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- ▶ 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)

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- ▶ 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)

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- ▶ 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 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 $1 + |\{d : t_i \in d\}|$.

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

- ▶ 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.

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- ▶ 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.

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- ▶ 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:

[lab/Hadoop/myExamples/tf-idf](https://github.com/ericniebler/lab/Hadoop/myExamples/tf-idf)

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

- ▶ [TermFrequency.java](#)
- ▶ [InverseDocumentFrequency.java](#)
- ▶ [TfIdf.java](#)

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- ▶ [TermFrequency.java](#)
- ▶ [InverseDocumentFrequency.java](#)
- ▶ [TfIdf.java](#)
- ▶ Supporting I/O classes:
 - ▶ [KeyValueTextIntInputFormat.java](#),
[KeyValueTextIntRecordReader.java](#)
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Step 1: Number of terms and unique terms

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

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- ▶ **Running an entire pass just to calculate these two values is overkill.** These two values can also be calculated as a by-product of the 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 }  
    ...  
}
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- ▶ 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);
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- ▶ Access the value of the counter from the Job object. For example:

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int numTerms = job.getCounters().findCounter(  
    TfIdfDriver.Counters.TERMS).getValue();
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- ▶ 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               .                      .
.                    .
.                    .
.
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- ▶ Reducer simply adds up the values with the same key and we have the term frequency.

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- ▶ 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:

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

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- ▶ *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

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idf = log(totalDocCount/docCount)
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result = tf * idf
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output(key= docId + "_" + term, value = result)
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- ▶ 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.

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- ▶ See Chapter 7 in the Hadoop book for more details.

- ▶ *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.