Making Sense of Performance in Data Analytics Frameworks

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Joint work with Ryan Rasti, Sylvia Ratnasamy, Scott Shenker, Byung-Gon Chun

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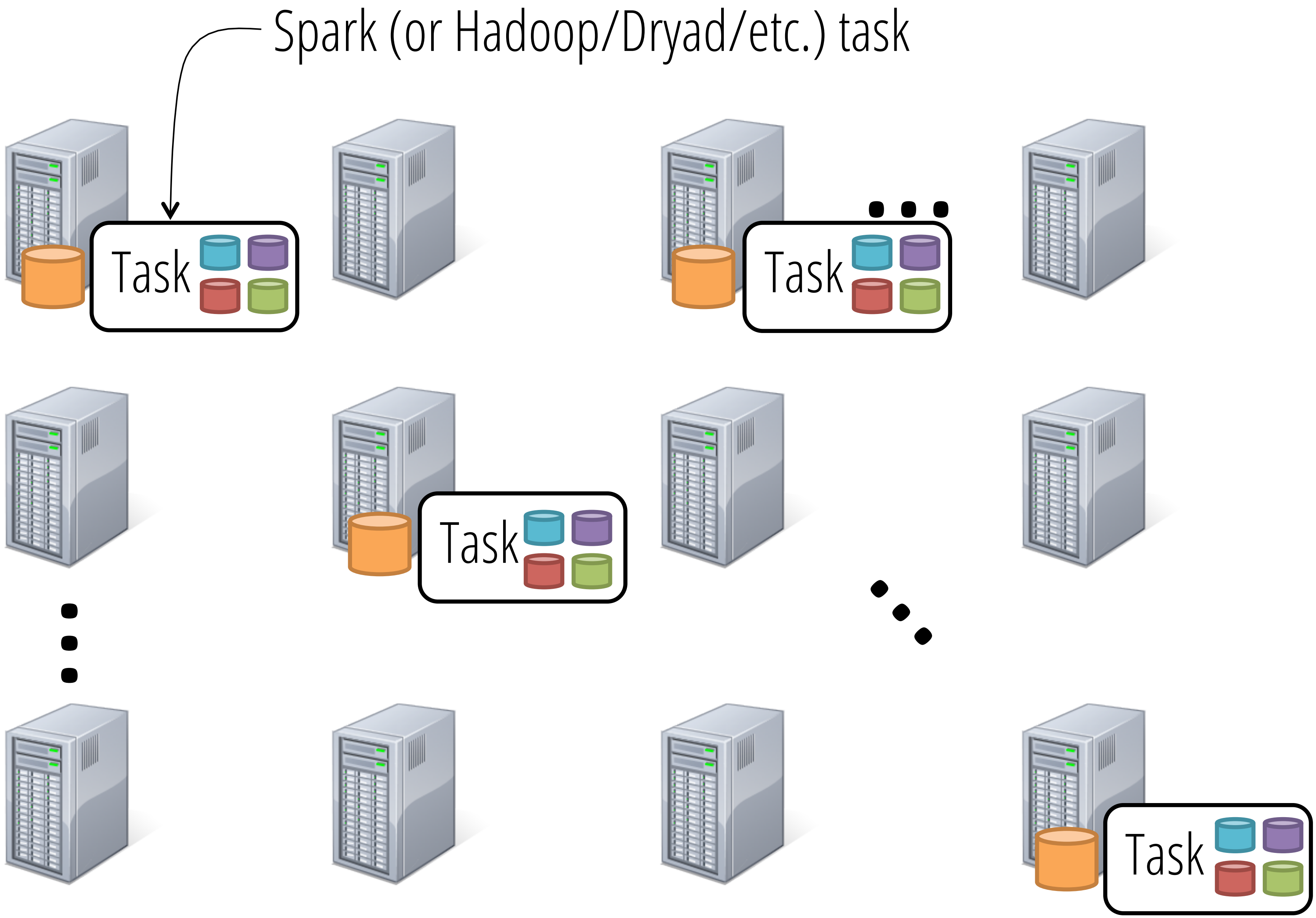
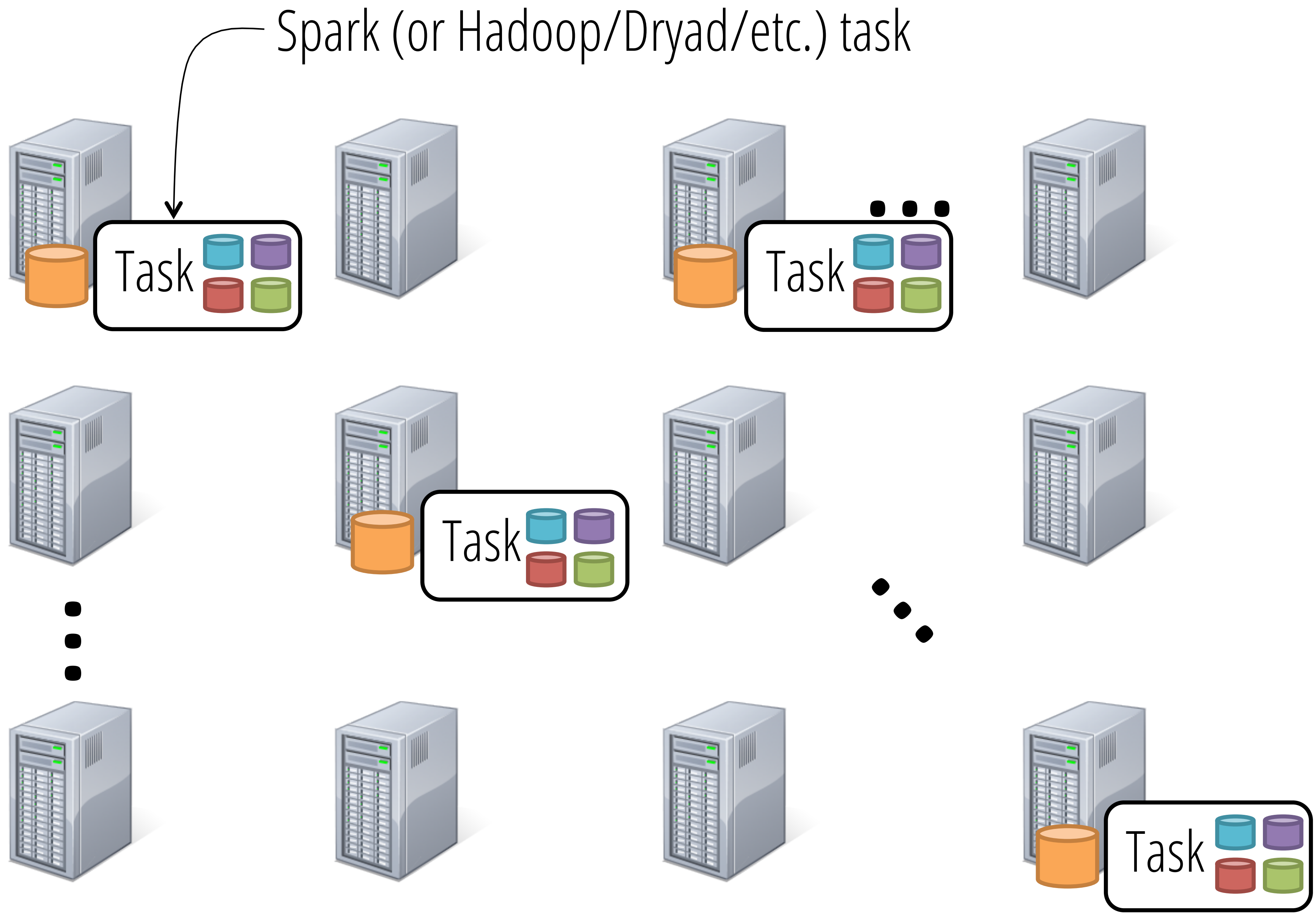
About Me

PhD student at UC Berkeley

Thesis work centers around performance of large-scale distributed systems

Spark PMC member


Spark (or Hadoop/Dryad/etc.) task
Task
Task
Task
Task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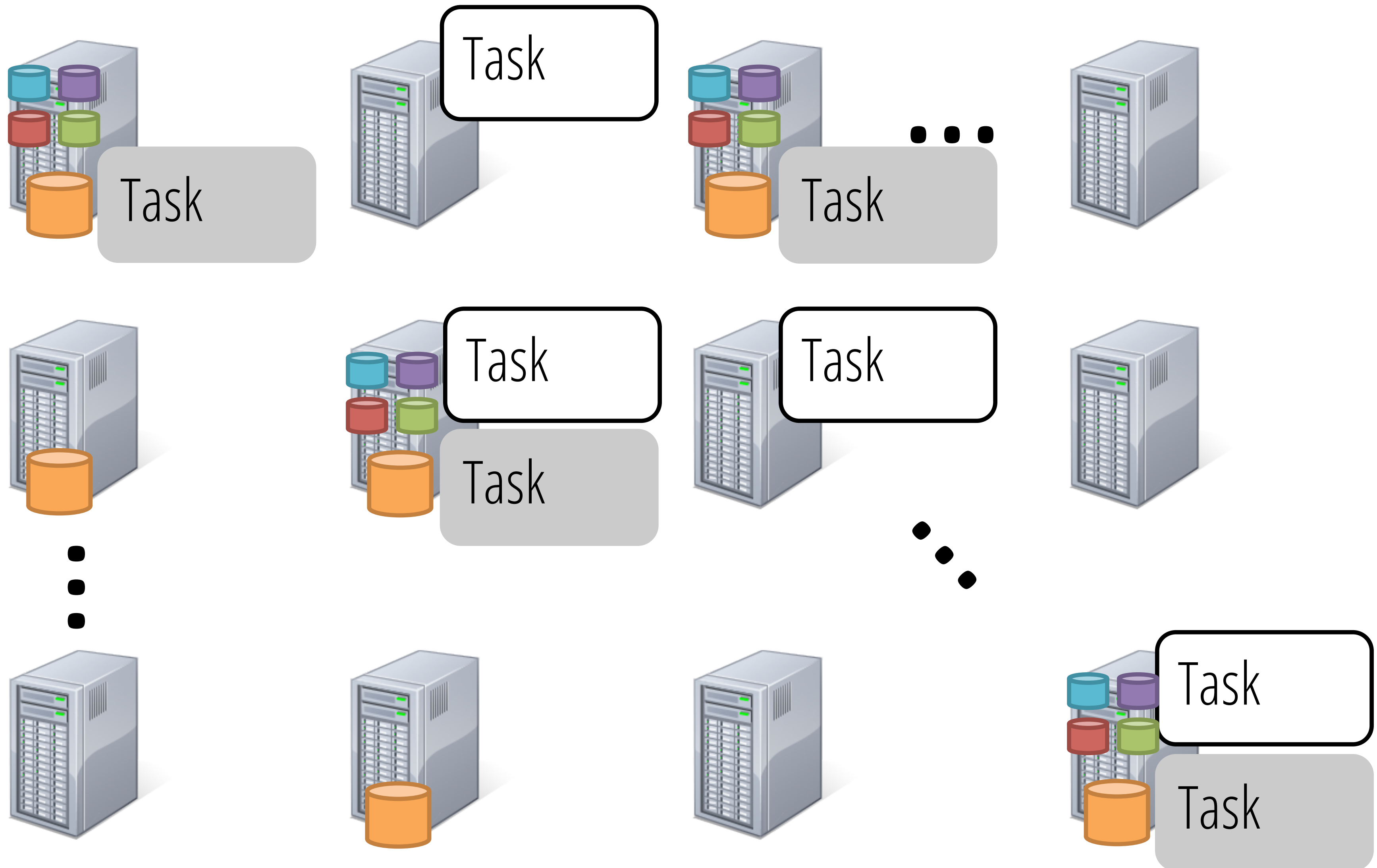
Task
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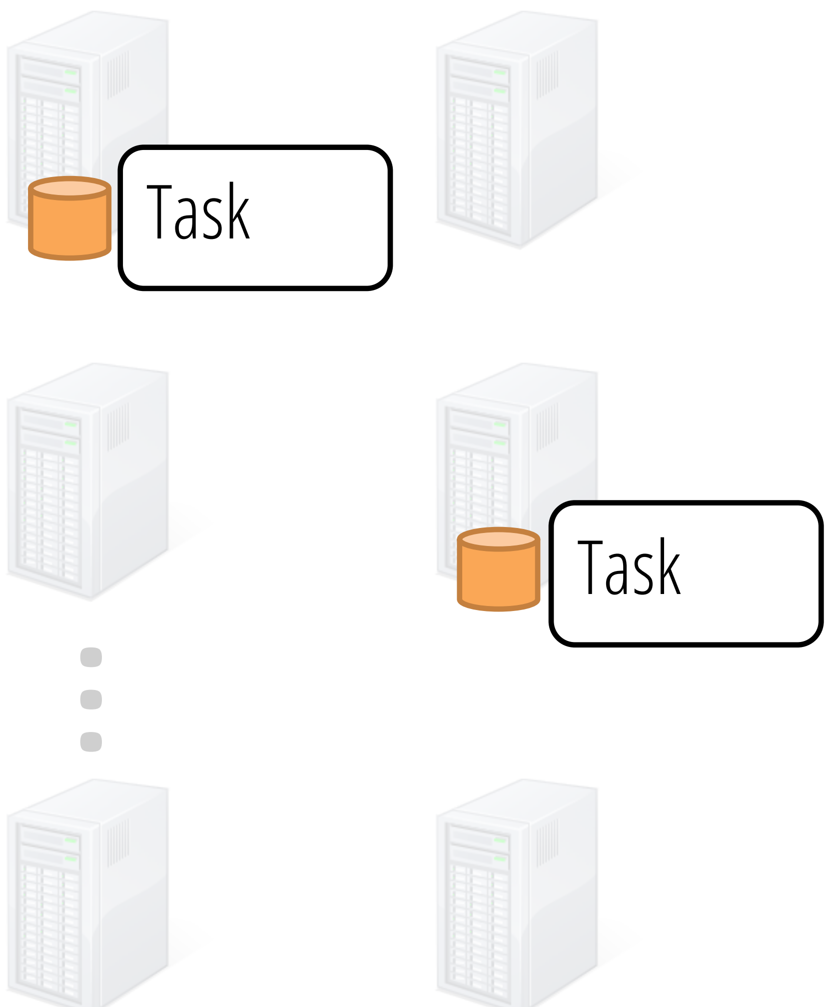
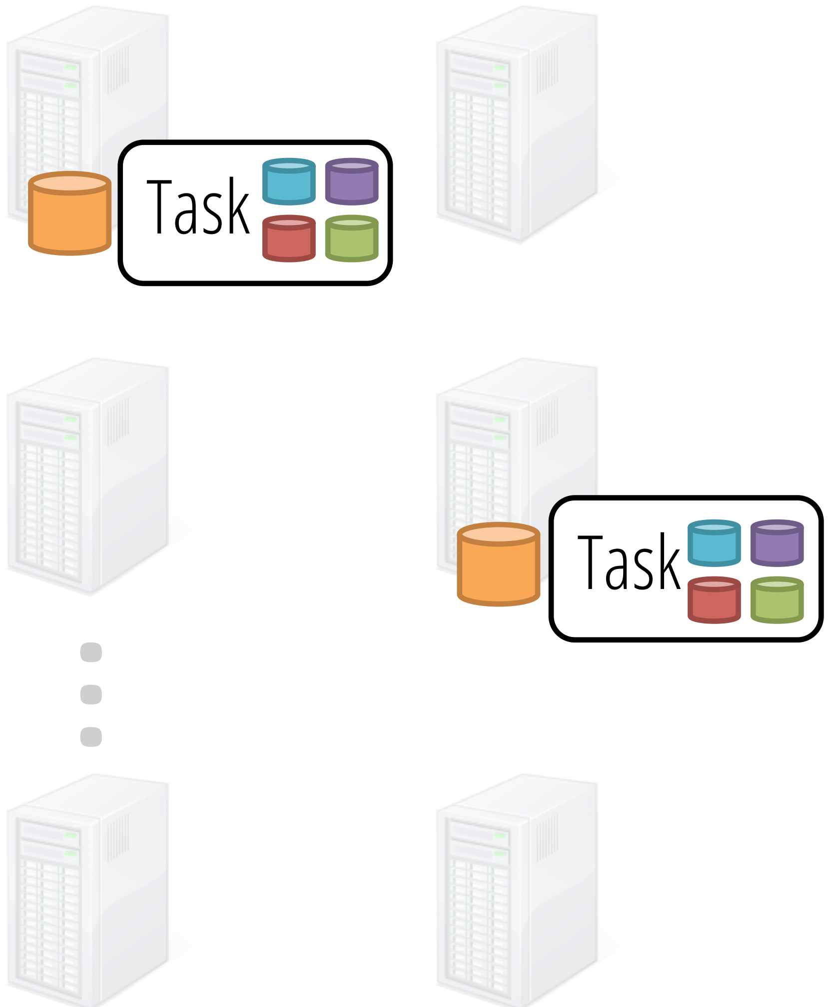
How can we make this job faster?



Cache input data in memory

How can we make this job faster?



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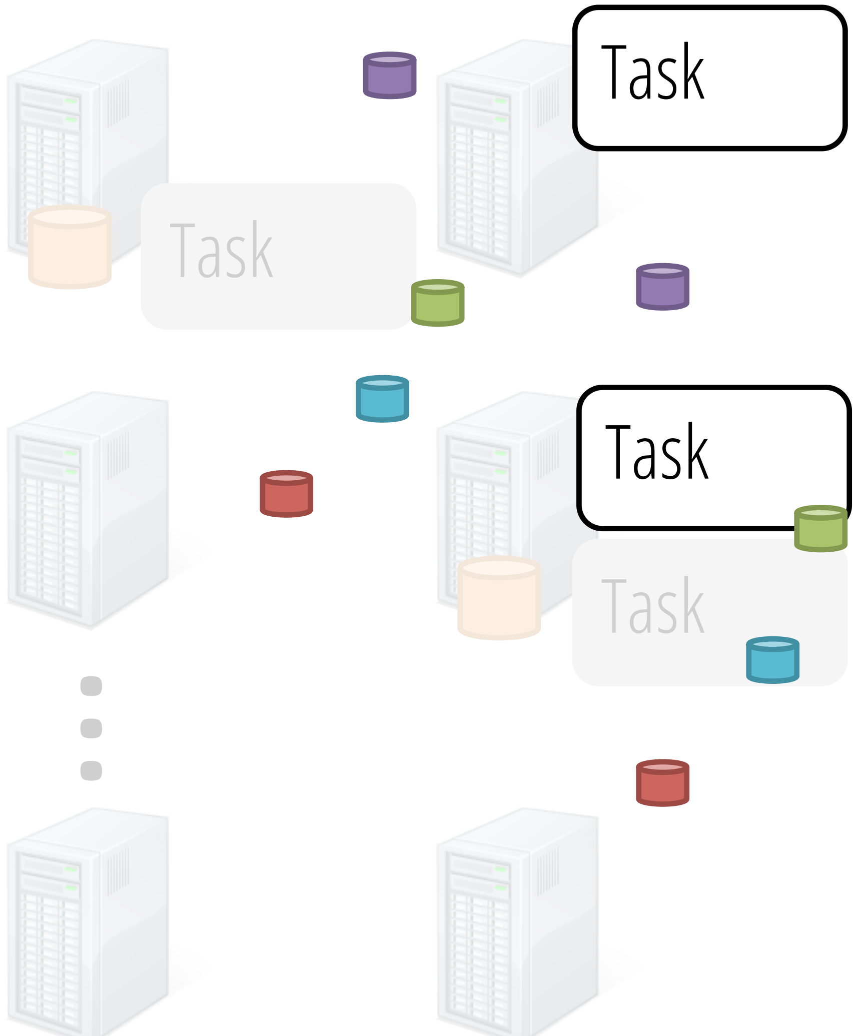

Cache input data in memory

Optimize the network

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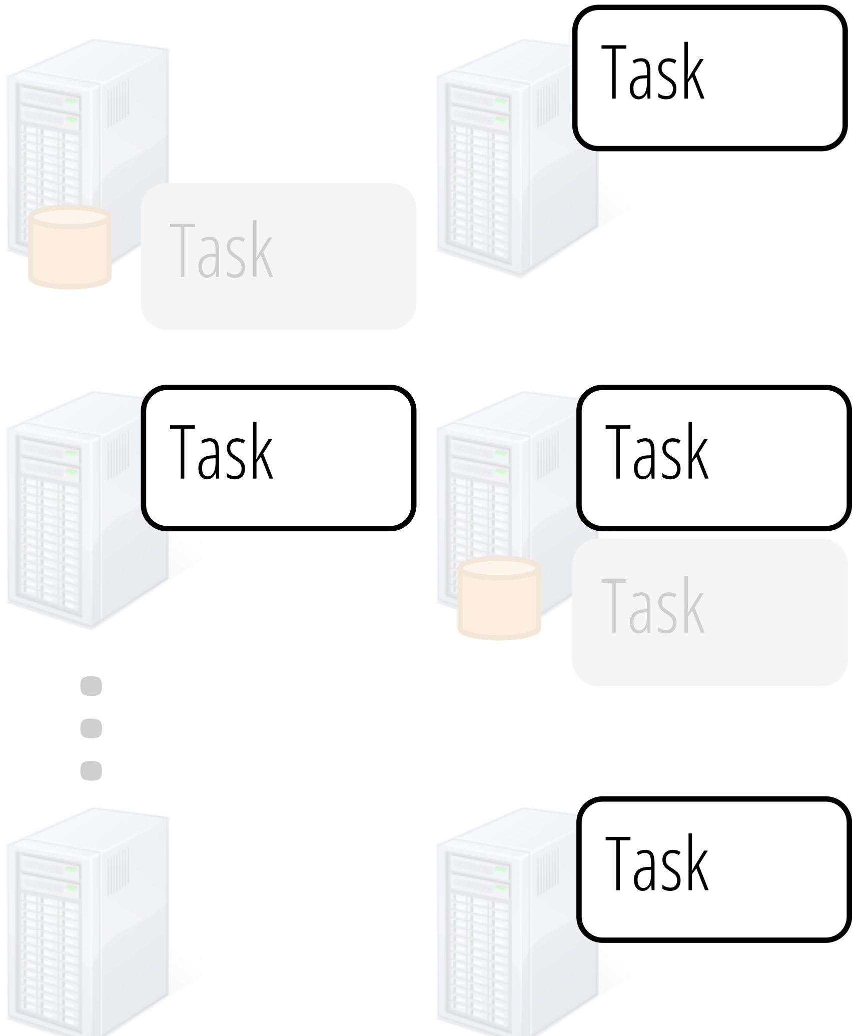

Cache input data in memory

Optimize the network

How can we make this job faster?

Cache input data in memory

Optimize the network

Mitigate effect of stragglers

Disk

Themis [SoCC ‘12], PACMan [NSDI ’12], Spark [NSDI ’12], Tachyon [SoCC ’14]

Network

Load balancing: VL2 [SIGCOMM ‘09], Hedera [NSDI ’10], Sinbad [SIGCOMM ’13]
Application semantics: Orchestra [SIGCOMM ’11], Baraat [SIGCOMM ‘14], Varys [SIGCOMM ’14]
Reduce data sent: PeriSCOPE [OSDI ‘12], SUDO [NSDI ’12]
In-network aggregation: Camdoop [NSDI ’12]
Better isolation and fairness: Oktopus [SIGCOMM ’11], EyeQ [NSDI ‘12], FairCloud [SIGCOMM ’12]

Stragglers

Scarlett [EuroSys ‘11], SkewTune [SIGMOD ‘12], LATE [OSDI ‘08], Mantri [OSDI ‘10], Dolly [NSDI ‘13], GRASS [NSDI ‘14], Wrangler [SoCC ’14]

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Missing: what's most important to end-to-end performance?

Disk

Themis [SoCC '12], PACMan [NSDI '12], Spark [NSDI '12], Tachyon [SoCC '14]

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[SIGC

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Better isol Cloud

[SIGCOMM '12]

Stragglers

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Widely-accepted mantras:

Network and disk I/O are bottlenecks

Stragglers are a major issue with unknown causes

This work

(1) How can we quantify performance bottlenecks?

Blocked time analysis

(2) Do the mantras hold?

Takeaways based on three workloads run with Spark

Takeaways based on three Spark workloads:

Network optimizations

can reduce job completion time by **at most 2%**

CPU (not I/O) often the bottleneck

<19% reduction in completion time from optimizing disk

Many straggler causes can be identified and fixed

Takeaways will not hold
for every single analytics workload
nor for all time

This work:

Accepted mantras are often not true

Methodology to avoid performance misunderstandings in the future

Outline

- **Methodology:** How can we measure Spark bottlenecks?
- **Workloads:** What workloads did we use?
- **Results:** How well do the mantras hold?
- **Why?:** Why do our results differ from past work?
- **Demo:** How can you understand your own workload?

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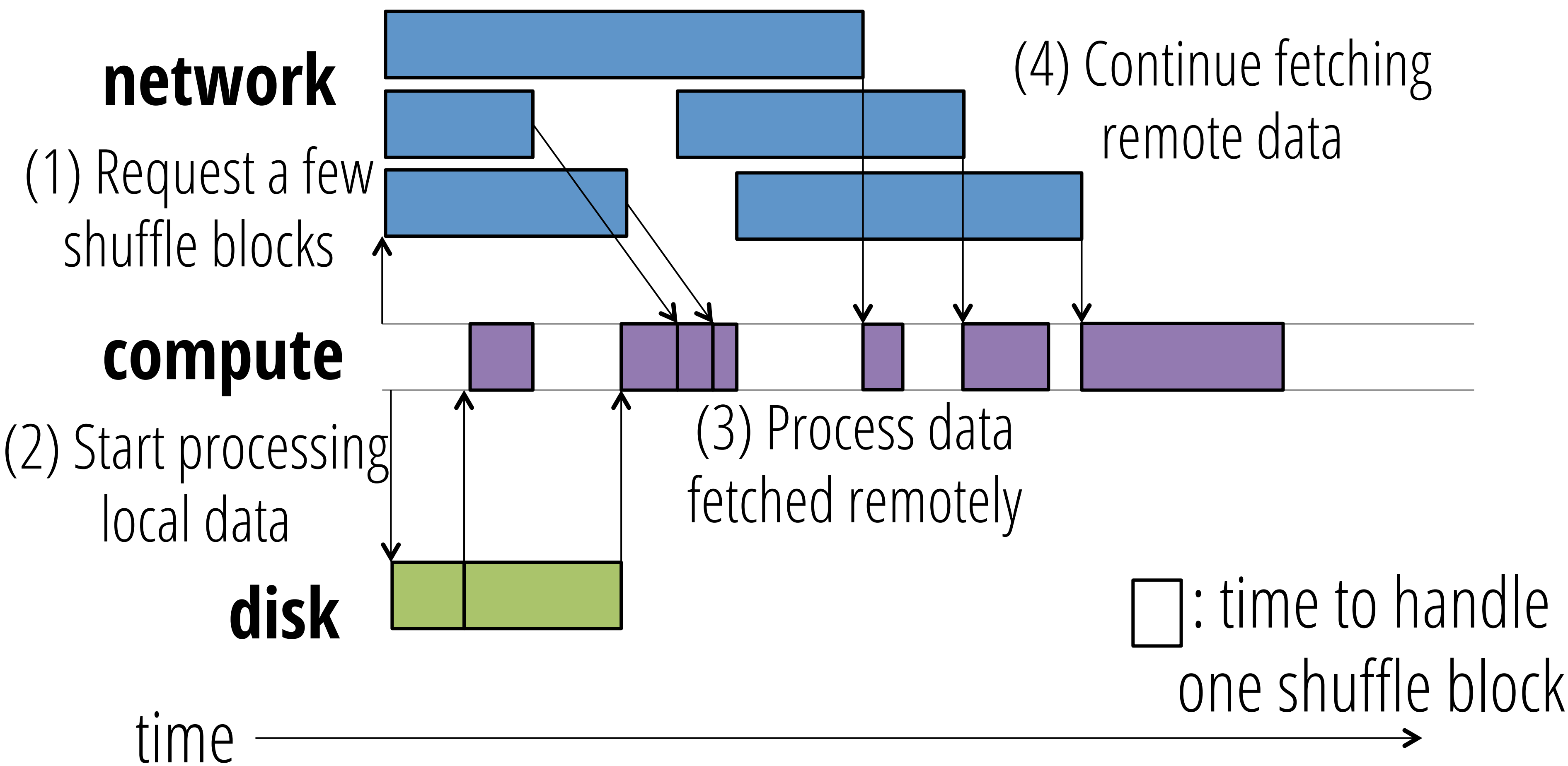
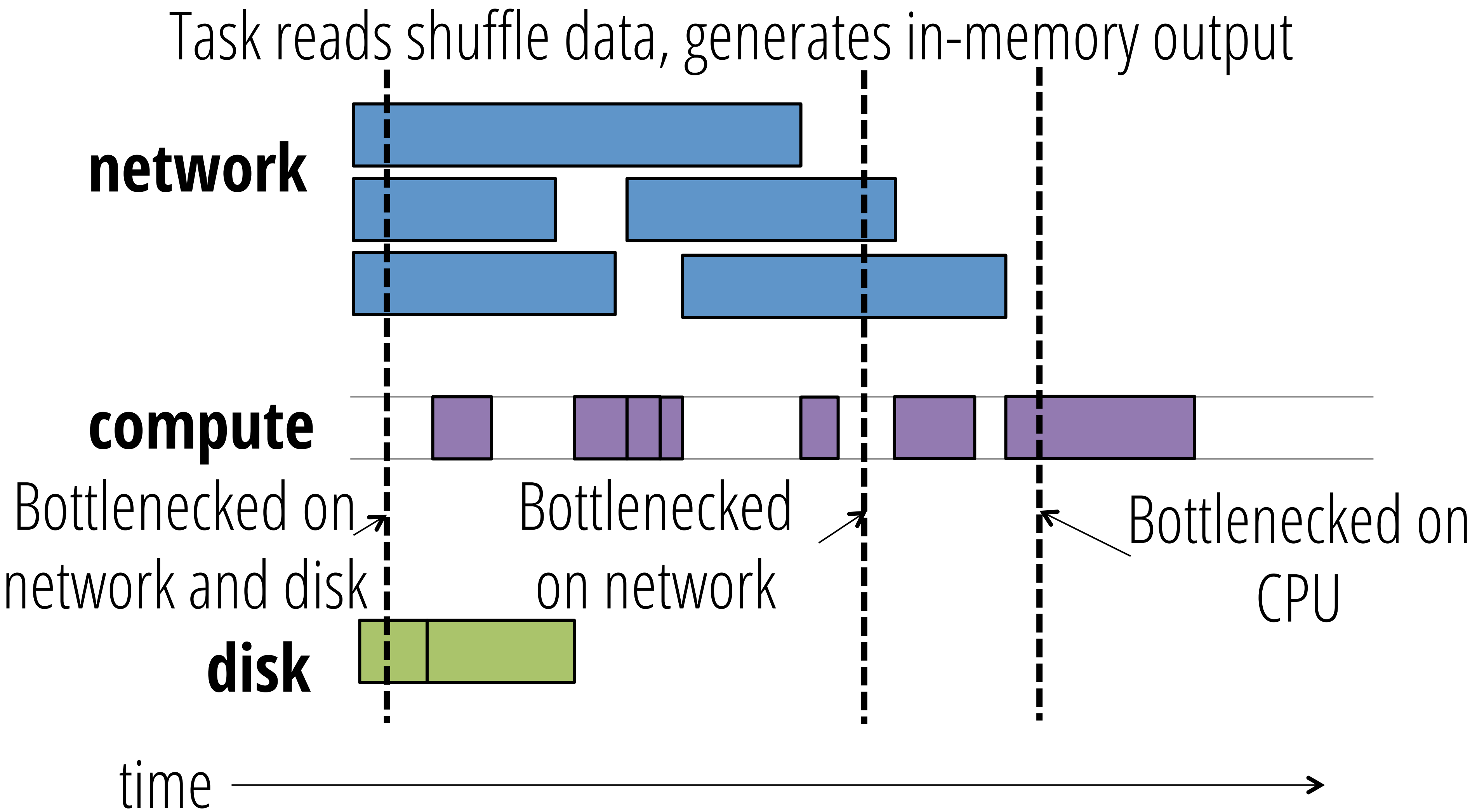
What’s the job’s bottleneck?

What exactly happens in a Spark task?

Task reads shuffle data, generates in-memory output



What’s the bottleneck for this task?



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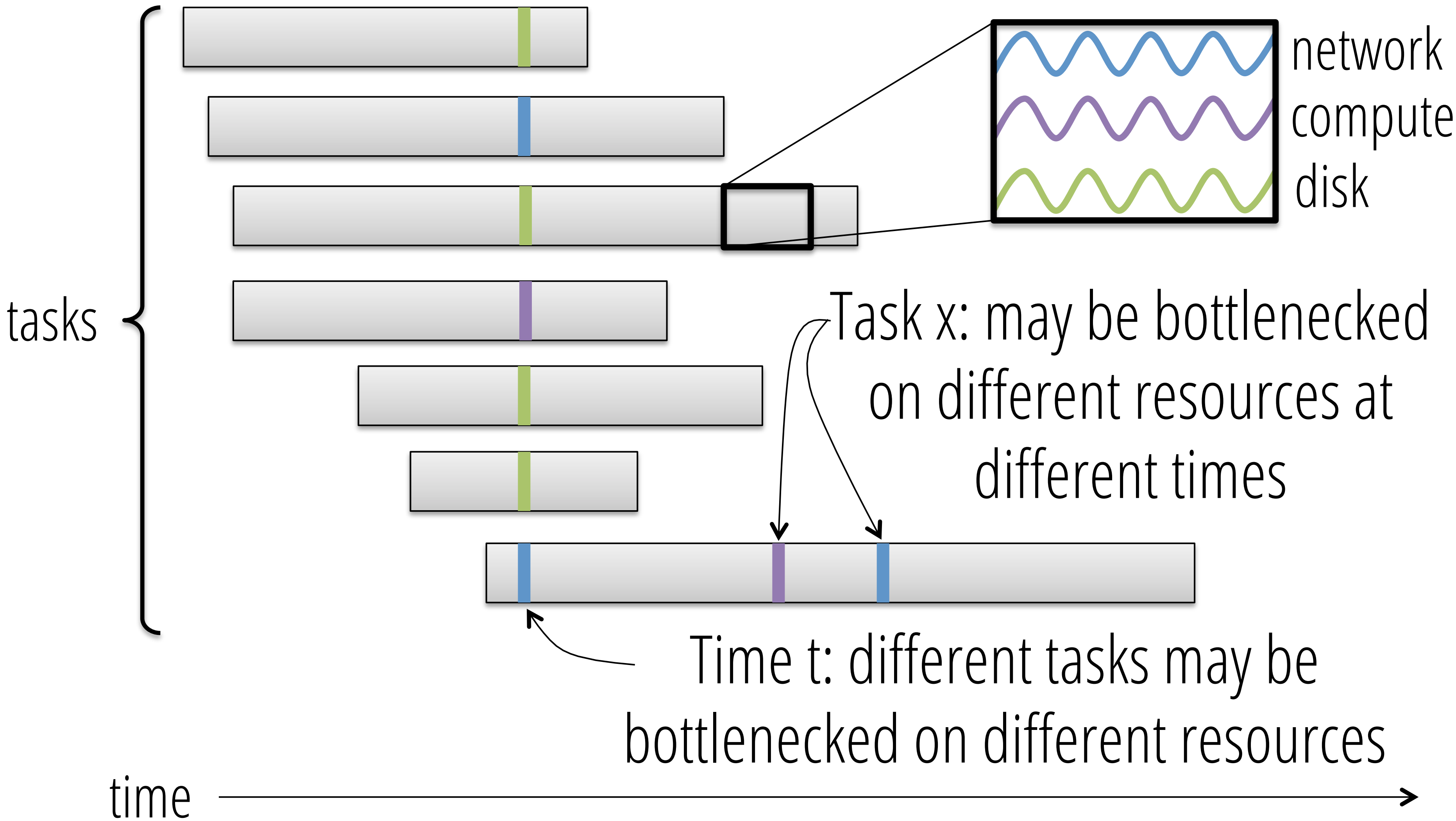
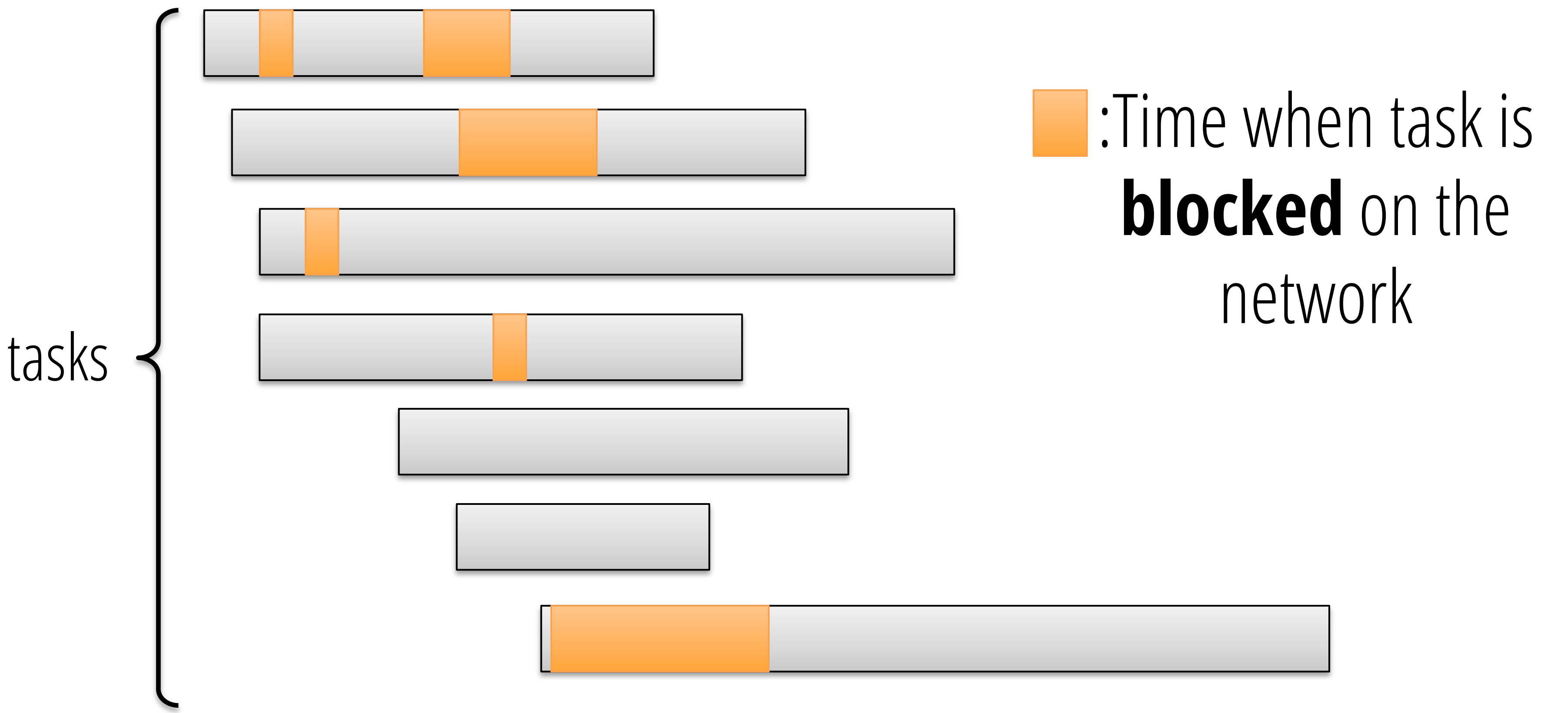
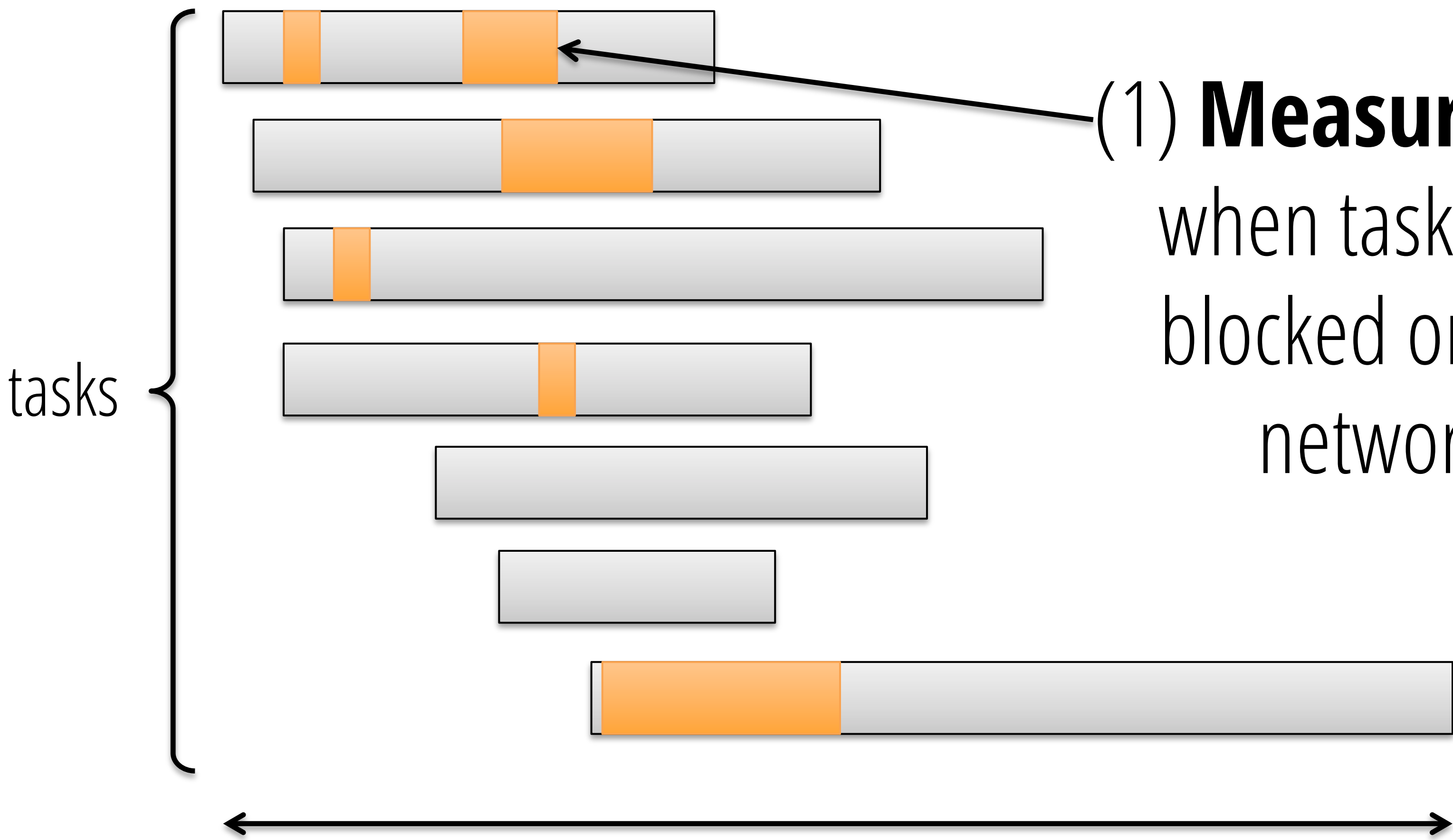


How does network affect the job's completion time?



Blocked time analysis: how much faster would the job complete if tasks never blocked on the network?

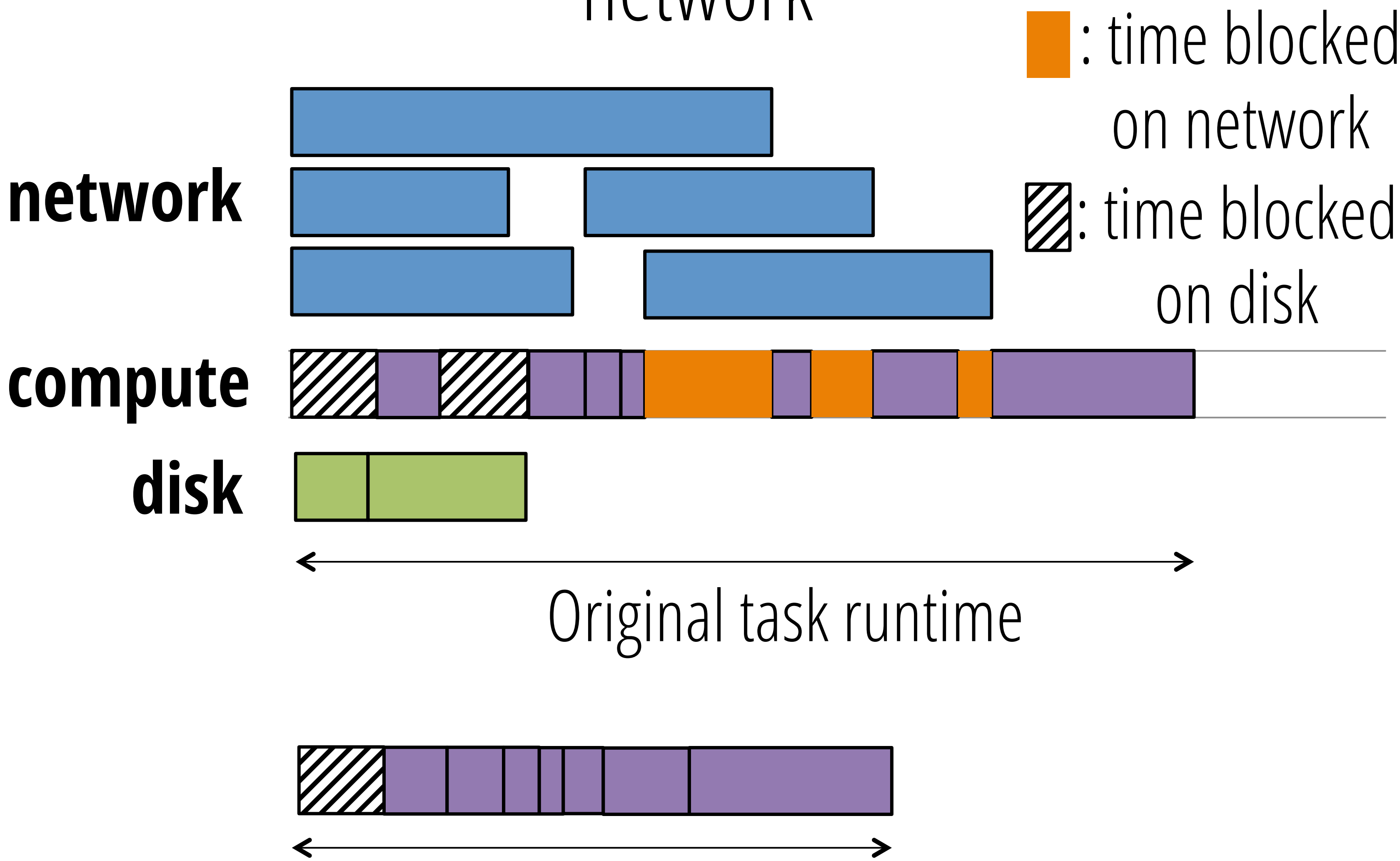
Blocked time analysis



(1) **Measure** time when tasks are blocked on the network

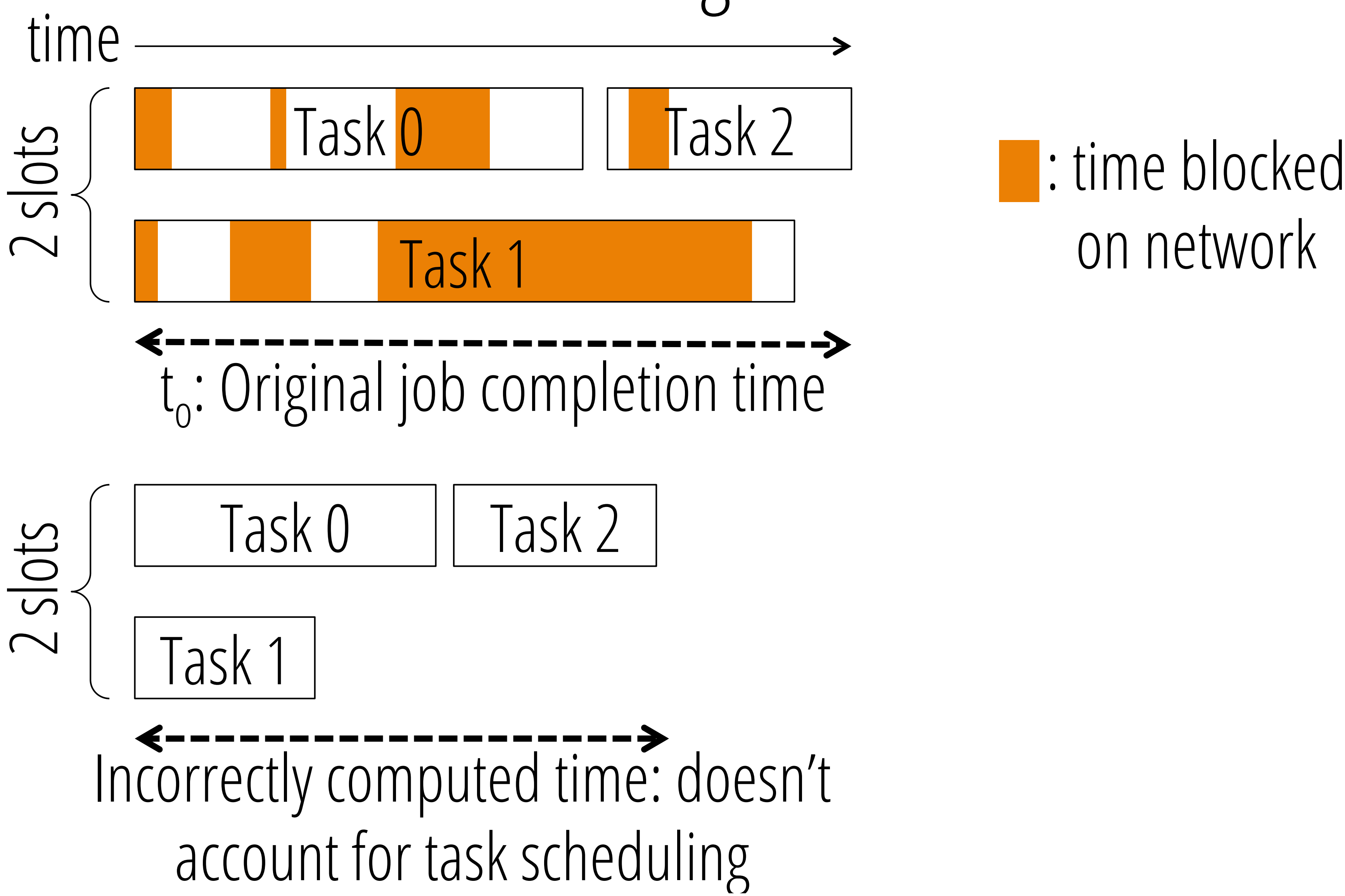
(2) **Simulate** how job completion time would change

(1) **Measure** time when tasks are blocked on network

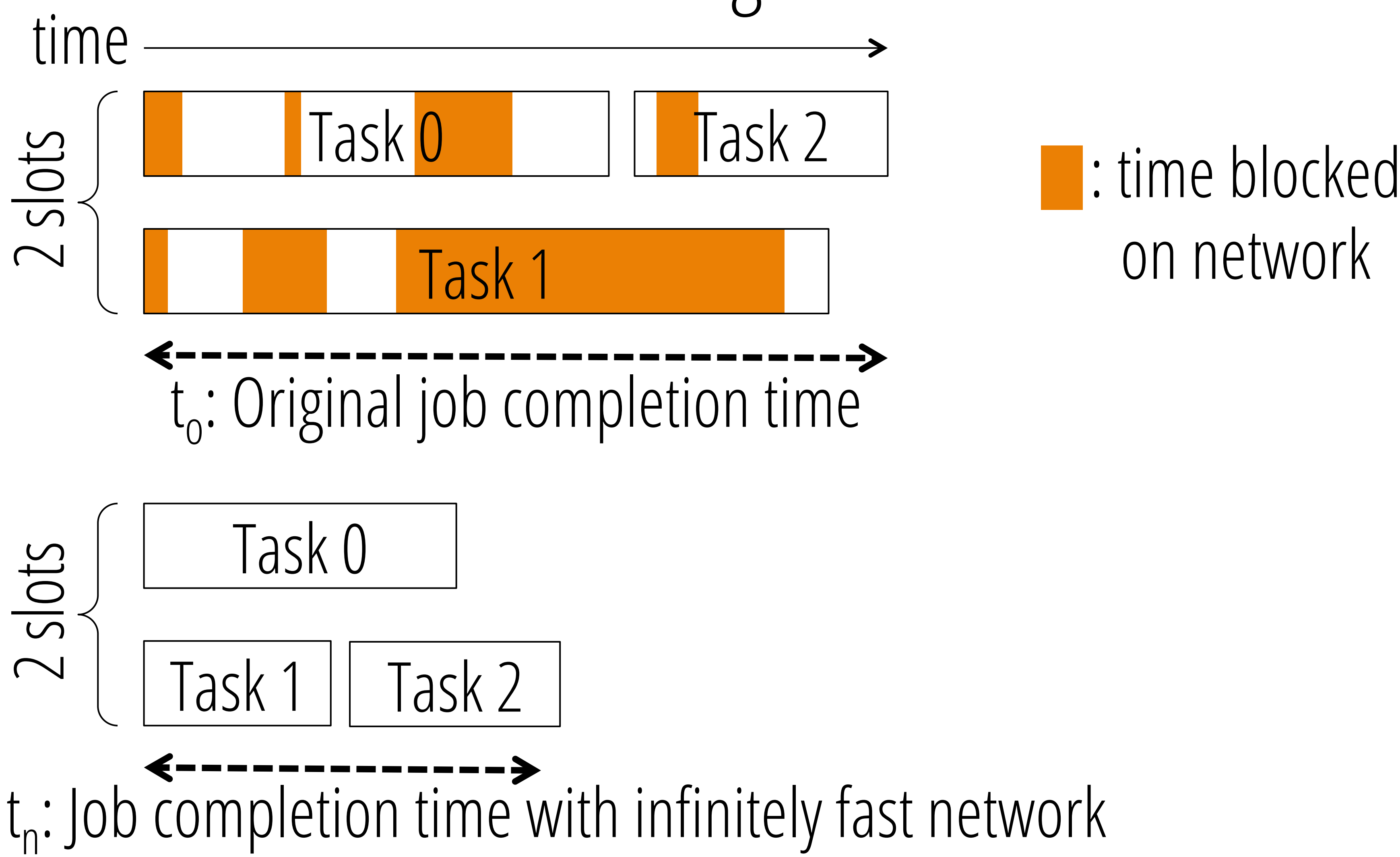


Best case task runtime if network were infinitely fast

(2) **Simulate** how job completion time would change



(2) **Simulate** how job completion time would change



Blocked time analysis: how quickly could a job have completed if a resource were infinitely fast?

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Large-scale traces?

Don’t have enough instrumentation for blocked-time analysis

SQL Workloads run on Spark

Only 3 workloads

TPC-DS (20 machines, 850GB;
60 machines, 2.5TB; 200 machines, 2.5TB)

Big Data Benchmark (5 machines, 60GB)

Databricks (Production; 9 machines, tens of GB)

Small cluster sizes

2 versions of each: in-memory, on-disk

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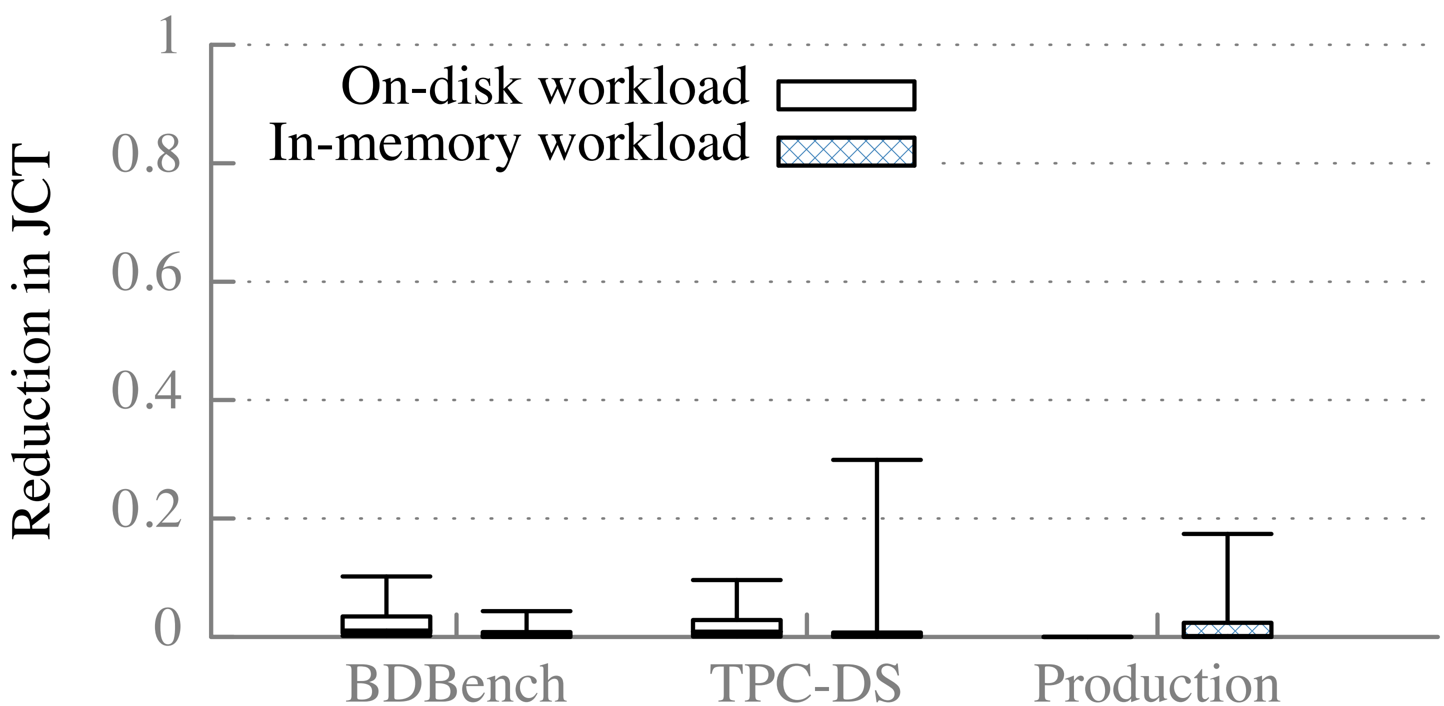
How much faster could jobs get from optimizing network performance?



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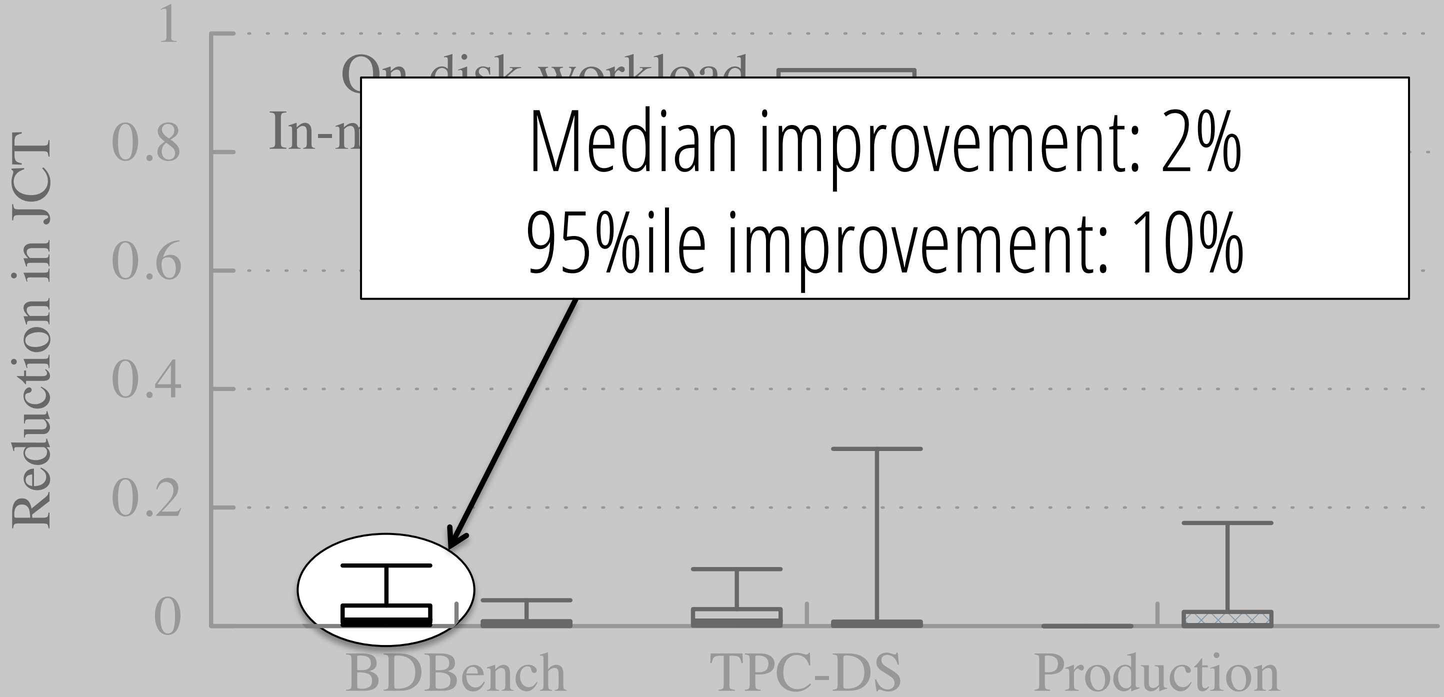

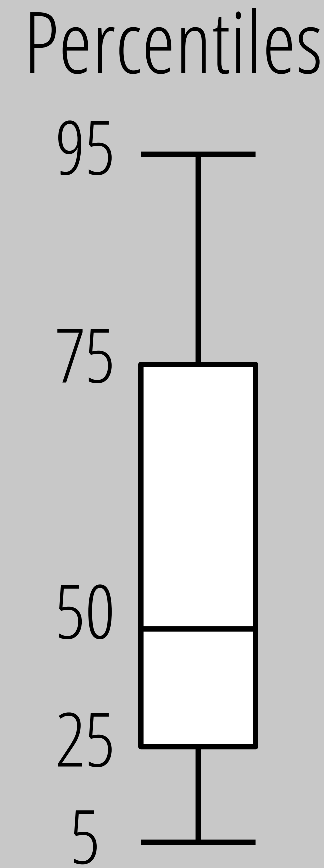

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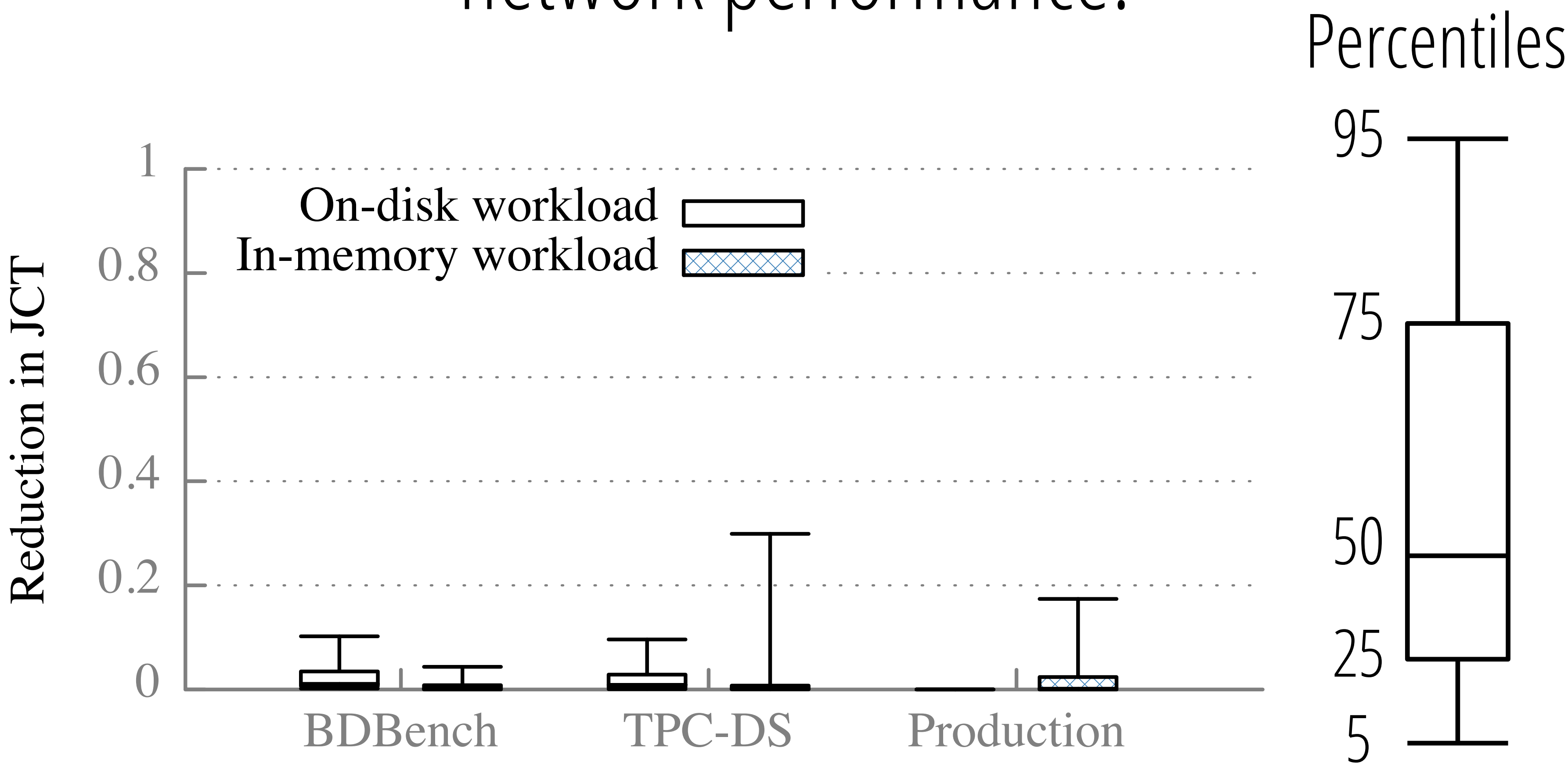
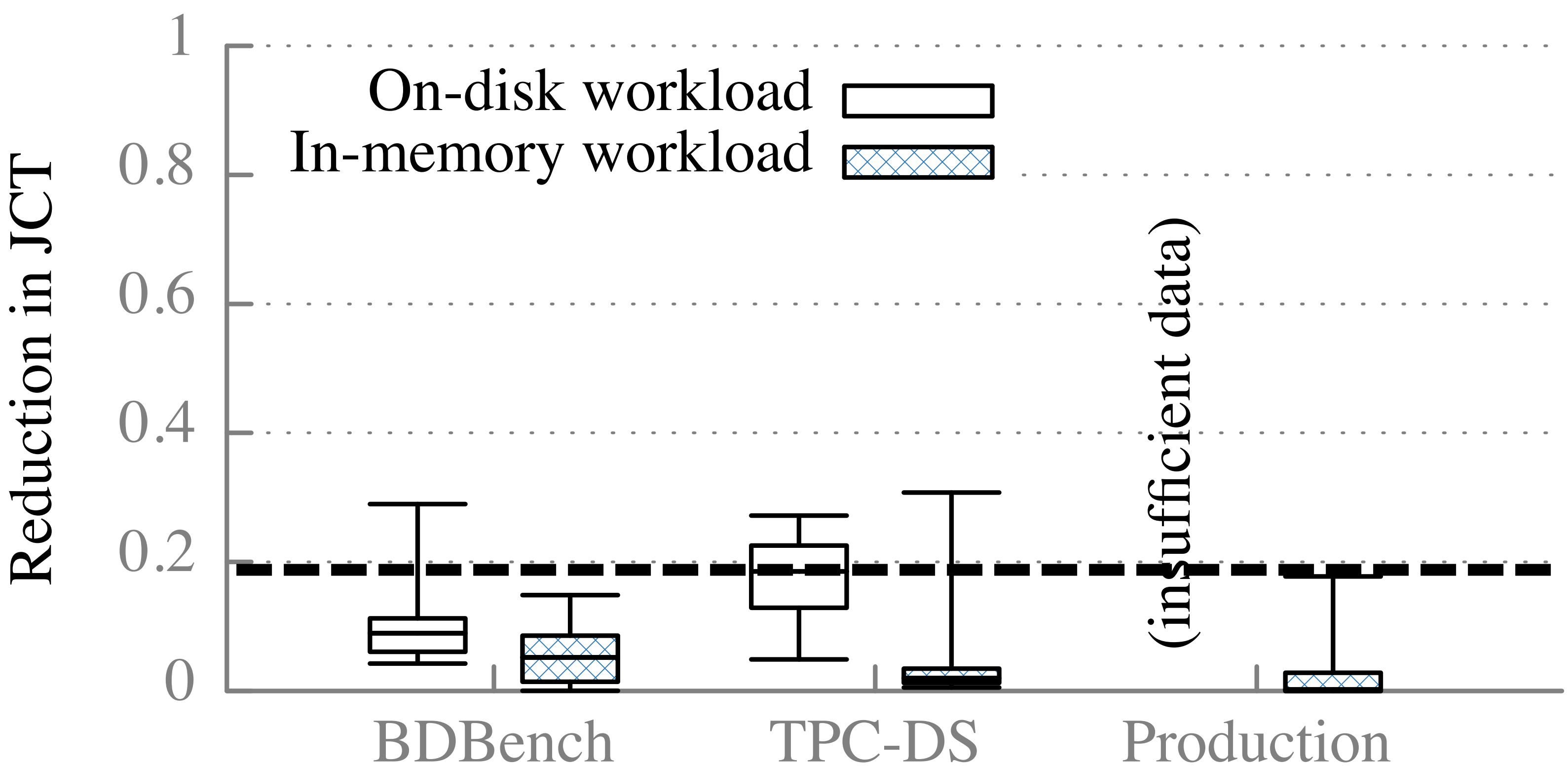


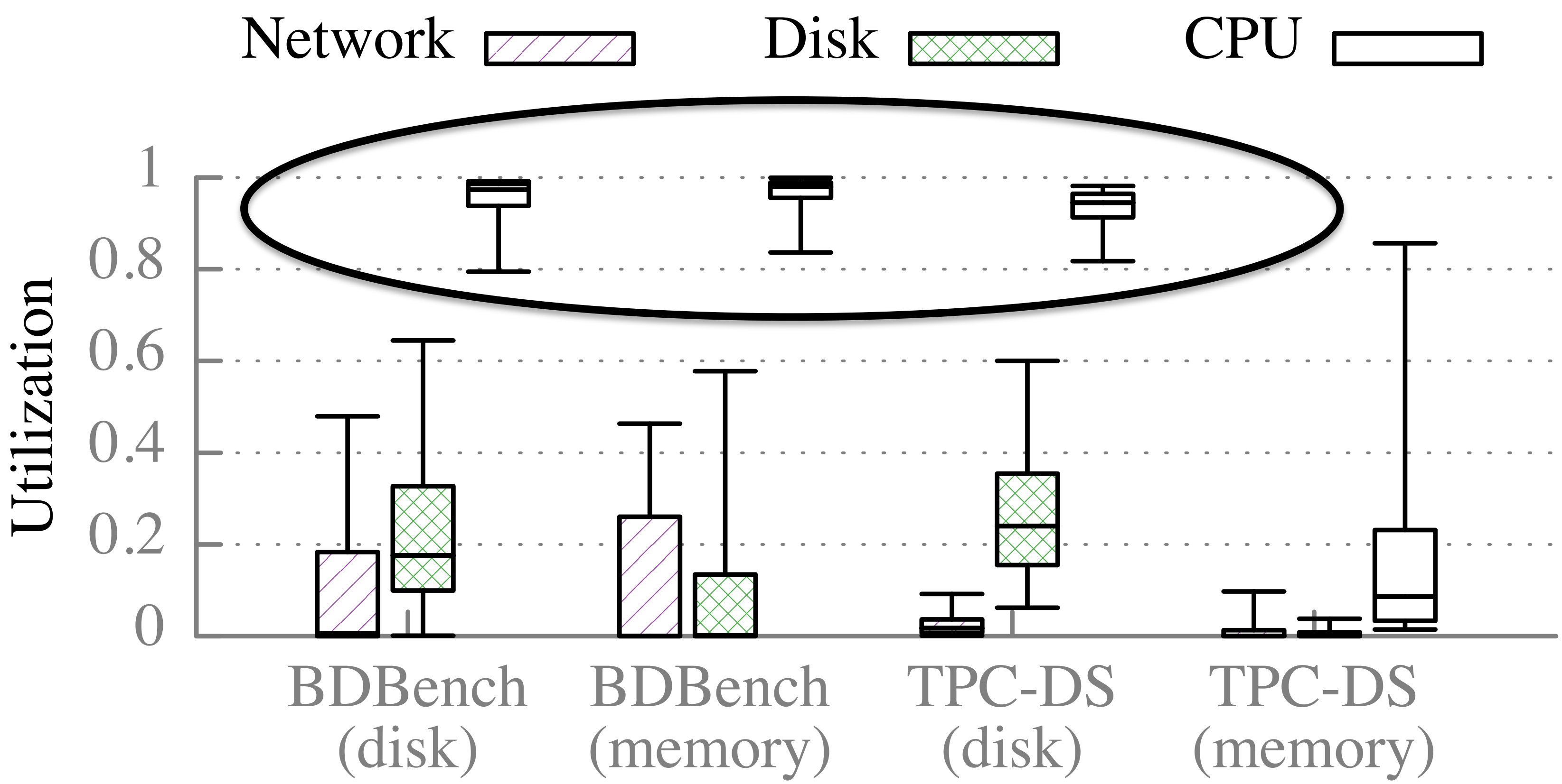
Median improvement at most 2%

How much faster could jobs get from optimizing disk performance?



Median improvement at most 19%

How important is CPU?



CPU much more highly utilized than disk or network!

What about stragglers?

5-10% improvement from eliminating stragglers
- Based on simulation

Can explain >60% of stragglers in >75% of jobs

Fixing underlying cause can speed up other tasks too!
- 2x speedup from fixing one straggler cause

Takeaways based on three Spark workloads:

Network optimizations
can reduce job completion time by **at most 2%**

CPU (not I/O) often the bottleneck
<19% reduction in completion time from optimizing disk

Many straggler causes can be identified and fixed

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  network
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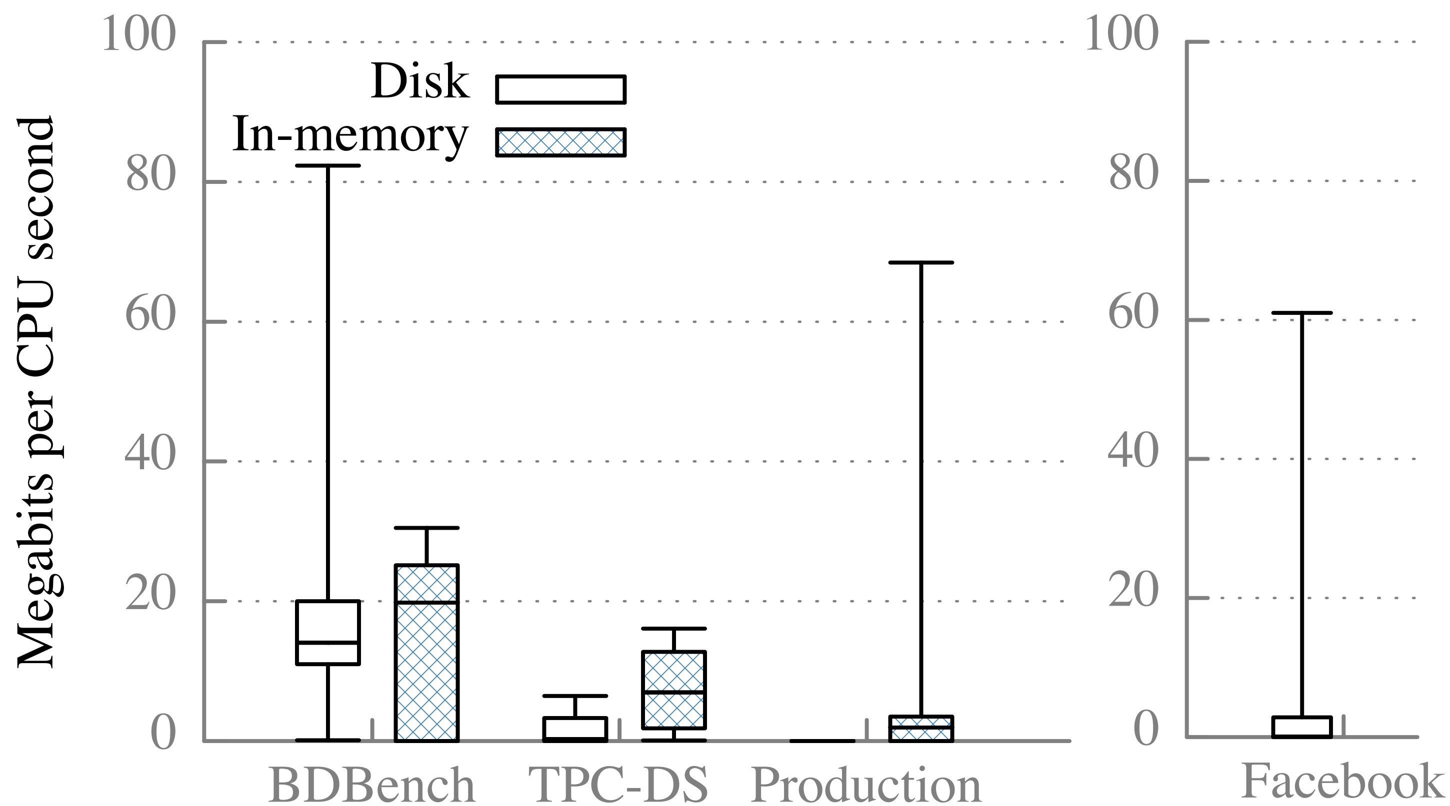
Why are our results so different than what's stated in prior work?

Are the workloads we measured unusually network-light?

How can we compare our workloads to large-scale traces used to motivate prior work?

How much data is transferred per CPU second?



Microsoft '09-'10: **1.9–6.35 Mb / task second**

Google '04-'07: **1.34–1.61 Mb / machine second**

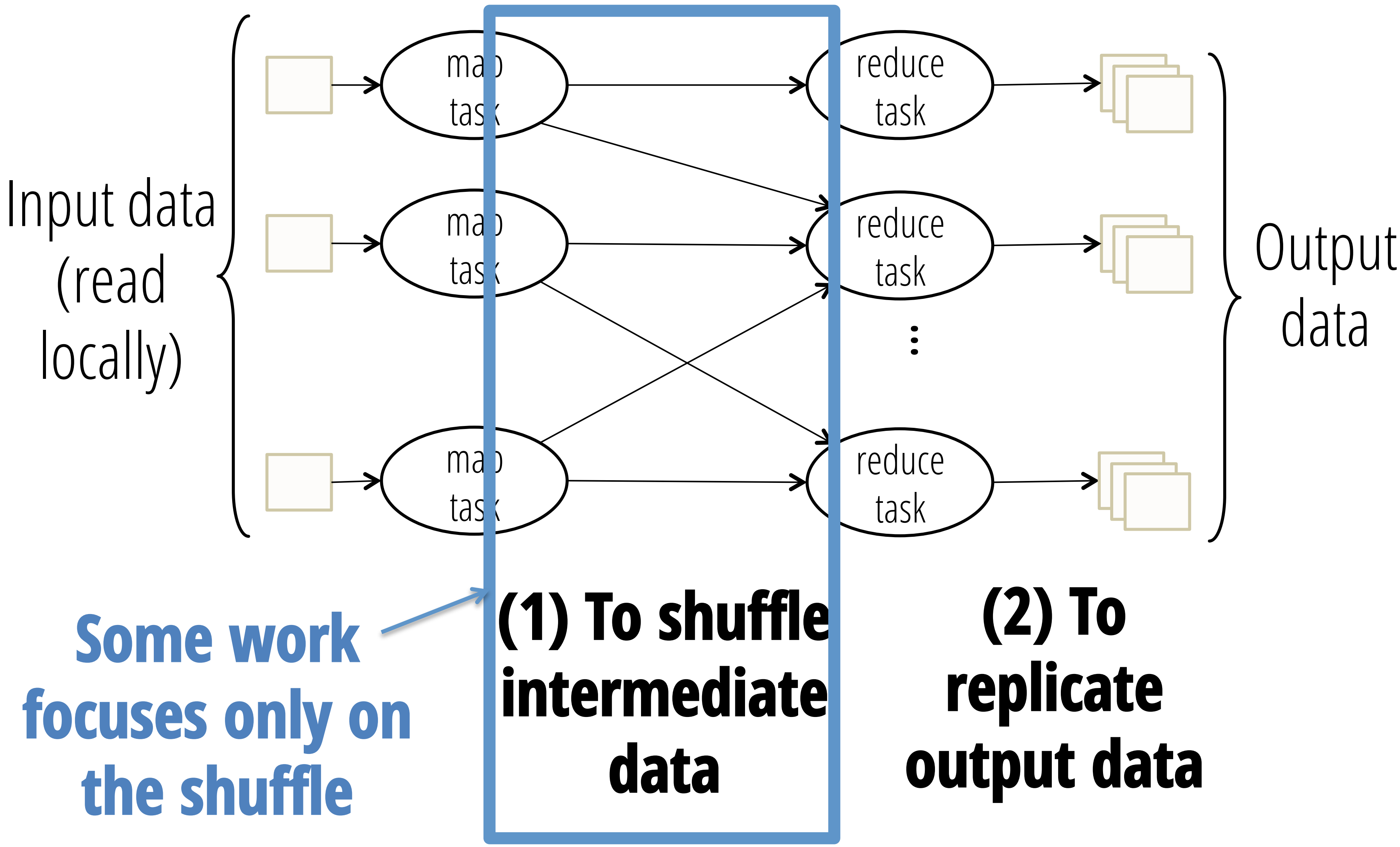
Why are our results so different than what's stated in prior work?

~~Our workloads are network light~~

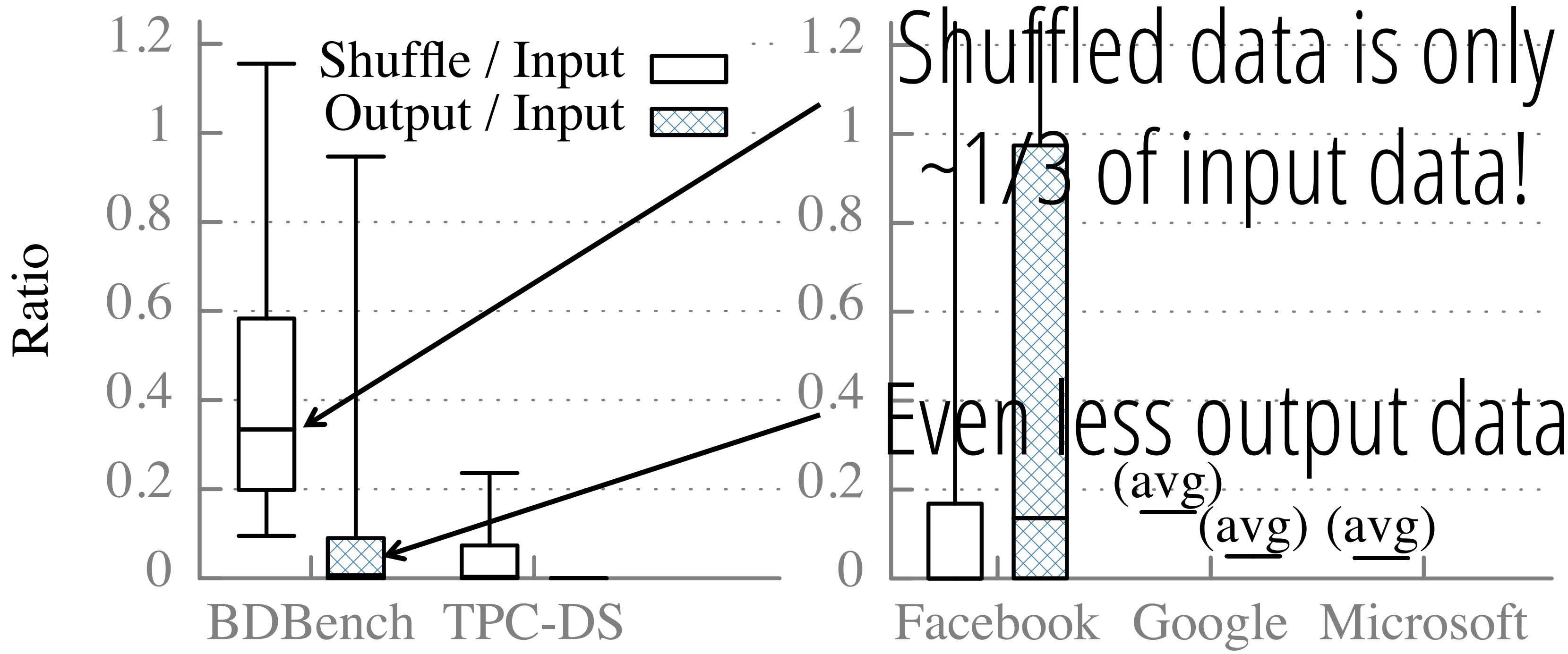
1) Incomplete metrics

2) Conflation of CPU and network time

When is the network used?



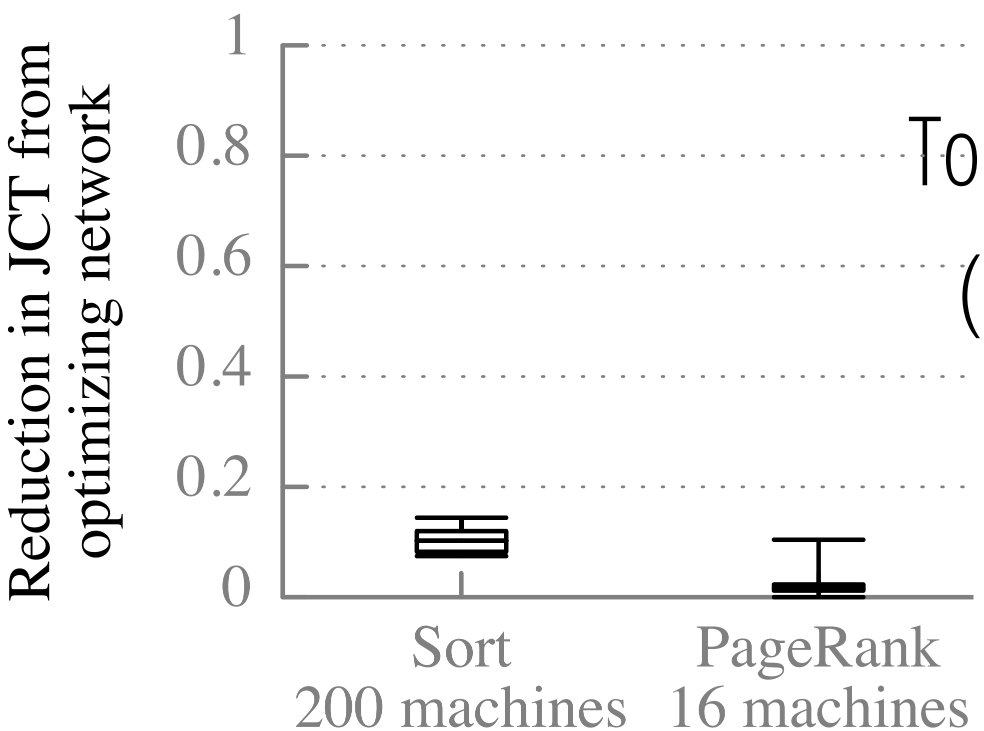
How does the data transferred over the network compare to the input data?



Not realistic to look only at shuffle!

Or to use workloads where all input is shuffled

Prior work conflates CPU and network time



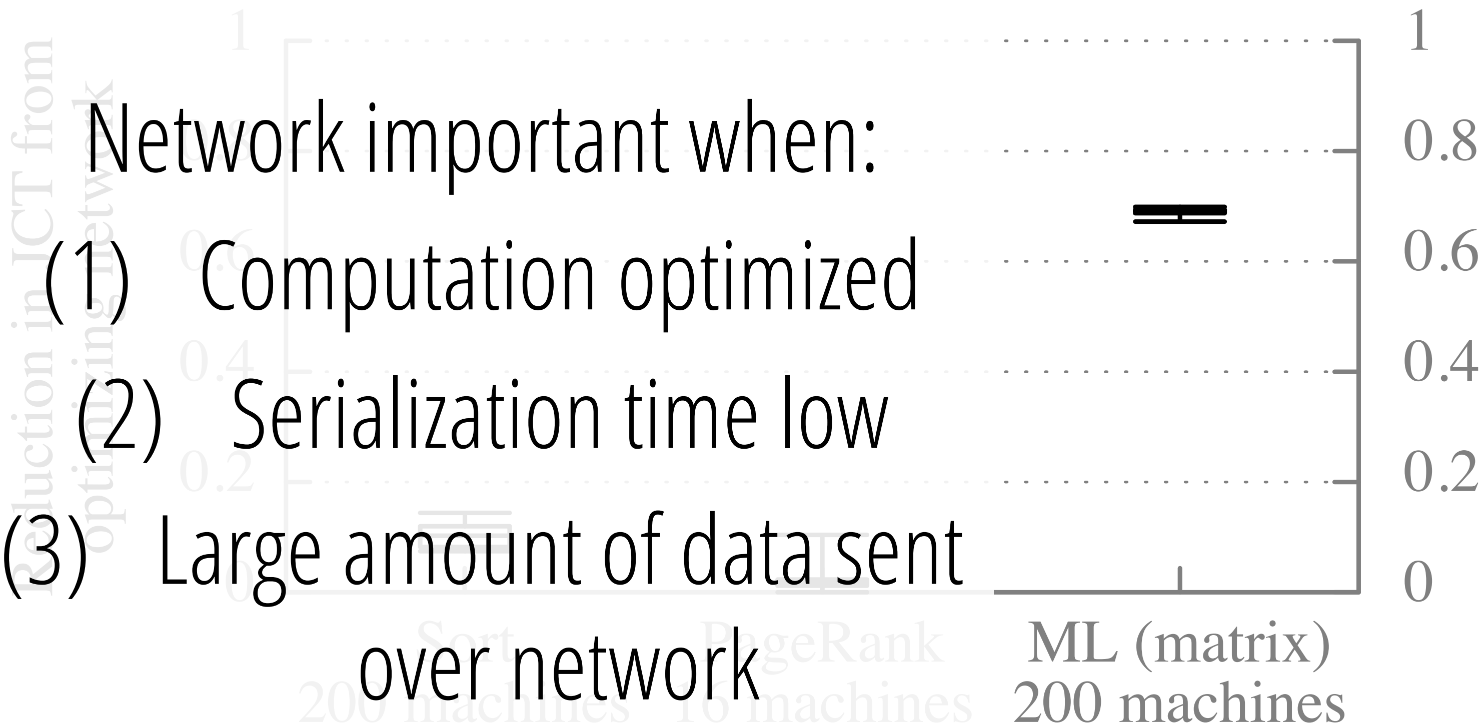
To send data over network:

(1) Serialize objects into bytes

(2) Send bytes

(1) and (2) often conflated.
Reducing application data sent reduces both!

When does the network matter?



Network important when:

(1) Computation optimized

(2) Serialization time low

(3) Large amount of data sent over network

Why are our results so different than what's stated in prior work?

~~Our workloads are network light~~

1) Incomplete metrics

e.g., looking only at shuffle time

2) Conflation of CPU and network time

Sending data over the network has an associated CPU cost

Limitations

Only three workloads

Small cluster sizes

Limitations aren't fatal

Only three workloads

Industry-standard workloads

Results sanity-checked with larger production traces

Small cluster sizes

Takeaways don't change when we move between cluster sizes

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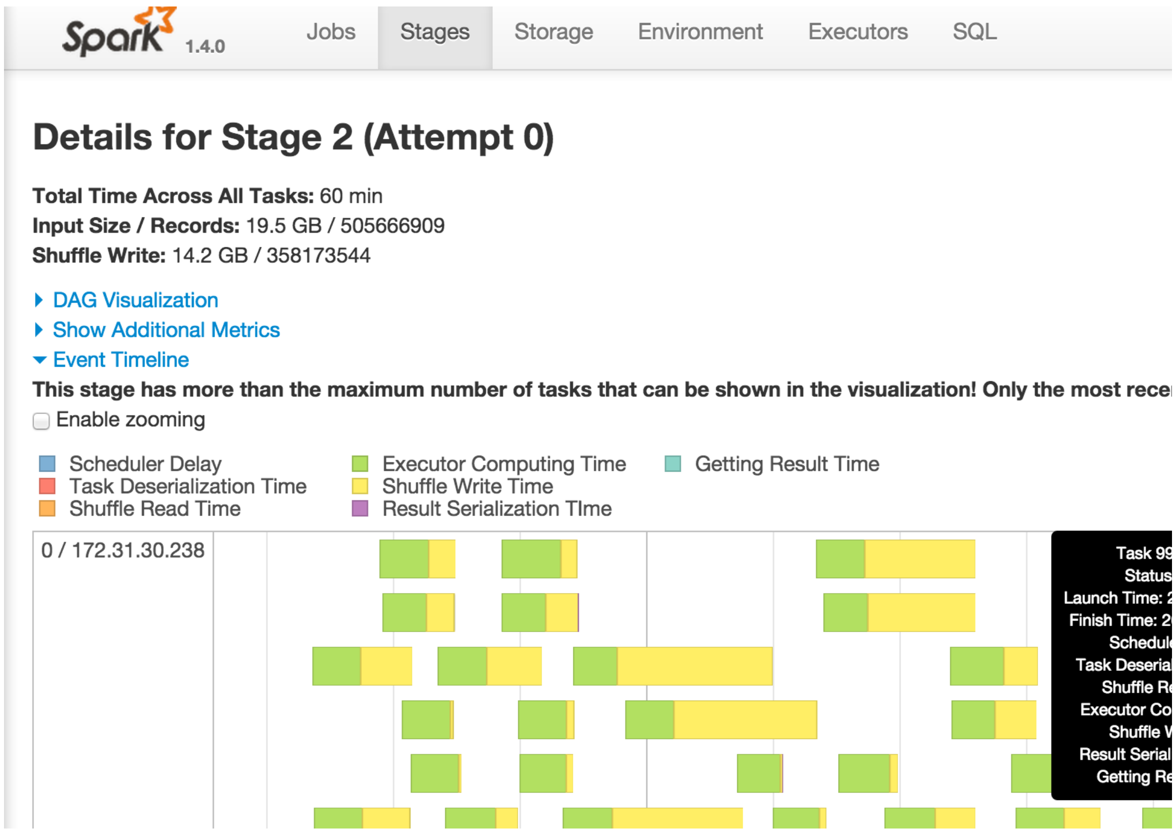
Demo

Demo



Often can tune parameters to shift the bottleneck

(e.g., change snappy to lzf)

What's missing from Spark metrics?

Time blocked on reading input data and writing output data (HADOOP-11873)

Time spent spilling intermediate data to disk (SPARK-3577)

Will change with time!

Network optimizations

can reduce job completion time by **at most 2%**

CPU (not I/O) often the bottleneck

<19% reduction in completion time from optimizing disk

Many straggler causes can be identified and fixed

Takeaway: performance understandability should be a first-class concern!

(almost) All Instrumentation now part of Spark

I want your workload! keo@eecs.berkeley.edu

All traces and tools publicly available: tinyurl.com/summit-traces