

Spark Program

# CHAPTER 10: NATURAL LANGUAGE PROCESSING

## **Chapter Objectives**

#### In this chapter, we will:

- → Explore unstructured text
- → Use NLTK and Spark pipeline transformation to process natural language
- → Visualize natural language with Word Clouds
- → Explore how to monitor and optimize Spark

# **Chapter Concepts**

#### **Natural Language**

**Optimizations** 

**Chapter Summary** 

## **Natural Language Processing**

- → Processing free-form text is not as simple as a formatted table-structured object
- → You need to break the natural language up into pieces and fix variations in the wording to try to standardize it and extract meaning
- → There are many different types of transformations you can do to text and they vary depending on the text and what you're trying to do with the results
- → Generally though, it comes down to some common steps:
  - Break the text up into sentences and words
  - Fix the words by adjusting everything to the same case
  - Remove punctuation
  - Standardize word variations to the root word
  - Remove insignificant words
  - Find natural word groupings that make up a phrase
  - Determine the overall sentiment of the words

#### **NLTK**

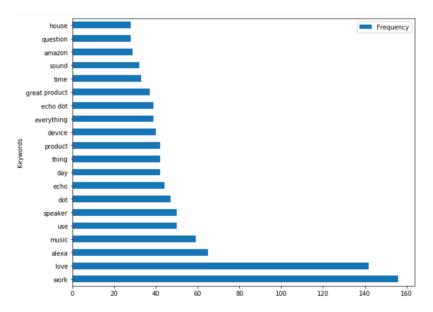
- → NLTK stands for Natural Language Tool Kit and is a comprehensive Python package with lots of functions to manipulate text
- → It is a stand-alone Python package, but it works in a distributed mode on Spark RDDs
- → Install it as normal: pip install nltk
- → Import it as normal: import nltk
- → Let's explore the features and examples in Jupyter

## **Spark Text Processing**

- → Spark also has some of its own text processing features
- → Found in pyspark.ml.features
- → Tokenizer breaks up a document into words
- → RegexTokenizer allows more control
- → StopWordsRemover removes insignificant words
- → HashingTF transforms a set of words and vectorizes them
- → IDF rescales the numbers in the vector to de-emphasize words that occur a lot in the entire corpus
- → Usually, just follow a common recipe to fix up a DataFrame into the shape you need for ML operations by putting the various steps into a pipeline

#### **Word Cloud**

→ Word Clouds and other charts can be made from the results of the text processing by bringing the small DataFrame results back to the driver



```
love speaker amazon day everything thing house dot great product echo
```

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## **Monitoring**

- → You can monitor the Spark processes by navigating in a browser to the address of the cluster and port 4040
  - locahost:4040
- → You will see various tabs where you can:
  - Watch the progress of jobs
  - Watch the progress of stages
  - See what objects are cached
  - Get an overview of the environment
  - See the nodes that are executing

## **Caching**

- → Because an RDD is a lazy evaluation of a chain of transformations, each time you do an action on that RDD or DataFrame, it recalculates everything from the very beginning
- → This can cause performance problems if you want to do several different actions to the same set of data
- → Caching is the answer—it allows you to pin the results of an RDD in the cluster for the duration of the session or until you manually release it
- → You can cache to either memory or disk or a combination of the two
- → You also have control over how many redundant copies it stores and whether it should store it as:
  - Deserialized which takes more memory but less CPU
  - Serialized Java object which is more memory efficient but uses more CPU
- → There are two methods, persist and cache, which is simply a shorthand for persist with the default option of memory only
- → To remove a cached object, use unpersist



#### **Broadcast Variables**

- → It is also sometimes desirable to keep a copy of a variable on each node instead of passing it around each time it receives instructions to do a new task
- → This is useful if you need to pass around something like a reference table to each node
- → Broadcast variables allow you to accomplish this

```
lookupTable = sc.broadcast([1, 2, 3])
lookupTable.value > [1, 2, 3]
```

#### **Accumulators**

- → Sometimes you want to create a counter that is global to the entire process
- → Using a regular Python variable would not scale out to the cluster level, so you need a special way to handle this so that each node can contribute to one global counter
- → There is an accumulator method on the Spark context meant just for this

```
counter = sc.accumulator(0)
def fun2(x):
    global counter
    counter += x

x0.foreach(fun2)
print (counter.value)
```

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