Tackling The Challenges of Big Data
Visualizing Twitter

Samuel Madden

Professor and Director of Big Data at CSAIL

Massachusetts Institute of Technology

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Introduction to Twitter Data

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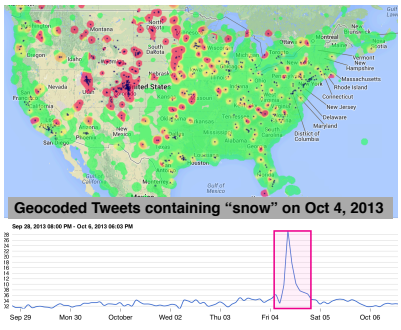
This Module

1. Understanding Twitter data
2. Demonstration of MapD, a Twitter visualization system
3. Technology behind MapD
4. Other Approaches to Interactive Analytics

Part 1: Twitter

- **500 million tweets a day**
  - > 8 million/day "geocoded"
- **More than just 140 characters:**
  - Geo Coordinates
  - Timestamp
  - User and Follower information
  - Reply Information
  - Hashtags
  - Device/Platform Used to Post

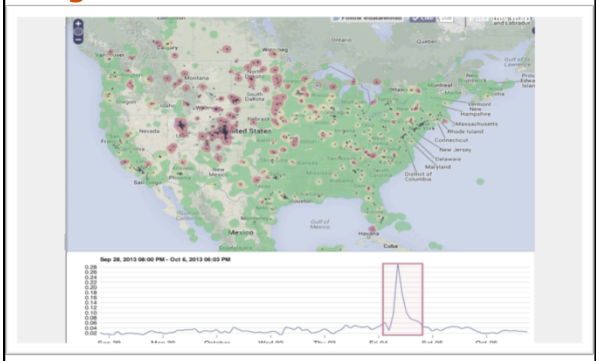
Geocoded Data



"Big Data" and Twitter

- **Volumes and rates are massive; need new tools to interactively visualize data**

"Big Data" and Twitter

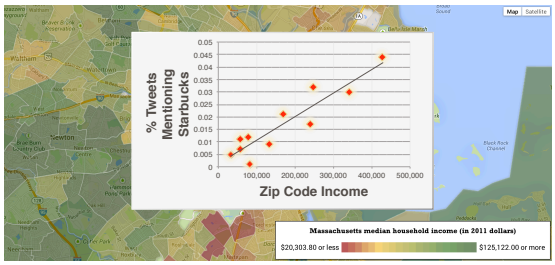


"Big Data" and Twitter

- **Volumes and rates are massive; need new tools to interactively visualize data**
- **Want to correlate with external and internal data sets**
  - E.g., brand preference vs census district income
- **Want to do deep analysis of content**
  - What product, show, or person is being discussed
  - What opinion is being expressed ("sentiment analysis")

Spatial Correlations

Requirement: Interactive learning and statistics



Source: http://www.richblockspoorblocks.com

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Use Case: Visualizing Twitter

Introduction to Twitter

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MapD Demo

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Part 2: MapD Demo

- **What is MapD?**
  - GPU Accelerated Database
  - With a Twitter Visualization in Front of it
- **What Will You See**
  - ~ 50 M tweets displayed
  - Nothing is pre-computed
- **Designed to tackle the "volume" and "velocity" challenges**

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MapD Demo

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How MapD Works

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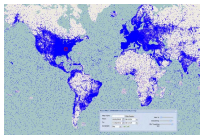
How Does MapD Work?

- ***Key insight:*** **GPUs have enough memory that a cluster of them can store substantial amounts of data**
- **Not an accelerator, but a full blown SQL Database!**



147,201,658 tweets from Oct 1, 2012 to Nov 6, 2012

Relative intensity of "tornado" on Twitter (with point overlay) from Febuary 29, 2012 to March 1, 2012

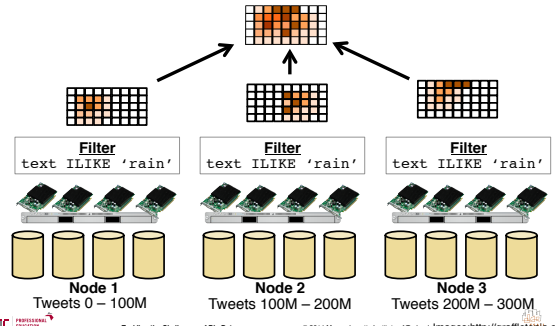
GPUs

- **Massive parallelism enables interactive browsing interfaces**
  - High End GPUs can provide
    - **250 GB/sec of bandwidth**
      - 5X conventional microprocessors
    - **4 Teraflops compute**
      - 10X conventional multi-core microprocessor
  - 7 – 70x speedup in database ops
- **Challenges**
  - Limited Memory on GPUs – But growing!
  - Limited bandwidth between CPU and GPU – Will Change!

"Shared Nothing" Processing

Multiple GPUs, with data partitioned between them

```
Query: Heatmap tweets containing "rain"
```



Images:http://graffletopia.com

Tweet Indexing on GPU

- **Encode tweets using a "dictionary"**

Filter
`text ILIKE 'rain'`

→

Filter
`SELECT tweetid FROM words WHERE id = 57663`

Word	Encoding
…	…
Rain	57663
Rainbow	57664
Rainman	57665
Rainy	57666
…	…

Example: Filtering in Parallel

- **oriented execution**
  - Avoids wasting memory bandwidth
- **Plan:**
  - Reduce bitmap of tweets to read
  - Read tweets, increment output bins

Filter
`SELECT tweetId FROM words WHERE id = 57663`

TweetId	WordId
…	…
1	57663
2	57664
2	27
3	8841
…	…

TweetId	Lat	Lon
…	…	
1	-41.5	23.1
2	-41.7	77.4
3	-37.4	48.2
4	28.4	-44.0
…		

Data Tables Reside in GPU Memory

Example: Filtering in Parallel

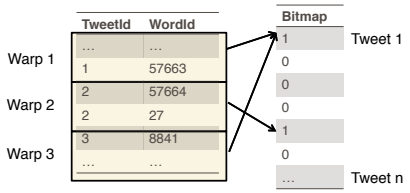
- **1000+ GPU Threads**
- **Running in "Warps"**
- **Threads in same warp run exactly the same instructions**
  - Balanced data per thread improves performance

	TweetId	WordId
	…	…
Warp 1	1	57663
Warp 2	2	57664
	2	27
Warp 3	3	8841
	…	…

Bitmap	
0	Tweet 1
0	
0	
0	
0	
0	
…	Tweet n

Example: Filtering in Parallel

- 1000+ GPU Threads
- Running in "Warps"
- Threads in same warp run exactly the same instructions
  - Need same amount of data to be efficient



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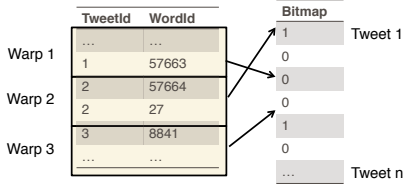

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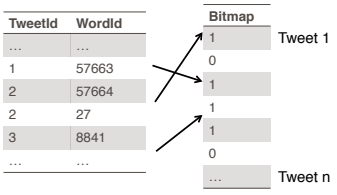

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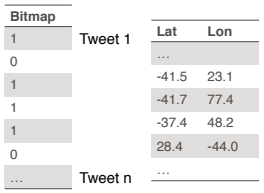

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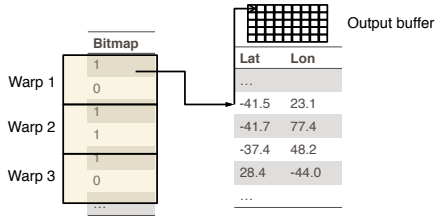

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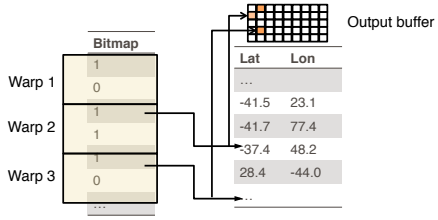

Parallel Plumbing

Once parallel versions of all operators are built, programmers can just think in terms of SQL

E.g.,

```
SELECT heatmap(lat,lon)
WHERE tweettext ILIKE "rain"
```

Scaling to 100's of millions of points in milliseconds

Summary

- ***Interactivity*** **can create a qualitative difference**
- **GPUs can dramatically accelerate some tasks**
  - **Compute intensive** tasks via parallelism
  - **Data intensive** tasks via increased memory bandwidth
- **Clever use of hardware enables dramatic speedups**
- **Arrays of multiple GPUs help solve large problems**

Try it yourself:
http://mapd.csail.mit.edu

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How MapD Works

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Other Approaches to Interactive Analytics

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Other Approaches to Interactive Analytics

- **Interactive Analytics Important in Many Situations**
- **Examples**
  - Fault Diagnostics
  - Intrusion Detection
  - Financial Analysis
  - Online Advertising
- **GPUs & Massive Parallelism are Just One Way Approach**

Other Techniques We'll Cover

- **Brute Force / Massive Parallelism**
  - MapD (Hadoop, and many others)
- **Partitioning**
  - Split the data, operate on the part you need
- **Sampling**
  - Operate on a Subset of the Data
- **Summarization**
  - Operate on a Summary of the Data

Partitioning

Sampling

Summarization

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