Big Data:
Scale Down, Scale Up, Scale Out

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Intel Science & Technology Center
for Cloud Computing

Keynote Talk at IPDPS'15
May 28, 2015

ISTC for Cloud Computing

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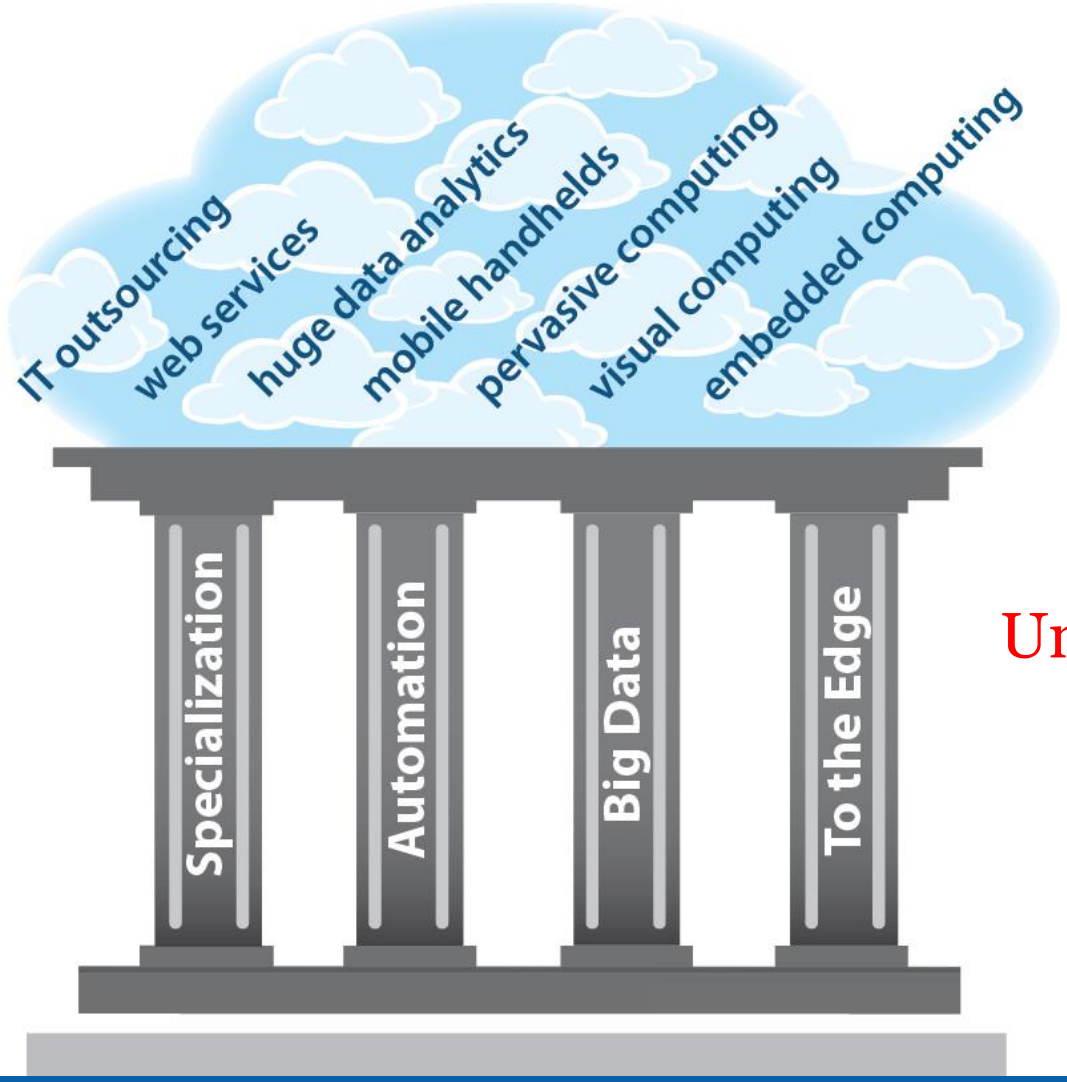

25 faculty
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Underlying Infrastructure enabling the future of cloud computing

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Big Data Performance Challenge

whenever the **volume** or **velocity** of data overwhelms current processing systems/techniques, resulting in **performance** that falls far short of desired

This talk: Focus on performance as key challenge

Many other challenges, including:

- variety of data, veracity of data
- analytics algorithms that scale
- programming
- security, privacy
- insights from the data, visualization

How to Tackle the Big Data Performance Challenge

Three approaches to improving performance by orders of magnitude are:

- ***Scale down*** the amount of data processed or the resources needed to perform the processing
- ***Scale up*** the computing resources on a node, via parallel processing & faster memory/storage
- ***Scale out*** the computing to distributed nodes in a cluster/cloud or at the edge

Scale down the amount of data processed or the resources needed to perform the processing

Goal: Answer queries much faster/cheaper than brute force

- Specific query? **memoized answer**
- Family of queries?
  - Retrieval? **good index**
  - With underlying common subquery (table)? **materialized view**
  - Aggregation? **data cube**

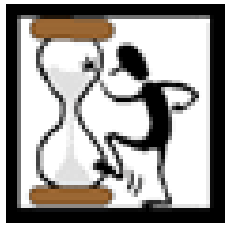
Important Scale Down tool: approximation (w/error guarantees)

Big Data Queries circa 1995

Decision Support Systems (DSS)

SQL Query

Exact Answer



Long Response Times!

- **Scale Down Insight: Often EXACT answers not required**
  - DSS applications usually *exploratory:* early feedback to help identify "interesting" regions
  - *Preview* answers while waiting. *Trial* queries
  - *Aggregate queries:* precision to "last decimal" not needed

Fast Approximate Answers

Often, only interested in leading digits of answer

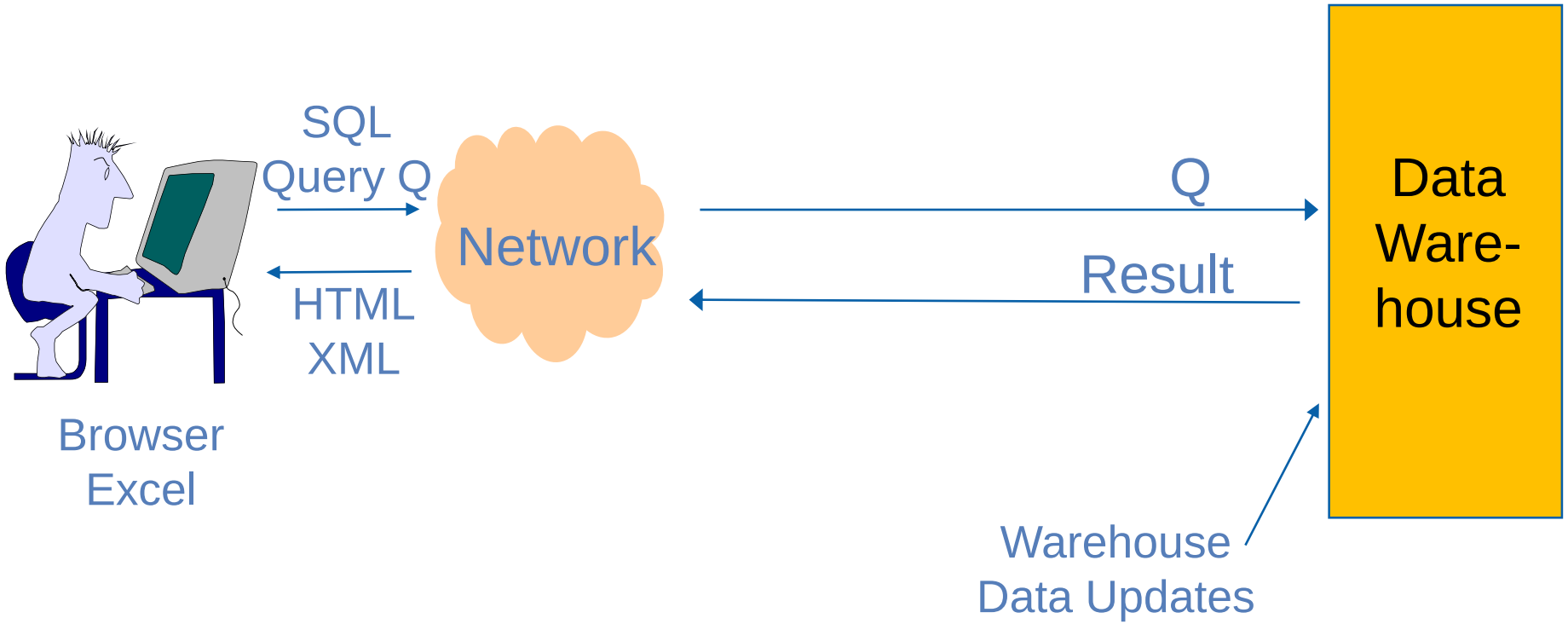
E.g., Average salary for…

$59,152.25 (exact) **in 10 minutes**

$59,000 +/- $500 (with 95% confidence) **in 10 seconds**

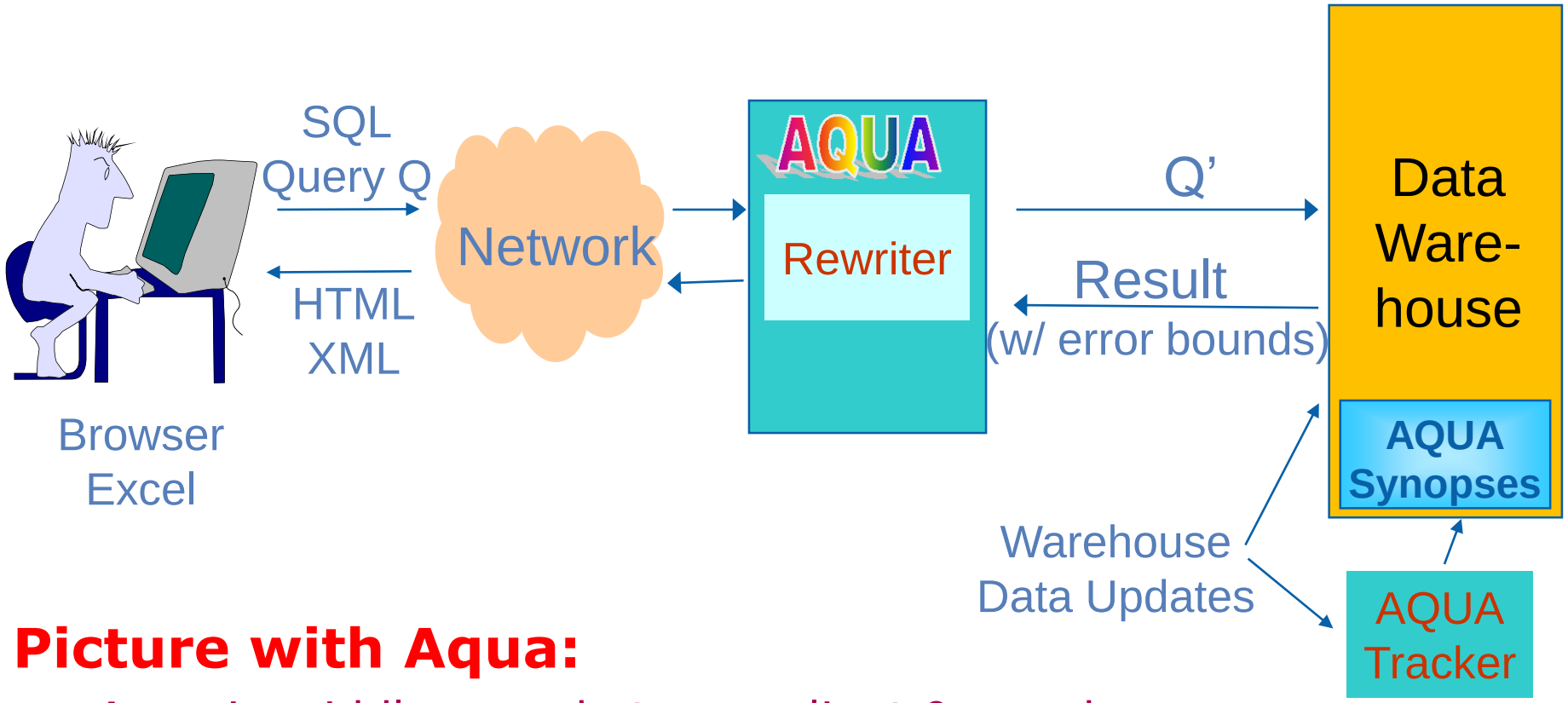
Orders of magnitude speed-up because synopses are orders of magnitude smaller than original data

The Aqua Architecture [Sigmod'98,…]



Picture without Aqua

The Aqua Architecture [Sigmod'98,…]



Picture with Aqua:

- Aqua is middleware, between client & warehouse (Client: + error bound reporting. Warehouse SW: unmodified)
- Aqua Synopses are stored in the warehouse
- Aqua intercepts the user query and rewrites it to be a query Q' on the synopses. Data warehouse returns approximate answer

Precomputed, Streaming Synopses

Our Insights (circa 1996)

- **Precomputed is often faster than on-the-fly**
  - Better access pattern than sampling
  - Small synopses can reside in memory

- **Compute synopses via one pass streaming**
  - Seeing entire data is very helpful: provably & in practice *(Biased sampling for group-bys, Distinct value sampling, Join sampling, Sketches & other statistical functions)*
  - Incrementally update synopses as new data arrives

Bottom Line:
Orders of magnitude faster on DSS queries

Example: Distinct-Values Queries

```
select count(distinct target-attr)
from rel
where P
```

Template

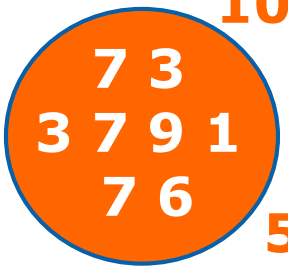
```
select count(distinct o_custkey)
from orders
where o_orderdate >= '2014-05-28'
```

Example using TPC-D/H/R schema

- **How many distinct customers placed orders in past year?**
  - Orders table has many rows for each customer, but must only count each customer once & only if has an order in past year

Distinct-Values Query Approaches

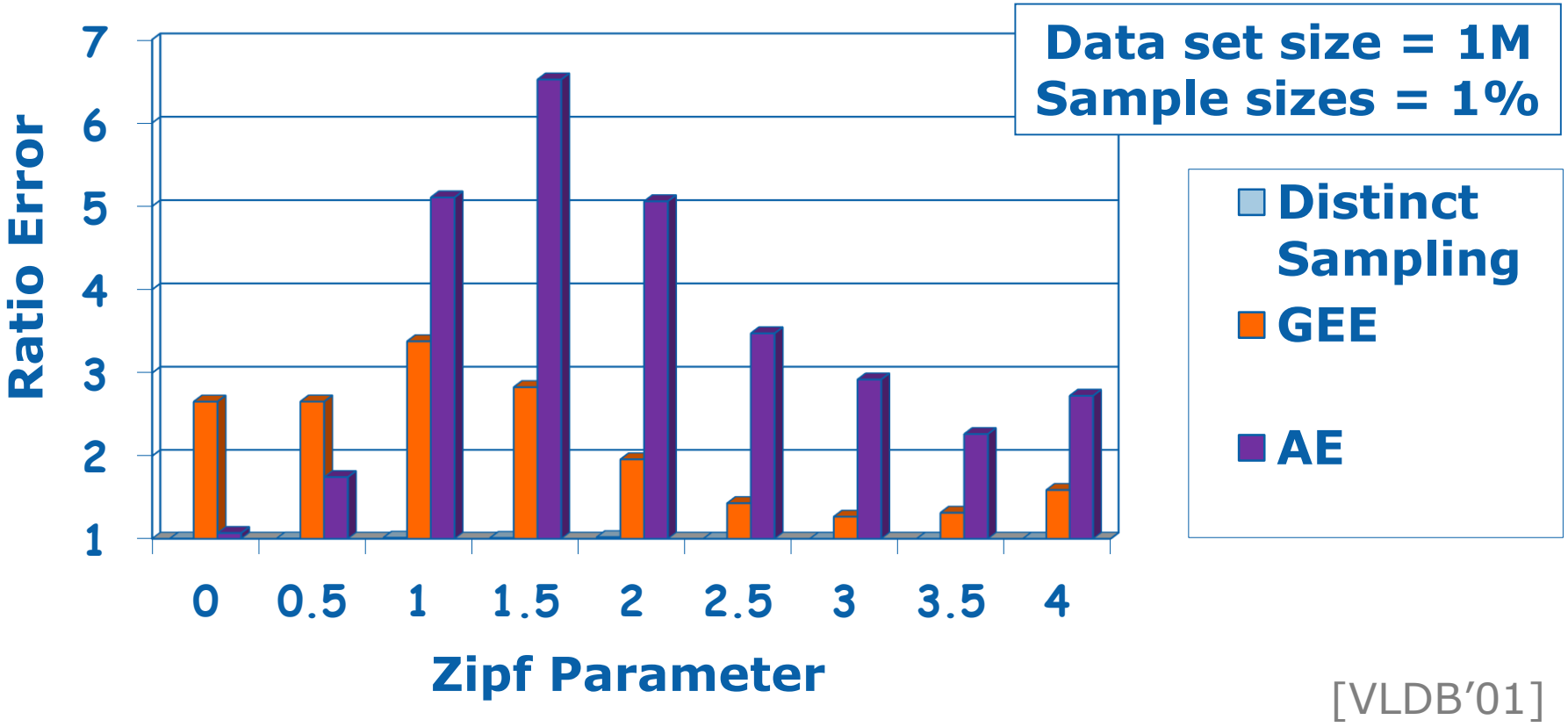
- **Estimate from Random Sample**
  - Statistics, Databases, etc
  - Lousy in practice
  - [Charikar'00] Need linear sample size



- **Flajolet-Martin'85** u=universe size
  - One-pass algorithm, stores O(log u) bits
  - Only produces count, can't apply a predicate

- **Our Approach: Distinct Sampling** [VLDB'01]
  - One-pass, stores O(t * log u) tuples
  - Yields sample of distinct values, with up to t-size uniform sample of rows for each value
  - First to provide provably good error guarantees

Accuracy vs. Data Skew



[VLDB'01]

Over the entire range of skew :

- **Distinct Sampling has 1.00-1.02 ratio error**
- **At least 25 times smaller relative error than GEE and AE**

Scale Down Today

- **Hundreds and hundreds of clever algorithms**
  - Synopsis-based approximations tailored to query families
  - Reduce data size, data dimensionality, memory needed, etc

- **Synopses routinely used in Big Data analytics applications at Google, Twitter, Facebook, etc**
  - E.g., Twitter's open source Summingbird toolkit
    - **Hyperloglog** – number of unique users who perform a certain action; followers-of-followers
    - **CountMin Sketch** – number of times each query issued to Twitter search in a span of time; building histograms
    - **Bloom Filters** – keep track of users who have been exposed to an event to avoid duplicate impressions (10^8 events/day for 10^8 users)

[Boykin et al, VLDB'14]

How to Tackle the Big Data Performance Challenge

- **Scale Down**
- **Scale Up** the computing resources on a node, via parallel processing & faster memory/storage
- **Scale Out**

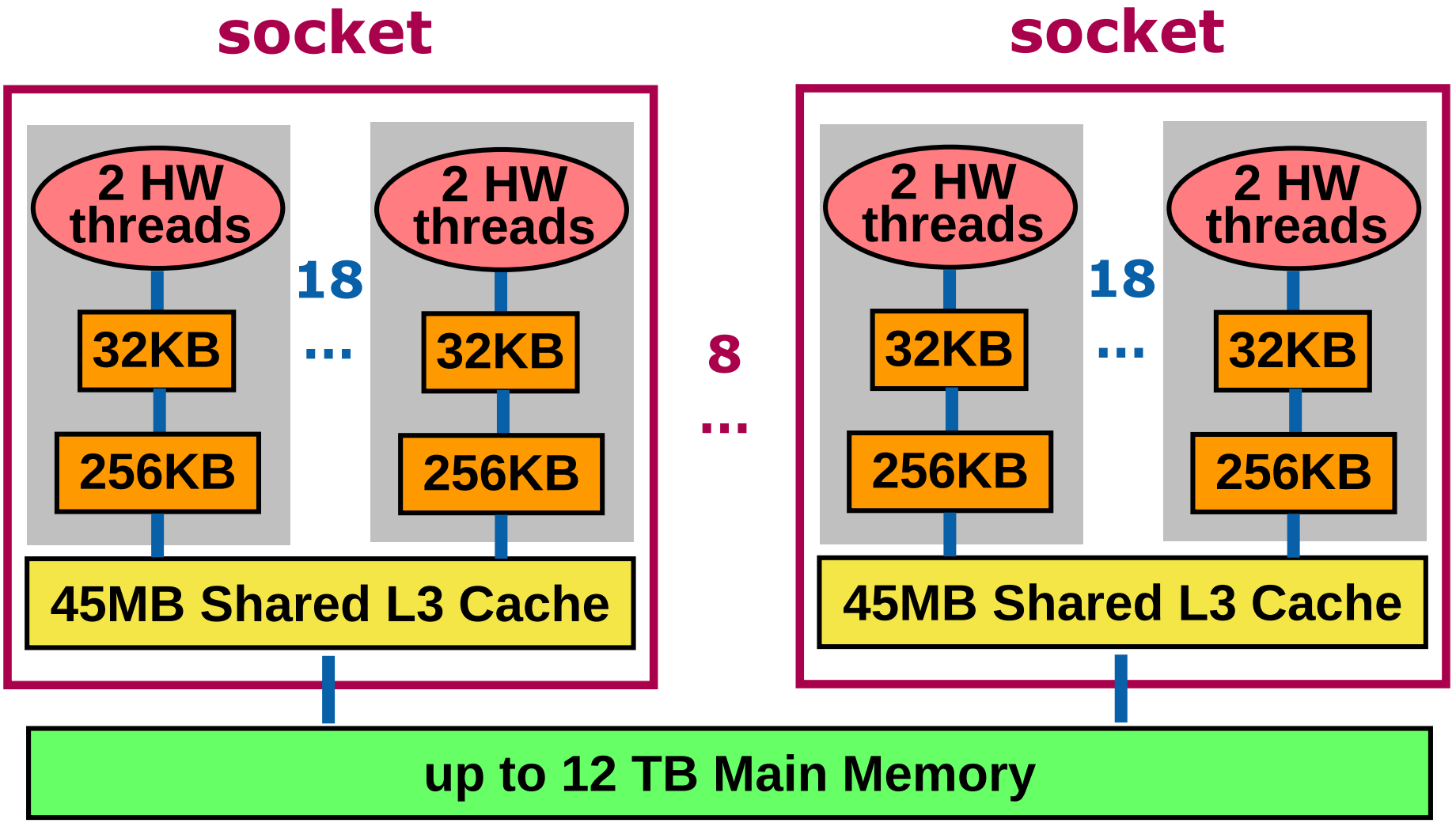
Why **Scale Up** when you can **Scale Out?**

- **Much of Big Data focus has been on Scale Out**
  - Hadoop, etc

- **But if data fits in memory of multicore then often order of magnitude better performance**
  - GraphLab1 (multicore) is 1000x faster than Hadoop (cluster)
  - Multicores now have 1-12 TB memory: most graph analytics problems fit!

- **Even when data doesn't fit, will still want to take advantage of Scale Up whenever you can**

Multicore: 144-core Xeon Haswell E7-v3



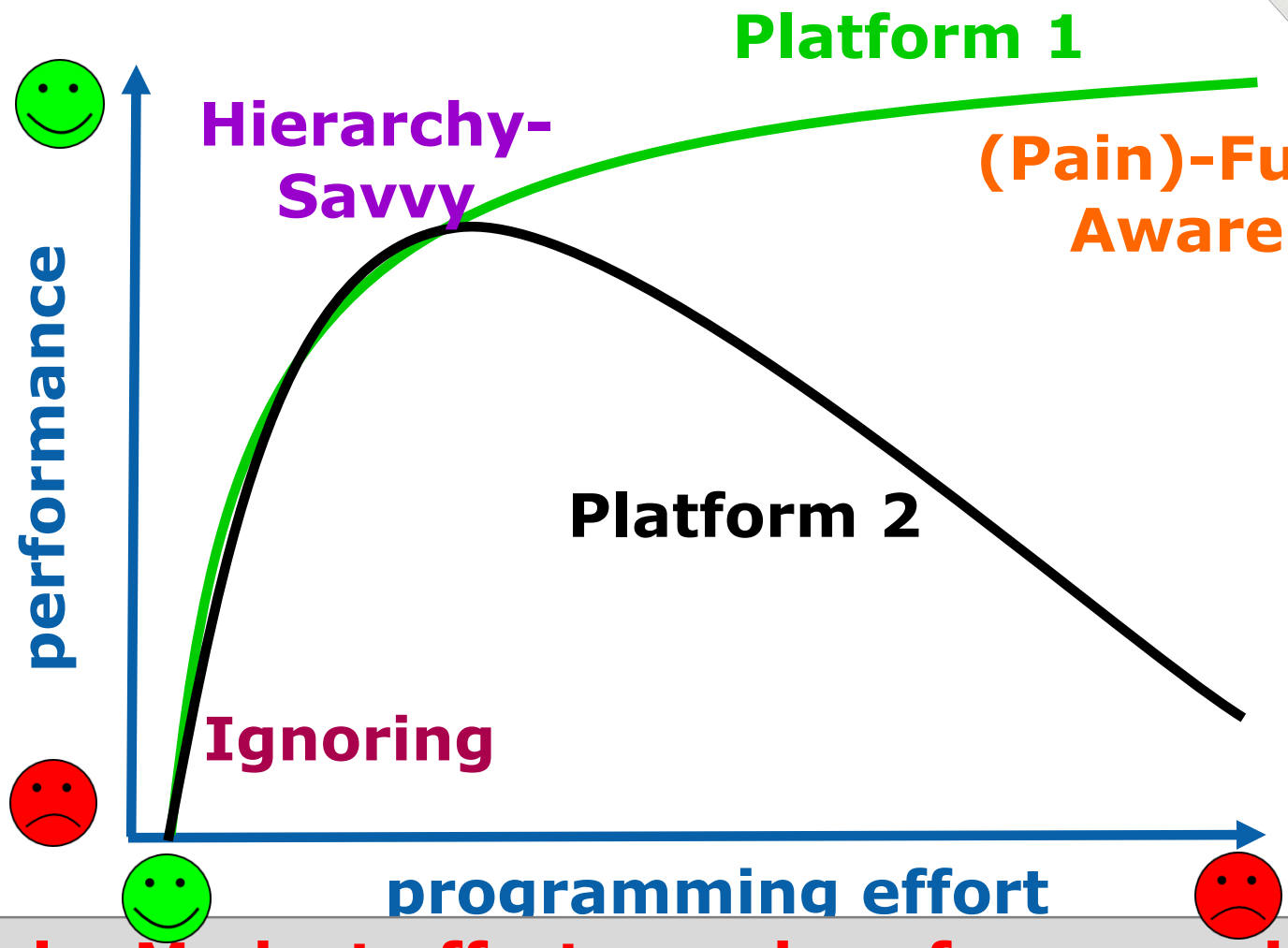
Attach: Hard Drives & Flash Devices

Hierarchy Trends

- **Good performance [energy] requires effective use of hierarchy**

- **Hierarchy getting richer**
  - More cores
  - More levels of cache
  - New memory/storage technologies
    - Flash/SSDs, emerging PCM
    - Bridge gaps in hierarchies – can't just look at last level of hierarchy

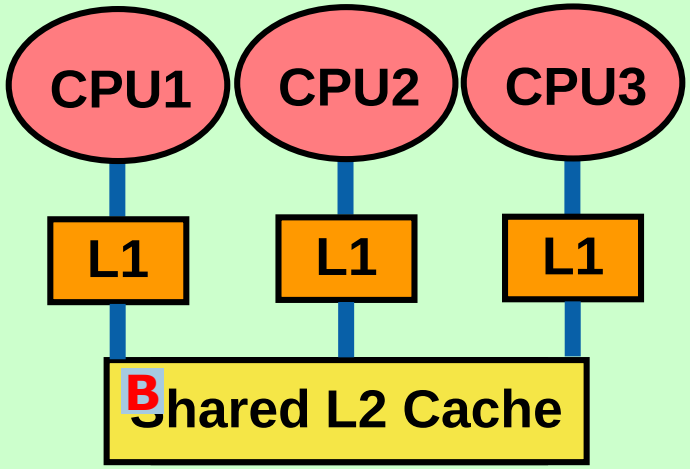
Hi-Spade: Hierarchy-Savvy Sweet Spot



Goals: Modest effort, good performance in practice, robust, strong theoretical foundation

What Yields Good Hierarchy Performance?

- **Spatial locality: use what's brought in**
- **Temporal locality: reuse it**
- **Constructive sharing: don't step on others' toes**



Stepping on toes

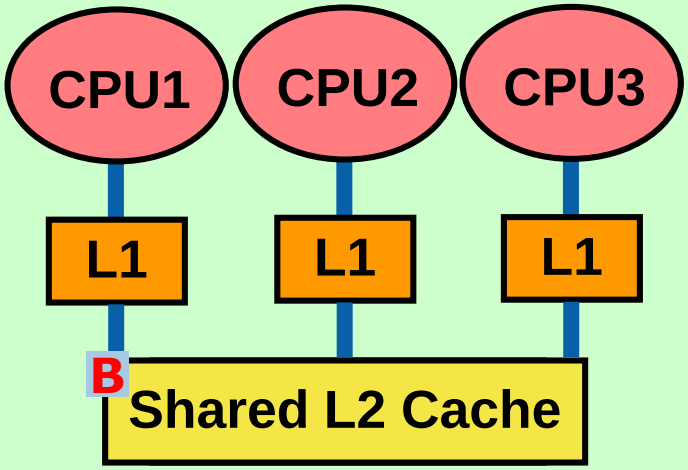
e.g., all CPUs write B at ≈ the same time

Two design options

- Cache-aware: Focus on the bottleneck level
- Cache-oblivious: Design for any cache size

Multicore Hierarchies' Key New Dimension: Scheduling

Scheduling of parallel threads has LARGE impact on hierarchy performance



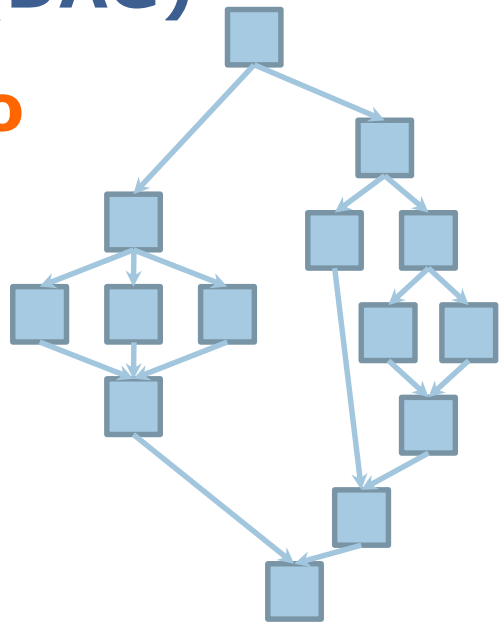
Recall our problem scenario:

all CPUs want to write B at ≈ the same time

Can mitigate (but not solve) if can schedule the writes to be far apart in time

Program-centric Analysis

- **Start with a portable program description: dynamic Directed Acyclic Graph (DAG)**
- **Analyze DAG without reference to cores, caches, connections…**

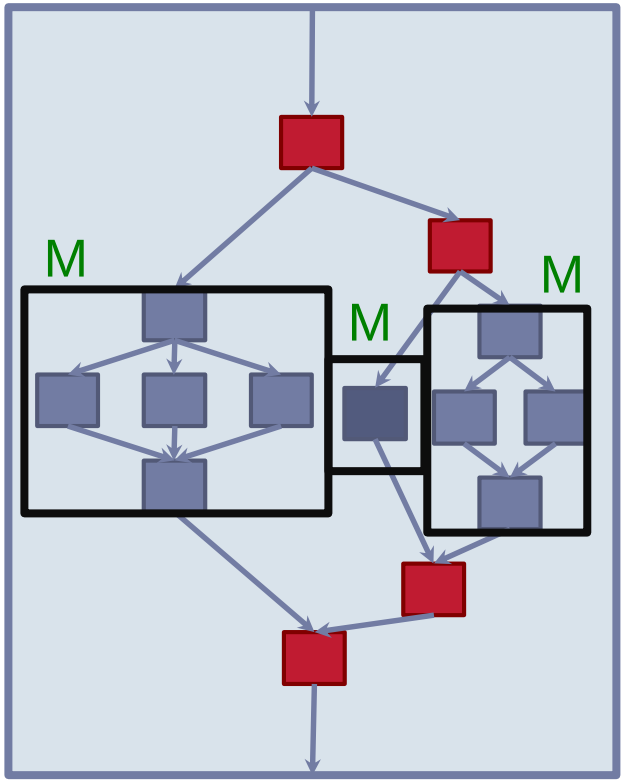


Program-centric metrics

- **Number of operations (Work, W)**
- **Length of Critical Path (Depth, D)**
- **Data reuse patterns (Locality)**

Our Goal: Program-centric metrics + Smart thread scheduler delivering provably good performance on many platforms

Parallel Cache Complexity Model



Decompose task into maximal subtasks that fit in space M & glue operations

Cache Complexity Q*(M,B) =

Σ Space for M-fitting subtasks
+ Σ Cache miss for every access in glue

M,B parameters either used in algorithm (cache-aware) or not (cache-oblivious)

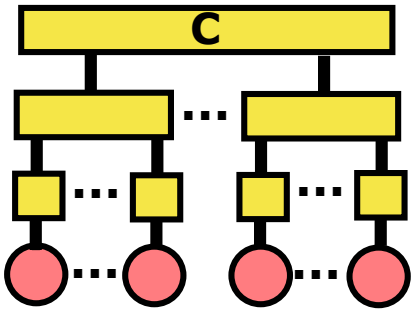
[Simhadri, 2013]

Space-Bounded Scheduler

[Chowdhury, Silvestri, Blakeley, Ramachandran IPDPS'10]

Key Ideas:

- **Assumes space use (working set sizes) of tasks are known (can be suitably estimated)**
- **Assigns a task to a cache C that fits the task's working set. Reserves the space in C. Recurses on the subtasks, using the CPUs and caches that share C (below C in the diagram)**



Cache costs: optimal $\sum_{\text{levels}} Q^*(M_i) \times C_i$ [SPAA'11]

where C_i is the miss cost for level i caches

Experiments on 32-core Nehalem: [SPAA'14]

reduces cache misses up to 65% vs. work-stealing

Sharing vs. Contention

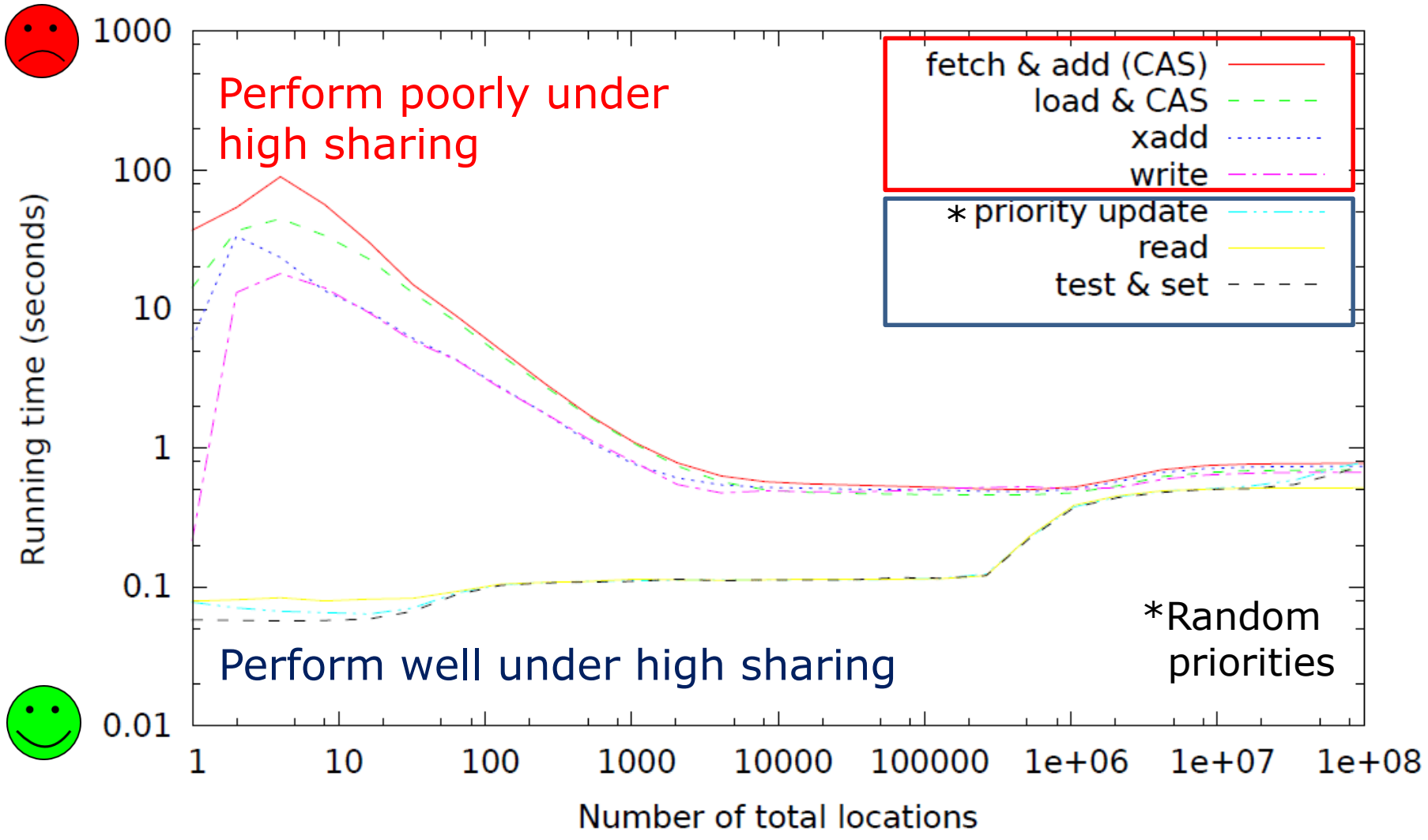
Sharing: operations that share the same memory location (or possibly other resource)

Contention: serialized access to a resource (potential performance penalty of sharing)

Replace concurrent update with Priority Update: updates only if higher priority than current

Priority Update has Low Contention under High Sharing

[SPAA'13]



5 runs of 10^8 operations on 40-core Intel Nehalem

Further Research Directions

- **Determinism at function call abstraction, Commutative Building Blocks, Deterministic Reservations for loops, Use of priority update** [PPoPP'12, SPAA'13, SODA'15]

- **Scaling Up by redesigning algorithms & data structures to take advantage of new storage/memory technologies**
  [VLDB'08, SIGMOD'10, CIDR'11, SIGMOD'11, SPAA'15]

How to Tackle the Big Data Performance Challenge

- **Scale Down**
- **Scale Up**
- **Scale Out** the computing to distributed nodes in a cluster/cloud or at the edge

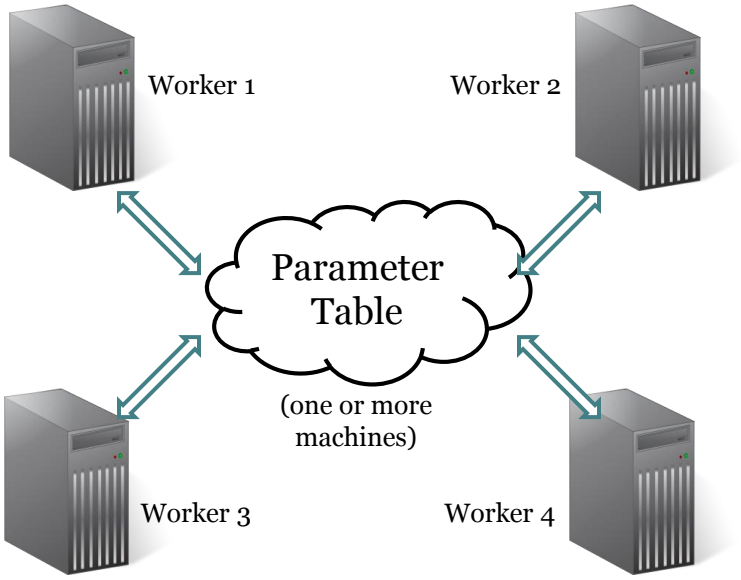
Big Learning Frameworks & Systems

- **Goal: Easy-to-use programming framework for Big Data Analytics that delivers good performance on large (and small) clusters**

- **Idea: Discover & take advantage of distinctive properties of Big Learning algorithms**
  - Use training data to learn parameters of a model
  - **Iterate until Convergence** approach is common
    - E.g., Stochastic Gradient Descent for Matrix Factorization or Multiclass Logistic Regression; LDA via Gibbs Sampling; Page Rank; Deep learning; …

Parameter Servers for Distributed ML

- **Provides all machines with convenient access to global model parameters**
- **Enables easy conversion of single-machine parallel ML algorithms**
  - "Distributed shared memory" programming style
  - Replace local memory access with PS access



† Ahmed et al. (WSDM'12), Power and Li (OSDI'10)

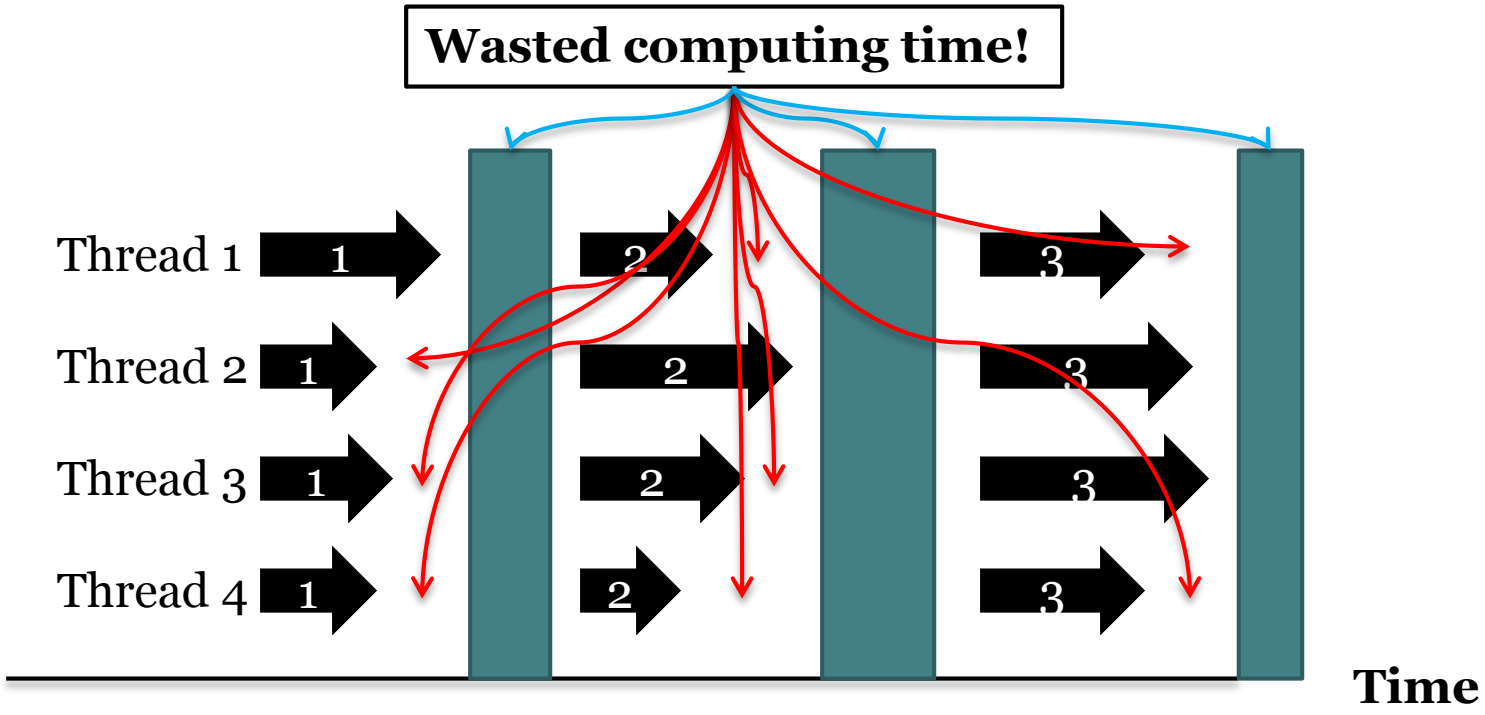
Single Machine Parallel

```
UpdateVar(i) {
  old = y[i]
  delta = f(old)
  y[i] += delta
}
```

Distributed with PS

```
UpdateVar(i) {
  old = PS.read(y,i)
  delta = f(old)
  PS.inc(y,i,delta)
}
```

The Cost of Bulk Synchrony

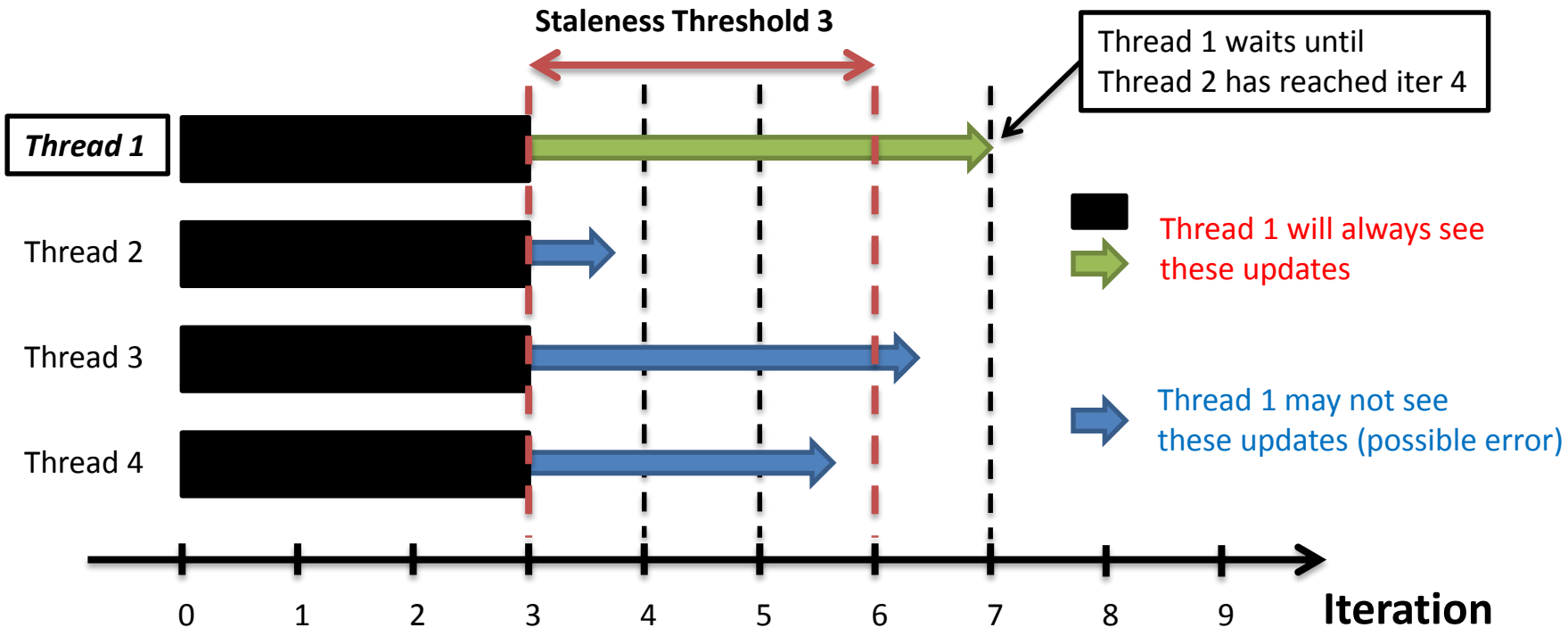


Threads must wait for each other
End-of-iteration sync gets longer with larger clusters

Precious computing time wasted

But: Fully asynchronous => No algorithm convergence guarantees

Stale Synchronous Parallel (SSP)



[NIPS'13]

Allow threads to *usually* run at own pace

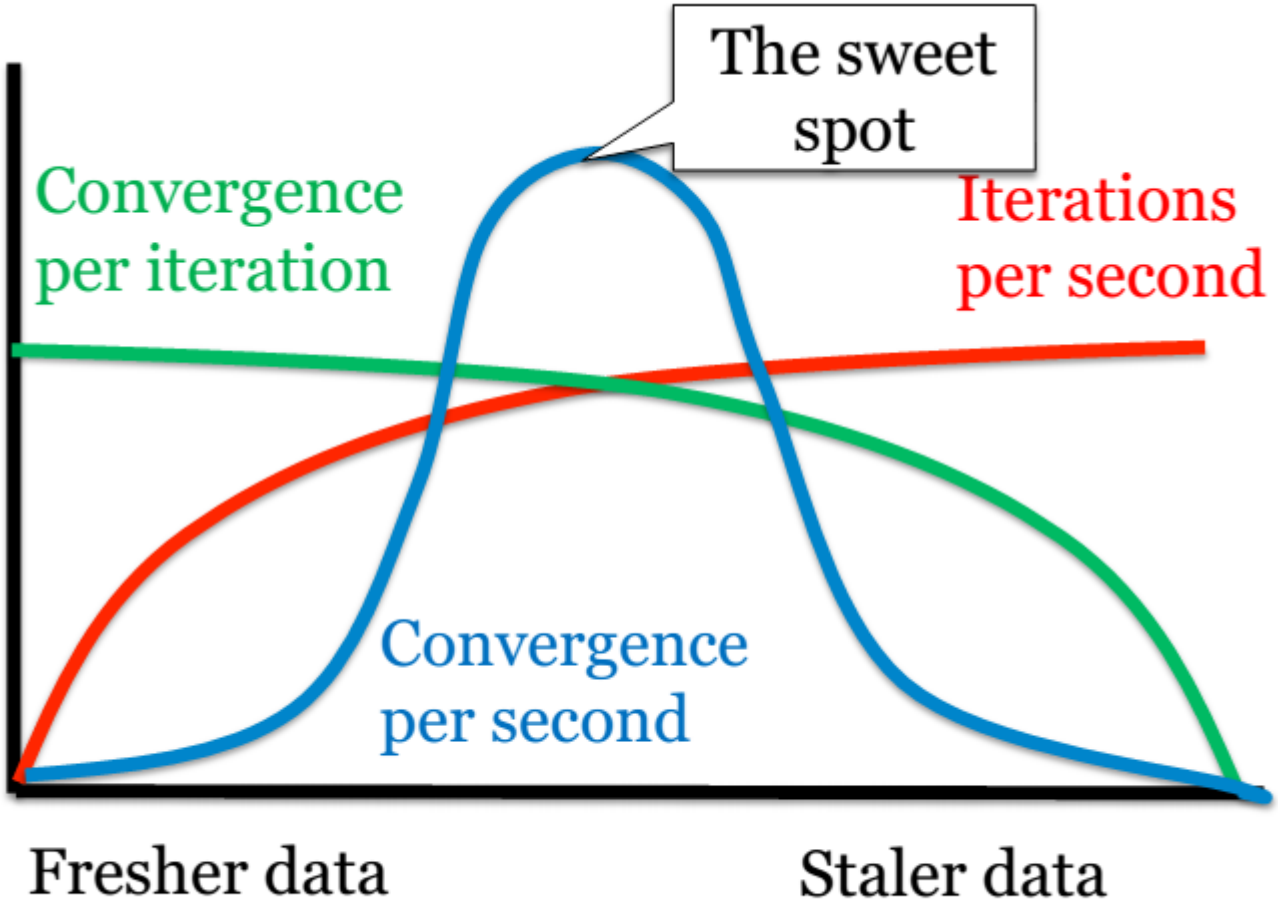
Fastest/slowest threads not allowed to drift >S iterations apart

Protocol: check cache first; if too old, get latest version from network

Consequence: fast threads must check network every iteration

Slow threads check only every S iterations – fewer network accesses, so catch up!

Staleness Sweet Spot



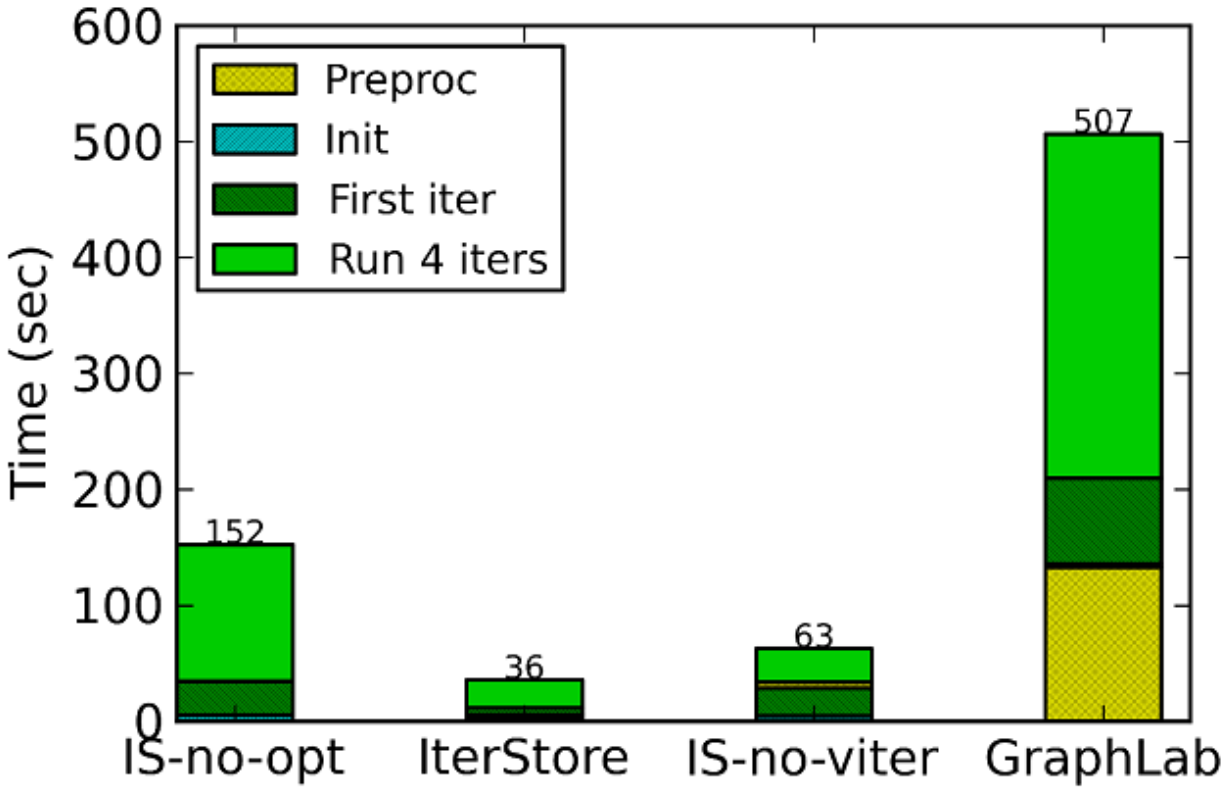
[ATC'14]

Enhancements to SSP

- **Early transmission of larger parameter changes, up to bandwidth limit** [SoCC'15]
- **Find sets of parameters with weak dependency to compute on in parallel**
  - Reduces errors from parallelization
- **Low-overhead work migration to eliminate transient straggler effects**
- **Exploit repeated access patterns of iterative algorithms (IterStore)** [SoCC'14]
  - Optimizations: prefetching, parameter data placement, static cache policies, static data structures, NUMA memory management

IterStore: Exploiting Iterativeness

Overall performance: CF, 5 iters



[SoCC'14]

Collaborative Filtering (CF) on NetFlix data set, 8 machines x 64 cores

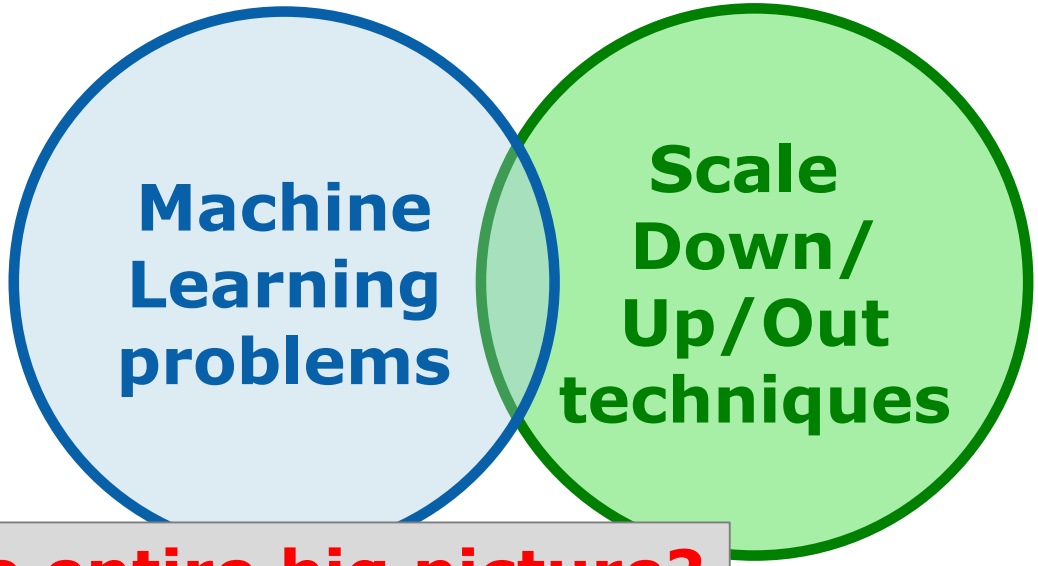
Big Learning Systems Big Picture

Framework approaches:

- BSP-style approaches: Hadoop, Spark
- Think-like-a-vertex: Pregel, GraphLab
- Parameter server: Yahoo!, **SSP**

Tend to revisit the same problems

Ad hoc solutions



What is the entire big picture?

Unified Scale Down, Scale Up, Scale Out Big Data System?

No system combines all three

Research questions:

- How best to combine: Programming & Performance challenges
- Scale down techniques for Machine Learning?
  E.g., Early iterations on data synopses
- Scale up techniques more broadly applied?
  Lessons from decades of parallel computing research
- Scale out beyond the data center?
  Lessons from IrisNet project? [Sigmod'03, PC 2003]

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Acknowledgment: Thanks to MANY collaborators

Appendix

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Slides 9-11:

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Acknowledgments

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A number of these slides were adapted from slides created by my co-authors, and I thank them for those slides.