Real-time Credit card Fraud detection using Spark Streaming, Spark ML, Spark SQL, Kafka, Cassandra and Airflow

Note: In the video course, I am automating both Spark ML and Spark Streaming Job using Apache Airflow. This is just to show how multiple Spark Jobs are automated using Apache Airflow.
In reality, the Spark ML Job will not be automated. It will be manually run once a week, or once a month to create a new model. The model will be tested for efficiency. Also, it will be compared with the efficiency of the previous model. If the new model is better than the previous model then the new model will be deployed. Spark Streaming Job will be restarted to pick the new model. Hence only Spark Streaming Job must be automated in a real scenario

1.Introduction

https://pixipanda.com/

Refer to this website for complete training content on Kafka, Spark, Spark SQL, Spark Streaming, Structured Streaming, Hive, Sqoop, HDFS, and MapReduce
Along with training content, I have also uploaded code and image for practice.

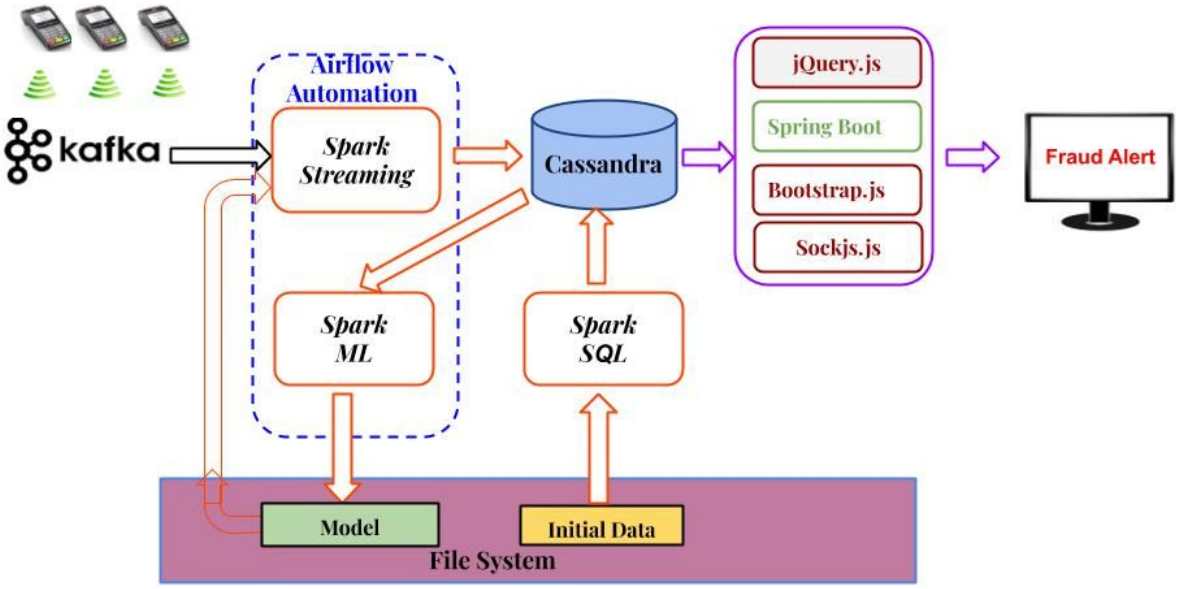
1.1 Domain Knowledge

Credit card fraud detection Domain Knowledge
Let's say you own a credit card. Your prior spending habits will be learned. Like how much amount you spend, at which merchant you spend, at what frequency you spend, what do you purchase, etc.
Based on this learning, your current credit transaction will be predicted as fraud if it deviates from your earlier spending habits otherwise it will be treated as a genuine transaction. And fraud transactions will be alerted in the dashboard.
Such predictions will be done on millions of transactions. Hence distributed frameworks are used which can scale as the transactions increase.

1.2 Course Description

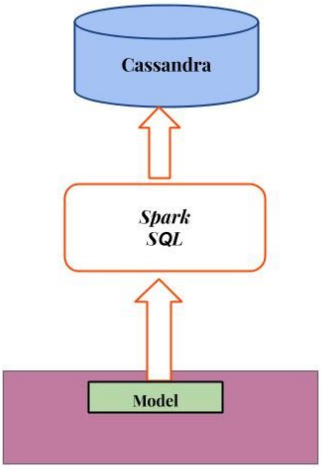
Real-time Credit card Fraud Detection is implemented using Spark Kafka and Cassandra.
Spark ML Pipeline Stages like String Indexer, Vector Slicer, Standard Scaler and Vector Assembler is used for Preprocessing
Machine Learning model is created using the Random Forest Algorithm
Data balancing is done using K-means Algorithm
Integration of Spark Streaming with Kafka and Cassandra
Exactly-once semantics is achieved using Spark Streaming custom offset management
Airflow Automation framework is used to automate Spark Jobs on Spark Standalone Cluster.

2. Architecture



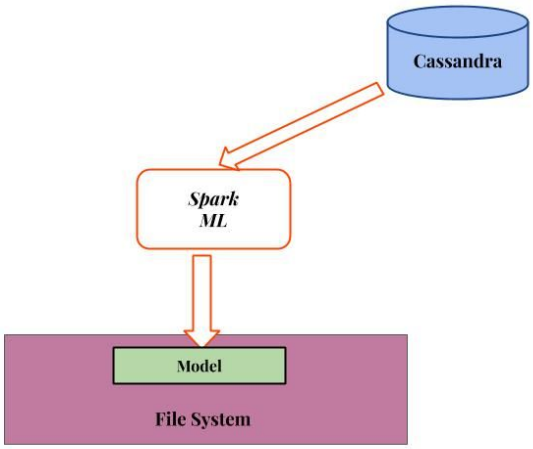
All the transaction data, ie historic data, captured from all the customers are stored in a File System. This file system could be HDFS or Amazon S3 or Azure Blob or it could be any other File System

2.1 Spark SQL Job



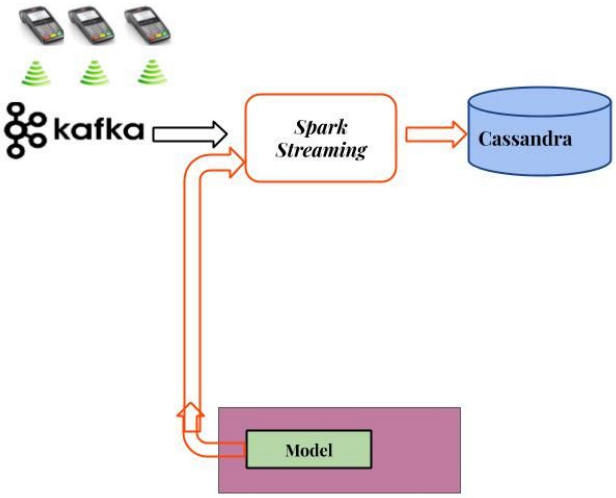
This Spark Job will import all the transaction data from the file system into the Cassandra database.
This job will import fraud transactions to fraud table and non-fraud transactions to a non-fraud table

2.2 Spark ML Job



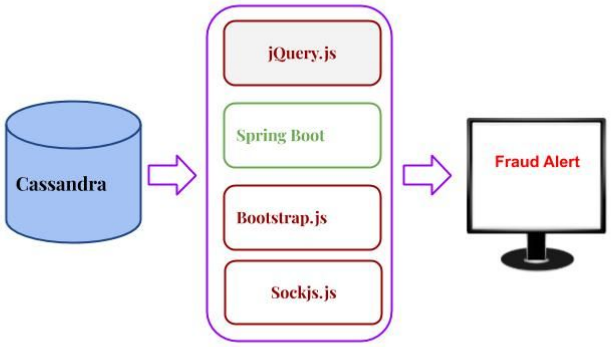
This Spark Job will read fraud and non-fraud transactions from Cassandra. It will train on this data and it will create a model. This model will be saved to the file system.

2.3 Spark Streaming Job



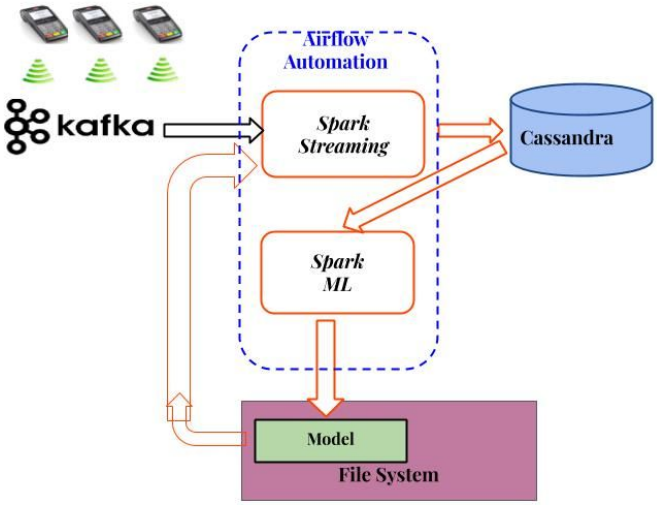
Streaming Job will load the model from the file system. It will then start consuming credit card transaction messages from Kafka.
Using this model it will predict whether a transaction is a fraud or not.
Finally, it will save the predictions to the Cassandra database. Fraud transactions are saved to the fraud table and the non-fraud transactions to the non-fraud table.

2.4 Fraud-alert dashboard



Fraud alert dashboard will internally query Cassandra for the lastest fraud transactions. If there are any fraud transactions, it will be displayed on the dashboard.

2.5 Airflow Automation



Airflow Automation is used to automate Spark Streaming and Spark ML Job.
Here we are automating Spark ML Job also. But in reality, Spark ML Job will be run manually by DataScience Team. It will be manually run once a week, or once a month to create a new model. The new model will be tested for efficiency. Also, it will be

compared with the efficiency of the previous model. If the new model is better than the previous model then the new model will be deployed.
Currently running Spark Streaming Job will be stopped and a new Streaming Job will be started to pick the new Model. Airflow automation is used to Stop and Start a new Spark Streaming Job whenever a new model is created.

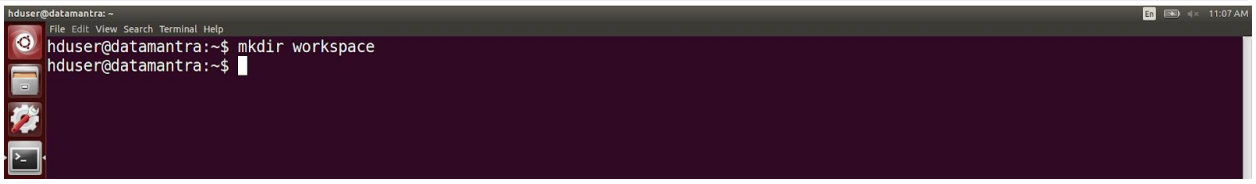
3. Image and Code Setup

Download and Install Oracle VirtualBox
https://www.virtualbox.org/wiki/Downloads
Import Ubuntu image.
http://bit.ly/udemy_ubuntu_image
Username: hduser
Password: hadoop123

3.1 Clone Code

Create a workspace directory
Create a workspace directory in your home directory

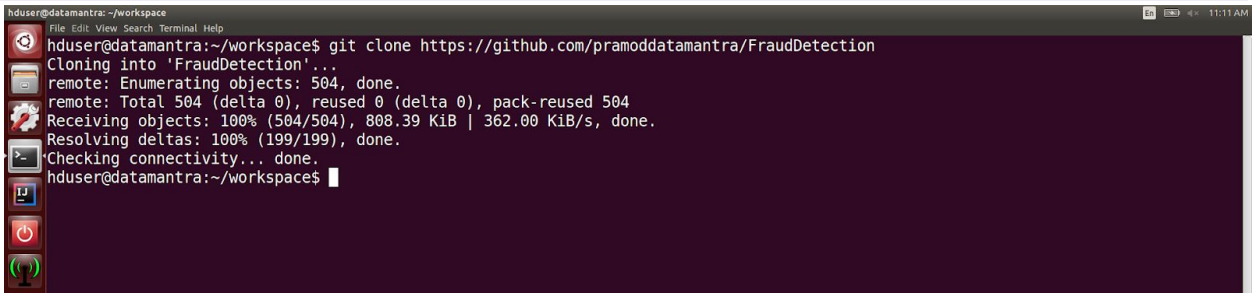
```
mkdir workspace
cd workspace
```



Clone FraudDection from GitHub

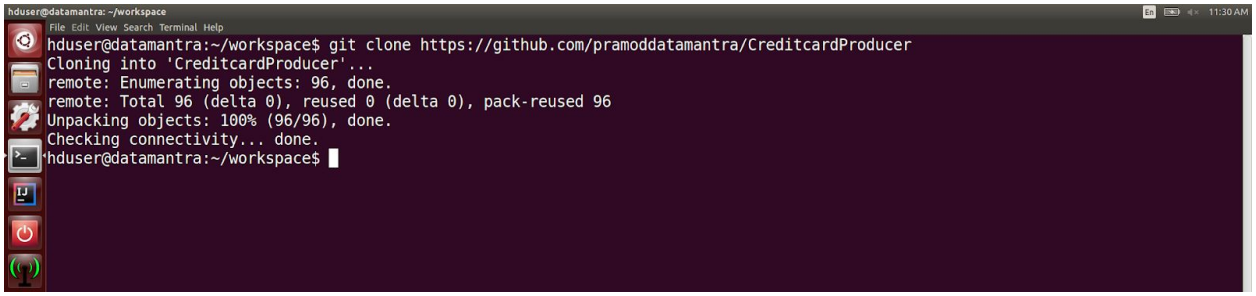
This is a branch code. It is a bit different from the code shown in the video.
Here we have VectorSlicer, StandardScaler and Confusion matrix.

```
git clone
https://github.com/pramoddatamantra/FraudDetection/tree/FraudDetection_ML
```



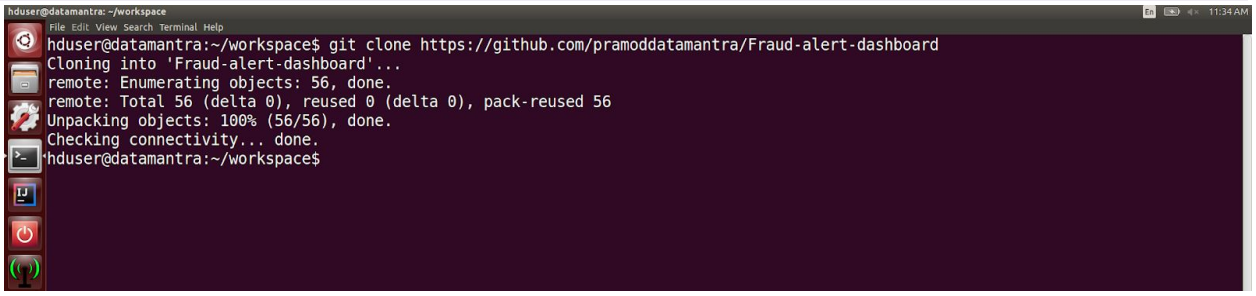
Clone Credit card producer from GitHub

```
git clone https://github.com/pramoddatamantra/CreditcardProducer
```



Clone Fraud-alert-dashboard

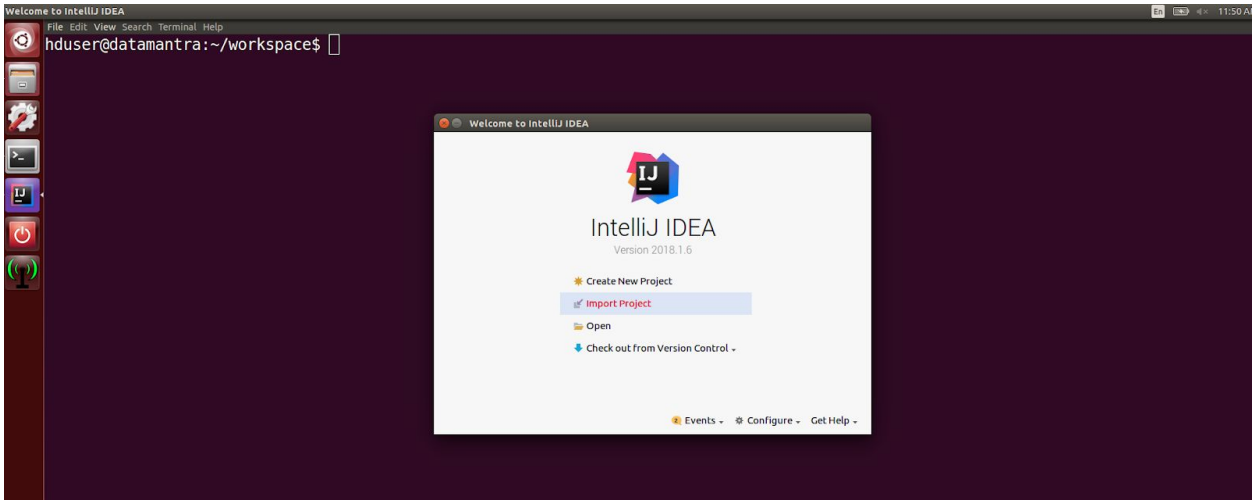
```
git clone https://github.com/pramoddatamantra/Fraud-alert-dashboard
```



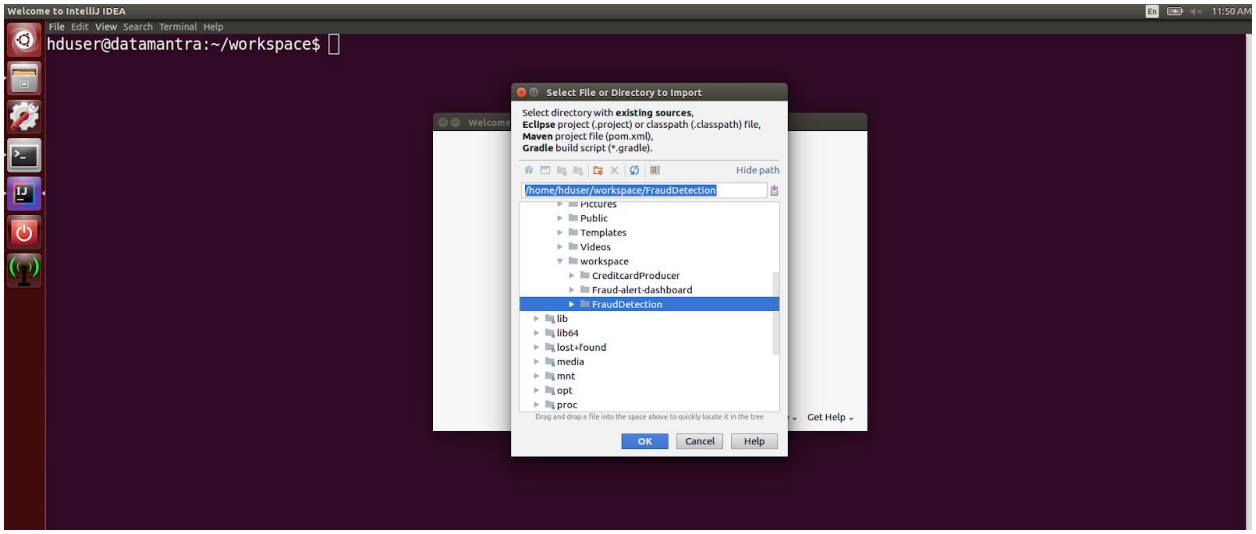
3.2 Import to IntelliJ

Import FraudDection to IntelliJ

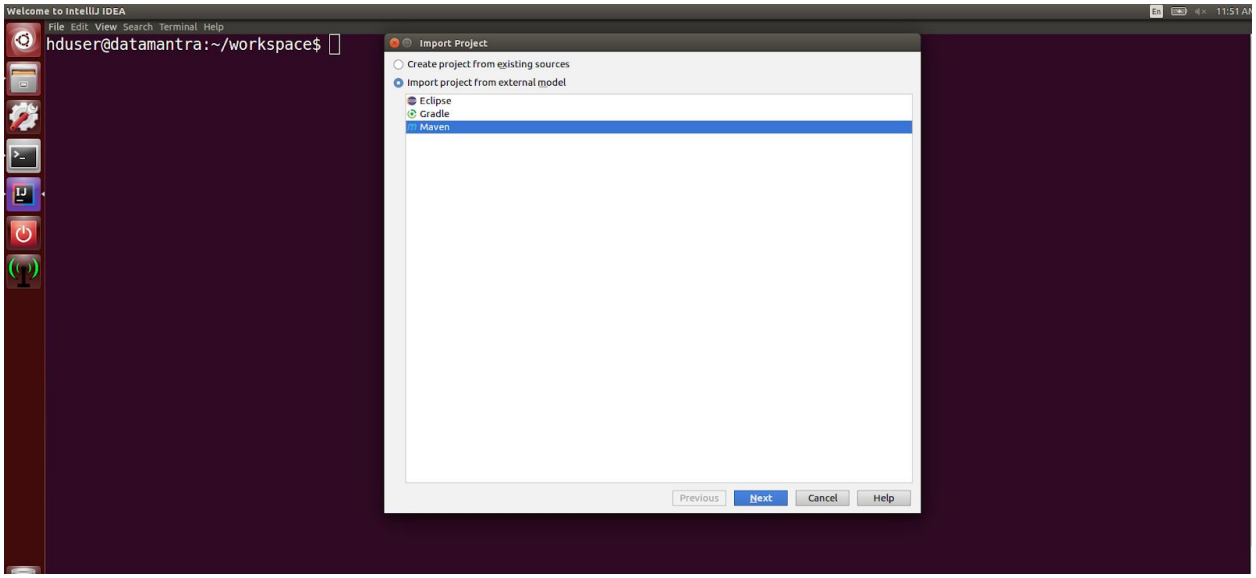
Click Import



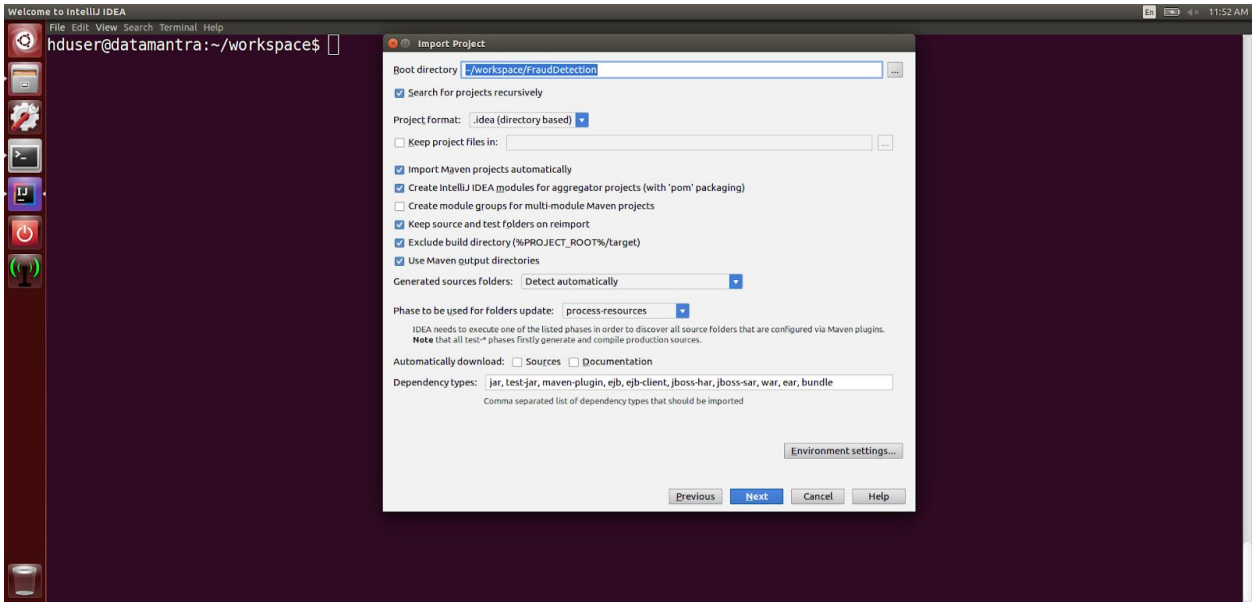
Select FraudDetection Project. Click OK. Click Next



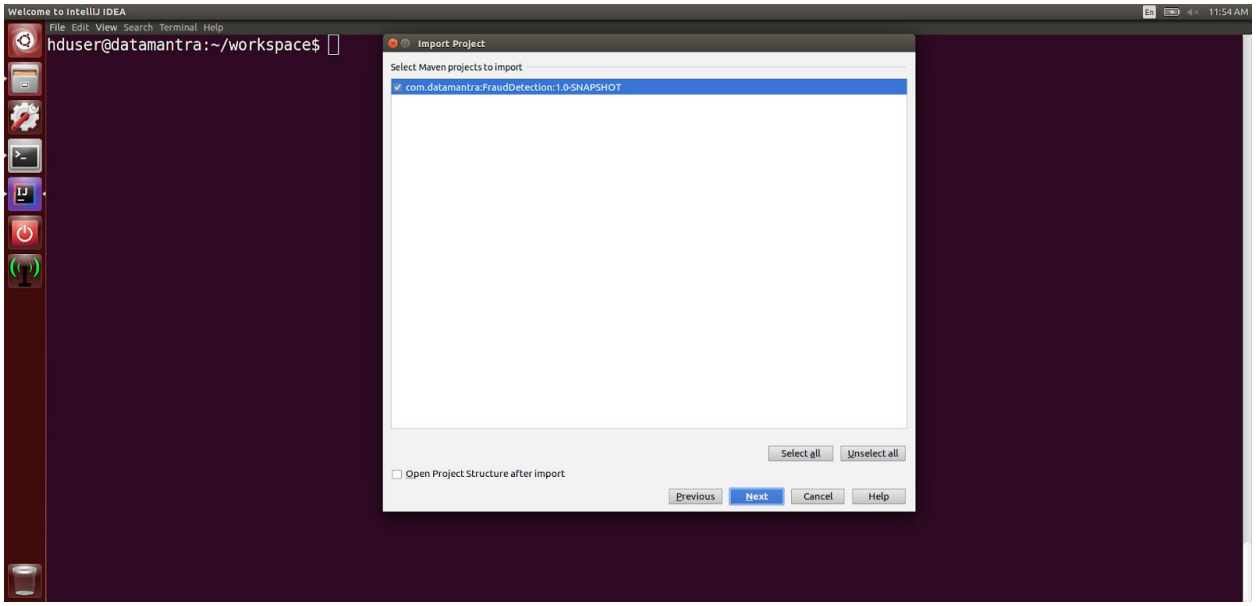
Select Maven. Click Next



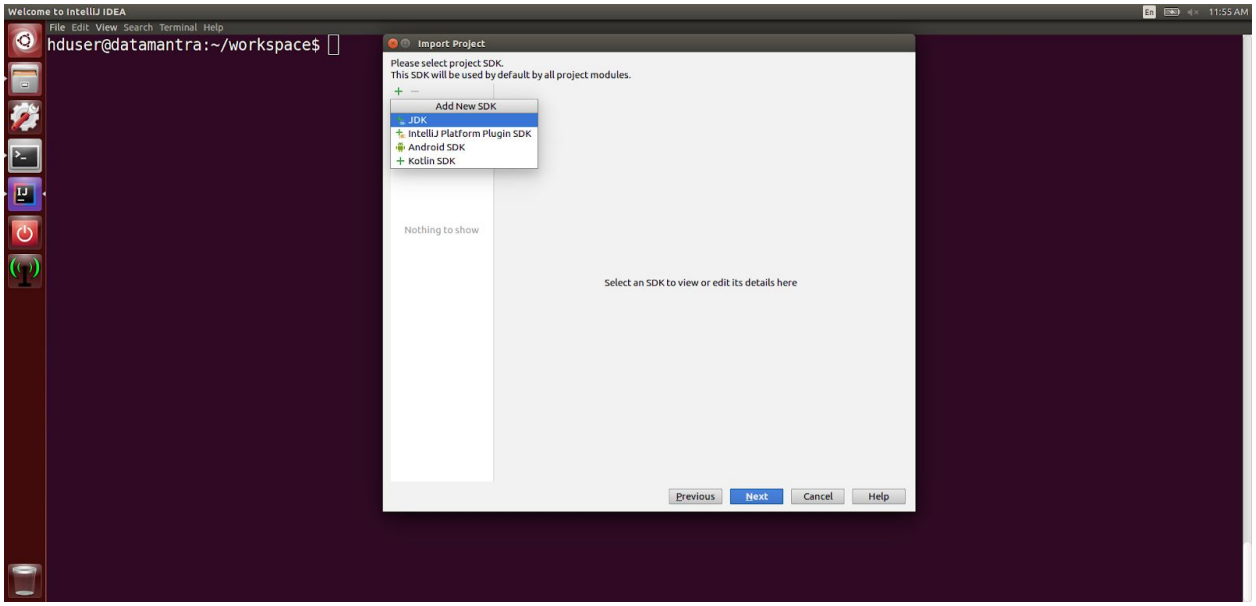
Checkmark “Search for projects recursively” and “Import Maven projects automatically” Click Next



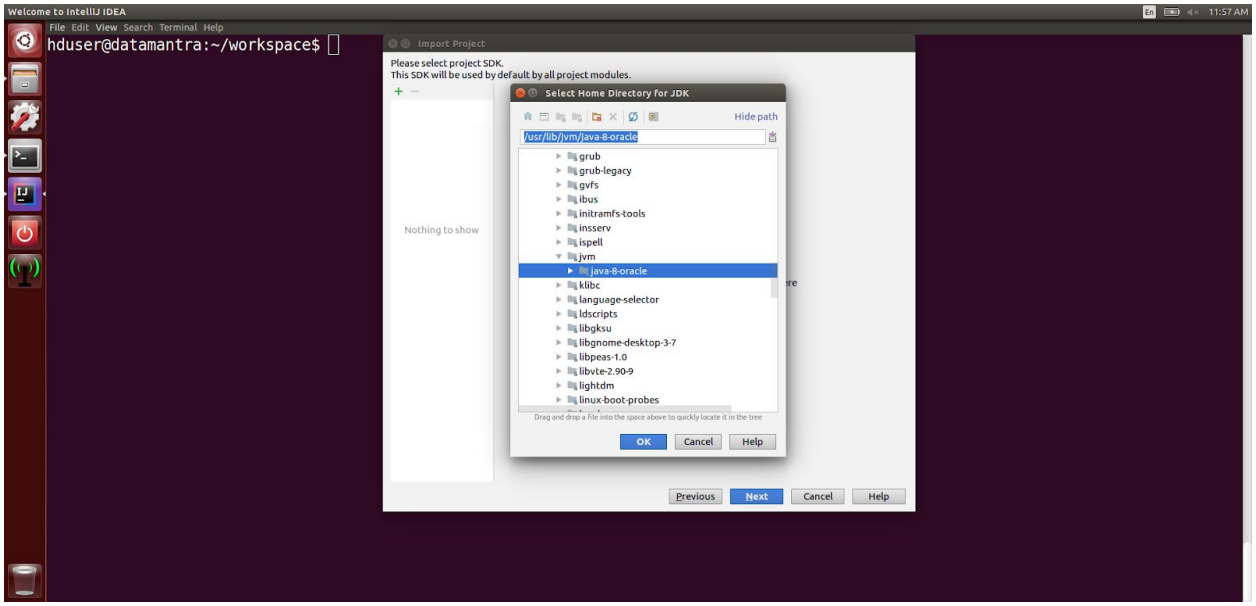
By default, the FraudDetection project will be selected. Click Next



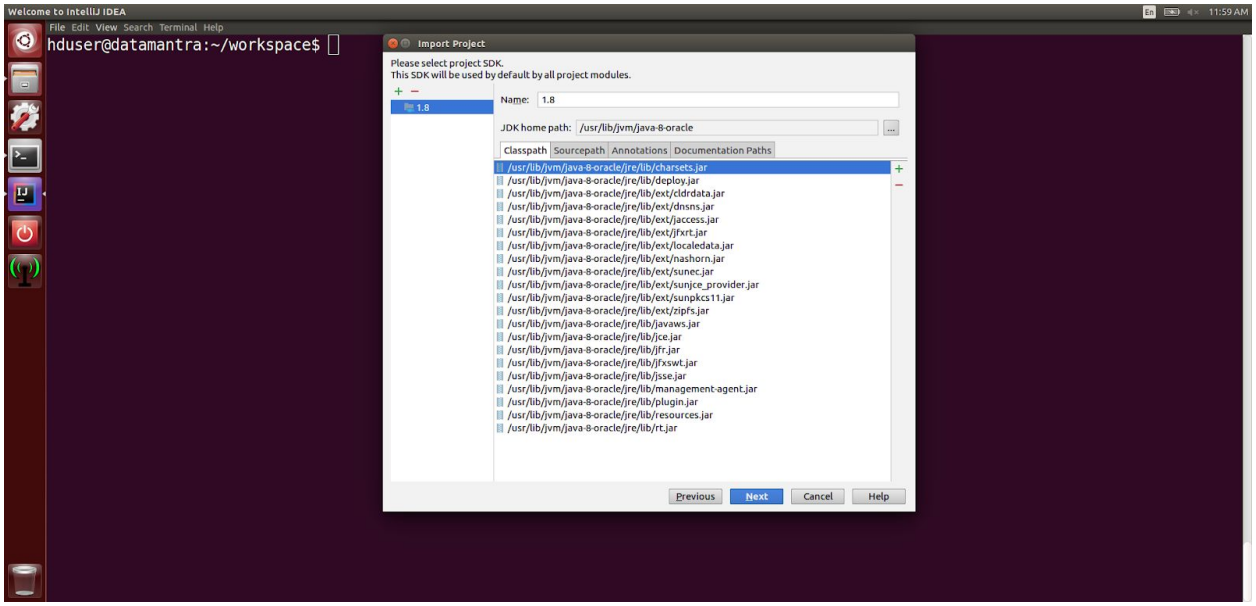
Select JDK



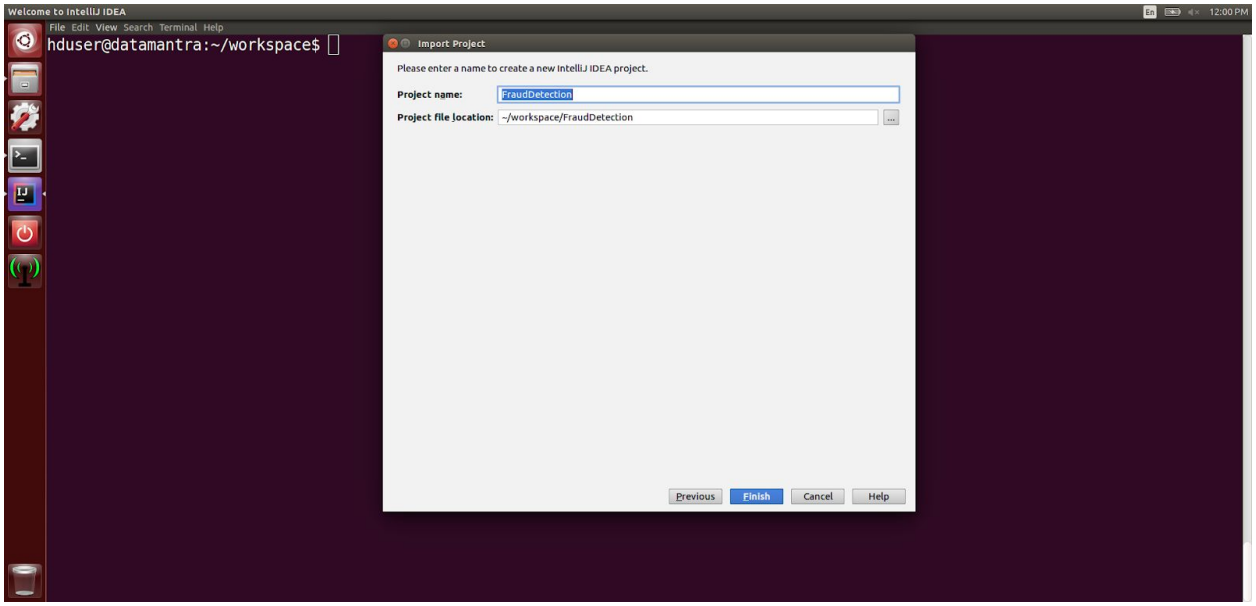
Select the java-8-oracle directory. Click OK and Click Next



Java 1.8 SDK is selected. Click Next



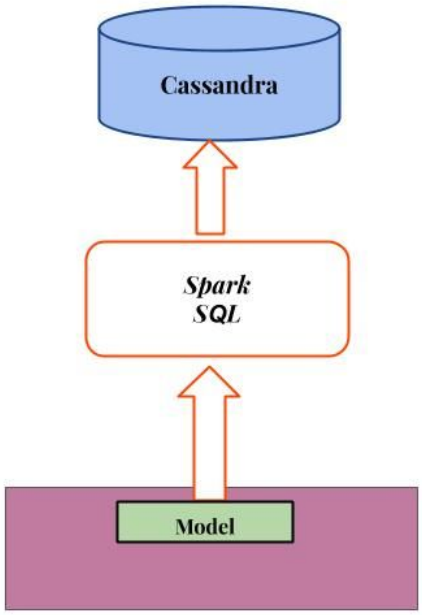
Let the project name and project path be as it is. Click Finish



Follow the above steps to import CreditcardProducer and Fraud-alert-dashboard project into IntelliJ

4. Initial Import Spark Job

4.1 Introduction



This Spark Job will read the customer data and transaction data from the filesystem.
It will do some ETL transformations on customer and transaction data, like computing age of the customer, distance between customer and merchant place, etc.
It will save these transformed into Cassandra.
It will save the customers data to customer table
Fraud transactions will be saved to fraud_transaction table and non-fraud transactions to non_fraud_transaction.

4.2 Transformation

4.2.1 Compute Age

Customer.csv has a column with DOB of the customer. From DOB we will age of the customer. Age will be used as a feature in the Spark ML Job

```
val customerDF = DataReader.read(SparkConfig.customerDatasource,
Schema.customerSchema)
```

```
val customerAgeDF = customerDF.withColumn("age",
(datediff(current_date(),to_date($"dob"))/365).cast(IntegerType))
```

4.2.2 Compute Distance

Customer.csv has customer's home location(latitude and longitude). Transactions.csv has Merchant Location(latitude and longitude). Using this information we will compute the distance between Customer and Merchant. Again distance will be used as a feature in Spark ML Job

```
val transactionDF = DataReader.read(SparkConfig.transactionDatasouce,
Schema.fruadCheckedTransactionSchema)
      .withColumn("trans_date", split($"trans_date", "T").getItem(0))
      .withColumn("trans_time", concat_ws(" ", $"trans_date",
$"trans_time"))
      .withColumn("trans_time", to_timestamp($"trans_time", "YYYY-MM-dd
HH:mm:ss") cast(TimestampType))

val distanceUdf = udf(Utils.getDistance _)

val processedDF = transactionDF.join(broadcast(customerAgeDF),
Seq("cc_num"))
      .withColumn("distance", lit(round(distanceUdf($"lat", $"long",
$"merch_lat", $"merch_long"), 2)))
      .select("cc_num", "trans_num", "trans_time", "category", "merchant",
"amt", "merch_lat", "merch_long", "distance", "age", "is_fraud")
```

4.2.3 Save to Cassandra

Customer data is saved to the customer table
Fraud transactions data is saved to fraud_transaction table
Genuine transactions data is saved to non_fraud_transaction table

```
/* Save Customer data to Cassandra */
    customerDF.write
      .format("org.apache.spark.sql.cassandra")
      .mode("append")
      .options(Map("keyspace" -> CassandraConfig.keyspace, "table" ->
CassandraConfig.customer))
      .save()
```

```
/* Save fraud transaction data to fraud_transaction cassandra table*/
fraudDF.write
      .format("org.apache.spark.sql.cassandra")
      .mode("append")
      .options(Map("keyspace" -> CassandraConfig.keyspace, "table" ->
CassandraConfig.fraudTransactionTable))
      .save()

/* Save non fraud transaction data to non_fraud_transaction cassandra
table*/
nonFraudDF.write
      .format("org.apache.spark.sql.cassandra")
      .mode("append")
      .options(Map("keyspace" -> CassandraConfig.keyspace, "table" ->
CassandraConfig.nonFraudTransactionTable))
      .save()
```

4.3 Demonstration

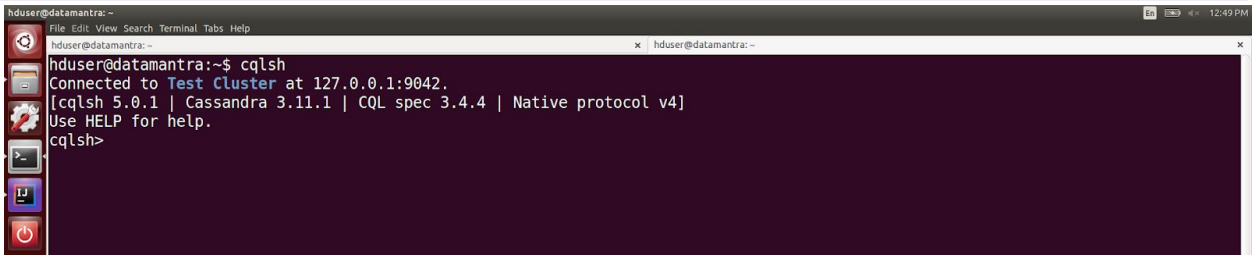
Start Cassandra Server

```
Cassandra -f
```

Connect to Cassandra Server

Connect to Cassandra Server using Cassandra Cqlsh client

```
cqlsh
```



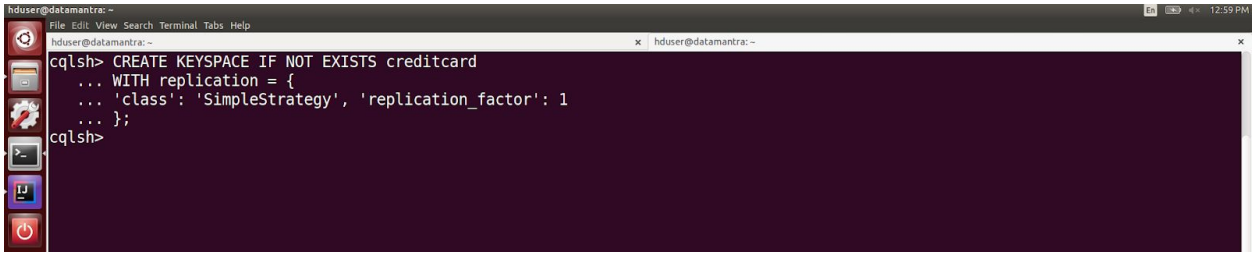
Create keyspace and tables

https://github.com/pramoddatamantra/FraudDetection/blob/master/src/main/resources/cassandra/creditcard.cql

Copy the contents of this file and paste it on cqlsh Cassandra client

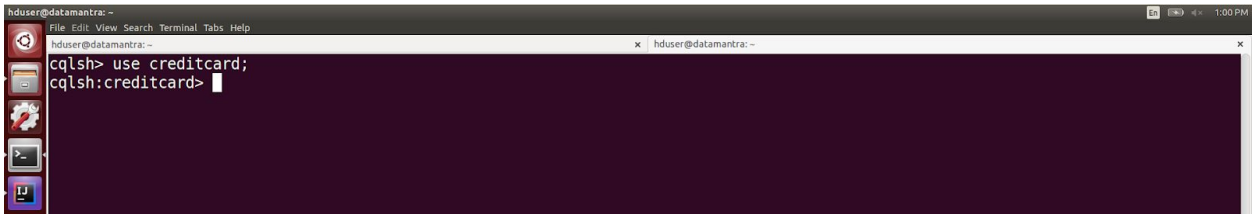
Create creditcard keyspace

```
CREATE KEYSPACE IF NOT EXISTS creditcard
WITH replication = {
'class': 'SimpleStrategy', 'replication_factor': 1
};
```



Use creditcard keyspace

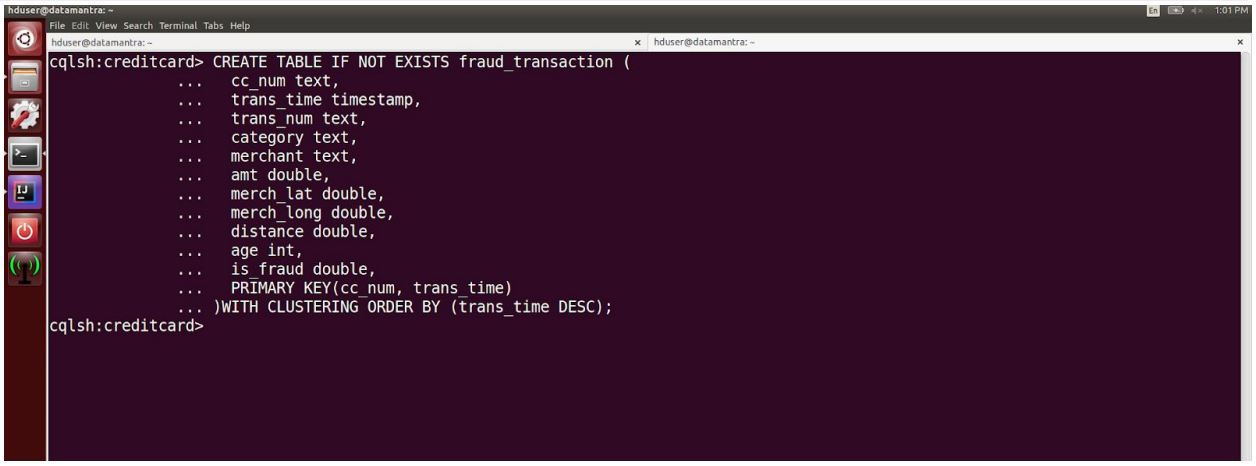
```
USE creditcard;
```



Create fraud_transaction table

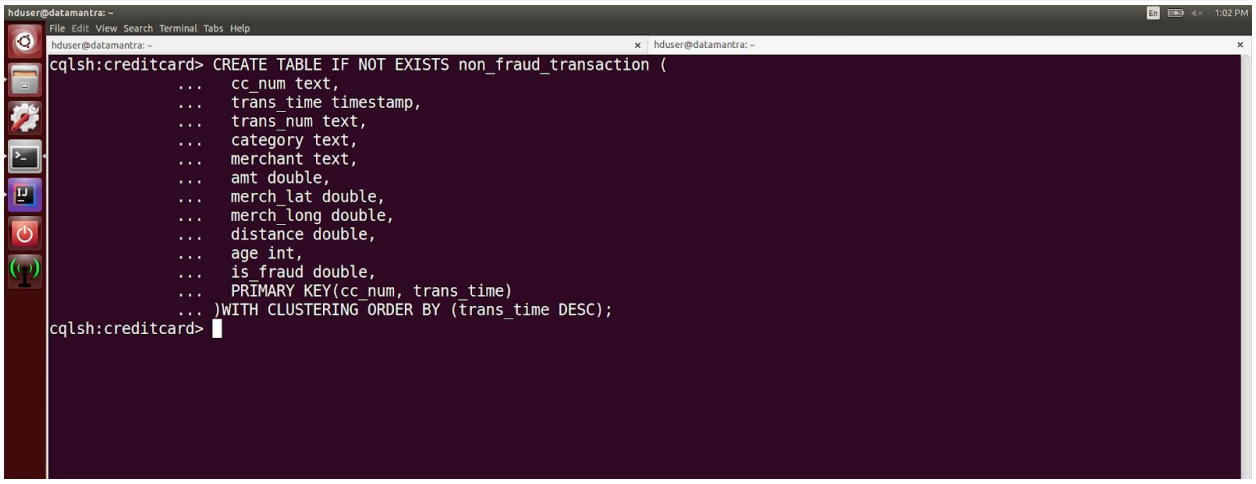
```
CREATE TABLE IF NOT EXISTS fraud_transaction (
  cc_num text,
  trans_time timestamp,
  trans_num text,
  category text,
  merchant text,
  amt double,
  merch_lat double,
  merch_long double,
  distance double,
  age int,
  is_fraud double,
```

```
  PRIMARY KEY(cc_num, trans_time)
)WITH CLUSTERING ORDER BY (trans_time DESC);
```



Create not_fraud_transaction table

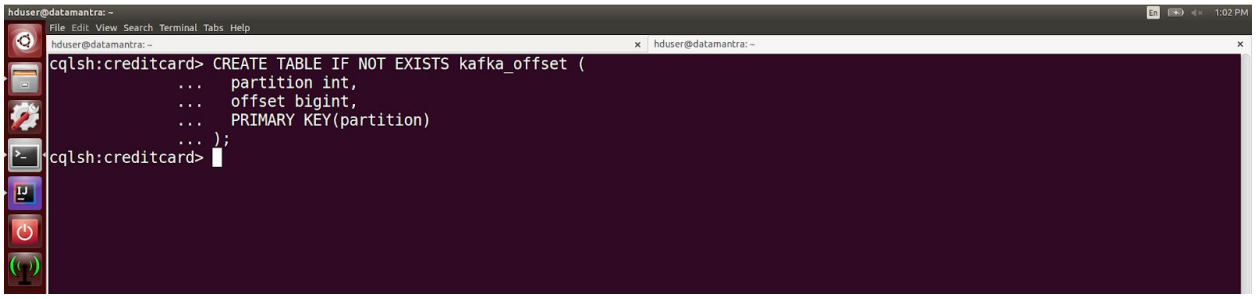
```
CREATE TABLE IF NOT EXISTS non_fraud_transaction (
  cc_num text,
  trans_time timestamp,
  trans_num text,
  category text,
  merchant text,
  amt double,
  merch_lat double,
  merch_long double,
  distance double,
  age int,
  is_fraud double,
  PRIMARY KEY(cc_num, trans_time)
)WITH CLUSTERING ORDER BY (trans_time DESC);
```



Create a kafk_offset table

Offset per partition will be saved in this table

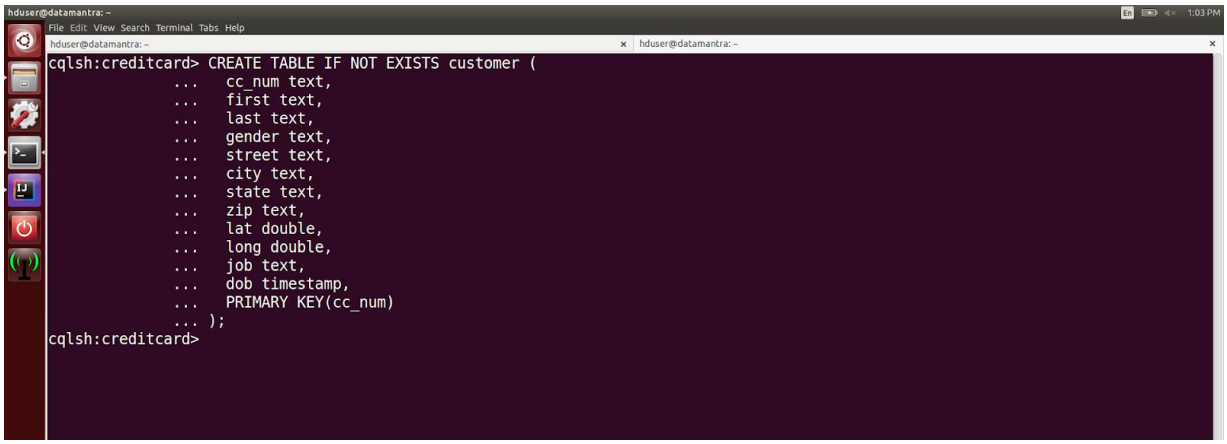
```
CREATE TABLE IF NOT EXISTS kafka_offset (
  partition int,
  offset bigint,
  PRIMARY KEY(partition)
);
```



Create a customer table

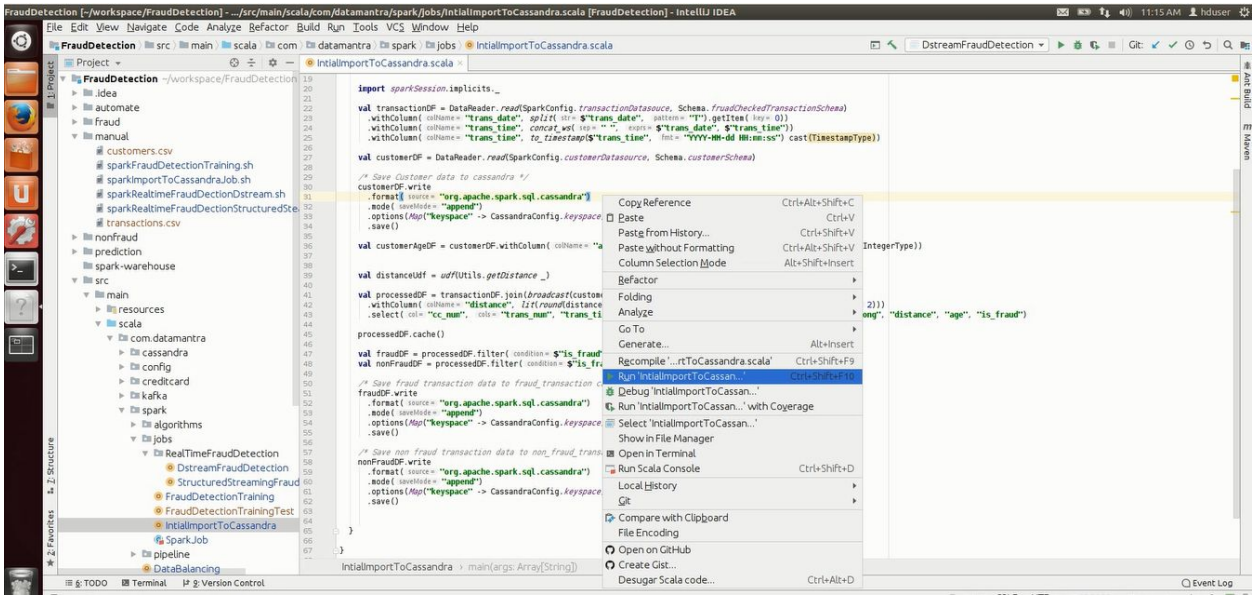
This table will have customer details

```
CREATE TABLE IF NOT EXISTS customer (
  cc_num text,
  first text,
  last text,
  gender text,
  street text,
  city text,
  state text,
  zip text,
  lat double,
  long double,
  job text,
  dob timestamp,
  PRIMARY KEY(cc_num));
```



Run IntialImportToCassandra.scala from IntelliJ

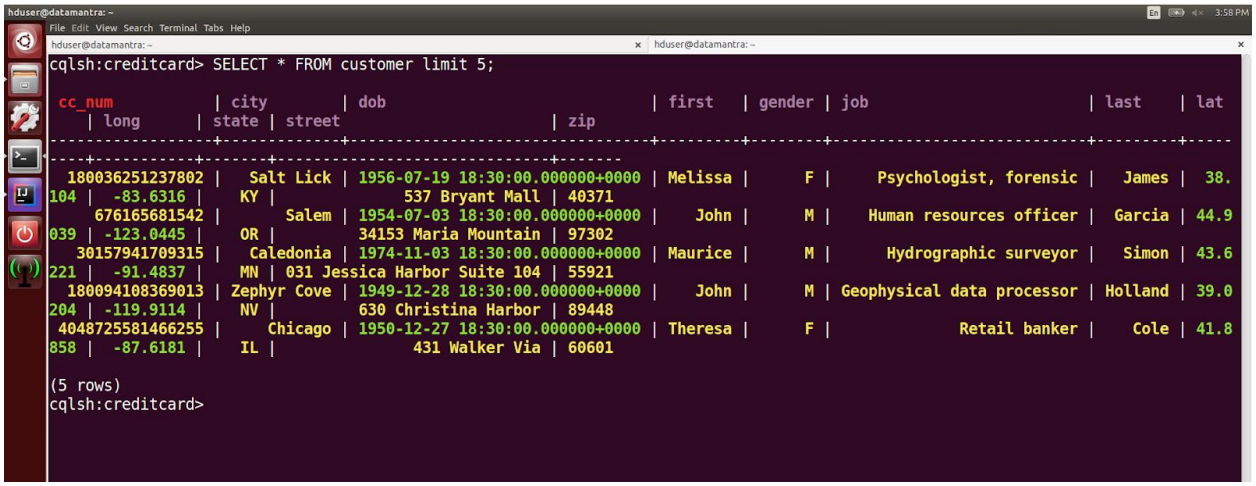
No Input parameter



Output

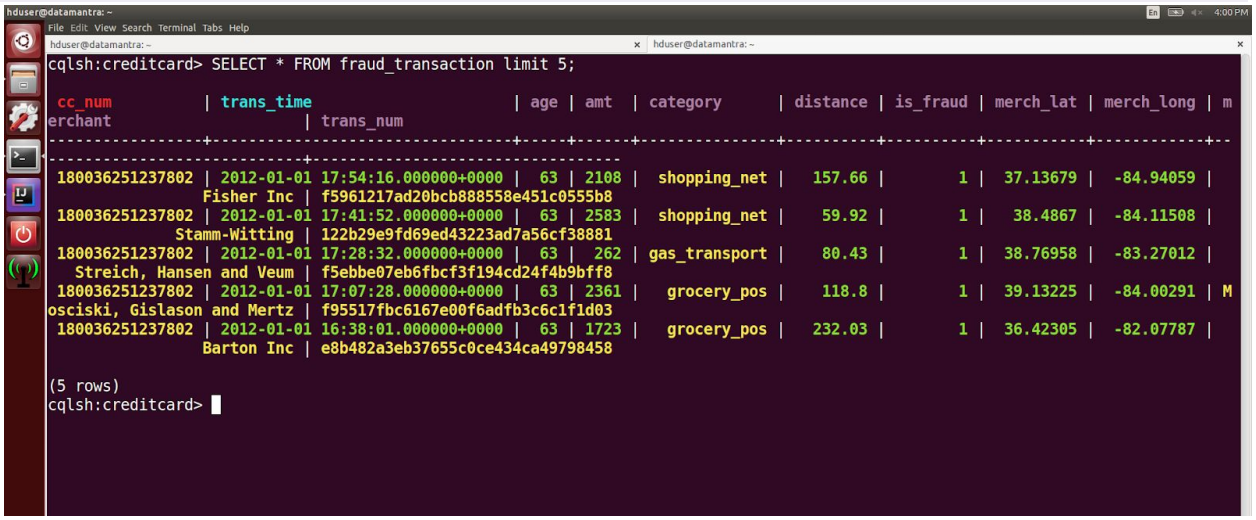
Transaction data and customer data must be saved in the corresponding table in Cassandra

```
SELECT * FROM customer limit 5
```



```
cqlsh:creditcard> SELECT * FROM customer limit 5;

 cc_num          | city        | dob                             | first   | gender | job                          | last    | lat
    | long      | state | street                       | zip
-----------------+-------------+---------------------------------+---------+--------+------------------------------+---------+-----
----+-----------+-------+------------------------------+-------
  180036251237802 |   Salt Lick | 1956-07-19 18:30:00.000000+0000 | Melissa |      F |     Psychologist, forensic |   James |  38.
104 |  -83.6316 |    KY |              537 Bryant Mall | 40371
     676165681542 |       Salem | 1954-07-03 18:30:00.000000+0000 |    John |      M |    Human resources officer |  Garcia | 44.9
039 | -123.0445 |    OR |          34153 Maria Mountain | 97302
   30157941709315 |   Caledonia | 1974-11-03 18:30:00.000000+0000 | Maurice |      M |      Hydrographic surveyor |   Simon | 43.6
221 |  -91.4837 |    MN | 031 Jessica Harbor Suite 104 | 55921
  180094108369013 | Zephyr Cove | 1949-12-28 18:30:00.000000+0000 |    John |      M | Geophysical data processor | Holland | 39.0
204 | -119.9114 |    NV |          630 Christina Harbor | 89448
 4048725581466255 |     Chicago | 1950-12-27 18:30:00.000000+0000 | Theresa |      F |              Retail banker |    Cole | 41.8
858 |  -87.6181 |    IL |               431 Walker Via | 60601

(5 rows)
cqlsh:creditcard>
```

```
SELECT * FROM fraud_transaction limit 5;
```



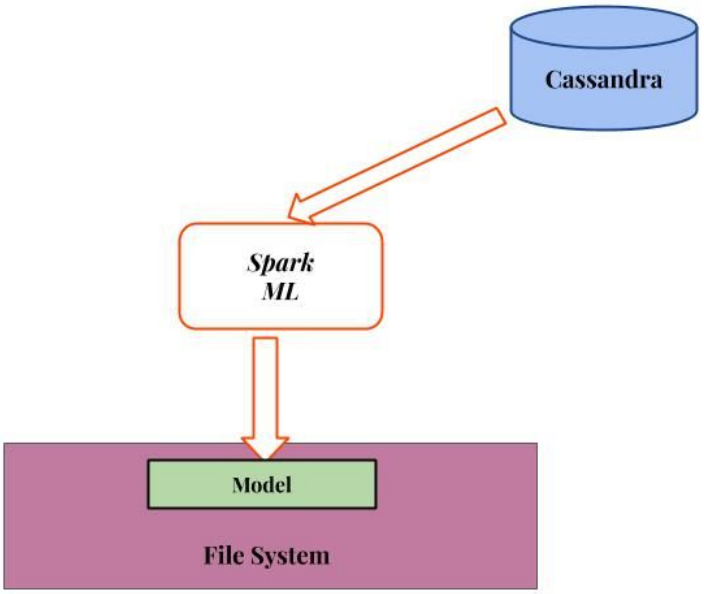
```
cqlsh:creditcard> SELECT * FROM fraud_transaction limit 5;

 cc_num          | trans_time                      | age | amt   | category      | distance | is_fraud | merch_lat | merch_long | m
erchant                  | trans_num
-----------------+---------------------------------+-----+-------+---------------+----------+----------+-----------+------------+--
-------------------------+----------------------------------
 180036251237802 | 2012-01-01 17:54:16.000000+0000 |  63 |  2108 |  shopping_net |   157.66 |        1 |  37.13679 |  -84.94059 |
                Fisher Inc | f5961217ad20bcb888558e451c0555b8
 180036251237802 | 2012-01-01 17:41:52.000000+0000 |  63 |  2583 |  shopping_net |    59.92 |        1 |   38.4867 |  -84.11508 |
            Stamm-Witting | 122b29e9fd69ed43223ad7a56cf38881
 180036251237802 | 2012-01-01 17:28:32.000000+0000 |  63 |   262 | gas_transport |    80.43 |        1 |  38.76958 |  -83.27012 |
   Streich, Hansen and Veum | f5ebbe07eb6fbcf3f194cd24f4b9bff8
 180036251237802 | 2012-01-01 17:07:28.000000+0000 |  63 |  2361 |   grocery_pos |    118.8 |        1 |  39.13225 |  -84.00291 | M
osciski, Gislason and Mertz | f95517fbc6167e00f6adfb3c6c1f1d03
 180036251237802 | 2012-01-01 16:38:01.000000+0000 |  63 |  1723 |   grocery_pos |   232.03 |        1 |  36.42305 |  -82.07787 |
                Barton Inc | e8b482a3eb37655c0ce434ca49798458

(5 rows)
cqlsh:creditcard>
```

```
SELECT * FROM fraud_transaction limit 5;
```

All the data is successfully imported to Cassandra Keyspace

5. Spark Training Job

5.1 Introduction



This Job will read fraud and non-fraud transaction data from Cassandra.
It will train on this data and it will create a model
This model will be saved to the file system.

Note: There are a few differences between this document and the video. Please consider this document over the video
As said earlier in an actual scenario, Spark ML Job must not be automated. It must be manually run, test and evaluated by the DataScience Team

5.2 Spark Training Steps

5.2.1 Read data from Cassandra

```
val fraudTransactionDF =
DataReader.readFromCassandra(CassandraConfig.keyspace,
CassandraConfig.fraudTransactionTable)
      .select("cc_num" , "category", "merchant", "distance", "amt", "age",
"is_fraud")

val nonFraudTransactionDF =
DataReader.readFromCassandra(CassandraConfig.keyspace,
CassandraConfig.nonFraudTransactionTable)
      .select("cc_num" , "category", "merchant", "distance", "amt", "age",
"is_fraud")

val transactionDF = nonFraudTransactionDF.union(fraudTransactionDF)
    transactionDF.cache()
```

```
+---------------+------------+--------------------------+--------+-----+---+--------+
|cc_num         |category    |merchant                  |distance|amt  |age|is_fraud|
+---------------+------------+--------------------------+--------+-----+---+--------+
|5157595343543285|gas_transport|Schmitt Inc              |0.73    |111.0|46 |0.0     |
|5157595343543285|kids_pets    |Beer-Jast                |1.73    |66.0 |46 |0.0     |
|5157595343543285|grocery_pos  |Hudson-Ratke             |1.23    |220.0|46 |0.0     |
|5157595343543285|entertainment|Kassulke Inc             |2.17    |100.0|46 |0.0     |
|5157595343543285|shopping_net |Boyer PLC                |1.33    |80.0 |46 |0.0     |
|5157595343543285|entertainment|Spencer PLC              |1.29    |141.0|46 |0.0     |
|5157595343543285|entertainment|Brown-Greenholt          |0.8     |221.0|46 |0.0     |
|5157595343543285|travel       |Kovacek Ltd              |1.5     |91.0 |46 |0.0     |
|5157595343543285|gas_transport|Kutch LLC                |0.71    |57.0 |46 |0.0     |
|5157595343543285|kids_pets    |Lowe, Dietrich and Erdman|1.41    |158.0|46 |0.0     |
|5157595343543285|kids_pets    |Bednar PLC               |1.99    |211.0|46 |0.0     |
|5157595343543285|kids_pets    |Hammes-Beatty            |0.88    |42.0 |46 |0.0     |
|5157595343543285|kids_pets    |Hilpert-Conroy           |0.97    |103.0|46 |0.0     |
|5157595343543285|gas_transport|Robel, Cummerata and Prosacco|1.26|100.0|46 |0.0     |
|5157595343543285|grocery_pos  |Strosin-Cruickshank      |1.02    |75.0 |46 |0.0     |
|5157595343543285|grocery_pos  |Schultz, Simonis and Little|1.8   |65.0 |46 |0.0     |
|5157595343543285|home         |Beier and Sons           |1.66    |112.0|46 |0.0     |
|5157595343543285|misc_pos     |Turner, Ruecker and Parisian|1.81 |27.0 |46 |0.0     |
|5157595343543285|entertainment|Howe PLC                 |1.56    |151.0|46 |0.0     |
|5157595343543285|entertainment|Bauch-Blanda             |1.88    |126.0|46 |0.0     |
+---------------+------------+--------------------------+--------+-----+---+--------+
only showing top 20 rows
```

"category", "merchant", "distance", "amt", "age" will be used a features to train the model
The data type of category and merchant columns is String. The data type of distance, amt, and age is Double/Int(Numeric)

5.2.2 String Values to Numeric Values

```
/*String Indexer for the category and merchant columns*/
    val categoryIndexer = new
StringIndexer().setInputCol("category").setOutputCol("category_indexed")
    val merchantIndexer = new
StringIndexer().setInputCol("merchant").setOutputCol("merchant_indexed")
```

StringIndexer transforms string values to double values. Because, ML Algorithms does not understand String values, it understands only numeric values. Input to StringIndexer is “category” and “merchant” column. Output is “category_indexed” and “merchant_indexed” column. StringIndexer will append these 2 columns to the result dataframe. StringIndexer will convert the category and merchant names to double values. As you can see here, 2 new columns are created, “cateory_indexed” and “merchant_indexed”

cc_num	category	merchant	distance	amt	age	is_fraud	category_indexed	merchant_indexed	
5157595343543285	gas_transport	Schmitt Inc	0.73	111.0	46	0.0	0.0	28.0	
5157595343543285	kids_pets	Beer-Jast	1.73	66.0	46	0.0	4.0	291.0	
5157595343543285	grocery_pos	Hudson-Ratke	1.23	220.0	46	0.0	1.0	310.0	
5157595343543285	entertainment	Kassulke Inc	2.17	100.0	46	0.0	9.0	470.0	
5157595343543285	shopping_net	Boyer PLC	1.33	80.0	46	0.0	5.0	78.0	
5157595343543285	entertainment	Spencer PLC	1.29	141.0	46	0.0	9.0	304.0	
5157595343543285	entertainment	Brown-Greenholt	0.8	221.0	46	0.0	9.0	527.0	
5157595343543285	travel	Kovacek Ltd	1.5	91.0	46	0.0	13.0	663.0	
5157595343543285	gas_transport	Kutch LLC	0.71	57.0	46	0.0	0.0	2.0	
5157595343543285	kids_pets	Lowe, Dietrich and Erdman	1.41	158.0	46	0.0	4.0	230.0	
5157595343543285	kids_pets	Bednar PLC	1.99	211.0	46	0.0	4.0	101.0	
5157595343543285	kids_pets	Hammes-Beatty	0.88	42.0	46	0.0	4.0	242.0	
5157595343543285	kids_pets	Hilpert-Conroy	0.97	103.0	46	0.0	4.0	223.0	
5157595343543285	gas_transport	Robel, Cummerata and Prosacco	1.26	100.0	46	0.0	0.0	32.0	
5157595343543285	grocery_pos	Strosin-Cruickshank	1.02	75.0	46	0.0	1.0	181.0	
5157595343543285	grocery_pos	Schultz, Simonis and Little	1.8	65.0	46	0.0	1.0	133.0	
5157595343543285	home	Beier and Sons	1.66	112.0	46	0.0	3.0	81.0	
5157595343543285	misc_pos	Turner, Ruecker and Parisian	1.81	27.0	46	0.0	7.0	229.0	
5157595343543285	entertainment	Howe PLC	1.56	151.0	46	0.0	9.0	201.0	
5157595343543285	entertainment	Bauch-Blanda	1.88	126.0	46	0.0	9.0	509.0	

only showing top 20 rows

5.2.3 Scaling Numeric Columns

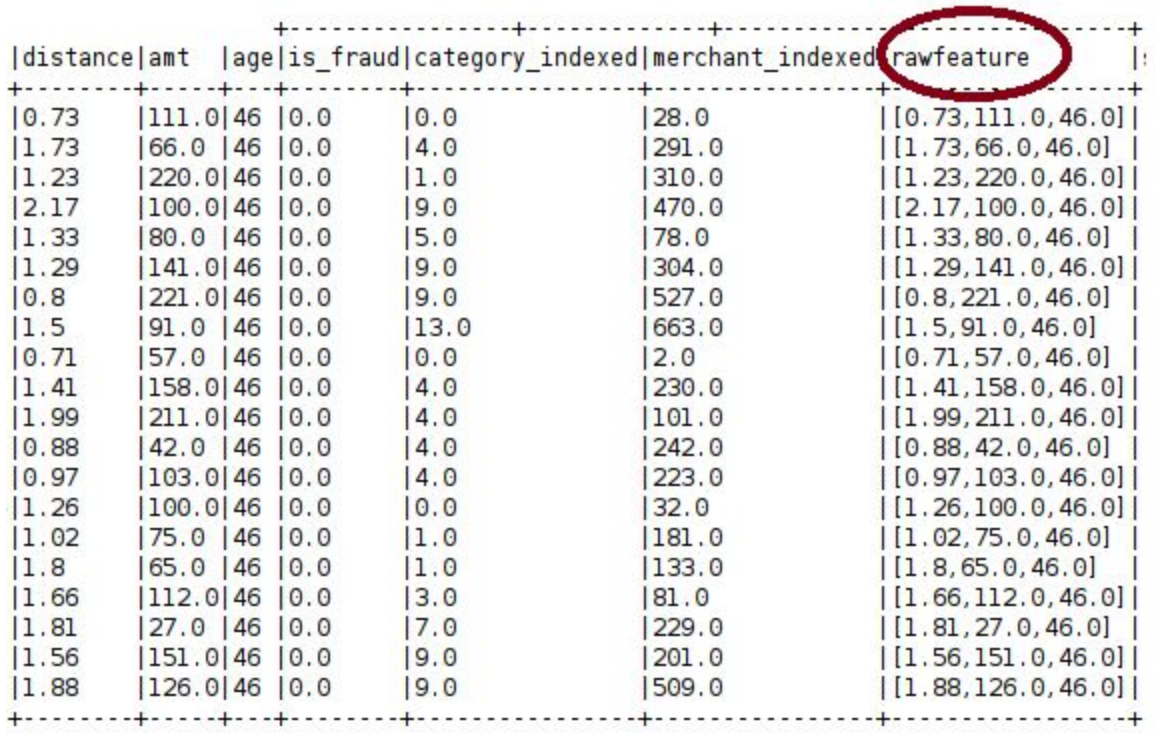
The main idea is to Normalize/Standardize (`mean = 0` and `standard deviation = 1`) your features before applying machine learning techniques.
`StandardScaler` does not work on double values. Hence, first we need to convert all 3 columns intto vector, then sliced it and finally scale it.

```
/*Transform raw numerical columns to vector. Slice the vector and Scale the vector.  Scaling is required so that all the column values are at the same level of measurement */
val numericAssembler = new VectorAssembler().setInputCols(Array("distance", "amt", "age" )).setOutputCol("rawfeature")
val slicer = new VectorSlicer().setInputCol("rawfeature").setOutputCol("slicedfeatures").setNames(Array("distance", "amt", "age"))
val scaler = new StandardScaler().setInputCol("slicedfeatures").setOutputCol("scaledfeatures")
```

VectorAssembler

`val numericAssembler = new VectorAssembler().setInputCols(Array("distance", "amt", "age" )).setOutputCol("rawfeature")`

`VectorAssembler` is used to transform multiple column values into a single vector column. Input to `VectorAssembler` is “distance”, “amt” and “age” columns. The output is the “rawfeature” column. It is a vector column.



distance	amt	age	is_fraud	category_indexed	merchant_indexed	rawfeature
0.73	111.0	46	0.0	0.0	28.0	[0.73,111.0,46.0]
1.73	66.0	46	0.0	4.0	291.0	[1.73,66.0,46.0]
1.23	220.0	46	0.0	1.0	310.0	[1.23,220.0,46.0]
2.17	100.0	46	0.0	9.0	470.0	[2.17,100.0,46.0]
1.33	80.0	46	0.0	5.0	78.0	[1.33,80.0,46.0]
1.29	141.0	46	0.0	9.0	304.0	[1.29,141.0,46.0]
0.8	221.0	46	0.0	9.0	527.0	[0.8,221.0,46.0]
1.5	91.0	46	0.0	13.0	663.0	[1.5,91.0,46.0]
0.71	57.0	46	0.0	0.0	2.0	[0.71,57.0,46.0]
1.41	158.0	46	0.0	4.0	230.0	[1.41,158.0,46.0]
1.99	211.0	46	0.0	4.0	101.0	[1.99,211.0,46.0]
0.88	42.0	46	0.0	4.0	242.0	[0.88,42.0,46.0]
0.97	103.0	46	0.0	4.0	223.0	[0.97,103.0,46.0]
1.26	100.0	46	0.0	0.0	32.0	[1.26,100.0,46.0]
1.02	75.0	46	0.0	1.0	181.0	[1.02,75.0,46.0]
1.8	65.0	46	0.0	1.0	133.0	[1.8,65.0,46.0]
1.66	112.0	46	0.0	3.0	81.0	[1.66,112.0,46.0]
1.81	27.0	46	0.0	7.0	229.0	[1.81,27.0,46.0]
1.56	151.0	46	0.0	9.0	201.0	[1.56,151.0,46.0]
1.88	126.0	46	0.0	9.0	509.0	[1.88,126.0,46.0]

VectorSlicer

```
val slicer = new VectorSlicer().setInputCol("rawfeature").setOutputCol("slicedfeatures").setNames(Array("distance", "amt", "age"))
```

VectorSlicer will slice a single vector into multiple vectors. Input to VectorSlicer is the output of VectorAssebler i.e “rawfeature” column. The output of VectorSlicer is the “slicedfeatures” column. This column contains “distance”, “amt” and “age” as individual vectors.

distance	amt	age	is_fraud	category_indexed	merchant_indexed	rawfeature	slicedfeatures
0.73	111.0	46	0.0	0.0	28.0	[0.73,111.0,46.0]	[0.73,111.0,46.0]
1.73	66.0	46	0.0	4.0	291.0	[1.73,66.0,46.0]	[1.73,66.0,46.0]
1.23	220.0	46	0.0	1.0	310.0	[1.23,220.0,46.0]	[1.23,220.0,46.0]
2.17	100.0	46	0.0	9.0	470.0	[2.17,100.0,46.0]	[2.17,100.0,46.0]
1.33	80.0	46	0.0	5.0	78.0	[1.33,80.0,46.0]	[1.33,80.0,46.0]
1.29	141.0	46	0.0	9.0	304.0	[1.29,141.0,46.0]	[1.29,141.0,46.0]
0.8	221.0	46	0.0	9.0	527.0	[0.8,221.0,46.0]	[0.8,221.0,46.0]
1.5	91.0	46	0.0	13.0	663.0	[1.5,91.0,46.0]	[1.5,91.0,46.0]
0.71	57.0	46	0.0	0.0	2.0	[0.71,57.0,46.0]	[0.71,57.0,46.0]
1.41	158.0	46	0.0	4.0	230.0	[1.41,158.0,46.0]	[1.41,158.0,46.0]
1.99	211.0	46	0.0	4.0	101.0	[1.99,211.0,46.0]	[1.99,211.0,46.0]
0.88	42.0	46	0.0	4.0	242.0	[0.88,42.0,46.0]	[0.88,42.0,46.0]
0.97	103.0	46	0.0	4.0	223.0	[0.97,103.0,46.0]	[0.97,103.0,46.0]
co 1.26	100.0	46	0.0	0.0	32.0	[1.26,100.0,46.0]	[1.26,100.0,46.0]
1.02	75.0	46	0.0	1.0	181.0	[1.02,75.0,46.0]	[1.02,75.0,46.0]
1.8	65.0	46	0.0	1.0	133.0	[1.8,65.0,46.0]	[1.8,65.0,46.0]
1.66	112.0	46	0.0	3.0	81.0	[1.66,112.0,46.0]	[1.66,112.0,46.0]
n 1.81	27.0	46	0.0	7.0	229.0	[1.81,27.0,46.0]	[1.81,27.0,46.0]
1.56	151.0	46	0.0	9.0	201.0	[1.56,151.0,46.0]	[1.56,151.0,46.0]
1.88	126.0	46	0.0	9.0	509.0	[1.88,126.0,46.0]	[1.88,126.0,46.0]

StandardScaler

```
val scaler = new StandardScaler().setInputCol("slicedfeatures").setOutputCol("scaledfeatures")
```

The main idea is to Normalize/Standardize (`mean = 0` and `standard deviation = 1`) your features before applying machine learning techniques.
Input to StandardScaler is the output of the VectorSlicer i.e “slicedfeatures” column. The output of StandardScaler is the “scaledfeatures” column. Now this column contains all normalized values

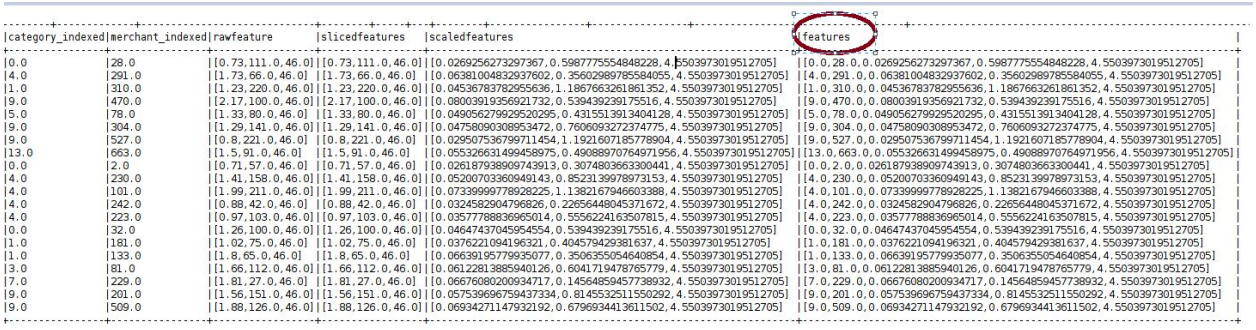
distance	amt	age	is_fraud	category_indexed	merchant_indexed	rawfeature	slicedfeatures	scaledfeatures
0.73	111.0	46	0.0	0.0	28.0	[0.73,111.0,46.0]	[0.73,111.0,46.0]	[0.0269256273297367,0.5987775554848228,4.5503973019512705]
1.73	66.0	46	0.0	4.0	291.0	[1.73,66.0,46.0]	[1.73,66.0,46.0]	[0.06381004832937602,0.35602989785584055,4.5503973019512705]
1.23	220.0	46	0.0	1.0	310.0	[1.23,220.0,46.0]	[1.23,220.0,46.0]	[0.045367837829555636,1.1867663261861352,4.5503973019512705]
2.17	100.0	46	0.0	9.0	470.0	[2.17,100.0,46.0]	[2.17,100.0,46.0]	[0.08003919356921732,0.539439239175516,4.5503973019512705]
1.33	80.0	46	0.0	5.0	78.0	[1.33,80.0,46.0]	[1.33,80.0,46.0]	[0.049056279929520295,0.4315513913404128,4.5503973019512705]
1.29	141.0	46	0.0	9.0	304.0	[1.29,141.0,46.0]	[1.29,141.0,46.0]	[0.04758090308953472,0.7606093272374775,4.5503973019512705]
0.8	221.0	46	0.0	9.0	527.0	[0.8,221.0,46.0]	[0.8,221.0,46.0]	[0.029507536799711454,1.1921607185778904,4.5503973019512705]
1.5	91.0	46	0.0	13.0	663.0	[1.5,91.0,46.0]	[1.5,91.0,46.0]	[0.055326631499458975,0.49088970764971956,4.5503973019512705]
0.71	57.0	46	0.0	0.0	2.0	[0.71,57.0,46.0]	[0.71,57.0,46.0]	[0.026187938909743913,0.3074803663300441,4.5503973019512705]
1.41	158.0	46	0.0	4.0	230.0	[1.41,158.0,46.0]	[1.41,158.0,46.0]	[0.05200703360949143,0.8523139978973153,4.5503973019512705]
1.99	211.0	46	0.0	4.0	101.0	[1.99,211.0,46.0]	[1.99,211.0,46.0]	[0.07339999778928225,1.1382167946603388,4.5503973019512705]
0.88	42.0	46	0.0	4.0	242.0	[0.88,42.0,46.0]	[0.88,42.0,46.0]	[0.0324582904796826,0.2265644804537167 2,4.5503973019512705]
0.97	103.0	46	0.0	4.0	223.0	[0.97,103.0,46.0]	[0.97,103.0,46.0]	[0.03577788836965014,0.5556224163507815,4.5503973019512705]
1.26	100.0	46	0.0	0.0	32.0	[1.26,100.0,46.0]	[1.26,100.0,46.0]	[0.04647437045954554,0.539439239175516,4.5503973019512705]
1.02	75.0	46	0.0	1.0	181.0	[1.02,75.0,46.0]	[1.02,75.0,46.0]	[0.0376221094196321,0.4045794293816 37,4.5503973019512705]
1.8	65.0	46	0.0	1.0	133.0	[1.8,65.0,46.0]	[1.8,65.0,46.0]	[0.06639195779935077,0.3506355054640854,4.5503973019512705]
1.66	112.0	46	0.0	3.0	81.0	[1.66,112.0,46.0]	[1.66,112.0,46.0]	[0.06122813885940126,0.6041719478765779,4.5503973019512705]
1.81	27.0	46	0.0	7.0	229.0	[1.81,27.0,46.0]	[1.81,27.0,46.0]	[0.06676080200934717,0.14564859457738932,4.5503973019512705]
1.56	151.0	46	0.0	9.0	201.0	[1.56,151.0,46.0]	[1.56,151.0,46.0]	[0.057539696759437334,0.8145532511550292,4.5503973019512705]
1.88	126.0	46	0.0	9.0	509.0	[1.88,126.0,46.0]	[1.88,126.0,46.0]	[0.0693427114793219 2,0.6796934413611502,4.5503973019512705]

5.2.4 Feature Column

Now all the feature columns has to be transformed into single feature column. i.e “category_index”, “merchant_index” and “scaledfeatures” columns into single “feature” column.

```
val vectorAssember = new
VectorAssembler().setInputCols(Array("category_indexed",
"merchant_indexed", "scaledfeatures")).setOutputCol("features")
```

One more VectorAssembler is created. Input to this VectorAssembler is the output of previous transformations i.e. “category_indexed”, “merchant_indexed” and “scaledfeatures” columns. Output is “feature column”. All the columns are combined as a single column of vector data type.



category_indexed	merchant_indexed	rawfeature	slicedfeatures	scaledfeatures	features
0.0	28.0	[0.73,111.0,46.0]	[0.73,111.0,46.0]	[0.0269256273297367,0.5987775554848228,4.5503973019512705]	[0.0,28.0,0.0269256273297367,0.5987775554848228,4.5503973019512705]
4.0	291.0	[1.73,66.0,46.0]	[1.73,66.0,46.0]	[0.06381004832937602,0.35602989785584055,4.5503973019512705]	[4.0,291.0,0.06381004832937602,0.35602989785584055,4.5503973019512705]
1.0	310.0	[1.23,220.0,46.0]	[1.23,220.0,46.0]	[0.045367837829555636,1.1867663261861352,4.5503973019512705]	[1.0,310.0,0.045367837829555636,1.1867663261861352,4.5503973019512705]
9.0	470.0	[2.17,100.0,46.0]	[2.17,100.0,46.0]	[0.08003919356921732,0.5394392391755516,4.5503973019512705]	[9.0,470.0,0.08003919356921732,0.5394392391755516,4.5503973019512705]
5.0	78.0	[1.33,80.0,46.0]	[1.33,80.0,46.0]	[0.04905627992952029 5,0.4315513913404128,4.5503973019512705]	[5.0,78.0,0.04905627992952029 5,0.4315513913404128,4.5503973019512705]
9.0	304.0	[1.29,141.0,46.0]	[1.29,141.0,46.0]	[0.047580903089534 72,0.7606093272374775,4.5503973019512705]	[9.0,304.0,0.047580903089534 72,0.7606093272374775,4.5503973019512705]
9.0	527.0	[0.8,221.0,46.0]	[0.8,221.0,46.0]	[0.029507536799711454,1.1921607185778904,4.5503973019512705]	[9.0,527.0,0.029507536799711454,1.1921607185778904,4.5503973019512705]
13.0	663.0	[1.5,91.0,46.0]	[1.5,91.0,46.0]	[0.055326631499458975,0.4908897076497 1956,4.5503973019512705]	[13.0,663.0,0.055326631499458975,0.4908897076497 1956,4.5503973019512705]
0.0	2.0	[0.71,57.0,46.0]	[0.71,57.0,46.0]	[0.026187938909743913,0.3074803663300441,4.5503973019512705]	[0.0,2.0,0.026187938909743913,0.3074803663300441,4.5503973019512705]
4.0	230.0	[1.41,158.0,46.0]	[1.41,158.0,46.0]	[0.05200703360949143,0.8523139978973153,4.5503973019512705]	[4.0,230.0,0.05200703360949143,0.8523139978973153,4.5503973019512705]
4.0	101.0	[1.99,211.0,46.0]	[1.99,211.0,46.0]	[0.07339999778928225,1.1382167946603388,4.5503973019512705]	[4.0,101.0,0.07339999778928225,1.1382167946603388,4.5503973019512705]
4.0	242.0	[0.88,42.0,46.0]	[0.88,42.0,46.0]	[0.03245829047968 26,0.2265644804537 1672,4.5503973019512705]	[4.0,242.0,0.03245829047968 26,0.2265644804537 1672,4.5503973019512705]
4.0	223.0	[0.97,103.0,46.0]	[0.97,103.0,46.0]	[0.03577788836965014,0.5556224163507815,4.5503973019512705]	[4.0,223.0,0.03577788836965014,0.5556224163507815,4.5503973019512705]
0.0	32.0	[1.26,100.0,46.0]	[1.26,100.0,46.0]	[0.046474370459545 54,0.5394392391755516,4.5503973019512705]	[0.0,32.0,0.046474370459545 54,0.5394392391755516,4.5503973019512705]
1.0	181.0	[1.02,75.0,46.0]	[1.02,75.0,46.0]	[0.037622109419632 1,0.4045794293816 37,4.5503973019512705]	[1.0,181.0,0.037622109419632 1,0.4045794293816 37,4.5503973019512705]
1.0	133.0	[1.8,65.0,46.0]	[1.8,65.0,46.0]	[0.06639195779935077,0.3506355054640854,4.5503973019512705]	[1.0,133.0,0.06639195779935077,0.3506355054640854,4.5503973019512705]
3.0	81.0	[1.66,112.0,46.0]	[1.66,112.0,46.0]	[0.06122813885940126,0.6041719478765779,4.5503973019512705]	[3.0,81.0,0.06122813885940126,0.6041719478765779,4.5503973019512705]
7.0	229.0	[1.81,27.0,46.0]	[1.81,27.0,46.0]	[0.06676080200934717,0.1456485945773893 2,4.5503973019512705]	[7.0,229.0,0.06676080200934717,0.1456485945773893 2,4.5503973019512705]
9.0	201.0	[1.56,151.0,46.0]	[1.56,151.0,46.0]	[0.05753969675943733 4,0.8145532511550292,4.5503973019512705]	[9.0,201.0,0.05753969675943733 4,0.8145532511550292,4.5503973019512705]
9.0	509.0	[1.88,126.0,46.0]	[1.88,126.0,46.0]	[0.06934271147932192,0.6796934413611502,4.5503973019512705]	[9.0,509.0,0.06934271147932192,0.6796934413611502,4.5503973019512705]

5.2.5 Pipeline Stages

A Spark `Pipeline` is specified as a sequence of stages, and each stage is either a `Transformer` or an `Estimator`. These stages are run in order, and the input `DataFrame` is transformed as it passes through each stage.

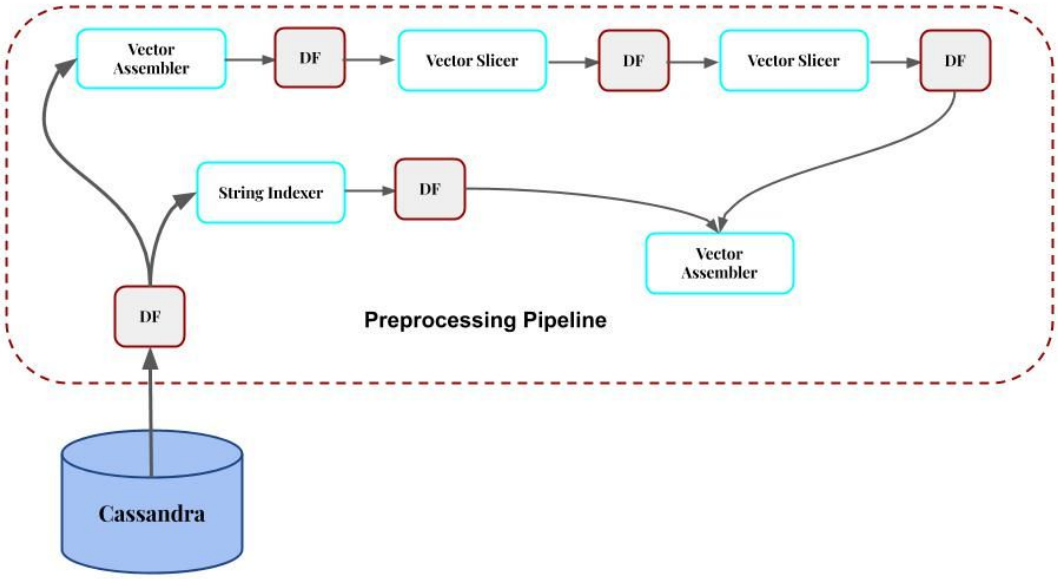
A `Transformer` is an algorithm that transforms one DataFrame to another by using the `transform()` method. For example, a feature transformer could read one column of a `DataFrame`, map it to another column, and output a new `DataFrame` with the mapped column appended to it.

An `Estimator` is an abstraction of learning algorithms and is responsible for fitting or training on a dataset to produce a `Transformer`. An `Estimator` implements a method named `fit()`, which accepts a `DataFrame` and produces a Model, which is a

`Transformer`.

`StringIndexer` is an `Estimator`.
`VectorAssembler` is a `Transformer`
`VectorSlicer` is a `Transformer`
`StandarScaler` is an `Estimator`

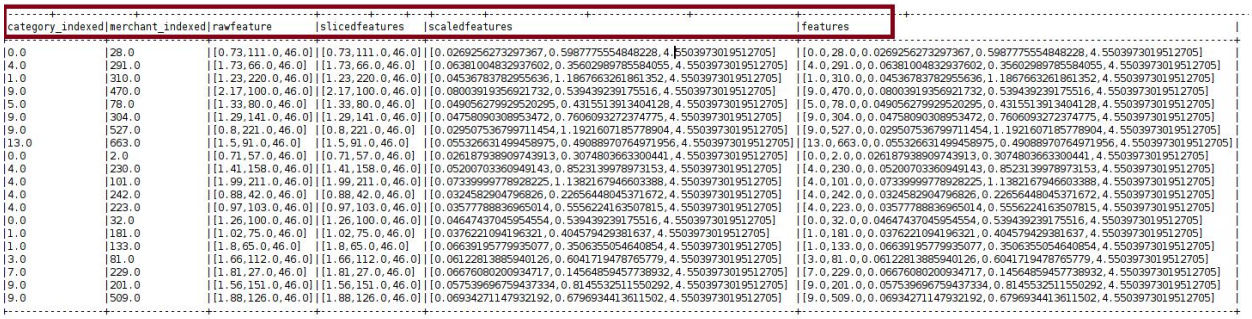
Preprocessing Pipeline Model




```
val pipeline = new Pipeline().setStages(Array(categoryIndexer,
merchantIndexer, numericAssembler, slicer, scaler, vectorAssember))
val preprocessingTransformerModel = pipeline.fit(transactionDF)
val featureDF = preprocessingTransformerModel.transform(transactionDF)
```

Here we are building preprocessing pipeline with our `categoryIndexer`, `merchantIndexer`, `numericAssembler`, `slicer`, `scaler`, and `vectorAssembler`.
`fit()` method returns a Model which is a `Transformer`
On calling transform() method on the `preprocessingTransformerModel`, transform method of all the stages are called in the order specified in the pipeline. As a

result, new columns will be added. All the output snapshots that we specified earlier for each individual Stage will actually happen on calling `transform()` method.



category_indexed	merchant_indexed	rawfeature	slicedfeatures	scaledfeatures	features
0.0	28.0	[0.73,111.0,46.0]	[0.73,111.0,46.0]	[0.0269256273297367,0.5987775554848228,4.5503973019512705]	[0.0,28.0,0.0269256273297367,0.5987775554848228,4.5503973019512705]
4.0	291.0	[1.73,66.0,46.0]	[1.73,66.0,46.0]	[0.06381004832937602,0.35602989785584055,4.5503973019512705]	[4.0,291.0,0.06381004832937602,0.35602989785584055,4.5503973019512705]
1.0	310.0	[1.23,220.0,46.0]	[1.23,220.0,46.0]	[0.045367837829555636,1.1867663261861352,4.5503973019512705]	[1.0,310.0,0.045367837829555636,1.1867663261861352,4.5503973019512705]
9.0	470.0	[2.17,100.0,46.0]	[2.17,100.0,46.0]	[0.080039193569217 32,0.539439239175516,4.5503973019512705]	[9.0,470.0,0.080039193569217 32,0.539439239175516,4.5503973019512705]
5.0	78.0	[1.33,80.0,46.0]	[1.33,80.0,46.0]	[0.04905627992952029 5,0.4315513913404128,4.5503973019512705]	[5.0,78.0,0.04905627992952029 5,0.4315513913404128,4.5503973019512705]
9.0	304.0	[1.29,141.0,46.0]	[1.29,141.0,46.0]	[0.047580903089534 72,0.7606093272374775,4.5503973019512705]	[9.0,304.0,0.047580903089534 72,0.7606093272374775,4.5503973019512705]
9.0	527.0	[0.8,221.0,46.0]	[0.8,221.0,46.0]	[0.029507536799711454,1.1921607185778904,4.5503973019512705]	[9.0,527.0,0.029507536799711454,1.1921607185778904,4.5503973019512705]
13.0	663.0	[1.5,91.0,46.0]	[1.5,91.0,46.0]	[0.055326631499458975,0.4908897076497 1956,4.5503973019512705]	[13.0,663.0,0.055326631499458975,0.4908897076497 1956,4.5503973019512705]
0.0	2.0	[0.71,57.0,46.0]	[0.71,57.0,46.0]	[0.026187938909743913,0.3074803663300441,4.5503973019512705]	[0.0,2.0,0.026187938909743913,0.3074803663300441,4.5503973019512705]
4.0	230.0	[1.41,158.0,46.0]	[1.41,158.0,46.0]	[0.0520070336094914 3,0.8523139978973153,4.5503973019512705]	[4.0,230.0,0.0520070336094914 3,0.8523139978973153,4.5503973019512705]
4.0	101.0	[1.99,211.0,46.0]	[1.99,211.0,46.0]	[0.073399997789282 25,1.1382167946603388,4.5503973019512705]	[4.0,101.0,0.073399997789282 25,1.1382167946603388,4.5503973019512705]
4.0	242.0	[0.88,42.0,46.0]	[0.88,42.0,46.0]	[0.032458290479682 6,0.2265644804537 1672,4.5503973019512705]	[4.0,242.0,0.032458290479682 6,0.2265644804537 1672,4.5503973019512705]
4.0	223.0	[0.97,103.0,46.0]	[0.97,103.0,46.0]	[0.035777888369650 14,0.5556224163507815,4.5503973019512705]	[4.0,223.0,0.035777888369650 14,0.5556224163507815,4.5503973019512705]
0.0	32.0	[1.26,100.0,46.0]	[1.26,100.0,46.0]	[0.046474370459545 54,0.539439239175516,4.5503973019512705]	[0.0,32.0,0.046474370459545 54,0.539439239175516,4.5503973019512705]
1.0	181.0	[1.02,75.0,46.0]	[1.02,75.0,46.0]	[0.037622109419632 1,0.4045794293816 37,4.5503973019512705]	[1.0,181.0,0.037622109419632 1,0.4045794293816 37,4.5503973019512705]
1.0	133.0	[1.8,65.0,46.0]	[1.8,65.0,46.0]	[0.066391957799350 77,0.3506355054640854,4.5503973019512705]	[1.0,133.0,0.066391957799350 77,0.3506355054640854,4.5503973019512705]
3.0	81.0	[1.66,112.0,46.0]	[1.66,112.0,46.0]	[0.061228138859401 26,0.6041719478765779,4.5503973019512705]	[3.0,81.0,0.061228138859401 26,0.6041719478765779,4.5503973019512705]
7.0	229.0	[1.81,27.0,46.0]	[1.81,27.0,46.0]	[0.066760802009347 17,0.1456485945773893 2,4.5503973019512705]	[7.0,229.0,0.066760802009347 17,0.1456485945773893 2,4.5503973019512705]
9.0	201.0	[1.56,151.0,46.0]	[1.56,151.0,46.0]	[0.057539696759437334,0.8145532511550292,4.5503973019512705]	[9.0,201.0,0.057539696759437334,0.8145532511550292,4.5503973019512705]
9.0	509.0	[1.88,126.0,46.0]	[1.88,126.0,46.0]	[0.069342711479321 92,0.6796934413611502,4.5503973019512705]	[9.0,509.0,0.069342711479321 92,0.6796934413611502,4.5503973019512705]

5.2.6 Split data

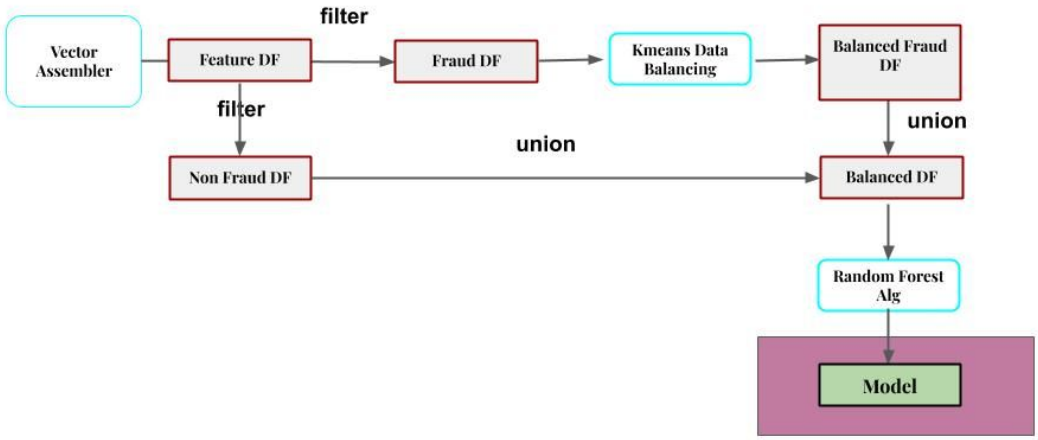
Split data into training and testing. Training data is 80% and Test data is 20%

```
val Array(trainData, testData) = featureDF.randomSplit(Array(0.8, 0.2))
```

5.2.7 Data Balancing

There will be usually more genuine transactions(millions) then fraud transactions(a few hundred). Such data is imbalanced data and must be balanced. So genuine transactions must be balanced. No. of genuine transactions are balanced(reduced) to no. of fraud transaction. Here we are using K Means Algorithm to balance genuine transactions. There are other ways to balance data.

No. of K-means centroid = no. of fraud transaction




```
object DataBalancing {

  val logger = Logger.getLogger(getClass.getName)

  def createBalancedDataframe(df:DataFrame, reductionCount:Int)(implicit
sparkSession:SparkSession) = {

    val kMeans = new KMeans().setK(reductionCount).setMaxIter(30)
    val kMeansModel = kMeans.fit(df)

    import sparkSession.implicits._
    kMeansModel.clusterCenters.toList.map(v => (v, 0)).toDF("features",
"is_fraud")
  }
}
```

```
val featureLabelDF = trainData.select("features", "is_fraud").cache()
val nonFraudDF = featureLabelDF.filter($"is_fraud" === 0)
val fraudDF = featureLabelDF.filter($"is_fraud" === 1)
val fraudCount = fraudDF.count()

val balancedNonFraudDF = DataBalancing.createBalancedDataframe(nonFraudDF,
fraudCount.toInt)
val finalfeatureDF = fraudDF.union(balancedNonFraudDF)
```

Output of the pipeline is a DataFrame which along with other columns contains a “feature” column and “is_fraud” column. Values of “is_fraud” column is either 1(fraud) or 0(non-fraud). We will select only these 2 columns as the training algorithm requires only these 2 columns.
Next, we separate fraud transactions from non-fraud transactions as 2 different dataframe.
Non-fraud transactions DataFrame is fed to the K-Means algorithm to balance the dataframe. K-Means Algorithm reduces no. of non-fraud transactions to no. of fraud transactions.
Output Dataframe of K-means is unioned with the fraud transaction dataframe.
Now we have a balanced dataframe.

5.2.8 Training

This is a classification problem. Either fraud or non-fraud. Here we are using Random Forest. In a real scenario, you must try different Classification algorithms. Evaluate these algorithms using confusion matrix, AUC, ROC, etc. But here we are not evaluating different algorithms. We are using Random Forest.

```
def randomForestClassifier(df: org.apache.spark.sql.DataFrame)(implicit
sparkSession:SparkSession) = {
    import sparkSession.implicits._
    val randomForestEstimator = new
RandomForestClassifier().setLabelCol("is_fraud").setFeaturesCol("features").setMax
Bins(700)
    val model = randomForestEstimator.fit(df)
    model
  }
```

```
val randomForestModel = Algorithms.randomForestClassifier(finalfeatureDF)
val predictionDF = randomForestModel.transform(testData)
    predictionDF.show(false)
```

RadomForest is an estimator. Hence we have to call fit() method. On calling the fit() method, the Random Forest algorithm will actually start training on the data and will

finally return a model, which is a transformer.
This is our Random Forest Model. Using this model we are predicting the test data by calling the transform() method.

features	rawPrediction	probability	prediction
[5.0,337.0,1.7807798458625863,8.690366143117563,7.616969396744517]	[0.0,20.0]	[0.0,1.0]	1.0
[1.0,79.0,5.554056114125689,1.3270205283717693,4.5503973019512705]	[1.0,19.0]	[0.05,0.95]	1.0
[3.0,239.0,3.6364350663544402,2.562336386083701,4.5503973019512705]	[1.0,19.0]	[0.05,0.95]	1.0
[2.0,18.0,6.1253957954101015,2.492209284990884,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[13.0,628.0,7.167011844439916,1.5104298696914449,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[13.0,604.0,6.207648054239297,2.524575639341415,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[9.0,519.0,5.412051093277077,3.0748036633004414,4.253632260519666]	[0.0,20.0]	[0.0,1.0]	1.0
[2.0,86.0,6.791159594453592,3.9217232688060015,4.253632260519666]	[2.0,18.0]	[0.1,0.9]	1.0
[1.0,65.0,5.718929475994076,2.9830989926406035,6.528830911495301]	[0.0,20.0]	[0.0,1.0]	1.0
[5.0,382.0,2.5649426363149184,5.000601747157034,6.528830911495301]	[2.0,18.0]	[0.1,0.9]	1.0
[2.0,109.0,4.640797850174619,2.1038130327845126,6.528830911495301]	[1.0,19.0]	[0.05,0.95]	1.0
[13.0,655.0,7.919822877042554,3.3445232828881992,6.528830911495301]	[0.0,20.0]	[0.0,1.0]	1.0
[4.0,223.0,3.314434071027589,1.5427962240419757,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[11.0,476.0,5.995931477701367,2.805084043712683,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[1.0,69.0,3.771800891423117,1.6668672490523444,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[11.0,494.0,5.026977738040842,1.6938392110111202,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[2.0,215.0,6.829888236503212,1.6560784642688342,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[2.0,174.0,5.095951605310168,2.8482391828467244,4.5503973019512705]	[0.0,20.0]	[0.0,1.0]	1.0
[1.0,133.0,0.4761778751053436,3.064014878516931,7.023439313881308]	[0.0,20.0]	[0.0,1.0]	1.0
[5.0,177.0,4.1314239961696,3.1179588024344826,7.023439313881308]	[1.0,19.0]	[0.05,0.95]	1.0

5.2.9 Confusion Matrix

```
=================== Confusion matrix ===========================
#############| Actual = 1                          Actual = 0
-------------+-------------------------------------------------
Predicted = 1| 91.000000                           83.000000
Predicted = 0| 0.000000                            2548.000000
================================================================

True Positive Rate: 1.0
False Positive Rate: 0.03154694
Precision: 0.5229885
```

TruePositive(TP) = Model predicting fraud transaction as fraud = 91
False Positive(FP) = Model predicting genuine transactions as fraud = 83
False Negative(FN) = Model predicting fraud transactions as genuine = 0
True Negative(TN) = Model predicting genuine transaction as genuine = 2548

Out of all 91 fraud transactions, the model has correctly predicted all 91 fraud transaction as fraud.
Out of 2631 genuine transactions, the model has wrongly predicted 83 as fraud transactions and correctly predicted 2548 as genuine transactions.

`True Positive Rate = TP/TP + FN  = 91.0/(91.0 + 0) = 1.0`
Out of all the fraud transactions, how much we predicted correctly, It should be high as possible.

`False Positive Rate (FPR) = FP/FP + TN`
Out of all the genuine transactions(not fraud), how much we predicted wrong(predicted as fraud). It should be low as possible

`Precision   = TP/(TP + FP) = 91/(91.0 + 83.0) = 0.5229885`
Out of all the fraud transactions that we have predicted correctly, how many are actually fraud.

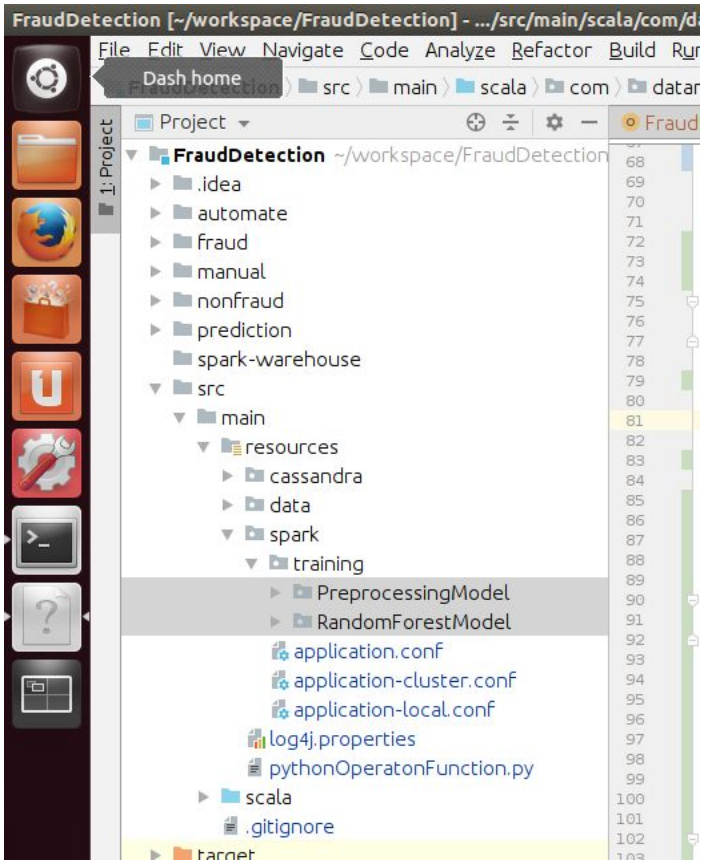
If there are more genuine transactions relative to fraud transactions then it is better to use **`Precision`** instead of **`False Positive Rate`**

This seems to be a decent Model. Since our data is a cooked up data, we will not do more evaluation. Usually, different Classification Model must be tried and then the model efficiency must be computed using ROC(**Receiver Operating Characteristics**) cure and finally models from different Algorithm must be compared using AOC(**Area Under Curve**). Once you get a good model, it must be deployed.

5.2.10 Save Model

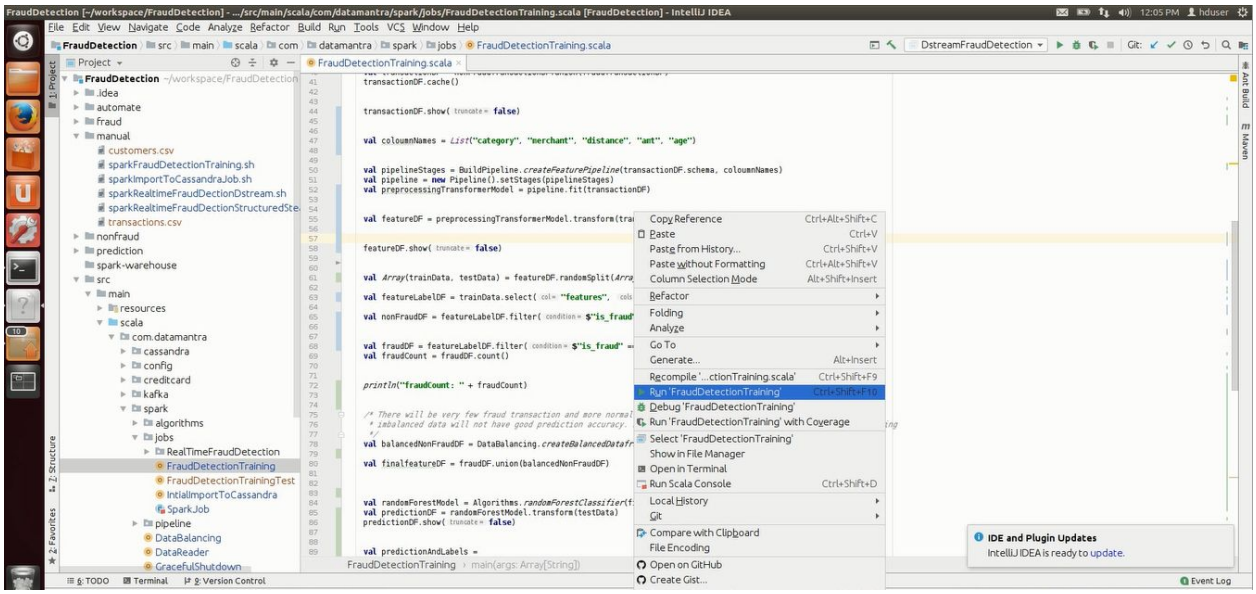
```
/* Save Preprocessing  and Random Forest Model */
randomForestModel.save(SparkConfig.modelPath)
preprocessingTransformerModel.save(SparkConfig.preprocessingModelPath)
```

Both preProcessing Model and Random Forest Model is saved to the file system



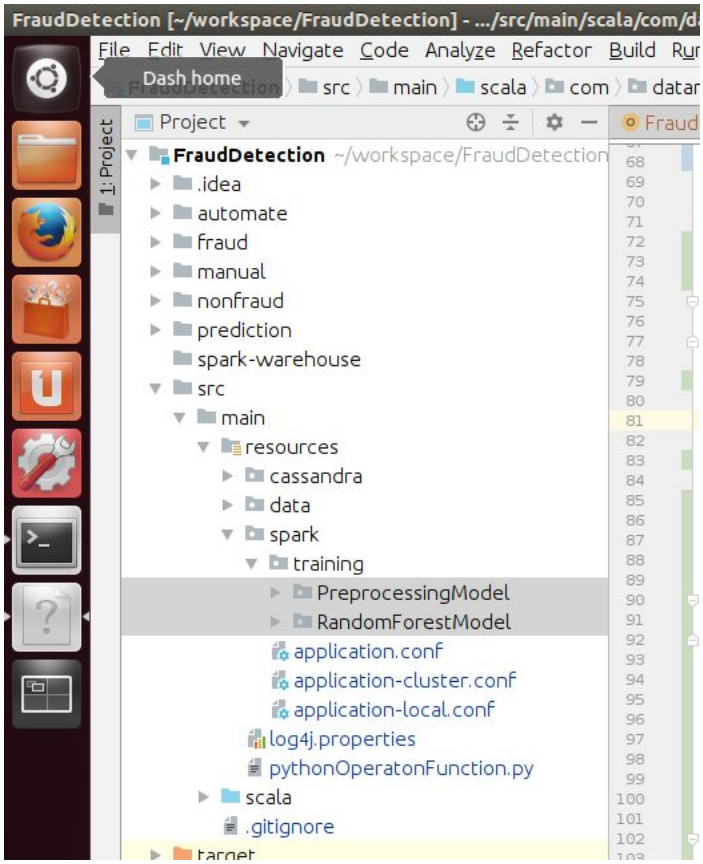
5.3 Demonstration

Run FraudDetectionTraining.scala from IntelliJ
No Input Parameters
Right-click on FraudDetectionTraining.scala file and Click Run



Output

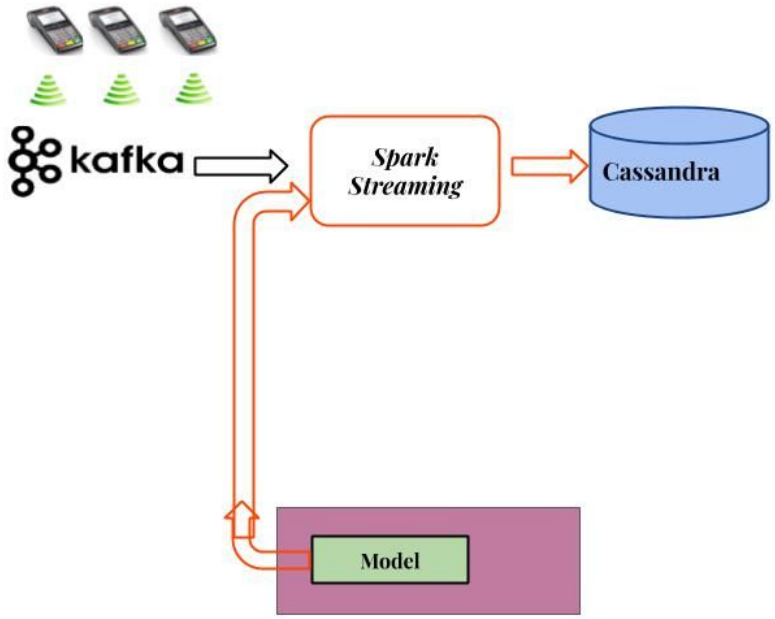
```
================== Confusion matrix ==========================
##############| Actual = 1                          Actual = 0
------------+-------------------------------------------------
Predicted = 1| 91.000000                          83.000000
Predicted = 0| 0.000000                           2548.000000
================================================================

True Positive Rate: 1.0
False Positive Rate: 0.03154694
Precision: 0.5229885
```



Preprocessing Model and Random Forest Model is saved to the File System

6. Spark Streaming

6.1 Introduction



Spark Streaming Job will load both Preprocessing Model and the Random Forest model that was created by the Spark ML Job.
It will start consuming credit card transaction messages from Kafka.
Using Preprocessing Model it will transform all the necessary columns(merchant, category, distance, amt, age) to feature column.
Using Random Forest Model it will predict whether a transaction is a fraud or not.
Predicted transactions will be saved to Cassandra Keyspace
Along with saving predicted transaction to Cassandra, we are also saving Kafka offset to Cassandra
In Fraud Detection, transaction must not be lost not there must be any duplicate transactions i.e it must be exactly-once semantics. Here we are achieving exactly-once semantics by manually committing offset

6.2 Fraud Prediction

6.2.1 Read Customer data

Read customer data and extract the age column

```
import sparkSession.implicits._
    val customerDF = DataReader.readFromCassandra(CassandraConfig.keyspace,
CassandraConfig.customer)
    val customerAgeDF = customerDF.withColumn("age",
(datediff(current_date(),to_date($"dob"))/365).cast(IntegerType))
    customerAgeDF.cache()
```

6.2.2 Load Models

Load Preprocessing Model and Random Forest Model from the previous Spark ML Job

```
val preprocessingModel =
PipelineModel.load(SparkConfig.preprocessingModelPath)
val randomForestModel =
RandomForestClassificationModel.load(SparkConfig.modelPath)
```

6.2.3 Read Offset

As soon as the streaming is started. First, we need to get the offset. Using this offset we can fetch messages from Kafka. We are saving offset to Cassandra. Hence reading it from Cassandra.

```
val storedOffsets = CassandraDriver.readOffset(CassandraConfig.keyspace,
                            CassandraConfig.kafkaOffsetTable,
KafkaConfig.kafkaParams("topic"))
```

6.2.4 Fetch Messages from Kafka

```
val ssc = new StreamingContext(sparkSession.sparkContext,
Duration(SparkConfig.batchInterval))
```

```
val stream = storedOffsets match {
      case None => {
        KafkaUtils.createDirectStream[String, String](ssc,
                        PreferConsistent,
                        Subscribe[String, String](topics, kafkaParams)
                        )
      }

      case Some(fromOffsets) => {
        KafkaUtils.createDirectStream[String, String](ssc,
                        PreferConsistent,
                        Assign[String, String](fromOffsets.keys.toList,
kafkaParams, fromOffsets))
      }
    }
```

First we are creating Streaming Context.
Next, we are fetching messages from Kafka using Direct Stream.
For the very first time, there will be no offset in Cassandra. Hence `storedOffsets` `will be None.` So messages will be fetched from the starting offset.
Let's say after some time Spark Streaming Job got restarted due to some error. By this time we have saved some offset to Cassandra. `storedOffsets` will be `Some`. Hence messages will be fetched from where the Streaming was restarted and not from the beginning

6.2.5 Prediction

```
transactionStream.foreachRDD(rdd => {

      if (!rdd.isEmpty()) {
                  ..........
         val featureTransactionDF =
preprocessingModel.transform(processedTransactionDF)
         val predictionDF =
randomForestModel.transform(featureTransactionDF)
          .withColumnRenamed("prediction", "is_fraud")
                  ..........
  }
}
```

On the received messages, Preprocessing Model is applied to transform columns into

the feature column. Then Random Forest Model is applied to predict whether a transaction is fraud or not.

6.3 Save Prediction

```
val preparedStatementFraud =
session.prepare(CreditcardTransactionRepository.cqlTransactionPrepare(keysp
ace, fraudTable))
            val preparedStatementNonFraud =
session.prepare(CreditcardTransactionRepository.cqlTransactionPrepare(keysp
ace, nonFraudTable))

partitionOfRecords.foreach(record => {
              val isFraud = record.getAs[Double]("is_fraud")
              if (isFraud == 1.0) {
                // Bind and execute prepared statement for Fraud Table

session.execute(CreditcardTransactionRepository.cqlTransactionBind(prepared
StatementFraud, record))
              }
              else if(isFraud == 0.0) {
                // Bind and execute prepared statement for NonFraud Table

session.execute(CreditcardTransactionRepository.cqlTransactionBind(prepared
StatementNonFraud, record))
              }
                ..........
})
```

If the transaction is fraud it is saved to fraud_transacation table
If the transaction is not fraud it is saved to non_fraud_transaction table

6.4 Save Offset

Get the max offset from the current batch and save it to kafka_offset Cassandra table

```
val preparedStatementOffset =
session.prepare(KafkaOffsetRepository.cqlOffsetPrepare(keyspace,
kafkaOffsetTable))
```

```
val partitionOffset:Map[Int, Long] = Map.empty
partitionOfRecords.foreach(record => {
                    ..........
//Get max offset in the current match
              val kafkaPartition = record.getAs[Int]("partition")
              val offset = record.getAs[Long]("offset")
              partitionOffset.get(kafkaPartition) match  {
                case None => partitionOffset.put(kafkaPartition, offset)
                case Some(currentMaxOffset) => {
                  if(offset > currentMaxOffset)
                    partitionOffset.update(kafkaPartition, offset)
                }

          }
})
partitionOffset.foreach(t => {
              // Bind and execute prepared statement for Offset Table

session.execute(KafkaOffsetRepository.cqlOffsetBind(preparedStatementOffset
, t))

})
```

6.5 Exactly-once Semantics

Whenever the Streaming Job restarts due to some error neither a single transaction must be lost nor there must be any duplicate transactions. This is exactly-once semantics

From Section 6.3 and 6.4, we can see that first, we are saving transactions to transaction tables. Next, we are saving offset to the kafka_offset table. Suppose after saving transactions, our Streaming job stopped due to some error. So only transactions of the current batch are saved and the offset is not saved. As soon as it is restarted, Streaming Job will fetch messages(transactions) from the previous offset. So now we have duplicate transactions. These duplicate transactions are saved to Cassandra. Transaction tables in Cassandra are designed to be idempotent writes. We have chosen `(cc_num, transaction_time)` as the primary key. So if we get duplicate transaction it will be overwritten as there cannot be duplicate rows for the same primary key.

This is how we are achieving exactly-once semantics. This is one of the ways to achieve exactly-once semantics.

6.6 Shutdown Spark Streaming Job

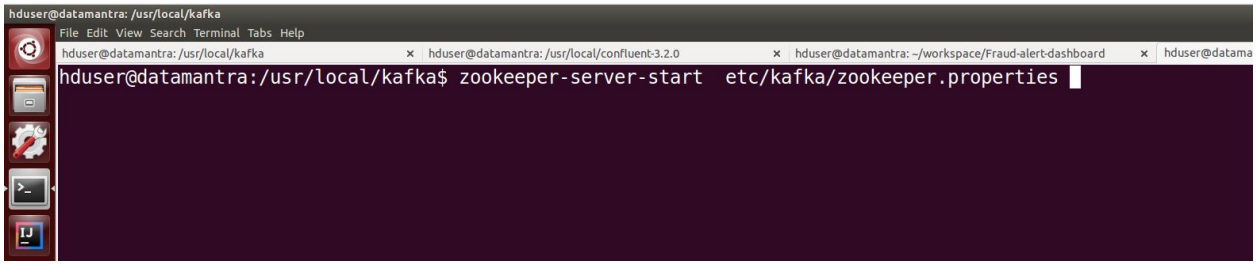
This function is used to Programmatically shutdown Spark Streaming Job. Whenever a new model is created we have to stop the currently running Streaming Job and must start a new Streaming Job which will pick the new model. A thread in Spark Streaming Job will call this function. This function will check if a dummy file, `/tmp/shutdownmarker`, exist or not. If it existing then this function will stop the Streaming Job.
This dummy file is created in the automation script(frauddetection.py)

```
def handleGracefulShutdown(checkIntervalMillis:Int,
ssc:StreamingContext)(implicit sparkSession: SparkSession)  {

    var isStopped = false

    while (! isStopped) {
      logger.info("calling awaitTerminationOrTimeout")
      isStopped = ssc.awaitTerminationOrTimeout(checkIntervalMillis)
      if (isStopped)
        logger.info("confirmed! The streaming context is stopped. Exiting
application...")
      else
        logger.info("Streaming App is still running. Timeout...")
      checkShutdownMarker
      if (!isStopped && stopFlag) {
        logger.info("stopping ssc right now")
        ssc.stop(true, true)
        sparkSession.stop
        logger.info("ssc is stopped!!!!!!!")
      }
    }

  }
```

6.7 Demonstration

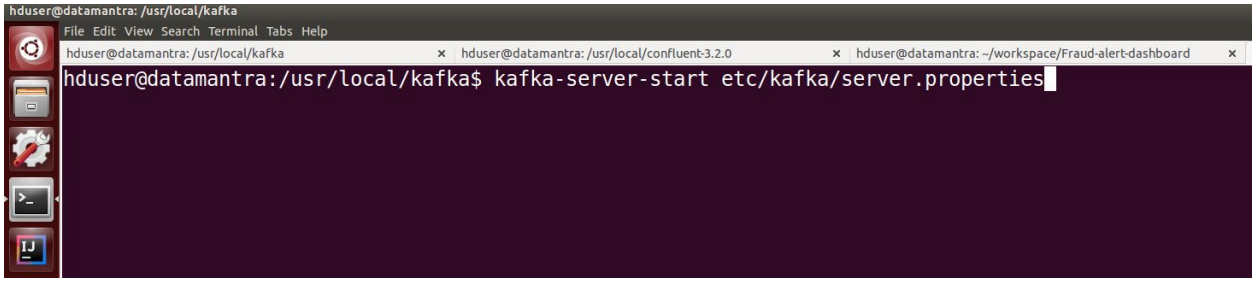
Start Zookeeper

```
cd /usr/local/kafka
zookeeper-server-start etc/kafka/zookeeper.properties
```



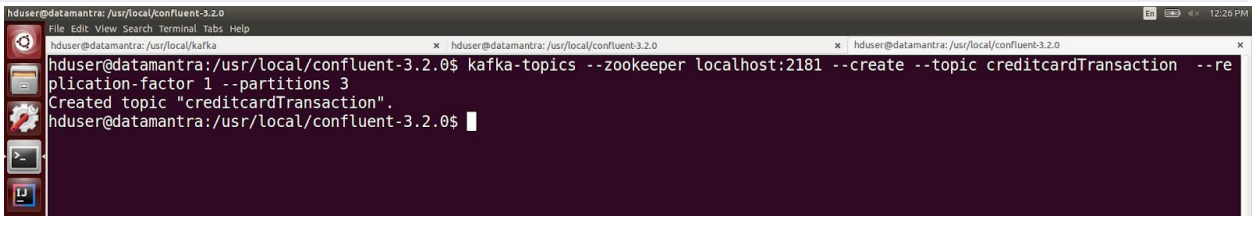
Start Kafka Server

```
kafka-server-start etc/kafka/server.properties
```



Create transaction topic

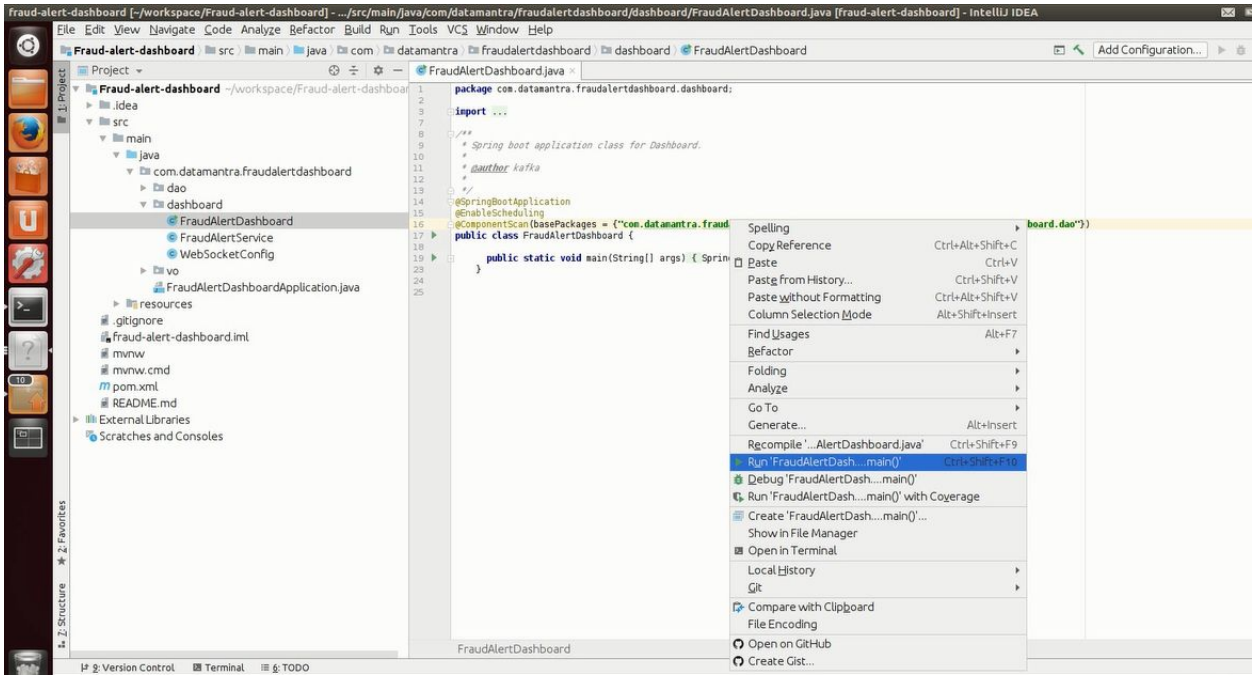
```
kafka-topics --zookeeper localhost:2181 --create --topic
creditcardTransaction  --replication-factor 1 --partitions 3
```

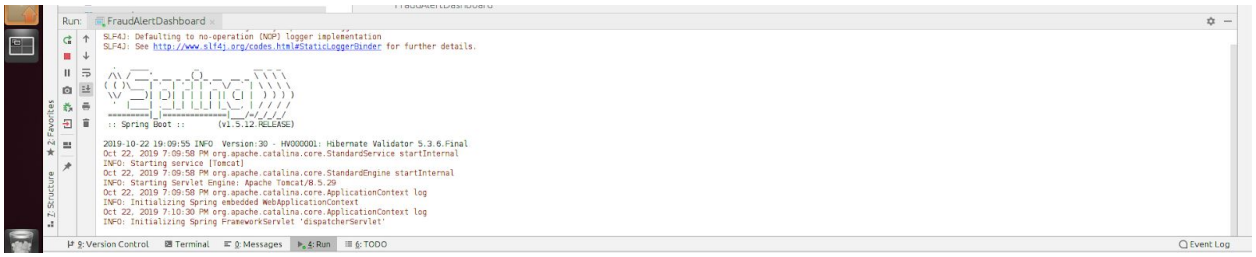


Run Fraud-alert-dashboard project from IntelliJ

No input parameters

Right Click on FraudAlertDashboard.java file and Run

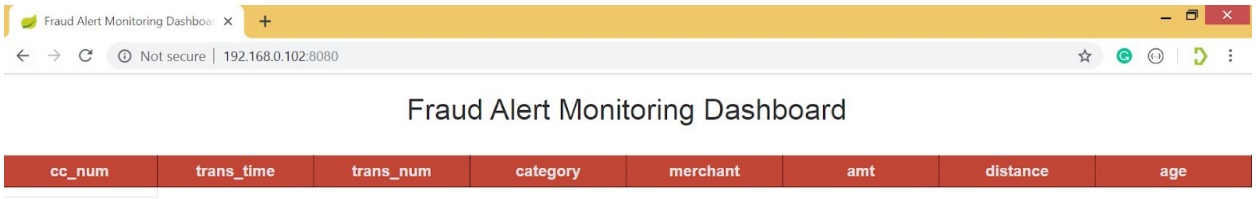




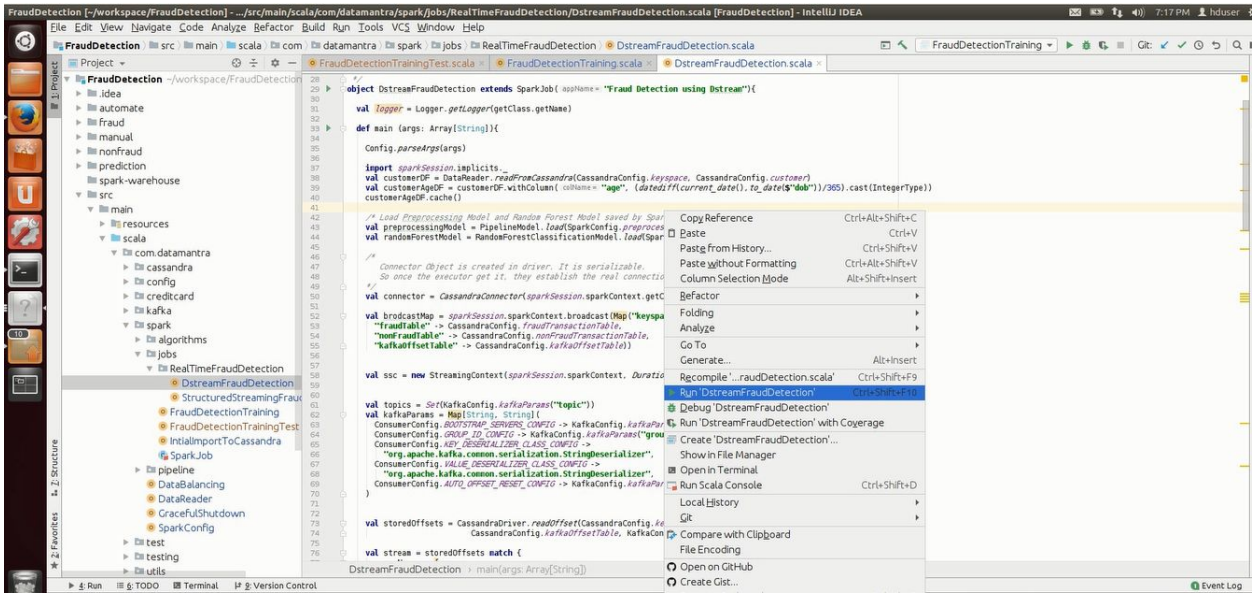
Output

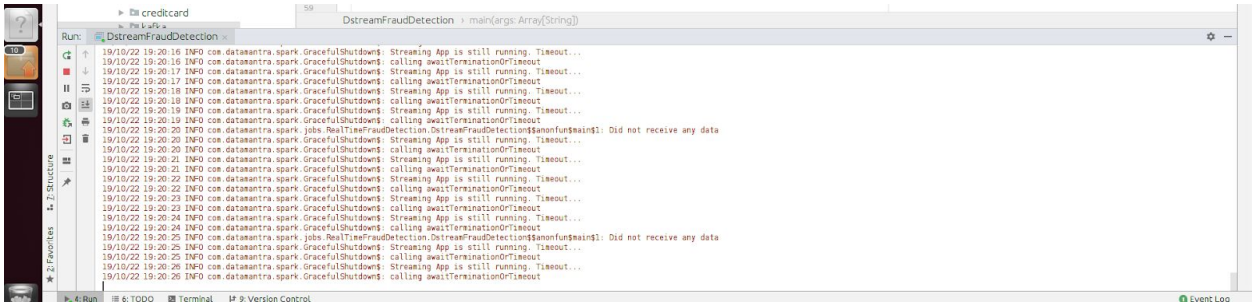
The fraud alert dashboard web server is up and running. Verify this by accessing through the web browser

http://<ubuntu-ipadd>:8080



Run Spark Streaming Job from Intellij



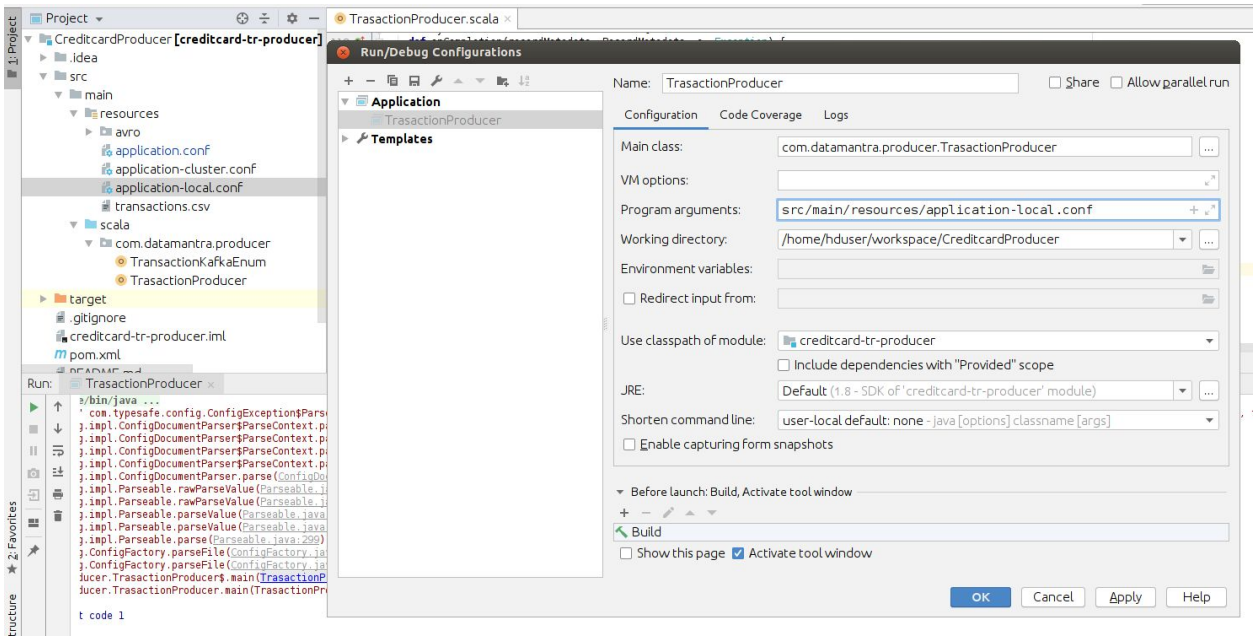


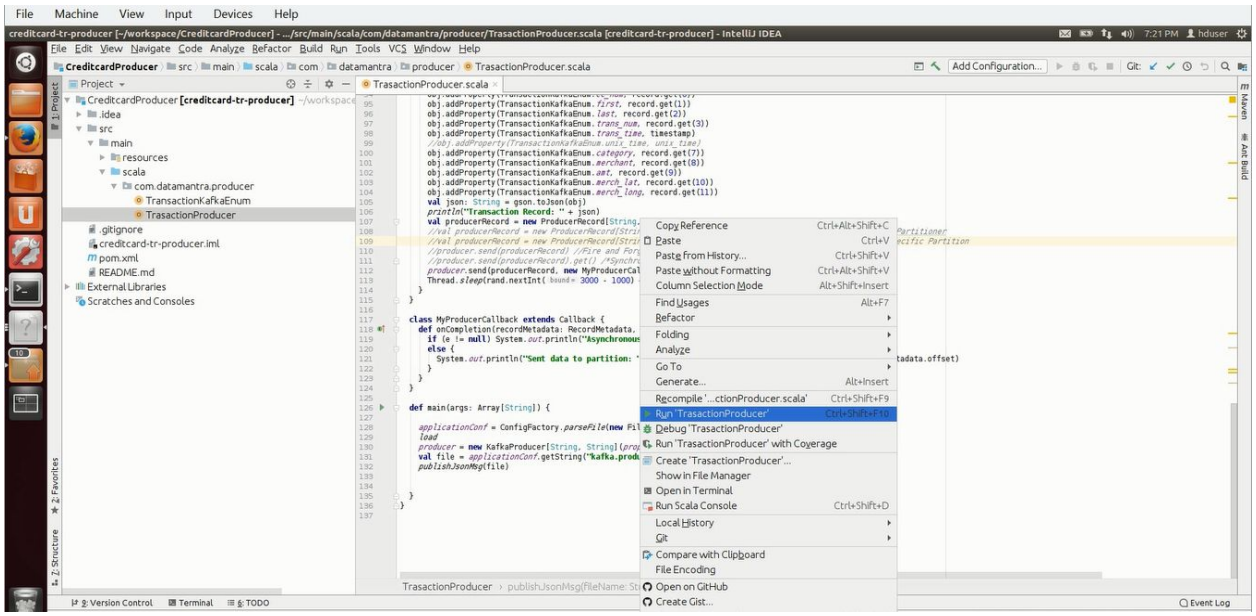
Run CreditcardProducer from IntelliJ

https://github.com/pramoddatamantra/CreditcardProducer

Input parameter is the configuration file

```
src/main/resources/application-local.conf
```

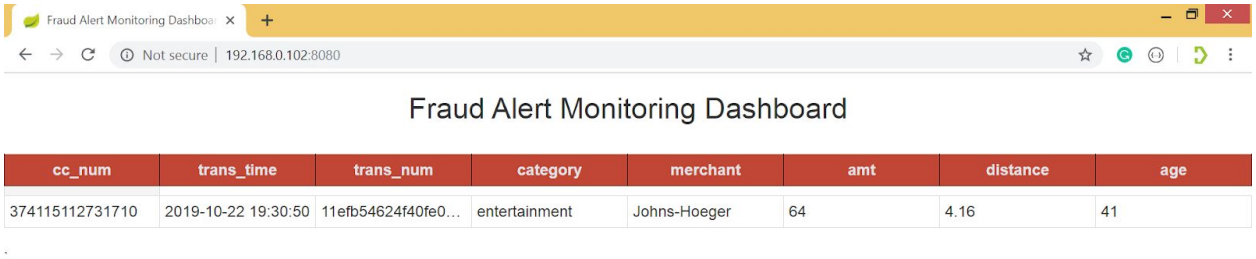

Project
CreditcardProducer [creditcard-tr-producer]
.idea
src
main
resources
avro
application.conf
application-cluster.conf
application-local.conf
transactions.csv
scala
com.datamantra.producer
TransactionKafkaEnum
TrasactionProducer
target
.gitignore
creditcard-tr-producer.iml
pom.xml
TrasactionProducer.scala
Run/Debug Configurations
Name: TrasactionProducer
Share
Allow parallel run
Application
TrasactionProducer
Templates
Configuration
Code Coverage
Logs
Main class: com.datamantra.producer.TrasactionProducer
VM options:
Program arguments: src/main/resources/application-local.conf
Working directory: /home/hduser/workspace/CreditcardProducer
Environment variables:
Redirect input from:
Use classpath of module: creditcard-tr-producer
Include dependencies with "Provided" scope
JRE: Default (1.8 - SDK of 'creditcard-tr-producer' module)
Shorten command line: user-local default: none - java [options] classname [args]
Enable capturing form snapshots
Before launch: Build, Activate tool window
Build
Show this page
Activate tool window
OK
Cancel
Apply
Help
Run:
TrasactionProducer


File Machine View Input Devices Help
creditcard-tr-producer [~/workspace/CreditcardProducer] - .../src/main/scala/com/datamantra/producer/TrasactionProducer.scala [creditcard-tr-producer] - IntelliJ IDEA
Copy Reference
Paste
Paste from History...
Paste without Formatting
Column Selection Mode
Find Usages
Refactor
Folding
Analyze
Go To
Generate...
Recompile '...ctionProducer.scala'
Run 'TrasactionProducer'
Debug 'TrasactionProducer'
Run 'TrasactionProducer' with Coverage
Create 'TrasactionProducer'...
Show in File Manager
Open in Terminal
Run Scala Console
Local History
Git
Compare with Clipboard
File Encoding
Open on GitHub
Create Gist...


Run:
TrasactionProducer
/usr/lib/jvm/java-8-oracle/bin/java ...
SLF4J: Class path contains multiple SLF4J bindings.
SLF4J: Found binding in [jar:file:/home/hduser/.m2/repository/org/slf4j/slf4j-log4j12/1.7.21/slf4j-log4j12-1.7.21.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/home/hduser/.m2/repository/org/slf4j/slf4j-nop/1.5.3/slf4j-nop-1.5.3.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: Found binding in [jar:file:/home/hduser/.m2/repository/org/slf4j/slf4j-jdk14/1.5.6/slf4j-jdk14-1.5.6.jar!/org/slf4j/impl/StaticLoggerBinder.class]
SLF4J: See http://www.slf4j.org/codes.html#multiple_bindings for an explanation.
SLF4J: Actual binding is of type [org.slf4j.impl.Log4jLoggerFactory]
log4j:WARN No appenders could be found for logger (org.apache.kafka.clients.producer.ProducerConfig).
log4j:WARN Please initialize the log4j system properly.
log4j:WARN See http://logging.apache.org/log4j/1.2/faq.html#noconfig for more info.
Transaction Record: {"cc_num":"180094108569013","first":"John","last":"Holland","trans_num":"80f5177be11f0bcd768e06a0b1b294c8","trans_time":"2019-10-22 19:30:08","category":"personal_care","merchant":"Hills-Boyer","amt":"64","merch_lat":"39.011566",
Sent data to partition: 0 and offset: 0
Transaction Record: {"cc_num":"4368593032190508","first":"Carla","last":"Fleming","trans_num":"7933d389bf18ef8a11a8a3014da6e6bc6c","trans_time":"2019-10-22 19:30:10","category":"gas_transport","merchant":"Friesen-DAmore","amt":"133","merch_lat":"40.14
Sent data to partition: 0 and offset: 1
Transaction Record: {"cc_num":"4361355512072","first":"Matthew","last":"Nelson","trans_num":"1467c318b5d73d22d674lf575db42f3f","trans_time":"2019-10-22 19:30:13","category":"entertainment","merchant":"Larson-Moen","amt":"119","merch_lat":"47.297797
Sent data to partition: 0 and offset: 2
Transaction Record: {"cc_num":"4037295225657274","first":"Antonio","last":"Garcia","trans_num":"4a3848719d72daaa32c938ce43e0eb03","trans_time":"2019-10-22 19:30:15","category":"shopping_pos","merchant":"Lynch Ltd","amt":"62","merch_lat":"40.078781",
Sent data to partition: 0 and offset: 3
Transaction Record: {"cc_num":"4515092388857440","first":"Timothy","last":"Silva","trans_num":"02d27e94f279e1013a4c323eb8bb6811","trans_time":"2019-10-22 19:30:18","category":"shopping_pos","merchant":"Baumbach, Strosin and Nicolas","amt":"198","mer
Sent data to partition: 0 and offset: 4

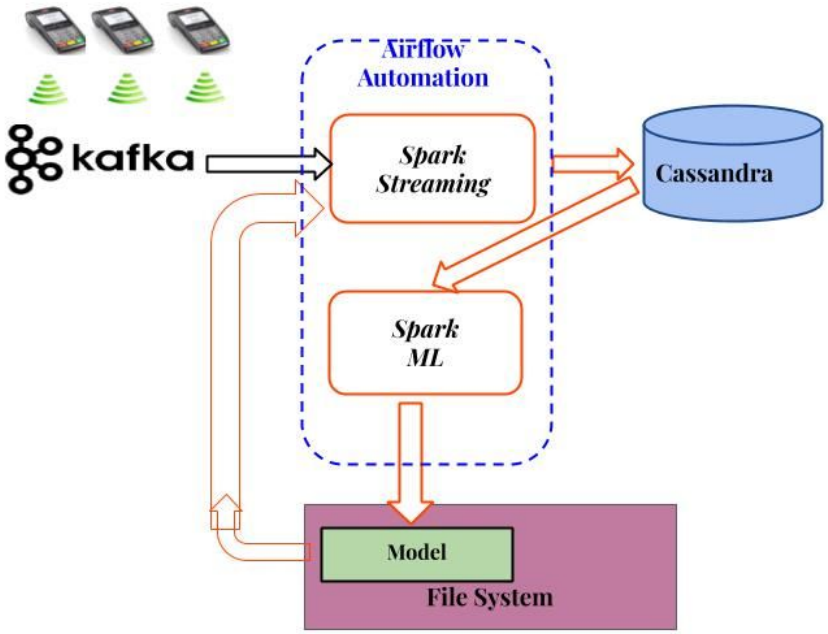
Output

Whenever Spark Streaming Job predicts a fraud transaction it will be displayed on Fraud Alert Dashboard



7. Airflow Automation

7.1 Introduction



Apache Airflow is an automation framework. It is used to automate Jobs. It is similar to oozie. You can write workflows using Python language instead of XML workflows. It is much easier than oozie.
Here we are automating both Spark Streaming and Spark ML Job. But in reality, Spark ML Job is not automated. It is manually run to create a Model. The model will be evaluated for efficiency. If the Model is efficient, only then it will be deployed. But here we will be automating Spark ML Job as well.

As new transaction data is captured, we need to recreate the model using both old data and new data. So the new model will be created usually once a week or once a month. But for the sake of demonstration, we run Spark ML Job every 20 mins. Once the new model is created, Spark Streaming Job has to pick this new Model. So we will stop the currently running Spark Streaming Job and start a new Streaming Job. This new Steaming Job will load the new Model and will start the prediction. So Airflow automation is used to create a new model every 20 mins and to Stop and Start Spark Streaming Job whenever a new model is created.

7.2 Automation Steps

1. **Remove Old Model**
   This training folder contains Preprocessing Model and Random Forest Model. We are just deleting the folder

```
remove_model = BashOperator(
        task_id='remove_model',
        bash_command='rm -rf' + ' ' + home +
'/frauddetection/spark/training',
        default_args=default_args)
```

2. **Create New Model**
   Here we are creating a new model by running Spark ML Job through spark-submit command

```
create_model = BashOperator(
        task_id='create_model',
        bash_command='spark-submit --class
com.datamantra.spark.jobs.FraudDetectionTraining --name "Fraud Detection
Spark ML Training" --master spark://datamantra:7077  --total-executor-cores
1' + ' ' + home + '/frauddetection/spark/fruaddetection-spark.jar' + ' ' +
home + '/frauddetection/spark/application-local.conf',
        default_args=default_args)
```

3. **Seep for 5 seconds(This step is optional)**

```
sleep = BashOperator(
        task_id='sleep',
        bash_command='sleep 5')
```

4. **Stop and Start Spark Streaming Job.**
   Here we are call stopStartStreamingJob function.

```
stop_start_streaming = PythonOperator(
        task_id='stop_start_streaming',
        python_callable=stopStartStreamingJob)
```

   In this function, first, we are stopping the currently running Streaming Job by creating a dummy file `/tmp/shutdownmarker`. A thread running in the Streaming Job will be

continuously checking for this file. As soon as this file is created, Streaming Job will be shutdown.

Next, we are waiting for the Streaming job to shutdown. As soon as it is shut down, we are deleting the dummy file so that newly started Streaming job must not get shutdown.

Finally, we are starting the new Streaming jo using the spark-submit command

```
def stopStartStreamingJob():
    stop_streaming = 'touch /tmp/shutdownmarker'
    os.system(stop_streaming)
    shutdown_flag = False

    while not shutdown_flag:
        URL = "http://localhost:8080/json"
        r = requests.get(url = URL)
        data = json.loads(r.content)
        activeapps = data['activeapps']
        if not activeapps:
            logger.info("No Active apps, Streaming app is shutdown")
            shutdown_flag = True
        else:
            logger.info("List is not empty")
            activeFlag = False
            for app in activeapps:
                if app['name'] == 'RealTime Creditcard FraudDetection':
                    logger.info("Streaming Job is still running")
                    activeFlag = True
                    break
            if activeFlag == False:
                logger.info("Streaming Job not in activeapps list.")
                shutdown_flag = True
            else:
                logger.info("Streaming Job is still Running")


    remove_shutdown_marker = 'rm -rf /tmp/shutdownmarker'
    os.system(remove_shutdown_marker)

    start_streaming = 'spark-submit --class
com.datamantra.spark.jobs.RealTimeFraudDetection.DstreamFraudDetection
--name "RealTime Creditcard FraudDetection" --master
spark://datamantra:6066 --deploy-mode cluster  --total-executor-cores 1' +
' ' + home + '/frauddetection/spark/fruaddetection-spark.jar' + ' ' + home
+ '/frauddetection/spark/application-local.conf'
```

```
    os.system(start_streaming)
```

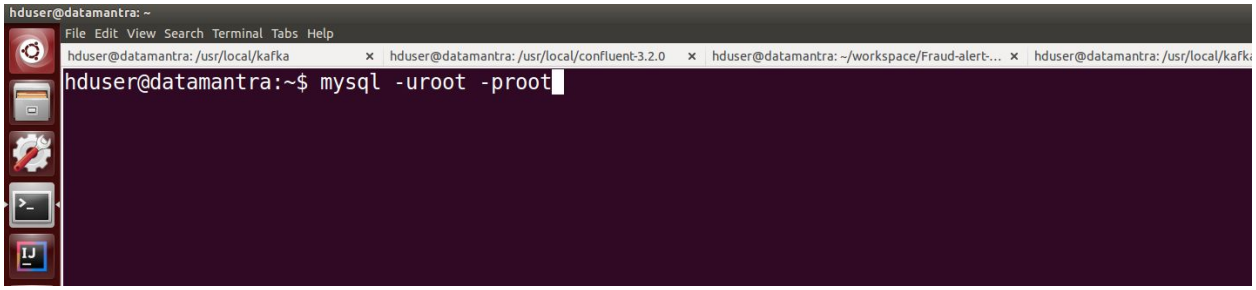
7.3 Configure Airflow

By default, apache airflow is configured with SQLite. But SQLite is not suitable for the Production environment. Hence modify configure airflow to use MySQL database

7.3.1 Create hduser and airflow database

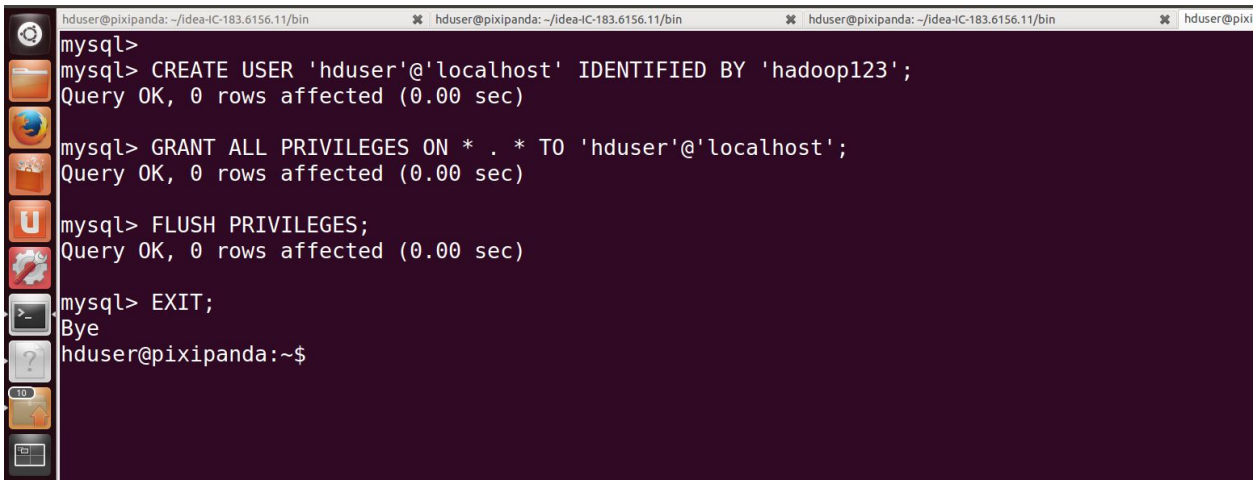
Create a new user and database in Mysql
Login to Mysql with root credentials

```
mysql -uroot -proot
```



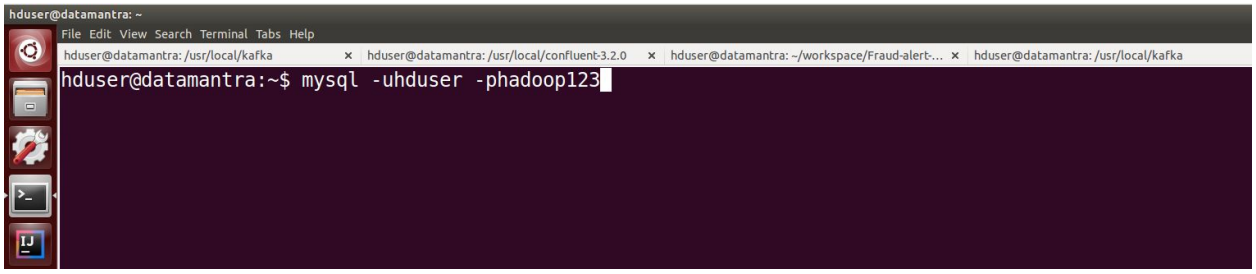
Create hduser with hadoop123 as password

```
CREATE USER 'hduser'@'localhost' IDENTIFIED BY 'hadoop123';
GRANT ALL PRIVILEGES ON * . * TO 'hduser'@'localhost';
FLUSH PRIVILEGES;
EXIT;
```



Login as hduser

```
mysql -uhduser -phadoop123
```



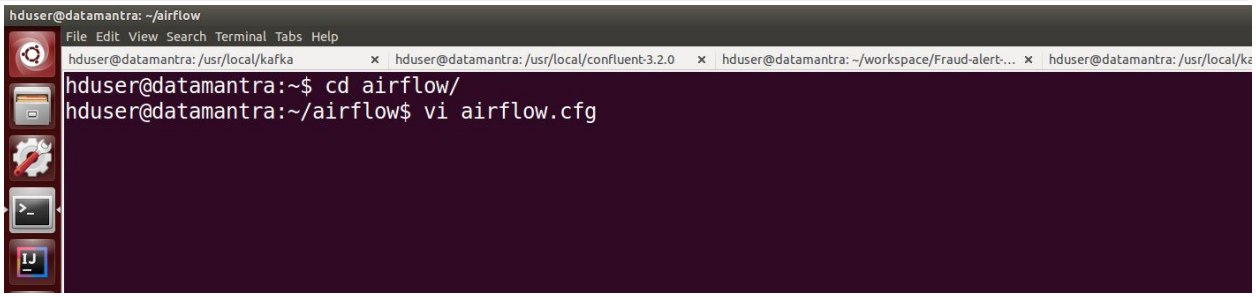
Create Airflow database and exit

```
CREATE DATABASE airflow;
EXIT;
```

7.3.2 Modify airflow.cfg

Modify the airflow.cfg file to use MySQL database

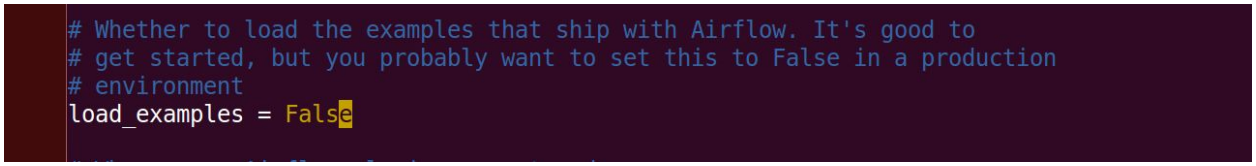
```
cd ~/airflow
vi airflow.cfg
```



Modify following fields, save and exit

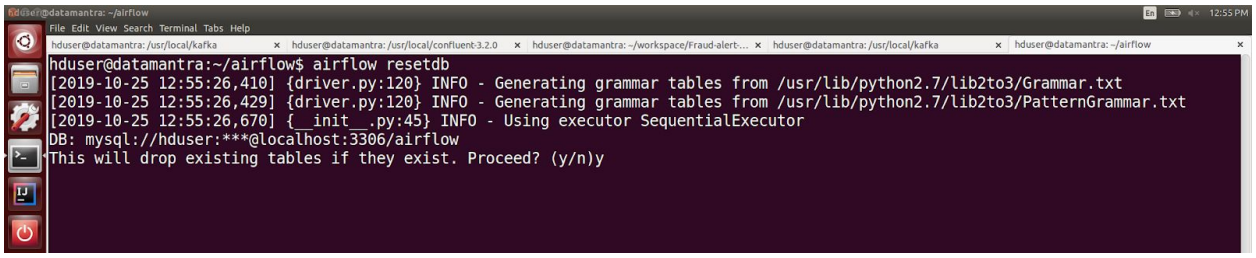
```
sql_alchemy_conn = mysql://hduser:hadoop123@localhost:3306/airflow
load_examples = False
```

Here we are configuring MySQL instead of SQLite.
Also instead of loading all the built-in example scripts of Airflow, only our script will be loaded.



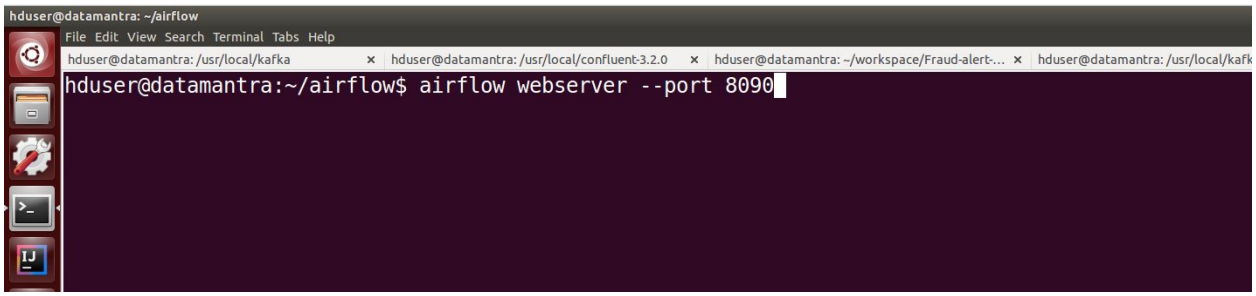
Rest Airflow Database

```
airflow resetdb
```



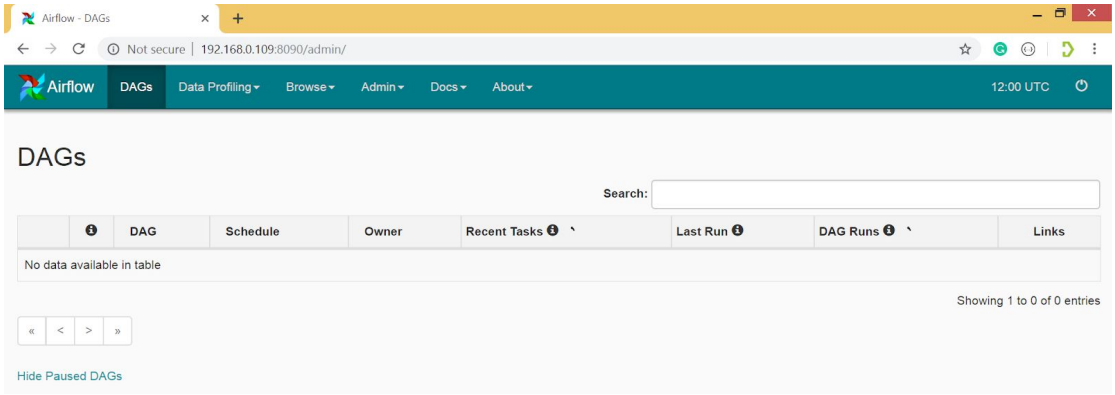
Start Airflow Webserver

`airflow webserver --port 8090`



Access Airflow Web Server

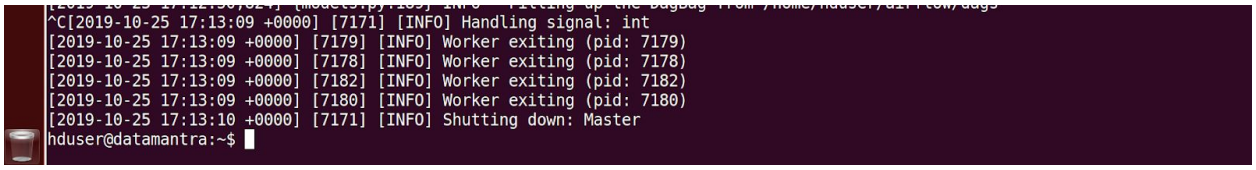
Access `https://<ubunt_ipaddress>:8080` to verify whether the airflow web server is up and running



Airflow is configured successfully

Stop Airflow Webserver

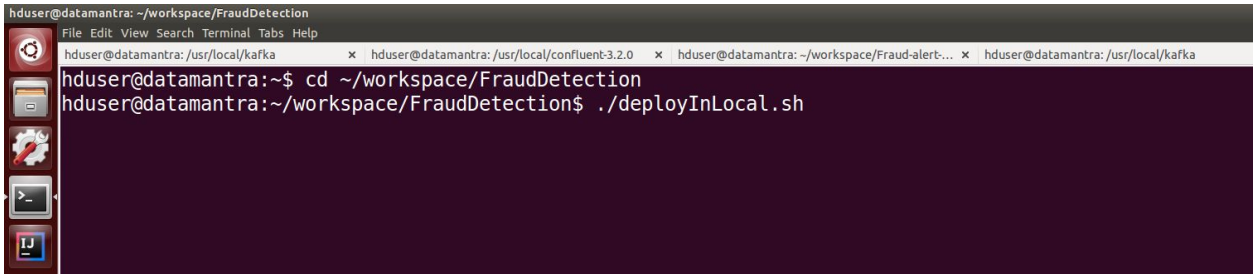
Stop Airflow Webserver by pressing CTRL C on the terminal where it was started. This was just to test whether Airflow is working. We will start again when we start automation



7.4 Build all Projects

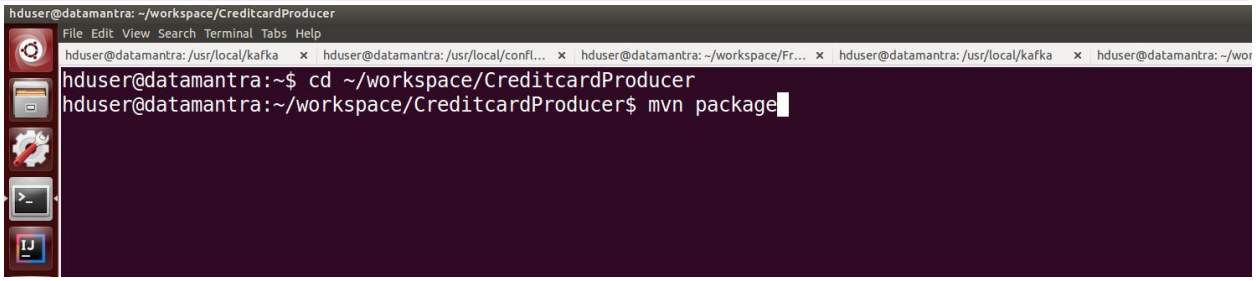
Build FraudDetectoin Project

```
cd ~/workspace/FraudDetection
./deployInLocal.sh
```



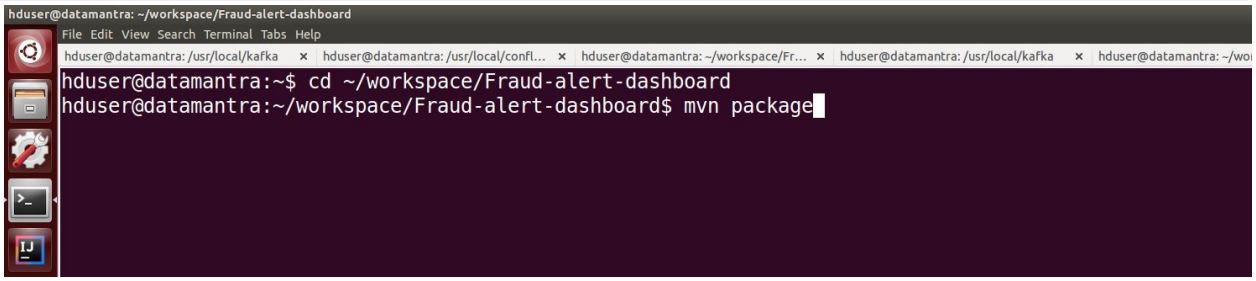
Build Creditcard Producer Project

```
cd ~/workspace/CreditcardProducer
mvn package
```



Build Fraud-Alert-Dashboard Project

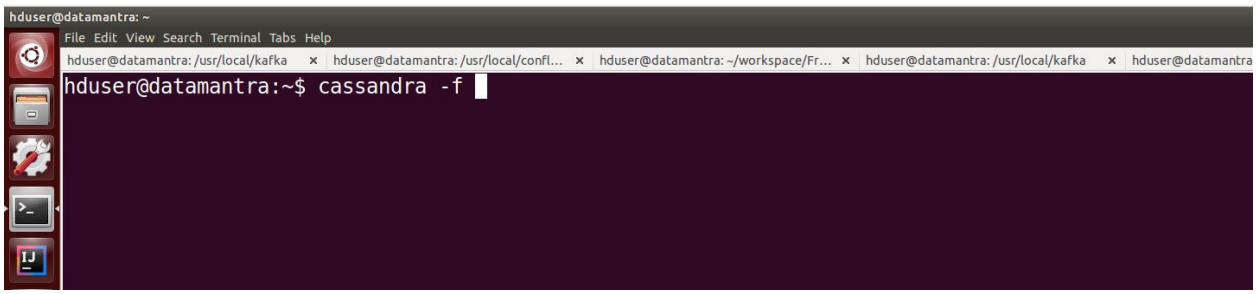
```
cd ~/workspace/Fraud-alert-dashboard
mvn package
```



7.5 Start all the Servers

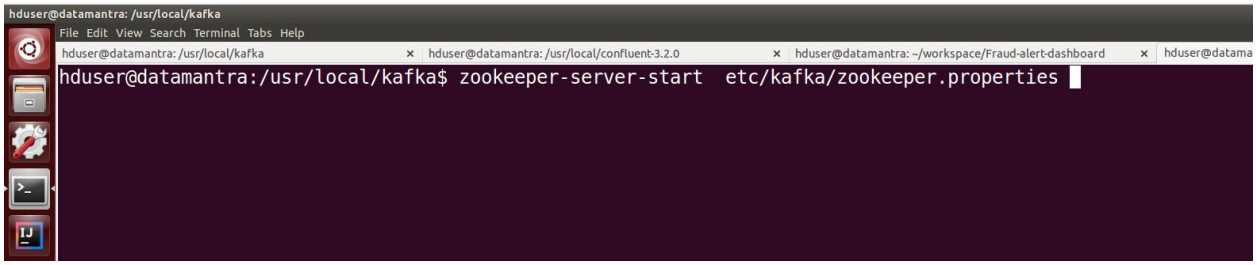
Start Cassandra Server

```
cassandra -f
```



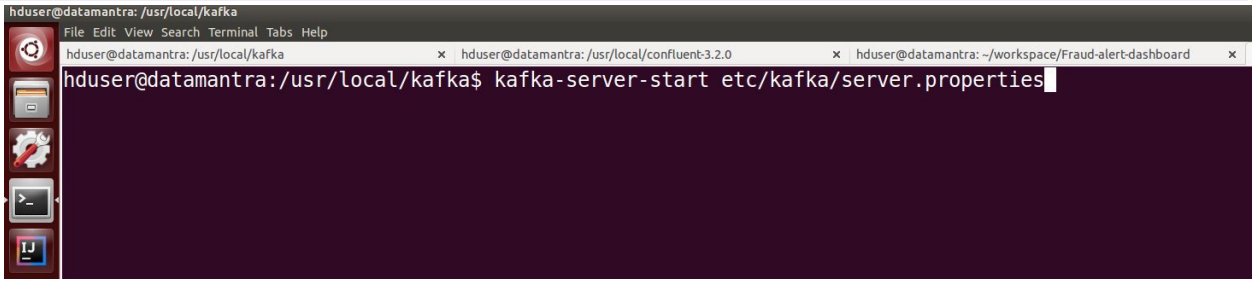
Start Zookeeper Server

```
cd /usr/local/kafka
zookeeper-server-start etc/kafka/zookeeper.properties
```



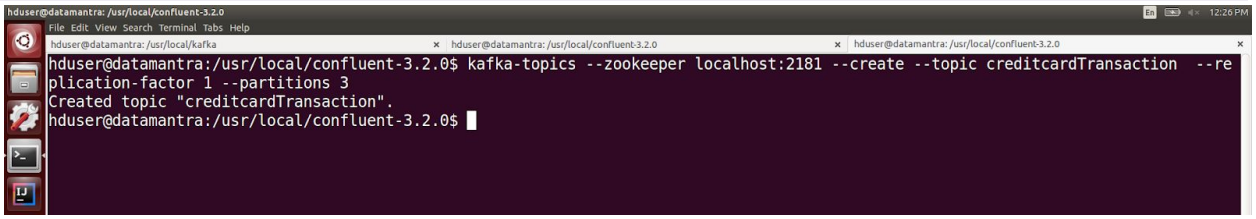
Start Kafka Server

```
kafka-server-start etc/kafka/server.properties
```



Create transaction topic

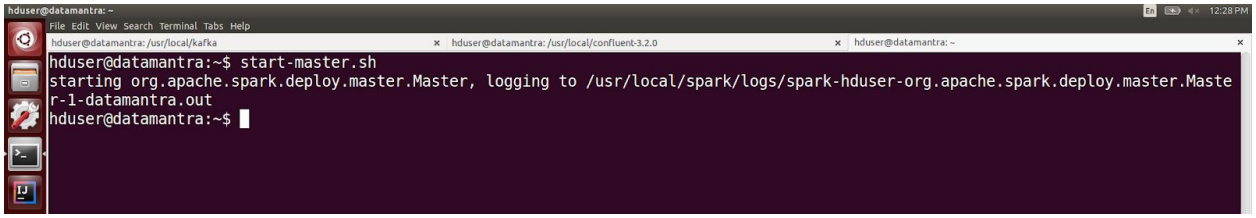
```
kafka-topics --zookeeper localhost:2181 --create --topic
creditcardTransaction  --replication-factor 1 --partitions 3
```



Spark Cluster Setup

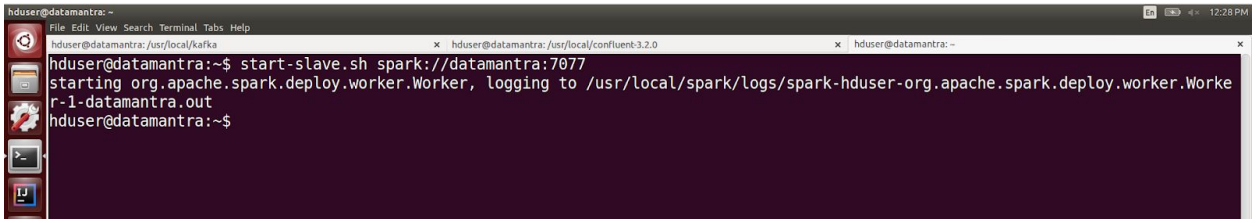
Start Spark Master

```
start-master.sh
```



Start Spark Slave

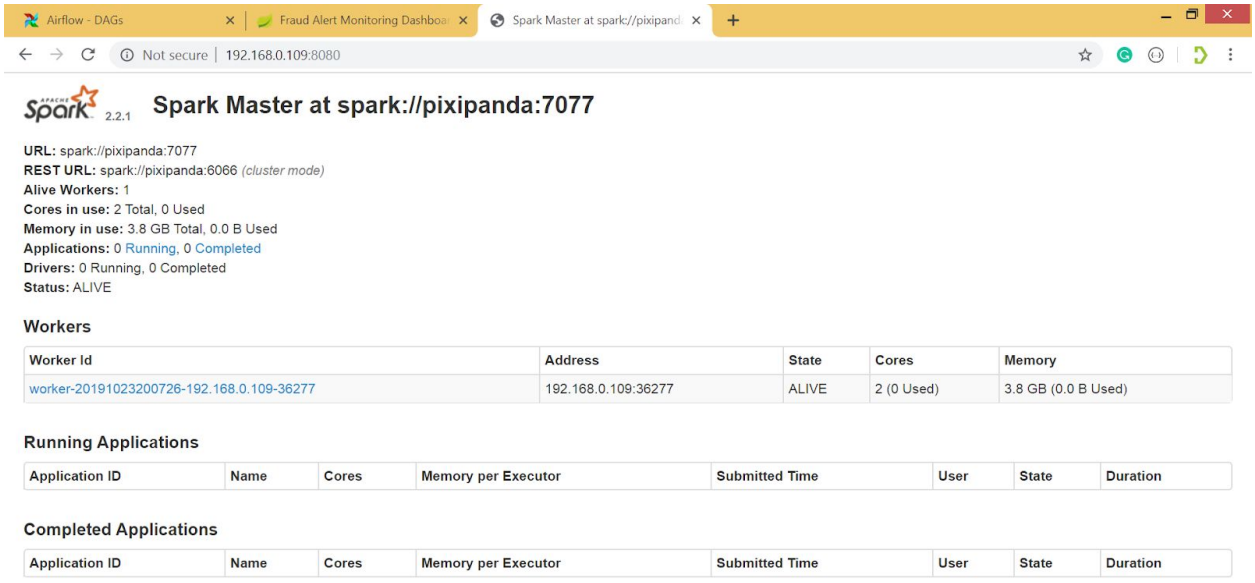
```
start-slave.sh spark://datamantra:7077
```



Access Spark Web UI

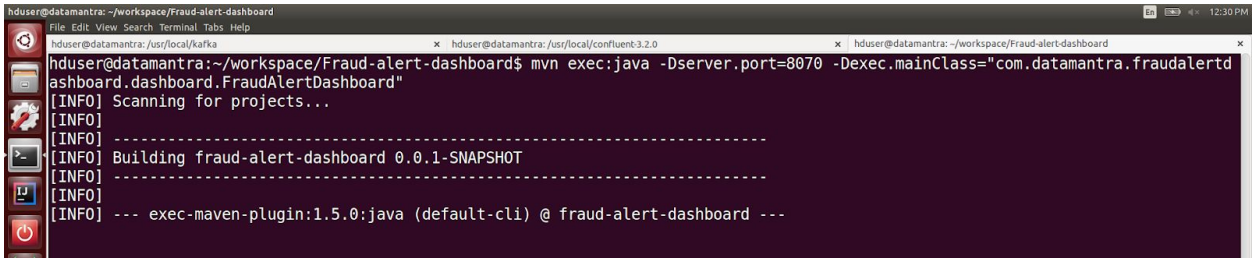
Check whether Spark Cluster is up and running

```
http://ubuntu_ip:8080/
```



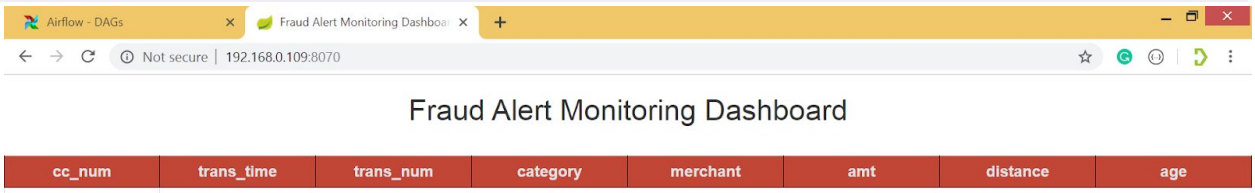
Start the dashboard for visualization

```
cd ~/workspace/Fraud-alert-dashboard/
mvn exec:java -Dserver.port=8070
-Dexec.mainClass="com.datamantra.fraudalertdashboard.dashboard.FraudAlertDa
shboard"
```



Access Dashboard Web UI

```
http://ubuntu_ip:8070
```

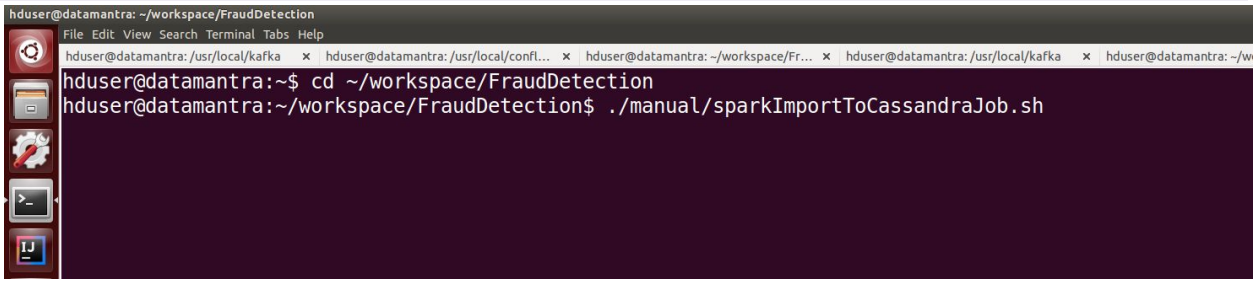


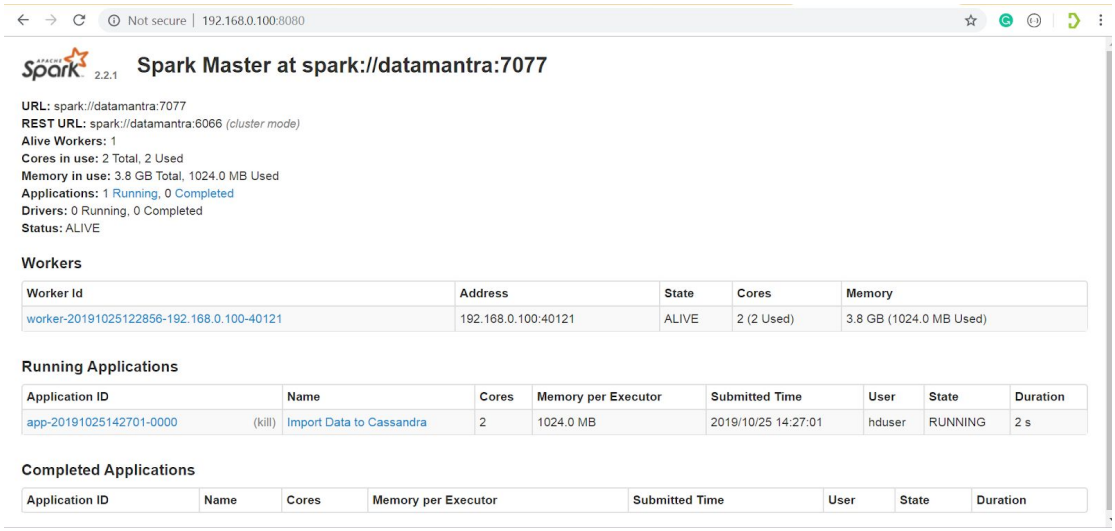
7.6 Airflow Automation

Start Spark Import Job

This Job will be started manually to import customer data and transaction data from the filesystem to Cassandra Keyspace.

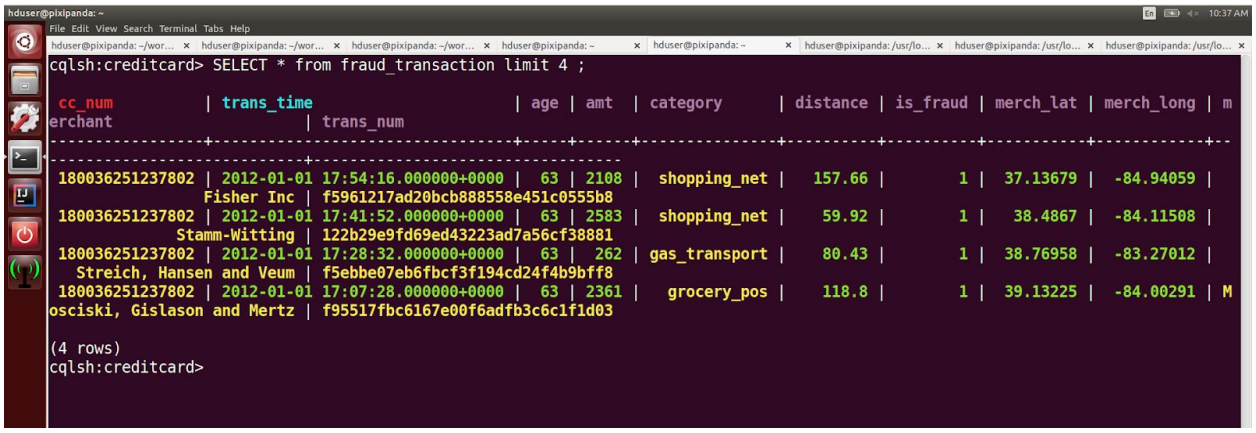
```
cd ~/workspace/FraudDetection
./manual/sparkImportToCassandraJob.sh
```





Output

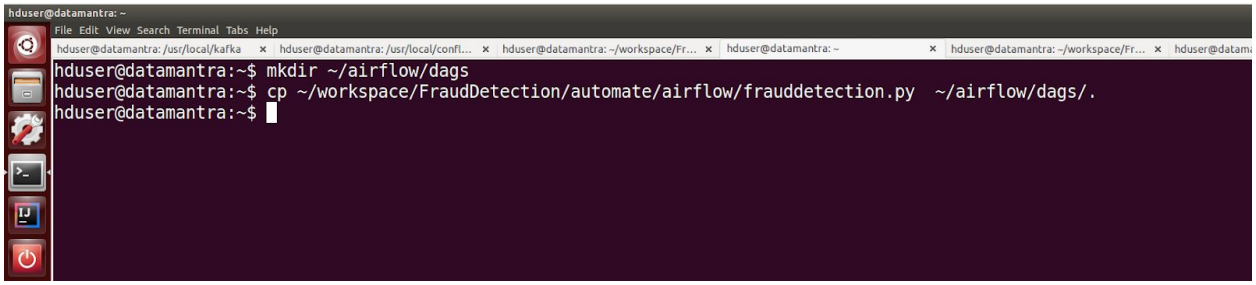
Transaction data and customer data is imported to Cassandra Keyspace



Create an Airflow DAG directory.

Automation scripts must be kept in this directory. Airflow will look for scripts in this directory and it will load the scripts to the web server. So copy frauddetection.py file from FraudDetection Project to airflow dags directory

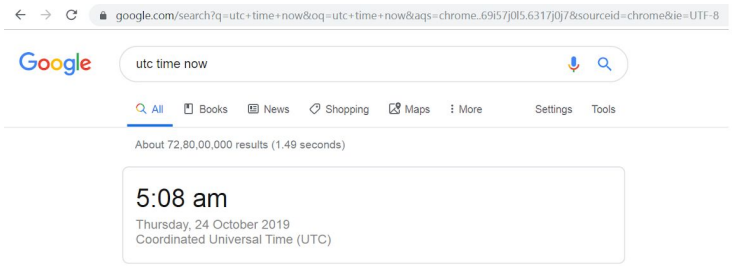
```
mkdir ~/airflow/dags
cp ~/workspace/FraudDetection/automate/airflow/frauddetection.py
~/airflow/dags/.
```



Change the start time in [frauddetection.py]

Airflow uses UTC timezone

UTC time in my system is 5:08 am. We will kick start the automation at 5:20 am

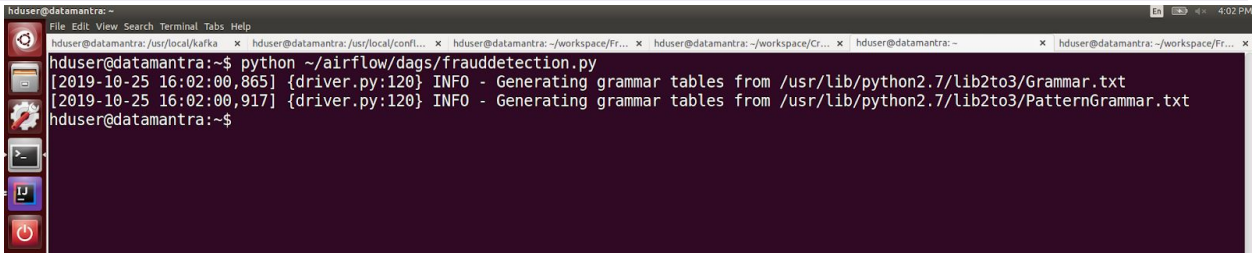


start_date is set to 2019, 10, 24, 5 i.e start date is set to 5:00 am
schedule_interval is set to '*/20 * * * *'. It means every 20 mins automation step will be evaluated.
Actual start time = start_date + schedule_interval = 5:00 + 20 mins = 5:20 am

```
default_args = {
    'owner': 'me',
    'start_date': dt.datetime(2019, 10, 24, 5),
    'retries': 1,
    'retry_delay': dt.timedelta(minutes=5),
}

with DAG(DAG_NAME,
         default_args=default_args,
         schedule_interval='*/20 * * * *',
         ) as dag:
```

Compile the changes

```
python ~/airflow/dags/frauddetection.py
```



Reset airflow database

Reset is done so that airflow tables are created in MySQL database

```
airflow resetdb
```

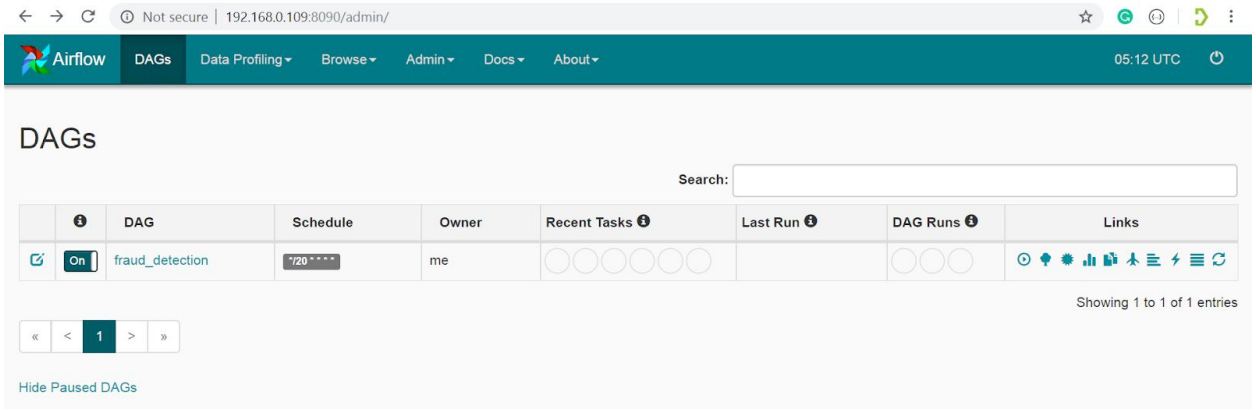
Start Airflow Webserver

```
airflow webserver --port 8090
```

Access Airflow Webserver

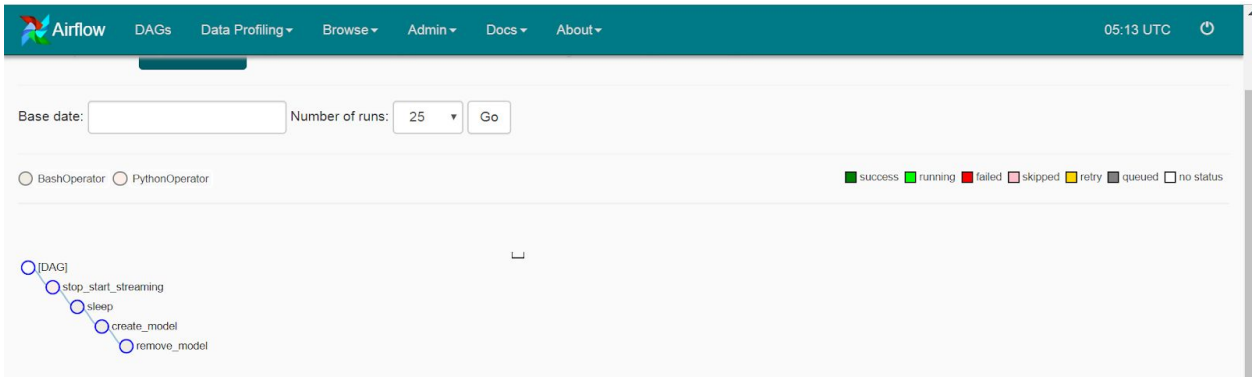
```
http://ubuntu_ipaddr:8090
```

Click on OFF button to set it ON



If you click on fraud_detection you will see the automation steps.

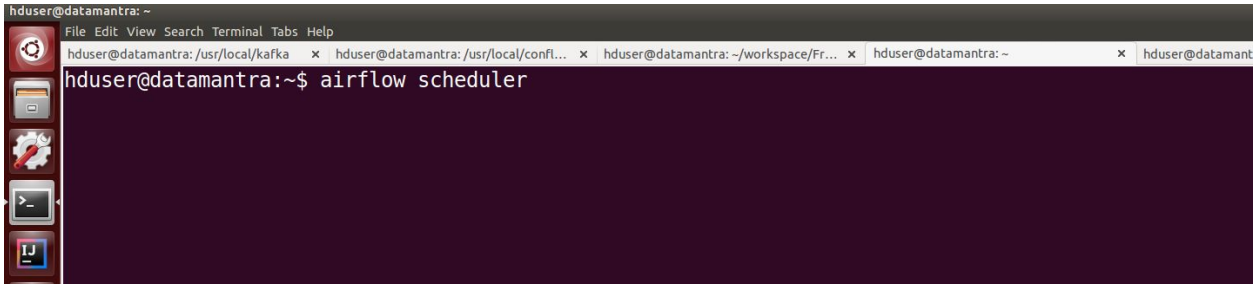
1. Remove Model is any exist
2. Create New Model by running Spark ML Job
3. Seep for 5 seconds(This step is optional)
4. Stop and Start Spark Streaming Job



Start Airflow Scheduler

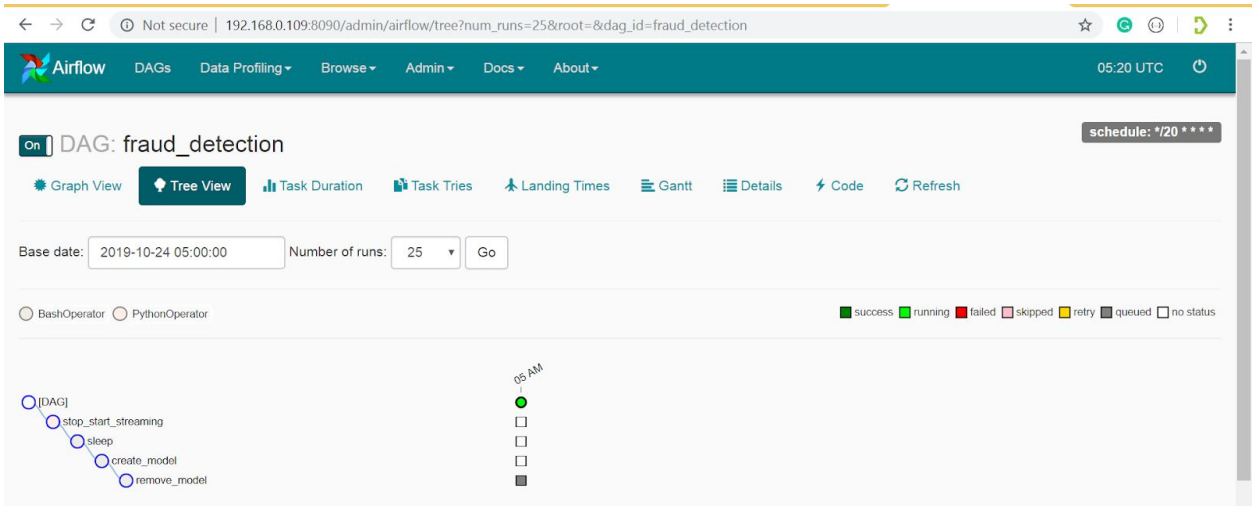
Airflow Scheduler is the one which will actually kick start your automation

```
airflow scheduler
```

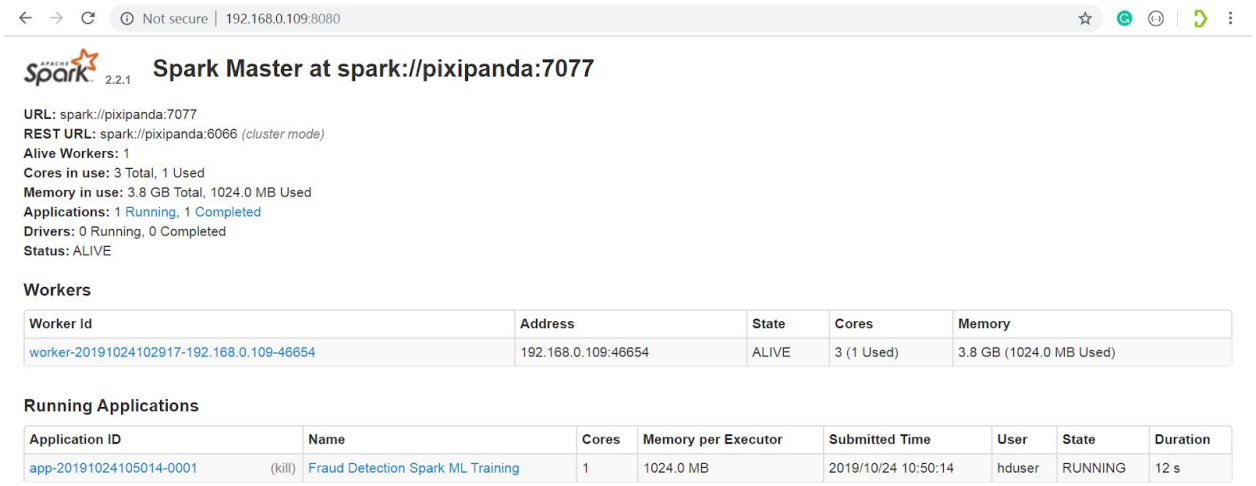


Output

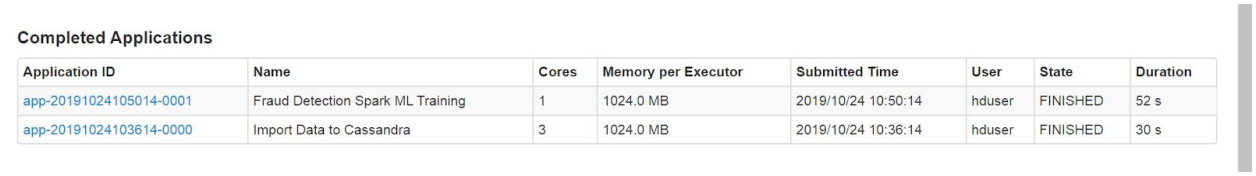
Automation start at 5:20 am UTC



Spark ML Job Scheduled

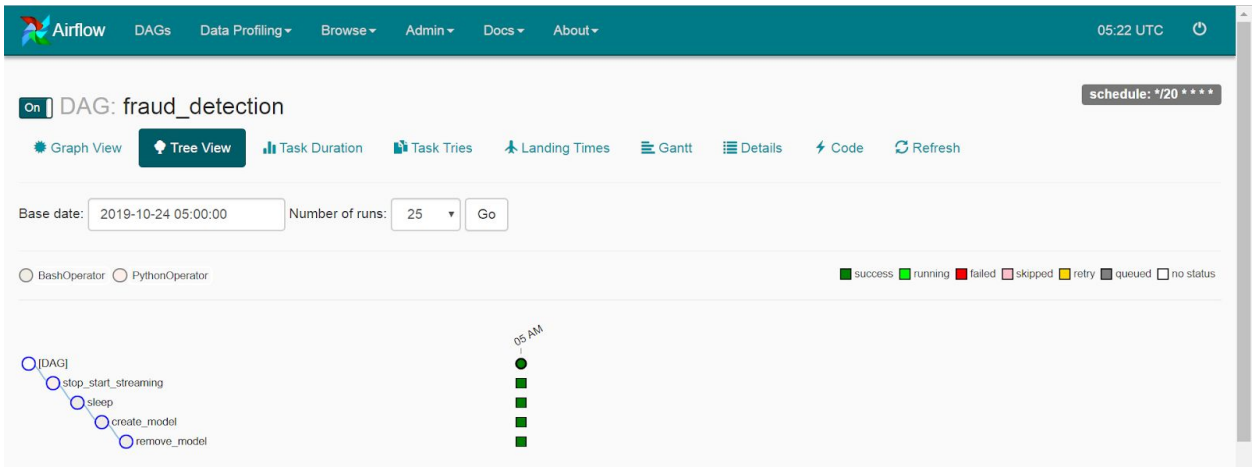


Spark ML Job Completed

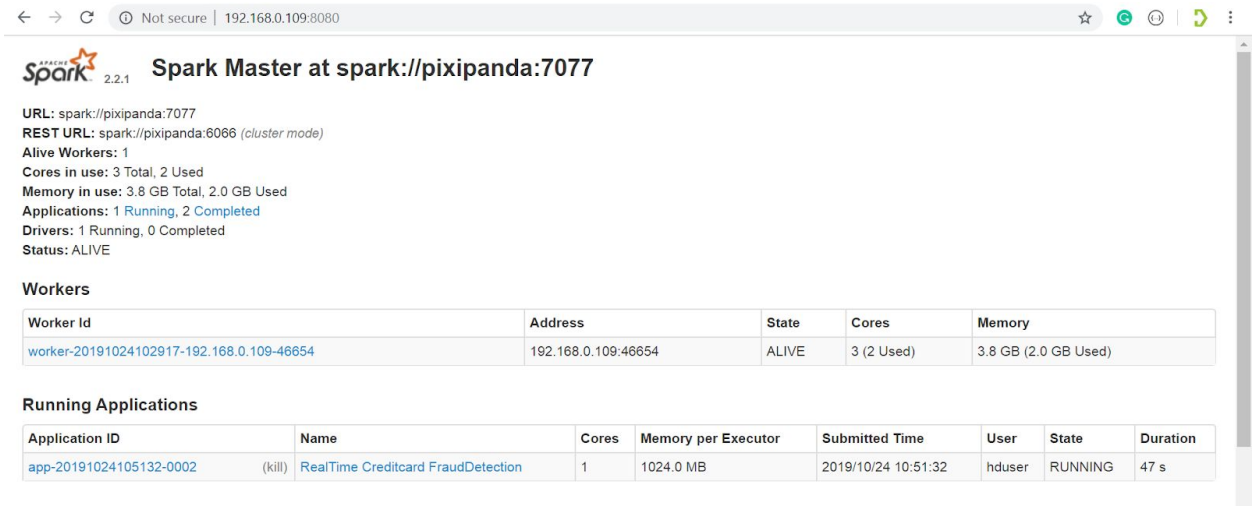


All automation steps completed.

This means Spark Streaming is up and running



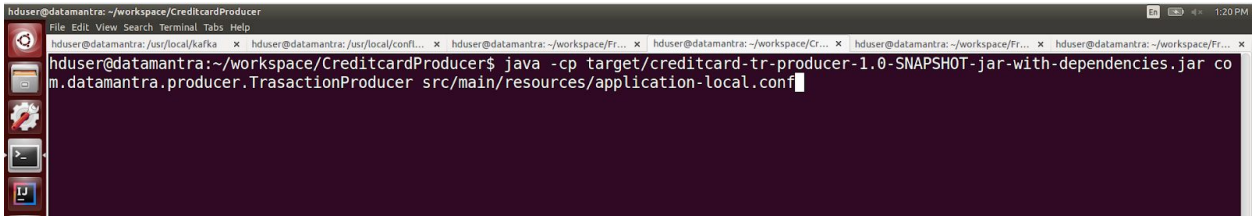
Spark Streaming Job is up and running



Start Kafka Producer

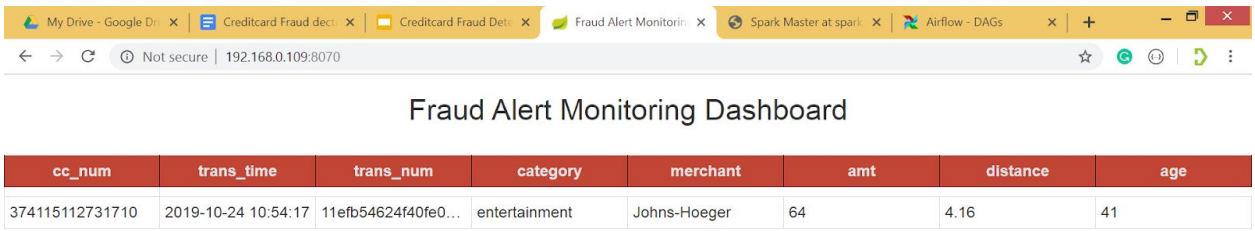
Spark Streaming Job is up and running, now we will start Kafka Producer

```
java -cp
target/creditcard-tr-producer-1.0-SNAPSHOT-jar-with-dependencies.jar
com.datamantra.producer.TrasactionProducer
src/main/resources/application-local.conf
```



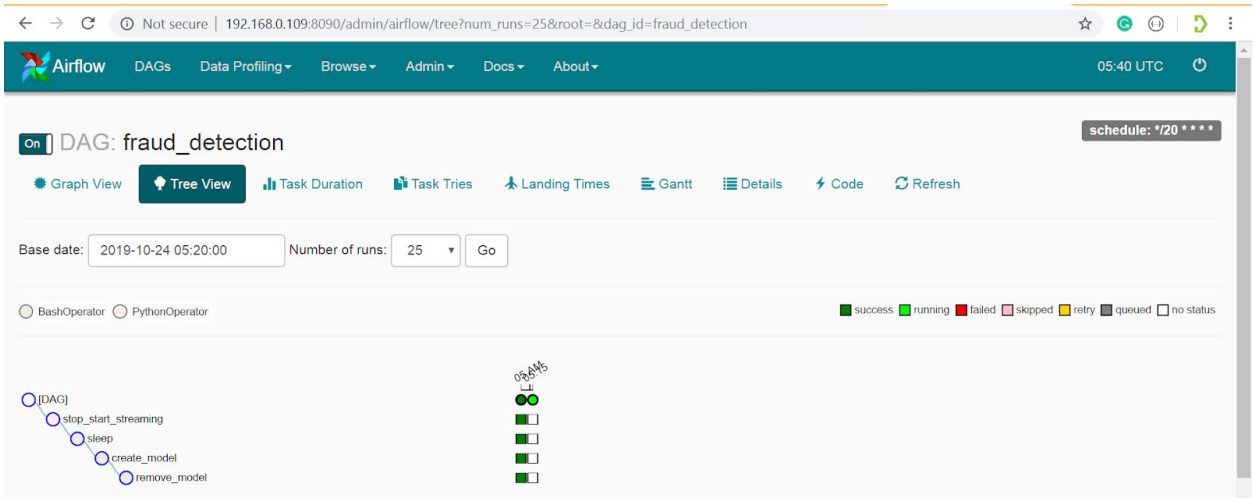
Output

A fraud alert is displayed on the dashboard



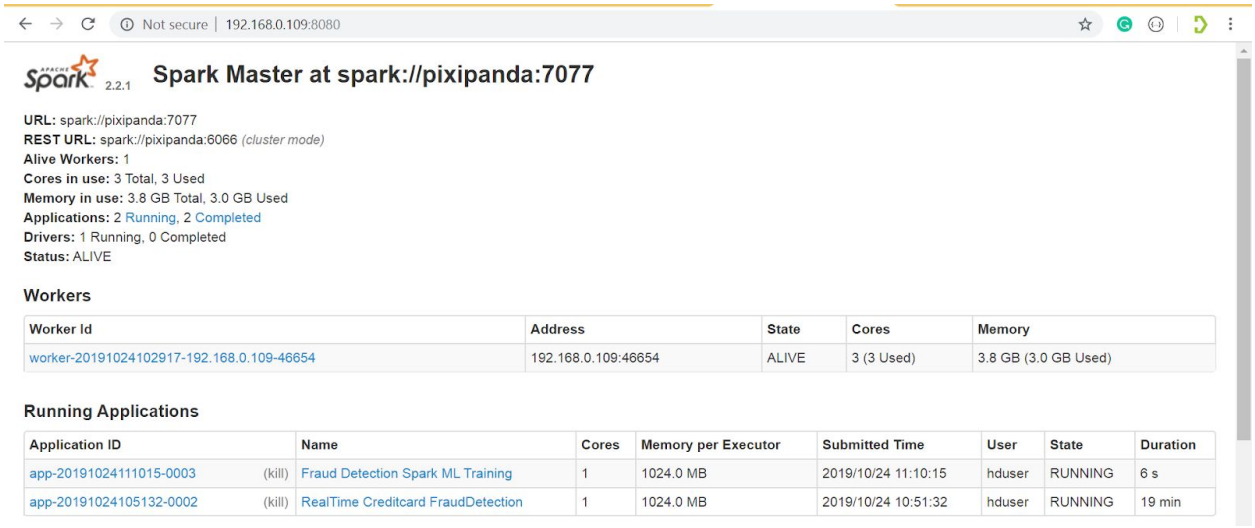
Next set of automation

Next set of automation steps scheduled at 5:40 am(every 20 mins)



Spark ML Job is running

This will create new model



Completed Applications

Application ID	Name	Cores	Memory per Executor	Submitted Time	User	State	Duration
app-20191024111015-0003	Fraud Detection Spark ML Training	1	1024.0 MB	2019/10/24 11:10:15	hduser	FINISHED	1.1 min
app-20191024105014-0001	Fraud Detection Spark ML Training	1	1024.0 MB	2019/10/24 10:50:14	hduser	FINISHED	52 s
app-20191024103614-0000	Import Data to Cassandra	3	1024.0 MB	2019/10/24 10:36:14	hduser	FINISHED	30 s

Spark Streaming Job Stopped

Completed Applications

Application ID	Name	Cores	Memory per Executor	Submitted Time	User	State	Duration
app-20191024105132-0002	RealTime Creditcard FraudDetection	1	1024.0 MB	2019/10/24 10:51:32	hduser	FINISHED	20 min
app-20191024111015-0003	Fraud Detection Spark ML Training	1	1024.0 MB	2019/10/24 11:10:15	hduser	FINISHED	1.1 min
app-20191024105014-0001	Fraud Detection Spark ML Training	1	1024.0 MB	2019/10/24 10:50:14	hduser	FINISHED	52 s
app-20191024103614-0000	Import Data to Cassandra	3	1024.0 MB	2019/10/24 10:36:14	hduser	FINISHED	30 s

New Streaming Job Started

This will load the new model created by the previous Spark ML Job. Transactions will be predicted using this new model.