On the Performance of MapReduce: A Stochastic Approach

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- Introduction
- Background
- Disk I/O
- Merge Overhead
- Runtime

Introduction

- MapReduce is a popular programming model for cluster computing, big data processing
- Resource constraints and data properties dictate MapReduce performance
 - Specifically, RAM size and distribution of key frequency impact both the run-time and volume of disk I/O
- Existing literature is missing an accurate performance model for external-memory sorting/merging
- Common to assume a linear relationship between input size and processing overhead
 - This includes disk spill, number of comparison in sort/merge

Introduction (2)

- Open questions:
 - Is this dependency indeed linear with some constant factor converting input size to various metrics of interest?
 - Does the constant stay the same in the full design space?
 - Is the constant easy to obtain/estimate?
- Our objective: analyze a shared-memory MapReduce system with a single host for all computation
 - Multiple CPU cores provide parallelism
 - Data distribution is only through disks, not network
- Due to limited space, we analyze only the external merge-sort as the underlying algorithm



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MapReduce Disk I/O

- Input is a stream of length T
 - Entries are key-value pairs, each K+D bytes
 - At time step *t*, one pair is processed by MapReduce
 - Keys belong to a finite set V of size n
 - Each key v is repeated $\mathcal{I}(v)$ times
 - Disk I/O consists of:
 - Input with *T* pairs (some duplicate)
 - Output with n unique pairs
 - Sorted runs of size L
- Total disk overhead is W = (K+D)(T+n+2L)
 - Our first goal is to derive *L*

MapReduce Disk I/O (2)

- Suppose RAM can hold m key-value pairs
- Let S_t denote the seen set at time t and $\epsilon_t = t/T$ be the fraction of input processed by t
 - Then, $k = \lceil T/m \rceil$ is the number of sorted runs, where each contains $E[|S_m|]$ pairs on average
- <u>Theorem 1</u>: The expected size of the seen set at t is: $E[|S_t|] = n - nE[(1 - \epsilon_t)^{\mathcal{I}}]$
- <u>Theorem 2</u>: Disk spill L of a merge-sort MapReduce is:

$$L = nk(K+D)\left(1 - E\left[(1-\epsilon_m)^{\mathcal{I}}\right]\right)$$

• Total I/O overhead is thus: $W = n(K+D) \left\{ E[\mathcal{I}] + 1 + 2k \left(1 - E[(1 - \epsilon_m)^{\mathcal{I}}] \right) \right\}_{9}$

MapReduce Disk I/O (3)

- Quite a complex function of m and \mathcal{I}
- Verification on real graphs
 - IRLbot host graph (640M nodes, 6.8B edges, 55 GB)
 - WebBase web graph (667M nodes, 4.2B edges, 33 GB)





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MapReduce Merge Overhead

- Selection tree for merging sorted runs, where each internal node
 - Executes binary comparison
 - Applies reduce operation
 - De-duplication makes
 upper nodes perform
 less work than lower

merged data depth $d = \log_2 k$ sorted runs

 <u>Theorem 3</u>: The number of comparisons in a binary selection tree with k leaf nodes is:

$$C_k = nk \sum_{i=1}^d \frac{1}{2^{i-1}} \left(1 - E\left[(1 - \epsilon_{im})^{\mathcal{I}} \right] \right)$$

Merge Rate Evaluation

Comparison with naïve model (no de-duplication):

$$\widehat{C}_k = n \log_2 k \cdot \left(1 - E[(1 - \epsilon_m)^{\mathcal{I}}] \right)$$



Comparison overhead and merge rate γ_m dictated by k– Higher k implies more de-duplication



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MapReduce Runtime



Thank you! Questions?