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Final Project Report

Feature Extraction & Selection, Classification

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Executive Summary

Given the tweets from the instructor and cleaned webpages from the Reducing Noise team, the planned tasks for our group were to find the best: (1) way to extract information that will be used for document representation; (2) feature selection method to construct feature vectors; and (3) way to classify each document into categories, considering the ontology developed in the IDEAL project. We have figured out an information extraction method for document representation, feature selection method for feature vector construction, and classification method. The categories will be associated with the documents, to aid searching and browsing using Solr. Our team handles both tweets and webpages. The tweets and webpages come in the form of text files that have been produced by the Reducing Noise team. The other input is a list of the specific events that the collections are about. We are able to construct feature vectors after information extraction and feature selection using Apache Mahout. For each document, a relational version of the raw data for an appropriate feature vector is generated. We applied the Naïve Bayes classification algorithm in Apache Mahout to generate the vector file and the trained model. The classification algorithm uses the feature vectors to go into classifiers for training and testing that works with Mahout. However, Mahout is not able to predict class labels for new data. Finally we came to a solution provided by Pangool.net [19], which is a Java, low-level MapReduce API. This package provides us a MapReduce Naïve Bayes classifier that can predict class labels for new data. After modification, this package is able to read in and output to Avro file in HDFS. The correctness of our classification algorithms, using 5-fold cross-validation, was promising.

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I. Introduction

Our team aims to classify provided tweets collections and webpage collections into pre-defined classes, which ultimately can help with Solr search engine. The Reducing Noise team provided us the cleaned tweets and webpages in HDFS for us to begin with.

At first, we are recommended to make use of Mahout, which is an open source machine-learning library. For text classification task, Mahout will be able to help us encode the features and then create vectors out of the features. It also provides techniques to set up training and testing sets. Specifically, Mahout can convert the raw text files into Hadoop's SequenceFile format. It can convert the SequenceFile entries into sparse vectors and modify the labels. It can split the input data into training and testing sets and run the built-in classifiers to train and test. Existing classification algorithms provided in Mahout include: (1) Stochastic gradient descent (SGD): OnlineLogisticRegression, CrossFoldLearner, AdaptiveLogisticRegression; (2) Support Vector Machine (SVM); (3) Naive Bayes; (4) Complementary Naive Bayes; (5) Random Forests. We tried our collections with Naïve Bayes classification algorithm since it is simple and very suitable for text classification tasks.

However, we find that Mahout Naïve Bayes classification algorithm is not able to predict class labels for new data. This means that we can only generate Naïve Bayes classifiers but we are not able to label new data. In order to solve this problem, we looked into available books and online tutorials and finally found a package from “Learning Apache Mahout Classification” [20], which could be used to predict class labels for new data using Mahout Naïve Bayes classifiers. However, we noticed that this package only works for Hadoop 1.1.1 and is not compatible with our cluster, which is Hadoop 2.5. We tried to modify the code and talk to the TAs, however, we did not successfully adapt this solution to our cluster.

Finally we came across another solution provided by Pangool.net [19], which is a Java, low-level MapReduce API. This package provides us a MapReduce Naïve Bayes classification algorithm and it can also predict class labels for new data. The most important thing is that this package is compatible with all versions of Hadoop. This package is modified to be able to read in and write to Avro files in HDFS. We used this package to generate Naïve Bayes classifiers for small collections of tweets and webpages, and large collections of tweets and webpages, for different teams. We showed the accuracy of our generated classifiers using 5-fold cross validations.

Our contribution can be summarized as:

- Investigation of classification algorithms provided by Apache Maout
- Naïve Bayes classifiers generated using Apache Mahout
- Prediction for class labels for new data using package provided in “Learning Apache Mahout Classificaiton” [20], but only works for Hadoop 1.1.1
- A MapReduce Naïve Bayes package called Pangool [19], which can be used to generate Naïve Bayes classifiers and predict for new data. It is modified to adapt to Avro format in HDFS.
- Evaluation of classfiers

Here is a list of what we are going to cover in the following sections. Section II gives an overview of related literature. More about the packages used is given in Section III. Section IV chronicles our development efforts. Section IV.1 gives an overview of Apache Mahout for classification. Section IV.2 gives our end-to-end handling of classification in conjunction with a small collection and searching with Solr. Section IV.3.5 gives our ultimate solution for predicting classes using Pangool [19], following discussion earlier in Section IV.3 about attempts to use Mahout. Section IV.4 describes evaluation tests. Section V summarizes our schedule while Section VI summarizes our efforts and conclusions, leading to Section VII which gives future plans.

II. Literature Review

1. Textbook

1.1 What is Classification?

From [15] chapter 13, we learn that many users have ongoing information needs. For example, a user might need to track developments in multi-core computer chips. One method of doing this is to issue the query multi-core AND computer AND chip against an index of recent newswire articles each morning. How can this repetitive task be automated? To this end, many systems support standing queries. A standing query is like any other query except that it is periodically executed on a collection to which new documents are incrementally added over time.

If the standing query is just multicore AND computer AND chip, the user will tend to miss many relevant new articles which use other terms such as “multicore processors”. To achieve good recall, standing queries thus have to be refined over time and can gradually become quite complex. In this example, using a Boolean search engine with stemming, the user might end up with a query like (multi core OR multi-core) AND (chip OR processor OR microprocessor).

To capture the generality and scope of the problem space to which standing queries belong, we now introduce the general notion of a classification problem. Given a set of classes, we seek to determine which class a given object belongs to. In the example, the standing query serves to divide new newswire articles into the two classes: documents about multicore computer chips and documents not about multicore computer chips. We refer to this as two-class classification.

A class need not be as narrowly focused as the standing query multicore computer chips. Often, a class describes a more general subject area like China or coffee. Such more general classes are usually referred to as topics, and the classification task is then called text classification, text categorization, topic classification, or topic spotting. Standing queries and topics differ in their degree of specificity, but the methods for solving routing, filtering, and text classification are essentially the same.

Apart from manual classification and hand-crafted rules, there is a third approach to text classification, namely, machine learning-based text classification. It is the approach that we focus on in our project. In machine learning, the set of rules or, more generally, the decision criterion of the text classifier, is learned automatically from training data. This approach is also called statistical text classification if the learning method is statistical. In statistical text classification, we require a number of good example documents (or training documents) for each class. The need for manual classification is not eliminated because the training documents come from a person who has labeled them – where labeling refers to the process of annotating each document with its class. But labeling is arguably an easier task than writing rules. Almost anybody can look at a document and decide whether or not it is related to China. Sometimes such labeling is already implicitly part of an existing workflow. For instance, the user may go through the news articles returned by a standing query each morning and give relevance feedback by moving the relevant articles to a special folder like multicore-processors.

1.2 Feature Selection

Feature selection is the process of selecting a subset of the terms occurring in the training set and using only this subset as features in text classification. Feature selection serves two main purposes. First, it makes training and applying a classifier more efficient by decreasing the size of the effective vocabulary. This is of particular importance for classifiers that, unlike NB, are expensive to train. Second, feature selection often increases classification accuracy by eliminating noise features. A noise feature is one that, when added to the document representation, increases the classification error on new data. Suppose a rare term, say arachno-centric, has no information about a class, say China, but all instances of arachno-centric happen to occur in China documents in our training set. Then the learning method might produce a classifier that wrongly assigns test documents containing arachno-centric to China. Such an incorrect generalization from an accidental property of the training set is called over-fitting.

We combine the definitions of term frequency and inverse document frequency, to produce a composite weight for each term in each document.

The tf-idf weighting scheme assigns to term t a weight in document d given by

$$\text{tf-idf}_{t,d} = \text{tf}_{t,d} \times \text{idf}_t.$$

In other words, $\text{tf-idf}_{t,d}$ assigns to term t a weight in document d that is
a. highest when t occurs many times within a small number of documents (thus lending high discriminating power to those documents);
b. lower when the term occurs fewer times in a document, or occurs in many documents (thus offering a less pronounced frequency relevance signal);
c. lowest when the term occurs in virtually all documents.

At this point, we may view each document as a vector with one component corresponding to each term in the dictionary, together with a weight for each component that is given by the previous equation. For dictionary terms that do not occur in a document, this weight is zero. This vector form will prove to be crucial to scoring and ranking. As a first step, we introduce the overlap score measure: the score of a document d is the sum, over all query terms, of the number of times each of the query terms occurs in d. We can refine this idea so that we add up not the number of occurrences of each query term t in d, but instead the tf-idf weight of each term in d.

1.3 Naïve Bayes Classification

The first supervised learning method introduced is the multinomial Naive Bayes or multinomial NB model, a probabilistic learning method. The probability of a document d being in class c is computed as $P(c|d) \propto P(c) \prod P(t_k|c)\ 1 \leq k \leq nd$ where $P(t_k|c)$ is the conditional probability of term t_k occurring in a document of class c. We interpret $P(t_k|c)$ as a measure of how much evidence t_k contributes that c is the correct class. P(c) is the prior probability of a document occurring in class c. If a document's terms do not provide clear evidence for one class versus another, we choose the one that has a higher prior probability.

$\langle t_1, t_2, \ldots, t_{nd} \rangle$ are the tokens in d that are part of the vocabulary we use for classification and nd is the number of such tokens in d.

1.4 Vector Space Classification

Chapter 14 in the textbook gives an introduction about vector space classification. Each document is represented as a vector and each component is for a term or word. Term are axes in the vector space, thus, vector spaces are high dimensionality. Generally vectors are normalized to unit length. Chapter 14 covers two vector space classification methods, Rocchio and kNN. Rocchio divides the vector space into regions centered on centroids or prototypes. kNN assigns the majority class of k nearest neighbors to a test document. This chapter talks about the difference between linear and nonlinear classifiers. It illustrates how to apply two-class classifiers to problems with more than two classes.

Rocchio classification uses standard TF-IDF weighted vectors to represent text documents. For training documents in each category, it computes the centroid of members of each class. It assigns test documents to the category with the closest centroid based on cosine similarity. The centroid of a class is computed as the vector average or center of mass of its members. The boundary between two classes in Rocchio classification is the set of points with equal distance from the two centroids. However, Rocchio did worse than Naive Bayes classifier in many cases. One reason is that Rocchio cannot handle nonconvex, multimodal classes.

kNN classification is interpreted as k nearest neighbor classification. To classify a document into a class, we need to find k nearest neighbors of the document, count number of documents in k nearest neighbors of the document that belong to the class, estimate the probability that the document belongs to the class and choose the majority class. One problem here is how to choose the value of k. Using only the closest example (1NN) to determine the class is subject to errors since there exists noise in the category label of a single training example. The more robust way is to find the k most similar examples and return the majority category of these k examples. The value of k is typically odd to avoid ties, however, we can break the ties randomly. 3 and 5 are the most common values to be used for k, but large values from 50 to 100 are also used. The nearest neighbor method depends on a similarity or distance metric. Simplest for continuous m-dimensional instance space is Euclidean distance. Simplest for m-dimensional binary instance space is Hamming distance, which counts number of features values that differ. Cosine similarity of TF-IDF weighted vectors is typically most effective for text classification. Feature selection and training are not necessary for kNN classification. kNN also scales well with a large number of classes, however, the scores can be hard to convert to probabilities.

Chapter 14 also introduces the bias-variance tradeoff. Bias is the squared difference between the true conditional probability of a document being in a class and the prediction of the learned classifier average over training sets. Thus, bias is large if the learning method produces classifiers that are consistently wrong. Variance is the variation of the prediction of learned classifier. It is calculated as the average squared difference between the prediction of the learned classifier and its average. Thus, variance is large if different training sets give rise to very different classifiers while variance is small if the training set has a minor effect on the classification decisions. Variance measures how inconsistent the decisions are, not whether they are correct or incorrect. The bias-variance tradeoff can be summarized as follows: linear methods like Rocchio and Naive Bayes have high bias for nonlinear problems because they can only model one type of class boundary (a linear hyperplane) and low variance because most randomly drawn training sets produce similar decision hyperplanes; however, nonlinear methods like kNN have low bias and high variance. High-variance learning methods are prone to over-fitting the train data. Since learning error includes both bias and variance, we know there is not a learning method that is optimal among all text classification problems because there is always a tradeoff between bias and variance.

Chapter 14 also talks about the difference between linear classifiers and nonlinear classifiers. Linear classifiers will classify based on a simple linear combination of the features. Such classifiers partition the space of features into regions separated by linear decision hyperplanes. Many common text classifiers are linear classifiers such as Naive Bayes, Rocchio, logistic regression, support vector machine with linear kernel and linear regression. If there exists a hyperplane that perfectly separates the two classes, then we call the two classes linearly separable.

Classification with more than two classes has two methods: any-of classification and one-of classification. When classes are not mutually exclusive, a document can belong to none, exact one, or more than one classes and the classes are independent of each other. This is called any-of classification. When classes are mutually exclusive, each document can belong to exactly one of the classes. This is called one-of classification. The difference is that when solving any-of classification task with linear classifiers, the decision of one classifier has no influence on the decisions of the other classifiers while when solving one-classification task with linear classifiers, we will assign the document to the class with the maximum score, or the maximum confidence value, or the maximum probability. We commonly use a confusion matrix to evaluate the performance, which shows for each pair of classes, how many documents from one class are incorrectly assigned to the other classes.

In summary, when choosing which classification method to use, we need to consider how much training data is available, how simple/complex is the problem, how noisy is the problem and how stable is the problem over time.

1.5 Support Vector Machine

Chapter 15 gives an introduction of support vector machine (SVM) classification method. Assume that we have a two-class linear separable train set. We want to build a classifier to divide them into two classes. For a 2D situation, the classifier is a line. When it comes to high dimensions, the decision boundary comes to be a hyperplane. Some methods find a separating hyperplane, but not the optimal one.

Support Vector Machine (SVM) finds an optimal solution. It maximizes the distance between the hyperplane and the “difficult points” close to the decision boundary. That is because first, if there are no points near the decision surface, then there are no very uncertain classification decisions. Secondly, if you have to place a fat separator between classes, you have less choices, and so the capacity of the model has been decreased.

So the main idea of SVMs is that it maximizes the margin around the separating hyperplane. That is because the larger margin we have, the more confidence we can get for our classification. Obviously, there should be some points at the boundary. Otherwise we can continue to expand the margin to make it larger until it reaches some points. These points are called the support vectors. So our job is to find the hyperplane with maximized margin with support vector on the two boundaries. If we have the training set, this problem comes to be a quadratic optimization problem.

Most of the time, we have noise data that we have to ignore because we want to build a hyperplane that is far away from all the data points. If we do not ignore these noise points, we may get a hyperplane with very "small margin" or we even cannot build a hyperplane. So in this case, SVM also allows some noise data to be misclassified.

To use the SVMs for classification, given a new point x, we can score its projection onto the hyperplane normal. We can also set threshold t such as:
Score > t: yes
Score < -t: no
Else: don't know

This solution works great for the datasets that are linearly separable. But sometimes, the dataset is too hard to separate. SVM also handles these datasets. What SVM does is trying to define a mapping function to transform the data from low dimension to higher dimension to make the data linearly separable in the high dimension, which is called the kernel trick. So instead of complicated computation, we can use kernels to stand for inner product, which will make our calculation easier.

In summary, SVM chooses hyperplane based on support vectors. It is a powerful and elegant way to define similarity metric. Based on our evaluation results, perhaps it is the best performing text classifier.

2. Papers

[6] takes advantages of data-mining techniques to get metadata from tweets gathered from the Internet. They discover the relationship of tweets. In this paper, they separate the method into 5 different steps, which are (1) selecting keywords to gather an initial set of tweets to analyze; (2) importing data; (3) preparing data; (4) analyzing data (topic, sentiment, and ecologic context); and (5) interpreting data. We find the steps in this paper extremely helpful to our project. We can use similar steps to play with our own CSV file. We can directly get data from others so we do not need the first step. But when it comes to importing and preparing data we can apply the method in this paper. The original contents in the tweets are not well prepared for data analysis. So we must stem the data, like excluding the punctuation and transforming verbs to their original term. Then we go to the fourth step, which is to analyze the tweets to find features. Finally, in this paper, it uses a method other than machine learning to build up the classification, but in our project we will apply machine-learning algorithm (MLA) to the classification problem.

Similarly, in [7], they apply a model-based method to deal with tweets and get the geo-locating information purely by the contents of the tweets. They have similar processing structure as [6]. They also import the data and make a metric to model the data and get the conclusion. Our structure for extracting features and classifying tweets should be based on the procedure mentioned above.

3. Tools and Packages

Mahout is an open source machine-learning library from Apache. The algorithms it implements fall under the broad umbrella of machine learning or collective intelligence. This can mean many things, but at the moment for Mahout it means primarily recommender engines (collaborative filtering), clustering, and classification. It is a Java library. It doesn't provide a user interface, a prepackaged server, or an installer. It's a framework of tools that intended to be used and adapted by developers.

It's also scalable. Mahout aims to be the machine-learning tool of choice when the collection of data to be processed is very large, perhaps far too large for a single machine. In its current incarnation, these scalable machine learning implementations in Mahout are written in Java, and some portions are built upon Apache's Hadoop distributed computation project.

Mahout supports Stochastic gradient descent (SGD), which is a widely used learning algorithm in which each training example is used to tweak the model slightly to give a more correct answer for that one example. An experimental sequential implementation of the support vector machine (SVM) algorithm has recently been added to Mahout. The behavior of the SVM algorithm will likely be similar to SGD in that the implementation is sequential, and the training speed for large data sizes will probably be somewhat slower than SGD. The Mahout SVM implementation will likely share the input flexibility and linear scaling of SGD and thus will probably is a better choice than Naive Bayes for moderate-scale projects. The Naive Bayes and complementary Naive Bayes algorithms in Mahout are parallelized algorithms that can be applied to larger datasets than are practical with SGD-based algorithms. Because they can work effectively on multiple machines at once, these algorithms will scale to much larger training data sets than will the SGD-based algorithms. Mahout has sequential and parallel implementations of random forests algorithm as well. This algorithm trains an enormous number of simple classifiers and uses a voting scheme to get a single result. The Mahout parallel implementation trains the many classifiers in the model in parallel.

Pangool [19] is a framework on top of Hadoop that implements Tuple MapReduce. Pangool is a Java, low-level MapReduce API. It aims to be a replacement for the Hadoop Java MapReduce API. By implementing an intermediate Tuple-based schema and configuring a Job conveniently, many of the accidental complexities that arise from using the Hadoop Java MapReduce API disappear. Things like secondary sort and reduce-side joins become extremely easy to implement and understand. Pangool's performance is comparable to that of the Hadoop Java MapReduce API. Pangool also augments Hadoop's API by making multiple outputs and inputs first-class and allowing instance-based configuration. It provides an implementation of M/R Naïve Bayes classification algorithm.

III. User Manual

1. Attachment Description

MRClassify-master/: A package that can use Naïve Bayes model we trained using Mahout to classify new unlabeled data. This package works fine with Hadoop 1.1.1, but it is not compatible with Hadoop 2.5.
generate.py: It can generate an individual text file for each tweet in the CSV file.
mr-naivebayes.jar: The MapReduce Naïve Bayes classifier is provided by Pangool [19]. It can generate Naïve Bayes classifier and label new data. It is modified for our project to read in and write to Avro format.

- **NaiveBayesClassifier.java:** This class can generate Naïve Bayes classifier. It can be modified for classifiers that have better performance.
- **NaiveBayesGenerate.java:** This class can label new data using the generated classifier. It can be modified to have different scoring technique for new data.

print_webpage.py: This script can generate plain text from AVRO file for webpages.
tweet_shortToLongURL_File.py: This script is provided by TA.
tweet_URL_archivingFile.py: This script is provided by TA and can be used to generate seed URLs for webpages to be crawled using Nutch.

2. Usage of Package

2.1 Generate Mahout Naïve Bayes Classification Model

Create a working directory for the dataset and all input/output:

```
export WORK_DIR=/user/cs5604s15_class/
```

Convert the full dataset into a <Text, Text> SequenceFile:

```
mahout seqdirectory -i ${WORK_DIR}/test -o ${WORK_DIR}/test-seq  -ow
```

Convert and preprocess the dataset into a <Text, VectorWritable> SequenceFile containing term frequencies for each document:

```
mahout seq2sparse -i ${WORK_DIR}/test-seq -o ${WORK_DIR}/test-vectors -lnorm -nv -wt tfidf
```

Split the preprocessed dataset into training and testing sets:

```
mahout split -i ${WORK_DIR}/test-vectors/tfidf-vectors --trainingOutput ${WORK_DIR}/test-train-vectors --testOutput ${WORK_DIR}/test-test-vectors --randomSelectionPct 40 --overwrite --sequenceFiles -xm sequential
```

Train the classifier:

```
mahout trainnb -i ${WORK_DIR}/test-train-vectors -el -o ${WORK_DIR}/model -li ${WORK_DIR}/labelindex -ow -c
```

Test the classifier:

```
mahout testnb -i ${WORK_DIR}/test-test-vectors -m ${WORK_DIR}/model -l ${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/test-testing –c
```

2.2 Predict Class Label for New Data Using Mahout Naïve Bayes Classifier

Note: This method only work for Hadoop 1.1.1.

Get the scripts and Java programs:

```
git clone https://github.com/fredang/mahout-naive-bayes-example.git
```

Compile:

```
mvn –version
mvn clean package assembly:single
```

Upload training data to HDFS:

```
hadoop fs -put data/tweets-to-classify.tsv tweets-to-classify.tsv
```

Run the MapReduce job:

```
hadoop jar target/mahout-naive-bayes-example2-1.0-jar-with-dependencies.jar model tweets-vectors/dictionary.file-0 tweets-vectors/df-count/part-r-00000 tweets-to-classify.tsv tweet-category
```

Copy the results from HDFS to the local file system:

```
hadoop fs -getmerge tweet-category tweet-category.tsv
```

Read the result by a file reader:

```
java -cp target/mahout-naive-bayes-example2-1.0-jar-with-dependencies.jar com.chimpler.example.bayes2.ResultReader data/tweets-to-classify.tsv [label index path] tweet-category.tsv
```

2.3 Pangool: MapReduce Naïve Bayes Classification and Class Label Prediction

Download Pangool:

```
git clone https://github.com/datasalt/pangool.git
```

Install:

```
mvn clean install
```
.

NaiveBayesGenerate.java: This class is used to generate the Naïve Bayes classifier model.
NaiveBayesClassifier.java: This class will use the model we generated to predict and label the new data.

We used the Naïve Bayes example under target/pangool-examples-0.71-SNAPSHOT-hadoop.jar

Train the classifier:

```
hadoop jar target/pangool-examples-0.71-SNAPSHOT-hadoop.jar naive_bayes_generate LDA/train_lda.txt lda-out-bayes-model
```

Testing the classifier:

```
hadoop jar target/pangool-examples-0.71-SNAPSHOT-hadoop.jar naive_bayes_classifier lda-out-bayes-model/p* LDA/test_lda.txt out-classify-lda
```

Using the modified classifier to handle input file and output file in AVRO format

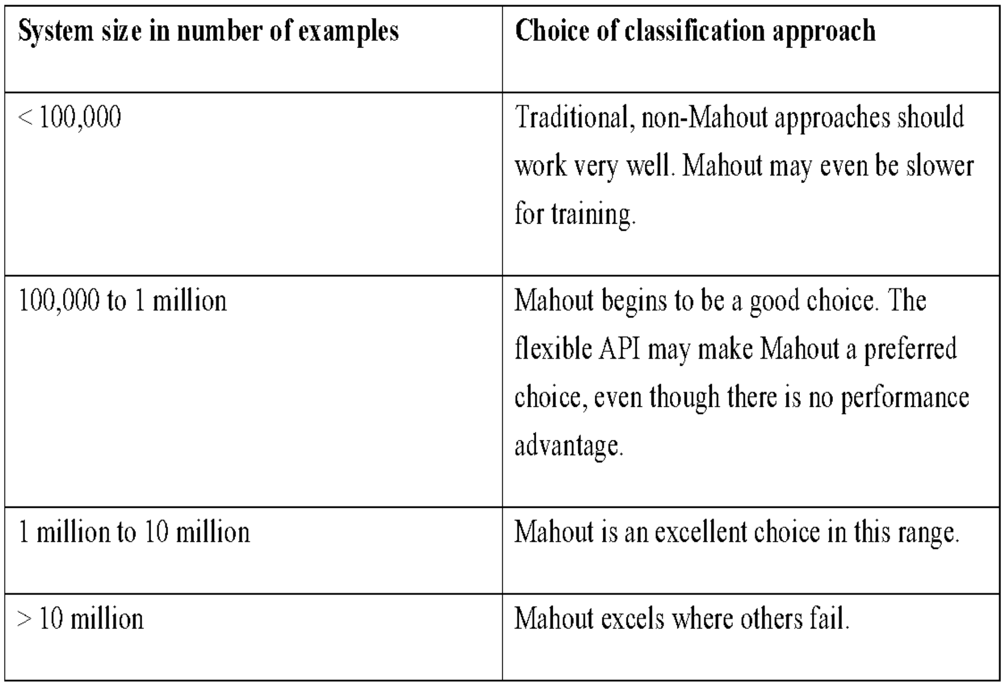
```
hadoop jar mr-naivebayes.jar lda-out-bayes-model/p*
/user/cs5604s15_noise/TWEETS_CLEAN/suicide_bomb_attack_S
classified_tweets_LDA_afghanistan_small
```

IV. Developer Manual

1. Algorithms

1.1 Classification Algorithms in Mahout

Mahout can be used on a wide range of classification projects, but the advantage of Mahout over other approaches becomes striking as the number of training examples gets extremely large. What large means can vary enormously. Up to about 100,000 examples, other classification systems can be efficient and accurate. But generally, as the input exceeds 1 to 10 million training examples, something scalable like Mahout is needed.



System size in number of examples	**Choice of classification approach**
< 100,000	Traditional, non-Mahout approaches should work very well. Mahout may even be slower for training.
100,000 to 1 million	Mahout begins to be a good choice. The flexible API may make Mahout a preferred choice, even though there is no performance advantage.
1 million to 10 million	Mahout is an excellent choice in this range.
> 10 million	Mahout excels where others fail.

Table 1: Comparison between Mahout and non-Mahout approach [16]

The reason Mahout has an advantage with larger data sets is that as input data increases, the time or memory requirements for training may not increase linearly in a non-scalable system. A system that slows by a factor of 2 with twice the data may be acceptable, but if 5 times as much data input results in the system taking 100 times as long to run, another solution must be found. This is the sort of situation in which Mahout shines.

In general, the classification algorithms in Mahout require resources that increase no faster than the number of training or test examples, and in most cases the computing resources required can be parallelized. This allows you to trade off the number of computers used against the time the problem takes to solve.

The main advantage of Mahout is its robust handling of extremely large and growing data sets. The algorithms in Mahout all share scalability, but they differ from each other in other characteristics, and these differences offer different advantages or drawbacks in different situations.

Size of data set	Mahout algorithm	Executive model	Characteristics
Small to medium (less than tens of millions of training examples)	Stochastic gradient descent (SGD) family: OnlineLogisticRegression, CrossFoldLearner, AdaptiveLogisticRegression	Sequential, online. incremental	Uses all types of predictor variables; sleek and efficient over the appropriate data range (up to millions of training examples)
Medium to large (millions to hundreds of millions of training examples)	Support Vector Machine (SVM) Na ïve Bayes Complementary Na ïve Bayes	Sequential Parallel Parallel	Experimental still: sleek and efficient over the appropriate data range Strongly prefers text-like data; medium to high overhead for training; effective and useful for data sets too large for SGD or SVM Somewhat more expensive to train than na ïve Bayes; effective and useful for data sets too large for SGD, but has similar limitations to na ïve Bayes
Small to medium (less than tens of millions of training examples)	Random forests	Parallel	Uses all types of predictor variables; high overhead for training; not widely used (yet); costly but offers complex and interesting classifications, handles nonlinear and conditional relationships in data better than other techniques

Table 2: Characteristics of the Mahout learning algorithms used for classification [16]

The algorithms differ somewhat in the overhead or cost of training, the size of the data set for which they're most efficient, and the complexity of analyses they can deliver.

Stochastic gradient descent (SGD) is a widely used learning algorithm in which each training example is used to tweak the model slightly to give a more correct answer for that one example. This incremental approach is repeated over many training examples. With some special tricks to decide how much to nudge the model, the model accurately classifies new data after seeing only a modest number of examples.

An experimental sequential implementation of the support vector machine (SVM) algorithm has recently been added to Mahout. The behavior of the SVM algorithm will likely be similar to SGD in that the implementation is sequential, and the training speed for large data sizes will probably be somewhat slower than SGD. The Mahout SVM implementation will likely share the input flexibility and linear scaling of SGD and thus will probably be a better choice than naive Bayes for moderate-scale projects.

The naive Bayes and complementary naive Bayes algorithms in Mahout are parallelized algorithms that can be applied to larger datasets than are practical with SGD-based algorithms. Because they can work effectively on multiple machines at once, these algorithms will scale to much larger training data sets than will the SGD-based algorithms.

The Mahout implementation of naive Bayes, however, is restricted to classification based on a single text-like variable. For many problems, including typical large data problems, this requirement isn't a problem. But if continuous variables are needed and they can't be quantized into word-like objects that could be lumped in with other text data, it may not be possible to use the naive Bayes family of algorithms.

In addition, if the data has more than one categorical word-like or text-like variable, it's possible to concatenate your variables together, disambiguating them by prefixing them in an unambiguous way. This approach may lose important distinctions because the statistics of all the words and categories get lumped together. Most text classification problems, however, should work well with naive Bayes or complementary naive Bayes.

Mahout has sequential and parallel implementations of the random forests algorithm as well. This algorithm trains an enormous number of simple classifiers and uses a voting scheme to get a single result. The Mahout parallel implementation trains the many classifiers in the model in parallel.

This approach has somewhat unusual scaling properties. Because each small classifier is trained on some of the features of all of the training examples, the memory required on each node in the cluster will scale roughly in proportion to the square root of the number of training examples. This isn't quite as good as naive Bayes, where memory requirements are proportional to the number of unique words seen and thus are approximately proportional to the logarithm of the number of training examples. In return for this less desirable scaling property, random forests models have more power when it comes to problems that are difficult for logistic regression, SVM, or naive Bayes. Typically these problems require a model to use variable interactions and discretization to handle threshold effects in continuous variables. Simpler models can handle these effects with enough time and effort by developing variable transformations, but random forests can often deal with these problems without that effort.

1.2 Classification Configuration

For classification of text, this primarily means encoding the features and then creating vectors out of the features, but it also includes setting up training and test sets. The complete set of steps taken is:

(1) Convert the raw text files into Hadoop's SequenceFile format.

(2) Convert the SequenceFile entries into sparse vectors and modify the labels.

(3) Split the input into training and test sets:

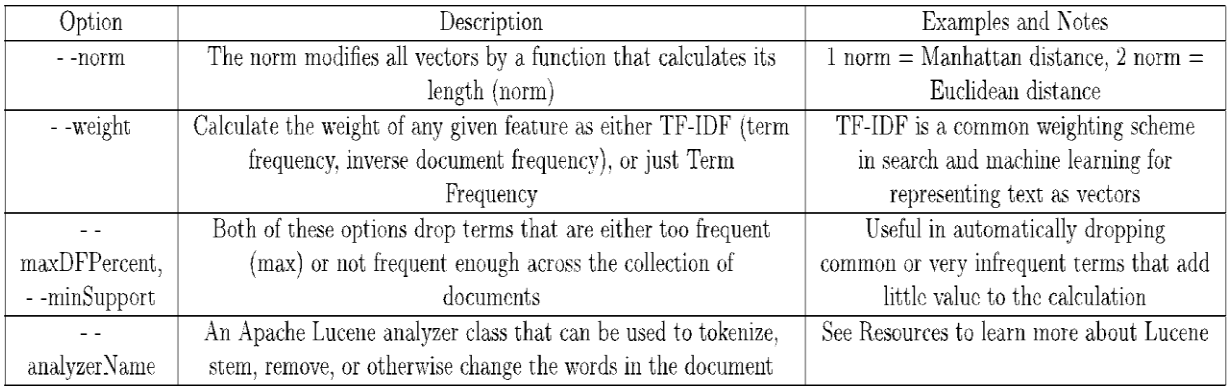
```
bin/mahout split --input $SEQ2SPLABEL --trainingOutput $TRAIN --testOutput $TEST
    --randomSelectionPct 20 --overwrite –sequenceFiles
```

(4) Run the naive Bayes classifier to train and test:

a. bin/mahout trainnb -i $TRAIN -o $MODEL -extractLabels --labelIndex $LABEL

b. bin/mahout testnb -i $TEST -m $MODEL --labelIndex $LABEL

The two main steps worth noting are Step (2) and Step (4). Step (2)a is the primary feature-selection and encoding step, and a number of the input parameters control how the input text will be represented as weights in the vectors.



Option	Description	Examples and Notes
- -norm	The norm modifies all vectors by a function that calculates its length (norm)	1 norm = Manhattan distance, 2 norm = Euclidean distance
- -weight	Calculate the weight of any given feature as either TF-IDF (term frequency, inverse document frequency), or just Term Frequency	TF-IDF is a common weighting scheme in search and machine learning for representing text as vectors
- - maxDFPercent, - -minSupport	Both of these options drop terms that are either too frequent (max) or not frequent enough across the collection of documents	Useful in automatically dropping common or very infrequent terms that add little value to the calculation
- - analyzerName	An Apache Lucene analyzer class that can be used to tokenize, stem, remove, or otherwise change the words in the document	See Resources to learn more about Lucene

Table 3: Options of Mahout feature vector generation [16]

The analysis process in Step (2)a is worth diving into a bit more, given that it is doing much of the heavy lifting needed for feature selection. A Lucene Analyzer is made up of a Tokenizer class and zero or more TokenFilter classes. The Tokenizer is responsible for breaking up the original input into zero or more tokens (such as words). TokenFilter instances are chained together to then modify the tokens produced by the Tokenizer. For example, the Analyzer used in the example:
<1> Tokenizes on whitespace, plus a few edge cases for punctuation.
<2> Lowercases all tokens.
<3> Converts non-ASCII characters to ASCII, where possible by converting diacritics and so on.
<4> Throws away tokens with more than 40 characters.
<5> Removes stop words.
<6> Stems the tokens using the Porter stemmer.

The end result of this analysis is a significantly smaller vector for each document, as well as one that has removed common "noise" words (the, a, an, and the like) that will confuse the classifier. This Analyzer was developed iteratively by looking at examples and then processing it through the Analyzer and examining the output, making judgment calls about how best to proceed.

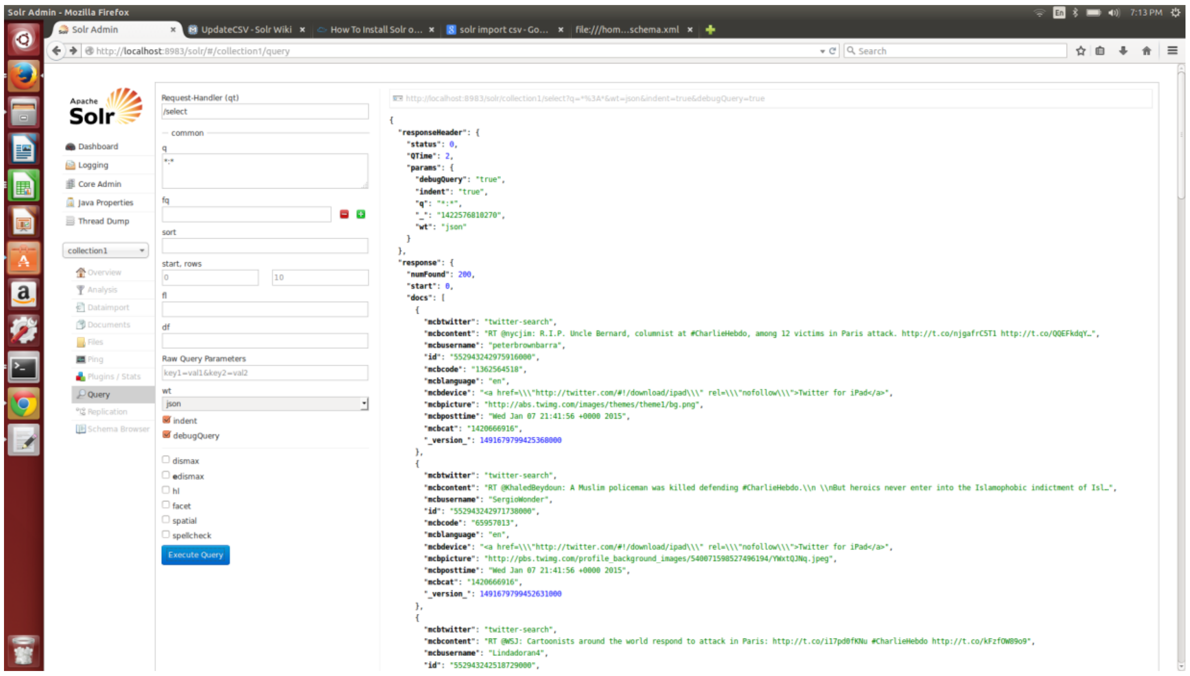
Step (2)b does some minor conversions of the data for processing as well as discards some content so that the various labels are evenly represented in the training data.

Step (4) is where the actual work is done both to build a model and then to test whether it is valid or not. In Step (4)a, the --extractLabelsoption simply tells Mahout to figure out the training labels from the input. (The alternative is to pass them in.) The output from this step is a file that can be read via the org.apache.mahout.classifier.naivebayes.NaiveBayesModel class. Step (4)b takes in the model as well as the test data and checks to see how good of a job the training did.

2. Environment Setup

2.1 Installation

Install Solr:
Installation progress:
1: Download the Java SE 7 JDK and export environment variables. Check “java -version”.
2: Download the Apache Ant binary distribution (1.9.4) from http://ant.apache.org/ and export environment variable ANT_HOME. Use “ant -version” to check.
3: Download the Apache Solr distribution (Source code) and extract to C:\solr\
4: Navigate to the Solr directory and use “ant compile” to compile Solr. (Use the ant ‘ ivy-bootstrap’ command to install ivy.jar before installing Solr)
5: Successfully installed Solr.
Or you can directly download the binary version of Solr and then launch Solr.
A screenshot of the Solr client webpage is shown in Figure 1.

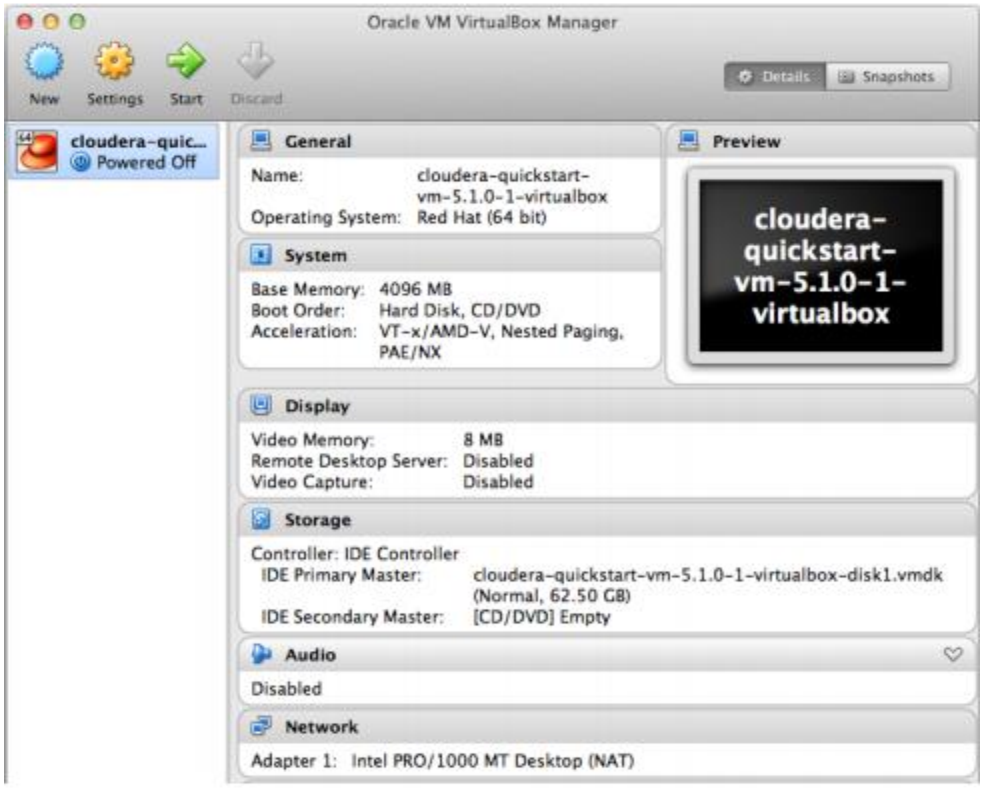


```
http://localhost:8983/solr/collection1/select?q=*%3A*&wt=json&indent=true&debugQuery=true
{
  "responseHeader": {
    "status": 0,
    "QTime": 2,
    "params": {
      "debugQuery": "true",
      "indent": "true",
      "q": "*:*",
      "_": "1422576810270",
      "wt": "json"
    }
  },
  "response": {
    "numFound": 200,
    "start": 0,
    "docs": [
      {
        "mcbtwitter": "twitter-search",
        "mcbcontent": "RT @nycjim: R.I.P. Uncle Bernard, columnist at #CharlieHebdo, among 12 victims in Paris attack. http://t.co/njgafrC5T1 http://t.co/QQEFkdqY…",
        "mcbusername": "peterbrownbarra",
        "id": "552943242975916000",
        "mcbcode": "1362564518",
        "mcblanguage": "en",
        "mcbdevice": "<a href=\\\"http://twitter.com/#!/download/ipad\\\" rel=\\\"nofollow\\\">Twitter for iPad</a>",
        "mcbpicture": "http://abs.twimg.com/images/themes/theme1/bg.png",
        "mcbposttime": "Wed Jan 07 21:41:56 +0000 2015",
        "mcbcat": "1420666916",
        "_version_": 1491679799425368000
      },
      {
        "mcbtwitter": "twitter-search",
        "mcbcontent": "RT @KhaledBeydoun: A Muslim policeman was killed defending #CharlieHebdo.\\n \\nBut heroics never enter into the Islamophobic indictment of Isl…",
        "mcbusername": "SergioWonder",
        "id": "552943242971738000",
        "mcbcode": "65957013",
        "mcblanguage": "en",
        "mcbdevice": "<a href=\\\"http://twitter.com/#!/download/ipad\\\" rel=\\\"nofollow\\\">Twitter for iPad</a>",
        "mcbpicture": "http://pbs.twimg.com/profile_background_images/540071598527496194/YWxtQJNq.jpeg",
        "mcbposttime": "Wed Jan 07 21:41:56 +0000 2015",
        "mcbcat": "1420666916",
        "_version_": 1491679799452631000
      },
      {
        "mcbtwitter": "twitter-search",
        "mcbcontent": "RT @WSJ: Cartoonists around the world respond to attack in Paris: http://t.co/i17pd0fKNu #CharlieHebdo http://t.co/kFzfOW89o9",
        "mcbusername": "Lindadoran4",
        "id": "552943242518729000",
```

Fig. 1: Solr Installation

Install Cloudera virtualbox VM:

1. Download latest version of Virtualbox and install.
2. Download cloudera-quickstart-vm-5.3.x.zip and then unzip to your virtualbox machine folder.
3. Run virtualbox and run “import applicance” in the File menu.
4. Find your Cloudera unzipped file and click open.
5. Click “Continue”.
6. Click “import”
7. Click “Continue”
8. Successfully import the virtualbox.



General
Name: cloudera-quickstart-vm-5.1.0-1-virtualbox
Operating System: Red Hat (64 bit)

System
Base Memory: 4096 MB
Boot Order: Hard Disk, CD/DVD
Acceleration: VT-x/AMD-V, Nested Paging, PAE/NX

Display
Video Memory: 8 MB
Remote Desktop Server: Disabled
Video Capture: Disabled

Storage
Controller: IDE Controller
IDE Primary Master: cloudera-quickstart-vm-5.1.0-1-virtualbox-disk1.vmdk (Normal, 62.50 GB)
IDE Secondary Master: [CD/DVD] Empty

Audio
Disabled

Network
Adapter 1: Intel PRO/1000 MT Desktop (NAT)

Fig. 2: Cloudera Virtual Machine Installation

9. Click “start” to start the virtual machine OS.

Install Mahout:
Prerequisites:
1. Java JDK 1.8
2. Apache Maven

Checkout the sources from the Mahout GitHub repository either via

```
git clone https://github.com/apache/mahout.git
```

Compiling
Compile Mahout using standard maven commands

```
mvn clean compile
```

2.2 Data Import

2.2.1 Approach

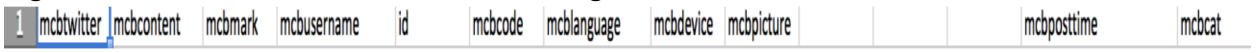
We renamed the test data CSV file to books.csv, put it at example/exampledocs/books.csv and uploaded it to the Solr example server.
We used HTTP-POST to send the CSV data over the network to the Solr server:

```
cd example/exampledocs
curl http://localhost:8983/solr/update/csv --data-binary @books.csv -H 'Content-type:text/plain;
```

charset=utf-8'

2.2.2 Steps

a. Modify the data CSV file
We added a row describing each column at the beginning of the data CSV file.
Figure 3 shows what we have added to the existing data CSV file:



1	mcbtwitter	mcbcontent	mcbmark	mcbusername	id	mcbcode	mcblanguage	mcbdevice	mcbpicture				mcbposttime	mcbcat

Fig. 3: Data CSV file modification example

b. Change schema.xml to define properties of the fields.
The schema declares what kinds of fields there are, which field should be used as the unique/primary key, which fields are required and how to index and search each field. For each new field, we add name, type, indexed and stored attribute. Name is mandatory and it is the name for the field. Type is mandatory and it is the name of a previously defined type from the <types> section. Indexed is set to true if this field should be indexed. Stored is set to true if this field should be retrievable.
Figure 4 shows what we have added to the existing schema.xml:

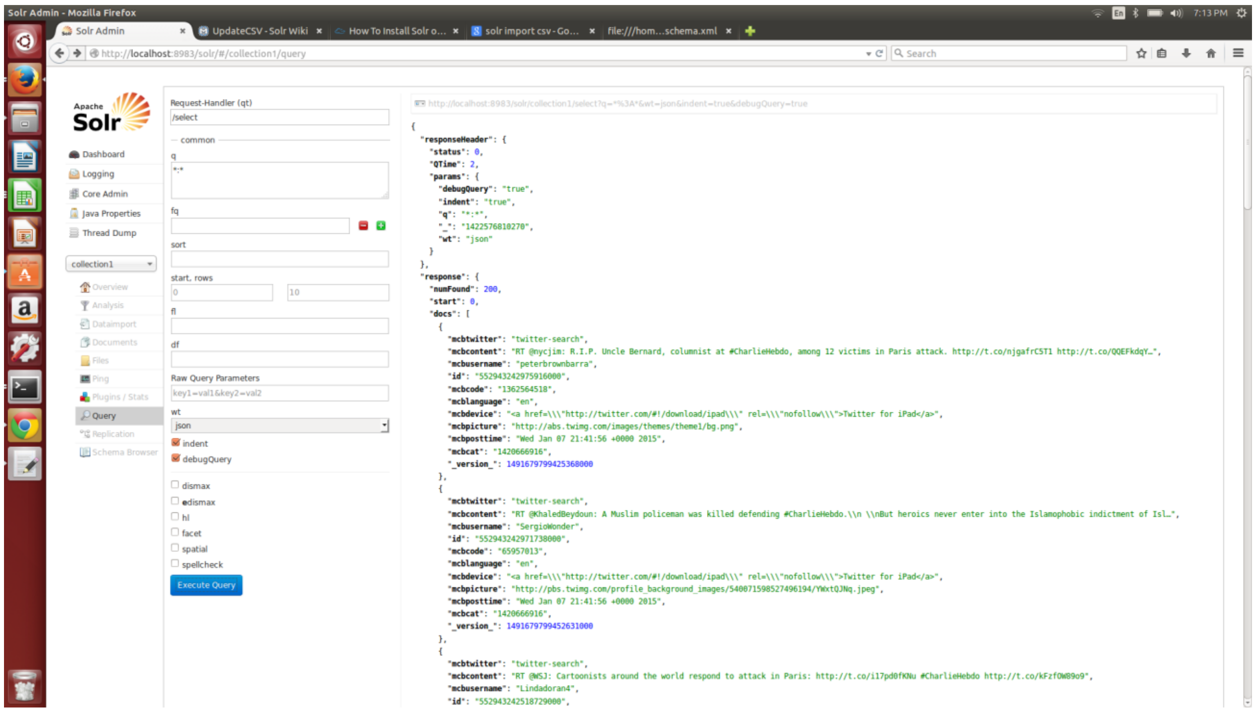
```
<field name="mcbtwitter" type="string" indexed="true" stored="true"/>
<field name="mcbcontent" type="string" indexed="true" stored="true"/>
<field name="mcbmark" type="string" indexed="true" stored="true"/>
<field name="mcbusername" type="text_general" indexed="true" stored="true"/>
<field name="mcbid" type="string" indexed="true" stored="true"/>
<field name="mcbcode" type="string" indexed="true" stored="true"/>
<field name="mcblanguage" type="string" indexed="true" stored="true"/>
<field name="mcbdevice" type="string" indexed="true" stored="true"/>
<field name="mcbpicture" type="string" indexed="true" stored="true"/>
<field name="mcbposttime" type="string" indexed="true" stored="true"/>
<field name="mcbcat" type="string" indexed="true" stored="true"/>
```

Fig. 4: Schema.xml modification example

c. Upload the CSV
d. Restart Solr

2.2.3 Results

We conducted a query without any keyword and the result was captured as shown in Figure 5, which shows we have successfully imported books.csv to Solr:



Request-Handler (qt): /select
q: *:*
start, rows: 0 10
Raw Query Parameters: key1=val1&key2=val2
wt: json
[✓] indent
[✓] debugQuery
dismax, edismax, hl, facet, spatial, spellcheck

```
http://localhost:8983/solr/collection1/select?q=*%3A*&wt=json&indent=true&debugQuery=true
{
  "responseHeader": {
    "status": 0,
    "QTime": 2,
    "params": {
      "debugQuery": "true",
      "indent": "true",
      "q": "*:*",
      "_": "1422576810270",
      "wt": "json"
    }
  },
  "response": {
    "numFound": 200,
    "start": 0,
    "docs": [
      {
        "mcbtwitter": "twitter-search",
        "mcbcontent": "RT @nycjim: R.I.P. Uncle Bernard, columnist at #CharlieHebdo, among 12 victims in Paris attack. http://t.co/njgafrC5T1 http://t.co/QQEFkdqY…",
        "mcbusername": "peterbrownbarra",
        "id": "552943242975916000",
        "mcbcode": "1362564518",
        "mcblanguage": "en",
        "mcbdevice": "<a href=\\\"http://twitter.com/#!/download/ipad\\\" rel=\\\"nofollow\\\">Twitter for iPad</a>",
        "mcbpicture": "http://abs.twimg.com/images/themes/theme1/bg.png",
        "mcbposttime": "Wed Jan 07 21:41:56 +0000 2015",
        "mcbcat": "1420666916",
        "_version_": 1491679799425368000
      },
      {
        "mcbtwitter": "twitter-search",
        "mcbcontent": "RT @KhaledBeydoun: A Muslim policeman was killed defending #CharlieHebdo.\\n \\nBut heroics never enter into the Islamophobic indictment of Isl…",
        "mcbusername": "SergioWonder",
        "id": "552943242971738000",
        "mcbcode": "65957013",
        "mcblanguage": "en",
        "mcbdevice": "<a href=\\\"http://twitter.com/#!/download/ipad\\\" rel=\\\"nofollow\\\">Twitter for iPad</a>",
        "mcbpicture": "http://pbs.twimg.com/profile_background_images/540071598527496194/YWxtQJNq.jpeg",
        "mcbposttime": "Wed Jan 07 21:41:56 +0000 2015",
        "mcbcat": "1420666916",
        "_version_": 1491679799452631000
      },
      {
        "mcbtwitter": "twitter-search",
        "mcbcontent": "RT @WSJ: Cartoonists around the world respond to attack in Paris: http://t.co/i17pd0fKNu #CharlieHebdo http://t.co/kFzfOW89o9",
        "mcbusername": "Lindadoran4",
        "id": "552943242518729000",
```

Fig. 5: Import CSV file to Solr

2.3 Upload Tweets and Webpages of Small Collection to Solr

a. Download our small collection. We use the accident data (z356t.csv) as our small collection.

b. Download the script from TA. We use the tweet_URL_archivingFile.py to deal with our z356.csv file. It extracts the URL of all the tweets. Then it calculates the frequency of each URL and then gives out a sorted result for the URL with its frequency in the file shortURLs_z356.txt. At this time, we can set a threshold and takes the URLs whose frequency is higher than the threshold. The tweet_URL_archivingFile.py will translate URLs in abbreviation version to their complete version. Then it will output a translation form, which includes the full version URLs with its corresponding abbreviation version in file short_origURLsMapping_z356.txt. Also, the script will download the real webpage of these URLs and save it as *.txt file.

c. We can see that from our threshold, we can only get 12 webpages. They totally appear 952 times.

d. We tried to upload the tweets with webpages to Solr. We discussed with our TA about how to upload them to Solr.

We think about 2 approaches:

1) Use the post.jar. But we still have to do preprocessing to merge the webpages and tweets.
2) Write our own script using Python/Java/C to do the preprocessing and then use an API library to connect to Solr inside the script and then upload our results to Solr.

We finally choose the second method to finish this job since we tried many times and still could not figure out how to successfully use the post.jar to upload the webpages and tweets at the same time.

e. We choose the solrpy library to connect to Solr inside the script and then use the script to preprocess the script and upload to Solr.

f. We first tested the solrpy library. This is the test code from the solrpy website.

```
# create a connection to a Solr server
s = solr.SolrConnection('http://example.org:8083/solr')
# add a document to the index
doc = dict(
    id=1,
    title='Lucene in Action',
    author=['Erik Hatcher', 'Otis Gospodneti'],
    )
s.add(doc, commit=True)
```

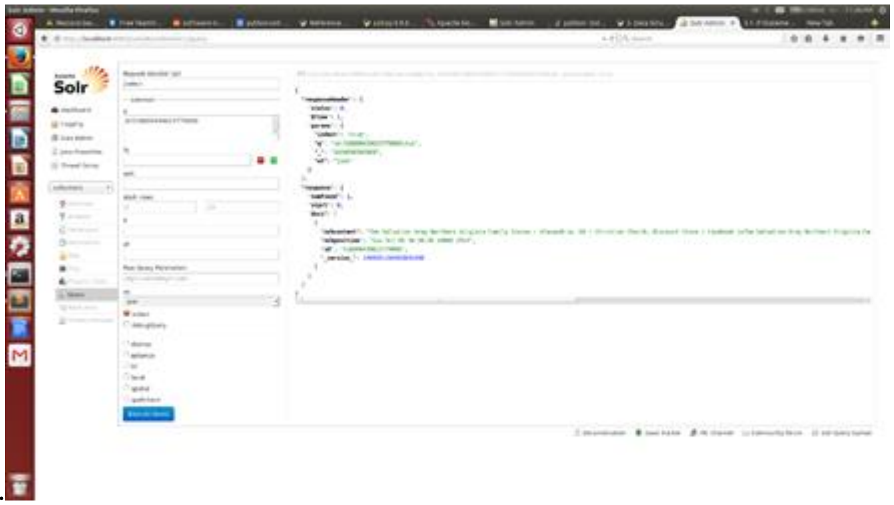
Here we came across a problem. This example does not work for our Solr. Finally we searched the internet and found that we should use s.add(_commit=True,**doc) instead of s.add(doc, commit=True). The key of the dic structure should be included in the schema of Solr.

g. Then we do the preprocessing for the metadata.
To be short, we need to read all the tweets in the z356.csv. For each tweet, we should extract the URL. Next, check if the URLs are selected because of their high frequency. Then we form a dictionary structure, which includes the ID, date, and its corresponding webpages as content. At last we upload the dictionary structure to Solr. This below is the code with annotation.

```
import solr
# create a connection to a Solr server
psolr = solr.SolrConnection('http://localhost:8983/solr')
# connect with Solr
f=open('z356t.csv',"rb")
text = [line.decode('utf-8').strip() for line in f.readlines()]
f.close ( )
pid=[]
pdate=[]
pcontent=[]
pwebpage=[]
pname=[]
for row in text:
        t=row.split("\t")
        pcontent.append(t[0])
        pname.append(t[1])
```

```
            pid.append(t[2])
            pdate.append(t[3])
#read the tweets
f=open('short_origURLsMapping_z356t.txt',"rb")
text = [line.decode('utf-8').strip() for line in f.readlines()]
f.close ( )
maap=dict([])
i=1;
for row in text:
            t=row.split("--") #split the full version URL and its corresponding abbreviation version
            q=t[1].split(",")
            for o in q:
            maap[o]=i
            i=i+1
page=[]
page.append("blank")
for j in range(1,13):
            s=str(j)+".txt"
            f=open(s,"rb")
    page.append(f.read().decode('utf-8').strip())
            f.close()
            # read webpage
for i in range(0,len(pid)):
            t=-1
            print i
            for j in maap.keys():
            if pcontent[i].find(j)>-1:
            t=maap[j] #Find the corresponding webpage number.
            if t==9:
            t=8
            if t>-1:
            print "upload"+str(t)
            upload=dict([])
            upload["id"]=pid[i]
            upload["mcbcontent"]=page[t]
        upload["mcbposttime"]=pdate[i]
            psolr.add(_commit=True,**upload)
               #upload to Solr
```

h. Figure 6 shows that we have successfully uploaded the tweets and their corresponding webpages to Solr.



.

Fig. 6: Tweets and webpages uploaded to Solr

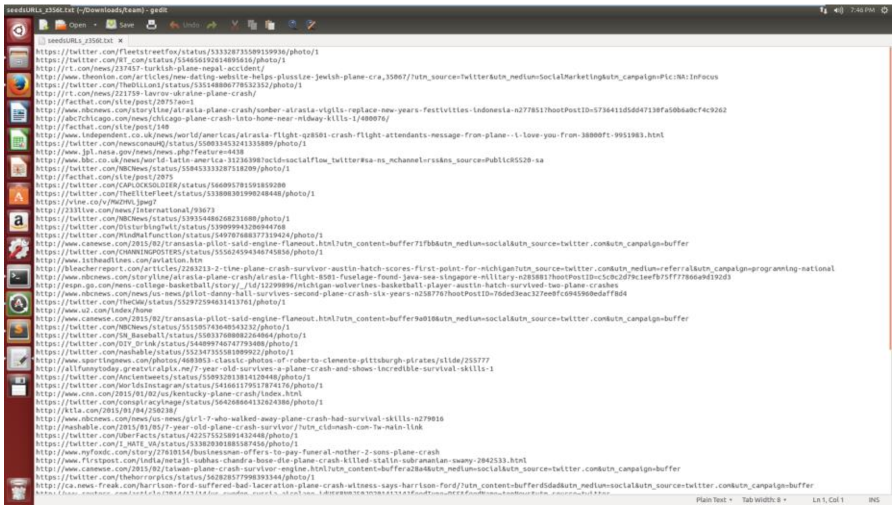
2.4 Load Webpages of Small Collection to HDFS

a. Download the new CSV file and Python script from TA
Hint: use pip to install Beautifuloap4 and requests which are used in the script. Otherwise the script cannot run.
b. Use the script to deal with the new csv file. The generated long URLs is shown in Figure 7.
c. Install Nutch (follow the Nutch tutorial provided by TA). Because we do not need Nutch to upload the new webpages to Solr, we need to modify the crawl script in Nutch.
d. We comment the code after "# note that the link inversion - indexing routine can be done within the main loop # on a per segment basis" until the end of the script in order to prevent this code from uploading data to Solr.
e. Use Nutch to crawl the webpages and upload them to HDFS:

- ❖ We put the URL seed we got from the script and save them to the directory "urls".
- ❖ We run the command:

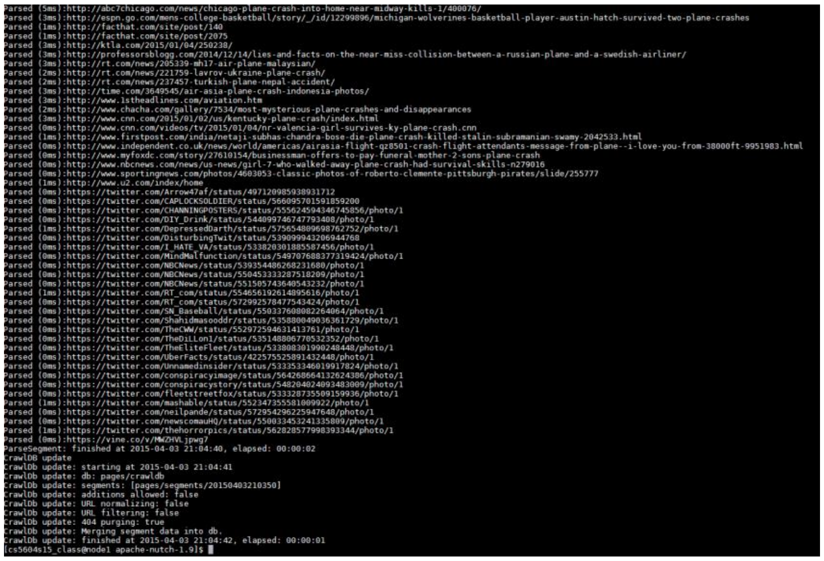
```
bin/crawl urls testcrawl/  TestCrawl/ http://localhost:8983/solr/   1
```

The screenshot after Nutch finished crawling the webpages is shown in Figure 8.



```
https://twitter.com/fleetstreetfox/status/533328735589159936/photo/1
https://twitter.com/RT_com/status/554656192614895616/photo/1
http://rt.com/news/237457-turkish-plane-nepal-accident/
http://www.theonion.com/articles/new-dating-website-helps-plussize-jewish-plane-cra,35067/?utm_source=Twitter&utm_medium=SocialMarketing&utm_campaign=Pic:NA:InFocus
https://twitter.com/TheDiLLon1/status/535148806770532352/photo/1
http://rt.com/news/221759-lavrov-ukraine-plane-crash/
http://facthat.com/site/post/2075?ao=1
http://www.nbcnews.com/storyline/airasia-plane-crash/somber-airasia-vigils-replace-new-years-festivities-indonesia-n277851?hootPostID=5736411d5dd47130fa50b6a0cf4c9262
http://abc7chicago.com/news/chicago-plane-crash-into-home-near-midway-kills-1/400076/
http://facthat.com/site/post/140
http://www.independent.co.uk/news/world/americas/airasia-flight-qz8501-crash-flight-attendants-message-from-plane--i-love-you-from-38000ft-9951983.html
https://twitter.com/newsconauHQ/status/550033453241335809/photo/1
http://www.jpl.nasa.gov/news/news.php?feature=4438
http://www.bbc.co.uk/news/world-latin-america-31236398?ocid=socialflow_twitter#sa-ns_mchannel=rss&ns_source=PublicRSS20-sa
https://twitter.com/NBCNews/status/558453333287518209/photo/1
http://facthat.com/site/post/2075
https://twitter.com/CAPLOCKSOLDIER/status/566095781591859200
https://twitter.com/TheEliteFleet/status/533808301998248448/photo/1
https://vine.co/v/MWZHVLjpwg7
http://233live.com/news/International/93673
https://twitter.com/NBCNews/status/539354486268231680/photo/1
https://twitter.com/DisturbingTwit/status/539099943206944768
https://twitter.com/MindMalfunction/status/549707688377319424/photo/1
http://www.canewse.com/2015/02/transasia-pilot-said-engine-flameout.html?utm_content=buffer71fbb&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer
https://twitter.com/CHANNINGPOSTERS/status/555624594346745856/photo/1
http://www.1stheadlines.com/aviation.htm
http://bleacherreport.com/articles/2263213-2-time-plane-crash-survivor-austin-hatch-scores-first-point-for-michigan?utm_source=twitter.com&utm_medium=referral&utm_campaign=programming-national
http://www.nbcnews.com/storyline/airasia-plane-crash/airasia-flight-8501-fuselage-found-java-sea-singapore-military-n285881?hootPostID=c5c0c2d79c1eefb75ff77866a9d192d3
http://espn.go.com/mens-college-basketball/story/_/id/12299896/michigan-wolverines-basketball-player-austin-hatch-survived-two-plane-crashes
http://www.nbcnews.com/news/us-news/pilot-danny-hall-survives-second-plane-crash-six-years-n258776?hootPostID=76ded3eac327ee0fc6945960edaff8d4
https://twitter.com/TheCWW/status/552972594631413761/photo/1
http://www.u2.com/index/home
http://www.canewse.com/2015/02/transasia-pilot-said-engine-flameout.html?utm_content=buffer9a010&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer
https://twitter.com/NBCNews/status/551505743640543232/photo/1
https://twitter.com/SN_Baseball/status/550337608082264064/photo/1
https://twitter.com/DIY_Drink/status/544899746747793408/photo/1
https://twitter.com/mashable/status/552347355581009922/photo/1
http://www.sportingnews.com/photos/4603053-classic-photos-of-roberto-clemente-pittsburgh-pirates/slide/255777
http://allfunnytoday.greatviralpix.me/7-year-old-survives-a-plane-crash-and-shows-incredible-survival-skills-1
https://twitter.com/Ancientweets/status/550932013814120448/photo/1
https://twitter.com/WorldsInstagram/status/541661179517874176/photo/1
http://www.cnn.com/2015/01/02/us/kentucky-plane-crash/index.html
https://twitter.com/conspiracyimage/status/564268664132624386/photo/1
http://ktla.com/2015/01/04/250238/
http://www.nbcnews.com/news/us-news/girl-7-who-walked-away-plane-crash-had-survival-skills-n279016
http://mashable.com/2015/01/05/7-year-old-plane-crash-survivor/?utm_cid=mash-com-Tw-main-link
https://twitter.com/UberFacts/status/422575525891432448/photo/1
https://twitter.com/I_HATE_VA/status/533820301885587456/photo/1
http://www.myfoxdc.com/story/27610154/businessman-offers-to-pay-funeral-mother-2-sons-plane-crash
http://www.firstpost.com/india/netaji-subhas-chandra-bose-die-plane-crash-killed-stalin-subramanian-swamy-2042533.html
http://www.canewse.com/2015/02/taiwan-plane-crash-survivor-engine.html?utm_content=buffera28a4&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer
https://twitter.com/thehorrorpics/status/562828577998393344/photo/1
http://ca.news-freak.com/harrison-ford-suffered-bad-laceration-plane-crash-witness-says-harrison-ford/?utm_content=bufferd5dad&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer
```

Fig. 7: LongURLs from the new tweets



```
Parsed (5ms):http://abc7chicago.com/news/chicago-plane-crash-into-home-near-midway-kills-1/400076/
Parsed (3ms):http://espn.go.com/mens-college-basketball/story/_/id/12299896/michigan-wolverines-basketball-player-austin-hatch-survived-two-plane-crashes
Parsed (1ms):http://facthat.com/site/post/140
Parsed (1ms):http://facthat.com/site/post/2075
Parsed (3ms):http://ktla.com/2015/01/04/250238/
Parsed (3ms):http://professorsblogg.com/2014/12/14/lies-and-facts-on-the-near-miss-collision-between-a-russian-plane-and-a-swedish-airliner/
Parsed (3ms):http://rt.com/news/205339-mh17-air-plane-malaysian/
Parsed (2ms):http://rt.com/news/221759-lavrov-ukraine-plane-crash/
Parsed (2ms):http://rt.com/news/237457-turkish-plane-nepal-accident/
Parsed (3ms):http://time.com/3649545/air-asia-plane-crash-indonesia-photos/
Parsed (3ms):http://www.1stheadlines.com/aviation.htm
Parsed (2ms):http://www.chacha.com/gallery/7534/most-mysterious-plane-crashes-and-disappearances
Parsed (3ms):http://www.cnn.com/2015/01/02/us/kentucky-plane-crash/index.html
Parsed (0ms):http://www.cnn.com/videos/tv/2015/01/04/nr-valencia-girl-survives-ky-plane-crash.cnn
Parsed (1ms):http://www.firstpost.com/india/netaji-subhas-chandra-bose-die-plane-crash-killed-stalin-subramanian-swamy-2042533.html
Parsed (0ms):http://www.independent.co.uk/news/world/americas/airasia-flight-qz8501-crash-flight-attendants-message-from-plane--i-love-you-from-38000ft-9951983.html
Parsed (0ms):http://www.myfoxdc.com/story/27610154/businessman-offers-to-pay-funeral-mother-2-sons-plane-crash
Parsed (0ms):http://www.nbcnews.com/news/us-news/girl-7-who-walked-away-plane-crash-had-survival-skills-n279016
Parsed (0ms):http://www.sportingnews.com/photos/4603053-classic-photos-of-roberto-clemente-pittsburgh-pirates/slide/255777
Parsed (1ms):http://www.u2.com/index/home
Parsed (0ms):https://twitter.com/Arrow47af/status/497120985938931712
Parsed (0ms):https://twitter.com/CAPLOCKSOLDIER/status/566095701591859200
Parsed (0ms):https://twitter.com/CHANNINGPOSTERS/status/555624594346745856/photo/1
Parsed (0ms):https://twitter.com/DIY_Drink/status/544099746747793408/photo/1
Parsed (1ms):https://twitter.com/DepressedDarth/status/575654809698762752/photo/1
Parsed (0ms):https://twitter.com/DisturbingTwit/status/539099943206944768
Parsed (0ms):https://twitter.com/I_HATE_VA/status/533820301885587456/photo/1
Parsed (0ms):https://twitter.com/MindMalfunction/status/549707688377319424/photo/1
Parsed (0ms):https://twitter.com/NBCNews/status/539354486268231680/photo/1
Parsed (0ms):https://twitter.com/NBCNews/status/550453333287518209/photo/1
Parsed (0ms):https://twitter.com/NBCNews/status/551505743640543232/photo/1
Parsed (1ms):https://twitter.com/RT_com/status/554656192614895616/photo/1
Parsed (0ms):https://twitter.com/RT_com/status/572992578477543424/photo/1
Parsed (0ms):https://twitter.com/SN_Baseball/status/550337608082264064/photo/1
Parsed (0ms):https://twitter.com/Shahidmasooddr/status/535880049036361729/photo/1
Parsed (0ms):https://twitter.com/TheCWW/status/552972594631413761/photo/1
Parsed (0ms):https://twitter.com/TheDiLLon1/status/535148806770532352/photo/1
Parsed (0ms):https://twitter.com/TheEliteFleet/status/533808301990248448/photo/1
Parsed (0ms):https://twitter.com/UberFacts/status/422575525891432448/photo/1
Parsed (0ms):https://twitter.com/Unnamedinsider/status/533353346019917824/photo/1
Parsed (0ms):https://twitter.com/conspiracyimage/status/564268664132624386/photo/1
Parsed (0ms):https://twitter.com/conspiracystory/status/548204024093483009/photo/1
Parsed (0ms):https://twitter.com/fleetstreetfox/status/533328735509159936/photo/1
Parsed (1ms):https://twitter.com/mashable/status/552347355581009922/photo/1
Parsed (0ms):https://twitter.com/neilpande/status/572954296225947648/photo/1
Parsed (0ms):https://twitter.com/newscomauHQ/status/550033453241335809/photo/1
Parsed (1ms):https://twitter.com/thehorrorpics/status/562828577998393344/photo/1
Parsed (0ms):https://vine.co/v/MWZHVLjpwg7
ParseSegment: finished at 2015-04-03 21:04:40, elapsed: 00:00:02
CrawlDB update
CrawlDb update: starting at 2015-04-03 21:04:41
CrawlDb update: db: pages/crawldb
CrawlDb update: segments: [pages/segments/20150403210350]
CrawlDb update: additions allowed: false
CrawlDb update: URL normalizing: false
CrawlDb update: URL filtering: false
CrawlDb update: 404 purging: true
CrawlDb update: Merging segment data into db.
CrawlDb update: finished at 2015-04-03 21:04:42, elapsed: 00:00:01
[cs5604s15_class@node1 apache-nutch-1.9]$ █
```

Fig. 8: Nutch finished crawling the webpages

f. After we get the webpages data from Nutch, we uploaded it to HDFS for reducing noise team. We put them under the directory /user/cs5604s15_class/pages/.

3. Naïve Bayes Classification

3.1 Transform Tweets to Sequence File and Feature Vector on Our Own Machine

In this section, we use Python and Mahout to transform our small collection CSV file to sequence file and vectors. So we can use the command line of Mahout to get the word count and tf-idf vector file for our small collection.

Mahout has utilities to generate vectors from a directory of text documents. Before creating the vectors, we first convert the documents to SequenceFile format. Sequence File is a Hadoop class which allows us to write arbitrary (key, value) pairs into it. The document vectorizer requires the key to be a text with a unique document ID, and value to be the text content in UTF-8 format.

After searching online, we still cannot figure out an approach to generate the CSV format tweet to sequence file. The only solution is what we found on the VTTECHWORK (https://vtechworks.lib.vt.edu/bitstream/handle/10919/47945/Mahout_Tutorial.pdf?sequence=11).

In order to transform the CSV format tweet to sequence file, we developed another way. We first use Python to read the CSV file and store each row into a separate text file with its row number being the file name. We put these text files into one directory.

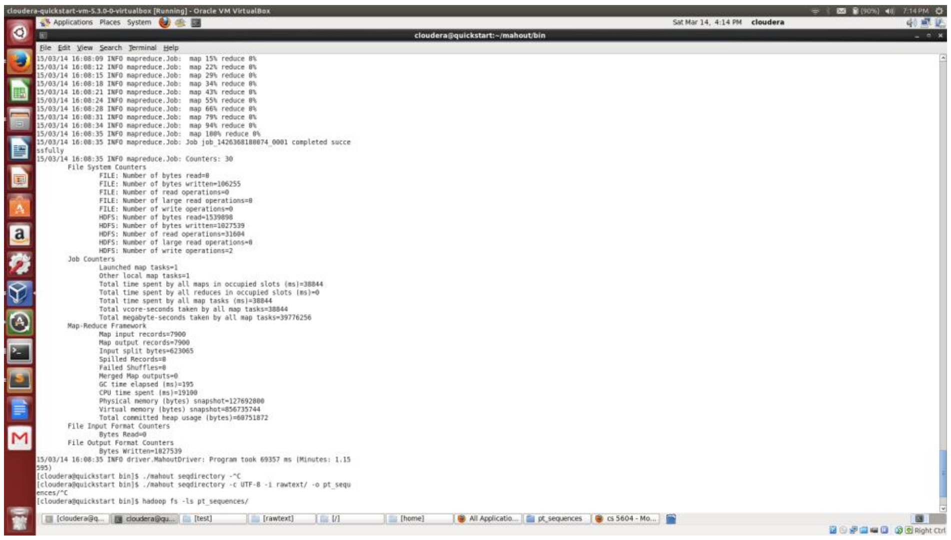
The Python code is like this:

```
import string
f=open('z356t.csv',"rb")
#text = [line.decode('utf-8').strip() for line in f.readlines()]
text = [line for line in f.readlines()]
f.close ( )
i=0;
for row in text:
        t=row.split("\t")
        filename="./rawtext/"+str(i)+".txt"
        f=open(filename.encode('utf-8'),"wbr")
        #print(t[0])
        f.write(t[0])
        f.close()
        i=i+1
```

After generating the directory, we use the command provide by Mahout to generate the sequence file.

```
mahout seqdirectory -c UTF-8 -i plaintext/ -o pt_sequences/
```

It uses MapReduce to transform the plaintext to sequence file. Figure 9 shows the print out message.



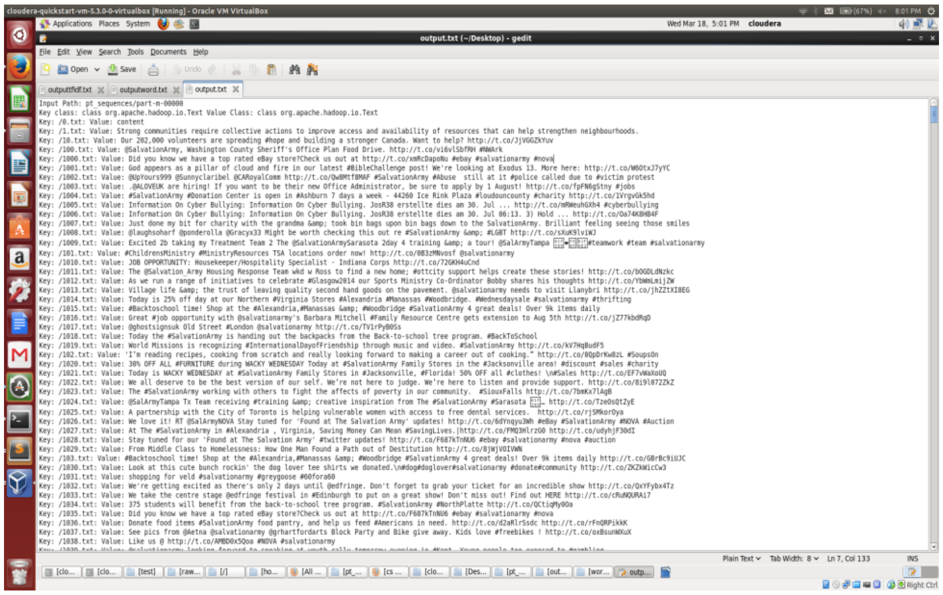
```
15/03/14 16:08:09 INFO mapreduce.Job:  map 15% reduce 0%
15/03/14 16:08:12 INFO mapreduce.Job:  map 22% reduce 0%
15/03/14 16:08:15 INFO mapreduce.Job:  map 29% reduce 0%
15/03/14 16:08:18 INFO mapreduce.Job:  map 34% reduce 0%
15/03/14 16:08:21 INFO mapreduce.Job:  map 43% reduce 0%
15/03/14 16:08:24 INFO mapreduce.Job:  map 55% reduce 0%
15/03/14 16:08:28 INFO mapreduce.Job:  map 66% reduce 0%
15/03/14 16:08:31 INFO mapreduce.Job:  map 79% reduce 0%
15/03/14 16:08:34 INFO mapreduce.Job:  map 94% reduce 0%
15/03/14 16:08:35 INFO mapreduce.Job:  map 100% reduce 0%
15/03/14 16:08:35 INFO mapreduce.Job: Job job_1426368188074_0001 completed succe
ssfully
15/03/14 16:08:35 INFO mapreduce.Job: Counters: 30
        File System Counters
                FILE: Number of bytes read=0
                FILE: Number of bytes written=106255
                FILE: Number of read operations=0
                FILE: Number of large read operations=0
                FILE: Number of write operations=0
                HDFS: Number of bytes read=1539898
                HDFS: Number of bytes written=1027539
                HDFS: Number of read operations=31604
                HDFS: Number of large read operations=0
                HDFS: Number of write operations=2
        Job Counters
                Launched map tasks=1
                Other local map tasks=1
                Total time spent by all maps in occupied slots (ms)=38844
                Total time spent by all reduces in occupied slots (ms)=0
                Total time spent by all map tasks (ms)=38844
                Total vcore-seconds taken by all map tasks=38844
                Total megabyte-seconds taken by all map tasks=39776256
        Map-Reduce Framework
                Map input records=7900
                Map output records=7900
                Input split bytes=623065
                Spilled Records=0
                Failed Shuffles=0
                Merged Map outputs=0
                GC time elapsed (ms)=195
                CPU time spent (ms)=19100
                Physical memory (bytes) snapshot=127692800
                Virtual memory (bytes) snapshot=856735744
                Total committed heap usage (bytes)=60751872
        File Input Format Counters
                Bytes Read=0
        File Output Format Counters
                Bytes Written=1027539
15/03/14 16:08:35 INFO driver.MahoutDriver: Program took 69357 ms (Minutes: 1.15
595)
[cloudera@quickstart bin]$ ./mahout seqdirectory -^C
[cloudera@quickstart bin]$ ./mahout seqdirectory -c UTF-8 -i rawtext/ -o pt_sequ
ences/^C
[cloudera@quickstart bin]$ hadoop fs -ls pt_sequences/
```

Fig. 9: Print out message from text file to sequence file

To check the result of the sequence file, we cannot read it directly because it is stored in binary format. We use Mahout seqdumper to transform this binary format file to a readable file. The command is:

```
mahout seqdumper -i /user/<user-name>/output/part-m-00000 -o ~/output/sequencefile.txt
```

The sequence file is shown in Figure 10.



```
Input Path: pt_sequences/part-m-00000
Key class: class org.apache.hadoop.io.Text Value Class: class org.apache.hadoop.io.Text
Key: /0.txt: Value: content
Key: /1.txt: Value: Strong communities require collective actions to improve access and availability of resources that can help strengthen neighbourhoods.
Key: /10.txt: Value: Our 202,000 volunteers are spreading #hope and building a stronger Canada. Want to help? http://t.co/JjVGGZkYuv
Key: /100.txt: Value: @SalvationArmy, Washington County Sheriff's Office Plan Food Drive. http://t.co/vi6vlSbfRH #NWArk
Key: /1000.txt: Value: Did you know we have a top rated eBay store?Check us out at http://t.co/xmRcDapoNu #ebay #salvationarmy #nova
Key: /1001.txt: Value: God appears as a pillar of cloud and fire in our latest #BibleChallenge post! We're looking at Exodus 13. More here: http://t.co/W6OtxJ7yYC
Key: /1002.txt: Value: @UpYours999 @Sunnyclaribel @CARoyalComm http://t.co/QwBMtf8MAF #SalvationArmy #Abuse  still at it #police called due to #victim protest
Key: /1003.txt: Value: .@ALOVEUK are hiring! If you want to be their new Office Administrator, be sure to apply by 1 August! http://t.co/fpFN6gStny #jobs
Key: /1004.txt: Value: #SalvationArmy #Donation Center is open in #Ashburn 7 days a week - 44260 Ice Rink Plaza #loudouncounty #charity http://t.co/1VrgvGk5hd
Key: /1005.txt: Value: Information On Cyber Bullying: Information On Cyber Bullying. JosR38 erstellte dies am 30. Jul ... http://t.co/mRWeuhGXh4 #cyberbullying
Key: /1006.txt: Value: Information On Cyber Bullying: Information On Cyber Bullying. JosR38 erstellte dies am 30. Jul 06:13. 3) Hold ... http://t.co/Oa74K8HB4F
Key: /1007.txt: Value: Just done my bit for charity with the grandma &amp; took bin bags upon bin bags down to the SalvationArmy. Brilliant feeling seeing those smiles
Key: /1008.txt: Value: @laughsoharf @ponderolla @Gracyx33 Might be worth checking this out re #SalvationArmy &amp; #LGBT http://t.co/sXuK9lviWJ
Key: /1009.txt: Value: Excited 2b taking my Treatment Team 2 The @SalvationArmySarasota 2day 4 training &amp; a tour! @SalArmyTampa #teamwork #team #salvationarmy
Key: /101.txt: Value: #ChildrensMinistry #MinistryResources TSA locations order now! http://t.co/0B3zMNvosf @salvationarmy
Key: /1010.txt: Value: JOB OPPORTUNITY: Housekeeper/Hospitality Specialist - Indiana Corps http://t.co/72GKH4uCnd
Key: /1011.txt: Value: The @Salvation_Army Housing Response Team wkd w Ross to find a new home; #ottcity support helps create these stories! http://t.co/bOGDLdNzkc
Key: /1012.txt: Value: As we run a range of initiatives to celebrate #Glasgow2014 our Sports Ministry Co-Ordinator Bobby shares his thoughts http://t.co/YbWmLmijZW
Key: /1013.txt: Value: Village life &amp; the trust of leaving quality second hand goods on the pavement. @salvationarmy needs to visit Llanybri http://t.co/jhZZtXI8EG
Key: /1014.txt: Value: Today is 25% off day at our Northern #Virginia Stores #Alexandria #Manassas #Woodbridge. #Wednesdaysale #salvationarmy #thrifting
Key: /1015.txt: Value: #Backtoschool time! Shop at the #Alexandria,#Manassas &amp; #Woodbridge #SalvationArmy 4 great deals! Over 9k items daily
Key: /1016.txt: Value: Great #job opportunity with @salvationarmy's Barbara Mitchell #Family Resource Centre gets extension to Aug 5th http://t.co/jZ77kbdRqD
Key: /1017.txt: Value: @ghostsignsuk Old Street #London @salvationarmy http://t.co/TV1rPyB0Ss
Key: /1018.txt: Value: Today the #SalvationArmy is handing out the backpacks from the Back-to-school tree program. #BackToSchool
Key: /1019.txt: Value: World Missions is recognizing #InternationalDayofFriendship through music and video. #SalvationArmy http://t.co/kV7HqBudF5
Key: /102.txt: Value: 'I'm reading recipes, cooking from scratch and really looking forward to making a career out of cooking." http://t.co/0QpDrKw8zL #SoupsOn
Key: /1020.txt: Value: 30% OFF ALL #FURNITURE during WACKY WEDNESDAY Today at #SalvationArmy Family Stores in the #Jacksonville area! #discount #sales #charity
Key: /1021.txt: Value: Today is WACKY WEDNESDAY at #SalvationArmy Family Stores in #Jacksonville, #Florida! 50% OFF all #clothes! \n#Sales http://t.co/EF7vWaXoUQ
Key: /1022.txt: Value: We all deserve to be the best version of our self. We're not here to judge. We're here to listen and provide support. http://t.co/8i9l072ZkZ
Key: /1023.txt: Value: The #SalvationArmy working with others to fight the affects of poverty in our community.  #SiouxFalls http://t.co/7bmKx7lAgB
Key: /1024.txt: Value: @SalArmyTampa Tx Team receiving #training &amp; creative inspiration from The #SalvationArmy #Sarasota  http://t.co/Tze0sQtZyE
Key: /1025.txt: Value: A partnership with the City of Toronto is helping vulnerable women with access to free dental services.  http://t.co/rjSMkorOya
Key: /1026.txt: Value: We love it! RT @SalArmyNOVA Stay tuned for 'Found at The Salvation Army' updates! http://t.co/6dYnqyu3Wh #eBay #SalvationArmy #NOVA #Auction
Key: /1027.txt: Value: At The #SalvationArmy in #Alexandria , Virginia, Saving Money Can Mean #SavingLives.|http://t.co/FMQ3HlrzG0 http://t.co/udyhjF30dI
Key: /1028.txt: Value: Stay tuned for our 'Found at The Salvation Army' #twitter updates! http://t.co/F687kTnNU6 #ebay #salvationarmy #nova #auction
Key: /1029.txt: Value: From Middle Class to Homelessness: How One Man Found a Path out of Destitution http://t.co/8jWjVOIVWN
Key: /103.txt: Value: #Backtoschool time! Shop at the #Alexandria,#Manassas &amp; #Woodbridge #SalvationArmy 4 great deals! Over 9k items daily http://t.co/GBrBc9iUJC
Key: /1030.txt: Value: Look at this cute bunch rockin' the dog lover tee shirts we donated.\n#dog#doglover#salvationarmy #donate#community http://t.co/ZKZkWicCw3
Key: /1031.txt: Value: shopping for veld #salvationarmy #greygoose #60fora60
Key: /1032.txt: Value: We're getting excited as there's only 2 days until @edfringe. Don't forget to grab your ticket for an incredible show http://t.co/QxYFybx4Tz
Key: /1033.txt: Value: We take the centre stage @edfringe festival in #Edinburgh to put on a great show! Don't miss out! Find out HERE http://t.co/cRuNQURAi7
Key: /1034.txt: Value: 375 students will benefit from the back-to-school tree program. #SalvationArmy #NorthPlatte http://t.co/QCtiqMy0Oa
Key: /1035.txt: Value: Did you know we have a top rated eBay store?Check us out at http://t.co/F687kTnNU6 #ebay #salvationarmy #nova
Key: /1036.txt: Value: Donate food items #SalvationArmy food pantry, and help us feed #Americans in need. http://t.co/d2aRlrSsdc http://t.co/rFnQRPikkK
Key: /1037.txt: Value: See pics from @Aetna @salvationarmy @grhartfordarts Block Party and Bike give away. Kids love #freebikes ! http://t.co/oxBsunWXuX
Key: /1038.txt: Value: Like us @ http://t.co/AMBD0x5Qoa #NOVA #salvationarmy
```

Fig. 10: Generated sequence file

From the result, we can see that we are on the right track. The key is the file name, which is the row number of the tweets and the values are the content of the tweets.

After that we try to create the vector file, which needs the word count and tf-idf. We also use the above-mentioned commend to transform the binary vector file to readable file.
This will take any plain text files in the directory "inputdirectory" and convert them to sequence files.

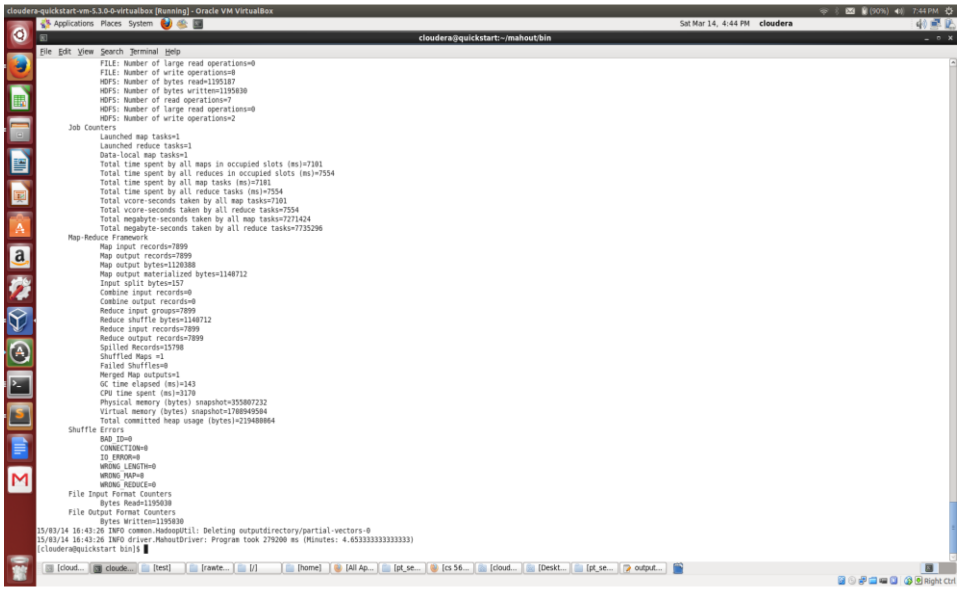
We specify the UTF8 character set to make sure each file inside the input directory is processed using the same set rather than being able to specify individual character sets. These sequence files must next be converted to vector files that Mahout can then run any number of algorithms on. To create these vector files, you will need to run the command:

```
mahout seq2sparse -i sequences -o outputdirectory –ow –chunk 100 –x 90 –seq –ml 50 –n 2 -nv
```

The '-nv' flag means that we use named vectors, so that the data files will be easier to inspect by hand.

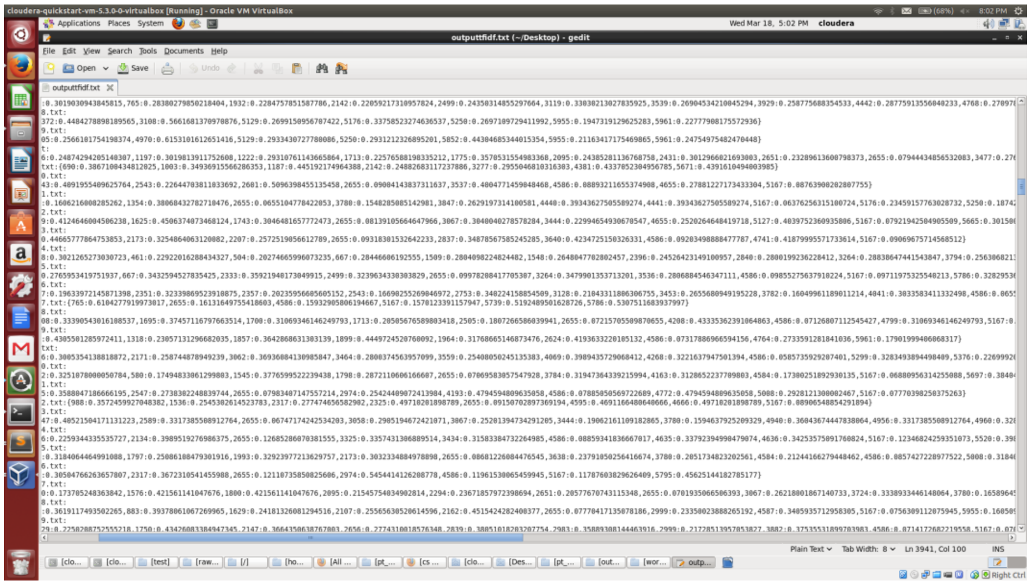
The '-x 90' flag means that any word that appears in more than 90% of the files is a stop word, or a word is too common and thus is filtered out (i.e. articles such as 'the', 'an', 'a', etc.).

Figure 11 shows the print out message when we have successfully generated the vectors. Figure 12 shows the generated tf-idf results while Figure 13 shows the generated word count results.


cloudera-quickstart-vm-5.3.0-0-virtualbox [Running] - Oracle VM VirtualBox
Applications Places System
Sat Mar 14, 4:44 PM cloudera
cloudera@quickstart:~/mahout/bin
File Edit View Search Terminal Help

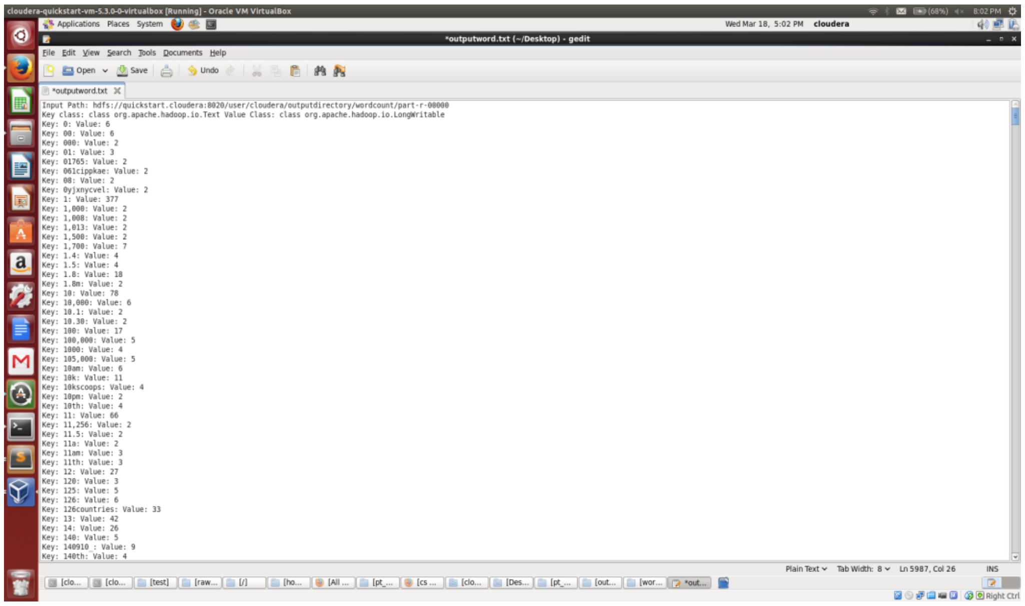
```
                FILE: Number of large read operations=0
                FILE: Number of write operations=0
                HDFS: Number of bytes read=1195187
                HDFS: Number of bytes written=1195030
                HDFS: Number of read operations=7
                HDFS: Number of large read operations=0
                HDFS: Number of write operations=2
        Job Counters
                Launched map tasks=1
                Launched reduce tasks=1
                Data-local map tasks=1
                Total time spent by all maps in occupied slots (ms)=7101
                Total time spent by all reduces in occupied slots (ms)=7554
                Total time spent by all map tasks (ms)=7101
                Total time spent by all reduce tasks (ms)=7554
                Total vcore-seconds taken by all map tasks=7101
                Total vcore-seconds taken by all reduce tasks=7554
                Total megabyte-seconds taken by all map tasks=7271424
                Total megabyte-seconds taken by all reduce tasks=7735296
        Map-Reduce Framework
                Map input records=7899
                Map output records=7899
                Map output bytes=1120388
                Map output materialized bytes=1140712
                Input split bytes=157
                Combine input records=0
                Combine output records=0
                Reduce input groups=7899
                Reduce shuffle bytes=1140712
                Reduce input records=7899
                Reduce output records=7899
                Spilled Records=15798
                Shuffled Maps =1
                Failed Shuffles=0
                Merged Map outputs=1
                GC time elapsed (ms)=143
                CPU time spent (ms)=3170
                Physical memory (bytes) snapshot=355807232
                Virtual memory (bytes) snapshot=1708949504
                Total committed heap usage (bytes)=219480064
        Shuffle Errors
                BAD_ID=0
                CONNECTION=0
                IO_ERROR=0
                WRONG_LENGTH=0
                WRONG_MAP=0
                WRONG_REDUCE=0
        File Input Format Counters
                Bytes Read=1195030
        File Output Format Counters
                Bytes Written=1195030
15/03/14 16:43:26 INFO common.HadoopUtil: Deleting outputdirectory/partial-vectors-0
15/03/14 16:43:26 INFO driver.MahoutDriver: Program took 279200 ms (Minutes: 4.653333333333333)
[cloudera@quickstart bin]$ ▌
```

Fig. 11: Print out message from sequence file to vectors


cloudera-quickstart-vm-5.3.0-0-virtualbox [Running] - Oracle VM VirtualBox
Applications Places System
Wed Mar 18, 5:02 PM cloudera
outputtfidf.txt (~/Desktop) - gedit
File Edit View Search Tools Documents Help
Open Save Undo
outputtfidf.txt
Plain Text Tab Width: 8 Ln 3941, Col 100 INS

```
:0.3019030943845815,765:0.28380279850218404,1932:0.2284757851587786,2142:0.22059217310957824,2499:0.24358314855297664,3119:0.33038213027835925,3539:0.26904534210845294,3929:0.258775688354533,4442:0.28775913556040233,4768:0.27897
8.txt:
372:0.4484278898189565,3108:0.5661681370970876,5129:0.2699150956787422,5176:0.33758523274636537,5250:0.2697109729411992,5955:0.1947319129625283,5961:0.22777908175572936}
9.txt:
05:0.2566101754198374,4970:0.6153101612651416,5129:0.2933430727780086,5250:0.2931212326895201,5852:0.44304685344015354,5955:0.21163417175469865,5961:0.24754975482470448}
t:
6:0.24874294205140307,1197:0.3019813911752608,1222:0.29310761143665864,1713:0.22576588198335212,1775:0.3570531554983368,2095:0.24385281136768758,2431:0.3012966021693003,2651:0.23289613600798373,2655:0.07944434856532083,3477:0.27
txt:{690:0.3867108434812025,1003:0.34936915566286353,1187:0.445192174964388,2142:0.24882683117237886,3277:0.2955046810316383,4381:0.4337052304956785,5671:0.4391610494003985}
0.txt:
43:0.4091955409625764,2543:0.22644703811033692,2681:0.5096398455135458,2655:0.09084143837311637,3537:0.4804771459848468,4586:0.08893211655374908,4655:0.27881227173433304,5167:0.08763900282807755}
1.txt:
:0.1606216008285262,1354:0.38068432782710476,2655:0.0655104778422053,3780:0.1548285085142981,3847:0.2629197314100581,4440:0.39343627505589274,4441:0.39343627505589274,5167:0.06376256315100724,5176:0.23459157763028732,5250:0.18742
2.txt:
9:0.4124646004506238,1625:0.4506374073468124,1743:0.3046481657772473,2655:0.08139105664647966,3067:0.3040040278578284,3444:0.22994654930670547,4655:0.2520264648419718,5127:0.4039752360935806,5167:0.07921942504905509,5665:0.30150
3.txt:
0.4466577786475385 3,2173:0.3254864063120082,2207:0.2572519056612789,2655:0.09318301532642233,2837:0.34878567585245285,3640:0.4234725150326331,4586:0.09203498888477787,4741:0.41879995571733614,5167:0.0906967571456851 2}
4.txt:
8:0.3021265273030723,461:0.22922016288434327,504:0.20274665996073235,667:0.28446606192555,1509:0.2804098224824482,1548:0.2648047702802457,2396:0.24526423149100957,2840:0.2800199236228412,3264:0.28838647441543847,3794:0.2563068213
5.txt:
0.2765953419751937,667:0.3432594527835425,2333:0.35921940173049915,2499:0.3239634338303829,2655:0.09978208417705307,3264:0.3479901353713201,3536:0.2806884546347111,4586:0.09855275637910224,5167:0.09711975325540213,5786:0.32829536
6.txt:
7:0.19633972145871398,2351:0.32339869523910875,2357:0.20235956605605152,2543:0.16698255269046972,2753:0.348224158854509,3128:0.21043311806306755,3453:0.2655680949195228,3782:0.16049961189011214,4041:0.3833583411332498,4586:0.0655
7.txt:{765:0.6104277919973017,2655:0.16131649755418603,4586:0.15932905806194667,5167:0.1570123391157947,5739:0.5192489501628726,5786:0.5307511683937997}
8.txt:
08:0.33390543016108537,1695:0.37457116797663514,1700:0.31069346146249793,1713:0.20505676589803418,2505:0.1807266586039941,2655:0.07215705509870655,4208:0.43335362391064863,4586:0.07126807112545427,4799:0.31069346146249793,5167:0.
9.txt:
:0.4305501285972411,1318:0.23057131296682035,1857:0.3642868631303139,1899:0.4449724520760092,1964:0.31768665146873476,2624:0.4193633220105132,4586:0.07317886966594156,4764:0.2733591281841036,5961:0.17901999406068317}
txt:
6:0.3005354138818872,2171:0.258744878949239,3062:0.36936884130985847,3464:0.2800374563957099,3559:0.25408050245135383,4069:0.3989435729068412,4268:0.3221637947501394,4586:0.0585735929207401,5299:0.3283493894498409,5376:0.22699926
0.txt:
2:0.3251078000050784,580:0.17494833061299883,1545:0.3776599522239438,1798:0.2872110606166607,2655:0.07069583057547928,3784:0.31947364339215994,4163:0.3128652237789803,4584:0.17380251892930135,5167:0.06880956314255088,5697:0.38484
1.txt:
5:0.3588047186666195,2547:0.2738302248839744,2655:0.07983407147557214,2974:0.25424409072413984,4193:0.4794594809635058,4586:0.07885050569722689,4772:0.4794594809635058,5088:0.2928121300082467,5167:0.07770398250375263}
2.txt:{988:0.3572459927048382,1536:0.2545302614523783,2317:0.277474656582902,2325:0.49710201898789,2655:0.09150702897369194,4595:0.4691166480640666,4666:0.49710201898789,5167:0.08906548854291894}
3.txt:
47:0.40521504171131223,2589:0.3317385508912764,2655:0.06747174242534203,3058:0.2985194672421071,3867:0.25201394734291205,3444:0.19062161109182865,3780:0.1594637925209329,4940:0.36043674447838064,4956:0.3317385508912764,4960:0.328
4.txt:
6:0.2259344335535727,2134:0.3989519276986375,2655:0.12685286070381555,3325:0.3357431306889514,3434:0.31583384732264985,4586:0.08859341836667017,4635:0.33792394990479074,4636:0.34253575091760824,5167:0.12346824259351073,5520:0.398
5.txt:
:0.3184064464991088,1797:0.25086108479301916,1993:0.32923977213629757,2173:0.3032334884978898,2655:0.08681226084476545,3638:0.23791050256416674,3780:0.2051734823202561,4584:0.21244166279448462,4586:0.0857427228977522,5008:0.3184
6.txt:
:0.30504766263657807,2317:0.3672310541455988,2655:0.12110735850825606,2974:0.5454414126208778,4586:0.11961530065459945,5167:0.11787603829626409,5795:0.45625144182785177}
7.txt:
0:0.173705248363842,1576:0.421561141047676,1800:0.421561141047676,2095:0.21545754034902814,2294:0.23671857972398694,2651:0.20577670743115348,2655:0.0701935066506393,3067:0.26218001867140733,3724:0.3338933446148064,3780:0.16589645
8.txt:
:0.3619117493502265,883:0.39378061067269965,1629:0.24181326081294516,2107:0.25565630520614596,2162:0.4515424282400377,2655:0.07770417135078186,2999:0.23350023888265192,4587:0.3405935712958305,5167:0.0756309112075945,5955:0.160509
9.txt:
29:0.22582088752555218,1750:0.43426083384947345,2147:0.3664350638767803,2656:0.2774310018576348,2839:0.38851018203207754,2983:0.35889308144463916,2999:0.21728513957853827,3882:0.37535531899703983,4586:0.0714172682219558,5167:0.07
```

Fig. 12: Generated tf-idf results



```
Input Path: hdfs://quickstart.cloudera:8020/user/cloudera/outputdirectory/wordcount/part-r-00000
Key class: class org.apache.hadoop.io.Text Value Class: class org.apache.hadoop.io.LongWritable
Key: 0: Value: 6
Key: 00: Value: 6
Key: 000: Value: 2
Key: 01: Value: 3
Key: 01765: Value: 2
Key: 061cippkae: Value: 2
Key: 08: Value: 2
Key: 0yjxnycvel: Value: 2
Key: 1: Value: 377
Key: 1,000: Value: 2
Key: 1,008: Value: 2
Key: 1,013: Value: 2
Key: 1,500: Value: 2
Key: 1,700: Value: 7
Key: 1.4: Value: 4
Key: 1.5: Value: 4
Key: 1.8: Value: 18
Key: 1.8m: Value: 2
Key: 10: Value: 78
Key: 10,000: Value: 6
Key: 10.1: Value: 2
Key: 10.30: Value: 2
Key: 100: Value: 17
Key: 100,000: Value: 5
Key: 1000: Value: 4
Key: 105,000: Value: 5
Key: 10am: Value: 6
Key: 10k: Value: 11
Key: 10kscoops: Value: 4
Key: 10pm: Value: 2
Key: 10th: Value: 4
Key: 11: Value: 66
Key: 11,256: Value: 2
Key: 11.5: Value: 2
Key: 11a: Value: 2
Key: 11am: Value: 3
Key: 11th: Value: 3
Key: 12: Value: 27
Key: 120: Value: 3
Key: 125: Value: 5
Key: 126: Value: 6
Key: 126countries: Value: 33
Key: 13: Value: 42
Key: 14: Value: 26
Key: 140: Value: 5
Key: 140910_: Value: 9
Key: 140th: Value: 4
```

Fig. 13: Generate word count results

The reason why we show word count here is that the row number of the word is that of the key number in the tf-idf table. So there are 5999 words here in the word count table, and the tf-idf key number varies from 1 to 5999.

Up to now, we successfully generate the sequence file and vector. The next step is to label the small collection and apply the Mahout Classification algorithms.

3.2 Commands for Classification with Mahout Na ïve Bayes Algorithm

We have two folders for tweets: one folder contains 100 text files of positive tweets that are related to the topic; the other folder contains 100 text files of negative tweets that are not related to the topic. All tweets are randomly selected using Python from the small collection we are given. Then we uploaded the tweets to the cluster. On the cluster, we followed example from [2] and performed a complete Na ïve Bayes classification. The step-by-step commands are listed as below.

Create a working directory for the dataset and all input/output:

```
export WORK_DIR=/user/cs5604s15_class/
```

Convert the full dataset into a <Text, Text> SequenceFile:

```
mahout seqdirectory -i ${WORK_DIR}/test -o ${WORK_DIR}/test-seq  -ow
```

Convert and preprocess the dataset into a <Text, VectorWritable> SequenceFile containing term frequencies for each document:

```
mahout seq2sparse -i ${WORK_DIR}/test-seq -o ${WORK_DIR}/test-vectors -lnorm -nv -wt tfidf
```

Split the preprocessed dataset into training and testing sets:

```
mahout split -i ${WORK_DIR}/test-vectors/tfidf-vectors --trainingOutput ${WORK_DIR}/test-train-vectors --testOutput ${WORK_DIR}/test-test-vectors --randomSelectionPct 40 --overwrite --sequenceFiles -xm sequential
```

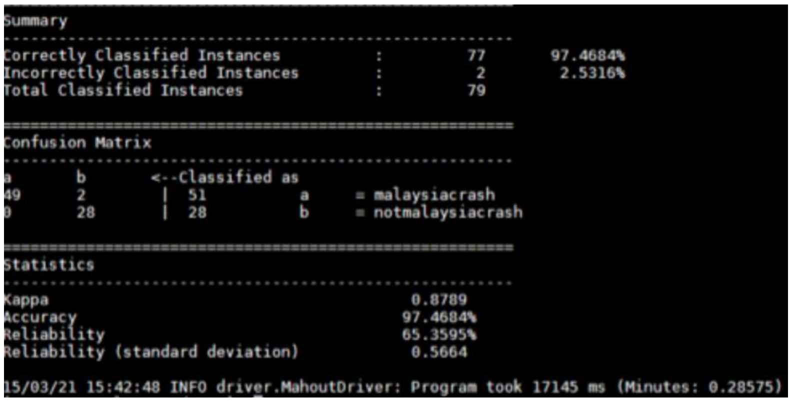
Train the classifier:

```
mahout trainnb -i ${WORK_DIR}/test-train-vectors -el -o ${WORK_DIR}/model -li ${WORK_DIR}/labelindex -ow -c
```

Test the classfier:

```
mahout testnb -i ${WORK_DIR}/test-test-vectors -m ${WORK_DIR}/model -l ${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/test-testing –c
```

A confusion matrix and the overall accuracy will be printed on the screen. Figure 14 is an example of the sample output.



```
-------------------------------------------------------
Summary
-------------------------------------------------------
Correctly Classified Instances          :         77      97.4684%
Incorrectly Classified Instances        :          2       2.5316%
Total Classified Instances              :         79

=======================================================
Confusion Matrix
-------------------------------------------------------
a       b       <--Classified as
49      2        |  51          a      = malaysiacrash
0       28       |  28          b      = notmalaysiacrash

=======================================================
Statistics
-------------------------------------------------------
Kappa                                       0.8789
Accuracy                                   97.4684%
Reliability                                65.3595%
Reliability (standard deviation)            0.5664

15/03/21 15:42:48 INFO driver.MahoutDriver: Program took 17145 ms (Minutes: 0.28575)
```

Fig. 14: Confusion Matrix and Accuracy Statistics from Na ïve Bayes classification

3.3 Applying Mahout Na ïve Bayes Classifier for Our Tweet Small Collection

Test 1: Tweets classification, no feature selection, test on train set. Commands are as follows:

```
export WORK_DIR=/user/cs5604s15_class

mahout seqdirectory -i ${WORK_DIR}/tweets -o ${WORK_DIR}/tweets-seq -ow

mahout seq2sparse -i ${WORK_DIR}/tweets-seq -o ${WORK_DIR}/tweets-vectors -lnorm -nv -wt tfidf

mahout split -i ${WORK_DIR}/tweets-vectors/tfidf-vectors --trainingOutput ${WORK_DIR}/tweets-train-vectors --testOutput ${WORK_DIR}/tweets-test-vectors --randomSelectionPct 20 --overwrite --sequenceFiles -xm sequential

mahout trainnb -i ${WORK_DIR}/tweets-train-vectors -el -o ${WORK_DIR}/model -li ${WORK_DIR}/labelindex -ow -c

mahout testnb -i ${WORK_DIR}/tweets-train-vectors -m ${WORK_DIR}/model -l ${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/tweets-testing -c
```

The overall accuracy is 96% and the confusion matrix is as follows:

	Positive	Negative
Positive	86	3
Negative	4	95

Test 2: Using Test 1, test on test set. Command is as follows:

```
mahout testnb -i ${WORK_DIR}/tweets-test-vectors -m ${WORK_DIR}/model -l
${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/tweets-testing –c
```

The overall accuracy is 70% and the confusion matrix is as follows:

	Positive	Negative
Positive	7	3
Negative	0	0

Test 3: Tweets classification, using feature selection, test on train set. Commands are as follows:

```
mahout seq2sparse -i ${WORK_DIR}/tweets-seq -o ${WORK_DIR}/tweets-vectors --norm 2 --weight
TFIDF --namedVector --maxDFPercent 90 --minSupport 2 --analyzerName
org.apache.mahout.text.MailArchivesClusteringAnalyzer
```

```
mahout split -i ${WORK_DIR}/tweets-vectors/tfidf-vectors --trainingOutput ${WORK_DIR}/tweets-
train-vectors --testOutput ${WORK_DIR}/tweets-test-vectors --randomSelectionPct 20 --overwrite --
sequenceFiles -xm sequential
```

```
mahout trainnb -i ${WORK_DIR}/tweets-train-vectors -el -o ${WORK_DIR}/model -li
${WORK_DIR}/labelindex -ow -c
```

```
mahout testnb -i ${WORK_DIR}/tweets-train-vectors -m ${WORK_DIR}/model -l
${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/tweets-testing -c
```

The overall accuracy is 99% and the confusion matrix is as follows:

	Positive	Negative
Positive	78	1
Negative	1	98

Test 4: Using Test 3, test on test set. Command is as follows:

```
mahout testnb -i ${WORK_DIR}/tweets-test-vectors -m ${WORK_DIR}/model -l
${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/tweets-testing –c
```

The overall accuracy is 100% and the confusion matrix is as follows:

	Positive	Negative
Positive	18	0
Negative	0	0

We can observe that feature selection for tweets can help improve accuracy.

We use the script from TA to download some of the webpages. Then we choose some positive (related to the topic) webpages and negative (not related to the topic) pages manually. At last, we upload these webpages to HDFS and repeat the same procedure as what we did for the tweets.

Test 5: Webpages classification, no feature selection, test on train set. Commands are as follows:

```
mahout seqdirectory -i ${WORK_DIR}/webpages -o ${WORK_DIR}/webpages-seq -ow
```

```
mahout seq2sparse -i ${WORK_DIR}/webpages-seq -o ${WORK_DIR}/webpages-vectors -lnorm -nv -
wt tfidf
```

```
mahout split -i ${WORK_DIR}/webpages-vectors/tfidf-vectors --trainingOutput
${WORK_DIR}/webpages-train-vectors --testOutput ${WORK_DIR}/webpages-test-vectors --
randomSelectionPct 20 --overwrite --sequenceFiles -xm sequential
```

```
mahout trainnb -i ${WORK_DIR}/webpages-train-vectors -el -o ${WORK_DIR}/model -li
${WORK_DIR}/labelindex -ow -c
```

```
mahout testnb -i ${WORK_DIR}/webpages-train-vectors -m ${WORK_DIR}/model -l
${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/webpages-testing –c
```

The overall accuracy is 100% and the confusion matrix is as follows:

	Positive	Negative
Positive	55	0
Negative	0	28

Test 6: Using Test 5, test on test set. Command is as follows:

```
mahout testnb -i ${WORK_DIR}/webpages-test-vectors -m ${WORK_DIR}/model -l
${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/webpages-testing –c
```

The overall accuracy is 94% and the confusion matrix is as follows:

	Positive	Negative
Positive	14	0
Negative	1	2

Test 7: Webpages classification, using feature selection, test on train set. Commands are as follows:

```
mahout seq2sparse -i ${WORK_DIR}/webpages-seq -o ${WORK_DIR}/webpages-vectors-fs --norm 2 -
-weight TFIDF --namedVector --maxDFPercent 90 --minSupport 2 --analyzerName
org.apache.mahout.text.MailArchivesClusteringAnalyzer
```

```
mahout split -i ${WORK_DIR}/webpages-vectors-fs/tfidf-vectors --trainingOutput
${WORK_DIR}/webpages-train-vectors-fs --testOutput ${WORK_DIR}/webpages-test-vectors-fs --
randomSelectionPct 20 --overwrite --sequenceFiles -xm sequential
```

```
mahout trainnb -i ${WORK_DIR}/webpages-train-vectors-fs -el -o ${WORK_DIR}/model -li
${WORK_DIR}/labelindex -ow -c
```

```
mahout testnb -i ${WORK_DIR}/webpages-train-vectors-fs -m ${WORK_DIR}/model -l
${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/webpages-testing –c
```

The overall accuracy is 84% and the confusion matrix is as follows:

	Positive	Negative
Positive	58	0
Negative	13	12

Test 8: Using Test 7, test on test set. Command is as follows:

```
mahout testnb -i ${WORK_DIR}/webpages-test-vectors-fs -m ${WORK_DIR}/model -l
${WORK_DIR}/labelindex -ow -o ${WORK_DIR}/webpages-testing –c
```

The overall accuracy is 65% and the confusion matrix is as follows:

	Positive	Negative
Positive	11	0

Negative	6	0

We concluded that the accuracy of webpage is not good here is mainly due to that we did not use the cleaned webpages. Original webpages is very noisy.

3.4 Using Mahout Naïve Bayes Classifier for Tweet Small Collections from Other Teams

We used the training tweet datasets from other groups and applied the Mahout Naive Bayes classification algorithm. If the results are not good, we apply feature selection to revise our model.

Team	No Feature Selection		Feature Selection	
	Test on Train Set	Test on Test set	Test on Train Set	Test on Test Set
LDA	99%	95%		
Hadoop	95%	76%	99%	81%
NER	100%	100%		
Reducing Noise	99%	93%		

3.5 Generate Class Label for New Data Using Mahout Naïve Bayes Model

We are able to use Mahout to train and test our classification model. However, the test data provided to Mahout has to be labeled. The next problem is how to apply the classification model to new unlabeled test data. However, Mahout does not provide any function to label new unlabeled test data. The generated classification model given by Mahout is in binary format.

Right now we find an article [17] about applying the Naive Bayes classifier to new unlabeled datasets. This method is also recommended in "Learning Apache Mahout Classification" [20]. We tried to follow the tutorial and try to apply the new classifier.

First of all, we get the scripts and Java programs used in the tutorials.

```
git clone https://github.com/fredang/mahout-naive-bayes-example.git
```

Then we want to compile the Java programs. However, our system does not have Maven. Thus, we downloaded and installed the latest version of Maven, which is Maven 3.3.1. We exported the JAVA_HOME. We can use this command to check if Maven is successfully installed.

```
mvn –version
```

Messages we get are as follows and we can see that Maven is successfully installed.

```
Apache Maven 3.3.1 (cab6659f9874fa96462afef40fcf6bc033d58c1c; 2015-03-13T16:10:27-04:00)
Maven home: /home/cs5604s15_class/maven/apache-maven-3.3.1
Java version: 1.7.0_55, vendor: Oracle Corporation
Java home: /usr/java/jdk1.7.0_55-cloudera/jre
Default locale: en_US, platform encoding: UTF-8
```

```
OS name: "linux", version: "2.6.32-504.8.1.el6.x86_64", arch: "amd64", family: "unix"
```

We continue to compile the code by running the command as follows.

```
mvn clean package assembly:single
```

We got some JAR files in the target directory after running the above command and we can use these files to generate labels for new data sets. To repeat the same procedure as described in the tutorial, we tried to use the same dataset. To get the tweets, we use these command:

```
git clone https://github.com/tweepy/tweepy.git
cd tweepy
sudo python setup.py install
```

We change the file script/twitter_fetcher.py with our new consumer keys/secrets and access token key/secrets to use the API to download tweets.

```
python scripts/twitter_fetcher.py 5 > tweets-train.tsv
```

The tweet files contains a list of tweets in a tab separated value format. The first number is the tweet ID followed by the tweet message, which is identical to our previous format. We want to use this method to generate labels for new tweets. We have the tweet-to-classify.tsv in our data directory. We upload it to HDFS by using the following command:

```
hadoop fs -put data/tweets-to-classify.tsv tweets-to-classify.tsv
```

We run the MapReduce job by using the following command:

```
hadoop jar target/mahout-naive-bayes-example2-1.0-jar-with-dependencies.jar model tweets-
vectors/dictionary.file-0 tweets-vectors/df-count/part-r-00000 tweets-to-classify.tsv tweet-category
```

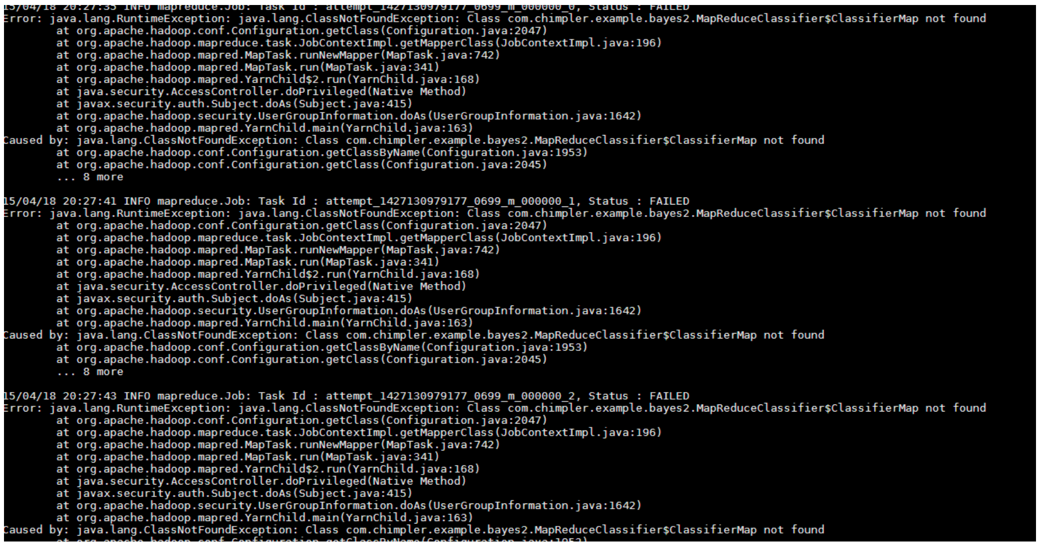
We can copy the results from HDFS to the local filesystem:

```
hadoop fs -getmerge tweet-category tweet-category.tsv
```

Our result should be able to read by a filereader by running the command:

```
java -cp target/mahout-naive-bayes-example2-1.0-jar-with-dependencies.jar
com.chimpler.example.bayes2.ResultReader data/tweets-to-classify.tsv [label index path] tweet-
category.tsv
```

However, on our cluster, we come across the error shown in Figure 15. We are still working on this issue. We hope that we can generate labels for new unlabeled test tweets when we solve this problem.



```
15/04/18 20:27:35 INFO mapreduce.Job: Task Id : attempt_1427130979177_0699_m_000000_0, Status : FAILED
Error: java.lang.RuntimeException: java.lang.ClassNotFoundException: Class com.chimpler.example.bayes2.MapReduceClassifier$ClassifierMap not found
        at org.apache.hadoop.conf.Configuration.getClass(Configuration.java:2047)
        at org.apache.hadoop.mapreduce.task.JobContextImpl.getMapperClass(JobContextImpl.java:196)
        at org.apache.hadoop.mapred.MapTask.runNewMapper(MapTask.java:742)
        at org.apache.hadoop.mapred.MapTask.run(MapTask.java:341)
        at org.apache.hadoop.mapred.YarnChild$2.run(YarnChild.java:168)
        at java.security.AccessController.doPrivileged(Native Method)
        at javax.security.auth.Subject.doAs(Subject.java:415)
        at org.apache.hadoop.security.UserGroupInformation.doAs(UserGroupInformation.java:1642)
        at org.apache.hadoop.mapred.YarnChild.main(YarnChild.java:163)
Caused by: java.lang.ClassNotFoundException: Class com.chimpler.example.bayes2.MapReduceClassifier$ClassifierMap not found
        at org.apache.hadoop.conf.Configuration.getClassByName(Configuration.java:1953)
        at org.apache.hadoop.conf.Configuration.getClass(Configuration.java:2045)
        ... 8 more

15/04/18 20:27:41 INFO mapreduce.Job: Task Id : attempt_1427130979177_0699_m_000000_1, Status : FAILED
Error: java.lang.RuntimeException: java.lang.ClassNotFoundException: Class com.chimpler.example.bayes2.MapReduceClassifier$ClassifierMap not found
        at org.apache.hadoop.conf.Configuration.getClass(Configuration.java:2047)
        at org.apache.hadoop.mapreduce.task.JobContextImpl.getMapperClass(JobContextImpl.java:196)
        at org.apache.hadoop.mapred.MapTask.runNewMapper(MapTask.java:742)
        at org.apache.hadoop.mapred.MapTask.run(MapTask.java:341)
        at org.apache.hadoop.mapred.YarnChild$2.run(YarnChild.java:168)
        at java.security.AccessController.doPrivileged(Native Method)
        at javax.security.auth.Subject.doAs(Subject.java:415)
        at org.apache.hadoop.security.UserGroupInformation.doAs(UserGroupInformation.java:1642)
        at org.apache.hadoop.mapred.YarnChild.main(YarnChild.java:163)
Caused by: java.lang.ClassNotFoundException: Class com.chimpler.example.bayes2.MapReduceClassifier$ClassifierMap not found
        at org.apache.hadoop.conf.Configuration.getClassByName(Configuration.java:1953)
        at org.apache.hadoop.conf.Configuration.getClass(Configuration.java:2045)
        ... 8 more

15/04/18 20:27:43 INFO mapreduce.Job: Task Id : attempt_1427130979177_0699_m_000000_2, Status : FAILED
Error: java.lang.RuntimeException: java.lang.ClassNotFoundException: Class com.chimpler.example.bayes2.MapReduceClassifier$ClassifierMap not found
        at org.apache.hadoop.conf.Configuration.getClass(Configuration.java:2047)
        at org.apache.hadoop.mapreduce.task.JobContextImpl.getMapperClass(JobContextImpl.java:196)
        at org.apache.hadoop.mapred.MapTask.runNewMapper(MapTask.java:742)
        at org.apache.hadoop.mapred.MapTask.run(MapTask.java:341)
        at org.apache.hadoop.mapred.YarnChild$2.run(YarnChild.java:168)
        at java.security.AccessController.doPrivileged(Native Method)
        at javax.security.auth.Subject.doAs(Subject.java:415)
        at org.apache.hadoop.security.UserGroupInformation.doAs(UserGroupInformation.java:1642)
        at org.apache.hadoop.mapred.YarnChild.main(YarnChild.java:163)
Caused by: java.lang.ClassNotFoundException: Class com.chimpler.example.bayes2.MapReduceClassifier$ClassifierMap not found
```

Fig. 15: Error message when generating classification labels for new unlabeled test data

We discussed with Mohamed and Sunshin about our problem. We also tried to come up with other possible solutions for classification label prediction, such as using Python and Hadoop streaming API, using Apache Spark and MLlib, or using other classification algorithms in Mahout. However, we found the only difference between our trial and the tutorial [17] was the version of Hadoop. The tutorial [17] was using Hadoop 1.1.1 and our cluster was using Hadoop 2.5. Thus, we tried to install Hadoop 1.1.1 on our own machine and this actually solved the problem. Our current progress is that we are able to predict labels for new unlabeled test data using trained Mahout Na ïve Bayes classification model using Hadoop 1.1.1. We state our efforts on Hadoop 1.1.1 installation and label prediction result as follows.

- Install Java 1.6
    - Download from
http://www.oracle.com/technetwork/java/javaee/downloads/java-ee-sdk-6u3-jdk-6u29-downloads-523388.html
    - Uncompress jdk-6u35-linux-x86-64.bin
        - chmod u+x jdk-6u35-linux-x64.bin
        - ./jdk-6u35-linux-x64.bin
    - Copy the directory jdk-1.6.035 to /usr/lib
        - sudo mkdir -p /usr/lib/jvm
        - sudo cp -r jdk1.6.0_35 /usr/lib/jvm/jdk1.6.0_35
    - Setup environment variable
        - sudo gedit /etc/profile
        - export JAVA_HOME=/usr/lib/jvm/jdk1.6.0_35
        - export JRE_HOME=${JAVA_HOME}/jre
        - export CLASSPATH=.:${JAVA_HOME}/lib:${JRE_HOME}/lib
        - export PATH=${JAVA_HOME}/bin:${JRE_HOME}/bin:$PATH
        - *source /etc/profile*
    - Test installation of Java
        - *java –version*

- Install Maven
    - Download from: https://maven.apache.org/download.cgi
    - Since version 3.3.1 is not compatible with Java 1.6, we changed to version 3.2.1

- Install Hadoop 1.1.1
    - Following the instructions from: http://6341986.blog.51cto.com/6331986/1143596
    - Download Hadoop 1.1.1: wget http://mirror.bit.edu.cn/apache/hadoop/common/hadoop-1.1.1/hadoop-1.1.1.tar.gz
    - Unzip: tar zxvf hadoop-1.1.1.tar.gz
    - Rename: mv hadoop-1.1.0 hadoop
    - Modify conf/core-site.xml: gedit conf/core-site.xml and add:

```
conf/core-site.xml:
<configuration>
   <property>
     <name>fs.default.name</name>
     <value>hdfs://localhost:9000</value>
   </property>
</configuration>
```

    - Modify conf/hdfs-site.xml:

```
<configuration>
<property>
<name>dfs.replication</name>
<value>1</value>
</property>
</configuration>
```

    - Modify conf/mapred-site.xml:

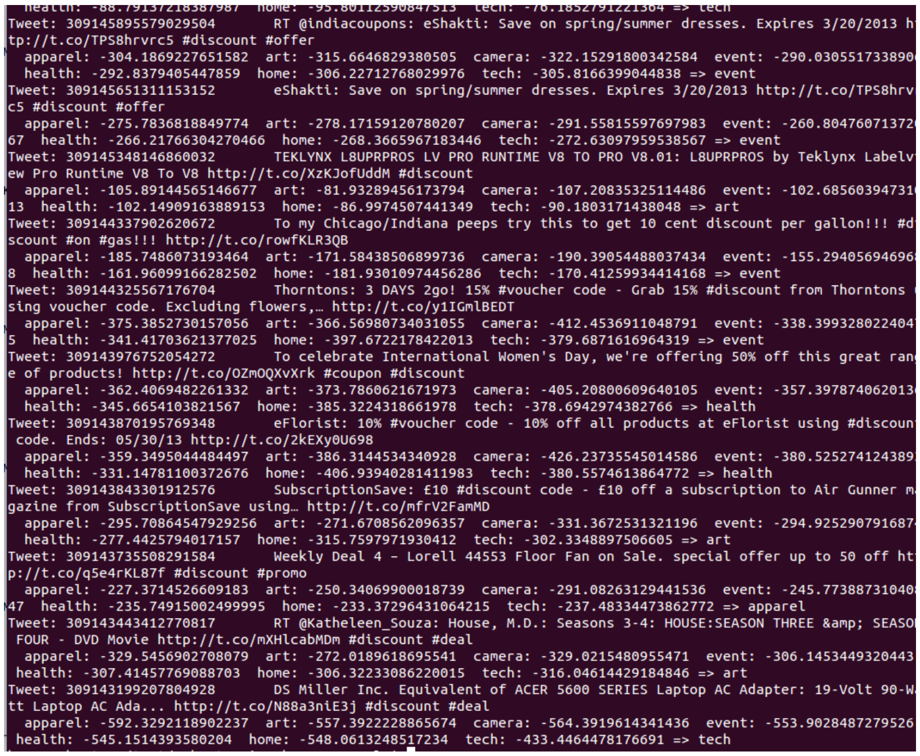
```
<property>
<name>mapred.job.tracker</name>
<value>localhost:9001</value>
</property>
</configuration>
```

    - In order for Hadoop to be able to find Java, add path of JDK at the end of conf/hadoop-env.sh
    - Format HDFS: bin/hadoop namenode -format
    - Start: bin/start-all.sh
    - Check start progress: jps
    - Check installation of Hadoop
        - Open http://localhost:50030 for status of MapReduce
        - Open http://localhost:50070 for status of HDFS

- Install Mahout 0.8
    - Download Mahout 0.8 from https://archive.apache.org/dist/mahout/0.8/
    - Download mahout-distribution-0.8.tar.gz and mahout-distribution-0.8.pom and convert this pom file to pom.xml
    - Use mvn to compile: mvn clean && mvn compile && mvn -DskipTests install

- Follow tutorial [17] again

We can see for each tweet, we give the tweet ID, tweet content and its score for each class and final result in terms of which class it belongs to (with "=>") as shown in Figure 16.



```
  health: -88.79137218387987  home: -95.80112590847513  tech: -76.1852791221364 => tech
Tweet: 309145895579029504       RT @indiacoupons: eShakti: Save on spring/summer dresses. Expires 3/20/2013 h
tp://t.co/TPS8hrvrc5 #discount #offer
  apparel: -304.1869227651582  art: -315.6646829380505  camera: -322.15291800342584  event: -290.030551733890
  health: -292.8379405447859  home: -306.22712768029976  tech: -305.8166399044838 => event
Tweet: 309145651311153152       eShakti: Save on spring/summer dresses. Expires 3/20/2013 http://t.co/TPS8hrv
c5 #discount #offer
  apparel: -275.7836818849774  art: -278.17159120780207  camera: -291.55815597697983  event: -260.80476071372
67  health: -266.21766304270466  home: -268.3665967183446  tech: -272.63097959538567 => event
Tweet: 309145348146860032       TEKLYNX L8UPRPROS LV PRO RUNTIME V8 TO PRO V8.01: L8UPRPROS by Teklynx Labelv
ew Pro Runtime V8 To V8 http://t.co/XzKJofUddM #discount
  apparel: -105.89144565146677  art: -81.93289456173794  camera: -107.20835325114486  event: -102.68560394731
13  health: -102.14909163889153  home: -86.9974507441349  tech: -90.1803171438048 => art
Tweet: 309144337902620672       To my Chicago/Indiana peeps try this to get 10 cent discount per gallon!!! #d
scount #on #gas!!! http://t.co/rowfKLR3QB
  apparel: -185.7486073193464  art: -171.58438506899736  camera: -190.39054488037434  event: -155.29405694696
8  health: -161.96099166282502  home: -181.93010974456286  tech: -170.41259934414168 => event
Tweet: 309144325567176704       Thorntons: 3 DAYS 2go! 15% #voucher code - Grab 15% #discount from Thorntons 
sing voucher code. Excluding flowers,… http://t.co/y1IGmlBEDT
  apparel: -375.3852730157056  art: -366.56980734031055  camera: -412.4536911048791  event: -338.399328022404
5  health: -341.41703621377025  home: -397.6722178422013  tech: -379.6871616964319 => event
Tweet: 309143976752054272       To celebrate International Women's Day, we're offering 50% off this great ran
e of products! http://t.co/OZmOQXvXrk #coupon #discount
  apparel: -362.4069482261332  art: -373.7860621671973  camera: -405.20800609640105  event: -357.397874062013
  health: -345.6654103821567  home: -385.3224318661978  tech: -378.6942974382766 => health
Tweet: 309143870195769348       eFlorist: 10% #voucher code - 10% off all products at eFlorist using #discoun
 code. Ends: 05/30/13 http://t.co/2kEXy0U698
  apparel: -359.3495044484497  art: -386.3144534340928  camera: -426.23735545014586  event: -380.525274124389
  health: -331.14781100372676  home: -406.93940281411983  tech: -380.5574613864772 => health
Tweet: 309143843301912576       SubscriptionSave: £10 #discount code - £10 off a subscription to Air Gunner m
gazine from SubscriptionSave using… http://t.co/mfrV2FamMD
  apparel: -295.70864547929256  art: -271.6708562096357  camera: -331.3672531321196  event: -294.925290791687
  health: -277.4425794017157  home: -315.7597971930412  tech: -302.3348897506605 => art
Tweet: 309143735508291584       Weekly Deal 4 – Lorell 44553 Floor Fan on Sale. special offer up to 50 off ht
p://t.co/q5e4rKL87f #discount #promo
  apparel: -227.3714526609183  art: -250.34069900018739  camera: -291.08263129441536  event: -245.77388731040
47  health: -235.74915002499995  home: -233.37296431064215  tech: -237.48334473862772 => apparel
Tweet: 309143443412770817       RT @Katheleen_Souza: House, M.D.: Seasons 3-4: HOUSE:SEASON THREE &amp; SEASO
 FOUR - DVD Movie http://t.co/mXHlcabMDm #discount #deal
  apparel: -329.5456902708079  art: -272.0189618695541  camera: -329.0215480955471  event: -306.1453449320443
 health: -307.41457769088703  home: -306.32233086220015  tech: -316.04614429184846 => art
Tweet: 309143199207804928       DS Miller Inc. Equivalent of ACER 5600 SERIES Laptop AC Adapter: 19-Volt 90-W
tt Laptop AC Ada... http://t.co/N88a3niE3j #discount #deal
  apparel: -592.3292118902237  art: -557.3922228865674  camera: -564.3919614341436  event: -553.9028487279526
 health: -545.1514393580204  home: -548.0613248517234  tech: -433.4464478176691 => tech
```

Fig. 16: Using Mahout Classification Model and Additional Program to Predict Class Labels of New Unlabeled Test Data

We can work on the small collections using our own Hadoop 1.1.1 and Mahout 0.8 now; however, we will run out of space for large collections. We then moved on for new method that can be used to predict class labels for new data.

3.5 Using Pangool to Predict Class Label for New Data

We found another Apache Hadoop implementation library, Pangool [19]. Pangool is a Java, low-level MapReduce API. It aims to be a replacement for the Hadoop Java MapReduce API. By implementing an intermediate Tuple-based schema and configuring a Job conveniently, many of the accidental complexities that arise from using the Hadoop Java MapReduce API disappear. Things like secondary sort and reduce-side joins become extremely easy to implement and understand. Pangool's performance is comparable to that of the Hadoop Java MapReduce API. Pangool also augments Hadoop's API by making multiple outputs and inputs first-class and allowing instance-based configuration. The reason why we used Pangool is that it is compatible with all kinds of Hadoop versions. This library does not have the same issue we come across with Mahout. Pangool provides an implementation of Na ïve Bayes.

Pangool has some features:

- Easier MapReduce development.
- Support for Tuples instead of just Key/Value pairs.
- Secondary sorting as easy as it can get.
- Built-in reduce-side joining capabilities.
- Performance and flexibility.

- Configuration by object instance instead of classes.
- First-class multiple inputs & outputs.
- Built-in serialization support for Thrift and ProtoStuff.
- 100% Hadoop compatibility. 0.20.X, 1.X, 2.X and YARN.

We download Pangool using: git clone https://github.com/datasalt/pangool.git. To install Pangool, we should use maven. The version we used here is maven 3.3.1, and the Java version we used is 1.7.0_55. After installation of maven, we just simple use this command: mvn clean install.

The Naïve Bayes implementation is under the directory pangool/examples/src/main/java/com/datasalt/pangool/examples/naivebayes/.

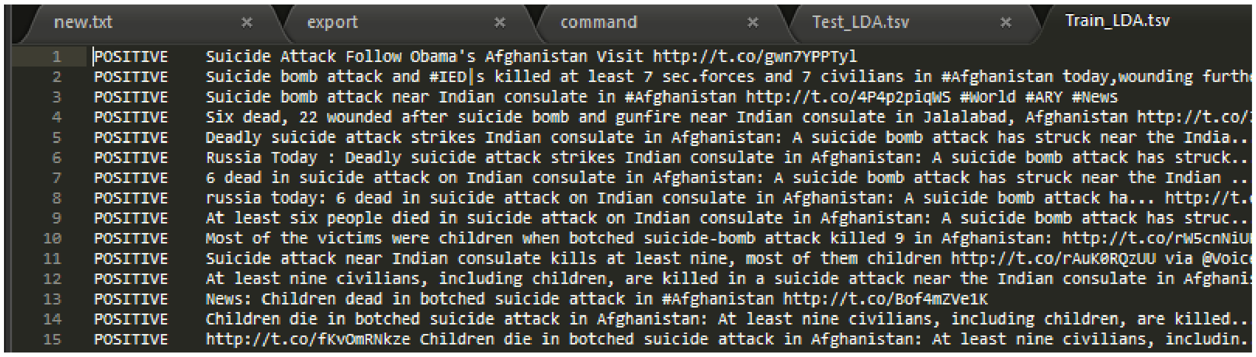
It has two classes:

NaiveBayesGenerate.java: This class is used to generate the Naïve Bayes classifier model.
NaiveBayesClassifier.java: This class will use the model we generated to predict and label the new data.

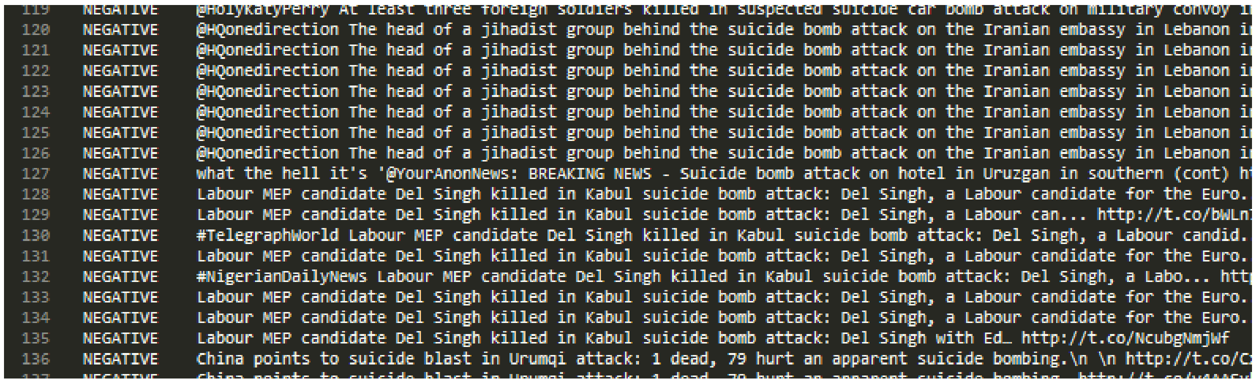
We used the Naïve Bayes example under target/pangool-examples-0.71-SNAPSHOT-hadoop.jar

Now we will give an example of the classification process.

First, we will label our data to generate the training set. For tweets, we will add a POSITIVE before the tweets that are related to this topic. We will add a NEGATIVE before the tweets that are not related to this topic. The label and the content of tweet are separated by a TAB. An example of the training set is as shown in Figure 17.



```
POSITIVE	Suicide Attack Follow Obama's Afghanistan Visit http://t.co/gwn7YPPTyl
POSITIVE	Suicide bomb attack and #IED|s killed at least 7 sec.forces and 7 civilians in #Afghanistan today,wounding furthe
POSITIVE	Suicide bomb attack near Indian consulate in #Afghanistan http://t.co/4P4p2piqWS #World #ARY #News
POSITIVE	Six dead, 22 wounded after suicide bomb and gunfire near Indian consulate in Jalalabad, Afghanistan http://t.co/
POSITIVE	Deadly suicide attack strikes Indian consulate in Afghanistan: A suicide bomb attack has struck near the India..
POSITIVE	Russia Today : Deadly suicide attack strikes Indian consulate in Afghanistan: A suicide bomb attack has struck..
POSITIVE	6 dead in suicide attack on Indian consulate in Afghanistan: A suicide bomb attack has struck near the Indian ..
POSITIVE	russia today: 6 dead in suicide attack on Indian consulate in Afghanistan: A suicide bomb attack ha... http://t.
POSITIVE	At least six people died in suicide attack on Indian consulate in Afghanistan: A suicide bomb attack has struc..
POSITIVE	Most of the victims were children when botched suicide-bomb attack killed 9 in Afghanistan: http://t.co/rW5cnNiU
POSITIVE	Suicide attack near Indian consulate kills at least nine, most of them children http://t.co/rAuK0RQzUU via @Voic
POSITIVE	At least nine civilians, including children, are killed in a suicide attack near the Indian consulate in Afghani
POSITIVE	News: Children dead in botched suicide attack in #Afghanistan http://t.co/Bof4mZVe1K
POSITIVE	Children die in botched suicide attack in Afghanistan: At least nine civilians, including children, are killed..
POSITIVE	http://t.co/fKvOmRNkze Children die in botched suicide attack in Afghanistan: At least nine civilians, includin.
```



```
NEGATIVE    @HolyKatyPerry At least three foreign soldiers killed in suspected suicide car bomb attack on military convoy i
NEGATIVE    @HQonedirection The head of a jihadist group behind the suicide bomb attack on the Iranian embassy in Lebanon i
NEGATIVE    @HQonedirection The head of a jihadist group behind the suicide bomb attack on the Iranian embassy in Lebanon i
NEGATIVE    @HQonedirection The head of a jihadist group behind the suicide bomb attack on the Iranian embassy in Lebanon i
NEGATIVE    @HQonedirection The head of a jihadist group behind the suicide bomb attack on the Iranian embassy in Lebanon i
NEGATIVE    @HQonedirection The head of a jihadist group behind the suicide bomb attack on the Iranian embassy in Lebanon i
NEGATIVE    @HQonedirection The head of a jihadist group behind the suicide bomb attack on the Iranian embassy in Lebanon i
NEGATIVE    @HQonedirection The head of a jihadist group behind the suicide bomb attack on the Iranian embassy in Lebanon i
NEGATIVE    what the hell it's '@YourAnonNews: BREAKING NEWS - Suicide bomb attack on hotel in Uruzgan in southern (cont) h
NEGATIVE    Labour MEP candidate Del Singh killed in Kabul suicide bomb attack: Del Singh, a Labour candidate for the Euro.
NEGATIVE    Labour MEP candidate Del Singh killed in Kabul suicide bomb attack: Del Singh, a Labour can... http://t.co/bWLn
NEGATIVE    #TelegraphWorld Labour MEP candidate Del Singh killed in Kabul suicide bomb attack: Del Singh, a Labour candid.
NEGATIVE    Labour MEP candidate Del Singh killed in Kabul suicide bomb attack: Del Singh, a Labour candidate for the Euro.
NEGATIVE    #NigerianDailyNews Labour MEP candidate Del Singh killed in Kabul suicide bomb attack: Del Singh, a Labo... htt
NEGATIVE    Labour MEP candidate Del Singh killed in Kabul suicide bomb attack: Del Singh, a Labour candidate for the Euro.
NEGATIVE    Labour MEP candidate Del Singh killed in Kabul suicide bomb attack: Del Singh, a Labour candidate for the Euro.
NEGATIVE    Labour MEP candidate Del Singh killed in Kabul suicide bomb attack: Del Singh with Ed… http://t.co/NcubgNmjWf
NEGATIVE    China points to suicide blast in Urumqi attack: 1 dead, 79 hurt an apparent suicide bombing.\n \n http://t.co/C
NEGATIVE    China points to suicide blast in Urumqi attack: 1 dead, 79 hurt an apparent suicide bombing. http://t.co/
```

Fig. 17: Example of Training Set

When we are done with labeling, we use the Na ïveBayesGenerate.java class to generate the model. The command is as follows:

hadoop jar target/pangool-examples-0.71-SNAPSHOT-hadoop.jar naive_bayes_generate LDA/train_lda.txt lda-out-bayes-model

The naive_bayes_generate is the class from Pangool. The LDA/train_lda.txt is the training data we showed in Figure . The lda-out-bayes-model is the Na ïve Bayes model we generated.

Then we used the labeled data to test the accuracy of our classifier. We split the labeled data into train set and test set (80% and 20%). The train set was used in last step. The test set was used without the label. We used the model and the NaiveBayesClassifier.java class to classify the testing data. We compared the manually assigned label and the predicted label and calculated the accuracy. The command is shown as:

hadoop jar target/pangool-examples-0.71-SNAPSHOT-hadoop.jar naive_bayes_classifier lda-out-bayes-model/p* LDA/test_lda.txt out-classify-lda

We used the na ïve_bayes_clasifier class with our model lda-out-bayes-model/p* to apply classification for the LDA/test_lda.txt and outputed the labeled data, out-classify-lda. We conducted 5-fold cross validation to make sure that our model works fine for this text classification task. We will show our summary of accuracy in Section IV.4.

We used this classifier to classify new data (small tweets, small webpages, large tweets and large webpages).

However, the input file and output file we used and generated are plain text. However, we need to read cleaned data from Reducing Noise team, which is in AVRO format. We should also have our output file in AVRO format in order for Hadoop team to upload to HBase. We give our thanks to Jose Cadena from Hadoop team. He helped us to modify the code and finally we can read in the AVRO file and generate the AVRO file with the correct schema. The command for labeling new data is shown as:

hadoop jar mr-naivebayes.jar lda-out-bayes-model/p*

/user/cs5604s15_noise/TWEETS_CLEAN/suicide_bomb_attack_S
classified_tweets_LDA_afghanistan_small

We used our new JAR file to classify the new data, which has already been cleaned by Reducing Noise team and generated the AVRO file that could be uploaded to HBase. In this project, we have other teams to label their own small collection of tweets. For small webpages, large tweets, and large webpages, we manually labeled some of the topics to compare the performance.

4. Evaluation

4.1 Cross Validation

Learning the parameters of a prediction function and testing it on the same data is a methodological mistake: a model that would just repeat the labels of the samples that it has just seen would have a perfect score but would fail to predict anything useful on yet-unseen data. This situation is called overfitting. To avoid it, it is common practice when performing a supervised machine learning experiment to hold out part of the available data as a test set. However, by partitioning the available data into sets, we drastically reduce the number of samples which can be used for learning the model, and the results can depend on a particular random choice for the pair of (train, validation) sets. A solution to this problem is a procedure called cross-validation (CV for short). A test set should still be held out for final evaluation, but the validation set is no longer needed when doing CV. In the basic approach, called k-fold CV, the training set is split into k smaller sets (other approaches are described below, but generally follow the same principles). The following procedure is followed for each of the k "folds":

- A model is trained using k – 1 of the folds as training data;
- The resulting model is validated on the remaining part of the data (i.e., it is used as a test set to compute a performance measure such as accuracy).

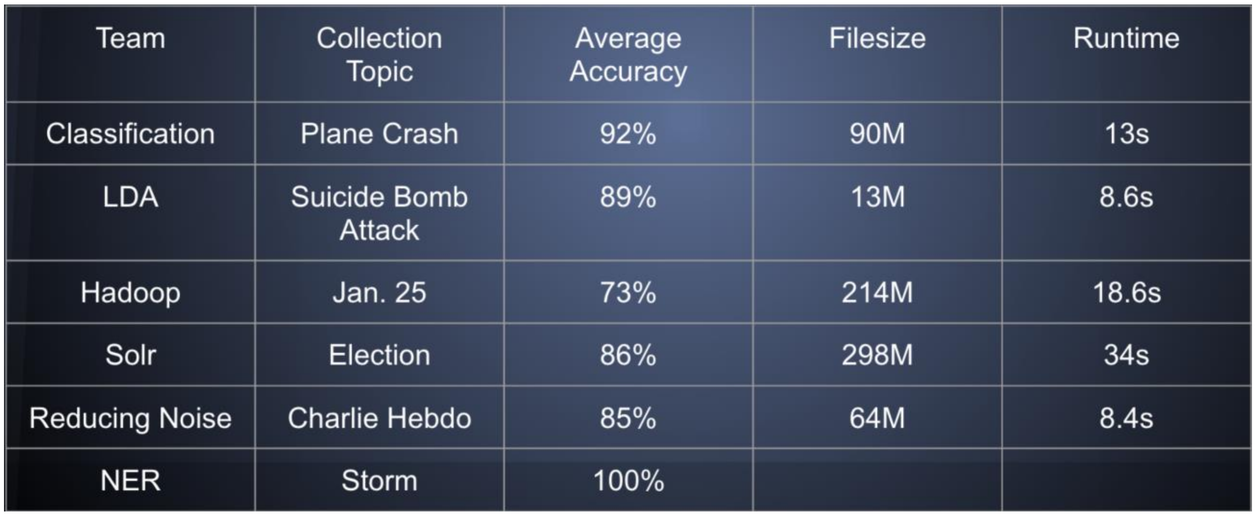
The performance measure reported by k-fold cross-validation is then the average of the values computed in the loop. This approach can be computationally expensive, but does not waste too much data (as it is the case when fixing an arbitrary test set), which is a major advantage in problems such as inverse inference where the number of samples is very small.

KFold divides all the samples in k groups of samples, called folds of equal sizes. The prediction function is learned using k – 1 folds, and the fold left out is used for testing.

4.2 Summary of Results

To summarize our classification results, we listed the collection we worked on, the average accuracy among the 5-fold cross validation, the size of new file for prediction, and the runtime of prediction. We can see that the accuracy is generally good. Although some of the new file is pretty large, the runtime is still acceptable. We noticed that the runtime would not increase linearly with respect to the filesize. This is because we found the number of mappers involved was different among the programs. Thus, for a larger file, the program will use more computing resources.

Our results of small collections of tweets are shown as:

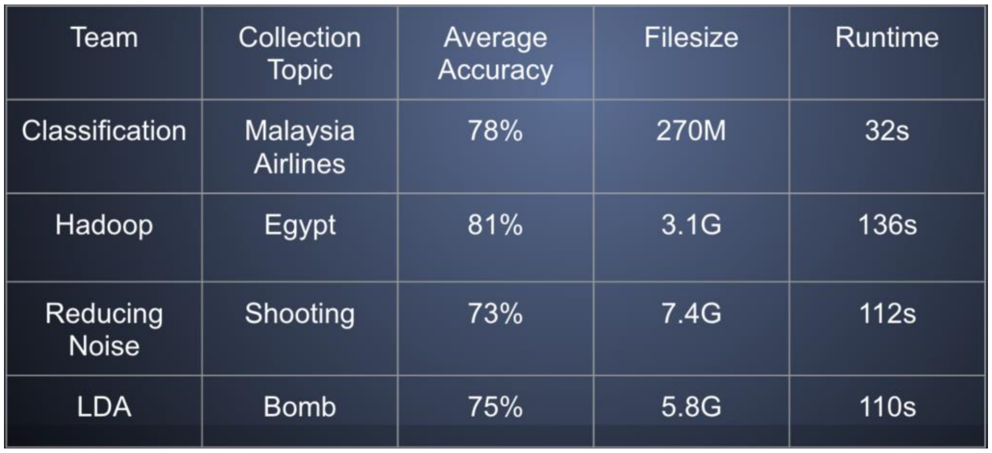


Team	Collection Topic	Average Accuracy	Filesize	Runtime
Classification	Plane Crash	92%	90M	13s
LDA	Suicide Bomb Attack	89%	13M	8.6s
Hadoop	Jan. 25	73%	214M	18.6s
Solr	Election	86%	298M	34s
Reducing Noise	Charlie Hebdo	85%	64M	8.4s
NER	Storm	100%		

Table 4: Results of Small Collections of Tweets

Since the performance of Hadoop team's collection, we looked into their data and found that the data contains many Arabic words. We thought that's the reason that causes the accuracy to not be good. We found the accuracy of NER team's data is 100%. We looked into their data and found that their negative tweets are selected from other collections. We did no further work on their data since the trained classifier would not be able to classify their collection.

Our results of large collections of tweets are shown as:

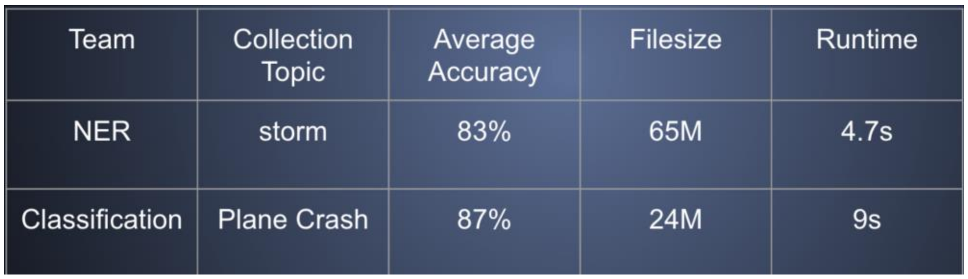


Team	Collection Topic	Average Accuracy	Filesize	Runtime
Classification	Malaysia Airlines	78%	270M	32s
Hadoop	Egypt	81%	3.1G	136s
Reducing Noise	Shooting	73%	7.4G	112s
LDA	Bomb	75%	5.8G	110s

Table 5: Results of Large Collections of Tweets

Our testing file came from the cleaned data produced by Reducing Noise team; thus, we could not work on all collections.

Our results of small collections of webpages are shown as:

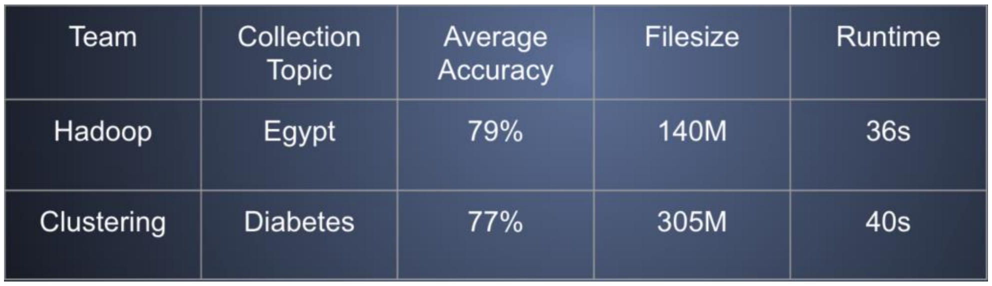


Team	Collection Topic	Average Accuracy	Filesize	Runtime
NER	storm	83%	65M	4.7s
Classification	Plane Crash	87%	24M	9s

Table 6: Results of Small Collections of Webpages

We can see that the sizes of webpages are not necessarily larger than the sizes of tweets. This is because we just extracted the “text_clean” field of webpages.

Out results of large collections of webpages are shown as:



Team	Collection Topic	Average Accuracy	Filesize	Runtime
Hadoop	Egypt	79%	140M	36s
Clustering	Diabetes	77%	305M	40s

Table 7: Results of Large Collections of Webpages

We also tried to work on the large collection of webpage for the Solr team. However, both the small and large collection of webpage for the Solr team seems to have less than 200 documents.

V. Timeline/Schedule

This table shows our schedule for this project.

Time	Work progress
Week 1	Literature Review
Week 2	Environment setup (JAVA, Solr, Python), data import (Solr). Test Python library scikit-learn and preprocessing the data. (for single node testing)
Week 3	Environment setup (Cloudera, Hadoop, Mahout). Test Mahout classification tool (Random Forest and Naive Bayes) for cluster Draft final report
Week 4	Test creating vectors from text using mahout.
Week 5	1. Use TA's script to play with the small collection. 2. Download the corresponding webpage for each tweet and process the URLs, then select tweets with high frequency and then upload them to Solr. 3. Finish documenting the schema that describes the specific output our team will produce for each of the web pages.
Week 6	Spring break
Week 7	Use Mahout to do feature selection for our example data (aircraft accident). 1.Converting directory of documents to SequenceFile format 2.Creating Vectors from SequenceFile 3.Creating Normalized TF-IDF Vectors from a directory of text documents 4.Converting existing vectors to Mahout's format
Week 8	1. Upload webpages to HDFS. 2. Further investigate into Mahout classification.
Week 9	1. Finished using Nutch to crawl webpages 2. Apply classification for tweets and webpages 3. Compare performance between without feature selection and with feature selection
Week 10	Apply classification on tweet datasets provided by LDA, RN, NER and Hadoop team
Week 11	Work on methods to generate classification labels for unlabeled test data Work on methods to apply classification to help searching in Solr
Week 12	Able to predict classification labels for new unlabeled test data using Hadoop 1.1.1
Week 13	Produce classification model and label predictions for tweets and webpages, for both small collections and large collections
Week 14	Submitting

VI. Conclusion

In this project, our task is to classify tweet and webpage collections into pre-defined classes in order to help with Solr search engine. We reviewed existing techniques and attempted to apply Apache Mahout Naïve Bayes classification algorithm at the beginning. Apache Mahout Naïve Bayes classification algorithm was able to provide accurate classifiers, however, it cannot predict labels for new data using the model. “Learning Apache Mahout Classification” [20] provided a solution package to predict class labels for new data using the classifiers generated by Mahout. However, this package was only able to work on Hadoop 1.1.1, and it was not compatible with our cluster, which is Hadoop 2.5. We finally decided to use another MapReduce Naïve Bayes package, Pangool [19], which was able to generate Naïve Bayes classifiers and predict class labels for new data. We finished prediction of small collections of tweets for our team, LDA team, Reducing Noise team, Solr team, and Hadoop team. We finished prediction of large collections of tweets for our team, LDA team, Reducing Noise team, and Hadoop team. We finished prediction of small collections of webpages for our team and NER team. We finished prediction of large collections of webpages for Hadoop team and Clustering team. The accuracy of our Naïve Bayes model was validated using 5-fold cross validation. Overall, The accuracy is satisfactory but still can be improved, and the running time for the predictions is reasonable.

VII. Future Work

For performance improvement, future researchers should consider using larger training sets. Currently due to the time limit, we are only able to label one hundred positive samples and one hundred negative samples for each collection to be used as training set. Future researchers can still work on developing a new package to label new data with the model generated by Apache Mahout. Future researchers can also work on modifying the prediction package provided in “Learning Apache Mahout Classification” [20] to make it compatible with higher versions of Hadoop, not just only Hadoop 1.1.1. Additional work is needed on the Pangool package [19] to build more accurate classifiers. Trying to use tf-idf values instead of word count in the feature vector, and using more representative features in feature selection, also may improve the accuracy.

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