Quartet: Harmonizing task scheduling and caching for cluster computing



Francis Deslauriers, Peter McCormick, George Amvrosiadis, Ashvin Goel & Angela Demke Brown

UNIVERSITY OF TORONTO

June 23, 2016

Analyses for the masses

- Data collection is cheap, so datasets are growing exponentially
- Cluster computing makes it easy to analyze these datasets, enabling:
 - Queries on entire datasets
 - Analysts running queries on the same corpus
 - Tuning queries

Data is often re-accessed

- Result is many queries running on the same large datasets
- Leads to significant data reuse

Data is often re-accessed

- Result is many queries running on the same large datasets
- Leads to significant data reuse



Data reuse does not help

- · We should expect data reuse improves performance due to caching
- We find that jobs do not see the benefits of reuse















Missed Opportunities

- Working sets don't fit in the page cache
- Jobs consume data independently of one another

Solution

- Key idea
 - Reorder work to first consume cached data
 - Jobs are made of small tasks with no ordering requirements
- Challenges
 - · Cache visibility: Jobs need to know what data is cached on the different nodes
 - $\circ\,$ Task reordering: Jobs need to reorder their tasks based on this knowledge
- Our Quartet system addresses both these challenges

Challenge 1: Cache Visibility

- Datanodes collect information about HDFS blocks that reside in memory
 - Requires the Duet kernel module that informs applications when pages are cached or evicted
- Nodes send this information periodically to the Quartet Manager
 - Changes to the number of resident pages of each block



Challenge 2: Task Reordering

- 1. Application Master registers blocks of interest with the Quartet manager
- 2. Quartet manager informs Application Master about cached blocks
- 3. Application Master prioritizes and places tasks based on block residency information













Experiments

- Spark and Hadoop implementations
- 24 nodes with a total of 384 GB of memory
- Different input sizes:
 - Smaller than physical memory (256 GB)
 - Slightly larger (512 GB)
 - Approximately 3 times (1024 GB)
- 3 replicas per block

Results - Cache Hit Rate of the second job



12 of 18

Results - Runtime reduction of the second job



Conclusions

- Observation: Workloads show significant amount of reuse
- Problem: Jobs are unable to take advantage of this reuse
- Solution:
 - · Add visibility on what is cached in each of the cluster nodes
 - Reorder tasks to take advantage of this cached data
- Future work: More realistic workloads and scalability

Conclusion

Thank you!

Conclusion

Questions?

Network Overhead

- Watchers updates are aggregated per HDFS blocks (128-256MB)
- Upper bound is the storage bandwidth
- Manager notifications is proportional to the size of the input and hardware
 - 10-100 KB/s in our experiments

Related Work

HDFS Cache Manager

- Requires manual changes in case of change of popularity
- Can't be used when input is larger than memory

PACMan

- Avoiding stragglers in single wave of Mappers
- Modify cache eviction policy to ensure that entire computation stages have memory locality