### COMP9313: Big Data Management

Revisit and Sam

Note for Question 1, 2, ... Sample Exam paper is included in the revisited part.

### MyExperience Survey

- The UNSW myExperience survey is still open Please submit your feedback.
- \* "Please participate in the myExperience Survey and take the opportunity to share your constructive thoughts on your earning experience. Your contributions help your teachers and shape the future of education at UNSW."
- You can access the survey by logging into Moodle or accessing myexperience.unsw.edu.au directly.

If the response rate from the class is more than 50%, everybody gets poorus mark added to the final mark :-)

### Final exam

- Time: Fri 16-Aug, 8 am 12 pm, 4 hours (Do not wait for the last minute to submit)
- Exam paper: will be released on our course website (Moodle and Ed) around 7:55 am on the exam day, allowing you for an extra 5 min to download the paper and upload your solutions.
- How to submit:
- Coding question submitted through Ed like project, and others through Moodle in one pot or doc file.
- You can submit multiple times, and we will mark the last one.

### Final exam

- Final written exam (50 pts)
- Double Pass: You also need to achieve at least 20 marks in the final exam to pass the course.
- 6 questions in total on 5 topics
- There will be consultations before the final exam. Detailed schedule will be released later.
- Special Considerations. The exam is covered by UNSW's Fit-to-Sit policy. That means that by sitting this exam, you are declaring yourself well enough to do so. You will be unable to apply for special consideration after the exam for circumstances affecting you before it began.

### **Overview**

- Hadoop MapReduce
  - > HDFS
  - MapReduce Concepts and Mechanism
  - MapReduce algorithm design
- Spark
  - > RDD
  - DataFrame
- Mining Data Streams
- Finding Similar Items
  - > Shingling, Minhash, LSH
- Graph Data Management

### **Exam Questions**

- Question 1: HDFS, MapReduce, and Spark concepts
- Question 2: MapReduce algorithm design (pseudo-code only)
- Question 3: Spark algorithm design
  - > RDD
  - DataFrame
- Question 4 Finding Similar Items
- Question 5 Mining Data Streams
- Question 6 Graph Data Management

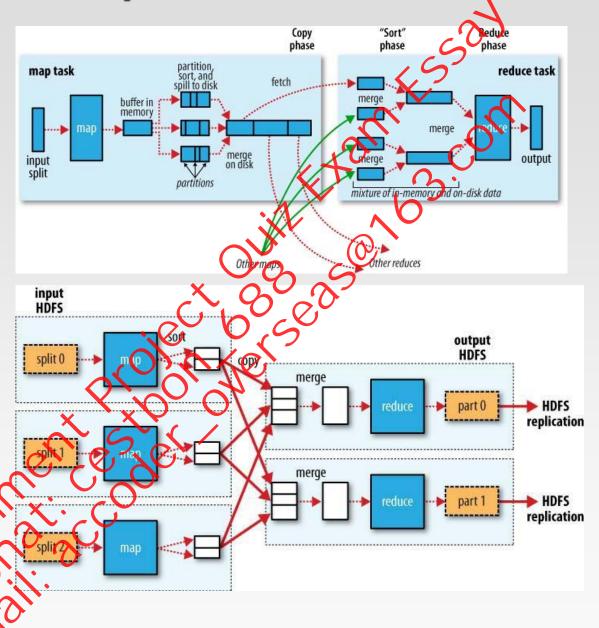
(a) (2 marks) Explain the data flow in MapReduce using the word count problem as an example.

(b) (2 marks) Explain the data Towin Spark using the word count problem as an example.

### Map and Reduce Functions

- Programmers specify two functions:
  - > map  $(k_1, v_1) \rightarrow list [< k_2, v_2 >]$ 
    - Map transforms the input into key-value pairs to process
  - > reduce  $(k_2, [v_2]) \rightarrow [\langle k_3, v_3 \rangle]$ 
    - Reduce aggregates the list of values for each key
    - All values with the same key are sent to the same reducer
- Optionally, also:
  - $\triangleright$  combine  $(k_2, [v_2]) \rightarrow [\langle k_3, v_3 \rangle]$
  - > partition ( $k_2$ , number of partitions)  $\rightarrow$  partition for  $k_2$
  - Grouping comparator, controls which keys are grouped together for a single call to Reducer.reduce() function
- The execution framework handles everything else...

# MapReduce Data Flow



Assume that you are given a data set crawled from a location-based social network, in which each line of the data is in format of (userID, a list of locations the user has visited <loc1, loc2, ...>). Your task is to compute for each location the set of users who have visited it, and the users are sorted in ascending order according to their IDs.

**Sample Solution** 

```
class Question1
       method map(self, userID, list of locations)
              foreach loc in the list of locations
                      Emit("loc, userID", "")
       method reduce_init(self)
              current loc = ""
              current_list = []
       method reduce(self, key, value)
              loc, userID = key.split(",")
              if loc != current loc
                  if current_loc!=""
                       Emit(current_loc, current_list)
                  current list = []
                  current_list.add(user)
                  current loc=loc
              else
                  current list.add(use
       method reduce final(self)
              Emit(carre
In JOBCONF, configure
       'mapledice map.output.key.field.separator':',',
        maniedac, partition. eypartitioner.options': '-k1,1',
               luce.partition.keycomparator.options':'-k1,1 -k2,2'
```

Given a table shown as below, find out the person(s) with the maximum salary in each department (employees could have the same salary).

EmployeeID	Name	Department	D Salary
001	Emma	1 7	100,000
002	Helen	2	85,000
003	Jack	3	85,000
004	James	1	110,000

#### Solution:

- Mapper: for each record, mit (apartificant + "," + salary, name)
- Combiner: find out all persons with the local maximum salary for each department
- Reducer: receives data ordered by (department, salary), the first one is the maximum salary in a department. Check the next one until reaching a smaller salary and ignore all remaining. Save all persons with this maximum salary in the department
- JOBCONF: key partitioned by "-k1,1", sorted by "-k1,1 -k2,2n"
- In the final, check the question requirement, asking for pseudo code or others...

#### What is RDD

- Resilient Distributed Datasets: A Fault-Tolerant Abstraction for In-Memory Cluster Computing. Matei Zaharia, et al. NSDI'12
  - RDD is a distributed memory abstraction that lets programmers perform in-memory computations on large clusters in a faulttolerant manner.

#### Resilient

Fault-tolerant, is able to recompute missing or damaged partitions due to node failures.

#### Distributed

Data residing on multiple nodes in a cluster.

#### Dataset

- A collection of partitioned elements, e.g. tuples or other objects (that represent records of the data you work with).
- RDD is the primary data abstraction in Apache Spark and the core of Spark it enables operations on collection of elements in parallel.

#### **DataFrame**

DataFrame more like a traditional database of two-dimensional form, in addition to data, but also to grasp the structural information of the data, that is, schema

		Name	Age	Height
				1
Person		String	Int	Double
Person		String	Int	Double
Person		String		Double
		5		
Person	, 9	String	Int	Double
Person	6	String	Int	Double
Person	10	String	Int	Double
RDD[Rerson]	The		DataFrame	

- RDD[Person] although with Person for type parameters, but the Spark framework itself does not understand internal structure of Person class
- Spark SQL can clearly know what columns are included in the dataset, and what is the name and type of each column. Thus, Spark SQL query optimizer can target optimization

\* RDD: Given a large text file, your task is to find out the top-k most frequent cooccurring term pairs. The co-occurrence of (w, u) is defined as: u and w appear
in the same line (this also means that (w, u) and (v, w) are treated equally).
Your Spark program should generate a list of key-value pairs ranked in
descending order according to the frequencies, where the keys are the pair of
terms and the values are the co-occurring frequencies (Plint: you need to
define a function which takes an array of terms as input and generate all
possible pairs).

```
val textFile = sc.textFile(inputFile)
val words = textFile.mals(_split()').toLoverCase)

// fill your code here, and store the result in a pair RDD topk

topk.foreach(x = x printin(x (1, x._2))
```

Note: python code is ek.

Given a set of marks from different courses (the input format is as shown in the left column), the task is to: compute average marks for every course and sort the result by course hame in alphabetical order.

```
Input:
student1:course1,90;course2,92;course3,80;course4,
79;course5,93
student2:course1,92;course2,77;course5,85
student3:course3,64;course4,97;course5,82
course3:72
course4:88
course5:86.67
```

#### Solution:

```
fileDF = spark.read.text("file:\#hothe/comp9313/tinydoc")

student = fileDF.selext(split(tileDF['value'], ':').getItem(0).alias('sid'), split(fileDF['value'], ':').getItem(1).alias('oourses'))

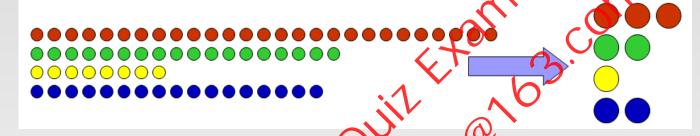
scDF = student.withColumn('course', explode(split('courses', ';')))

scDF2.=scDF.select(split(scDF['course'], ',').getItem(0).alias('cname'), split(scDF['course'], ',').getItem(A)(alias('mark'))

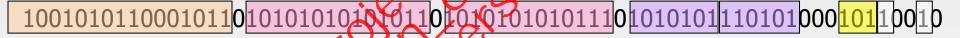
avgDF = scDF2.groupBy('cname').agg(avg('mark')).orderBy('cname')
```

## Mining Data Streams

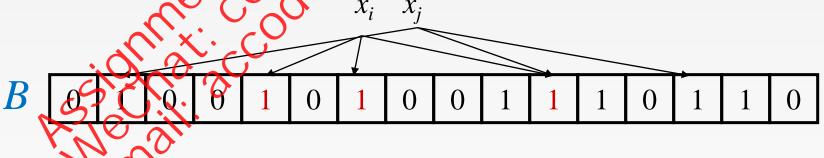
Sampling from a data stream



Sliding window – counting bits (DGIM)



Filtering data stream -chloom filter



## Mining Data Streams

- Finding Frequent Elements
  - > Boyer-Moore voting algorithm, Misra-Gries algorithm
  - count-min sketch
- Counting data stream FM-Skets
  - ► Estimate  $d = c2^R$  for scaling constant  $c \approx 1.3$  (original paper)

- Use an example to explain the reservoir sampling algorithm
  - Store all the first s elements of the stream for
  - Suppose we have seen n-1 elements, and now the interest element arrives (n > s)
    - ✓ With probability **s/n**, keep the **n**th element else discard it
    - ✓ If we picked the **n**<sup>th</sup> element, then it replaces one of the **s** elements in the sample **S**, picked uniformly at random

Suppose we are maintaining a count of 1s using the DGIM method. We represent a bucket by (i, t), where i is the number of 1s in the bucket and t is the bucket timestamp (time of the most recent 1).

Consider that the current time is 200, window size is 60, and the current list of buckets is: (16, 148) (8, 162) (8, 177) (4, 183) (2, 192) (1, 197) (1, 200). At the next ten clocks, 201 through 210, the stream has 0101010101. What will the sequence of buckets be at the end of these ten inputs?

### **Sample Solution**

- There are 5 1s in the stream. Each one will update to windows to be:
  - (1) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(1, 197)(1, 200), (1, 202) => (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1) 202)
  - (2) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1, 204)
  - > (3) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1, 202), (1, 204), (1; 206)
    - => (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (2, 204), (1, 206)
    - => (16, 148)(8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206)
  - > (4) Windows Size is 60, so (16,148) should be dropped.
  - (16, 148)(8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208) => (8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208)
  - > (5) (8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208), (1, 210) => (8,762)(8,177)(4, 183)(4, 200), (2, 204), (2, 208), (1, 210)

Consider a Bloom filter of size m = 7 (i.e., 7 bits) and 2 hash functions that both take a string (lowercase) as input:

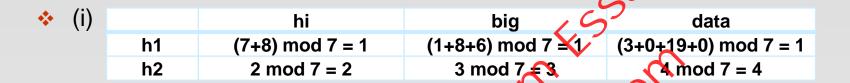
$$h1(str) = \sum_{(c \text{ in str})} (c-'a') \mod 7$$

$$h2(str) = str.length \mod 7$$

Here, c - 'a' is used to compute the position of the letter c in the 26 alphabetical letters, e.g.,  $h1("bd") = (3 + 3) \mod 7 = 4$ .

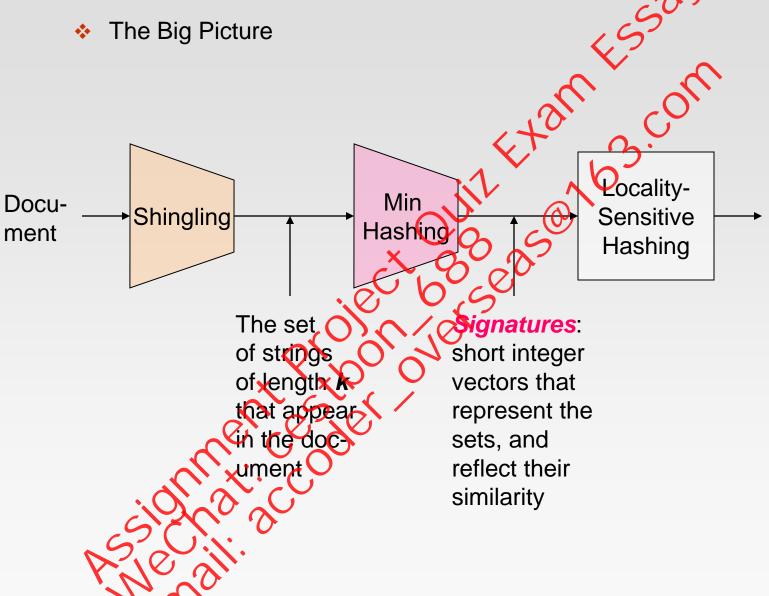
- (i) Given a set of string S = "hi" "big", "data"}, show the update of the Bloom filter
- (ii) Given a string "spark", use the Bloom filter to check whether it is contained in 6.
- (iii) Given S in (i) and the Bloom filter with 7 bits, what is the percentage of the false positive probability (a correct expression is sufficient you need not give the actual number)?

### **Sample Solution**



$$(1 - e^{-\frac{km}{n}})^k = 0.3313$$

# Finding Similar Items,



### Candidate pairs

those pairs of signatures that we need to test for similarity

We want to compute min-hash signature for two columns,  $C_1$  and  $C_2$  using two pseudo-random permutations of columns using the following function:

$$h_1(n) = 3n + 2 \mod 7$$
  
 $h_2(n) = 2n - 1 \mod 7$ 

Here, n is the row number in original ordering. Instead of explicitly reordering the columns for each hash function, we use the implementation discussed in class, in which we read each data in a column once in a sequential order, and update the min hash signatures as we pass through them.

1

Complete the steps of the algorithm and give the resulting signatures for  $C_1$  and  $C_2$ 

### **Solution**

Row	$C_1$	$C_2$	
0	0	1	
1	1	0	
2	0	1	
3	0	0	
4	1	1	
5	1	1	
6	1	0	

$$h_1(n) = 3n + 2 \mod 7$$
  
 $h_2(n) = 2n - 1 \mod 7$ 

$$h_1(2) = 1.5$$
 1  
 $h_2(2) = 3.1$  3

$$h1(4) = 0 \ 0$$
 $h2(4) = 0 \ 0$ 

Suppose we wish to find similar sets, and we do by minhashing the sets 10 times and then applying locality-sensitive hashing using 5 bands of 2 rows (minhash values) each. If two sets had Jaccard similarity 0.6, what is the probability that they will be dentified in the locality-sensitive hashing as candidates (i.e. they hash at least once to the same bucket)? You may assume that there are no coincidences, where two unequal values hash to the same bucket. A correct expression is sufficient: you need not give the actual number. \* Solution:  $1 - (1 - t')^b$ >  $1 - (1 - 0.6^2)^5$ 

### Graph - Shortet path (iteration 1)

#### Map:

Read s --> 0 | n1: 10, n2: 5

Emit: (n1, 10), (n2, 5), and the adjacency list (s, n1: 10, n2: 5)

The other lists will also be read and emit, but they do not contribute, and thus ignored

#### \* Reduce:

Receives: (n1, 10), (n2, 5), (s,<0, (n1) 10, n2: 5)>)

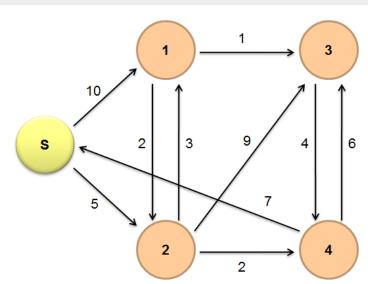
The adjacency list of each pode will also be received, ignored in example

#### Emit:

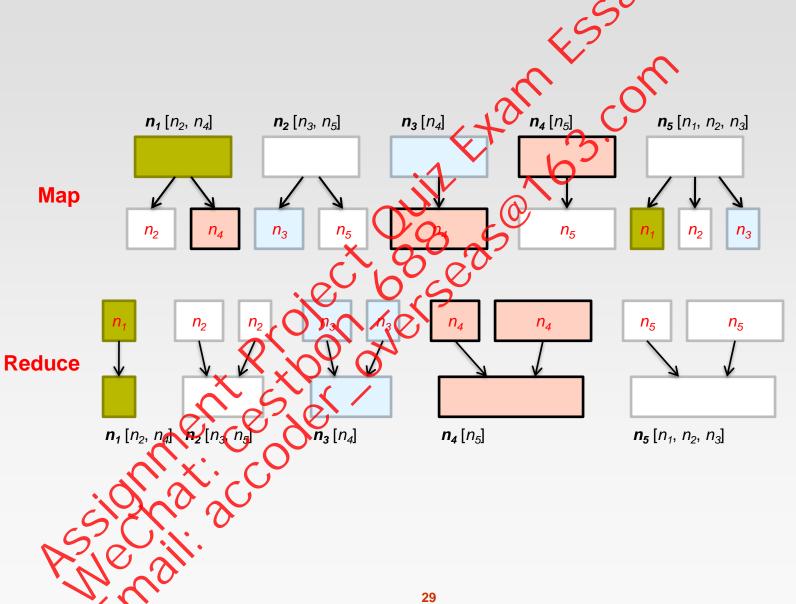
s --> 0 | n1: 10, n2: 5

n1 --> 10 | n2: 2(h3:1

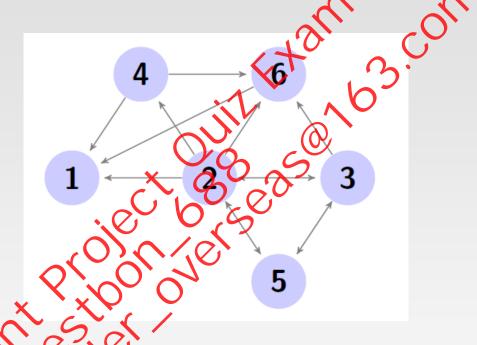
n2 --> 5 | n1.3, n3.9, n4.2



### PageRank in MapReduce (One treration)

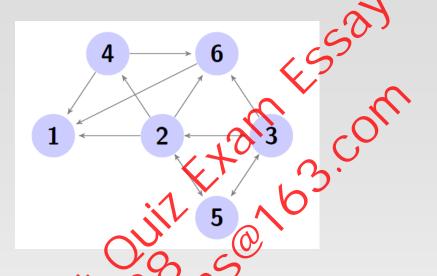


A directed graph G has the set of nodes {1,2,3,4,5,6} with the edges arranged as follows.



\* Set up the PageRank equations, assuming  $\beta = 0.8$  (jump probability = 1-  $\beta$ ). Denote the PageRank of node a by r(a).

### **Solution**



$$r(1) = 0.8(\frac{1}{6} \cdot r(1) + \frac{1}{2} \cdot r(1) + \frac{1}{6} \cdot r(2)) + \frac{0.2}{6}$$
 (1)

$$r(2) = 0.8(\frac{1}{6} \cdot r(1) + \frac{1}{3} r(3) + \frac{1}{2} r(5)) + \frac{0.2}{6}$$
 (2)

$$r(3) = 0.8(\frac{1}{6} r(1) + \frac{1}{2} r(2) + \frac{1}{2} r(5)) + \frac{0.2}{6}$$
(3)

$$r(4) = 0 \left( \frac{1}{6} \cdot r \left( \frac{1}{2} \right) + \frac{1}{6} \left( \frac{1}{2} \right) \right) + \frac{0.2}{6}$$
 (4)

$$r(5) = 0.8(\frac{1}{6} \cdot r(1)) + \frac{1}{5} \cdot r(2) + \frac{1}{3} \cdot r(3)) + \frac{0.2}{6}$$
 (5)

$$r(6) = 0.8(\frac{1}{6})r(1) + \frac{1}{5} \cdot r(2) + \frac{1}{3} \cdot r(3) + \frac{1}{2} \cdot r(4)) + \frac{0.2}{6}$$
 (6)

#### **Computer Updates**

You must ensure that auto-updates are disabled on your computer prior to the online assessment.

Special consideration will NOT be awarded on the grounds that your computer performed an update during an online assessment.

If you upload the wrong document or wrong version of your exam

- Students are responsible for uploading the correct version of the correct document. Once uploaded, there will be no opportunity to replace or re-upload your exam papers AFTER the end of the exam.
- The documents submitted will be the documents that are marked.
  There is NO provision for students who upload incorrect or incomplete documents.
- \* Therefore, you must check the work before you submit.

#### Communication during the exam

- Students are NOT permitted to communicate with other people during the exam (including the reading and submission periods).
- Attempts to communicate with other students will be considered to be serious academic misconduct.
- This includes communication imperson, by email, text, message, telephone, or internet, i.e., do the work yourself

Sharing answers with others or posting them online

Any attempts to collaborate or share your answers with others will be considered a very serious case of academic misconduct

#### Checklist

- Be logged in at your computer and ready to go 20 minutes before the exam commences.
- Ensure your device has power, and the charger is plugged in.
- If applicable remind your roommates or family that you'll be taking an exam to avoid interruptions.

You can attempt the questions in any order, arrange your time wisely.

Read all questions carefully

\* Be fully prepared before the exam: don't forget to eat lunch, take break and relax yourself, no need to panic

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