

Module 1 Quiz

Quiz, 10 questions

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1.

Assume that `MapReduce(f, g, data)`, performs map function `f` on the input data, followed by reduce function `g`, as introduced in Lecture 1.1. What does the function *mystery*, provided below in pseudocode notation, compute?

Hint: Determining the omitted type information might be helpful.

```
1  f(k, v) {  
2    return [(v, (k, 1))]    // a collection of one pair  
3  }  
4  
5  g(pair1, pair2) {  
6    return (pair1[0] + pair2[0], pair1[1] + pair2[1])  
7  }  
8  
9  mystery(data) {  
10   for (k, (v1, v2)) in MapReduce(f, g, data)  
11     add (k, v1 / v2) to results  
12   return results  
13 }
```

- ☒ A. For each input value, the average corresponding input key.
- ☐ B. For each input key, the average corresponding input value.
- ☐ C. For each input value, the average position in the ordering of input keys.
- ☐ D. For each position in the ordering of input keys, the average of the previous input values.

1
point

Module 1 Quiz

Quiz, 10 questions

2.

Consider the following pseudo-code using MapReduce. What does *mystery2* print when its input is a collection with a single key/value pair entry?

Hint: Determining the omitted type information might be helpful.

```
1  m(k, v) {
2    vs = v.tokenize("\n")
3    res = []
4    for i in 0 ... vs.length - 1
5      ws = vs[i].tokenize(" ")
6      for w in ws
7        res += ([w, k], [i + 1])
8    return res
9  }
10
11 r(v1, v2) {
12   res = []
13   for v in v1
14     res += v
15   for v in v2
16     res += v
17   return res
18 }
19
20 mystery2(data) {
21   for (k, v) in MapReduce(m, r, data)
22     print(k[0] + " = " + v)
23 }
24
```

- ☐ A. For each input value, all the words that occur in each line.
- ☐ B. For each line in the input value, the average length of the words it contains.
- ☐ C. For each line in the input value, the number of words it contains.
- ☒ D. For each input value, the words and the line numbers they appear in.
- ☐ E. For each input value, the words and the line numbers they appear in in sorted order.

1
point

3.

Which of the following statements are true?

Module 1 Quiz

Quiz, 10 questions

- ☒ A. Hadoop is able to provide strong fault tolerance because map-reduce is a functional operation.
 - ☐ B. Hadoop is used to speed up tasks executing on a single computer.
 - ☐ C. The user of Hadoop is responsible for specifying how the computers in the network communicate with each other.
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1
point

4.

Suppose we want to use Hadoop to perform a word count on the following words, given as a sequence of key-value pairs: (the, 1), (dog, 1), (chased, 1), (the, 1), and (cat, 1). Which of the following could be the output of the "group" step of the computation? Assume no reduction operation can occur during the "group" step.

- ☐ A. Group 1: (the, 1). Group 2: (dog, 1). Group 3: (chased, 1). Group 4: (the, 1). Group 5: (cat, 1).
 - ☐ B. Group 1: (the, 2). Group 2: (dog, 1). Group 3: (chased, 1). Group 4: (cat, 1).
 - ☒ C. Group 1: (the, 1) and (the, 1). Group 2: (dog, 1). Group 3: (chased, 1). Group 4: (cat, 1).
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1
point

5.

Which of the following statements are true?

- ☐ A. Hadoop is a generalization of Spark.
 - ☒ B. Spark benefits from using nodes with large memory.
 - ☐ C. Spark only supports eager or strict evaluation. (It does not use lazy evaluation.)
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Module 1 Quiz

Quiz, 10 questions

1
point

6.

Which of the following are terminal operations in Spark?

- ☐ A. Map
 - ☒ B. Reduce
 - ☐ C. Filter
 - ☒ D. Collect
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1
point

7.

Why might the notion of an “inverse document frequency” be important in determining the similarity between two arbitrary documents in a corpus?

- ☒ A. The inverse document frequency ensures that words appearing across many documents are discounted in comparison to words that are unique to a few documents.
 - ☐ B. The inverse document frequency adds prominence to words that are common to many documents, enabling a programmer to compute similarity metrics more precisely.
 - ☐ C. The inverse document frequency allows the programmer to more easily apply the MapReduce model of computation to a large corpus of documents.
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1
point

8.

For this question, you are encouraged to search the Internet and read about topics relevant to elementary text-mining and tf-idf.

Module 1 Quiz

Quiz, 10 questions

Which of the following might serve as a valid means of computing which document is most similar to document D_1 in a corpus of text documents? For simplicity, assume all relevant tf-idf weights have been appropriately normalized and computed, and that resources (time, memory, secondary storage, etc) are not issues of concern.

I. For each document in the corpus, use a vector representation of the appropriate tf-idf weights to compute its cosine similarity to D_1 . Those documents yielding the highest cosine similarity to D_1 are considered “most similar”.

II. For each document in the corpus, find the sum of its tf-idf weights corresponding to the words that appear in D_1 . Those documents yielding the highest sum of relevant tf-idf weights are considered “most similar”.

III. For each document in the corpus, compare its total word count to the word count of D_1 . Those documents yielding the smallest absolute difference in word counts are considered “most similar”.

- ☒ A. I and II
 - ☐ B. II and III
 - ☐ C. III only
 - ☐ D. I and III
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1
point

9.

In Spark, what does the reduceByKey transformation do?

- ☒ A. For a set of (key, value) pairs, groups all values that have the same key and then applies a reduction operator to collapse those values into a single value. A single (key, value) pair is then emitted per key.
- ☐ B. For a set of (key, value) pairs, groups all values that have the same key. A single pair of a key and the list of all values is then emitted.
- ☐

Module 1 Quiz

Quiz, 10 questions

C. For a set of (key, value) pairs, counts the number of (key, value) pairs for each unique key. For each unique key, emits a (key, value) pair that is that key with the number of pairs that had it.



D. For a set of (key, value) pairs and a given key, removes all (key, value) pairs that have that same key.

1
point

10.

Why is Page Rank an algorithm that fits well with Spark?



Spark offers Page Rank transformations specifically for supporting the Page Rank algorithm (e.g. join).



Spark is optimized for iterative, in-memory workloads. Page Rank is an example of one.



Page Rank was originally designed to run on top of Spark, and so algorithmically fits well with the provided transformations.



Very few distributed programming models could support a distributed join operation.



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