# 第10章 **大规模文本挖掘**

在本章，我们打算再回头来谈谈之前章节中所介绍的一些程序库，但这回要谈的是如何在大数据环境中扩大规模地使用这些库。因此，我们会假设读者对于Hadoop+Hive这样的大数据框架已经有了一定的了解。在此基础之上，我们会对一些Python库进行一些相应的探讨，例如NLTK、scikit-learn和pandas这几个库都可以被应用于带有大规模非结构化数据的Hadoop集群。

我们将会讨论到一些讨论NLP和文本挖掘领域中常见的用例，在这过程中，我们也会给出一些代码片段，以便帮助您完成相关的工作。具体来说，我们要来看三个会涉及到绝大多数文本挖掘问题的主要示例。通过这些示例，我们会告诉您如何通过大规模地执行NLTK来完成本书最初几章中所介绍的那些NLP任务。此外，我们还将通过几个例子来介绍如何在大数据条件下执行文本分类任务。

当然，机器学习和NLP还有另一高度规模化应用的问题就是它们是否可并行化。我们在这里将会简单地讨论一下上一章中的一些问题，看看这些问题是否属于大数据问题。或者是否在某些条件下可以用大数据的方式来解决这些问题。

由于我们到目前为止所学习的大多数库都是用Python编写的，所以如何用Python（Hadoop）来处理大数据也是本章的主要问题之一。

在阅读完本章之后，我们希望读者：

* 能很好地了解Hadoop，Hive这些与大数据相关的技术。并在其条件下使用Python。
* 根据教程一步一步地掌握如何在大数据条件下使用NLTK、Scikit和PySpark。

## 在Hadoop上使用Python的不同方式

在Hadoop上运行一个Python进程的方式有很多种。在这里，我们将会讨论其中一些当前最为流行的方式，并通过这些方式在Hadoop上用Python来实现流式的MapReduce作业[[1]](#footnote-1)、Hive中的Python UDF、以及Python hadoop包装器。

### Python的流式操作

通常，一个典型的Hadoop作业必须要被写成map+reduce函数的形式。用户需要根据给定任务来编写相应的map+reduce函数的实现。这些mapper和reducer通常是用Java来实现的。而与此同时Hadoop也为我们提供流式操作的接口，用户可以基于这些接口来写一个Python封装器，并用其它任意一种语言来编写之前由Java所实现的mapper和reducer函数。接下来，我们会来看一个用Python编写的单词计数示例。而且本章稍后还会介绍如何用NLTK库再实现一次。

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| --- |
| 如果您还不太了解情况，可以看看下面链接中的资料  <http://www.michael-noll.com/tutorials/writingan-hadoop-mapreduce-program-in-python/>，以便了解一下Python环境下的MapReduce模式。. |

### Hive/Pig下的UDF

另一种使用Python处理大数据的方式就是在Hive / Pig中编写**UDF（User Defined Function）**。 这种方法的思路认为：我们在NLTK中所执行的大多数操作都是高度可并行化的。譬如说词性标注、标识化处理、词形还原、停用词移除以及NER这些都是可高度分布式执行的操作。因为其中的每一行内容都独立于其它行，所以我们在执行这些操作时不需要根据任何上下文。

因此，如果我们在集群上的每个节点上都部署了NLTK及其它Python库，也可以用Python来编写一些**用户定义函数（UDF）**，以借助NLTK和scikit这些库的功能。这是其引用NLTK最简单的一种方法，对于scikit的大规模引用则更是如此。我们会在本章后续内容中具体介绍这两个库的情况。

### 流式操作的封装器

各种不同组织所实现的封装器可以被列成一份长长的列表，以便能让Python在集群上执行相关的任务。这其中有一些封装使用起来其实相当简单，但问题是它们都有性能较差这个问题。我在下面也列出了一些，如果您想了解它们，可以去这些项目的网站去阅读一下相关介绍：

* Hadoopy
* Pydoop
* Dumbo
* Mrjob

|  |
| --- |
| 如果想查看一份更详细的目前Hadoop上可供选择的Python库列表，读者可以参阅下面这篇文章：  http://blog.cloudera.com/blog/2013/01/a-guide-topython-frameworks-for-hadoop/. |

## Hadoop上的NLTK

我们之前已经从一个库的角度对NLTK进行了充分的讨论，并介绍了它的一只鹅最常用的函数。目前，NLTK已经可以解决许多NLP问题，这其中有许多都是高度可并行化的方案。这也是为什么我们要试着在Hadoop上使用NLTK的原因。

在Hadoop上，运行NLTK的最佳途径就是将其安装在集群的所有节点上。这实现起来并不困难。有几种方式都可以做到这一点，例如我们可以将资源文件以流参数的形式来发送。但通常我们宁愿选择下面的第一个选项。

### UDF

There are a variety of ways in which we can make NLTK run on Hadoop. Let's talk about one example of using NLTK by doing tokenization in parallel using a Hive UDF.

有多种方法可以使NLTK在Hadoop上运行。 让我们谈谈使用Hive UDF通过并行执行标记化使用NLTK的一个示例。

For this use case, we have to follow these steps:

对于此用例，我们必须按照以下步骤操作：

1. We have chosen a small dataset where only two columns exist. We have to create the same schema in Hive: 我们选择了一个只有两列的小数据集。 我们必须在Hive中创建相同的模式：

|  |  |
| --- | --- |
| **ID** | **Content** |
| UA0001 | "I tried calling you. The service was not up to the mark" |
| UA0002 | "Can you please update my phone no" |
| UA0003 | "Really bad experience" |
| UA0004 | "I am looking for an iPhone" |

1. Create the same schema in Hive. The following Hive script will do this for you: 在Hive中创建相同的模式。 以下Hive脚本将为您执行此操作：

Hive script

CREATE TABLE $InputTableName (

ID String,

Content String

)

ROW FORMAT DELIMITED

FIELDS TERMINATED BY '\t';

1. Once we have the schema, essentially, we want to get something like tokens of the content in a separate column. So, we just want another column in the $outTable with the same schema, and the added column of tokens: Hive script一旦我们有了模式，本质上，我们想要在一个单独的列中得到像内容的令牌。 所以，我们只想在$ outTable中有另一个具有相同模式的列，以及添加的令牌列：Hive脚本

CREATE TABLE $OutTableName (

ID String,

Content String,

Tokens String

)

1. Now, we have the schemas ready. We have to write the UDF in Python to read the table line by line and then apply a tokenize method. This is very similar to what we did in *Chapter 3*, *Part of Speech Tagging*. This is the piece of function that is analogous to all the examples in *Chapter 3*, *Part of Speech Tagging*. Now, if you want to get POS tags, Lemmatization, and HTML, you just need to modify this UDF. Let's see how the UDF will look for our tokenizer: 现在，我们已经准备好了模式。 我们必须在Python中编写UDF以逐行读取表，然后应用tokenize方法。 这与我们在第3章“语音标记”部分中所做的非常相似。 这是一个类似于第3章“语音标签部分”中所有示例的函数。 现在，如果你想得到POS标签，Lemmatization和HTML，你只需要修改这个UDF。 让我们看看UDF如何查找我们的tokenizer：

>>> import sys

>>> import datetime

>>> import pickle

>>> import nltk

>>> nltk.download('punkt')

>>> for line in sys.stdin:

>>> line = line.strip()

>>> print>>sys.stderr, line

>>> id, content= line.split('\t')

>>> print>>sys.stderr,tok.tokenize(content)

>>> tokens =nltk.word\_tokenize(concat\_all\_text)

>>> print '\t'.join([id,content,tokens])

1. Just name this UDF something like: nltk\_scoring.py. 5.只是命名这个UDF像：nltk\_scoring.py。
2. Now, we have to run the insert hive query with the TRANSFORM function to apply the UDF on the given content and to do tokenization and dump the tokens in the new column: Hive script  
   6.现在，我们必须使用TRANSFORM函数运行insert hive查询，以便对给定内容应用UDF，并在新列中进行标记化和转储令牌：Hive脚本

add FILE nltk\_scoring.py;

add FILE english.pickle; #Adding file to DistributedCache INSERT OVERWRITE TABLE $OutTableName

SELECT

TRANSFORM (id, content)

USING 'PYTHONPATH nltk\_scoring.py'

AS (id string, content string, tokens string )

FROM $InputTablename;

1. If you are getting an error like this, you have not installed the NLTK and NLTK data correctly: 7.如果您收到此类错误，则说明您尚未正确安装NLTK和NLTK数据：

raiseLookupError(resource\_not\_found) LookupError:

\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

\*\*\*\* Resource u'tokenizers/punkt/english.pickle' not found. Please use the NLTK Downloader to obtain the resource: >>> nltk.download() Searched in:

'/home/nltk\_data'

'/usr/share/nltk\_data'

'/usr/local/share/nltk\_data'

'/usr/lib/nltk\_data'

'/usr/local/lib/nltk\_data'

1. If you are able to run this Hive job successfully, you will get a table named OutTableName, that will look something like this: 8.如果您能够成功运行此Hive作业，您将获得一个名为OutTableName的表，如下所示：

|  |  |  |
| --- | --- | --- |
| **ID** | **Content** |  |
| UA0001 | "I tried calling you, The service was not up to the mark" | [" I", " tried", "calling", "you", "The",  "service" "was", "not", "up", "to", "the", "mark"] |
| UA0002 | "Can you please update my phone no" | ["Can", "you", "please" "update", " my",  "phone" "no"] |
| UA0003 | "Really bad experience" | ["Really"," bad" "experience"] |
| UA0004 | "I am looking for an iphone" | ["I", "am", "looking", "for", "an", "iPhone"] |

### Python的流操作

Let's try the second option of Python streaming. We have Hadoop streaming, where we can write our own mapper and reducer functions, and then use Python streaming with mapper.py, as it looks quite similar to our Hive UDF. Here we are using the same example with map-reduce python streaming this will give us a option of choosing a Hive table or using a HDFS file directly. We will just go over the content of the file and tokenize it. We will not perform any reduce operation here, but for learning, I included a dummy reducer, which just dumps it. So now, we can ignore the reducer from the execution command completely. Here is the code for the Mapper.py:

让我们试试Python流的第二个选项。 我们有Hadoop流，我们可以编写自己的mapper和reducer函数，然后使用mapper.py的Python流，因为它看起来非常类似于我们的Hive UDF。 这里我们使用与map-reduce python流相同的示例，这将给我们选择一个Hive表或直接使用HDFS文件。 我们将只讨论文件的内容并将其标记化。 我们不会在这里执行任何reduce操作，但是为了学习，我包括一个虚拟reducer，它只是转储它。 所以现在，我们可以完全忽略来自执行命令的reducer。 这里是Mapper.py的代码：

Mapper.py

**>>>import sys**

**>>>import pickle**

**>>>import nltk >>>for line in sys.stdin:**

**>>> line = line.strip()**

**>>> id, content = line.split('\t')**

**>>> tokens =nltk.word\_tokenize(concat\_all\_text)**

**>>> print '\t'.join([id,content,topics])**

Here is the code for the Reducer.py:

Reducer.py

**>>>import sys**

**>>>import pickle**

**>>>import nltk >>>for line in sys.stdin:**

**>>> line = line.strip()**

**>>> id, content,tokens = line.split('\t')**

**>>> print '\t'.join([id,content,tokens])**

The following is the Hadoop command to execute a Python stream:Hive script

hadoop jar <path>/hadoop-streaming.jar \ -D mapred.reduce.tasks=1 -file <path>/mapper.py \

-mapper <path>/mapper.py \

-file <path>/reducer.py \

-reducer <path>/reducer.py \

-input /hdfspath/infile \

-output outfile

## Hadoop 上的Scikit-learn

The other important use case for big data is machine learning. Specially with Hadoop, scikit-learn is more important, as this is one of the best options we have to score a machine learning model on big data. Large-scale machine learning is currently one of the hottest topics, and doing this in a big data environment such as Hadoop is all the more important. Now, the two aspects of machine learning models are building a model on big data and to build model on a significantly large amount of data and scoring a significantly large amount of data.

大数据的另一个重要用例是机器学习。特别是使用Hadoop，scikit-learn更重要，因为这是我们为大数据评分机器学习模型的最佳选择之一。大型机器学习是目前最热门的话题之一，在大数据环境（如Hadoop）中这样做更加重要。现在，机器学习模型的两个方面是在大数据上构建模型，并在大量数据上构建模型并对大量数据进行打分。

To understand more, let's take the same example data we used in the previous table, where we have some customer comments. Now, we can build, let's say, a text classification mode using a significant training sample, and use some of the learnings from *Chapter 6*, *Text Classification* to build a Naive Bayes, SVM, or a logistic regression model on the data. While scoring, we might need to score a huge amount of data, such as customer comments. On the other hand building the model itself on big data is not possible with scikit-learn, we will require tool like spark/Mahot for that. We will take the same step-by-step approach of scoring using a pre-trained model as we did with NLTK. While building the mode on big data will be covered in the next section. For scoring using a pre-trained model specifically when we are working on a text mining kind of problem. We need two main objects (a vectorizer and modelclassifier) to be stored as a serialized pickle object.

为了了解更多，让我们采用我们在上表中使用的相同示例数据，其中我们有一些客户评论。现在，我们可以使用重要的训练样本构建文本分类模式，并使用第6章中的一些学习文本分类来构建数据上的朴素贝叶斯，SVM或逻辑回归模型。在评分时，我们可能需要对大量数据进行评分，例如客户评论。另一方面，用大数据构建模型本身是不可能与scikit-learn，我们将需要工具像spark / Mahot的。我们将使用与NLTK一样使用预训练模型的相同的逐步方法进行评分。而在大数据上构建模式将在下一节中介绍。特别是当我们正在处理文本挖掘类问题时，使用预训练模型进行评分。我们需要两个主要对象（vectorizer和modelclassifier）作为序列化的pickle对象存储。

|  |
| --- |
| Here, pickle is a Python module to achieve serialization by which the object will be saved in a binary state on the disk and can be consumed by loading again.  <https://docs.python.org/2/library/pickle.html> |

Build an offline model using scikit on your local machine and make sure you pickle objects. For example, if I use the Naive Bayes example from *Chapter 6*, *Text Classification*, we need to store vectorizer and clf as pickle objects:

使用scikit在本地机器上构建离线模型，并确保选择对象。 例如，如果我使用第6章“文本分类”中的朴素贝叶斯示例，我们需要将vectorizer和clf存为pickle对象：

>>> vectorizer = TfidfVectorizer(sublinear\_tf=True,

min\_df=in\_min\_df, stop\_words='english', ngram\_range=(1,2), max\_df=in\_max\_df)

>>> joblib.dump(vectorizer, "vectorizer.pkl", compress=3)

>>> clf = GaussianNB().fit(X\_train,y\_train)

>>> joblib.dump(clf, "classifier.pkl")

The following are the steps for creating a output table which will have all the customer comments for the entire history:

以下是创建输出表的步骤，其中包含整个历史记录的所有客户注释：

1. Create the same schema in Hive as we did in the previous example. The following Hive script will do this for you. This table can be huge; in our case, let's assume that it contains all the customer comments about the company in the past: 1.在Hive中创建与上一个示例中相同的模式。 以下Hive脚本将为您执行此操作。 这个表可以是巨大的; 在我们的例子中，让我们假设它包含过去公司的所有客户评论：

Hive script

CREATE TABLE $InputTableName (

ID String,

Content String

)

ROW FORMAT DELIMITED

FIELDS TERMINATED BY '\t';

1. Build an output table with the output column like the predict and probability score: 2.使用输出列构建输出表，如预测和概率分数：

Hive script

CREATE TABLE $OutTableName (

ID String, Content String, predict String, predict\_score double )

1. Now, we have to load these pickle objects to the distributed cache using the addFILE command in Hive: 现在，我们必须使用Hive中的addFILE命令将这些pickle对象加载到分布式缓存：

add FILE vectorizer.pkl;

add FILE classifier.pkl;

1. The next step is to write the Hive UDF, where we are loading these pickle objects. Now, they start behaving the same as they were on the local. Once we have the classifier and vectorizer object, we can use our test sample, which is nothing but a string, and generate the TFIDF vector out of this. The vectorizer object can be used now to predict the class as well as the probability of the class: 下一步是写Hive UDF，我们在这里加载这些pickle对象。 现在，他们开始行为与他们在当地的一样。 一旦我们有了分类器和矢量化器对象，我们可以使用我们的测试样本，这只是一个字符串，并生成TFIDF向量。 vectorizer对象现在可以用来预测类以及类的概率：

Classification.py

**>>>import sys**

**>>>import pickle**

**>>>import sklearn**

**>>>from sklearn.externals import joblib**

**>>>clf = joblib.load('classifier.pkl')**

**>>>vectorizer = joblib.load('vectorizer.pkl')**

**>>>for line in sys.stdin:**

**>>> line = line.strip()**

**>>> id, content= line.split('\t')**

**>>> X\_test = vectorizer.transform([str(content)])**

**>>> prob = clf.predict\_proba(X\_test)**

**>>> pred = clf.predict(X\_test)**

**>>> prob\_score =prob[:,1]**

**>>> print '\t'.join([id, content,pred,prob\_score])**

1. Once we have written the classification.py UDF, we have to also add this UDF to the distributed cache and then effectively, run this UDF as a TRANSFORM function on each and every row of the table. The Hive script for this will look like this: 一旦我们写了classification.py UDF，我们还必须将这个UDF添加到分布式缓存，然后有效地在表的每一行上运行这个UDF作为TRANSFORM函数。 这样的Hive脚本将如下所示：

Hive script

add FILE classification.py;

INSERT OVERWRITE TABLE $OutTableName

SELECT

TRANSFORM (id, content)

USING 'python2.7 classification.py'

AS (id string, scorestringscore string )

FROM $Tablename;

1. If everything goes well, then we will have the output table with the output schema as: 6.如果一切顺利，那么我们将输出表与输出模式：

|  |  |  |  |
| --- | --- | --- | --- |
| **ID** | **Content** | **Predict** | **Prob\_score** |
| UA0001 | "I tried calling you, The service was not up to the mark" | Complaint | 0.98 |
| UA0002 | "Can you please update my phone no " | No | 0.23 |
| UA0003 | "Really bad experience" | Complaint | 0..97 |
| UA0004 | "I am looking for an iPhone " | No | 0.01 |

So, our output table will have all the customer comments for the entire history, scores for whether they were complaints or not, and also a confidence score. We have choosen a Hive UDF for our example, but the similar process can be done through the Pig and Python steaming in a similar way as we did in NLTK.

因此，我们的输出表将包含整个历史的所有客户评论，是否是投诉的分数，以及置信分数。 我们为我们的示例选择了一个Hive UDF，但是类似的过程可以通过Pig和Python通过类似于NLTK中的方式进行。

This example was to give you a hands-on experience of how to score a machine learning model on Hive. In the next example, we will talk about how to build a machine learning/NLP model on big data.

这个例子是给你一个如何在Hive上学习机器学习模型的实践经验。 在下一个例子中，我们将讨论如何在大数据上构建机器学习/ NLP模型。

## PySpark

Let's go back to the same discussion we had of building a machine learning/NLP model on Hadoop and the other where we score a ML model on Hadoop. We discussed second option of scoring in depth in the last section. Instead sampling a smaller data-set and scoring let’s use a larger data-set and build a large-scale machine learning model step-by-step using PySpark. I am again using the same running data with the same schema:

让我们回到我们在Hadoop上构建一个机器学习/ NLP模型的讨论，另一个我们在Hadoop上得到一个ML模型。 我们在最后一节深入讨论了第二个评分选项。 相反，对较小的数据集和评分进行抽样，我们使用更大的数据集，并使用PySpark逐步构建大型机器学习模型。 我再次使用相同的运行数据具有相同的模式：

|  |  |  |
| --- | --- | --- |
| **ID** | **Comment** | **Class** |
| UA0001 | I tried calling you, The service was not up to the mark | 1 |
| UA0002 | Can you please update my phone no | 0 |
| UA0003 | Really bad experience | 1 |
| UA0004 | I am looking for an iPhone | 0 |
| UA0005 | Can somebody help me with my password | 1 |
| UA0006 | Thanks for considering my request for | 0 |

Consider the schema for last 10 years worth of comments of the organization. Now, instead of using a small sample to build a classification model, and then using a pretrained model to score all the comments, let me give you a step-by-step example of how to build a text classification model using PySpark.

考虑组织的最近10年的评价的模式。 现在，不是使用一个小样本来构建分类模型，然后使用预训练模型对所有注释进行评分，让我给你一个分步示例，说明如何使用PySpark构建文本分类模型。

The first thing that we need to do is we need to import some of the modules. Starting with SparkContext, which is more of a configuration, you can provide more parameters, such as app names and others for this.

我们需要做的第一件事是，我们需要导入一些模块。 从SparkContext开始，这是一个更多的配置，你可以提供更多的参数，如应用程序名称和其他。

**>>>from pyspark import SparkContext**

**>>>sc = SparkContext(appName="comment\_classifcation")**

|  |
| --- |
| For more information, go through the article at  http://spark.apache.org/docs/0.7.3/api/pyspark/ pyspark.context.SparkContext-class.html. |

The next thing is reading a tab delimited text file. Reading the file should be on HDFS. This file could be huge (~Tb/Pb):

接下来是阅读制表符分隔的文本文件。 读取文件应该在HDFS上。 这个文件可能很大（〜Tb / Pb）：

>>> lines = sc.textFile("testcomments.txt")

The lines are now a list of all the rows in the corpus:

这些行现在是语料库中所有行的列表：

>>>parts = lines.map(lambda l: l.split("\t"))

>>>corpus = parts.map(lambda row: Row(id=row[0], comment=row[1], class=row[2]))

The part is a list of fields as we have each field in the line delimited on "\t".

该部分是字段列表，因为我们有“\ t”分隔的行中的每个字段。

Let's break the corpus that has [ID, comment, class (0,1)] in the different RDD objects:

让我们打破在不同RDD对象中具有[ID，注释，类（0,1）]的语料库：

>>>comment = corpus.map(lambda row: " " + row.comment)

>>>class\_var = corpus.map(lambda row:row.class)

Once we have the comments, we need to do a process very similar to what we did in *Chapter 6*, *Text Classification*, where we used scikit to do tokenization, hash vectorizer and calculate TF, IDF, and tf-idf using a vectorizer.

一旦我们得到了注释，我们需要做一个非常类似于第6章文本分类的过程，在这里我们使用scikit进行标记化，散列矢量化和使用矢量化计算TF，IDF和tf-idf。

The following is the snippet of how to create tokenization, term frequency, and inverse document frequency:

以下是如何创建标记化，术语频率和反向文档频率的代码段：

>>>from pyspark.mllib.feature import HashingTF

>>>from pyspark.mllib.feature import IDF

# https://spark.apache.org/docs/1.2.0/mllib-feature-extraction.html

>>>comment\_tokenized = comment.map(lambda line: line.strip().split(" "))

>>>hashingTF = HashingTF(1000) # to select only 1000 features

>>>comment\_tf = hashingTF.transform(comment\_tokenized)

>>>comment\_idf = IDF().fit(comment\_tf)

>>>comment\_tfidf = comment\_idf.transform(comment\_tf)

We will merge the class with the tfidf RDD like this:

我们将类与tfidf RDD合并，如下所示：

>>>finaldata = class\_var.zip(comment\_tfidf)

We will do a typical test, and train sampling:

我们将做一个典型的测试，并训练取样：

>>>train, test = finaldata.randomSplit([0.8, 0.2], seed=0)

Let's perform the main classification commands, which are quite similar to scikit. We are using a logistic regression, which is widely used classifier. The pyspark.mllib provides you with a variety of algorithms.

让我们执行主分类命令，这与scikit非常相似。 我们使用逻辑回归，这是广泛使用的分类器。 pyspark.mllib为您提供了各种算法。

|  |
| --- |
| For more information on pyspark.mllib visit https://spark. apache.org/docs/latest/api/python/pyspark.mllib.html |

The following is an example of Naive bayes classifier:

以下是Naive bayes分类器的示例：

>>>from pyspark.mllib.regression import LabeledPoint

>>>from pyspark.mllib.classification import NaiveBayes

>>>train\_rdd = train.map(lambda t: LabeledPoint(t[0], t[1]))

>>>test\_rdd = test.map(lambda t: LabeledPoint(t[0], t[1]))

>>>nb = NaiveBayes.train(train\_rdd,lambda = 1.0)

>>>nb\_output = test\_rdd.map(lambda point: (NB.predict(point.features), point.label)) >>>print nb\_output

The nb\_output command contains the final predictions for the test sample. The great thing to understand is that with just less than 50 lines, we built a snippet code for an industry-standard text classification with even petabytes of the training sample.

nb\_output命令包含测试样本的最终预测。 最好的理解是，只有不到50行，我们为一个行业标准的文本分类构建了一个片段代码，甚至PB级的训练样本。

## 本章小结

To summarize this chapter, our objective was to apply the concepts that we learned so far in the context of big data. In this chapter, you learned how to use some Python libraries, such as NLTK and scikit with Hadoop. We talked about scoring a machine learning model, or an NLP-based operation.

总结本章，我们的目标是应用我们迄今为止在大数据的背景下学到的概念。 在本章中，您学习了如何使用一些Python库，如NLTK和scikit与Hadoop。 我们谈论了评分机器学习模型或基于NLP的操作。

We also saw three major examples of the most-common use cases. On understanding these examples, you can apply most of the NLTK, scikit and PySpark functions.

我们还看到了最常见用例的三个主要例子。 理解这些示例，您可以应用大多数NLTK，scikit和PySpark函数。

This chapter was a quick and brief introduction to NLP and text mining on big data. This is one of the hottest topics, and each term and tool which I talked about in the example snippet could be a book in itself. I tried to give you a hacker's approach, to give you an introduction to big data and text mining on a large scale. I encourage you to read more about some of these big data technologies such as Hadoop, Hive, Pig, and Spark and try to explore some of the examples we gave in this chapter.

本章是对大数据的NLP和文本挖掘的快速简要介绍。 这是最热门的主题之一，我在示例代码片段中谈到的每个术语和工具本身都可能是一本书。 我试图给你一个黑客的方法，给你一个大规模的大数据和文本挖掘的介绍。 我鼓励你阅读更多关于一些大数据技术，如Hadoop，Hive，Pig和Spark，并尝试探索我们在本章中提供的一些例子。

1. 译者注：MapReduce是一种编程方式，主要用于针对大规模数据集的并行计算。 [↑](#footnote-ref-1)