Spam Detection System in Hadoop

1) Cloud Infrastructure Setup

a. Create a Hadoop cluster using GCP (Google Cloud Platform) Dataproc.

I have chosen my cloud platform as GCP and I have created a cluster on it using Dataproc Compute Engine. The cluster is set to have 1 master and 3 worker nodes with the region selected as us-central1 and the zone as us-central1-f.

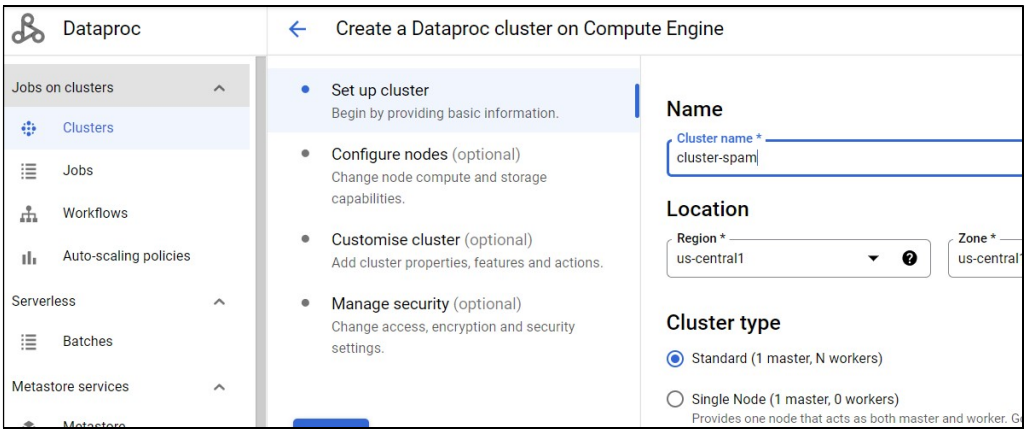


Figure 1: Dataproc with 1master, N-worker

To configure my nodes, I selected the machine from the family of General Purpose of N1 series and machine type as 'n1-standard-4 (4 vCPU, 15 GB memory)'. I have taken the same configuration for my worker nodes as well.

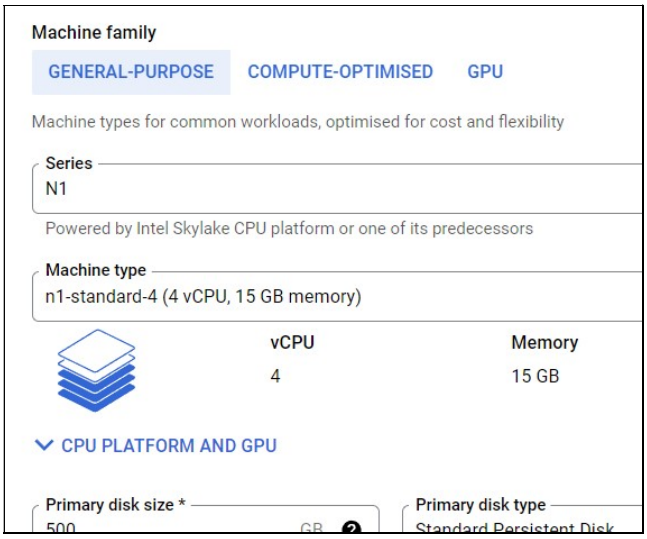


Figure 2: Master node

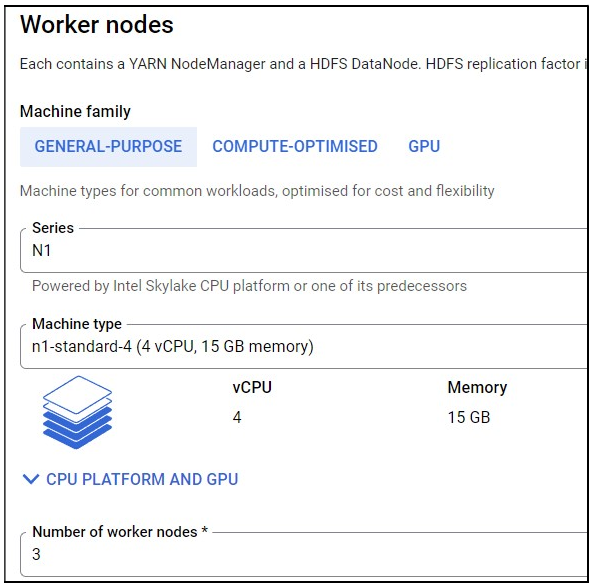


Figure 3: Worker Node

After the cluster has been created, we can verify the same from the Dataproc VM instances of our cluster.

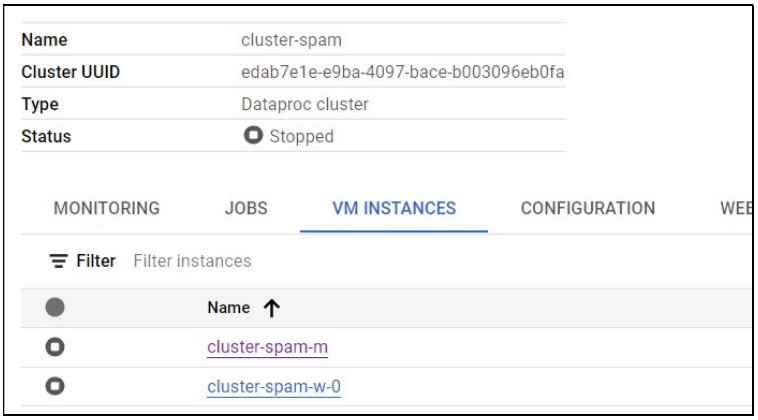


Figure 4: Cluster with 1 master, 3 worker

b. Environment check at the cluster.

In the dataproc cluster, Hadoop, pig, hive, and java was successfully installed. We have also created a directory of my user name under the '/user/' with the command: hdfs dfs -mkdir /<user_name>.

We have also checked the version of the same to verify whether the installations have been properly done.

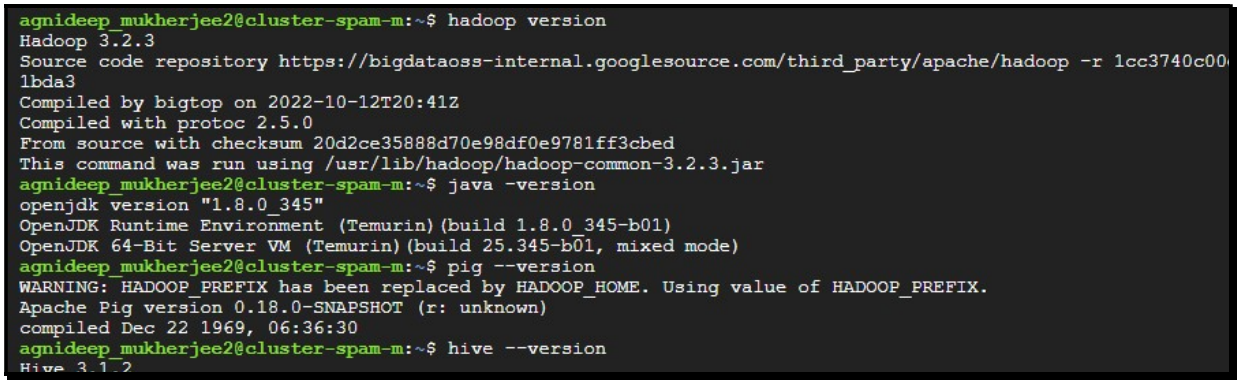


Figure 5: Version check for Hadoop, Java, Pig, Hive

I have checked whether the cluster has been set up properly by using the '~$ env' command.

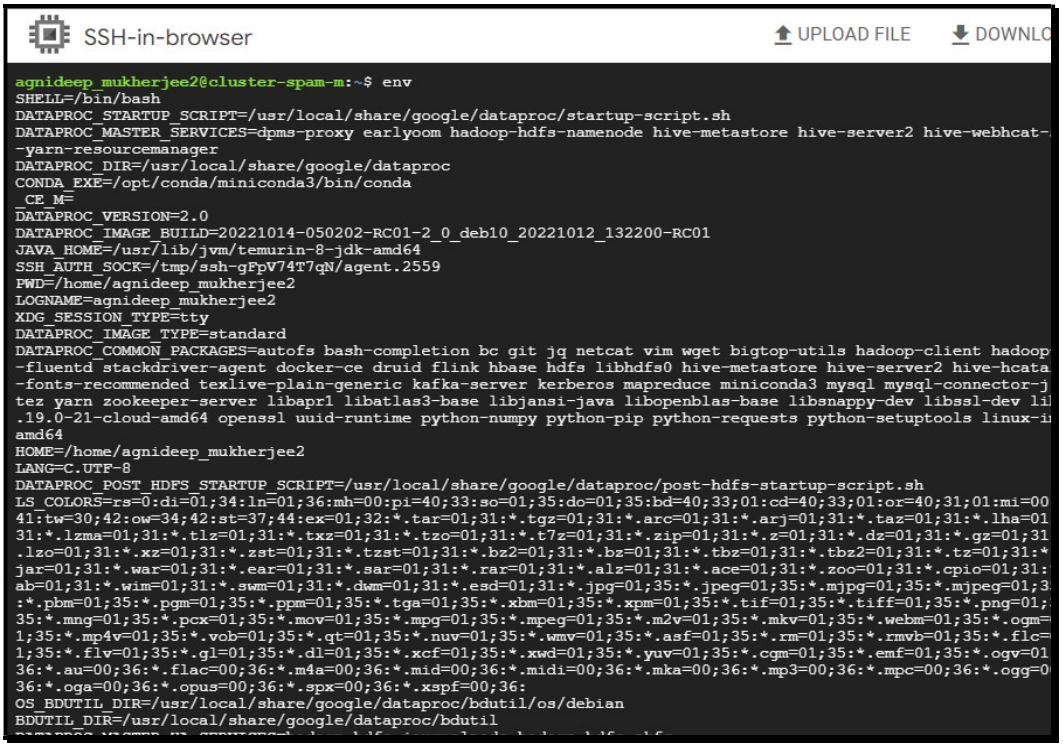


Figure 6: Environment check

I have also provided access to professor Manoj on my cloud system, such that my project can by verified.

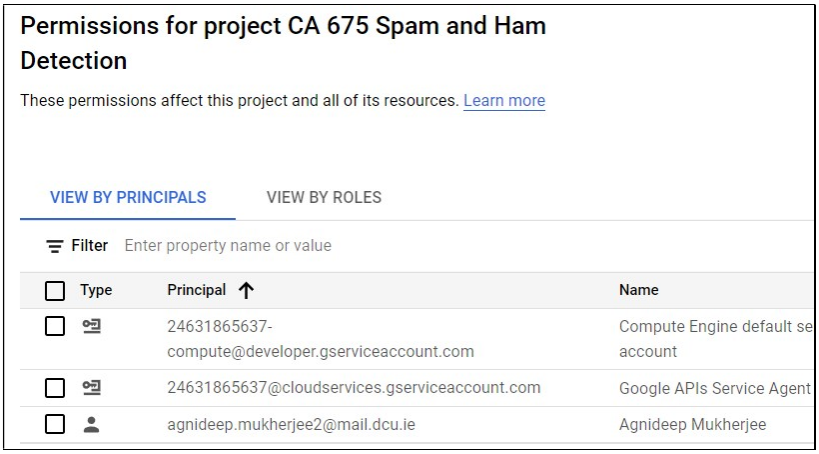


Figure 7: Access control

2) Choosing the dataset.

a. Data from Kaggle.com

Link: https://www.kaggle.com/datasets/naveedhn/amazon-product-review-spam-and-non-spam

I have chosen a fairly large and complex dataset from Kaggle.com about the spam and ham reviews that different user on Amazon provides under the 'Cell phone and accessories' category.

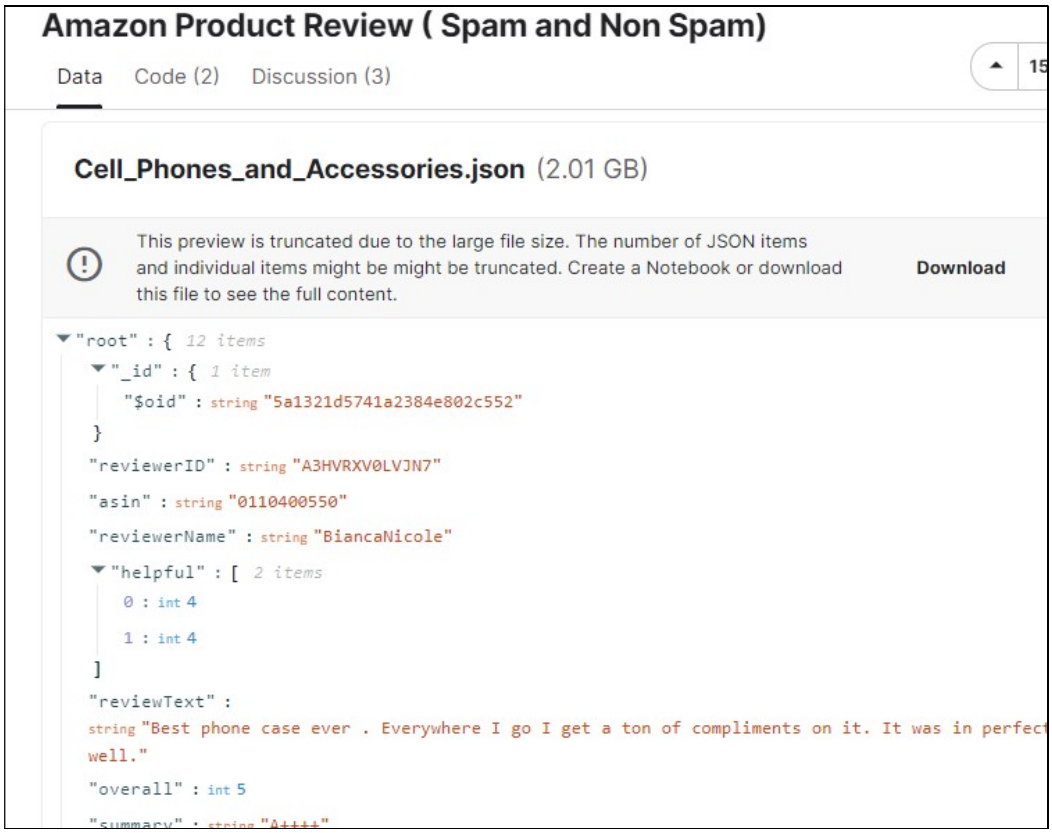


Figure 8: Dataset preview

The dataset is of 1.87 Gb in size and of type .JSON and has 12 attributes which makes it more complex, and interesting to apply analytics on.

b. Loading the data in the GCP bucket

I have loaded the data in the GCP bucket with the gsutil path as "*gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-spam-m/Cell_Phones_and_Accessories.json*"

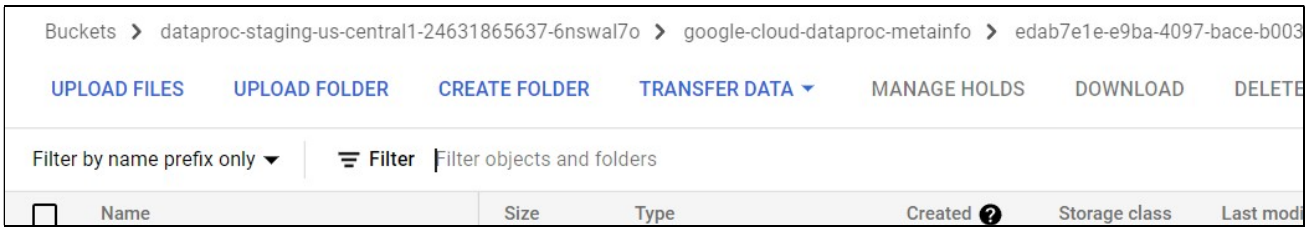


Figure 9: Dataset uploaded in Google Bucket

3) Cleaning the data

The data has been cleaned has been performed with the following commands in Apache Pig.

```
>>cleanedtable1= FOREACH tableframe GENERATE id AS id, reviewerID AS reviewerID, reviewerName AS reviewerName,
REPLACE(reviewText,'([^a-zA-Z\\s]+)','') AS reviewText, class AS class;
```

```
>> cleanedtable1_5= FOREACH tableframe GENERATE id AS id, reviewerID AS reviewerID, reviewerName AS reviewerName,
REPLACE(reviewText, '[\r\n]+',' ') AS reviewText, class AS class;

>>cleanedtable2= FOREACH cleanedtable1_5 GENERATE id AS id, reviewerID AS reviewerID, reviewerName AS reviewerName,
LOWER(reviewText) AS reviewText, class AS class;

>>cleanedtable3 = FILTER cleanedtable2 BY reviewerName != 'Amazon Customer' AND reviewerName != 'No Name';

>>cleanedtable4 = FILTER cleanedtable3 BY reviewerName is not null AND reviewerID is not null;

>>cleanedtable5 = FILTER cleanedtable4 by reviewText is not null;

>>cleanedtable = FILTER cleanedtable5 by class==0 OR class==1;

>>STORE cleanedtable INTO
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0
fa/cluster-spam-m/cleanedtable.json' USING JsonStorage();
```

In the first cleanedtable1 I used Regular Expression (Regex) to remove the special characters and numbers present in the review text. Also, I have restricted the unnecessary attributes from the original table, which made the new data more concise and useful for analysis.

In the cleanedtable1_5 I took the help of Regular Expression again to replace the new lines with spaces.

In cleanedtable2 I have loaded the review text by lowercasing the entire review text such that my analysis will be irrespective of the cases on the same word.

I have verified in cleanedtable3 that there are a fairly large amount of reviewers as 'Amazon Customer' and 'No Name', perhaps because there have been comments from Guest Accounts, so I am removing them to perform a better analysis.

In cleanedtable4 and cleanedtable5 I have removed all the rows where the reviewer name, id and text are null.

Finally since the 'class' is the attribute which classifies if the data is spam or ham, I have taken only those rows where the data has been already classified.

At the last I have stored the cleaned table in the cloud bucket such that when we go further on the analysis we will not need to perform the cleaning over and over again, we can directly load the data in the pig using the JsonLoader();

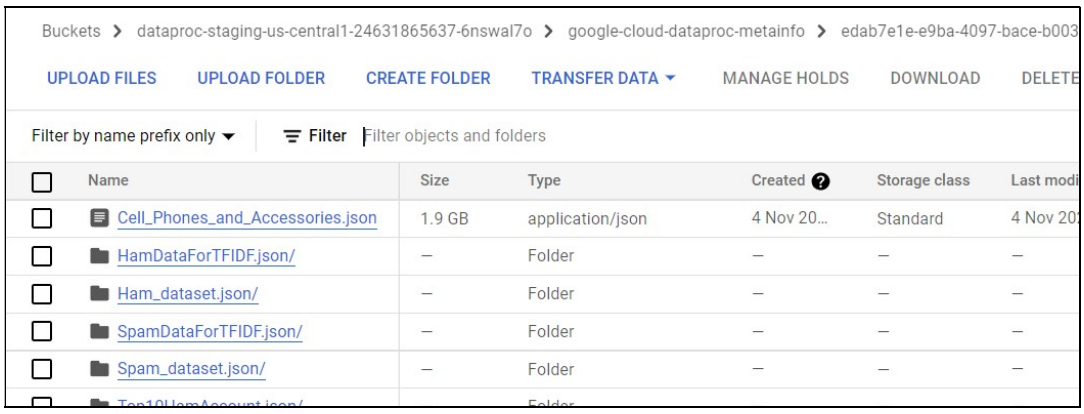


Figure 10: Cleaned Table uploaded in Google Bucket

4) Ham or Spam using Apache Pig

a. Differentiate Ham and Spam Dataset

```
>>filter_spam = FILTER cleanedtable BY class == 1;
>>spamgroup= GROUP filter_spam ALL;
>>spamcount= FOREACH spamgroup GENERATE COUNT (filter_spam.reviewerID);
>>dump spamcount;

>>filter_ham = FILTER cleanedtable BY class == 0;
>>hamgroup= GROUP filter_ham ALL;
>>hamcount= FOREACH hamgroup GENERATE COUNT (filter_ham.reviewerID);
>>dump hamcount;


>>STORE filter_spam INTO
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-spam-m/Spam_dataset.json' USING JsonStorage();

>>STORE filter_ham INTO
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-spam-m/Ham_dataset.json' USING JsonStorage();
```

I have split the spam and the ham dataset in Apache pig using the 'class' attribute present in the original dataset, which represents whether a data is a spam or ham. After the split, I stored them separately in two variables filter_spam and filter_ham variable. To check whether the split has been performed correctly I have grouped the dataset and with foreach loop I have taken the count of the 'reviewerID', which is unique.

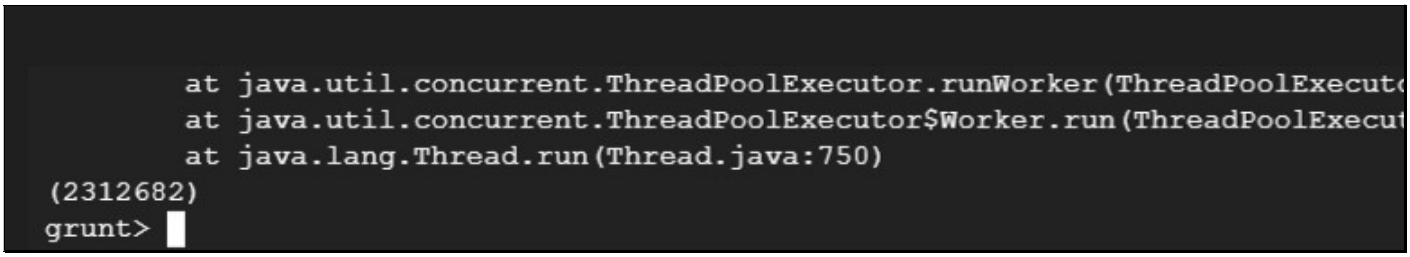


Figure 11: Total count of Spam Data

Figure 12: Total count of Ham Data

After that, I stored the 2 different datasets in the google cloud bucket, such that the data remains ready even after the instances are closed.

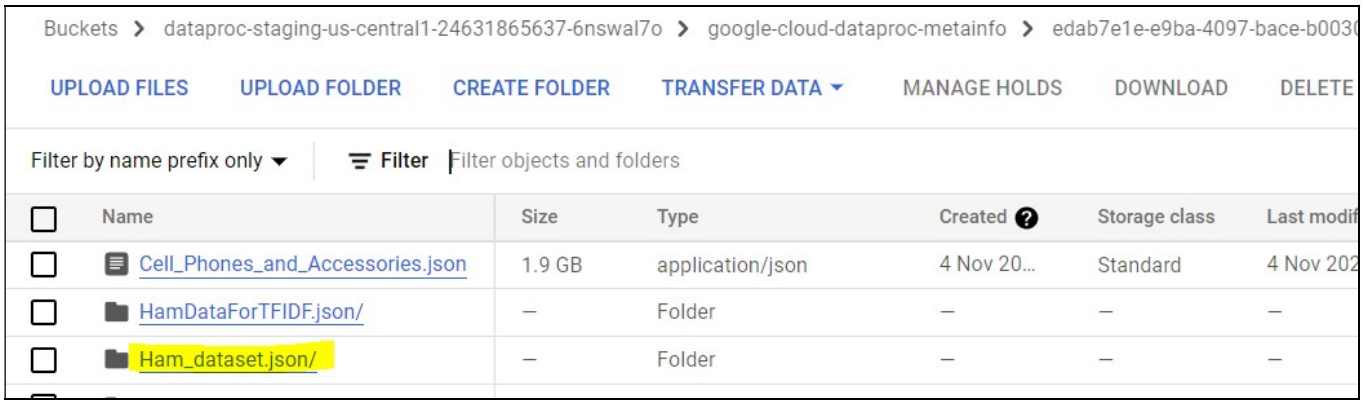


Figure 13: Ham and Spam Dataset stored in Google Bucket

b. Top 10 Spam Account

I have written the following code in Apache pig to find the top 10 Spam Account.

```
>>spamtest = LOAD
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-spam-m/Spam_dataset.json' USING JsonLoader('id:(oid:chararray), reviewerID:chararray, reviewerName:chararray, reviewText:chararray, summary:chararray, class:int');

>>spamReviewerGroup = GROUP spamtest by reviewerID;
>>spamReviewerCount = FOREACH spamReviewerGroup GENERATE FLATTEN(group) as reviewerID, COUNT($1) as count;
>>spamReviewerOrdered= ORDER spamReviewerCount by count DESC;
>>top10SpamReviewer= LIMIT spamReviewerOrdered 10;
>>SpamTotalData1= JOIN top10SpamReviewer by reviewerID, spamtest by reviewerID;
>>SpamNameAndId= FOREACH SpamTotalData1 GENERATE top10SpamReviewer::reviewerID as reviewerID, spamtest::reviewerName as reviewerName, top10SpamReviewer::count as count;
Dump SpamNameAndId;
>>SpamNameAndId1= DISTINCT SpamNameAndId;
>>Dump SpamNameAndId1;

>>STORE SpamNameAndId1 INTO
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-spam-m/Top10SpamAccount.json' USING JsonStorage();
```

At first, I loaded the spam data from the google cloud bucket, which we had previously saved. Furthermore, I created a new table frame by grouping the spam table with the reviewerId and adding the count of the rows in another column mentioned as ‘count’.
I have used ‘FLATTEN()’ operartor to un-nest the tuples which got created when I grouped spamtest by the reviewerId.
Following that I have sorted the table by descending order of the count because my aim is to find the Top 10 spam accounts and stored them in ‘spamReviewerOrdered’.
Now, the challenge is the table frame, spamReviewerOrdered does not have the name of the reviewer, it only possesses the reviewerId and the count. So, in order to overcome this, I have joined the table frame top10SpamReviewer and spamtest with reviewerId as the pivot.
After the join is successfully done, with the FOREACH loop I have iterated through the table and picked only those attributes which are important to me i.e Reviewer ID, Reviewer Name and Count.
In the variable SpamNameAndId1, we have taken only the distinct values and printed in the console.

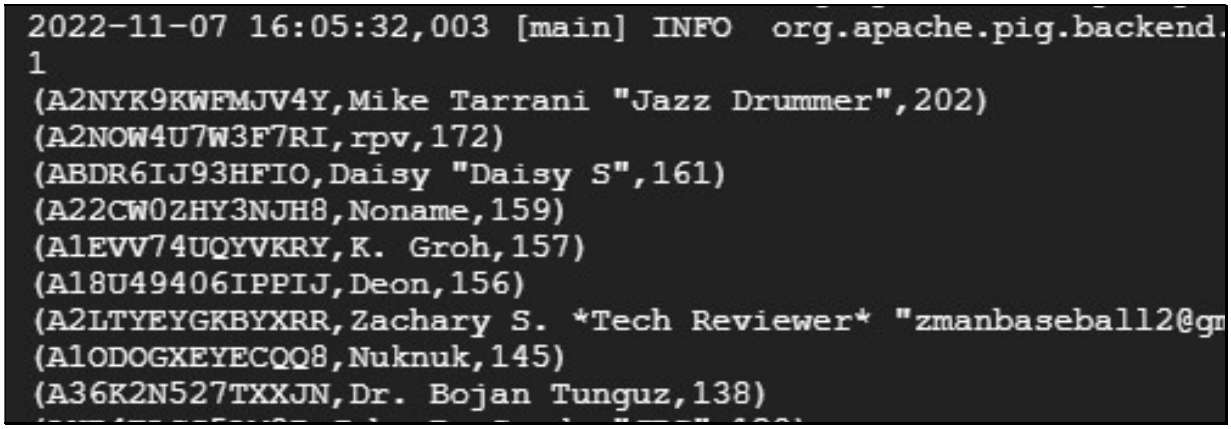


Figure 14: Top 10 Spam Accounts

a. Top 10 Ham Account

I have performed the steps with the same logic which I had previously performed while calculating the Top 10 Spam accounts.

The code is as follows.

```
>>hamtest = LOAD
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-ham-m/ham_dataset.json' USING JsonLoader('id:(oid:chararray), reviewerID:chararray, reviewerName:chararray, reviewText:chararray, summary:chararray, class:int');

>>hamReviewerGroup = GROUP hamtest by reviewerID;

>>hamReviewerCount = FOREACH hamReviewerGroup GENERATE FLATTEN(group) as reviewerID, COUNT($1) as count;

>>hamReviewerOrdered= ORDER hamReviewerCount by count DESC;

>>top10hamReviewer= LIMIT hamReviewerOrdered 10;

>>hamTotalData1= JOIN top10hamReviewer by reviewerID, hamtest by reviewerID;

>>hamNameAndId= FOREACH hamTotalData1 GENERATE top10hamReviewer::reviewerID as reviewerID, hamtest::reviewerName as reviewerName, top10hamReviewer::count as count;

>>hamNameAndId1= DISTINCT hamNameAndId;


>>STORE hamNameAndId1 INTO
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-spam-m/Top10hamAccount.json' USING JsonStorage();
```

```
2022-11-07 16:23:40,928 [main] INFO  org.apache.pig.backend
1
(A3LDPF5FMB782Z,Alan  Houston,40)
(A27IN57YAPDJ8S,DEEJAYNIGHT,26)
(A1VAUKYQDX4H2E,MrsBellaire,23)
(A34LXQ9YBD2IZT,Smokerg1rl,20)
(A28Q5CQAOGNUM3,Shelly-Ann,20)
(A1KRF81GTI2KKT,tropical girl,20)
(A3AYSYSLHU26U9,Amazon Deity,19)
(A2QRXQPHDMFCQV,SanjeevP "Bottom Line",19)
(A680RUE1FDO8B,Jerry Saperstein,19)
```

Figure 15: Top 10 Ham Accounts

I have saved both the top 10 Spam and Ham accounts in the google cloud bucket using JsonLoader()

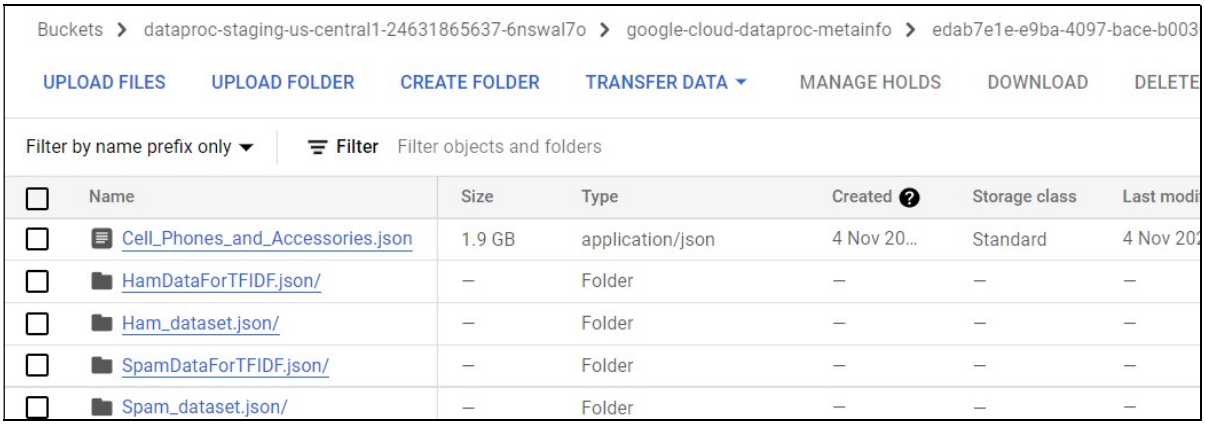


Figure 16: Top 10 Ham and Spam Accounts stored in Google Cloud Bucket

5) TF-IDF using Map Reduce

a. Top 10 Spam keywords for top 10 spam accounts.

The statistical technique known as Term Frequency - Inverse Document Frequency (TF-IDF) is frequently employed in information retrieval and natural language processing. It gauges a term's significance within a document in relation to a group of papers (i.e., relative to a corpus).

Formula-

- Tf=(Total number of times the term appears in a document/total number of terms in the document)
- Idf= Log(number of the document in the corpus/number of documents in the corpus containing the term)
- Tfidf= Tf*Idf

i. Data Preparation

In the data preparation step, we have taken the help of Apache Pig to load the spam data and find the top 10 spam reviewer (the logic has been previously explained when we calculated the top 10 spam reviewers).

In the variable SpamTotalData1 we have joined top10SpamReviewer and spamtest by reviewerId. After that from the resultant variable we have iterated the through the rows and only picked the attributes I require for the TF-IDF process i.e the reviewer name, reviewer id and the text and saved it the cloud storage.

So, the data which we possess right now has all the text comments by the top the spam accounts.

```
>>spamtest = LOAD
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-spam-m/Spam_dataset.json' USING JsonLoader('id:(oid:chararray), reviewerID:chararray, reviewerName:chararray, reviewText:chararray, summary:chararray, class:int');


>>spamReviewerGroup = GROUP spamtest by reviewerID;
>>spamReviewerCount = FOREACH spamReviewerGroup GENERATE FLATTEN(group) as reviewerID, COUNT($1) as count;
>>spamReviewerOrdered= ORDER spamReviewerCount by count DESC;
>>top10SpamReviewer= LIMIT spamReviewerOrdered 10;
>>SpamTotalData1= JOIN top10SpamReviewer by reviewerID, spamtest by reviewerID;
>>SpamTotalData= FOREACH SpamTotalData1 GENERATE top10SpamReviewer::reviewerID as reviewerID, spamtest::reviewerName as reviewerName, spamtest::reviewText as reviewText;

>>STORE SpamTotalData INTO
'gs://dataproc-staging-us-central1-24631865637-6nswal7o/google-cloud-dataproc-metainfo/edab7e1e-e9ba-4097-bace-b003096eb0fa/cluster-spam-m/SpamDataForTFIDF.json' USING JsonStorage();
```

The next challenge is to concatenate all the rows of different comments and store it in a text file which will be required while performing TFIDF on top 10 spam accounts.
To overcome this, we have taken the aid of python to concatenate the data of each row and create a text file for each reviewer. We have loaded the json file which we had stored in cloud: SpamDataForTFIDF in our python code. Using data model we have joined the reviewText for each reviewer and have written the data in text file.

ReviewConcatinator.py

C: > Users > 91847 > Downloads > TFIDF MapReduce > ReviewConcati

```
1   import json
2
3   with open('SpamDataForTFIDF.json','r') as f:
4       data = json.load(f)
5
6   data_model = {}
7   for obj in data:
8       reviewerID = obj.get('reviewerID')
9       if reviewerID in data_model:
10          data_model[reviewerID]+=[obj.get('reviewT
11      else:
12          data_model[reviewerID]=[]
13
14  for key,value in data_model.items():
15      review = ' '.join(value)
```

Figure 17: Python code to merge all texts for each reviewer

After this code has generated the 10 text files, I have stored them in the cloud bucket, such that they can be used further by the TF-IDF map reduce code. Now we have the all the data required to perform the further steps.

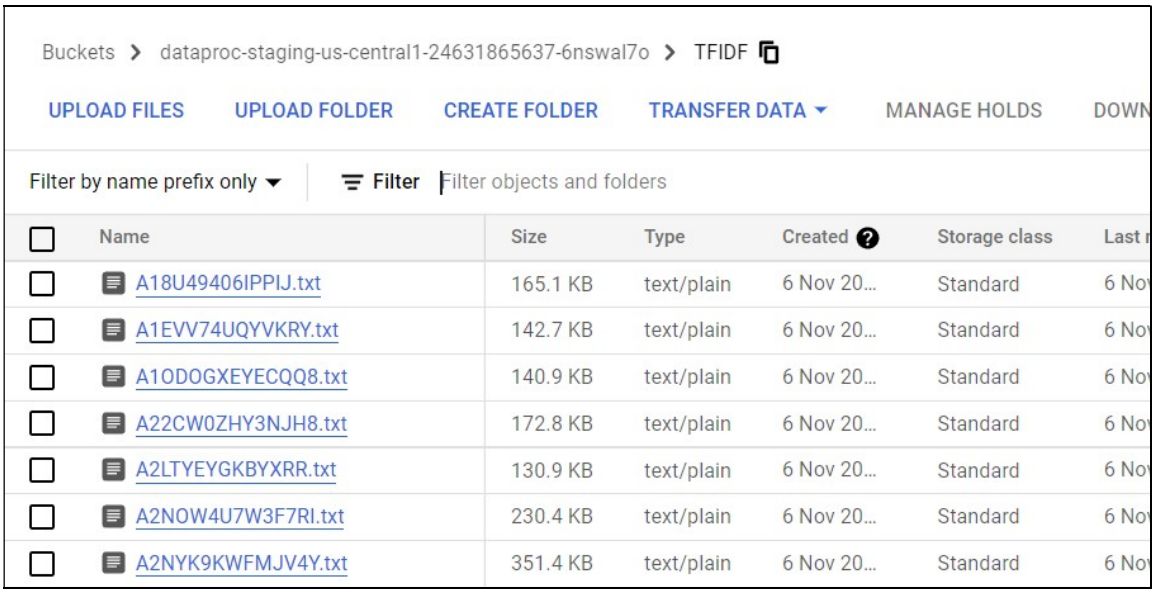


Figure 18: Text Files uploaded in Google Cloud Bucket

ii. Creating Mappers and Reducers

Python scripts are used in Hadoop to implement TFIDF. There are four mapper program files and three reduction program files in all. There are four stages to the implementation process. Three mappers and three reducers are used in the first phase. In the initial phase we remove the stopwords from the text and clean it further, following that we calculate the word count and the TF. The final phase calculates the TF-IDF and creates a single file containing the spam or ham word lists of 10 users and their TF-IDF scores using the fourth mapper.

One phase's output is used as an input for the following phase. Each text file is provided to the MapReduce.sh script as an input.

This method is applied to each of the ten text files, and the resulting text file for each of the ten text files gets merged at '/home/agnideep_mukherjee2/TFIDF/results/'.

I have also created run shell scripts to integrate the mappers and reducers and provide the input and output path of each phase.

C: > Users > 91847 > Downloads > TFIDF MapReduce > $ run-A1KRF81GTI2KKT.sh

```
hadoop jar /usr/lib/hadoop/hadoop-streaming.jar \
-file /home/agnideep_mukherjee2/TFIDF/mapper_1.py \
-mapper  'python3 mapper_1.py' \
-file /home/agnideep_mukherjee2/TFIDF/reducer_1.py \
-reducer 'python3 reducer_1.py' \
-input gs://dataproc-staging-us-central1-24631865637-6nswal7o/TFIDF_Ham/A1KRF81GTI2KKT.txt \
-output gs://dataproc-staging-us-central1-24631865637-6nswal7o/TFIDF_Ham/out1

hadoop jar /usr/lib/hadoop/hadoop-streaming.jar \
-file /home/agnideep_mukherjee2/TFIDF/mapper_2.py \
-mapper  'python3 mapper_2.py' \
-file /home/agnideep_mukherjee2/TFIDF/reducer_2.py \
-reducer 'python3 reducer_2.py' \
-input gs://dataproc-staging-us-central1-24631865637-6nswal7o/TFIDF_Ham/out1/ \
-output gs://dataproc-staging-us-central1-24631865637-6nswal7o/TFIDF_Ham/out2

hadoop jar /usr/lib/hadoop/hadoop-streaming.jar \
-file /home/agnideep_mukherjee2/TFIDF/mapper_3.py \
-mapper  'python3 mapper_3.py' \
-file /home/agnideep_mukherjee2/TFIDF/reducer_3.py \
-reducer 'python3 reducer_3.py' \
-input gs://dataproc-staging-us-central1-24631865637-6nswal7o/TFIDF_Ham/out2/ \
-output gs://dataproc-staging-us-central1-24631865637-6nswal7o/TFIDF_Ham/out3

hadoop jar /usr/lib/hadoop/hadoop-streaming.jar \
```

Figure 19: Example of a run shell script

I have upload the 4 mappers and 3 Reducers and Run scripts for the 10 spam text files generated in data processing phase in our Hadoop File system as

```
agnideep_mukherjee2@cluster-spam-m:~$ cd TFIDF
agnideep_mukherjee2@cluster-spam-m:~/TFIDF$ ls
mapper_1.py  reducer_1.py  run-A1KRF81GTI2KKT.sh  run-A2QRXQPHDMFCQV.sh  run-
mapper_2.py  reducer_2.py  run-A1VAUKYQDX4H2E.sh  run-A34LXQ9YBD2IZT.sh  run-
mapper_3.py  reducer_3.py  run-A27IN57YAPDJ8S.sh  run-A3AYSYSLHU26U9.sh  sort
mapper_4.py  results       run-A28Q5CQAOGNUM3.sh  run-A3LDPF5FMB782Z.sh
```

Figure 20: Files uploaded in Hadoop File System

I have also created a python script ‘sort_results.py’ for sorting the top 10 results and displaying them in an understandable tabular format.

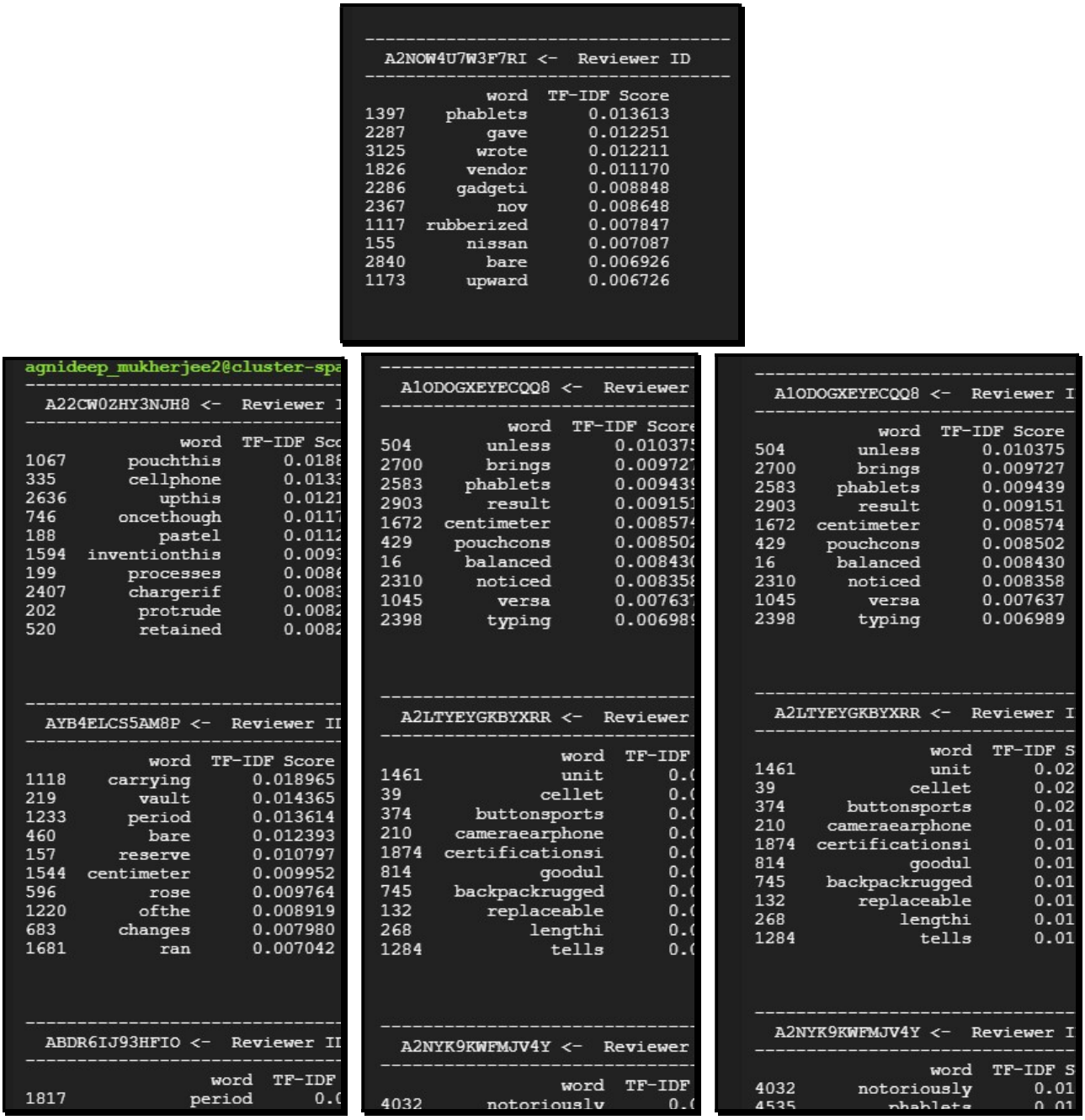
C: > Users > 91847 > Downloads > TFIDF MapReduce > sort_results_ham.py

```
import pandas as pd;
import glob;

folderPath = "/home/agnideep_mukherjee2/TFIDF_Spam/results";

allFiles = glob.glob(folderPath + "/*.txt");

for completeFilePath in allFiles:
    filename = completeFilePath.split('/tfidResults/')[1];
    print('-------------------------------------');
    print('    '+filename.split('.')[0]+' <- Reviewer ID');
    df = pd.read_csv(completeFilePath, sep="\t",header=None,names=["word","
    print('-------------------------------------');
    df["word"] = df["word"].str.split(" ",n=1,expand=True);
```

Figure 21: Python code to print all the TF-IDF results in tabular format

iii. Initiating the process through cloud ssh.

Now I shall run the shell scripts run-<reviewerID> one by one for 10 Spam account reviewers and Print the data in tabular format using sort_results.py



A2NOW4U7W3F7RI <- Reviewer ID

	word	TF-IDF Score
1397	phablets	0.013613
2287	gave	0.012251
3125	wrote	0.012211
1826	vendor	0.011170
2286	gadgeti	0.008848
2367	nov	0.008648
1117	rubberized	0.007847
155	nissan	0.007087
2840	bare	0.006926
1173	upward	0.006726

agnideep_mukherjee2@cluster-spa

A22CW0ZHY3NJH8 <- Reviewer I

	word	TF-IDF Sc
1067	pouchthis	0.0188
335	cellphone	0.0133
2636	upthis	0.0121
746	oncethough	0.0117
188	pastel	0.0112
1594	inventionthis	0.0093
199	processes	0.0086
2407	chargerif	0.0083
202	protrude	0.0082
520	retained	0.0082

AYB4ELCS5AM8P <- Reviewer II

	word	TF-IDF Score
1118	carrying	0.018965
219	vault	0.014365
1233	period	0.013614
460	bare	0.012393
157	reserve	0.010797
1544	centimeter	0.009952
596	rose	0.009764
1220	ofthe	0.008919
683	changes	0.007980
1681	ran	0.007042

ABDR6IJ93HFIO <- Reviewer II

	word	TF-IDF
1817	period	0.0

A1ODOGXEYECQQ8 <- Reviewer

	word	TF-IDF Score
504	unless	0.010375
2700	brings	0.009727
2583	phablets	0.009439
2903	result	0.009151
1672	centimeter	0.008574
429	pouchcons	0.008502
16	balanced	0.008430
2310	noticed	0.008358
1045	versa	0.007637
2398	typing	0.006989

A2LTYEYGKBYXRR <- Reviewer

	word	TF-IDF
1461	unit	0.0
39	cellet	0.0
374	buttonsports	0.0
210	cameraearphone	0.0
1874	certificationsi	0.0
814	goodul	0.0
745	backpackrugged	0.0
132	replaceable	0.0
268	lengthi	0.0
1284	tells	0.0

A2NYK9KWFMJV4Y <- Reviewer

	word	TF-IDF
4032	notoriously	0.0

A1ODOGXEYECQQ8 <- Reviewer I

	word	TF-IDF Score
504	unless	0.010375
2700	brings	0.009727
2583	phablets	0.009439
2903	result	0.009151
1672	centimeter	0.008574
429	pouchcons	0.008502
16	balanced	0.008430
2310	noticed	0.008358
1045	versa	0.007637
2398	typing	0.006989

A2LTYEYGKBYXRR <- Reviewer I

	word	TF-IDF S
1461	unit	0.02
39	cellet	0.02
374	buttonsports	0.02
210	cameraearphone	0.01
1874	certificationsi	0.01
814	goodul	0.01
745	backpackrugged	0.01
132	replaceable	0.01
268	lengthi	0.01
1284	tells	0.01

A2NYK9KWFMJV4Y <- Reviewer I

	word	TF-IDF S
4032	notoriously	0.01

Figure 22: TF-IDF results for Spam

b. TF-IDF of Top 10 ham keywords for top 10 ham accounts

I have followed the same steps and logic that I have previously applied while calculating TF-IDF for top 10 spam keywords in the top 10 spam accounts.

I am attaching the result for the same.

A64S8V75ITLFG <- Reviewer ID

	word	TF-IDF Score
743	badsomeone	0.045709
290	buyingsome	0.017680
142	load	0.014230
448	sorts	0.014230
103	capacitythese	0.009918
300	difference	0.009056
830	backthe	0.008193
43	noticed	0.008193
732	useful	0.007762
880	put	0.007331

agnideep_mukherjee2@cluster-spam-m:~/TF

A2QRXQPHDMFCQV <- Reviewer ID

	word	TF-IDF Score
56	versa	0.016893
597	between	0.014078
495	period	0.013609
69	canon	0.011732
272	unusable	0.011262
788	handy	0.010793
7	caller	0.010793
566	noise	0.009385
210	changing	0.008916
87	friendliness	0.008447

A3AYSYSLHU26U9 <- Reviewer ID

	word	TF-IDF Score
400	car	0.021107
340	interfered	0.017684
362	paisley	0.013691
303	until	0.009698
139	rubber	0.008557
712	touch	0.007986
560	available	0.006845
776	recognized	0.006275
623	together	0.005705
845	looking	0.005705

A3LDPF5FMB782Z <- Reviewer ID

	word	TF-IDF Score
404	phase	0.021192
593	five	0.020400
41	levels	0.014656
1018	amazing	0.013270
1069	moneythe	0.012082
48	menu	0.011487
576	carpetfor	0.009705
1175	major	0.009705
589	email	0.008913
1047	expanding	0.007328

A1KRF81GTI2KKT <- Reviewer ID

	word	TF-IDF Score
163	moment	0.010471
1155	twisted	0.009043
299	scored	0.006663
6	carrying	0.006663
447	distinct	0.006188
454	fingernail	0.005712
418	voltage	0.005712
1134	processthe	0.005712
663	each	0.005712
730	turn	0.005236

A1VAUKYQDX4H2E <- Reviewer ID

	word	TF-IDF Score
216	bubbles	0.051813
72	out	0.025907
178	protection	0.020725
50	products	0.018135
167	broke	0.015544
17	cut	0.015544
136	home	0.012953
80	thus	0.012953
123	around	0.012953
97	use	0.012953

A34LXQ9YBD2IZT <- Reviewer ID

	word	TF-IDF Score
113	bubbles	0.046200
149	once	0.028316
145	full	0.017884
192	one	0.014903
346	very	0.013413
374	under	0.013413
118	few	0.013413
90	looked	0.011923
268	sinkthe	0.010432
256	lightweight	0.010432

A28Q5CQAOGNUM3 <- Reviewer ID

	word	TF-IDF Score
274	pretty	0.025114
125	thought	0.015982
118	over	0.013699
231	car	0.013699
10	okayish	0.013699
168	phones	0.011416
216	once	0.011416
47	major	0.011416
221	purchased	0.011416
250	purchasing	0.011416

A27IN57YAPDJ8S <- Reviewer ID

	word	TF-IDF Score
72	peformance	0.037180
79	scratching	0.027885
243	goin	0.024787
398	bunch	0.024012
198	bubble	0.017041
54	donated	0.014717
34	problems	0.013943
177	picky	0.013168
70	mirror	0.010844
60	glue	0.010070

A680RUE1FDO8B <- Reviewer ID

	word	TF-IDF Score
163	moment	0.010471
1155	twisted	0.009043
299	scored	0.006663
6	carrying	0.006663
447	distinct	0.006188
454	fingernail	0.005712
418	voltage	0.005712
1134	processthe	0.005712
663	each	0.005712
730	turn	0.005236

Figure 23: TF-IDF for Ham Accounts

6) References

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