The Quest for Scalable Support of Data Intensive Applications in Distributed Systems

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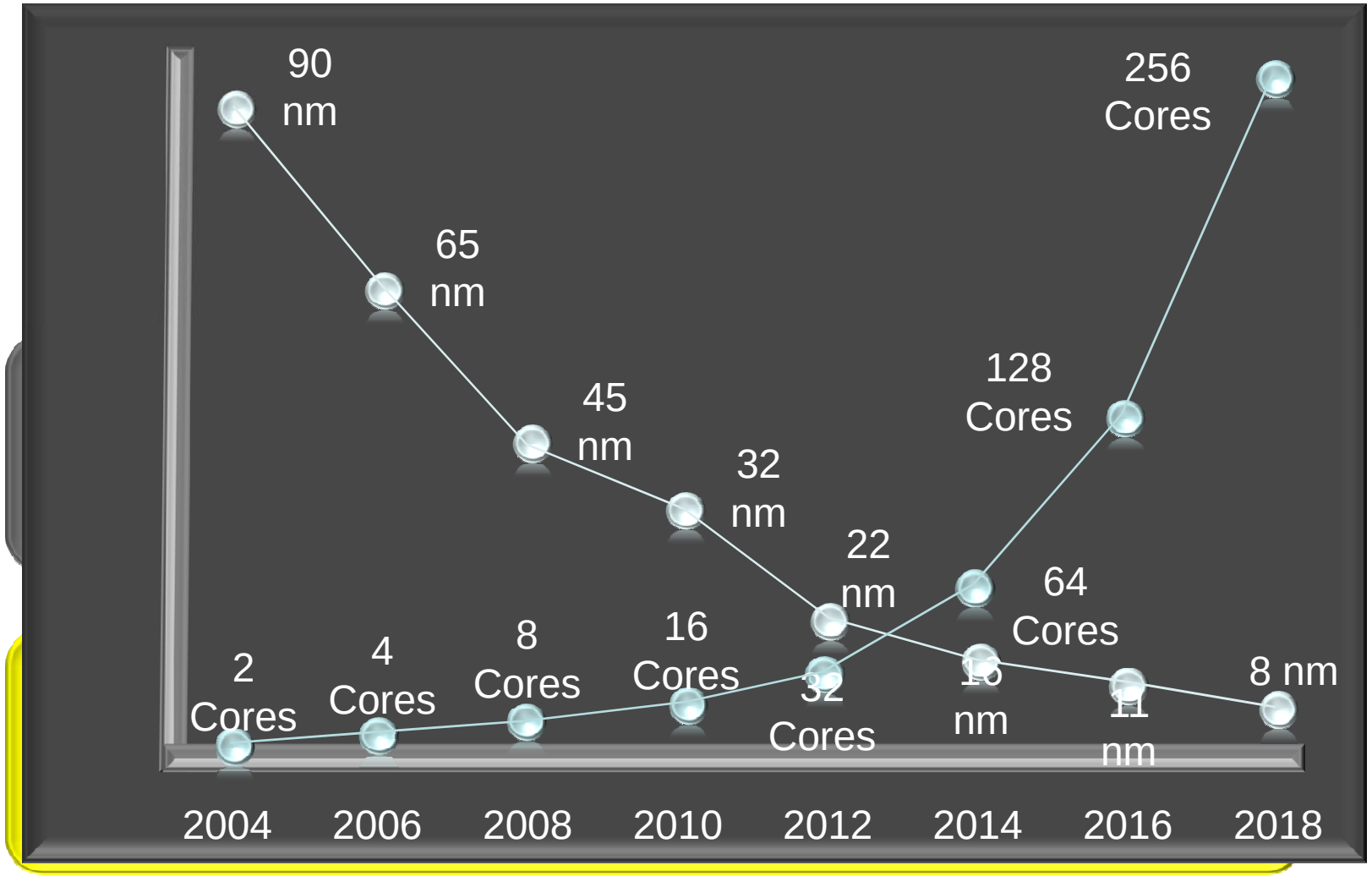
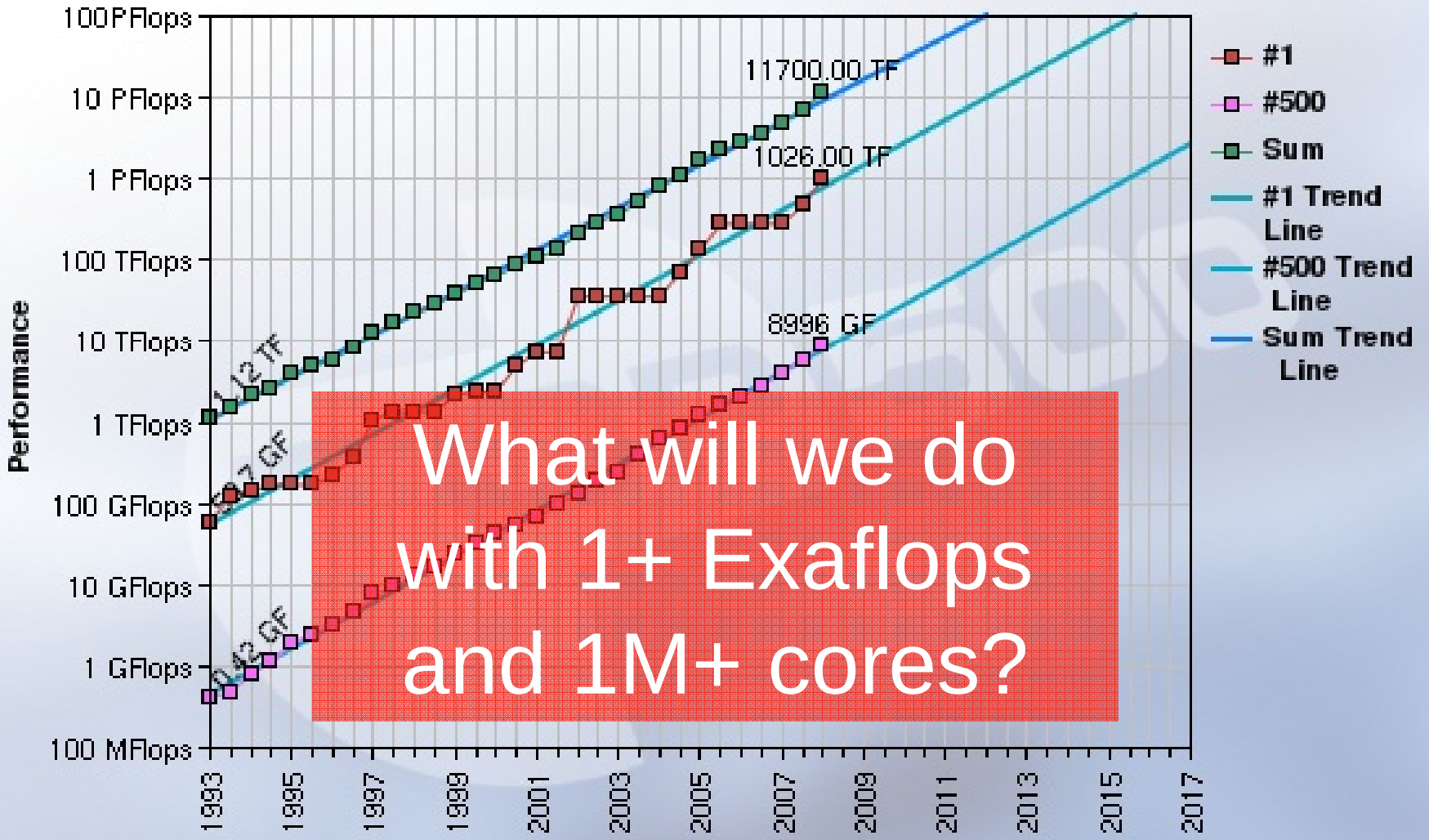
University of Chicago, PADS Seminar
November 12th, 2008

Many-Core Growth Rates

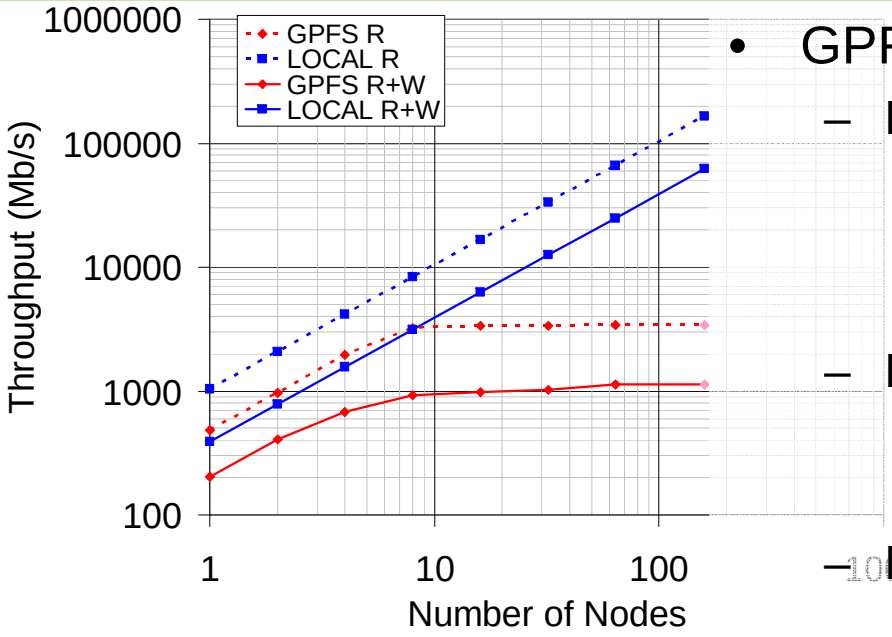


Projected Performance Development



What will we do with 1+ Exaflops and 1M+ cores?

Storage Resource Scalability



- GPFS vs. LOCAL
  - Read Throughput
    - 1 node: 0.48Gb/s vs. 1.03Gb/s ➔ **2.15x**
    - 160 nodes: 3.4Gb/s vs. 165Gb/s ➔ **48x**
    - **11Mb/s per CPU vs. 515Mb/s per CPU**
  - Read+Write Throughput:
    - 1 node: 0.2Gb/s vs. 0.39Gb/s ➔ **1.95x**
    - 160 nodes: 1.1Gb/s vs. 62Gb/s ➔ **55x**
  - Metadata (mkdir / rm -rf)
    - 1 node: 151/sec vs. 199/sec ➔ **1.3x**
    - 160 nodes: 21/sec vs. 31840/sec ➔ **1516x**

- IBM BlueGene/P
  - 160K CPU cores
  - GPFS 8GB/s I/O rates (16 servers)
  - Experiments on 160K CPU BG/P achieved 0.3Mb/s per CPU core
  - Experiments on 5.7K CPU SiCortex achieved 0.06Mb/s per CPU core

Programming Model Issues

- **Multicore** processors
- Massive **task parallelism**
- Massive **data parallelism**
- Integrating **black box applications**
- Complex **task dependencies** (task graphs)
- **Failure**, and other execution management issues
- **Dynamic task graphs**
- Documenting **provenance** of data products
- **Data management**: input, intermediate, output
- **Dynamic data access** involving large amounts of data

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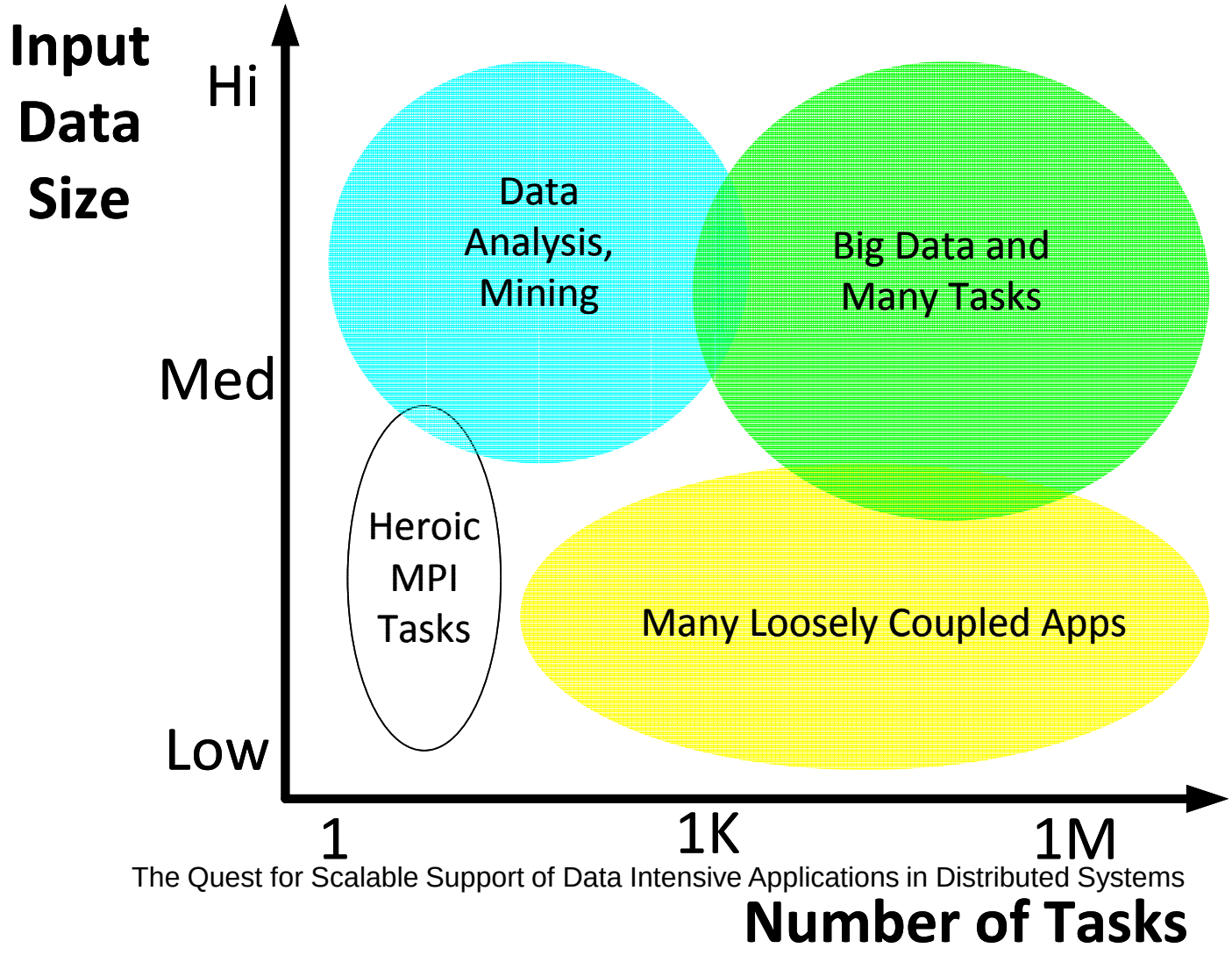
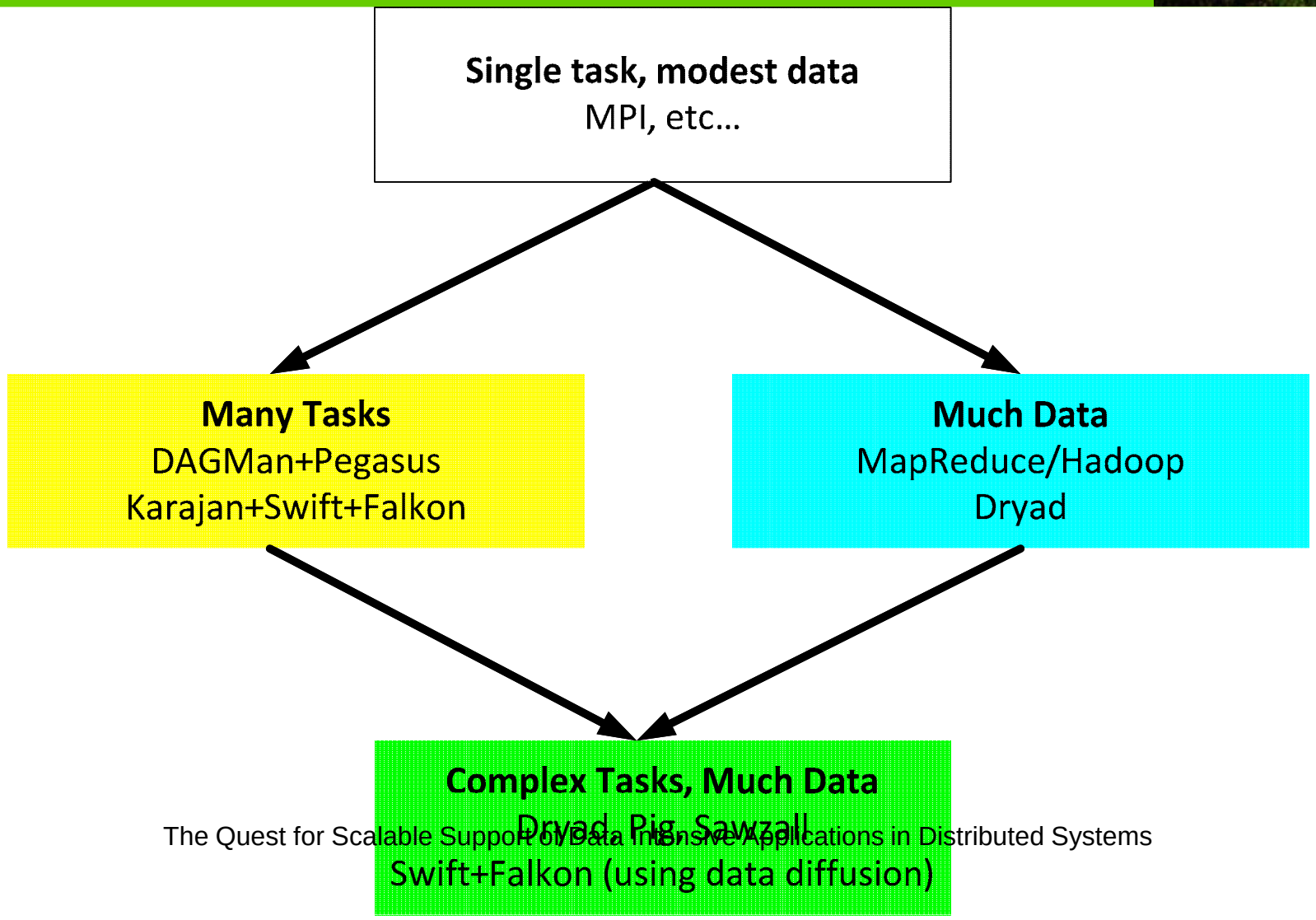
Problem Types



An Incomplete and Simplistic View of Programming Models and Tools

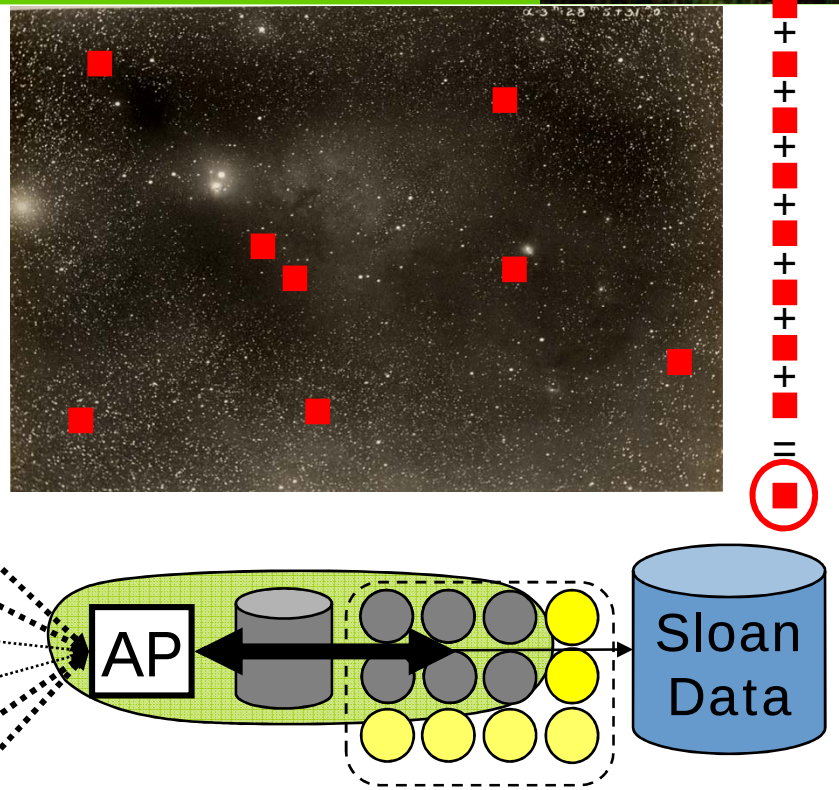


MTC: Many Task Computing

- Loosely coupled applications
  - High-performance computations comprising of multiple distinct activities, coupled via file system operations or message passing
  - Emphasis on using many resources over short time periods
  - Tasks can be:
    - small or large, independent and dependent, uniprocessor or multiprocessor, compute-intensive or data-intensive, static or dynamic, homogeneous or heterogeneous, loosely or tightly coupled, large number of tasks, large quantity of computing, and large volumes of data…

Motivating Example: AstroPortal Stacking Service

- Purpose
  - On-demand “stacks” of random locations within ~10TB dataset
- Challenge
  - Processing Costs:
    - O(100ms) per object
  - Data Intensive:
    - 40MB:1sec
  - Rapid access to 10-10K “random” files
  - Time-varying load



Hypothesis

"Significant performance improvements can be obtained in the analysis of large dataset by leveraging information about data analysis workloads rather than individual data analysis tasks."

- **Important concepts related to the hypothesis**
  - **Workload**: a complex query (or set of queries) decomposable into simpler tasks to answer broader analysis questions
  - **Data locality** is crucial to the efficient use of large scale distributed systems for scientific and data-intensive applications
  - Allocate computational and caching storage resources, **co-scheduled** to optimize workload performance

Abstract Model

- AMDASK: An Abstract Model for DAta-centric taSK farms
  - Task Farm: A common parallel pattern that drives independent computational tasks
- Models the efficiency of data analysis workloads for the MTC class of applications
- Captures the following data diffusion properties
  - Resources are acquired in response to demand
  - Data and applications diffuse from archival storage to new resources
  - Resource “caching” allows faster responses to subsequent requests
  - Resources are released when demand drops
  - Considers both data and computations to optimize performance

AMDASK: Base Definitions

- **Data Stores:** Persistent & Transient
  - Store capacity, load, ideal bandwidth, available bandwidth
- **Data Objects:**
  - Data object size, *data object's storage location(s),* copy time
- **Transient resources:** compute speed, resource state
- **Task:** application, input/output data

AMDASK: Execution Model Concepts

- Dispatch Policy
  - next-available, first-available, max-compute-util, max-cache-hit
- Caching Policy
  - random, FIFO, LRU, LFU
- Replay policy
- Data Fetch Policy
  - Just-in-Time, Spatial Locality
- Resource Acquisition Policy
  - one-at-a-time, additive, exponential, all-at-once, optimal
- Resource Release Policy
  - distributed, centralized

AMDASK: Performance Efficiency Model

- B: Average Task Execution Time:
  - K: Stream of tasks
  - μ(k): Task k execution time

$$B = \frac{1}{|K|}\sum_{k \in K} \mu(\kappa)$$

- Y: Average Task Execution Time with Overheads:
  - o(k): Dispatch overhead
  - ς(δ,τ): Time to get data

$$Y = \begin{cases} \frac{1}{|K|}\sum_{\kappa \in K}[\mu(\kappa) + o(\kappa)], & \delta \in \phi(\tau), \delta \in \Omega \\ \frac{1}{|K|}\sum_{\kappa \in K}[\mu(\kappa) + o(\kappa) + \zeta(\delta, \tau)], & \delta \notin \phi(\tau), \delta \in \Omega \end{cases}$$

- V: Workload Execution Time:
  - A: Arrival rate of tasks
  - T: Transient Resources

$$V = \max\left(\frac{B}{|T|}, \frac{1}{A}\right) * |K|$$

- W: Workload Execution Time with Overheads

$$W = \max\left(\frac{Y}{|T|}, \frac{1}{A}\right) * |K|$$

AMDASK: Performance Efficiency Model

- **Efficiency**

$$\mathrm{E} = \frac{V}{W} \longrightarrow E = \begin{cases} 1, & \frac{Y}{|T|} \leq \frac{1}{A} \\ \max\left(\frac{B}{Y}, \frac{|\mathrm{T}|}{\mathrm{A} * Y}\right), & \frac{Y}{|T|} > \frac{1}{A} \end{cases}$$

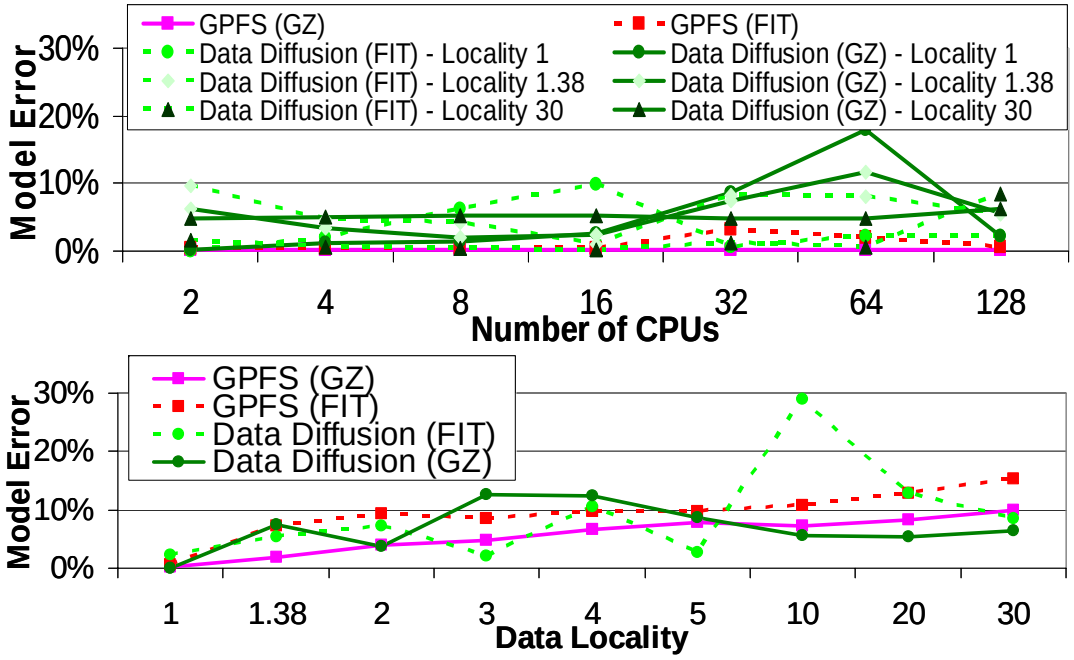
- **Speedup**

$$S = E * |T|$$

- **Optimizing Efficiency**
  - Easy to maximize either efficiency or speedup independently
  - Harder to maximize both at the same time
    - Find the smallest number of *transient resources* |T| while maximizing speedup*efficiency

Model Validation

- Stacking service (large scale astronomy application)
- 92 experiments
- 558K files
  - Compressed: 2MB each ➔ 1.1TB
  - Un-compressed: 6MB each ➔ 3.3TB



Falkon: a Fast and Light-weight tasK executiON framework

- ***Goal:*** enable the ***rapid and efficient*** execution of many independent jobs on large compute clusters
- Combines three components:
  - a ***streamlined task dispatcher***
  - ***resource provisioning*** through multi-level scheduling techniques
  - ***data diffusion*** and data-aware scheduling to leverage the co-located computational and storage resources
- Integration into Swift to leverage many applications
  - Applications cover many domains: astronomy, astro-physics, medicine, chemistry, economics, climate modeling, etc

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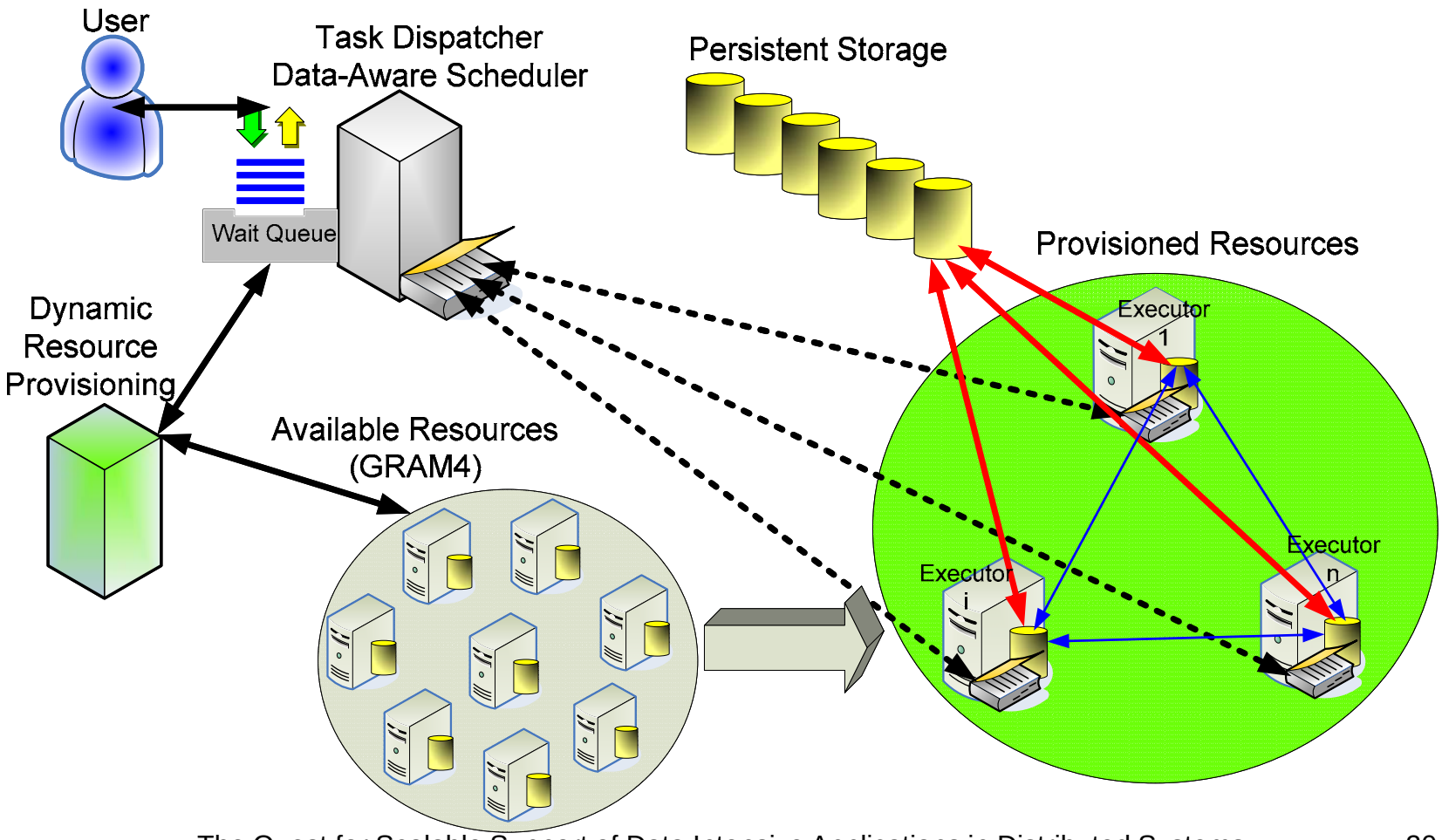
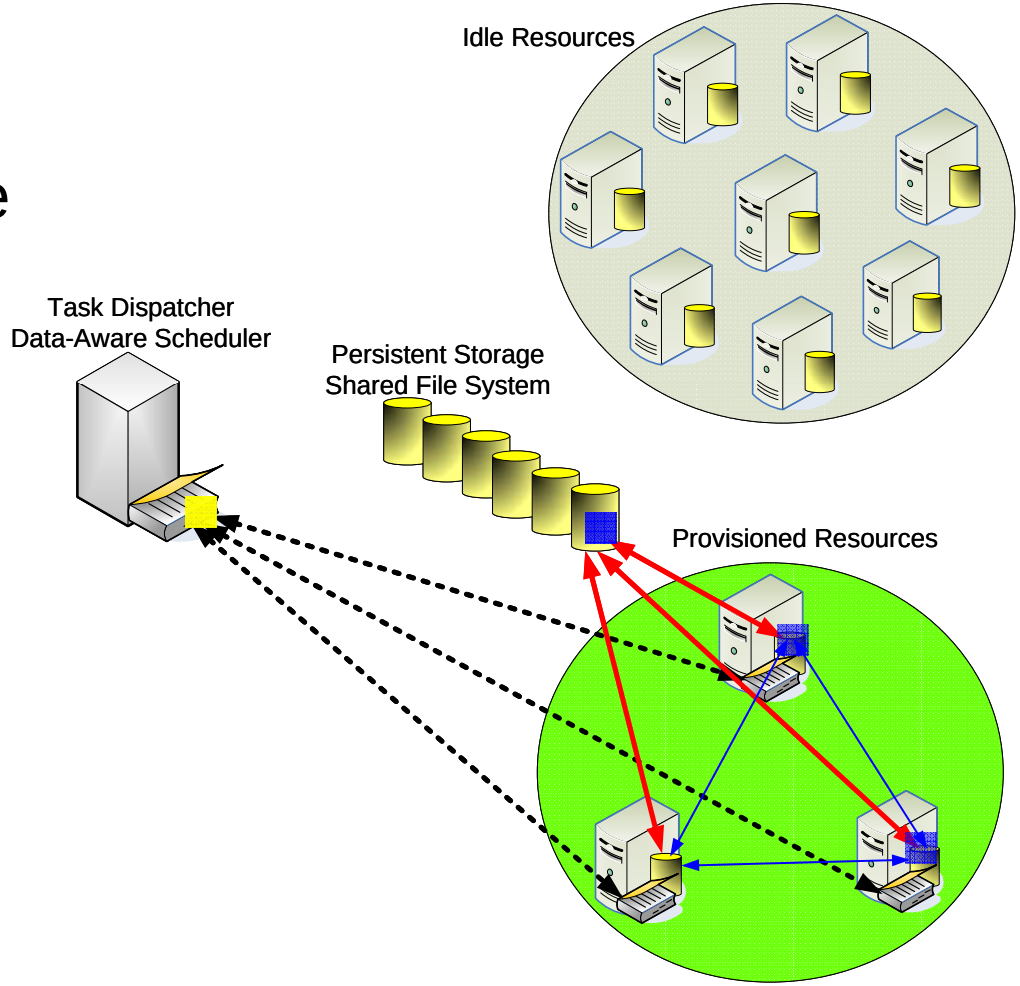
Falkon Overview



Data Diffusion

- Resource acquired in response to demand
- Data and applications diffuse from archival storage to newly acquired resources
- Resource “caching” allows faster responses to subsequent requests
  - Cache Eviction Strategies: RANDOM, FIFO, LRU, LFU
- Resources are released when demand drops



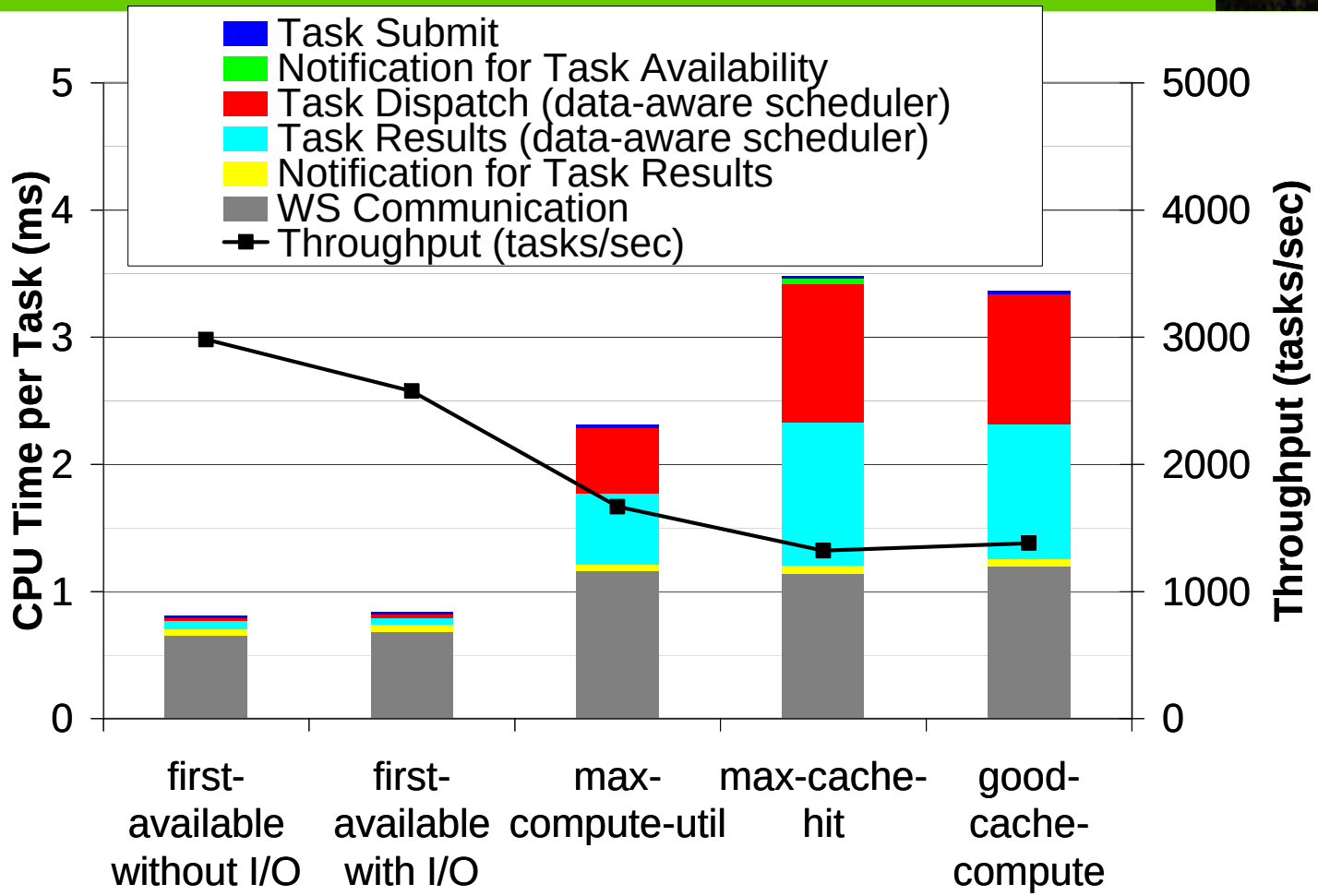
Data Diffusion

- Considers both data and computations to optimize performance
  - Supports data-aware scheduling
  - Can optimize compute utilization, cache hit performance, or a mixture of the two
- Decrease dependency of a shared file system
  - Theoretical linear scalability with compute resources
  - Significantly increases meta-data creation and/or modification performance
- Central for “data-centric task farm” realization

Scheduling Policies

- first-available:
  - simple load balancing
- max-cache-hit
  - maximize cache hits
- max-compute-util
  - maximize processor utilization
- good-cache-compute
  - maximize both cache hit and processor utilization at the same time

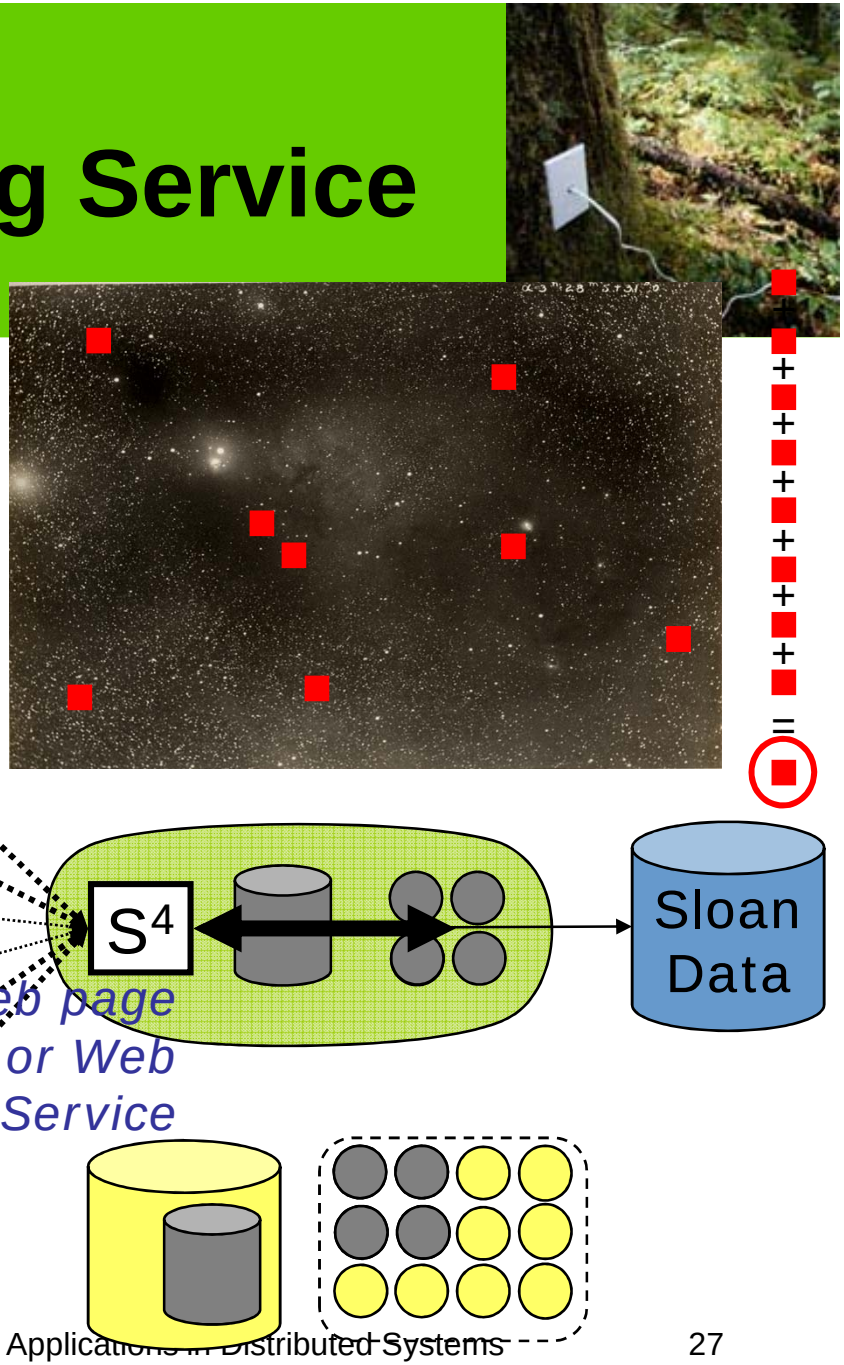
Data-Aware Scheduler Profiling



AstroPortal Stacking Service

- Purpose
  - On-demand “stacks” of random locations within ~10TB dataset
- Challenge
  - Rapid access to 10-10K “random” files
  - Time-varying load
- Sample Workloads

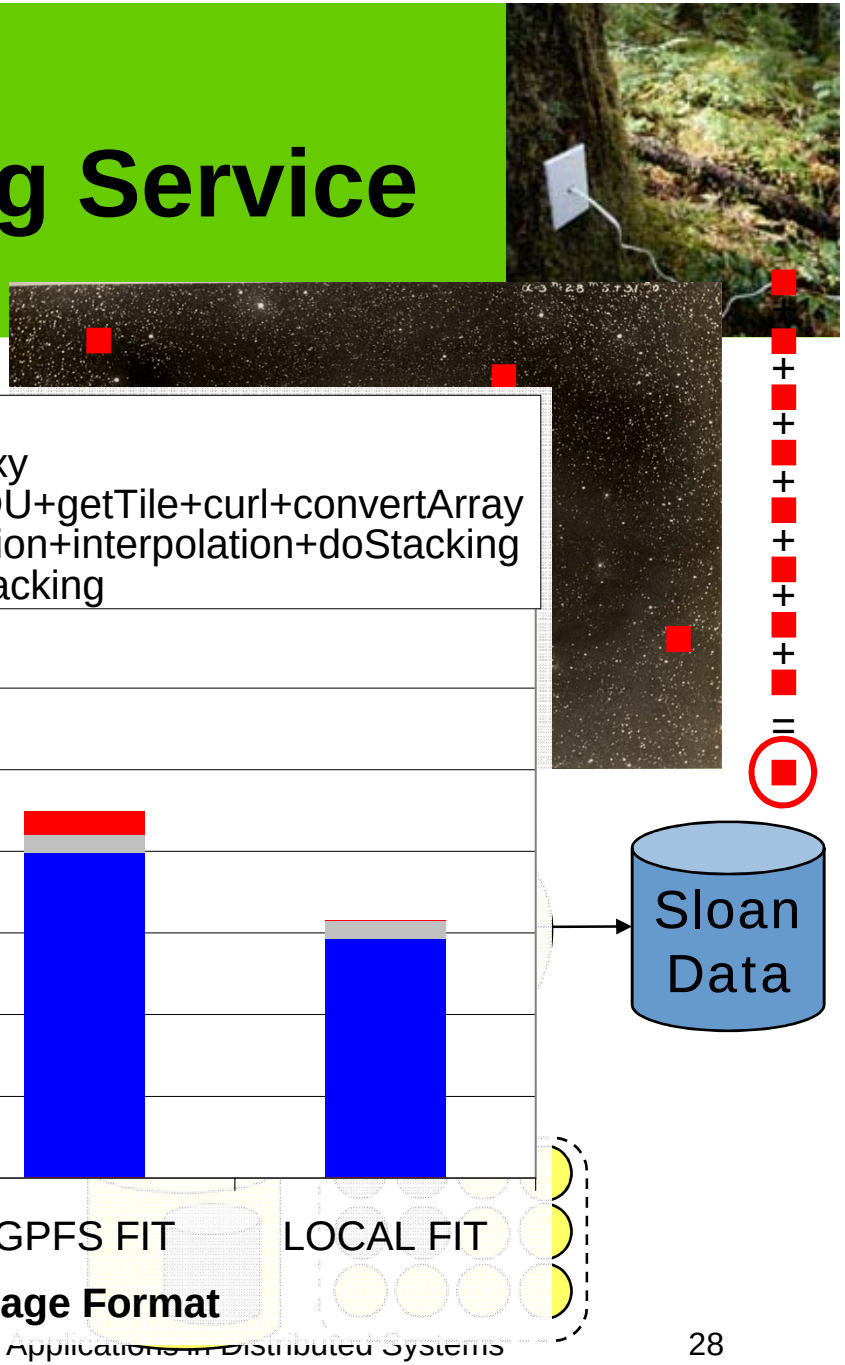
Locality	Number of Objects	Number of Files
1	111700	111700
1.38	154345	111699
2	97999	49000
3	88857	29620
4	76575	19145
5	60590	12120
10	46480	4650
20	40460	2025
30	23695	790



AstroPortal Stacking Service

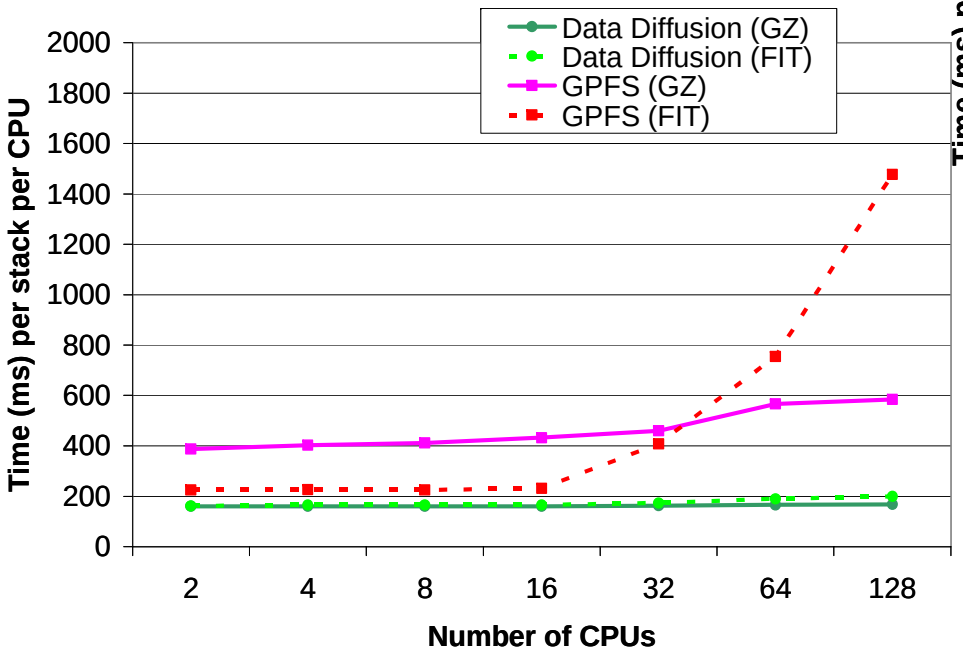
- Purpose
  - On-demand stacks of random locations within the Sloan Data
- Challenge
  - Rapidly read a large number of small files
  - Time-varying load
- Sample workload

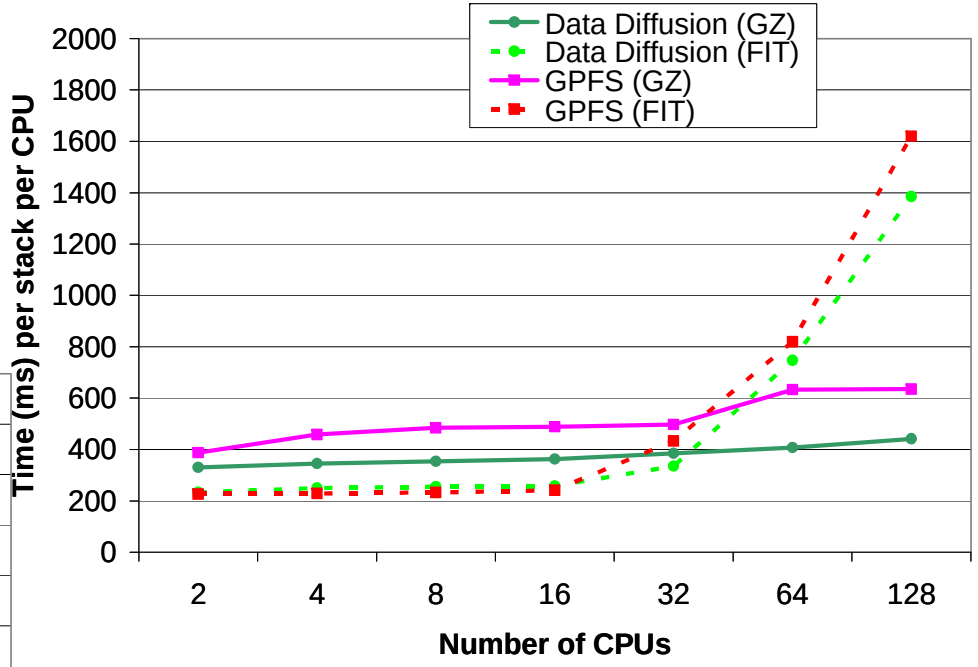
Locality	Number of Files	Size (MB)
1	111700	1746
1.38	154345	2406
2	97999	1529
3	88857	1396
4	76575	1193
5	60590	946
10	46480	4650
20	40460	2025
30	23695	790



AstroPortal Stacking Service with Data Diffusion

Low data locality ➔
- Similar (but better) performance to GPFS

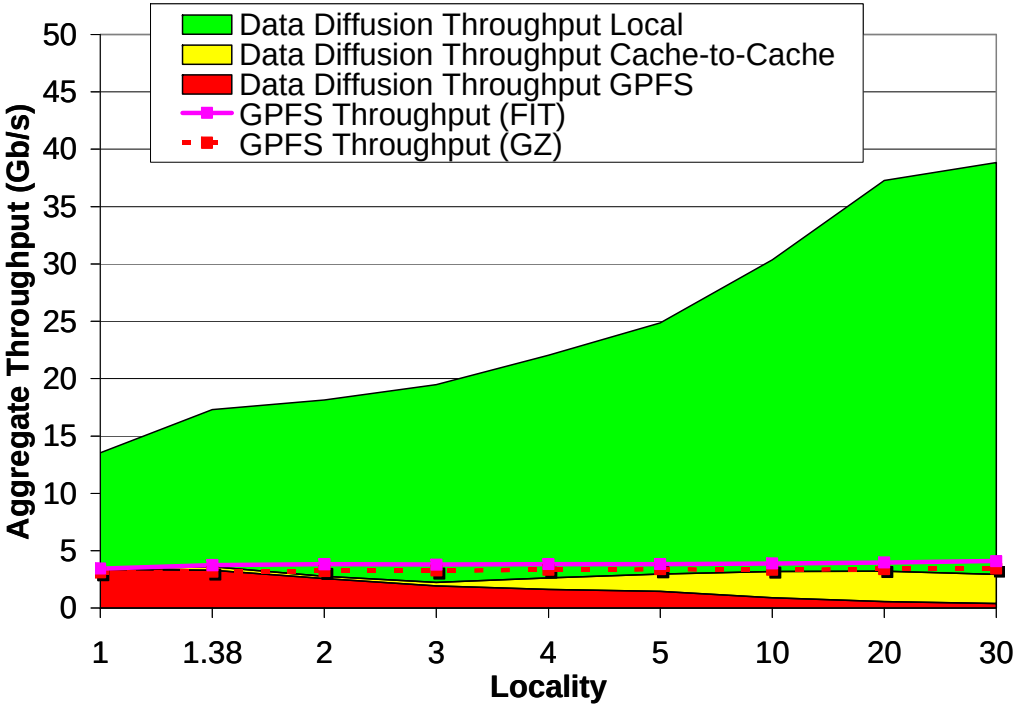


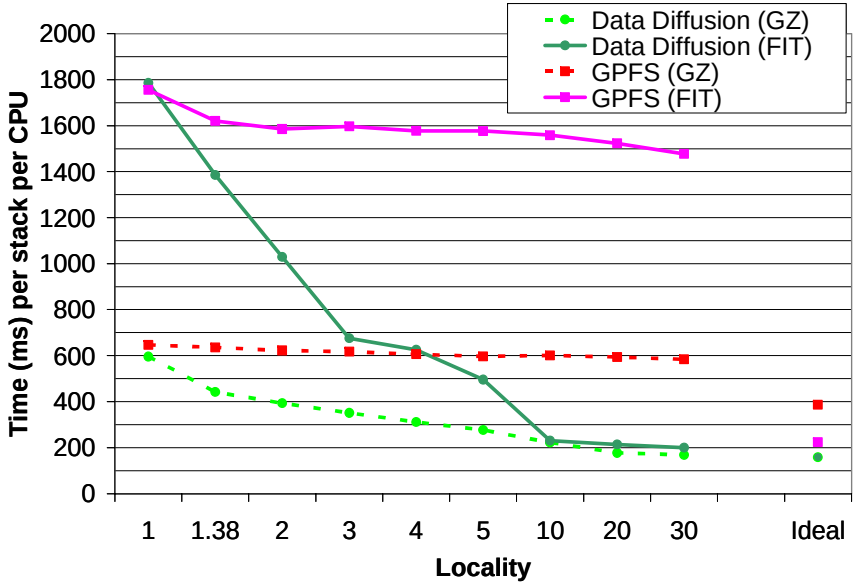


➔High data locality
- Near perfect scalability

AstroPortal Stacking Service with Data Diffusion

- Aggregate throughput:
  - 39Gb/s
  - 10X higher than GPFS
- Reduced load on GPFS
  - 0.49Gb/s
  - 1/10 of the original load

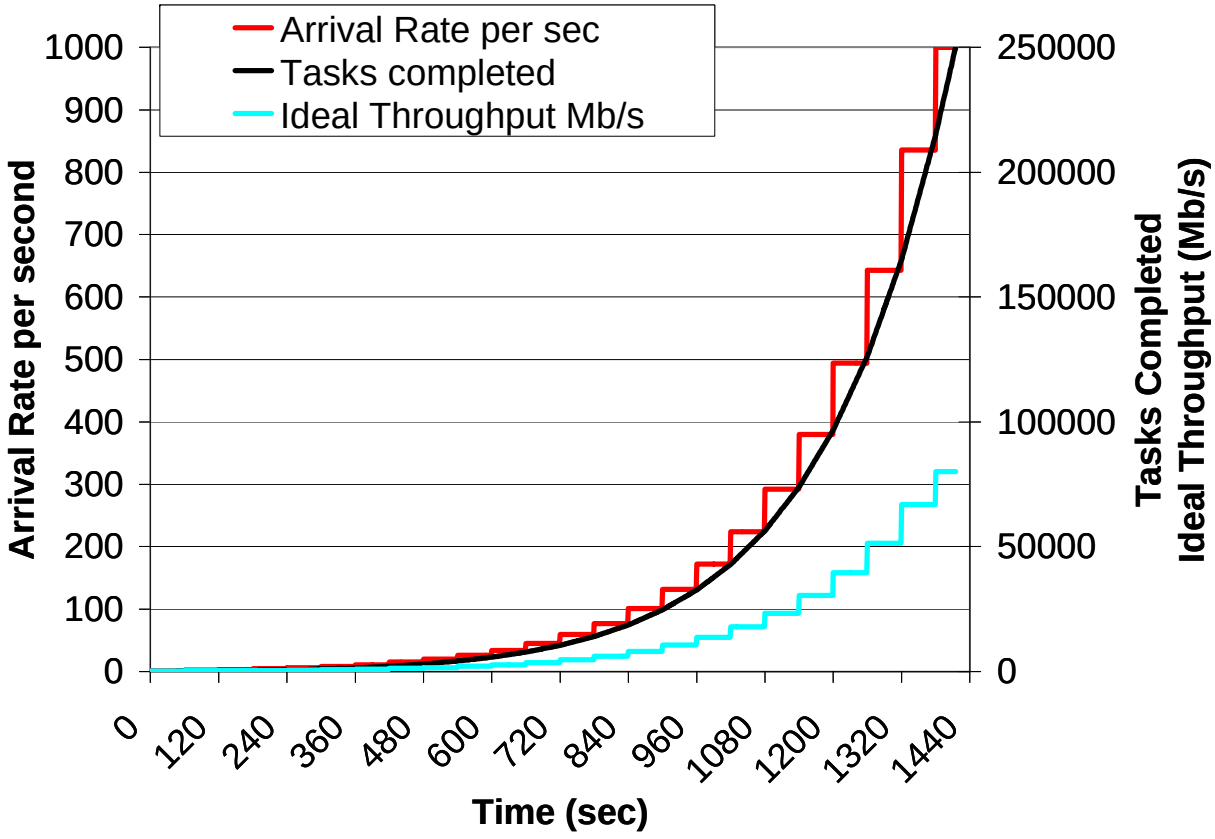




- Big performance gains as locality increases

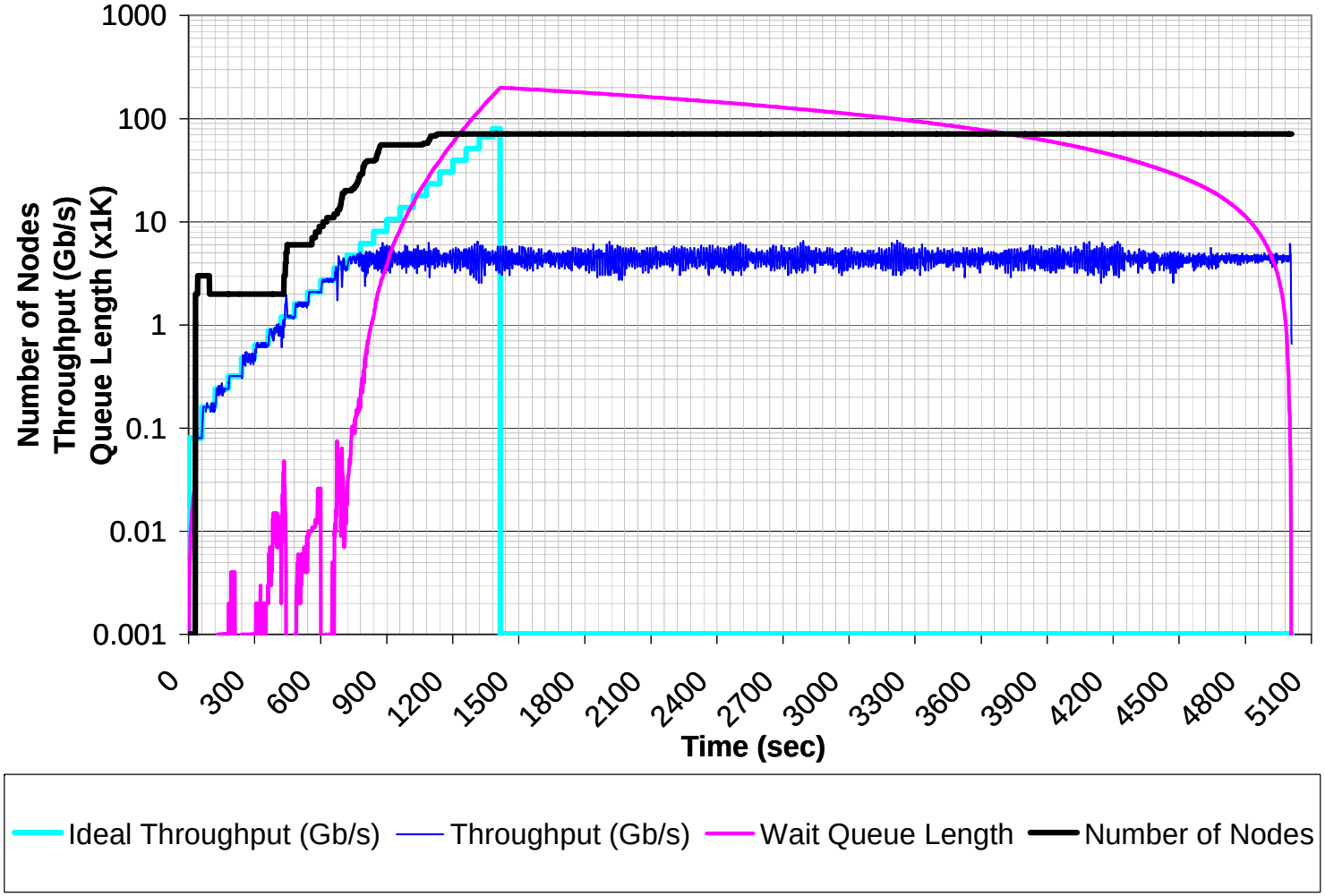
Monotonically Increasing Workload

- 250K tasks
  - 10MB reads
  - 10ms compute
- Vary arrival rate:
  - Min: 1 task/sec
  - Increment function: CEILING(*1.3)
  - Max: 1000 tasks/sec
- 128 processors
- Ideal case:
  - 1415 sec
  - 80Gb/s peak throughput



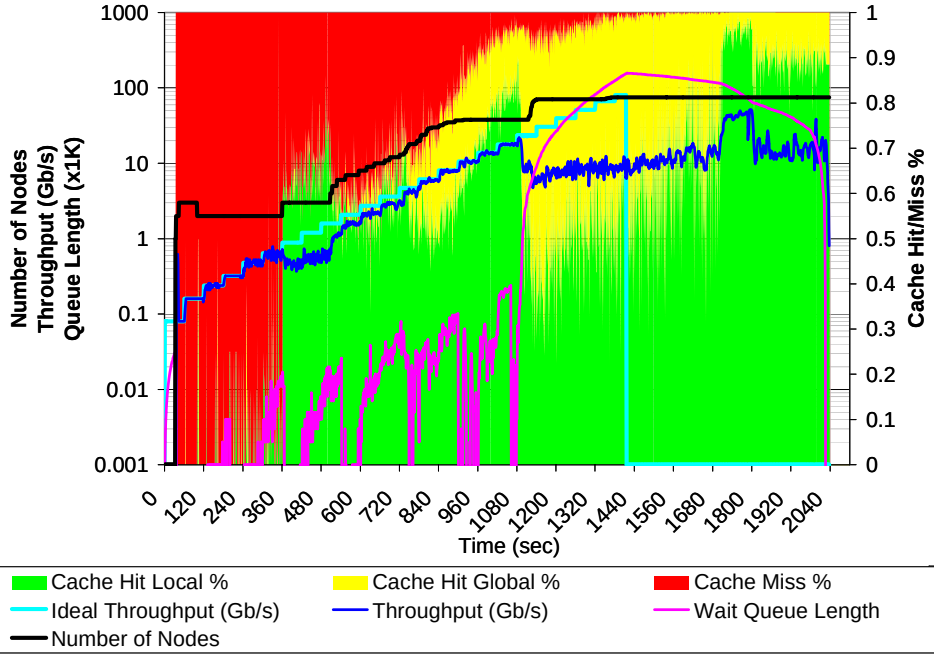
Data Diffusion: First-available (GPFS)

- **GPFS vs. ideal**: 5011 sec vs. 1415 sec

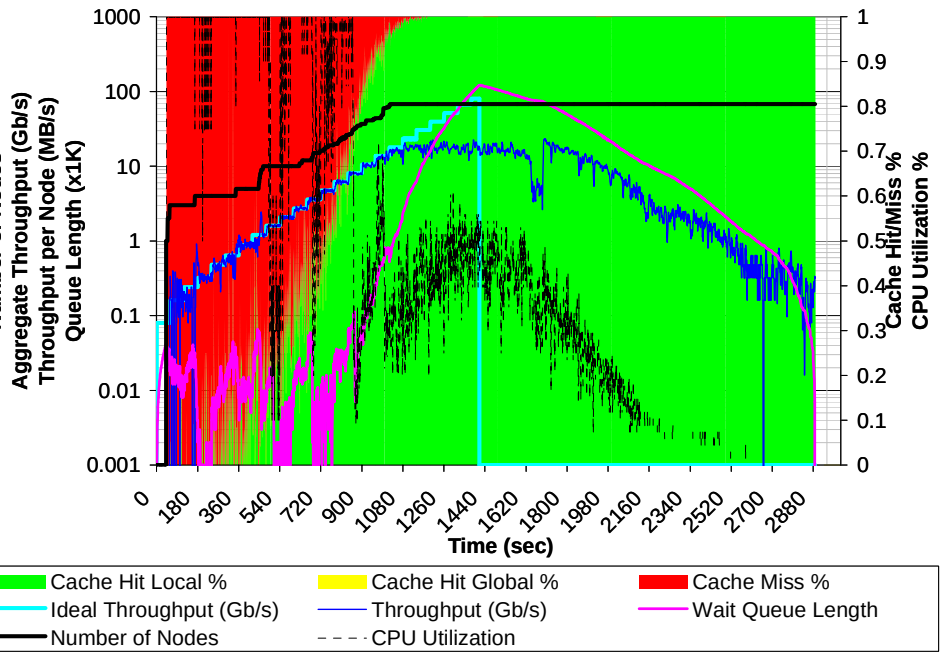


Data Diffusion: Max-compute-util & max-cache-hit

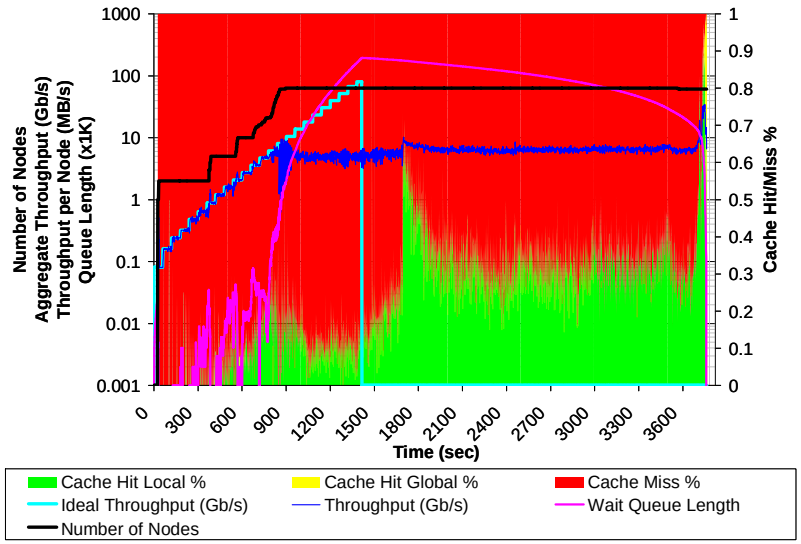
Max-compute-util



Max-cache-hit

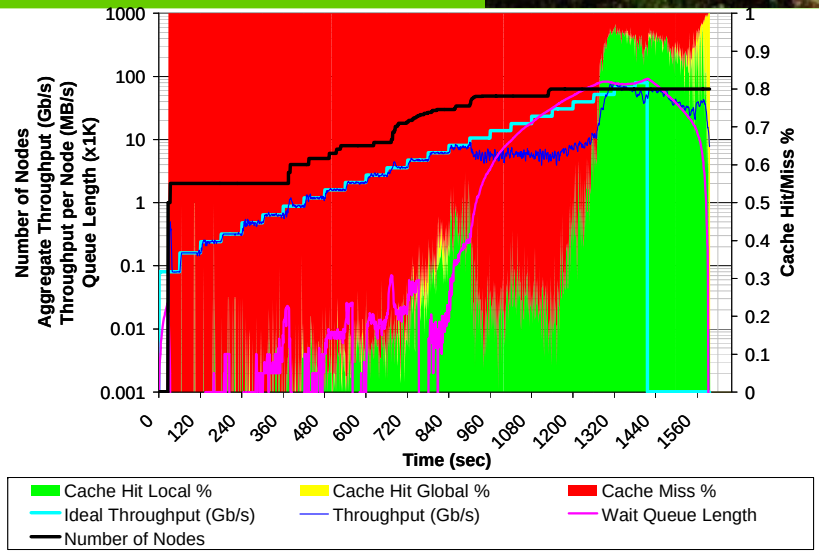


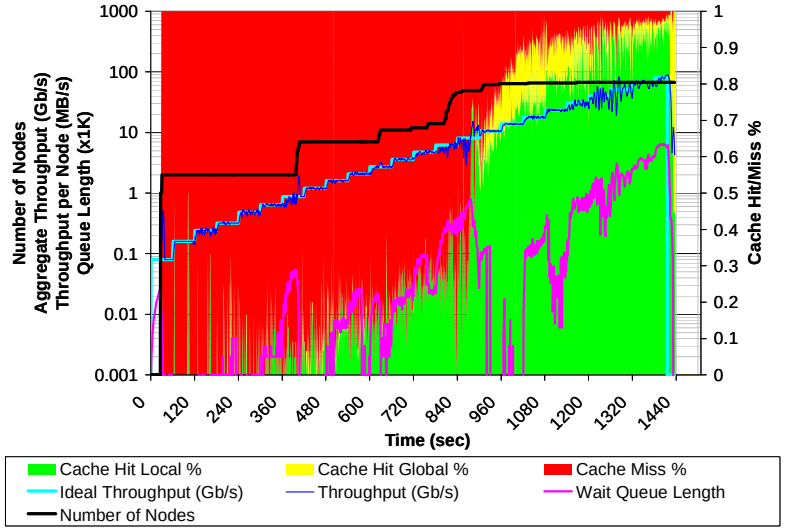
Data Diffusion: Good-cache-compute



← 1GB

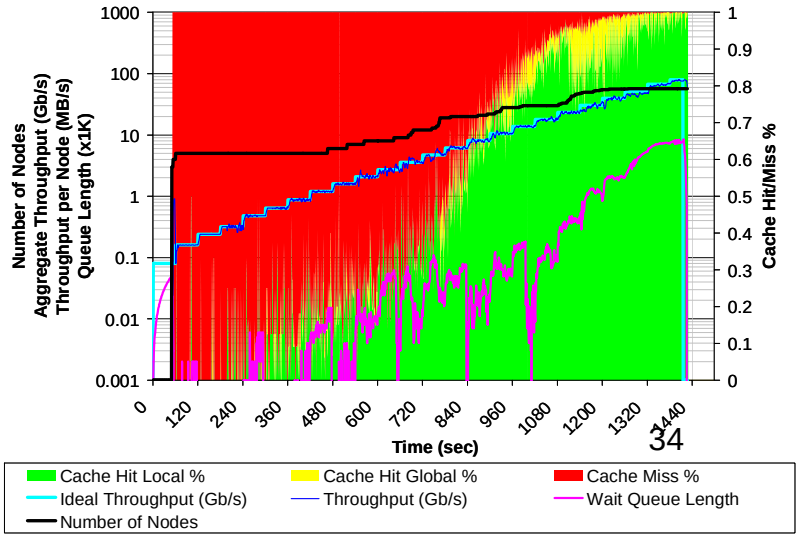
1.5GB →





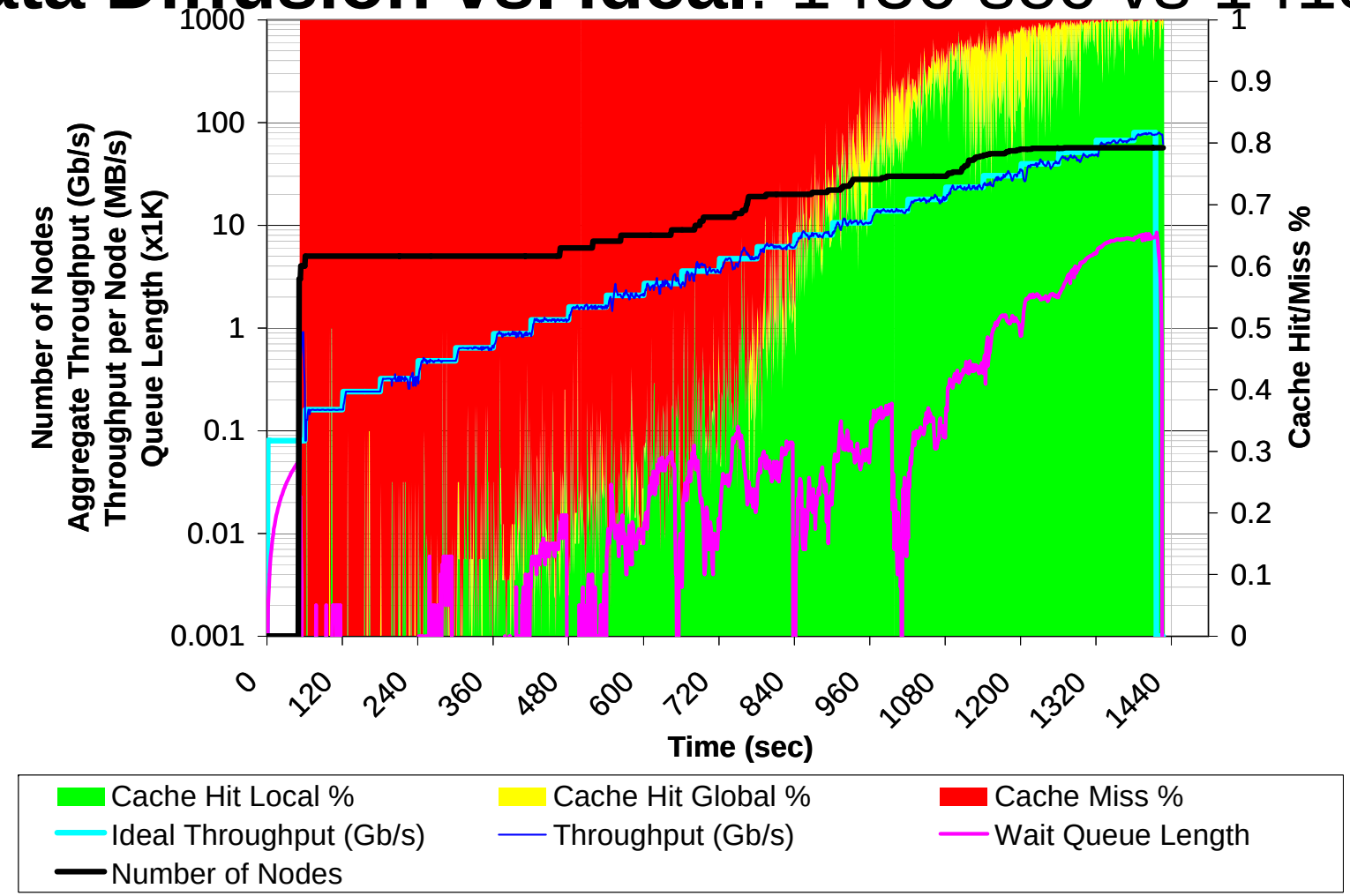
← 2GB

4GB →

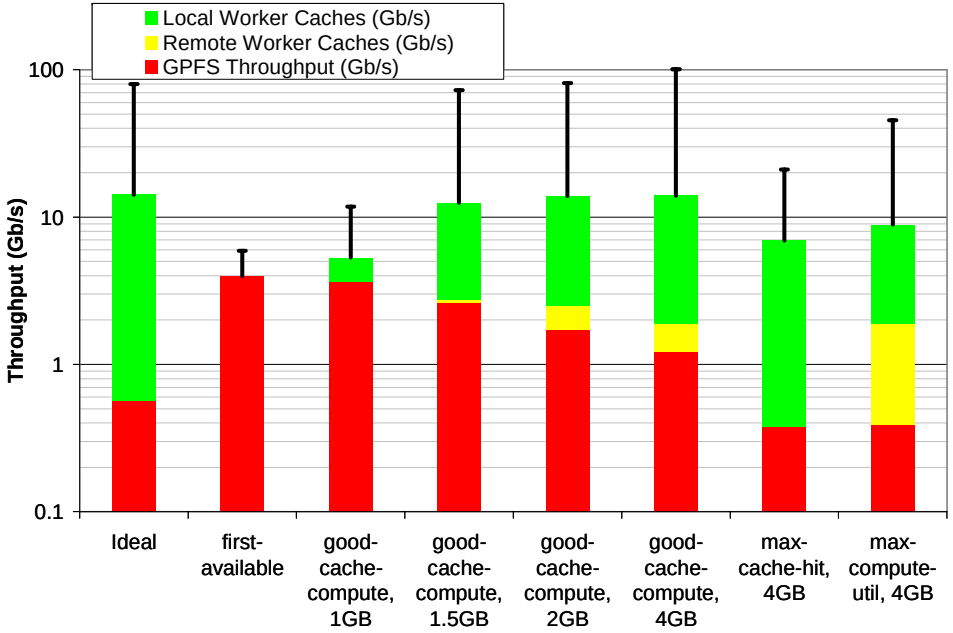


Data Diffusion: Good-cache-compute

- **Data Diffusion vs. ideal**: 1436 sec vs 1415 sec

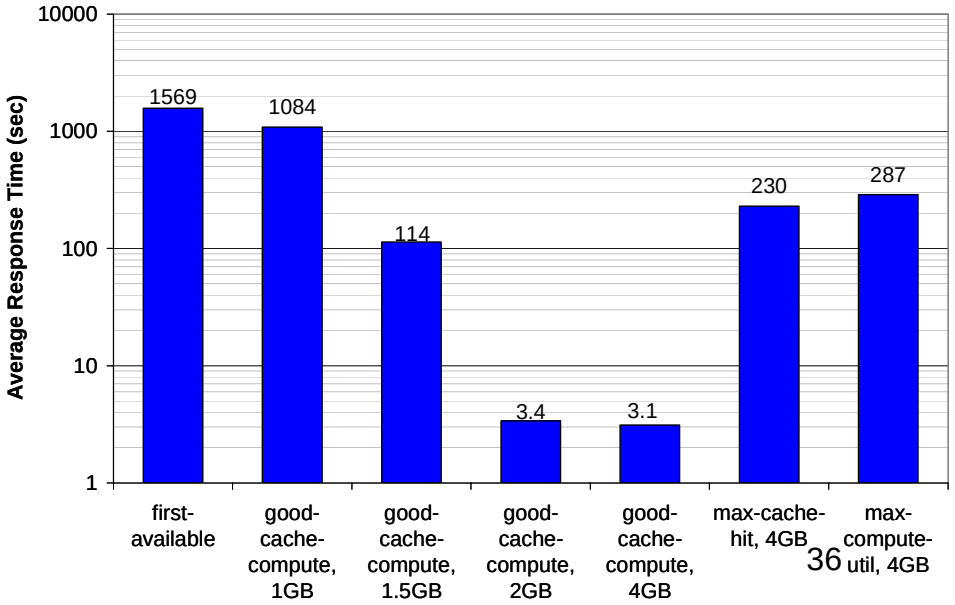


Data Diffusion: Throughput and Response Time



⬅Throughput:

- Average: 14Gb/s vs 4Gb/s
- Peak: 100Gb/s vs. 6Gb/s

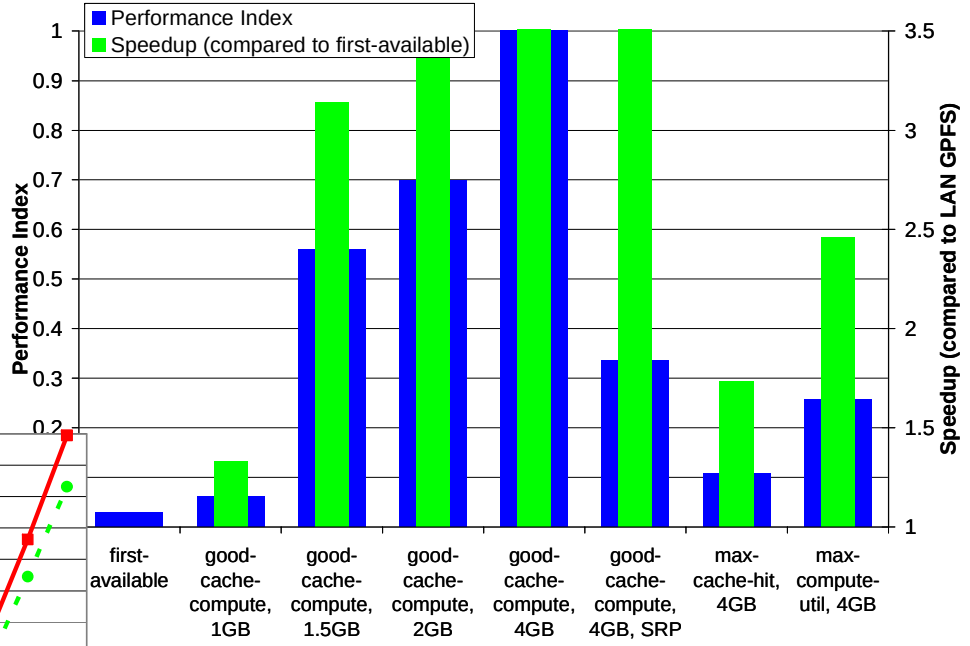


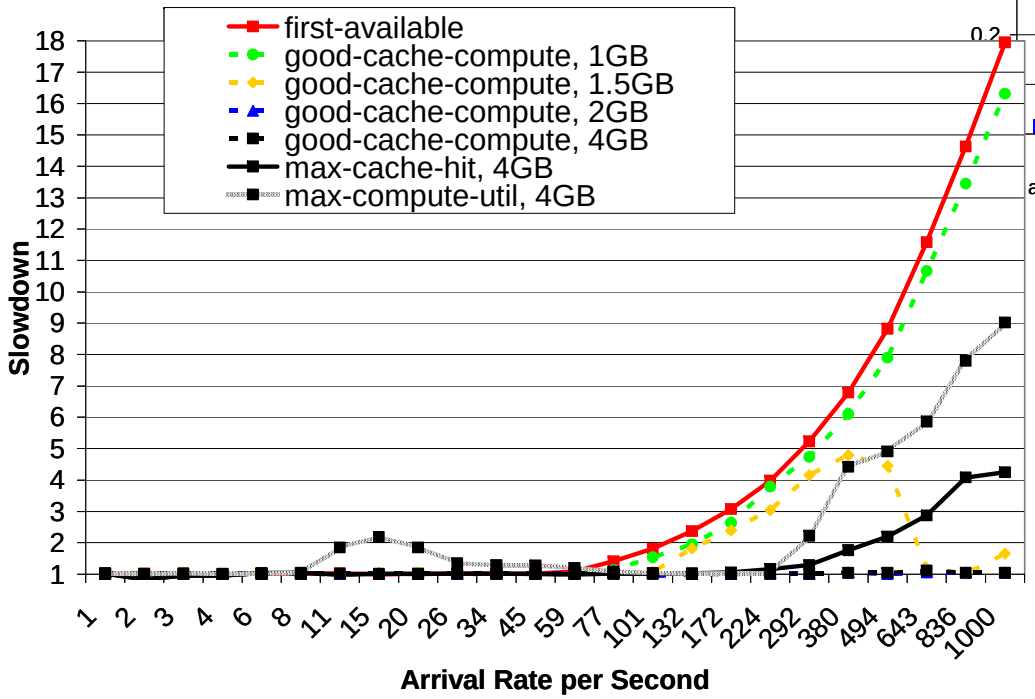
Response Time ➔

- 3 sec vs 1569 sec ➔ 506X

Data Diffusion: Performance Index, Slowdown, and Speedup

- Performance Index:
  - 34X higher
- Speedup
  - 3.5X faster than GPFS



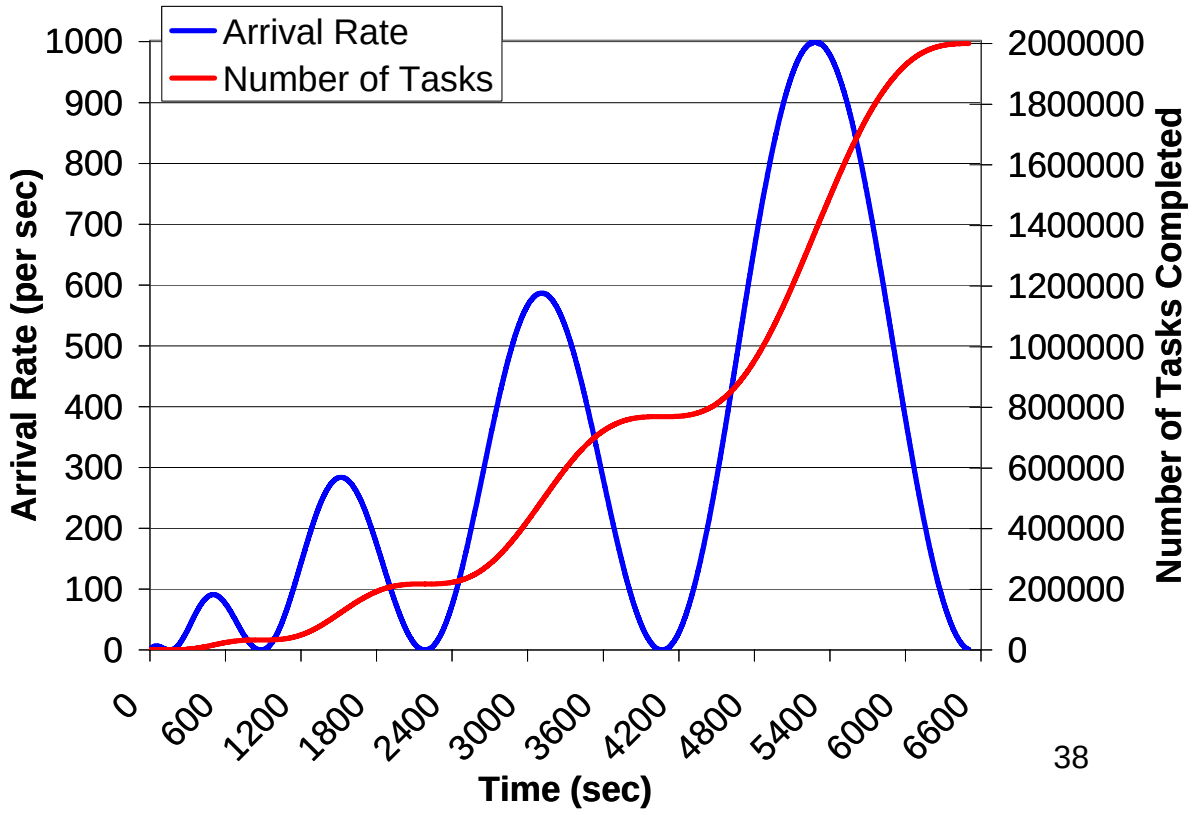


- Slowdown:
  - 18X slowdown for GPFS
  - Near ideal 1X slowdown for large enough caches

Sin-Wave Workload

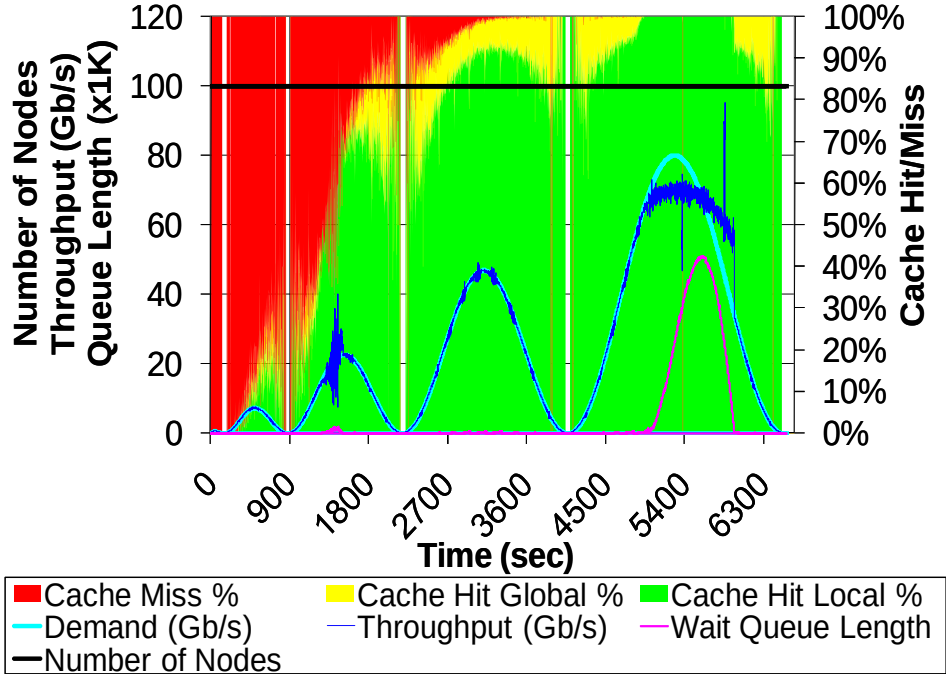
- 2M tasks
  - 10MB reads
  - 10ms compute
- Vary arrival rate:
  - Min: 1 task/sec
  - Arrival rate function:
  - Max: 1000 tasks/sec
- 200 processors
- Ideal case:
  - 6505 sec
  - 80Gb/s peak throughput

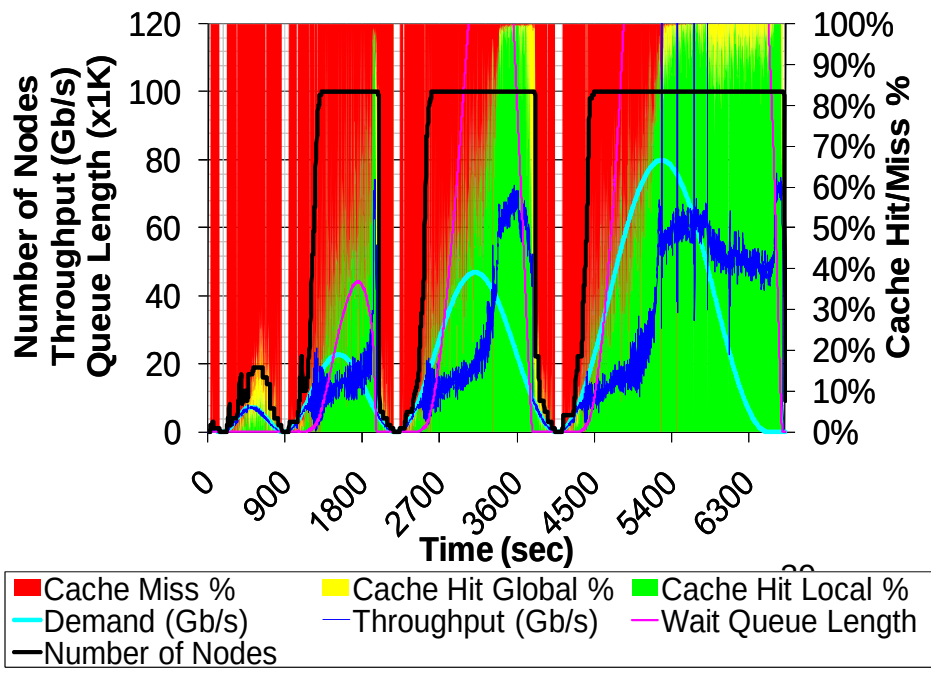
$$A = \lfloor (\sin(sqrt(time + 0.11) * 2.859678) + 1) * (time + 0.11) * 5.705 \rfloor$$



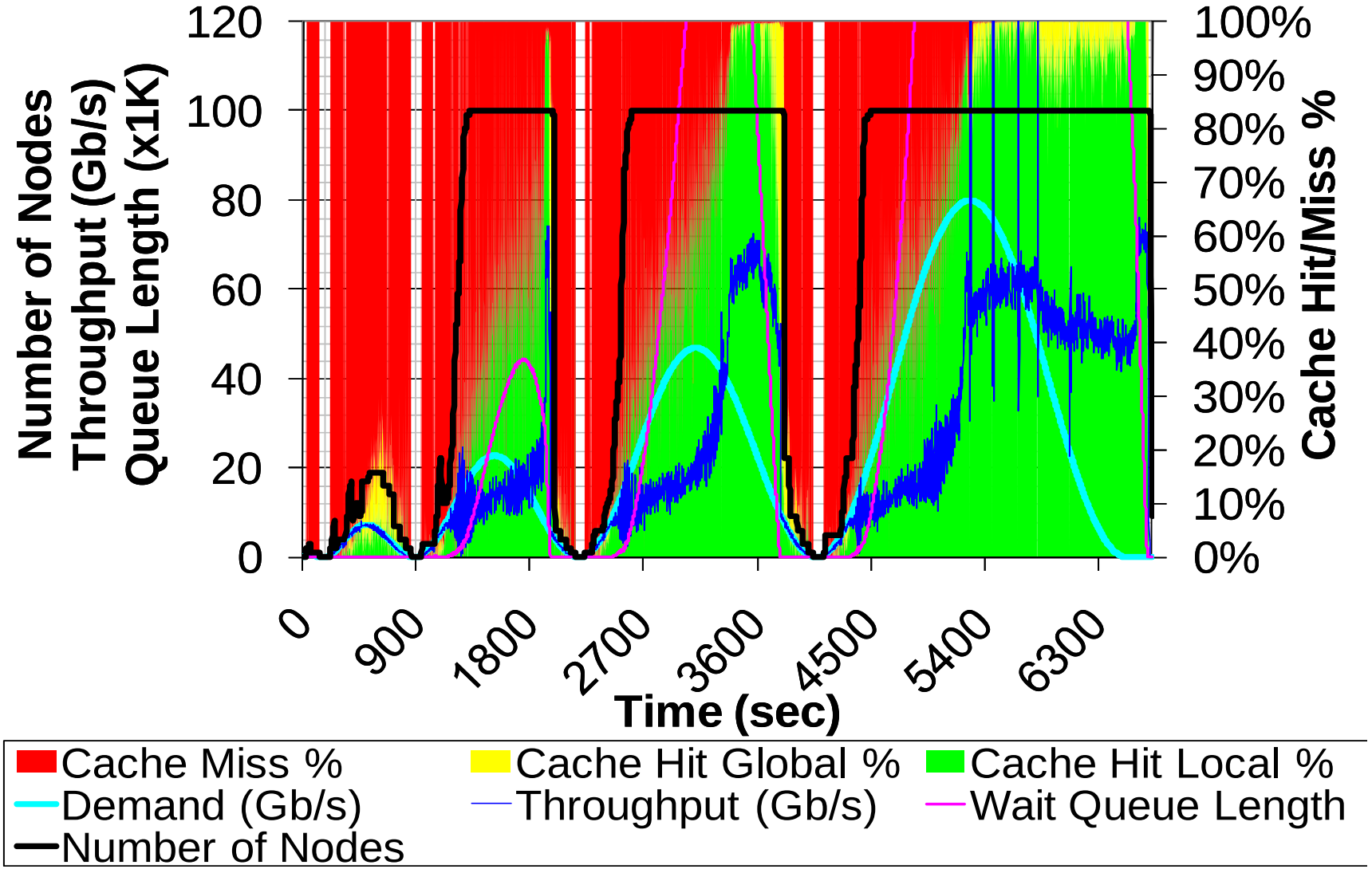
Sin-Wave Workload

- GPFS ➔ 5.7 hrs, ~8Gb/s, 1138 CPU hrs
- DF+SRP ➔ 1.8 hrs, ~25Gb/s, 361 CPU hrs
- DF+DRP ➔ 1.86 hrs, ~24Gb/s, 253 CPU hrs





Sin-Wave Workload



All-Pairs Workload

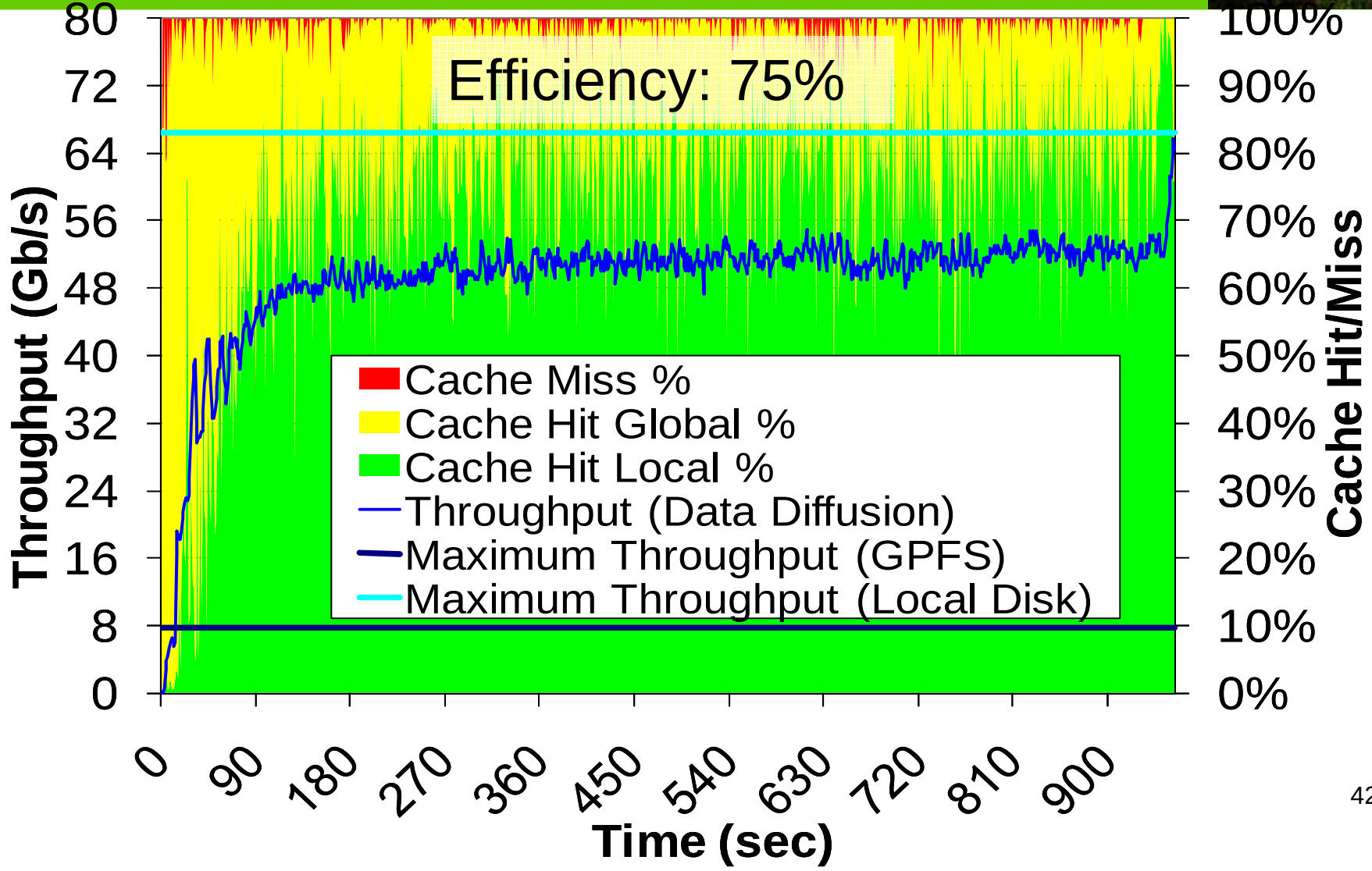
- 500x500
  - 250K tasks
  - 24MB reads
  - 100ms compute
  - 200 CPUs
- 1000x1000
  - 1M tasks
  - 24MB reads
  - 4sec compute
  - 4096 CPUs
- Ideal case:
  - 6505 sec
  - 80Gb/s peak throughput

- All-Pairs(set A, set B, function F) returns matrix M:
- Compare all elements of set A to all elements of set B via function F, yielding matrix M, such that

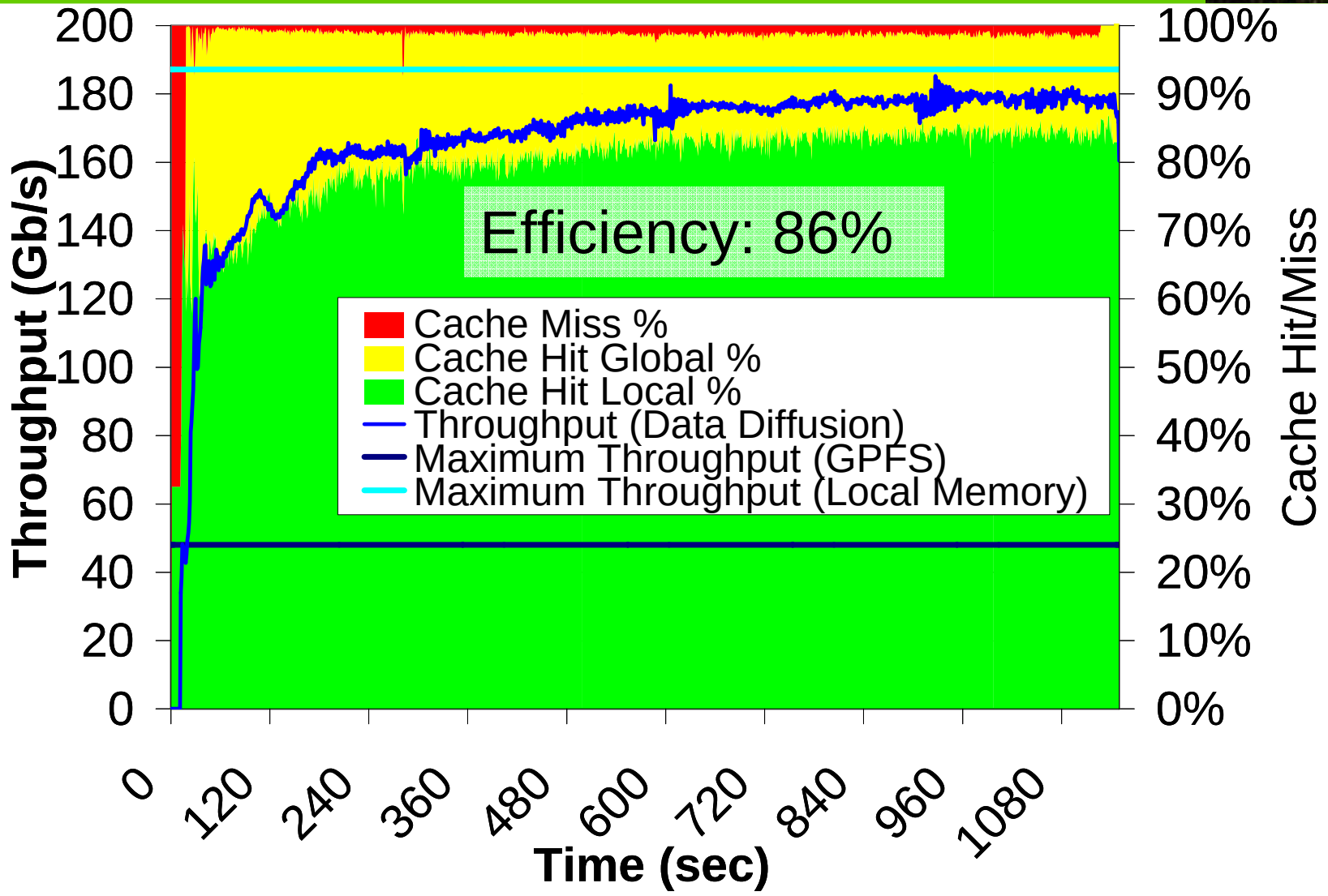
M[i,j] = F(A[i],B[j])

```
1 foreach $i in A
2     foreach $j in B
3         submit_job F $i $j
4     end
5 end
```

All-Pairs Workload 500x500 on 200 CPUs

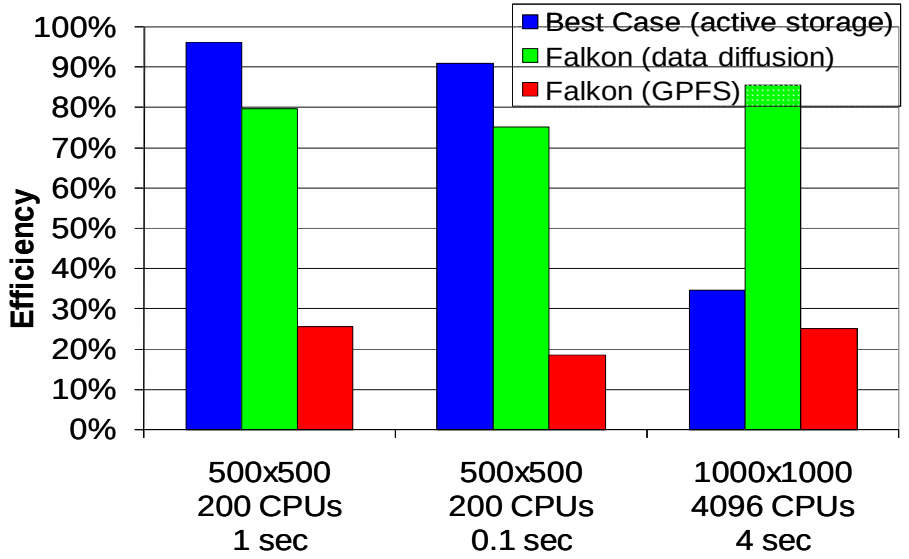


All-Pairs Workload 1000x1000 on 4K emulated CPUs



All-Pairs Workload
Data Diffusion vs. Active Storage

- Push vs. Pull
  - Active Storage:
    - Pushes ***workload*** working set to all nodes
    - Static spanning tree
  - Data Diffusion
    - Pulls ***task*** working set
    - Incremental spanning forest



Experiment	Approach	Local Disk/Memory (GB)	Network (node-to-node) (GB)	Shared File System (GB)
500x500 200 CPUs 1 sec	Best Case (active storage)	6000	1536	12
	Falkon (data diffusion)	6000	1698	34
500x500 200 CPUs 0.1 sec	Best Case (active storage)	6000	1536	12
	Falkon (data diffusion)	6000	1528	62
1000x1000 4096 CPUs 4 sec	Best Case (active storage)	24000	12288	24
	Falkon (data diffusion)	24000	4676	384

All-Pairs Workload
Data Diffusion vs. Active Storage

- Best to use active storage if
  - Slow data source
  - Workload working set fits on local node storage
  - Good aggregate network bandwidth
- Best to use data diffusion if
  - Medium to fast data source
  - Task working set << workload working set
  - Task working set fits on local node storage
  - Good aggregate network bandwidth
- If task working set does not fit on local node storage
  - Use parallel file system (i.e. GPFS, Lustre, PVFS, etc)

Limitations of Data Diffusion

- Needs Java 1.4+
- Needs IP connectivity between hosts
- Needs local storage (disk, memory, etc)
- Per task workings set must fit in local storage
- Task definition must include input/output files metadata
- Data access patterns: write once, read many

Related Work: Data Management

- [*Beynon01*]: **DataCutter**
- [*Ranganathan03*]: **Simulations**
- [*Ghemawat03,Dean04,Chang06*]: **BigTable**, **GFS**, **MapReduce**
- [*Liu04*]: **GridDB**
- [*Chervenak04,Chervenak06*]: **RLS** (Replica Location Service), **DRS** (Data Replication Service)
- [*Tatebe04,Xiaohui05*]: **GFarm**
- [*Branco04,Adams06*]: **DIAL/ATLAS**
- [*Kosar06*]: **Stork**
- [*Thain08*]: **Chirp/Parrot**

Conclusion: None focused on the co-location of storage and generic black box computations with data-aware scheduling while operating in a dynamic environment

Scaling from 1K to 100K CPUs without Data Diffusion

- At 1K CPUs:
  - 1 Server to manage all 1K CPUs
  - Use shared file system extensively
    - Invoke application from shared file system
    - Read/write data from/to shared file system
- At 100K CPUs:
  - N Servers to manage 100K CPUs (1:256 ratio)
  - Don’t trust the application I/O access patterns to behave optimally
    - Copy applications and input data to RAM
    - Read input data from RAM, compute, and write results to RAM
    - Archive all results in a single file in RAM
    - Copy 1 result file from RAM back to GPFS
- Great potential for improvements
  - Could leverage the Torus network for high aggregate bandwidth
  - Collective I/O (CIO) Primitives
  - Roadblocks: machine global IP connectivity, Java support, and time

Mythbusting

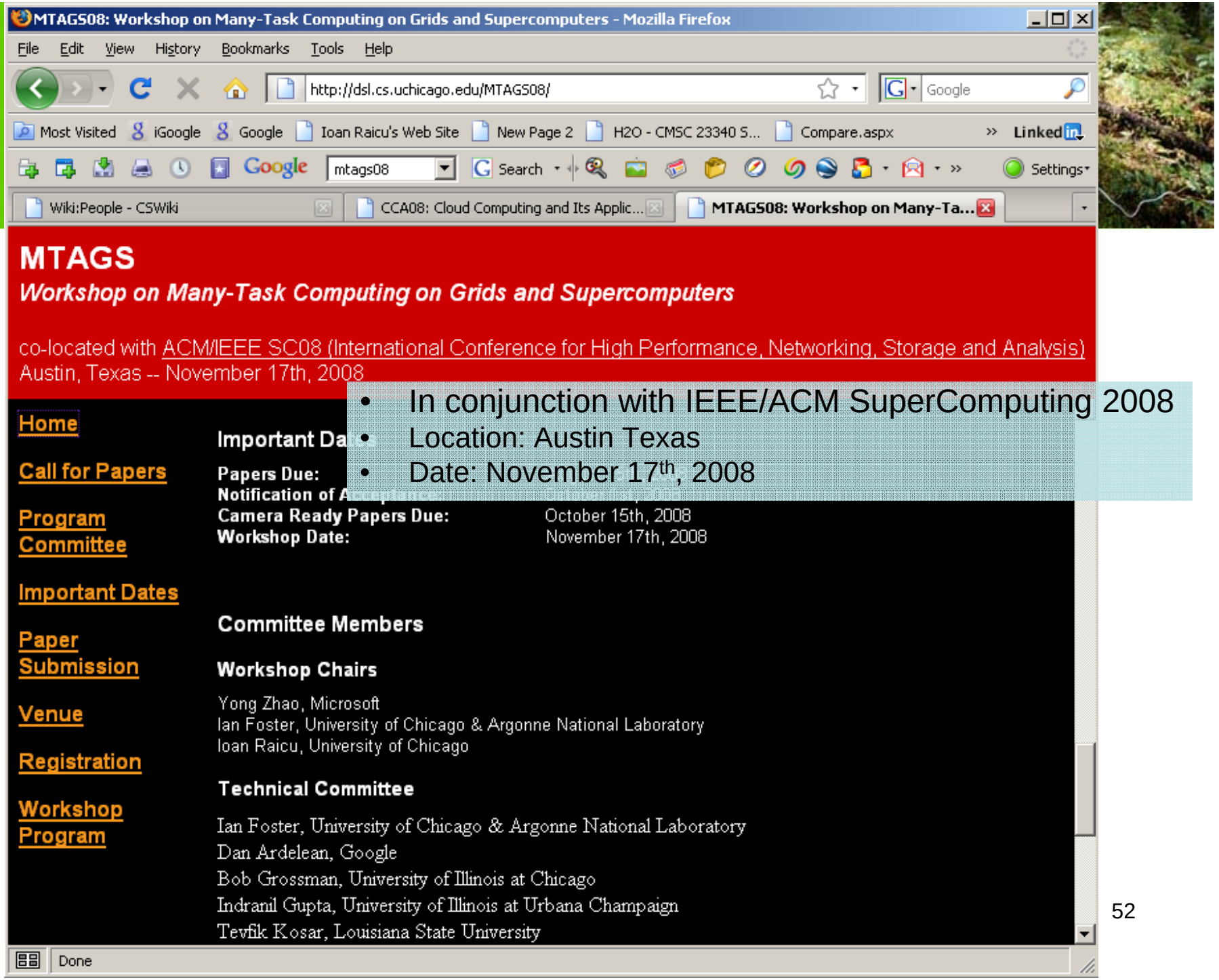
- ~~Embarrassingly~~ Happily parallel apps are trivial to run
  - Logistical problems can be tremendous
- Loosely coupled apps do not require “supercomputers”
  - Total computational requirements can be enormous
  - Individual tasks may be tightly coupled
  - Workloads frequently involve large amounts of I/O
  - Make use of idle resources from “supercomputers” via backfilling
  - Costs to run “supercomputers” per FLOP is among the best
    - BG/P: 0.35 gigaflops/watt **(higher is better)**
    - SiCortex: 0.32 gigaflops/watt
    - BG/L: 0.23 gigaflops/watt
    - x86-based HPC systems: an order of magnitude lower
- Loosely coupled apps do not require specialized system software
- Shared file systems are good for all applications
  - They don’t scale proportionally with the compute resources
  - Data intensive applications don’t perform and scale well

Conclusions & Contributions

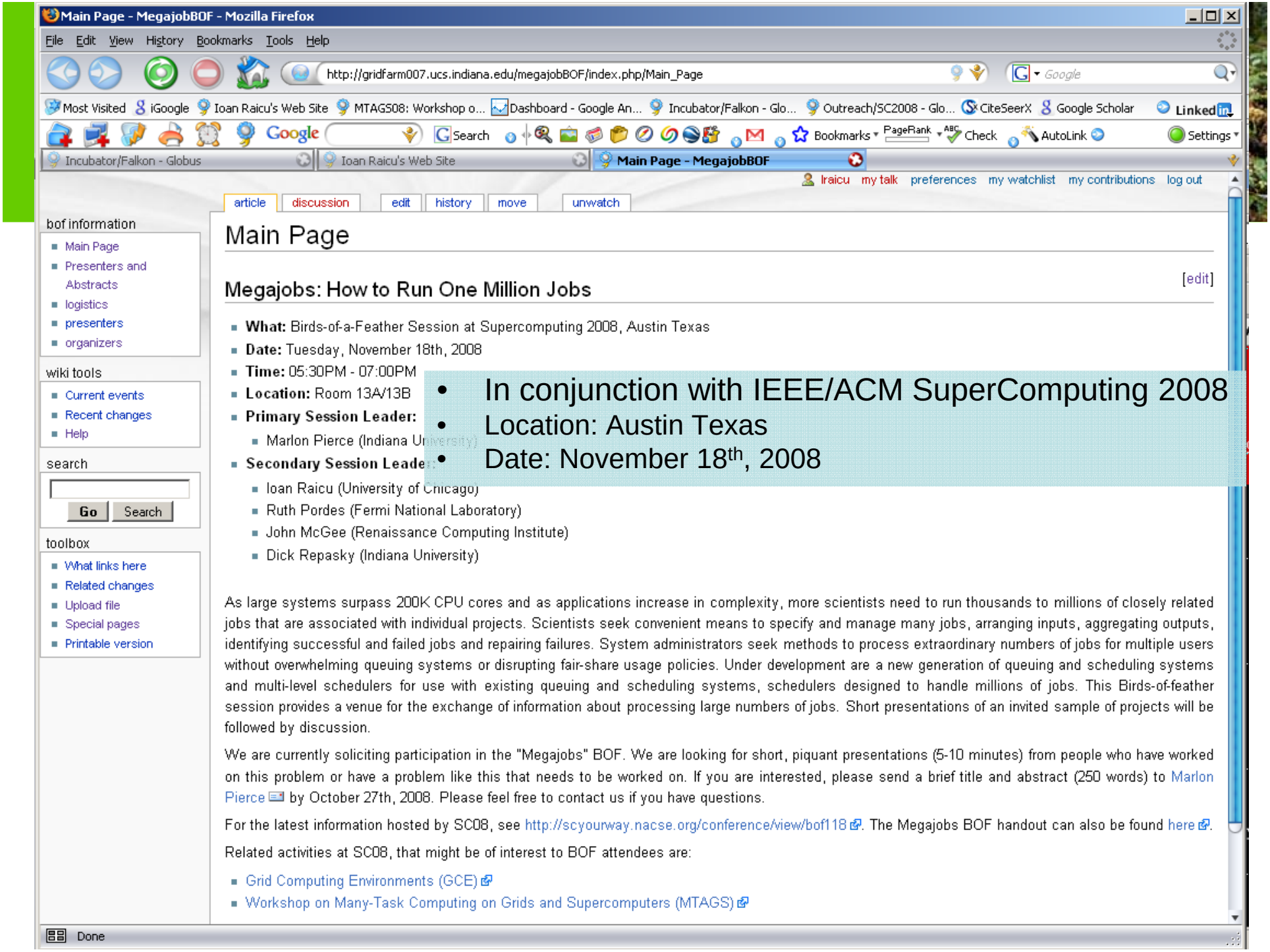
- Defined an *abstract model for performance efficiency of data analysis workloads* using data-centric task farms
- Provide a reference implementation (Falkon)
  - Use a streamlined dispatcher to increase task throughput by several orders of magnitude over traditional LRMs
  - Use multi-level scheduling to reduce perceived wait queue time for tasks to execute on remote resources
  - Address data diffusion through co-scheduling of storage and computational resources to improve performance and scalability
  - Provide the benefits of dedicated hardware without the associated high cost
  - Show effectiveness of data diffusion:
    - real large-scale astronomy application and a variety of synthetic workloads

More Information

- More information: http://people.cs.uchicago.edu/~iraicu/
- Related Projects:
  - Falkon:
    - http://dev.globus.org/wiki/Incubator/Falkon
  - AstroPortal:
    - http://people.cs.uchicago.edu/~iraicu/projects/Falkon/astro_portal.htm
  - Swift:
    - http://www.ci.uchicago.edu/swift/index.php
- Funding:
  - NASA: Ames Research Center, Graduate Student Research Program (GSRP)
  - DOE: Mathematical, Information, and Computational Sciences Division subprogram of the Office of Advanced Scientific Computing Research, Office of Science, U.S. Dept. of Energy
  - NSF: TeraGrid



- In conjunction with IEEE/ACM SuperComputing 2008
- Location: Austin Texas
- Date: November 17th, 2008



- In conjunction with IEEE/ACM SuperComputing 2008
- Location: Austin Texas
- Date: November 18th, 2008