CMSC5741 Big Data Tech. & Apps.

Lecture 2: MapReduce and F ts

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Outline

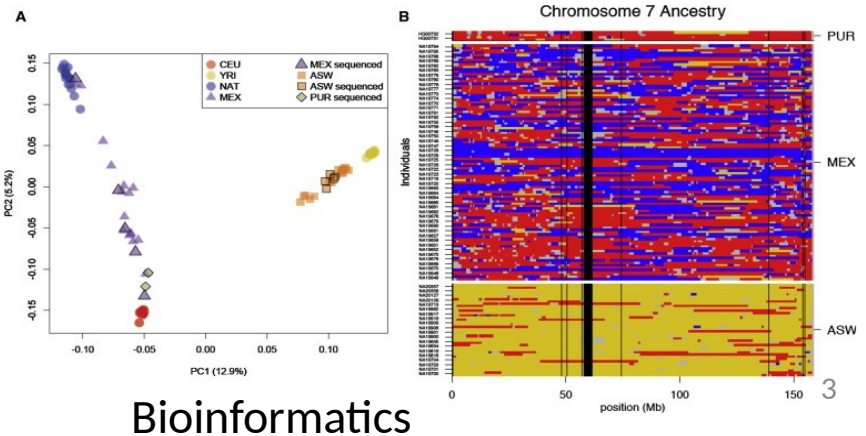
- Introduction
- The Hadoop Distributed File System (HDFS)
- MapReduce
- Hadoop
- Hadoop Streaming
- Problems Suited for MapReduce
- TensorFlow
- Frequent Itemsets
- Conclusion

Introduction

- Much of the course will be devoted to learning with big data

Facebook

Netflix



Bioinformatics

Introduction

- Challenges:
  - How to distribute computation?
  - Distributed/p s hard
- MapReduce a bove
  - Google's computational/d lation model
  - Elegant way to work with Big Data

Motivation: Data Volume Now

The scale of data today and tomorrow:

- 2008: Google processes 20 PB a day
- 2009: Facebook has 2.5 PB user data + 15 TB/day
- 2009: eBay has 6.5 PB user data +
- 2013: Estimated size of digital wo
- 2016: 2.5 exabytes (EB) created everyday
- 2017: Google holds 10-15 exabytes of data
- By 2020: 44ZB (10^{21}) will be produced (5.2 TB for every person)

Motivation: Google Example

- 20+ billion web pages x 20KB = 400+ TB
- 1 computer reads 30-35 MB/sec from disk
  - ~4 months to rea
- ~1,000 hard drive nly text data)
- Takes even more resources to d ork with the data
- Today, a standard architecture for such problem is emerging:
  - Cluster of commodity Linux nodes
  - Commodity network (ethernet) to connect them
  - It was estimated that Google had over 2.5M machines in 16 data centers worldwide (one center includes 9,941 miles of cable)

Large-scale Computing

- Large-scale computing for data mining problems on commodity hardware
- Challenges:
  1. How do you
  2. How can we make it easy to ibuted programs?
  3. How can you handle machine failures?
     - One server may stay up 3 years (1,000 days)
     - If you have 1,000 servers, expect to lose 1/day
     - It is estimated that Google had 2.5M machines in 2016
       - 2,500 machine fails every day!

Idea and Solution

- Issue: Copying data over a network takes time
- Idea:
  - Bring computation close to the data
  - Store files multipl
- MapReduce addr
  - Google's computational/data man del
  - Elegant way to work with big data
  - Storage Infrastructure – File system
    - Google: GFS; Hadoop: HDFS
  - Programming model
    - Map-reduce

Relationship

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The Hadoop Distributed File System (HDFS)

- With hundreds of machines at hand, failure is the norm rather than exception
- Traditional file [illegible] not cope with the scale and failur[illegible] ters
- The Hadoop Distributed File [illegible] (HDFS) is a natural solution to this problem
  - Distributed File System
  - Provides global file namespace
  - Replica to ensure data recovery

The Hadoop Distributed File System (HDFS)

- A HDFS instance may consist of thousands of server machines, each storing part of the file system's data.
- Since we have ponents, and each compone obability of failure, it means that there some component that is non-functional.
- Detection of faults and quick, automatic recovery from them are a core architectural goal of HDFS.

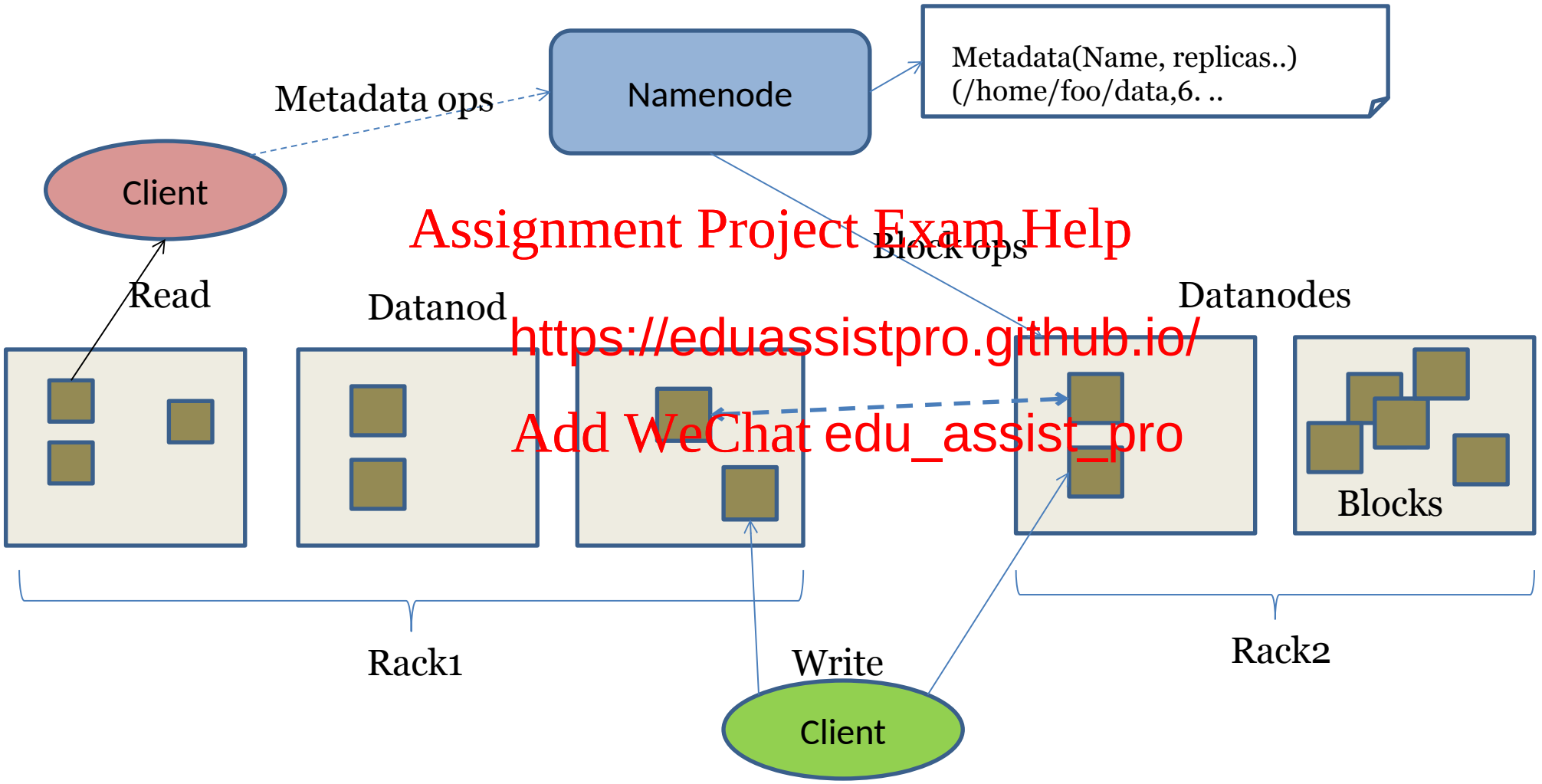
Data Characteristics

- Streaming data access
- Batch processing rather than interactive user access
- Write-once-read-many: once created, written and closed, need not be changed
- This assumption simplifies coherency in concurrent accesses

HDFS Architecture

- Master/slave architecture
  - Master: NameNode
  - Slave: DataNo
- HDFS exposes pace (NameNode) and allows user data to be files.
- A file is split into one or more blocks and set of blocks are stored in DataNodes.

HDFS Architecture



File System Namespace

- Namenode maintains the file system.
  - Hierarchical file system with directories and files.
  - Create, remove, move, rename, etc.
  - Any meta info change to the file system is recorded by the Namenode.
- An application can specify the number of replicas of the file needed: replication factor of the file. This information is stored in the Namenode.

Data Replication

- HDFS is designed to store very large files across machines in a large cluster.
  - Each file is a sequence of blocks.
  - All blocks in th re of the same size.
- Blocks are repli ance.
- Block size and replicas are ble per file.
- The NameNode receives a Heartbeat and a BlockReport from each DataNode in the cluster.
- BlockReport contains all the blocks on a DataNode.

Replica Selection

- Replica selection for read operation: HDFS tries to minimize the bandwidth consumption and latency.
- If there is a rep ode then that is preferred.
- HDFS cluster may span mul centers: replica in the local data center is preferred over the remote one.

Safemode Startup

- Each DataNode checks in with Heartbeat and BlockReport.
- NameNode verifies that each block has acceptable number of replicas.
- After a configurab y replicated blocks check in with the NameNode, N exits Safemode.
- It then makes the list of blocks o be replicated.
- NameNode then proceeds to replicate these blocks to other DataNodes.

Filesystem Metadata

- The HDFS namespace is stored by NameNode.
- NameNode uses a transaction log called the EditLog to record every to the filesystem meta data.
  - For example, creating a new
  - Change replication factor of a file
  - EditLog is stored in the NameNode's local filesystem

NameNode

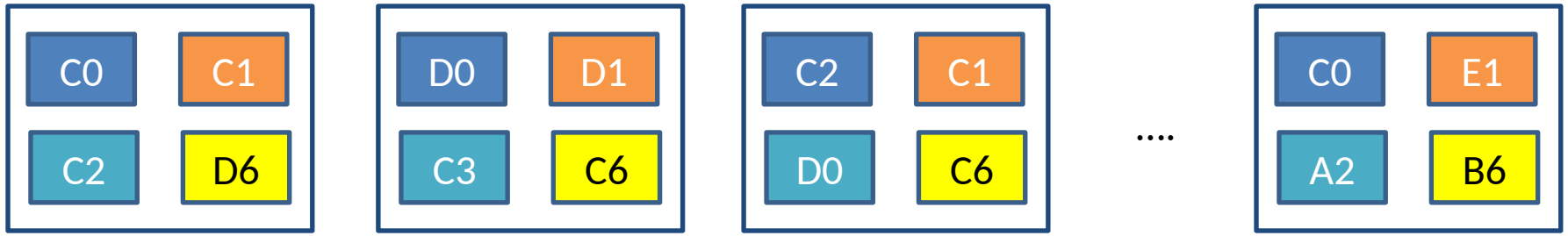
- Keeps image of entire file system namespace.
- When the Namenode starts up
  - Gets the FsImage and EditLog.
  - Update FsIma ation.
  - Stores a copy of the FsImag .
- In case of crash
  - Last checkpoint is recovered.

DataNode

- A DataNode stores data in files in its local file system.
  - Each block of HDFS is a separate file.
  - These files are placed in different directories.
  - Creation of ne ed by heuristics.
- When the filesystem starts
  - Generates Blockreport.
  - Sends this report to NameNode.

HDFS Summary

- Reliable distributed file system
- Data kept in "chunks" spread across machines
- Each chunk re t machine and racks
  - Seamless recovery from di ine failure



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MapReduce

- Warm-up task
  - We have a huge text document
  - Count the nu tinct word appears in the file
- Sample application
  - Analyze web server logs to find popular URLs

Task: Word Count

- Using Unix tool chain, we can count the occurrences of words:
  - `words (doc.txt) | sort | uniq -c`
    - Where `words` ords in it, one per line
- This way of counting capture ce of MapReduce
  - Mapper (done by words)
  - Group by keys and sort (done by sort)
  - Reducer (done by uniq)
  - Hadoop handles the partition and parallelization

MapReduce: Overview

- Sequentially read a lot of data
- Map:
  - Extract some
- Group by key:
- Reduce:
  - Aggregate, summarize, filter or transform
- Write the result

MapReduce

- Input: a set of key-value paris
- Programmer must specifies two methods:
  - Map(k,v) -> <
    - Takes a key-value pair and outputs a set of key-value pairs
    - There is one Map call for each (k,v) pair
  - Reduce (k', <v'>) -> <k', v''>
    - All values v' with the same key k' are reduced together and processed in v' order
    - There is one Reduce function call per unique key k'

MapReduce: Word Count Example

- Now that one document changes to a large corpus of documents

MapReduce: Word Count Example

```
// key: document name; value: text of the document
Map(key, value):
  for each word w in value:
    emit(w, 1)

// key: a word; value: an iterator over counts
Reduce(key, value
  result = 0
  for each count v in values:
    results += v
  emit(key, result)
```

In-class Practice

- Go to practice

MapReduce: Environment

- MapReduce environment takes care of:
  - Partitioning the input data
  - Scheduling th n across a set of machines
  - Performing the "group by"
  - Handling machine failures
  - Managing required inter-machine communication

MapReduce

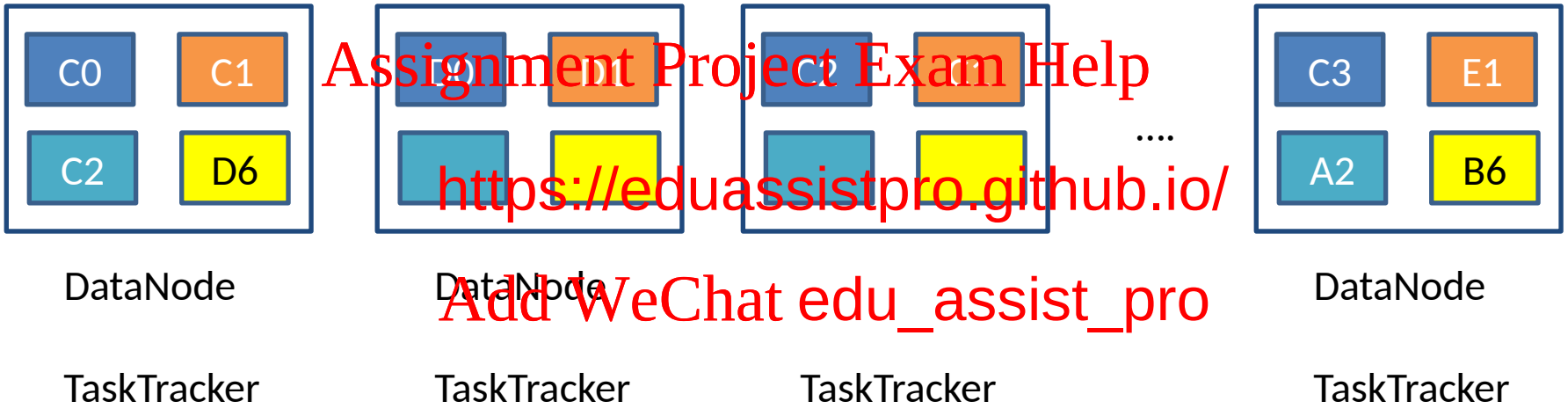
Map:
Read input and produces a set of key-value pairs

Group by key:
Collect all pairs with the same key

Reduce:
Collect all values belonging to the key and output

MapReduce

- Move computation to the data



Bring computation directly to the data!

DataNode also serve as compute servers

Data Flow

- Input and final output are stored on a distributed file system (FS):
  - Scheduler tri ks "close" to physical stor ata
- Intermediate results are s local FS of Map and Reduce workers
- Output is often input to another MapReduce task

Coordination: Master

- Master node takes care of coordination:
  - Task status: (idle, in-progress, completed)
  - Idle tasks get
  - When a map
    location and sizes of its *R* i e files, one for each reducer
  - Master pushes this info to reducers
- Master pings workers periodically to detect failures

Dealing with Failures

- Map worker failure
  - Map tasks completed or in-progress at worker are reset to idle
  - Reduce workers are notified when task is rescheduled on another worker
- Reduce worker failure
  - Only in-progress tasks are rese
  - Reduce task is restarted
- Master failure
  - MapReduce task is aborted and client is notified.

How Many Map and Reduce Jobs?

- M map tasks, R reduce tasks
- Rule of a thumb:
  - Make M muc er of nodes in the cluster
  - One chunk per map is com
  - Improves dynamic load balancing and speeds up recovery from worker failures
- Usually R is smaller than M
  - Output is spread across R files

Refinement: Combiners

- Often a Map task will produce many pairs of the form (k,v1), (k,v2), … for the same key k
  - E.g., popular words in the word count example
- Can save network time by pre-aggregating values in the mapper:
  - Combine(k, list(v)) -> v2
  - Combiner is usually the same as the reduce function
- Works only if reduce function is commutative and associative

Refinement: Partition Function

- Want to control how keys get partitioned
  - Inputs to map tasks are created by contiguous splits of input file
  - Reduce needs t th the same intermediate k orker
- System uses a default partiti .
  - `Hash(key) mod R`
- Sometimes useful to override the hash function:
  - E.g., `hash(hostname(URL)) mod R` ensures URLs from a host end up in the same output file

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Hadoop

- Hadoop is an open source implementation of MapReduce framework
  - Hadoop Distr FS) as storage
  - Hadoop hand distribution, task monitoring and failure rec
  - All you need to do is to write two Java classes
    - Mapper
    - Reducer

Hadoop

- Follow the MapReduce architecture, the Hadoop has a master/slave design

MapReduce	jobtrack	ktracker
HDFS	namenode	datanode

Word Count in Hadoop

- Mapper

```
public static class MapClass extends MapReduceBase
implements Mapper {
  private final static IntWritable one = new IntWritable(1);
  private Text word

  public void map(WritableComparabl           able value,
  OutputCollector output, Reporter
  throws IOException {
    String line = ((Text)value).toString();
    StringTokenizer itr = new StringTokenizer(line);
    while (itr.hasMoreTokens()) {
      word.set(itr.nextToken());
      output.collect(word, one);
    }
  }
}
```

Word Count in Hadoop

- Reducer

```
public static class Reduce extends MapReduceBase implements
Reducer {
  public void reduc                              y, Iterator
  values, OutputCol                              reporter)
  throws IOExceptio
    int sum = 0;
    while (values.hasNext()) {
      sum += ((IntWritable) values.next()).get();
    }
    output.collect(key, new IntWritable(sum));
  }
}
```

Word Count in Hadoop

- Main

```
public static void main(String[] args) throws IOException {
  //checking goes here
  JobConf conf = new JobConf();

  conf.setOutputKe
  conf.setOutputVa                                ass);

  conf.setMapperClass(MapClass.c
  conf.setCombinerClass(Reduce.class);
  conf.setReducerClass(Reduce.class);

  conf.setInputPath(new Path(args[0]));
  conf.setOutputPath(new Path(args[1]));

  JobClient.runJob(conf);
}
```


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Hadoop Streaming

- To enjoy the convenience brought by Hadoop, one has to implement mapper and reducer in Java
  - Hadoop defin and complex class hierarchy
  - There is a learning curve
- Hadoop streaming allows you to use any language to write the mapper and reducer

Hadoop Streaming

- Using Hadoop Streaming, you need to write
  - Mapper
    - Read input from standard input (STDIN)
    - Write map r … STDOUT)
      - Key value are separated using
  - Group by key
    - Done by Hadoop
  - Reducer
    - Read input (Mapper's output) from standard input (STDIN)
    - Write output (Final result) to standard output (STDOUT)

Hadoop Streaming

- Allows you to start writing MapReduce application that can be readily deployed without having to learn Hadoop data types
- Speed up dev
- Utilize rich features and li ries from other languages (Python, Ruby)
- Efficiency critical application can be implemented in efficient language (C, C++)

Hadoop Streaming: Word Count Mapper

```
#!/usr/bin/env python

import sys

# input comes from STDIN (standard input)
for line in sys.st
    # remove leadi                    ace
    line = line.strip()
    # split the line into words
    words = line.split()
    # increase counters
    for word in words:
        # write the results to STDOUT (standard output);
        # what we output here will be the input for the
        # Reduce step, i.e. the input for reducer.py
        #
        # tab-delimited; the trivial word count is 1
        print '%s\t%s' % (word, 1)
```

Hadoop Streaming: Word Count Reducer

```
#!/usr/bin/env python
from operator import itemgetter
import sys
current_word = None
current_count = 0
word = None
for line in sys.stdin:
    line = line.s
    word, count =
    try:
        count = int(count)
    except ValueError:
        continue
    if current_word == word:
        current_count += count
    else:
        if current_word:
            print '%s\t%s' % (current_word, current_count)
        current_count = count
        current_word = word
if current_word == word:
    print '%s\t%s' % (current_word, current_count)
```

Hadoop Streaming: How to Run?

- To run the sample code

```
$HADOOP_HOME/bin/hadoop jar $HADOOP_HOME/hadoop-streaming.jar \
-input inputPathInHDFS \
-output outputPathon
-file pathToMapper.p
-mapper mapper.py \
-file pathToReducer.py \
-reducer reducer.py
```


- -file caches the argument to every tasktracker
- The above command distribute the mapper.py and reducer.py to every tasktracker

Hadoop Streaming: Word Count

```
#!/usr/bin/env python
"""A more advanced Mapper, using Python iterators and generators."""

import sys
def read_input(file):
    for line in file:
        yield line.spl
def main(separator='\t
    # input comes from STDIN (standard
    data = read_input(sys.stdin)
    for words in data:
        # write the results to STDOUT (standard output);
        # what we output here will be the input for the
        # Reduce step, i.e. the input for reducer.py
        #
        # tab-delimited; the trivial word count is 1
        for word in words:
            print '%s%s%d' % (word, separator, 1)
if __name__ == "__main__":
    main()
```

Hadoop Streaming: Word Count

```
#!/usr/bin/env python
"""A more advanced Reducer, using Python iterators and generators."""

from itertools import groupby
from operator import itemgetter
import sys
def read_mapper_output(file, separator='\t'):
    for line in file:
        yield line.rstrip().s
def main(separator='\t'):
    # input comes from STDIN
    data = read_mapper_output(sys.stdin, separat
    # groupby groups multiple word-count pairs b
    # and creates an iterator that returns conse                    ng their group:
    #   current_word - string containing a word (the key)
    #   group - iterator yielding all ["&lt;current_word&gt;", "&lt;count&gt;"] items
    for current_word, group in groupby(data, itemgetter(0)):
        try:
            total_count = sum(int(count) for current_word, count in group)
            print "%s%s%d" % (current_word, separator, total_count)
        except ValueError:
            # count was not a number, so silently discard this item
            pass
if __name__ == "__main__":
    main()
```

Demo

- Given a list of academic paper authors and their papers, we try to output:
  - The most use the title for each author
- We use a python based M c framework implementation called mincemeat.

Demo

- Input Data
  - Books, Ph.D. Thesis, web pages, academic papers
  - Input format
    - Publication t
    - Affiliation
    - Abbreviation code
    - Authors
    - Title


```
tr/gte/TM-0014-06-88-165:::Frank Manola:::Distributed Object
Management Technology.
tr/ibm/IWBS94:::Christoph Beierle::Udo Pletat:::The Algebra of
Feature Graph Specifications
```

Demo

- To run the demo:
  - In terminal 1, type:
    - `python demo.py`
    - This set the ma in program
  - In terminal 2, type:
    - python mincemeat.py -p changem
    - “changeme” is the authentication password
    - 127.0.0.1 is the server address
    - This starts the Map-Reduce framework

Demo

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Example: Host Size

- Suppose we have a large web corpus
- Look at the metadata file
  - Lines of the fo)
- For each host, r of bytes
  - That is, the sum of the page ll URLs from that particular host
- Other examples:
  - Link analysis and graph processing
  - Machine learning algorithms

Example: Language Model

- Statistical machine translation:
  - Need to count number of times every 5-word sequence occurs in a large corpus of documents
- Very easy wit
  - Map:
    - Extract (5-word sequence, count) from document
  - Reduce:
    - Combine the counts

Example: Join By MapReduce

- Compute the natural join R(A,B) x S(B,C)
- R and S are each stored in files
- Tuples are pai

A	B
a1	b1
a2	b1
a3	b2
a4	b3

X

B	C
b2	c1
b2	c2
b3	c3

=

A	C
a3	c1
a3	c2
a4	c3

Note – Other relational-algebra operations: Selection, Projection, Union/Interaction/Difference, Grouping/Aggregation

MapReduce Join

- Use a hash function from B-values to
- A Map process turns:
  - Each input tup
  - Each input tup
- Map processes send each k pair with key to Reduce process
  - Hadoop does this automatically; just tell it what is
- Each Reduce process matches all the pairs with all and outputs .

Cost Measures for Algorithms

- In MapReduce we quantify the cost of an algorithm using
  - Communication cost
    - total I/O of al
  - Elapsed communication cost
    - Max of I/O alone any path
  - (Elapsed) computation cost
    - Analogous, but count only running time of processes
  - Note that here the big-O notation is not the most useful (adding more machines is always an option)

Example: Cost Measures

- For a MapReduce algorithm:
- Communication cost = input file size + 2 (sum of the sizes of all ap processes to Reduce proce he output sizes of the Reduce processes.
- Elapsed communication cost is the sum of the largest input + output for any map process, plus the same for any reduce process

What Cost Measures Mean

- Either the I/O (communication) or processing (computation) cost dominates
  - Ignore one or
- Total cost tell hit from your friendly neighborhood clo
- Elapsed cost is wall-clock time using parallelism

Cost of MapReduce Join

- Total communication cost
  - O(|R| + |S| + |RS|)
- Elapsed communication cost = O(s), where s is the I/O limit
  - We're going to pic rocesses so that the I/O limit *s* is respected
  - We put a limit *s* on the amount of in that any one process can have
  - *s* could be:
    - What fits in main memory
    - What fits on local disk
- With proper indexes, computation cost is linear in the input + output size
  - So computation cost is like communication cost

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TensorFlow

- Interface for expressing machine learning algorithms, and an implementation for executing large-scale alg
- Dataflow fram s to native CPU / GPU code
- Drastic reduction in development time
- Visualization (TensorBoard)

Programming Model

- Express a numeric computation as a **graph**
  - Graph nodes are **operations** which have any number of inputs and outputs
  - Graph edges between nodes

Big Data: Distributed Environment

- Portability: deploy computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a

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Frequent Itemsets

- Simple question: Find sets of items that appear together "frequently" in baskets
- Support for itemset: Number of baskets containing all items in
  - Often expressed as of baskets
- Given a support th s that appear in at least baskets are called frequent itemse

TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Support of {Beer, Bread} = 2

Example: Frequent Itemsets

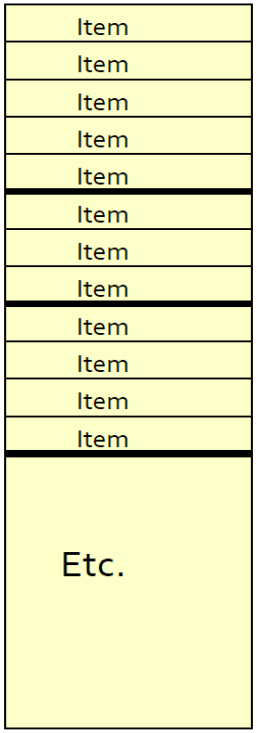
- Items = {milk, coke, pepsi, beer, juice}
- Minimum support = 3 baskets

B1 =	
B3 =	
B5 = {m,p,b}	B6
B7 = {c,b,j}	B8

- Frequent itemsets: {m}, {c}, {b}, {j},
  {m,b}, {b,c}, {c,j}

Itemsets: Computation Model

- Typically, data is kept in flat files rather than in a database system:
  - Stored on dis
  - Stored basket
  - Baskets are small but we h baskets and many items
    - Expand baskets into pairs, triples, etc. as you read baskets
    - Use k nested loops to generate all sets of size k



Items are positive integers, and boundaries between baskets are –1.

Computation Model

- The true cost of mining disk-resident data is usually the number of disk I/O's
- In practice, as ithms read the data in passes n turn
- We measure the cost by t r of passes an algorithm makes over the data

Main-Memory Bottleneck

- For many frequent-itemset algorithms, main-memory is the critical resource
  - As we read b nt something, e.g., occurrences
  - The number of different th n count is limited by main memory
  - Swapping counts in/out is a disaster

Naïve Algorithm to Count Pairs

- Read file once, counting in main memory the occurrences of each pair:
  - From each basket of n items, generate its $n(n-1)/2$ pairs by two nested lo
- Fails if (#items)^2 exceeds m ry
  - Remember: #items can be 100K (Wal-Mart) or 10B (Web pages)
    - Suppose 10^5 items, counts are 4-byte integers
    - Number of pairs of items: $10^5(10^5-1)/2 = 5*10^9$
    - Therefore, $2*10^{10}$ (20 gigabytes) of memory needed

A-Priori Algorithm

- A two-pass approach called a-priori limits the need for main memory
- Key idea: *mon*
  - If a set of ite
    times, so does every **subset**
- Contrapositive for pairs:
  - If item *i* does not appear in *s* baskets, then no pair including *i* can appear in *s* baskets

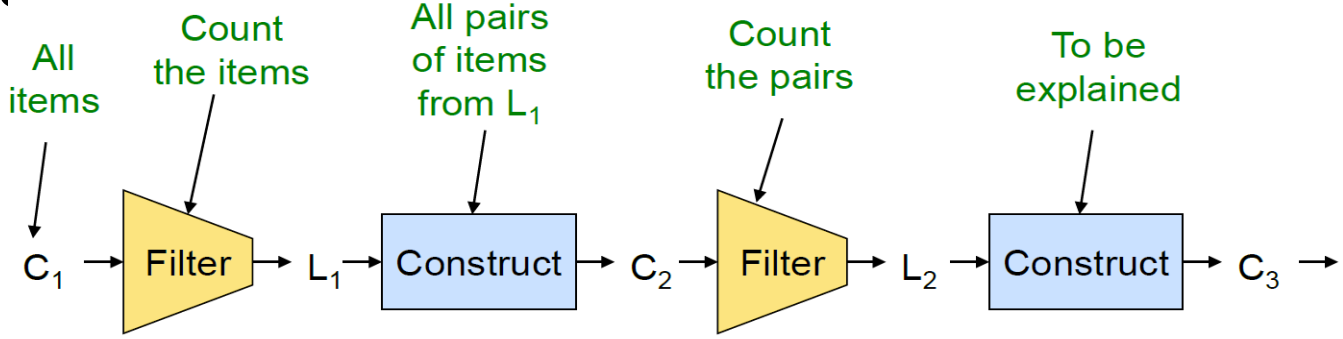
A-Priori Algorithm

- Pass 1: Read baskets and count in main memory the occurrences of each individual item
  - Requires only memory proportional to #items
- Items that appea frequent items
- Pass 2: Read bask main memory only those pairs where both elemen ent (from Pass 1)
  - Requires memory proportional to square of frequent items only (for counts)
  - Plus a list of the frequent items (so you know what must be counted)

Main-Memory: Picture of A-Priori

Frequent Triplets, Etc.

- Now we know how to find frequent pairs, how about frequent triplets and frequent k-tuples?
- For each k, we construct two sets of k-tuples (sets of size k):
- = candidate k-tuples = those t be frequent sets (support > s) based on inform the pass for *k*–1
- = the set of truly frequent *k*-tuples



Example

- Hypothetical steps of the A-Priori algorithm
- = { {b} {c} {j} {m} {n} {p} }
- Count the support of itemsets in
- Prune non-freque
- Generate = { {b,c} {b,j} {b,m} {c,j} }
- Count the support of itemsets in
- Prune non-frequent: = { {b,m} {b,c} {c,m} {c,j} }
- Generate = { {b,c,m} {b,c,j} {b,m,j} {c,m,j} }
- Count the support of itemsets in
- Prune non-frequent: = { {b,c,m} }

A-Priori for All Frequent Itemsets

- One pass for each *k* (itemset size)
- Needs room in main memory to count each candidate *k*-tuple
- For typical market-basket data and reasonable support (e.g., 1%), *k* = 2 requires
- Many possible e Lo port *s* as itemset gets bigger
  - Association rules with intervals:
    - For example: Men over 65 have 2 cars
  - Association rules when items are in a taxonomy
    - Bread, Butter → FruitJam
    - BakedGoods, MilkProduct → PreservedGoods

Map-Reduce Implementation

- Divide the file in which we want to find frequent itemsets into equal chunks randomly.
- Solve the frequ for the smaller chunk at each n unk is the entire dataset)
- Given:
  - Each chunk is fraction of the whole input file (total chunks)
  - is the support threshold for the algorithm
  - or is the threshold as we process a chunk

Map-Reduce Implementation

- At each node, we can use A-Priori algorithm to solve the smaller problem
- Take the grou [illegible] that have been found frequen [illegible] hunks.
  - Every itemset that is frequ [illegible] whole file is frequent in at least one chunk
  - All the true frequent itemsets are among the candidates

Map-Reduce Implementation

- We can arrange the aforementioned algorithm in a two-pass Map-Reduce framework
  - First Map-Re the candidate itemsets
  - Second Map-Reduce cycle e the true frequent itemsets.

Map-Reduce Implementation

First Mapper

- Run A-Priori algorithm on the chunk using support threshold
- Output the freque for that chunk (F, c the key (itemset) and its count (or proportion)

First Reducer

- Output the candidate itemsets to verify in the second pass
  , c), discard c and all ca sets

Map-Reduce Implementation

Second Mapper

- For all the candidate itemsets produced by first reducer, count the frequenc chunk

Second Reducer

- Aggregate the output of second mapper, and sum the get the frequency of te itemsets in the ut file
- Filter the itemsets with support smaller than

Outline

- Introduction
- The Hadoop Distributed File System (HDFS)
- MapReduce
- Hadoop
- Hadoop Streaming
- Problems Suited for MapReduce
- TensorFlow
- Frequent Itemsets
- Conclusion

Conclusion

- HDFS is a reliable distributed file system
- MapReduce is a distributed computing environment
  - Hadoop is an o ation of MapReduce
  - Hadoop Strea y language to write MapReduce code
- Frequent Itemsets problem can be solved efficiently using its monotonicity property
  - A-Priori algorithm

One-Slide Takeaway

- HDFS is a distributed file system built with robust in mind
- MapReduce is a convenient paradigm to implement parallel program
- Hadoop is an op ation of MapReduce
- Hadoop streaming allows you y language to program mapper and reducer
- Monotonicity property enable efficient algorithms for Frequent Itemsets problem

References

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- Hadoop in Action,
- Hadoop File System ppt by B. Ram
- Intro & MapReduce, pdf by Jure Leskovec
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- Writing an Hadoop MapReduce Program in Python, http://www.michael-noll.com/tutorials/writing-an-hadoop-mapreduce-program-in-python/

In-Class Practice

Given the following input:

I spent long spells at sea on all types of vessel; I followed officer training with the Surface Fleet and with the Royal Marines.

1. Write the output of the word count mapper's above input.
2. Write the output of the word count mapper's output after the shuffle process.
3. Write the output of the word count reducer's output for the above input.