Scripts Execution

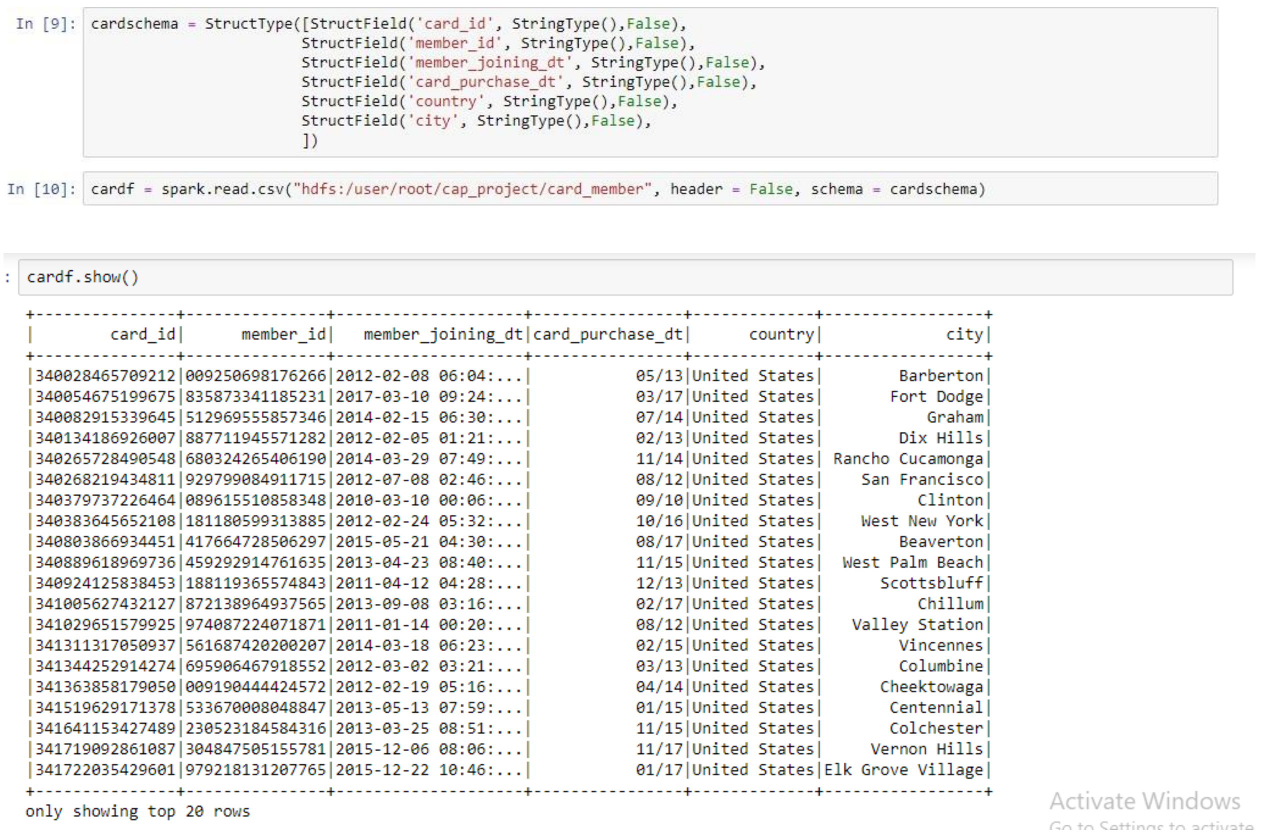
Explanation of the solution to the batch layer problem

1) Solution to the current problem statement is developed on Pyspark.
2) As 1st step, we need to load data which is present in RDS to HDFS using Sqoop import commands.

```
Table 1 (member_score)

sqoop import \
--connect jdbc:mysql://upgradawsrds1.cyaielc9bmnf.us-east-
1.rds.amazonaws.com/cred_financials_data \
--table member_score \
--username upgraduser --password upgraduser \
--target-dir /user/root/cap_project/member_score \
-m 1

Table 2 (card_member)

sqoop import \
--connect jdbc:mysql://upgradawsrds1.cyaielc9bmnf.us-east-
1.rds.amazonaws.com/cred_financials_data \
--table card_member \
--username upgraduser --password upgraduser \
--target-dir /user/root/cap_project/card_member \
-m 1
```

3) Load card_transactions.csv to HDFS after moving it to EC2-USER by using command
hadoop fs -copyFromLocal /home/ec2-user/card_transaction.csv
cap_project/card_transaction.csv
4) Now, connect to putty instance and load jupyter notebook from root user, by using command
jupyter notebook --port 7861 --allow-root

5) Open a new notebook and load a spark context.
6) Start reading all 3 files namely CARD_MEMBER, MEMBER_SCORE & CARD_TRANSACTIONS in Pyspark notebook into predefined file schemas.
7) Once read is successful, put a command df.show() to see data is read successfully.

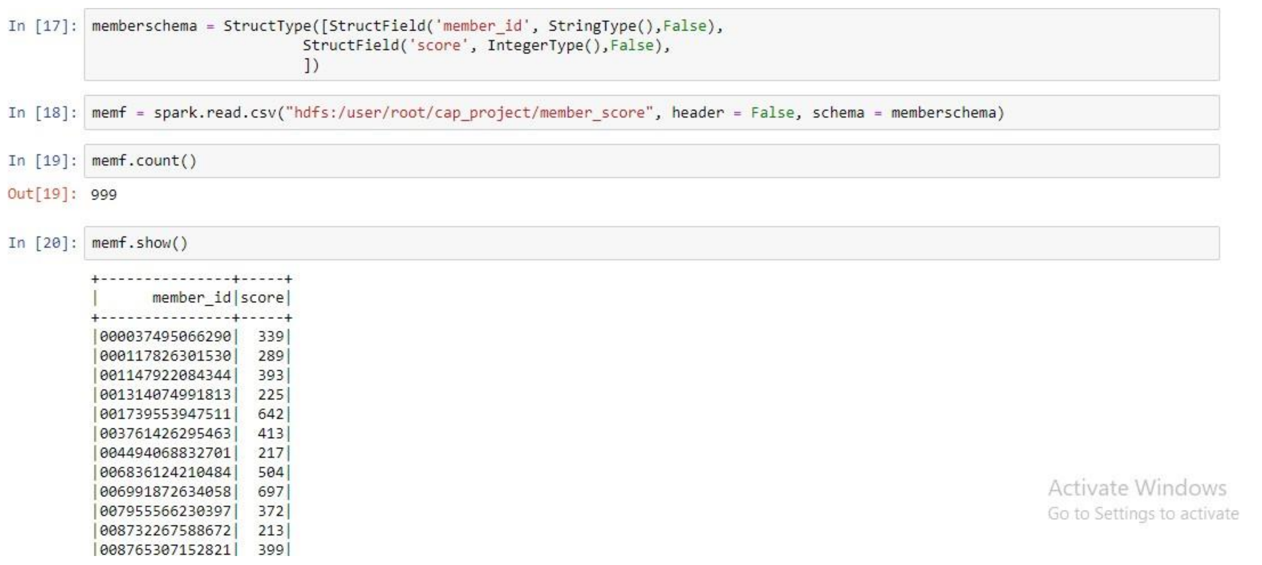


```
In [9]:  cardschema = StructType([StructField('card_id', StringType(),False),
                                 StructField('member_id', StringType(),False),
                                 StructField('member_joining_dt', StringType(),False),
                                 StructField('card_purchase_dt', StringType(),False),
                                 StructField('country', StringType(),False),
                                 StructField('city', StringType(),False),
                                 ])
```

```
In [10]: cardf = spark.read.csv("hdfs:/user/root/cap_project/card_member", header = False, schema = cardschema)
```

```
: cardf.show()
```

```
+---------------+---------------+--------------------+----------------+-------------+-----------------+
|        card_id|      member_id|   member_joining_dt|card_purchase_dt|      country|             city|
+---------------+---------------+--------------------+----------------+-------------+-----------------+
|340028465709212|009250698176266|2012-02-08 06:04:...|           05/13|United States|        Barberton|
|340054675199675|835873341185231|2017-03-10 09:24:...|           03/17|United States|       Fort Dodge|
|340082915339645|512969555857346|2014-02-15 06:30:...|           07/14|United States|           Graham|
|340134186926007|887711945571282|2012-02-05 01:21:...|           02/13|United States|        Dix Hills|
|340265728490548|680324265406190|2014-03-29 07:49:...|           11/14|United States| Rancho Cucamonga|
|340268219434811|929799084911715|2012-07-08 02:46:...|           08/12|United States|    San Francisco|
|340379737226464|089615510858348|2010-03-10 00:06:...|           09/10|United States|          Clinton|
|340383645652108|181180599313885|2012-02-24 05:32:...|           10/16|United States|    West New York|
|340803866934451|417664728506297|2015-05-21 04:30:...|           08/17|United States|        Beaverton|
|340889618969736|459292914761635|2013-04-23 08:40:...|           11/15|United States|  West Palm Beach|
|340924125838453|188119365574843|2011-04-12 04:28:...|           12/13|United States|      Scottsbluff|
|341005627432127|872138964937565|2013-09-08 03:16:...|           02/17|United States|          Chillum|
|341029651579925|974087224071871|2011-01-14 00:20:...|           08/12|United States|   Valley Station|
|341311317050937|561687420200207|2014-03-18 06:23:...|           02/15|United States|        Vincennes|
|341344252914274|695906467918552|2012-03-02 03:21:...|           03/13|United States|         Columbine|
|341363858179050|009190444424572|2012-02-19 05:16:...|           04/14|United States|      Cheektowaga|
|341519629171378|533670008048847|2013-05-13 07:59:...|           01/15|United States|        Centennial|
|341641153427489|230523184584316|2013-03-25 08:51:...|           11/15|United States|       Colchester|
|341719092861087|304847505155781|2015-12-06 08:06:...|           11/17|United States|     Vernon Hills|
|341722035429601|979218131207765|2015-12-22 10:46:...|           01/17|United States|Elk Grove Village|
+---------------+---------------+--------------------+----------------+-------------+-----------------+
only showing top 20 rows
```



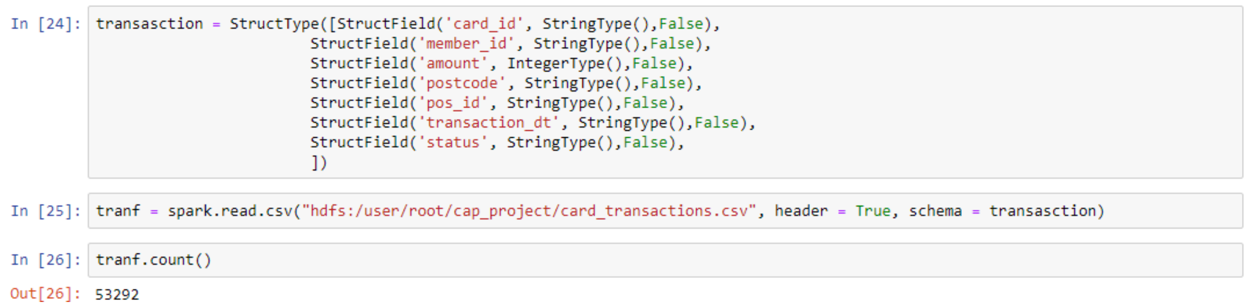
```
In [17]: memberschema = StructType([StructField('member_id', StringType(),False),
                                   StructField('score', IntegerType(),False),
                                   ])
```

```
In [18]: memf = spark.read.csv("hdfs:/user/root/cap_project/member_score", header = False, schema = memberschema)
```

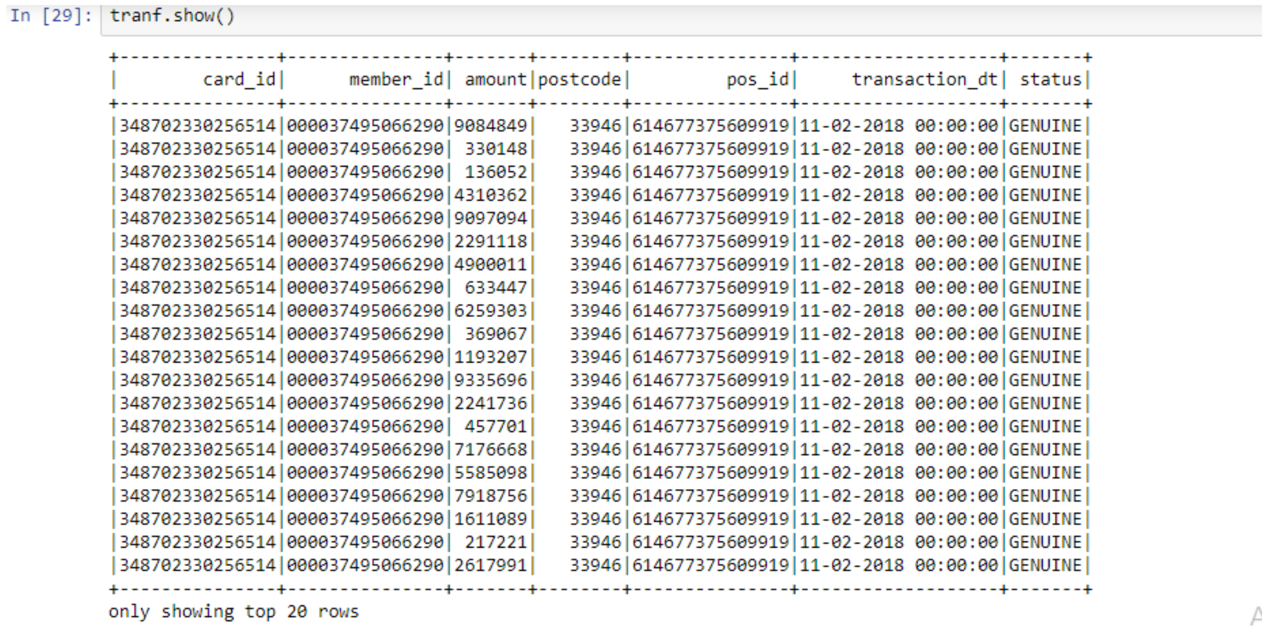
```
In [19]: memf.count()
Out[19]: 999
```

```
In [20]: memf.show()
```

```
+---------------+-----+
|      member_id|score|
+---------------+-----+
|000037495066290|  339|
|000117826301530|  289|
|001147922084344|  393|
|001314074991813|  225|
|001739553947511|  642|
|003761426295463|  413|
|004494068832701|  217|
|006836124210484|  504|
|006991872634058|  697|
|007955566230397|  372|
|008732267588672|  213|
|008765307152821|  399|
```

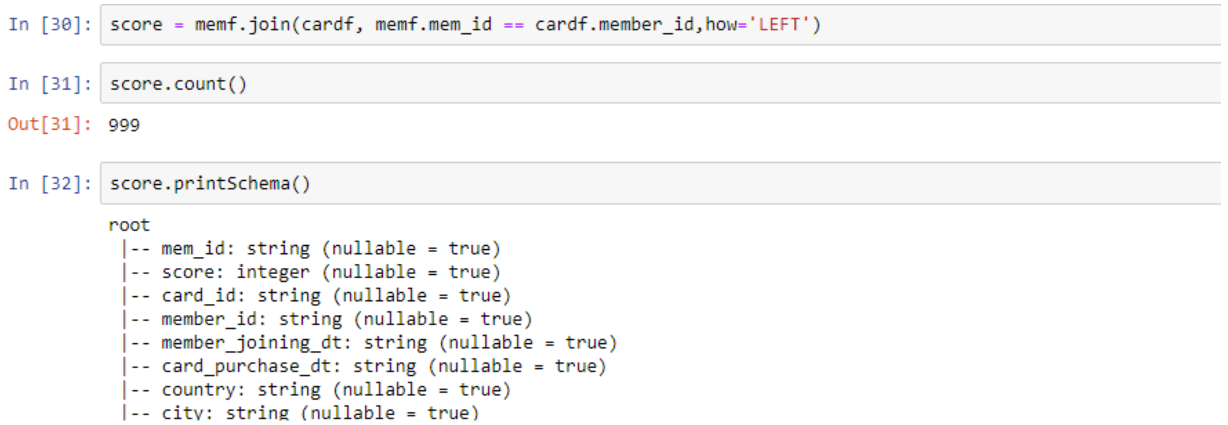


```
In [24]: transasction = StructType([StructField('card_id', StringType(),False),
                         StructField('member_id', StringType(),False),
                         StructField('amount', IntegerType(),False),
                         StructField('postcode', StringType(),False),
                         StructField('pos_id', StringType(),False),
                         StructField('transaction_dt', StringType(),False),
                         StructField('status', StringType(),False),
                         ])

In [25]: tranf = spark.read.csv("hdfs:/user/root/cap_project/card_transactions.csv", header = True, schema = transasction)

In [26]: tranf.count()

Out[26]: 53292
```



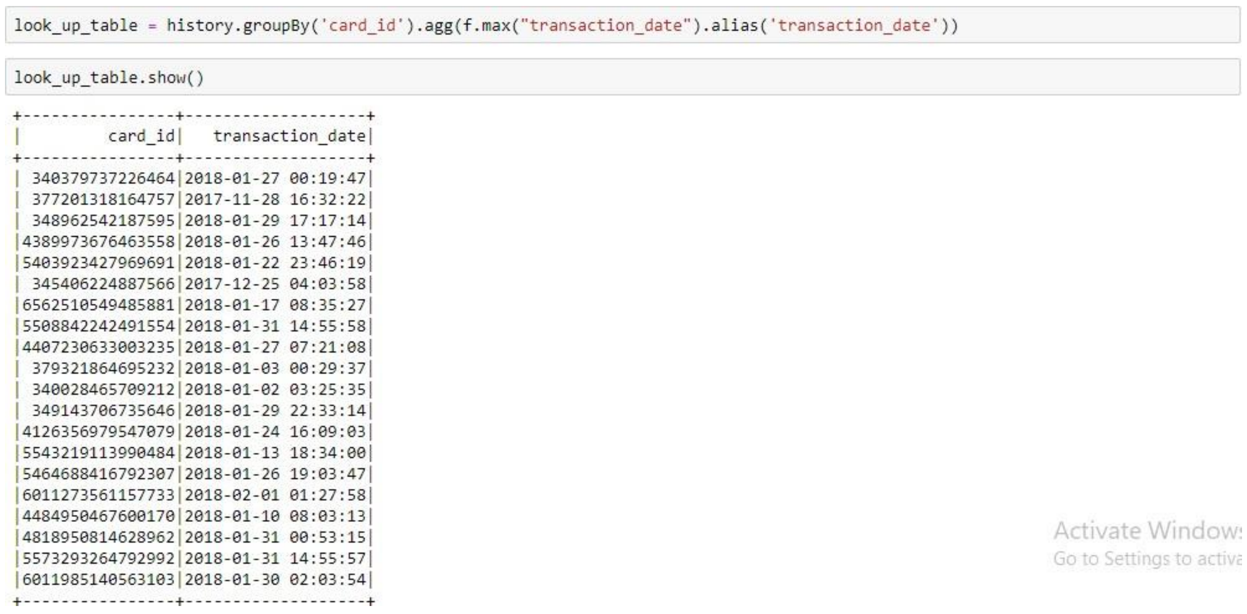
```
In [29]: tranf.show()

+---------------+---------------+-------+--------+--------------+-------------------+-------+
|        card_id|      member_id| amount|postcode|        pos_id|     transaction_dt| status|
+---------------+---------------+-------+--------+--------------+-------------------+-------+
|348702330256514|000037495066290|9084849|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290| 330148|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290| 136052|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|4310362|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|9097094|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|2291118|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|4900011|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290| 633447|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|6259303|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290| 369067|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|1193207|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|9335696|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|2241736|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290| 457701|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|7176668|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|5585098|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|7918756|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|1611089|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290| 217221|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
|348702330256514|000037495066290|2617991|   33946|614677375609919|11-02-2018 00:00:00|GENUINE|
+---------------+---------------+-------+--------+--------------+-------------------+-------+
only showing top 20 rows
```

8) Once we load all input data, next we need to join all these files to form an amalgam and extract only relevant fields out of them that are need for our analysis.
9) First join card_member & member_score dataframes and slide credit score into card_member by using member_id field as join key



```
In [30]: score = memf.join(cardf, memf.mem_id == cardf.member_id,how='LEFT')

In [31]: score.count()

Out[31]: 999

In [32]: score.printSchema()

root
 |-- mem_id: string (nullable = true)
 |-- score: integer (nullable = true)
 |-- card_id: string (nullable = true)
 |-- member_id: string (nullable = true)
 |-- member_joining_dt: string (nullable = true)
 |-- card_purchase_dt: string (nullable = true)
 |-- country: string (nullable = true)
 |-- city: string (nullable = true)
```

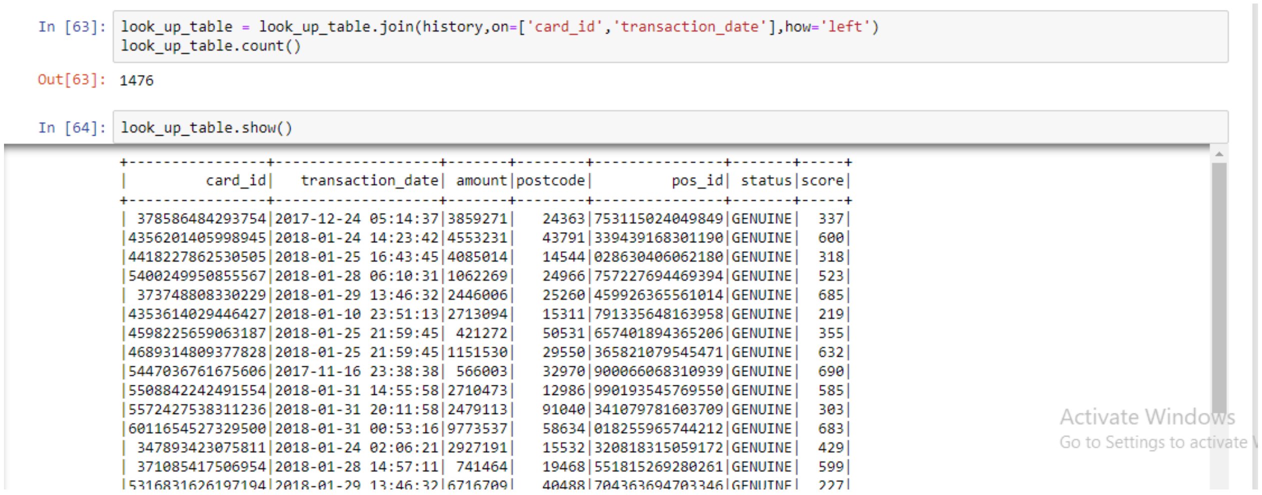
10) With the fresh dataframe, use member ID once again as common key and join with card_transaction.csv to load postcode, pos_id, status, amount & transaction date fields from history transactions.
11) To arrive at derived columns like latest_transaction date, group the combined dataframe on card_id such that all transactions on same card id collate and get max(transaction date). Append this column to combined dataframe.



```
look_up_table = history.groupBy('card_id').agg(f.max("transaction_date").alias('transaction_date'))
```

```
look_up_table.show()
```

```
+----------------+-------------------+
|         card_id|   transaction_date|
+----------------+-------------------+
| 340379737226464|2018-01-27 00:19:47|
| 377201318164757|2017-11-28 16:32:22|
| 348962542187595|2018-01-29 17:17:14|
|4389973676463558|2018-01-26 13:47:46|
|5403923427969691|2018-01-22 23:46:19|
| 345406224887566|2017-12-25 04:03:58|
|6562510549485881|2018-01-17 08:35:27|
|5508842242491554|2018-01-31 14:55:58|
|4407230633003235|2018-01-27 07:21:08|
| 379321864695232|2018-01-03 00:29:37|
| 340028465709212|2018-01-02 03:25:35|
| 349143706735646|2018-01-29 22:33:14|
|4126356979547079|2018-01-24 16:09:03|
|5543219113990484|2018-01-13 18:34:00|
|5464688416792307|2018-01-26 19:03:47|
|6011273561157733|2018-02-01 01:27:58|
|4484950467600170|2018-01-10 08:03:13|
|4818950814628962|2018-01-31 00:53:15|
|5573293264792992|2018-01-31 14:55:57|
|6011985140563103|2018-01-30 02:03:54|
+----------------+-------------------+
```

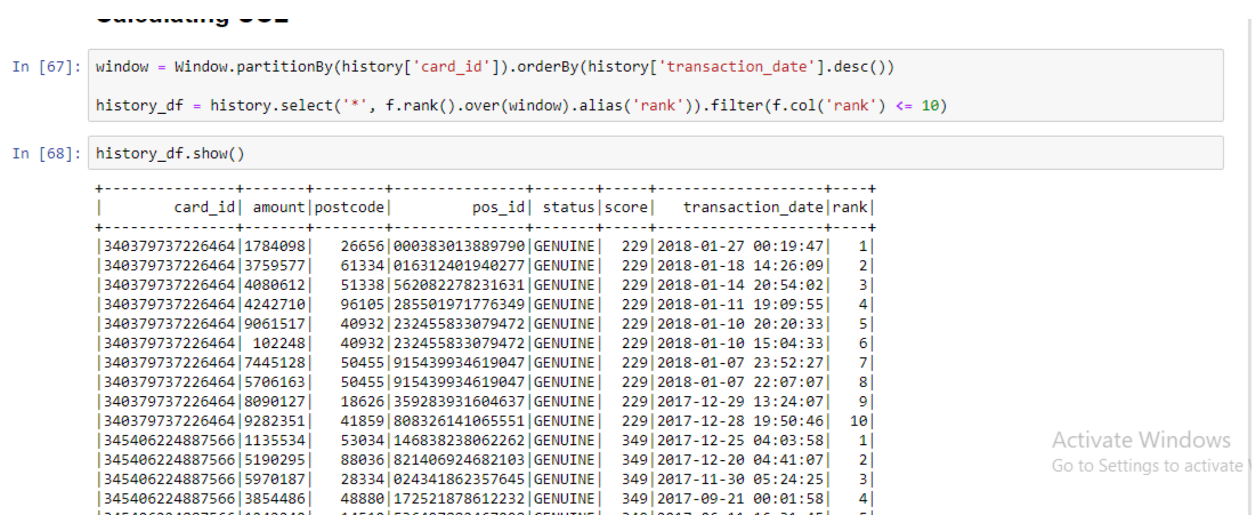


```
In [63]: look_up_table = look_up_table.join(history,on=['card_id','transaction_date'],how='left')
         look_up_table.count()

Out[63]: 1476

In [64]: look_up_table.show()
```

```
+----------------+-------------------+-------+--------+---------------+-------+-----+
|         card_id|   transaction_date| amount|postcode|         pos_id| status|score|
+----------------+-------------------+-------+--------+---------------+-------+-----+
| 378586484293754|2017-12-24 05:14:37|3859271|   24363|753115024049849|GENUINE|  337|
|4356201405998945|2018-01-24 14:23:42|4553231|   43791|339439168301190|GENUINE|  600|
|4418227862530505|2018-01-25 16:43:45|4085014|   14544|028630406062180|GENUINE|  318|
|5400249950855567|2018-01-28 06:10:31|1062269|   24966|757227694469394|GENUINE|  523|
| 373748808330229|2018-01-29 13:46:32|2446006|   25260|459926365561014|GENUINE|  685|
|4353614029446427|2018-01-10 23:51:13|2713094|   15311|791335648163958|GENUINE|  219|
|4598225659063187|2018-01-25 21:59:45| 421272|   50531|657401894365206|GENUINE|  355|
|4689314809377828|2018-01-25 21:59:45|1151530|   29550|365821079545471|GENUINE|  632|
|5447036761675606|2017-11-16 23:38:38| 566003|   32970|900066068310939|GENUINE|  690|
|5508842242491554|2018-01-31 14:55:58|2710473|   12986|990193545769550|GENUINE|  585|
|5572427538311236|2018-01-31 20:11:58|2479113|   91040|341079781603709|GENUINE|  303|
|6011654527329500|2018-01-31 00:53:16|9773537|   58634|018255965744212|GENUINE|  683|
| 347893423075811|2018-01-24 02:06:21|2927191|   15532|320818315059172|GENUINE|  429|
| 371085417506954|2018-01-28 14:57:11| 741464|   19468|551815269280261|GENUINE|  599|
|5316831626197194|2018-01-29 13:46:32|6716709|   40488|704363694703346|GENUINE|  227|
```

12) Now, calculate the UCL value that mainly revolves around "amount" field. We all know UCL can be calculated as moving average + 3 *(standard deviation). Hence we open a window frame where we group input dataframe rows on card_id and order by transaction date to get all transactions on card in chronological order.
13) Now, once you group & order by transactions rank these chronological transactions starting from 1 till go on.
14) Pick rows only whose rank is less than 10, by which we select moving average of top 10 latest transactions done on card_id.

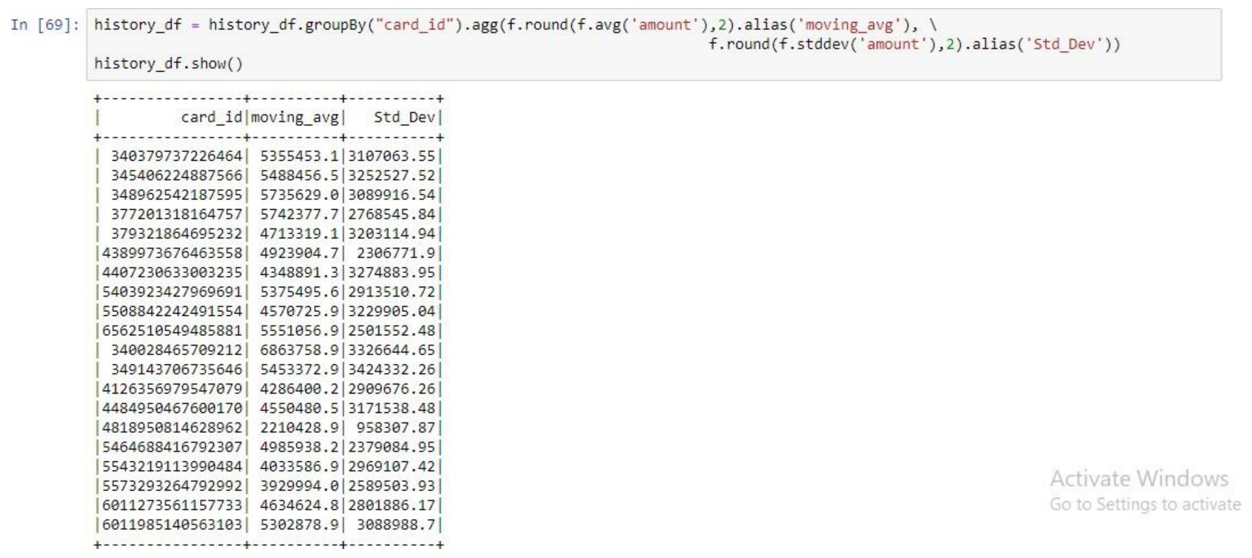
15) Import SQL functions library in pyspark and perform avg() function on top 10 rows of grouped card_id.
16) Similarly, perform stddev() to derive standard deviation on these top 10 rows selected by rank.
17) Perform computation as per formula given to deduce UCL value and append this to original dataframe obtained at step 11.



```
In [67]: window = Window.partitionBy(history['card_id']).orderBy(history['transaction_date'].desc())

         history_df = history.select('*', f.rank().over(window).alias('rank')).filter(f.col('rank') <= 10)
```

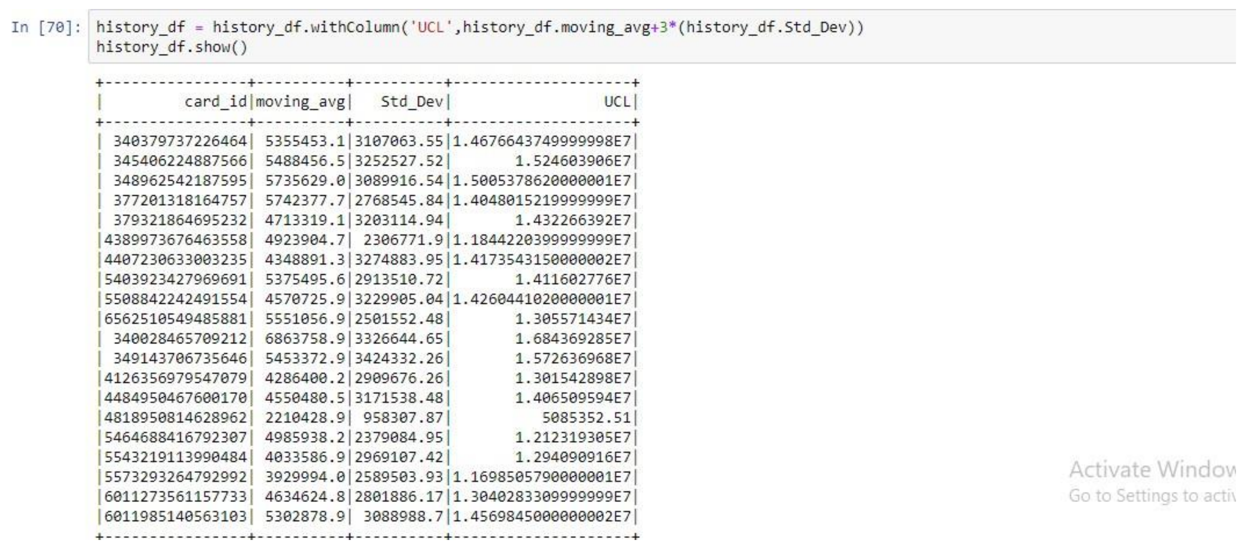
```
In [68]: history_df.show()
```

```
+---------------+-------+--------+---------------+-------+-----+-------------------+----+
|        card_id| amount|postcode|         pos_id| status|score|   transaction_date|rank|
+---------------+-------+--------+---------------+-------+-----+-------------------+----+
|340379737226464|1784098|   26656|000383013889790|GENUINE|  229|2018-01-27 00:19:47|   1|
|340379737226464|3759577|   61334|016312401940277|GENUINE|  229|2018-01-18 14:26:09|   2|
|340379737226464|4080612|   51338|562082278231631|GENUINE|  229|2018-01-14 20:54:02|   3|
|340379737226464|4242710|   96105|285501971776349|GENUINE|  229|2018-01-11 19:09:55|   4|
|340379737226464|9061517|   40932|232455833079472|GENUINE|  229|2018-01-10 20:20:33|   5|
|340379737226464| 102248|   40932|232455833079472|GENUINE|  229|2018-01-10 15:04:33|   6|
|340379737226464|7445128|   50455|915439934619047|GENUINE|  229|2018-01-07 23:52:27|   7|
|340379737226464|5706163|   50455|915439934619047|GENUINE|  229|2018-01-07 22:07:07|   8|
|340379737226464|8090127|   18626|359283931604637|GENUINE|  229|2017-12-29 13:24:07|   9|
|340379737226464|9282351|   41859|808326141065551|GENUINE|  229|2017-12-28 19:50:46|  10|
|345406224887566|1135534|   53034|146838238062262|GENUINE|  349|2017-12-25 04:03:58|   1|
|345406224887566|5190295|   88036|821406924682103|GENUINE|  349|2017-12-20 04:41:07|   2|
|345406224887566|5970187|   28334|024341862357645|GENUINE|  349|2017-11-30 05:24:25|   3|
|345406224887566|3854486|   48880|172521878612232|GENUINE|  349|2017-09-21 00:01:58|   4|
```



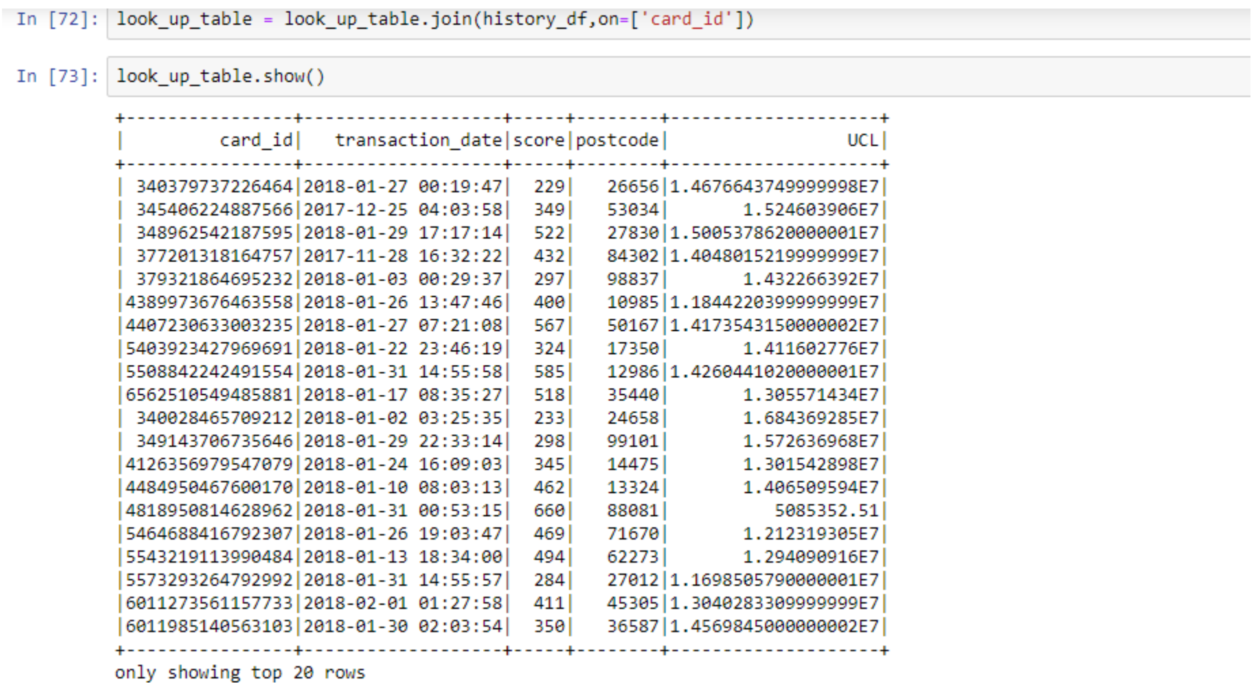
```
In [69]: history_df = history_df.groupBy("card_id").agg(f.round(f.avg('amount'),2).alias('moving_avg'), \
                                                          f.round(f.stddev('amount'),2).alias('Std_Dev'))
         history_df.show()
```

```
+----------------+----------+----------+
|         card_id|moving_avg|   Std_Dev|
+----------------+----------+----------+
| 340379737226464| 5355453.1|3107063.55|
| 345406224887566| 5488456.5|3252527.52|
| 348962542187595| 5735629.0|3089916.54|
| 377201318164757| 5742377.7|2768545.84|
| 379321864695232| 4713319.1|3203114.94|
|4389973676463558| 4923904.7| 2306771.9|
|4407230633003235| 4348891.3|3274883.95|
|5403923427969691| 5375495.6|2913510.72|
|5508842242491554| 4570725.9|3229905.04|
|6562510549485881| 5551056.9|2501552.48|
| 340028465709212| 6863758.9|3326644.65|
| 349143706735646| 5453372.9|3424332.26|
|4126356979547079| 4286400.2|2909676.26|
|4484950467600170| 4550480.5|3171538.48|
|4818950814628962| 2210428.9| 958307.87|
|5464688416792307| 4985938.2|2379084.95|
|5543219113990484| 4033586.9|2969107.42|
|5573293264792992| 3929994.0|2589503.93|
|6011273561157733| 4634624.8|2801886.17|
|6011985140563103| 5302878.9| 3088988.7|
+----------------+----------+----------+
```



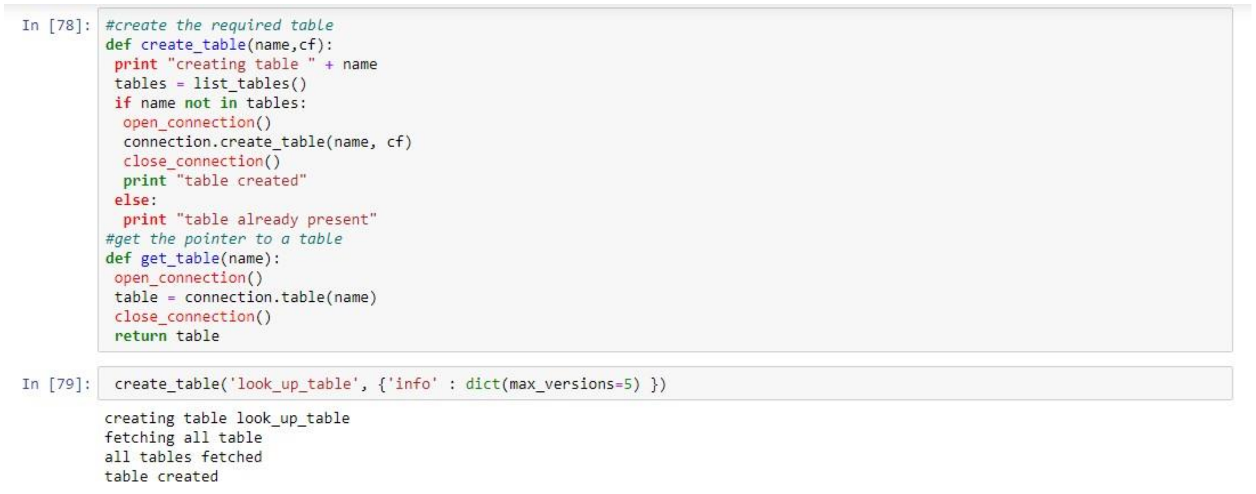
```
In [70]: history_df = history_df.withColumn('UCL',history_df.moving_avg+3*(history_df.Std_Dev))
         history_df.show()

+----------------+----------+----------+--------------------+
|         card_id|moving_avg|   Std_Dev|                 UCL|
+----------------+----------+----------+--------------------+
| 340379737226464| 5355453.1|3107063.55|1.4676643749999998E7|
| 345406224887566| 5488456.5|3252527.52|        1.524603906E7|
| 348962542187595| 5735629.0|3089916.54|1.5005378620000001E7|
| 377201318164757| 5742377.7|2768545.84|1.4048015219999999E7|
| 379321864695232| 4713319.1|3203114.94|        1.432266392E7|
|4389973676463558| 4923904.7| 2306771.9|1.1844220399999999E7|
|4407230633003235| 4348891.3|3274883.95|1.4173543150000002E7|
|5403923427969691| 5375495.6|2913510.72|        1.411602776E7|
|5508842242491554| 4570725.9|3229905.04|1.4260441020000001E7|
|6562510549485881| 5551056.9|2501552.48|        1.305571434E7|
| 340028465709212| 6863758.9|3326644.65|        1.684369285E7|
| 349143706735646| 5453372.9|3424332.26|        1.572636968E7|
|4126356979547079| 4286400.2|2909676.26|        1.301542898E7|
|4484950467600170| 4550480.5|3171538.48|        1.406509594E7|
|4818950814628962| 2210428.9| 958307.87|          5085352.51|
|5464688416792307| 4985938.2|2379084.95|        1.212319305E7|
|5543219113990484| 4033586.9|2969107.42|        1.294090916E7|
|5573293264792992| 3929994.0|2589503.93|1.1698505790000001E7|
|6011273561157733| 4634624.8|2801886.17|1.3040283309999999E7|
|6011985140563103| 5302878.9| 3088988.7|1.4569845000000002E7|
+----------------+----------+----------+--------------------+
```

18) Final dataset looks like –

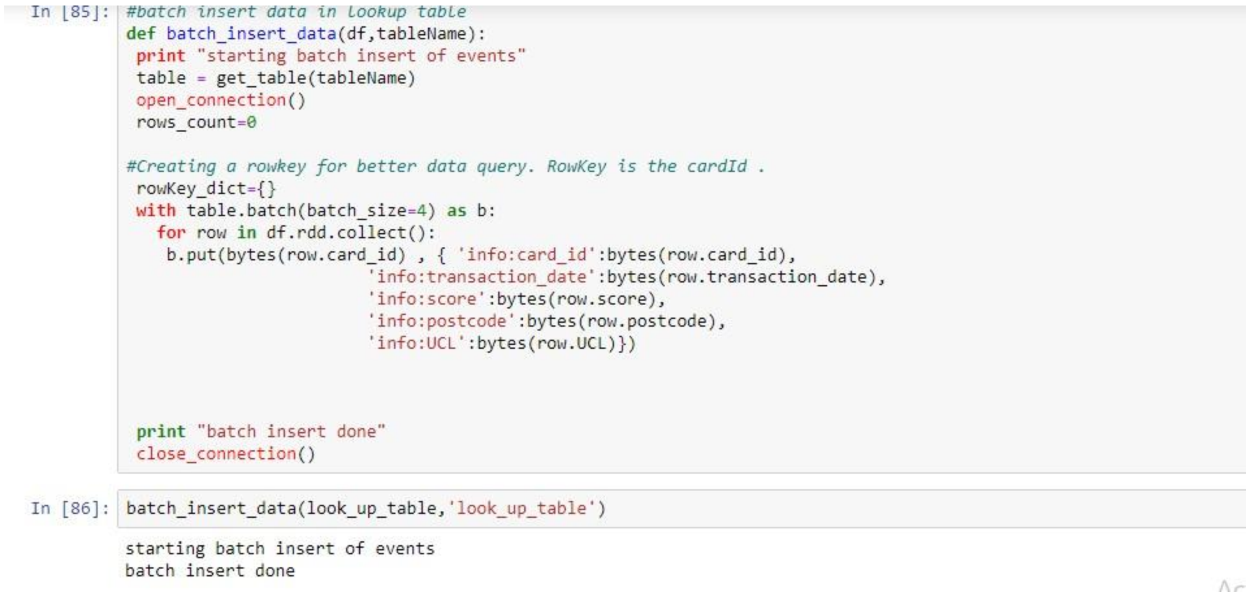


```
In [72]: look_up_table = look_up_table.join(history_df,on=['card_id'])

In [73]: look_up_table.show()

+----------------+-------------------+-----+--------+--------------------+
|         card_id|   transaction_date|score|postcode|                 UCL|
+----------------+-------------------+-----+--------+--------------------+
| 340379737226464|2018-01-27 00:19:47|  229|   26656|1.4676643749999998E7|
| 345406224887566|2017-12-25 04:03:58|  349|   53034|        1.524603906E7|
| 348962542187595|2018-01-29 17:17:14|  522|   27830|1.5005378620000001E7|
| 377201318164757|2017-11-28 16:32:22|  432|   84302|1.4048015219999999E7|
| 379321864695232|2018-01-03 00:29:37|  297|   98837|        1.432266392E7|
|4389973676463558|2018-01-26 13:47:46|  400|   10985|1.1844220399999999E7|
|4407230633003235|2018-01-27 07:21:08|  567|   50167|1.4173543150000002E7|
|5403923427969691|2018-01-22 23:46:19|  324|   17350|        1.411602776E7|
|5508842242491554|2018-01-31 14:55:58|  585|   12986|1.4260441020000001E7|
|6562510549485881|2018-01-17 08:35:27|  518|   35440|        1.305571434E7|
| 340028465709212|2018-01-02 03:25:35|  233|   24658|        1.684369285E7|
| 349143706735646|2018-01-29 22:33:14|  298|   99101|        1.572636968E7|
|4126356979547079|2018-01-24 16:09:03|  345|   14475|        1.301542898E7|
|4484950467600170|2018-01-10 08:03:13|  462|   13324|        1.406509594E7|
|4818950814628962|2018-01-31 00:53:15|  660|   88081|          5085352.51|
|5464688416792307|2018-01-26 19:03:47|  469|   71670|        1.212319305E7|
|5543219113990484|2018-01-13 18:34:00|  494|   62273|        1.294090916E7|
|5573293264792992|2018-01-31 14:55:57|  284|   27012|1.1698505790000001E7|
|6011273561157733|2018-02-01 01:27:58|  411|   45305|1.3040283309999999E7|
|6011985140563103|2018-01-30 02:03:54|  350|   36587|1.4569845000000002E7|
+----------------+-------------------+-----+--------+--------------------+
only showing top 20 rows
```

19) Now, summon our good friend happybase to load this dataframe into NoSQL database i.e. Hbase.
20) Create a connection to Hbase, Check if table you want to create already exists and create one if it doesn’t exist.
21) Batch load data from dataframe to table created.

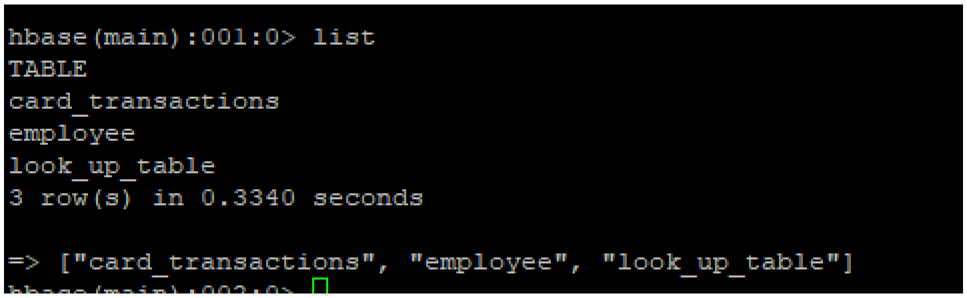


```
In [78]: #create the required table
         def create_table(name,cf):
          print "creating table " + name
          tables = list_tables()
          if name not in tables:
           open_connection()
           connection.create_table(name, cf)
           close_connection()
           print "table created"
          else:
           print "table already present"
         #get the pointer to a table
         def get_table(name):
          open_connection()
          table = connection.table(name)
          close_connection()
          return table

In [79]:  create_table('look_up_table', {'info' : dict(max_versions=5) })

         creating table look_up_table
         fetching all table
         all tables fetched
         table created
```



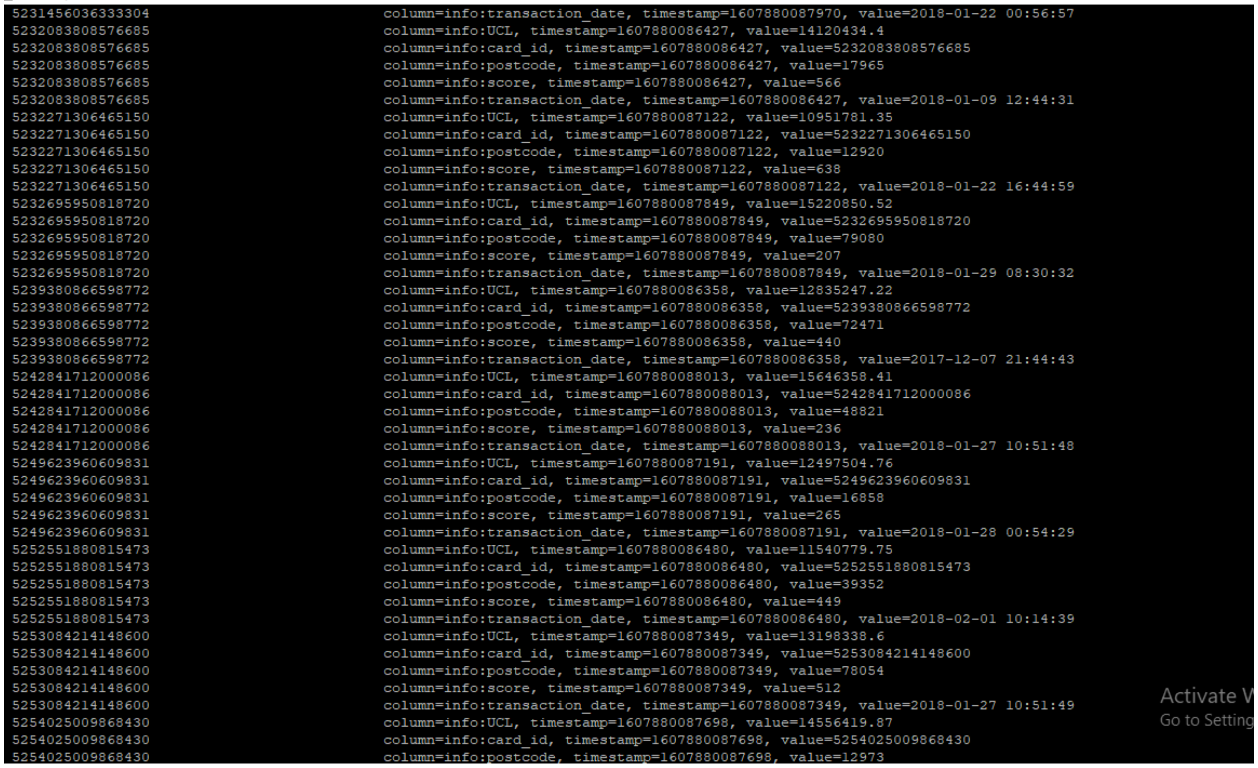
```
In [85]: #batch insert data in lookup table
         def batch_insert_data(df,tableName):
          print "starting batch insert of events"
          table = get_table(tableName)
          open_connection()
          rows_count=0

         #Creating a rowkey for better data query. RowKey is the cardId .
          rowKey_dict={}
          with table.batch(batch_size=4) as b:
            for row in df.rdd.collect():
             b.put(bytes(row.card_id) , { 'info:card_id':bytes(row.card_id),
                                   'info:transaction_date':bytes(row.transaction_date),
                                   'info:score':bytes(row.score),
                                   'info:postcode':bytes(row.postcode),
                                   'info:UCL':bytes(row.UCL)})


          print "batch insert done"
          close_connection()

In [86]: batch_insert_data(look_up_table,'look_up_table')

         starting batch insert of events
         batch insert done
```

22) Open Putty, login as root user. Go to Hbase Shell and list existing tables.
23) Our look_up_table should already be appearing there, scan it to see if data is loaded as expected.

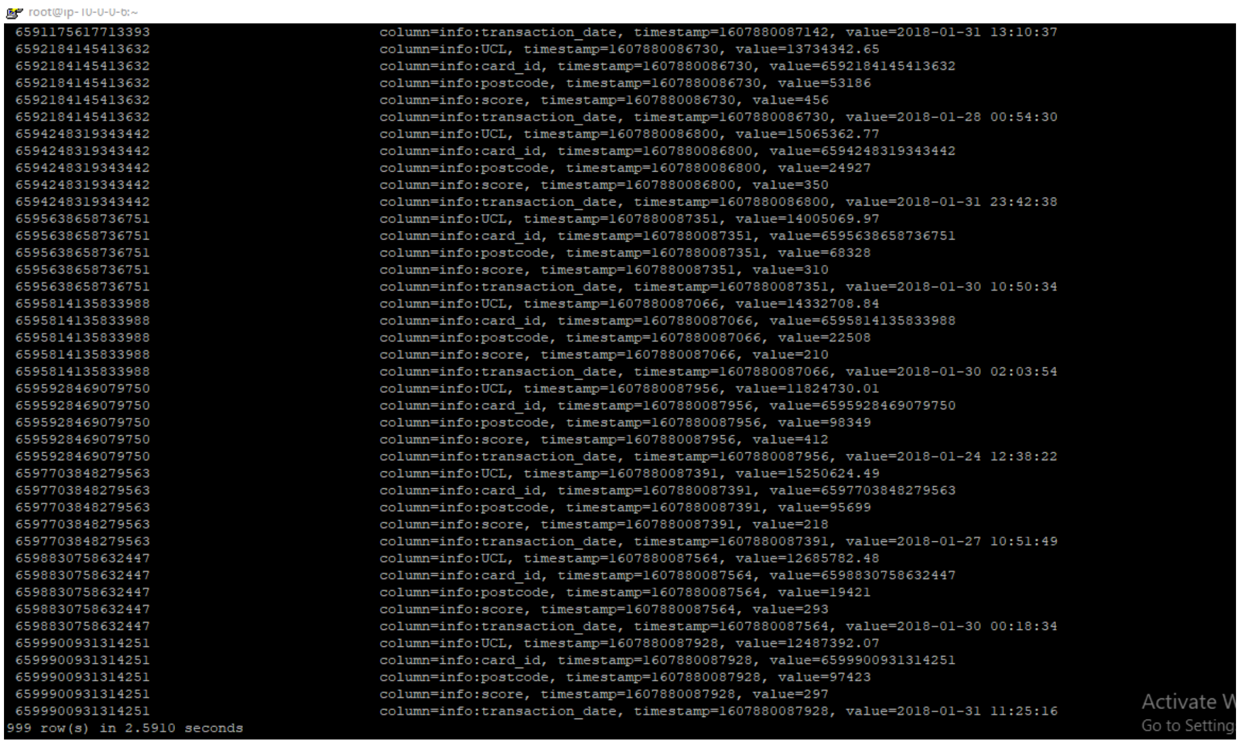


```
hbase(main):001:0> list
TABLE
card_transactions
employee
look_up_table
3 row(s) in 0.3340 seconds

=> ["card_transactions", "employee", "look_up_table"]
```

Give command scan ‘look_up_table’ to see data inserted into table.



```
 5231456036333304                         column=info:transaction_date, timestamp=1607880087970, value=2018-01-22 00:56:57
 5232083808576685                         column=info:UCL, timestamp=1607880086427, value=14120434.4
 5232083808576685                         column=info:card_id, timestamp=1607880086427, value=5232083808576685
 5232083808576685                         column=info:postcode, timestamp=1607880086427, value=17965
 5232083808576685                         column=info:score, timestamp=1607880086427, value=566
 5232083808576685                         column=info:transaction_date, timestamp=1607880086427, value=2018-01-09 12:44:31
 5232271306465150                         column=info:UCL, timestamp=1607880087122, value=10951781.35
 5232271306465150                         column=info:card_id, timestamp=1607880087122, value=5232271306465150
 5232271306465150                         column=info:postcode, timestamp=1607880087122, value=12920
 5232271306465150                         column=info:score, timestamp=1607880087122, value=638
 5232271306465150                         column=info:transaction_date, timestamp=1607880087122, value=2018-01-22 16:44:59
 5232695950818720                         column=info:UCL, timestamp=1607880087849, value=15220850.52
 5232695950818720                         column=info:card_id, timestamp=1607880087849, value=5232695950818720
 5232695950818720                         column=info:postcode, timestamp=1607880087849, value=79080
 5232695950818720                         column=info:score, timestamp=1607880087849, value=207
 5232695950818720                         column=info:transaction_date, timestamp=1607880087849, value=2018-01-29 08:30:32
 5239380866598772                         column=info:UCL, timestamp=1607880086358, value=12835247.22
 5239380866598772                         column=info:card_id, timestamp=1607880086358, value=5239380866598772
 5239380866598772                         column=info:postcode, timestamp=1607880086358, value=72471
 5239380866598772                         column=info:score, timestamp=1607880086358, value=440
 5239380866598772                         column=info:transaction_date, timestamp=1607880086358, value=2017-12-07 21:44:43
 5242841712000086                         column=info:UCL, timestamp=1607880088013, value=15646358.41
 5242841712000086                         column=info:card_id, timestamp=1607880088013, value=5242841712000086
 5242841712000086                         column=info:postcode, timestamp=1607880088013, value=48821
 5242841712000086                         column=info:score, timestamp=1607880088013, value=236
 5242841712000086                         column=info:transaction_date, timestamp=1607880088013, value=2018-01-27 10:51:48
 5249623960609831                         column=info:UCL, timestamp=1607880087191, value=12497504.76
 5249623960609831                         column=info:card_id, timestamp=1607880087191, value=5249623960609831
 5249623960609831                         column=info:postcode, timestamp=1607880087191, value=16858
 5249623960609831                         column=info:score, timestamp=1607880087191, value=265
 5249623960609831                         column=info:transaction_date, timestamp=1607880087191, value=2018-01-28 00:54:29
 5252551880815473                         column=info:UCL, timestamp=1607880086480, value=11540779.75
 5252551880815473                         column=info:card_id, timestamp=1607880086480, value=5252551880815473
 5252551880815473                         column=info:postcode, timestamp=1607880086480, value=39352
 5252551880815473                         column=info:score, timestamp=1607880086480, value=449
 5252551880815473                         column=info:transaction_date, timestamp=1607880086480, value=2018-02-01 10:14:39
 5253084214148600                         column=info:UCL, timestamp=1607880087349, value=13198338.6
 5253084214148600                         column=info:card_id, timestamp=1607880087349, value=5253084214148600
 5253084214148600                         column=info:postcode, timestamp=1607880087349, value=78054
 5253084214148600                         column=info:score, timestamp=1607880087349, value=512
 5253084214148600                         column=info:transaction_date, timestamp=1607880087349, value=2018-01-27 10:51:49
 5254025009868430                         column=info:UCL, timestamp=1607880087698, value=14556419.87
 5254025009868430                         column=info:card_id, timestamp=1607880087698, value=5254025009868430
 5254025009868430                         column=info:postcode, timestamp=1607880087698, value=12973
```



```
 6591175617713393                         column=info:transaction_date, timestamp=1607880087142, value=2018-01-31 13:10:37
 6592184145413632                         column=info:UCL, timestamp=1607880086730, value=13734342.65
 6592184145413632                         column=info:card_id, timestamp=1607880086730, value=6592184145413632
 6592184145413632                         column=info:postcode, timestamp=1607880086730, value=53186
 6592184145413632                         column=info:score, timestamp=1607880086730, value=456
 6592184145413632                         column=info:transaction_date, timestamp=1607880086730, value=2018-01-28 00:54:30
 6594248319343442                         column=info:UCL, timestamp=1607880086800, value=15065362.77
 6594248319343442                         column=info:card_id, timestamp=1607880086800, value=6594248319343442
 6594248319343442                         column=info:postcode, timestamp=1607880086800, value=24927
 6594248319343442                         column=info:score, timestamp=1607880086800, value=350
 6594248319343442                         column=info:transaction_date, timestamp=1607880086800, value=2018-01-31 23:42:38
 6595638658736751                         column=info:UCL, timestamp=1607880087351, value=14005069.97
 6595638658736751                         column=info:card_id, timestamp=1607880087351, value=6595638658736751
 6595638658736751                         column=info:postcode, timestamp=1607880087351, value=68328
 6595638658736751                         column=info:score, timestamp=1607880087351, value=310
 6595638658736751                         column=info:transaction_date, timestamp=1607880087351, value=2018-01-30 10:50:34
 6595814135833988                         column=info:UCL, timestamp=1607880087066, value=14332708.84
 6595814135833988                         column=info:card_id, timestamp=1607880087066, value=6595814135833988
 6595814135833988                         column=info:postcode, timestamp=1607880087066, value=22508
 6595814135833988                         column=info:score, timestamp=1607880087066, value=210
 6595814135833988                         column=info:transaction_date, timestamp=1607880087066, value=2018-01-30 02:03:54
 6595928469079750                         column=info:UCL, timestamp=1607880087956, value=11824730.01
 6595928469079750                         column=info:card_id, timestamp=1607880087956, value=6595928469079750
 6595928469079750                         column=info:postcode, timestamp=1607880087956, value=98349
 6595928469079750                         column=info:score, timestamp=1607880087956, value=412
 6595928469079750                         column=info:transaction_date, timestamp=1607880087956, value=2018-01-24 12:38:22
 6597703848279563                         column=info:UCL, timestamp=1607880087391, value=15250624.49
 6597703848279563                         column=info:card_id, timestamp=1607880087391, value=6597703848279563
 6597703848279563                         column=info:postcode, timestamp=1607880087391, value=95699
 6597703848279563                         column=info:score, timestamp=1607880087391, value=218
 6597703848279563                         column=info:transaction_date, timestamp=1607880087391, value=2018-01-27 10:51:49
 6598830758632447                         column=info:UCL, timestamp=1607880087564, value=12685782.48
 6598830758632447                         column=info:card_id, timestamp=1607880087564, value=6598830758632447
 6598830758632447                         column=info:postcode, timestamp=1607880087564, value=19421
 6598830758632447                         column=info:score, timestamp=1607880087564, value=293
 6598830758632447                         column=info:transaction_date, timestamp=1607880087564, value=2018-01-30 00:18:34
 6599900931314251                         column=info:UCL, timestamp=1607880087928, value=12487392.07
 6599900931314251                         column=info:card_id, timestamp=1607880087928, value=6599900931314251
 6599900931314251                         column=info:postcode, timestamp=1607880087928, value=97423
 6599900931314251                         column=info:score, timestamp=1607880087928, value=297
 6599900931314251                         column=info:transaction_date, timestamp=1607880087928, value=2018-01-31 11:25:16
999 row(s) in 2.5910 seconds
```

Logic Final

1) Import all necessary libraries and functions.
2) Define spark context and add .py files required along with csv given in resources list.
3) Connect to kafka topic using topic name “transactions-topic-verified” and server 18.211.252.152:9092.
4) Read the kafka stream into appropriate schema to make data readable.
5) Look Up Table Name: look_up_table
   Card Transaction table Name: card_transactions
6) Define following user defined functions to perform activities required for rule execution anddetermine if transaction is fraudulent or genuine.
   a. Name of function: ucl_dataInput:
      CARD_ID
      Output: UCL from look_up_table
   b. Name of function: score_dataInput:
      CARD_ID
      Output: Credit Score from look up table.
   c. Name of function: postcode_dataInput:
      card_id
      Output: post code from look up table.
   d. Name of function: distance_calc
      Input: post codes from lookup table & kafka stream.
      Output: Distance between 2 locations of current transaction and previoustransaction.
   e. Name of function: time_cal
      Input: transaction date from lookup table & kafka streamOutput: difference between transaction dates in seconds.
   f. Name of function: lTransD_dataInput:
      CARD_ID
      Output: transaction date from look up table.
   g. Name of function: speed_calc
      Input: Distance & Time calculated from above distance_calc & time_cal functions Output: Speed which is mathematically calculated by multiplying distance * 1000 and dividing by time.
   h. Name of function: status_res
      Input: Amount from current transaction read thru kafka stream, UCL from look uptable, Credit_Score from look up table & Speed calculated from user defined functions.
      Output: Status as transaction if its genuine or fraud.

7) Execute above user define functions in same order given above. These functions perform usall required logic to deduce if transaction is fraud or genuine. These functions are agents to derive inputs to function status_res (function H).
8) Here are the rules performed on top of inputs supplied to function H.
   a. If current transaction amount is greater than UCL of look up table for that card_id,mark transaction as Fraud. Else, proceed to check below:
      i. If credit score of that card_id under process is less than 250, rejecttransaction

as FRAUD. Else, proceed to check below:

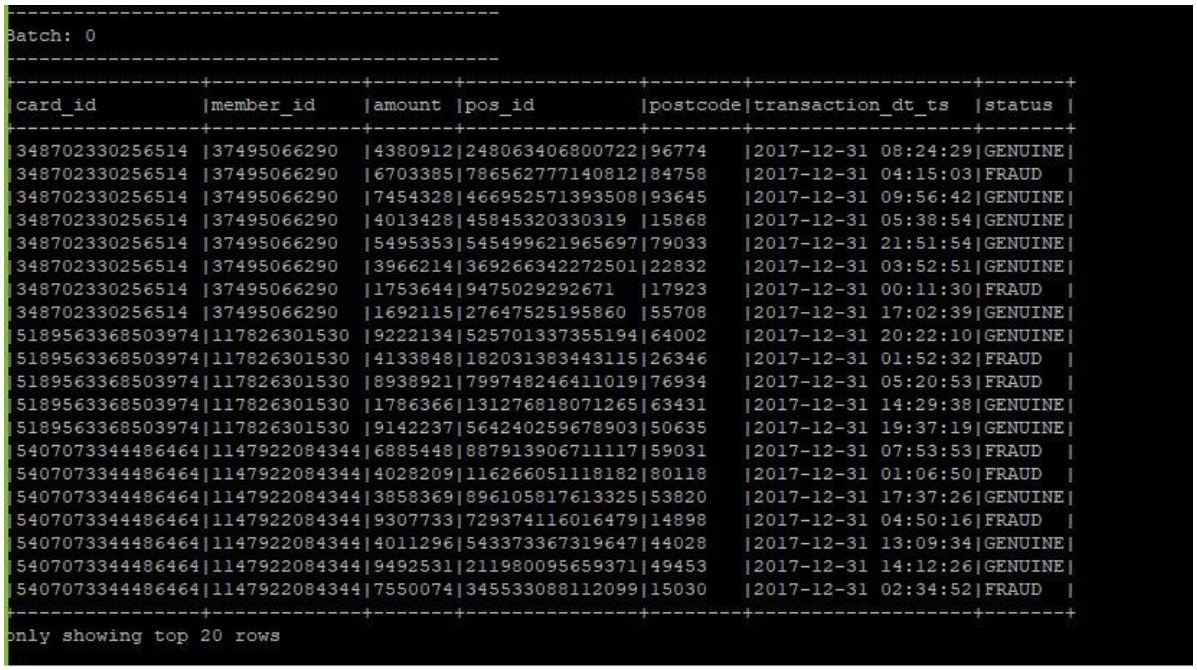
1. If speed calculated is greater than 250, recognize the transaction as "FRAUD". If speed is between 0 and 250, mark the transaction as genuine.

9) To summarize, a transaction is qualified to be genuine only when:
    a. Credit score of member is greater than 200,
    b. Speed is between 0 & 250
    c. Amount on current transaction is less than UCL calculated.

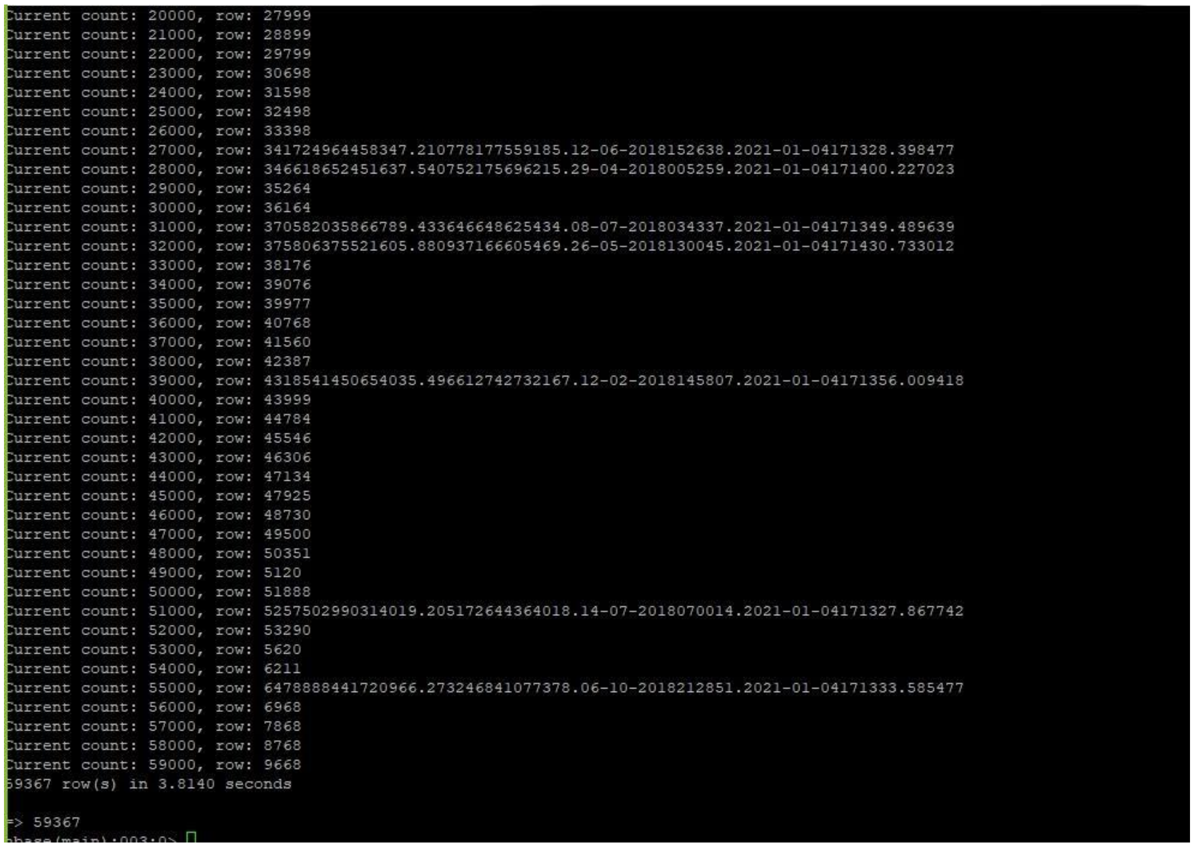
10) Functions "A", "B", "C", "F" & "H" contact dao.py to call the look up table (table details givenin point 5 above) for designated purposes.
    In process of calling dao.py from this driver.py file, I followed approach called "Import" which loads other .py files in same directory.
    Establish a spark context to add python files and csv files before we put the command import.

11) Function "D" uses geomap.py to calculate distance between last transaction & current transaction locations. This is in turn used in calculating speed which is one of factors for determining status of transaction.

12) Function "H" status_res also calls look_up_table using write_data function when transactionis genuine.
    Apart from this, it updates card_transactions table with latest information of posid, amount, transaction date and member ID.



```
-------------------------------------------
Batch: 0
-------------------------------------------
+----------------+------------+-------+---------------+--------+-------------------+-------+
|card_id         |member_id   |amount |pos_id         |postcode|transaction_dt_ts  |status |
+----------------+------------+-------+---------------+--------+-------------------+-------+
|348702330256514 |37495066290 |4380912|248063406800722|96774   |2017-12-31 08:24:29|GENUINE|
|348702330256514 |37495066290 |6703385|786562777140812|84758   |2017-12-31 04:15:03|FRAUD  |
|348702330256514 |37495066290 |7454328|466952571393508|93645   |2017-12-31 09:56:42|GENUINE|
|348702330256514 |37495066290 |4013428|45845320330319 |15868   |2017-12-31 05:38:54|GENUINE|
|348702330256514 |37495066290 |5495353|545499621965697|79033   |2017-12-31 21:51:54|GENUINE|
|348702330256514 |37495066290 |3966214|369266342272501|22832   |2017-12-31 03:52:51|GENUINE|
|348702330256514 |37495066290 |1753644|9475029292671  |17923   |2017-12-31 00:11:30|FRAUD  |
|348702330256514 |37495066290 |1692115|27647525195860 |55708   |2017-12-31 17:02:39|GENUINE|
|5189563368503974|117826301530|9222134|525701337355194|64002   |2017-12-31 20:22:10|GENUINE|
|5189563368503974|117826301530|4133848|182031383443115|26346   |2017-12-31 01:52:32|FRAUD  |
|5189563368503974|117826301530|8938921|799748246411019|76934   |2017-12-31 05:20:53|FRAUD  |
|5189563368503974|117826301530|1786366|131276818071265|63431   |2017-12-31 14:29:38|GENUINE|
|5189563368503974|117826301530|9142237|564240259678903|50635   |2017-12-31 19:37:19|GENUINE|
|5407073344486464|1147922084344|6885448|887913906711117|59031   |2017-12-31 07:53:53|FRAUD  |
|5407073344486464|1147922084344|4028209|116266051118182|80118   |2017-12-31 01:06:50|FRAUD  |
|5407073344486464|1147922084344|3858369|896105817613325|53820   |2017-12-31 17:37:26|GENUINE|
|5407073344486464|1147922084344|9307733|729374116016479|14898   |2017-12-31 04:50:16|FRAUD  |
|5407073344486464|1147922084344|4011296|543373367319647|44028   |2017-12-31 13:09:34|GENUINE|
|5407073344486464|1147922084344|9492531|211980095659371|49453   |2017-12-31 14:12:26|GENUINE|
|5407073344486464|1147922084344|7550074|345533088112099|15030   |2017-12-31 02:34:52|FRAUD  |
+----------------+------------+-------+---------------+--------+-------------------+-------+
only showing top 20 rows
```



```
Current count: 20000, row: 27999
Current count: 21000, row: 28899
Current count: 22000, row: 29799
Current count: 23000, row: 30698
Current count: 24000, row: 31598
Current count: 25000, row: 32498
Current count: 26000, row: 33398
Current count: 27000, row: 341724964458347.210778177559185.12-06-2018152638.2021-01-04171328.398477
Current count: 28000, row: 346618652451637.540752175696215.29-04-2018005259.2021-01-04171400.227023
Current count: 29000, row: 35264
Current count: 30000, row: 36164
Current count: 31000, row: 370582035866789.433646648625434.08-07-2018034337.2021-01-04171349.489639
Current count: 32000, row: 375806375521605.880937166605469.26-05-2018130045.2021-01-04171430.733012
Current count: 33000, row: 38176
Current count: 34000, row: 39076
Current count: 35000, row: 39977
Current count: 36000, row: 40768
Current count: 37000, row: 41560
Current count: 38000, row: 42387
Current count: 39000, row: 4318541450654035.496612742732167.12-02-2018145807.2021-01-04171356.009418
Current count: 40000, row: 43999
Current count: 41000, row: 44784
Current count: 42000, row: 45546
Current count: 43000, row: 46306
Current count: 44000, row: 47134
Current count: 45000, row: 47925
Current count: 46000, row: 48730
Current count: 47000, row: 49500
Current count: 48000, row: 50351
Current count: 49000, row: 5120
Current count: 50000, row: 51888
Current count: 51000, row: 5257502990314019.205172644364018.14-07-2018070014.2021-01-04171327.867742
Current count: 52000, row: 53290
Current count: 53000, row: 5620
Current count: 54000, row: 6211
Current count: 55000, row: 6478888441720966.273246841077378.06-10-2018212851.2021-01-04171333.585477
Current count: 56000, row: 6968
Current count: 57000, row: 7868
Current count: 58000, row: 8768
Current count: 59000, row: 9668
59367 row(s) in 3.8140 seconds

=> 59367
hbase(main):003:0>
```