Course overview: 10-605/805

William Cohen

ADMINISTRIVIA

Who/Where/When

- Office Hours:
  - Still TBA for all of us, check the wiki
- Course assistant: Dorothy Holland-Minkley (dfh@cs)
- Wiki: google://"cohen CMU"→teaching →
  - http://curtis.ml.cmu.edu/w/courses/index.php/Machine_Learning_with_Large_Datasets_10-605_in_Fall_2016
  - this should point to everything else: Piazza, Autolab, ….
- Instructor:
  - William W. Cohen
- TAs:
  - Bhuwan Dhingra; Yuxing Zhang; Xu Lanxiao
  - Tzu-Ming Kuo; Chenran Li; Yulan Huang
  - Karandeep Johar; Jingyuan Liu

How Many

- This room holds 150
- There are 330 signed up + waitlisted
- I hope the waitlist clears but I can't promise
  - It always has before

- It's coming back next fall (I'm on leave spring)
- Materials will be on-line

Who/Where/When

- William W. Cohen
  - 1990-mid 1990's: AT&T Bell Labs (working on ILP and scalable propositional rule-learning algorithms)
  - Mid 1990's—2000: AT&T Research (text classification, data integration, knowledge-as-text, information extraction)
  - 2000-2002: Whizbang! Labs (info extraction from Web)
  - 2002-2008, 2010-now: CMU (IE, biotext, social networks, learning in graphs, info extraction from Web, scalable first-order learning)
    - 2008-2009: Visiting Scientist at Google

TAs

TA – Bhuwan Dhingra (GHC 6227)

I am a second year PhD student in LTI working with Prof William Cohen and Prof Russ Salakhutdinov. My research focuses on deep learning for natural language processing, and I have been involved in a variety of different projects. Outside work I enjoy hiking and traveling. I've been told I am a calm person, so don't hesitate with any of your questions!

Karandeep Johar– MS in CS

I am a second year Masters student in the Computer Science Department , School of Computer Science

I’m interested in scaling machine learning algorithms for large datasets and solving problems that arise when we try and apply them in real world contexts.

Lanxiao Xu – MLD

I'm a second year Masters student in MLD, School of Computer Science.

I took this course last year and was very interested in building machine learning models in large scale context.

The contents of this course is very closely related to how people apply ML techniques in practice. You will learn a lof of awesome things such as Hadoop, Spark and Pig, which are constantly used in industry.

Tzu-Ming Kuo– MCDS in LTI

I'm a second year Masters student in LTI, School of Computer Science.

I'm interested in applying Machine Learning to solve various problems. This summer I interned at LinkedIn data science team, augmenting LinkedIn Economic Graph. Many topics I learnt in this course was really helpful and crucial to my intern project!

Chenran Li

Second year MIIS student.

Took 10-605 last year and enjoyed it a lot.

Interned at Google this summer and caught a lot of Psyducks there.

Jingyuan Liu

I'm a second year master student from MIIS program, LTI.

Took 10605 a year ago, super fun experience!

RA in Petuum Team, implemented scalable machine learning algorithms with Parameter Server.

Intern in LinkedIn Data Science Team, data extraction and clean with MapReduce (sclading), scalable regression model.

Yuxing Zhang – MS in MLD

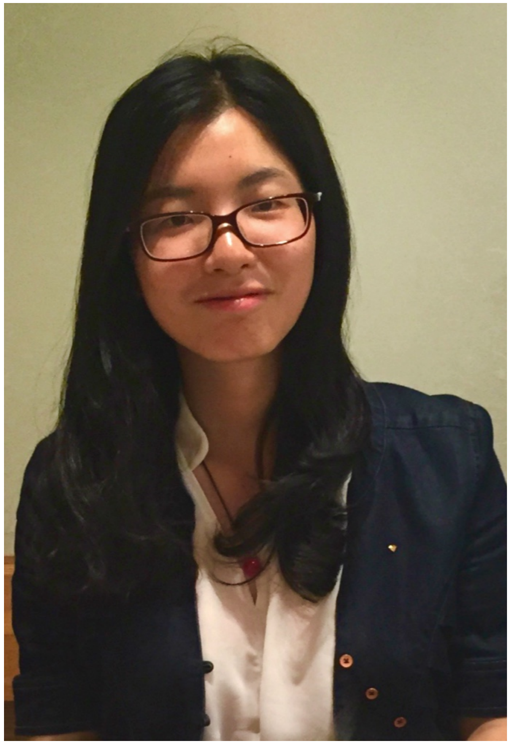
I'm a second year master student in machine learning department.

I'm interested in working on large scale machine learning systems. I took 605 last year and found it a very interesting and useful course.

Yulan Huang – MIIS in LTI

I'm a second year Masters student in LTI, School of Computer Science.

I'm interested in applying machine learning techniques to real world problems. I took 605 last year and enjoyed it a lot. You will have a deeper understanding about both machine learning algorithms and machine learning in distributed systems.



What/How

I kind of like language tasks, especially for this task:

– The data (usually) makes sense

– The models (usually) make sense

– The models (usually) are complex, so

- More data actually helps
- Learning simple models *vs* complex ones is sometimes computationally different

What/How

- Programming Language:
  - Java and Hadoop
  - Python (more than last year)
- Resources:
  - Your desktop/laptop (to start)
    - You'll need approximately 0.5Tb space.
  - Opencloud hadoop cluster:
    - 104 worker nodes, with 8 cores, 16 GB RAM, 4 1TB.
    - 30 worker nodes, with 8 cores, 16 GB RAM, 250Gb+
  - Amazon Elastic Cloud
    - Amazon EC2 [http://aws.amazon.com/ec2/]
    - Allocation: $50 worth of time per student

What/How: 10-605

- **Lecture** course for MS and advanced undergrads
- 60% assignments (6/7)
  - Mostly biweekly programming assignments
    - Not a lot of lines of code, but it will take you time to get them right
  - You can drop one, but some are cumulative
- 15% midterm
- 20% final
- 5% class participation & quizzes

What/How: ~~10-605~~ 805

- **Project** course for PhDs and MS students
  - MS students, send me your cv for *permission* to enroll
- 40% assignments (4/7)
- 15% midterm
- 40% project (no final)
  - open-ended, self-directed project
  - final deliverable is a conference-length paper
- 5% class participation & quizzes

What/How: 10-605 students working on a project with an 10-805 student

- **Lecture** course for MS and advance undergrads
- 50% assignments (5/7)
  - Biweekly programming assignments
    - Not a lot of lines of code, but it will take you time to get them right
  - You can drop one, but some are very cumulative
- 15% midterm
- 30% project (no final)
- 5% class participation & quizzes

- There will be some match-making we do but it's up to the 805 students to decide how much help they want/need.

What/How: 10-605 students working on a project with an 10-805 student

- **Lecture** course for MS and advance undergrads
- 50% assignments (5/7)
  - Biweekly programming assignments
    - Not a lot of lines of code, but it will take you time to get them right
  - You can drop one, but some are very cumulative
- 15% midterm
- 30% project (no final)
- 5% class participation & **quizzes**

- There will be some match-making we do but it's up to the 805 students to decide how much help they want/need.

Quizzes and class participation

- You should keep up with lectures
- The 5% is to keep you honest
- I’ve tried two things:
  - Piazza polls (so sign in for Piazza with your andrew account)
  - QnA quizzes

- All of these will close w/in 24 hours
- What matters most is IF you do them
- There is one for today so check the wiki!

What/How: 10-805 and 11-805

- Projects
  - 2012: everyone did projects and 5 HWs
    - Guest lectures from industry, experts
  - 2013: projects were optional
    - not everyone wanted to do projects in
    - I wanted to give more programming depth
  - 2014: nobody did projects
    - I had too many students
  - Spring/fall 2015, fall 2016
    - 805/605 split

What/How: cheating vs working together

- I have a long and explicit policy
  - stolen from Roni Rosenfeld - read the web page
  - tl;dr: transmit information like they did in the stone age, brain-to-brain, and document it
  - do not copy anything digitally
  - exceptions (eg projects) will be explicitly stated

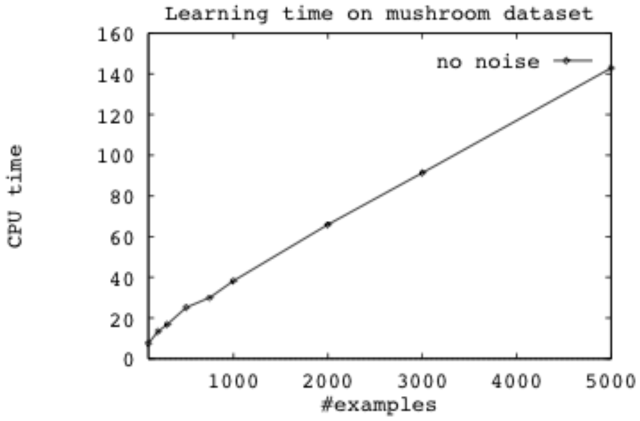
  - *everybody involved will fail* by default
  - *every* infraction *always* gets reported up to the Office of Academic Integrity, the head of your program, the dean of your school, ….

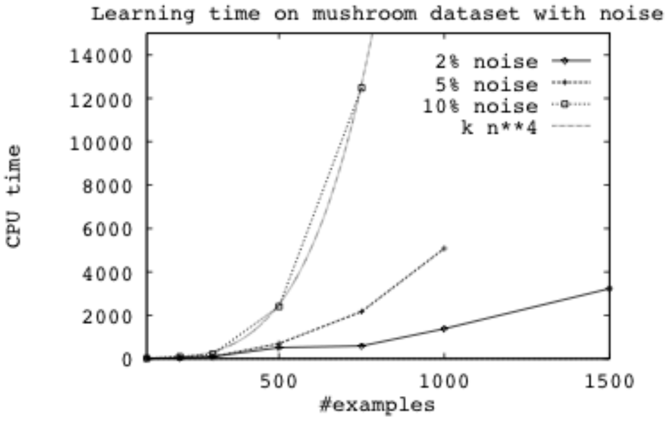
What/How: 601 co-req

- You should have as a prereq or co-req one of the MLD’s intro ML courses: 10-401, 10-601, 10-701, 10-715
- Lectures are designed to *complement* that material
  - computational aspects vs informational aspects
- If it’s a co-req you need permission
  - via email to wcohen+coreq@gmail.com
  - we’re gonna check

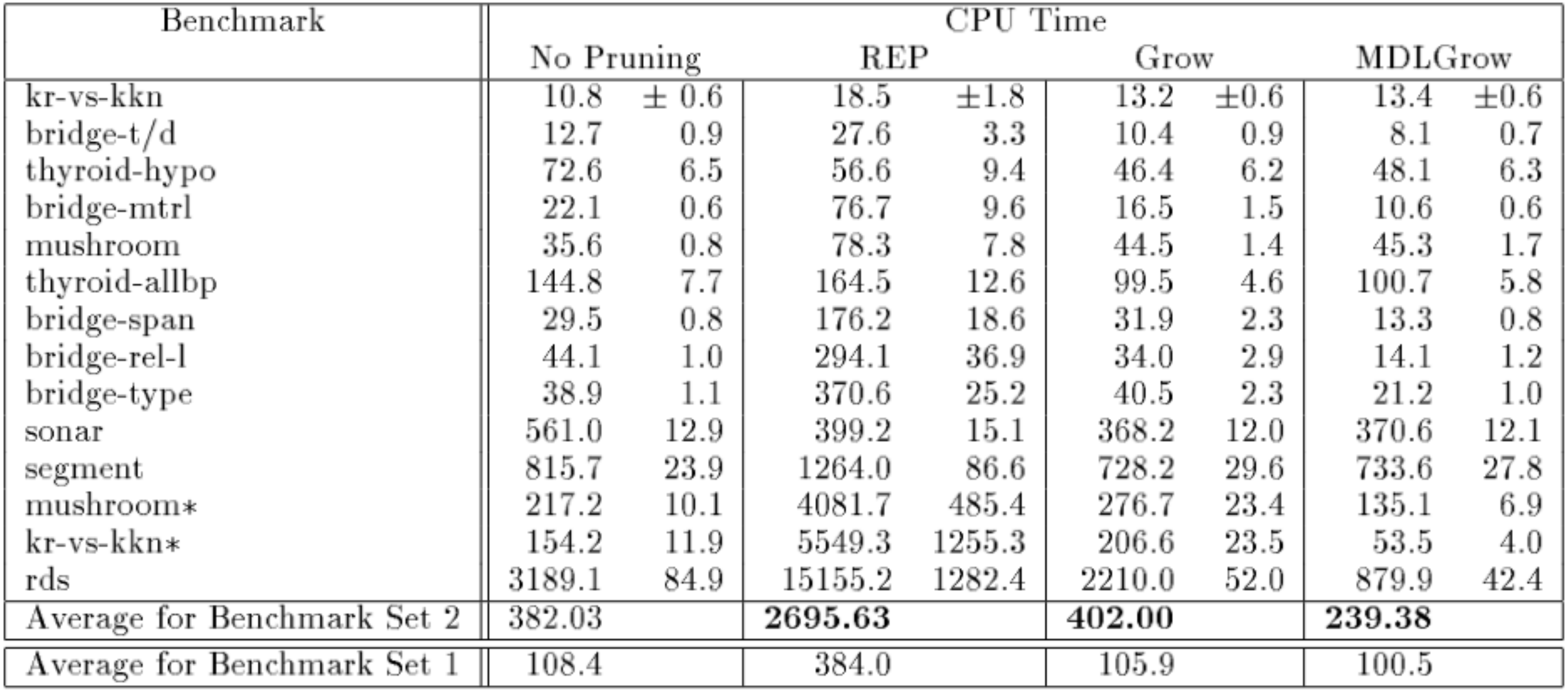
BIG DATA HISTORY: FROM THE DAWN OF TIME TO THE PRESENT

Big ML c. 1993 (Cohen, "Efficient…Rule Learning", IJCAI 1993)





```
$ ripper ../tdata/talks
Final hypothesis is:
talk_announcement :- WORDS ~ talk, WORDS ~ Subject_talk (54/1).
talk_announcement :- WORDS ~ '2d416' (26/3).
talk_announcement :- WORDS ~ system, WORDS ~ 'To_1126@research' (4/0).
talk_announcement :- WORDS ~ mh, WORDS ~ time (5/1).
talk_announcement :- WORDS ~ talk, WORDS ~ used (3/0).
talk_announcement :- WORDS ~ presentations (2/1).
default non_talk_announcement (390/1).
```



Benchmark	CPU Time							
	No Pruning		REP		Grow		MDLGrow	
kr-vs-kkn	10.8	± 0.6	18.5	±1.8	13.2	±0.6	13.4	±0.6
bridge-t/d	12.7	0.9	27.6	3.3	10.4	0.9	8.1	0.7
thyroid-hypo	72.6	6.5	56.6	9.4	46.4	6.2	48.1	6.3
bridge-mtrl	22.1	0.6	76.7	9.6	16.5	1.5	10.6	0.6
mushroom	35.6	0.8	78.3	7.8	44.5	1.4	45.3	1.7
thyroid-allbp	144.8	7.7	164.5	12.6	99.5	4.6	100.7	5.8
bridge-span	29.5	0.8	176.2	18.6	31.9	2.3	13.3	0.8
bridge-rel-l	44.1	1.0	294.1	36.9	34.0	2.9	14.1	1.2
bridge-type	38.9	1.1	370.6	25.2	40.5	2.3	21.2	1.0
sonar	561.0	12.9	399.2	15.1	368.2	12.0	370.6	12.1
segment	815.7	23.9	1264.0	86.6	728.2	29.6	733.6	27.8
mushroom*	217.2	10.1	4081.7	485.4	276.7	23.4	135.1	6.9
kr-vs-kkn*	154.2	11.9	5549.3	1255.3	206.6	23.5	53.5	4.0
rds	3189.1	84.9	15155.2	1282.4	2210.0	52.0	879.9	42.4
Average for Benchmark Set 2	382.03		**2695.63**		**402.00**		**239.38**	
Average for Benchmark Set 1	108.4		384.0		105.9		100.5	

Table 3: Comparing runtimes

More on this paper

Algorithm

- Phase 1: build rules
  - Discrete greedy search:
  - Starting with empty rule set, add conditions greedily
- Phase 2: prune rules
  - starting with phase 1 output, remove conditions

```
talk_announcement :-

default non_talk_announcement .
```

More on this paper

Algorithm

- Phase 1: build rules
  - Discrete greedy search:
  - Starting with empty rule set, add conditions greedily
- Phase 2: prune rules
  - starting with phase 1 output, remove conditions, greedily

talk_announcement :- WORDS ~ talk, WORDS ~ Subject_talk, ~~WORDS ~ p_comma (54/0)~~.
talk_announcement :- WORDS ~ '2d416', ~~WORDS ~ be (19/0)~~.
talk_announcement :- WORDS ~ show, WORDS ~ talk (7/0).
talk_announcement :- WORDS ~ mh, WORDS ~ time, ~~WORDS ~ research (4/0)~~.
talk_announcement :- WORDS ~ system, WORDS ~ 'To_1126@research' (3/0).
talk_announcement :- WORDS ~ '2d416', WORDS ~ memory (3/0).
~~talk_announcement :- WORDS ~ interfaces, WORDS ~ From_p_exclaim_point (2/0).~~
talk_announcement :- WORDS ~ presentations, ~~WORDS ~ From_att (2/0)~~.
default non_talk_announcement .

More on this paper

Algorithm

- Phase 1: build rules
  - Discrete greedy search:
  - Starting with empty rule set, add conditions greedily
- Phase 2: prune rules
  - starting with phase 1 output, remove conditions, greedily

```
talk_announcement :- WORDS ~ talk, WORDS ~ Subject_talk (54/1).
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talk_announcement :- WORDS ~ system, WORDS ~ 'To_1126@research' (4/0).
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talk_announcement :- WORDS ~ talk, WORDS ~ used (3/0).
talk_announcement :- WORDS ~ presentations (2/1).
default non_talk_announcement (390/1).
```

More on this paper

Algorithm

- Fit the POS,NEG example
- While POS isn't empty:
  - – Let **R** be "if True ➔ pos"
  - – While NEG isn't empty:
    - **L1** Pick the "best" [i] condition **c** of the form "xi=True" or "xi=false"
    - Add **c** to the LHS of **R**
    - Remove examples that don't satisfy **c** from NEG
  - Add **R** to the rule set [ii]
  - Remove examples that satisfy **R** from POS
- Prune the rule set:
  - – …

cubic!

[i] "Best" is wrt some statistics on **c**'s coverage of POS,NEG

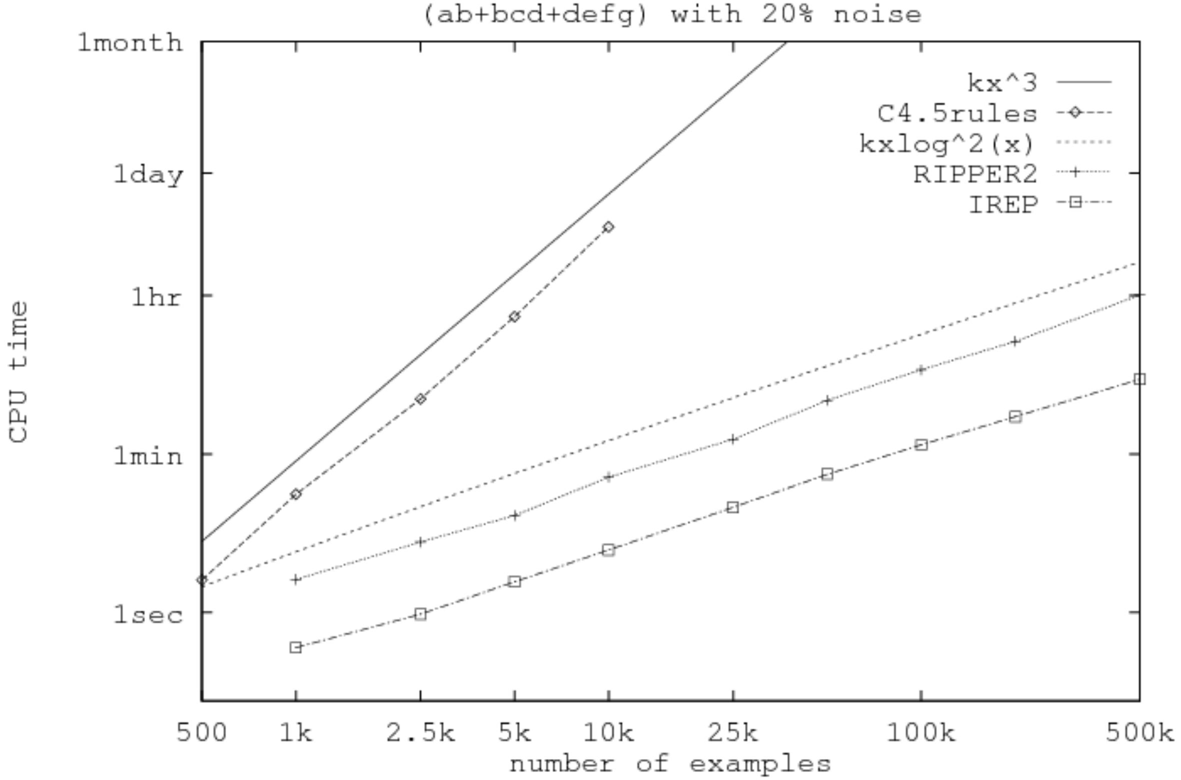
[ii] R is now of the form "if xi1=_ and xi2=_ and … ➔ pos"

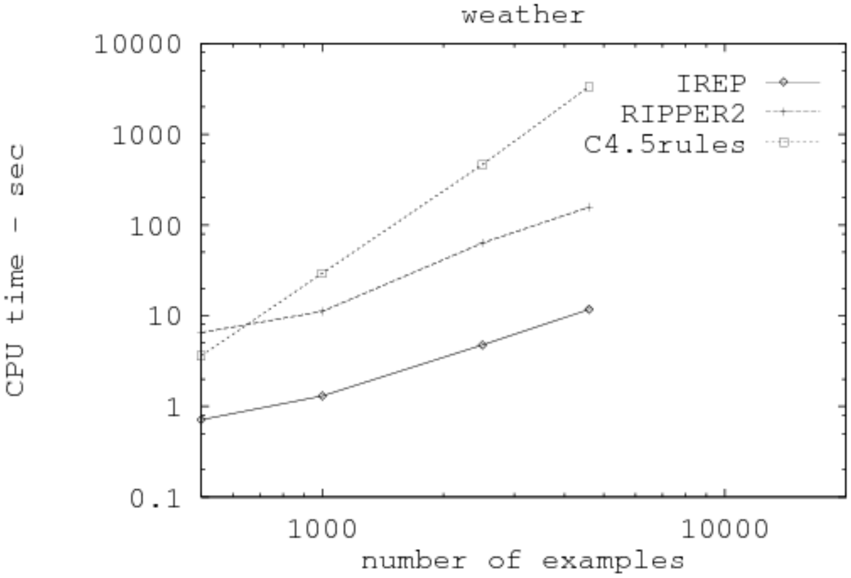
Analysis

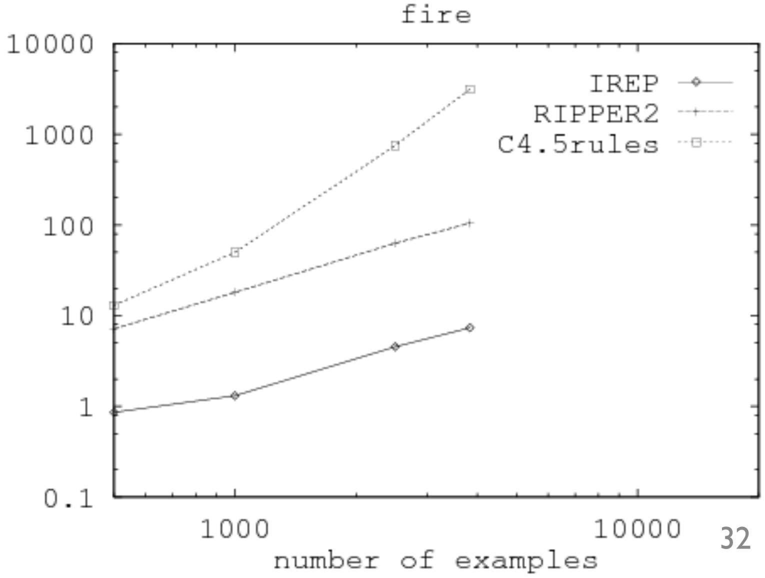
- The total number of iterations of L1 is the number of conditions in the rule set – call it *m*
- Picking the "best" condition requires looking at all examples – say there are *n* of these
- Time is at least *m*n*
- The problem:
  - – When there are noisy positive examples the algorithm builds rules that cover just 1-2 of them
  - – So with huge noisy datasets you build huge rulesets

quadratic

Related paper from 1995…







So in mid 1990’s.....

- Experimental datasets were small
- Many commonly used algorithms were *asymptotically* “slow”

- Not many people really cared

Big ML c. 2001 (Banko & Brill, "Scaling to Very Very Large…", ACL 2001)

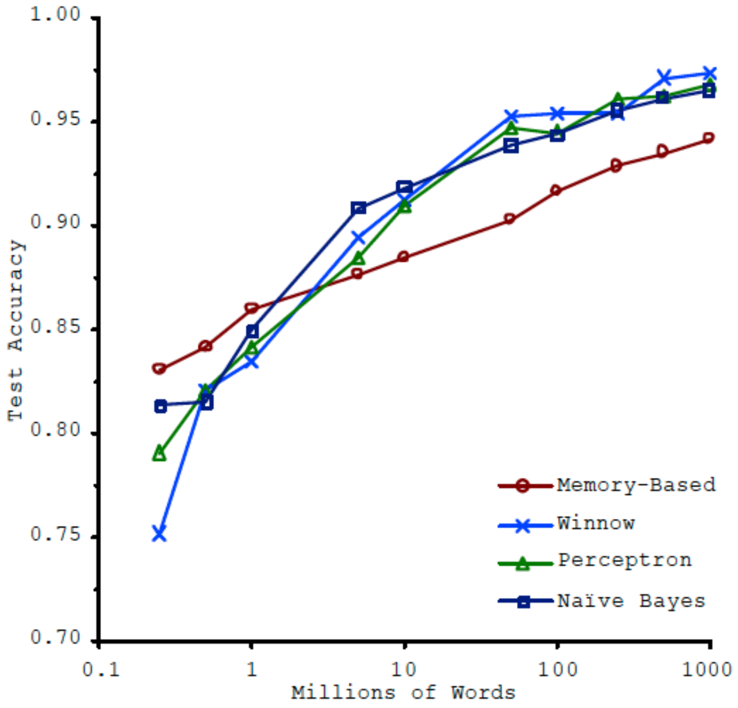


Figure 1. Learning Curves for Confusion Set Disambiguation

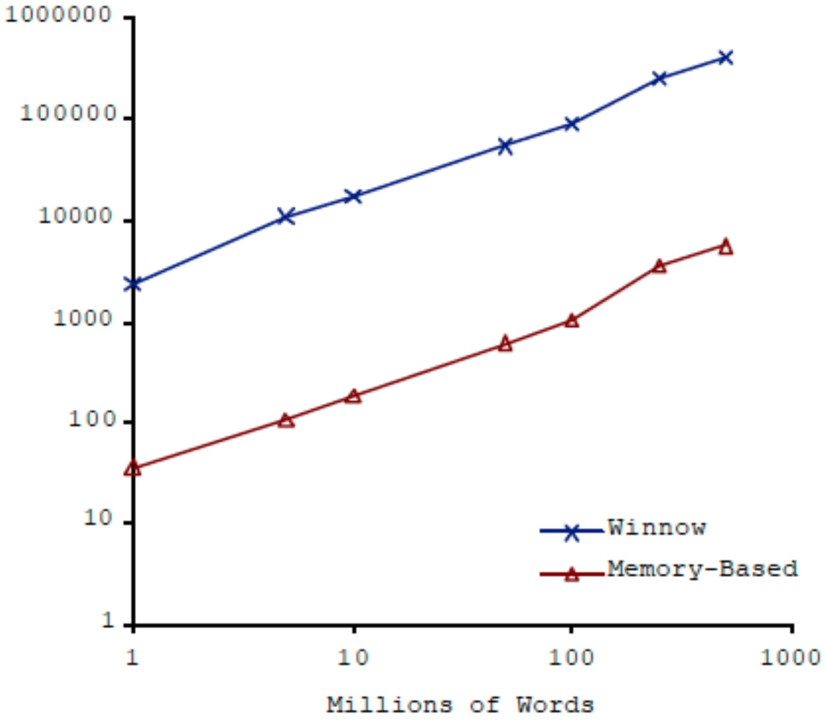


Figure 2. Representation Size vs. Training Corpus Size

Task: distinguish pairs of easily-confused words ("affect" vs "effect") in context

Big ML c. 2001 (Banko & Brill, “Scaling to Very Very Large…”, ACL 2001)

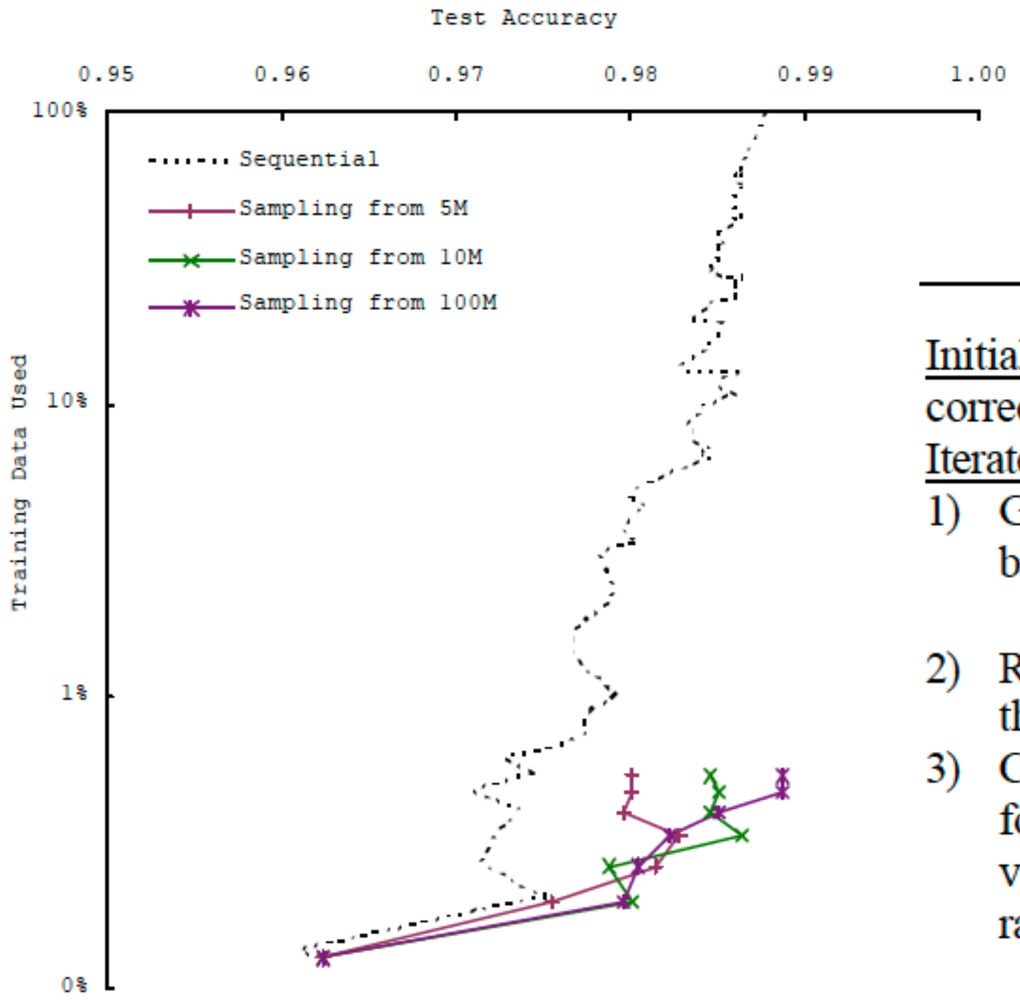


Figure 4. Active Learning with Large Corpora

Initialize: Training data consists of X words correctly labeled

Iterate :

1) Generate a committee of classifiers using bagging on the training set

2) Run the committee on unlabeled portion of the training set

3) Choose M instances from the unlabeled set for labeling - pick the M/2 with the greatest vote entropy and then pick another M/2 randomly – and add to training set

Why More Data Helps: A Demo

- Data:
  - All 5-grams that appear >= 40 times in a corpus of 1M English books
    - approx 80B words
    - 5-grams: 30Gb compressed, 250-300Gb uncompressed
    - Each 5-gram contains frequency distribution over *years*
  - Wrote code to compute
    - Pr(A,B,C,D,E|C=affect or C=effect)
    - Pr(any subset of A,…,E|any other fixed values of A,…,E with C=affect V effect)
  - Demo:
    - /Users/wcohen/Documents/code/pyhack/bigml
    - eg: python ngram-query.py data/aeffect-train.txt _ _B effect _ _

Why More Data Helps

- Data:
  - All 5-grams that appear >= 40 times in a corpus of 1M English books
    - approx 80B words
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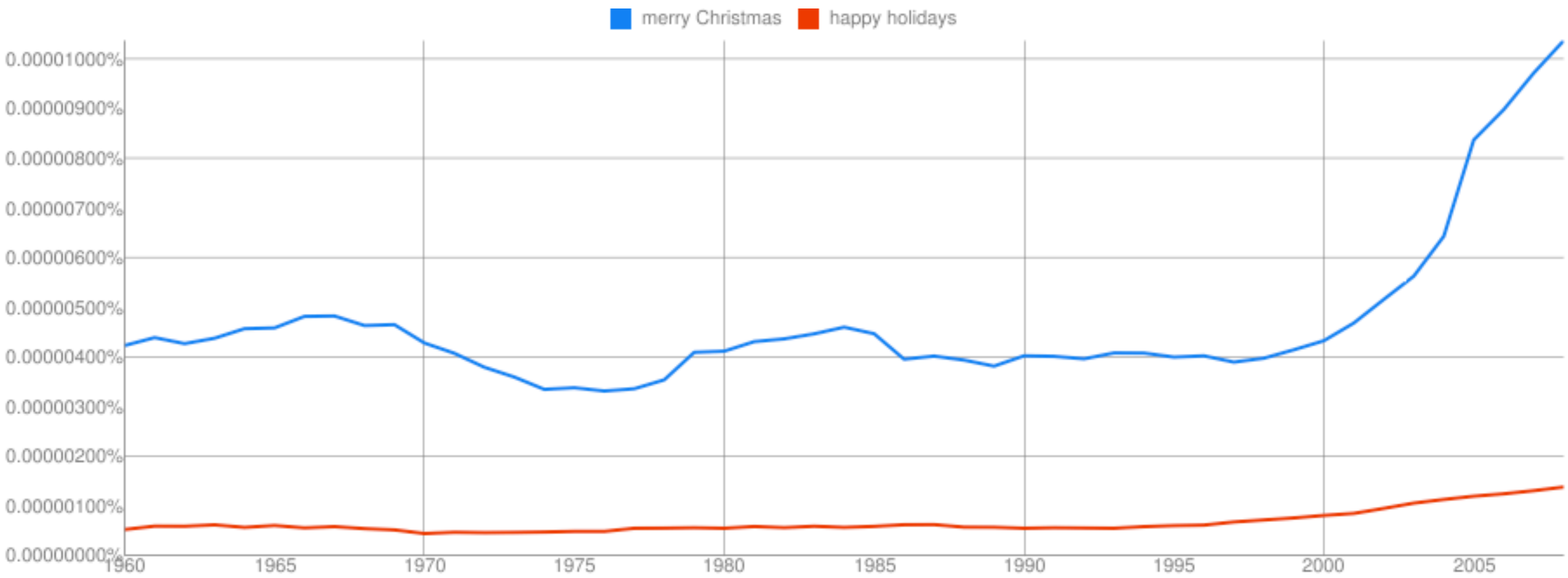
    - Each 5-gram contains frequency distribution over *years*
  - Wrote code to compute
    - Pr(A,B,C,D,E|C=affect or C=effect)
    - Pr(any subset of A,…,E|any other fixed values of A,…,E with C=affect V effect*)*
- Observations [from playing with data]:
  - Mostly effect not affect
  - Most common word before affect is not
  - After not effect most common word is a
  - …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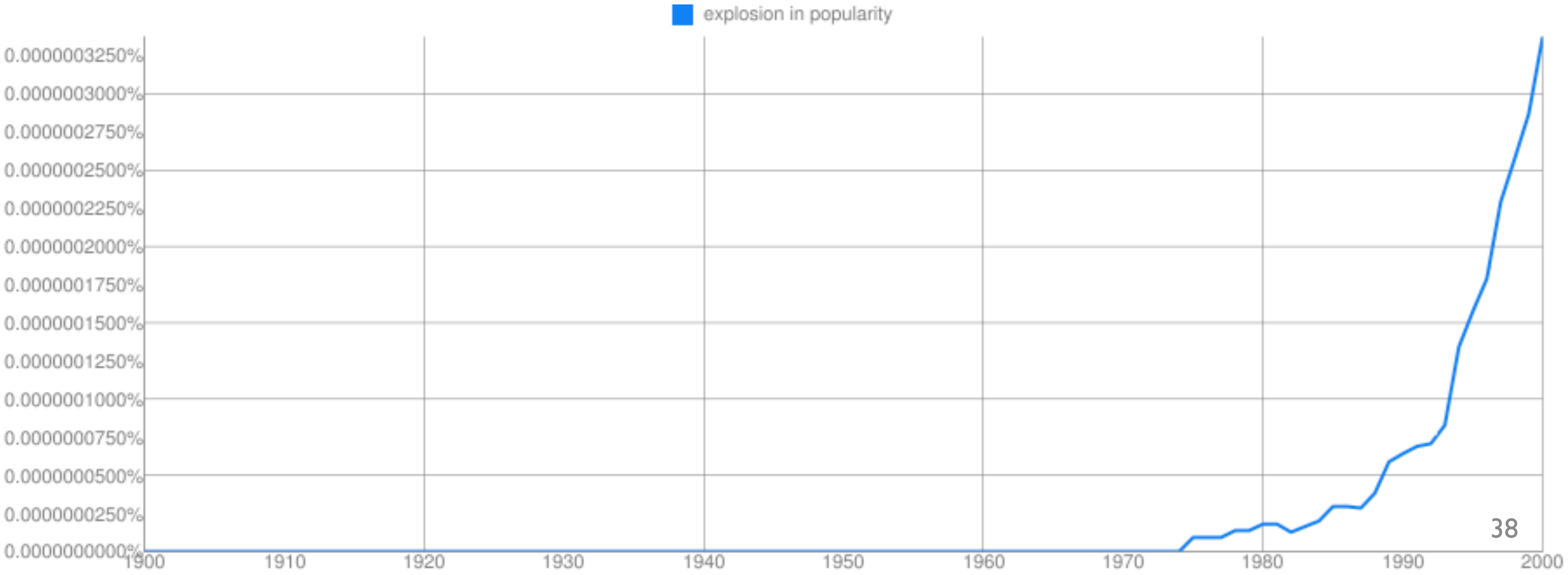
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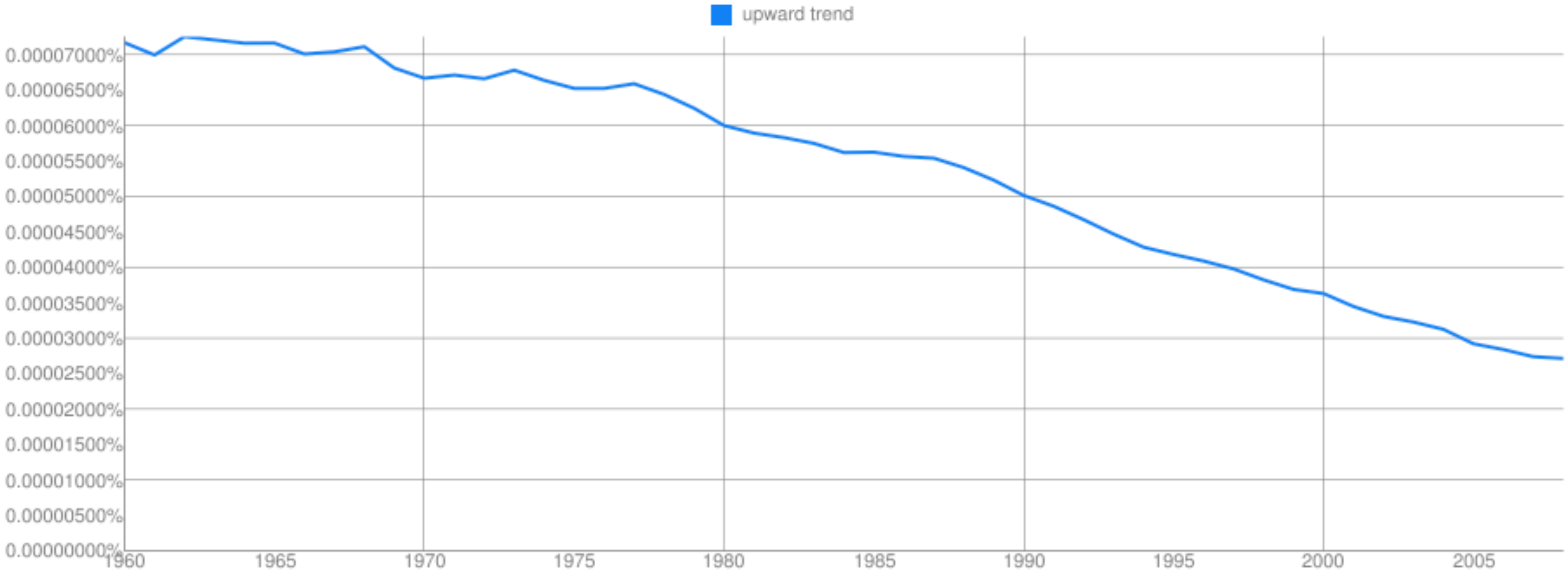

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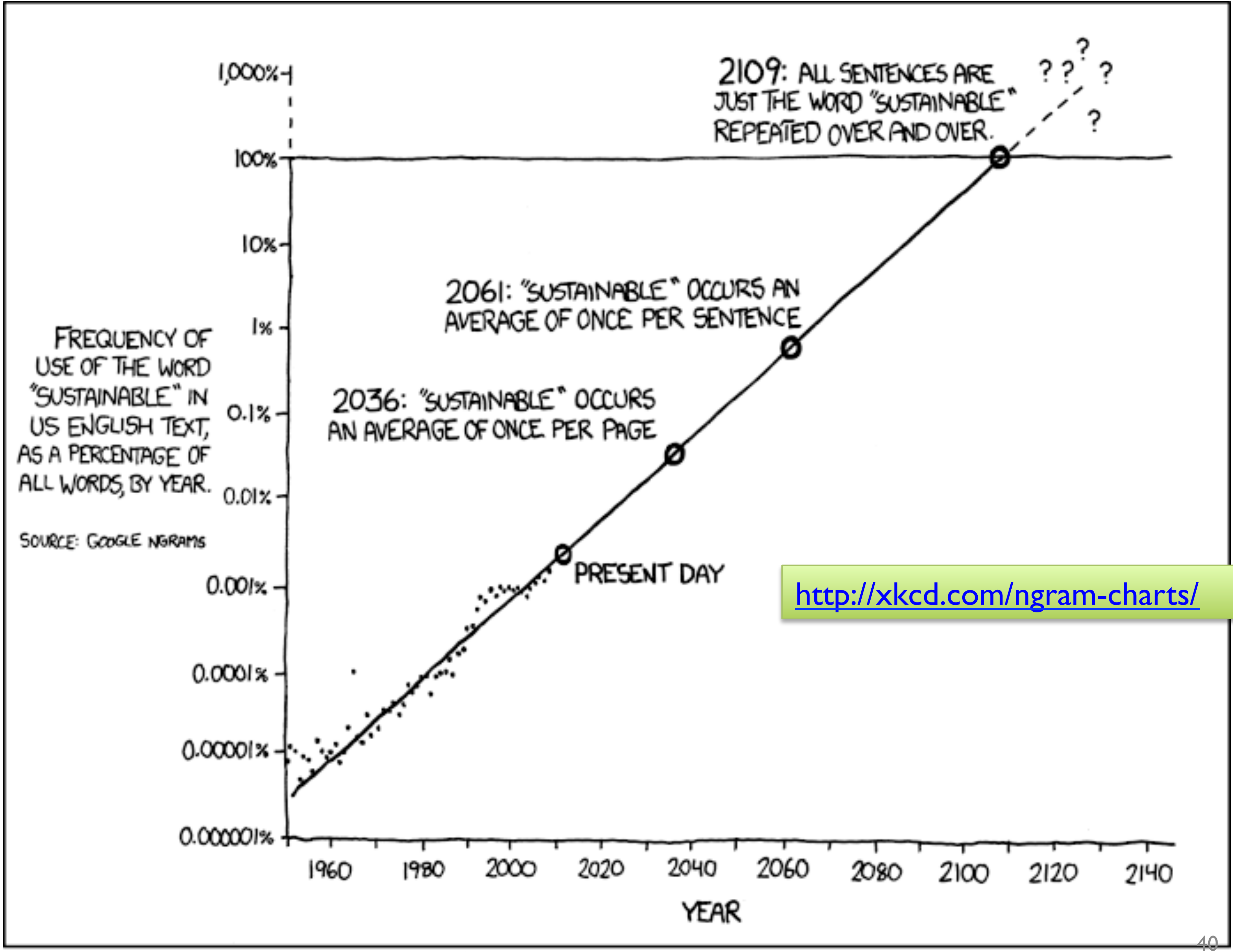


THE WORD "SUSTAINABLE" IS UNSUSTAINABLE.

http://xkcd.com/ngram-charts/

Big ML c. 2001 (Banko & Brill, "Scaling to Very Very Large…", ACL 2001)

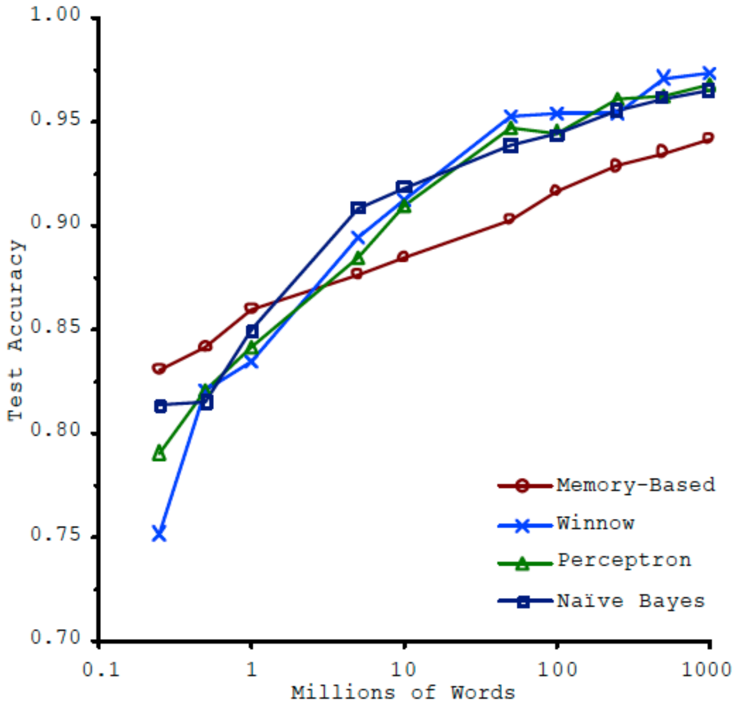


Figure 1. Learning Curves for Confusion Set Disambiguation

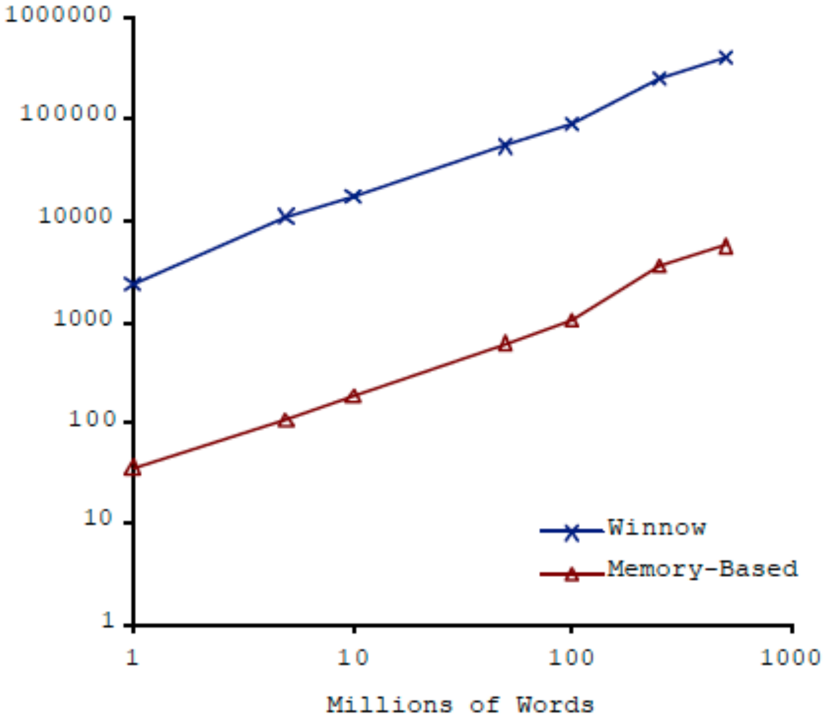


Figure 2. Representation Size vs. Training Corpus Size

Task: distinguish pairs of easily-confused words ("affect" vs "effect") in context

So in 2001…..

- We’re learning:
  - “there’s no data like more data”
  - For many tasks, there’s no real *substitute* for using lots of data

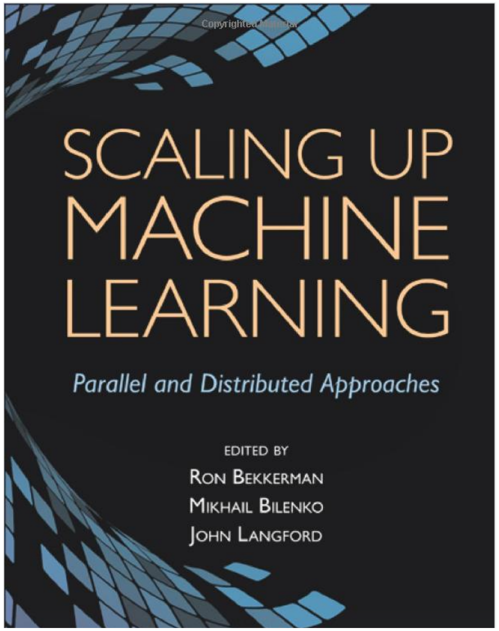
...and in 2009

Eugene Wigner's article *"The Unreasonable Effectiveness of Mathematics in the Natural Sciences"* examines why so much of physics can be neatly explained with simple mathematical formulas such as $f = ma$ or $e = mc^2$. Meanwhile, sciences that involve human beings rather than elementary particles have proven more resistant to elegant mathematics. Economists suffer from physics envy over their inability to neatly model human behavior. An informal, incomplete grammar of the English language runs over 1,700 pages.

Perhaps when it comes to natural language processing and related fields, we're doomed to complex theories that will never have the elegance of physics equations. But if that's so, we should stop acting as if our goal is to author extremely elegant theories, and instead embrace complexity and make use of the best ally we have: the unreasonable effectiveness of data.

Norvig, Pereira, Halevy, "The Unreasonable Effectiveness of Data", 2009

…and in 2012



SCALING UP MACHINE LEARNING

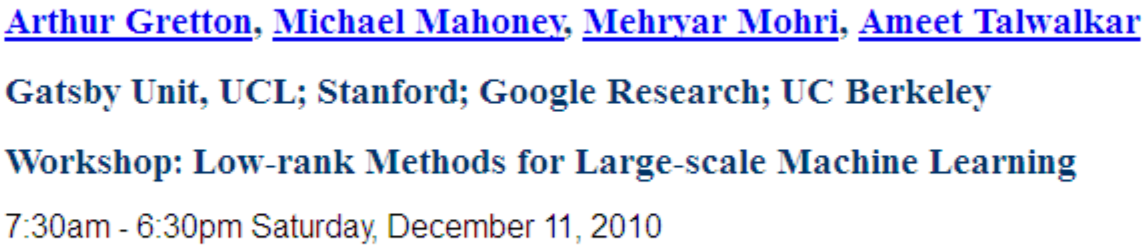
Parallel and Distributed Approaches

EDITED BY

Ron Bekkerman

Mikhail Bilenko

John Langford

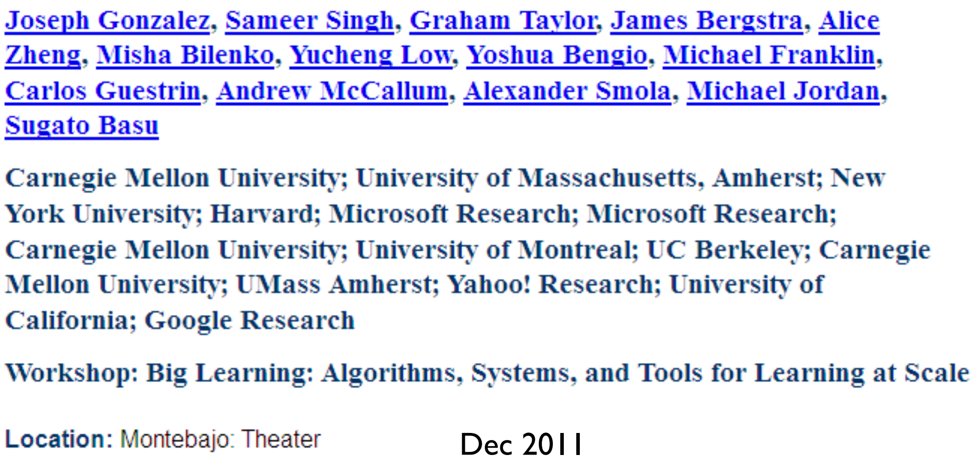


Arthur Gretton, Michael Mahoney, Mehryar Mohri, Ameet Talwalkar

Gatsby Unit, UCL; Stanford; Google Research; UC Berkeley

Workshop: Low-rank Methods for Large-scale Machine Learning

7:30am - 6:30pm Saturday, December 11, 2010



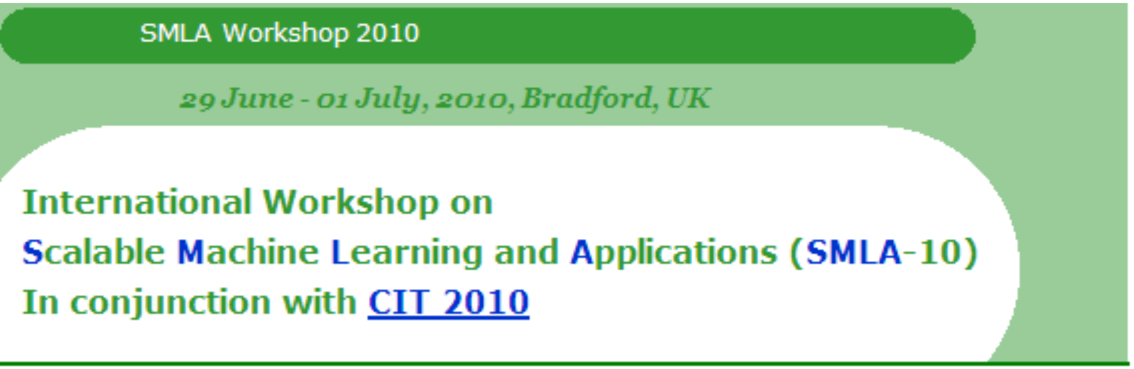
Joseph Gonzalez, Sameer Singh, Graham Taylor, James Bergstra, Alice Zheng, Misha Bilenko, Yucheng Low, Yoshua Bengio, Michael Franklin, Carlos Guestrin, Andrew McCallum, Alexander Smola, Michael Jordan, Sugato Basu

Carnegie Mellon University; University of Massachusetts, Amherst; New York University; Harvard; Microsoft Research; Microsoft Research; Carnegie Mellon University; University of Montreal; UC Berkeley; Carnegie Mellon University; UMass Amherst; Yahoo! Research; University of California; Google Research

Workshop: Big Learning: Algorithms, Systems, and Tools for Learning at Scale

Location: Montebajo: Theater

Dec 2011



SMLA Workshop 2010

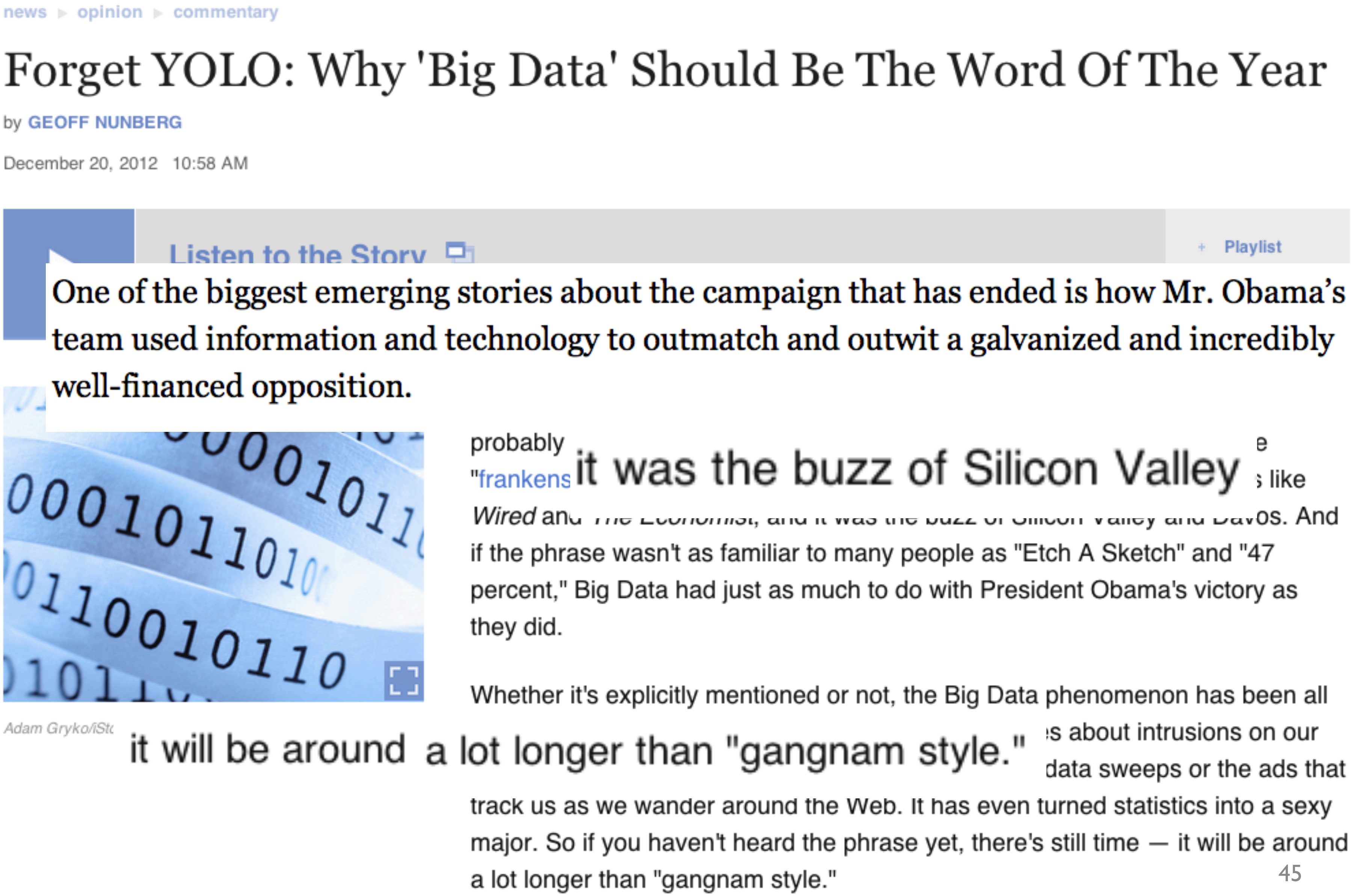
29 June - 01 July, 2010, Bradford, UK

International Workshop on

Scalable Machine Learning and Applications (SMLA-10)

In conjunction with CIT 2010

...and in 2013



news ▸ opinion ▸ commentary

Forget YOLO: Why 'Big Data' Should Be The Word Of The Year

by GEOFF NUNBERG

December 20, 2012 10:58 AM

Listen to the Story

+ Playlist

One of the biggest emerging stories about the campaign that has ended is how Mr. Obama's team used information and technology to outmatch and outwit a galvanized and incredibly well-financed opposition.

Adam Gryko/iStc

probably … e

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it was the buzz of Silicon Valley

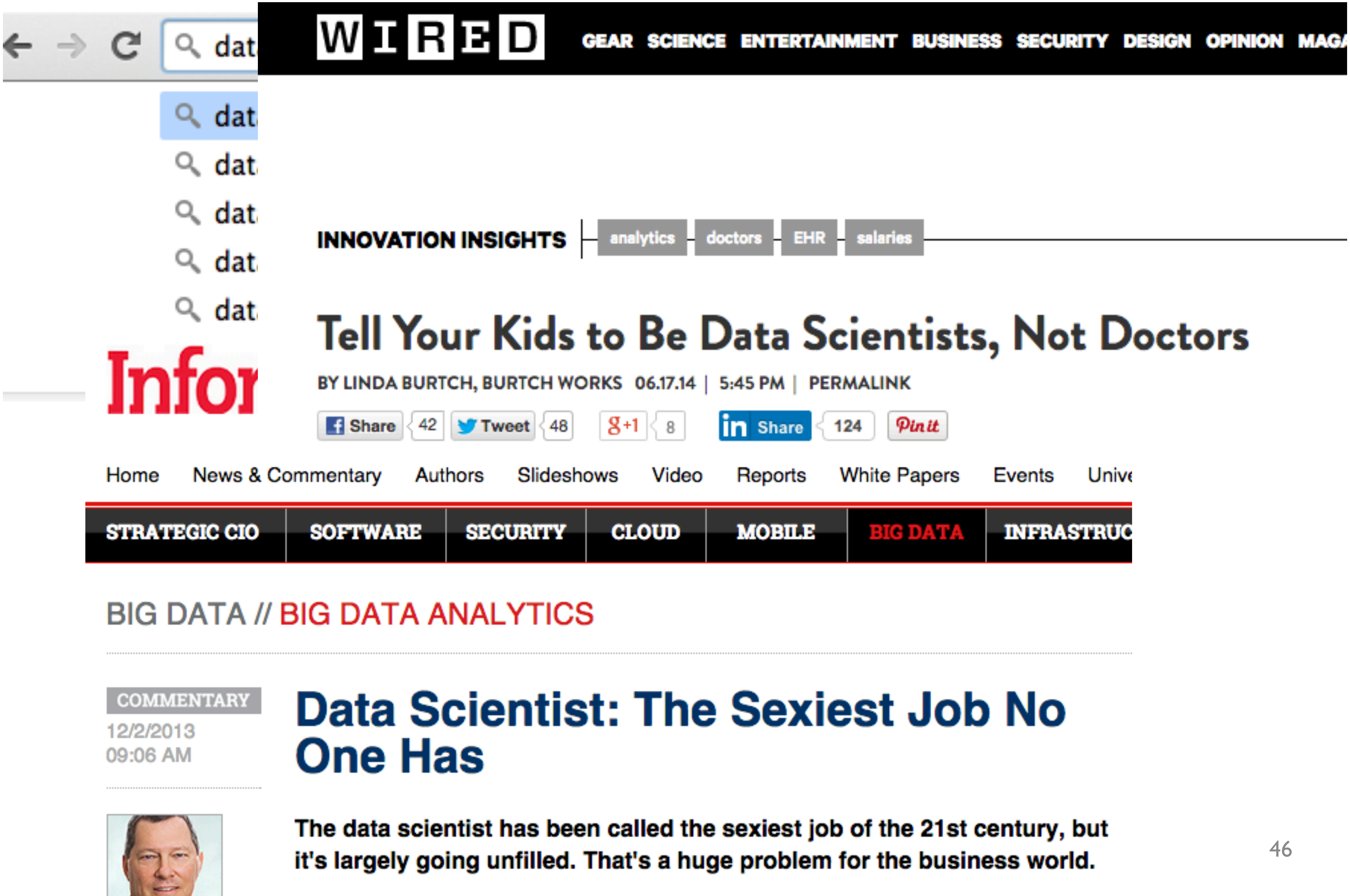
Wired and *The Economist*, and it was the buzz of Silicon Valley and Davos. And if the phrase wasn't as familiar to many people as "Etch A Sketch" and "47 percent," Big Data had just as much to do with President Obama's victory as they did.

Whether it's explicitly mentioned or not, the Big Data phenomenon has been all

it will be around a lot longer than "gangnam style."

…s about intrusions on our … data sweeps or the ads that track us as we wander around the Web. It has even turned statistics into a sexy major. So if you haven't heard the phrase yet, there's still time — it will be around a lot longer than "gangnam style."

...and in 2014



Tell Your Kids to Be Data Scientists, Not Doctors

BY LINDA BURTCH, BURTCH WORKS 06.17.14 | 5:45 PM | PERMALINK

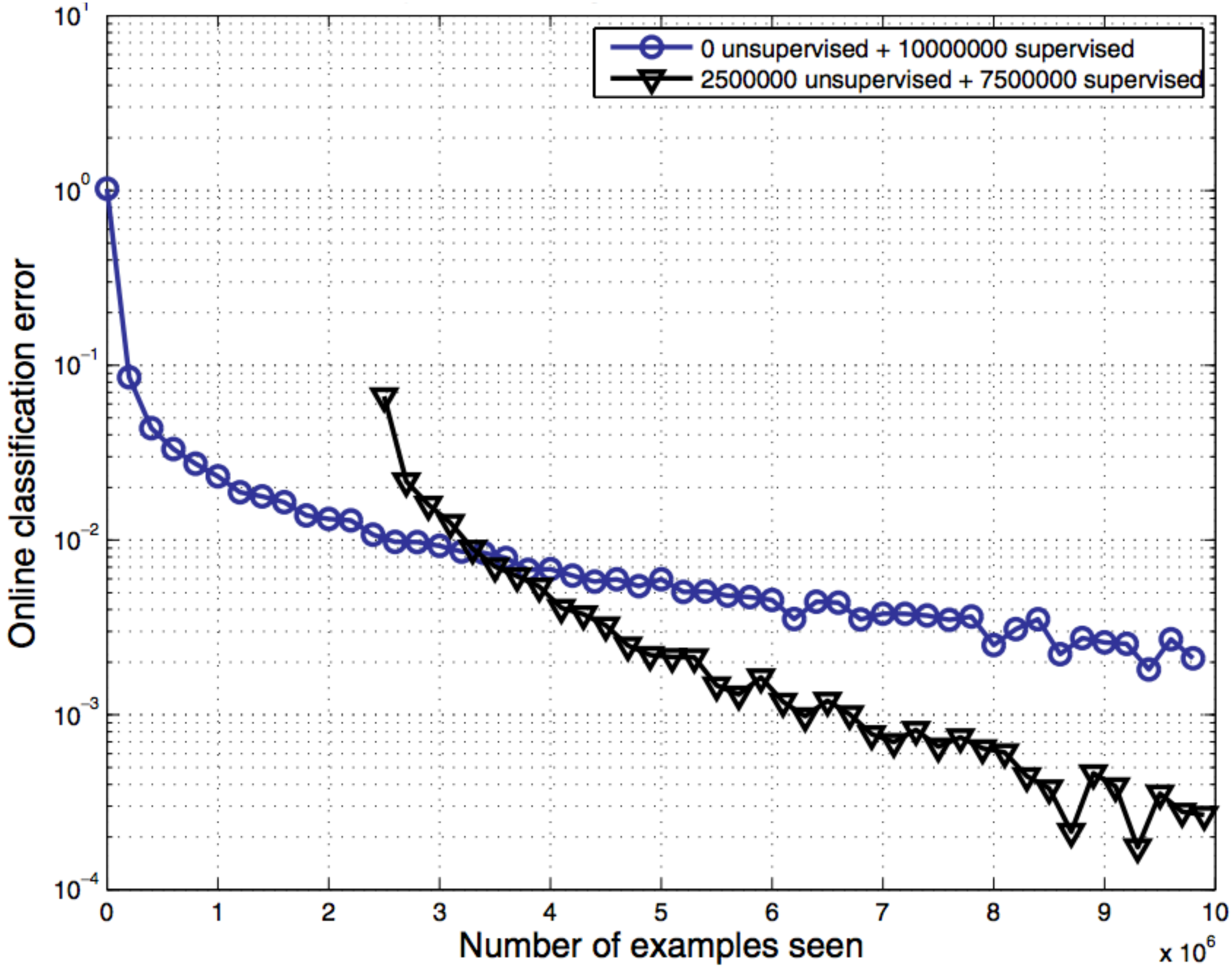
BIG DATA // BIG DATA ANALYTICS

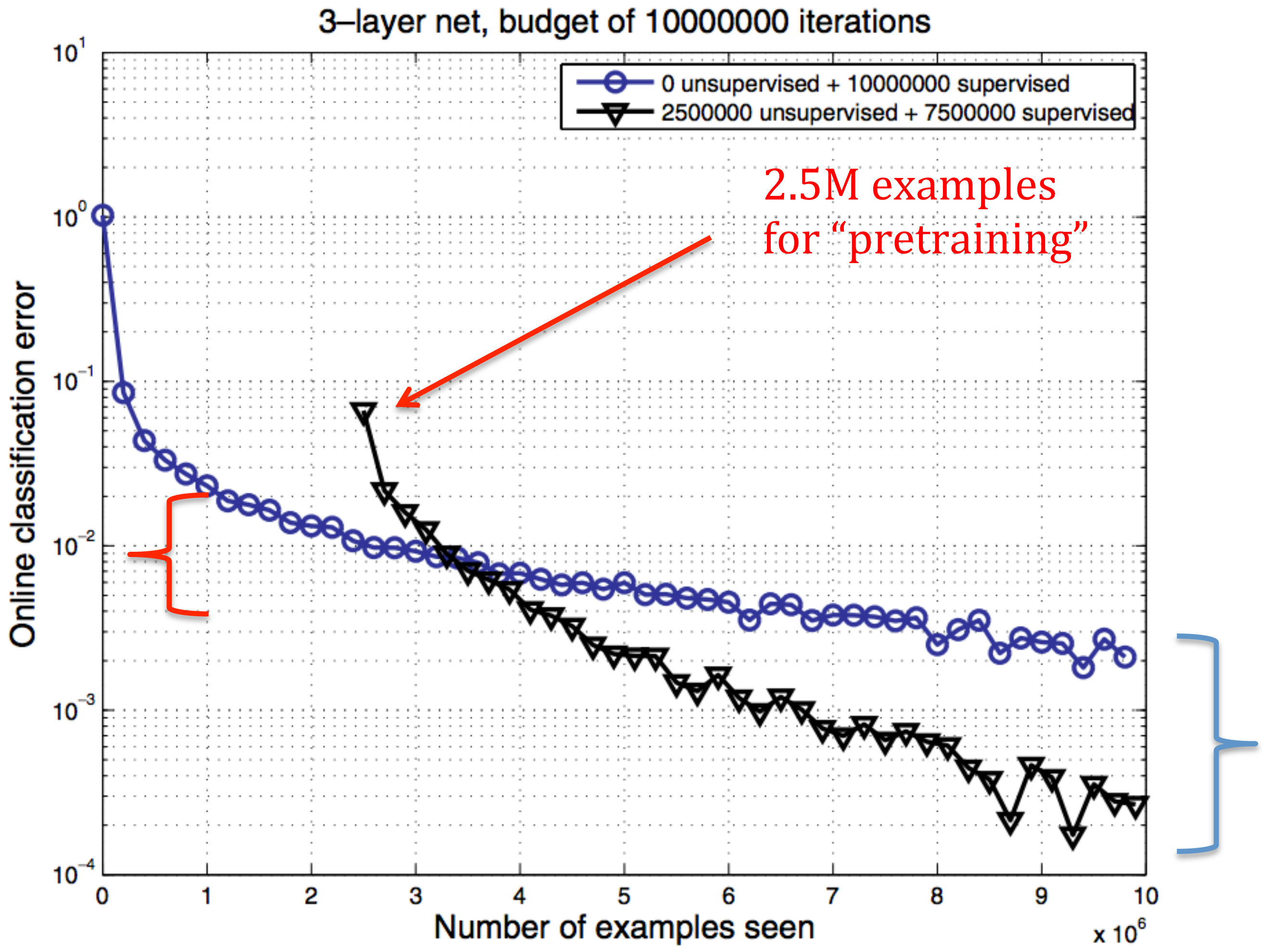
COMMENTARY
12/2/2013
09:06 AM

Data Scientist: The Sexiest Job No One Has

The data scientist has been called the sexiest job of the 21st century, but it's largely going unfilled. That's a huge problem for the business world.

Bengio, Foundations & Trends, 2009





2.5M examples for "pretraining"

1M vs 10M examples

naïve vs clever optimization

Fig. 4.2 Deep architecture trained online with 10 million examples of digit images, either with pre-training (triangles) or without (circles). The classification error shown (vertical axis, log-scale) is computed online on the next 1000 examples, plotted against the number of examples seen from the beginning. The first 2.5 million examples are used for unsupervised pre-training (of a stack of denoising auto-encoders). The oscillations near the end are because the error rate is too close to 0, making the sampling variations appear large on the log-scale. Whereas with a very large training set regularization effects should dissipate, one can see that without pre-training, training converges to a poorer apparent local minimum: unsupervised pre-training helps to find a better minimum of the online error. Experiments were performed by Dumitru Erhan.

Today….

- Commonly used deep learning datasets:
  - – Images:
    - ImageNet: 20k+ categories, 14M+ images
    - MS COCO: 91 categories, 2.5M labels, 328k images
  - – Reading comprehension:
    - Children's book test: 600k + context/query pairs
    - CNN/Daily mail: ~300k docs, 1.2M cloze questions
  - – Other:
    - Ubuntu dialog: 7M+ utterances, 1M+ dialogs
    - …

REVIEW: ASYMPTOTIC COMPLEXITY

How do we use very large amounts of data?

- Working with big data is *not** about
  - code optimization
  - learning details of todays hardware/software:
    - GraphLab, Hadoop, Spark, parallel hardware, ….
- Working with big data *is* about
  - Understanding the cost of what you want to do
  - Understanding what the tools that are available offer
  - Understanding how much can be accomplished with linear or nearly-linear operations (e.g., sorting, …)
  - Understanding how to organize your computations so that they effectively use whatever's fast
  - Understanding how to test/debug/verify with large data

* according to William

Asymptotic Analysis: Basic Principles

Usually we only care about positive f(n), g(n), n here…

$$f(n) \in O(g(n)) \text{ iff } \exists k, n_0 : \forall n > n_0, f(x) \leq k \cdot g(n)$$

$$f(n) \in \Omega(g(n)) \text{ iff } \exists k, n_0 : \forall n > n_0, f(x) \geq k \cdot g(n)$$

Asymptotic Analysis: Basic Principles

Less pedantically:

$$f(n) = O(g(n)) \text{ iff } \exists k, n_0 : \forall n > n_0, f(x) \le k \cdot g(n)$$

$$f(n) = \Omega(g(n)) \text{ iff } \exists k, n_0 : \forall n > n_0, f(x) \ge k \cdot g(n)$$

Some useful rules:

$$O(n^4 + n^3) = \mathrm{O}(n^4)$$

Only highest-order terms matter

$$O(3n^4 + 127n^3) = \mathrm{O}(n^4)$$

Leading constants don't matter

$$O(\log n^4) = O(4 \cdot \log n) = O(\log n)$$

Degree of something in a log doesn't matter

Back to rule pruning….

Algorithm

- Fit the POS,NEG exampleWhile POS isn't empty:
  - Let **R** be "if True ➔ pos"
  - While NEG isn't empty:
    - Pick the "best" [1] condition **c** of the form "xi=True" or "xi=false"
    - Add **c** to the LHS of **R**
    - Remove examples that don't satisfy **c** from NEG
  - Add **R** to the rule set [2]
  - Remove examples that satisfy **R** from POS
- Prune the rule set:
  - For each condition **c** in the rule set:
    - Evaluate the accuracy of the ruleset w/o **c** on heldout data
  - If removing any **c** improves accuracy
    - Remove **c** and repeat the pruning step

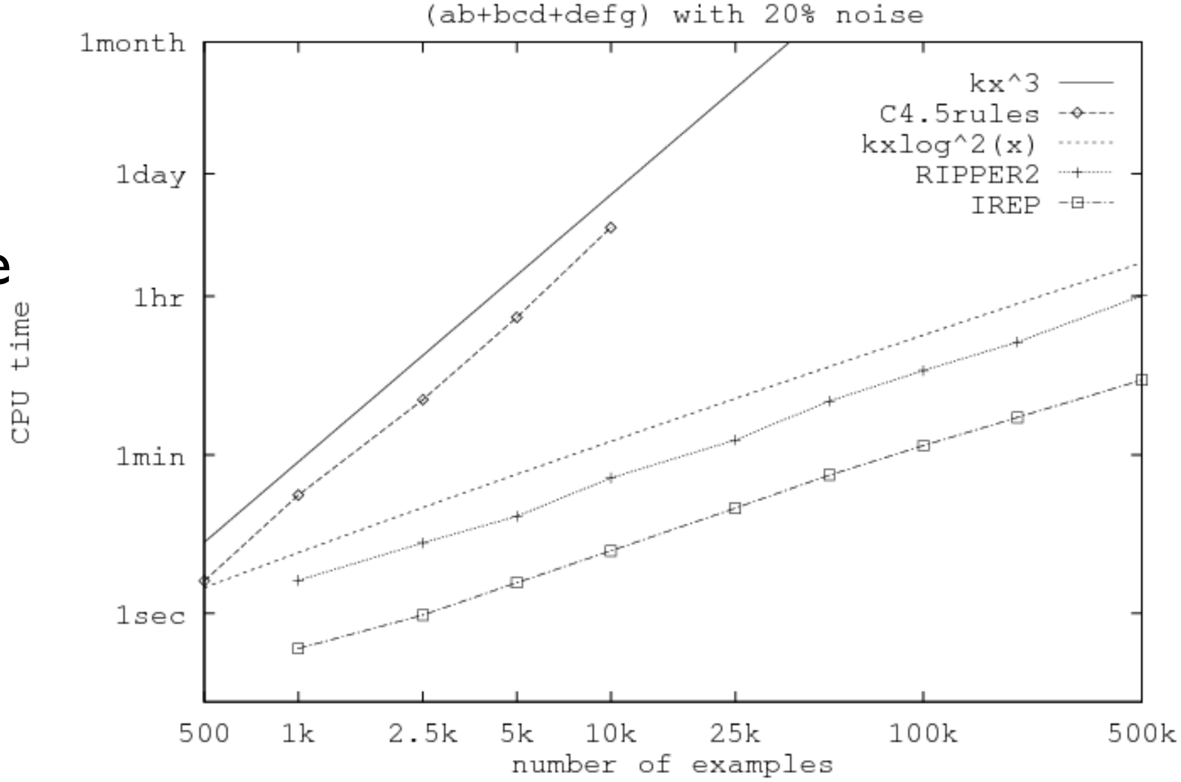
Analysis

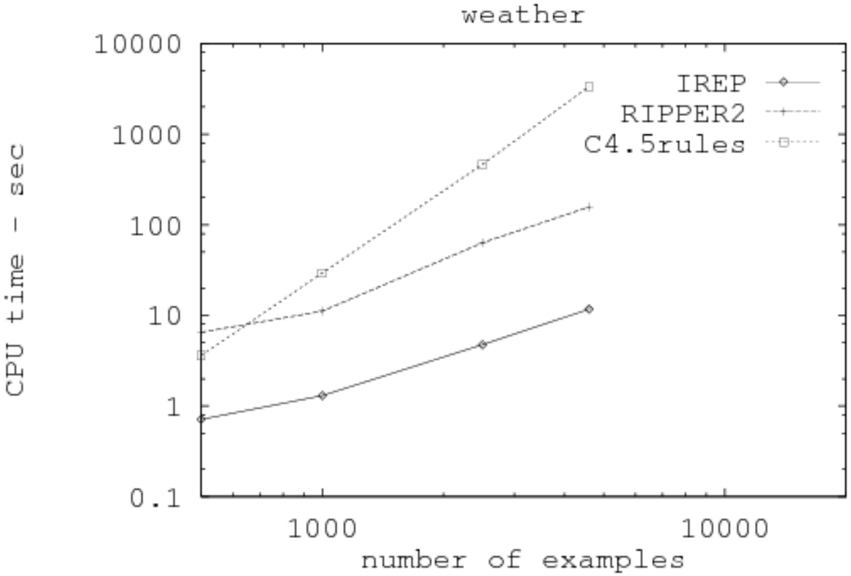
- Assume *n* examples
- Assume *m* conditions in rule set
- Growing rules takes time at least $\Omega(m*n)$ if evaluating **c** is $\Omega(n)$
- When data is clean *m* is small, fitting takes linear time
- When k% of data is noisy, *m* is $\Omega(n*0.01*k)$ so growing rules takes $\Omega(n^2)$
- Pruning a rule set with $m = 0.01*kn$ extra conditions is *very* slow: $\Omega(n^3)$ if implemented naively

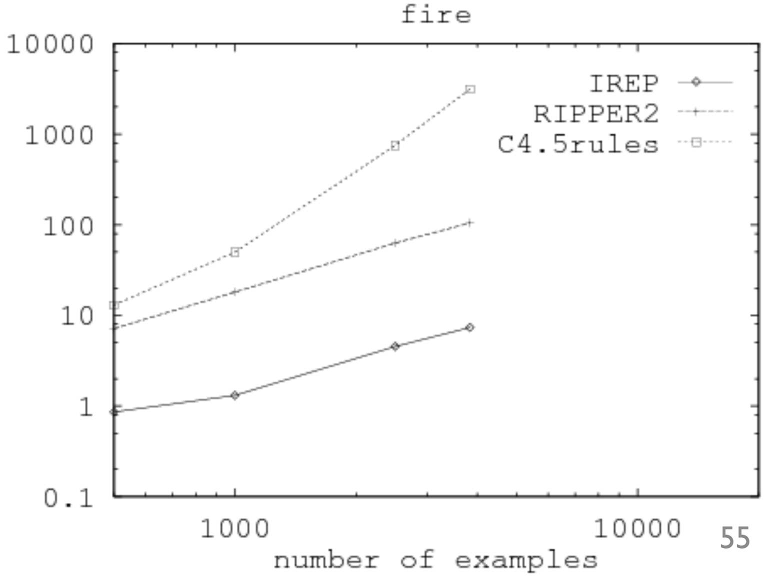
[1] "Best" is wrt some statistics on **c**'s coverage of POS,NEG

[2] **R** is now of the form "if xi1=_ and xi2=_ and … ➔ pos"

Empirical analysis of complexity: plot run-time on a log-log plot and measure the slope (using linear regression)







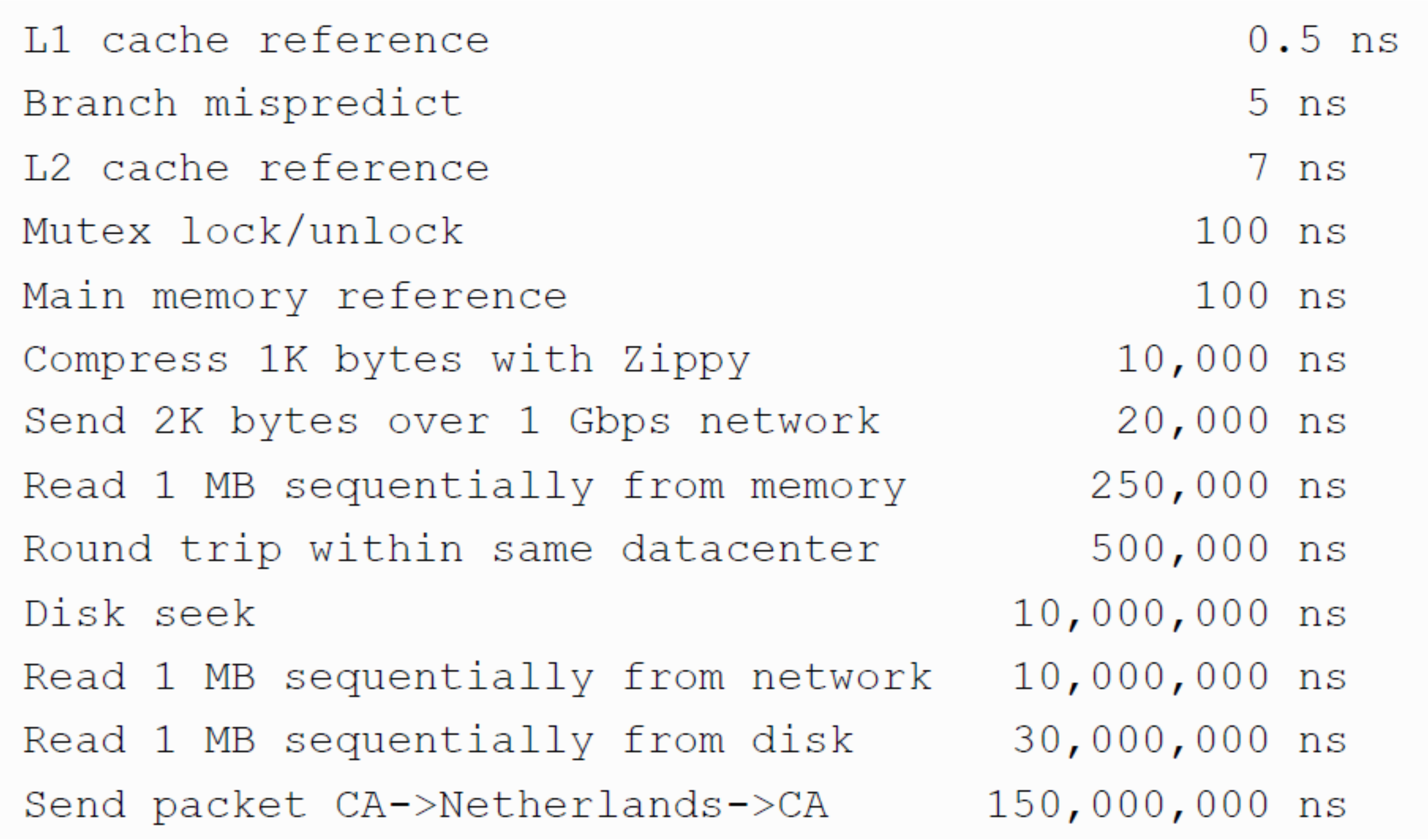
Where do asymptotics break down?

- When the constants are too big
  - or *n* is too small
- When we can’t predict what the program will do
  - Eg, how many iterations before convergence? Does it depend on data size or not?
  - This is when you need experiments
- When there are different types of operations with different costs
  - We need to understand what we should count

What do we count?

- Compilers don’t warn Jeff Dean. Jeff Dean warns compilers.
- Jeff Dean builds his code before committing it, but only to check for compiler and linker bugs.
- Jeff Dean writes directly in binary. He then writes the source code as a documentation for other developers.
- Jeff Dean once shifted a bit so hard, it ended up on another computer.
- When Jeff Dean has an ergonomic evaluation, it is for the protection of his keyboard.
- gcc -O4 emails your code to Jeff Dean for a rewrite.
- When he heard that Jeff Dean's autobiography would be exclusive to the platform, Richard Stallman bought a Kindle.
- Jeff Dean puts his pants on one leg at a time, but if he had more legs, you’d realize the algorithm is actually only O(logn)

Numbers (Jeff Dean says) Everyone Should Know



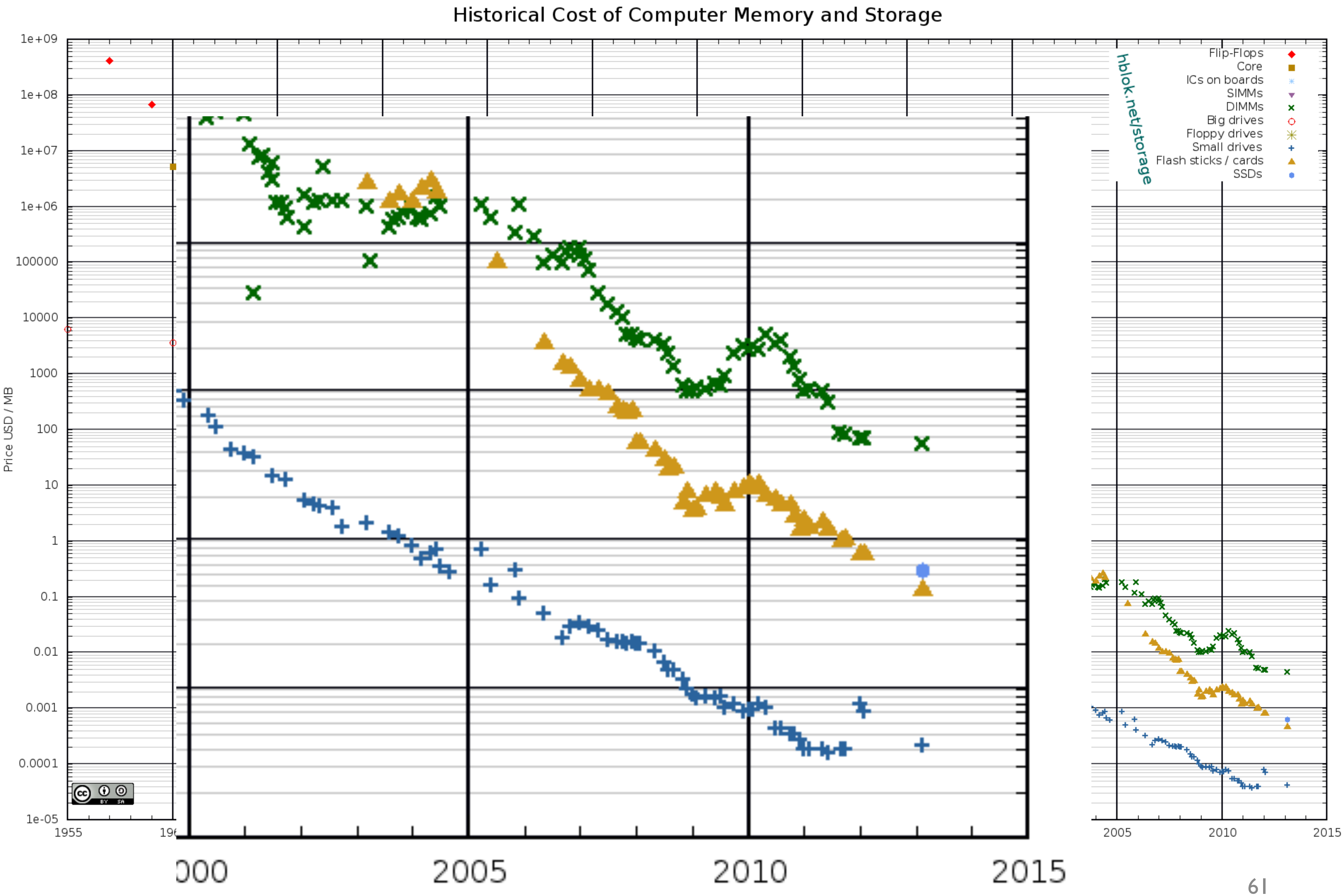
```
L1 cache reference                            0.5 ns
Branch mispredict                             5 ns
L2 cache reference                            7 ns
Mutex lock/unlock                           100 ns
Main memory reference                       100 ns
Compress 1K bytes with Zippy             10,000 ns
Send 2K bytes over 1 Gbps network        20,000 ns
Read 1 MB sequentially from memory      250,000 ns
Round trip within same datacenter       500,000 ns
Disk seek                            10,000,000 ns
Read 1 MB sequentially from network  10,000,000 ns
Read 1 MB sequentially from disk     30,000,000 ns
Send packet CA->Netherlands->CA     150,000,000 ns
```

Update: Colin Scott, UCB

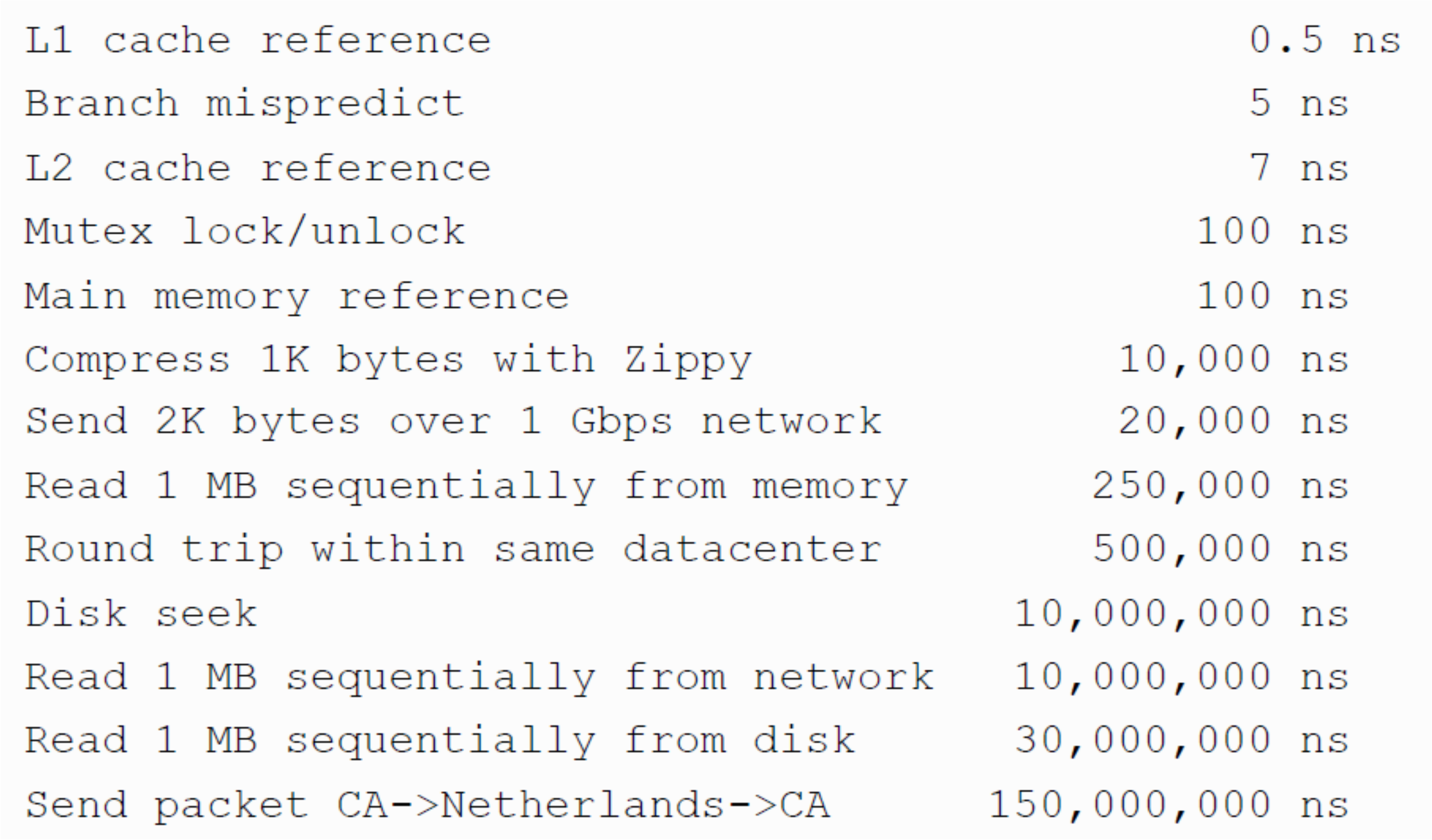
file:///Users/wcohen/Documents/code/interactive_latencies/interactive_latency.html

What's Happening with Hardware?

- Clock speed: stuck at 3Ghz for ~ 10 years
- Net bandwidth doubles ~ 2 years
- Disk bandwidth doubles ~ 2 years
- SSD bandwidth doubles ~ 3 years
- Disk seek speed doubles ~ 10 years
- SSD latency nearly saturated


Historical Cost of Computer Memory and Storage
Price USD / MB
1e+09
1e+08
1e+07
1e+06
100000
10000
1000
100
10
1
0.1
0.01
0.001
0.0001
1e-05
1955
196
000
2005
2010
2015
hblok.net/storage
Flip-Flops
Core
ICs on boards
SIMMs
DIMMs
Big drives
Floppy drives
Small drives
Flash sticks / cards
SSDs
BY SA

Numbers (Jeff Dean says) Everyone Should Know



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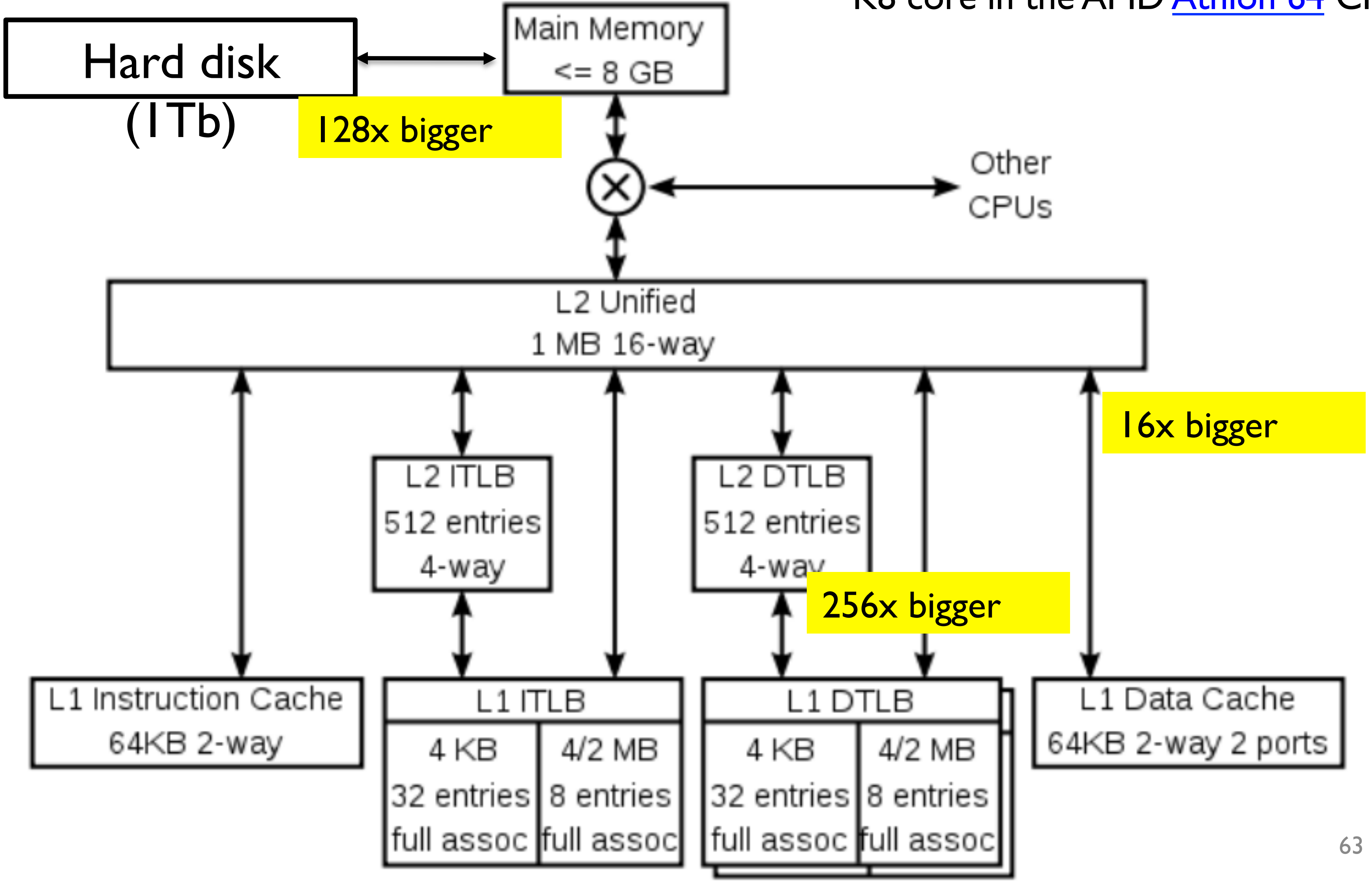
```

A typical CPU (not to scale)

K8 core in the AMD Athlon 64 CPU



Hard disk (1Tb)

128x bigger

Main Memory <= 8 GB

Other CPUs

L2 Unified 1 MB 16-way

16x bigger

L2 ITLB 512 entries 4-way

L2 DTLB 512 entries 4-way

256x bigger

L1 Instruction Cache 64KB 2-way

L1 ITLB

4 KB 32 entries full assoc

4/2 MB 8 entries full assoc

L1 DTLB

4 KB 32 entries full assoc

4/2 MB 8 entries full assoc

L1 Data Cache 64KB 2-way 2 ports

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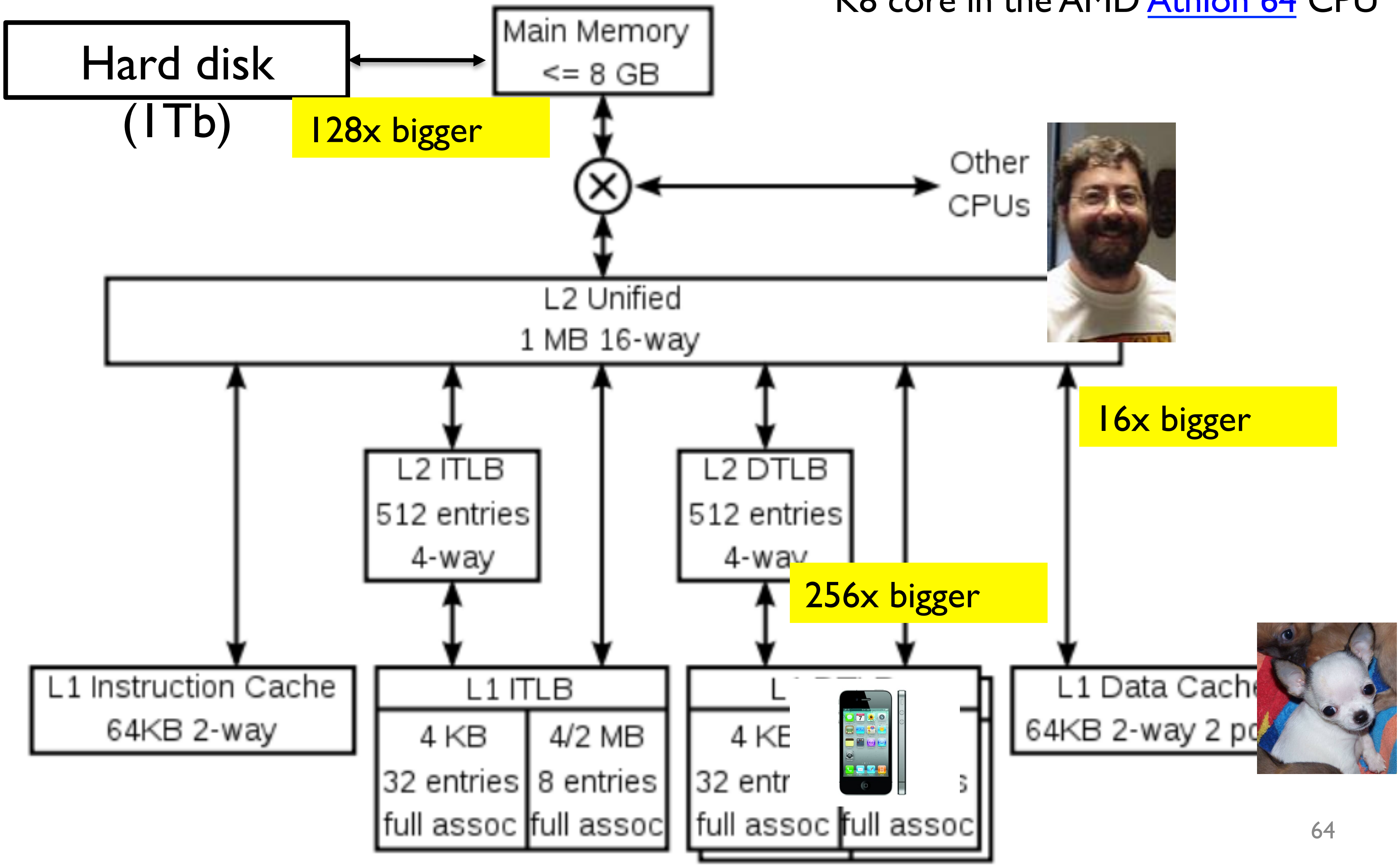

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full assoc	full assoc

L

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full assoc	full assoc

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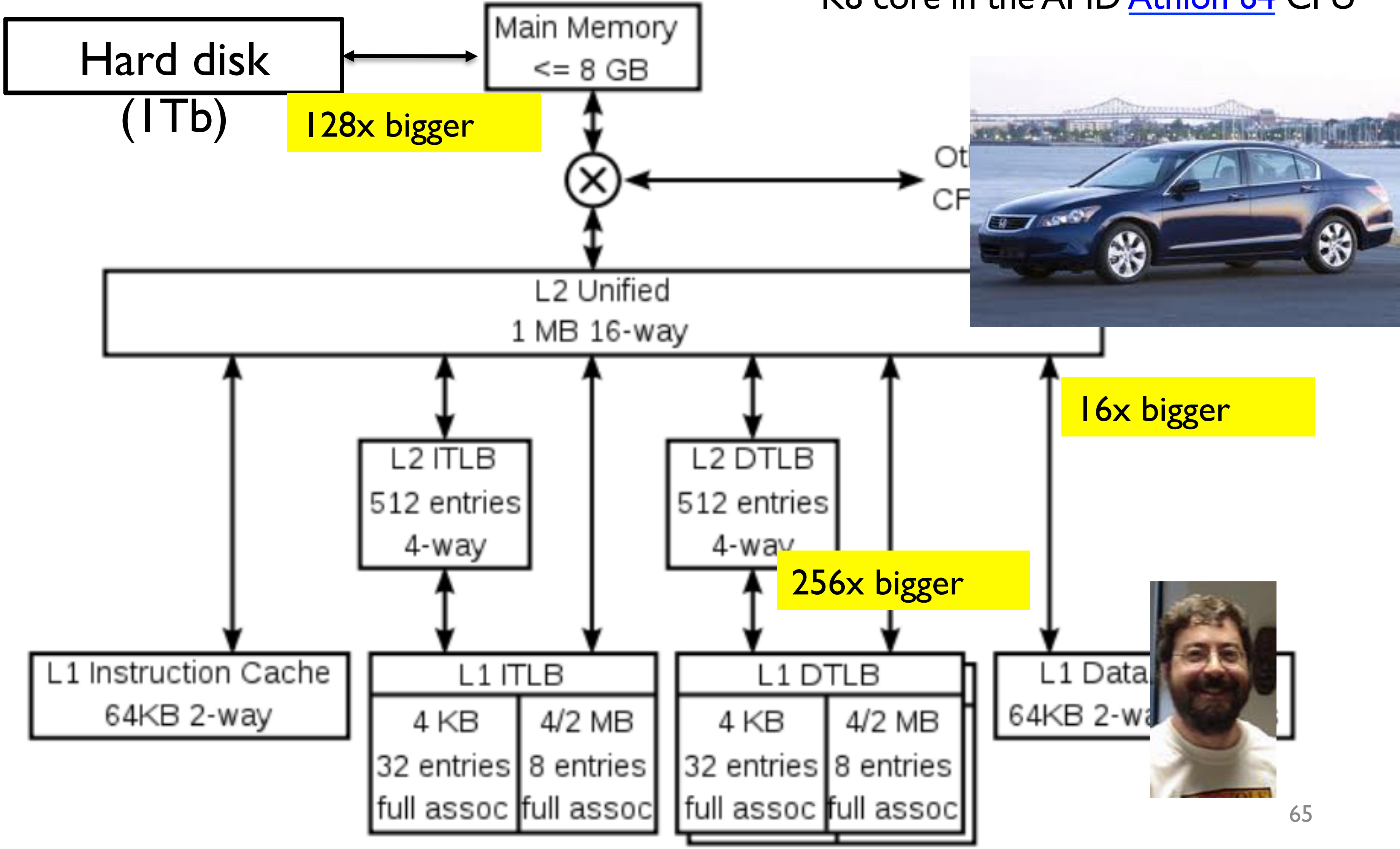

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L1 Data
64KB 2-wa

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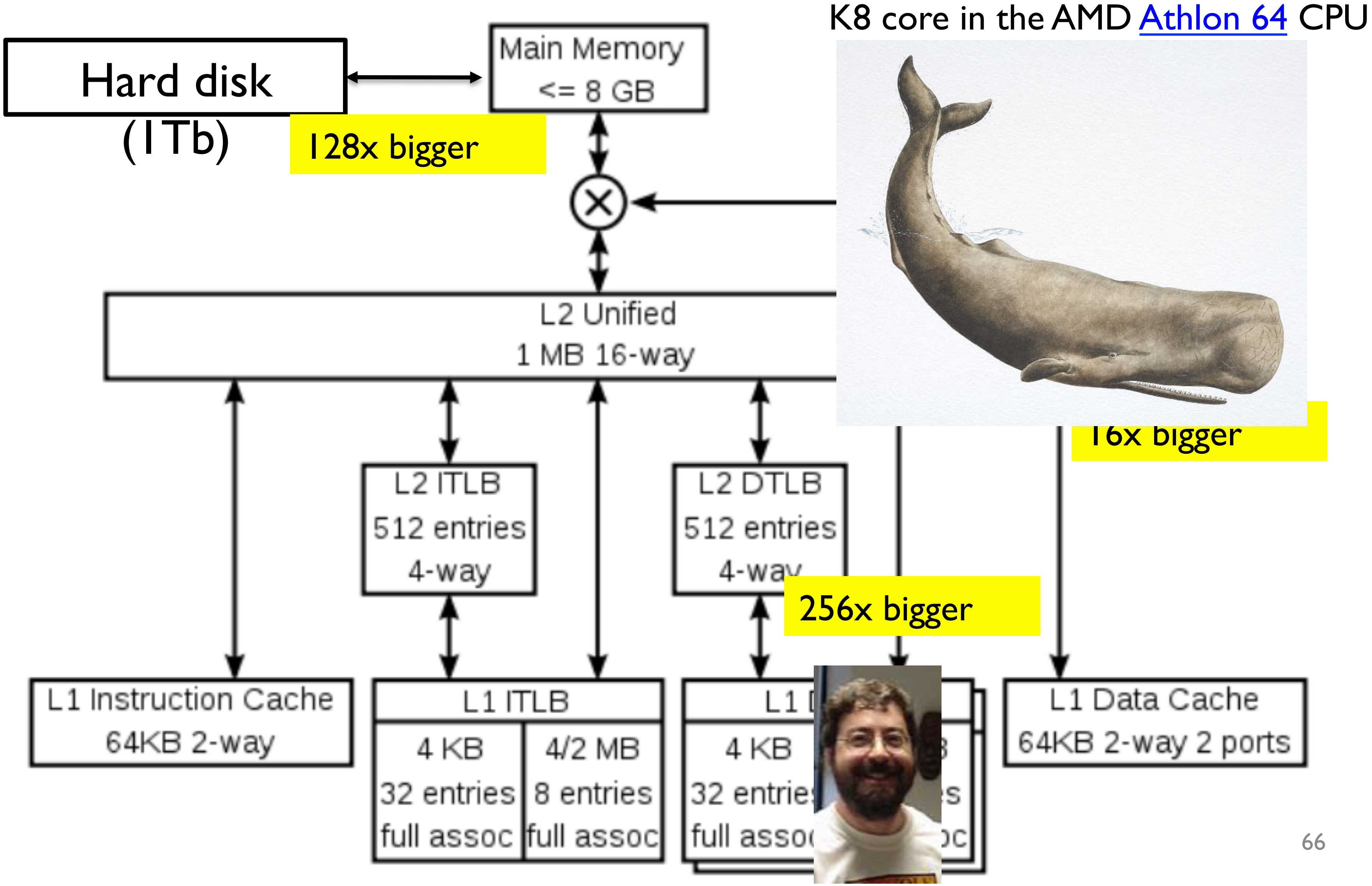

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L2 ITLB

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L1 Data Cache

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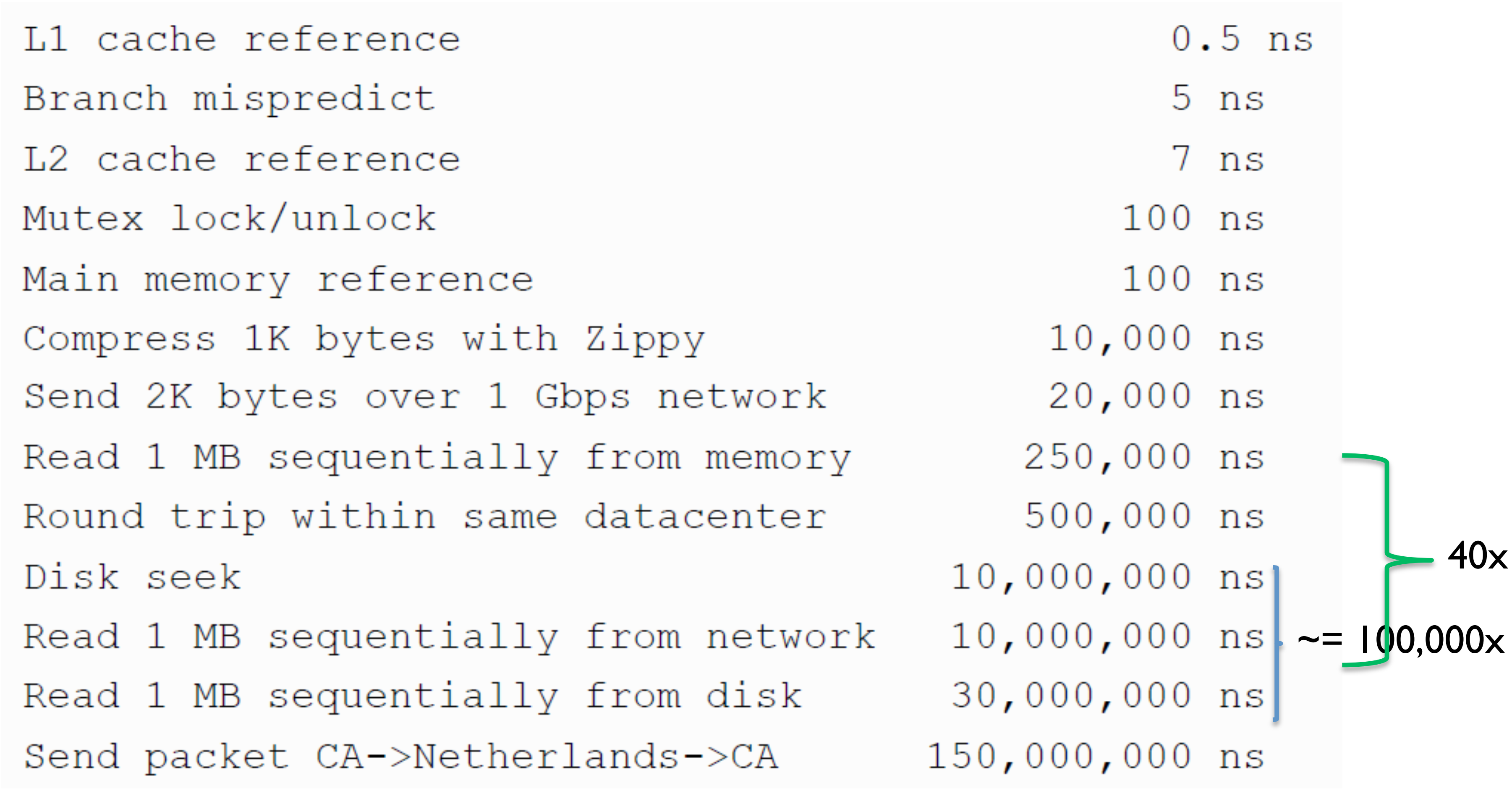
A typical disk

Numbers (Jeff Dean says) Everyone Should Know



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40x

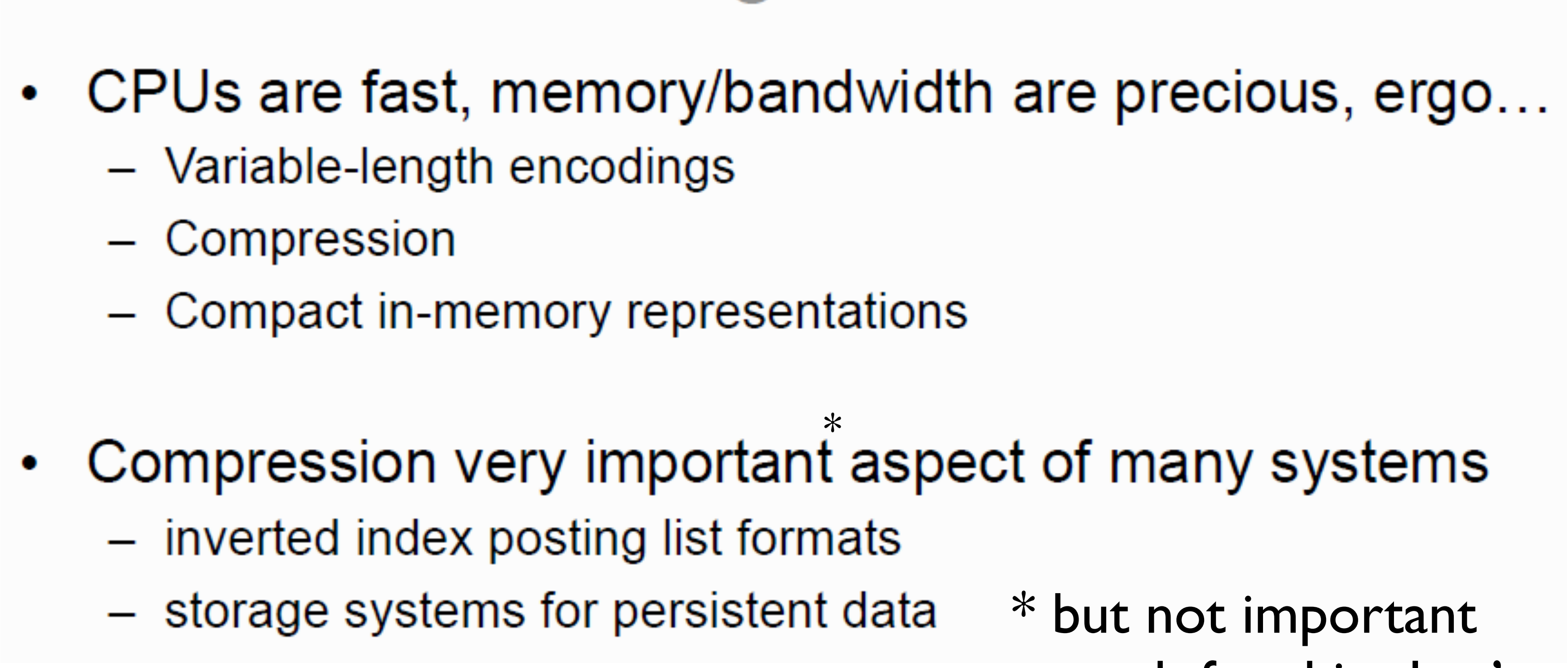
~= 100,000x

What do we count?

- Compilers don't warn Jeff Dean. Jeff Dean warns compilers.
- ….
- Memory access/instructions are *qualitatively different* from disk access
- Seeks are *qualitatively different* from sequential reads on disk
- Cache, disk fetches, etc work best when you stream through data *sequentially*
- Best case for data processing: stream through the data *once* in *sequential order,* as it's found on disk.

Other lessons -?

Encoding Your Data



- CPUs are fast, memory/bandwidth are precious, ergo…
  - Variable-length encodings
  - Compression
  - Compact in-memory representations

- Compression very important* aspect of many systems
  - inverted index posting list formats
  - storage systems for persistent data

* but not important enough for this class's assignments….

What/How

- Next lecture: probability review and Naïve Bayes.
- Homework:
  - Watch the review lecture I linked to on the wiki
- I'm *not* going to repeat it