Introduction to Data Science Bootcamp

Big Data Analytics

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Download lecture notes and lab material

git clone https://github.com/julianafreire/2018-FGV-Big-Data

or from Dropbox

https://tinyurl.com/ychacmo6

Big Data: What is the **Big** deal?

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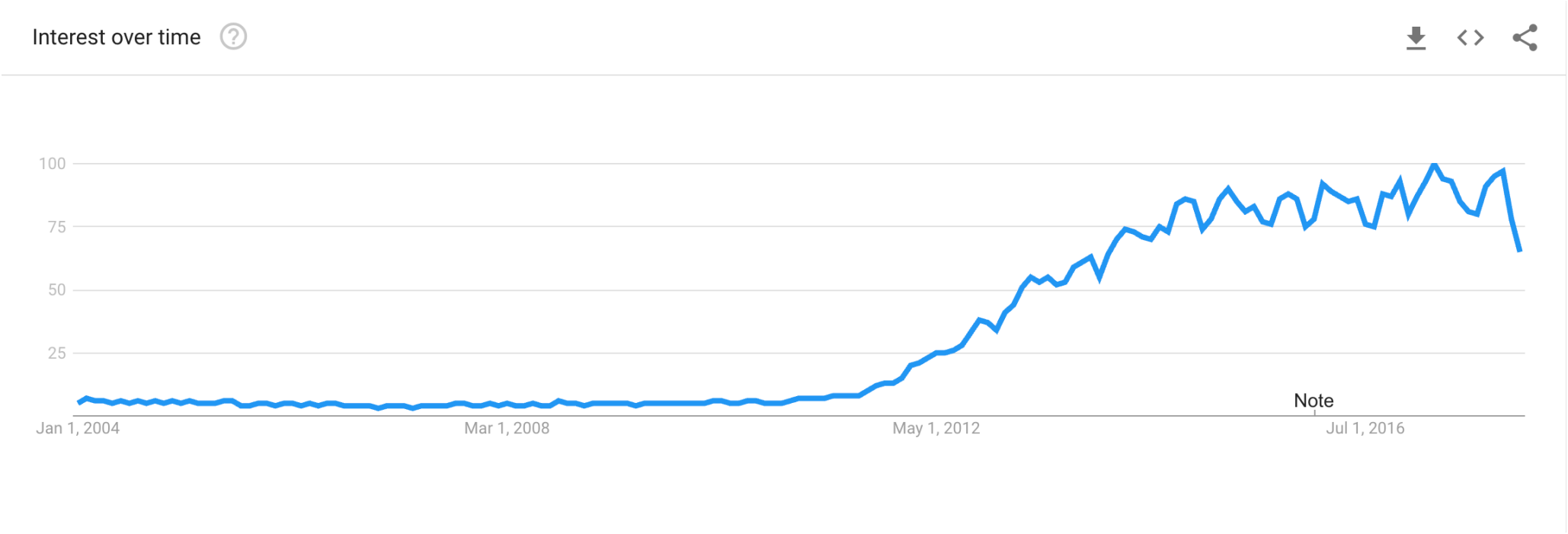
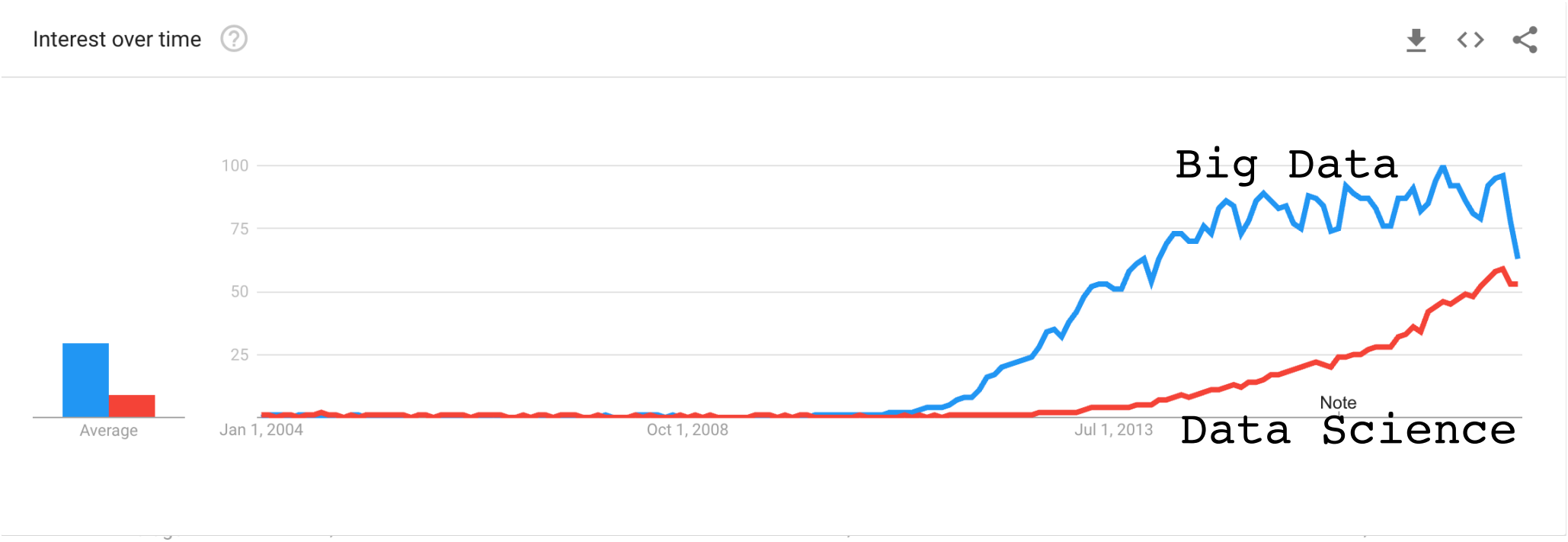
Google Trends: Big Data



https://www.google.com/trends/explore?date=all&q=big%20data

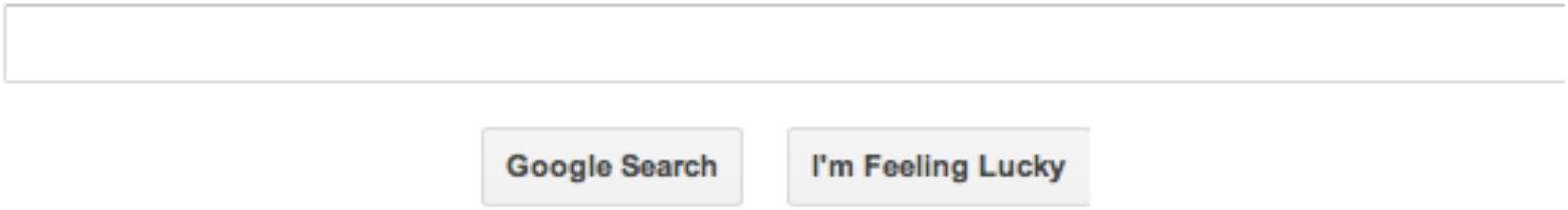
Google Trends: Big Data vs. Data Science



https://www.google.com/trends/explore?date=all&q=data%20science,big%20data

Big Data: What is the **Big** deal?

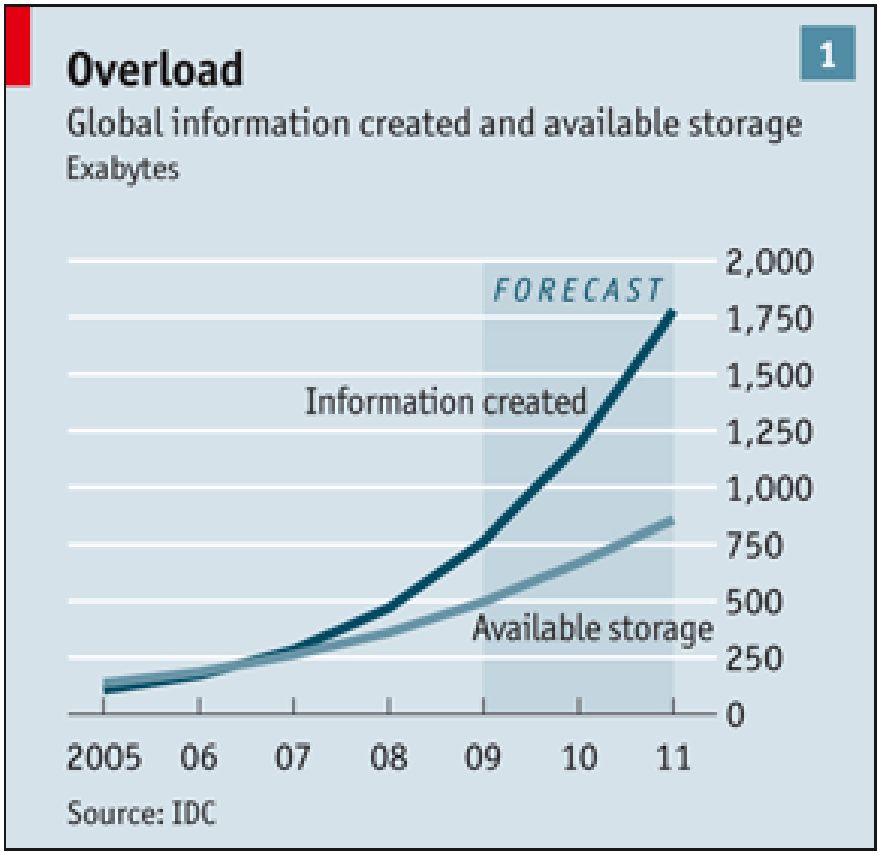
- Many success stories
  - Google: many billions of pages indexed, products, structured data
  - Facebook: 2.07 billion users each month
  - Twitter: 330 million monthly active users, **500 million tweets/day**
- This has changed society!



https://www.omnicoreagency.com/twitter-statistics
https://www.omnicoreagency.com/facebook-statistics/

Data Volumes are Exploding

- We are producing more data than we are able to store (or analyze!)

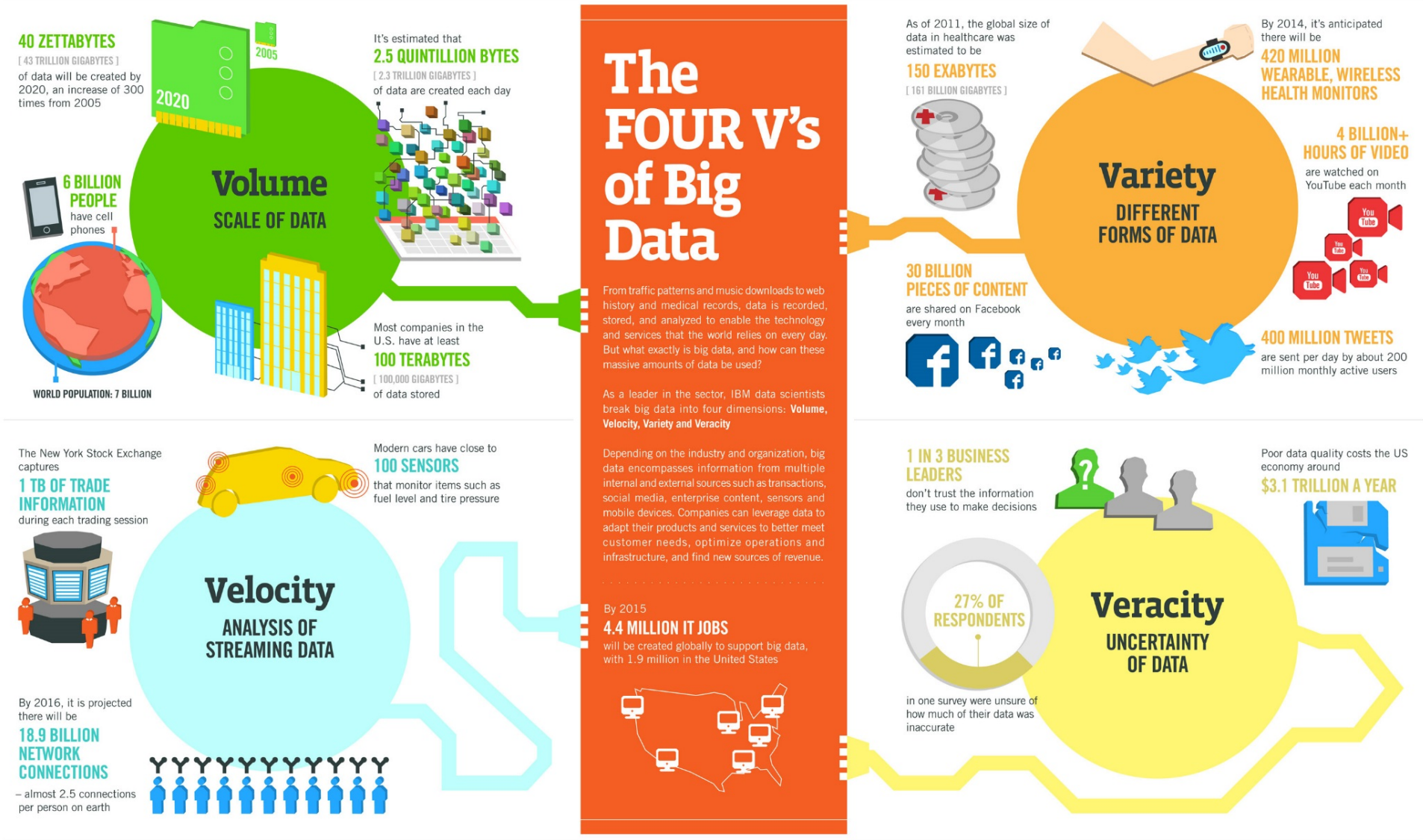


Economist, 2010

New Data and Applications

- Search engines – large-scale crawls, indexing, many users consuming data
  - 20 PB a day circa 2008
- Social networks – many users producing data
  - 2.5 PB of user data + 15 TB/day circa 4/2009
- Urban data – lots of sensors and data, need to clean, integrate, and analyze data
  - NYC Open Data: 1,200+ data sets
- Online shopping – many users consuming and producing data
- Science: Petabytes of data generated each day, e.g., Australian radio telescopes, Large Hadron Collider, climate,…
- Many new and diverse requirements for data management, no one-size-fits-all solution!

4 Vs of Big Data



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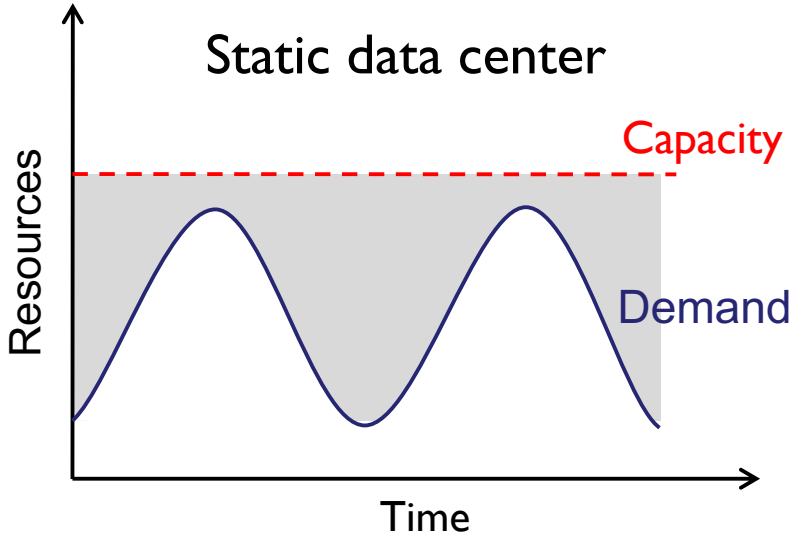
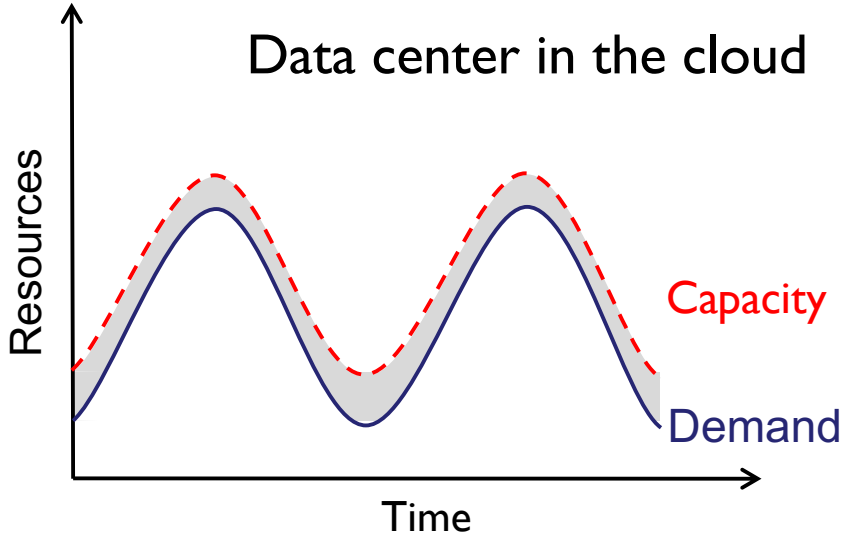
New Computing Infrastructure

- Meet the cloud!
- "[Hardware, Infrastructure, Platform] as a service"
- Utility Computing: pay-as-you-go computing
  - Illusion of infinite resources
  - No up-front cost
  - Fine-grained billing (e.g., hourly)





Warehouse Scale Computing

Google's data center in Oregon

Data Lifecycle

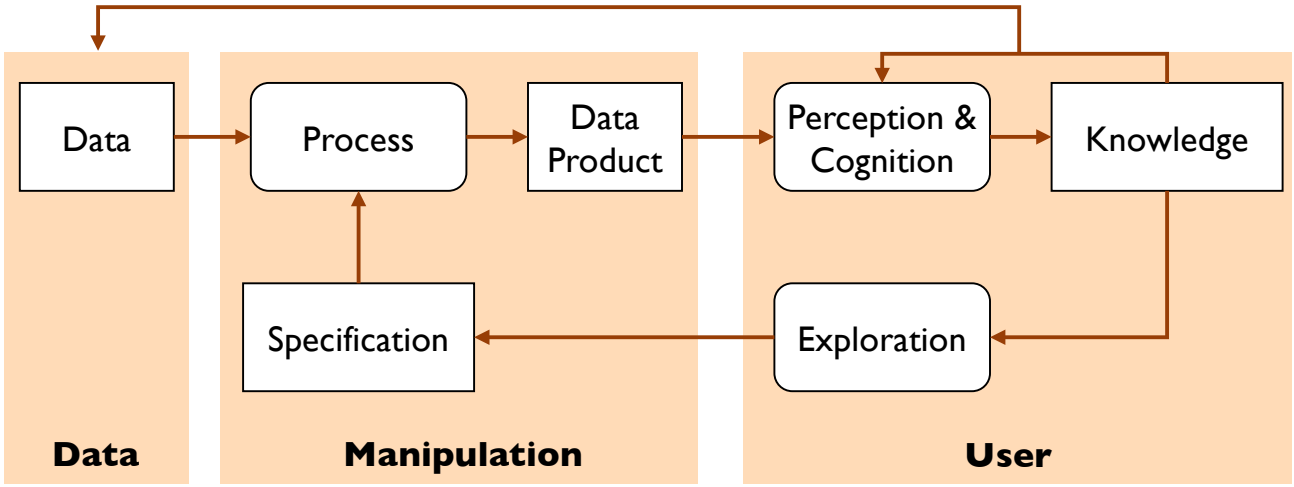
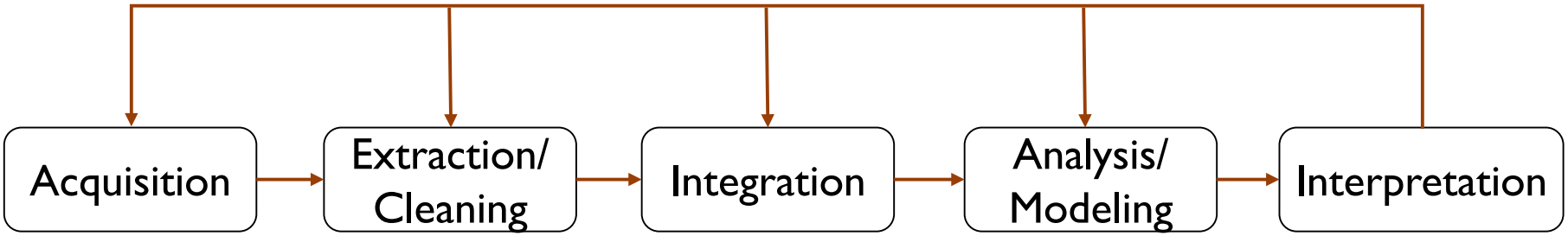


Figure modified from J. van Wijk, IEEE Vis 2005

Big Data Lifecycle



- The 4 Vs lead to new challenges and opportunities
- Data discovery: how to find relevant data?
- Large-scale cleaning and integration: 10s-100s of data sets
- Interactive analysis: how to handle very large data? How to find interesting ‘features’?
- Explainability and transparency

Outline

- Introduction to Programming with Big Data
  - Map Reduce vs. Parallel Databases
- Running Example: Big Urban Data
- Data Cleaning
  - Overview and Challenges
  - Cleaning the NYC Taxi Data: A Case Study
- Data exploration
  - Usability and Interactivity
  - Finding Interesting Features
  - Using Data to Discover and Explain Data
- Transparency and Reproducibility

New Programming Infrastructure: Map Reduce

MapReduce: Motivation

- Dean & Ghemawat, OSDI 2004

"many … at Google have implemented hundreds of special-purpose computations that process large amounts of raw data, such as crawled documents, web request logs, etc., to compute various kinds of derived data, such as inverted indices, …summaries of the number of pages crawled per host, the set of most frequent queries in a day…

Most such computations are conceptually straightforward…

issues of how to parallelize the computation, distribute the data, and handle failures conspire to obscure the original simple computation with large amounts of complex code to deal with these issues.''

Parallelization Challenges

- How do we assign work units to workers?
- What if we have more work units than workers?
- What if workers need to share partial results?
- How do we aggregate partial results?
- How do we know all the workers have finished?
- What if workers die?
- What if hardware fails?

What is the common theme of all of these problems?

Map Reduce: Big Ideas

- Abstraction
  - Hide system-level details from the developers
  - Developer specifies the computation that needs to be performed and the execution framework ("runtime") handles actual execution
- Scale out: Large number of commodity low-end servers is more effective for data-intensive applications
  - 8 128-core machines vs. 128 8-core machines
- Cope with common failures
  - Automatic task restarts
  - Store files multiple times for reliability
- Move processing to data
- Avoid random access: organize computations into long streaming operations

(Dean and Ghemawat, OSDI 2004)

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- Avoid random access: organize computations into long streaming operations

- 1 TB database containing 10^{10} 100 byte records
- Random access: each update takes ~30ms (seek,read, write)
  Updating 1% of the records takes ~35 days
- Sequential access: 100MB/s throughput
  Reading the whole database and rewriting all the records, takes 5.6 hours

(Dean and Ghemawat, OSDI 2004)

Typical Big-Data Problem

- Iterate over a large number of records
- Extract something of interest from each record
- Sort and shuffle intermediate results
- Aggregate intermediate results
- Generate final output

Key idea in Map Reduce: provide a functional abstraction for these two operations

(Dean and Ghemawat, OSDI 2004)

Typical Big-Data Problem in Map Reduce

- Iterate over a large number of records
- Map: Extract something of interest from each record

  map (k, v) → <k', v'>*

  There is one Map call for each (k,v) pair
- Sort and shuffle intermediate results
- Reduce: Aggregate intermediate results

  reduce (k', <v'>*) → <k', v''>*

  There is one Reduce per unique key k'
- Generate final output

Structure remains the same, Map and Reduce functions change to fit the problem

(Dean and Ghemawat, OSDI 2004)

Word Count in Python

```
def word_count_dict(filename):
  """Returns a word/count dict for this filename."""
  # Utility used by count() and Topcount().
  word_count = {} # Map each word to its count
  input_file = open(filename, 'r')
  for line in input_file:
    words = line.split()
    for word in words:
      word = word.lower()
      # Special case if we're seeing this word for the first time.
      if not word in word_count:
        word_count[word] = 1
      else:
        word_count[word] = word_count[word] + 1
  input_file.close() # Not strictly required, but good form.
  return word_count
```

https://github.com/mlafeldt/google-python-class/blob/master/basic/solution/wordcount.py

Word Count in Map Reduce

```
Map(String docid, String text):
    for each word w in text:
        Emit(w, 1);

Reduce(String term, Iterator<Int> values):
    int sum = 0;
    for each v in values:
        sum += v;
        Emit(term, value);
```

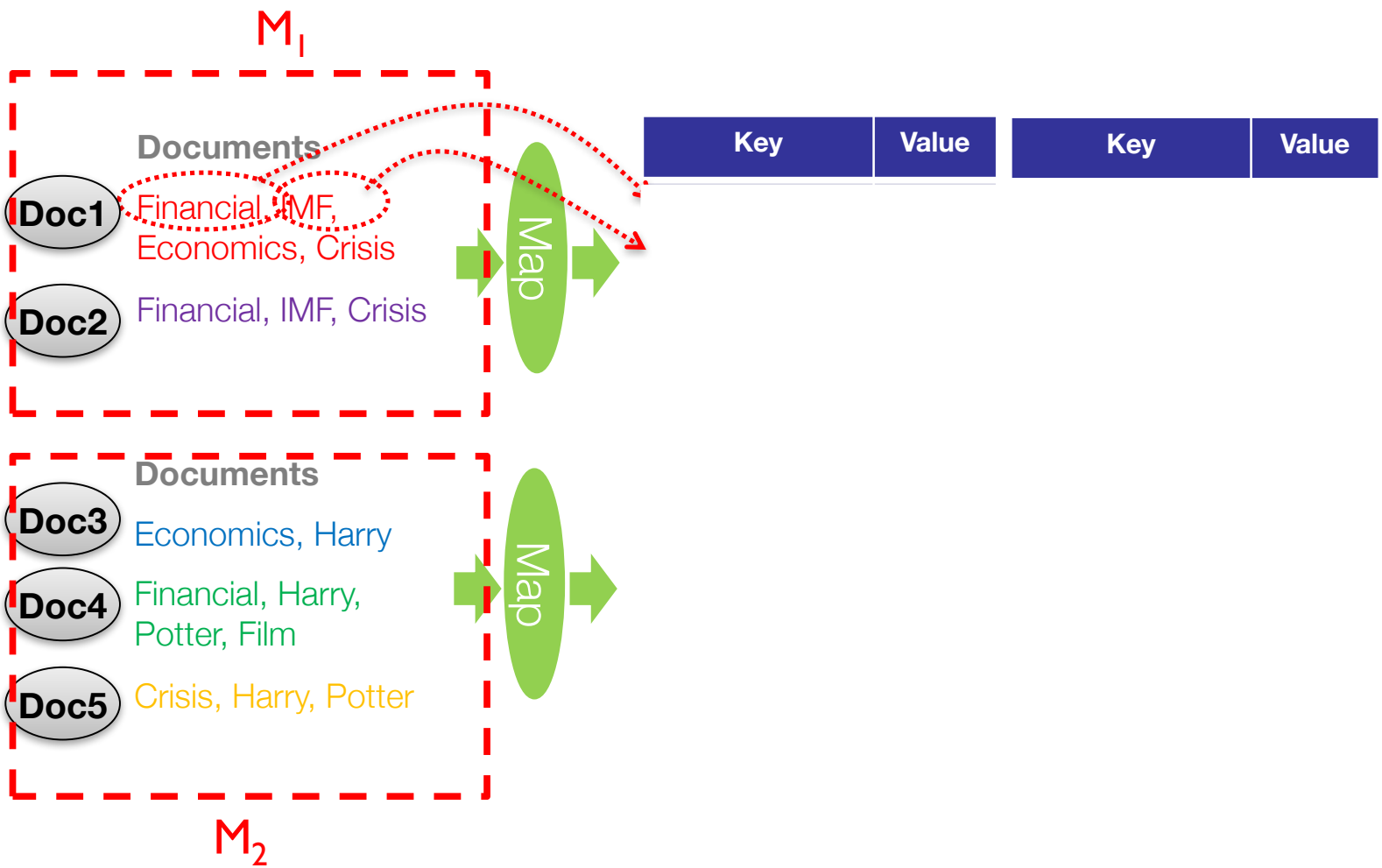
k_1 v_1 k_2 v_2

map (docid, text) → [(word, 1)]

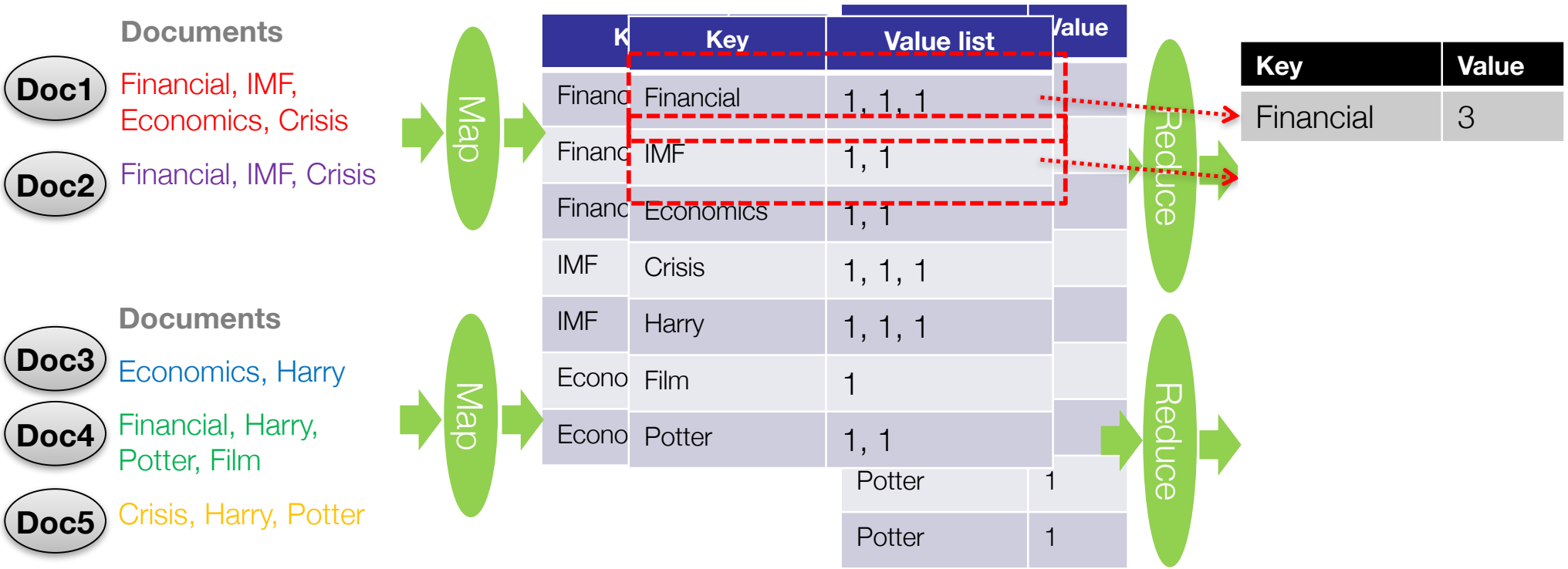
k_2 $[v_2]$ k_3 v_3

reduce (word, [1, …, 1]) → [(word, count)]

Word Counting with MapReduce



Word Counting with MapReduce



Before reduce functions are called, for each distinct key, a list of associated values is generated

Challenge Question

What is the average time spent per URL?

```
SELECT url, AVG(time)
FROM visits
GROUP BY url
```

URL	User	Time
www.google.com	Juliana	39
www.twitter.com	DJT	1456
www.twitter.com	Mary	300
www.cnn.com	John	123

How would you write this query in Map Reduce?

- Map over tuples, emit time, keyed by url
- Framework *automatically groups values by keys*
- Compute average in reducer

Designing Algorithms for Map Reduce

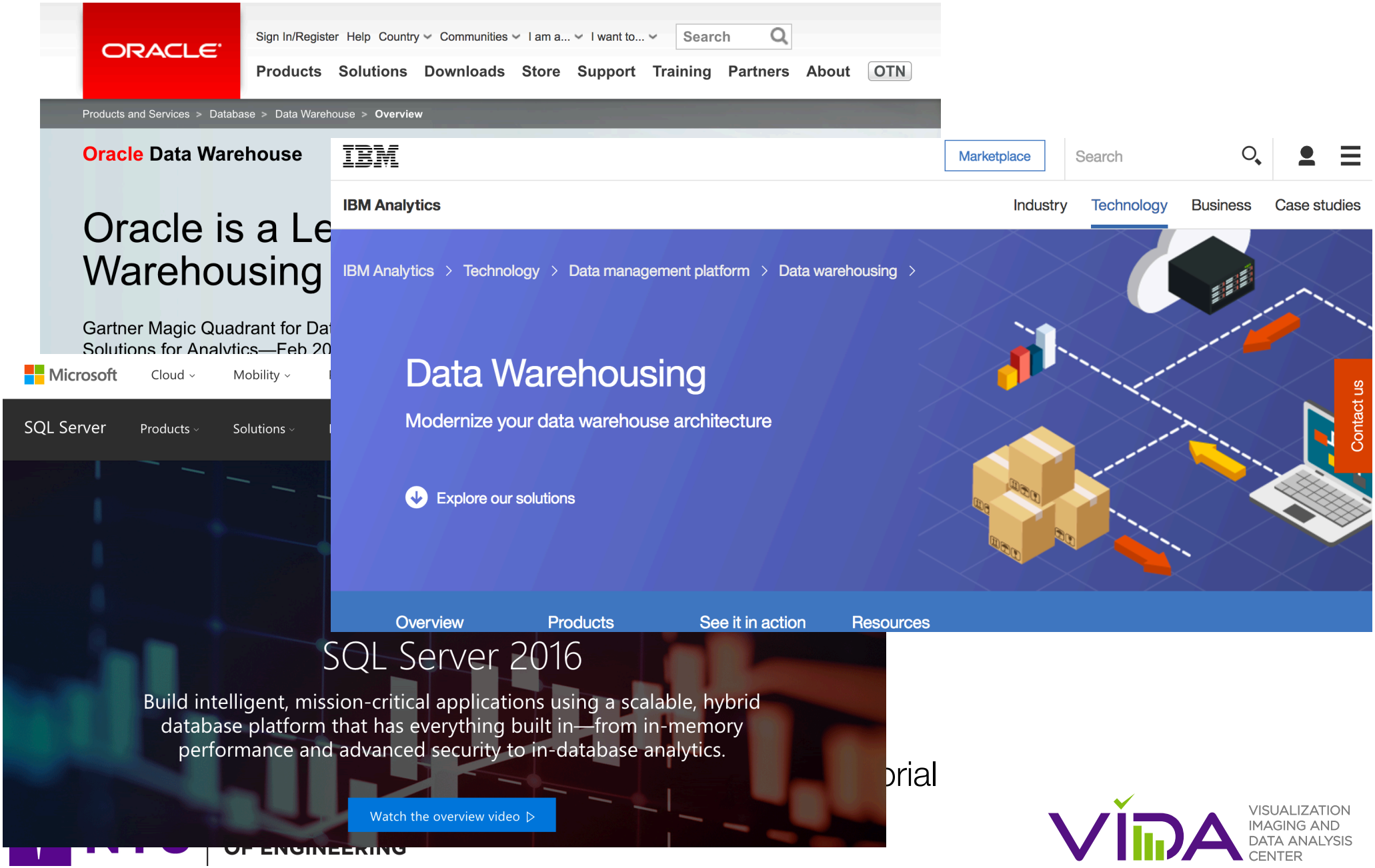
- Need to adapt to a restricted model of computation
- Goals
  - Scalability: adding machines will make the algorithm run faster
  - Efficiency: resources will not be wasted
- The translation some algorithms into MapReduce isn't always obvious
- But there are useful *design patterns* that can help
- All complexities related to parallelism and fault tolerance are automatically handled by the environment!

See Data-Intensive Text Processing with MapReduce
Jimmy Lin and Chris Dyer, 2010

Platforms for Large-Scale Data Analysis

- **Parallel DBMS technologies**
  - Proposed in the late eighties
  - Matured over the last two decades
  - Multi-billion dollar industry: Proprietary DBMS Engines intended as Data Warehousing solutions for very large enterprises
- **Map Reduce**
  - Data-parallel *programming model*
  - Works on the cloud
  - Pioneered by Google, and popularized by Yahoo! (open-source Hadoop)
  - [Dean et al., OSDI 2004, CACM Jan 2008, CACM Jan 2010]

Parallel DBMS technologies



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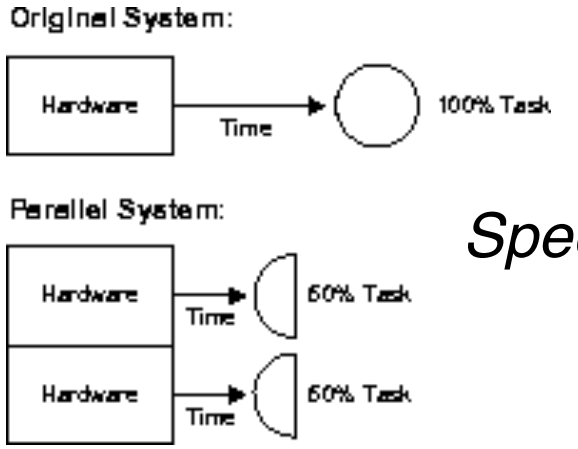
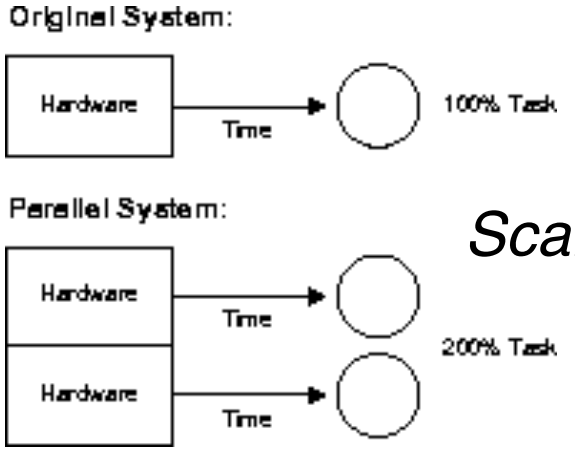
Parallel DBMSs

- Aim to improve performance by executing operations in parallel
- Benefit: easy and cheap to scale
  - Add more nodes, get higher speed
  - Reduce the time to run queries
  - Higher transaction rates
  - Ability to process more data
- Challenges: minimize overheads and efficiently deal with contention

docs.oracle.com



Speedup



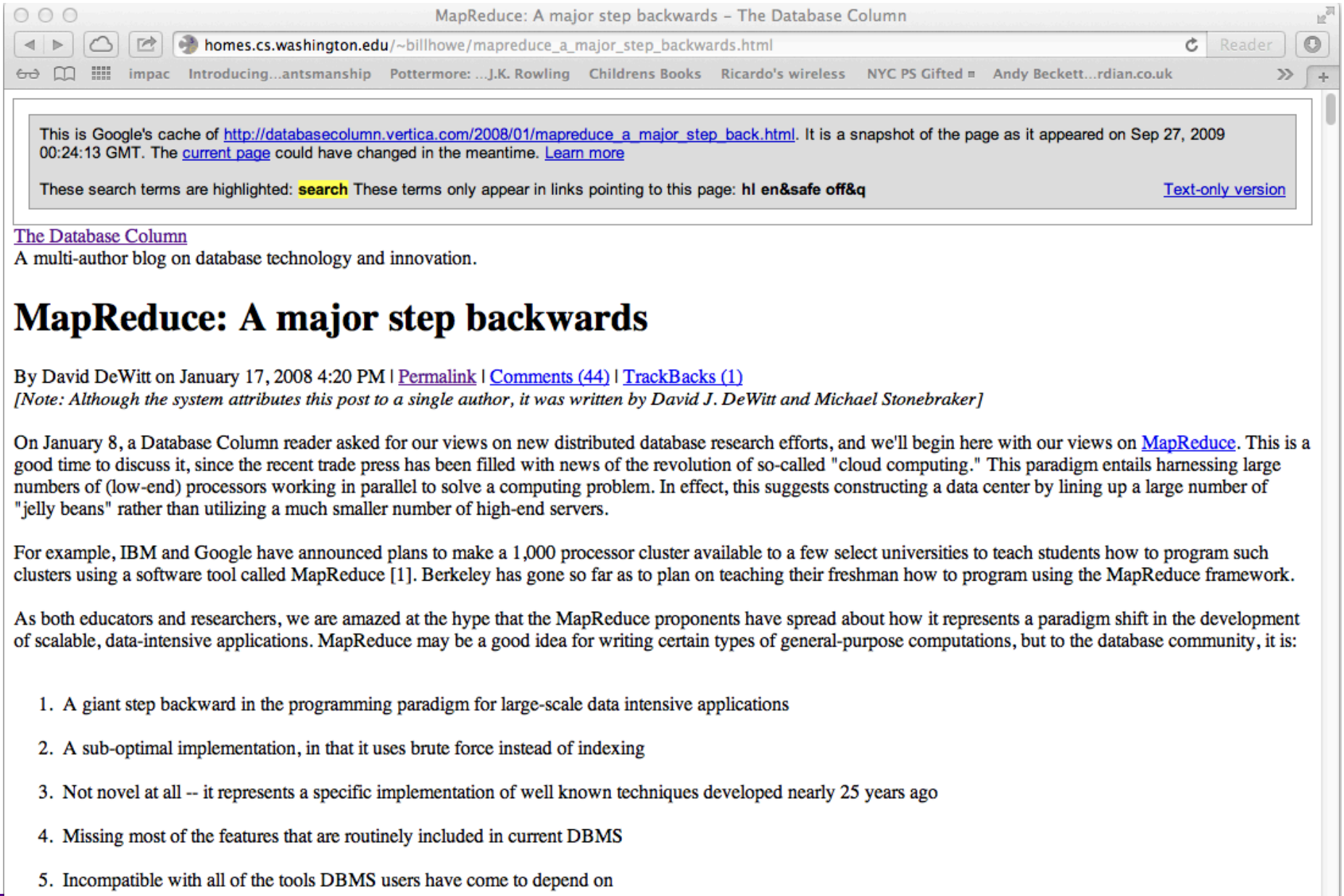
Scaleup

Parallel DBMS technologies

- Research Projects: Gamma, Grace – many papers!
- Popularly used for more than two decades
  - Commercial: Multi-billion dollar industry
- All the advantages of relational databases
  - Relational Data Model
  - Familiar SQL interface: declarative queries hide complexities from users
  - Advanced query optimization
  - Indexing
  - Data integrity and security
- *Well understood and studied*
- *Very reliable, easy for the end user*
- ***Very expensive***

Modified from Agrawal et al., VLDB 2010 Tutorial

The Debate Starts…



MapReduce: A major step backwards – The Database Column

homes.cs.washington.edu/~billhowe/mapreduce_a_major_step_backwards.html

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This is Google's cache of http://databasecolumn.vertica.com/2008/01/mapreduce_a_major_step_back.html. It is a snapshot of the page as it appeared on Sep 27, 2009 00:24:13 GMT. The current page could have changed in the meantime. Learn more

These search terms are highlighted: search These terms only appear in links pointing to this page: hl en&safe off&q Text-only version

The Database Column
A multi-author blog on database technology and innovation.

MapReduce: A major step backwards

By David DeWitt on January 17, 2008 4:20 PM | Permalink | Comments (44) | TrackBacks (1)
[Note: Although the system attributes this post to a single author, it was written by David J. DeWitt and Michael Stonebraker]

On January 8, a Database Column reader asked for our views on new distributed database research efforts, and we'll begin here with our views on MapReduce. This is a good time to discuss it, since the recent trade press has been filled with news of the revolution of so-called "cloud computing." This paradigm entails harnessing large numbers of (low-end) processors working in parallel to solve a computing problem. In effect, this suggests constructing a data center by lining up a large number of "jelly beans" rather than utilizing a much smaller number of high-end servers.

For example, IBM and Google have announced plans to make a 1,000 processor cluster available to a few select universities to teach students how to program such clusters using a software tool called MapReduce [1]. Berkeley has gone so far as to plan on teaching their freshman how to program using the MapReduce framework.

As both educators and researchers, we are amazed at the hype that the MapReduce proponents have spread about how it represents a paradigm shift in the development of scalable, data-intensive applications. MapReduce may be a good idea for writing certain types of general-purpose computations, but to the database community, it is:

1. A giant step backward in the programming paradigm for large-scale data intensive applications
2. A sub-optimal implementation, in that it uses brute force instead of indexing
3. Not novel at all -- it represents a specific implementation of well known techniques developed nearly 25 years ago
4. Missing most of the features that are routinely included in current DBMS
5. Incompatible with all of the tools DBMS users have come to depend on

http://homes.cs.washington.edu/~billhowe/mapreduce_a_major_step_backwards.html

The Debate Continues…

- A comparison of approaches to large-scale data analysis. Pavlo et al., SIGMOD 2009
  - http://dl.acm.org/citation.cfm?id=1559865; http://dsl.serc.iisc.ernet.in/~course/DBMS/papers/benchmarks-sigmod09.pdf
  - *Parallel DBMS beats MapReduce by a lot!*
  - Many were outraged by the comparison
- MapReduce: A Flexible Data Processing Tool. Dean and Ghemawat, CACM 2010
  - Pointed out inconsistencies and mistakes in the comparison
  - http://cacm.acm.org/magazines/2010/1/55744-mapreduce-a-flexible-data-processing-tool/fulltext
- MapReduce and Parallel DBMSs: Friends or Foes? Stonebraker et al., CACM 2010
  - Toned down claims…
  - http://cacm.acm.org/magazines/2010/1/55743-mapreduce-and-parallel-dbmss-friends-or-foes/fulltext

Map Reduce: Data Analytics in the Cloud

- Programming model that supports scalability for large data volumes: Divide-And-Conquer (i.e., *data partitioning*)
  - It is not a database!
- Cost-efficiency:
  - Commodity nodes (cheap, but unreliable)
  - Commodity network
  - Automatic fault-tolerance (fewer admins)
  - *Easy to use* (fewer programmers)

Complex Functions

- MapReduce was designed for *complex* tasks that manipulate diverse data:
  - Extract links from Web pages and aggregating them by target document
  - Generate inverted index files to support efficient search queries
  - Process all road segments in the world and rendering map images
- These data do not fit well in the relational paradigm
  - SQL is not Turing-complete!
- Parallel databases support
  - Tabular data
  - SQL operations
  - User Defined Functions (UDF), but these have limitations

Heterogeneous Systems

- MapReduce can support different storage backends and it can be used to combine data from different sources
  - Production MapReduce environments use a plethora of storage systems: files, RDBMS, Bigtable, column stores
  - http://static.googleusercontent.com/media/research.google.com/en//archive/bigtable-osdi06.pdf
- Parallel databases require all data to be pre-loaded and in the same system
  - Would you use a ParDB to load Web pages retrieved by a crawler and build an inverted index?

Structured Data and Schemas

S

- Schemas were key to the success of database: enable structured queries, efficiency, data sharing
- The original version of Hadoop had no support for schemas!
- Google's MapReduce implementation supports the Protocol Buffer format: high-level language is used to describe the input and output types
  - Platform-neutral, extensible mechanism for serializing structure data

https://developers.google.com/protocol-buffers/

  - Compiler-generated code hides the details of encoding/decoding data
  - Use optimized binary representation --- compact and faster to encode/decode; huge performance gains

Fault Tolerance

- Pull model is necessary to provide fine-grained fault tolerance
- It may lead to the creation of many small files on disk
- Use implementation tricks to mitigate these costs
  - Keep this in mind when writing your MapReduce programs!

Architectural Elements: ParDB vs. MR

- Schema support:
  - Relational paradigm: rigid structure of rows and columns
  - Flexible structure, but need to write parsers and challenging to share results
  - Use protocol buffers!
- Indexing
  - B-trees to speed up access
  - No built-in indexes --- programmers must code indexes
  - Can use MR-based storage systems
- Programming model
  - Declarative, high-level language
  - Imperative, write programs
  - SQL and other higher-level languages are supported
- Data distribution
  - Use knowledge of data distribution to automatically optimize queries
  - Programmer must optimize the access

Architectural Elements: ParDB vs. MR

- Execution strategy and fault tolerance:
  - Pipeline operators (push), failures dealt with at the transaction level – if a single node fails, the entire query must be restarted
  - Write intermediate files (pull), provide fault tolerance
  - Can use Spark instead of MR

Map Reduce: Takeaway

- MapReduce's data-parallel programming model hides complexity of distribution and fault tolerance

- Principal philosophies:
  - *Make it scale*, so you can throw hardware at problems
  - *Make it cheap*, saving hardware, programmer and administration costs (but requiring fault tolerance)

- Map Reduce is not suitable for all problems, but when it works, it may save you a lot of time

Beyond Map Reduce

- Spark: leverage main memory to support streaming + analytics + iterative computations

  https://spark.apache.org/

- DB features added to the *Cloud* environment
  - Shark: large-scale data warehouse system for Spark
    - SQL API https://amplab.cs.berkeley.edu/software/
    - Now https://spark.apache.org/sql/
  - HadoopDB: hybrid of DBMS and MapReduce technologies that targets analytical workloads
  - Apache Hbase: random, real-time read/write access to Big Data
  - Apache Accumulo (https://accumulo.apache.org): distributed key/value store – similar to BigTable
  - ElasTraS: An elastic, scalable, and self-managing transactional database for the cloud

Beyond Map Reduce

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"Spark can be as much as 10 times faster than MapReduce for batch processing and up to 100 times faster for in-memory analytics"

Map Reduce Implementations

- Google has a proprietary implementation in C++
  - Bindings in Java, Python
- Hadoop is an open-source implementation in Java
  - Development led by Yahoo, used in production
  - Now an Apache project
  - Rapidly expanding software ecosystem
- Lots of custom research implementations
  - For GPUs, cell processors, etc.

Map Reduce: References

- You can get free time on AWS and Azure
  - https://www.awseducate.com/Registration
  - https://azure.microsoft.com/en-us/free
- Several online tutorials
- http://hadoop.apache.org
- Jeffrey Dean and Sanjay Ghemawat, MapReduce: Simplified Data Processing on Large Clusters. Usenix OSDI, 2004: http://www.usenix.org/events/osdi04/tech/full_papers/dean/dean.pdf
- David DeWitt, Michael Stonebraker, MapReduce: A major step backwards, craighenderson.blogspot.comhttp://scienceblogs.com/goodmath/2008/01/databases_are_hammers_mapreduc.php
- Mining of Massive Data Sets (version 2.1), by Anand Rajaraman, Jure Leskovec and Jeff Ullman. http://www.mmds.org
- Data-Intensive Text Processing with MapReduce, by Jimmy Lin and Chris Dyer. http://lintool.github.com/MapReduceAlgorithms/index.html

Free!

Running Example:
Big Urban Data

Urban Data: What is the **Big** deal?

- Cities are the loci of economic activity
- 50% of the world population lives in cities, by 2050 the number will grow to 70%
- Growth leads to problems, e.g., transportation, environment and pollution, housing, infrastructure
- Good news: Lots of data being collected from traditional and *unsuspecting* sensors

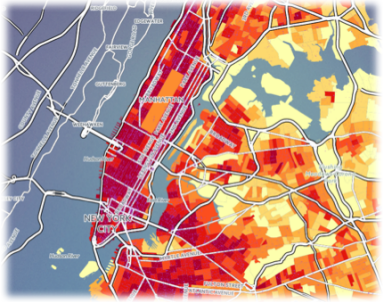
Data Exhaust from Cities

Infrastructure

Condition, Operations

Environment

Meteorology, pollution, noise, flora, fauna

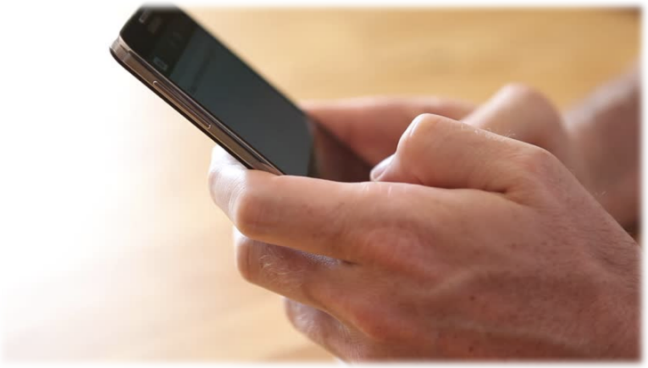


People

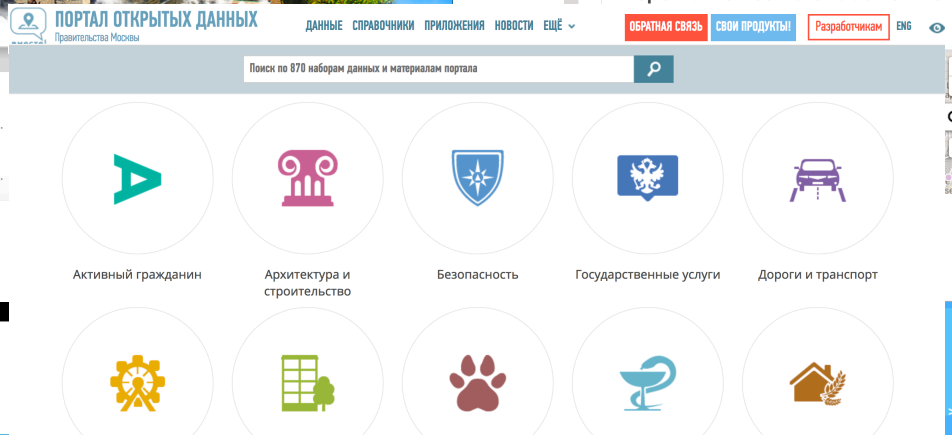
Relationships, economic activities, health, nutrition, opinions, …

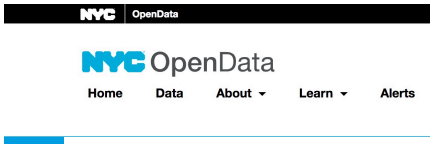
flickr

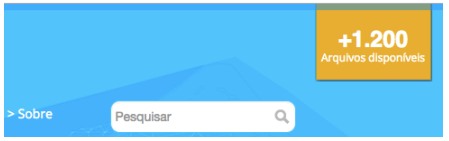
twitter



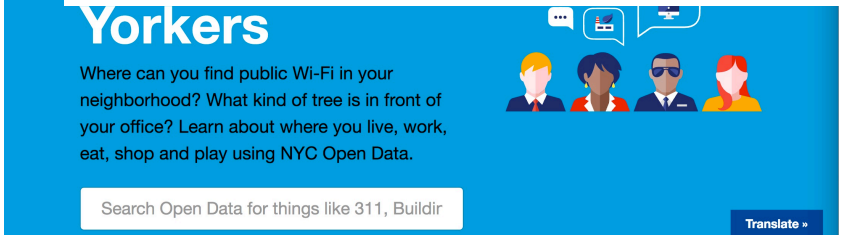
Data Exhaust from Cities

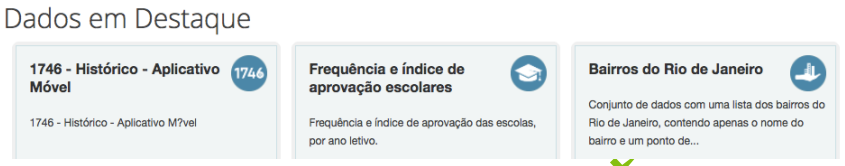






Opportunity: Use data to make cities more efficient and sustainable, and improve the lives of their residents





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Urban Data: Success Stories

OneBusAway

Serving up fresh real-time transit information for the region.

http://onebusaway.org

- Real-time arrival predictions
- 94% reported increased or greatly increased satisfaction with public transit
- Significant decrease in actual wait time per user, and an even greater decrease in *perceived* wait time
- 78% of riders reported increased walking – a significant public health benefit

Benefit residents

Urban Data: Success Stories

- NYC gets 25,000 illega complaints a year and **inspectors** to handle
- Data-driven approach
  1. Integrated information from 19 different agencies that provided indication of issues in buildings, e.g., late taxes, foreclosure proceedings, service cuts, ambulance visits, rodent infestation, crime
  2. Compared with 5 years of fire data
  3. Created a prediction system

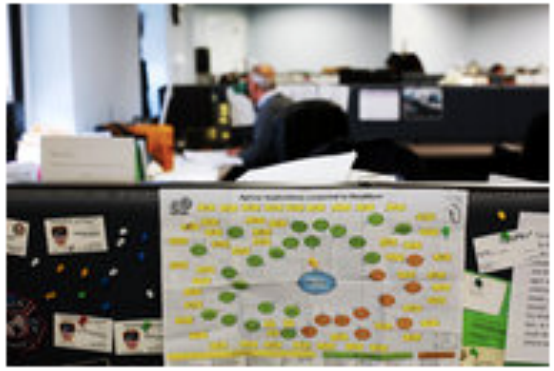
- Result: hit rate for inspections went from 13% to 70%

major fire hazards, cauldrons of crime, drugs, disease, and pest infestation

Todd Heisler/The New York Times

Michael Flowers, right, oversees a small group of tech-savvy and civic-minded statisticians working across from City Hall.

Enlarge This Image



Todd Heisler/The New York Times

"All we do," Mr. Flowers said, is "process massive amounts of information and use it to do things more effectively."

Make City more efficient

Urban Data: What is hard?

Infrastructure

Condition, operations

Environment

Meteorology, pollution, noise, flora, fauna

People

Relationships, economic activities, health, nutrition, opinions, …

- City components interact in complex ways over space and time
- Need to analyze the city *data exhaust* to understand these interactions

Urban Data: What is hard?

- There are lots of data, but how can we **discover** what is relevant for a given question/analysis?
- Data are **dirty and heterogeneous**
- **Data analysis and modeling** is challenging even for skilled data scientists

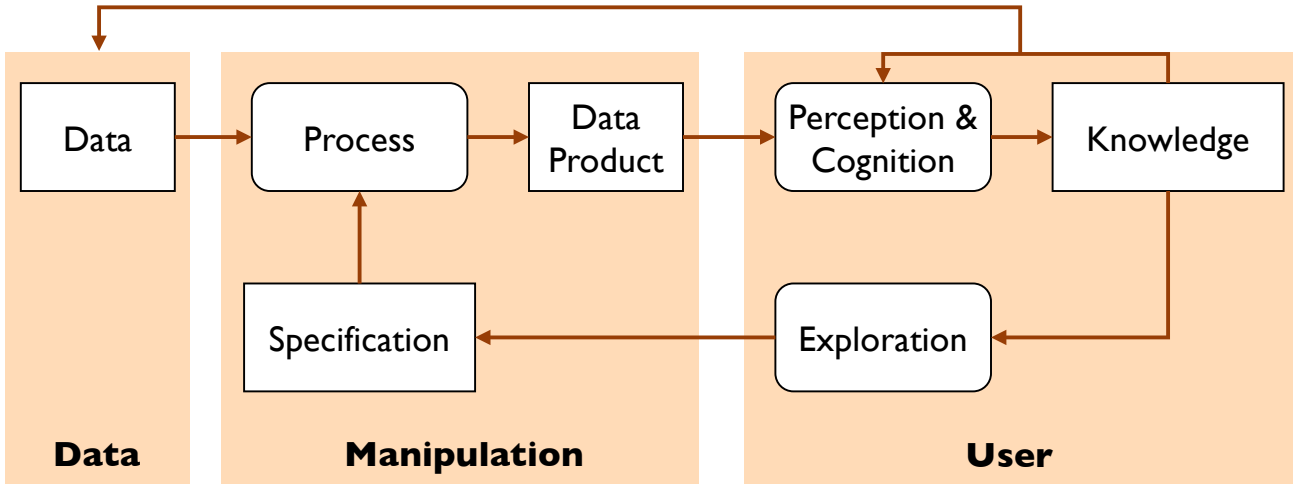


Figure modified from J. van Wijk, IEEE Vis 2005

Urban Data: What is hard?

- There are lots of data, but how can we **discover** what is relevant for a given question/analysis?
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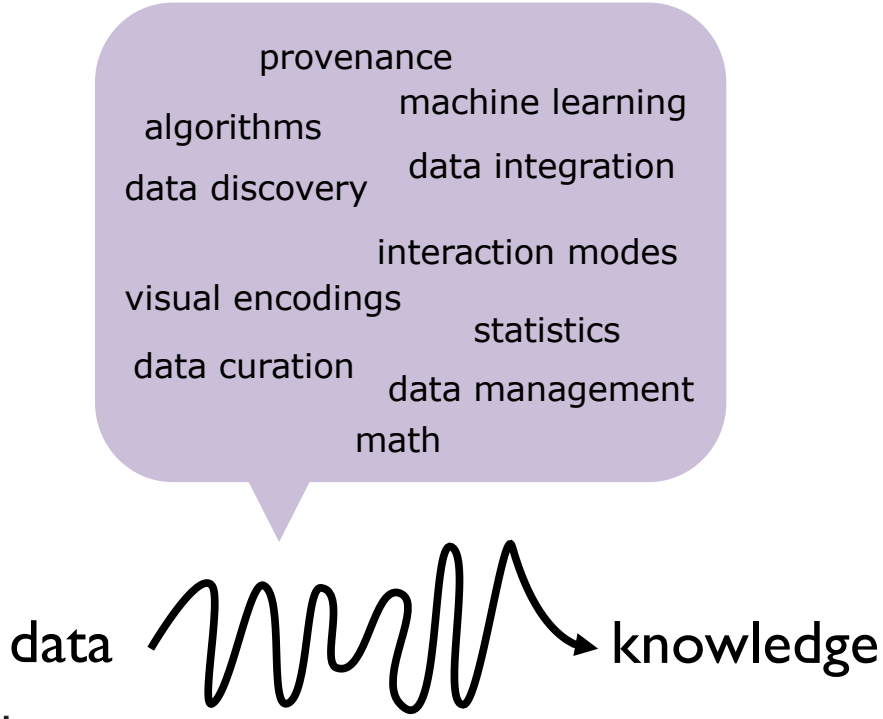

Urban Data Analysis: Desiderata

- Scalable tools and techniques that help *domain experts* find, clean, integrate, *interactively* explore and explain data
- Cater to different kinds of users with little or no CS training
- *Automate* tedious tasks as much as possible
- Guide users in the exploration process

Data analysis for all!

Big Data Analysis: Desiderata

- Scalable tools and techniques that help *domain experts* find, clean, integrate, *interactively* explore and explain data
- Cater to different kinds of users with little or no CS training
- *Automate* tedious tasks as much as possible
- Guide users in the exploration process

Data analysis for all!

Skip to outline

Open Urban Data (as of 2014)

- Study: 20 cities in North America, 9,000 data sets
- Investigated
  - Nature of the data
  - Opportunities for integration

"People are tribal, but data doesn't care"

Mike Flowers

[Barbosa et al., Big Data 2014]

STRUCTURED OPEN URBAN DATA:

Understanding the Landscape

Luciano Barbosa,[1] Kien Pham,[2] Claudio Silva,[2,3] Marcos R. Vieira,[1] and Juliana Freire[2,3]

Abstract

A growing number of cities are now making urban data freely available to the public. Besides promoting transparency, these data can have a transformative effect in social science research as well as in how citizens participate in governance. These initiatives, however, are fairly recent and the landscape of open urban data is not well known. In this study, we try to shed some light on this through a detailed study of over 9,000 open data sets from 20 cities in North America. We start by presenting general statistics about the content, size, nature, and popularity of the different data sets, and then examine in more detail structured data sets that contain tabular data. Since a key benefit of having a large number of data sets available is the ability to fuse information, we investigate opportunities for data integration. We also study data quality issues and time-related aspects, namely, recency and change frequency. Our findings are encouraging in that most of the data are structured and published in standard formats that are easy to parse; there is ample opportunity to integrate different data sets; and the volume of data is increasing steadily. But they also uncovered a number of challenges that need to be addressed to enable these data to be fully leveraged. We discuss both our findings and issues involved in using open urban data.

Introduction

For the first time in history, more than half of the world's population lives in urban areas[1]; in a few decades, the world's population will exceed 9 billion, 70% of whom will live in cities. The exploration of urban data will be essential to inform both policy and administration, and enable cities to deliver services effectively, efficiently, and sustainably while keeping their citizens safe, healthy, prosperous, and well-informed.[2–4]

While in the past, policymakers and scientists faced significant constraints in obtaining the data needed to evaluate their policies and practices, recently there has been an explosion in the volume of open data. In an effort to promote transparency, many cities in the United States and around the world are publishing data collected by their governments (see, e.g., refs.[5–8]).

Having these data available creates many new opportunities. In particular, while individual data sets are valuable, by integrating data from multiple sources, the integrated data are often more valuable than the sum of their parts. The benefits of integrating city data have already led to many success stories. In New York City (NYC), by combining data from multiple agencies and using predictive analytics, the city increased the rate of detecting dangerous buildings, as well as improved the return on the time of building inspectors looking for illegal apartments.[2] Policy changes have also been triggered by studies that, for example, showed correlations

[1]IBM Research, Rio de Janiero, Brazil.
[2]Department of Computer Science and Engineering, NYU School of Engineering, Brooklyn, New York.
[3]NYU Center for Urban Science and Progress, Brooklyn, New York.

BIG DATA SEPTEMBER 2014 • DOI: 10.1089/big.2014.0020

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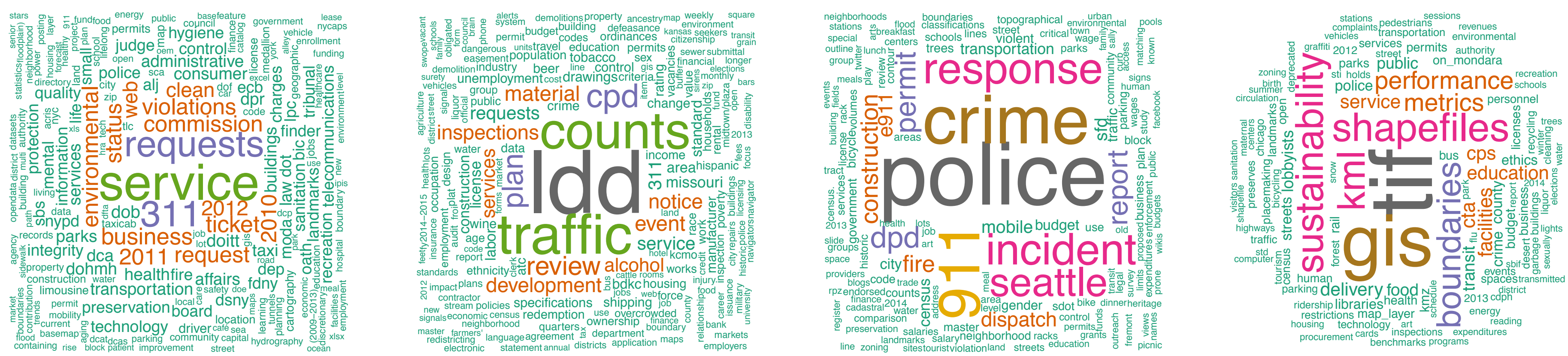
Some Findings

- 75% of the data sets are available in tabular formats, e.g., CSV: *ability to pose 'complex' queries and re-use data cleaning/integration techniques*
- Many topics are covered: potential to connect different data



(a) NYC (b) Kansas City (c) Seattle (d) Chicago

Some Findings

- Most data are available in tabular formats, e.g., CSV
- Many topics are covered
- Number of data sets is growing
  - In 2013, more data sets were added than in the 3 previous years combined
- *Data are small*: 70GB for all cities
  - Compare against 1 year of taxi data: 50GB/year
- There are big and small tables

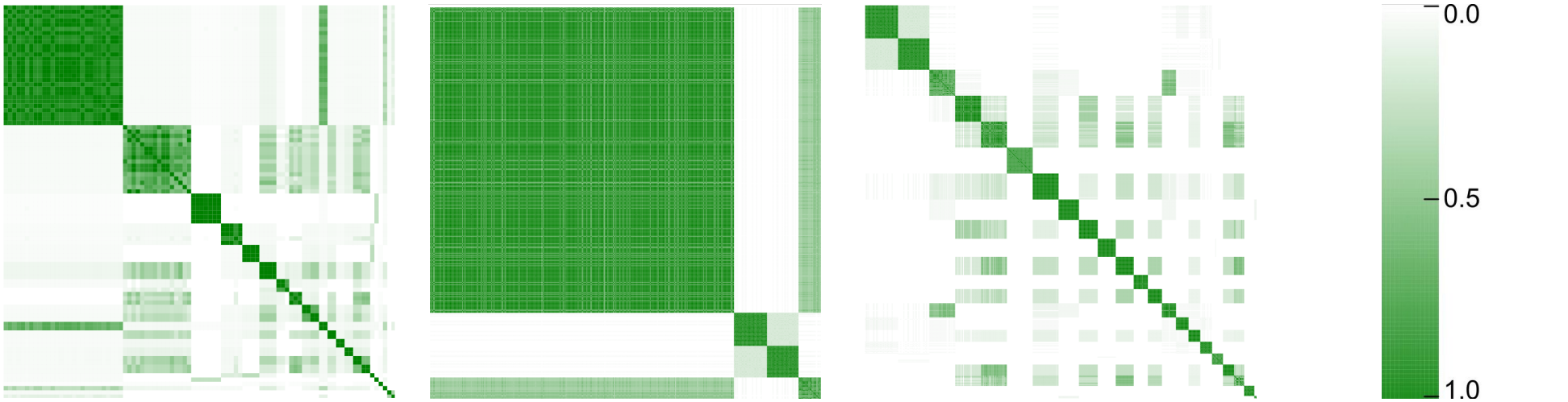
No. of records	*Percentage of total*
0–1K	65.3
1K–10K	17.0
10K–100K	11.7
100K–1M	5.5
1M–10M	0.3

>800M trips (5 years)

Some Findings

- Most data are available in tabular formats, e.g., CSV
- Many topics are covered
- Number of data sets is growing
  - In 2013, more data sets were added than in the 3 previous years combined
- *Data is small*: 70GB for all cities
  - Compare against 1 year of taxi data: 50GB/year
- There are big and small tables
- Lots of *spatio-temporal data*
  - Over 50% of the tables have lat+long and over 40% have date
- There is ample opportunity for integration – significant overlap across tables: schema and spatial!

Integration Opportunities



(a) Boston (b) 4 largest NYC clusters (c) NYC without 311 data set (d) Similarity Scale

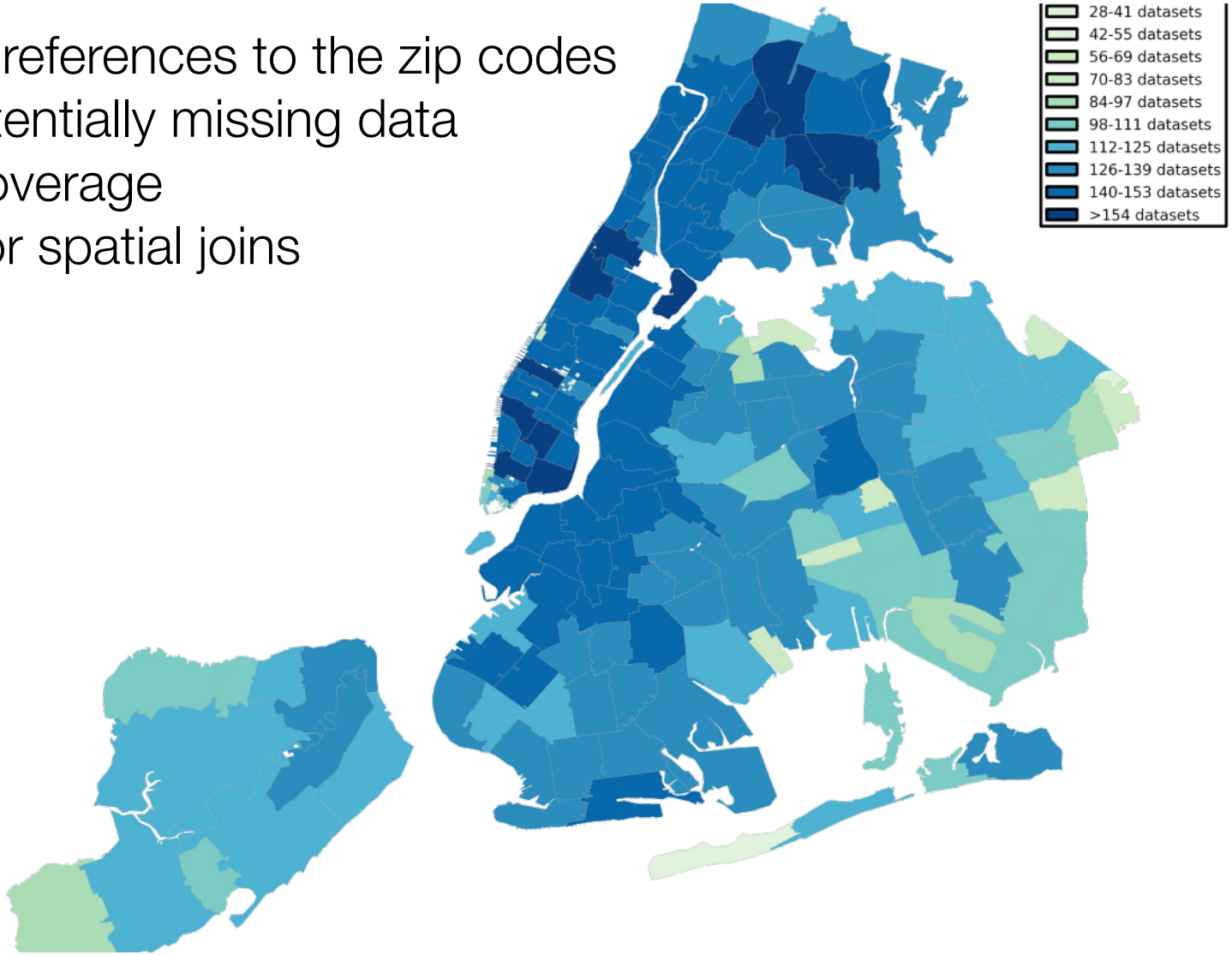
Attribute overlap among tables

- Potential for joining tables
- Hints about horizontally partitioned tables

Integration Opportunities

Frequency of references to the zip codes

- Identify potentially missing data
- Quantify coverage
- Potential for spatial joins



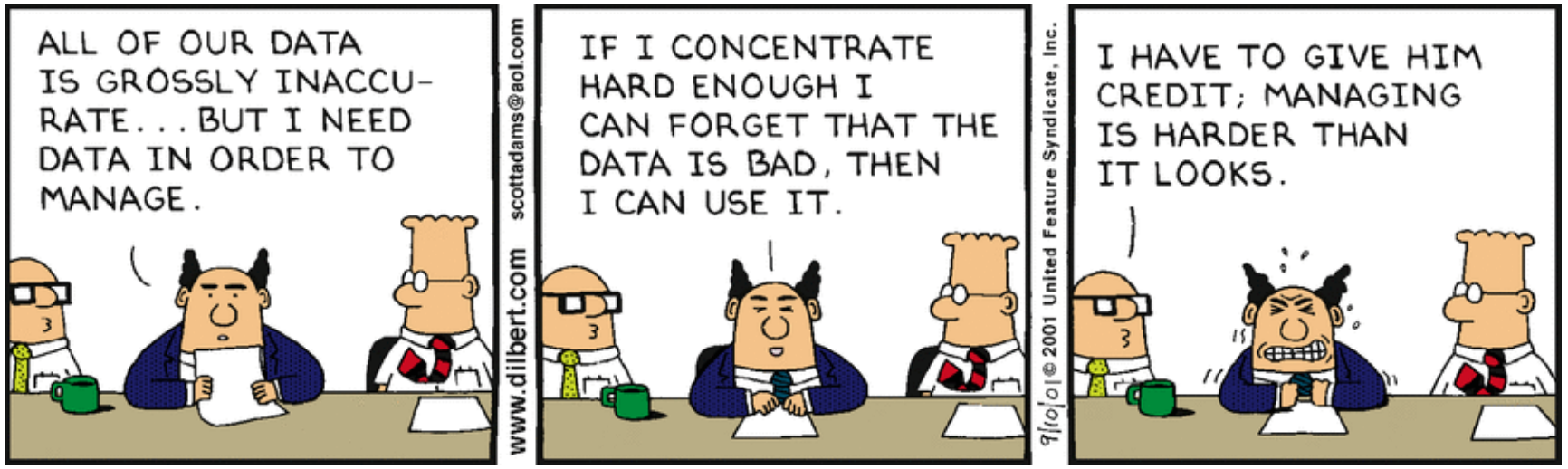
Geographical coverage and overlap

It’s not all roses…

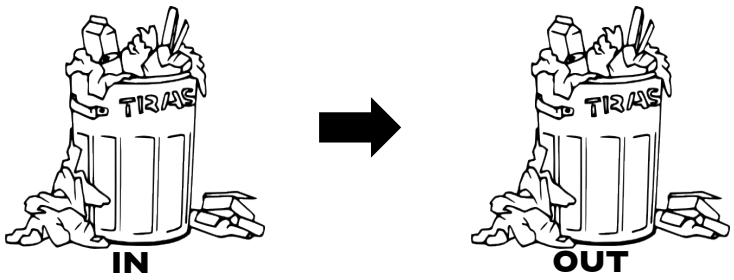
Outline

- Introduction to Programming with Big Data
  - Map Reduce vs. Parallel Databases
- Running Example: Big Urban Data
- Data Cleaning
  - Overview and Challenges
  - Cleaning the NYC Taxi Data: A Case Study
- Data exploration
  - Usability and Interactivity
  - Finding Interesting Features
  - Using Data to Discover and Explain Data
- Transparency and Reproducibility

Data Quality → Analysis Quality



- **Data is a critical resource** that supports analytics and decision making
- As data volumes increase, so does the complexity of managing it and the **risks of poor data quality**.



The Impact of Data Quality

Because of poor data quality …

- 88% of data integration projects fail or significantly over-run budgets
- 75% of organizations have additional costs
- 33% of organizations delayed or cancelled new IT systems
- $611bn per year is lost in the US

In [Marsh 2005] summarizing reports by **Gartner Group**, **PriceWaterhouseCoopers**, and **The Data Warehousing Institute**.

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Warehousing Inst

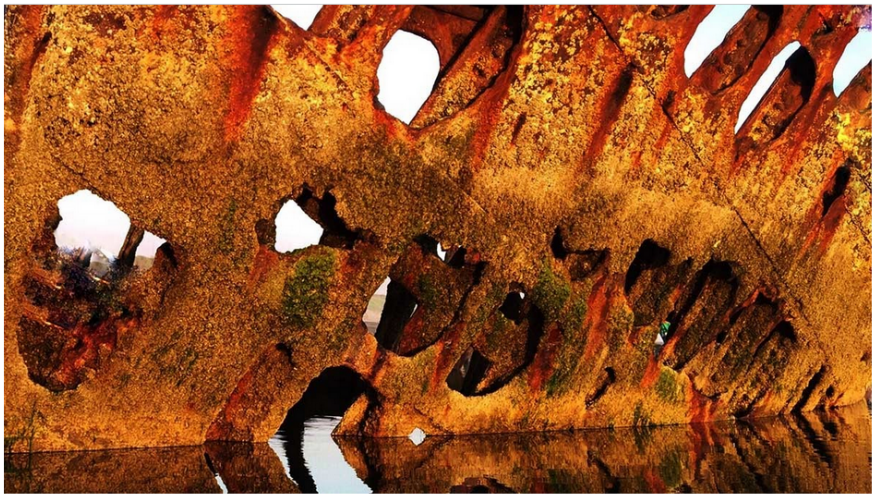
DATA

Bad Data Costs the U.S. $3 Trillion Per Year

by Thomas C. Redman

SEPTEMBER 22, 2016

SAVE SHARE COMMENT TEXT SIZE PRINT $8.95 BUY COPIES



Consider this figure: $136 billion per year. That's the research firm IDC's estimate of the size of the big data market, worldwide, in 2016. This figure should surprise no one with an interest in big data.

But here's another number: $3.1 *trillion*, IBM's estimate of the yearly cost of poor quality data, in the US alone, in 2016. While most people who deal in data every day know that bad data is costly, this figure stuns.

While the numbers are not really comparable, and there is considerable variation around each, one can only conclude that right now, improving data quality represents the far larger data opportunity. Leaders are well-advised to develop a deeper appreciation for the opportunities improving data quality present and take fuller advantage than they do today.

The reason bad data costs so much is that decision makers, managers, knowledge workers, data scientists and others must accommodate it in their everyday work. And doing so is both time-consuming and expensive. The data they need has plenty

Modified from H. Müller

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Big Data Cleaning: Big Problem

SECTIONS HOME SEARCH

The New York Times

Rise of Bitcoin Competitor Ripple Creates Wealth to Rival Zuckerberg

What You Need to Do Because of Flaws in Computer Chips

CRITIC'S NOTEBOOK
How HQ Trivia Became the Best Worst Thing on the Internet

BITS
Farhad and Mike's Week in Tech: Another Huge Security Flaw

TECH TIP
Sharing Online A
With Google Pho

TECHNOLOGY

For Big-Data Scientists, 'Janitor Work' Is Key Hurdle to Insights

https://www.nytimes.com/2014/08/18/technology/for-big-data-scientists-hurdle-to-insights-is-janitor-work.html

Big Data Cleaning: Big Problem

MAR 23, 2016 @ 09:33 AM 15,078 VIEWS

Cleaning Big Data: Most Time-Consuming, Least Enjoyable Data Science Task, Survey Says

Gil Press, CONTRIBUTOR

I write about technology, entrepreneurs and innovation. **FULL BIO**

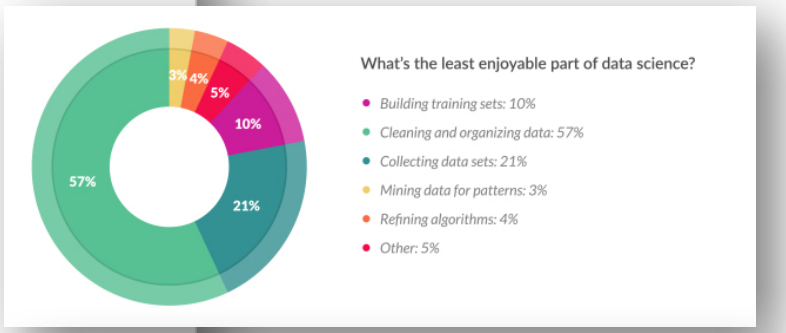
Opinions expressed by Forbes Contributors are their own.

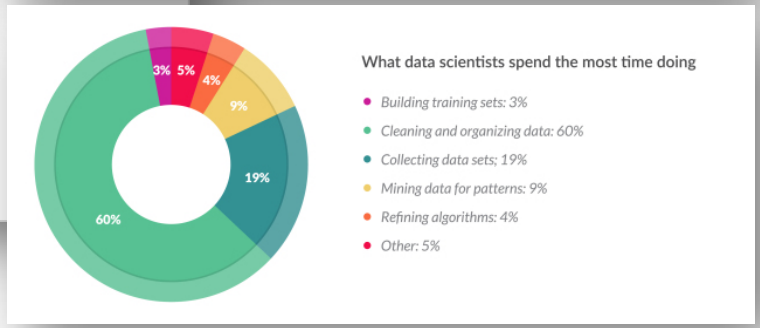
TWEET THIS

data scientists found that they spend most of their time massaging rather than mining or modeling data.

76% of data scientists view data preparation as the least enjoyable part of their work

A new survey of data scientists found that they spend most of their time massaging rather than mining or modeling data. Still, most are happy with having the sexiest job of the 21st century. The survey of about 80 data scientists was conducted for the second year in a row by CrowdFlower, provider of a "data enrichment" platform for data scientists. Here are the highlights:





- *Least enjoyable part of Data Science?*
  - Collecting data (21%)
  - Cleaning and organizing data (57%)
- *Spend most time doing*
  - Collecting data (19%)
  - Cleaning and organizing data (60%)

https://www.forbes.com/sites/gilpress/2016/03/23/data-preparation-most-time-consuming-least-enjoyable-data-science-task-survey-says

Modified from H. Müller

Data Cleaning

"the process of starting with raw data from one or more sources and maintaining reliable quality for your applications"

"the exercise of detecting errors, and possibly modifying the database, such that the data conforms to a set of data quality rules"

- Steps:

1. **Identify errors:** different types of errors require different detection techniques
2. **Fixing errors:** approaches can be automated or require the user in the loop

Data Cleaning Mechanisms and Operations

- Integrity constraints
- Similarity join
- Clustering
- Parsing
- More during the lab

Integrity Constraints

- Usually declared as part of the database schema

```
CREATE TABLE Account
    (ID              integer,
     State           character NOT NULL,
     ZIP             integer,
     PRIMARY KEY (ID));
```

ID	State	ZIP
1	NULL	85376
2	AZ	85376
3	NY	90012

ID	State	ZIP
1	NY	85376
1	AZ	85376
3	NY	90012

Integrity Constraints

- Have been increasingly used as data quality rules
  - Checking the validity of the data upon addition or update – data ingestion
  - Cleaning the dirty data at various points during the processing pipeline

ZIP → State

ID	State	ZIP
1	NY	85376
2	AZ	85376
3	NY	90012

Either tuple 1 or tuple 2 is incorrect!

Integrity Constraints

- Have been increasingly used as data quality rules
  - Checking the validity of the data upon addition or update
  - Cleaning the dirty data at various points during the processing pipeline
  - Derive missing values

ZIP → State

ID	State	ZIP
1	NY	85376
2	AZ	85376
3	NY	90012
4	NULL	90012

What is the State for tuple 4?

- In Databases, one defines the constraints when the database is created
- For Big Data, often the constraints must be inferred

Data Cleaning Operations

- Similarity join: join similar data [Chaudhuri et al., ICDE 2006]
  - Useful for record matching as well as deduplication

```
SELECT *
FROM R, S
WHERE sim(R.A,S.B,α)
```

ID	Name	Street	City	Phone
r1	Sweetlegal Investments Inc	202 North	Redmond	425-444-5555
r2	ABC Groceries Corp	Amphitheatre Pkwy	Mountain View	4081112222
r3	Cable television services	One Oxford Dr	Cambridge	617-123-4567
s1	Sweet legal Invesments Incorporated	202 N	Redmond	
s2	ABC Groceries Corpn.	Amphitheetre Parkway	Mountain View	
s3	Cable Services	One Oxford Dr	Cambridge	6171234567

Similarity Functions: Edit Distance

- The *edit distance* of two strings A and B is the number of inserts and deletes of characters needed to turn A into B.
- Edit similarity is 1-(Edit Distance/ max(|A|,|B|))
- Good for typographical errors

ED("John Doe","Jon Doe") = ?

ED("Swee**tl**egal Investment**s**","Swee**lt**egal Investment**.**") = ?

- ED fails to capture the similarity between two strings that use the same set of tokens with different ordering, e.g., Sweetlegal Investment","Investment Sweetlegal"

Similarity Functions: Jaccard

- The *Jaccard similarity* between two sets A and B is the ratio of the size of the intersection over the size of the union

  |A intersection B| / |A union B|

- Need to transform strings into sets – use q-grams
- For A = “Sweet”, B =“Sweat.”, and q = 2

  Q(s1) = {**Sw; we**; ee; et} and Q(s2) = {**Sw; we**; ea; at}

  Jaccard(Q(s1), Q(s2)) = 2/6 = 1/3
- Q-grams based Jaccard similarities are very useful for longer strings, such as addresses or documents

Similarity Functions: Cosine

- The *cosine similarity* is a vector-based similarity measure
- Need to transform strings into high-dimensional vectors
  - E.g., each token becomes a dimension For A = “Sweet Inc”, B =“Sweet”

  v(s1) = {1,1} and v(s2) = {1,0}

  cosine(v(s1), v(s2)) = cosine(45) = 0.707
- Useful for larger strings such as web documents, addresses, or text records
- To avoid high-dimensionality and noise due to irrelevant words, stop-words (such as “the,” “an,” etc.), and commonly occurring words are often eliminated

Similarity Functions: Soundex

- Phonetic approach for measuring the similarity between strings
- Convert any string to some code based on the pronunciation of the word, and then compare the codes of the strings
- For American English see http://en.wikipedia.org/wiki/Soundex

Similarity Functions: Summary

- No single string similarity function is uniformly good – choice usually depends on the data and application domain
  - E.g., Matching products – slightly different representations are meaningless

    "Apple iPhone 7 , GSM Unlocked, 32GB"

    "Apple iPhone 7 (GSM Unlocked) 32Gigabytes"
  - E.g., Matching addresses – slightly different representations are significant

    "148th Ave" and "147th Ave"
- Use a classifier to learn and determine whether two fields are similar by combining multiple similarity measures

Data Cleaning Operations

- Clustering
  - Group similar records for de-duplication: pair-wise comparison only within a group
  - Grouping similar values to find 'dirt'
  - Use similarity measures we just discussed
- Parsing: transform input data into the structure defined in the application

Player Name	Grand Slams Won
R. Federer	13
D. Ferrer	4
Rafa Nadal	6
Rafael Nadal	3

Player ID	Names of Players
1	R. Federer
2	D. Ferrer
3	Rafa Nadal, Rafael Nadal

Transform "15633 148th Ave Bellevue WA 98004" into

House number: 15633

Street name: 148th Ave

City: Bellevue

State: WA

Zip: 98004

Data Cleaning Tools: Verticals

- Data cleaning functionality for specific domains, e.g.,http://www.trilliumsoftware.com
- By incorporating domain knowledge, solutions can be comprehensive and easier to deploy
  - Example: a data cleaning package for addresses can incorporate the format of a typical address record, and lookup tables *zipcodes, city, state) to standardize the format
- Downside: solutions are not generic and cannot be ported to other domains
  - A solution developed for U.S. addresses cannot be applied to the domain of electronic products, or to addresses in Brazil

Data Cleaning Tools: Generic Platforms

- Provide a suite of operators for cleaning
- ETL Platforms: Microsoft SQL Server Integration Services and IBM Websphere Information Integration
  - Extensible: applications can plug in their own custom operators
  - A data transformation and cleaning solution is built by composing the default and custom operators to obtain an operator tree or a graph
  - E.g., But need to have a DB backend…
- Interactive tools: e.g., OpenRefine, Trifacta Wrangler, TAMR
  - User in the loop: focus on making is easy to clean data
  - We will use OpenRefine during the lab

https://www.tamr.com, https://www.trifacta.com/products/wrangler, http://openrefine.org

Cleaning Small Data

- What to do:
  - Remove errors
  - Fill in missing information
  - Transform units and formats
  - Map and align columns
  - Remove duplicates records
  - Fix integrity constraint violations
  - Specify domain knowledge as integrity constraints
- Very rich literature and many tutorials
- Some tools are available

Modified from Chu & Ilyas

Big Data + Data Quality: Challenges

- Constraints are not know a priori – they need to be discovered
- Size and complexity: huge volume of heterogeneous data from multiple sources
- Speed: dynamic data, collected and analyzed at high velocity
- Evolution: considerable variability of data, semantics over time
- Active area of research
  - Learn/infer constraints (semantics) from the data
  - Automatically identify data glitches
- Need (semi) automated methods and toolkits
  - Get ready to build your own!

Complete Knowledge infeasible

Need scalable solutions

Domain knowledge becomes obsolete

Modified from D. Srivastava

Quality Issues in Urban Data

Challenge: Inconsistent Metadata

Hard to understand semantics

Payment_type	A numeric code signifying how the passenger paid for the trip. **1= Credit card** **2= Cash** **3= No charge** **4= Dispute** **5= Unknown** **6= Voided trip**
VendorID	A code indicating the TPEP provider that provided the record. **1= Creative Mobile Technologies, LLC; 2= VeriFone Inc.**

Data Dictionary – Yellow Taxi Trip Records September 28, 2015 Page 1 of 1

This data dictionary describes yellow taxi trip data. For dictionaries describing green taxi and FHV data, please visit http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml.

Field Name	Description
VendorID	A code indicating the TPEP provider that provided the record. **1= Creative Mobile Technologies, LLC; 2= VeriFone Inc.**
tpep_pickup_datetime	The date and time when the meter was engaged.
tpep_dropoff_datetime	The date and time when the meter was disengaged.
Passenger_count	The number of passengers in the vehicle. This is a driver-entered value.
Trip_distance	The elapsed trip distance in miles reported by the taximeter.
Pickup_longitude	Longitude where the meter was engaged.
Pickup_latitude	Latitude where the meter was engaged.
RateCodeID	The final rate code in effect at the end of the trip. **1= Standard rate** **2=JFK** **3=Newark** **4=Nassau or Westchester** **5=Negotiated fare** **6=Group ride**
Store_and_fwd_flag	This flag indicates whether the trip record was held in vehicle memory before sending to the vendor, aka "store and forward," because the vehicle did not have a connection to the server. **Y= store and forward trip** **N= not a store and forward trip**
Dropoff_longitude	Longitude where the meter was disengaged.
Dropoff_ latitude	Latitude where the meter was disengaged.
Payment_type	A numeric code signifying how the passenger paid for the trip. **1= Credit card** **2= Cash** **3= No charge** **4= Dispute** **5= Unknown** **6= Voided trip**
Fare_amount	The time-and-distance fare calculated by the meter.
Extra	Miscellaneous extras and surcharges. Currently, this only includes the $0.50 and $1 rush hour and overnight charges.
MTA_tax	$0.50 MTA tax that is automatically triggered based on the metered rate in use.

Showing 135,335,924 out of 135,335,924 rows

Click to sort largest first

vendorid	tpep_pickup_datetime	dropoff_datetime	passenger_count	trip_distance	pickup_longitude	pickup_latitude	ratecodeid	store_and_fwd_flag	dropoff_longitude	dropoff_latitude	payment_type	fare_amount	extra	mta_tax	tip_amount	tolls_amount
CMT	08/08/2011 11:49:24 PM	08/08/2011 11:57:45 PM	1	2.5	-74.00563	40.740509	1	N	-74.016117	40.711134	CRD	8.5	0.5	0.5	0	0
CMT	09/15/2011 03:54:48 AM	09/15/2011 03:58:54 AM	1	1.2	0	0	1	N	0	0	CRD	5.3	0.5	0.5	1.89	0
CMT	07/05/2011 04:03:40 PM	07/05/2011 04:15:53 PM	1	1.7	-73.978989	40.736481	1	N	-73.977367	40.754893	CSH	8.1	1	0.5	0	0
CMT	09/03/2011 07:47:57 PM	09/03/2011 07:59:32 PM	3	1.3	-73.992899	40.729957	1	N	-74.008172	40.716759	CSH	7.7	0	0.5	0	0
CMT	01/10/2011 09:07:22 AM	01/10/2011 09:13:06 AM	1	1	-73.990681	40.734814	1	N	-73.998295	40.74209	CRD	5.7	0	0.5	0.93	0
CMT	04/29/2011 09:41:47 PM	04/29/2011 10:08:26 PM	1	3.1	-73.989607	40.731801	1	N	-73.982571	40.757293	CSH	14.1	0.5	0.5	0	0
CMT	06/25/2011 02:58:07 PM	06/25/2011 03:05:53 PM	2	1.4	-73.96	40.7816	1	N	-73.9669	40.7642	CSH	6.5	0	0.5	0	0
CMT	01/26/2011 01:10:25 PM	01/26/2011 01:18:59 PM	1	2.2	-73.946743	40.772331	1	N	-73.97567	40.760758	CSH	7.7	0	0.5	0	0
CMT	06/16/2011 12:12:11 AM	06/16/2011 12:29:45 AM	1	5.8	-73.983032	40.726829	1	N	-73.977406	40.789431	CRD	15.7	0.5	0.5	3.34	0
CMT	01/27/2011 09:00:40 PM	01/27/2011 09:07:52 PM	1	1.4	-73.98935	40.741689	1	N	-73.981712	40.758483	CRD	6.1	0.5	0.5	2	0
CMT	09/02/2011 01:45:10 PM	09/02/2011 01:55:59 PM	1	1	-73.990709	40.755932	1	N	-73.974292	40.751193	CSH	7.3	0	0.5	0	0

Challenge: Evolving Data

Analyses may break for new data

Removed data

VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	pickup_longitude	pickup_latitude	RatecodeID	store_and_fwd_flag	dropoff_longitude	dropoff_latitude	payment_type	fare_amount	extra	mta_tax	tip_amount	tolls_amount
3	2016 Jul 17 06:46:27 PM	2016 Jul 17 06:53:03 PM	1	0.87			1	N			1	6	0	0.5	0.68	
3	2016 Jul 02 12:48:30 AM	2016 Jul 02 01:03:52 AM	1	2.63			1	N			2	12	0.5	0.5	0	
3	2016 Sep 11 12:17:32 AM	2016 Sep 11 12:29:47 AM	1	1.81			1	N			1	9.5	0.5	0.5	2.16	
3	2016 Jul 13 05:18:46 PM	2016 Jul 13 05:28:25 PM	1	0.91			1	N			1	7.5	1	0.5	2.33	
3	2016 Jul 06 03:17:09 PM	2016 Jul 06 03:20:45 PM	1	0.55			1	N			1	4.5	0	0.5	1.06	
3	2016 Jul 01 11:11:24 PM	2016 Jul 01 11:31:05 PM	1	2.06			1	N			1	13.5	0.5	0.5	0	
3	2016 Jul 17 03:19:41 PM	2016 Jul 17 03:33:01 PM	1	1.71			1	N			2	10	0	0.5	0	
3	2016 Jul 02 11:22:15 AM	2016 Jul 02 11:29:26 AM	1	1.5			1	N			2	7.5	0	0.5	0	
3	2016 Jul 16 01:37:03 PM	2016 Jul 16 02:00:16 PM	1	4.33			1	N			1	19	0	0.5	0	
3	2016 Aug 07 06:33:27 PM	2016 Aug 07 06:58:23 PM	1	3.15			1	N			1	17	0	0.5	2.67	
3	2016 Sep 15 12:12:21 PM	2016 Sep 15 12:17:48 PM	1	0.49			1	N			1	5.5	0	0.5	1.26	

Different data types

vendorid	tpep_pickup_datetime	dropoff_datetime	passenger_count	trip_distance	pickup_longitude	pickup_latitude	ratecodeid	store_and_fwd_flag	dropoff_longitude	dropoff_latitude	payment_type	fare_amount	extra	mta_tax	tip_amount	tolls_amount
CMT	08/08/2011 11:49:24 PM	08/08/2011 11:57:45 PM	1	2.5	-74.00563	40.740509	1	N	-74.016117	40.711134	CRD	8.5	0.5	0.5	0	0
CMT	09/15/2011 03:54:48 AM	09/15/2011 03:58:54 AM	1	1.2	0	0	1	N	0	0	CRD	5.3	0.5	0.5	1.89	0
CMT	07/05/2011 04:03:40 PM	07/05/2011 04:15:53 PM	1	1.7	-73.978989	40.736481	1	N	-73.977367	40.754893	CSH	8.1	1	0.5	0	0
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CMT	09/02/2011 01:45:10 PM	09/02/2011 01:55:59 PM	1	1	-73.990709	40.755932	1	N	-73.974292	40.751193	CSH	7.3	0	0.5	0	0

Rows 1-11 out of 135,335,924

Challenge: Data Quality Issues

DOHMH New York City Restaurant Inspection Results

DBA	STREET	BUILDING
MADANGSUI	WEST 35 STREET	35
@NINE	9 AVENUE	592
TACO HUT	BROADWAY	3210

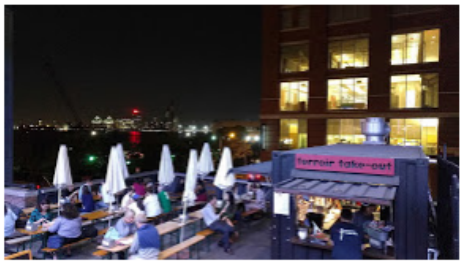
https://data.cityofnewyork.us/Health/DOHMH-New-York-City-Restaurant-Inspection-Results/43nn-pn8j

Challenge: Data Quality Issues

DOHMH New York City Restaurant Inspection Results

DBA	STREET	BUILDING
MADANGSUI	WEST 35 STREET	35
@NINE	9 AVENUE	592
TACO HUT	BROADWAY	3210
TERROIR AT THE PORCH	**W 15th Street @ 10th Ave**	**HIGHLINE**



https://data.cityofnewyork.us/Health/DOHMH-New-York-City-Restaurant-Inspection-Results/43nn-pn8j

Challenge: Data Quality Issues

DOHMH New York City Restaurant Inspection Results

DBA	STREET	BUILDING
MADANGSUI	WEST 35 STREET	35
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TACO HUT	BROADWAY	3210
TERROIR AT THE PORCH	**W 15th Street @ 10th Ave**	**HIGHLINE**

People that generate data get ‘creative’ to fit information to data models.

Lack of provenance information means we have to attempt to understand their decisions and the data generation process.

https://data.cityofnewyork.us/Health/DOHMH-New-York-City-Restaurant-Inspection-Results/43nn-pn8j

Challenge: Data Quality Issues

- Columns containing Telephone Numbers in NYC Open Data
- Think of a (simple) way to distinguish the ‘Good’ from the ‘Bad’ and to transform the bad into good.

.	(000)000-0000
0	(201)368-1000
212 NEW YORK	(201)373-9599
311	(718) 206-1088
511	(718) 206-1121
911	(718) 206-1420
0000000000	(718) 206-4420
1111111	(718) 206-4481
1111111111	(914) 681-6200
1212669311	(718) 868-2300 x206
2012162746	(718) 206-0545/(718) 298-0117
2015954606	(718) 262-9072/(718) 658-1537
2033631907	(718) 297-4708/c: (347) 806-4588
9737924762	(888) 8NYC-TRS
9737924769	(888)-VETS-NYS
Fax7189801021	1-800-CUNY-YES
Fax:7189187823	800-624-4143

Challenge: Data Quality Issues

- Columns containing Boroughs, Cities, Neighborhoods in NYC Open Data
- Cities, neighborhoods and boroughs all mixed: how to fix this?

borough (0)
BRONX
BROOKLYN
MANHATTAN
QUEENS
STATEN ISLAND

city (1)
ASTORIA
BRONX
BROOKLYN
CHELSEA
CLINTON
FLUSHING
HARLEM
JAMAICA QUEENS
MANHATTAN
NEW YORK
STATEN ISLAND

manhattan neighborhood (2)
CHELSEA
CHINATOWN
CLINTON
HARLEM
SOHO
TRIBECA

Challenge: Data Quality Issues

- Assumption about valid values in a column, i.e., the domain

  Data Type (INT, DECIMAL, TEXT, DATE)

- Semantic constraints often not explicitly documented

  ZIP Code is a 5 digit number between 10000 and 99999

  Monetary value in US$

  Date in format YYYY-MM-DD

  Name in format <first> <last>

Attribute: illegal and missing values

- Pairs of records that contradict each other or violate a functional dependency ZIP → City

ZIP	City
10003	NYC
10003	Chicago

- Uniqueness violations, conflicting values, missing records

Toolbox of a Data Cleaner

- *External (High Quality) Data Sources*
  - E.g., lookup tables for city names and ZIP codes
- *Integrity Constraints*
  - Define and enforce constraints that high quality data adhere to
- *Regular Expressions*
  - Define format of values
- *String Similarity Functions and Clustering*
  - Identify typos at data entry
  - Find records that represent the same entity (duplicates)
- *Conflict Resolution Functions*
  - Resolve contradicting information

Skip to case study

Modified from H. Müller

Find Attribute Outlier Values

- *Sort attribute values in alphabetical order*
  - 'Interesting' values often appear at the beginning and end of list

*The following examples are from the **DOB Permit Issuance** dataset in **NYC Open Data***

owner_s_business_name
(JOANNE H. SIEGMUN 2ND OWNER)
(PERSONAL RESIDENCE)
(PRIVATE RESIDENCE)
(TENANT IN COMMON)
(TENANTS IN COMMON)
****
****
****
++++++++++
-
--

.
..
[…]

[…]
_____N/A
altered state restoration
c/o Bowery Hotel
c/o Cooper Square Realty
c/o Leibovitz Studio
individual
mtp investment
n/a
na
new hempstead home for the adult
none
not applcable
owner
renaissanc
same
sierra realty corp.
wm maidmanfamily lp

Outliers in Alphabetical Order

city
(646)4396000
, FLORAL PARK
,ELMSFORD
.
1
10012
10013
10452
10462
105

A large number of quality problems are a result of ‘parsing errors’ or invalid file formats (e.g., too many or missing column delimiters in CSV file).

```
QUEENS|4144683|147-57 |78 AVE |421156046|01|A1||06688|00040
|408|11367|1|YES|||PL|ISSUED|RENEWAL|PL|02| | |NOT APPLICABLE
|11/06/2016|11/06/2016|11/06/2017|11/10/2015|CONSTANTINE |KOUMPAROULIS
|ARIANA CONTRACTING INC |7187215018|MASTER PLUMBER |0001101| | | | | |
| | |INDIVIDUAL ||N/A |ARTUR |KHAIMOV |147-57 |78TH AVENUE |KEW
GARDENS |NY|11367 |6464022132|11/07/2016
```

Find Attribute Outlier Values

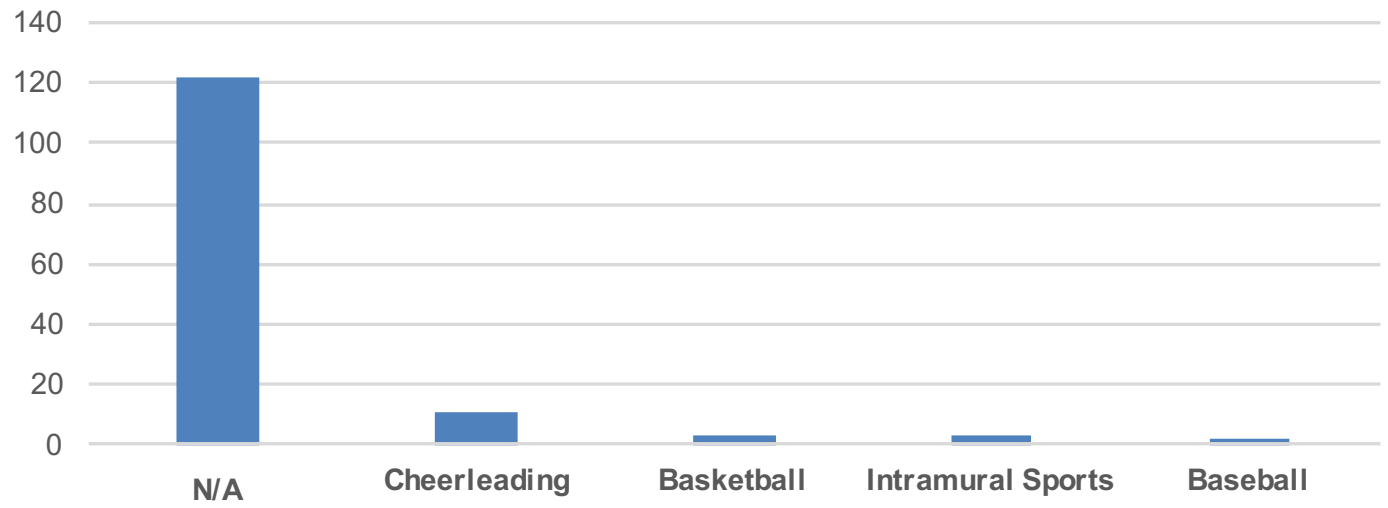
- *Sort attribute values in alphabetical order*
  - 'Interesting' values often appear at the beginning or end of list.
- *Frequency outliers*
  - NULL values sometimes have significantly different frequency (high or low) compared to other column values.

Frequency Outliers

DOE High School Directory 2013-2014

NYC Open Data

school_sports



Frequency Outliers (cont.)

- *Values that frequently occur as high frequency outliers*
  - Values that occur with frequency >50% in + 15,000 columns of NYC Open Data datasets

Value	Number of Columns
0	(x 262)
N/A	(x 71)
UNSPECIFIED	(x 67)
S	(x 57)
-	(x 50)
0.00	(x 47)
NY	(x 38)
1	(x 25)
0.0	(x 20)
IND	(x 12)
CLOSED	(x 10)
100	(x 8)
NOT AVAILABLE	(x 8)
0 UNSPECIFIED	(x 6)
NONE	(x 5)

Find Attribute Outlier Values

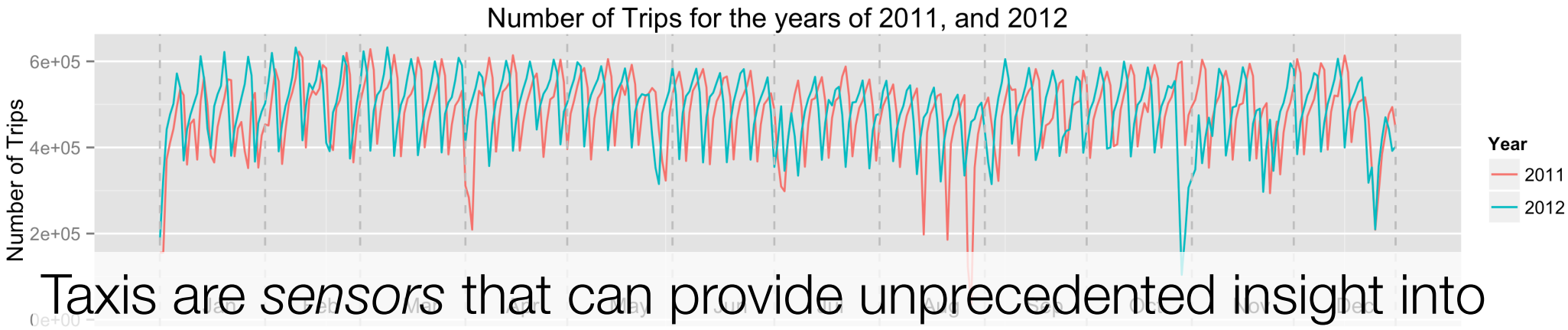
- *Sort attribute values in alphabetical order*
  - 'Interesting' values often appear at the beginning or end of list
- *Frequency outliers*
  - NULL values sometimes have significantly different frequency (high or low) compared to other column values
- *Regular expressions*
  - Find values that do not match the expected format of a column
- Often identify outliers and potential problems during data exploration

Data Quality: A Case Study using NYC Taxi Trips

NYU TANDON SCHOOL OF ENGINEERING

VIDA VISUALIZATION IMAGING AND DATA ANALYSIS CENTER

NYC Taxis



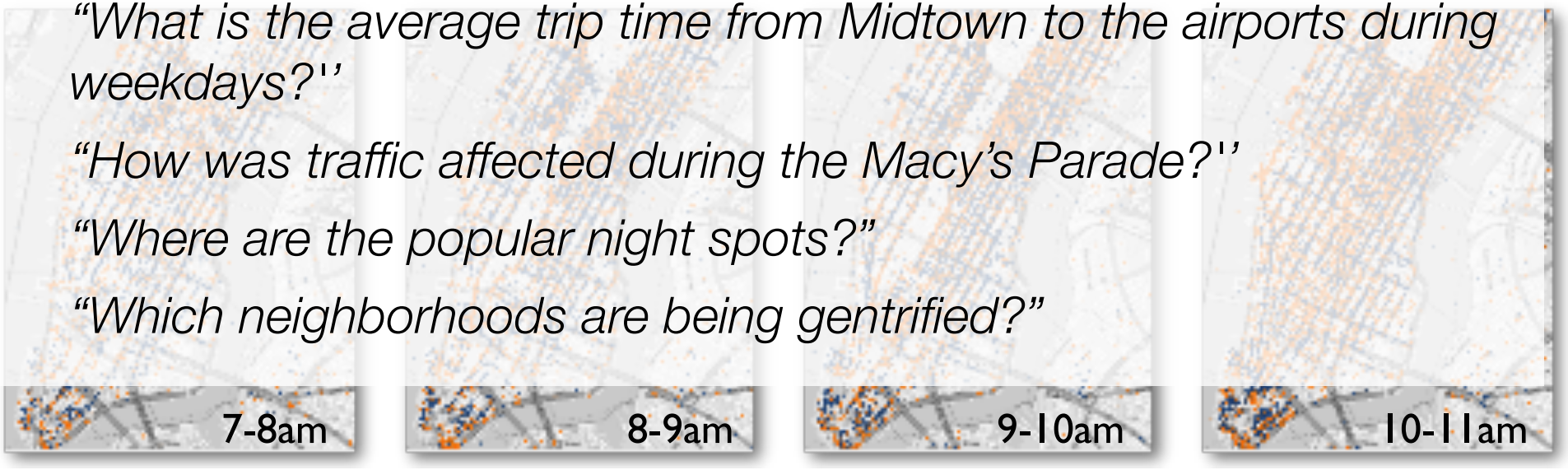
Taxis are *sensors* that can provide unprecedented insight into city life: economic activity, human behavior, mobility patterns

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

"How was traffic affected during the Macy's Parade?''

"Where are the popular night spots?"

"Which neighborhoods are being gentrified?"



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VIDA VISUALIZATION IMAGING AND DATA ANALYSIS CENTER

Taxi Data: What to Clean and not to Clean

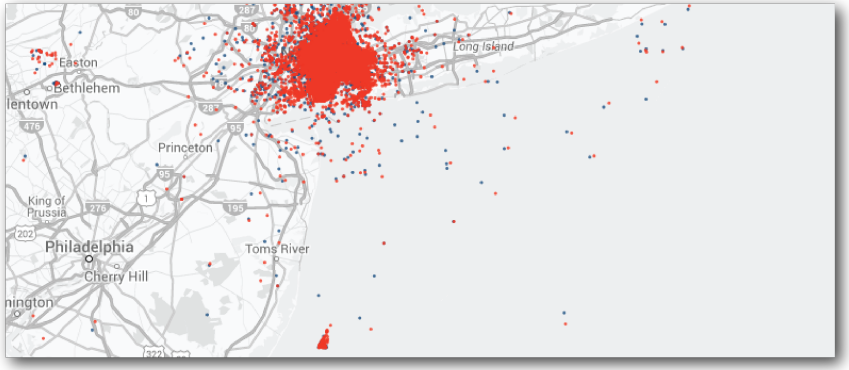
Dataset	Statistic	Trip Duration (min)	Trip Distance (mi)	Fare Amount (US$)	Tip Amount (US$)
2008	Min	0.00	0.00	0.00	0.00
	Avg	16.74	2.71	0.09	0.10
	Max	1440.00	50.00	10.00	8.75
2009	Min	0.00	0.00	2.50	0.00
	Avg	7.75	6.22	6.04	0.38
	Max	180.00	180.00	200.00	200.00
2010	Min	-1,760.00	-21,474,834.00	-21,474,808.00	-1,677,720.10
	Avg	6.76	5.89	9.84	2.11
	Max	1,322.00	16,201,631.40	93,960.07	938.02
2011	Min	0.00	0.00	2.50	0.00
	Avg	12.35	2.80	10.25	2.22
	Max	180.00	100.00	500.00	200.00
2012	Min	0.00	0.00	2.50	0.00
	Avg	12.32	2.88	10.96	2.32
	Max	180.00	100.00	500.00	200.00

Negative values are clearly errors.
But high tip may not be an error…

Different processes were used to process data in different years,
but no provenance information is provided

Taxi Data: What to Clean and not to Clean

(a)

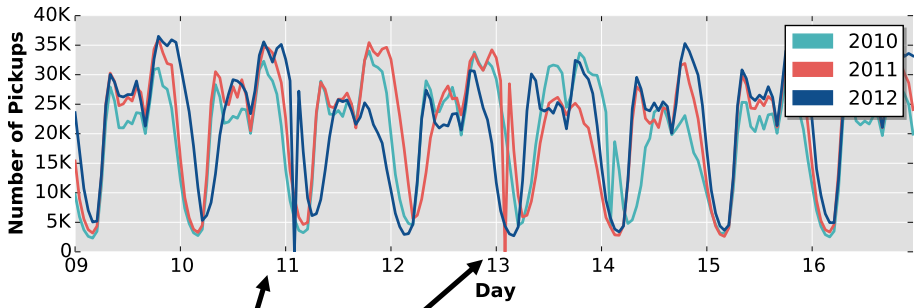


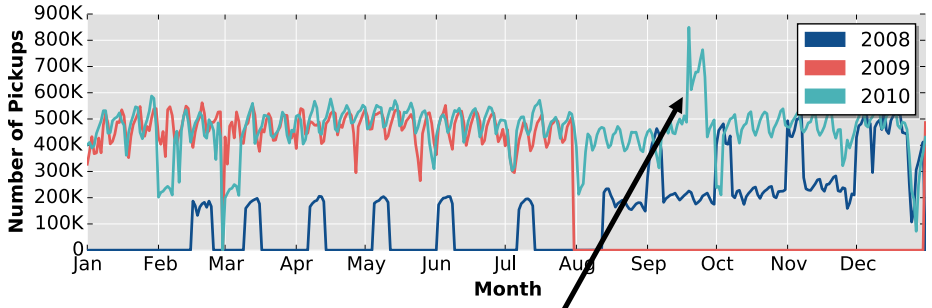
(b)

(c)

Need to consider spatial constraints:
Trips in rivers, ocean and Central America

Taxi Data: What to Clean and not to Clean





No trips at 2am

Daylight savings:
March 13, 2011
March 11, 2012

Missing data in 2008

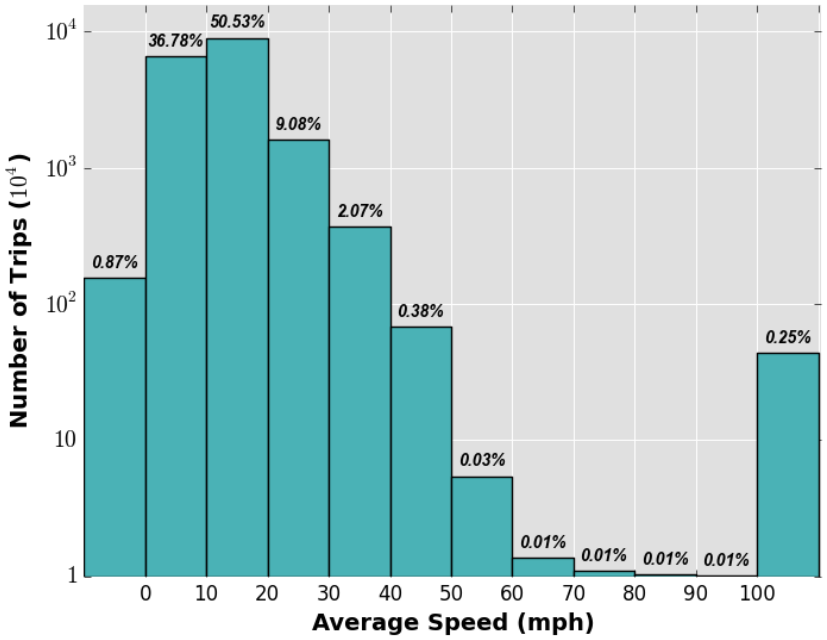
Big spike on Sept 19th, 2010

Missing data in 2009

Unusually large number of consecutive and extremely short trips (lasting less than a minute)

Taxi Data: What to Clean and not to Clean

- Ghost trips
  - Overlapping trips for the same taxi, i.e., for a given taxi, a new trip starts before the previous trip has ended
- Speed too high or too low
  - Incorrect values can negatively impact predictive models which rely on average speeds
  - Speed = 0, easily an error
  - But what about high speeds?



Takeaway: Big Data Cleaning

- Data cleaning has been performed as a pre-processing step

  Dirty Data → *Clean Data*

- Cleaning is an integral part of data exploration: constraints that should be checked in the cleaning function, and which might not be evident at first, are naturally discovered
- Different question/analyses require different cleaning strategies

  DirtyData × *UserTask* → (*CleanData*, *Explanation*)

- Map Reduce provides a scalable framework for executing cleaning scripts
  - Need a scalable data cleaning library – analogous to sklearn for data cleaning

Takeaway: Big Data Cleaning (cont.)

- Spatio-temporal data adds a new set of constraints and issues that need to be considered
- Visualization is essential!
- Traditional cleaning techniques are useful
- Need domain knowledge
- Cleaning a large number of data sets is hard
- It is not always clear what is dirt and what is a feature
- Promising *research* direction: New techniques that leverage multiple data sets
  - Holistic data cleaning and integration
  - Use data to explain data (more soon!)

Data Cleaning References

- Tutorial: *Data Cleaning: Overview and Emerging Challenges* http://sigmod2016.org/sigmod_tutorial1.shtml
- Tutorial: Knowledge curation and knowledge fusion: challenges, models, and applications (SIGMOD 2015) http://lunadong.com/talks/KFTutorial_sigmod.pptx
- *Profiling relational data: a survey.* VLDB J. 24(4): 557-581 (2015)
- Data Cleaning: A Practical Perspective. Venkatesh Ganti and Anish Das Sarma (2013)
- **Trends in Cleaning Relational Data: Consistency and Deduplication. Ihab Illias and Xu Chu (2015)**
-

Exploring Data:
Usability and Interactivity

Exploring Taxi Data: Challenges

- Data: ~500k trips/day; 868 million trips in 5 years
  - *spatio-temporal:* pick up + drop off
  - *trip attributes*: e.g., distance traveled, fare, tip
- Government, policy makers and scientists are unable to *interactively* explore the *whole* data
  - Too many data slices to examine
- Our goal: Design a *usable* interface, efficiently support *interactive + exploratory* queries

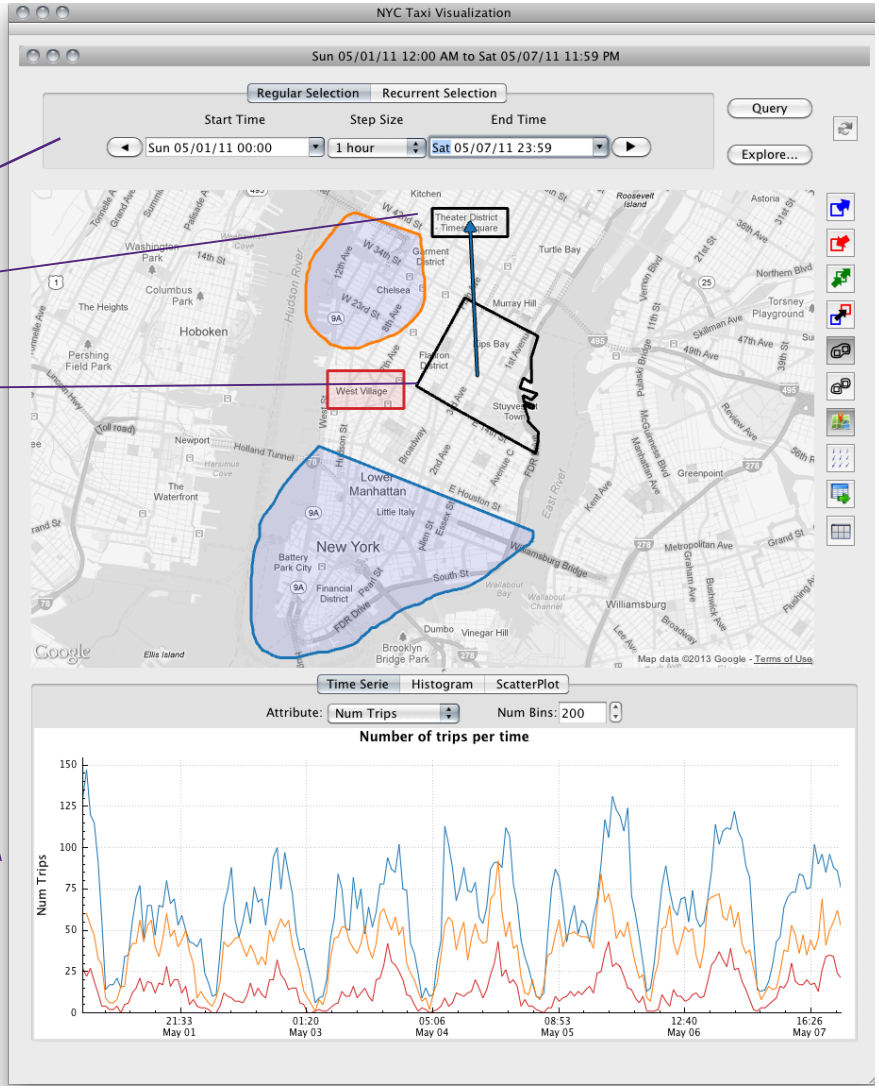
Exploring Taxi Data

Usability through Visual Operations

Users select a data slice by specifying spatial, temporal and attribute constraints

```
SELECT *
FROM trips
WHERE pickup_time in (5/1/11,5/7/11)
AND dropoff_loc in “Times Square”
AND pickup_loc in “Gramercy”
```

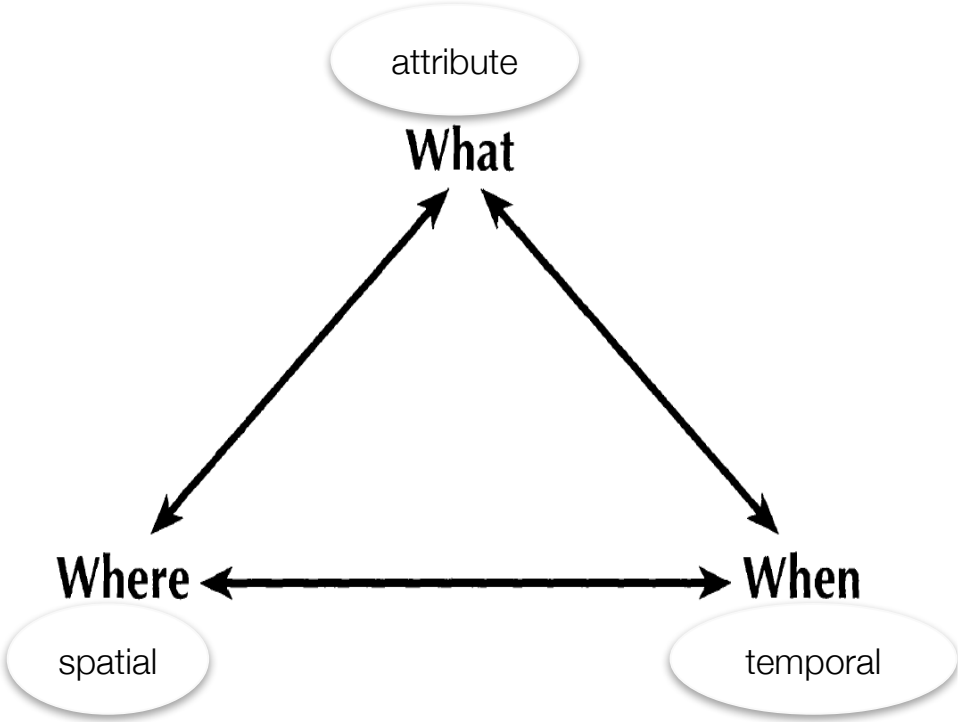
Data selection and result exploration are unified



Visual Query Model

Expressiveness:

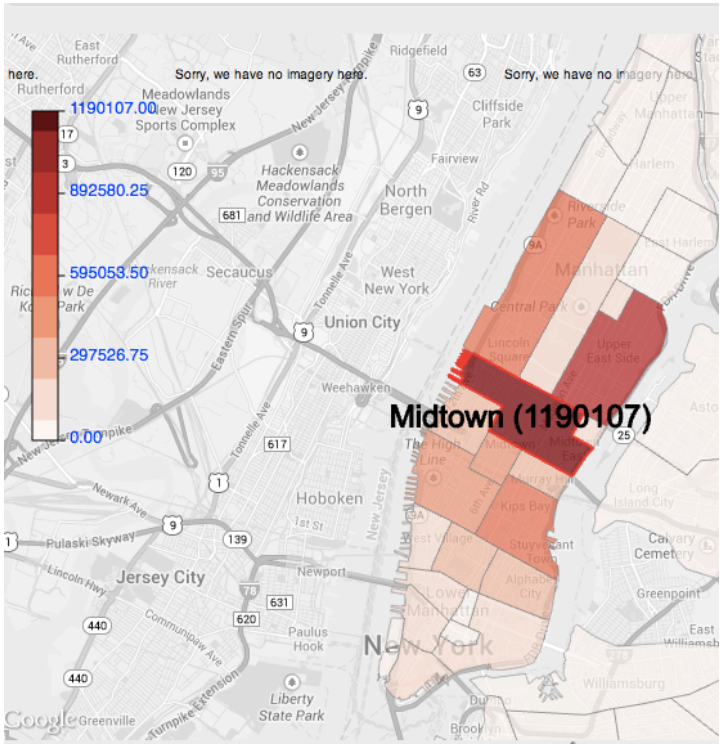
- when + where → what: *"What is the average trip time from Midtown to the airports during weekdays?''*
- when + what → where: *"Where are the hot spots in Manhattan in weekends?"*
- where + what → when: *"When were activities restored in Lower Manhattan after the Sandy hurricane?"*



Peuquet's Triad

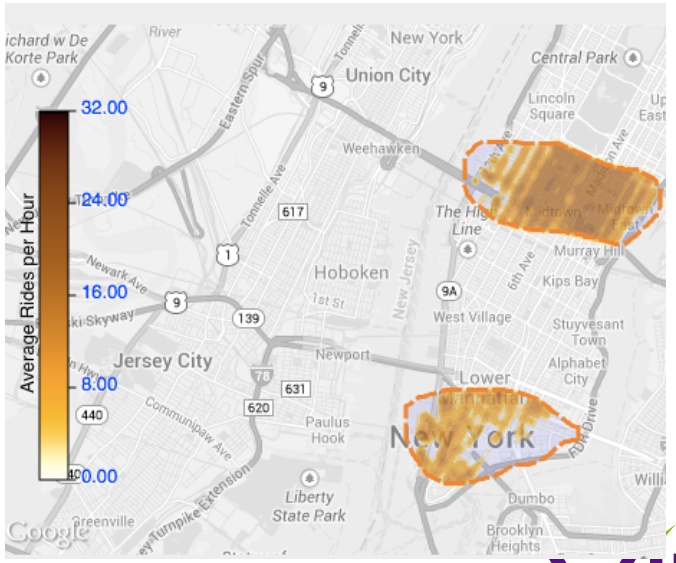
Model is also able to express other types of queries, including *when → what + where*, *where → when + what*, and *what → where + when*

Selecting Regions – Spatial Constraints



Predefined polygons, e.g., zip, neighborhoods, etc

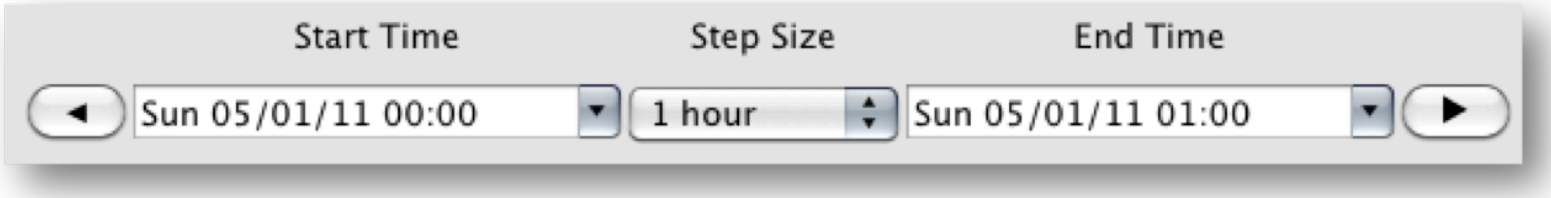
Free selection

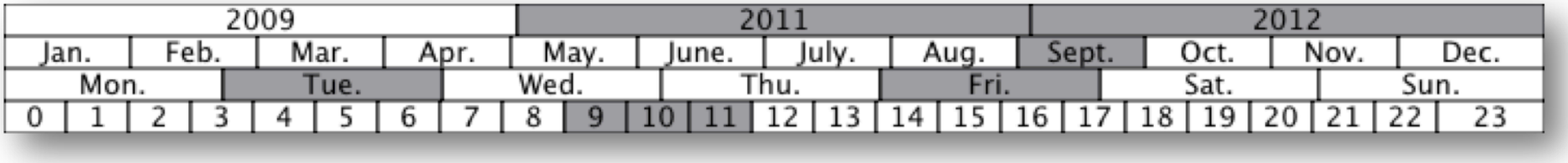


Group regions

Selecting Time – Temporal Constraints

Time interval

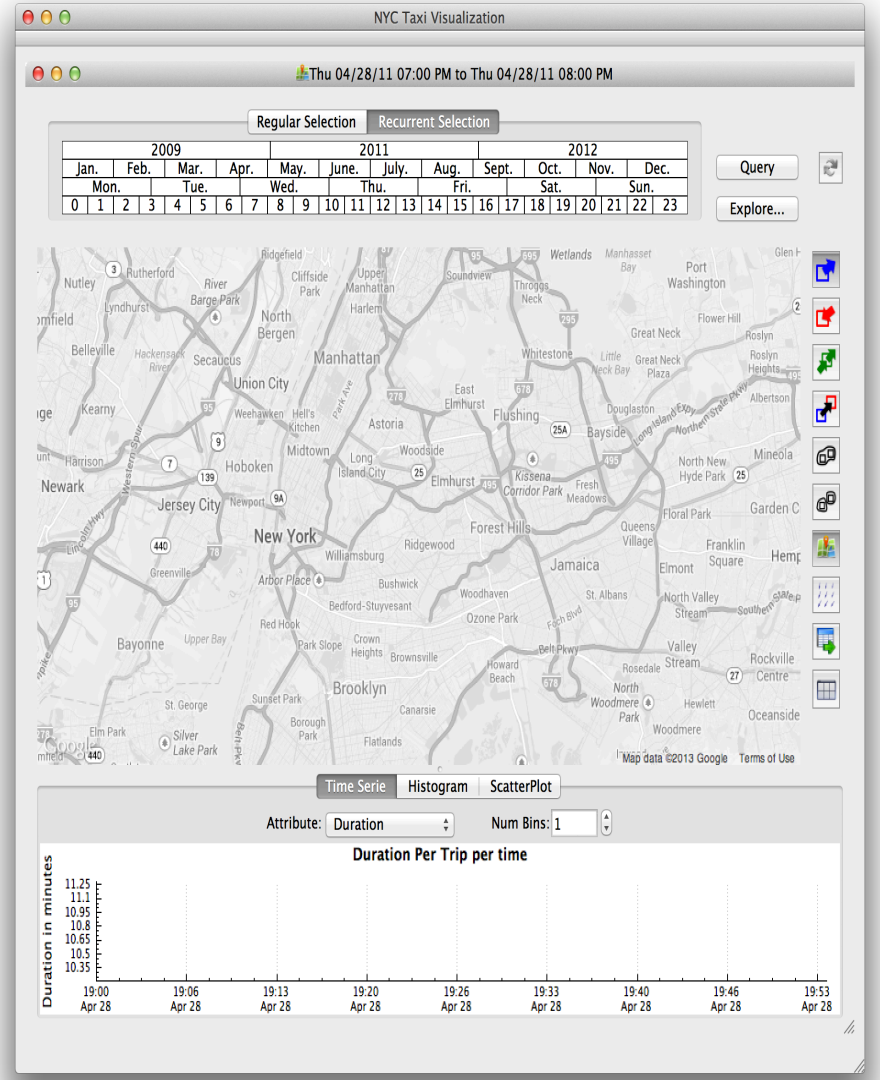




Recurrent time patterns

When + Where → What

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



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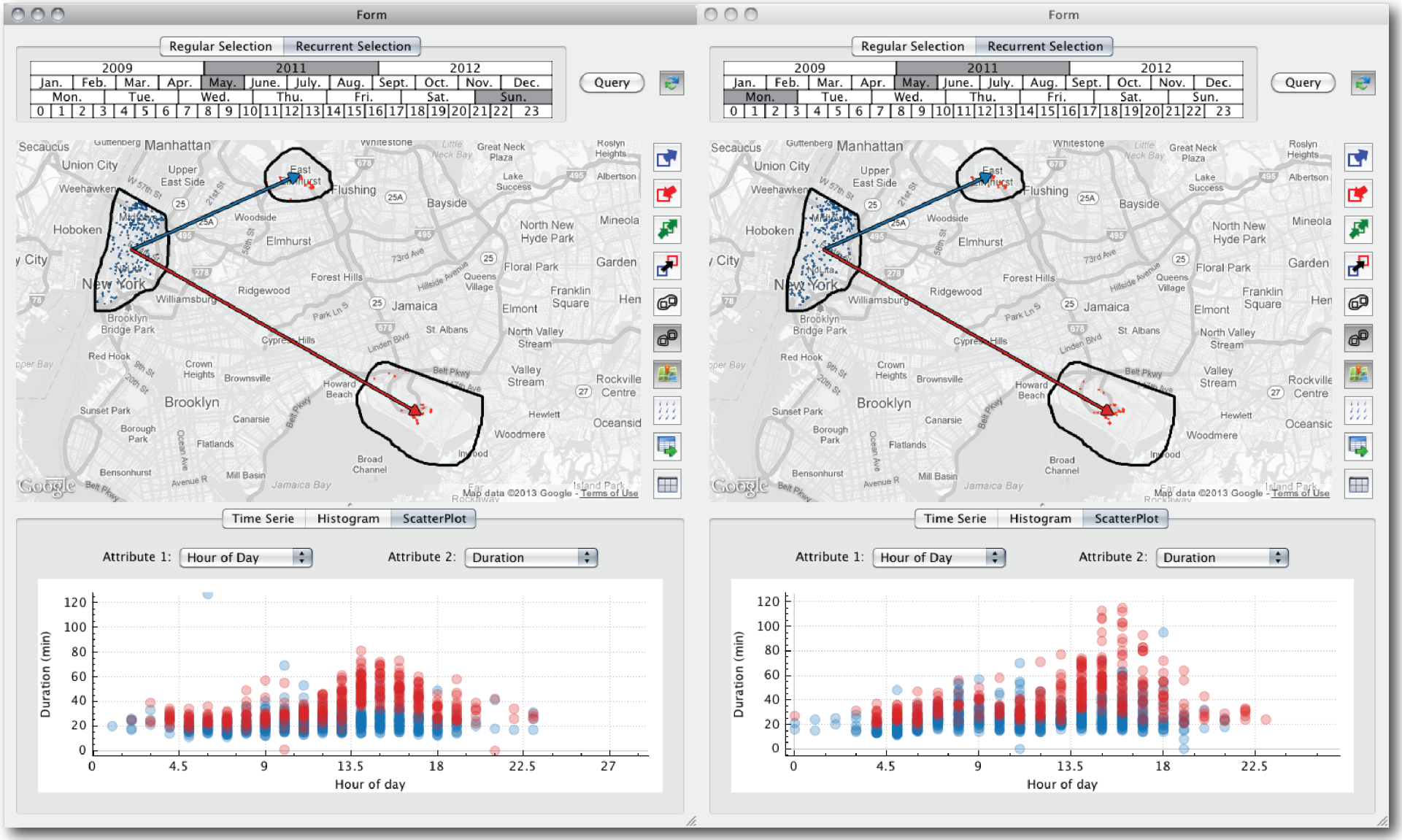
Composing Queries

A query is associated with the set of trips contained in its results – queries can be composed.

Different visualizations can be applied to query results

Lines in plot are linked to the queries by their color.

TaxiVis: Studying Mobility



[Ferreira et al., IEEE TVCG 2013]

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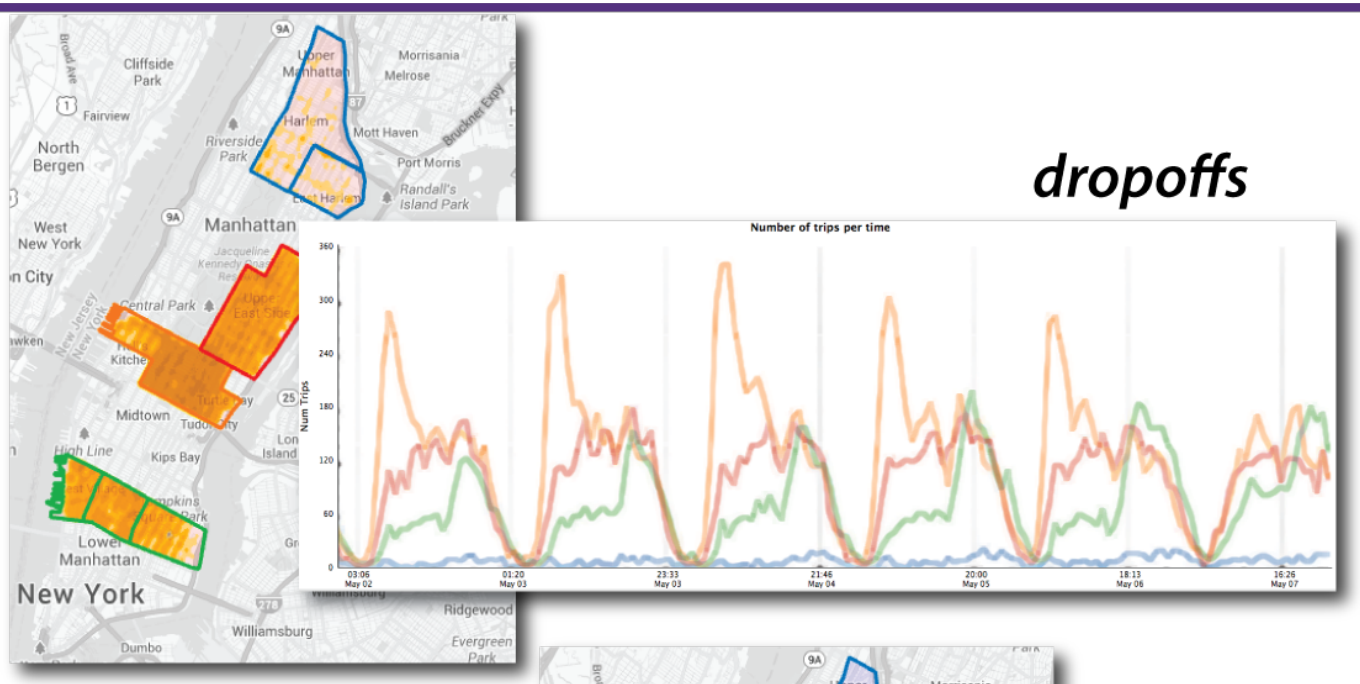
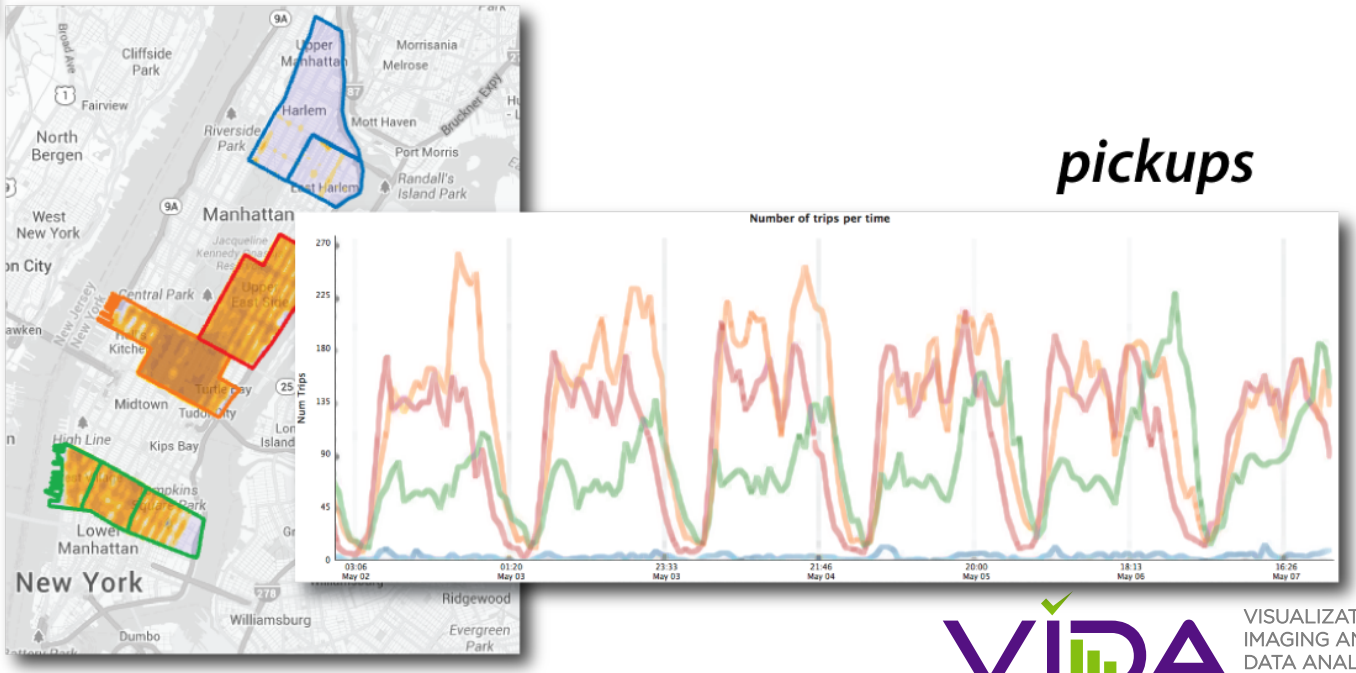
TaxiVis: Comparing Neighborhoods





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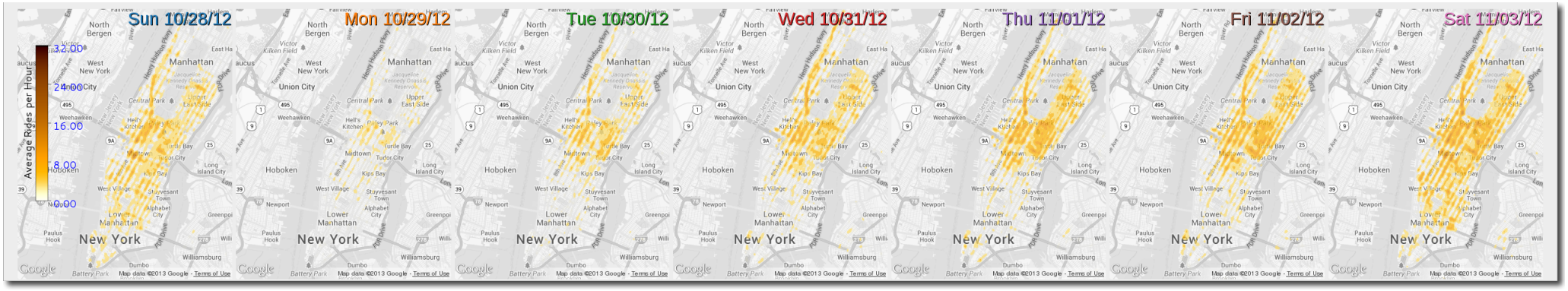
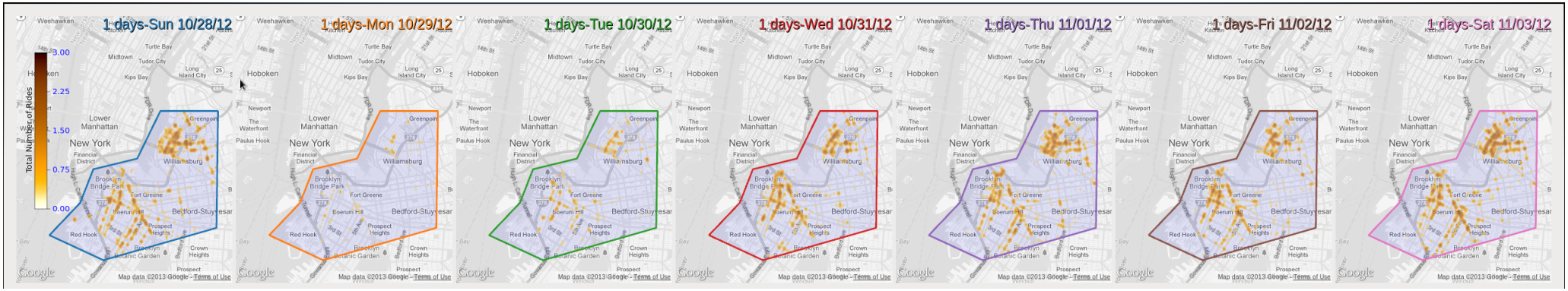
Exploring the Effect of Major Events: Sandy





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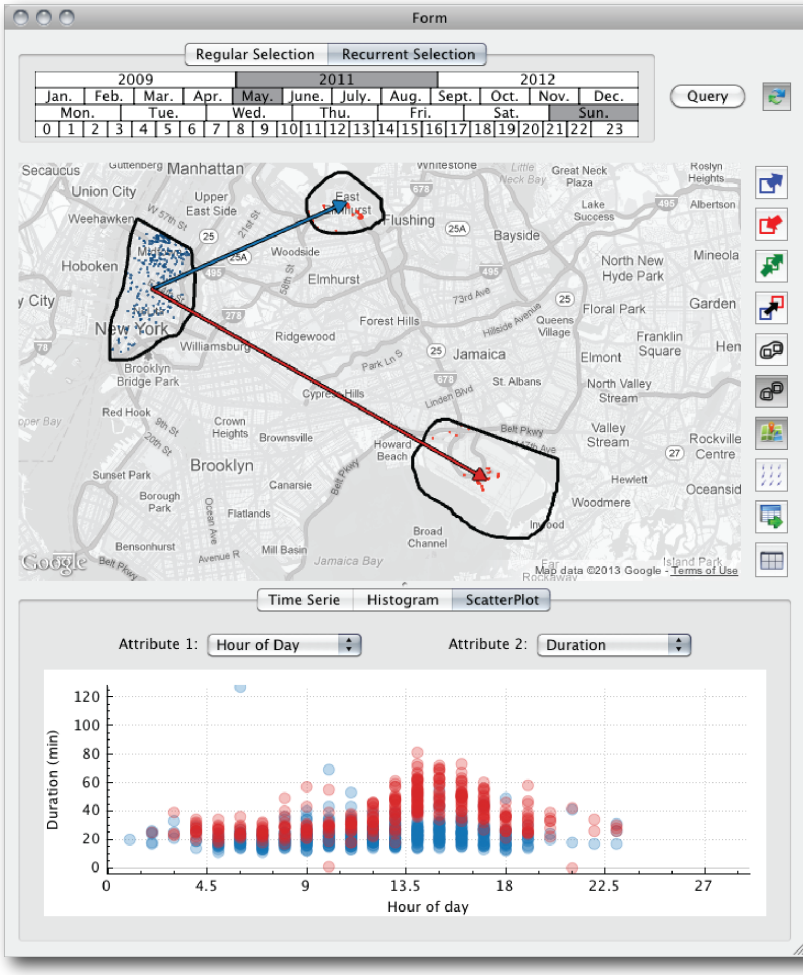
Challenge: *Interactive* Query Evaluation

- Typical query:

Find all trips that occurred between

lower Manhattan and the two airports,
JFK and LGA,

during all Sundays in May 2011



Query time (sec)	**PostgreSQL**	**ComDB**
	503.9	20.6

"increased latency reduces the rate at which users make observations, draw generalizations and generate hypotheses"

[Liu and Heer, IEEE TVCG 2014]

Challenge: *Interactive* Query Evaluation

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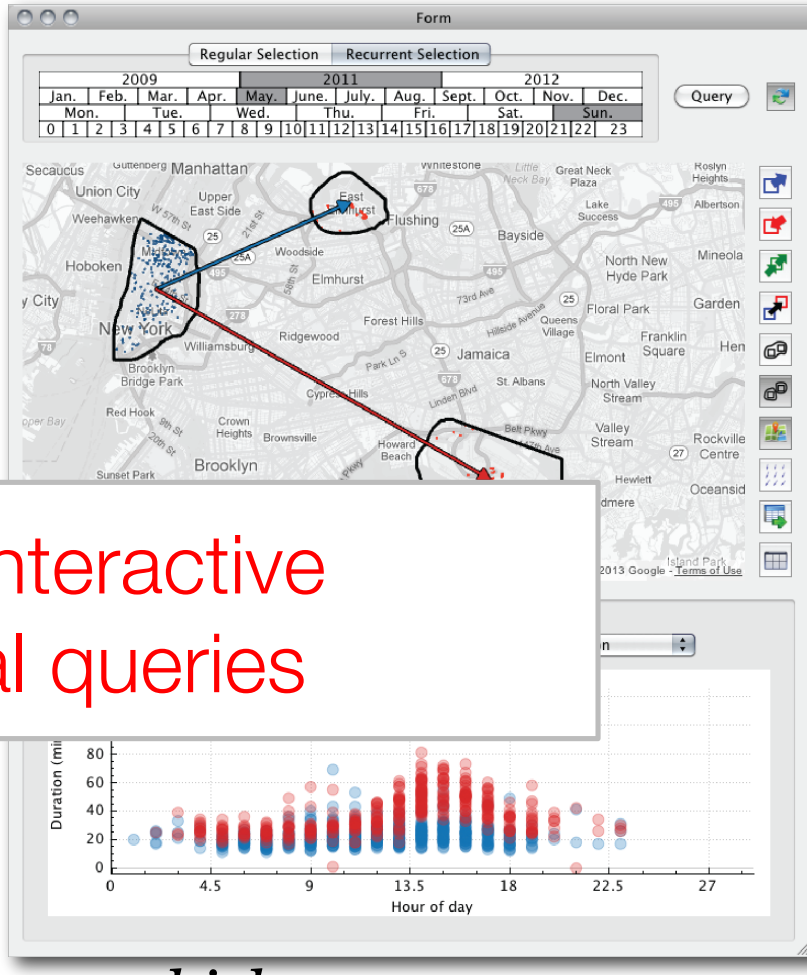


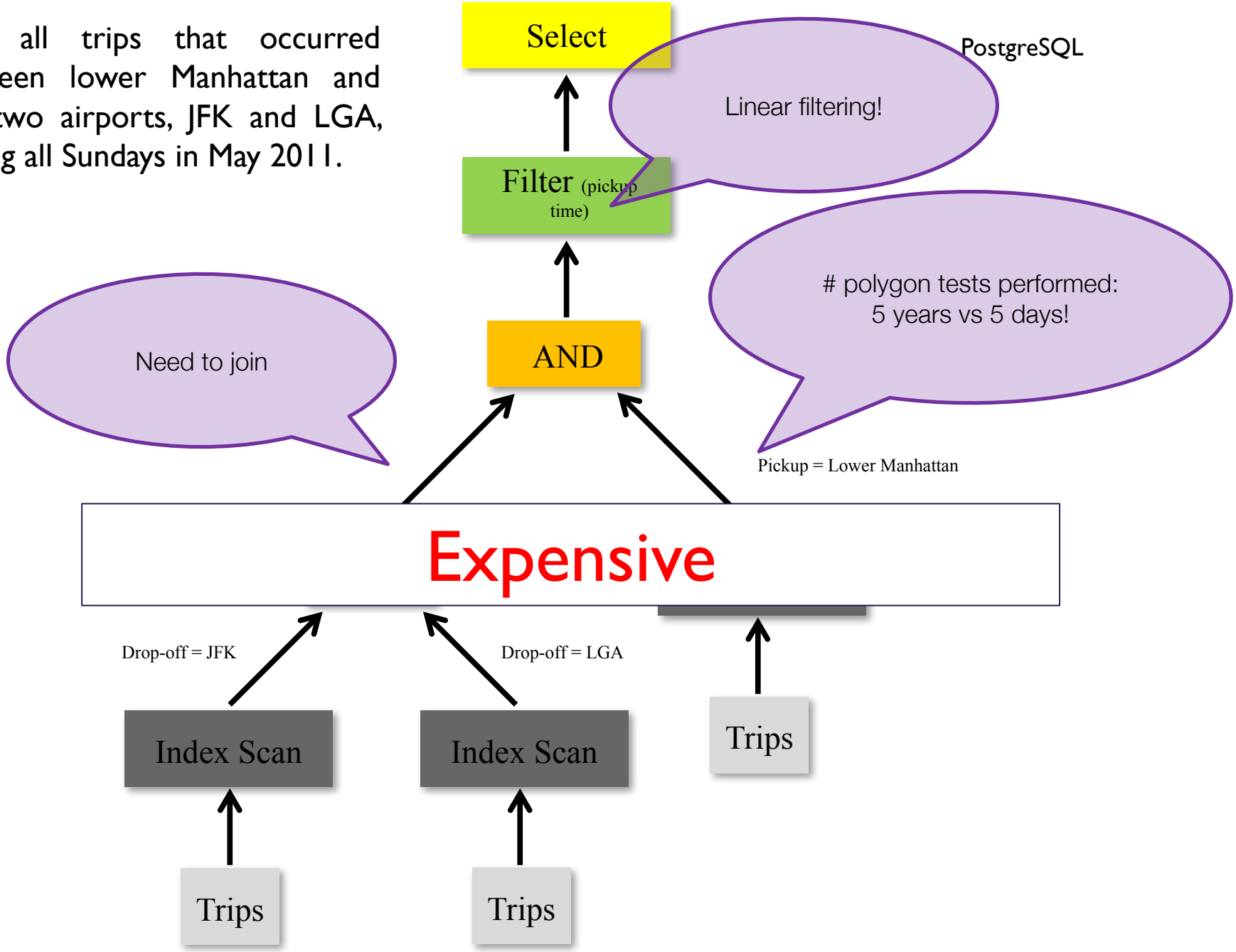
Query time (sec)	503.9	20.6

Goal: Support interactive spatio-temporal queries

"increased latency reduces the rate at which users make observations, draw generalizations and generate hypotheses"

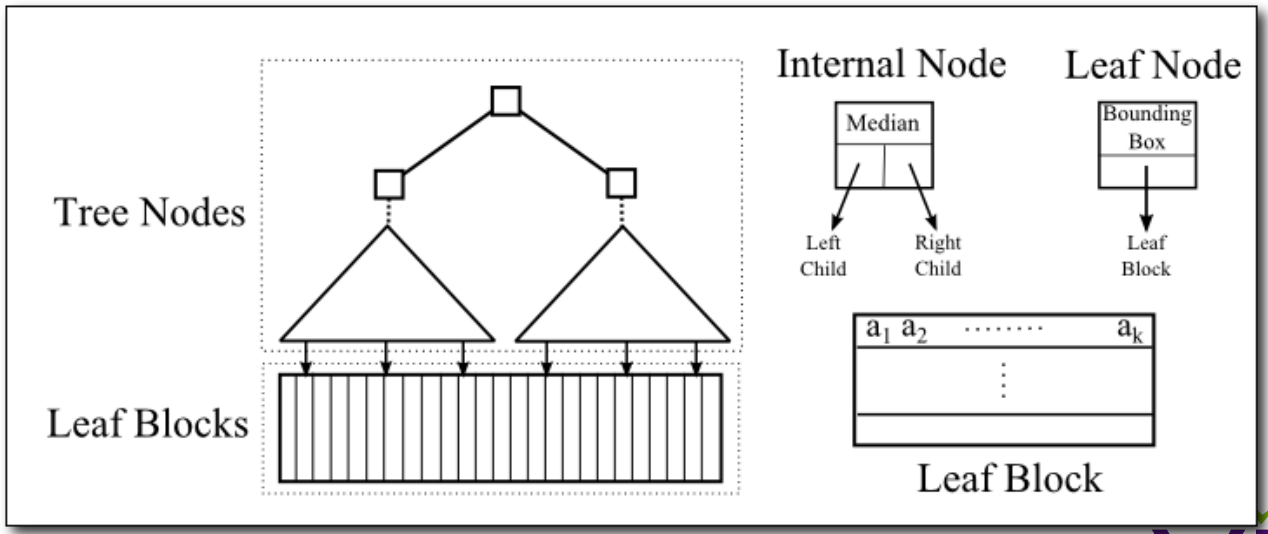
[Liu and Heer, TVCG 2014]

Find all trips that occurred between lower Manhattan and the two airports, JFK and LGA, during all Sundays in May 2011.



STIG: Supporting Interactive Queries

- Spatio-temporal index based on out-of-core kd-tree using GPUs (STIG)
- Can index and simultaneously filter multiple attributes: avoid joins and reduce the number of point-in-polygon (PIP) tests
- Block-based kd-tree
  - Tree nodes store kd-tree
  - Leaf nodes represent a *set of k-dimensional nodes:* Point to a leaf block containing records that satisfy the path constraints



[Doraiswamy et al., ICDE 2016]

STIG: Supporting Interactive Queries (cont.)

- Spatio-temporal index based on out-of-core kd-tree using GPUs
- Can index and simultaneously filter multiple attributes: avoid joins and reduce the number of point-in-polygon (PIP) tests
- Block-based kd-tree
  - Tree nodes store kd-tree
  - Leaf nodes represent a *set of k-dimensional nodes:* Point to a leaf block containing records that satisfy the path constraints
  - Create *big* blocks – tree is small and fits in memory
  - Use GPU to search the blocks in parallel – speeds up PIP tests
- Source code available at

  https://github.com/harishd10/mongodb

Performance Evaluation

Setup:

- 12-code Xeon processor @2.4 GHz
- 8 TB storage
- 256 GB memory
- 3 x NVIDIA GeForce TITAN
  - 6 GB memory

Performance: Taxi Data

Find all trips between Lower Manhattan and the two airports, JFK and LGA, during all Sundays in May 2011.

Query	MongoDB	PostgreSQL		ComDB	
	Time	Time	Speed up	Time	Speed up
1		503.9		20.6	
2		501.9		23.3	
3		437.8		21.6	
4		437.1		32.6	

Time in Seconds

868 million trips; ~13k results/query

Performance: Taxi Data

Find all trips between Lower Manhattan and the two airports, JFK and LGA, during all Sundays in May 2011.

Query	MongoDB	PostgreSQL		ComDB	
	Time	Time	Speed up	Time	Speed up
1	0.075	503.9	6718	20.6	274
2	0.080	501.9	6273	23.3	291
3	0.067	437.8	6534	21.6	322
4	0.070	437.1	6244	32.6	465

Time in Seconds

868 million trips; ~13k results/query

Performance: Twitter Data

Query	MongoDB	PostgreSQL		ComDB	
	Time	Time	Speed up	Time	Speed up
1	0.246	161.2	655	109.6	445
2	0.288	151.2	525	157.7	547
3	0.558	286.0	512	216.8	388

Time in Seconds

1.1 billion tweets; 130k-370k results/query

TaxiVis: Status

- Demoed to NYC DOT and TLC

---------- Forwarded message ----------
From: [redacted]@tlc.nyc.gov>
Date: Thu, Oct 24, 2013 at 4:58 PM
Subject: NYC taxi data
To: "Claudio Silva (csilva@nyu.edu)" <csilva@nyu.edu>, "Huy Vo (huy.vo@nyu.edu)" <huy.vo@nyu.edu>, "Caryn Joy Knutsen (caryn.knutsen@nyu.edu)" <caryn.knutsen@nyu.edu>, "Kim Alfred (kim.alfred@nyu.edu)" <kim.alfred@nyu.edu>
[redacted]>

Hi all,

First, I would like to thank you all for coming to data. We were truly blown away! In fact, we ha product like the one you've demonstrated to us [redacted] for us on Monday. We think that could be a gre future use for our data in combination with othe

[redacted]

Cheers,

[redacted]

"The speed at which the tool permits us to work has saved multiple hours of staff time and has dramatically improved the unit's output and capabilities."

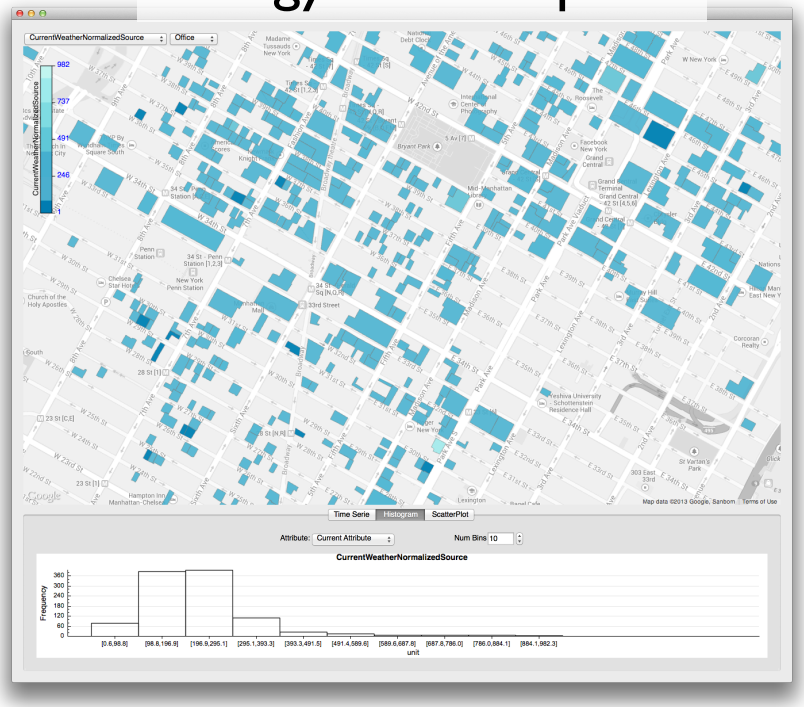
Assistant Commissioner, DoT

TaxiVis: Status

- Demoed to NYC DOT and TLC
- System is open source
  - https://github.com/ViDA-NYU/TaxiVis
- Used to explore different data sets

Property Ownership

Energy Consumption



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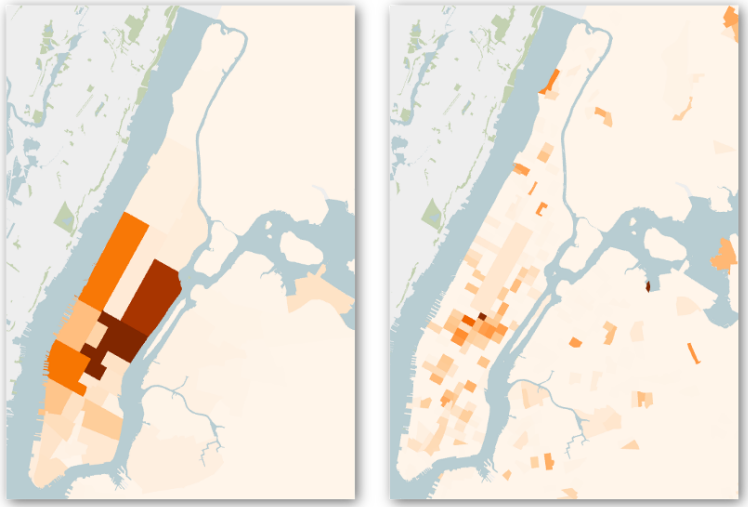
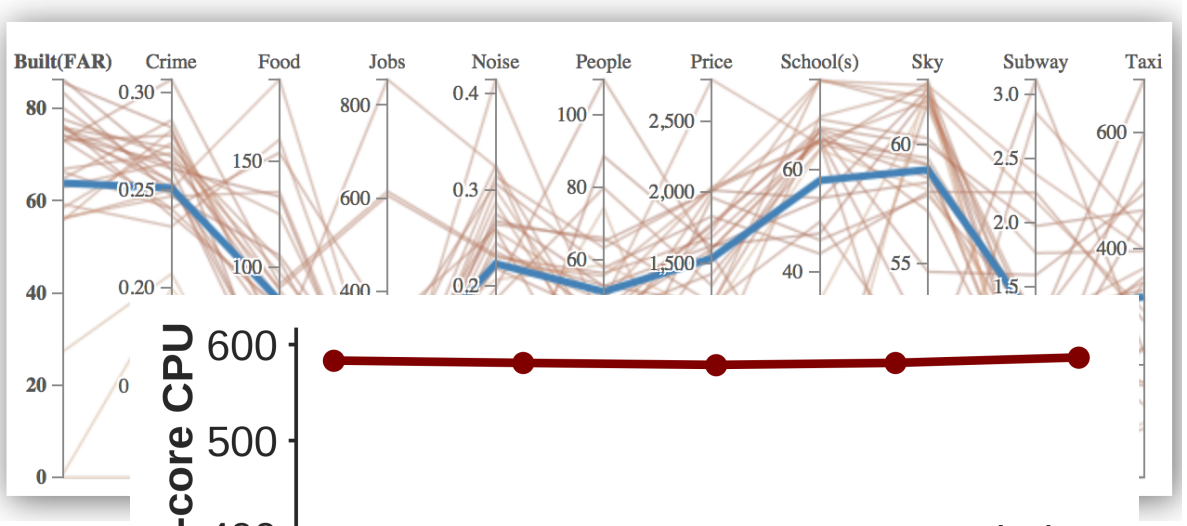
What Next: Urbane

https://www.youtube.com/watch?v=_B35vxCgDw4&feature=youtu.be

[Ferreira et al., IEEE VAST 2015]

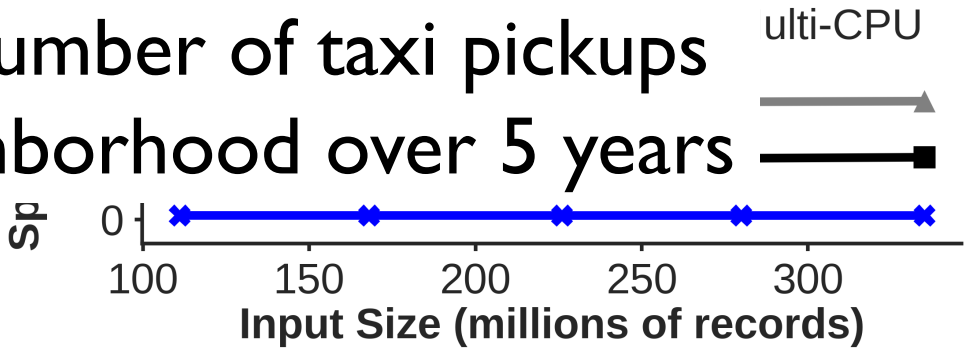
Spatial Aggregation





- Convert spatial join + aggreg operatic
- Exploit
- Support interactive respons commodity laptops/desktops

1.1 sec to count number of taxi pickups in each NYC neighborhood over 5 years



[Tzirita et al., VLDB 2018]

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A Unified Index for Spatio-Temporal Keyword Queries

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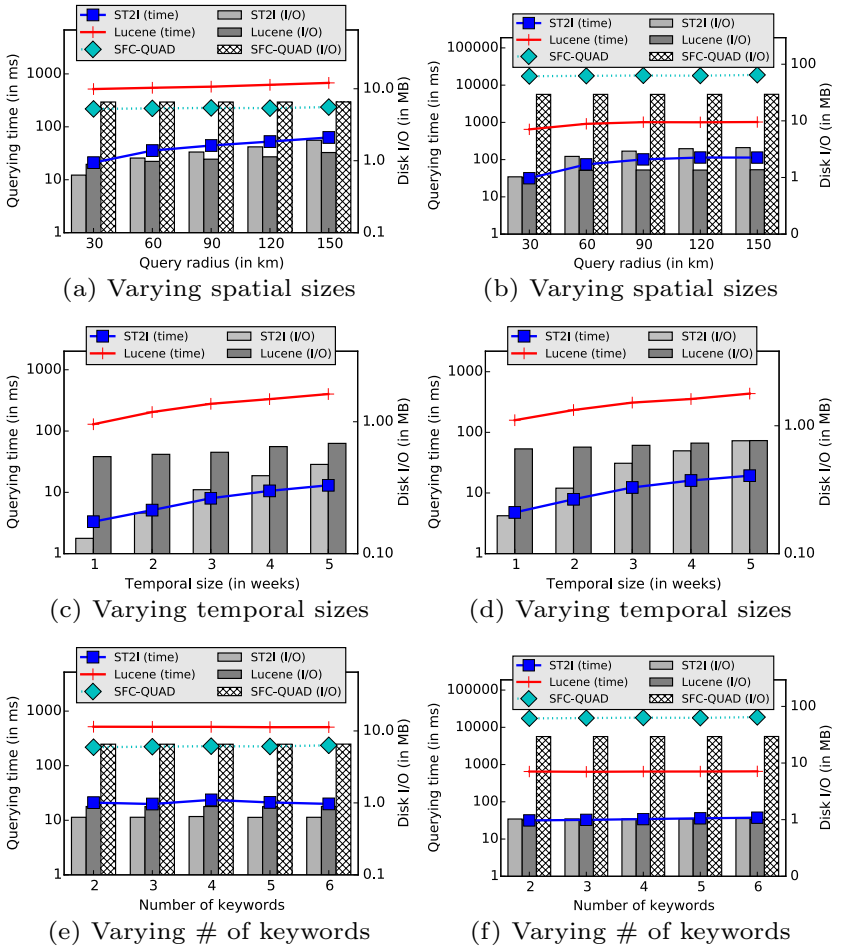
ABSTRACT

From tweets to urban data sets, there has been an explosion in the volume of textual data that is associated with both temporal and spatial components. Efficiently evaluating queries over these data is challenging. Previous approaches have focused on the spatial aspect. Some used separate indices for space and text, thus incurring the overhead of storing separate indices and joining their results. Others proposed a combined index that either inserts terms into a spatial structure or adds a spatial structure to an inverted index. These benefit queries with highly-selective constraints that match the primary index structure but have limited effectiveness and pruning power otherwise. We propose a new indexing strategy that uniformly handles text, space and time in a single structure, and is thus able to efficiently evaluate queries that combine keywords with spatial and temporal constraints. We present a detailed experimental evaluation using real data sets which shows that not only our index attains substantially lower query processing times, but it can also be constructed in a fraction of the time required by state-of-the-art approaches.



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a query such as q_3 in Table 1, which retrieves all tweets containing a term and that was posted at given location

[Hoang-Vu et al., CIKM 2016]

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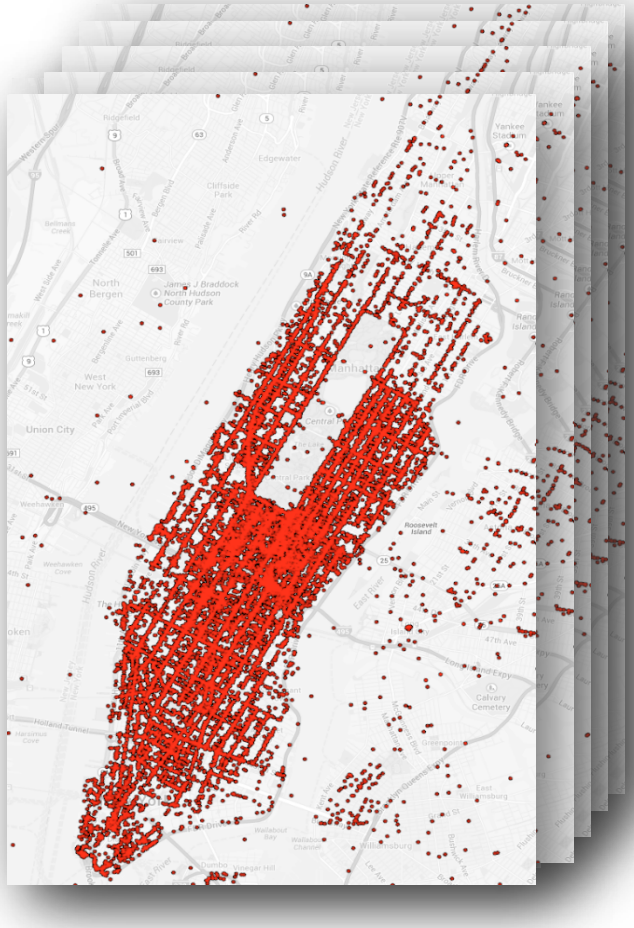
Exploring Data:
Finding Interesting Features

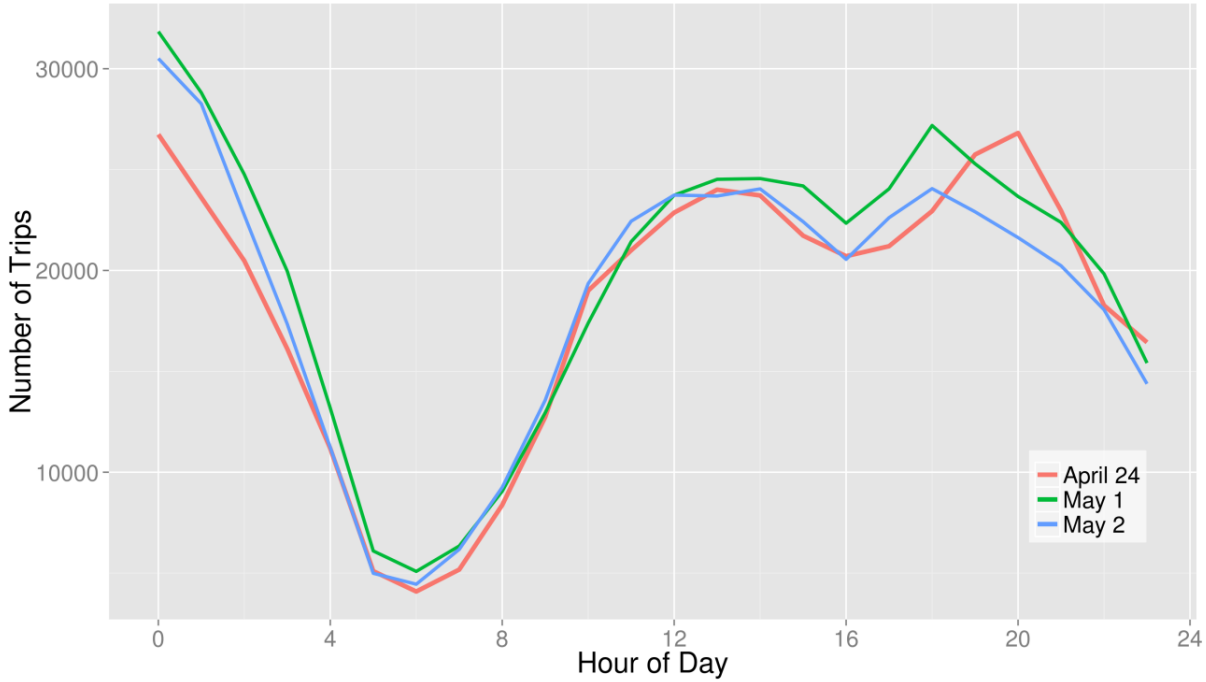
Taxi Data: Too Many Slices



- 365*24 1-hour slices in one year
- Which slices are interesting?

Reducing the Number of Slices

Aggregate over space



Aggregate over time

April 24 May 1 May 8

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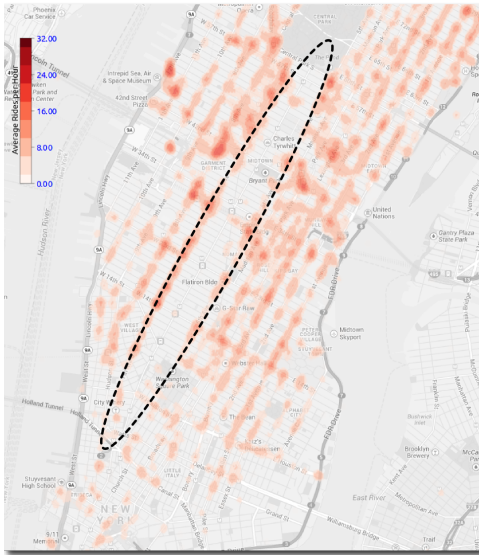
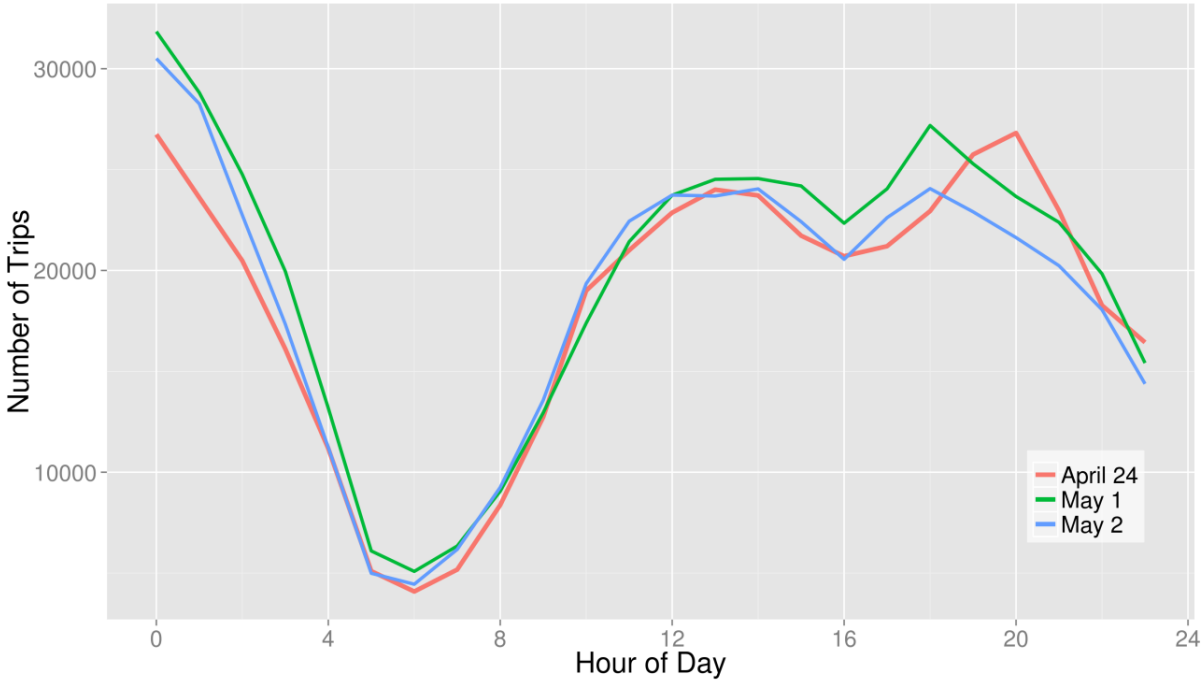
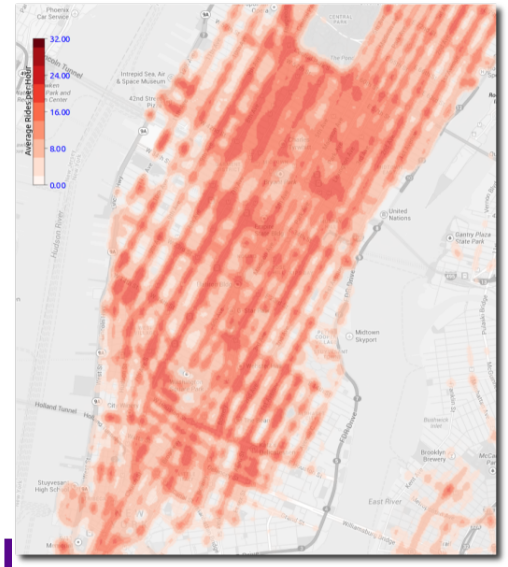
Miss Interesting Slices

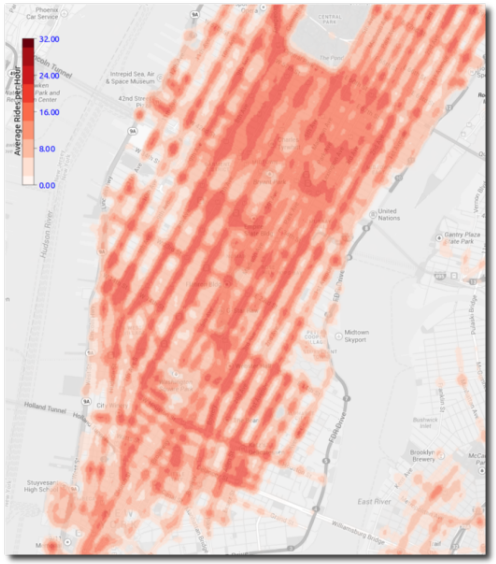


May 1 (8-9am)

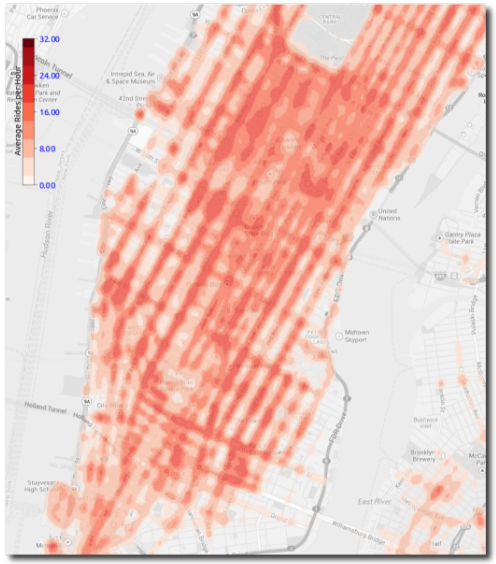




April 24



May 1



May 8

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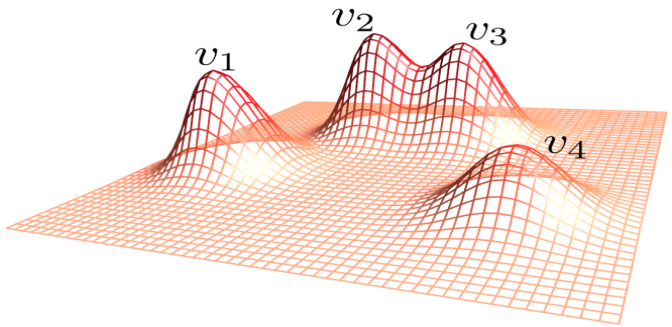
Finding Interesting Slices

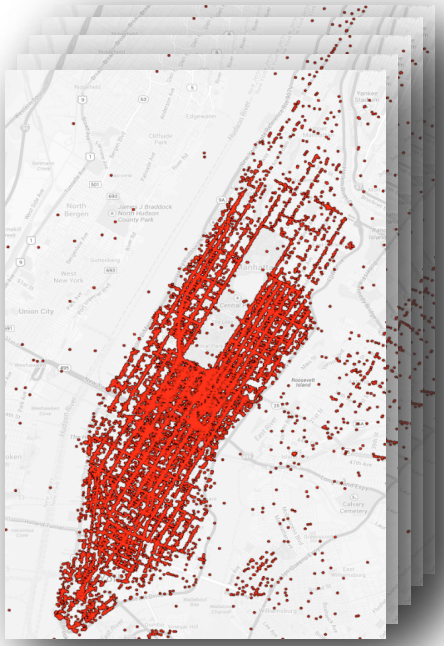
- Desiderata: automatically identify *events* with arbitrary spatial structure and at multiple temporal scales
- Our solution: Use computational topology techniques to efficiently discover events
  - Model data as a time-varying scalar function
  - Identify regions of maxima and minima: a region is *interesting* if its behavior differs from that of its neighborhood

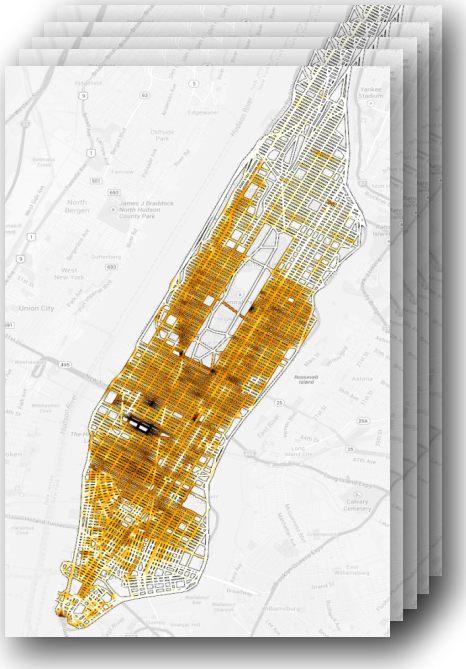


[Doraiswamy et al., IEEE TVCG 2014]

Identifying Potential Events

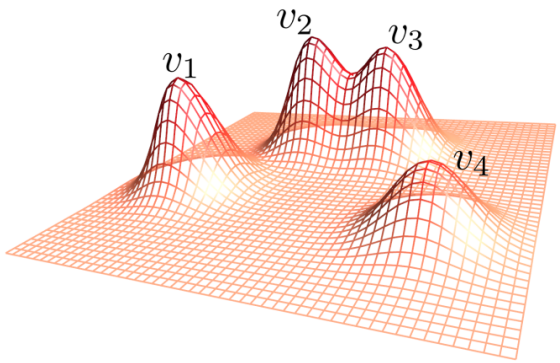
- Model data as a time-varying scalar function defined on a graph
  - $f : G \rightarrow R$
  - Taxi data: Graph = road network; Function = density of taxis
  - Subway data: Graph = track network; Function = delay of trains

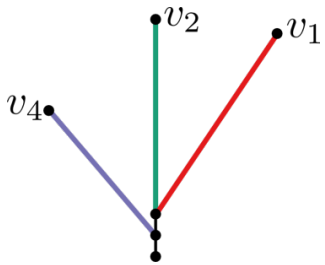


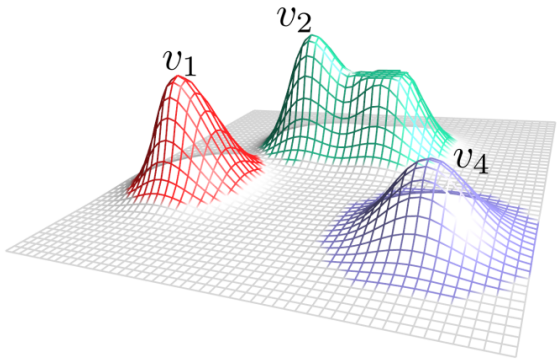


Identifying Potential Events

- Use Merge Trees to efficiently identify events in each time step
- Compute the regions corresponding to the set of *maxima* and *minima – the set of potential events*
  - Intuition: a region is interesting if its behavior differs from that of its neighborhood
  - Unimportant events can be simplified

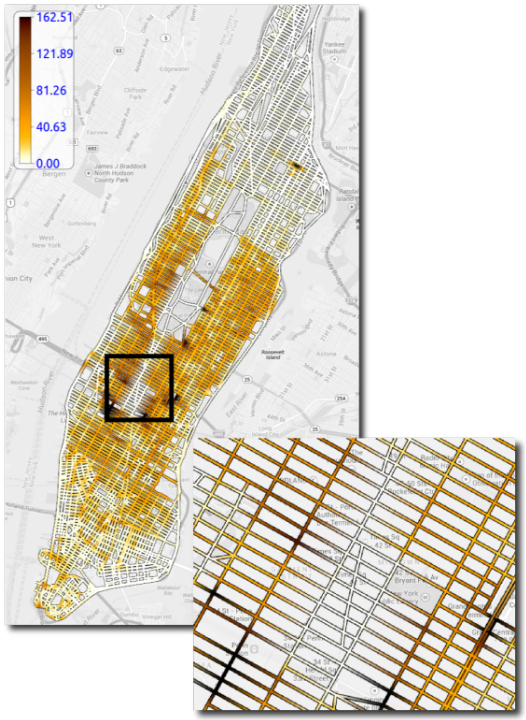






Taxi Data: Potential Events

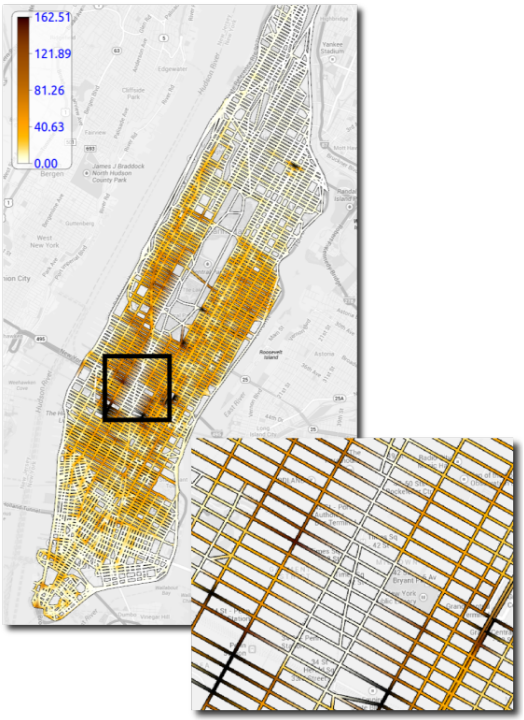
- Minima: lack of taxis
  - Regions where density is lower than local neighborhood
  - Could denote road blocks, e.g., Macy's parade

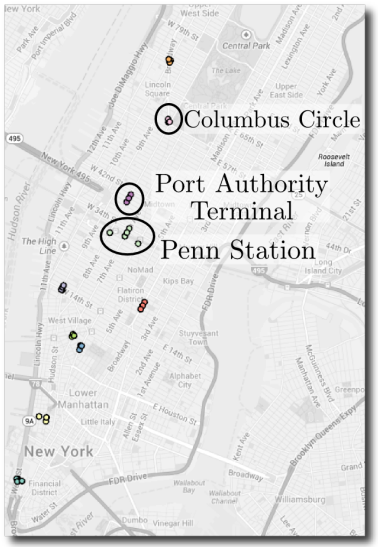


Scalar function corresponding to the time step 10 am-11 am on 24 November 2011

Taxi Data: Potential Events

- Minima: lack of taxis
  - Regions where density is lower than local neighborhood
  - Could denote road blocks, e.g., Macy's parade
- Maxima: popular taxi locations
  - Regions where density is higher than local neighborhood
  - Could denote tourist locations, train stations





Querying Events

5 Borough Bike Tour 2011 (1 May 2011)

Query

Dominican Day Parade 2011 (14 August 2011)

5 Borough Bike Tour 2012 (6 May 2012)

Dominican Day Parade 2012 (12 August 2012)

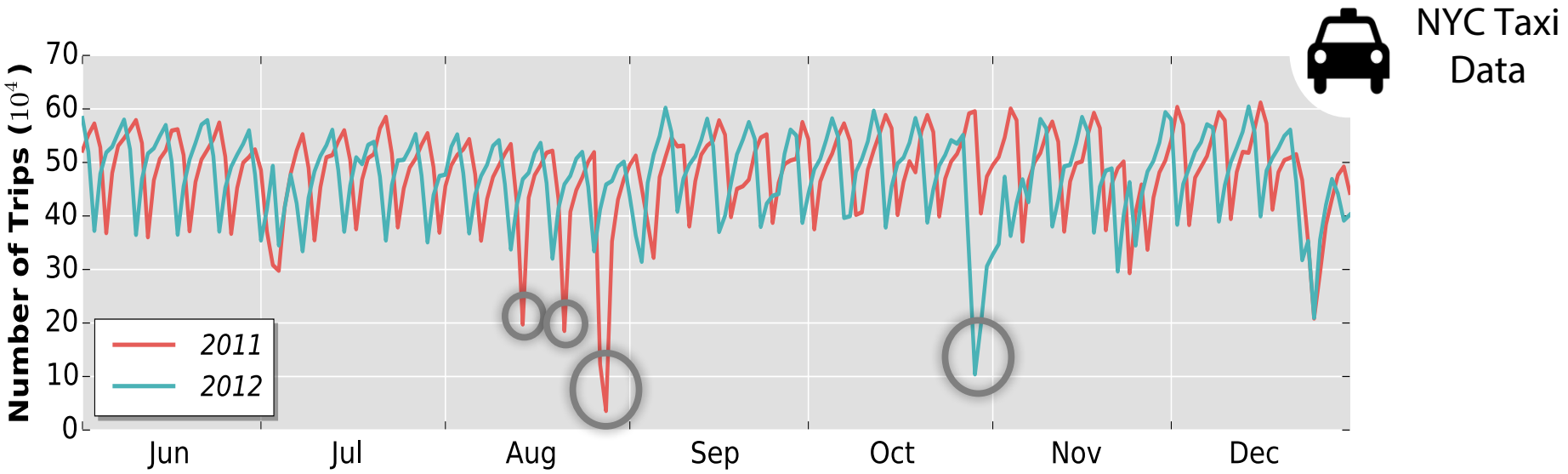
Gaza Solidarity Protest NYC (18 November 2012)

NYU TANDON SCHOOL OF ENGINEERING

CENTER

Using Data to Explain Data

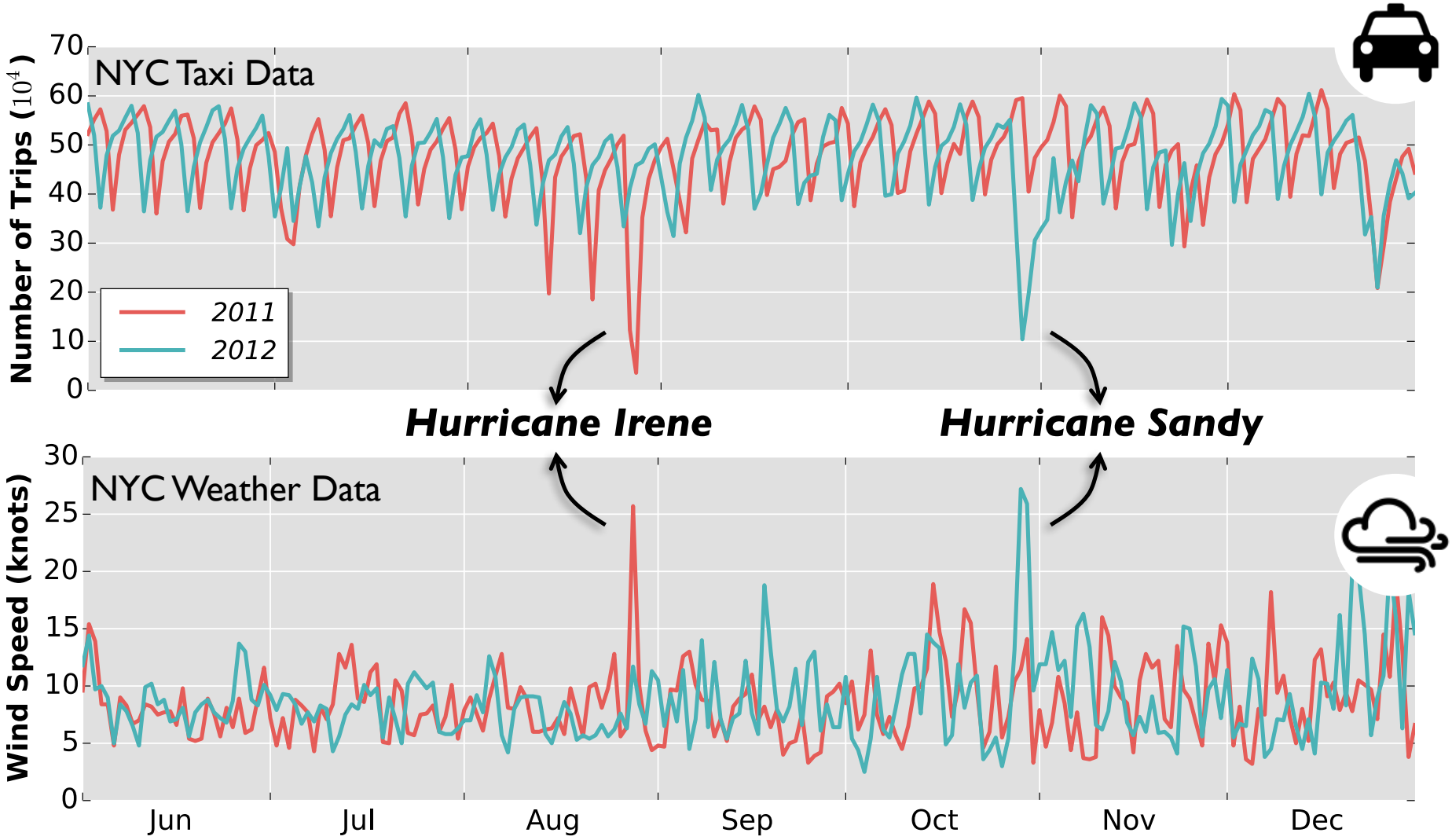
Explaining Events



- Are these big drops data quality issues in the data?
- Or do they correspond to *real* events?

Find all data sets related to the Taxi data set

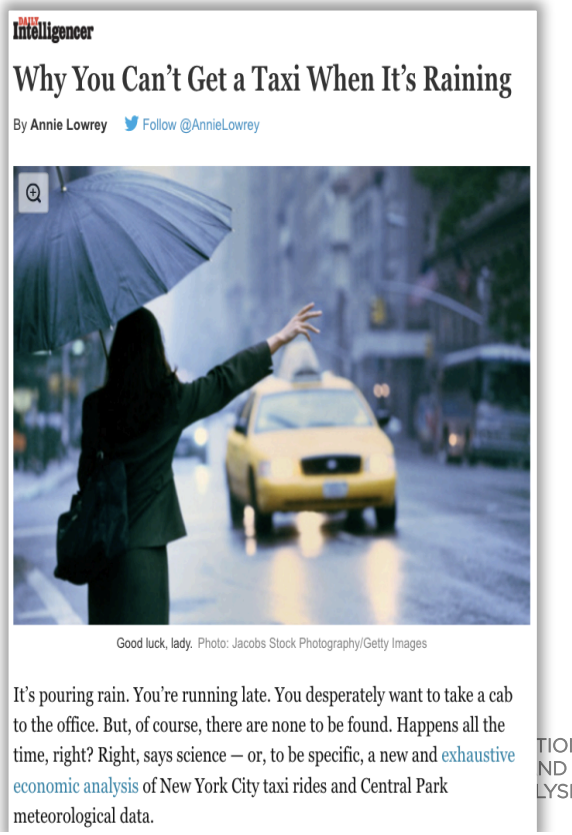
Using Data to Explain Events



Using Data to Explain and Predict NYC

1. Would a reduction in traffic speed reduce the number of accidents? What other factors contribute to accidents?
2. Why it is so hard to find a taxi when it is raining?

http://nymag.com/daily/intelligencer/2014/11/why-you-cant-get-a-taxi-when-its-raining.html



Intelligencer

Why You Can't Get a Taxi When It's Raining

By Annie Lowrey Follow @AnnieLowrey

Good luck, lady. Photo: Jacobs Stock Photography/Getty Images

It's pouring rain. You're running late. You desperately want to take a cab to the office. But, of course, there are none to be found. Happens all the time, right? Right, says science — or, to be specific, a new and exhaustive economic analysis of New York City taxi rides and Central Park meteorological data.

Urban Data Interactions

By uncovering **relationships** between data sets, we can

- Better understand a city and how its different components interact
- Discover important attributes that can inform the construction of predictive models

Where to start?

- Data are available!
- Answers are likely in the data
- But there are too many data sets, and even more attributes to consider

NYC OpenData — 1,200 data sets (and counting) — 8 attributes per data set

weather — > 200 attributes

Which data sets to analyze?

The Data Polygamy Framework

- **Discover relationships** between data sets to better understand urban data and how the different components of city interact
- Each data set can be related to **zero or more** data sets through several attributes

Data sets are polygamous!

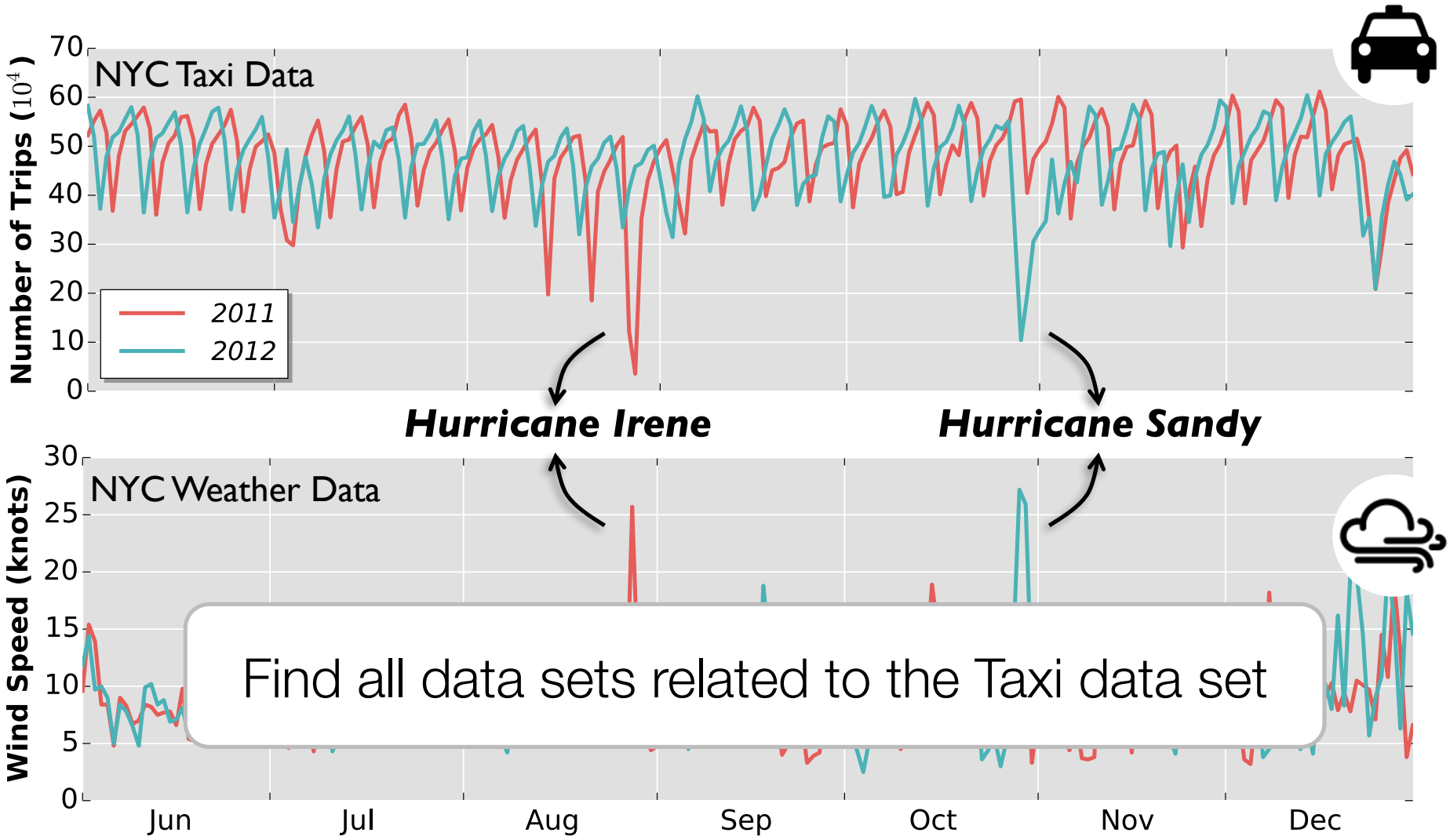
- Guide users in **data discovery and analysis** by allowing them to pose ***relationship queries***

Find all data sets related to a given data set $\mathbb{D}$

- **Support both hypothesis generation and testing**

[Chirigati et al., ACM SIGMOD 2016]

Hypothesis Generation



Hypothesis Testing

- Hypothesis: Taxi drivers set an income goal, and on rainy days they reach the goal faster

Taxi Fare

x

Precipitation

Find relationships between Weather and Taxi data sets

DAILY Intelligencer

Why You Can't Get a Taxi When It's Raining

By **Annie Lowrey** Follow @AnnieLowrey

Good luck, lady. Photo: Jacobs Stock Photography/Getty Images

It's pouring rain. You're running late. You desperately want to take a cab to the office. But, of course, there are none to be found. Happens all the time, right? Right, says science — or, to be specific, a new and exhaustive economic analysis of New York City taxi rides and Central Park meteorological data.

http://nymag.com/daily/intelligencer/2014/11/why-you-cant-get-a-taxi-when-its-raining.html

Challenge: Defining a Relationship

- Must take both space and time into account
- How and when are two data sets related?
  - Some relationships become visible through *atypical* behavior
- Conventional techniques (e.g., Pearson's correlation, mutual information, DTW, etc.) take into account the entire data and miss relationships that occur only at certain times/locations
  - E.g., most of the time, taxi trips and wind speed are not related

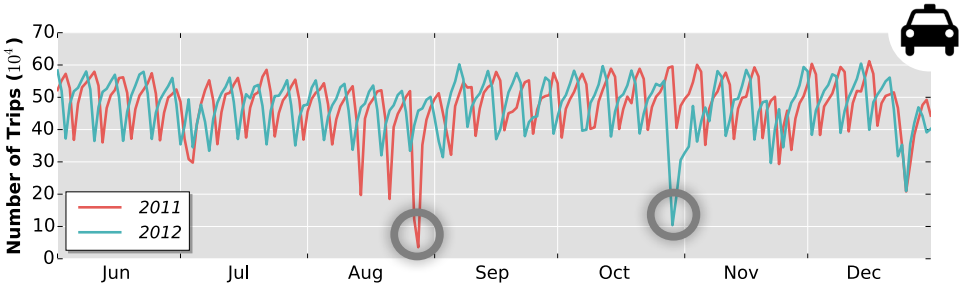
Challenge: Identifying Meaningful Relationships

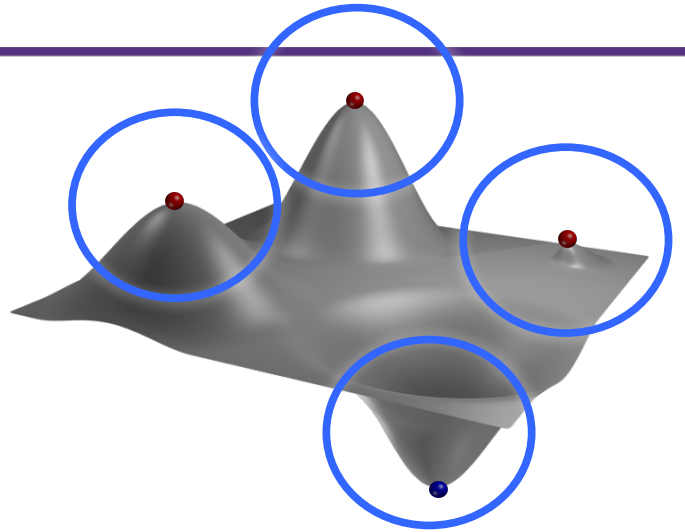
- Many data sets, each consisting of many attributes
  - Relationships can be between any of the attributes
  - Weather data: >200 attributes; NYC Open data: 8 attributes per data set on an average
- Data sets can be large
  - Taxi data: 180M trips per year
- Data at multiple spatio-temporal different resolutions
- Combinatorially large number of relationships to evaluate
  - ~2.4 million possible relationships among NYC Open Data alone for a single spatio-temporal resolution

meaningful relationship ⟷ needle in a haystack

How and when are two data sets related?

- Topology-based relationships





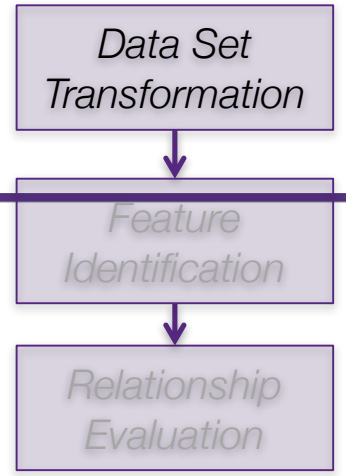
Peaks
Valleys
Critical Poin

- Topological representation captures salient features of the data

> A salient feature is a spatio-temporal region whose behavior differs from its neighborhood

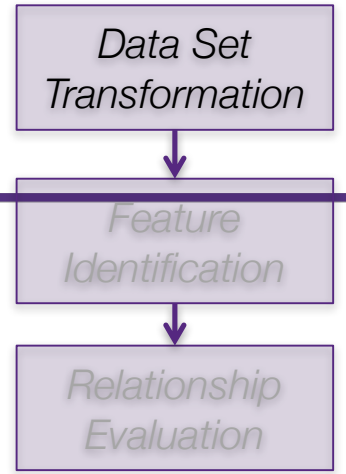
- Supports arbitrary spatial structures and time intervals
- Efficient feature identification through Merge Tree Index
- ***Definition*:** Two data sets are related if their **salient features** are related

Data Set to Scalar Functions

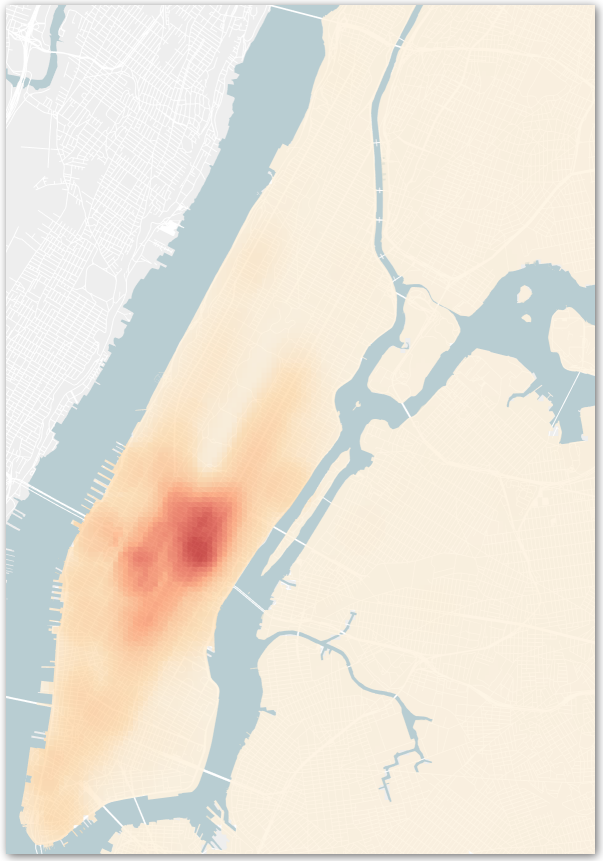


- Each data set represented as a set of time-varying scalar functions
  - $f : [\mathbb{S} \times \mathbb{T}] \rightarrow \mathbb{R}$
  - Maps each point in space and time to a real value
- Different functions can be used
  - Count: Captures the activity of an entity corresponding to the data, e.g., number of trips, number of unique taxis, etc.
  - Attribute: Captures attribute value variation, e.g., average taxi fare
- Functions computed at all possible resolutions

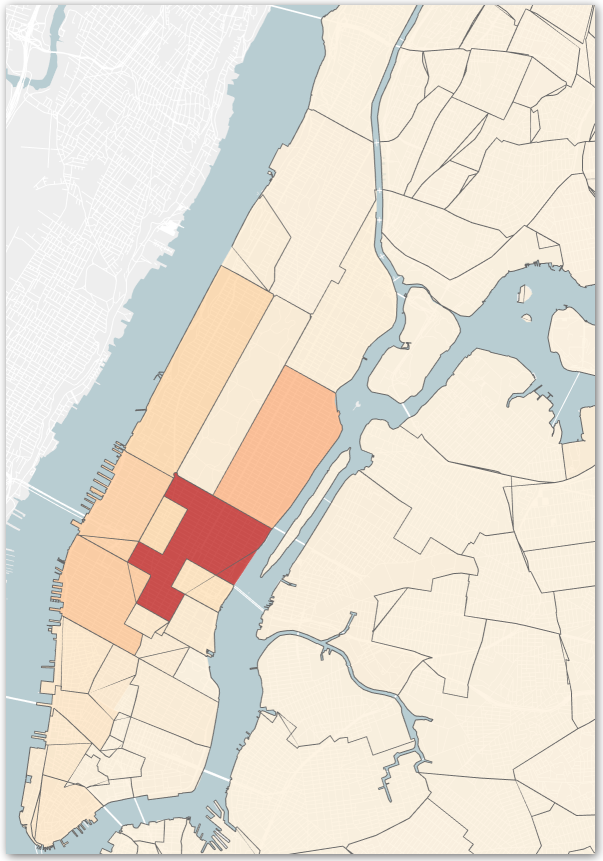
Data Set to Scalar Functions



- Example: Density function of Taxi data

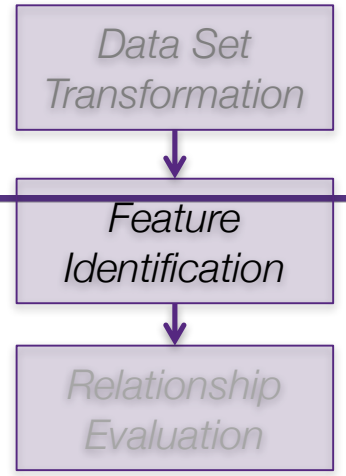


$\mathbb{S}$: *High Resolution Grid*



$\mathbb{S}$: *Neighborhood Resolution*

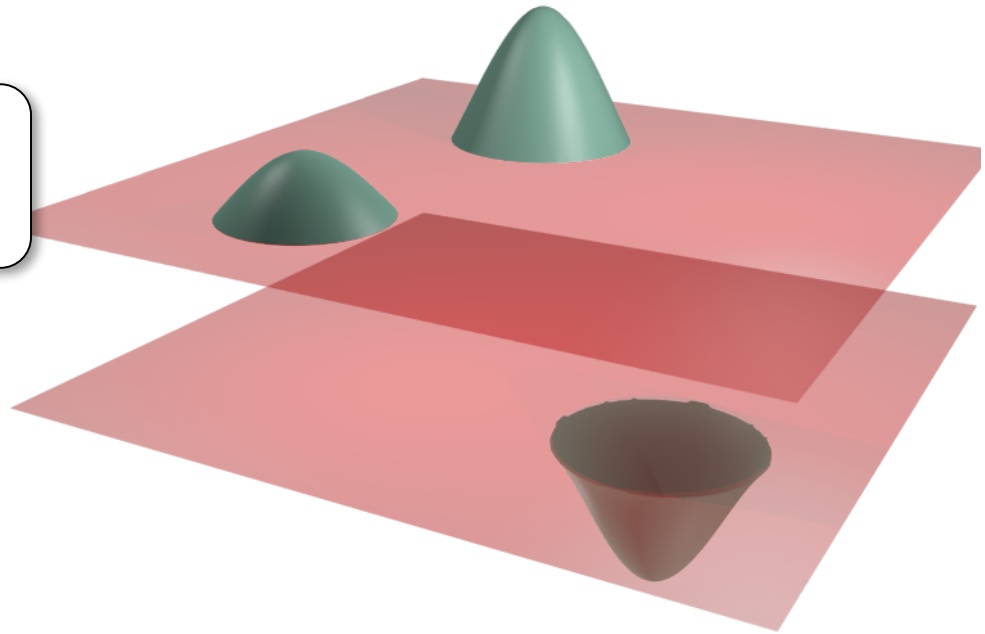
Identify Salient Features



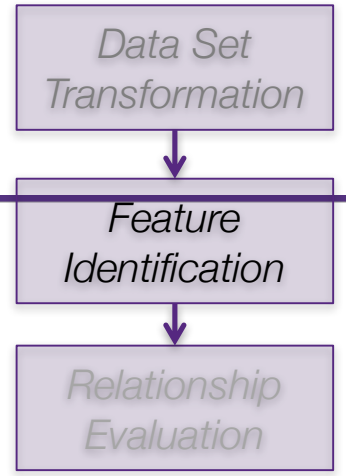
- Topological features of *a scalar function*
  - Neighborhood of critical points
  - Features represented as spatio-temporal points
  - Positive and negative features

Advantage

1. Naturally captures *salient* features



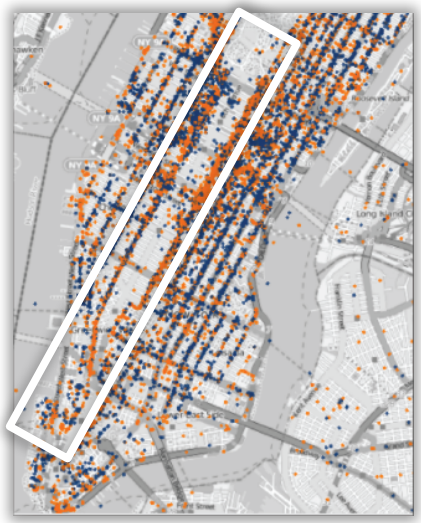
Identify Salient Features



- Topological features of *a scalar function*
  - Neighborhood of critical points
  - Features represented as spatio-temporal points
  - Positive and negative features

8am - 9am
May 1 2011

5 Boro Bike Tour

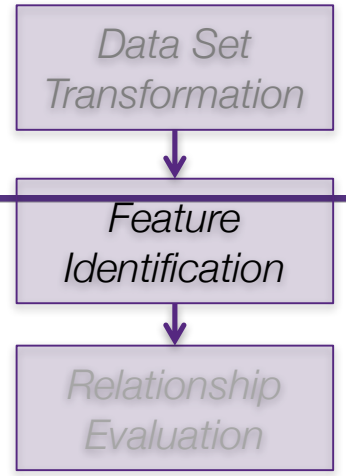


Negative Feature

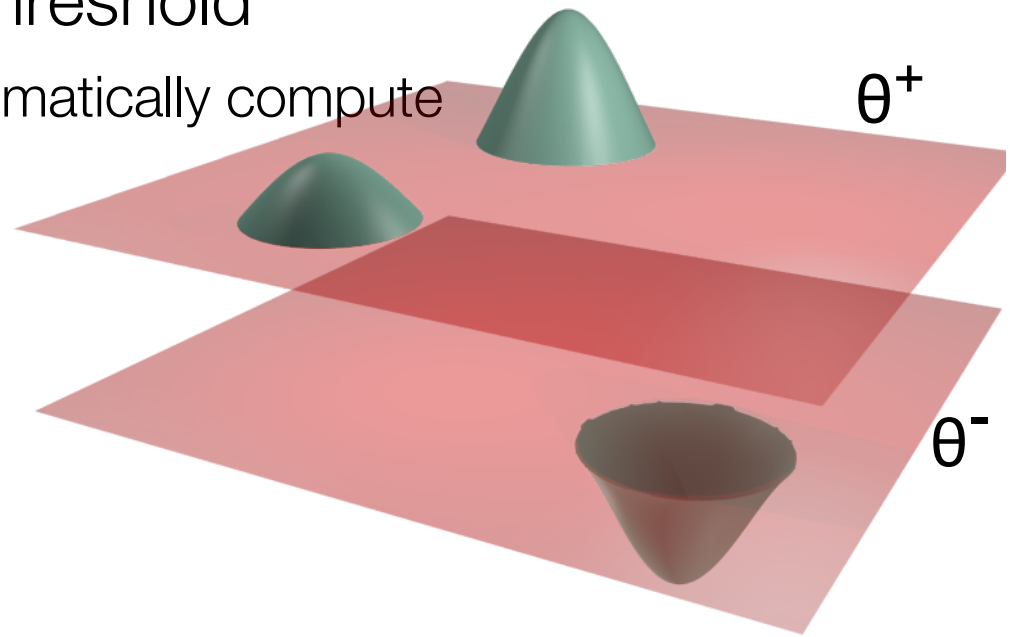
Advantage

2. Features can have arbitrary shapes

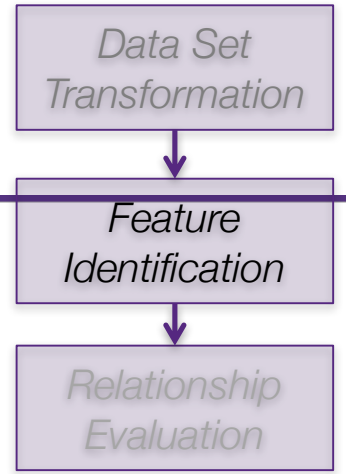
Identify Salient Features



- Topological features of *a scalar function*
  - Neighborhood of critical points
  - Features represented as spatio-temporal points
  - Positive and negative features
- Neighborhood defined by a threshold
  - Use *topological persistence* to automatically compute thresholds in a data-driven fashion



Identify Salient Features

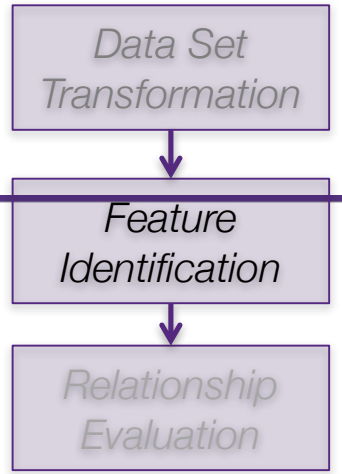


- Topological features of *a scalar function*
  - Neighborhood of critical points
  - Features represented as spatio-temporal points
  - Positive and negative features
- Neighborhood defined by a threshold
  - Use *topological persistence* to automatically compute thresholds in a data-driven fashion

Advantage

3. Data driven and robust

Identify Salient Features

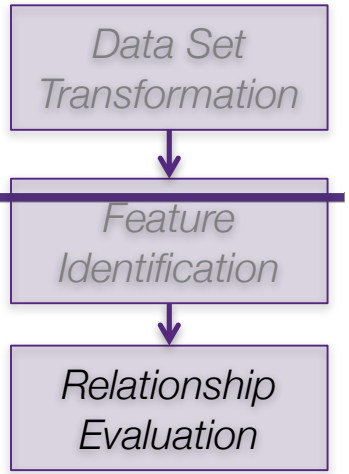


- Topological features of *a scalar function*
  - Neighborhood of critical points
  - Features represented as spatio-temporal points
  - Positive and negative features
- Neighborhood defined by a threshold
  - *Topological persistence used* to automatically compute thresholds
- *Merge Tree Index* used to identify features at all resolutions
  - *O(n log n)* to construct
  - Computing features is output sensitive

Advantage

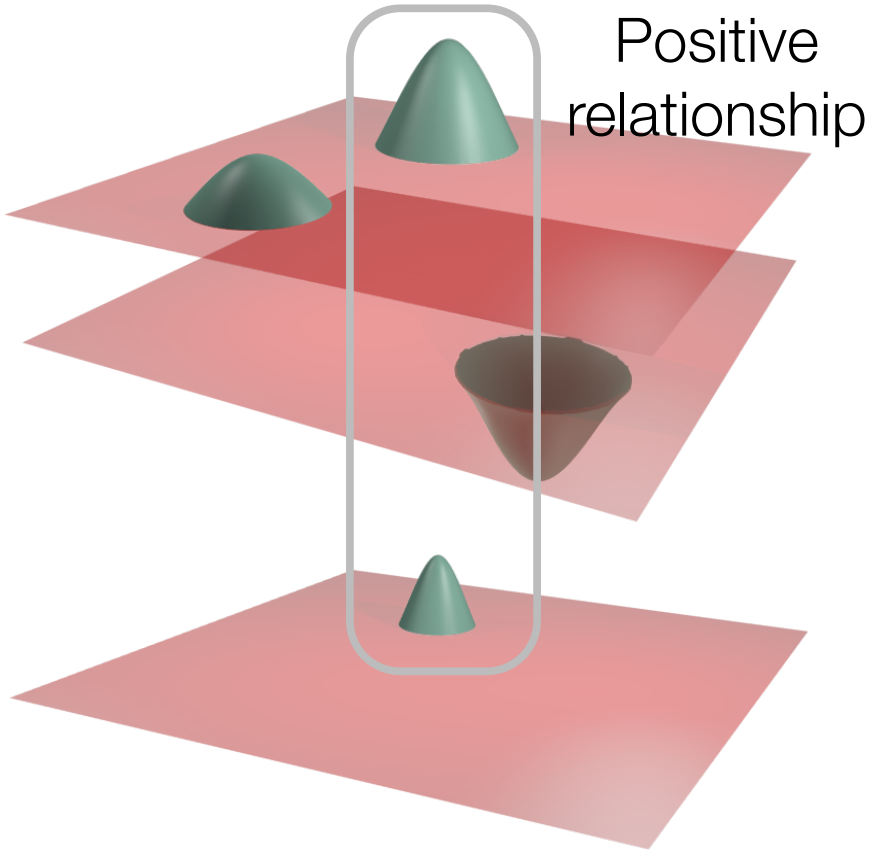
4. Very efficient

Evaluating Relationships

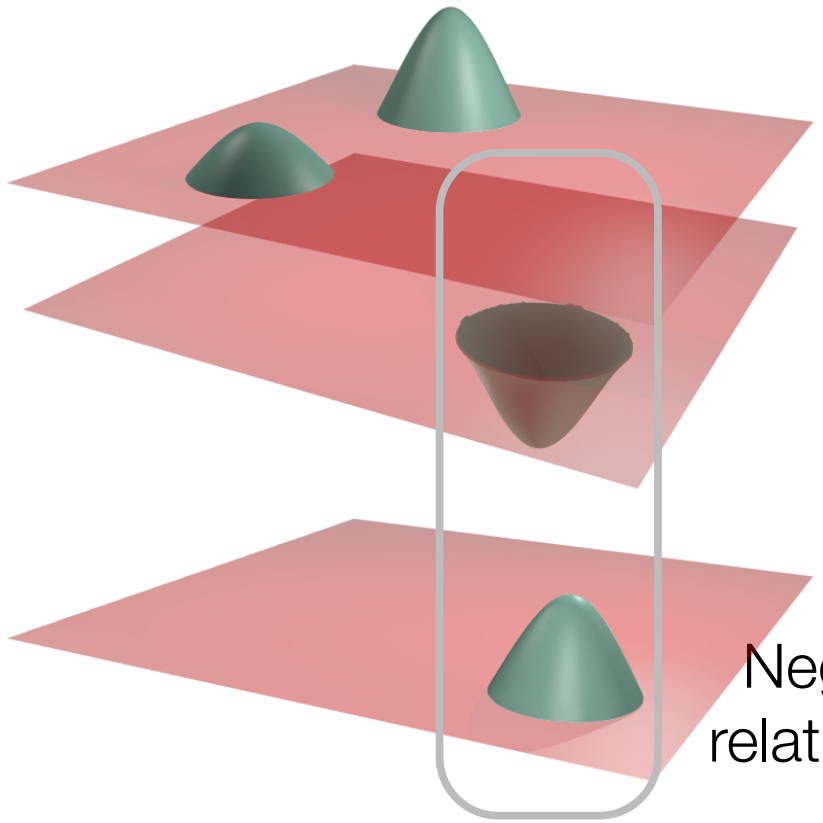


- Relationship between functions *f* and *g* consists of the set of spatio-temporal points that are features in both functions
- Let Σ_1 and Σ_2 be the set of features of f_1 and f_2. f_1 and f_2 are *feature-related* at a spatio-temporal point $x = (s,t)$ if $x \in \Sigma_1 \wedge \Sigma_2$
  - E.g., for Hurricane Sandy, there is a negative feature in the taxi density function and a positive feature in the wind speed function
- *Relationship Score:* Captures the nature of the relationship – positive or negative

Identifying Relationships

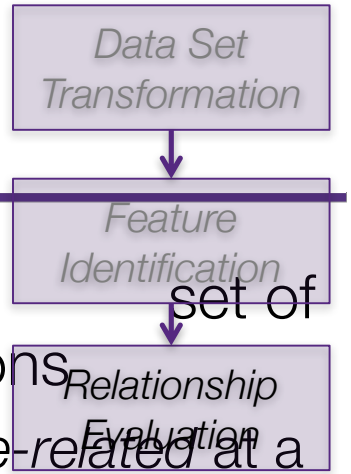


Identifying Relationships



Negative relationship

Evaluating Relationships



- Relationship between functions *f* and *g* consists of the set of spatio-temporal points that are features in both functions
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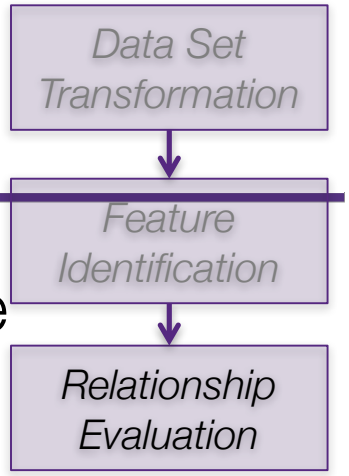
  - E.g., for Hurricane Sandy, there is a negative feature in the taxi density function and a positive feature in the wind speed function
- *Relationship Score:* Captures the nature of the relationship – positive or negative
- *Relationship Strength:* How often the functions are related – strong or weak
- Restricted Monte Carlo procedure to test the statistical significance accounting for the spatial and temporal proximity
  - Prune potentially coincidental relationships

Skip to Experiments

Evaluating Relationships



- Monte Carlo procedure to test the statistical significance accounting for the spatial and temporal proximity
  - Prune potentially coincidental relationships

Relationship between functions *f* and *g* , with score τ^*

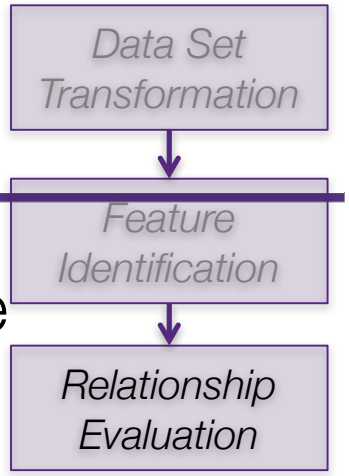
H0: The two functions are not related
H1: The two functions are related

$$p = \frac{\sum_i^N \mathrm{I}(\tau_i \geq \tau^*)}{N}$$

N permutations

Reject the null hypothesis if $p \leq \alpha$

Evaluating Relationships

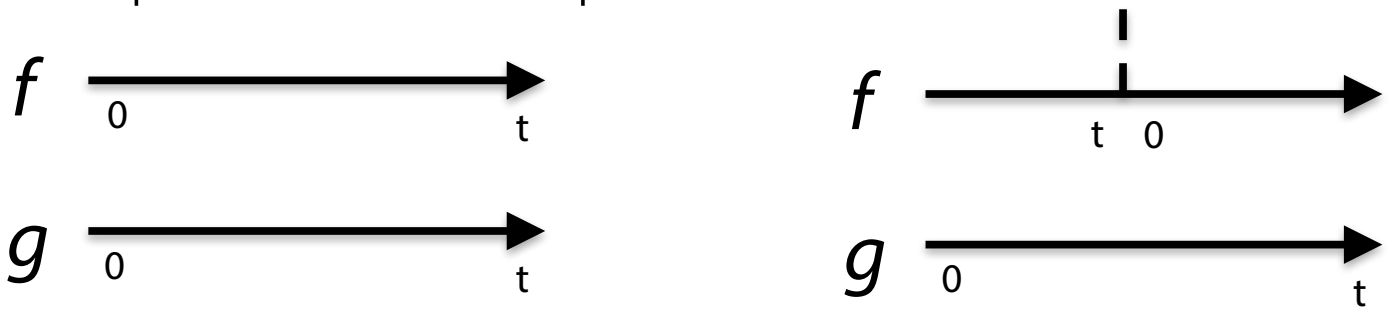


- Monte Carlo procedure to test the statistical significance accounting for the spatial and temporal proximity
  - Prune potentially coincidental relationships

Statistical Significance

Permutations: need to respect spatio-temporal correlations of the data!

Temporal case → Temporal shifts



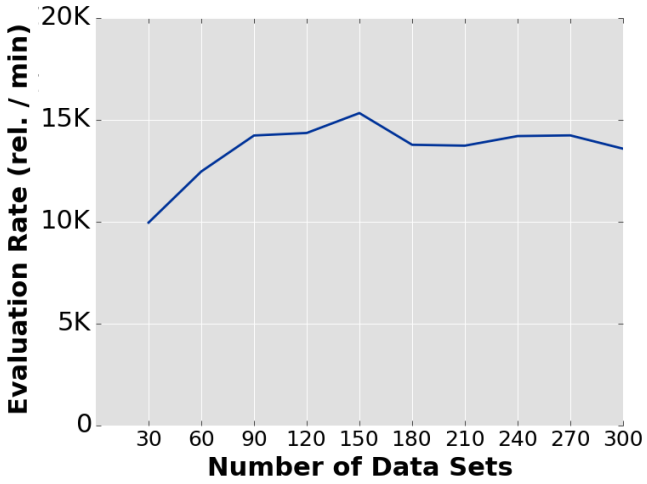
Spatial case → Spatial shifts

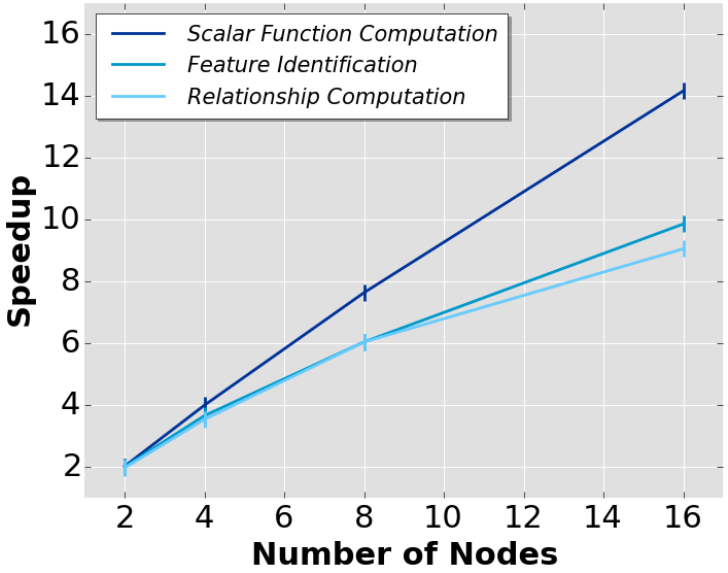
Experimental Evaluation

- Implemented using Map Reduce
  - Feature identification and relationship evaluation are independent operations
- Two collections of data sets used for experiments
  - NYC Urban: *9 data sets* from NYC agencies
  - NYC Open Data: 300 spatio-temporal data sets
- Setup
  - 20 compute nodes, AMD Opteron(TM) Processor 6272 (4x16 cores) running at 2.1GHz, 256GB of RAM – *for most experiment*
  - *Amazon EMR:* m1.medium (for master) and r3.2xlarge (for slaves) – *for scalability tests*

Quantitative Evaluation

- Approach is efficient: 200 min to compute scalar functions and features for NYC Open Data; and 60 min for NYC Urban
- Query rate: evaluate 10^4 relationships per minute
- Scales linearly with number of nodes
- Assessed correctness and robustness

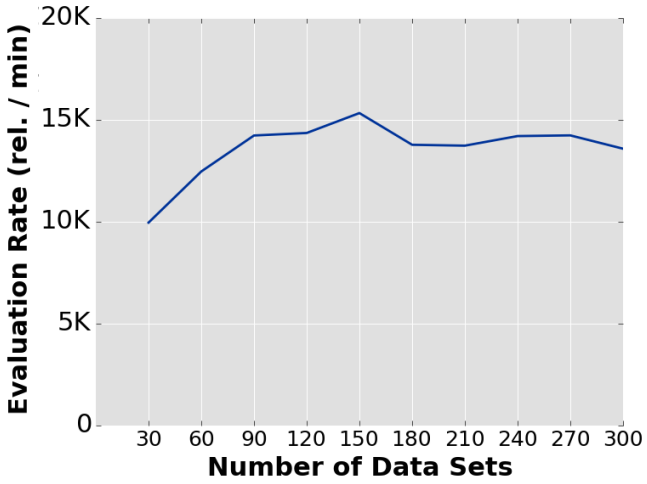


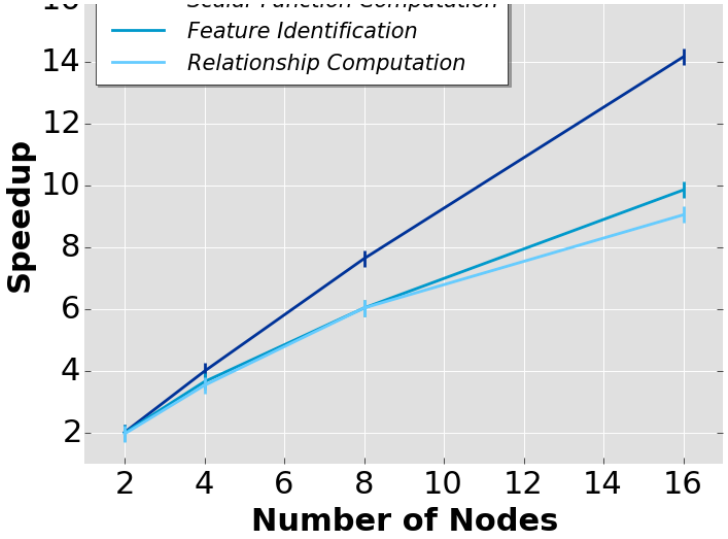


Details in [Chirigati et al., ACM SIGMOD 2016]

Quantitative Evaluation

- Approach is efficient: 200 min to compute scalar functions and features for NYC Open Data; and 60 min for NYC Urban
- Scales linearly with number of nodes
- Code, data, and reproducible experiments available at:
- https://github.com/ViDA-NYU/data-polygamy





Details in [Chirigati et al., ACM SIGMOD 2016]

Qualitative Evaluation

Does the approach uncover *interesting*, *non-trivial* relationships?

Details in [Chirigati et al., ACM SIGMOD 2016]

(Some) Interesting Relationships

1. Would a reduction in traffic speed reduce the number of accidents?

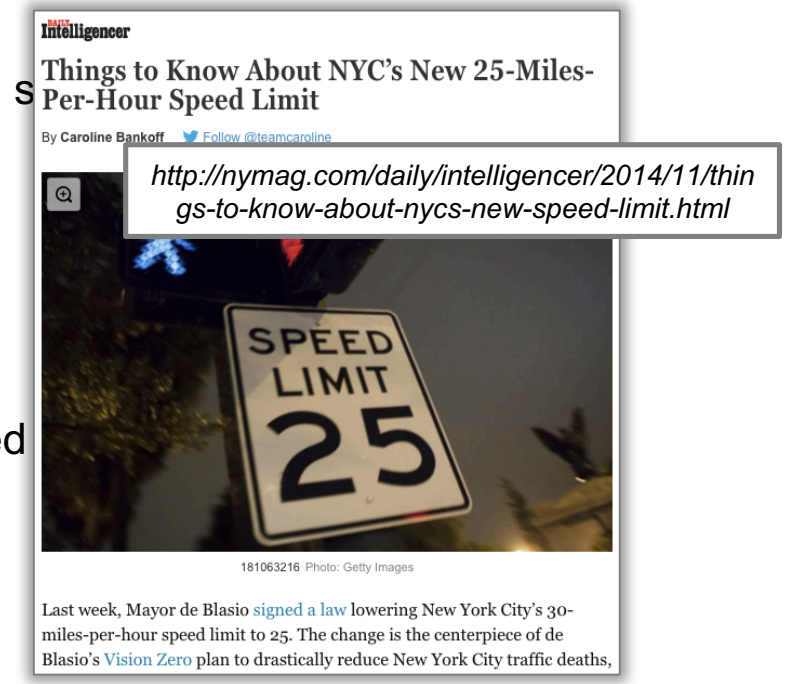
Find all relationships between Collisions and Traffic Speed data sets

 # Collisions x *Traffic Speed*

Positive relationship between number of collisions and s

 # Deaths x *Traffic Speed*

Positive relationship between number of persons killed speed


Intelligencer

Things to Know About NYC's New 25-Miles-Per-Hour Speed Limit

By Caroline Bankoff Follow @teamcaroline

http://nymag.com/daily/intelligencer/2014/11/things-to-know-about-nycs-new-speed-limit.html

181063216 Photo: Getty Images

Last week, Mayor de Blasio signed a law lowering New York City's 30-miles-per-hour speed limit to 25. The change is the centerpiece of de Blasio's Vision Zero plan to drastically reduce New York City traffic deaths,

(Some) Interesting Relationships

2. Why it is so hard to find a taxi when it is raining?

Find all relationships between Taxi and Weather data sets

 # Taxi  **X** *Precipitation* 

Negative relationship between number of taxis and average precipitation

Hypothesis: Taxi drivers are target earners

Taxi Fare  **X** *Precipitation*  ⟶ *Suggests that hypothesis is true*

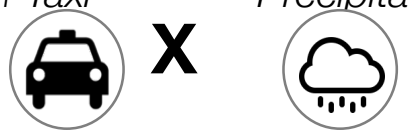
Strong positive relationship between precipitation and average fare

(Some) Interesting Relationships

2. Why it is so hard to find a taxi when it is raining?

Find all relationships between Taxi and Weather data sets

 # Taxi X *Precipitation*



This hypothesis had been refuted by [Farber 2014]

- Farber did not find a correlation (using OLS regression) between drivers' earnings and rainfall.
- But (i) he did not take into account the amount of rainfall—instead, he used a binary value indicating whether it rained or not; and (ii) he considered the entire time period—periods with very sparse rainfall are considered equivalent to those having higher rainfall.

It is important to consider salient features

(Some) Interesting Relationships

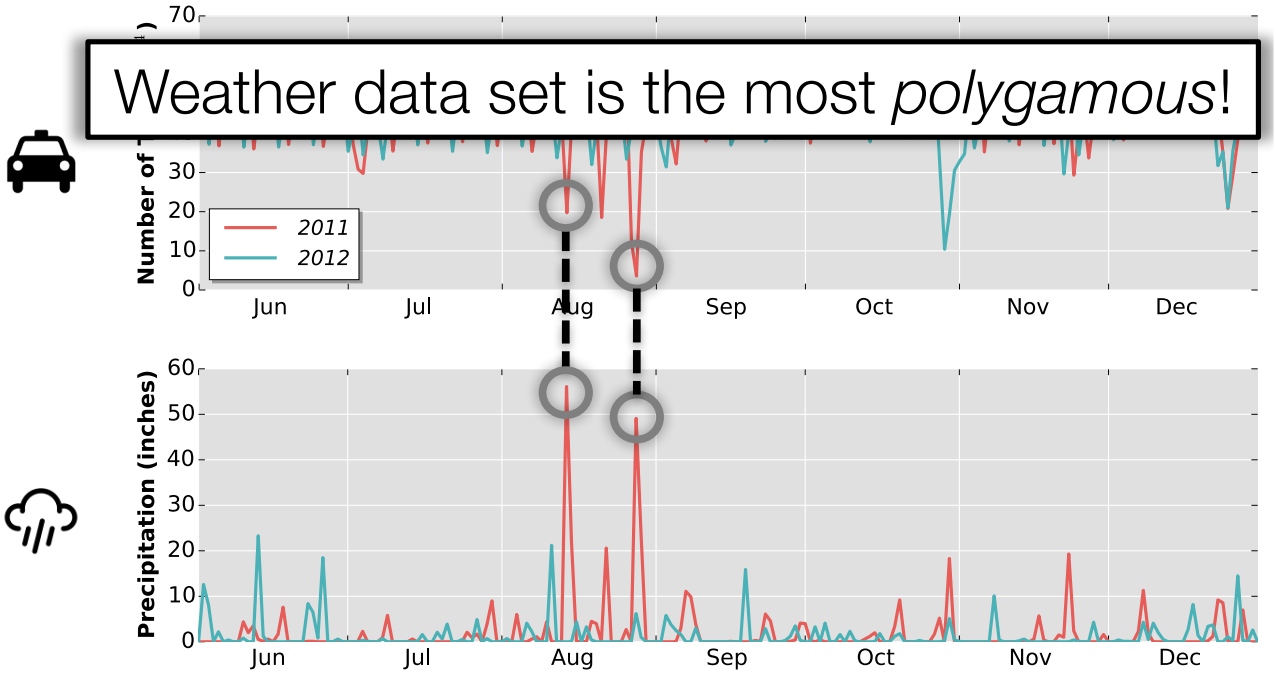
3. Why is the number of taxi trips too low?

 # Taxi **X** *Precipitation*

Negative relationship between number of taxis and average precipitation

 # Taxi **X** *Wind speed*

Negative relationship between number of taxis and wind speed



(Some) Interesting Relationships

- Citi Bike and Weather

 # Citi Bike stations  X *Snow* 

Negative relationship between snow precipitation and active Citi Bike stations

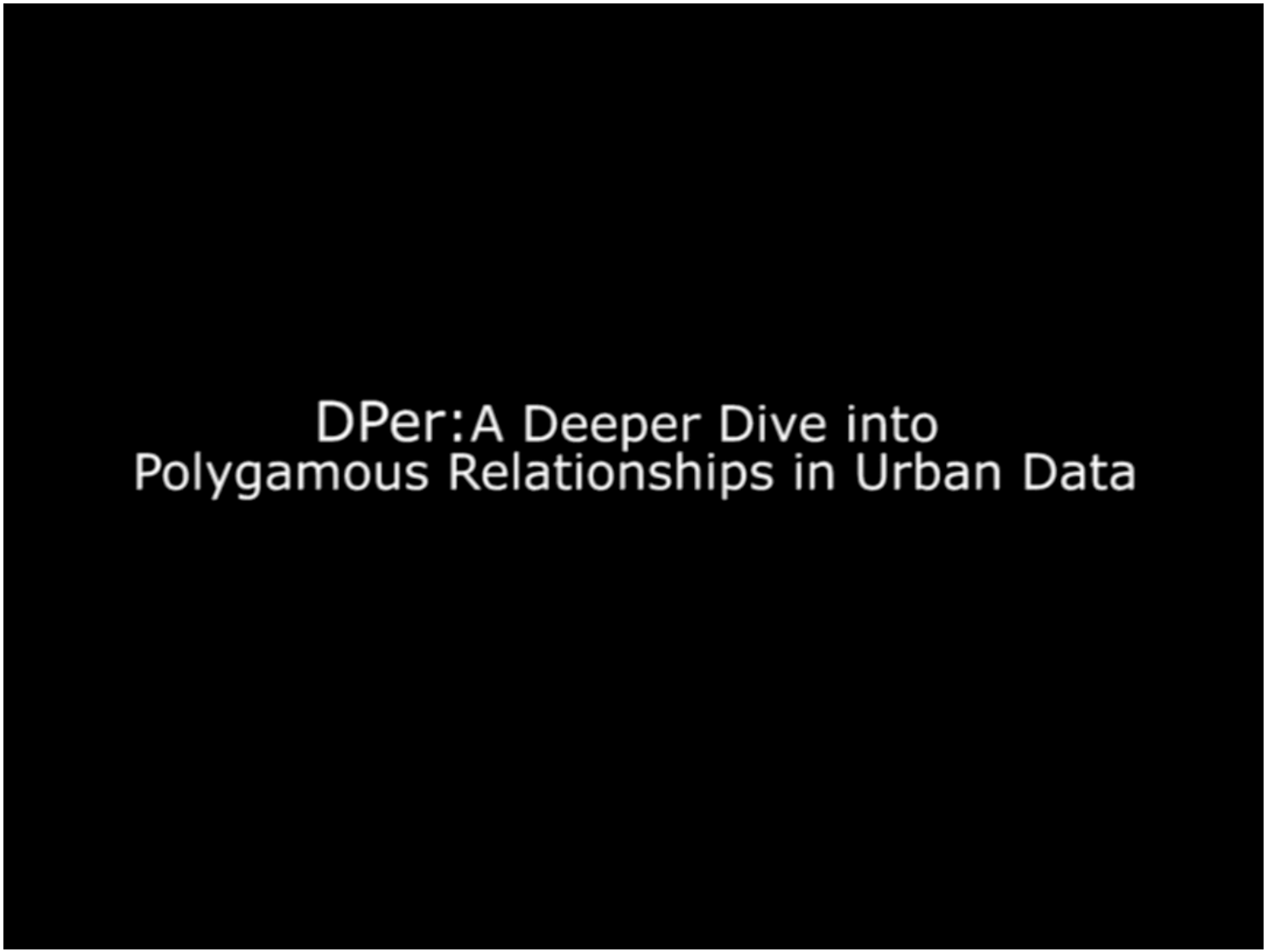
(day, city)	✓
(hour, city)	⊘

Data Polygamy: Ongoing Work

- It's hard to evaluate!
  - No ground truth available
  - Need benchmark
  - Need real use cases from domain experts
- ~ 100 *significant* relationships per resolution
  - More relationships (and their implications) can be understood by having domain experts

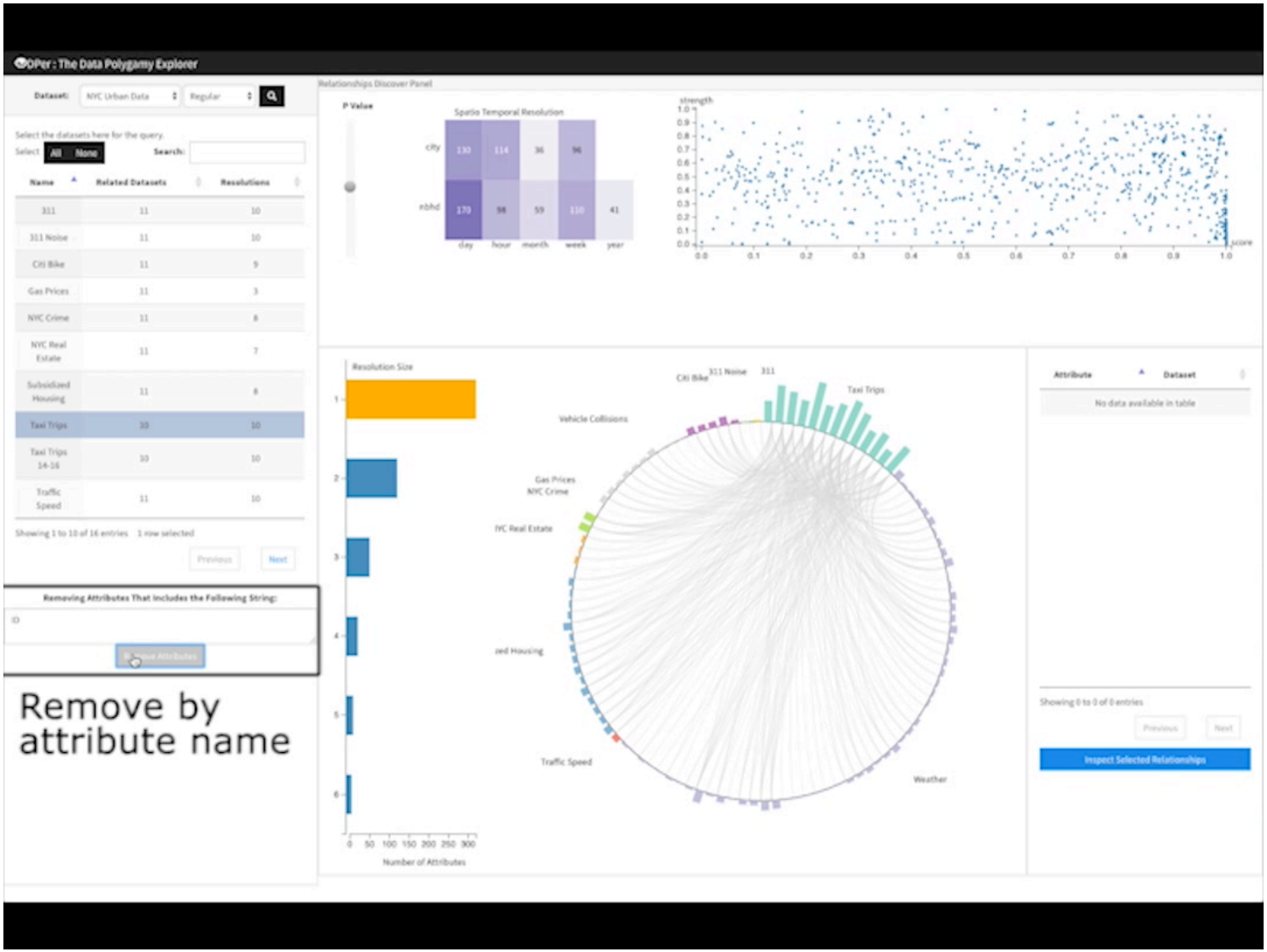
How to explore and analyze the relationships?

Visually Exploring Relationships



https://vgc.poly.edu/~juliana/videos/dper2.mov

Visually Exploring Relationships



https://vgc.poly.edu/~juliana/videos/dper2.mov

[Chirigati et al., ACM SIGMOD 2017]

Takeaway: Big Data Exploration

- Usability is of paramount importance
  - Need to empower domain experts to explore their data
- Exploration requires interactivity – improve the rate at which *users make observations, draw generalizations and generate hypotheses*
- Not always Cloud is the answer – smart algorithms can go a long way to attain scalability
- Visualization is essential
- Need better methods to guide users in exploration
  - Find patterns, outliers, and explain them!
- Warning: a risk with big data is that you will "discover" patterns that are meaningless – watch out for bogus patterns/events

Transparency and Reproducibility

Science and Reproducibility

- Reproducibility is the cornerstone of science
- *If I have seen further it is by standing on the shoulders of giants.*

  Isaac Newton
- If we can't trust previous results, we have to start over from scratch
  - Science is incremental and self-correcting
- To increase impact, visibility [Vandewalle et al. 2009] and research quality [Begley and Ellis 2012]
- *Without reproducibility, people die!*

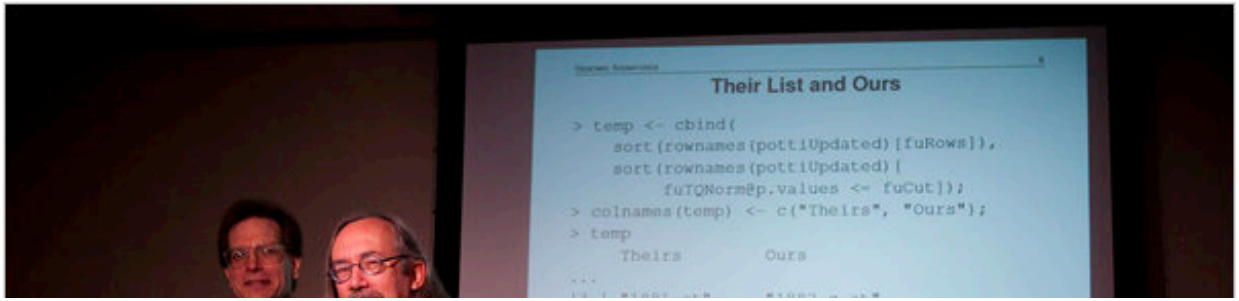
John Wilbanks, AMPS Workshop on Reproducibility 2011

Science and Reproducibility

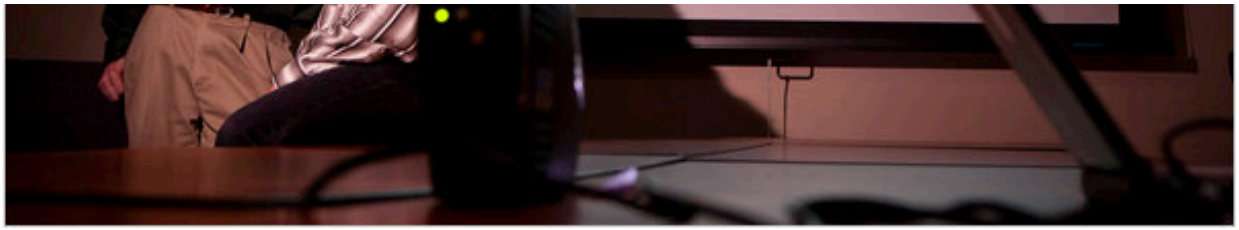
The New York Times

WORLD | U.S. | N.Y. / REGION | BUSINESS

How Bright Promise in Cancer Testing Fell Apart



But the research at Duke turned out to be wrong. Its gene-based tests proved worthless, and the research behind them was discredited. Ms. Jacobs died a few months after treatment, and her husband and other patients' relatives have retained lawyers.



Michael Stravato for The New York Times

Keith Baggerly, left, and Kevin Coombes, statisticians at M. D. Anderson Cancer Center, found flaws in research on tumors.

By GINA KOLATA
Published: July 7, 2011

When Juliet Jacobs found out she had lung cancer, she was terrified, but realized that her hope lay in getting the best treatment medicine could offer. So she got a second opinion, then a third. In February of 2010, she ended up at Duke University, where she entered a research study whose promise seemed stunning.

RECOMMEND
TWITTER
COMMENTS (76)
E-MAIL

Nobel Laureate Retract Prize

By KENNETH CHANG
Published: September 23, 2010

Linda B. Buck, who shared the 2004 Medicine for deciphering the working retracted two scientific papers after sh unable to repeat the findings.

NYU TANDON SCHOOL OF ENGINEERING

VIDA IMAGING AND DATA ANALYSIS CENTER

Science and Reproducibility

			Real GDP growth Debt/GDP				
4	Country	Coverage	30 or less	30 to 60	60 to 90	90 or above	30 or less
26			3.7	3.0	3.5	1.7	5.5
27	Minimum		1.6	0.3	1.3	-1.8	0.8
28	Maximum		5.4	4.9	10.2	3.6	13.3
29							
30	US	1946-2009	n.a.	3.4	3.3	-2.0	n.a.
31	UK	1946-2009	n.a.	2.4	2.5	2.4	n.a.
32	Sweden	1946-2009	3.6	2.9	2.7	n.a.	6.3
33	Spain	1946-2009	1.5	3.4	4.2	n.a.	9.9
34	Portugal	1952-2009	4.8	2.5	0.3	n.a.	7.9
35	New Zealand	1948-2009	2.5	2.9	3.9	-7.9	2.6
36	Netherlands	1956-2009	4.1	2.7	1.1	n.a.	6.4
37	Norway	1947-2009	3.4	5.1	n.a.	n.a.	5.4
38	Japan	1946-2009	7.0	4.0	1.0	0.7	7.0
39	Italy	1951-2009	5.4	2.1	1.8	1.0	5.6
40	Ireland	1948-2009	4.4	4.5	4.0	2.4	2.9
41	Greece	1970-2009	4.0	0.3	2.7	2.9	13.3
42	Germany	1946-2009	3.9	0.9	n.a.	n.a.	3.2
43	France	1949-2009	4.9	2.7	3.0	n.a.	5.2
44	Finland	1946-2009	3.8	2.4	5.5	n.a.	7.0
45	Denmark	1950-2009	3.5	1.7	2.4	n.a.	5.6
46	Canada	1951-2009	1.9	3.6	4.1	n.a.	2.2
47	Belgium	1947-2009	n.a.	4.2	3.1	2.6	n.a.
48	Austria	1948-2009	5.2	3.3	-3.8	n.a.	5.7
49	Australia	1951-2009	3.2	4.9	4.0	n.a.	5.9
50							
51			4.1	2.8	2.8	=AVERAGE(L30:L44)	

In this p aying pop-
historical c costs? Are
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of GDP ar 08, 2009b).
wise; aver ly difficult
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debt levels
Our top on external
Public debt has been soaring in the wake of the and by private entities. For emerging markets, overnments
recent global financial maelstrom, especially in the epicenter countries. This should not be surprising, given the experience of earlier severe we find that there exists a significantly more severe threshold for total gross external debt (public and private)—which is almost exclu-

ALIZATION
ING AND
ANALYSIS
ER

Reproducibility and Data Science

- Reproducibility is important not just for science
- Many decisions are made based on results of computational analyses
- Need transparency!

Subsidized housing

Computational hedge funds

Crime sentencing

Policing and crime prevention

Loan approval

Facebook ranking

Taxi fare increases

…

How?

Provenance: a key ingredient for reproducibility

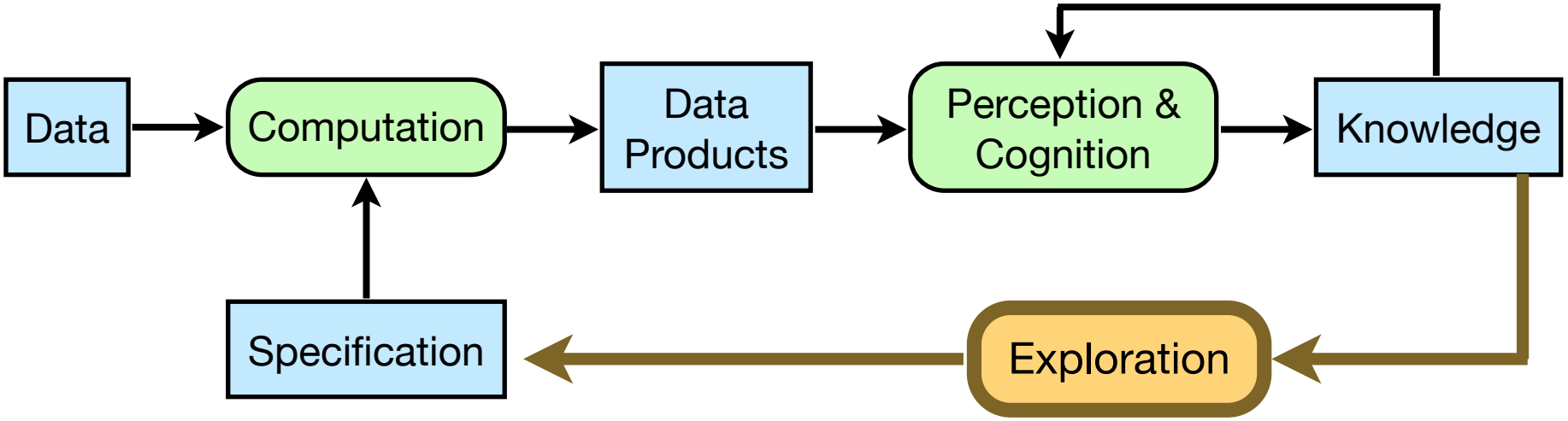
"The source or origin of an object; its history and pedigree; a record of the ultimate derivation and passage of an item through its various owners."

The Oxford English Dictionary

Helps determine the value, accuracy and authorship of an object

Used in many fields: works of art and antiques, archives and books, ***science***, …

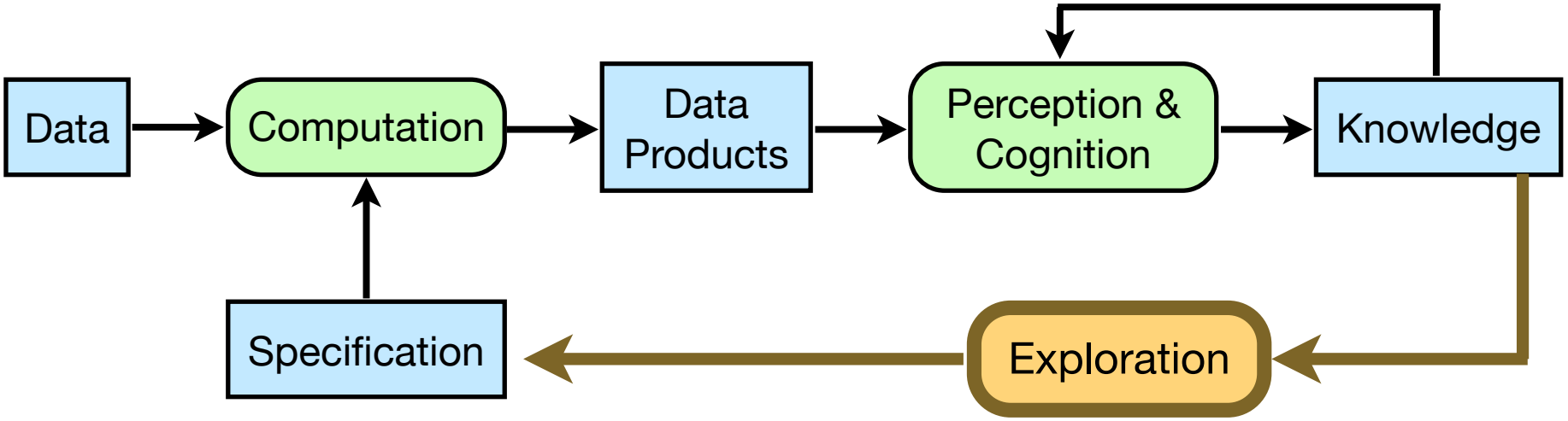
Data Lifecycle: The Exploration Pipeline



[Modified from Van Wijk, Vis 2005]

- Iterative process to generate and test hypotheses
- Easy to get lost---derive a result and not remember how you got there
- Lots of data: both input and derived
- Complex processes that encompass multiple tools

Data Lifecycle: The Exploration Pipeline



[Modified from Van Wijk, Vis 2005]

- It
- E
  you get there
- Lots of data: both input and derived
- Complex processes that encompass multiple tools

Need systematic mechanisms to capture provenance

ow

Trust, Sharing and Collaboration

- Result transparency
  - Show me your work!
  - Allow results to be verified → trust the results

    Keep track of what you do and the steps you follow – the provenance of your work
- Hard *data science* problems require people with different expertise to collaborate
  - Need to share *work,* but this can be challenging…
  - *E.g.,* **A** sends their analysis script to **B**, but **B** cannot run it…
    - Missing or incorrect versions of libraries
    - Hard-coded file names: /home/A/myinputfile.txt
    - …

    Follow best practices for sharing and reproducibility

Reproducibility: Best Practices

- Never use spreadsheets!

OCT 30, 2017 @ 08:07 PM 958

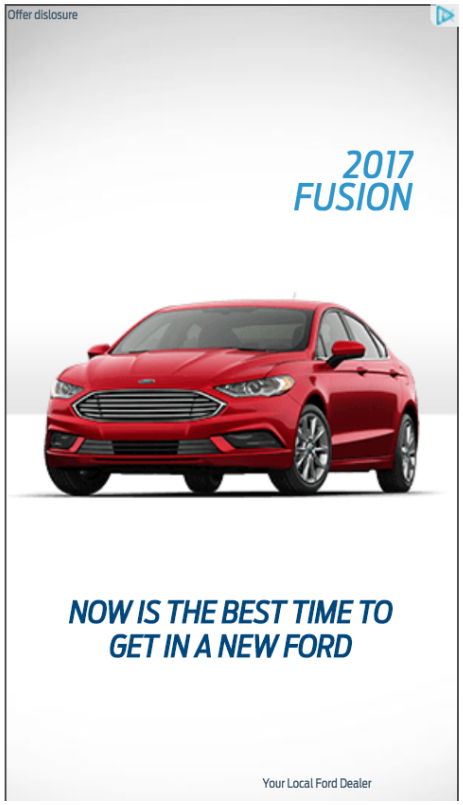
The Little Black Book of Billionaire Secrets

You Can Reduce Business Risk By Phasing Out Spreadsheets For Business

Meta S. Brown, CONTRIBUTOR

I decode analytics for business people. FULL BIO

Opinions expressed by Forbes Contributors are their own.



https://www.forbes.com/sites/metabrown/2017/10/30/you-can-reduce-business-risk-by-phasing-out-spreadsheets-for-business/#d80a9a047a04

Reproducibility: Best Practices

- Never use spreadsheets!
- Do scripting instead
  - Lots of tools, e.g., Python (and the rich Python environment)
  - Easy to reproduce a script
- Adopt literate programming, e.g., Jupyter Notebook
  - “a prose first approach where exposition with human-friendly text is punctuated with code blocks”
- Keep track of the code/techniques/parameters you tried and the associated results
  - Version control systems are your friends, e.g., git, github
- Watch out for portability -- need provenance for the computing environment
  - ReproZip provides a solution for this: https://www.reprozip.org/

Conclusions

- Data has been democratized and the Big Data stack enables us to explore, better understand, and leverage the growing volumes of data
- But there are many challenges
- We covered some of these challenges and a small subset of the solutions
- There are also many open (research) problems in
  - Cleaning and integration
  - Data analysis and exploration
  - Modeling and prediction
- Often new solutions need to be designed – important to learn the foundational aspects of Data Science

Acknowledgments

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ALFRED P. SLOAN FOUNDATION

고맙습니다

Merci

Thank you

Obrigada

благодаря

Kiitos

धन्यवाद

Tack

Danke

Ευχαριστω

Bedankt