

RHadoop Advanced Usage



December 3, 2013













Outline



- 1 Review
- 2 Converting Models to MapReduce
- Regression with MapReduce
- K-Means with MapReduce
- 5 Performance Considerations
- 6 How rmr Works

MapReduce Basics: Map



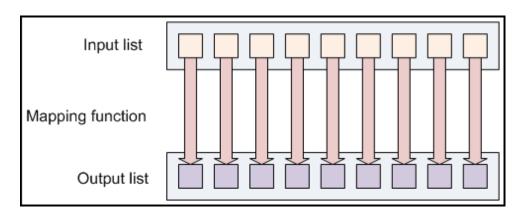


Figure : Map



MapReduce Basics: Reduce



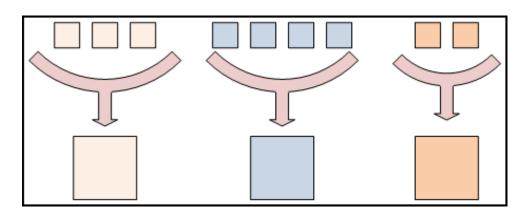
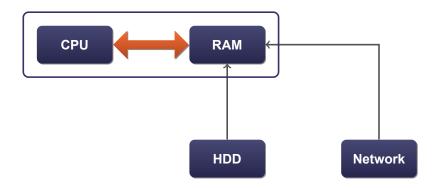


Figure: Reduce



Hadoop Basics

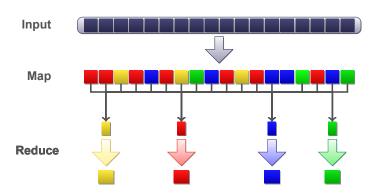






MapReduce Data Flow







Hadoop: The Metaphor



You've decided to hire the monkeys, what could possibly go wrong?

- Certain parts of the pile are heavier than others
- They see something shiny
- They get hungry

Hadoop: Potential Problems



What problems can happen when trying to run a job?

- Certain parts of the data take longer to process
- Hardware problems: machine dies, network traffic
- Software problems: run out of memory

Hadoop: Solutions



Hadoop can handle all of these things and more, using:

- Data redundancy
- Load-balancing
- Job monitoring and resubmitting

Hadoop: Architecture



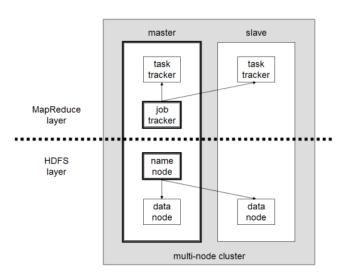


Figure: MapReduce and HDFS on Hadoop



Hadoop: Terminology



- Job: High-level MapReduce "program" you submit
- Task: Lower-level subtask assigned to nodes

Centralized Jobs are composed of Tasks, which are distributed and redundant, so that Task failures don't result in Job failures.

MapReduce on Hadoop



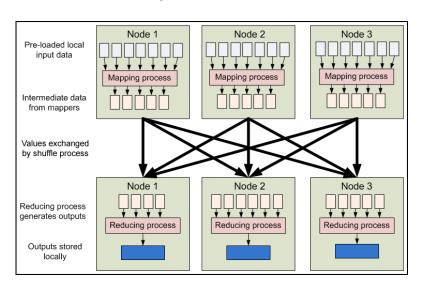
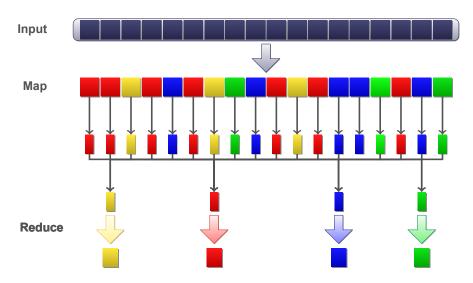


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MapReduce Data Flow







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Core Concepts



- Identify computational bottlenecks
- Track the data "size" through your model

Data vs Computation



- Different perspectives, similar results
- Largely a matter of your intuition



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Least-Squares Regression



```
x <- 1:100
y <- x + 10*rnorm(100)
mod <- lm(y~x)
plot(mod)</pre>
```



$$y = \beta X + \epsilon$$



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$$\beta = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$



$$y = \beta X + \epsilon$$

- \blacksquare How do we solve for β
- $\beta = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$
- How do we MapReduce this?

How Big is the Data?



For least-squares regression:

$$\beta = (X^T X)^{-1} X^T y \tag{1}$$

Discuss the following:

- What **can** you do without Hadoop?
- What can't you do without Hadoop?
- How would you implement this on Hadoop?

How Big is the Data?



- For large number of "rows": *n*, and much smaller number of "columns": *k*
- X is n by k
- (X^TX) is only k by k
- $X^T y$ is only k by ka

OLS via MapReduce



```
XtX =
values(
  from.dfs(
    mapreduce(
      input = X,
      map =
      function(., Xi)
        keyval(1, list(t(Xi) %*% Xi)),
    reduce = Sum,
    combine = TRUE)))[[1]]
```

OLS via MapReduce



```
Xty =
values(
  from.dfs(
    mapreduce(
    input = X,
    map = function(., Xi)
       keyval(1, list(t(Xi) %*% y)),
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```

OLS via MapReduce



solve(XtX, Xty)



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K-Means Review



- Unsupervised learning
- Cluster analysis
- Finds K clusters that minimize distances from cluster centers

K-Means Example



K-Means Algorithm



Iteratively assign points to clusters and update cluster centers around their assigned points

- Initialize cluster centers
- 2 Assign each point to the closest cluster
- 3 Update each cluster center to be the average of the points assigned to it
- 4 Repeat 2-3 until no cluster center changes

Where is the Bottleneck?



For k-means clustering, discuss the following:

- Where is the computational bottleneck?
- How could you rewrite that bottleneck as a Map?
- How could you collect the results of that Map with Reduce?

K-Means with MapReduce



■ What is the computational bottleneck?

K-Means with MapReduce



- What is the computational bottleneck?
- Distance calculations: ie finding the closest cluster

K-Means via MapReduce



```
dist.fun =
    function(C, P) {
        apply(
          C,
        1,
        function(x)
        colSums((t(P) - x)^2))}
```

K-Means via MapReduce



```
ns.map =
      function(., P) {
        nearest = {
          if(is.null(C))
            sample(
              1:num.clusters,
              nrow(P),
              replace = T)
          else {
            D = dist.fun(C, P)
            nearest = max.col(-D)}}
        if(!(combine || in.memory.combine))
          keyval(nearest, P)
        else
          keyval(nearest, cbind(1, P))}
```



K-Means via MapReduce



```
kmeans.reduce = {
    if (!(combine || in.memory.combine) )
        function(., P)
        t(as.matrix(apply(P, 2, mean)))
    else
        function(k, P)
        keyval(
            k,
            t(as.matrix(apply(P, 2, sum))))}
```

K-Means + MapReduce: Good Idea



K: How many clusters?

K-Means + MapReduce: Good Idea



- K: How many clusters?
- That was one iteration



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Tasks Execute on One Node



Each application of a map or reduce function occurs on a single machine in the cluster.

■ What if the data can't fit on a node?

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- What if the data can't fit on a node?
- What if the task is taking "too long"

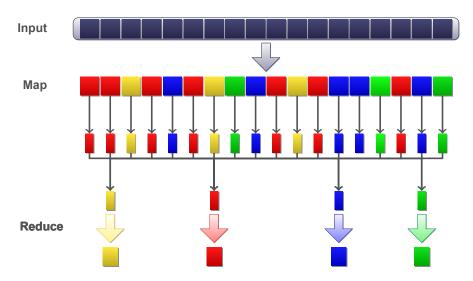
Tasks Execute on One Node



Each application of a map or reduce function occurs on a single machine in the cluster.

- What if the data can't fit on a node?
- What if the task is taking "too long"
- Your jobs may fail









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- A function used to consolidate mapper output locally before the big shuffle/sort happens across nodes
- When to use?



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- Whenever you can
- Why?
- Combine allows you to reduce the size of the map output
- So what?
- Less data to send over the network, shuffle-sort and reduce, with less data being cached to HD

Combine vs Reduce: Standard deviation



How could you rewrite this as a combine function?

```
reduce = function(k,v) {
    keyval(k,sd(v))
}
```

• Remeber this? $Var[X] = E[X - \mu_X]^2 = E[X^2] - E[X]^2$

Combine vs Reduce: Standard deviation



```
combine = function(k,v) {
    keyval(k,list(v=sum(v),vsquared=sum(v^2)))
}
```

When can't you combine?



- median
- other quantiles
- any other time you need relative position information

wordcount: Combine



...and thatâ \(\sigma\) s why the reducer code uses sum() and not length():

```
reduce = function(word, counts) {
  keyval(word, sum(counts))
}
```

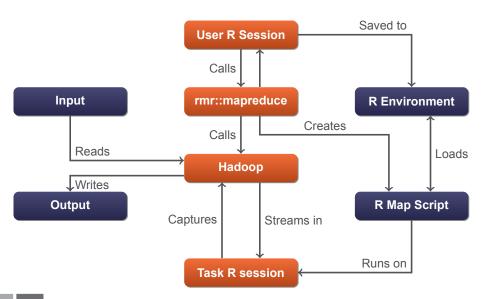
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The rmr Data Flow







rmr Is Hadoop Streaming



Ultimately, rmr2::mapreduce simply initializes a Hadoop Streaming job and submits it to the cluster. Most job configuration is simply configuration of the Hadoop Streaming job.

Here are some options you may want to know:

- mapred.child.java.opts Command-line options for the jvm, useful to reduce java memory consumption
- mapred.map.tasks Explicitly set the number of map tasks
- mapred.reduce.tasks Explicitly set the number of reduce tasks
- mapred.job.name Give your job a name, you can more easily monitor it

For more information, see the documentation.

