Making Sense of Performance in Data Analytics Frameworks

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Large-scale data analytics has become widespread
More resource-efficient

Faster
Spark (or Hadoop/Dryad/etc.) task
Spark (or Hadoop/Dryad/etc.) task
**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]

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

**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?

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Widely-accepted mantras:
Network and disk I/O are bottlenecks

Disk
Themis [SoCC ‘12], ACMMan [NSDI ‘12], Spark [NSDI ‘12], Tachyon [SoCC ‘14]

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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 bottlenecks?
- **Workloads:** What workloads did we use?
- **Results:** How well do the mantras hold?
- **Why?:** Why do our results differ from past work?
What is the job’s bottleneck?

Task x: may be bottlenecked on different resources at different times.

Time t: different tasks may be bottlenecked on different resources.

network, compute, disk
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

time

2 slots

- Task 0
- Task 1
- Task 2

2 slots

- Task 0
- Task 1
- Task 2

$t_o$: Original job completion time

$t_n$: Incorrectly computed time: doesn’t account for task scheduling

*: time blocked on network

2 slots

- Task 0
- Task 2

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Blocked time analysis: how quickly could a job have completed if a resource were infinitely fast?
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• **Methodology:** How can we measure bottlenecks?

• **Workloads:** What workloads did we use?

• **Results:** How well do the mantras hold?

• **Why?:** Why do our results differ from prior work?
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?

![Graph showing reduction in JCT for different workloads.]

- On-disk workload
- In-memory workload

Reduction in JCT

- BDBench
- TPC-DS
- Production
How much faster could jobs get from optimizing network performance?

Median improvement: 2%
95th percentile improvement: 10%
How much faster could jobs get from optimizing network performance?

Median improvement at most 2%

Median improvement at most 2%
How much faster could jobs get from optimizing disk performance?

Median improvement at most 19%

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**

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Many straggler causes can be identified and fixed
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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?

(1) To shuffle intermediate data
(2) To replicate output data

Some work focuses only on the shuffle.
How does the data transferred over the network compare to the input data?

Shuffled data is only \(\sim 1/3\) of input data!

Even less output 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

One framework (Spark)
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

One framework (Spark)
  Results sanity-checked with production traces from other frameworks
  We instrumented and evaluated Hadoop, with consistent results
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!
Instrument systems for blocked time analysis
(almost) All Instrumentation now part of Spark

All traces publicly available: tinyurl.com/nsdi-traces
Backup Slides
Why is the CPU time so high?

Compression and serialization are costly.
What can be done to reduce compute time?

In a previous blog post, we looked back and surveyed performance improvements made to Spark in the past year. In this post, we look forward and share with you the next chapter, which we are calling Project Tungsten. 2014 witnessed Spark setting the world record in large-scale sorting and saw major improvements across the entire engine from Python to SQL to machine learning. Performance optimization, however, is a never ending process.

Project Tungsten will be the largest change to Spark’s execution engine since the project’s inception. It focuses on substantially improving the efficiency of memory and CPU for Spark applications, to push performance closer to the limits of modern hardware. This effort includes three initiatives:

1. **Memory Management and Binary Processing**: leveraging application semantics to manage memory explicitly and eliminate the overhead of JVM object model and garbage collection
2. **Cache-aware computation**: algorithms and data structures to exploit memory hierarchy
3. **Code generation**: using code generation to exploit modern compilers and CPUs

The focus on CPU efficiency is motivated by the fact that Spark workloads are increasingly bottlenecked by CPU and memory use rather than IO and network communication. This trend is shown by recent research on the performance of big data workloads (Custerhout et al) and we’ve arrived at similar findings as part of our ongoing tuning and optimization efforts for Databricks Cloud customers.

Why is CPU the new bottleneck? There are many reasons for this. One is that hardware configurations offer increasingly large aggregate IO bandwidth, such as 10Gbps links in networks and high bandwidth SSD’s or striped HDD arrays for storage. From a software perspective, Spark’s optimizer now allows many workloads to avoid significant disk IO by pruning input data that is not needed in a given job. In Spark’s shuffle subsystem, serialization and hashing (which are CPU bound) have been shown to be key bottlenecks, rather than raw network throughput of underlying hardware. All these trends mean that Spark today is often constrained by CPU efficiency and memory pressure rather than IO.