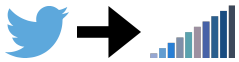
StockFlix



Big Data Programming Project - Increment 2

Team Members

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1. Introduction:

Stock Market Analysis using Big Data Hadoop. This undertaking depends on Big Data investigation of Stock Market. The everyday item paces and daily commodity rates of different organization shares are gathered and are examined with the assistance of question strategy. One can without much of a stretch have a market watch for any day he/she needs to take a gander at falling in the year 2016.

The client can discover his benefit/misfortune for the offer he/she claims with the assistance of current value pace of that offer put away in our database. One can likewise contrast various offers' highs and lows and regard to the market position. This undertaking targets giving basic and simple examination of the Stock Market according to the client's necessity. The investigation result can be gotten as tables, diagrams and pie graphs. The client gets a decision to pick the strategy for his investigation dependent on the content he chooses. Social organized information has been taken so as to finish this examination task.

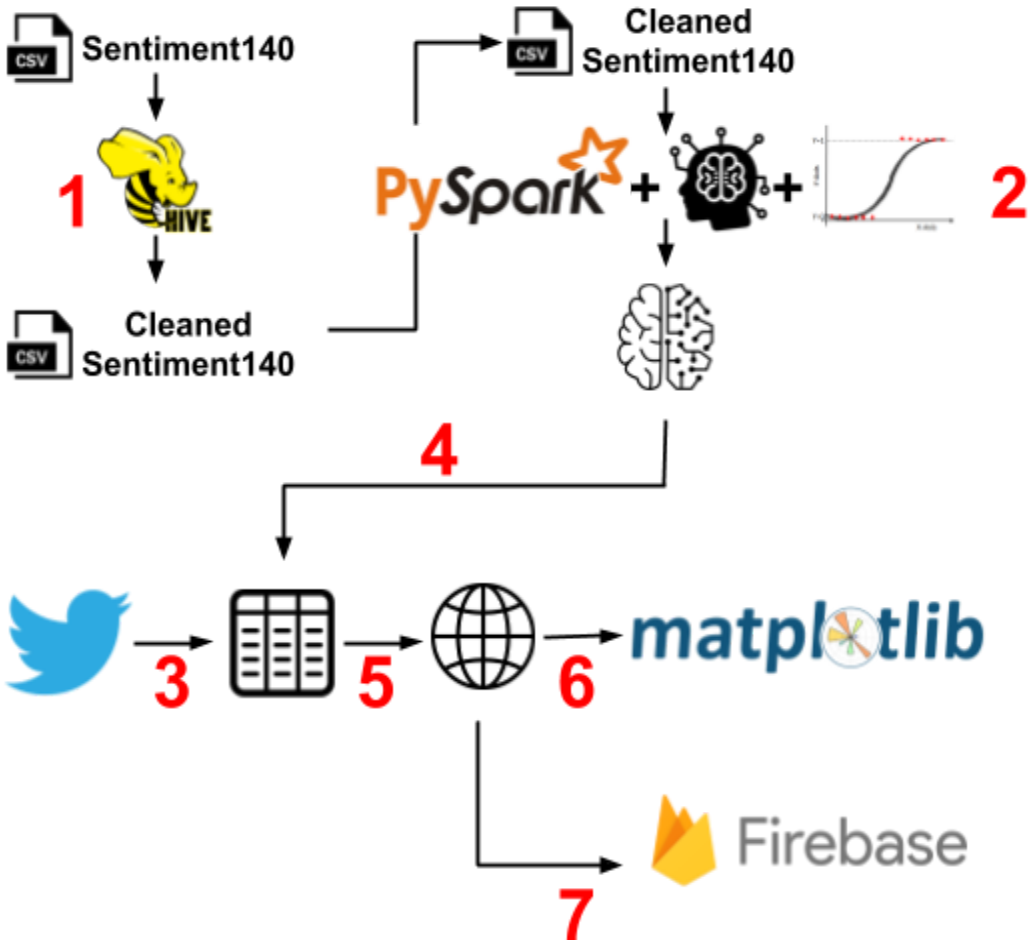
2. Background:

The stock market is viewed as a convoluted and nonlinear framework. Presently stock market expectations is perceived as a drawing point for financial investors. The historical values is considered as the principal factor to anticipate the financial exchange pattern. Authentic information might be unstructured and need uncommon taking care of on putting away and handling. The motivation behind this task is to dissect the financial exchange information and get general knowledge on this information through perception to discover stock conduct and incentive in danger for each stock.

With regards to putting resources into stocks, it is significant that the speculator is equipped for directing a careful examination. Specialized investigation will enable us to do the way toward determining future value developments dependent on past value developments inside the stock information. It will be useful for the speculators to settle on monetary choices of purchasing, holding, or selling stocks. In spite of the fact that it is difficult to make 100% precise expectations, it can assist speculators with envisioning what's to come.

3. Model:

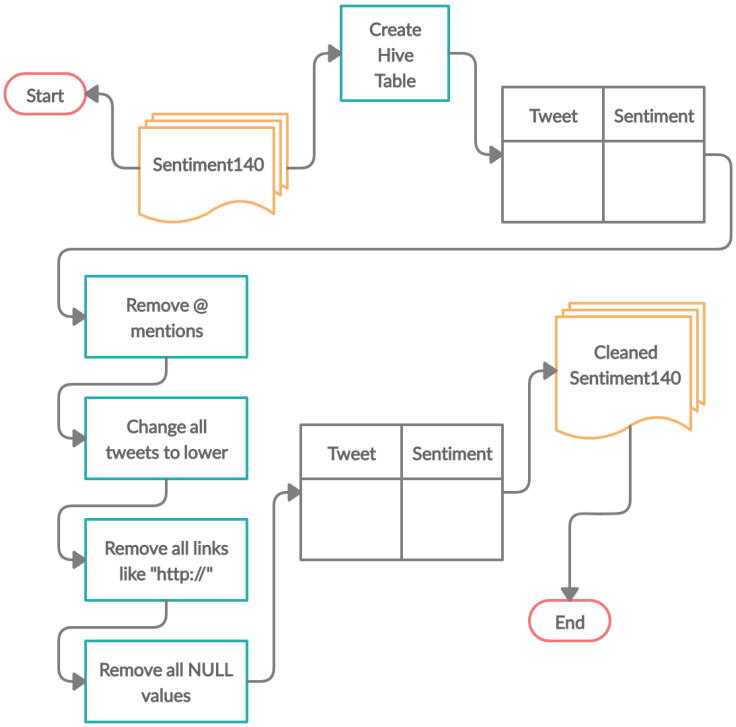
a. Architecture Diagram



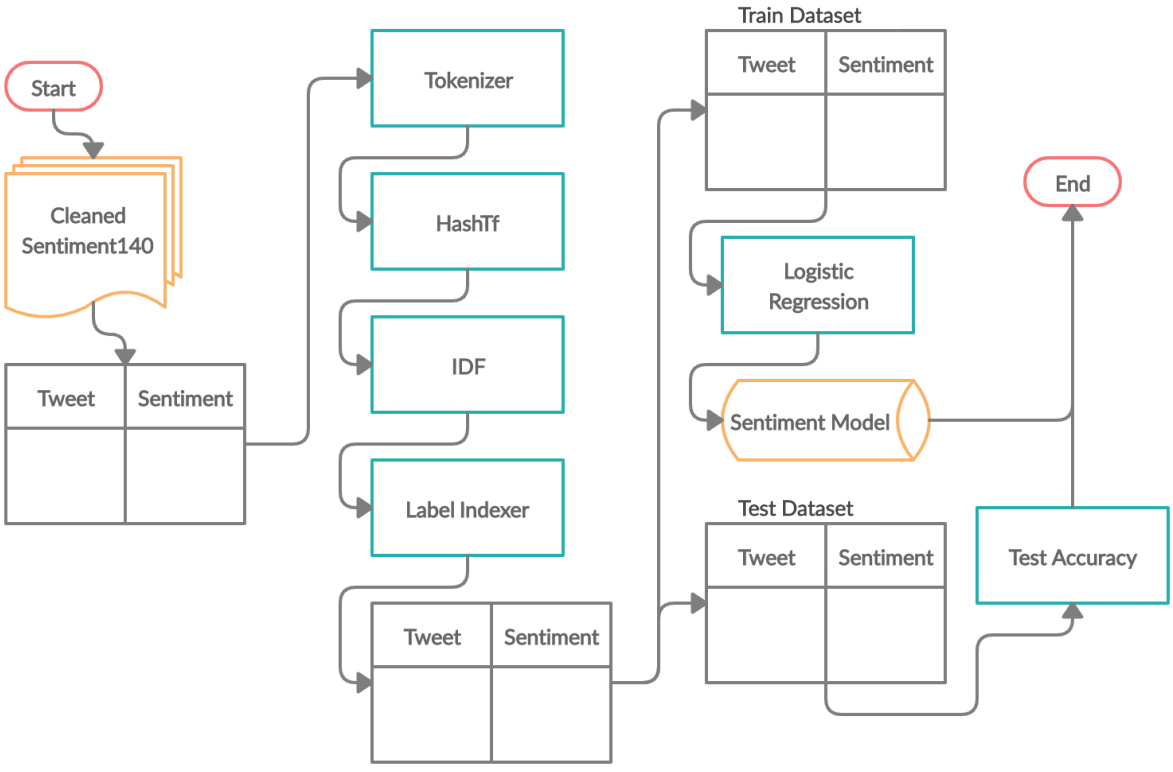
Number	Description
1	Preprocessing **sentiment140** Dataset by creating **Hive tables and queries.**
2	Using **PySpark + MILib + Logistic Regression** to create a sentiment model.
3	Setting **twitter streaming connection.**
4	Loading the **trained sentiment model.**
5	Combining the **tweet and its sentiment** using the **twitter streaming and trained sentiment model.**
6	Using **MatPlotLib** to create graphs for analysis.
7	Publishing the collected data to **Firebase**

b. Workflow Diagram

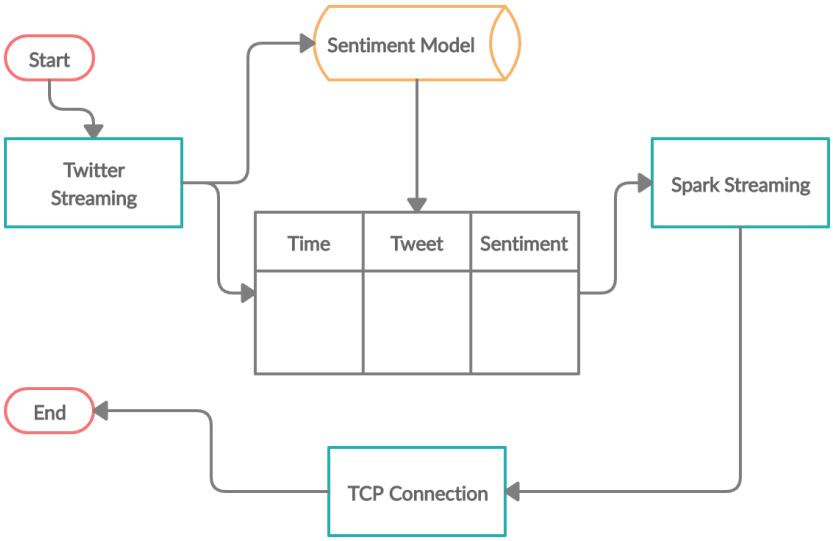
Data Preprocessing



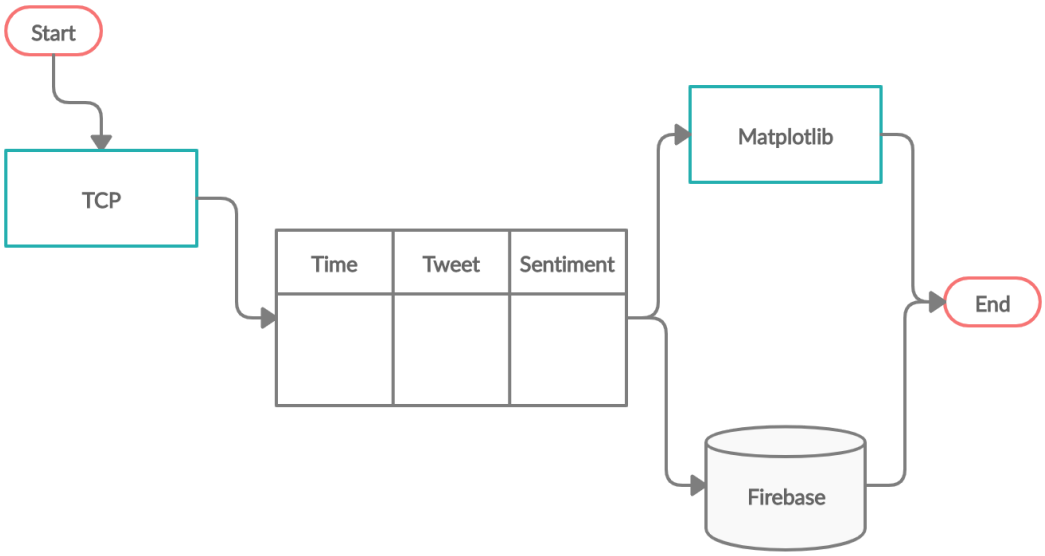
Training Sentiment Model



Twitter Streaming to TCP Streaming



TCP Streaming to Visualization and Real Time Database



4. Dataset:

a. Dataset Description:

i. We used Sentiment140 dataset.

ii. Tweets from “Sentiment140” originated from a Stanford research project data set included 1.6 million tweets which was loaded to train our model.

iii. **Source:** https://www.kaggle.com/kazanova/sentiment140

Target:	The polarity of the tweet (0 = negative, 2 = neutral, 4 = positive)
ids:	The id of tweet (2087)
date:	The date of tweet (Sat May 16 23:58:44 UTC 2009)
flag:	The query (lyx). If there is no query, then this value is NO_QUERY.
user:	The user that tweeted (robotickilldozr)
text:	The text of tweet (Lyx is cool)

b. Data Preprocessing:

Step-1 : **Start Hive.**

Query-1 : `[cloudera@quickstart ~]$ hive`

Step-2 : **Create Hive Table.**

Query-2 :
```
hive> CREATE TABLE twitter
    > (sentiment STRING, id STRING, date STRING,
    > query STRING, tweet STRING)
    > ROW FORMAT DELIMITED FIELDS BY ‘,’
    > STORED AS textfile;
```

Step-3 : **Load sentiment140 dataset.**

Query-3 :
```
hive> LOAD DATA LOCAL INPATH
    > ‘/home/cloudera/Downloads/twitter_data.csv’
    > INTO TABLE twitter;
```

Step-4 : **Verify the created table.**

Query-4 : `hive> SELECT * FROM twitter;`

```
[cloudera@quickstart ~]$ hive

Logging initialized using configuration in file:/etc/hive/conf.dist/hive-log4j.properties
WARNING: Hive CLI is deprecated and migration to Beeline is recommended.
hive> create table twitter (sentiment STRING,id STRING,date STRING, query STRING, user STRING, tweet STRING) row format delimited fields terminated by ',' stored as textfile;
OK
Time taken: 3.668 seconds
hive> show tables;
OK
movies
my_stocks
olympic
petrol
ratings
twitter
users
zomato
Time taken: 0.333 seconds, Fetched: 8 row(s)
hive> load data local inpath '/home/cloudera/Downloads/twitter_data.csv' into table twitter;
Loading data to table default.twitter
Table default.twitter stats: [numFiles=1, totalSize=238803811]
OK
Time taken: 4.706 seconds
hive> select * from twitter limit 10;
OK
"0"     "1467810369"    "Mon Apr 06 22:19:45 PDT 2009"  "NO_QUERY"      "_TheSpecialOne_"       "@switchfoot http://twitpic.com/2y1zl - Awww
"0"     "1467810672"    "Mon Apr 06 22:19:49 PDT 2009"  "NO_QUERY"      "scotthamilton" "is upset that he can't update his Facebook by texting it... and might cry as a result
```

Step-5 **: Count the Number of records inserted into the table.**

Query-5 : `hive> SELECT COUNT(*) FROM twitter;`

```
hive> SELECT COUNT(*) FROM twitter;
Query ID = cloudera_20191121173636_55323b9e-c22c-4c76-8cd4-cb551276bf27
Total jobs = 1
Launching Job 1 out of 1
Number of reduce tasks determined at compile time: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapreduce.job.reduces=<number>
Starting Job = job_1574385201027_0002, Tracking URL = http://quickstart.cloudera:8088/proxy/application_1574385201027_0002/
Kill Command = /usr/lib/hadoop/bin/hadoop job  -kill job_1574385201027_0002
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 1
2019-11-21 17:37:13,823 Stage-1 map = 0%,  reduce = 0%
2019-11-21 17:37:26,447 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 4.1 sec
2019-11-21 17:37:39,663 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 6.67 sec
MapReduce Total cumulative CPU time: 6 seconds 670 msec
Ended Job = job_1574385201027_0002
MapReduce Jobs Launched:
Stage-Stage-1: Map: 1  Reduce: 1   Cumulative CPU: 6.67 sec   HDFS Read: 238815699 HDFS Write: 8 SUCCESS
Total MapReduce CPU Time Spent: 6 seconds 670 msec
OK
1600000
Time taken: 41.545 seconds, Fetched: 1 row(s)
hive>
```

Step-6 **: Remove Unnecessary columns.**

Query-6 : `hive> CREATE TABLE filtered_twitter AS`
`> SELECT sentiment, tweet FROM twitter;`

```
hive> create table filtered_twitter as select sentiment,tweet from twitter;
Query ID = cloudera_20191121175959_0cc3a3ec-7acb-4193-a950-bb13c75c06b5
Total jobs = 3
Launching Job 1 out of 3
Number of reduce tasks is set to 0 since there's no reduce operator
Starting Job = job_1574385201027_0004, Tracking URL = http://quickstart.cloudera:8088/proxy/application_1574385201027_0004/
Kill Command = /usr/lib/hadoop/bin/hadoop job  -kill job_1574385201027_0004
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 0
2019-11-21 18:00:07,476 Stage-1 map = 0%,  reduce = 0%
2019-11-21 18:00:25,476 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 8.69 sec
MapReduce Total cumulative CPU time: 8 seconds 690 msec
Ended Job = job_1574385201027_0004
Stage-4 is selected by condition resolver.
Stage-3 is filtered out by condition resolver.
Stage-5 is filtered out by condition resolver.
Moving data to: hdfs://quickstart.cloudera:8020/user/hive/warehouse/.hive-staging_hive_2019-11-21_17-59-52_551_7864535268436388181-1/-ext-10001
Moving data to: hdfs://quickstart.cloudera:8020/user/hive/warehouse/filtered_twitter
Table default.filtered_twitter stats: [numFiles=1, numRows=1600000, totalSize=109055240, rawDataSize=107455240]
MapReduce Jobs Launched:
Stage-Stage-1: Map: 1   Cumulative CPU: 8.69 sec   HDFS Read: 238811630 HDFS Write: 109055332 SUCCESS
Total MapReduce CPU Time Spent: 8 seconds 690 msec
OK
Time taken: 34.324 seconds
```

Step-7 **: Verify the filtered table.**

Query-7 : `hive> SELECT * FROM filtered_twitter limit 10;`

```
hive> select * from filtered_twitter limit 10;
OK
"0"     "@switchfoot http://twitpic.com/2y1zl - Awww
"0"     "is upset that he can't update his Facebook by texting it... and might cry as a result  School today also. Blah!"
"0"     "@Kenichan I dived many times for the ball. Managed to save 50%  The rest go out of bounds"
"0"     "my whole body feels itchy and like its on fire "
"0"     "@nationwideclass no
"0"     "@Kwesidei not the whole crew "
"0"     "Need a hug "
"0"     "@LOLTrish hey  long time no see! Yes.. Rains a bit
"0"     "@Tatiana_K nope they didn't have it "
"0"     "@twittera que me muera ? "
Time taken: 0.142 seconds, Fetched: 10 row(s)
hive>
```

Step-8 : **Remove '@' mentions in the tweets.**

Query-8 :
```
hive> CREATE TABLE filtered_twitter_2 as
    > SELECT sentiment,
    > TRANSLATE(tweet, '@([A-Z][a-z])*', '')
    > FROM filtered_twitter;
```

```
hive> create table filtered_twitter_2 as select sentiment, TRANSLATE(tweet, '@([A-Z][a-z])*', '') from filtered_twitter;
Query [redacted]
Total jobs = 3
Launching Job 1 out of 3
Number of reduce tasks is set to 0 since there's no reduce operator
Starting Job = job_1574385201027_0007, Tracking URL = http://quickstart.cloudera:8088/proxy/application_1574385201027_0007/
Kill Command = /usr/lib/hadoop/bin/hadoop job  -kill job_1574385201027_0007
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 0
2019-11-21 18:30:04,790 Stage-1 map = 0%,  reduce = 0%
2019-11-21 18:30:28,902 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 14.74 sec
MapReduce Total cumulative CPU time: 14 seconds 740 msec
Ended Job = job_1574385201027_0007
Stage-4 is selected by condition resolver.
Stage-3 is filtered out by condition resolver.
Stage-5 is filtered out by condition resolver.
Moving data to: hdfs://quickstart.cloudera:8020/user/hive/warehouse/.hive-staging_hive_2019-11-21_18-29-49_565_68670443370418301-1/-ext-10001
Moving data to: hdfs://quickstart.cloudera:8020/user/hive/warehouse/filtered_twitter_2
Table default.filtered_twitter_2 stats: [numFiles=1, numRows=1600000, totalSize=101796152, rawDataSize=100196152]
MapReduce Jobs Launched:
Stage-Stage-1: Map: 1   Cumulative CPU: 14.74 sec   HDFS Read: 109059022 HDFS Write: 101796246 SUCCESS
Total MapReduce CPU Time Spent: 14 seconds 740 msec
OK
Time taken: 42.057 seconds
```

Step-9 : **Verify the step-8.**

Query-9 :
```
hive> SELECT * FROM filtered_twitter_2 LIMIT 10;
```

```
hive> select * from filtered_twitter_2 limit 10;
OK
"0"     "switchfoot http://twitpic.com/2y1l  www
"0"     "is upset tht he cn't updte his Fcebook by texting it... nd might cry s  result  School tody lso. Blh!"
"0"     "Kenichn I dived mny times for the bll. Mnged to sve 50%  The rest go out of bounds"
"0"     "my whole body feels itchy nd like its on fire "
"0"     "ntionwideclss no
"0"     "Kwesidei not the whole crew "
"0"     "Need  hug "
"0"     "LOLTrish hey  long time no see! Yes.. Rins  bit
"0"     "Ttin_K nope they didn't hve it "
"0"     "twitter que me muer ? "
Time taken: 0.211 seconds, Fetched: 10 row(s)
hive>
```

Step-10 : **Change all the tweet text to lowercase.**

Query-10 : `hive> CREATE TABLE filtered_twitter_3 AS tweet`
`> FROM filtered_twitter_2;`

```
hive> create table filtered_twitter_3 as select sentiment, lower(tweet) as tweet from filtered_twitter_2;
Query ID = cloudera_20191121190000_[illegible]
Total jobs = 3
Launching Job 1 out of 3
Number of reduce tasks is set to 0 since there's no reduce operator
Starting Job = job_1574385201027_0009, Tracking URL = http://quickstart.cloudera:8088/proxy/application_1574385201027_0009/
Kill Command = /usr/lib/hadoop/bin/hadoop job  -kill job_1574385201027_0009
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 0
2019-11-21 19:00:06,927 Stage-1 map = 0%,  reduce = 0%
2019-11-21 19:00:25,805 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 10.59 sec
MapReduce Total cumulative CPU time: 10 seconds 590 msec
Ended Job = job_1574385201027_0009
Stage-4 is selected by condition resolver.
Stage-3 is filtered out by condition resolver.
Stage-5 is filtered out by condition resolver.
Moving data to: hdfs://quickstart.cloudera:8020/user/hive/warehouse/.hive-staging_hive_2019-11-21_18-59-53_413_2382564270350494251-1/-ext-10001
Moving data to: hdfs://quickstart.cloudera:8020/user/hive/warehouse/filtered_twitter_3
Table default.filtered_twitter_3 stats: [numFiles=1, numRows=1600000, totalSize=101796139, rawDataSize=100196139]
MapReduce Jobs Launched:
Stage-Stage-1: Map: 1   Cumulative CPU: 10.59 sec   HDFS Read: 101799700 HDFS Write: 101796233 SUCCESS
Total MapReduce CPU Time Spent: 10 seconds 590 msec
OK
Time taken: 33.8 seconds
```

Step-11 : **Verify Step-10.**

Query-11 : `hive> SELECT * FROM filtered_twitter_3 LIMIT 10;`

```
hive> select * from filtered_twitter_3 limit 10;
OK
"0"     "switchfoot http://twitpic.com/2y1l  www
"0"     "is upset tht he cn't updte his fcebook by texting it... nd might cry s  result  school tody lso. blh!"
"0"     "kenichn i dived mny times for the bll. mnged to sve 50%  the rest go out of bounds"
"0"     "my whole body feels itchy nd like its on fire "
"0"     "ntionwideclss no
"0"     "kwesidei not the whole crew "
"0"     "need  hug "
"0"     "loltrish hey  long time no see! yes.. rins  bit
"0"     "ttin_k nope they didn't hve it "
"0"     "twitter que me muer ? "
Time taken: 0.115 seconds, Fetched: 10 row(s)
hive>
```

Step-12 : **Save to CSV.**

Query-12 : `[cloudera@quickstart  - ]$ hive -e`
`$ 'SELECT * FROM filtered_twitter_3' |`
`$ sed 's/[\t]/,/g' >`
`$ /home/cloudera/cleaned_twitter_data.csv`

```
hive> [cloudera@quickstart ~]$ hive -e 'select * from filtered_twitter_3' | sed 's/[\t]/,/g' > /home/cloudera/Downloads/cleaned_twitter_data.csv

Logging initialized using configuration in file:/etc/hive/conf.dist/hive-log4j.properties
OK
Time taken: 1.9 seconds, Fetched: 1600000 row(s)
[cloudera@quickstart ~]$
```

5. Implementation:

a. Training Sentiment Analysis Model:

Step 1: Creating a Spark and SQL context.

```
try:
    conf = ps.SparkConf().setAll([('spark.executor.memory', '16g'), ('spark.driver.memory', '16g')])
    sc = ps.SparkContext(conf=conf)
    sql_c = SQLContext(sc)
    log.info("Created a Spark Context")
    return sql_c, sc
except ValueError as e:
    log.error(e)
```

Step 2: Reading the cleaned twitter dataset.

```
log.info("Data has been read successfully.")
df = sql_c.read.format(reading_format).options(header=read_header, infer_schema=infer_schema).load(data_path)
log.info(str(df.count()) + " has been read.")
return df
```

Step 3: Removing NA's in the cleaned twitter dataset.

```
log.info("NA's has been removed from the dataset.")
return df.dropna()
```

Step 4: Split the cleaned twitter dataset into train and test dataset.

```
log.info(
    "Dataframe has been split into " + str(train_size) + "," + str(val_size) + "," + str(
        test_size) + " size for train, val and test")
return df.randomSplit([train_size, val_size, test_size], seed=seed_value)
```

Step 5: Tokenizing, Hashing, IDF and Labeling the cleaned twitter dataset.

```
log.info("Tokenizing the feature column and output is written into words column")
tokenizer = Tokenizer(inputCol=feature_column_name, outputCol="words")

log.info("Hashing the words column and output is written into tf column")
hashtf = HashingTF(numFeatures=number_of_features, inputCol="words", outputCol="tf")

log.info("IDF the tf column and output is written into  features column")
idf = IDF(inputCol="tf", outputCol="features", minDocFreq=document_frequency)

log.info("Labeling the target column and output is written into label column")
label_string_idx = StringIndexer(inputCol=target_column_name, outputCol="label")

log.info("Making all the above method into a pipeline")
pipeline = Pipeline(stages=[tokenizer, hashtf, idf, label_string_idx])

log.info("Fit train, test and validation set on the created pipeline")
pipeline_fit = pipeline.fit(tr_set)
pipeline_fit.save(pipleline_model_path)
train_df = pipeline_fit.transform(tr_set)
val_df = pipeline_fit.transform(vl_set)
test_df = pipeline_fit.transform(tst_set)
return train_df, val_df, test_df
```

Step 6: Training the dataset using Logistic Regression.

```
log.info("Fitting the train dataset using LogisticRegression")
lr = LogisticRegression(maxIter=max_iter)
lr_model = lr.fit(train_df)
return lr_model
```

Step 7: Evaluating the trained model.

```
log.info("Evaluating the trained model")
predictions = model.transform(test_df)
evaluator = BinaryClassificationEvaluator(rawPredictionCol="rawPrediction")
log.info(evaluator.evaluate(predictions))
```

We got *0.835307342791311* as Accuracy.

b. Twitter Streaming to TCP:

Step 1: Setting TCP Connection.

```
s = socket.socket(socket.AF_INET, socket.SOCK_STREAM)  # Create a socket object
host = Constants.TCP_IP  # Get local machine name
port = Constants.port_number  # Reserve a port for your service.
s.bind((host, port))  # Bind to the port
log.info("Listening on port: %s" % str(port))
return s
```

Step 2: Setting Twitter Streaming Connection.

```
log.info("Twitter Authentication has been setup successfully")
consumer_key = tc.consumerKey
consumer_secret = tc.consumerSecret
access_token = tc.accessToken
access_secret = tc.accessTokenSecret
auth = OAuthHandler(consumer_key, consumer_secret)
auth.set_access_token(access_token, access_secret)
return auth
```

Step 3: Sending data from Twitter Streaming to TCP.

```
s = self.client_socket
s.listen(5)  # Now wait for client connection.
c, addr = s.accept()  # Establish connection with client.

print("Received request from: " + str(addr))

msg = json.loads(data)
```

c. Load Trained Sentiment Model and Predict

Step 1: .load() to load the trained tf, idfmodel and .createDataFrame to create data frame.
Step 2: model.transform will transform the features.
Step 3: again .load() will load the sentiment model.
Step 4: remaining to predict sentiment of the text.

```
model = PipelineModel.load(Constants.sentiment_tf_idf_model_path)
v = sql_context.createDataFrame([
    ("a", msg['text'].replace('\n', '')),
], ["_c0", "text"])
v = model.transform(v)
model2 = LogisticRegressionModel.load(Constants.sentiment_analysis_model_path)
v = model2.transform(v)
v_list = v.select('prediction').collect()
sentiment = str(v_list[0].prediction)
```

d. Combine data from Streaming and Sentiment:

This will combine the sentiment and send it to TCP.

```
s_data = tweet_time + ' ~@ ' + text + ' ~@ ' + sentiment + ' ~@ ' +
str(hashtags)
```

Tweeted Time	Tweet Text	Sentiment	HashTags

e. TCP to Matplotlib:

Step 1: Import appropriate libraries for PySpark.

```
import findspark

findspark.init()

from pyspark import SparkContext
from pyspark.streaming import StreamingContext
from pyspark.sql import SQLContext
from pyspark.sql.functions import desc
import json
import pickle
```

Step 2: Creating Streaming Context.

```
sc = SparkContext()
ssc = StreamingContext(sc, 10)
sqlContext = SQLContext(sc)

socket_stream = ssc.socketTextStream("localhost", 9009)

lines = socket_stream.window(20,20)
```

This streaming context will

a. Listen to **localhost.**
b. Port number **9009.**
c. Listen for every **10 seconds.**
d. Streaming window size of **20, 20.**

Step 3: Split each line by "~@" and register as a SQL table tweets.

```
lines.map( lambda text: text.split( "~@" ) )
```

```
.foreachRDD(lambda rdd: rdd.toDF().registerTempTable("tweets"))
```

Step 4: Import appropriate libraries for visualization.

```
import time
from IPython import display
import matplotlib.pyplot as plt
import seaborn as sns
import pandas
# Only works for Jupyter Notebooks!
%matplotlib inline

ssc.start()
```

Step 5: To verify the data from TCP.

Query: `SELECT * FROM tweets`

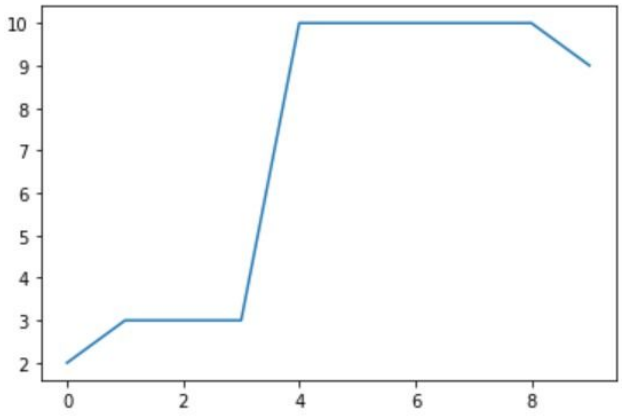
```
count = 0
while count < 1:
    time.sleep( 2 )

    df_source = sqlContext.sql('select * from tweets' )
    df = df_source.toPandas()
    print(df)
```

```
                                _1  \
 0  Sat Nov 23 03:41:44 +0000 2019
 1  Sat Nov 23 03:41:44 +0000 2019
 2  Sat Nov 23 03:41:44 +0000 2019

                                                    _2     _3  _4
 0   @Amapola89219147 @evoespueblo Amapola ...uds ...   1.0
 1   @AliciaAtout @MLW As a fan already of MLW you...   1.0
 2   POKEMON ESPADA #8: BERTO EL TIPO OVEJA https:...   1.0
```

Analysis-1: Finding number of people right now.

Query: `SELECT COUNT(*) as cnt FROM tweets WHERE _1 IS NOT NULL`

```
count = 0
series = []
time_series = []
iterator = 0

while count < 1:
    time.sleep(2)

    query_10_source = sqlContext.sql("SELECT count(*) as cnt FROM tweets WHERE _1 IS NOT NULL")
    query_10_list = query_10_source.collect()

    for item in query_10_list:
        series.append(item.cnt)
        time_series.append(iterator)
        iterator = iterator + 1

    display.clear_output(wait=True)

    plt.plot(time_series, series)
    plt.xlabel('Time')
    plt.ylabel('Count')
    plt.show()
```



Analysis-2: Finding trending hashtags.

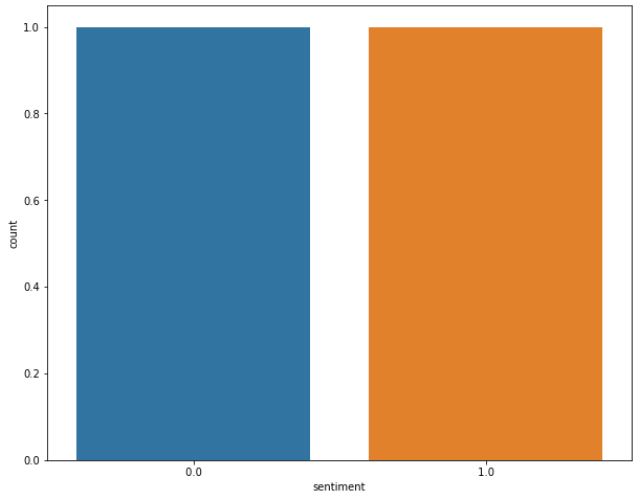
Query: `SELECT _4 FROM tweets`

```
count = 0
hashtags = " "

while count < 1:
    time.sleep(2)

    query_2_source = sqlContext.sql("SELECT _4 FROM tweets")
    query_2_list = query_2_source.select('_4').collect()

    for item in query_2_list:
        hashtags = hashtags + item._7

    wordcloud = WordCloud().generate(hashtags)

    display.clear_output(wait=True)
    plt.figure( figsize = (10, 8))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()
```

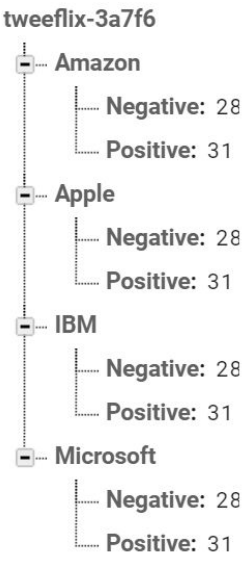
Analysis-3: Finding number of people talking positive and negative in twitter.

Query: `SELECT cast(count(*) as int) as count, _3 as sentiment FROM tweets WHERE _3 IS NOT NULL GROUP BY _3`

```
while True:
    time.sleep(2)

    query_1_source = sqlContext.sql("SELECT cast(count(*) as int) as count, _3
    query_1_df = query_1_source.toPandas()

    display.clear_output(wait=True)
    plt.figure( figsize = (10, 8))
    sns.barplot( x="sentiment", y="count", data=query_1_df)
    plt.show()
```



f. TCP to Firebase:




```
firebase = pyrebase.initialize_app(firebaseConfig)

db = firebase.database()
```

6. Results

Task	Result
Sentiment Analysis	83.53% and took 77 seconds to train
Average number of people tweeting right now	6
Average number of people talking positive	4
Average number of people talking negative	1

7. Works Completed:

Work Completed			
Task	**Description**	**Contributor**	**Percentage**
1	**Finding correct dataset.**	**Jayden Tran**	**33.33%**
2	**Creating hive table and loading the dataset.**		
3	**Using hive queries to do preprocessing.**		
4	**Saving preprocessed data to CSV.**		
5	**Tokenizing, IDF, TDF and Label Indexer on the cleaned data.**		
6	**Training the cleaned data using Logistic Regression.**	**Alper Erel**	**33.33%**
7	**Saving the trained model.**		
8	**Evaluating the trained model.**		
9	**Setting up twitter credentials.**		
10	**Setting twitter streaming**		

	connection.		
11	**Setting TCP connection.**		
12	**Sending data from twitter streaming to TCP.**		
13	**Listening to TCP connection.**	**Kavin Kumar Arumugam**	**33.33%**
14	**Processing the data from TCP.**		
15	**Creating graphs using the data from TCP.**		
16	**Setting up Firebase connection.**		
17	**Pushing the results to realtime database.**		

8. Works to be Completed:

a. Front end.
b. Collect stock data using stock APIs.
c. Deploy the created ones into Heroku

9. References and Bibliography:

1) https://m.benzinga.com/article/9602734
2) https://www.investopedia.com/terms/s/stock-analysis.asp
3) https://cleartax.in/s/stock-market-analysis