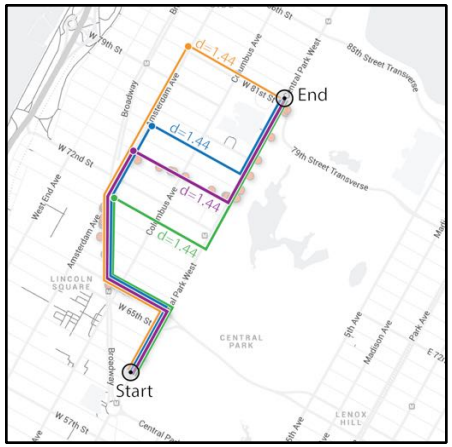
Idea: Taxis as Sensors

- ~13,000 taxis operate in Manhattan
- 500,000 trips per day
- Taxi data
  - **Start** and **end** positions of every trip
  - Trip distance and duration
- How to obtain the path taken?
  - Efficient

[http://newyorknotebook.net/006-on-hailings-cabs-and-other/]

Taxis as Sensors

- Two steps to derive traffic information
  - Identify plausible routes of taxis
  - Use this information to derive traffic speeds over the city
- Validated with real data



Actual GPS Track

Visualizing Traffic Flow

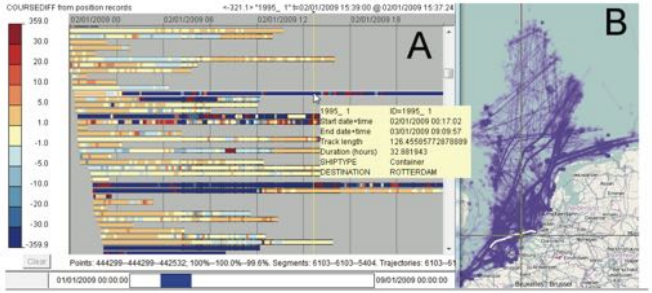
Challenges: Visualizing Traffic Flow

- Existing work
  - Focuses on object movement

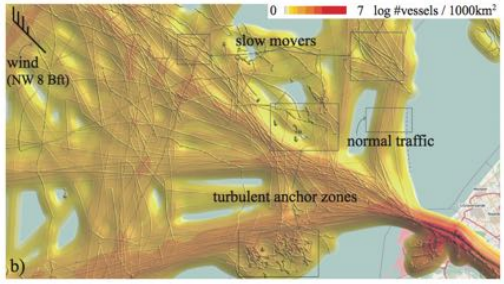
  [Andrienko et al. Information Visualization 2013]
  - Density-based visualizations

  [Willems et al. CGF 2009][Scheepens et al. TVCG 2011]
  - Visualizations to explore attributes

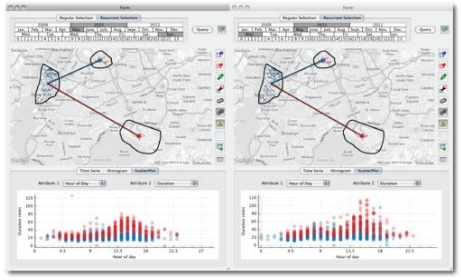
  [Tominski et al. TVCG 2012][Wang et al. TVCG 2013][Ferreira et al. TVCG 2013]
- Is there a way visualize the flow of traffic?



[Andrienko et al. IV 2013]



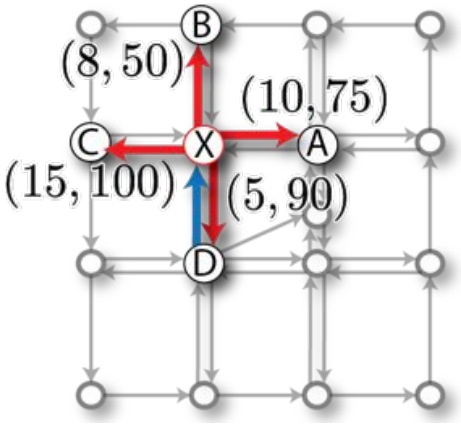
[Willems et al. CGF 2009]



[Ferreira et al. TVCG 2013]

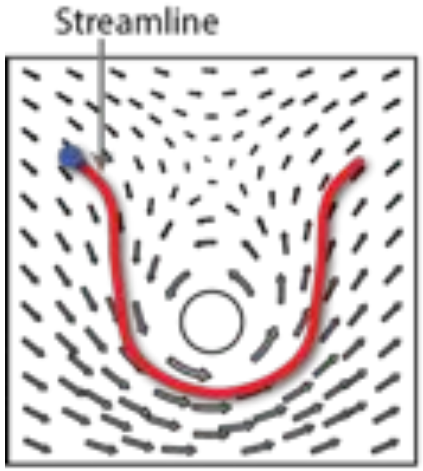
Traffic Function

- Vector-valued function

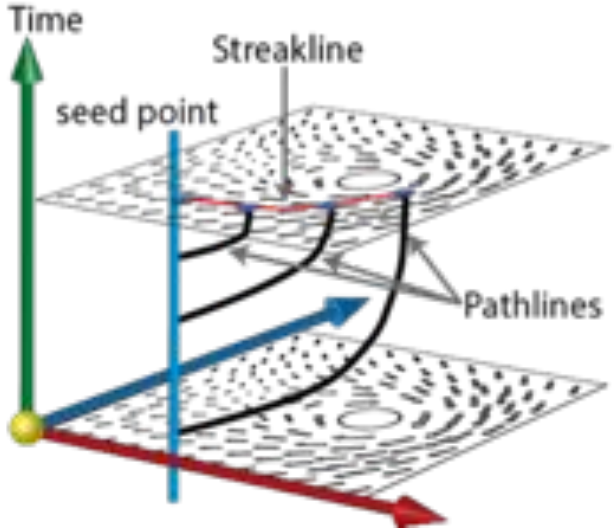


Visualizing Traffic Flow

- Flow lines from vector fields



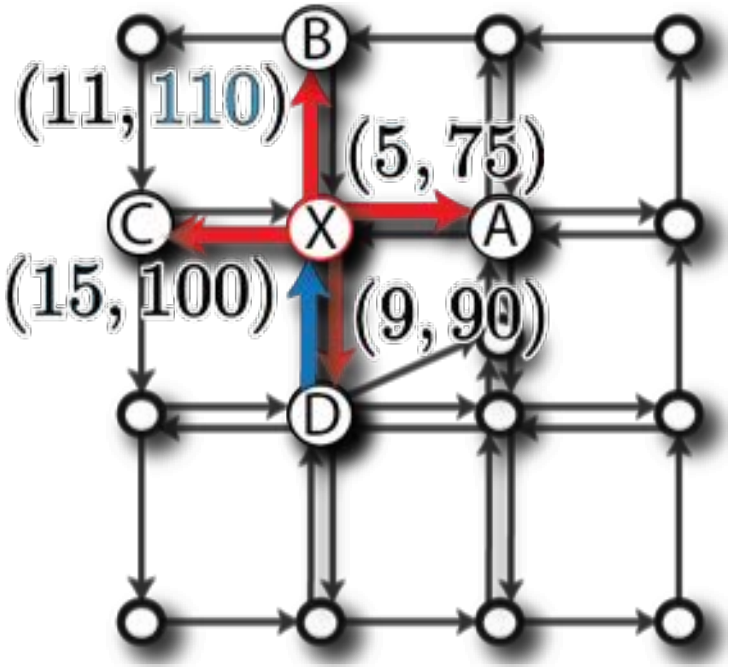
Time Instant



Over Time

Visualizing Traffic Flow

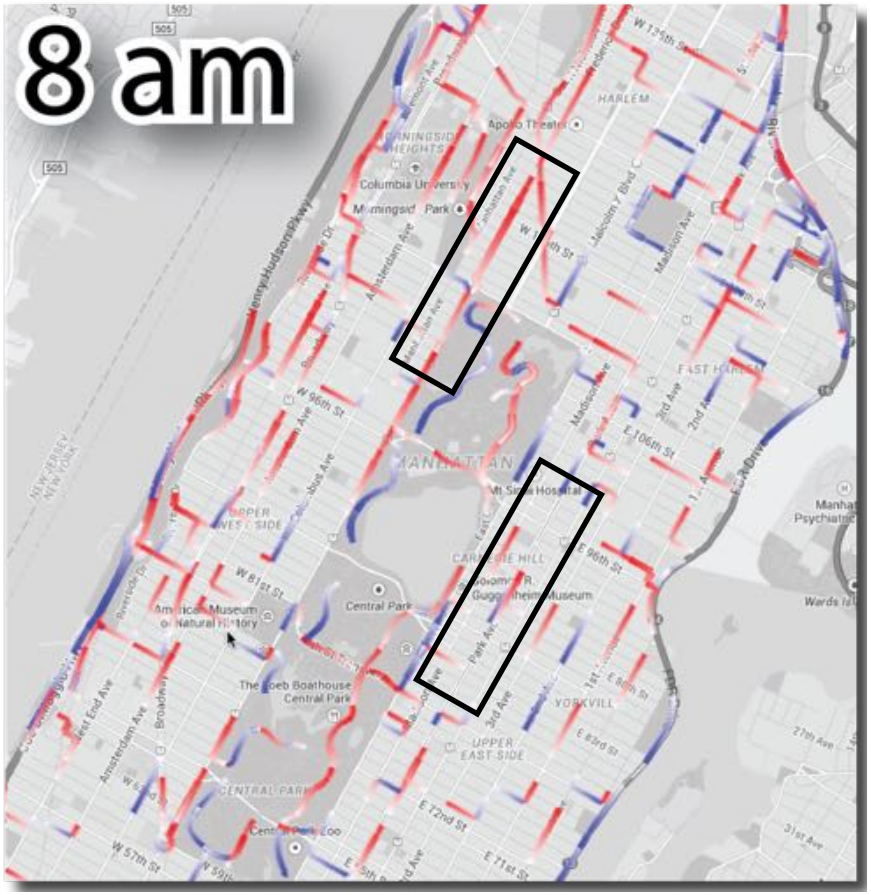
- Challenge
  - Direction of flow is not unique
- Direction based on application
  - Lowest speed
  - Highest speed
  - Probable taxi movement



Traffic Dynamics in Manhattan

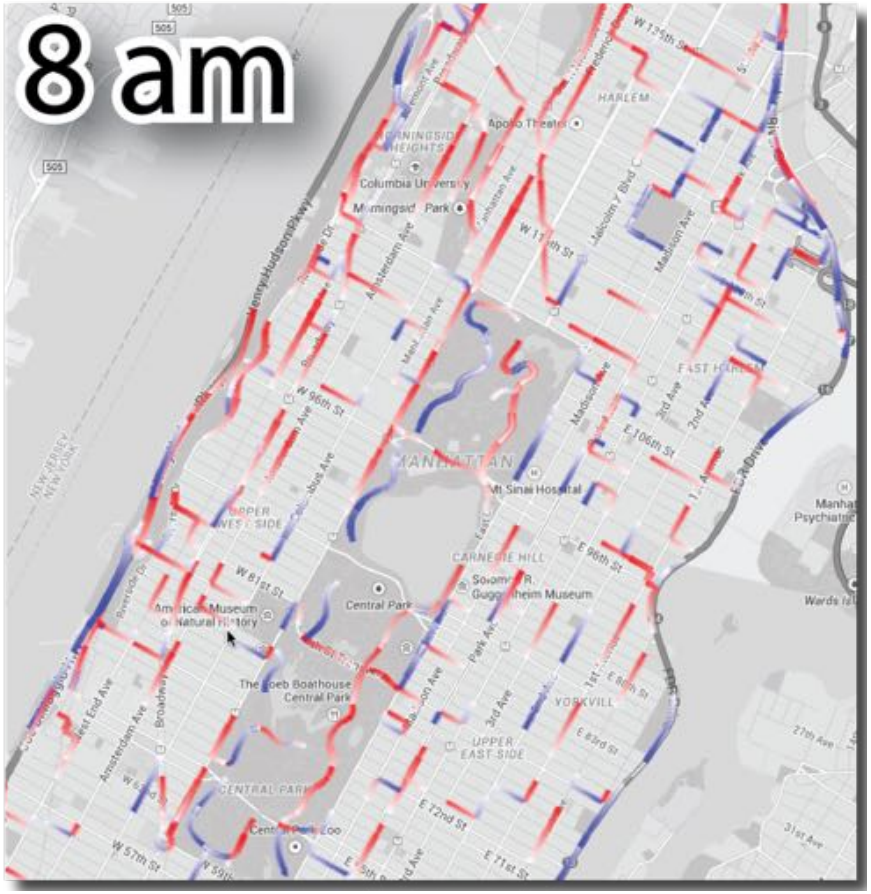
High Speed Traffic Flow

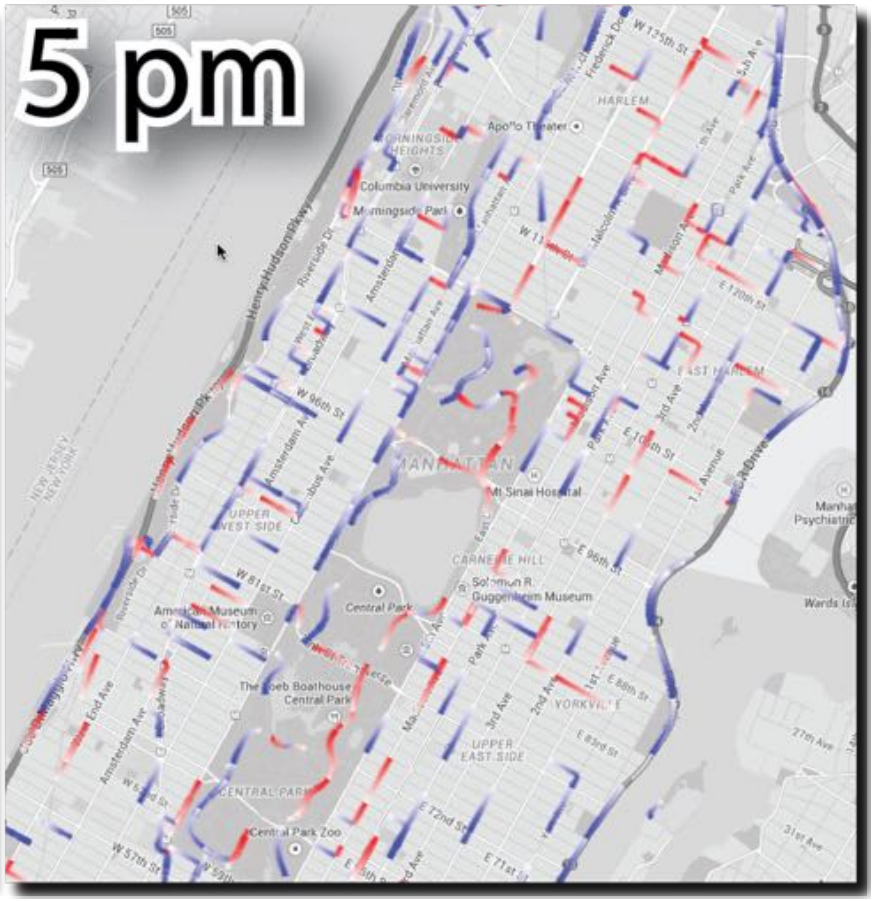
- Path lines
  - 1 minute
- Direction
  - highest speed
- Seed points
  - Road intersections
  - Uniformly at random



Red lines indicate northward direction
Blue lines indicate southward direction

High Speed Traffic Flow





Red lines indicate northward direction

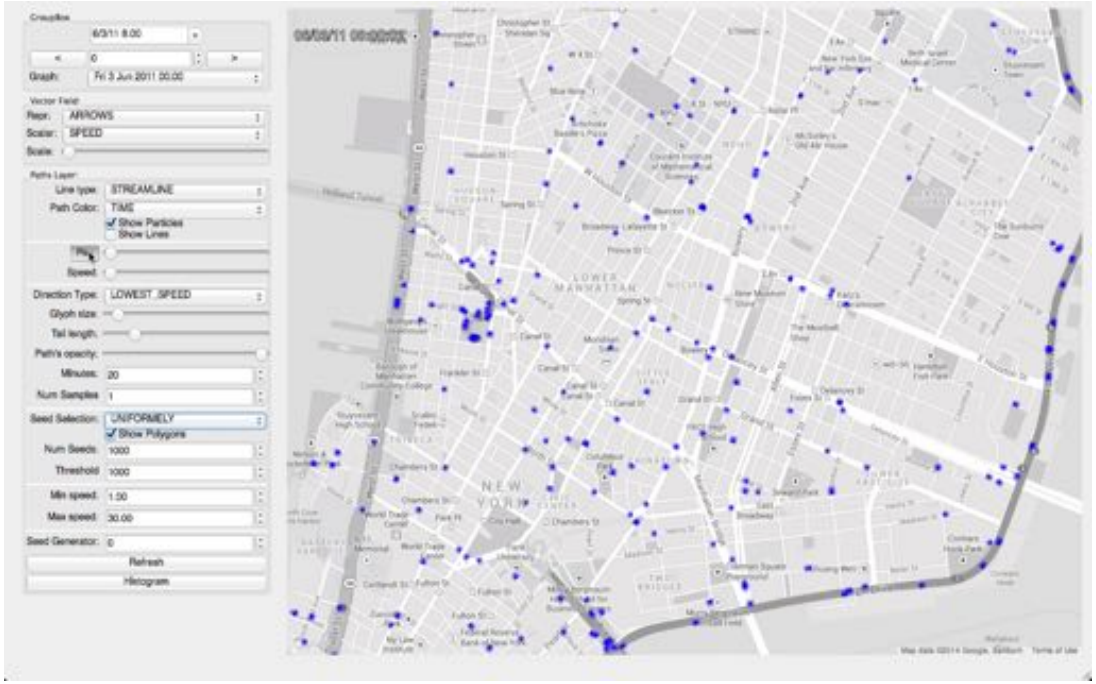
Blue lines indicate southward direction

Taxi Flow

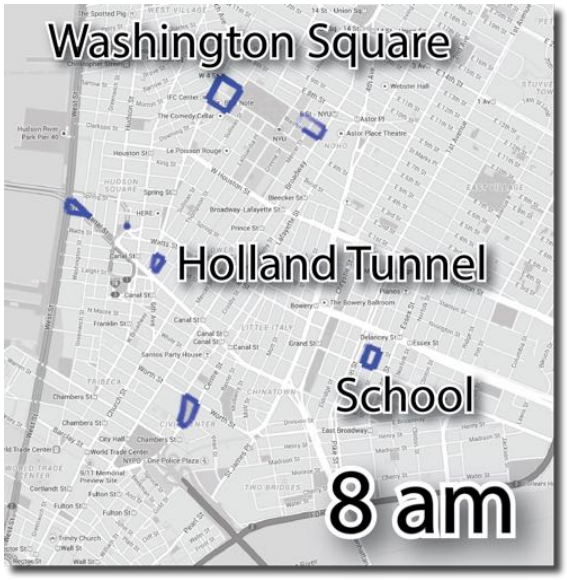
- Path lines
  - 20 minutes
- Seed points
  - Midtown Manhattan
- Direction
  - Density of taxis

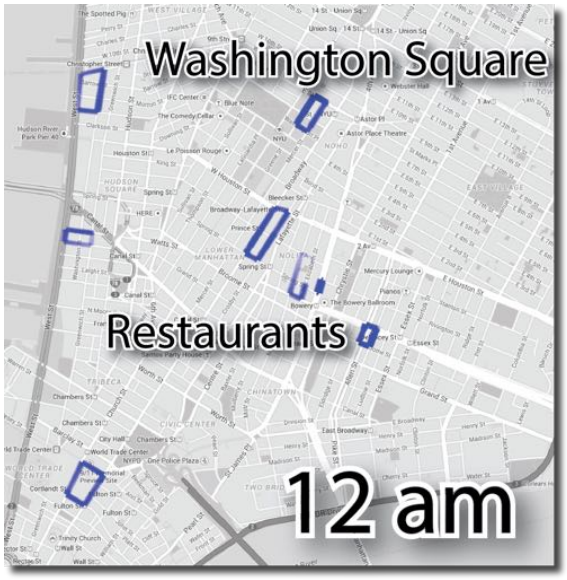
Traffic Bottlenecks

- Direction
  - Lowest speed
- Streamlines
  - Study bottlenecks at different time instants

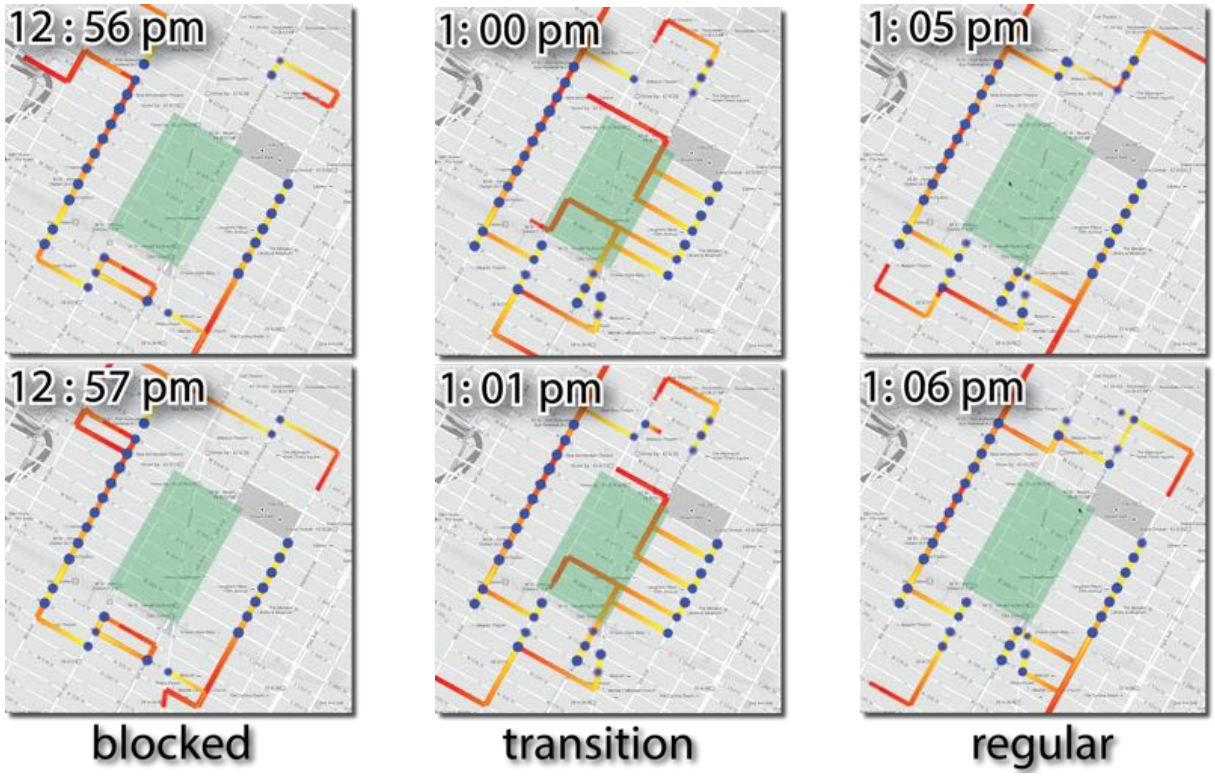


Traffic Bottlenecks





Simulating Road Blocks

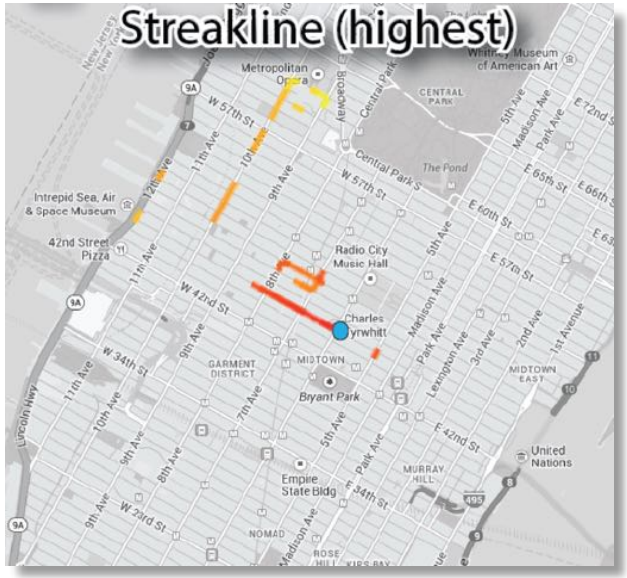


Conclusions

- Taxi as sensors to obtain traffic information
  - Closest path model
  - Efficient
  - Validated with real data
- Adapt visualization techniques from vector fields
  - Particle advection
  - Global techniques

Future Work

- Raised interesting questions
  - What do the large orbits mean?
  - Streak lines
- Try vector field topology to automatically identify patterns



SciVis techniques can provide insightful views into domains traditionally not part of it

Acknowledgements

- NYC TLC and DoT
- This work was supported in part by
  - Google Faculty Award
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  - NSF award CNS-1229185
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Thank You!

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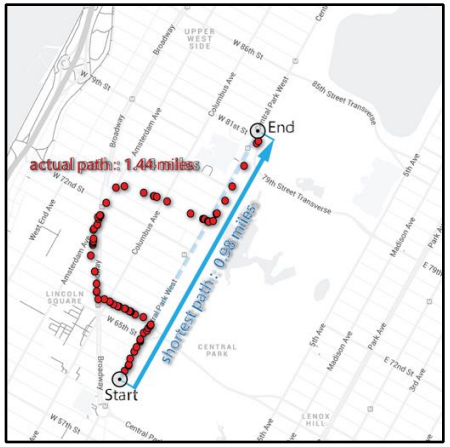
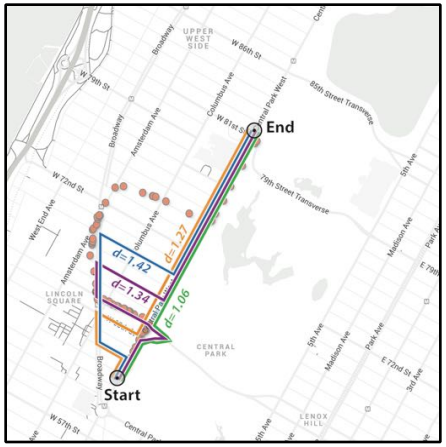
Estimate Traffic Information

- Identify plausible routes of taxis



Actual GPS track



k-shortest path

[Santi et al. CoRR 2013]

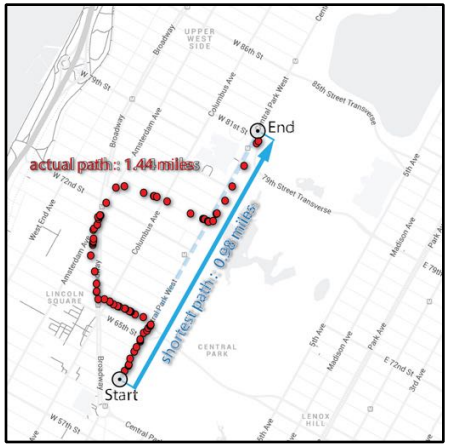
- Non-linear optimization techniques

  [Zhan et al. Transport. Res. C-Emer. 2013]

  - Cannot handle large data

Estimate Traffic Information

- Identify plausible routes of taxis



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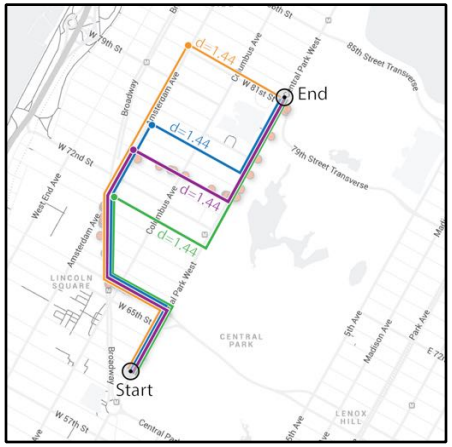


k-closest path

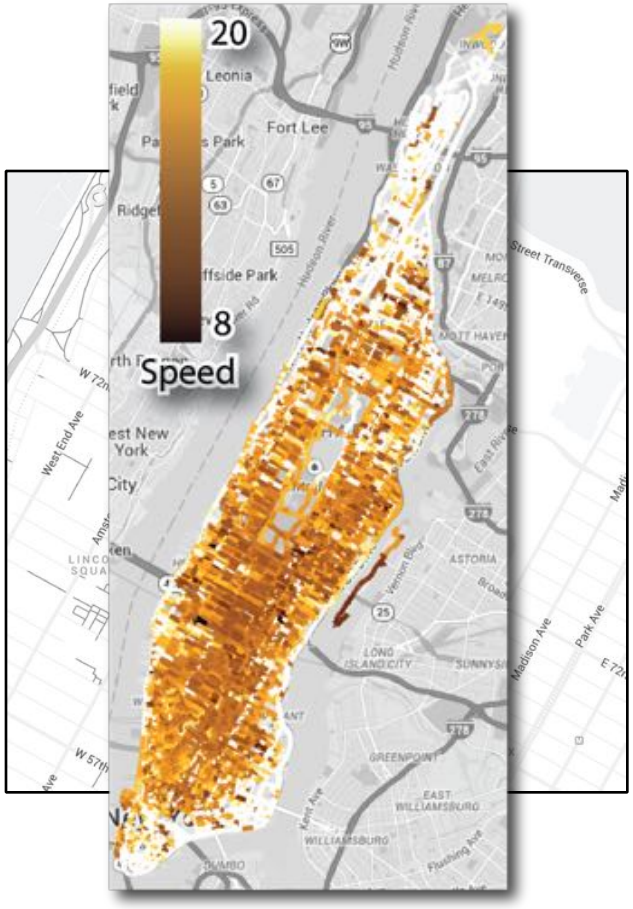
Closest Path Algorithm

- Intuition
  - The actual route comprises of segments
  - Each segment is the shortest path between two points
- Given number of way-points *n*
  - Identify paths for all possible *n*-set of way-points
- *n* = 1
  - 82.8% accuracy
  - Linear time (after pre-processing)

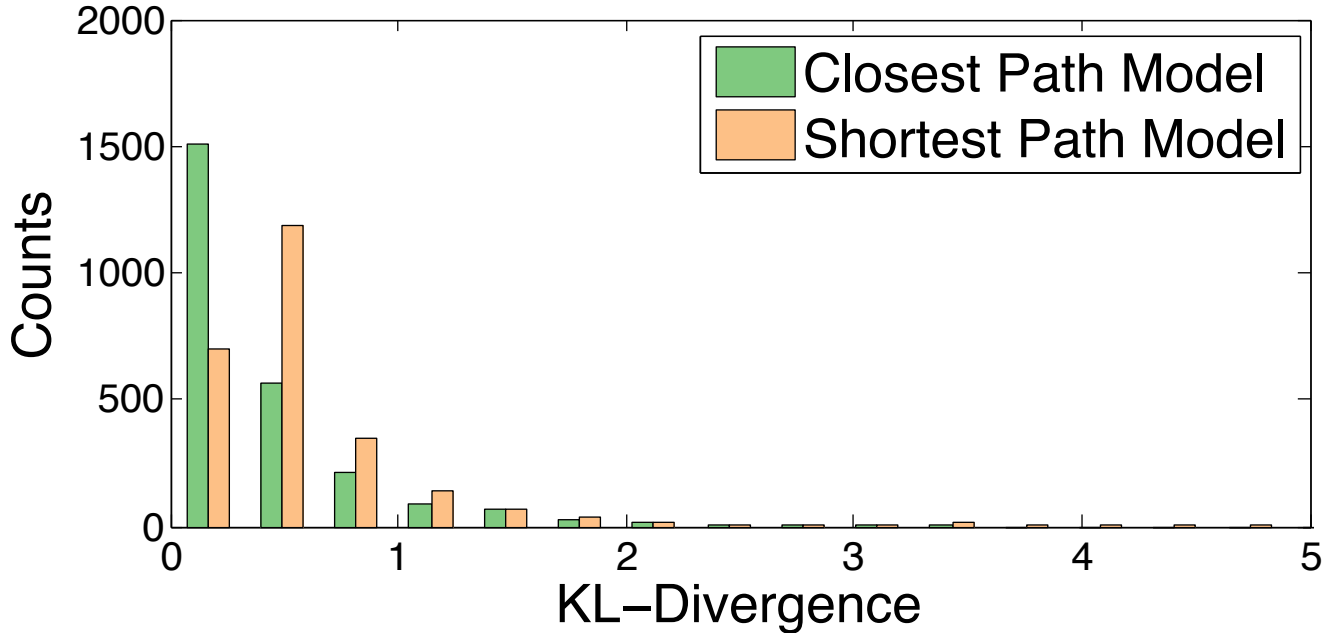
Estimate Traffic Information

- Each path
  - Assign speed to every segment
  - Assign weight inversely proportional to closeness to actual trip distance
- Each road segment

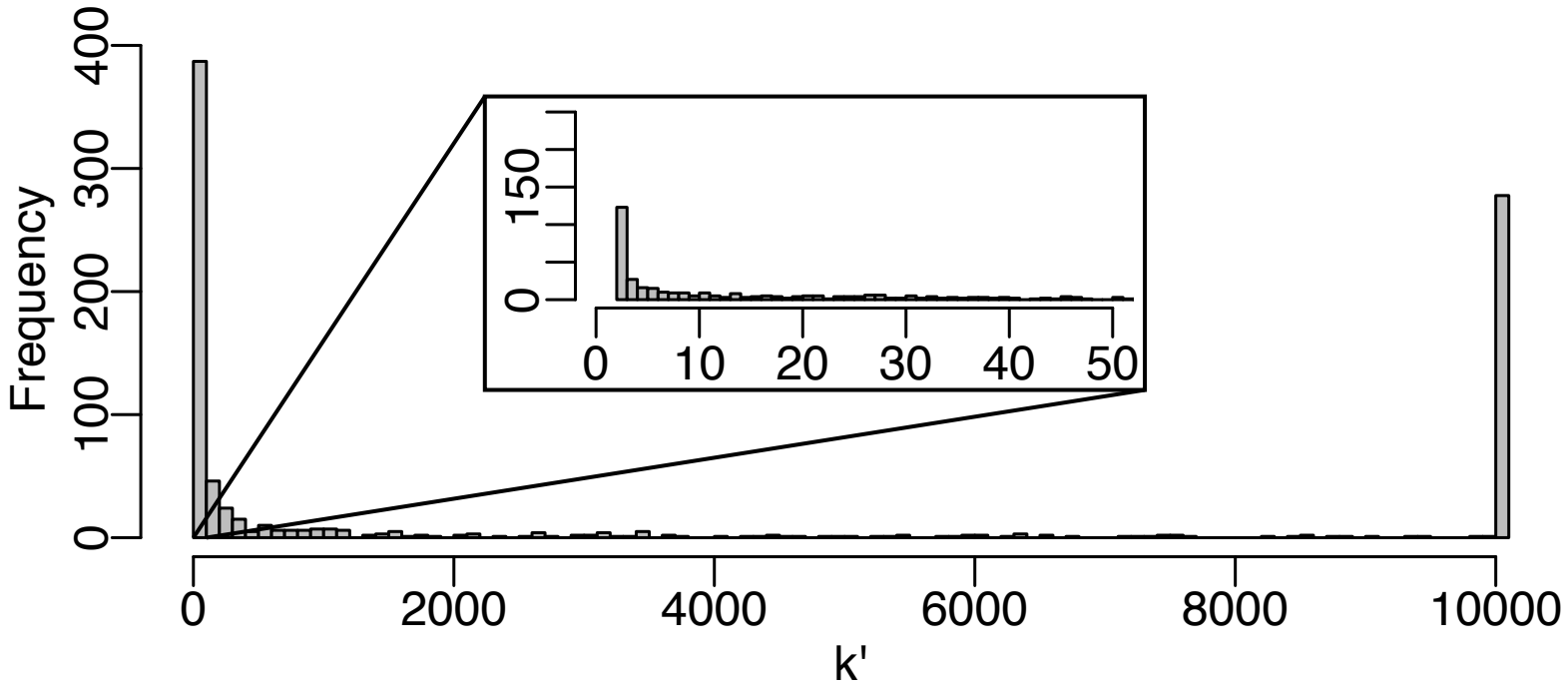
$$\bar{s}_i = \frac{\sum_{j=1}^{n} s_i^j \times w_i^j}{\sum_{j=1}^{n} w_i^j} \qquad \sigma_i^2 = \frac{\sum_{j=1}^{n} (s_i^j - \bar{s}_i)^2 \times w_i^j}{\frac{n-1}{n} \sum_{j=1}^{n} w_i^j}$$



Model Validation



k-shortest paths



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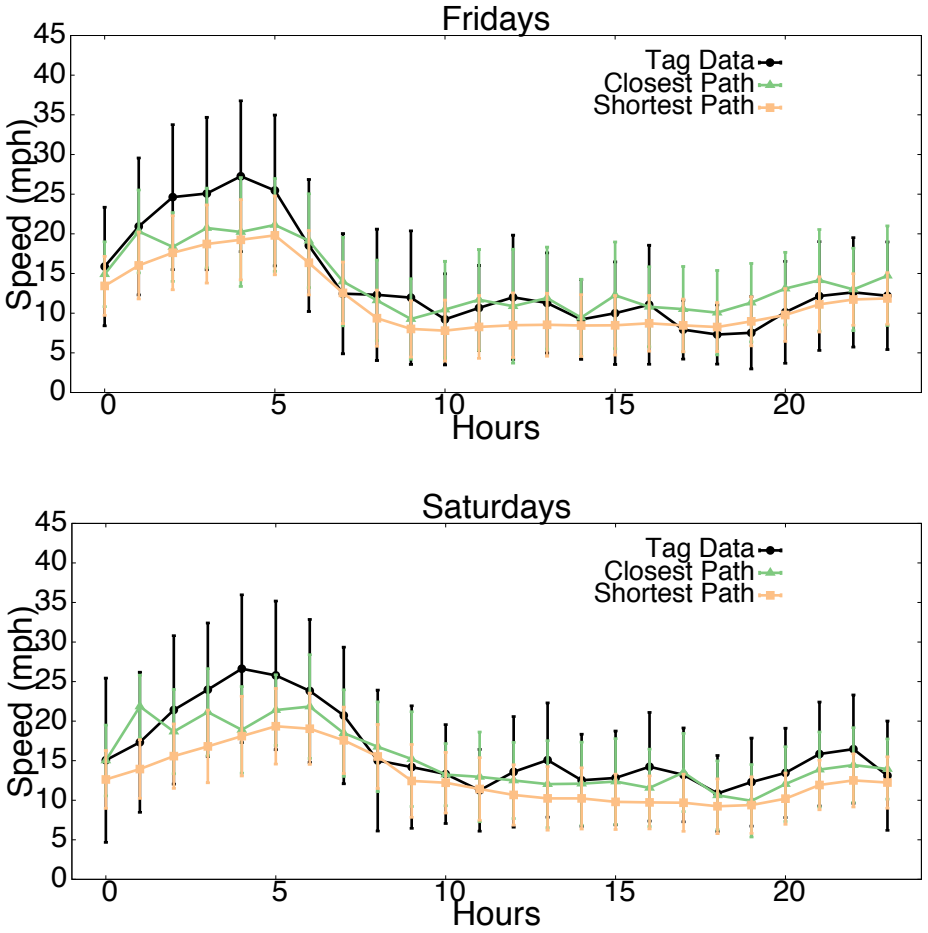
Fridays
Tag Data
Closest Path
Shortest Path
Speed (mph)
Hours
0
5
10
15
20
25
30
35
40
45
Saturdays
Tag Data
Closest Path
Shortest Path
Speed (mph)
Hours

Trip Lengths in Manhattan