BIA-678 Presentation - Data Streaming and Credit Card Fraud Detection model

Speaking order:

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Agenda

- Introduction
- EDA (Exploratory Data Analysis) and Data Preprocessing
- Implementation Framework
- Scale comparison & evaluation
- Performance Measurements
- Conclusion

Introduction

EMR Analytics

- Train 4 models on different algorithms
- Make predictions and evaluate accuracy

Local v.s Distributed

Compare training and test time

PySpark

Use PySpark on AWS to separate data to train and test dataset

Data Streaming

Every 30 seconds streaming 5,000 data rows and make predictions

Future

- Data Staging
- Store data to MongoDB
- Kafka
- Virtualization by Tableau/Power BI

Dataset Overview

- From Kaggle. The size of the data:

```
In [6]: data.shape
Out[6]: (284807, 31)
```

- Missing data:

```
In [13]: data.isnull().sum().any()
Out[13]: False
```

- Check how imbalance the dataset is

Class	count
0	227429
1	417

- The brief summary of the dataset:

```
df_sub1.describe().show()
```

summary	Amount	Class	Time
count	227846	227846	227846
mean	90.82474026317597	0.001830183545026...	79043.08588695874
stddev	250.50323615893055	0.04274157216455668	39506.09954343867
min	0.0	0	0.0
max	19656.53	1	145248.0

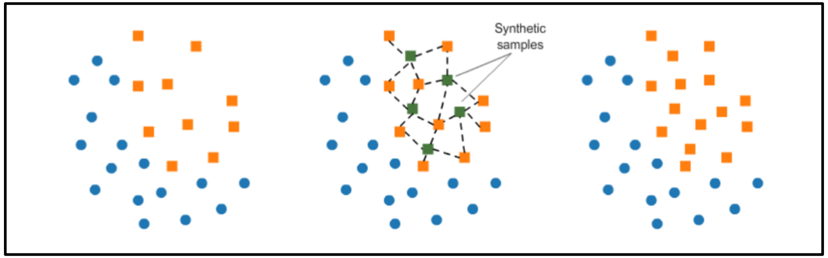
Resampling

- Implement both **SMOTE** (Synthetic Minority Over-sampling Technique) and **Down Sampling** in PySpark to re-sample the dataset.
- **10k** fraud v.s. **10k** normal
- **80%** training set & **20%** test set. We also retain **10%** of the data for simulating the streaming process.

2. Down-sampling

```
In [8]:  # down sampling to meet the SMOTE
         df_down = df.filter("Class=0").rdd.takeSample(False,10332, seed=0)

In [10]: # convert the list to dataframe for outfile

         df_down1 = sqlContext.createDataFrame(df_down)

In [11]: df_down1.coalesce(1).write.csv('s3://storechen/678_down.csv')

In [12]: print((df_down1.count(), len(df_down1.columns)))

         (10332, 31)
```

1. Over-sampling: SMOTE



Source: https://www.kaggle.com/rafjaa/resampling-strategies-for-imbalanced-datasets

```python
def SmoteSampling(vectorized, k = 5, minorityClass = 1, majorityClass = 0, percentageOver = 200, percentageUnder = 100):
    if(percentageUnder > 100|percentageUnder < 10):
        raise ValueError("Percentage Under must be in range 10 - 100");
    if(percentageOver < 100):
        raise ValueError("Percentage Over must be in at least 100");
    dataInput_min = vectorized[vectorized['label'] == minorityClass]
    dataInput_maj = vectorized[vectorized['label'] == majorityClass]
    feature = dataInput_min.select('features')
    feature = feature.rdd
    feature = feature.map(lambda x: x[0])
    feature = feature.collect()
    feature = np.asarray(feature)
    nbrs = neighbors.NearestNeighbors(n_neighbors=k, algorithm='auto').fit(feature)
    neighbours =  nbrs.kneighbors(feature)
```

Code for implementing SMOTE in PySpark

EDA (Exploratory Data Analysis)

- The Max & Min transaction amount

```
from pyspark.sql.functions import max,min
df_sub1.select(max("Amount"),min("Amount")).show()
```

```
+-----------+-----------+
|max(Amount)|min(Amount)|
+-----------+-----------+
|   19656.53|        0.0|
+-----------+-----------+
```

- Correlation

```
from pyspark.sql.functions import corr
df_sub1.select(corr("Class","Amount")).show()
print("The correlation is pretty low")
```

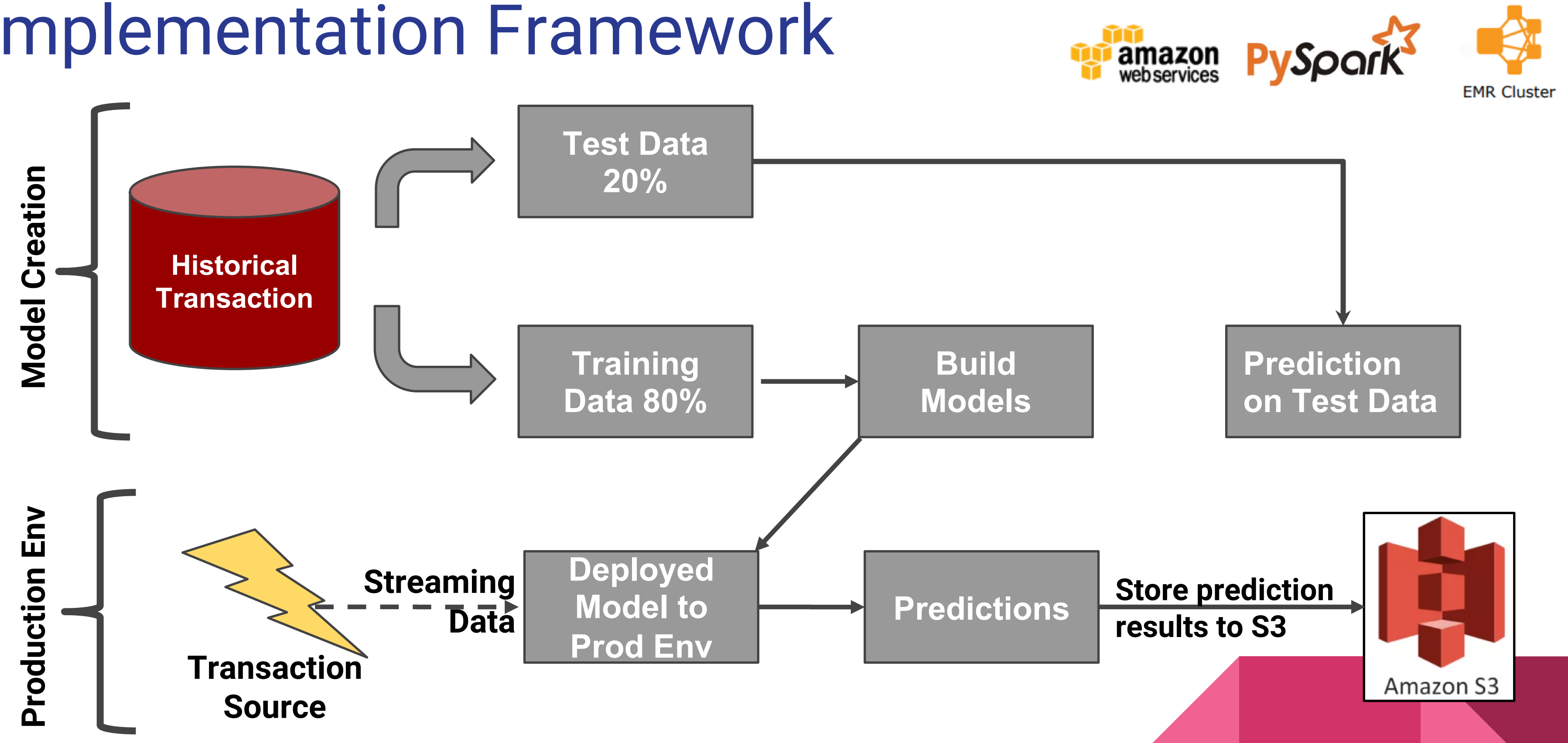
```
+--------------------+
| corr(Class, Amount)|
+--------------------+
|0.005953969765854438|
+--------------------+
```

- The Top 10 Transactions:

```
df_sub1.orderBy(df_sub1["Amount"].desc()).show(10)
```

```
+--------+-----+--------+
|  Amount|Class|    Time|
+--------+-----+--------+
|19656.53|    0| 48401.0|
| 18910.0|    0| 95286.0|
|12910.93|    0| 42951.0|
|11898.09|    0| 46253.0|
|11789.84|    0|119713.0|
| 8790.26|    0| 55709.0|
|  8360.0|    0|144755.0|
| 7879.42|    0| 30537.0|
|  7766.6|    0|128027.0|
| 7712.43|    0|  1264.0|
+--------+-----+--------+
```

Implementation Framework



Streaming Data in Production Environment

- Data is streamed from our local machine to S3, using a AWS SDK Boto3
- Size and the frequency of the stream data can be fully configured.
- We stream 5k transactions every 30 seconds
- After data are streamed to the production environment, system makes prediction results.

```
def upload_to_aws(local_file, bucket, s3_file):
    s3 = boto3.client('s3', aws_access_key_id=ACCESS_KEY,
                      aws_secret_access_key=SECRET_KEY)
```

stream0.csv	Nov 28, 2019 7:45:14 AM GMT+0700
stream1.csv	Nov 28, 2019 7:45:46 AM GMT+0700
stream2.csv	Nov 28, 2019 7:46:18 AM GMT+0700
stream3.csv	Nov 28, 2019 7:46:49 AM GMT+0700
stream4.csv	Nov 28, 2019 7:47:21 AM GMT+0700

Streaming Data in Production Environment

- Stream of data keeps coming into the environment where the classification model is deployed
- The program is able to produce prediction result continuously
- The prediction results are stored back to another directory on S3 for further analysis purpose such as BI tools/ Visualization etc.

```
Test result of stream0 is
Accuracy of LogisticRegression is = 0.9978
F1 of LogisticRegression = 0.998126

Test result of stream1 is
Accuracy of LogisticRegression is = 0.9996
F1 of LogisticRegression = 0.999578

Test result of stream2 is
Accuracy of LogisticRegression is = 0.9992
F1 of LogisticRegression = 0.9992

Test result of stream3 is
Accuracy of LogisticRegression is = 0.999
F1 of LogisticRegression = 0.999029
```

Type a prefix and press Enter to search. Press ESC to clear.

Upload | Create folder | Download | Actions

US East (N. Virginia)

Viewing 1 to 9

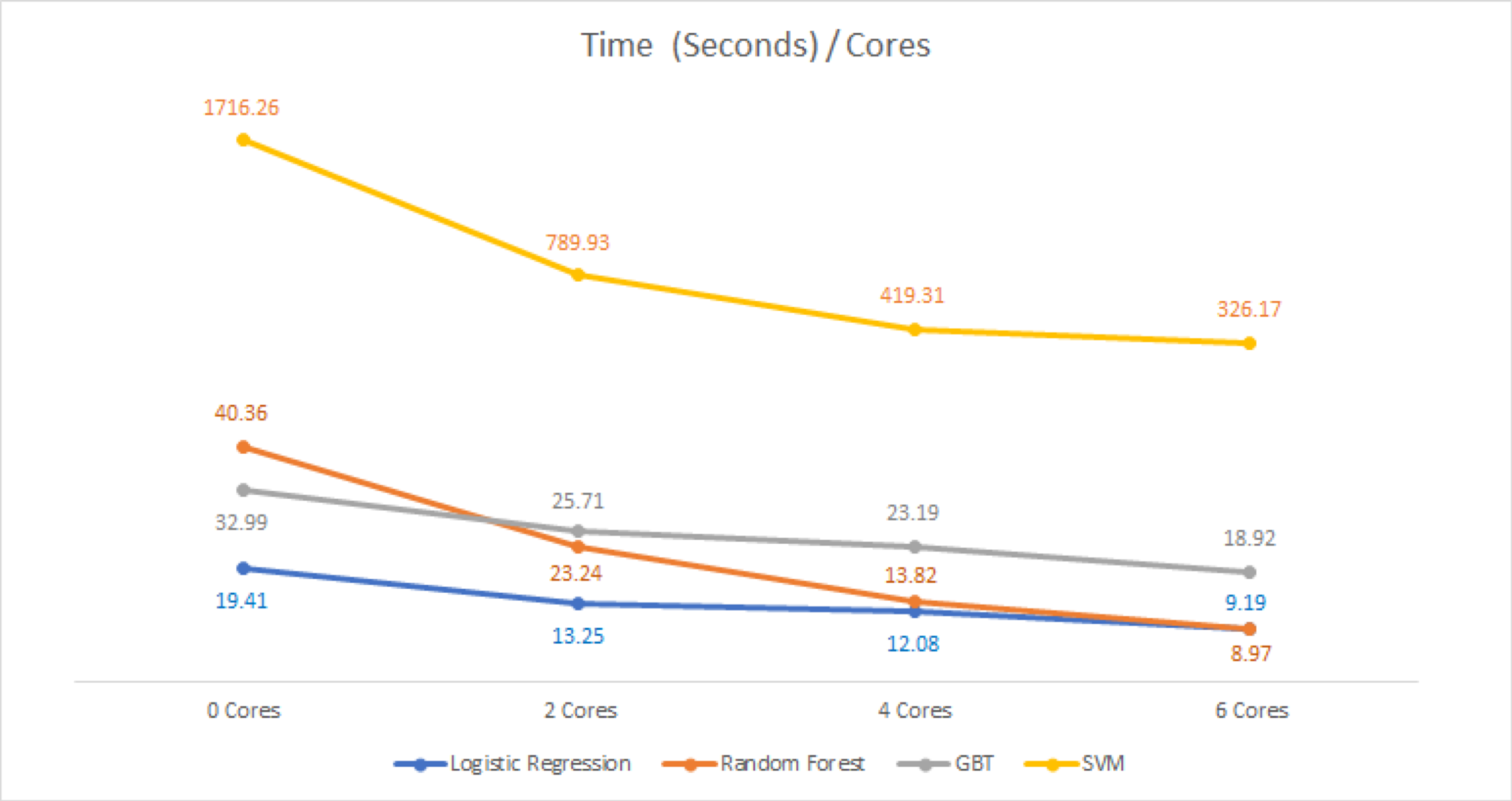
Name	Last modified	Size	Storage class
prediction0.csv	--	--	--
prediction1.csv	--	--	--
prediction2.csv	--	--	--
prediction3.csv	--	--	--
prediction4.csv	--	--	--

```
lrprediction_stream[2].show(5)

+--------------------+-----+--------------------+--------------------+----------+
|            features|label|       rawPrediction|         probability|prediction|
+--------------------+-----+--------------------+--------------------+----------+
|[67478.0,1.007833...|    0|[8.67523896400722...|[0.99982926701474...|       0.0|
|[67478.0,1.267602...|    0|[6.93116946998853...|[0.99902409552563...|       0.0|
|[67480.0,-1.07630...|    0|[7.98574887150973...|[0.99965983817278...|       0.0|
|[67482.0,-0.79236...|    0|[6.37341728977651...|[0.99829658829535...|       0.0|
|[67483.0,-1.22259...|    0|[8.22202776017821...|[0.99973140244960...|       0.0|
+--------------------+-----+--------------------+--------------------+----------+
only showing top 5 rows
```

Scale comparison & Evaluation

- Training data set consists of > 235K transactions, 31 features
- Measuring the training time under LogisticRegression, RandomForest, Gradient-boosted Tree, Support Vector Machine, under different number of cores.
- Parameter setting of models in each hardware sizing is identical

Time/ Cores	Logistic Regression	Random Forest	GBT	SVM
0 Core (Master only)	**19.41 seconds**	40.36 seconds	32.99 seconds	**1716.26 seconds**
2 Cores	**13.25 seconds**	23.24 seconds	25.71 seconds	**789.93 seconds**
4 Cores	**12.08 seconds**	13.82 seconds	23.19 seconds	**419.31 seconds**
6 Cores	9.19 seconds	**8.97 seconds**	18.92 seconds	**326.17 seconds**


Time (Seconds) / Cores
1716.26
789.93
419.31
326.17
40.36
32.99
25.71
23.24
23.19
13.82
18.92
19.41
13.25
12.08
9.19
8.97
0 Cores
2 Cores
4 Cores
6 Cores
Logistic Regression
Random Forest
GBT
SVM

Performance Measurements

- Based on the test data set consisting of ~ 4k transactions

Measuring Metrics	Logistic Regression	Random Forest	Gradient-boosted Tree	SVM
Accuracy	0.9819	**0.9789**	0.9816	**0.9829**
F1	0.9809	**0.9789**	**0.9824**	0.9819

Conclusion & Suggestions for Future work

- Cloud computing does take less time than local computing, the training time significantly decrease with stronger hardware
- The time required to run the program is unstable
- Connection to NoSQL DB such as Cassandra or MongoDB for further processing such as Dashboard/ Report
- Full integration with Kafka for a more robust data streaming capability