

# Map Reduce and Streaming Calculations

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# Agenda for the week

- Map-Reduce
- Poisson resampling
- Streaming Calculations
  - ① Reservoir Sampling
  - ② Storing Items in Sets
  - ③ Counting in single pass
  - ④ Frequent Items in a stream
  - ⑤ Estimating CDF/PDF in streaming mode
- Background Reading

# Overview

1 Map Reduce

2 Poisson resampling

# Hello World in Map Reduce

## Counting words in some text

But I must explain to you how all this mistaken idea of denouncing pleasure and praising pain was born and I will give you a complete account of the system.

- Step 0: Parse text word by word.
- Step 1: Emit one word at a time
- Step 2: Group same words together
- Step 3: Count occurrence of each word

# Word Count - Emit

But	1	
I	1	
must	1	
explain		1
to	1	
you	1	
how	1	
all	1	
this	1	
mistaken		1
idea	1	
of	1	
denouncing		1
pleasure		1

# Word Count - Emit

and	1	
praising		1
pain	1	
was	1	
born	1	
and	1	
I	1	
will	1	
give	1	
you	1	
a	1	
complete		1
account		1
of	1	
the	1	
system.		1

# Word Count - Sort and Group

But	1	
I	1	
I	1	
a	1	
account		1
all	1	
and	1	
and	1	
born	1	
complete		1
denouncing		1
explain		1
give	1	
how	1	
idea	1	
mistaken		1

# Word Count - Sort and Group

must	1	
of	1	
of	1	
pain	1	
pleasure		1
praising		1
system.		1
the	1	
this	1	
to	1	
was	1	
will	1	
you	1	
you	1	



# Word Count - Aggregate

But	1	
I	2	
a	1	
account		1
all	1	
and	2	
born	1	
complete		1
denouncing		1
explain		1
give	1	
how	1	
idea	1	
mistaken		1

# Map Reduce

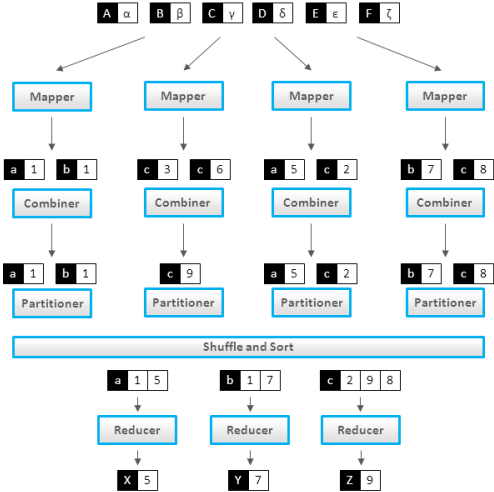


Figure: Source: [highlyscalable.com](http://highlyscalable.com) blog

# MR Demo

# Map Reduce Examples

- Word Count

# Map Reduce Examples

- Word Count
- Unique Count

# Map Reduce Examples

- Word Count
- Unique Count
- Total Sales, Average Sales by Customer

# Map Reduce Examples

- Word Count
- Unique Count
- Total Sales, Average Sales by Customer
- Click-Through-Rate of Advertising Campaigns

# Map Reduce Examples

- Word Count
- Unique Count
- Total Sales, Average Sales by Customer
- Click-Through-Rate of Advertising Campaigns
- Little Bag of Bootstraps to Build Models



# HDFS: Hadoop Distributed File System

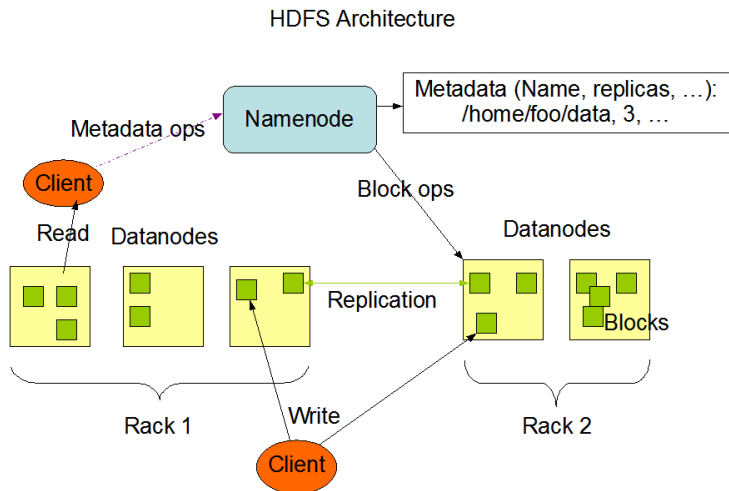


Figure: Source: Apache Foundation

# Hadoop Ecosystem

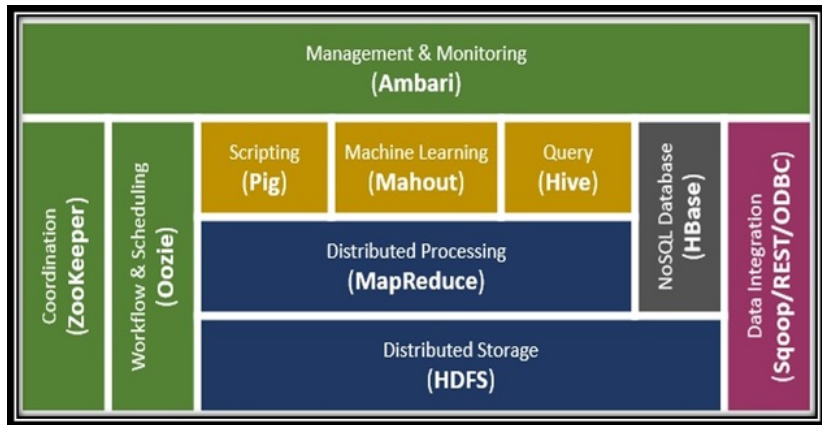


Figure: Source: Apache Foundation

# Overview

1 Map Reduce

2 Poisson resampling

# Poisson Resampling for Efficient Bootstrapping

## Bootstrapping Big Data

- Bootstrap is not efficient when dealing with Big Data  $\approx 63.2\%$  of data gets resampled per bootstrap
- Need several bootstrap samples depending on what you are trying to estimate (e.g. std err or percentiles)
- Little Bag of Bootstraps is one technique (saw last week)
- Poisson Resampling is another technique

# Poisson Resampling

## Motivation

Let's start with a tiny sample  $\{1.5, 2.5, 3.5, 4.5\}$  and do bootstrap

Sample 1	$\{1.5, 1.5, 3.5, 2.5\}$
Sample 2	$\{2.5, 1.5, 3.5, 2.5\}$
Sample 3	$\{3.5, 4.5, 4.5, 4.5\}$

We can actually describe this in terms of sample counts

Sample 1	$\{2, 1, 1, 0\}$
Sample 2	$\{1, 2, 1, 0\}$
Sample 3	$\{0, 0, 1, 3\}$

These counts follow a  $Multinomial(4, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4})$  distribution. Generally,  $Multinomial(n, \frac{1}{n}, \dots, \frac{1}{n})$

# Poisson Resampling

## Big Data Problem

Not all data resides in the same place. Data is distributed. Also, in streaming cases, we may not even know  $n$  in advance



Can we *approximate* bootstrapping without bringing all the data to one place?

# Poisson Resampling

## Approximation

What if we independently sample each data point using a  $Binomial(n, \frac{1}{n})$ ? All sampling can be done in parallel. For large  $n$ , this is *close-enough* to multinomial sampling that it doesn't matter in practice. But, we still need to know  $n$  in advance!

## Poisson Distribution

$$\lim_{n \rightarrow \infty} Binomial(n, \frac{1}{n}) = Poisson(1)$$

$Poisson(\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$  doesn't need to know  $n$ !

# Poisson Resampling in Action



# Poisson Resampling in Map-Reduce

- Independently sample in your map task using  $Poisson(1)$
- Emit those  $k$  samples
- Reducers get independent datasets, run their aggregations, and return back results
  - Aggregations could be statistics, or even entire models!

