

# DeepDive & Analytics Systems

Christopher Ré

# Course Announcements

- OHs: Note that we have / are shifting these to provide better coverage before Project Part 3 & the final!
  - See the calendar on the website
  - Come to OHs early- don't leave questions / problems till the last minute!
- Piazza @1253, "Final Exam Review Session- Topic requests"
  - Please suggest / vote on topics for the final review session!!!
- Course evaluations online- please fill these out ☺
  - We want your feedback to make the course even better next time!
  - I read **every** evaluation.

# Course Announcements

- We received some feedback that examples used in the course might feel exclusionary to groups in the class
  - Not our intention!
  - Please keep giving us this kind of feedback.
  - We try very hard to consider these issues, and pick examples for lecture & assignments that are not more suited to some groups than others... but we are not always perfect
  - We'll keep trying.

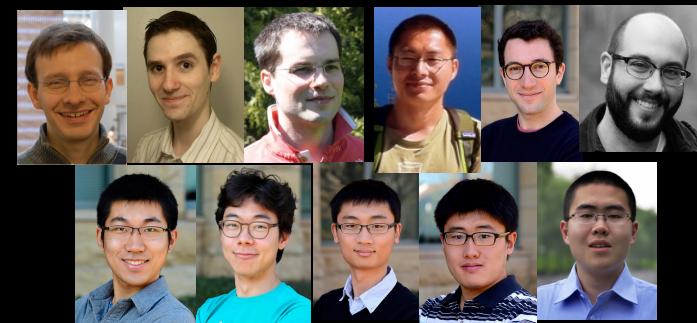
# Research Lecture

1. A taste of new applications driving research (*Dark Data*)
2. A crash course in data analytics (*The Algorithm for Big Data?*)
3. Hardware trends driving analytics systems

SHAMELESSLY BIASED BY MY GROUP'S WORK.

# What you will learn about in this section

1. Dark Data Systems & DeepDive
  
2. ACTIVITY: Ask me questions!



The DeepDive Team

<http://deepdive.stanford.edu/>



## Dark Data System: ETL on Steroids

**Quality** that can exceed paid human  
annotators and volunteers



Extraction, Integration, & Cleaning  
are *inference problems*

Focus on key step for end-to-end  
application quality



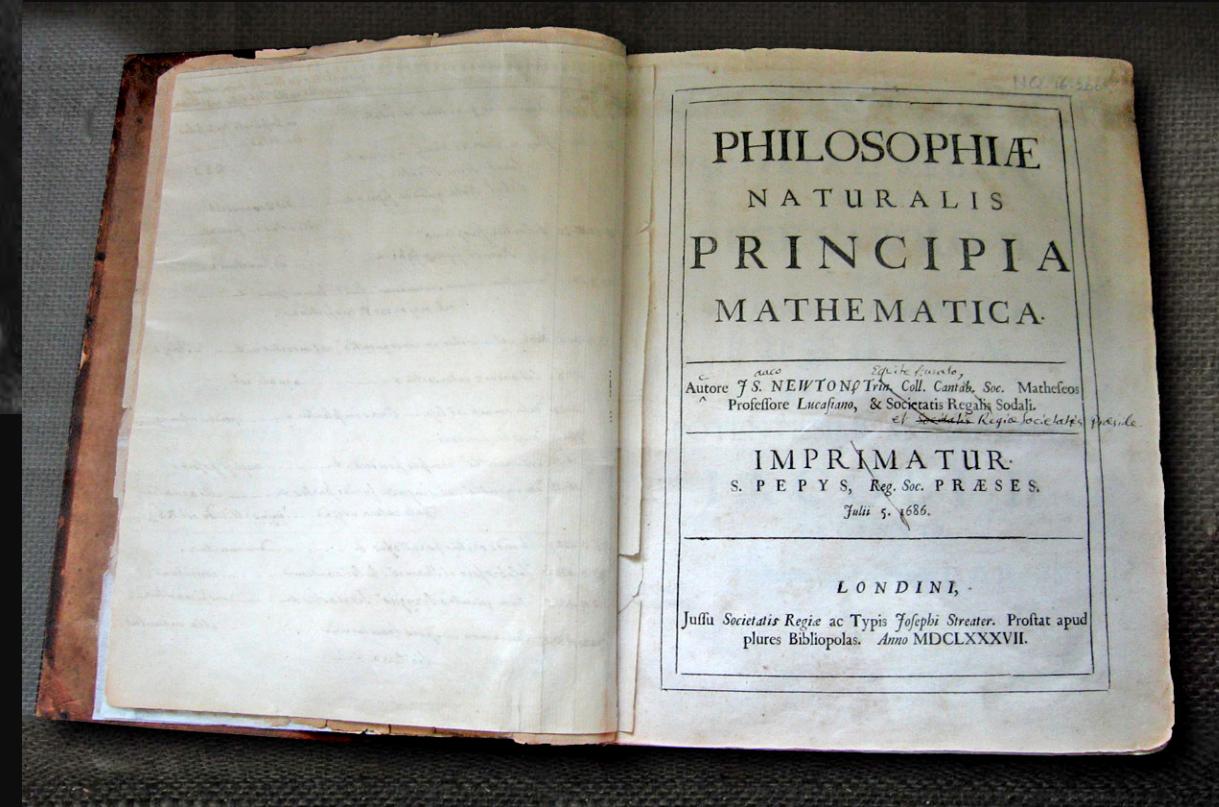
Enables non-CS users, but  
**scale** is a challenge.

**Modern hardware** is changing how to  
build analytics systems.

First, a story...



Newton



Principia  
Mathematica

Turns out,  
Newton was **not** alone

# Millennia of Knowledge in Libraries



# Now: freely available & digital

A screenshot of a Google Books search results page. The search query "principia mathematica" is entered in the search bar. The results are for "Books". The first result is the title page of "The Mathematical Principles of Natural Philosophy, Volume 1, Issue 1" by Sir Isaac Newton, translated by Andrew Motte. The page shows the full title: "MATHEMATICAL PRINCIPLES OF NATURAL PHILOSOPHY.", author "BY SIR ISAAC NEWTON.", and translator "BY ANDREW MOTTE.". It also includes a "Translated into English" note. On the left, there is a thumbnail of the book cover, a "EBOOK - FREE" button, and options to "Get this book in print" and "Write review". The top navigation bar includes a user profile for "Chris Re", a search icon, and other account-related icons.

principia mathematica

Books

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14 Reviews Write review

The Mathematical Principles of Natural Philosophy, Volume 1, Issue 1

By Sir Isaac Newton, Andrew Motte, William Davis, John Machin, William Emerson

Result 1 of 2 in this book for principia mathematica - [Previous](#) [Next](#) - [View all](#) [Clear search](#)

MATHEMATICAL PRINCIPLES  
OF  
NATURAL PHILOSOPHY.  
BY  
SIR ISAAC NEWTON.  
Translated into English  
BY ANDREW MOTTE.

The world's scientific  
knowledge is **accessible**.

# But we're still human...



The world's scientific  
knowledge is **accessible**,  
but not **readable**.

# Today, some pressing problems require **macroscopic knowledge**



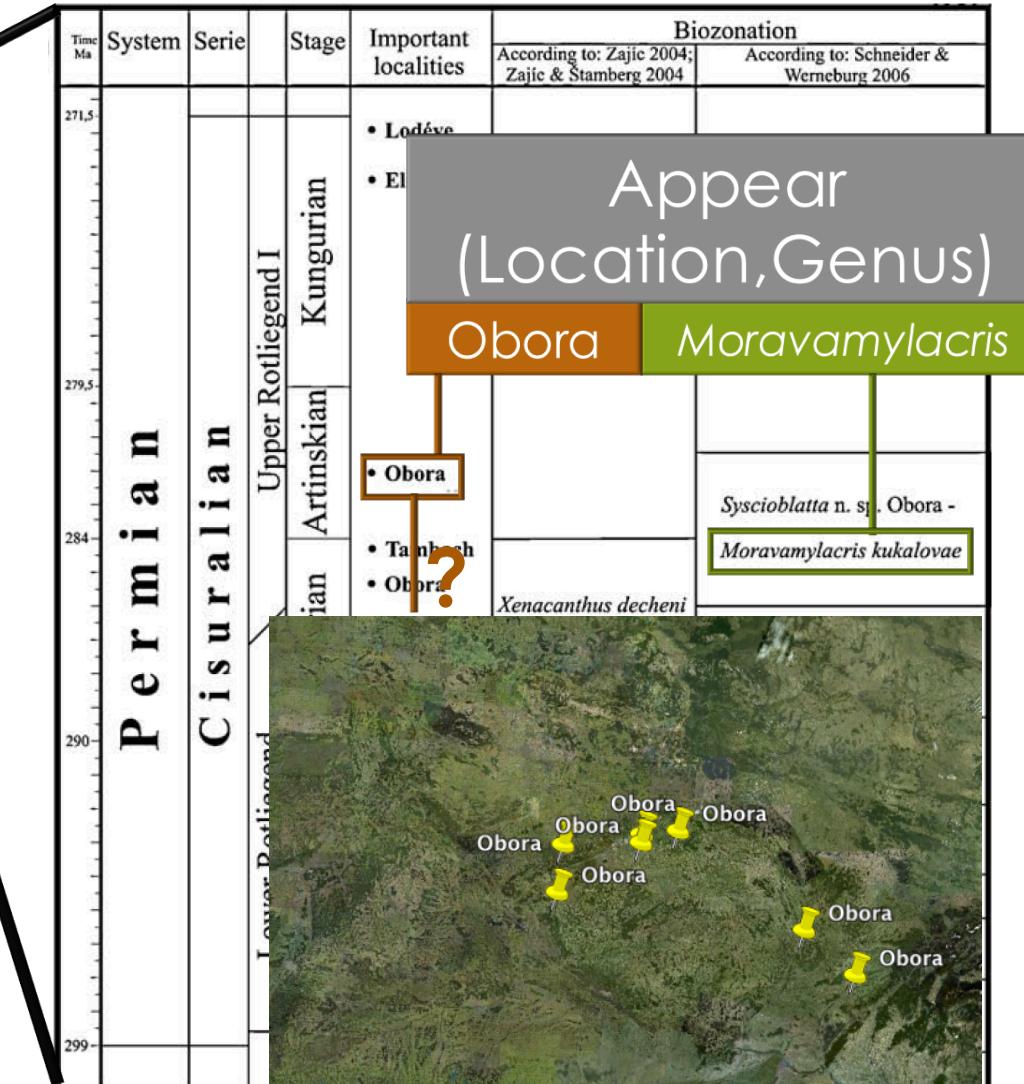
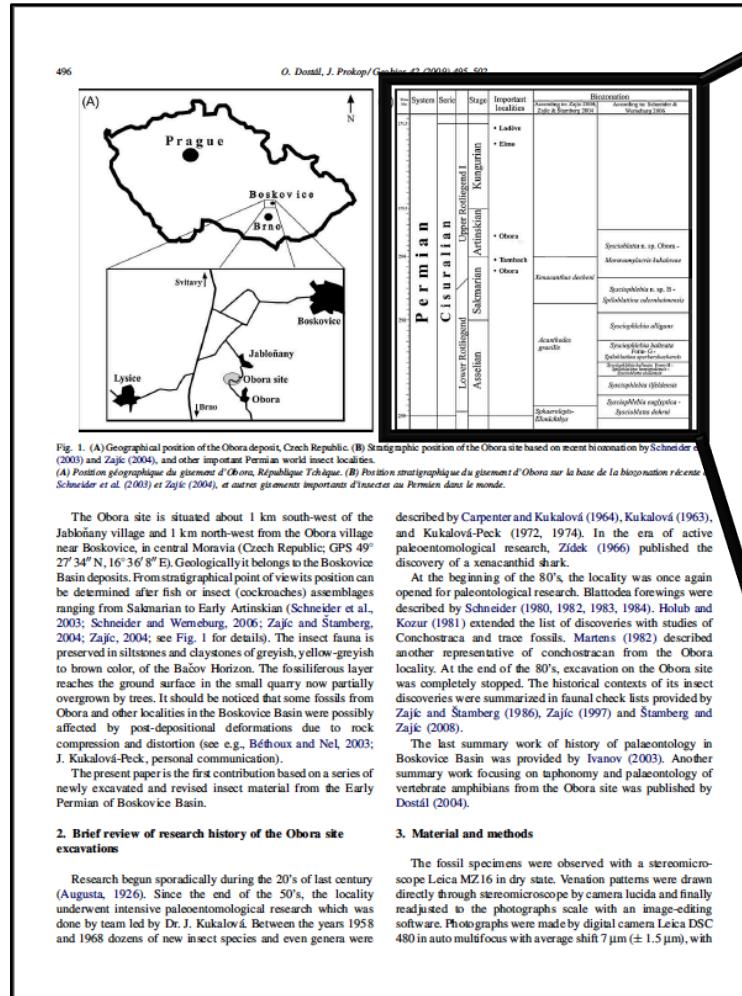
Health



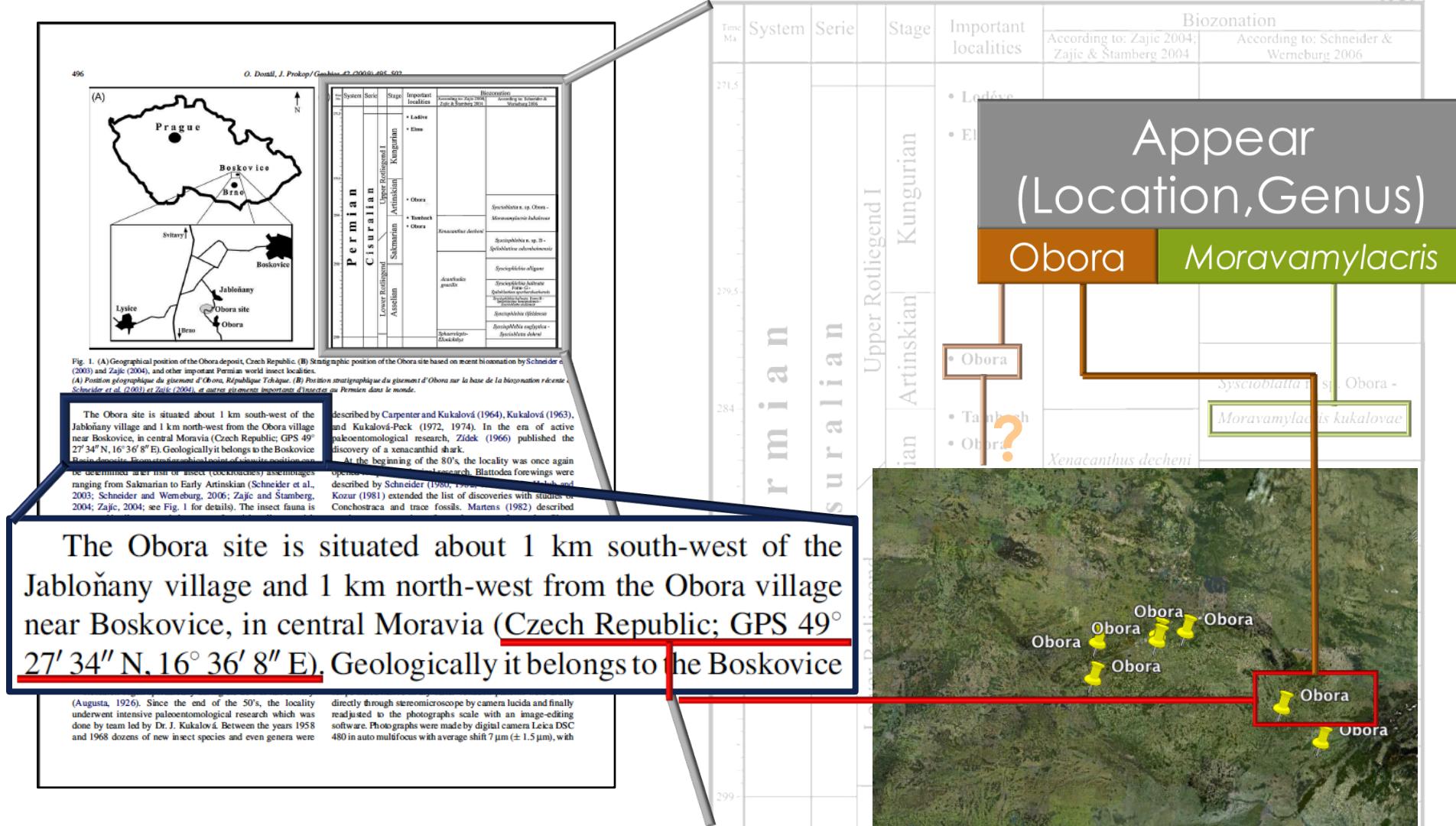
Financial  
Markets

Could we build a machine  
to **read** for us?

# Data are buried in tables, but not in a self-contained way



Data are buried in tables,  
but not in a self-contained way



# PaleoDeepDive

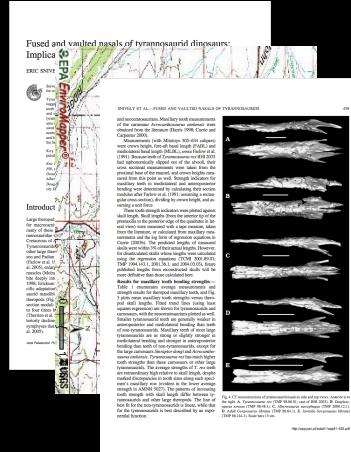


Shanan Peters (Geo) and Miron Livny (CS)  
DeepDive.Stanford.edu (**Ce Zhang** et al.)

# PaleoDeepDive

## The Goal

Extract paleobiological facts to build higher coverage fossil record.



T. Rex are found dating to the upper Cretaceous.

↓  
Statistical Inference

Appears("T. Rex", "Cretaceous")



## Aggressive Approach

Every character, word, part of speech is a variable  
**statistical Inference** on billions of variables.

# PaleoDB

Human-created



329 volunteers



13 years



46K documents

200+ Papers,  
17 Nature/Science

Formation  
**Precision**

# PaleoDeepDive

Machine-created

10x documents.

100x extractions.

Preliminary Precision

PaleoDB Volunteers: **0.84**

PaleoDeepDive: **0.94**

Hope: knowledge bases can  
help **accelerate science.**



Tree of Life



Drug Repurposing



Genomics

*Used by a number of companies.  
and winner of TAC14 Slot Filling competitions.*

# Human Trafficking on the (Dark) Web...



**Hypothesis:** Trafficked individuals offer **lower cost** and **riskier** sexual services.

**In Plain sight:** Web ads for such services

## Challenges:

1. Need **high-resolution information** to build model.
  - services for what rate, ethnicity, location, etc.
2. Scientific papers are **clear**—dark web is **obfuscated**.

# Human Trafficking on the (Dark) Web...



Web  
Text



**VIDA**  
*Where data comes to life*

 Deep Dive

**Structured Info:** Phone #,  
Rates of Service, ...

Normal two call agency. Jessica was ready when I arrived at body. A couple of tattoos but not in visual-annoying locations. pleasing the client - definitely not GFE. She does the basics recommending - I may repeat but only because of her looks.

**Drug\_Abuse?  
Forced\_Prostitution?**

**Use:** law enforcement/ NGOs

# In Use by Law Enforcement



New York DA use MEMEX Data for all trafficking investigations this year. **Real Arrests**

For DARPA MEMEX, we were operational in 6 months

- Processed >35M documents (~26M records)
- Tens of columns (location, phone #, price, etc)
- With compute times of less than a day
- >90% Precision for most relations

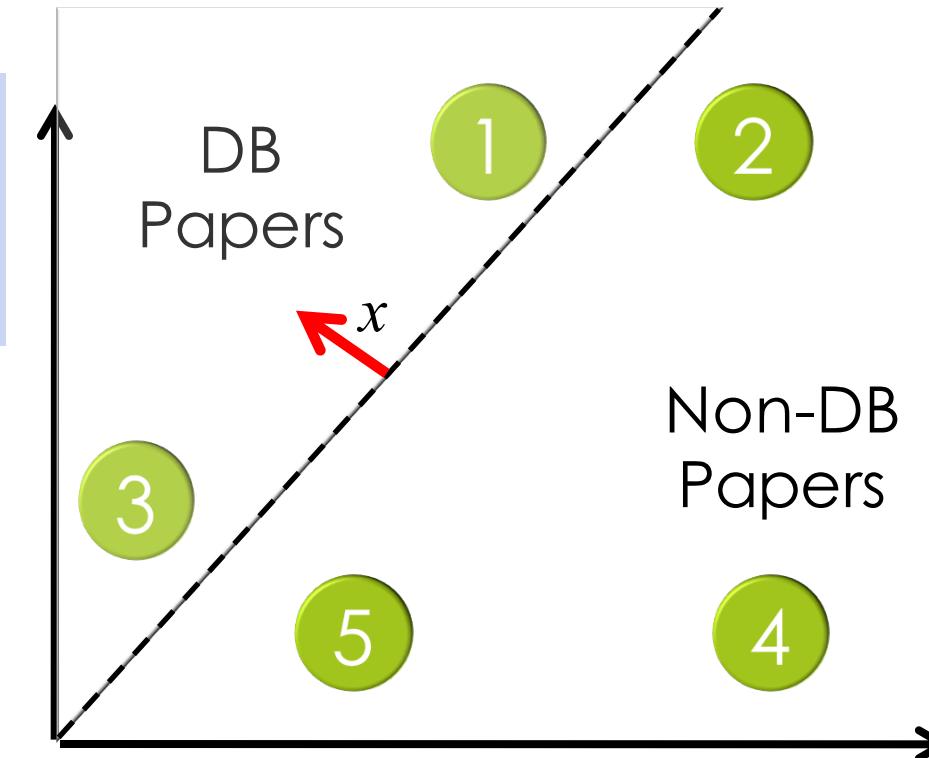
# What you will learn about in this section

1. A Crash Course in Analytics
2. ACTIVITY: Run SGD!

# Example: Linear Models

Label papers as DB  
Papers or Non-DB  
Papers

1. Map papers to  $\mathbb{R}^d$
2. Classify via plane



How do we pick a good plane,  $x$ ?

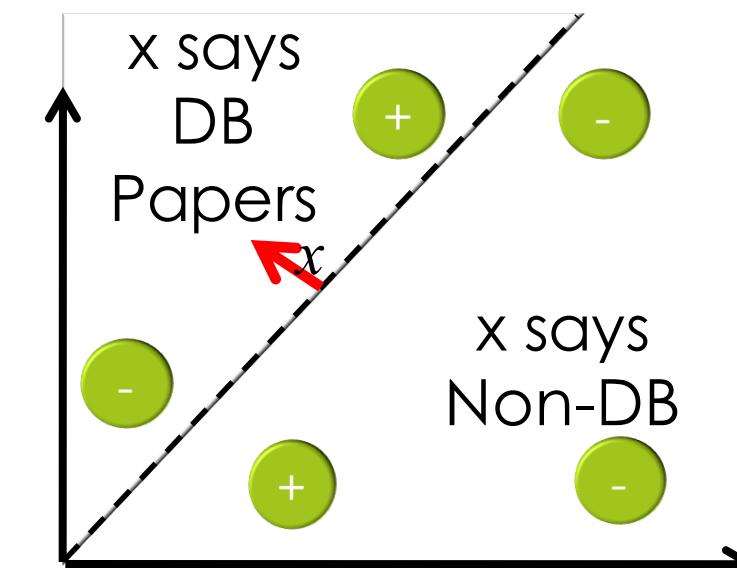
# Example: Linear Models

Input: Labeled papers.  
Each point labeled as DB paper (+) or not (-)

Idea: score each plane

$$\min_x \sum_{i=1}^N f(x, y_i)$$

$y_i$  is a paper vector and its label



$f$  is convex  
function in  $x$

e.g. squared distance (*least squares*), hinge loss (*svm*),  
log loss (*logistic regression*)

# Separable Inverse Problems

$$\min_x P(x) + \sum_{i=1}^N f(x, y_i)$$

x	the model
$y_i$	a data item
f	scores the error
P	Enforces prior

**Paper Classification:**  $y_i$  is the paper with its label, and  $x$  is a vector of weights

**Neutrinos:**  $x$  is neutrino path and  $y_i$  is a DOM reading

**Conditional Random Fields, Low-rank factorizations (relaxations), Logistic regression, Lasso, etc.**

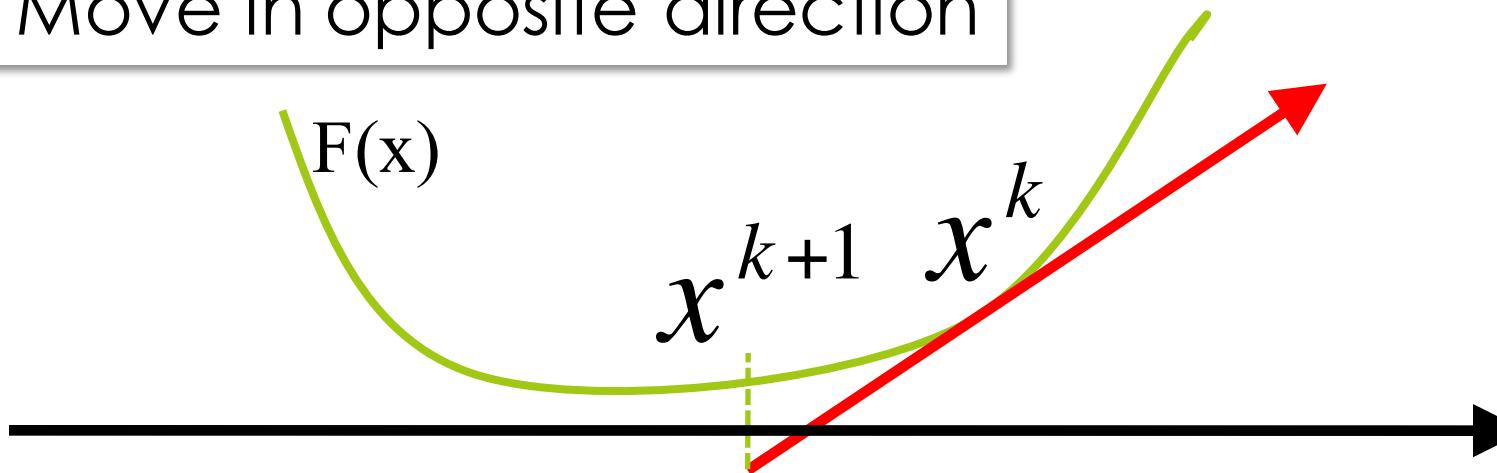
**Claim:** General data analysis technique that is no more difficult to compute than SQL AVG

# Background: Gradient Methods

$$F(x) = \sum_{i=1}^N f(x, y_i) \quad x^{k+1} = x^k - \alpha \nabla F(x^k)$$

*Gradient Methods: Iterative*

1. Start at current  $x^k$ ,
2. Take gradient at  $x^k$ , and
3. Move in opposite direction



# Background: Incremental Gradient Methods

[Robbins & Monro, 1951]

$$F(x) = \sum_{i=1}^N f(x, y_i)$$

Gradient Methods:

1. Start at current  $x$ ,
2. **Approximate** gradient at  $x$  by selecting  $j$  in  $[N]$

$$G(x, y_j) = N \nabla f(x, y_j) \quad \nabla F(x) \approx G(x, y_j)$$

3. Move in opposite direction

$$x^{k+1} = x^k - \alpha G(x^k, y_j)$$

**Single** data item to approximate gradient

# Incremental Gradient Methods

Why use iGMs? iGMs converge to an optimal for many problems, but the real reason is:

iGMs are *fast.*  $x+ = -\alpha G(x^k, y_j)$

Technical Connection:

iGM isomorphic to computing a SQL AVG

Solve statistical models in an RDBMS for free

# IO Aware iGMs

iGMs involve cheap numerical computations,  
but require reading / writing a lot of data...

$$x+ = -\alpha G(x^k, y_j)$$

We need to use our IO aware cost models to  
think about performance here!

# Activity 19-1

# iGMS $\approx$ User Defined Aggregate (UDA)

RDBMS UDA defined by 3 Functions

1. Initialize (State)
2. Transition(State, data)
3. Terminate(State)

State in  $\mathbf{R}^2$  : (# terms, total)

Transition( (n, T), d ) = (n, T) + (1,d)

Terminate( (n,T) ) = T/n

**AVG**

State in  $\mathbf{R}^d$  : model  $x$

Transition(  $x, y_j$  ) =  $x - \alpha G(x, y_j)$

Terminate(  $x$  ) =  $x$

**iGM**

Widely used...

MADlib



ORACLE®



iGM can be integrated into existing databases for free.

**Significance:** Reuse DB internals for shuffling, compression, shared-nothing parallelism, and shared-memory allocators.

# What you will learn about in this section

1. Trends that impact Analytics
2. Multicore
3. NUMA
4. SIMD

To get rid of **algorithms**,  
we need a **fast** engine....

Modern **hardware** is amazing.

# Message

**Statistical algorithms** have  
**relaxed** notions of correctness;  
leads to **new opportunities** for:

- Algorithms,
- Systems, and
- Hardware.

# The Key Balance

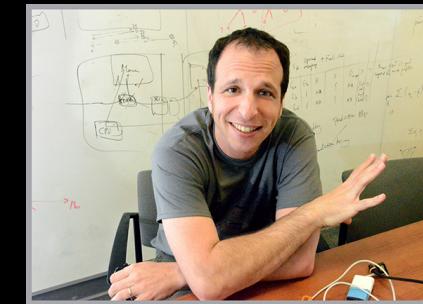


**Key Issue:** Balance  
Statistical versus Hardware  
Efficiency.

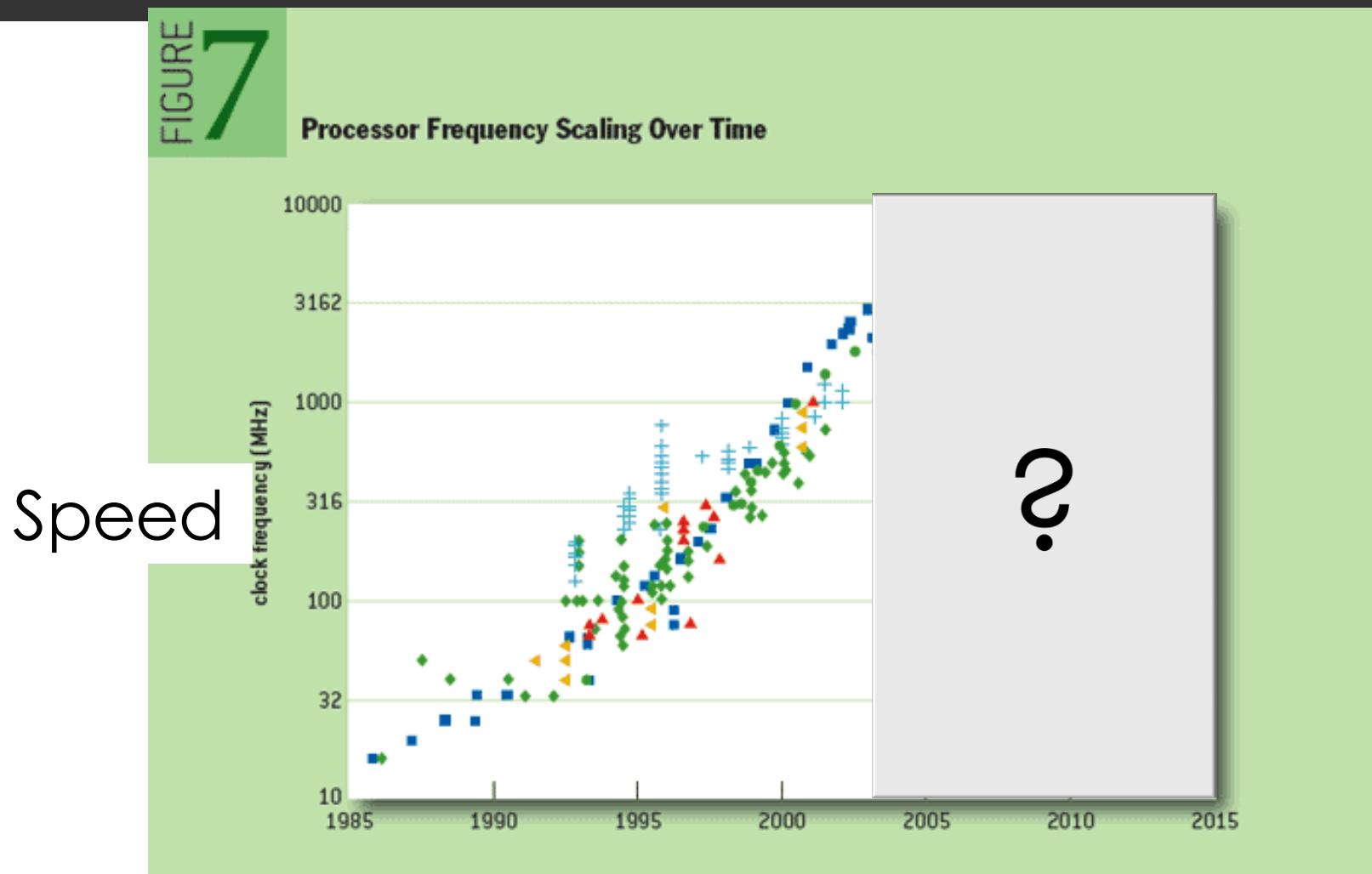
Modern **hardware** is amazing  
in 3 major trends for analytics:  
(1) **Multicore**,  
(2) **NUMA**, and  
(3) **SIMD**.

Message: **Relaxing consistency** allows major  
performance improvements

# Trend 1: Multicore [NIPS11]



# Single Cores are not getting faster.



CPUDB: Danowitz et al. CACM QUEUE 2012

Chips contain multiple cores, so throughput is increasing... but need to rewrite algos!

# Statistical Analytics Crash Course

Staggering amount of machine learning/stats can be written as:

$$\min_x \sum_{i=1}^N f(x, y_i)$$

N (number of  $y_i$ s, data) typically in the billions  
Ex: Classification, Recommendation, Deep Learning.

De facto iteration to solve large-scale problems: **SGD**.

$$x^{k+1} = x^k - \alpha N \nabla f(x^k, y_j)$$

Select one term,  $j$ , and estimate gradient.

Billions of tiny iterations.

# How do we run SGD in Parallel?

**Data Systems Perspective of SGD.**

$$x^{k+1} = x^k - \alpha N \nabla f(x^k, y_j)$$

**Insane conflicts:** Billions of tiny jobs (~100 instructions), RW conflicts on  $x$ , which is called **the model**.

How can we hope to speed this up with parallelism? Serializability?

**Multiple cores** need locks to communicate!

# How do we run SGD in Parallel?

**High-level idea:** Go Hogwild! (comment out the locks!) answer is only *statistically* correct.

**Thm:** If we do ***no locking***, SGD still converges to right answer—at essentially the same theoretical rate!

**Hogwild!** [Niu, Recht, Ré, Wright NIPS11]

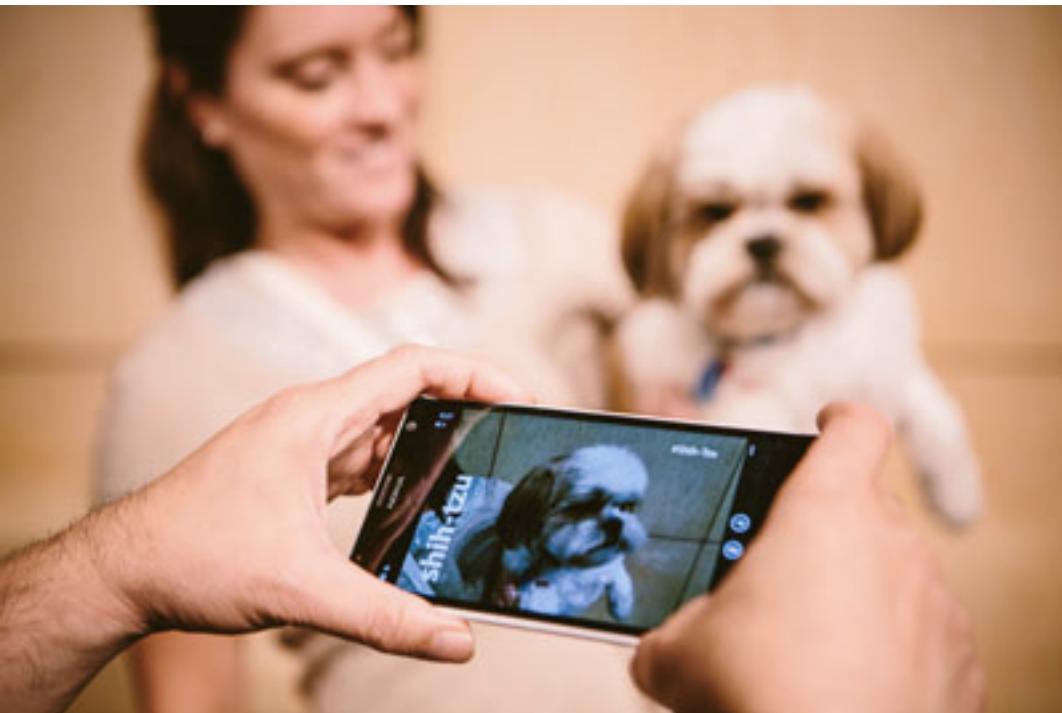
**AsySCD** [Liu, Wright et al. ICML14, JMLR14]

**Buckwild!** [De Sa, Olukotun, Ré NIPS15]

Technical conditions on ratio of processors, delays, (semantic) sparsity.

# Cortana: Microsoft's Digital Assistant

AI breakthrough: Microsoft's 'Project Adam' identifies dog breeds, points to future of machine learning



*All web companies have similar: image rec, voice, mobile, search, etc.*

*“...using a technology called, of all things,  
**Hogwild!**”*

<http://www.wired.com/2014/07/microsoft-adam/>

<http://www.geekwire.com/2014/artificial-intelligence-breakthrough-microsofts-project-adam-identifies-dog-breeds/>

# A larger trend?

Relaxing **consistency** to be  
**architecturally aware** can be a  
big performance win.



Microsoft

Google



ORACLE® MADlib



A larger trend?

Relaxing **consistency** to  
optimize around **architecture-  
specific IO cost models** can be  
a big performance win.



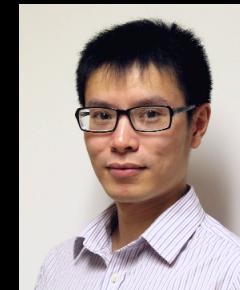
Microsoft

Google

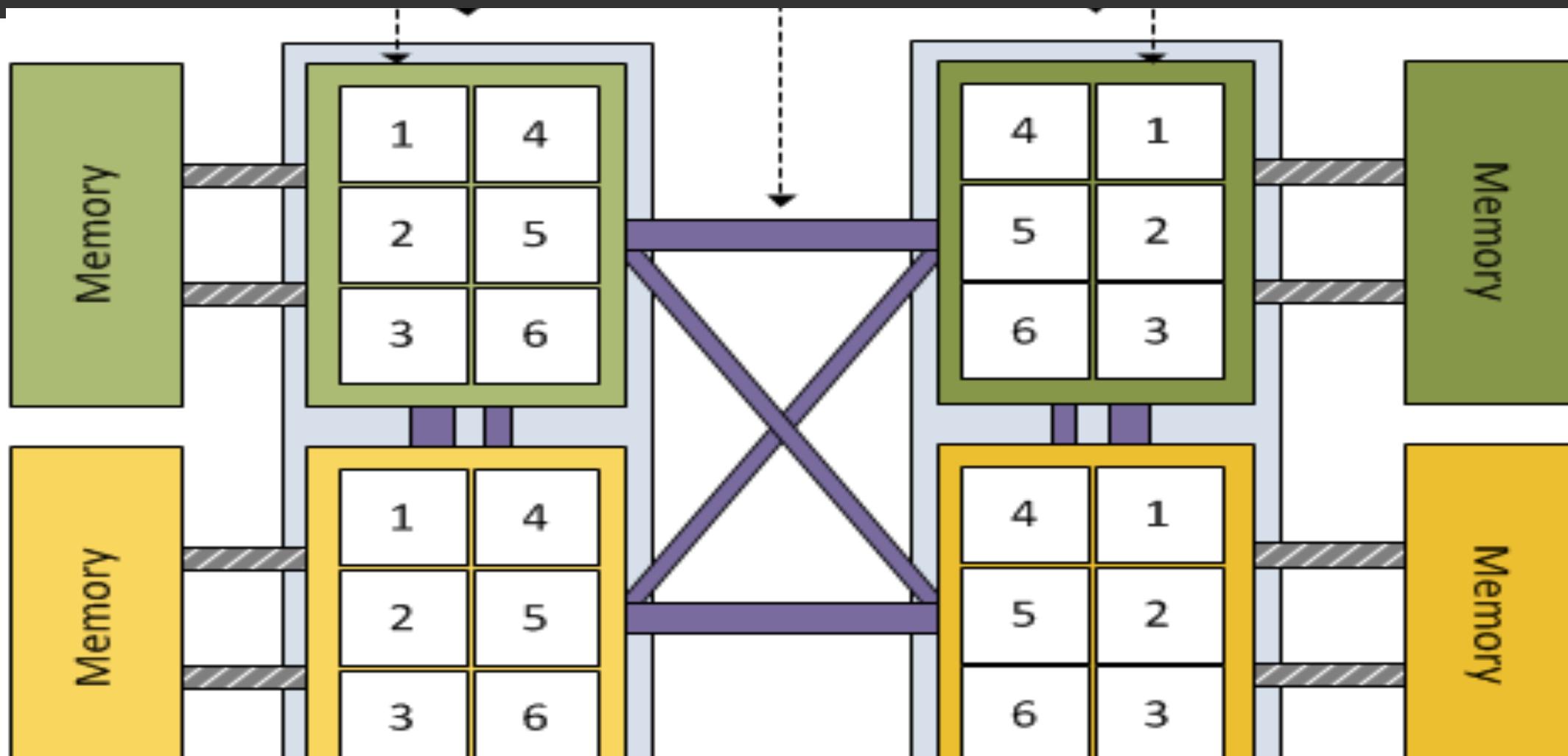


ORACLE® MADlib

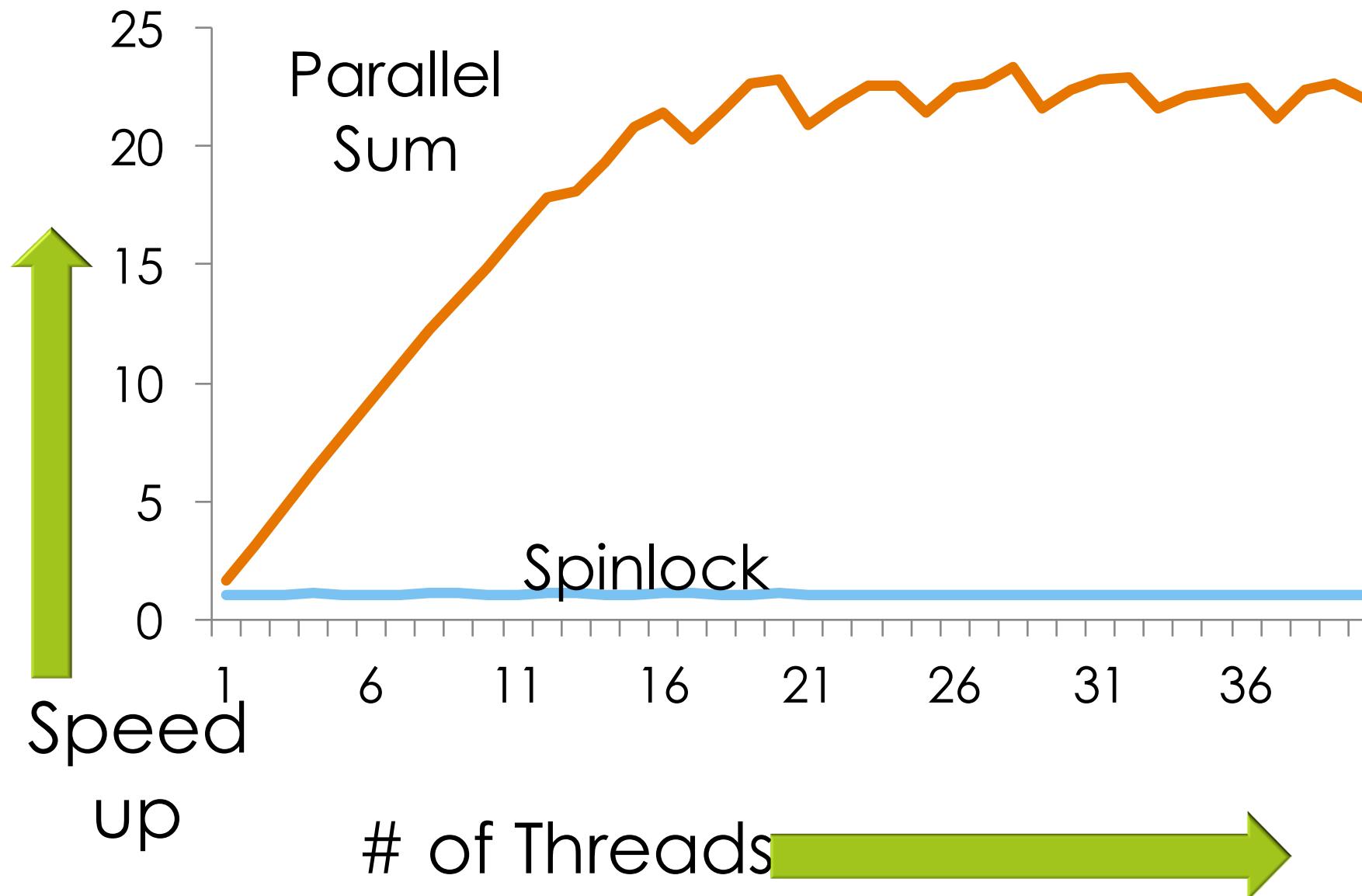
## Trend 2: **NUMA** [VLDB15, ICML14]



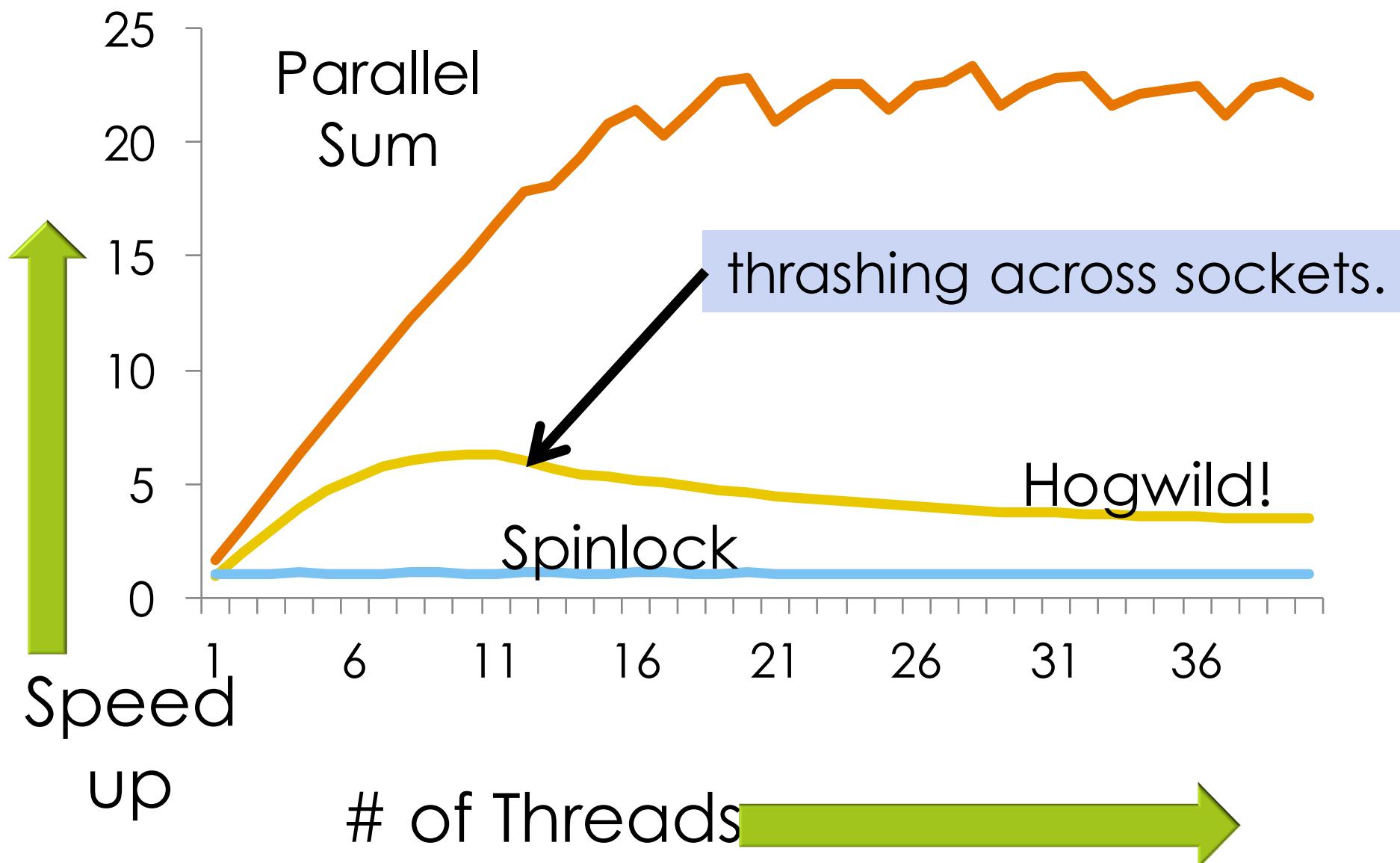
# Simplified 4 socket.



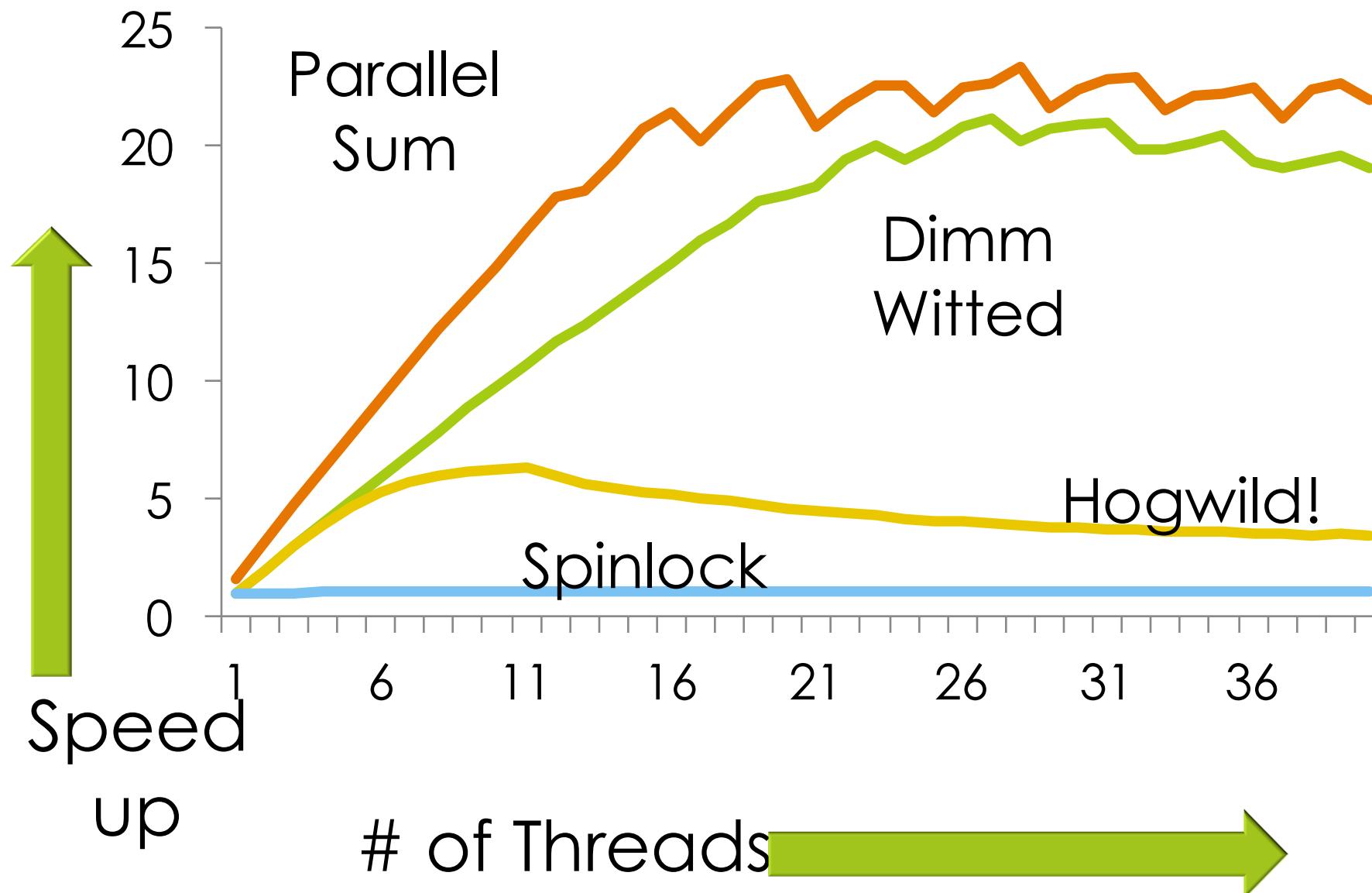
# One Example: Quadratic Programming with Orthant Constraints.



# One Example.

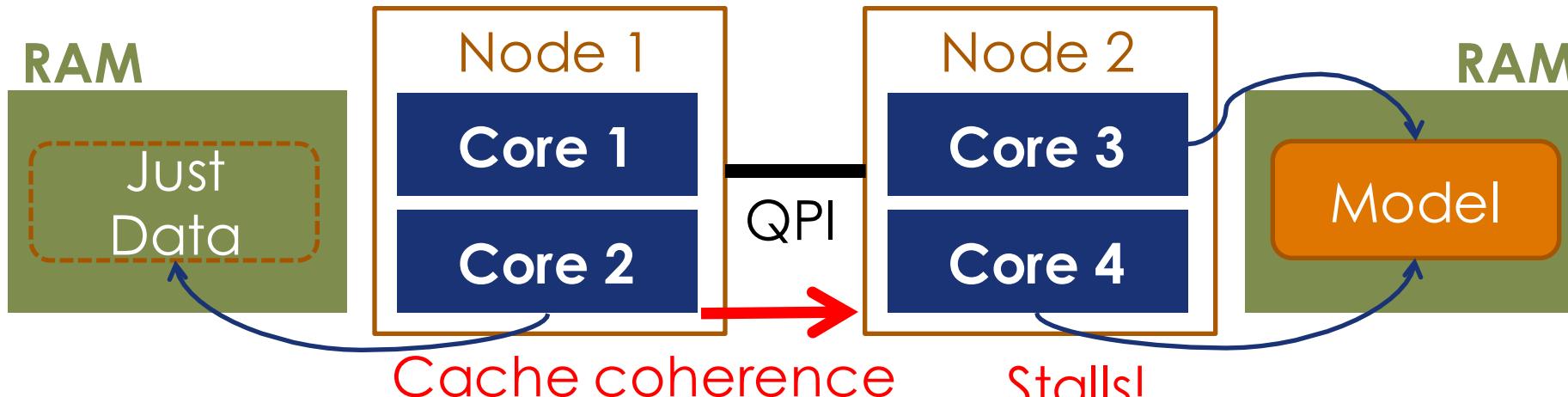


# What about multiple sockets?

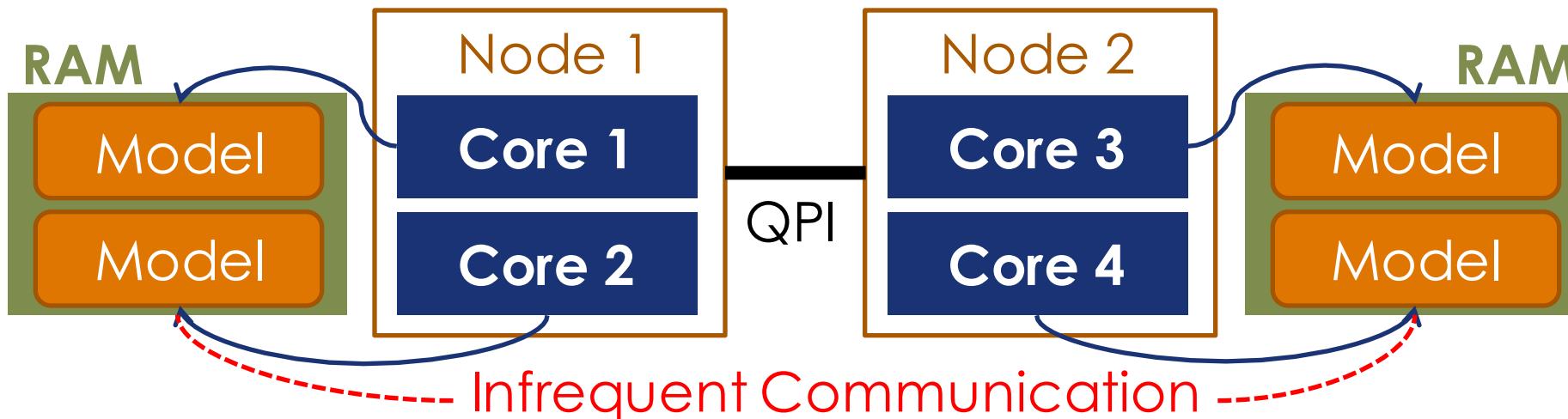


# Model Replication

PerMachine (Hogwild!)



PerCore

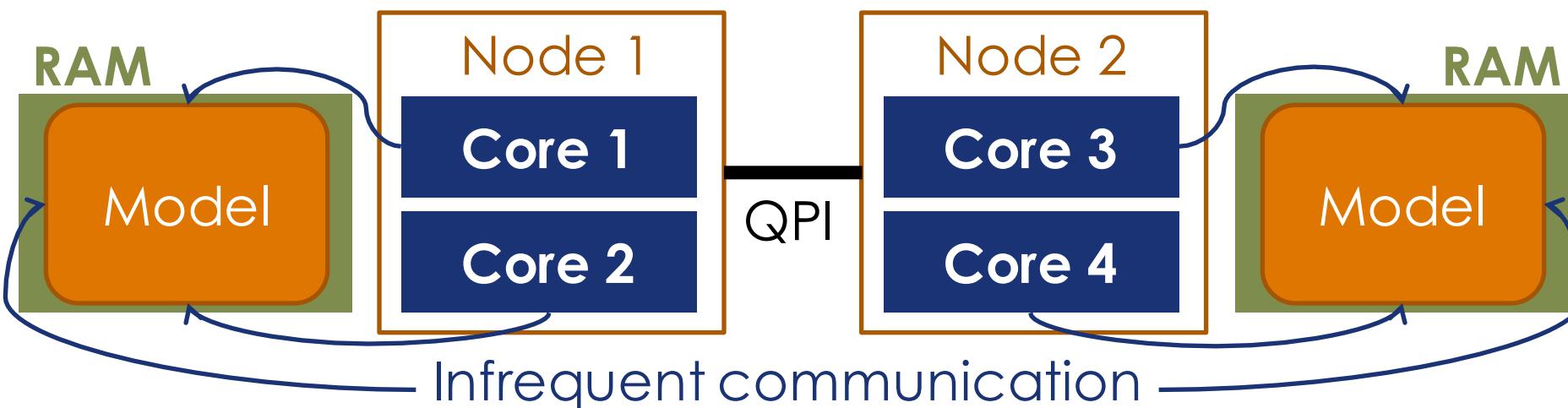


# Model Replication

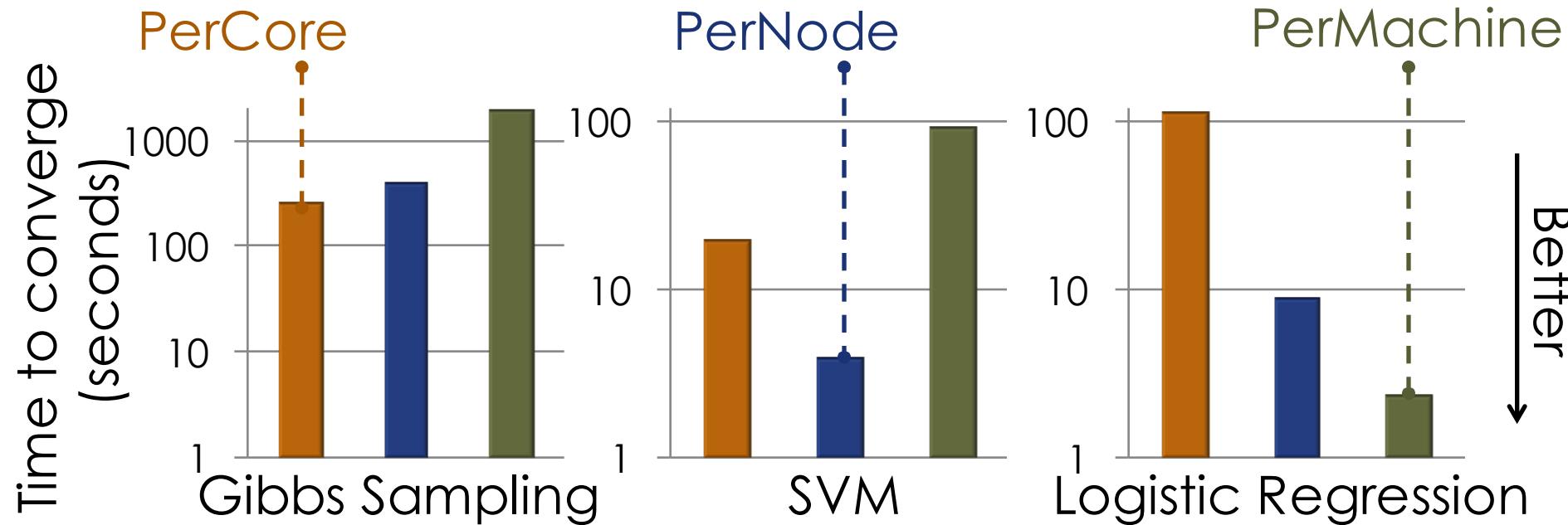
	Statistical Efficiency	Hardware Efficiency
Hogwild!	High	Low
PerCore	Low	High

In between both **Hogwild!** and **PerCore**?

PerNode

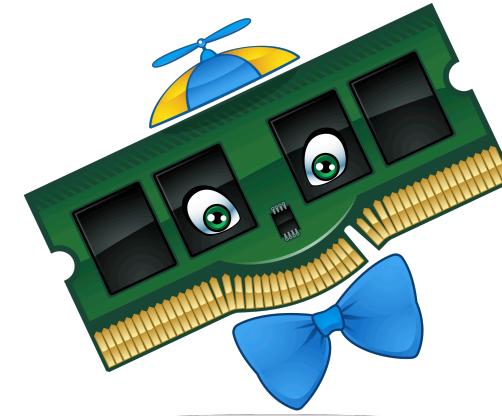


# Model Replication Results



- (1) No one method dominates the other.
- (2) Each can be significantly better.

# Statistical versus Hardware Efficiency



Relaxing consistency  
results in new tradeoffs.

1. Access methods
  - {Row, Column, Row-col}
2. Model Replication
  - {Core, Node, Machine}
3. Data Replication [SODA16]
  - {Full, Importance, Shard}

Can be 100x faster than classical  
choices, e.g., MLlib or GraphLab

## Trend 3: SIMD [NIPS15]



Modern processors offer **fine-grained** parallelism.

# SIMD Processing: Fine-grained parallelism

## Single instruction multiple data (SIMD)

Standard Addition

$R_1$	4
$R_2$	4
$R_1 + R_2 =$	8

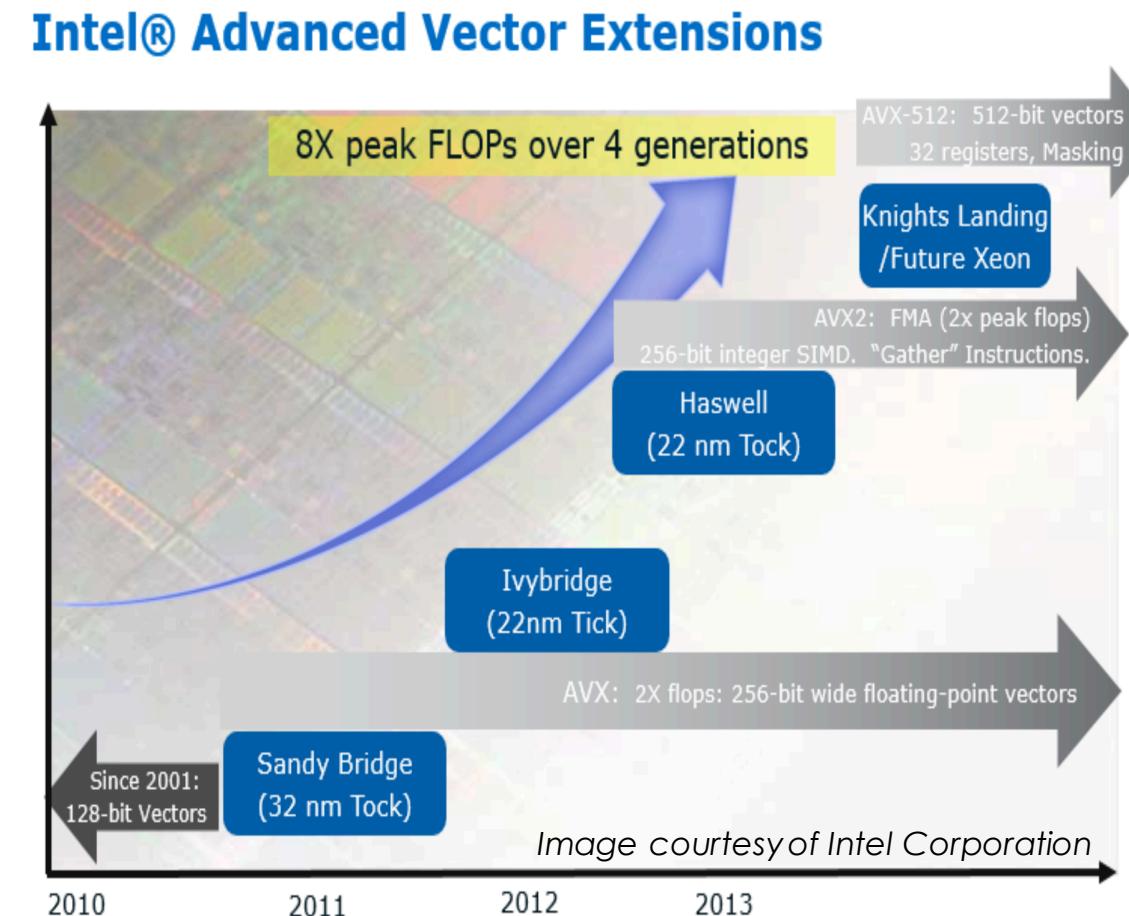
SIMD Addition  
(4 way)

$R_1$	1	2	3	4
$R_2$	2	4	6	8
$R_1 + R_2 =$	3	6	9	12

**Same** operation on  
***multiple data points*** in parallel

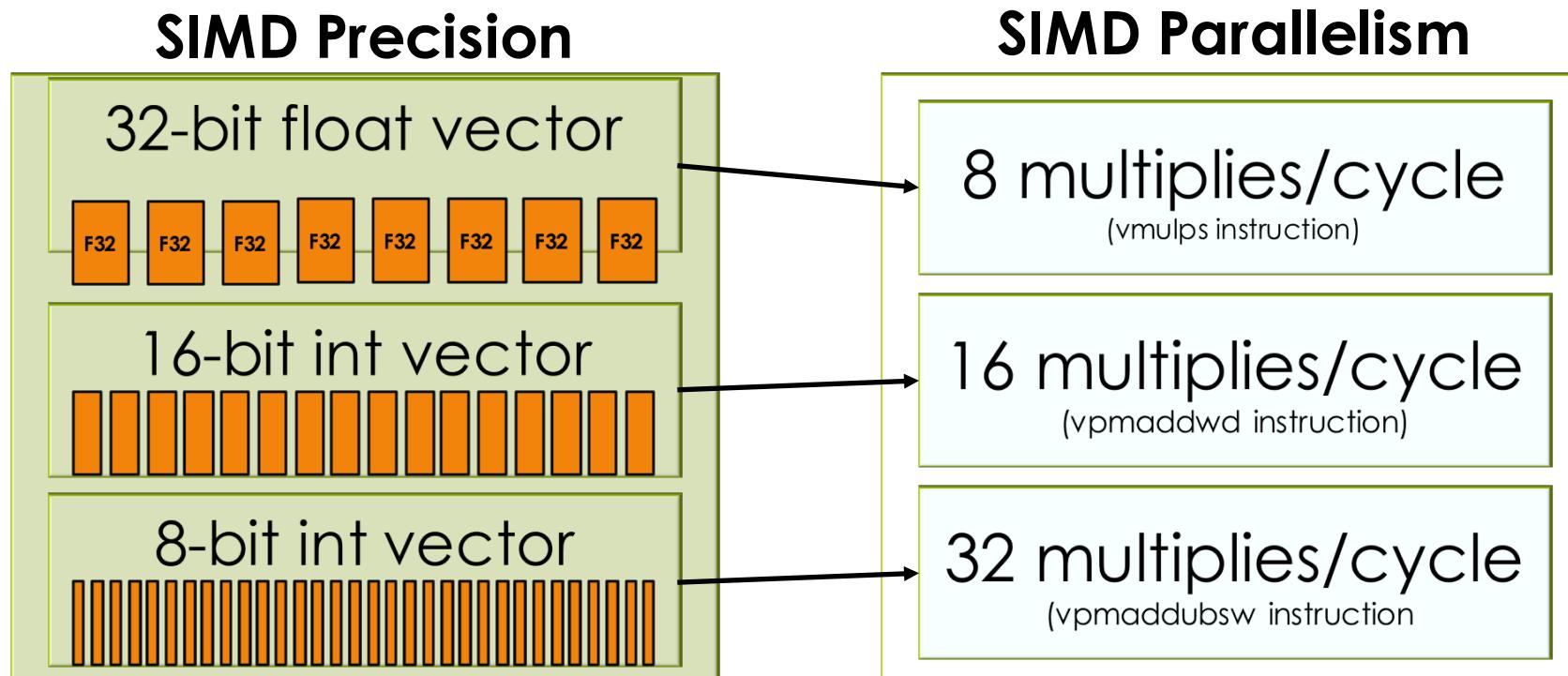
# SIMD Trend: Doubling again!

SIMD bandwidth has **doubled each** of the last four generations.



Good old days of Moore's Law! ...  
If we can take advantage of **parallelism**

# Precision vs. Parallelism



**Tradeoff between precision & parallelism**

# BUCKWILD! [NIPS15]

BUCKWILD! Is an asynchronous SGD that  
**down-sample precision of data**

## **Statistical theory:**

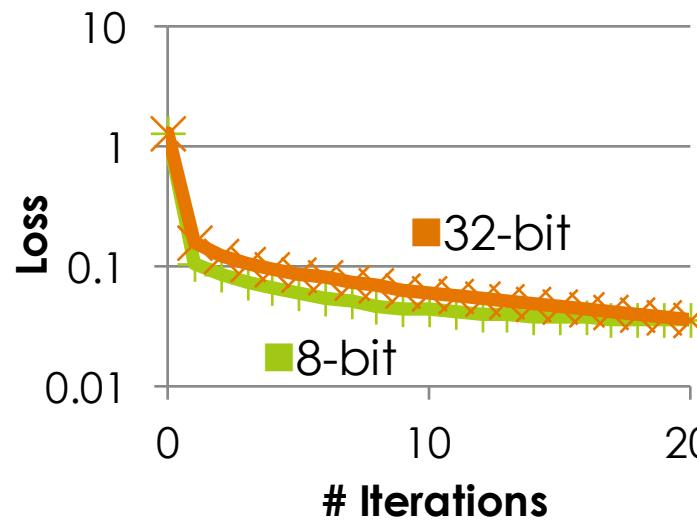
- Low-precision arithmetic essentially **no additional error**
  - when round-off error below the **noise floor** from the stochastic sampling.

## **Systems:**

- Low-precision **increases effective memory bandwidth**
- It also decreases the load on the cache hierarchy.
- Near-linear compute speedup from SIMD.

# Statistical vs. Hardware Efficiency

**Same statistical efficiency!**



**Improved hardware efficiency!**

- 8-bit gives about 2.5x speed up!
- Also, we can scale up to more threads without becoming memory bound

BUCKWILD! same **statistical efficiency**, while greater **hardware efficiency**.

# Conclusion

1. Statistical Algorithms offers new opportunity
2. Hardware v. Statistical Efficiency.

# Conclusion

We can trade off ***statistical efficiency*** to focus on optimizing our IO cost  
***(hardware efficiency)***!