

Designing and Modeling High-Performance MapReduce and DAG Execution Framework on Modern HPC Systems

Introduction

MapReduce is the de-facto parallel programming model for big data processing

Open-source implementations from Apache (Hadoop, Spark, Tez) are the most popular frameworks

because of proven scalability and fault-tolerance

Java sockets based communication model for bulk data transfer in shuffle Costly frequent disk operations in the job execution workflow

Cannot take advantage of global file systems because of shared-nothing based architecture



map $(k_1, v_1) \rightarrow list (k_2, v_2)$

Research Framework



RDMA-based MapReduce



for each request of ReduceTasks

Performance evaluation shows 39% (31%) reduction in time with **2 HDD/node** (**1 HDD/node**) for HDFS

MRoIB [1] introduces RDMA-based shuffle, replacing the slower HTTP-based request response messages MOFs are divided into small packets and are shuffled instead in this PQ for sorting operation



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Hybrid Overlapping in MapReduce

reduce (k₂, list(v₂)) -> list (k₃, v₃)

HOMR [3] (Hybrid Overlapping in MapReduce) is designed to have maximum possible overlapping across all phases of MapReduce

Shuffled data in ReduceTask All-Average weight assignment HOMR also ensures faster job execution over other high performance interconnects (10GigE, IPoIB) because of map3 its new shuffle algorithms; provides the map4 Shuffled data in ReduceTask fastest execution over RDMA

HOMR assigns weights to different maps to signify how much data to shuffle on each request; this assignment can be greedy / all-average

Initial static weight assignment is updated by on-demand adjustment which makes each shuffle to bring only the map outputs needed; Intelligent shuffling provides faster job execution pipeline

MapReduce over Lustre

global file system in HPC clusters, such as Lustre Lustre and extract further benefits

HiBD High-Performance Big Data

Greedy weight assignment

f_{номк}=0.4

f_{номг}=0.4

f_{номг}=**0.4**

f_{HOMR}=0.4

f_{HOMR}=0.5

f_{номг}=0.05

f_{номг}=0.05

- Default MapReduce cannot take advantage of the underlying
- We propose an advanced design of HOMR, that can utilize
- The intermediate data directory can be configured to the local disks [4] or Lustre [6] or a combination of both [7]

Tuning, Profiling, and Prediction

implementation [8]

Automatic tuning, profiling is performed for MapReduce implementations in Hadoop, Spark, and HOMR with file systems – HDFS, Lustre, and Tachyon Generalized configuration

parameter space is devised to facilitate different MapReduce implementations

MACGYVER can also perform profiling and performance prediction using performance analytical models Performance of map and reduce tasks are modeled from execution times of each phase in these tasks. For example, execution time for a single Reduce task can be modeled as $t_{RT} = t_{shuffle} + t_{merge} + t_{reduce}$ • For RDMA-based MR, execution time can be re-modeled [2] $t_{RT} = \max\{t_{shuffle}, t_{merge}\} + \alpha * t_{reduce}$ Simplified prediction model Starfish (MR-0x-IPoIB) Starfish (MR-2x-IPoIB) MACGYVER (MR-0x-IPoIB)

- 5] is empirically derived from the detailed performance model
- Compared to Starfish,

MACGYVER can achieve better speedup for different applications

Conclusion and Future Work

For large scale data processing, HOMR achieves significant performance benefits compared to default Hadoop MapReduce; leverages benefit from modern HPC resources (RDMA and Lustre) Future plan is to design advanced DAG execution framework (e.g. Tez) with modern HPC resources

Software Distribution

HOMR is publicly available in "RDMA for Apache Hadoop" public release (<u>http://hibd.cse.ohio-state.edu</u>) As of Sep '16, more than **17,850 downloads (190 different organizations**) have taken place from this site

References

[1] M. W. Rahman, N. S. Islam, X. Lu, J. Jose, H. Subramoni, H. Wang, and D. K. Panda, High-Performance RDMA-based Design of Hadoop MapReduce over InfiniBand Int'l Workshop on High Performance Data Intensive Computing (HPDIC), held in conjunction with Int'l Parallel and Distributed Processing Symposium (IPDPS), May 2013 [2] M. W. Rahman, X. Lu, N. S. Islam, and D. K. Panda, Does RDMA-based Enhanced Hadoop MapReduce Need a New Performance Model?, ACM Symposium on Cloud Computing (SoCC), October 2013 (Poster Paper) [3] M. W. Rahman, X. Lu, N. S. Islam, and D. K. Panda, HOMR: A Hybrid Approach to Exploit Maximum Overlapping in MapReduce over High Performance Interconnects, International Conference on Supercomputing (ICS), June 2014 [4] M. W. Rahman, X. Lu, N. S. Islam, R. Rajachandrasekar, and D. K. Panda, MapReduce over Lustre: Can RDMA-based Approach Benefit?, 20th International European Conference on Parallel Processing (Euro-Par), August, 2014 [5] M. W. Rahman, X. Lu, N. S. Islam, and D. K. Panda, Performance Modeling for RDMA-Enhanced Hadoop MapReduce, 43rd International Conference on Parallel Processing (ICPP), September 2014 [6] M. W. Rahman, X. Lu, N. S. Islam, R. Rajachandrasekar, and D. K. Panda, High-Performance Design of YARN MapReduce on Modern HPC Clusters with Lustre and RDMA, 29th IEEE International Parallel & Distributed Processing Symposium (IPDPS), May 2015 [7] M. W. Rahman, N. S. Islam, X. Lu, and D. K. Panda, A Comprehensive Study of MapReduce over Lustre for Intermediate Data Placement and Shuffle Strategies on HPC Clusters, Under Review

[8] M. W. Rahman, N. S. Islam, X. Lu, D. Shankar, and D. K. Panda, MACGYVER: A MapReduce-centric Gray-Box Versatile Tuning and Prediction Framework for Hadoop

and Spark, Under Review

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• We design a generalized parameter tuning and prediction framework (MACGYVER) for any MapReduce

