Scripts Execution

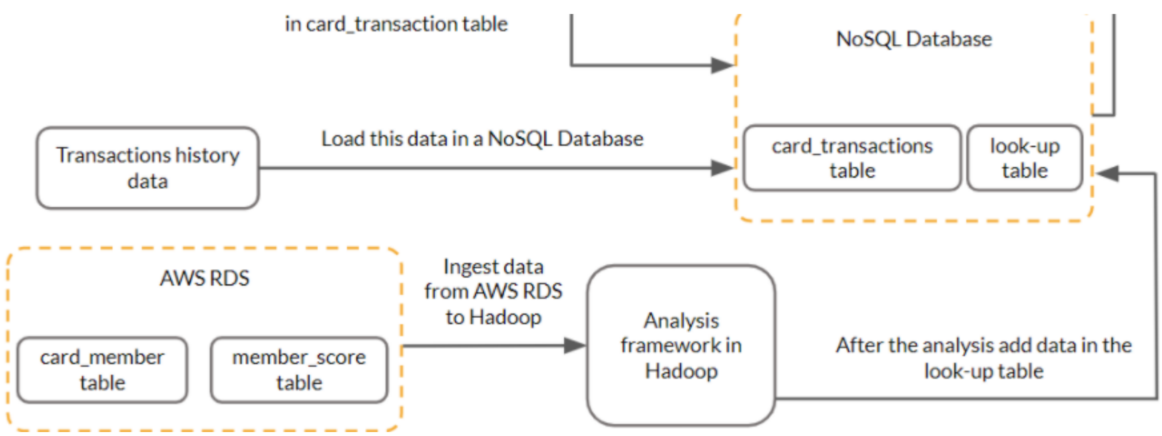
Explanation of the solution to the batch layer problem

Step by step process followed for the completion of tasks till **task 4.** The steps are documented here.

Problem Statement: Credit card fraud is defined as a form of identity theft in which an individual uses someone else's credit card information to make purchase or to withdraw funds from the account. It can be Fraudulent transactions or customer information.

We have **following tasks** to be performed as per **batch layer problem** (till task4)

Task1: Load the transactions history data (card_transactions.csv) in a NoSQL database
Task2: Ingest the relevant data from AWS RDS to Hadoop
Task3: Create a lookup-table with columns specified
Task4: Load the data in lookup table



Task1: Load the transactions history data (card_transactions.csv) in a NoSQL database

Steps:

1. Downloaded the card_transactions.csv from the resources
2. Copied to ec2-user local folder
3. Copied from ec2-user to hdfs (/user/root/capstone_project) using hadoop fs -put <src> <dest>
4. Using Pyspark read this csv file and created a dataframe

5. Created hbase table for card_transactions
6. Loaded the data from card_transactions.csv to card_transactions table in hbase
7. Used 'list' command in hbase to see the table created
8. Used scan "card_transactions" to check on the data
9. Used count "card_transactions" to check on count of data.

root@ip-10-0-0-149:~

```
login as: ec2-user
Authenticating with public key "imported-openssh-key"
Last login: Sat Oct 16 08:11:14 2021 from 106.202.196.118
[ec2-user@ip-10-0-0-149 ~]$ ls
card_transactions.csv
[ec2-user@ip-10-0-0-149 ~]$ sudo -i
[root@ip-10-0-0-149 ~]# hadoop fs -put /home/ec2-user/card_transactions.csv /user/root/capstone_project
[root@ip-10-0-0-149 ~]#
```

```
-rwxrwxrwx   3 root supergroup   44529095 2021-05-15 11:19 /user/root/online_dat
a
[root@ip-10-0-0-138 ~]# hadoop fs -ls /user/root/capstone_proj
Found 3 items
drwxr-xr-x   - root supergroup          0 2021-10-10 06:40 /user/root/capstone_proj/card_member
-rw-r--r--   3 root supergroup    4829520 2021-10-10 15:13 /user/root/capstone_proj/card_transactions.csv
drwxr-xr-x   - root supergroup          0 2021-10-10 06:38 /user/root/capstone_proj/member_score
[root@ip-10-0-0-138 ~]#
```

```python
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),
                        ])
```

Reading Past Transactions data (source as csv)

```python
trans_df = spark.read.csv("hdfs:/user/root/capstone_proj/card_transactions.csv", header = True, schema = transasction)
```

```python
# create table for  card_transactions.csv file.
create_table('card_transactions', {'info' : dict(max_versions=5) })
```

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

```python
#Batch insert data of card_transactions.csv file.
batch_insert_csvdata('card_transactions.csv','card_transactions')
```

```
starting batch insert of events
batch insert done
```

```
hbase(main):002:0> list
TABLE
card_transactions
lookup_table
2 row(s) in 0.0080 seconds

=> ["card_transactions", "lookup_table"]
hbase(main):003:0>
```

root@ip-10-0-0-149:~

```
 6591175617713393          column=info:transaction_date, timestamp=1634375007372, value=2018-01-31 13:10:37
 6592184145413632          column=info:UCL, timestamp=1634375006787, value=13734342.65
 6592184145413632          column=info:card_id, timestamp=1634375006787, value=6592184145413632
 6592184145413632          column=info:postcode, timestamp=1634375006787, value=53186
 6592184145413632          column=info:score, timestamp=1634375006787, value=456
 6592184145413632          column=info:transaction_date, timestamp=1634375006787, value=2018-01-28 00:54:30
 6594248319343442          column=info:UCL, timestamp=1634375006872, value=15065362.77
 6594248319343442          column=info:card_id, timestamp=1634375006872, value=6594248319343442
 6594248319343442          column=info:postcode, timestamp=1634375006872, value=24927
 6594248319343442          column=info:score, timestamp=1634375006872, value=350
 6594248319343442          column=info:transaction_date, timestamp=1634375006872, value=2018-01-31 23:42:38
 6595638658736751          column=info:UCL, timestamp=1634375007621, value=14005069.97
 6595638658736751          column=info:card_id, timestamp=1634375007621, value=6595638658736751
 6595638658736751          column=info:postcode, timestamp=1634375007621, value=68328
 6595638658736751          column=info:score, timestamp=1634375007621, value=310
 6595638658736751          column=info:transaction_date, timestamp=1634375007621, value=2018-01-30 10:50:34
 6595814135833988          column=info:UCL, timestamp=1634375007288, value=14332708.84
 6595814135833988          column=info:card_id, timestamp=1634375007288, value=6595814135833988
 6595814135833988          column=info:postcode, timestamp=1634375007288, value=22508
 6595814135833988          column=info:score, timestamp=1634375007288, value=210
 6595814135833988          column=info:transaction_date, timestamp=1634375007288, value=2018-01-30 02:03:54
 6595928469079750          column=info:UCL, timestamp=1634375008323, value=11824730.01
 6595928469079750          column=info:card_id, timestamp=1634375008323, value=6595928469079750
 6595928469079750          column=info:postcode, timestamp=1634375008323, value=98349
 6595928469079750          column=info:score, timestamp=1634375008323, value=412
 6595928469079750          column=info:transaction_date, timestamp=1634375008323, value=2018-01-24 12:38:22
 6597703848279563          column=info:UCL, timestamp=1634375007681, value=15250624.49
 6597703848279563          column=info:card_id, timestamp=1634375007681, value=6597703848279563
 6597703848279563          column=info:postcode, timestamp=1634375007681, value=95699
 6597703848279563          column=info:score, timestamp=1634375007681, value=218
 6597703848279563          column=info:transaction_date, timestamp=1634375007681, value=2018-01-27 10:51:49
 6598830758632447          column=info:UCL, timestamp=1634375007878, value=12685782.48
 6598830758632447          column=info:card_id, timestamp=1634375007878, value=6598830758632447
 6598830758632447          column=info:postcode, timestamp=1634375007878, value=19421
 6598830758632447          column=info:score, timestamp=1634375007878, value=293
 6598830758632447          column=info:transaction_date, timestamp=1634375007878, value=2018-01-30 00:18:34
 6599900931314251          column=info:UCL, timestamp=1634375008288, value=12487392.07
 6599900931314251          column=info:card_id, timestamp=1634375008288, value=6599900931314251
 6599900931314251          column=info:postcode, timestamp=1634375008288, value=97423
 6599900931314251          column=info:score, timestamp=1634375008288, value=297
 6599900931314251          column=info:transaction_date, timestamp=1634375008288, value=2018-01-31 11:25:16
999 row(s) in 0.4250 seconds

hbase(main):009:0>
```

Task2: Ingest the relevant data from AWS RDS to Hadoop

Steps:

1. Checked the details for ingesting data from resources.
2. Used sqoop import for importing data to hadoop

Table 1:member_score

sqoop import \
--connect jdbc:mysql://upgradawsrds1.cyaielc9bmnf.us-east1.rds.amazonaws.com/cred_financials_data \
--table member_score \
--username upgraduser --password upgraduser \
--target-dir /user/root/capstone_project/member_score \
-m 1

Table 2: card_member

sqoop import \
--connect jdbc:mysql://upgradawsrds1.cyaielc9bmnf.us-east1.rds.amazonaws.com/cred_financials_data \
--table card_member \
--username upgraduser --password upgraduser \
--target-dir /user/root/capstone_project/card_member \
-m 1

```
[root@ip-10-0-0-149 ~]# hadoop fs -ls /user/root/capstone_project
Found 2 items
drwxr-xr-x   - root supergroup          0 2021-10-16 07:29 /user/root/capstone_project/card_member
drwxr-xr-x   - root supergroup          0 2021-10-16 07:23 /user/root/capstone_project/member_score
```

Task3: Create a lookup-table with columns specified

Steps:

1. Once the card_member and member_score data is available in task2 is available in Pyspark as dataframes
2. Used this as a source and merged databases for relevant columns
3. Calculated extra columns required and created lookup table in hbase

```
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),
                         ])
```

```
#read the data
card_df = spark.read.csv("hdfs:/user/root/capstone_project/card_member", header = False, schema = cardschema)
```

```
+---------------+---------------+--------------------+----------------+-------------+-----------------+
|        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
```

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

```
#read the data
mem_df = spark.read.csv("hdfs:/user/root/capstone_project/member_score", header = False, schema = memberschema)
```

```
mem_df.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|
|009136568025042|  308|
|009190444424572|  559|
|009250698176266|  233|
|009873334520465|  298|
|011716573646690|  249|
|011877954983420|  497|
|012390918683920|  407|
|012731668664932|  612|
+---------------+-----+
only showing top 20 rows
```

Join the card_member and member_score tables to extract credit score of each member

```
score = mem_df.join(card_df, mem_df.mem_id == card_df.member_id,how='LEFT')
```

```
score.count()
```

```
999
```

```
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)
```

Extract required columns from the joined dataframe

```
score.show()
```

```
+----------------+-----+----------------+
|          mem_id|score|          cardid|
+----------------+-----+----------------+
|000037495066290|  339| 348702330256514|
|000117826301530|  289|5189563368503974|
|001147922084344|  393|5407073344486464|
|001314074991813|  225| 378303738095292|
|001739553947511|  642| 348413196172048|
|003761426295463|  413| 348536585266345|
|004494068832701|  217|5515987071565183|
|006836124210484|  504|5400251558458125|
|006991872634058|  697|4573337022888445|
|007955566230397|  372|4708912758619517|
|008732267588672|  213|5342400571435088|
|008765307152821|  399|4237648081700588|
|009136568025042|  308| 371814781663843|
|009190444424572|  559| 341363858179050|
|009250698176266|  233| 340028465709212|
|009873334520465|  298|5495445301620991|
|011716573646690|  249|4795844193055110|
|011877954983420|  497|5164771396791995|
|012390918683920|  407|5423921058459194|
|012731668664932|  612|5379610024035907|
+----------------+-----+----------------+
only showing top 20 rows
```

Join both Transaction history and score Dataframe which is a merged and extracted data frame from both RDS tables

```
hist = trans_df.join(score, trans_df.member_id == score.mem_id,how='outer') #outer join on member_id between score ar
```

```
hist.count() #53210
```

```
53210
```

```
hist.printSchema()
```

```
root
 |-- card_id: string (nullable = true)
 |-- member_id: string (nullable = true)
 |-- amount: integer (nullable = true)
 |-- postcode: string (nullable = true)
 |-- pos_id: string (nullable = true)
 |-- transaction_dt: string (nullable = true)
 |-- status: string (nullable = true)
 |-- mem_id: string (nullable = true)
 |-- score: integer (nullable = true)
 |-- cardid: string (nullable = true)
```

```
hist = hist.select('card_id', 'amount', 'postcode', 'pos_id','transaction_dt','status','score')
```

```
hist.show()
```

```
+---------------+-------+--------+---------------+-------------------+-------+-----+
|        card_id| amount|postcode|         pos_id|     transaction_dt| status|score|
+---------------+-------+--------+---------------+-------------------+-------+-----+
|340379737226464|6126197|   46933|167473544283898|01-05-2016 08:10:50|GENUINE|  229|
|340379737226464|7949232|   61840|664980919335952|01-10-2016 10:38:52|GENUINE|  229|
|340379737226464| 943839|   91743|633038040069180|02-08-2016 00:31:25|GENUINE|  229|
|340379737226464|3764114|   91743|633038040069180|02-08-2016 21:35:27|GENUINE|  229|
|340379737226464|6221251|   98384|064948657945290|02-10-2016 14:44:14|GENUINE|  229|
|340379737226464|2868312|   26032|856772774421259|02-12-2016 21:55:43|GENUINE|  229|
|340379737226464|4418586|   20129|390339673634463|02-12-2017 17:05:51|GENUINE|  229|
|340379737226464|7439113|   91763|315067016872305|03-04-2017 11:43:59|GENUINE|  229|
|340379737226464|8217180|   16063|208378790148728|03-05-2017 16:47:43|GENUINE|  229|
|340379737226464|8505852|   64070|695556848392133|03-06-2017 03:07:27|GENUINE|  229|
|340379737226464|8535431|   29817|683602833507395|04-08-2016 20:59:31|GENUINE|  229|
|340379737226464|6317993|   28425|258522244165233|05-05-2017 00:23:45|GENUINE|  229|
|340379737226464|3256860|   16845|933410474855991|05-10-2017 15:09:09|GENUINE|  229|
|340379737226464|1423779|   97640|789378980336517|06-02-2017 02:10:00|GENUINE|  229|
|340379737226464|3783517|   70552|963177679534627|06-12-2016 03:10:30|GENUINE|  229|
|340379737226464|3300714|   75750|072728631441941|07-01-2017 05:52:58|GENUINE|  229|
|340379737226464|5706163|   50455|915439934619047|07-01-2018 22:07:07|GENUINE|  229|
|340379737226464|7445128|   50455|915439934619047|07-01-2018 23:52:27|GENUINE|  229|
|340379737226464| 140120|   18915|691571327905821|07-02-2017 20:18:04|GENUINE|  229|
|340379737226464|7720484|   48423|548702836055067|07-03-2016 14:59:35|GENUINE|  229|
+---------------+-------+--------+---------------+-------------------+-------+-----+
only showing top 20 rows
```

To calculate the latest transaction date of that card:

- group the merged dataset on card_id
- aggreagte to max of transaction date.
- Alias the aggregated date as transaction_date

```
+----------------+-------------------+
|         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|
+----------------+-------------------+
only showing top 20 rows
```

Join previous last step data frame (score) with look_up_table dataset created above. This step frames all required cols for look_up_table except the UCL.

```
lookup_table = lookup_table.join(score, lookup_table.card_id == score.cardid,how='INNER')
```

```
lookup_table.count()  #check the count (999)
```

```
999
```

```
lookup_table.show()
```

```
+----------------+-------------------+---------------+-----+----------------+
|         card_id|   transaction_date|         mem_id|score|          cardid|
+----------------+-------------------+---------------+-----+----------------+
| 340379737226464|2018-01-27 00:19:47|089615510858348|  229| 340379737226464|
| 345406224887566|2017-12-25 04:03:58|296206661780881|  349| 345406224887566|
| 348962542187595|2018-01-29 17:17:14|366246487993992|  522| 348962542187595|
| 377201318164757|2017-11-28 16:32:22|924475891017022|  432| 377201318164757|
| 379321864695232|2018-01-03 00:29:37|082567374418739|  297| 379321864695232|
|4389973676463558|2018-01-26 13:47:46|295554828848966|  400|4389973676463558|
|4407230633003235|2018-01-27 07:21:08|761335698364860|  567|4407230633003235|
|5403923427969691|2018-01-22 23:46:19|922077754605834|  324|5403923427969691|
|5508842242491554|2018-01-31 14:55:58|634200295989311|  585|5508842242491554|
|6562510549485881|2018-01-17 08:35:27|659982919406634|  518|6562510549485881|
| 340028465709212|2018-01-02 03:25:35|009250698176266|  233| 340028465709212|
| 349143706735646|2018-01-29 22:33:14|343824445342591|  298| 349143706735646|
|4126356979547079|2018-01-24 16:09:03|015582765997171|  345|4126356979547079|
|4484950467600170|2018-01-10 08:03:13|570539968421790|  462|4484950467600170|
|4818950814628962|2018-01-31 00:53:15|819006616594636|  660|4818950814628962|
|5464688416792307|2018-01-26 19:03:47|434792568351651|  469|5464688416792307|
|5543219113990484|2018-01-13 18:34:00|501241235491851|  494|5543219113990484|
|5573293264792992|2018-01-31 14:55:57|350307876868039|  284|5573293264792992|
|6011273561157733|2018-02-01 01:27:58|314862932674883|  411|6011273561157733|
|6011985140563103|2018-01-30 02:03:54|393165367933607|  350|6011985140563103|
+----------------+-------------------+---------------+-----+----------------+
only showing top 20 rows
```

Calculating UCL:

- Calculate the moving average and standard deviation of the last 10 transactions for each card_id for the data present in Hadoop and NoSQL database
- 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
- 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

```python
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)
```

```python
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|
|345406224887566|1242240|   14510|536497882467098|GENUINE|  349|2017-06-11 16:31:45|   5|
|345406224887566|9222549|   68358|875905403447795|GENUINE|  349|2017-06-10 21:13:03|   6|
|345406224887566|8726784|   64487|617331009748827|GENUINE|  349|2017-03-16 03:04:40|   7|
|345406224887566|2415599|   99137|751829480922658|GENUINE|  349|2017-03-08 12:29:44|   8|
|345406224887566|9671941|   65614|607206139883123|GENUINE|  349|2017-01-21 08:42:47|   9|
|345406224887566|7454950|   18249|368724323320131|GENUINE|  349|2016-12-30 04:46:01|  10|
+---------------+-------+--------+---------------+-------+-----+-------------------+----+
only showing top 20 rows
```

Import sql function and then calculate Stddev on amount field
UCL i.e. moving average + 3 * (standard deviation)

```python
import pyspark.sql.functions as f
```

```python
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|
```

```
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|
```

Join latest dataframe with previous to get all the required data. Final lookup table looks as below:

```
lookup_table.show()  #Final data set look as below
```

```
+----------------+-------------------+-------+--------+---------------+-------+-----+--------------------+
|         card_id|   transaction_date| amount|postcode|         pos_id| status|score|                 UCL|
+----------------+-------------------+-------+--------+---------------+-------+-----+--------------------+
| 340379737226464|2018-01-27 00:19:47|1784098|   26656|000383013889790|GENUINE|  229|1.4676643749999998E7|
| 345406224887566|2017-12-25 04:03:58|1135534|   53034|146838238062262|GENUINE|  349|        1.524603906E7|
| 348962542187595|2018-01-29 17:17:14|7408949|   27830|453850044027107|GENUINE|  522|1.5005378620000001E7|
| 377201318164757|2017-11-28 16:32:22|4799826|   84302|287431794718846|GENUINE|  432|1.4048015219999999E7|
| 379321864695232|2018-01-03 00:29:37|5702120|   98837|638380208258390|GENUINE|  297|        1.432266392E7|
|4389973676463558|2018-01-26 13:47:46|7196505|   10985|588476547410852|GENUINE|  400|1.1844220399999999E7|
|4407230633003235|2018-01-27 07:21:08|  38579|   50167|697070998627535|GENUINE|  567|1.4173543150000002E7|
|5403923427969691|2018-01-22 23:46:19|1576154|   17350|734614251977032|GENUINE|  324|        1.411602776E7|
|5508842242491554|2018-01-31 14:55:58|2710473|   12986|990193545769550|GENUINE|  585|1.4260441020000001E7|
|6562510549485881|2018-01-17 08:35:27|5939348|   35440|901627725704672|GENUINE|  518|        1.305571434E7|
| 340028465709212|2018-01-02 03:25:35|8696557|   24658|246987608008994|GENUINE|  233|        1.684369285E7|
| 349143706735646|2018-01-29 22:33:14|9246599|   99101|743905143665678|GENUINE|  298|        1.572636968E7|
|4126356979547079|2018-01-24 16:09:03|1770784|   14475|698032801419746|GENUINE|  345|        1.301542898E7|
|4484950467600170|2018-01-10 08:03:13|2284955|   13324|653851258729390|GENUINE|  462|        1.406509594E7|
|4818950814628962|2018-01-31 00:53:15|2316346|   88081|127695801600255|GENUINE|  660|          5085352.51|
|5464688416792307|2018-01-26 19:03:47|4067979|   71670|111365575664933|GENUINE|  469|        1.212319305E7|
|5543219113990484|2018-01-13 18:34:00| 549641|   62273|039213658608911|GENUINE|  494|        1.294090916E7|
|5573293264792992|2018-01-31 14:55:57|4827477|   27012|805073498705051|GENUINE|  284|1.1698505790000001E7|
|6011273561157733|2018-02-01 01:27:58|5272574|   45305|063916192266113|GENUINE|  411|1.3040283309999999E7|
|6011985140563103|2018-01-30 02:03:54|1725430|   36587|914045782120401|GENUINE|  350|1.4569845000000002E7|
+----------------+-------------------+-------+--------+---------------+-------+-----+--------------------+
only showing top 20 rows
```

Drop duplicates on this DF to remove redundant transactions done of card_id, transaction date, score & post code.

```
lookup_table = lookup_table.dropDuplicates((['card_id','transaction_date','postcode']))
```

```
lookup_table.count()  #1000
```

```
1000
```

Task4: Load the data in lookup table

Steps:

1. Used hbase as NoSQL database.
2. Open the connection.
3. Created definitions for opening and closing connections.
4. Created definitions for listing, creating and bulk load data.
5. Bulk loaded data in the lookup table in hbase.
6. Used ‘list’ command in hbase to see the table created.
7. Used scan “lookup_table” to check on the data.
8. Used count “lookup_table” to check on count of data.

```
import happybase
#create connection
connection = happybase.Connection('localhost', port=9090 ,autoconnect=False)
```

```
def open_connection():
    connection.open()
#close the opened connection
def close_connection():
    connection.close()
#list all tables in Hbase
def list_tables():
    print "fetching all table"
    open_connection()
    tables = connection.tables()
    close_connection()
    print "all tables fetched"
    return tables
```

```
#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
```

```
create_table('lookup_table', {'info' : dict(max_versions=5) })
```

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

```
#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()
```

```
batch_insert_data(lookup_table,'lookup_table')
```

```
starting batch insert of events
batch insert done
```

```python
# create table of card_transactions.csv file.
create_table('card_transactions', {'info' : dict(max_versions=5) })
```

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

```python
def batch_insert_csvdata(filename,tableName):
    print "starting batch insert of events"
    file = open(filename, "r")
    table = get_table(tableName)
    open_connection()
    i=0

    for line in file:
        temp = line.strip().split(",")

        #Skip the first row
        if temp[0]!='card_id':

            table.put(bytes(i) , { 'info:card_id':bytes(temp[0]),
                                    'info:member_id':bytes(temp[1]),
                                    'info:amount':bytes(temp[2]),
                                    'info:postcode':bytes(temp[3]),
                                    'info:pos_id':bytes(temp[4]),
                                    'info:transaction_dt':bytes(temp[5]),
                                    'info:status':bytes(temp[6])})
        i=i+1



    file.close()
    print "batch insert done"
    close_connection()
```

```python
#Batch insert data of card_transactions.csv file.
batch_insert_csvdata('card_transactions.csv','card_transactions')
```

```
starting batch insert of events
batch insert done
```

Validate the table created and data in Hbase:

1) Login to putty as root user
2) Start thrift server using below command

/opt/cloudera/parcels/CDH/lib/hbase/bin/hbase-daemon.sh start thrift -p 9090

3) Give command hbase shell
4) Give command “list”

```
hbase(main):007:0> list
TABLE
card_transactions
lookup_table
2 row(s) in 0.0070 seconds

=> ["card_transactions", "lookup_table"]
hbase(main):008:0>
```

root@ip-10-0-0-149:~

```
 6591175617713393                 column=info:transaction_date, timestamp=1634375007372, value=2018-01-31 13:10:37
 6592184145413632                 column=info:UCL, timestamp=1634375006787, value=13734342.65
 6592184145413632                 column=info:card_id, timestamp=1634375006787, value=6592184145413632
 6592184145413632                 column=info:postcode, timestamp=1634375006787, value=53186
 6592184145413632                 column=info:score, timestamp=1634375006787, value=456
 6592184145413632                 column=info:transaction_date, timestamp=1634375006787, value=2018-01-28 00:54:30
 6594248319343442                 column=info:UCL, timestamp=1634375006872, value=15065362.77
 6594248319343442                 column=info:card_id, timestamp=1634375006872, value=6594248319343442
 6594248319343442                 column=info:postcode, timestamp=1634375006872, value=24927
 6594248319343442                 column=info:score, timestamp=1634375006872, value=350
 6594248319343442                 column=info:transaction_date, timestamp=1634375006872, value=2018-01-31 23:42:38
 6595638658736751                 column=info:UCL, timestamp=1634375007621, value=14005069.97
 6595638658736751                 column=info:card_id, timestamp=1634375007621, value=6595638658736751
 6595638658736751                 column=info:postcode, timestamp=1634375007621, value=68328
 6595638658736751                 column=info:score, timestamp=1634375007621, value=310
 6595638658736751                 column=info:transaction_date, timestamp=1634375007621, value=2018-01-30 10:50:34
 6595814135833988                 column=info:UCL, timestamp=1634375007288, value=14332708.84
 6595814135833988                 column=info:card_id, timestamp=1634375007288, value=6595814135833988
 6595814135833988                 column=info:postcode, timestamp=1634375007288, value=22508
 6595814135833988                 column=info:score, timestamp=1634375007288, value=210
 6595814135833988                 column=info:transaction_date, timestamp=1634375007288, value=2018-01-30 02:03:54
 6595928469079750                 column=info:UCL, timestamp=1634375008323, value=11824730.01
 6595928469079750                 column=info:card_id, timestamp=1634375008323, value=6595928469079750
 6595928469079750                 column=info:postcode, timestamp=1634375008323, value=98349
 6595928469079750                 column=info:score, timestamp=1634375008323, value=412
 6595928469079750                 column=info:transaction_date, timestamp=1634375008323, value=2018-01-24 12:38:22
 6597703848279563                 column=info:UCL, timestamp=1634375007681, value=15250624.49
 6597703848279563                 column=info:card_id, timestamp=1634375007681, value=6597703848279563
 6597703848279563                 column=info:postcode, timestamp=1634375007681, value=95699
 6597703848279563                 column=info:score, timestamp=1634375007681, value=218
 6597703848279563                 column=info:transaction_date, timestamp=1634375007681, value=2018-01-27 10:51:49
 6598830758632447                 column=info:UCL, timestamp=1634375007878, value=12685782.48
 6598830758632447                 column=info:card_id, timestamp=1634375007878, value=6598830758632447
 6598830758632447                 column=info:postcode, timestamp=1634375007878, value=19421
 6598830758632447                 column=info:score, timestamp=1634375007878, value=293
 6598830758632447                 column=info:transaction_date, timestamp=1634375007878, value=2018-01-30 00:18:34
 6599900931314251                 column=info:UCL, timestamp=1634375008288, value=12487392.07
 6599900931314251                 column=info:card_id, timestamp=1634375008288, value=6599900931314251
 6599900931314251                 column=info:postcode, timestamp=1634375008288, value=97423
 6599900931314251                 column=info:score, timestamp=1634375008288, value=297
 6599900931314251                 column=info:transaction_date, timestamp=1634375008288, value=2018-01-31 11:25:16
999 row(s) in 0.4250 seconds

hbase(main):009:0>
```

Validation as per mentioned:

Count of card_transactions.csv: 53292

```
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),
                           ])
```

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

```
tranf.count()
```

```
53292
```

Count of sqoop jobs :999

```
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),
                         ])
```

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

```
#Checking number of records loaded from HDFS, looks they are loaded as expected.
cardf.count()
```

```
999
```

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

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

```
memf.count()
```

```
999
```