

Information Retrieval Example using Map-Reduce

- ▶ **Information Retrieval** is the process of finding information in response to a query from a source of information.
- ▶ *“But do you know that, although I have kept the diary [on a phonograph] for months past, it never once struck me how I was going to find any particular part of it in case I wanted to look it up?”*
—Dr Seward, Bram Stoker’s Dracula, 1897
- ▶ The source of information can be a **text corpus** consisting of structured text files such as books or web pages, or it can be meta-data stored in structured format such as XML (for example to search in corpus of sound files or image files).
- ▶ In this example, we will look at the calculation of ***term-frequency-inverse-document-frequency***, which is a basic problem in information retrieval.

Term Frequency–Inverse Document Frequency (TF-IDF)

- ▶ The **tf-idf** weight (*term frequency–inverse document frequency*) is a statistical measure used to evaluate how important a word is to a document in a collection or corpus.
- ▶ The importance increases proportionally to the number of times a word appears in the document but is offset by the frequency of the word in the corpus.
- ▶ Variations of the tf-idf weighting scheme are often used by search engines as a central tool in scoring and ranking a document's relevance given a user query. (<http://en.wikipedia.org/wiki/Tf-idf>)
- ▶ The concept of Inverse Document Frequency was introduced by British computer scientist Karen Spärck Jones.
http://en.wikipedia.org/wiki/Karen_Sp%C3%A4rck_Jones

TF-IDF Definition (Part 1)

- ▶ Let D be the collection of **documents** in the corpus. Let T be the collection of **terms** (unique tokens) in the collection D .
- ▶ The **term frequency (tf)** for a given term t_i within a particular document d_j is defined as the number of occurrences of that term in the d_j th document. We denote this with $n_{i,j}$: the number of occurrences of the term t_i in the document d_j .

$$tf_{i,j} = n_{i,j}$$

- ▶ The term frequency is often normalized to prevent a bias towards larger documents, as shown below:

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}}$$

where $n_{i,j}$ is the number of occurrences of the term t_i in the document d_j . Note that we are using the total number of terms, $\sum_k n_{k,j}$ for normalization. Instead we can use the maximum as well.

TF-IDF Definition (Part 2)

- ▶ The **inverse document frequency (idf)** is obtained by dividing the total number of documents by the number of documents containing the term t_i , and then taking the logarithm of that quotient:

$$idf_i = \log \frac{|D|}{|\{d : t_i \in d\}|}$$

with

- ▶ $|D|$: total number of documents in the collection
- ▶ $|\{d : t_i \in d\}|$: number of documents where the term t_i appears. To avoid divide-by-zero, we can use $1 + |\{d : t_i \in d\}|$.
- ▶ For a given corpus D , then the **tf-idf** is then defined as:

$$(tf-idf)_{i,j} = tf_{i,j} \times idf_i$$

- ▶ A high weight in $tf-idf$ is obtained by a high term frequency and a low document frequency of the term in the collection.
- ▶ For common terms, the ratio in idf approaches 1, bringing the logarithm closer to 0.

What do we need to compute?

- ▶ Given a corpus of text, we want to calculate **tf-idf** for every document and every term.
- ▶ We need to calculate, over the corpus, the following:
 - ▶ **number of terms,**
 - ▶ **number of unique terms,**
 - ▶ **number of documents,**
 - ▶ **number of occurrences of every term in every document and**
 - ▶ **the number of documents containing each term.**

New Map-Reduce and Hadoop Techniques

- ▶ Use of Hadoop counters.
- ▶ Use reducers for data pass-through instead of only reducing the data. This is typically done to add a new dimension to the data.
- ▶ Extending `FileInputFormat` classes to create custom key/value pairs rather than the default ones.

Example Code

See the full code in the code examples repo at:

[CS535-resources/examples/Hadoop/myExamples/tf-idf](https://github.com/CS535-resources/examples/Hadoop/myExamples/tf-idf)

The main class is [TfIdfDriver.java](#) and the map/reduce classes are:

- ▶ [TermFrequency.java](#)
- ▶ [InverseDocumentFrequency.java](#)
- ▶ [TfIdf.java](#)
- ▶ Supporting I/O classes:
 - ▶ [KeyValueTextIntInputFormat.java](#),
[KeyValueTextIntRecordReader.java](#)
 - ▶ [KeyValueTextTextInputFormat.java](#),
[KeyValueTextTextRecordReader.java](#)

Step 1: Number of terms and unique terms

- ▶ Run the same algorithm as the word count. Output looks like:

```
the 123455  
from 65002  
about 33004  
.  
.  
.
```

- ▶ Number of unique terms is simply the number of lines in the output. Number of terms is the total of the second column.
- ▶ **Running an entire pass just to calculate these two values is overkill.** These two values can also be calculated as a by-product of Step 2 by using global counters that Hadoop allows a job to increment/decrement.

Hadoop Global Counters

- Declare an enum to represent the counters. The enum name is the group of the counter, and each field of the enum is the name of the counter that will be reported in this same group.

```
public class TfIdfDriver {  
    static enum Counters { DOCUMENTS, TERMS }  
    ...  
}
```

- Increment the desired counters from the map and reduce methods through the Context object. For example (context is an instance of a Context object):

```
context.getCounter(TfIdfDriver.Counters.TERMS).increment(1);  
context.getCounter(TfIdfDriver.Counters.DOCUMENTS).increment(1);
```

- Access the value of the counter from the Job object. For example:

```
int numTerms = job.getCounters().findCounter(  
    TfIdfDriver.Counters.TERMS).getValue();
```

- For other methods, see the class `org.apache.hadoop.mapreduce.Counter`

Step 2: Term Frequency

- Change the output from previous map step to produce “docId-term” pairs.

map1:	map2:	map3:
1_the 1	2_the 1	37_london 1
1_the 1	2_the 1	.
1_the 1	2_from 1	.
1_to 1	.	.
.	.	.
.	.	.
.	.	.

- Reducer simply adds up the values with the same key and we have the term frequency.

```
1_the 3
1_to 1
...
2_the 2
2_from 1
...
37_london 1
```

- We also get the number of terms and number of documents in this step using global counters.
- See the code at [tf-idf/src/TermFrequency.java](#)

Step 3: Inverse Document Frequency (Try 1)

- ▶ Use the output from the previous step as the input. Take every key from the input data, split it to (1, the) and write to map's output that we have at least one document containing the word the:

```
the 1
to 1
...
the 1
from 1
...
london 1
```

- ▶ Reduce simply computes the length of the list and outputs:

```
the 2
to 1
from 1
london 1
...
```

- ▶ Now we have two outputs: one with TF values and another with IDF values but no way to combine them.... Let's try another way.

Step 3: Inverse Document Frequency (Try 2)

- ▶ We will use a MapReduce technique known as **data pass-through**. The output from the mapper in the previous attempt has more information that we can pass along for later use. We write `docId_tf` instead of simply writing "1" as before.

```
the 1_3
to 1_3
...
the 2_2
from 2_1
...
london 37_1
```

- ▶ Reduce computes the length of the list and outputs key/value pairs shown below (where the format of the value is (docCount, docId, countInDoc)):

```
the 2_1_3
the 2_2_2
to 1_1_3
from 1_2_1
london 1_37_1
...
```

where the key/value `2_1_3` reads as: there are 2 documents that contain the term `the`, and the document with id 1 contains 3 such terms.

- ▶ *Note that the reducer didn't reduce the data but added a new dimension to it.*
- ▶ See the code at [tf-idf/src/InverseDocumentFrequency.java](#)

Step 4: Calculating the tf-idf

- ▶ Assume we have counted the number of documents (`totalDocCount`) and the number of terms (`totalTermCount`), we can write a mapper (with no need for reduce) to finish the process.

- ▶ Mapper input:

```
term = key  
(docCount, docId, countInDoc) = value.split("_")
```

- ▶ Mapper output:

```
tf = countInDoc/totalTermCount  
idf = log(totalDocCount/docCount)  
result = tf * idf  
output(key = docId + "_" + term, value = result)
```

- ▶ See the code at `tf-idf/src/TfIdf.java`

Supporting I/O Classes

- ▶ [KeyValueTextIntInputFormat.java](#), [KeyValueTextIntRecordReader.java](#). These classes are used by the InverseDocumentFrequency mapper for input since we want the first field in the input to be returned as a Text key (instead of the default, which is the byte offset of current line in the input file) and the second field to be returned as an integer value.
- ▶ [KeyValueTextTextInputFormat.java](#), [KeyValueTextTextRecordReader.java](#). These classes are used by the TfIdf mapper for input since we want the first field in the input line to be returned as a Text key and the second field to be returned as a Text object.

- ▶ *Tf-idf*. <http://en.wikipedia.org/wiki/Tf-idf>.
- ▶ *Map/Reduce for real problems: Calculating TF-IDF using Hadoop*. Explains how to use map-reduce to calculate tf-idf but does not provide any code.
<http://romankirillov.info/hadoop.pdf>. The website is no longer in existence but forms the basis for these slides.