CSC 445
Big Data Management and Analysis

Fall 2021

Course Logistics

- Instructor: Huy T. Vo — Office Hours: Thursday, 2-4pm
- Class Format: mixtures of lectures and hands-on labs
  - Be ready to follow along during class
- Expected to be proficient in Python
  - First half of the course is mostly in notebooks/colab
  - Second half will be run on NYU HPC
- Need to familiarize with shell and command lines

Course Objectives

- Preparations for handling Big Data (in a data science team)
  - Broad understanding of big data and its ecosystem
  - Ability to identify big data challenges and how to tackle them
  - Understanding of big data programming paradigm
  - Knowledge in how to perform computation and analytics using big data platforms

Expected Outcomes

- Big Data Computing Concepts
  - Streaming: Python's generators
  - Functional Programming: map/reduce/filter and beyond
- Big Data Programming Paradigm
  - Hadoop: streaming
  - Spark: RDD, DataFrame, and SQL
- Overview of NoSQL

Preparation

- Make sure to install on your computer:
  - Having a google account for using Google Colab
- We will be using NYU HPC
  - I will request access for everyone

Grading

- 4 Assignments: 60% total (15% each)
- 1 In-class Exam: 15%
- 1 Final Challenge (“mini final project”): 25%
  - Solve a big data problem using the techniques learned in class
- Coding Plagiarism is heavily penalized

Textbooks

- No required textbooks: supplemental materials may be distributed during class
- Suggested readings (most available electronically through NYU Library)
  - *Hadoop : The Definitive Guide-Storage and Analysis at Internet Scale, 4th Edition* (O'Reilly Media, Incorporated, 2015) by T. White
  - *PySpark Recipes A Problem-Solution Approach with PySpark2* (Apress, Berkeley, CA, 2018) by R. K. Mishra
  - *Next generation databases : NoSQL, NewSQL, and Big Data* (Apress, Berkeley, CA, 2015) by G. Harrison
  - *Data Science and Big Data Analytics* (John Wiley & Sons, Indianapolis IN, 2015) by EMC Education Services
  - *Probabilistic Data Structures and Algorithms for Big Data Applications* (Books on Demand, 2019) by A. Gakhov

Data Mining vs. Machine Learning vs. Big Data Analytics

- Modern Data Mining requires both ML and BD
- The differences lie in the learning outcomes
  - We focus on the “structuredness” of big data and the principles of how to handle them efficiently
  - See Syllabus for tentative topics
- Hands-on! Hands-on! Hands-on!
  - Coding is required and crucial
  - We focus on Tools and Technologies

Tentative Schedule

Date	Topic
Week 1	Introduction
Week 2	Streaming
Week 3	Distributed File System & Parallel Computing
Week 4	MapReduce & Apache Hadoop
Week 5	Apache Spark
Week 6	Hadoop/Spark on NYU-HPC
Week 7	Spatial Data
Week 8	Textual and Social Media Data
Week 9	Network and Graph Data
Week 10	Exam
Week 11	NoSQL and Cloud Computing
Week 12	Final Challenge & Wrap-Up

Question?

Introduction to Big Data

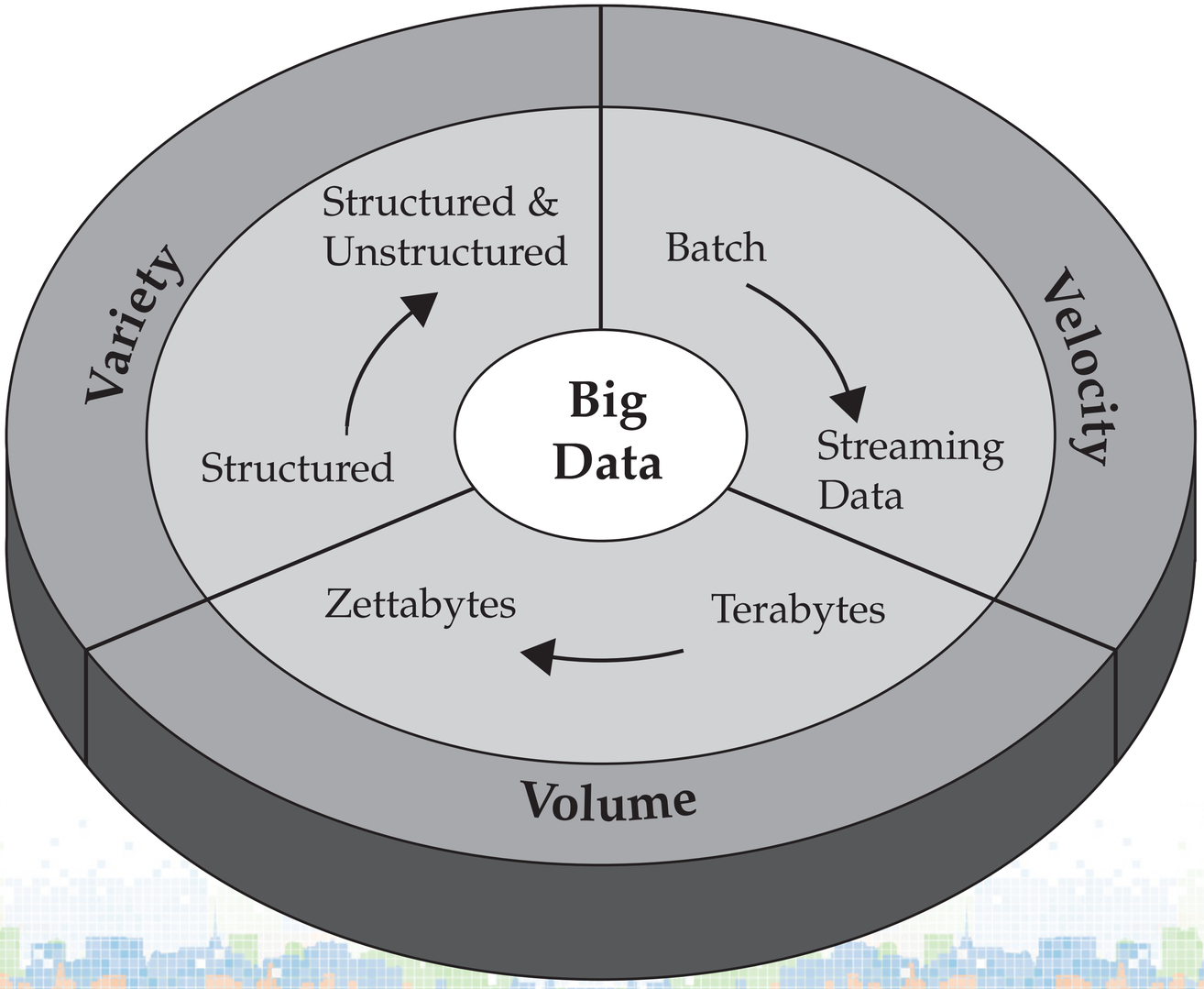
Center for Urban
Science + Progress

Big Data Analytics — Warehousing Perspective

Further Readings

- Chapter 1 and 2 of *Data Science and Big Data Analytics*

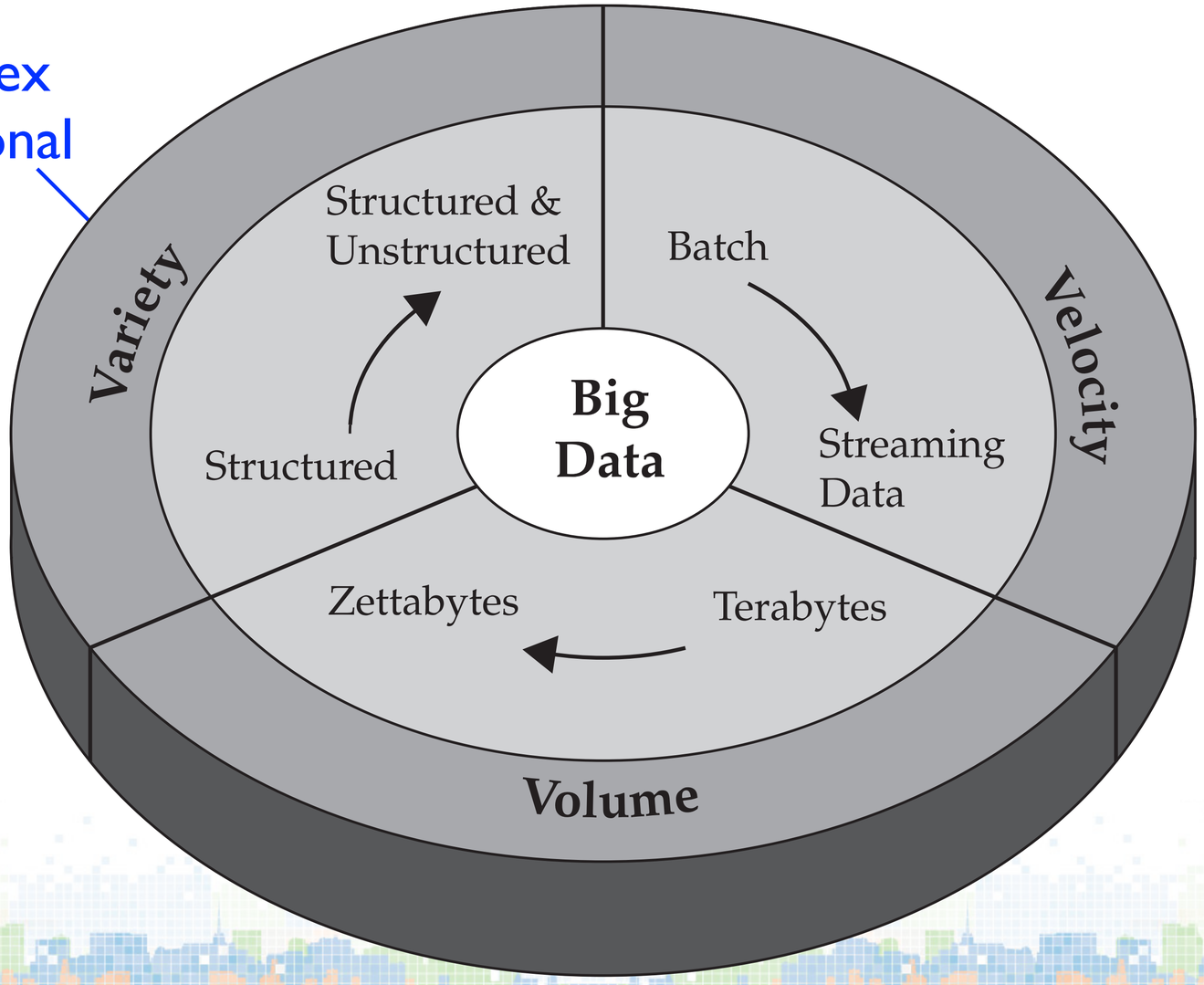
Big Data Characteristics



[Source: IBM, 2012]
[Source: MapR 2014]

Big Data Characteristics

data format are complex
not everything is relational

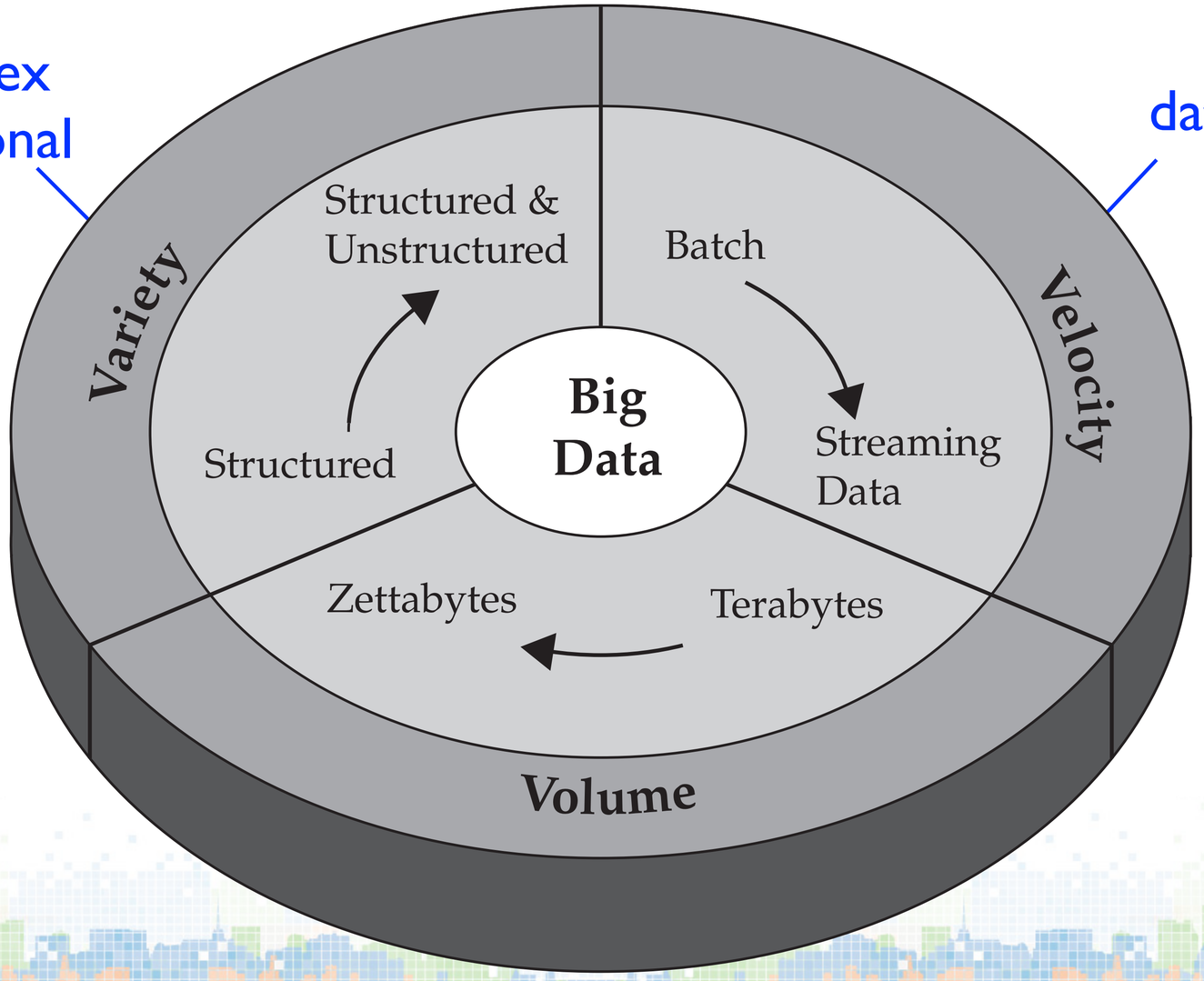


[Source: IBM, 2012]
[Source: MapR 2014]

Big Data Characteristics

data format are complex
not everything is relational

data are dynamic

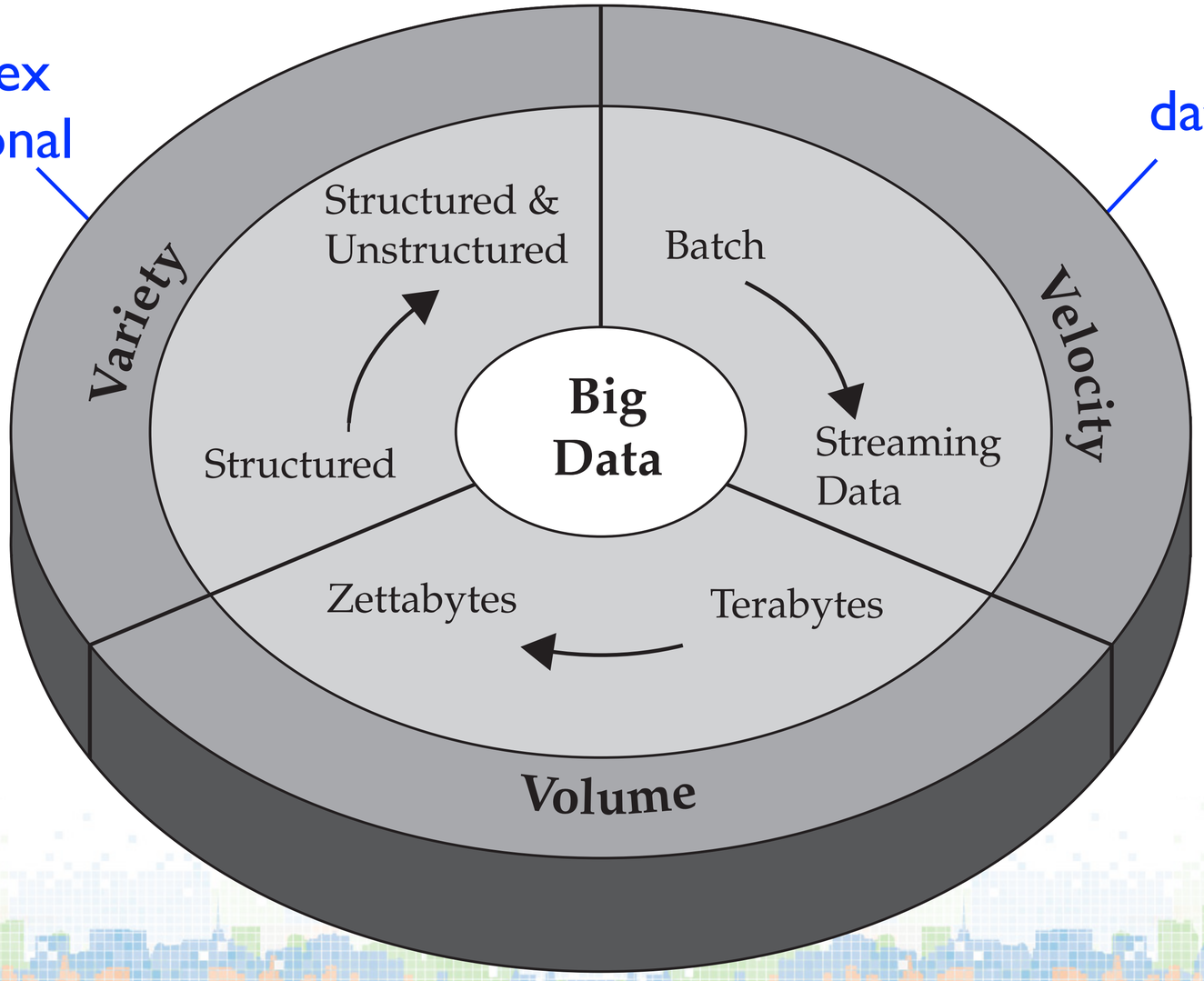


[Source: IBM, 2012]
[Source: MapR 2014]

Big Data Characteristics

data format are complex
not everything is relational

data are dynamic



Veracity

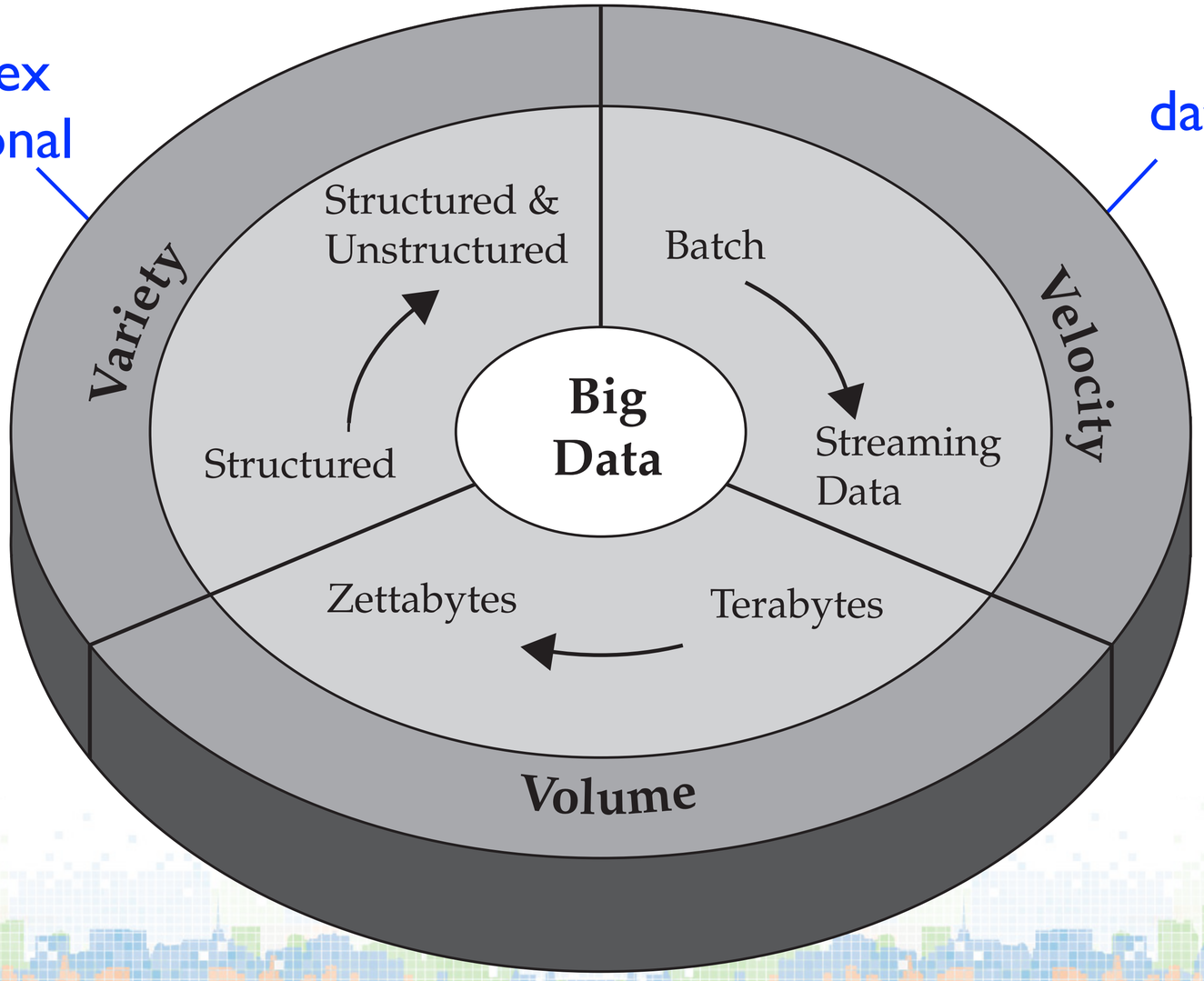
Value

[Source: IBM, 2012]
[Source: MapR 2014]

Big Data Characteristics

data format are complex
not everything is relational

data are dynamic



Veracity

Variability

Value

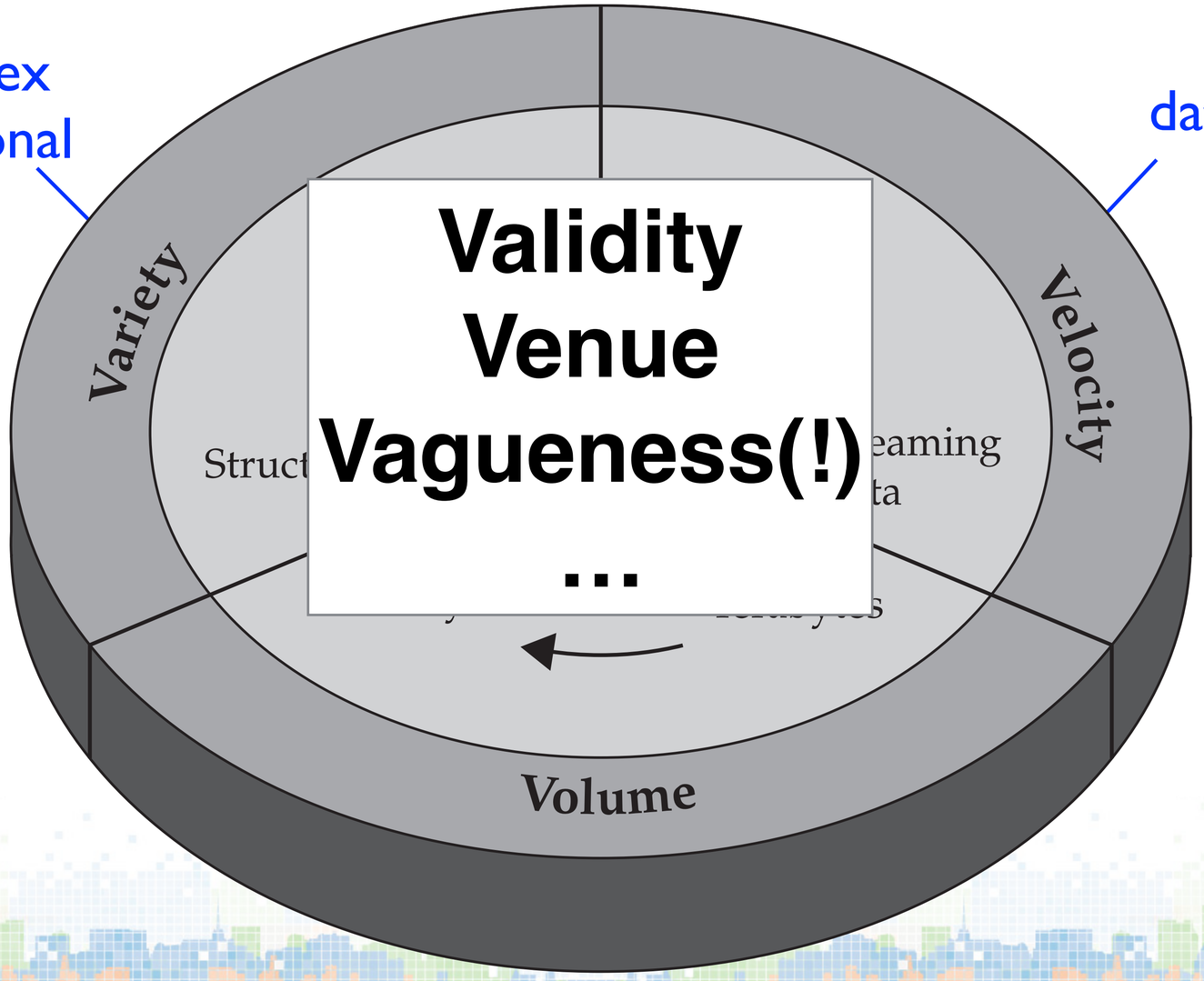
Visualization

[Source: IBM, 2012]
[Source: MapR 2014]

Big Data Characteristics

data format are complex
not everything is relational

data are dynamic



Veracity

Value

Variability

Visualization

[Source: IBM, 2012]
[Source: MapR 2014]

Big Data — Computing

Big Data — Computing

“Big data is an all-encompassing term for any collection of data sets so **large and complex** that it becomes **difficult** to process using **traditional** data processing **applications**.”

— *Wikipedia:Big_Data (05/2015)*

Big Data “Problems”

- Data that is too large:
  - Excel/ArcGIS couldn’t load the data — *need a more scalable tool?*
  - Too many files to perform analysis manually — *need an automated tool?*
- Data that is too complex:
  - Searching the entire parameter space is too expensive for my simulator — *need a distributed algorithm?*
  - Too expensive to run a sentimental analysis model on millions of tweets — *need to approximation technique or to leverage parallelism?*

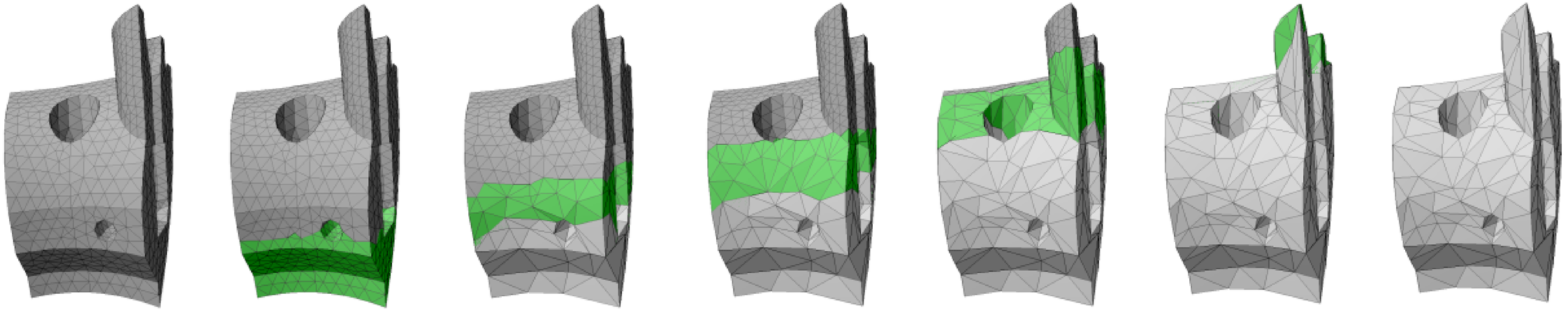
Background — Research Interests

- developing **scalable** techniques and systems for **large-scale** data **visualization** and **analysis**
  - Streaming algorithms
  - Big data management
  - Parallel and distributed computing

Background — Research Interests

- developing **scalable** techniques:
  - large-scale data **visualization** and **analysis**

Streaming Algorithms

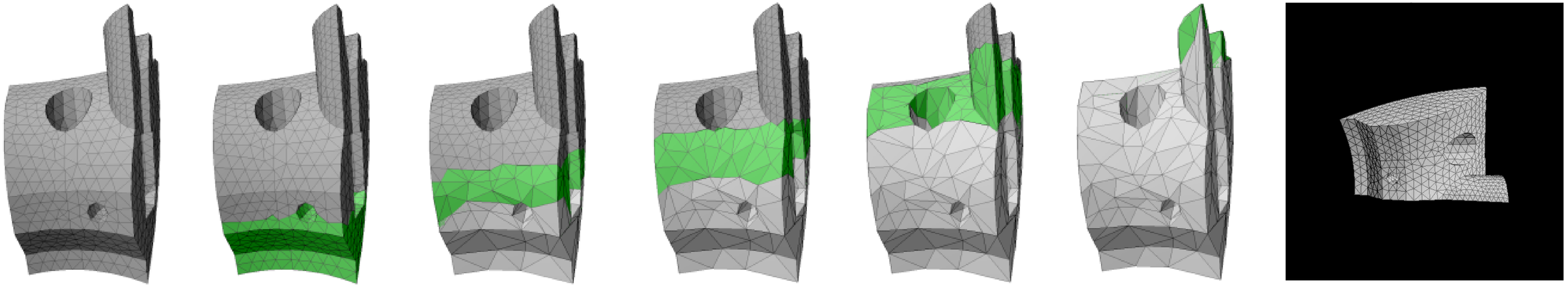


[IEEE TVCG 2007]

Background — Research Interests

- developing **scalable** techniques:
  - large-scale data **visualization** and **analysis**

Streaming Algorithms

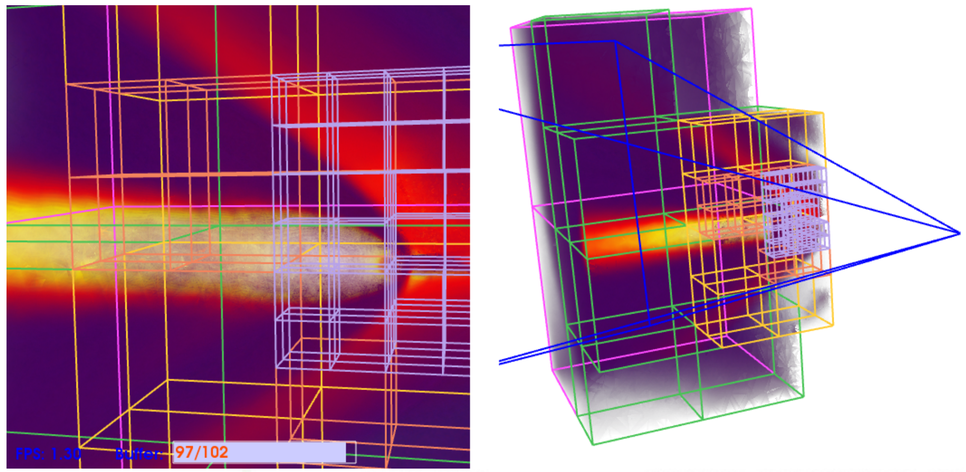


[IEEE TVCG 2007]

Background — Research Interests

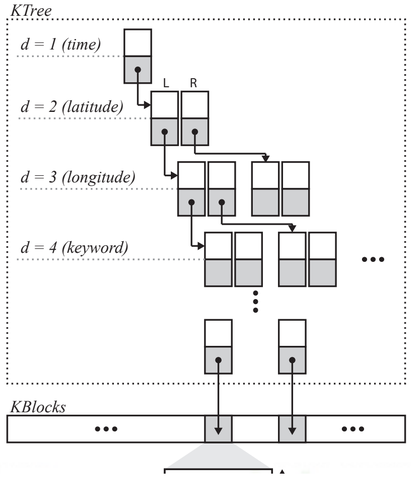
- developing **scalable** techniques:
  - large-scale data **visualization** and **analysis**

Big Data Management



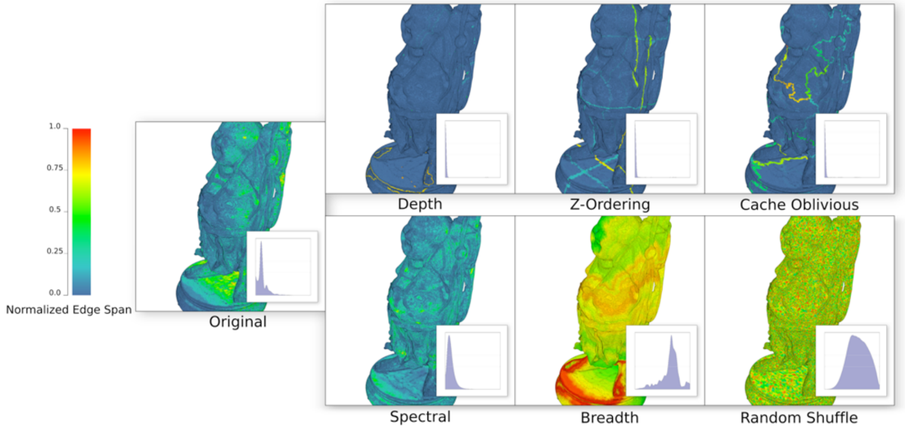
Out-of-Core Data Structure

[EG PGV 2007]



Spatio-Temporal Indexing

[IEEE TVCG 2013]

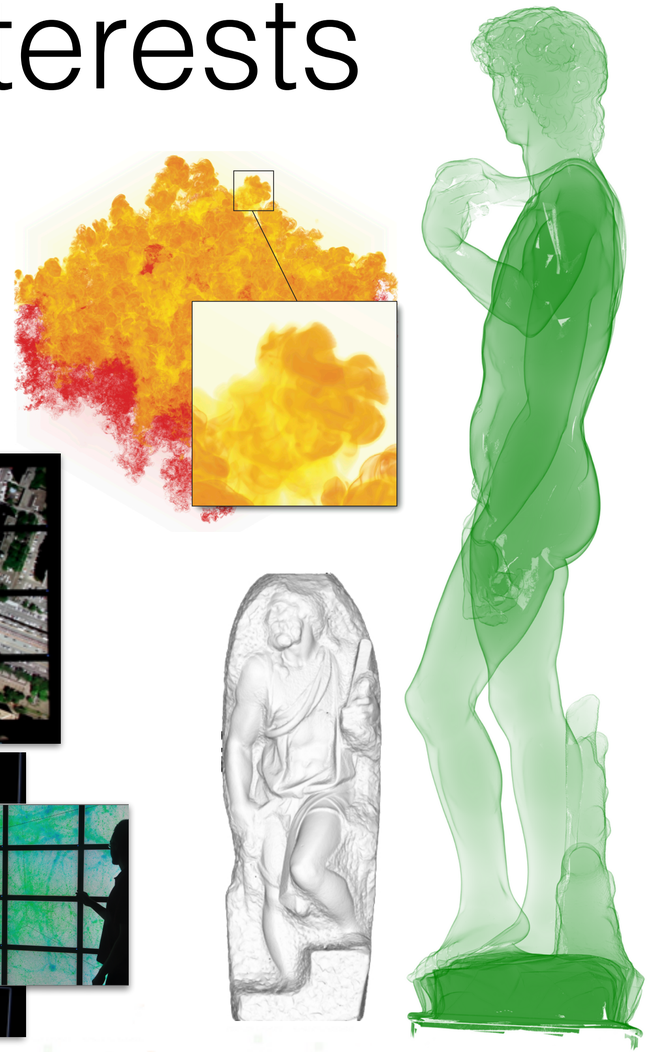


Cache-Coherent Mesh Layout

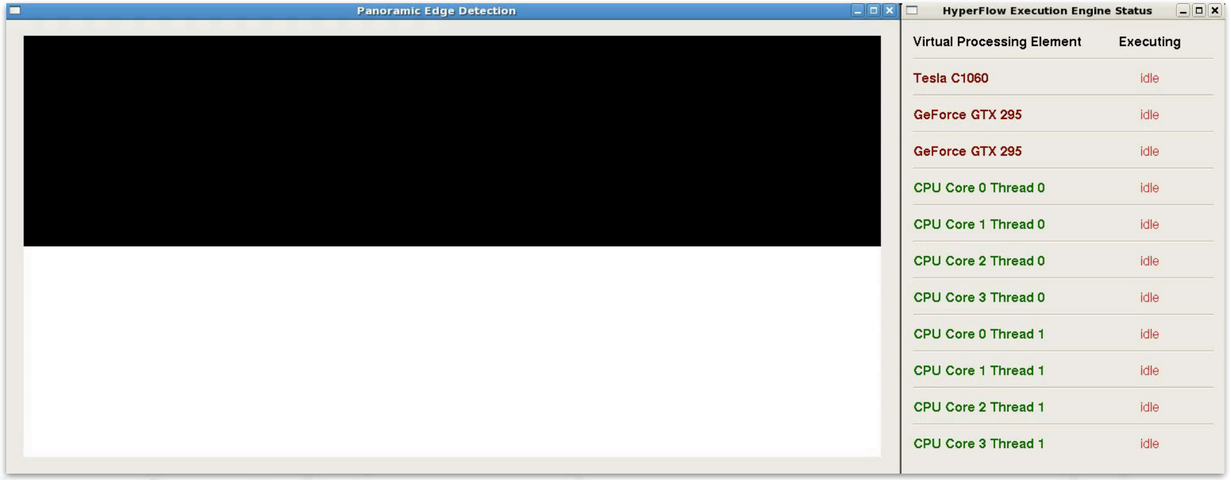
[JGT 2012]

Background — Research Interests

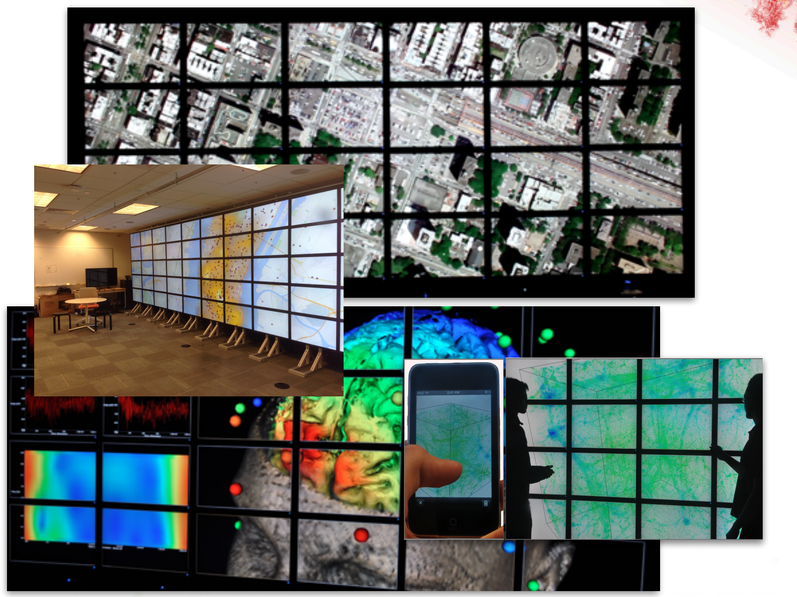
- developing **scalable** techniques:
  - large-scale data **visualization** and **analysis**



Parallel and Distributed Computing



Multi-core, GPGPUs, and clusters of machines
[EG PGV 2012]

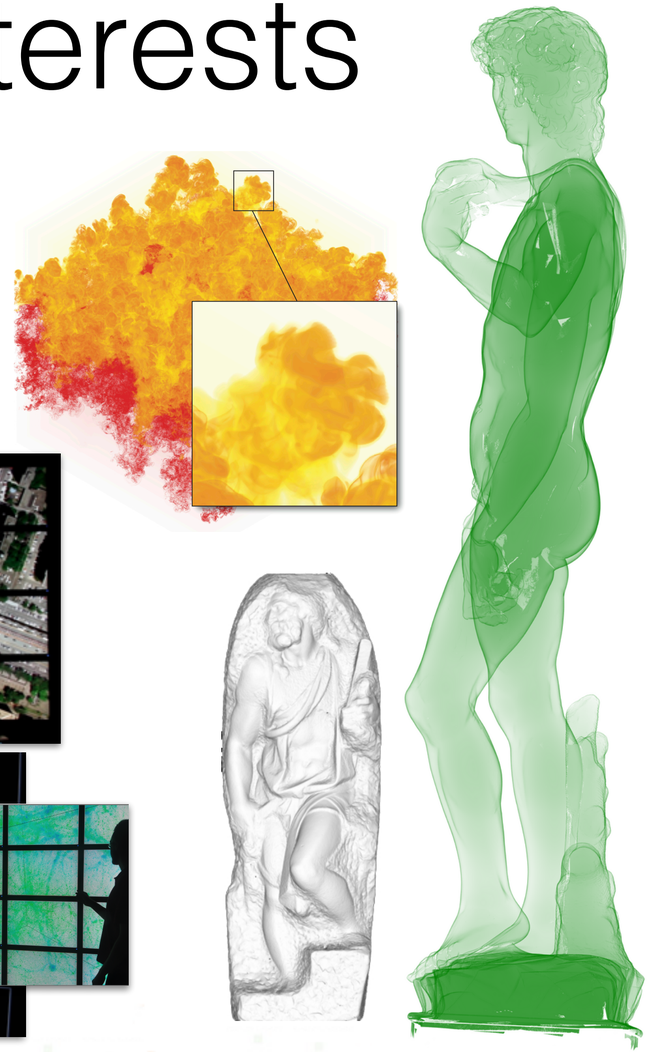


Scalable Displays
[VDA 2012, POWERWALL 2013]

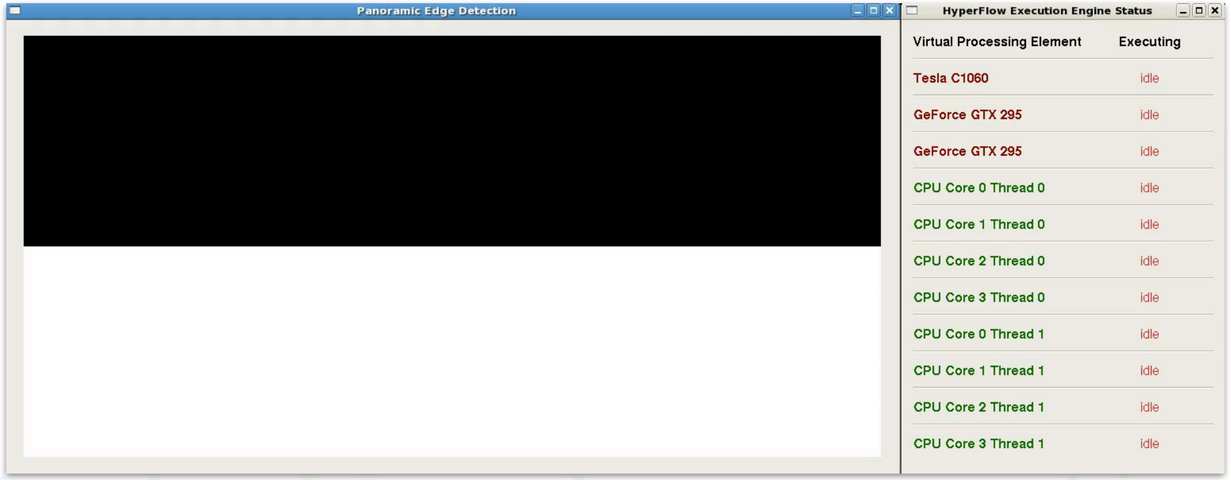
MapReduce
[LDAV 2012]

Background — Research Interests

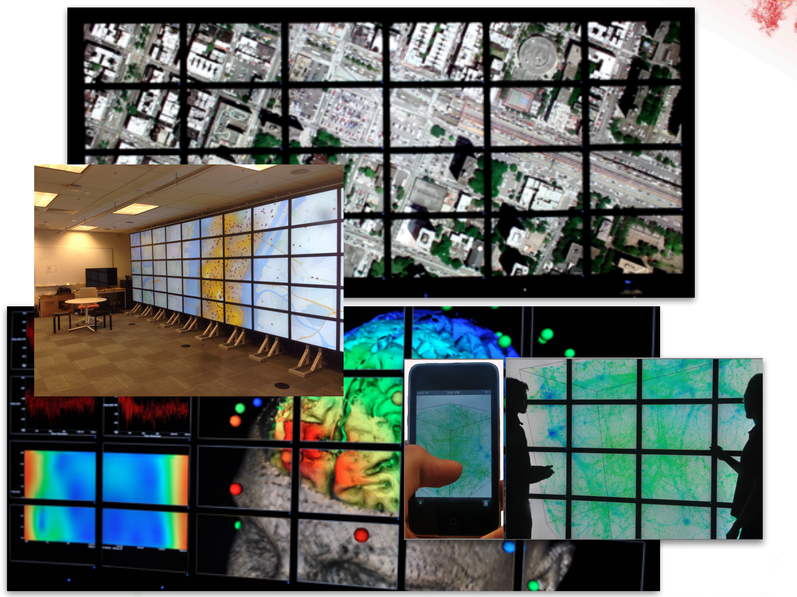
- developing **scalable** techniques:
  - large-scale data **visualization** and **analysis**



Parallel and Distributed Computing



Multi-core, GPGPUs, and clusters of machines
[EG PGV 2012]

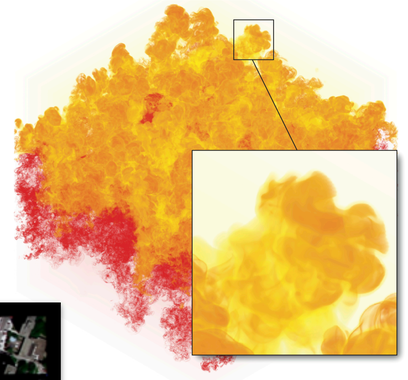


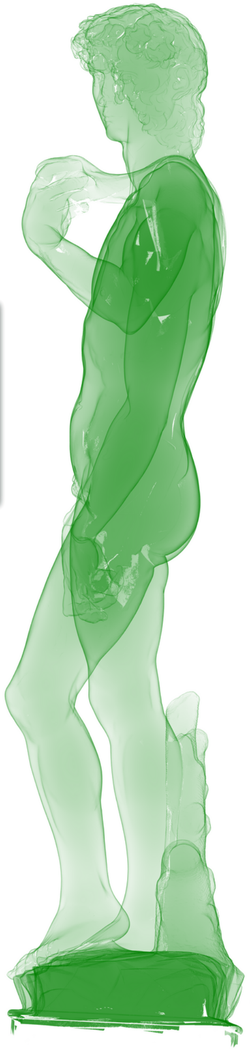
Scalable Displays
[VDA 2012, POWERWALL 2013]

MapReduce
[LDAV 2012]

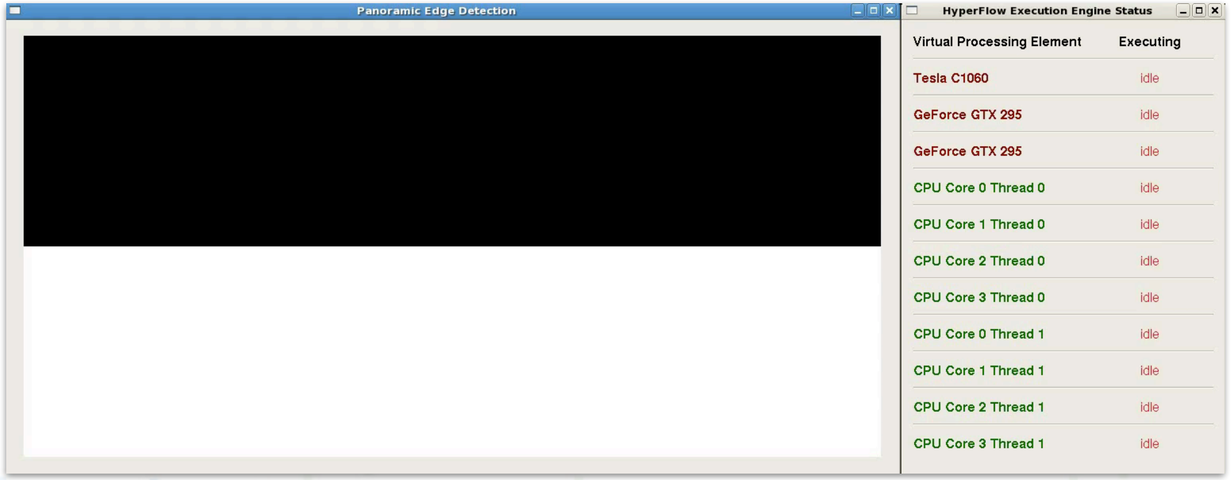
Background — Research Interests

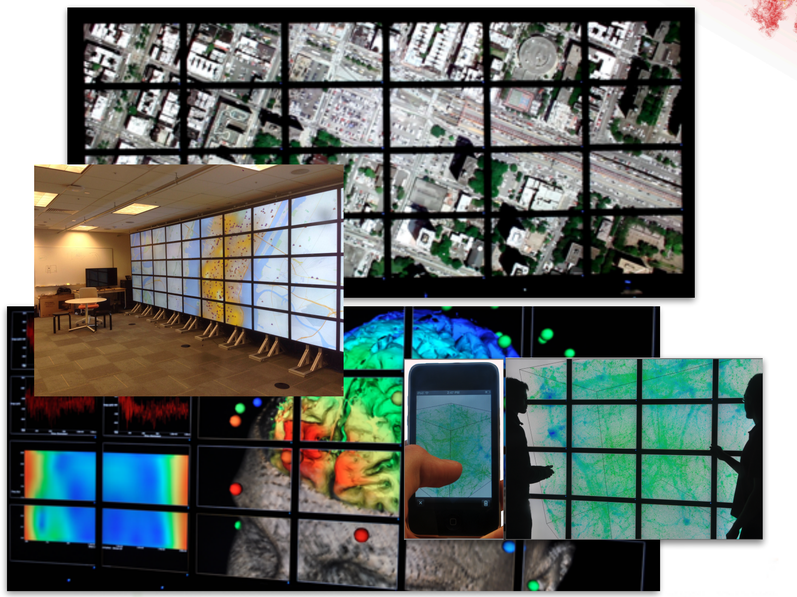
- developing **scalable** techniques:
  - large-scale data **visualization** and **analysis**





Parallel and Distributed Computing





Multi-core, GPGPUs, and clusters of machines
[EG PGV 2012]

Scalable Displays
[VDA 2012, POWERWALL 2013]

MapReduce
[LDAV 2012]

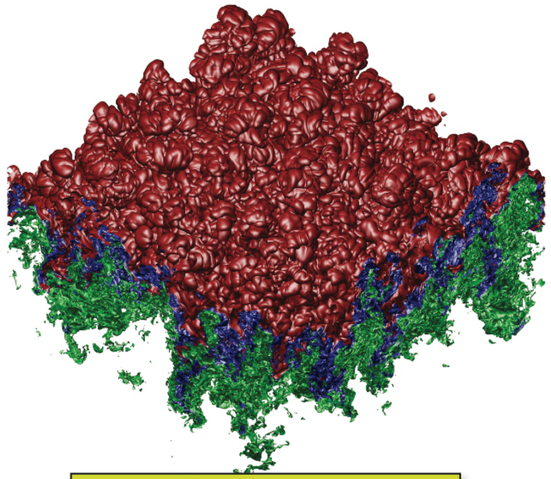
Computer Graphics

Research using Big Data

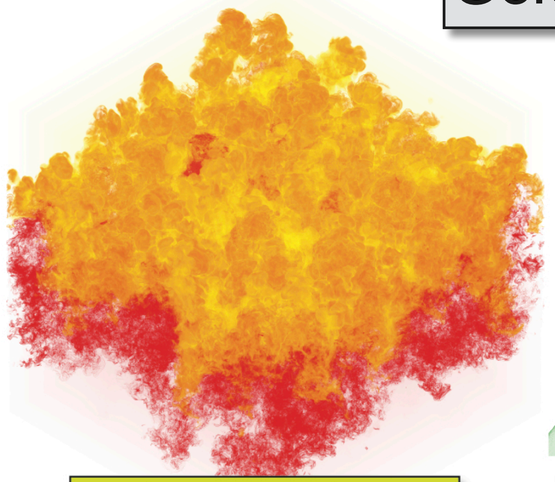
27 Billion Voxels (108GB)

Scientific Data

1 Billion Triangles (30GB)



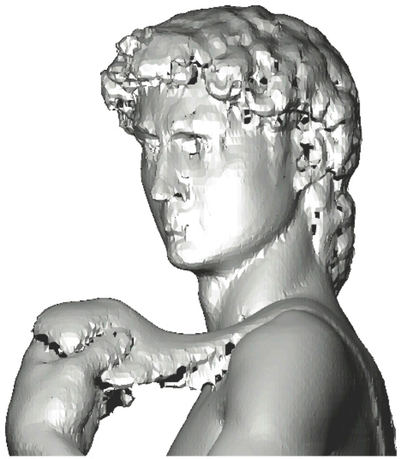
Isosurface Extraction



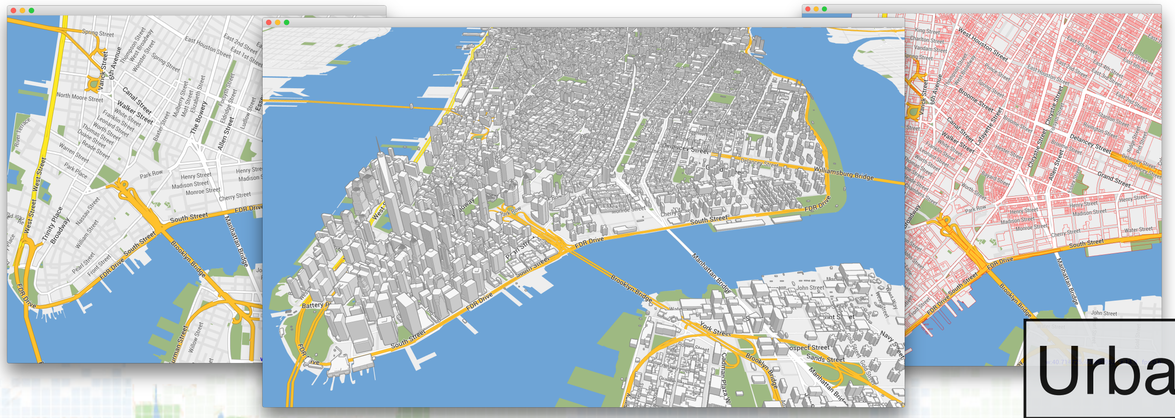
Volume Rendering

Translucency Rendering

Gigapixel Rendering

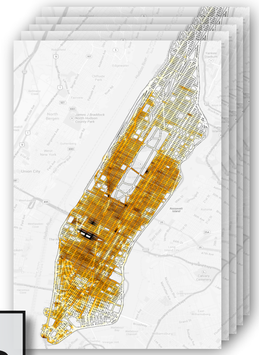


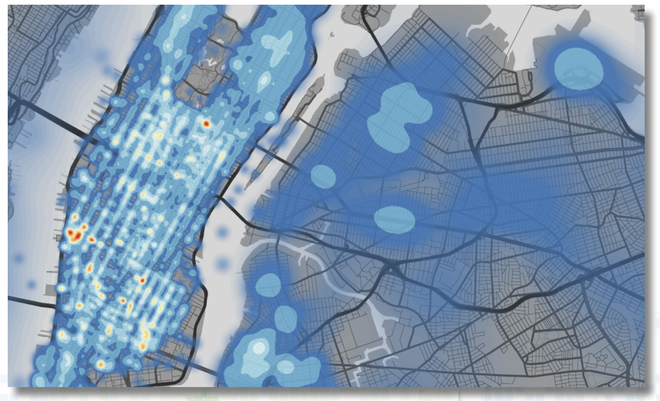
Simplification



millions of primitives and visibility tests

Urban Data





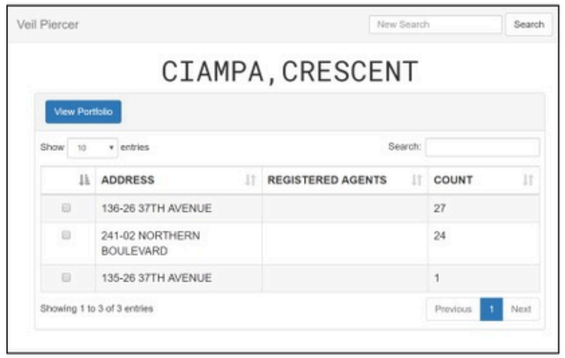
hundreds of millions of records

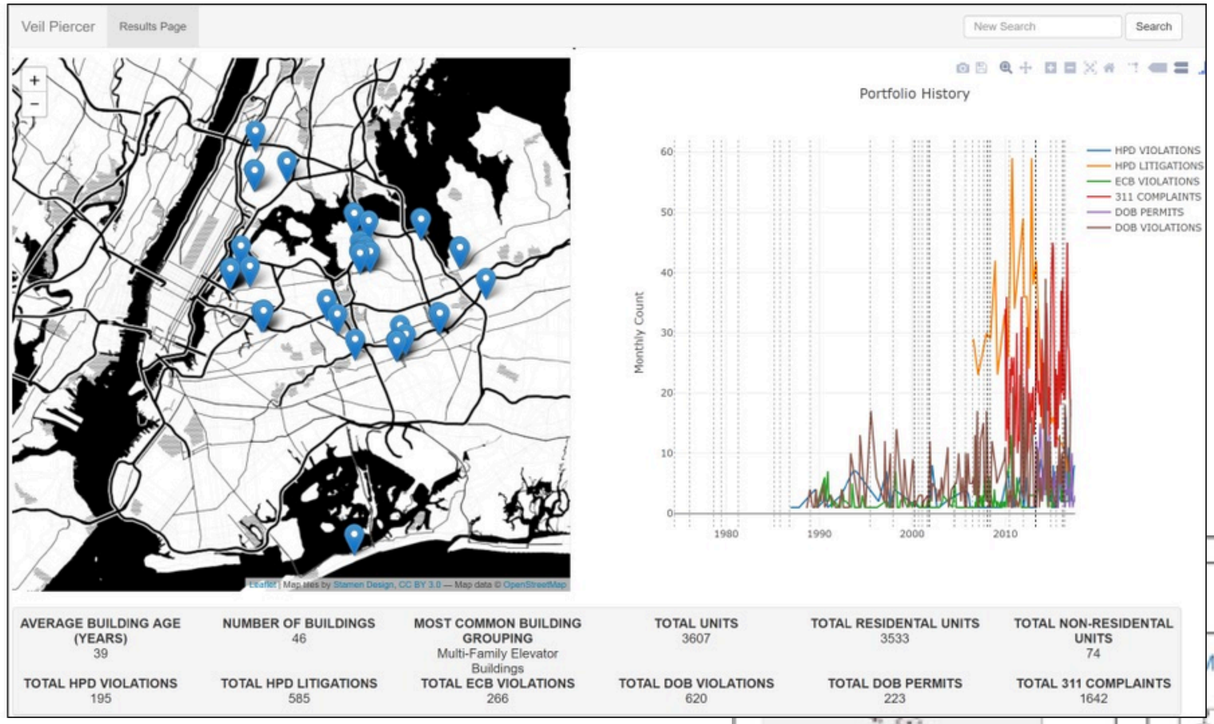
Our Main Objectives

- Improve the performance and quality of Visual Analytic applications, with a focus on *“big” cities, i.e.:*
  - Big (spatio-temporal) data
  - Urban domain (urban science/informatics)
- We make applications:
  - Efficient, and scalable
  - Easy to use for non-experts
  - Can be developed rapidly by domain experts

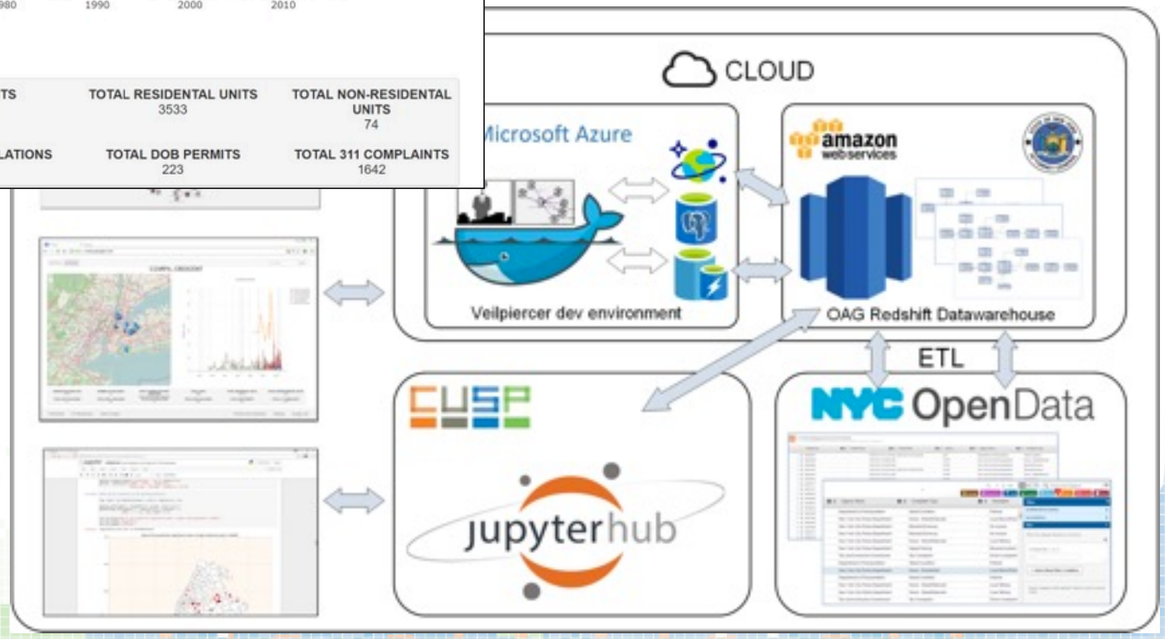
Examples of Past CUSP Capstone Projects with *Big Data*

Examples of CUSP Co-sponsored Capstone Projects





- 12 data sets
- 40 GB++
- Real-time queries



Piercing the Veil of the Corporate Landlord
(with NYSOAG)

Fighting harmful landlord practices to harass rent-stabilize tenants

Examples of CUSP Co-sponsored Capstone Projects

~150K drivers in NYC, only 69 Relief Stands…

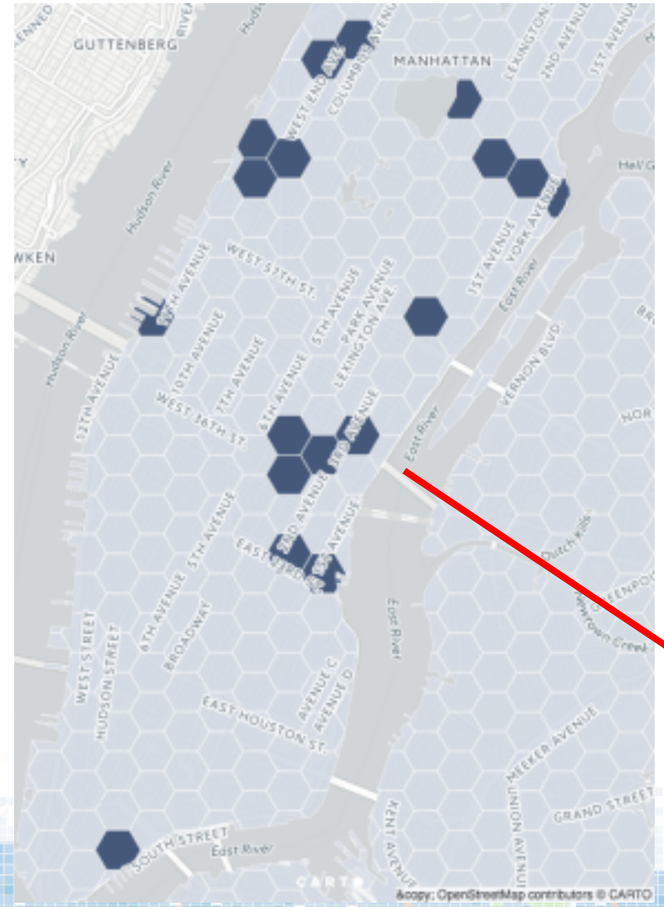


Image capture: Jun 2016 © 2017 Google United States

High violations, drop offs, cheap restaurants

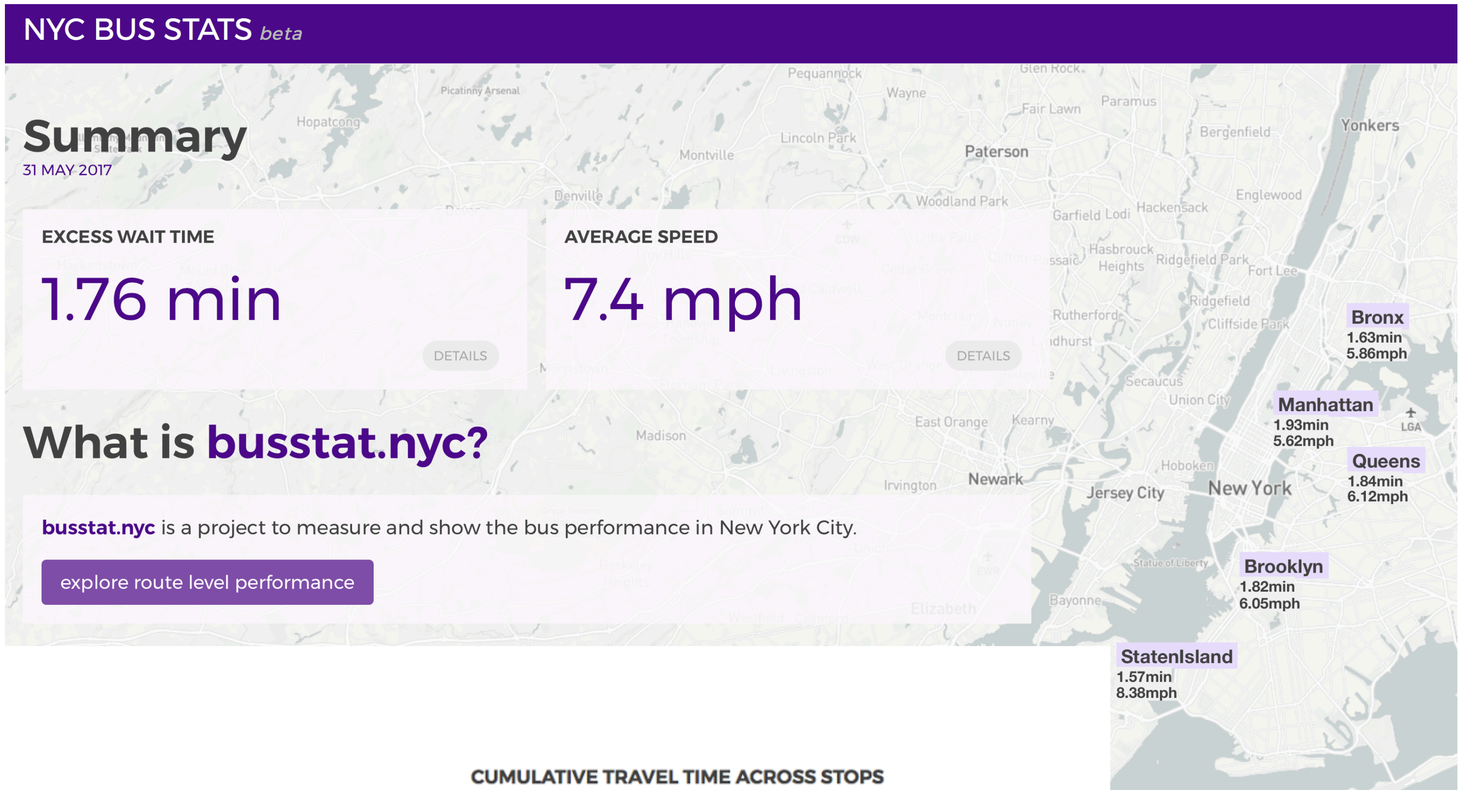
Optimizing Taxi Relief Stands
(with TLC)
300GB, 4 billion data points

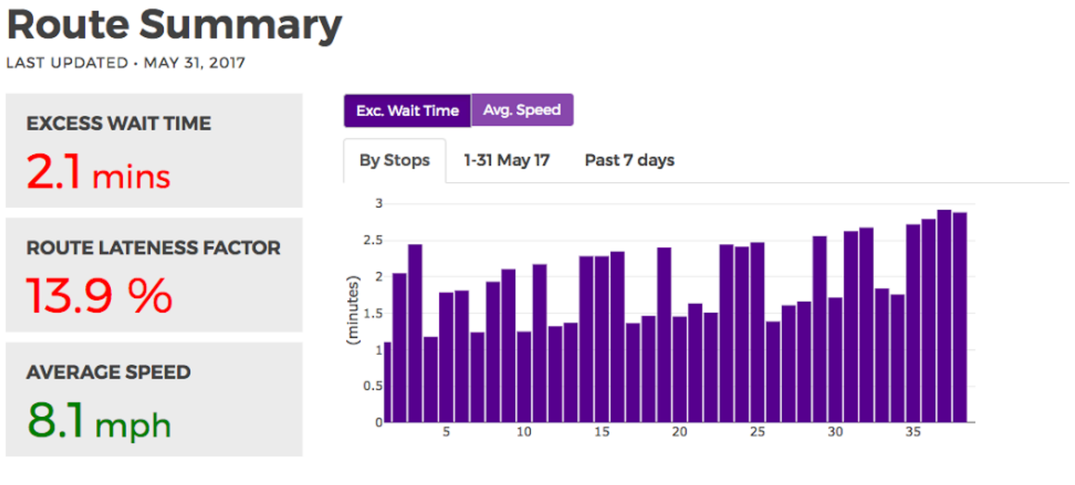
Examples of CUSP Co-sponsored Capstone Projects

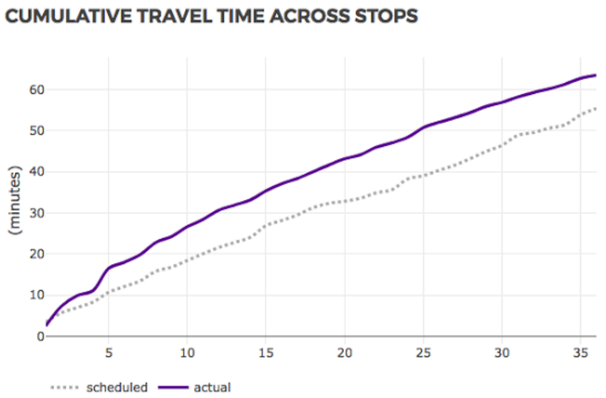
NYC Bus Profile Dashboard
(with TransitCenter)

A performance measurement tool for riders, agency board members, and staff — data driven

1TB of data







Big Data is not just about size!

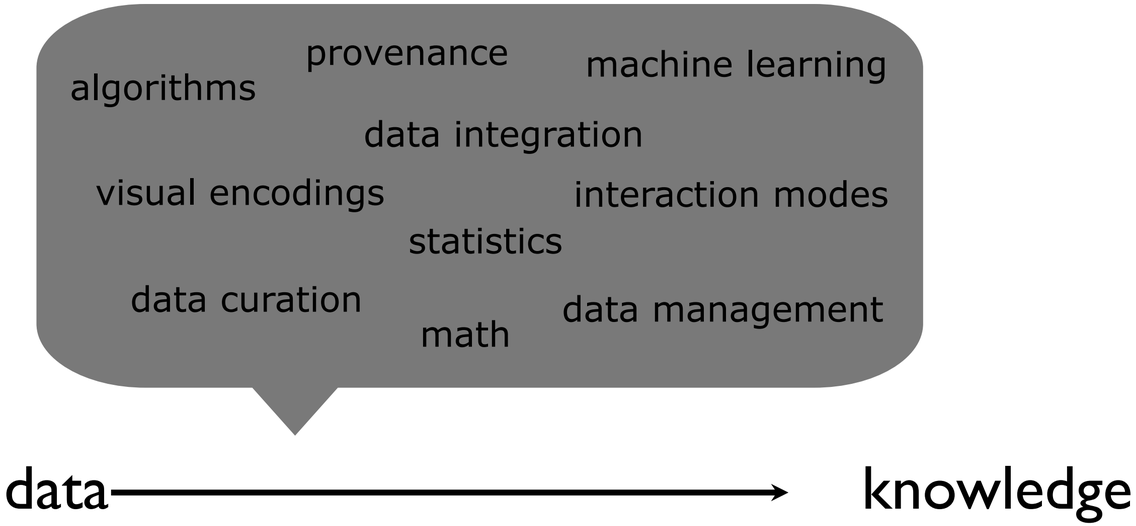
- Scalability for batch computations is not the biggest problem
  - Lots of work on distributed systems, parallel databases, …
  - Data were “in good hands”

Big Data is not just about size!

- Scalability for batch computations is not the biggest problem
  - Lots of work on distributed systems, parallel databases, …
  - Data were “in good hands”
- Scalability for people is!
  - Data owners are non-expert

Big Data is not just about size!

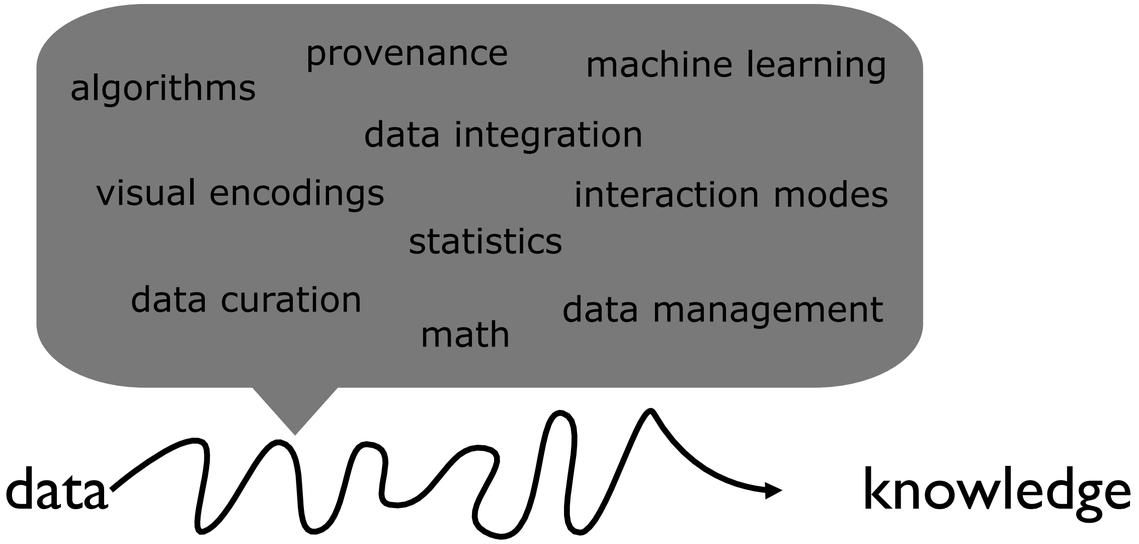
- Scalability for batch computations is not the biggest problem
  - Lots of work on distributed systems, parallel databases, …
  - Data were “in good hands”
- Scalability for people is!
  - Data owners are non-expert



Big Data is not just about size!

- Scalability for batch computations is not the biggest problem
  - Lots of work on distributed systems, parallel databases, …
  - Data were “in good hands”
- Scalability for people is!
  - Data owners are non-expert

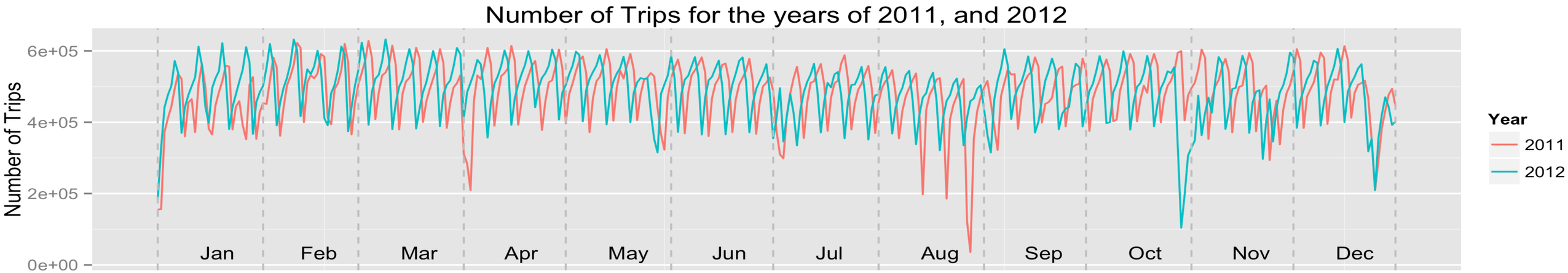
regardless of whether data are big or small



Big Urban Data — Space + Time

- Several hundred millions to billions of records
- Spatial + Temporal attributes
  - Can have >1 spatial and temporal attributes
- Main objectives in urban informatics: discovering trends and anomalies; and detecting and predicting events
  - Needs to query data intensively
- However, “canned” queries are difficult to frame
  - Needs interactive visualization to explore big urban data

Exploring NYC Taxis



Taxis are ***sensors*** that can provide unprecedented insight into city life: economic activity, human behavior, mobility patterns, …

"What is the average trip time from Midtown to the airports during weekdays?''

"How the taxi fleet activity varies during weekdays?"

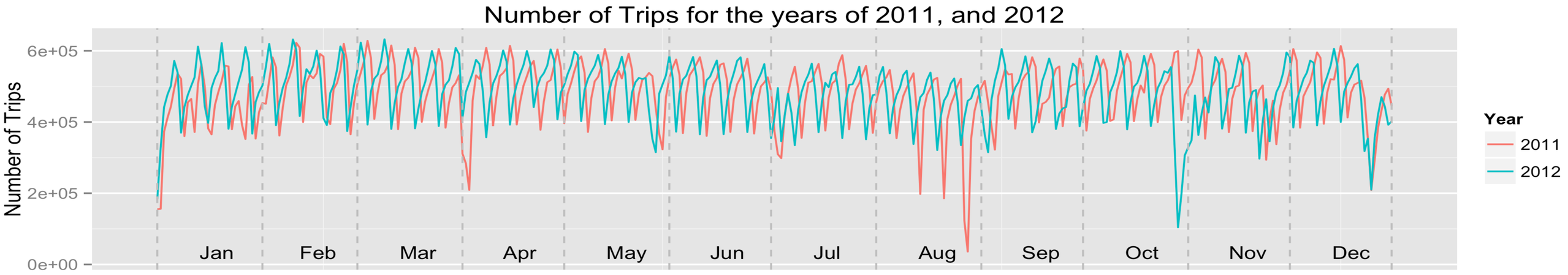
"How was the taxi activity in Midtown affected during a presidential visit?''

"How did the movement patterns change during Sandy?"

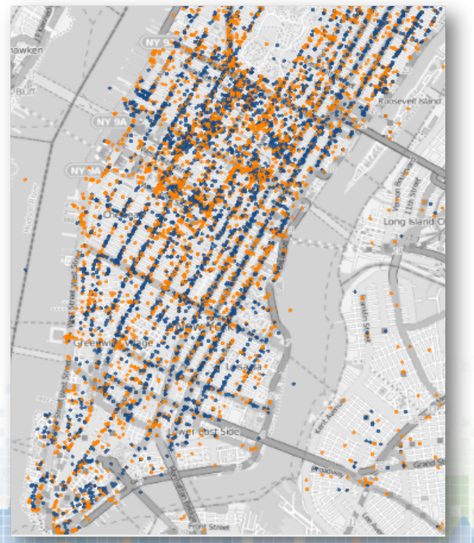
"Where are the popular night spots?"

[TVCG 2013]

Exploring NYC Taxis



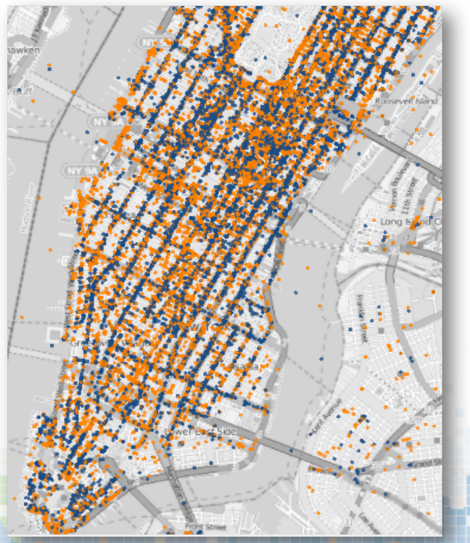
7-8am

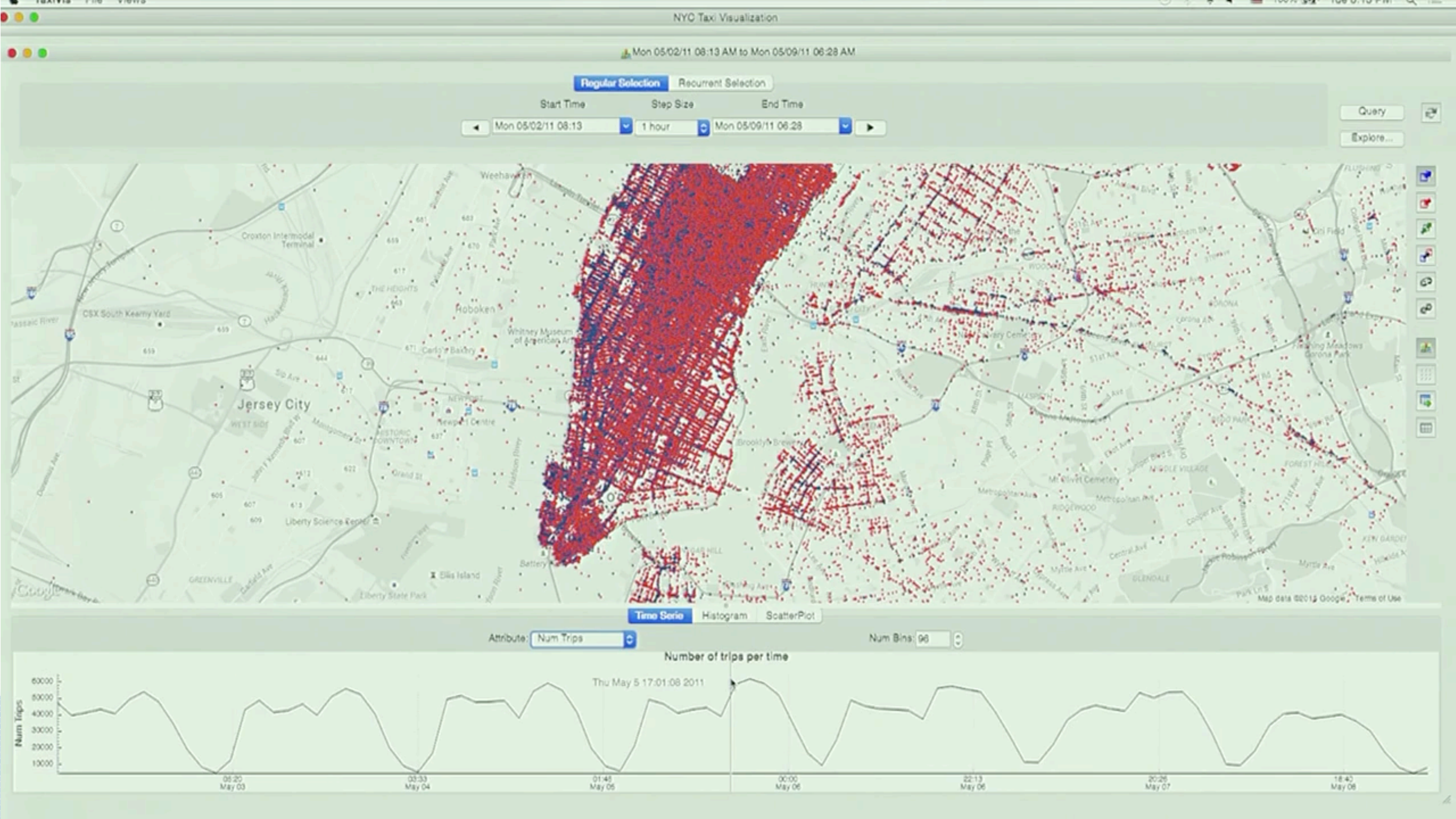


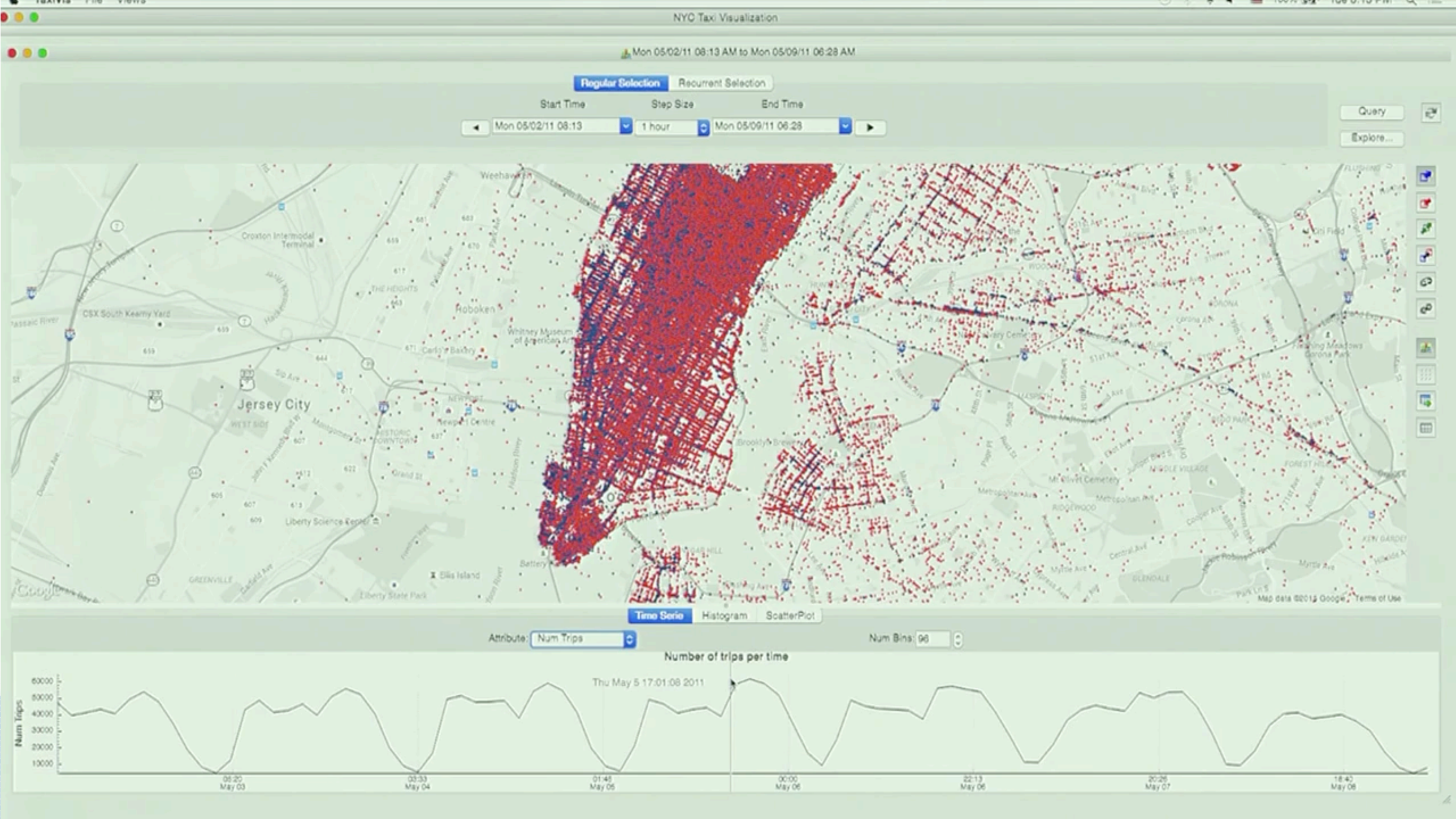
8-9am

9-10am

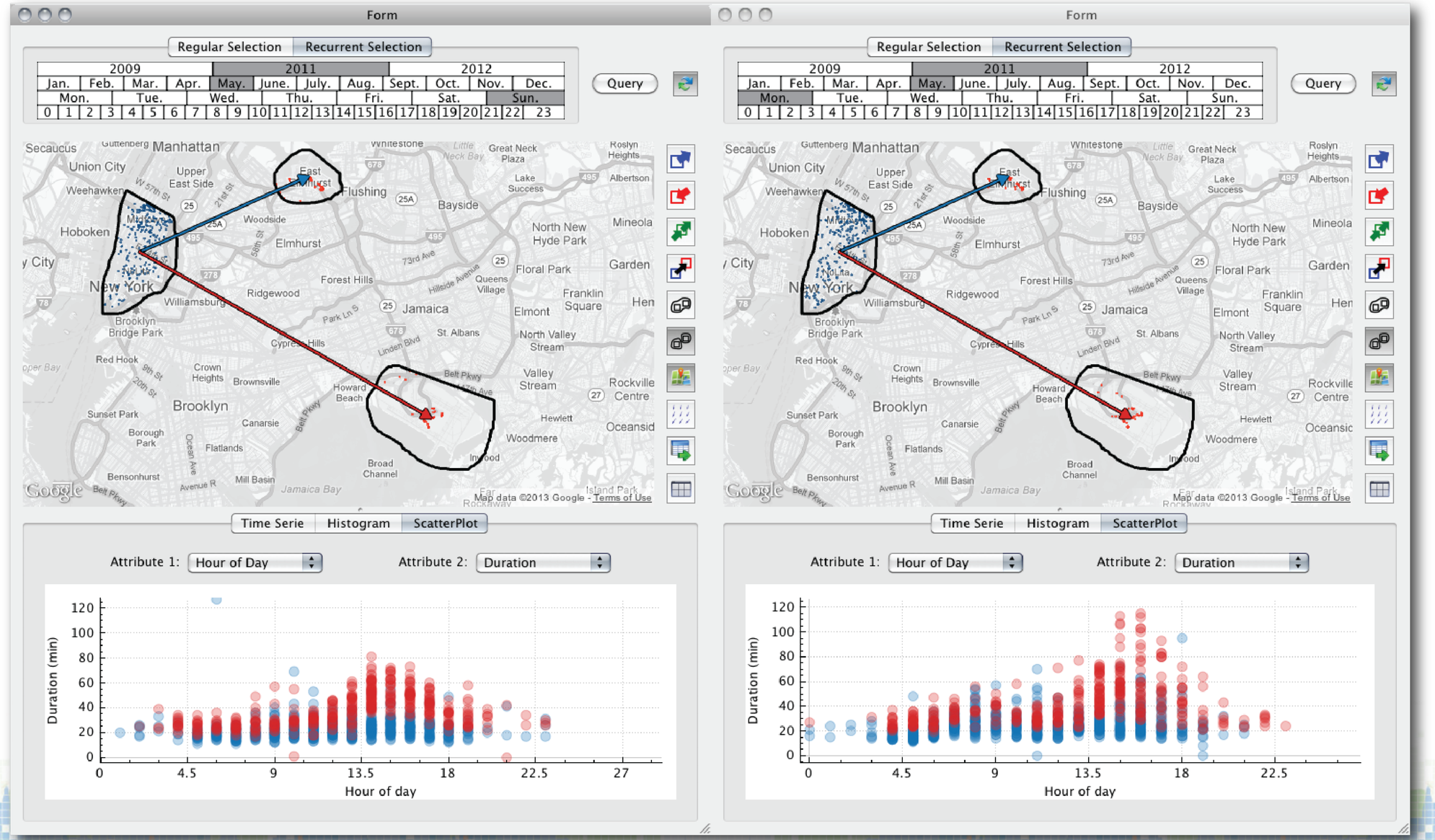
10-11am



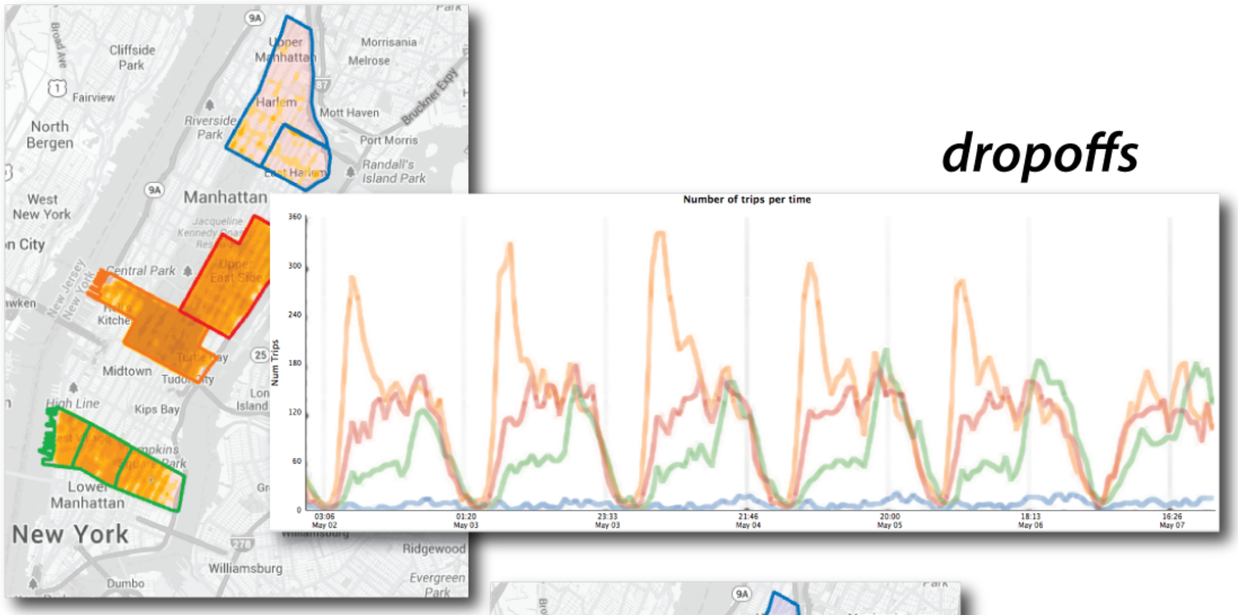

NYC Taxi Visualization
Mon 05/02/11 08:13 AM to Mon 05/09/11 06:28 AM
Regular Selection
Recurrent Selection
Start Time
Step Size
End Time
Mon 05/02/11 08:13
1 hour
Mon 05/09/11 06:28
Query
Explore...
Weehawken
Croxton Intermodal Terminal
CSX South Kearny Yard
Hoboken
Jersey City
Liberty Science Center
Ellis Island
Liberty State Park
Map data ©2012 Google Terms of Use
Time Series
Histogram
ScatterPlot
Attribute:
Num Trips
Num Bins:
96
Number of trips per time
Thu May 5 17:01:08 2011
Num Trips
60000
50000
40000
30000
20000
10000
06:20
May 03
03:33
May 04
01:46
May 05
00:00
May 06
22:13
May 06
20:26
May 07
18:40
May 08


NYC Taxi Visualization
Mon 05/02/11 08:13 AM to Mon 05/09/11 06:28 AM
Regular Selection
Recurrent Selection
Start Time
Step Size
End Time
Mon 05/02/11 08:13
1 hour
Mon 05/09/11 06:28
Query
Explore...
Weehawken
Croxton Intermodal Terminal
CSX South Kearny Yard
Hoboken
Jersey City
Liberty Science Center
Ellis Island
Liberty State Park
Map data ©2012 Google Terms of Use
Time Series
Histogram
ScatterPlot
Attribute:
Num Trips
Num Bins:
96
Number of trips per time
Thu May 5 17:01:08 2011
Num Trips
60000
50000
40000
30000
20000
10000
06:20
May 03
03:33
May 04
01:46
May 05
00:00
May 06
22:13
May 06
20:26
May 07
18:40
May 08

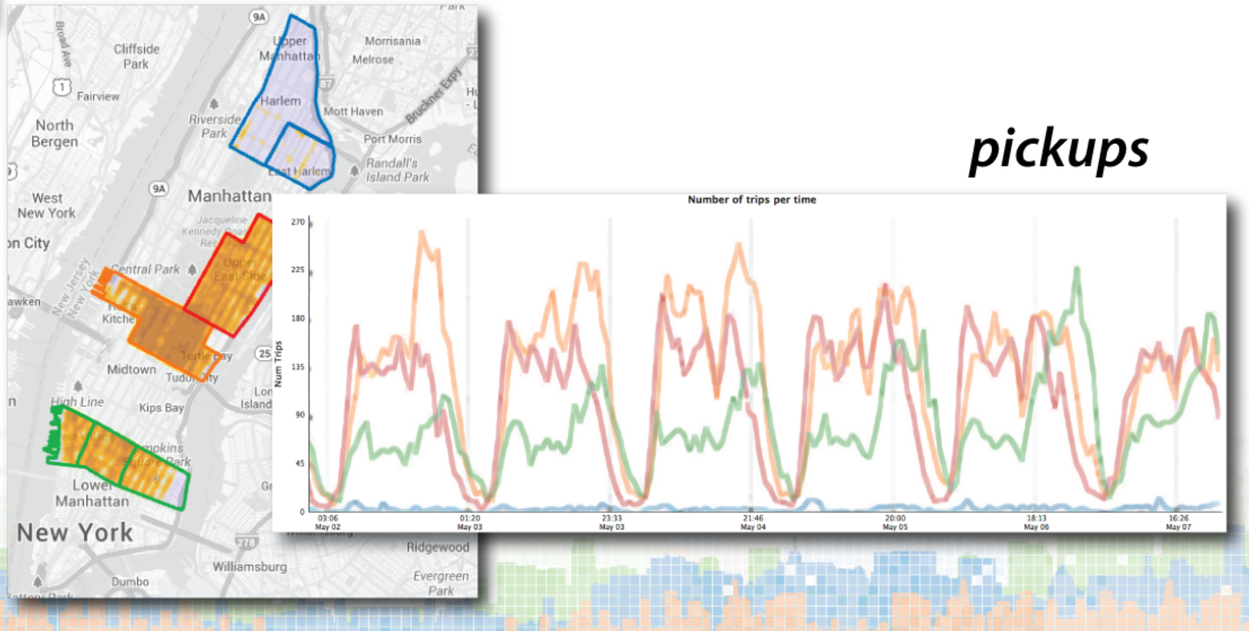
TaxiVis: Mobility



TaxiVis: Comparing Neighborhoods

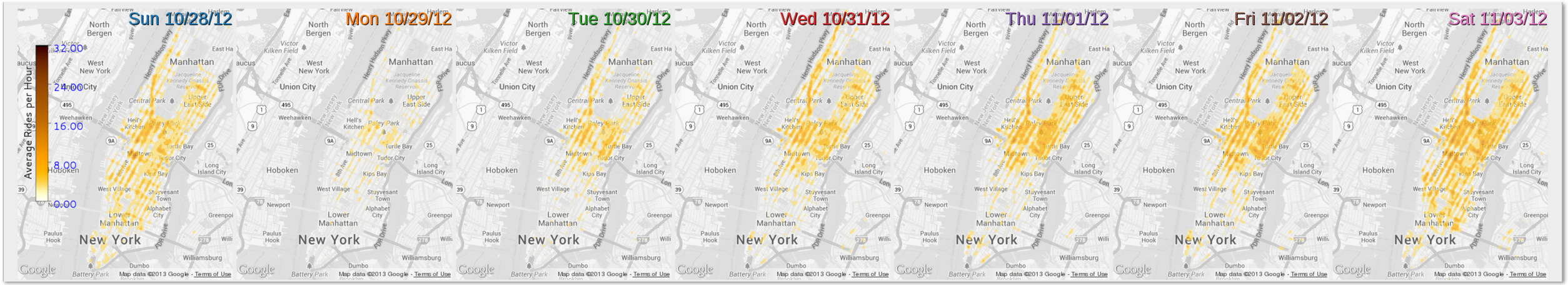


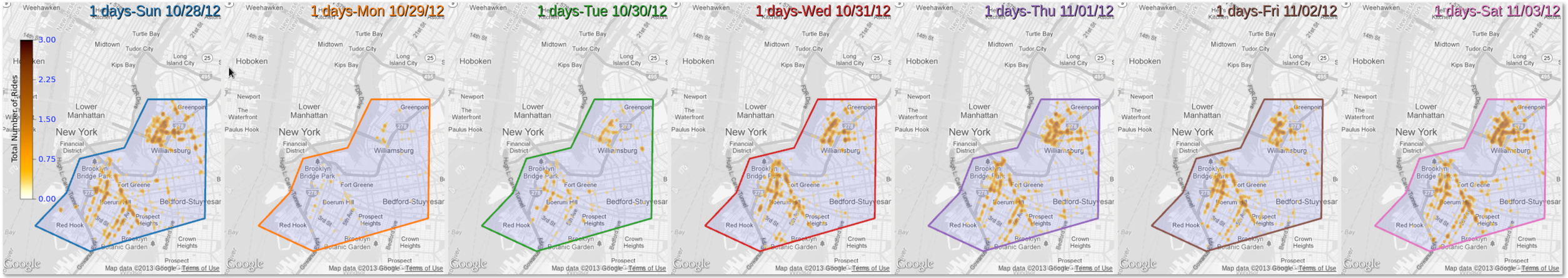
dropoffs



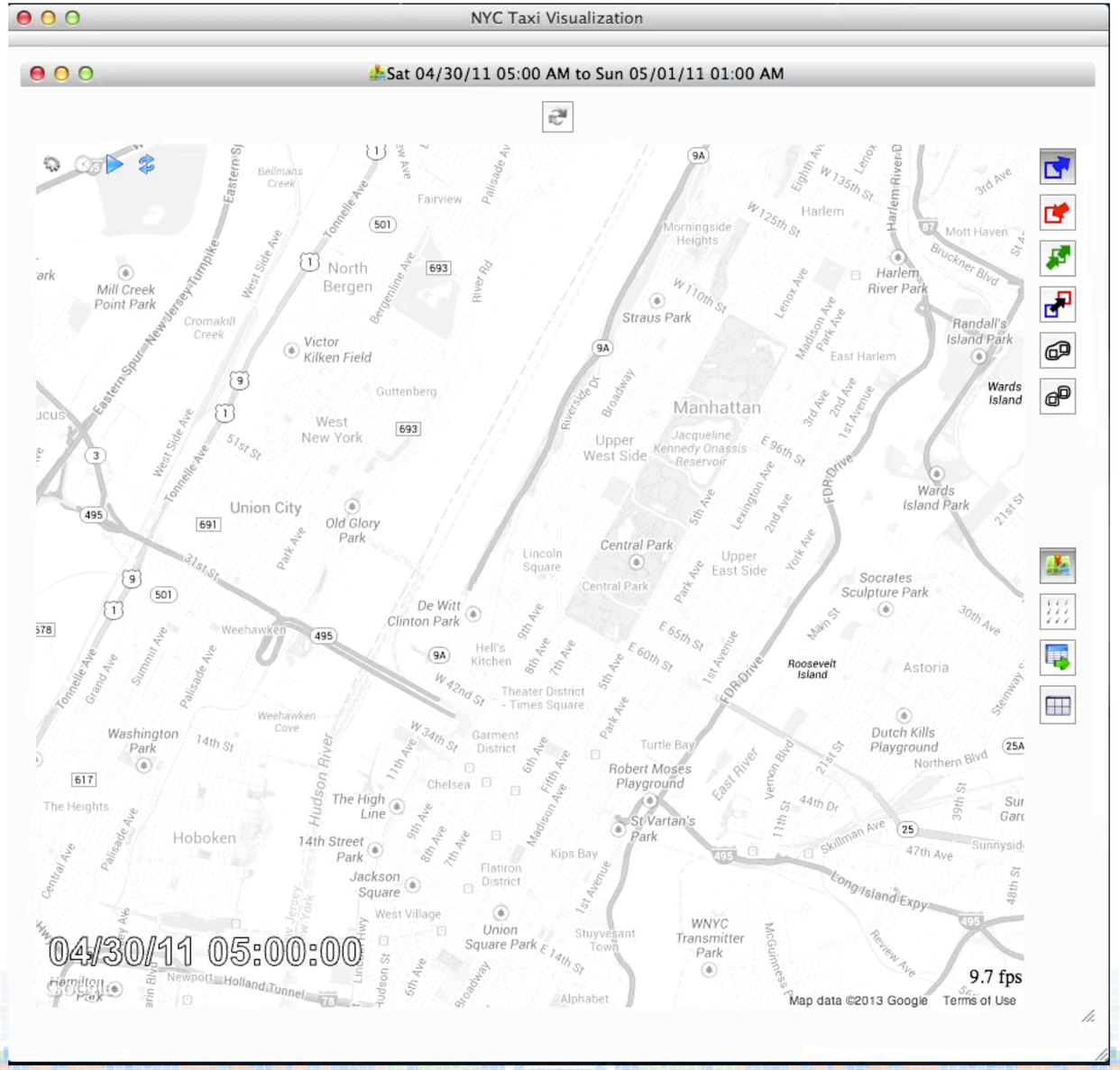
pickups

Exploring the Effect of Major Events: Sandy



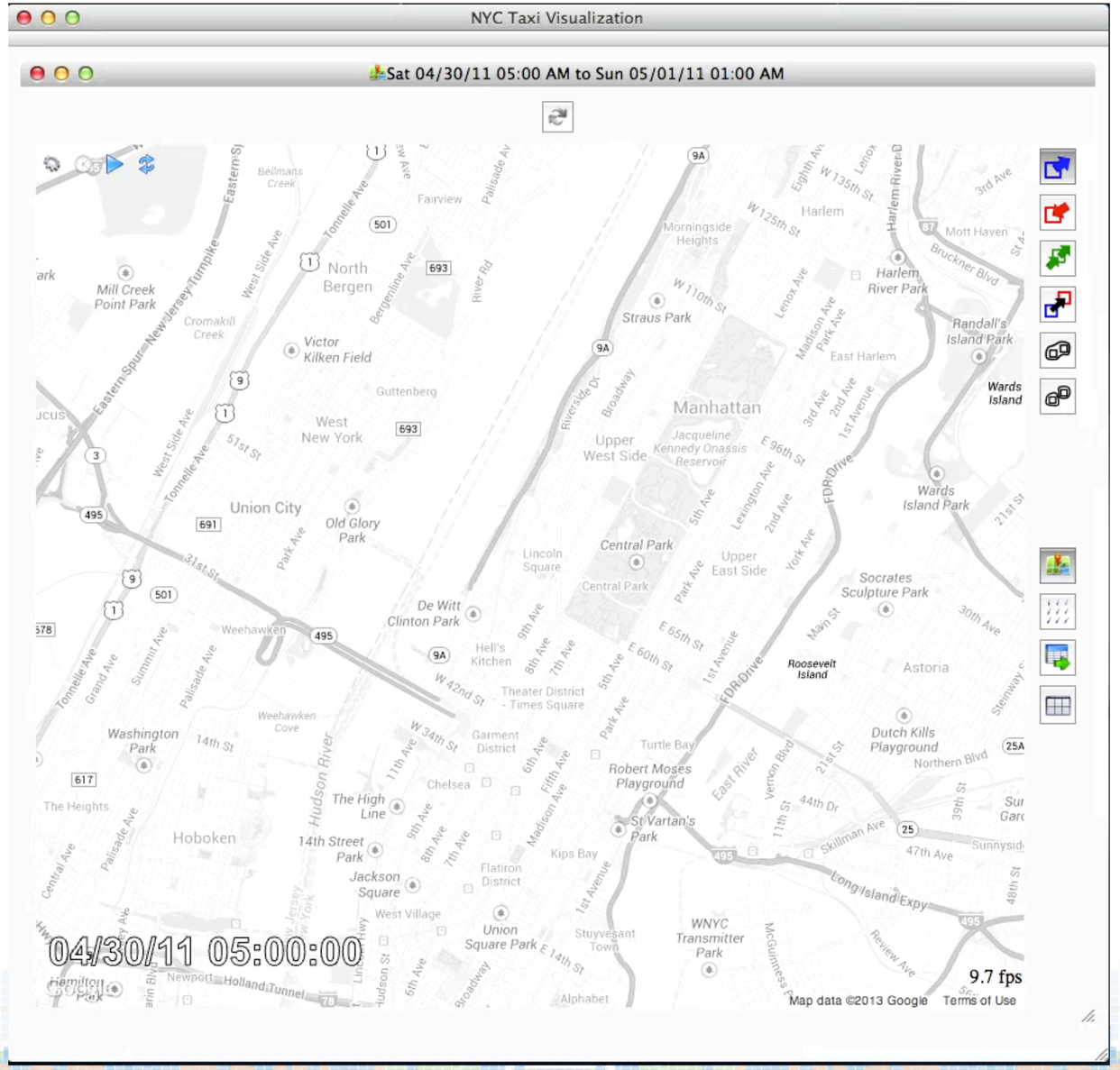


Life of a Taxi in a Day



[IEEE Big Data 2013]

Life of a Taxi in a Day



[IEEE Big Data 2013]

Thank you!