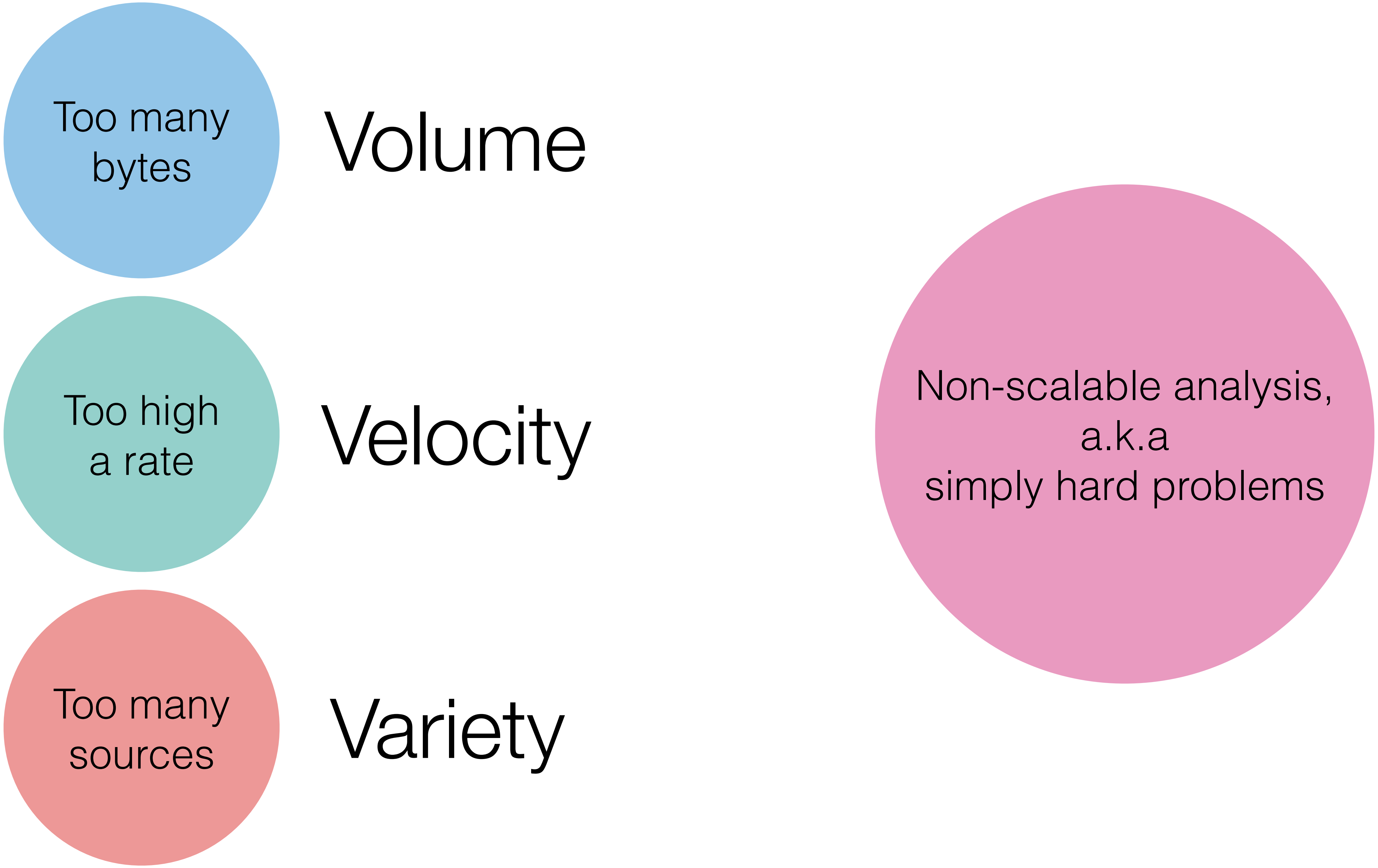
Big Data Problems

Per Persson

What is Big Data?

and what's
the problem?



Too many
bytes

Volume

Too high
a rate

Velocity

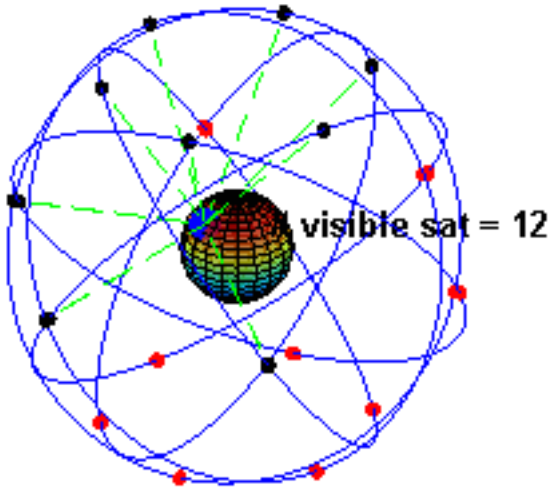
Too many
sources

Variety

Non-scalable analysis,
a.k.a
simply hard problems

Volume

Too many bytes



GPS data is ≈100 bytes @ 0.1Hz
⇒ 40kB/h ⇒ ≈**1MB/day**

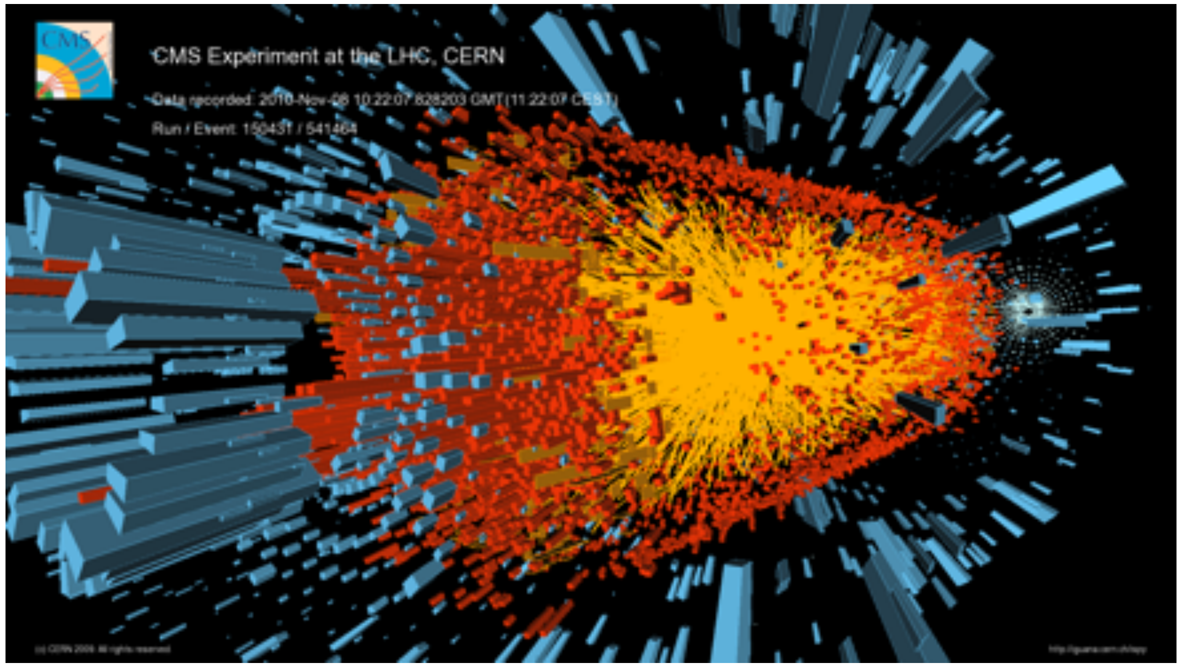
Phones w. GPS: ≈3×10^9 to date
⇒ 3×10^9×1MB ⇒ ≈**3PB/day**

Moving 3PB @ 1Gbps ⇒ ≈**1 year**

References: Feldman13

Velocity

Too high
a rate


CMS
CMS Experiment at the LHC, CERN
Data recorded: 2010-Nov-08 10:22:07.828203 GMT(11:22:07 CEST)
Run / Event: 150431 / 541464

The **Large Hadron Collider** (LHC) generates data at a rate of 1PB/s.

Fast electronics selects one in 10000 events in a first pass.

15000 core cluster select 1% of the remaining events for analysis.

Single Tier-0 DC with 73000 cores does reconstruction and storage.

Tier-0 DC distributes data to 11 Tier-1 and 140 Tier-2 DCs.

Continuously 1.5 million jobs and 10GB/s transfer rate globally.

References: cern13

Variety

Too many sources

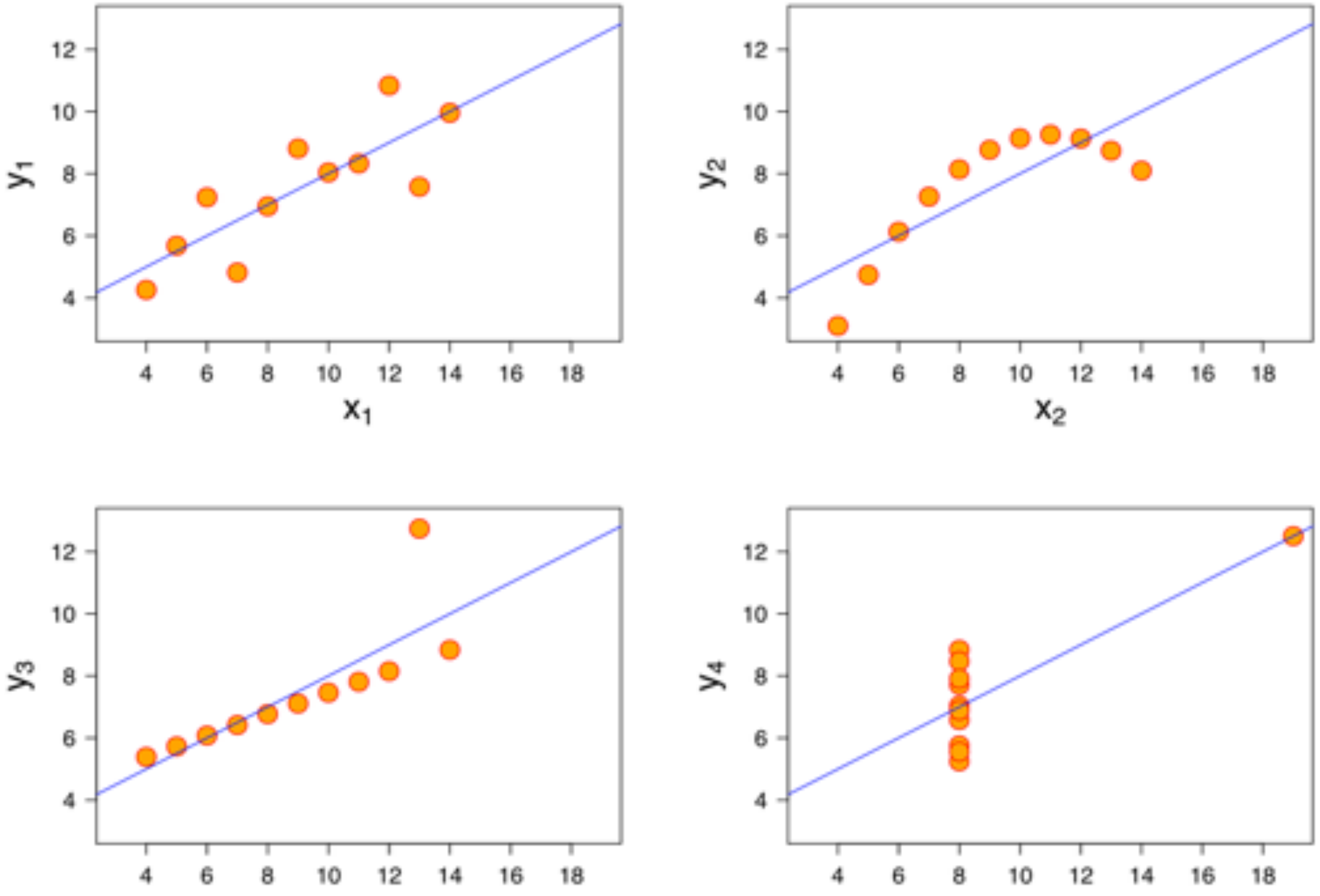
- ETL: Extract, Transform, and Load (labor intensive)
  - OK for up to 10-20 sources, doable up to 30 sources
  - Prohibitively expensive at 50 sources
- Data Curation (with help from tools)
  - Ingest – from an alien source
  - Validate – if bad data gets into your store…, it stays there
  - Transform – align with your schema/ontology
  - Clean – real data is invariably dirty
  - Consolidate – merge it with your previous data
  - Visualize – this is important!
- Example: Novartis
  - Consolidate 8000 electronic lab journals
  - No common schema, no common language, no rules whatsoever…

References: Stonebraker13

Visualization

	1		2		3		4	
	x	**y**	**x**	**y**	**x**	**y**	**x**	**y**
	10,00	8,04	10,00	9,14	10,00	7,46	8,00	6,58
	8,00	6,95	8,00	8,14	8,00	6,77	8,00	5,76
	13,00	7,58	13,00	8,74	13,00	12,74	8,00	7,71
	9,00	8,81	9,00	8,77	9,00	7,11	8,00	8,84
	11,00	8,33	11,00	9,26	11,00	7,81	8,00	8,47
	14,00	9,96	14,00	8,10	14,00	8,84	8,00	7,04
	6,00	7,24	6,00	6,13	6,00	6,08	8,00	5,25
	4,00	4,26	4,00	3,10	4,00	5,39	19,00	12,50
	12,00	10,84	12,00	9,13	12,00	8,15	8,00	5,56
	7,00	4,82	7,00	7,26	7,00	6,42	8,00	7,91
	5,00	5,68	5,00	4,74	5,00	5,73	8,00	6,89
Mean	9,00	7,50	9,00	7,50	9,00	7,50	9,00	7,50
Variance	11,00	4,13	11,00	4,13	11,00	4,12	11,00	4,12
Corr.	0,82		0,82		0,82		0,82	
Lin.reg.	y=3+0.5x		y=3+0.5x		y=3+0.5x		y=3+0.5x	

Anscombe's quartet

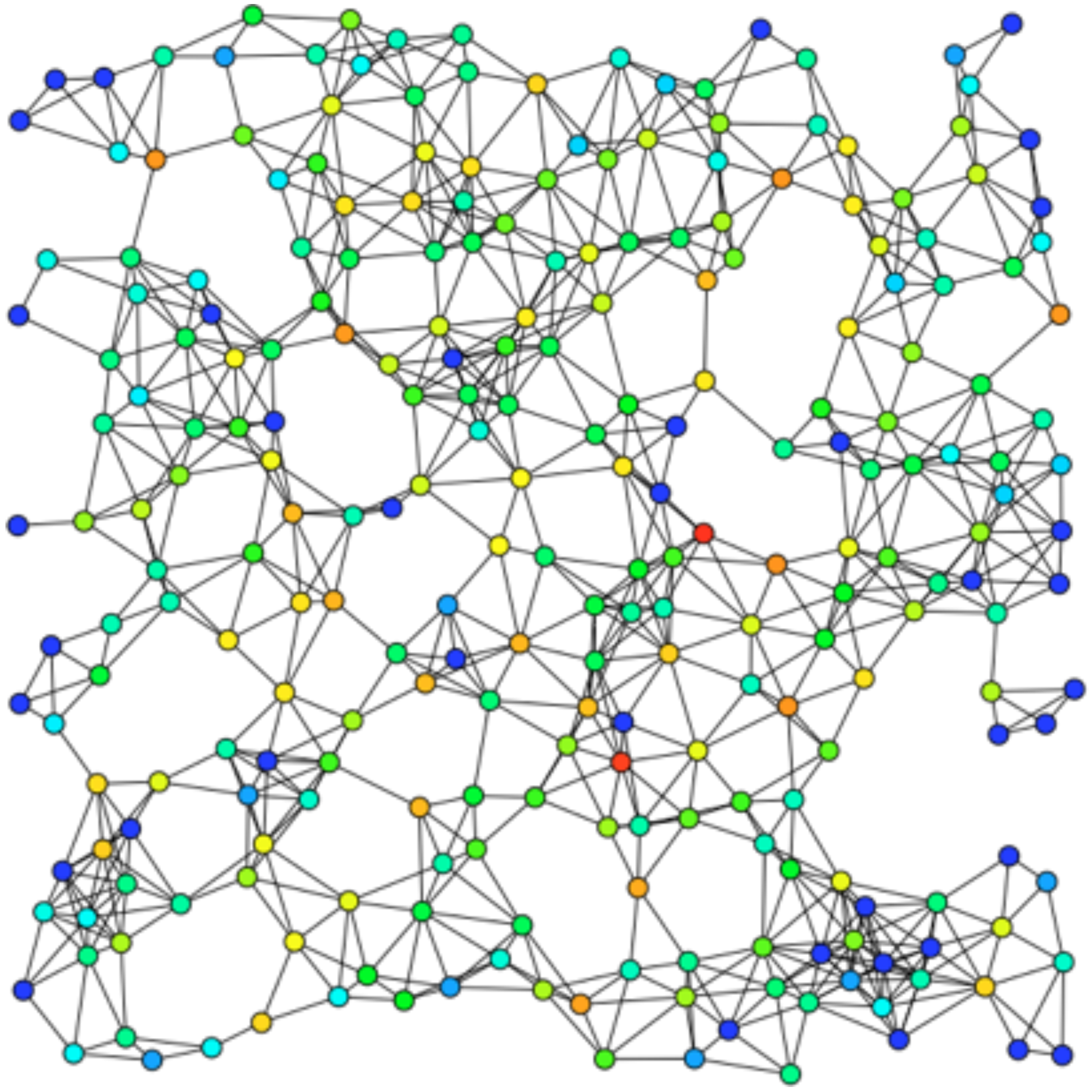


References: Anscombe73

Simply hard problems

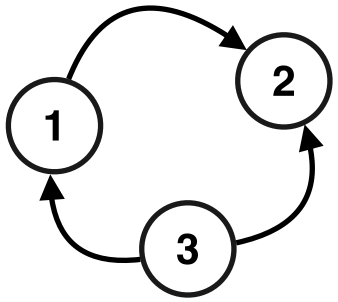
Non-scalable analysis

- Graph queries
- Collaborative filtering
- k-means clustering
- Logistic regression



References:

PageRank(ing)



$$\mathbf{A} = \begin{bmatrix}0 & 0 & 1\\1 & 0 & 1\\0 & 0 & 0\end{bmatrix}$$

Count in-degree

$$x_i = \sum_j A_{ij} \Rightarrow \mathbf{x} = \begin{bmatrix}1\\2\\0\end{bmatrix}$$

In-degree centrality

Weight by node rank

$$x'_i = \sum_j A_{ij} x_j \Leftrightarrow \mathbf{x}' = \mathbf{A}\mathbf{x}$$

Weighted in-degree centrality

Recursively refine

$$\mathbf{x}^{t+1} = \mathbf{A}^t \mathbf{x} \Rightarrow \mathbf{A}\mathbf{x} = \lambda \mathbf{x}$$

Eigencentrality

Fix the contagious 0

$$\mathbf{x} = \alpha \mathbf{A}\mathbf{x} + \beta \mathbf{1} \Rightarrow \mathbf{x} = [\beta = 1] = \left(\mathbf{1} - \alpha \mathbf{A}\right)^{-1} \mathbf{1} = \begin{bmatrix}1.5\\2.25\\1\end{bmatrix}$$

Katz centrality

Compensate for Yahoo!

$$x'_i = \alpha \sum_j A_{ij} \frac{x_j}{k_j^{\text{out}}} + \beta, \quad \text{where} \quad k_j^{\text{out}} = \sum_i A_{ij}$$

Determine α

$$\mathbf{x} = \mathbf{D}\left(\mathbf{D} - \alpha \mathbf{A}\right)^{-1} \mathbf{1}, \quad \text{where} \quad D_{ii} = \max\left(k_i^{\text{out}}, 1\right) \Rightarrow 0 < \alpha < 1$$

With α=0.85

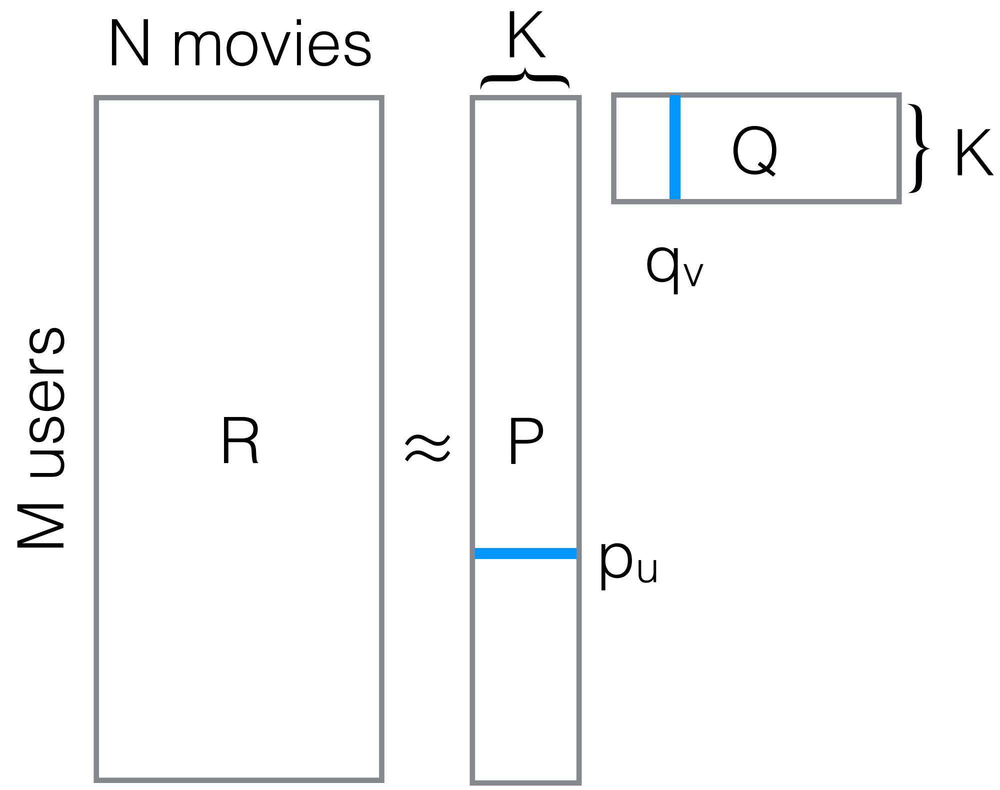
$$\mathbf{x} = \begin{bmatrix}1.4250\\2.6362\\1.0000\end{bmatrix}$$

PageRank

References: Page99, Newman10 pp.168-178

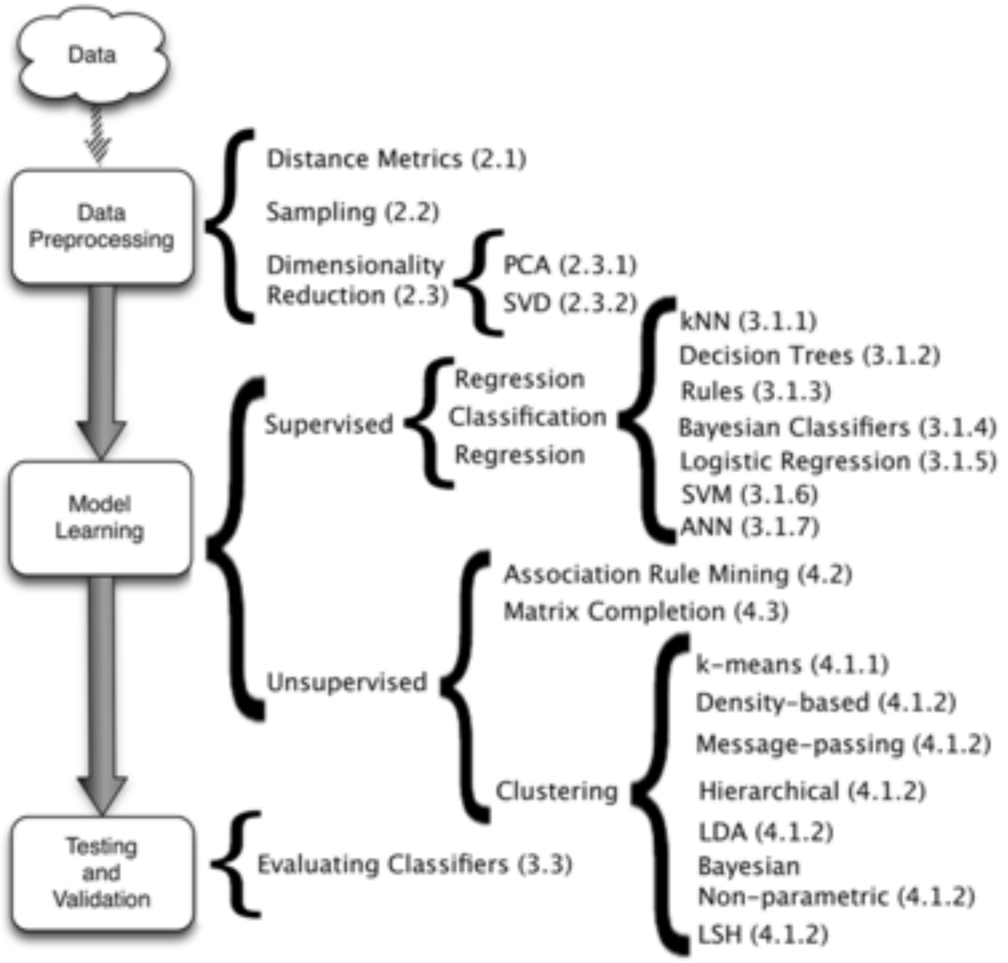
Recommendations

Naïve approach



R is **sparse** (99.9% empty) matrix of ratings, M=500000, N=17000
Find **dense** matrices P and Q, such that p_u & p_v accurately estimates u:s rating of v.

Realistic approach

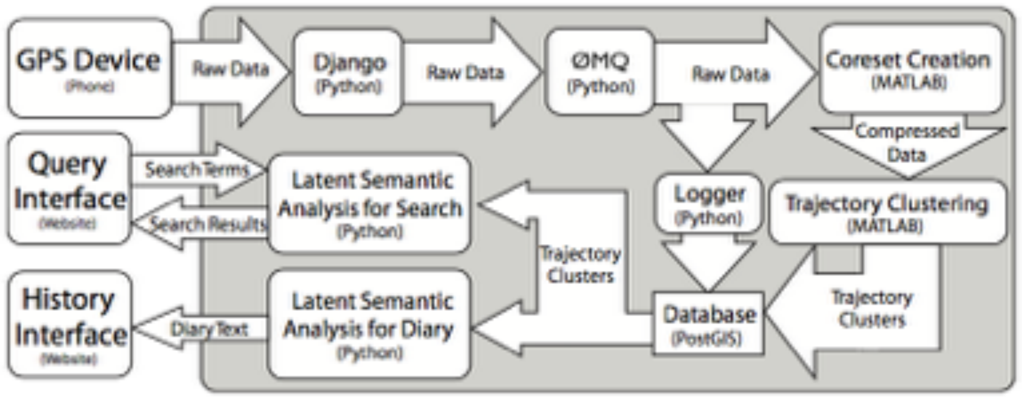


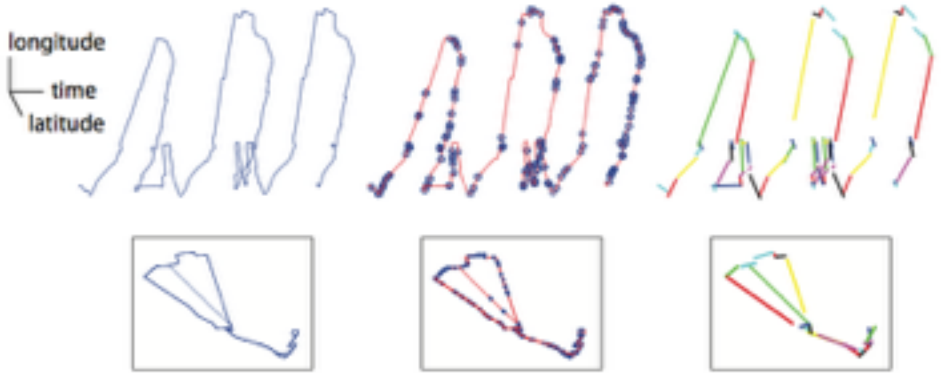
From: Amatriain et al. “Data Mining Methods for Recommender Systems” in “Recommender Systems Handbook“

References:Satish14, Amatriain14

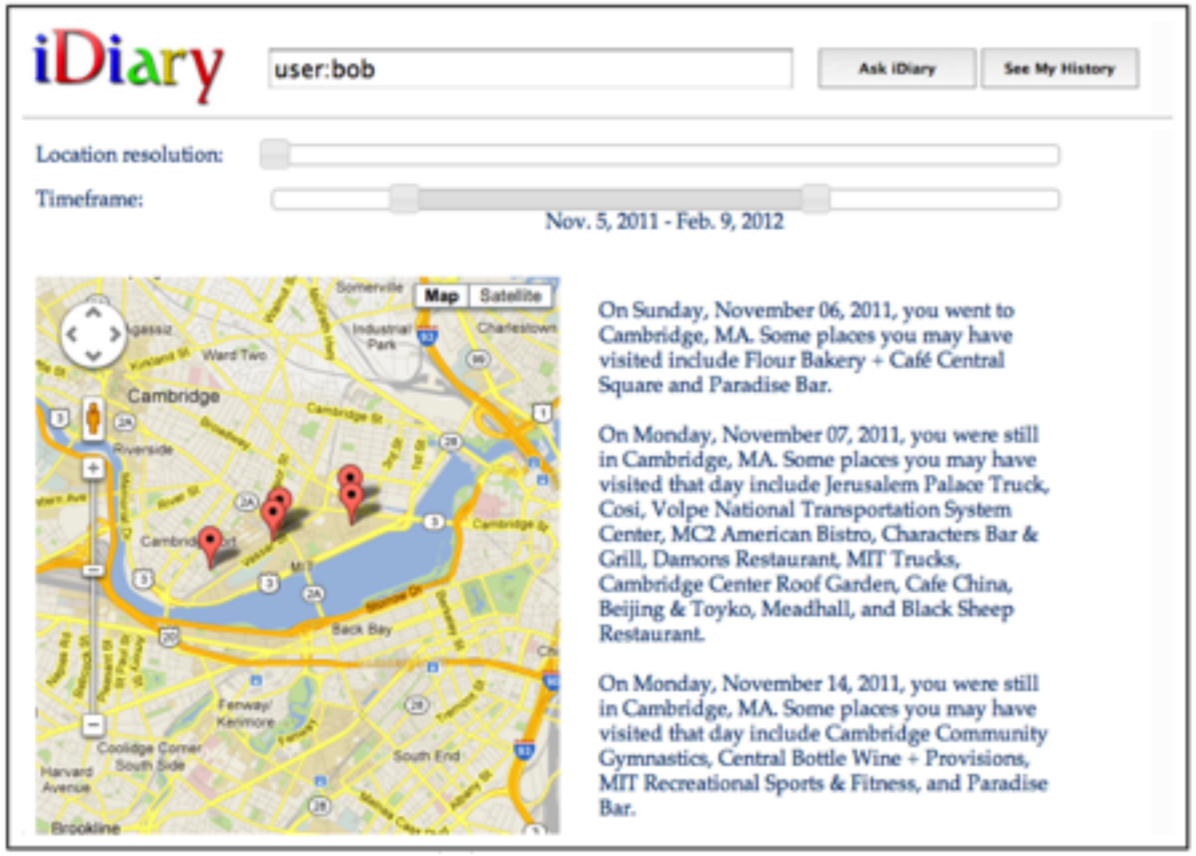
Life-logging

- Combines GPS, Yelp, maps, search, and semantic analysis





(a) GPS Signal (b) Coreset (c) Clustering



user:bob

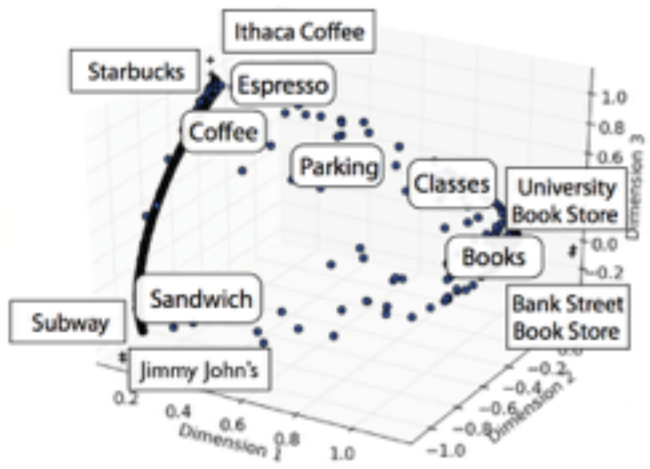
Location resolution:

Timeframe: Nov. 5, 2011 - Feb. 9, 2012

On Sunday, November 06, 2011, you went to Cambridge, MA. Some places you may have visited include Flour Bakery + Café Central Square and Paradise Bar.

On Monday, November 07, 2011, you were still in Cambridge, MA. Some places you may have visited that day include Jerusalem Palace Truck, Cosi, Volpe National Transportation System Center, MC2 American Bistro, Characters Bar & Grill, Damons Restaurant, MIT Trucks, Cambridge Center Roof Garden, Cafe China, Beijing & Toyko, Meadhall, and Black Sheep Restaurant.

On Monday, November 14, 2011, you were still in Cambridge, MA. Some places you may have visited that day include Cambridge Community Gymnastics, Central Bottle Wine + Provisions, MIT Recreational Sports & Fitness, and Paradise Bar.



References: Feldman13

The law of the instrument

I suppose it is tempting, if the only tool you have is a hammer, to treat everything as if it were a nail

Abraham Maslow

- MapReduce for everything?
  - Hive/Pig/…
  - Dryad/Spark/…
  - Pregel/Giraph/…
- Some people actually think so…
  - Benefits of a familiar tool outweighs drawbacks

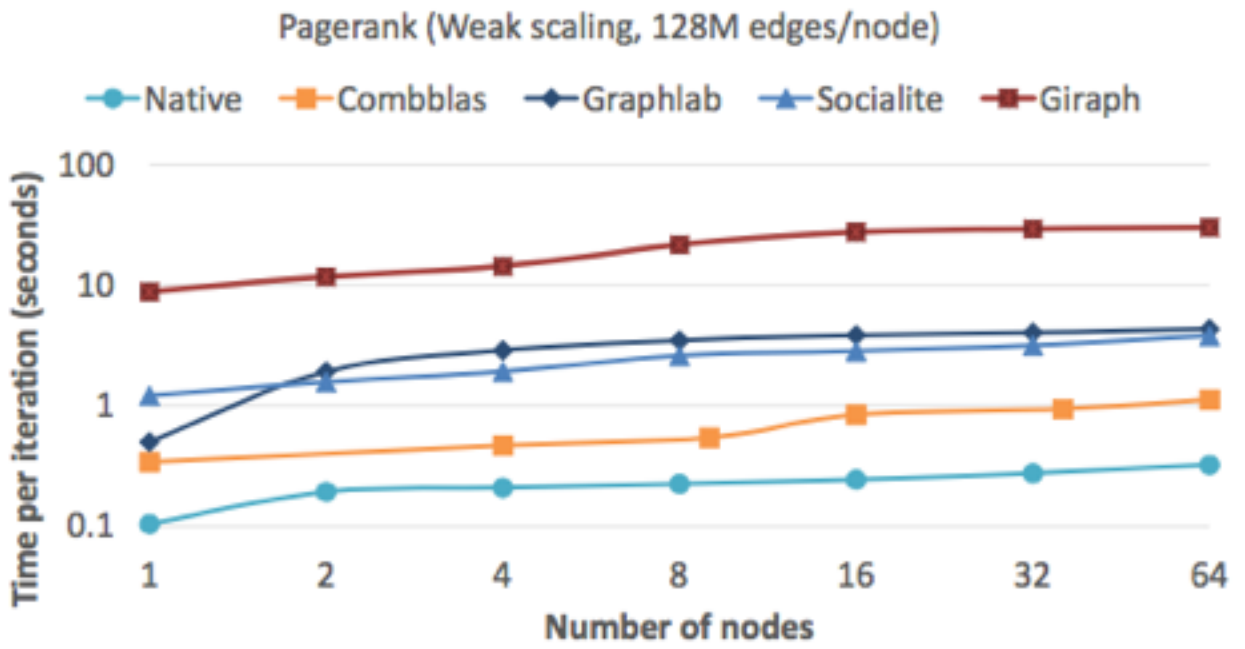
References: Kaplan64, Maslow66, Lin13

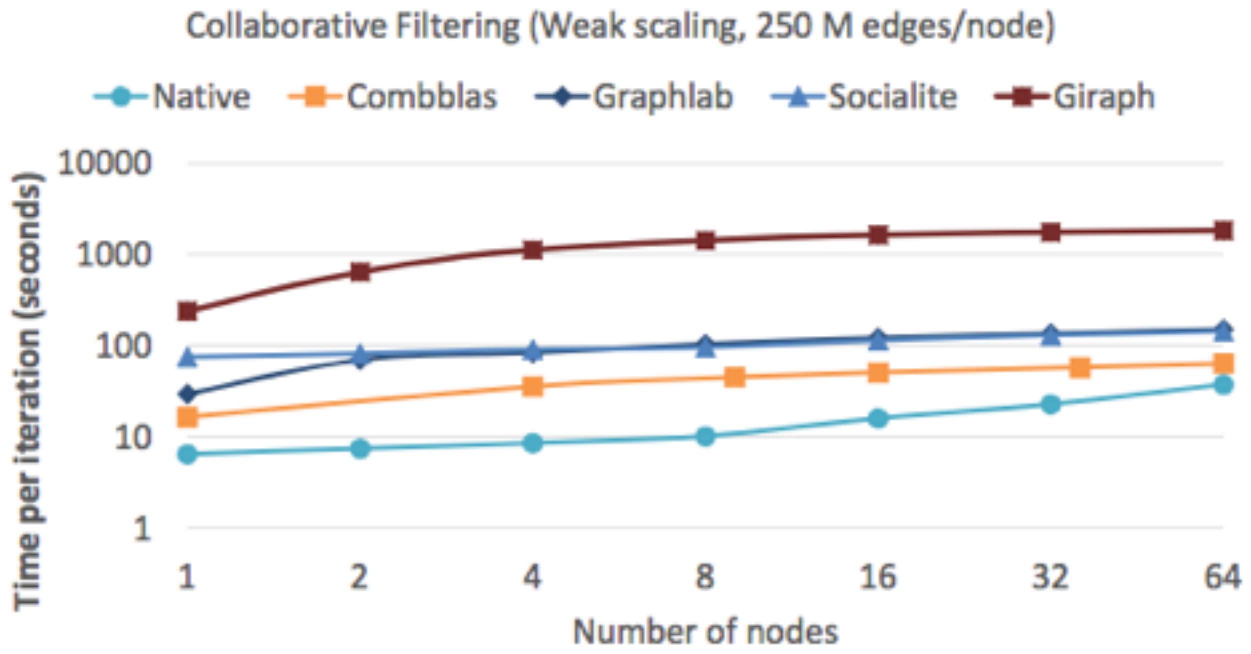
Speed bumps and Ninjas

- How bad can using a golden hammer be?
- How much can you benefit from a Ninja programmer?
- Do you pay your cloud provider as you go?

Releasing the Ninjas

- How much performance is lost with a hammer?
- Custom code vs. standard graph tools
- Apparently 2x-30x (500x) depending on problem/tool

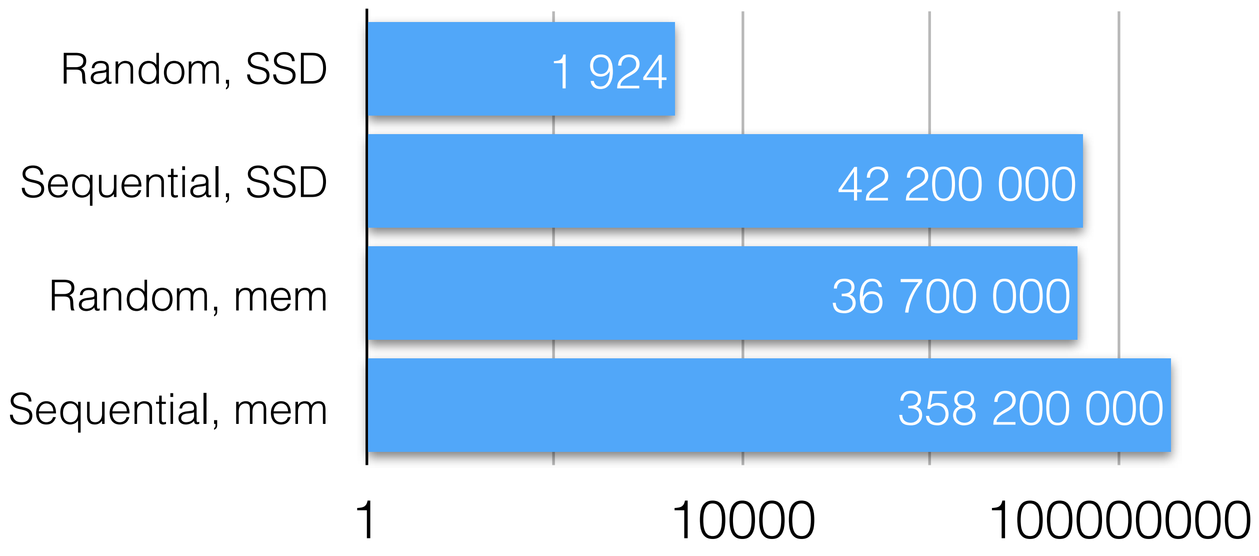




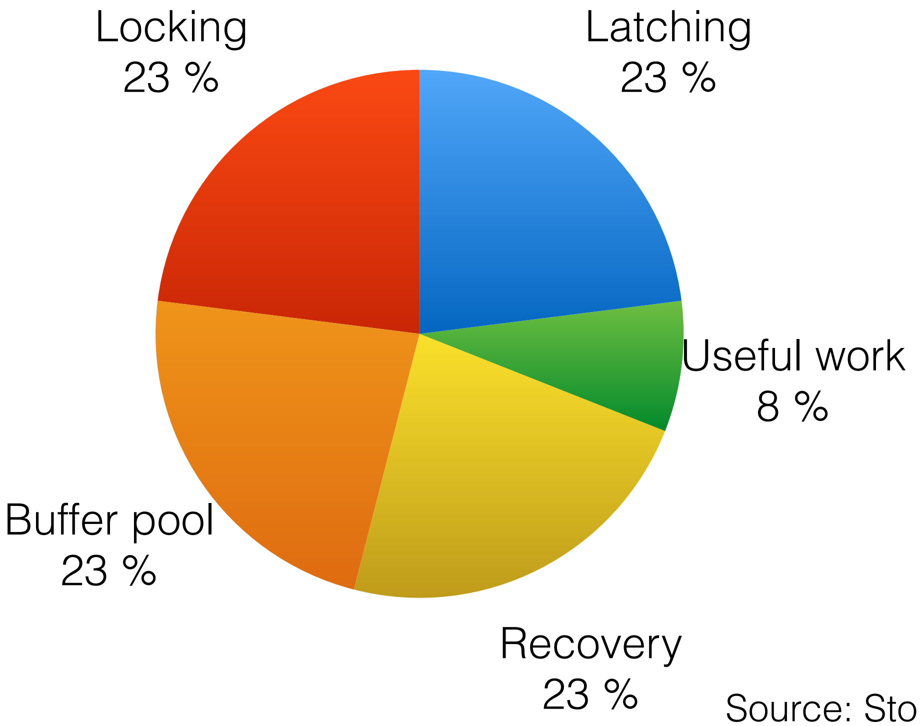
References: Satish14

Speedbumps ahead

- Beware of RDBMS
  - Custom: 15min
  - PostgreSQL: fail after 6h
- Row vs column store
- ≈90% wasted on locks and queue management
- 10-100x faster with column, in-memory, single-threaded, lock-free implementation



Source: Jacobs09



Source: Stonebraker14

References: Jacobs09, Stonebraker14

Conclusions

- Understand your data (curation, compression)
- Understand your questions (relax, property testing)
- Understand your algorithms
- Understand your tool(s) (cost/benefit analysis)
- Cloud can “hide” inefficiencies in algorithm
  - pay as you go could mean wasting money

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