Muppet: MapReduce-Style processing for fast data

by Wang Lam et al.

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Outline

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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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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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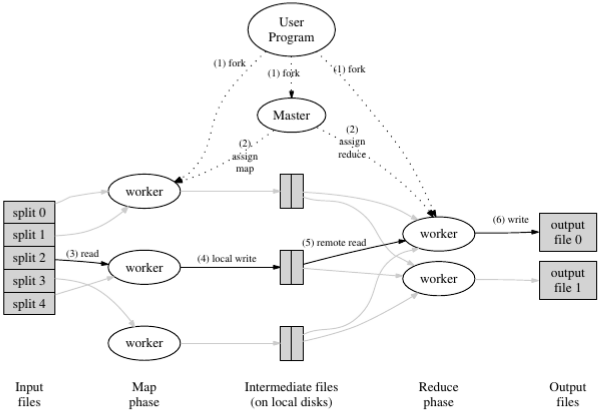

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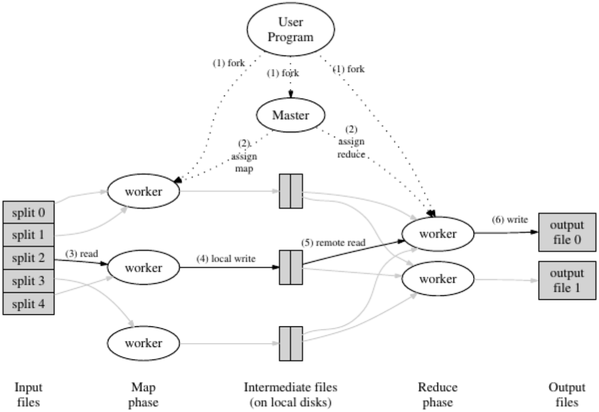

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Streaming Data

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.
b) Given a foursquare checkin stream, maintain the count of checkins per retailer.

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MapReduce deficiencies

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   1. computations that produce and consume streams of data
   2. MapReduce system needs to look at a snapshot of data
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   - MapReduce Theory
   - MapReduce System
2. Muppet
   - Motivation
   - Muppet Framework

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2. Manage “dynamic” datastructures
3. High speed processing of streaming data
4. Should be easy to “scale up” by throwing machines at the growing stream rate

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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

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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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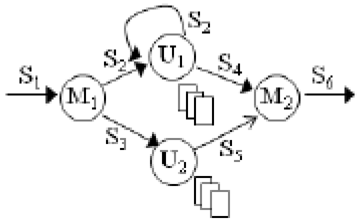

(a)

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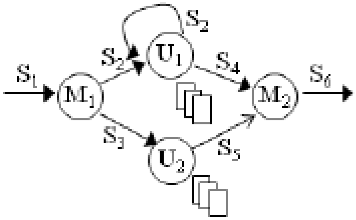

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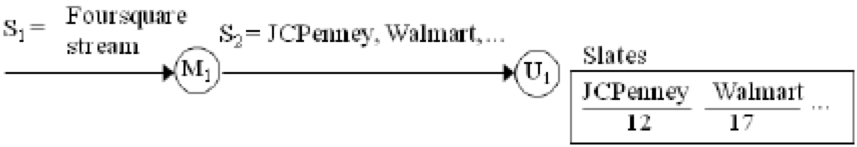

(b)

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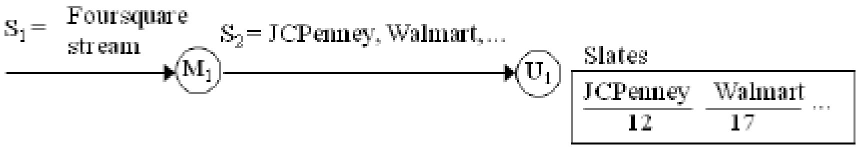

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