Muppet: MapReduce-Style processing for fast data

December 22, 2013

Outline

1. MapReduce framework
   - MapReduce Theory
   - MapReduce System
2. Muppet
   - Motivation
   - Muppet Framework

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Function Objects

Definition

A function object is a function that can be manipulated as objects. e.g. Comparator objects used in c++ stl sort function.

An Example

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struct myclass {
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$fold(f, L[i:j]) = f(L[i], fold(f, L[i+1:j]))$

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MapReduce folds over a sorted result of a map

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MapReduce System

1. Programming model to express computations such that the resulting program is "easily" parallelizable.
    1. The parallelization is taken care of by an algorithm rather than a programmer.

1. Associated system that allows executing programs based on the MR programming model on a cluster of commodity machines.
    1. Programmer only needs to write map and reduce functions and set few configuration parameters.
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MapReduce System

1. Map: Takes input key value pair and outputs a set of "intermediate" key value pairs.
2. The MapReduce framework groups the intermediate key value pairs and produces key, value list.
3. Reduce: Takes key, value list and summarizes the list.

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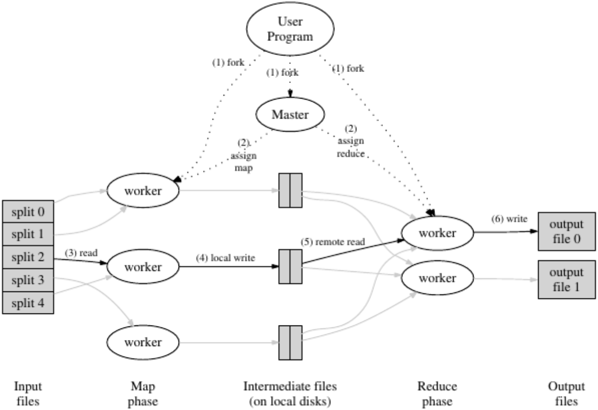
Execution Overview



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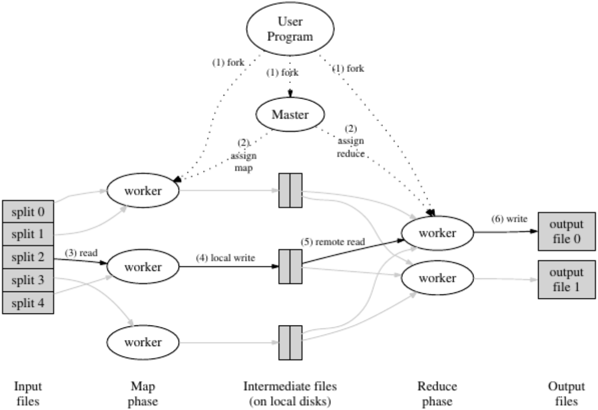

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Streaming Data

1. The data continuously keeps flowing at high speed.
2. Challenge: Compute summary information based on the high speed streaming data

Examples

a) How to detect "hot topics" on twitter quickly, given the high speed stream of all public tweets.
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   1. Fresh data cannot be included in the middle of MapReduce execution
   2. There is no such thing as a snapshot in a stream
2. Given that the input stream is high speed, the recovery from failure should be very quick.

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2. Manage dynamic datastructures and make them quereable
3. High speed processing of streaming data
4. Should be easy to scale up by throwing machines at the growing data size

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Events and Streams

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Event e is a tuple $< sid, ts, k, v >$

sid- Stream ID that the e belongs to

ts- Global time stamps, to allow well defined merging of multiple streams

k- key that need not be unique across events, used to group events

v- value field

Definition

A Stream is a sequence of events in the increasing order of time stamp *ts*

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Map Function

1. A map function subscribes to one or more streams.
2. Events are fed to the map function in the increasing order of time stamps ts
3. A map function takes an event as an input and produces zero or more events $map(event) \rightarrow event*$ to various streams

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Update Function

1. Input characteristics same as map function
2. An Update function $U(e, S_{U,k})$ is also given a slate $S_{U,k}$ along with the event e having a key k
3. The slate $S_{U,k}$ is an in memory datastructure used to keep all the summary information about the events with key k seen by U
4. The pair $< U, k >$ uniquely identifies a slate.
   1. $S_{U_1,k}$ and $S_{U_2,k}$ are two different slates even though the key is the same.
5. Slate is "live" in memory datastructure that is continuously updated with the streaming data

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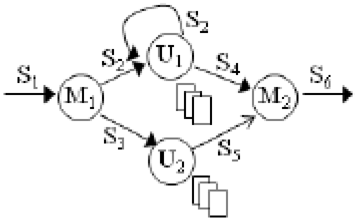

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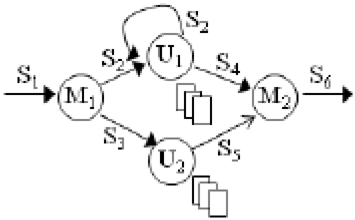

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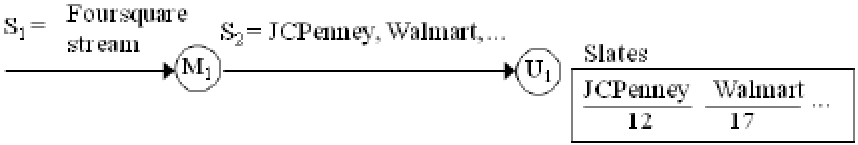

(b)

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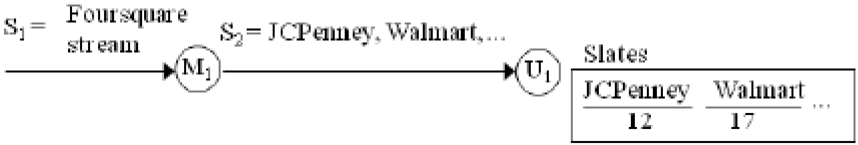

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