Final Research Report

Detecting Unknown Mining Pools and their Behaviour within Bitcoin using Parallelized Machine Learning

RESEARCHERS

Srinjoy Chakravarty

Dr. Handan Liu

Srishti Ashok Mishra

Contents

Introduction

What is Blockchain?

A blockchain is a time-stamped series of an immutable record of data that is managed by a cluster of computers around the world and it not owned by any single entity. Each of these blocks of data are secured and bound to each other using cryptographic principles hashing. In simple terms, blockchain is a chain of blocks; the words “block” and “chain” are the digital information and public database, respectively. The core components of blockchain architecture are:

Node — computing ***peer*** within the ***network***

Transaction — immutable ledger ***record*** indicating a ***transfer*** of ***value***

Block — *data-structure* used to batch transactions and ***relay*** them ***peer-to-peer***

Chain — a ***sequence*** of blocks in ***chronological*** order

Cryptocurrency — algorithmic value token generated outside central bank or governmental purview

Miners — powerful nodes which create new monetary supply

Consensus — decentralized code-driven governance to validate all network activity

Machine learning algorithms when applied on big data, allow us to analyze the actual extent of ‘cybersecurity’ behind the ‘proof-of-work’ generated by various entities, powering the distributed ledger technologies, that claim to be pseudonymous and decentralized in nature

Background

By analyzing the different characteristics of bitcoin transactions and identifying the behavior of publicly-known Bitcoin pools in choosing which transactions to mine, we build a Machine Learning Classifier that is able to predict whether a transaction is mined by a mining pool or not

Objective

By classifying address signatures, we can identify mining entities and their potentially malicious behavior on the network to help the community make more responsible mining decisions.

Motivation

Imagine if Nakamoto had moved one of his coins (he hasn’t moved his coins in years) and our classifier flagged it to have mined by an Unknown Mining Pool. Our deep-dive analysis would certain be useful.

Problem Analysis and Algorithms

We use a combination of different Classification Algorithms and an Artificial Neural Network (ANN) to train our prediction models.

1. Serial Model 1 = Random Forest (SKLearn)

- We check the accuracy of our classifier by plotting a Precision-Recall Curve and calculating the area under it
- We use a Confusion Matrix to list out false positives and false negatives
- These transactions are then further investigated with network analysis

2. Serial Model 2 = Gaussian Naive Bayes (SKLearn)

3. Serial AI Model = Artificial Neural Net (TensorFlow)

4. Parallelized ML Model = Multi-Node Stacked Classifier over Distributed Memory

(using Open-source MPI)

Description of Dataset

- We use Google BigQuery to dynamically query the live incoming blocks of the Bitcoin Blockchain using their ETL Dataset API. The API returns two tables: **Transactions** and **Blocks** which contain a host of features including *block_id, is_miner, address, transaction_id, timestamp, input, output,* (updated every 10 minutes i.e. Average Bitcoin Block Time)
  - **Link:** https://tinyurl.com/yyalnexb

Data Extraction and Transformation (ETL)

- The data is extracted by connecting to Google BigQuery by linking a service account key (environment variable) to a JSON keystore file which is obtained from the GCP console

- Google BigQuery allows the use of API client python libraries including the functions you need to connect your Jupyter Notebook to the BigQuery : sudo pip3 install google-cloud-bigquery

- We set the environment variable called “GOOGLE_APPLICATION_CREDENTIALS” to point our Notebook to BigQuery’s service account key

- There are two main tables we utilized as our primary schema: a ***“blocks”*** table and a ***“transactions”*** table, which were uniquely combined with SQL queries.

- SQL queries extract, transform, load bitcoin mining pool address signatures and provide statistics of their behaviour over time [1]

- Connecting to client :

```
import os
os.environ["GOOGLE_APPLICATION_CREDENTIALS"]=r"C:\Users\srish\Documents\NEU\Parallell ML and AI\Untitled Folder\json\My Firs
client = bigquery.Client()
```

```
time_start = time.time()
df = client.query(sql).to_dataframe()
print('Time elapsed: {} seconds' .format(time.time() - time_start))
```

•Extraction joins were from **bigquery-public-data.crypto_bitcoin.transactions** and **bigquery-public-data.bitcoin_blockchain.blocks**

- Every time our code is run, the amount of extracted data is about 1.3 GB+ with 30 columns *(out of which we use 26 as features x1, x2, x3….xn)*

```
 #   Column                    Dtype
---  ------                    -----
 0   is_miner                  bool
 1   address                   object
 2   output_month_min          int64
 3   output_month_max          int64
 4   input_month_min           int64
 5   input_month_max           int64
 6   output_active_time        int64
 7   input_active_time         int64
 8   io_max_lag                int64
 9   io_min_lag                int64
 10  output_active_months      int64
 11  total_tx_output_count     int64
 12  total_tx_output_value     object
 13  mean_tx_output_value      object
 14  stddev_tx_output_value    float64
 15  total_output_tx           int64
 16  mean_monthly_output_value object
 17  mean_monthly_output_count float64
 18  input_active_months       int64
 19  total_tx_input_count      int64
 20  total_tx_input_value      object
 21  mean_tx_input_value       object
 22  stddev_tx_input_value     float64
 23  total_input_tx            int64
 24  mean_monthly_input_value  object
 25  mean_monthly_input_count  float64
 26  mean_output_idle_time     float64
 27  stddev_output_idle_time   float64
 28  mean_input_idle_time      float64
 29  stddev_input_idle_time    float64
dtypes: bool(1), float64(8), int64(14), object(7)
memory usage: 1.3+ GB
```

- To preprocess and clean the data, we drop the columns with null values, and then split the data into training and testing sets to train the model. We choose a training to testing ratio of 80:20 to optimize for accuracy without the dangers of overfitting.

Concepts and Definitions

- **Pool:** A pool is a platform with specialized software where miners combine the computational power of their equipment for more efficient mining of a certain cryptocurrency.

- **Mining Pool:** A pool for mining is an association of miners, who are seeking for best reward. The computing power of each participant' device makes up the total hashrate of the pool. Such cooperation gives much more chances to find a block and get a reward, which is distributed among the participants according to the system accepted by the operator of the particular pool for mining.

In simpler terms - A mining pool can be compared to a lottery pool. Your chances of winning the popular lottery are very low, but when you team up with a lot of other people and agree to share the money you win if you succeed, your chances are multiplied by the number of participants.

•**Pooled Mining:** Pooled mining, "pools" all of the resources of the clients in that pool to generate the solution to a given block. When the pool solves a block, the 6.25 Bitcoin block reward (approximately $73,588 block reward) is split and distributed amongst the pools participants.

•**Solo Mining:** Solo mining is when a miner performs the mining operations alone without joining a pool. All mined blocks are generated to the miner's credit.

- **UTXO** stands for the unspent output from bitcoin transactions. Each bitcoin transaction begins with coins used to balance the ledger. UTXOs are processed continuously and are responsible for beginning and ending each transaction. Confirmation of transaction results in the removal of spent coins from the *UTXO* database.

Source: https://tinyurl.com/yxaq7vx6

- Mempool is the node's holding area for all the pending transactions. It is the node's collection of all the unconfirmed transactions it has already seen enabling it to decide whether or not to relay a new transaction..

Source: https://tinyurl.com/yxg2skom

Benchmarking Disk Read/Write Speed with Pandas Binary Formats

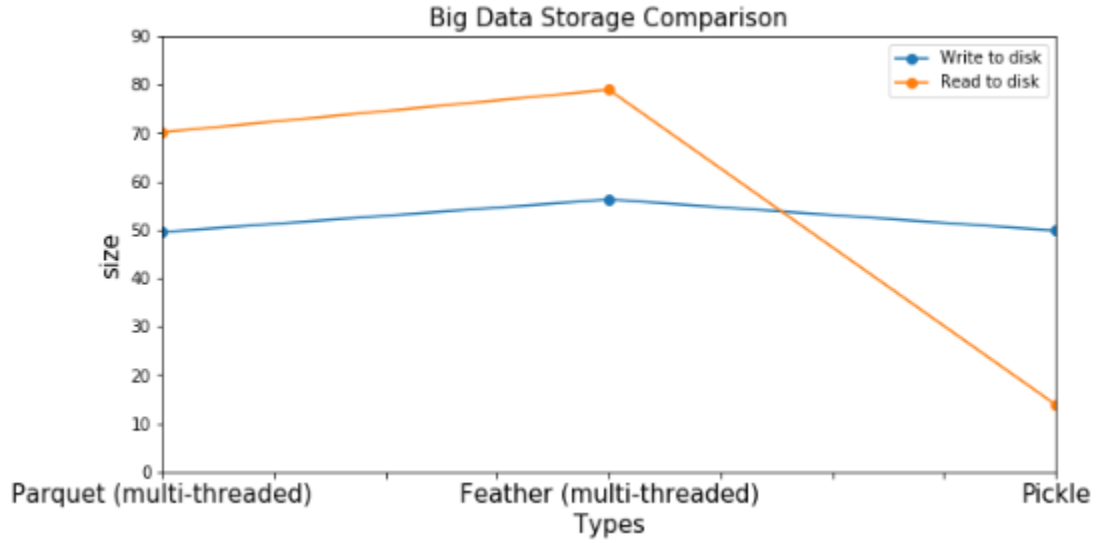
- When the number of observations in your dataset is high, the process of saving and loading data back into the memory becomes slower, and each kernel's restart steals time and forces you to wait until the data reloads
- There are plenty of panda-supported binary formats to store the data on disk.
- Methods used are: Parquet, Feature, HDF5, Pickle
- Parquet : Parquet is a standard Storage format for analytics that is supported by AWS, BigQuery, Impala, Hive and Spark and is designed for long-term storage with layers of encoding and compression

```
bitcoin2_parquet:
1min 5s ± 2.47 s per loop (mean ± std. dev. of 7 runs, 1 loop each)
bitcoin2_parquet:
1min 33s ± 739 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

- Feather: Feather is a binary data format for quick loading and transformation which enables faster I/O speeds and less memory and with which data frames can be exchanged between Python and R

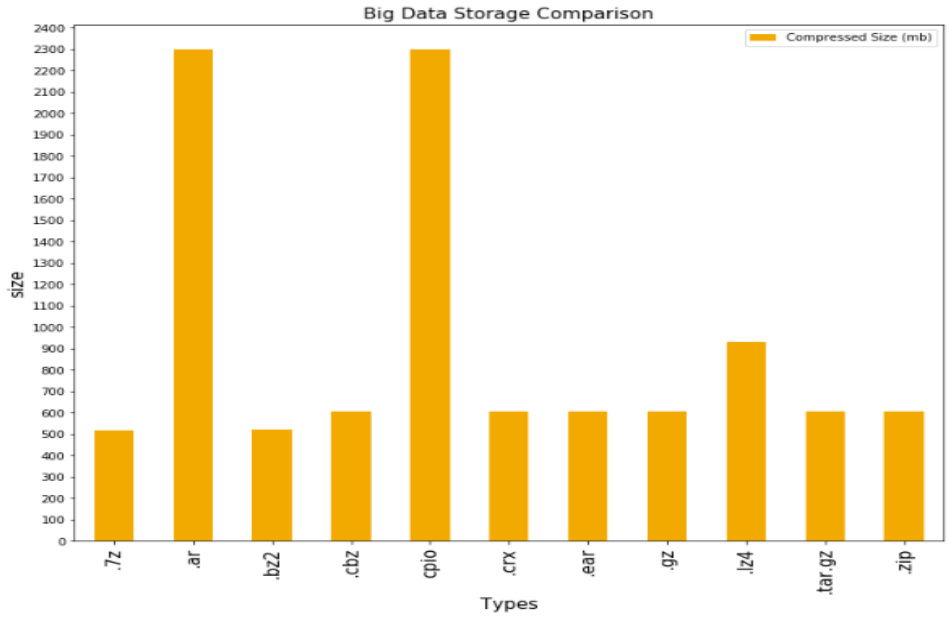
```
bitcoin2_feather:
1min ± 1.25 s per loop (mean ± std. dev. of 7 runs, 1 loop each)
bitcoin2_feather:
```

- Pickle : Pickles are primarily used in serialization and deserialization of Python object structures from byte streams to act as file or database storage, maintain program state across sessions, or transport data over the network



Dataset Compression (Post - ETL)

- We tried 27 different data compression techniques to minimize the size of our dataset (1.3+ GB) and reduce network latency when passing data between local workstations, servers and high-performance cluster nodes. The file format with the Highest Compression Ratio was .7zip with Space Saving Score of 78.35%
- Space Saving = (Compressed Size) / (Uncompressed Size)
- 0.7835 = 1 - 519.3 / 2,982.4



- Processing : Cleaning data to drop columns that contain features with null values
- Removing columns with non-numerical features from x variables

```
X = unpickled_dataframe.drop(labels = ['is_miner','address'], axis = 1)
```

Setting 'is_miner' as the target y variable

```
y = unpickled_dataframe['is_miner'].values
```

Row numbers identify which data points are selected in the training and test se

Random Forest Hyper-parameters

- Training the random forest classification model on the training set
- Running model jobs in parallel using all the processors available with n_jobs
- Entropy chosen as criterion to measure quality of splits by information gain
- 200 trees used in random forest for sufficient accuracy

Prediction and Probability

Make predictions (y_pred) from our test features (X_test) using our Random Forest model

```
y_pred = rf_classifier_max_cpus.predict(X_test)
y_pred
```

Predicts the Probability of each row belonging to a Mining Pool (true)...

```
positive_class_probabilities = rf_classifier_max_cpus.predict_proba(X_test)[:,1]
positive_class_probabilities
```

Optimizing Model Persistence (Pickle vs. JobLib)

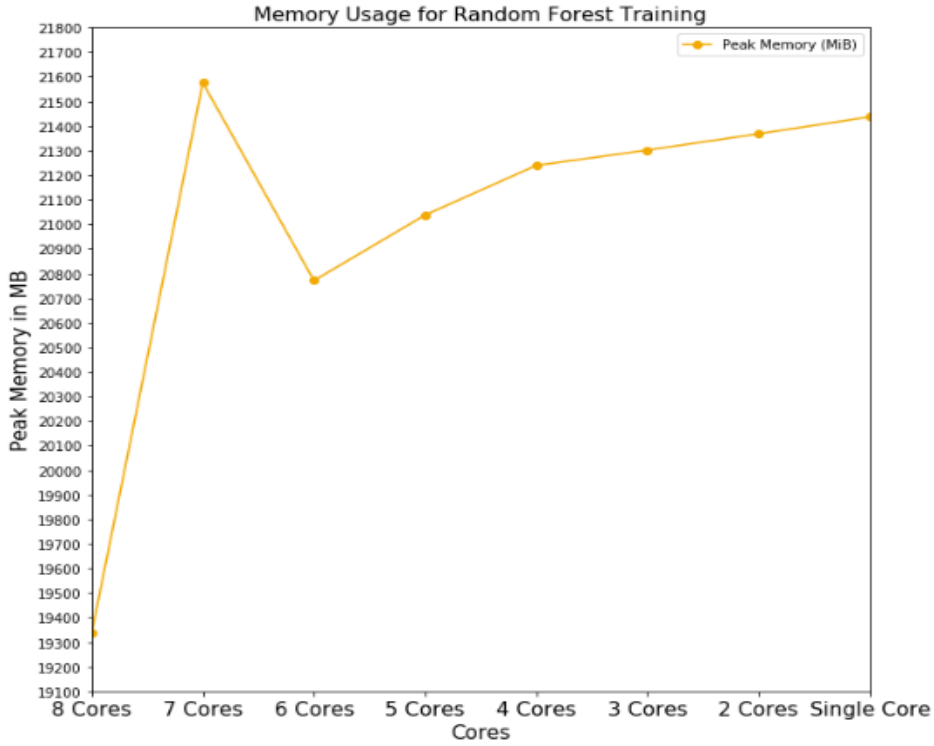
The idea behind any Data Science is to be able to build a model and throw away all the data.

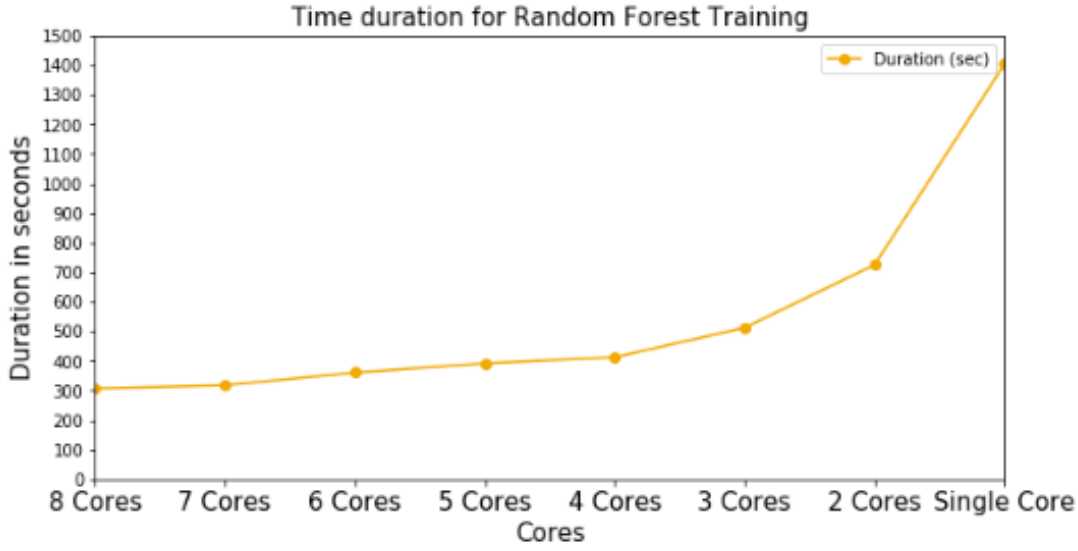
We compared data write speeds of both Pickle vs JobLib (the palatalization library) behind sci-kit learning (written in Cython) and found that **j**oblib was usually significantly faster on large numpy arrays because it has a special handling for the array buffers of the numpy data structure.

```
from joblib import dump, load
dump(rf_classifier_8_cpus, 'model_rf_8_cpu.joblib')
```

```
['model_rf_8_cpu.joblib']
```

Optimizing Random Forest Model Training with Multiple Cores (Memory vs Duration)

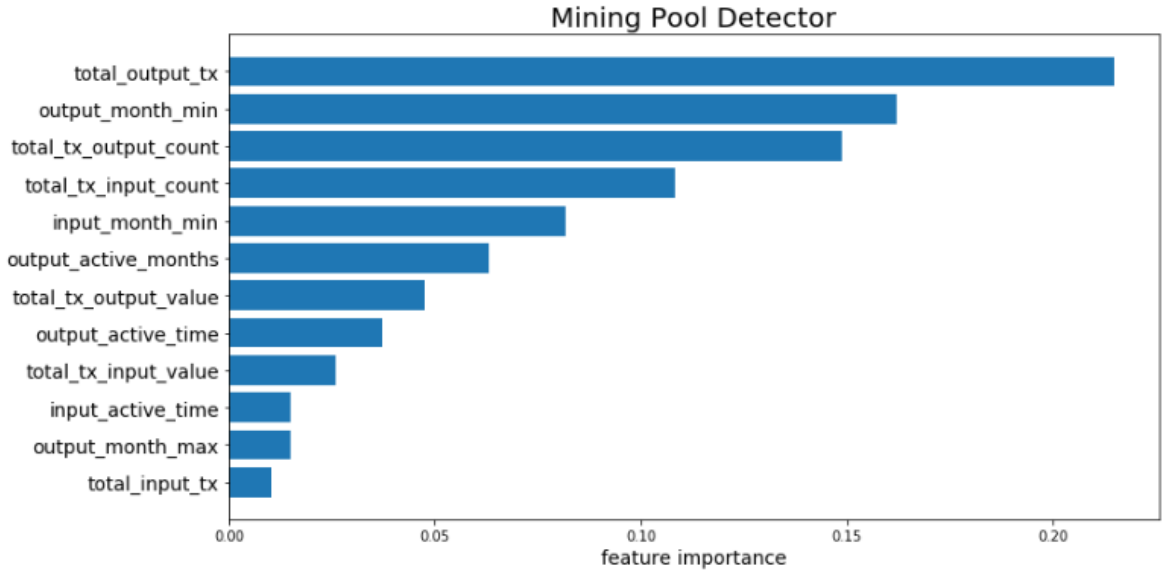




•To check how good our model has been trained, we focused mainly on the area below the Prevision-Recall Curve

Best Mining Pool Indicator

- Which features *(in the bitcoin transaction)* **best indicate** whether it will be mined by a publicly known mining pool (provide the most signal)?
- To understand which features, provide the most signals about the mining pool, we plot the top 12 features that are important according to the analysis



We found that the total amount of transaction outputs **(UTXO)** of a Bitcoin transaction, proved to be the heaviest contributor to whether a transaction would be picked up by a known Mining Pool from the **mempool**.

Precision-Recall Trade-off

Objective: Predict the Probability of each row belonging to a Mining Pool

- An ideal system with high precision and high recall will return many results, with all results labeled correctly
- A system with high recall but low precision returns many results, but most of its predicted labels are incorrect when compared to the training labels
- A system with high precision but low recall is just the opposite, returning very few results, but most of its predicted labels are correct when compared to the training labels

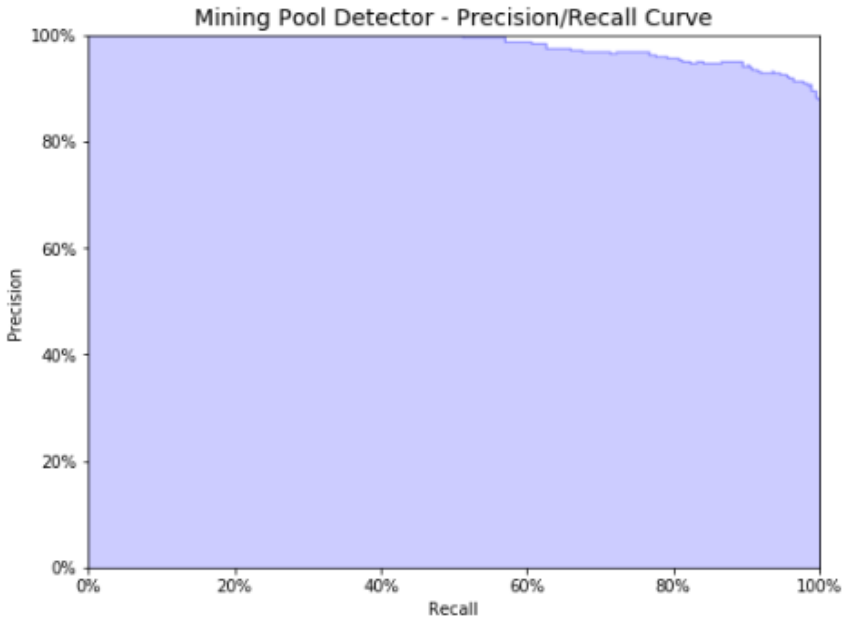
***matplotlib.pyplot.step* parameters:**

- The color = #f2a900 parameter ensures the plotline is bitcoin orange
- The alpha = 1 parameter makes the plotline 100% opaque vs. the area under the curve alpha = 0.4 i.e. 40% opaque
- The where = post parameter ensures y-values are continued constantly to the right from every x-position

An ideal system with high precision and high recall will return many results, with all results labeled correctly

Source: https://tinyurl.com/yxbjk26m

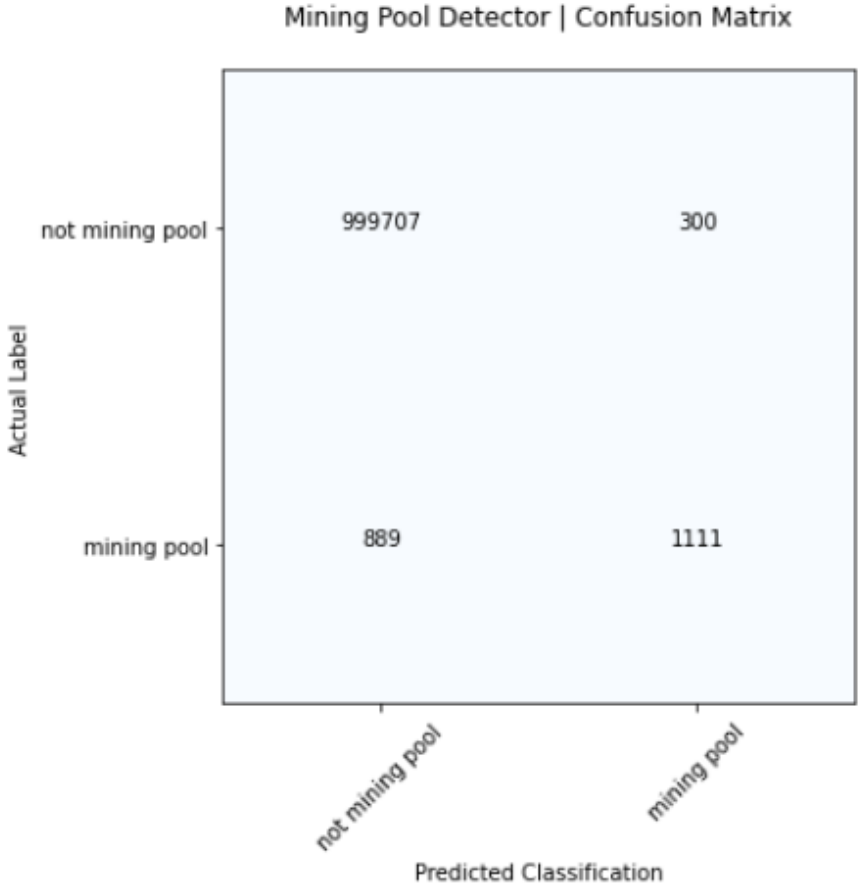
Mining Pool Detector – Precision/Recall Curve



Our curve when applied on a heavily trained model should great Precision even at the highest end of the Recall spectrum.

Confusion Matrix Computation

A confusion matrix is a 2x2 table used to **visualize the learning performance** of a supervised classification algorithm (Random Forest) on a set of test data for which the true values are known



Predicting whether Mining Pool vs Non Mining Pool (y-pred)

Make predictions (y_pred) from our test features (X_test) using our Random Forest model (8-CPU version)

```
y_pred_rf_max_cpus = rf_classifier_max_cpus.predict(X_test)
y_pred_rf_max_cpus
```

Result: The confusion matrix from our predictive model allows us to use **‘False Positives’** to identify transactions that have been mined by a **Shadow/ Dark** mining pool

Reasoning: data points (transactions) where our model predicts **mined_by_mining_pool == true**, but in actuality have been labeled by the network as **mined_by_mining_pool == false**

This poses the question about why this is? Why does the public not have information about these mining pools? Are they covert on purpose? Do they have nefarious network activity?

Objective: identify **node addresses** flagged to be ‘unknown’ by our prediction classifiers (false-positive) and do further data analytics (node centrality metrics etc.) to unravel **malicious** network activity

We decided to investigate more by taking a sample **False Positive** *node address* for our **network analysis** section below. The node address we decided to pick (from the list of unnknown mining pools that our ML classifier listed out) was: **1PuVaCWwDK8VmFj4EN8e2EgxvDpjeyJmRx**

So we went ahead and customized yet another SQL statement for Google BigQuery:

```
In [6]: q_input = """
        WITH time AS
            (
                SELECT TIMESTAMP_MILLIS(timestamp) AS trans_time,
                    inputs.input_pubkey_base58 AS input_key,
                    outputs.output_pubkey_base58 AS output_key,
                    outputs.output_satoshis AS satoshis,
                    transaction_id AS trans_id
                FROM `bigquery-public-data.bitcoin_blockchain.transactions`
                    JOIN UNNEST (inputs) AS inputs
                    JOIN UNNEST (outputs) AS outputs
                WHERE inputs.input_pubkey_base58 = '1PuVaCWwDK8VmFj4EN8e2EgxvDpjeyJmRx'
                    OR outputs.output_pubkey_base58 = '1PuVaCWwDK8VmFj4EN8e2EgxvDpjeyJmRx'
            )
        SELECT input_key, output_key, satoshis, trans_id,
            EXTRACT(DATE FROM trans_time) AS date
        FROM time
        --ORDER BY date
        """
blockchain_helper.estimate_query_size(q_input)
```

Unknown Mining Pool Detection

Our machine learning classifier generates the following list of Unknown Bitcoin Mining pool node addresses.

```
False Positive addresses
      is_miner                              address  output_month_min  \
1628     False  1Hb3hzFmhYyvDSzKRSntW3WLukXDGz6chx        1425168000
2062     False  1Ni9hm89ptrin2TrJcuAM3ScBk9Hu7DR6G        1420070400
2121     False  142r1ZSDWdnHPDLEUUMHD5km9MASq9hXFr        1391212800
2105     False  12tQgEyqJLkbcCsU9r5bDM8fbT5SLBTVUa        1438387200
303      False  12rE2EopYdkbktzKAKsMoPW3r8het9dHaJ        1404172800
1060     False   1tu62iemzhhsbkekpzwaGxP1VYbu2i1xF        1391212800
667      False  1CwmksPZUfZbEh7efyzpueF8rBnHm99DFa        1388534400
1606     False  1FGo3xa9T48ErmS4vUsKzwJgvuwtDjPKwP        1351728000
2095     False  1KcRW4srjAGuvgjxQzZbQ8t4p243DanFVF        1354320000
2102     False  1EeMdKMWkywnd7Jqxp4PtWinegnAPANRzW        1343779200
1179     False  1KC9XPdVbVYSoxvhzpnVBoEZjYwbTMAHWG        1404172800
140      False  1AM9ZtodFG3unDPs7pEm9JP9ibNXg7st5z        1306886400
1647     False  1LcGBxWGtoiXU7wJ2Aumdf3Auo8wb9VaNq        1356998400
84       False  1Ktw9xTRfU68ZU48h8piZ6DzKkVFkHcUr5        1367366400
1561     False  1GuL9wFGBntBixnW7y8fQ6JP2fvho5wrRQ        1385856000
```

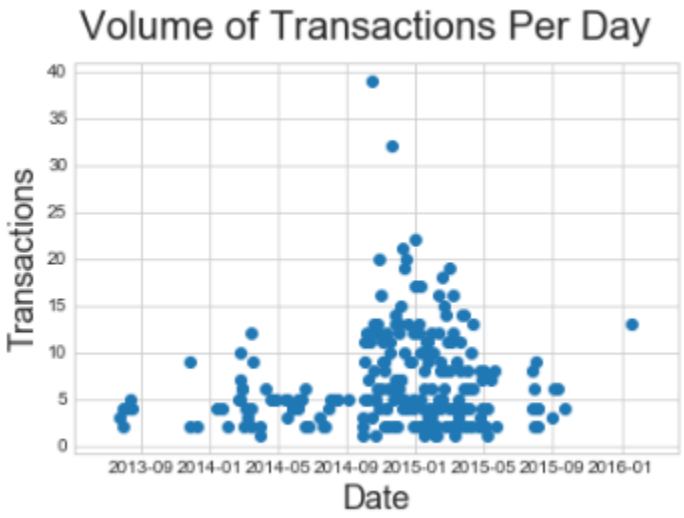
Network Analysis: Bitcoin blockchain data

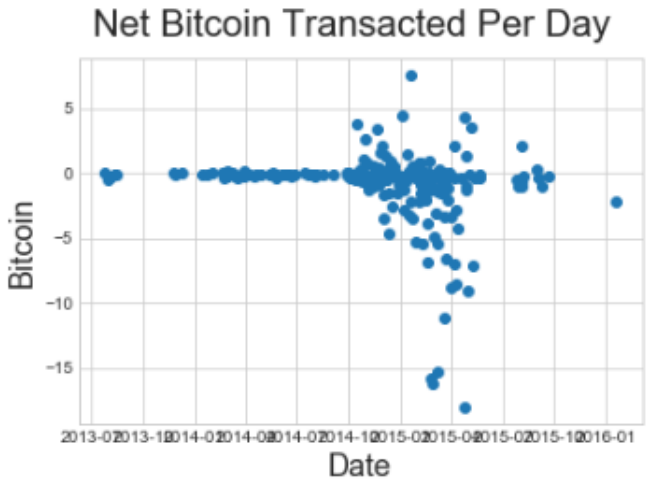
•We decided to adopt some great work* on Bitcoin activity analysis to investigate our chosen unknown node address: **1PuVaCWwDK8VmFj4EN8e2EgxvDpjeyJmRx**

* https://tinyurl.com/y3ms538b

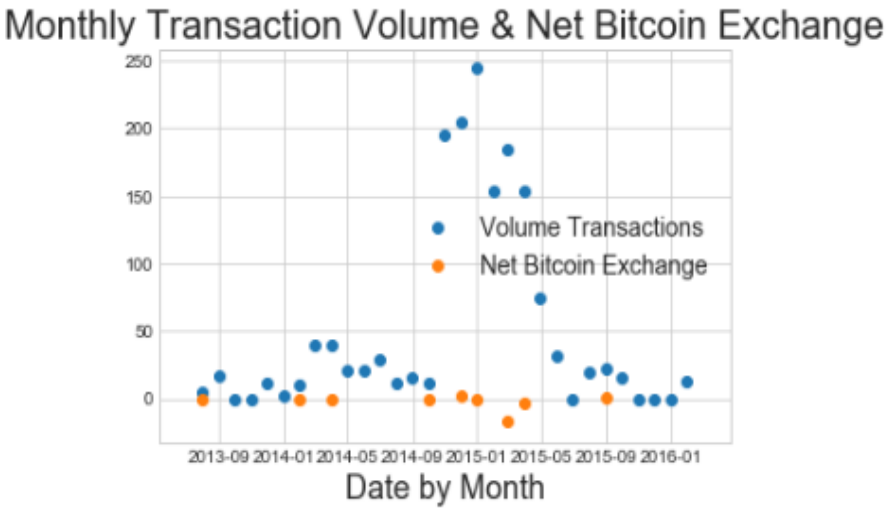
•**Data cleaning and processing:** We first applied some data transformations, converting the satoshis used in the wallet of our chosen Node Address to bitcoin, and converting the sending out of bitcoins into negative values

•**Exploratory Data Analysis** includes, unique addresses that were included in the transaction history of our chosen Node wallet, the top addresses that our **Unknown Node wallet** interacted with, the transaction activity of our chosen **Unknown Mining Node** across time and plotting the Date vs Transaction graph to see the volume of transactions per day





- Furthermore, we looked at the difference between input transactions and output transactions (which indicates cleaning of stained bitcoin by breaking them into chunks and harder to trace) and the total amount of bitcoins sent each month



We then used a Network X Graph to plot the top 20 wallets that our Unknown (Dark/ Shadow) Mining Node Address sent and received bitcoins from.

We noticed that amongst the top nodes our **Unknown Node Wallet** was sending Bitcoin to,

Address **1NxaBCFQwejSZbQfWcYNwgqML5wWoE3rK4** seemed to come out on top. We therefore decided to use Graph Theory to investigate this suspicious address further.

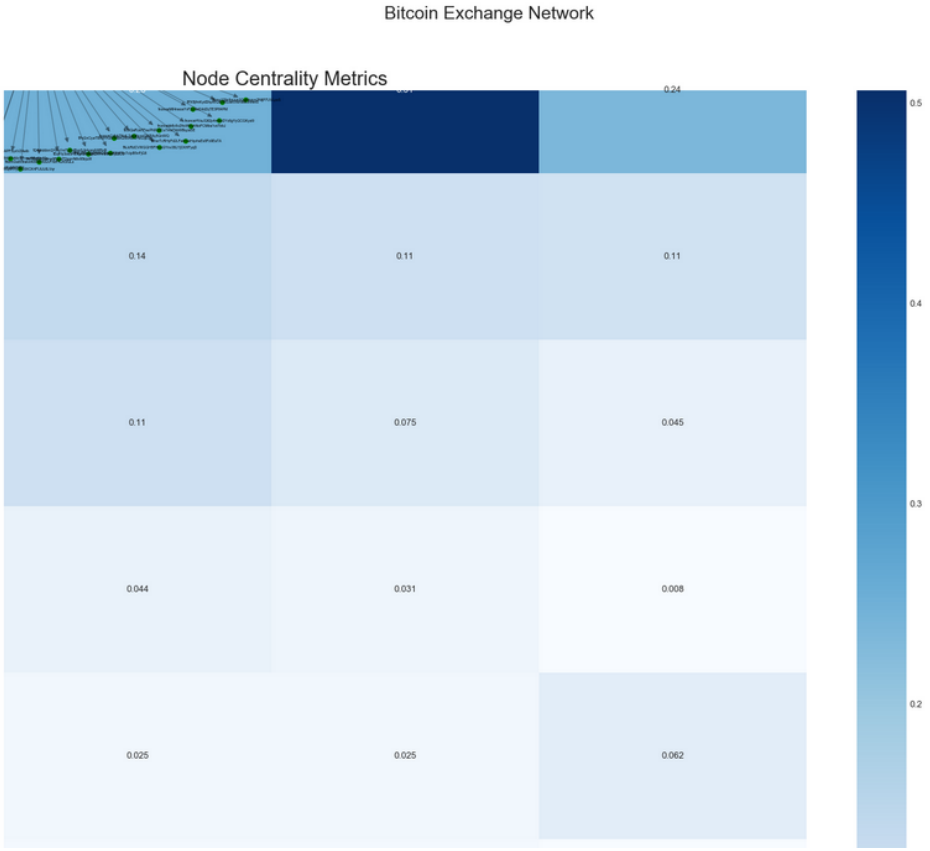
Node Centrality Analysis

- We decided to compute the degree centrality for the node address **1NxaBCFQwejSZbQfWcYNwgqML5wWoE3rK4**

- Also, see what fraction of nodes it is connected to (amongst the top interaction nodes with our original node address)

Compute the degree centrality for nodes

We found that the address **1BT4DYrt3ZoSz6WeGEZzrj4tdidUcpCfQ6** accounted for almost **76%** funds sent to **1NxaBCFQwejSZbQfWcYNwgqML5wWoE3rK4** (our unknown mining node's most frequently send address)



Serial Model Comparison – ANN vs RF vs NB

Artificial Neural Network

•We trained the pickled data from our original Google Big Query on different models including an Artificial Neural Network, Random Forest Classifier, Naïve Bayes,

•Scaling : Data preparation involved using techniques such as the normalization and standardization to rescale input and output variables prior to training a neural network model

- Feature Scaling is a method used to normalize the range of independent variables or features of data.

- **Hyperparameters** used are B*atch_size, learn_rate* and *epoch*

We encoded out dependent and independent variable and converting it to a binary class matrix

- y_train_ann.shape is (4008025, 2)
- y_test_ann.shape is (1002007, 2)

- We use a sequential model, The Sequential model allows us to build deep neural networks by stacking layers one on top of another
- Added dense layer, with **tanh** as our activation function f or the neurons!

```
seed = 1
np.random.seed(seed)

# Creating model
ann = Sequential()
ann.add(Dense(26, activation = 'tanh', kernel_initializer = 'glorot_uniform'))
ann.add(Dense(11, activation = 'tanh'))
ann.add(Dropout(0.5))
ann.add(Dense(6, activation = 'tanh'))
ann.add(Dense(num_classes, activation = 'softmax'))
```

Model fitting on 4008025 samples :

```
time_start = time.time()
ann.fit(np.array(x_train_ann), y_train_ann, batch_size = batch_size, epochs = epochs, validation_data = (x_test_ann, y_test_
print('Time elapsed: {} seconds' .format(time.time() - time_start))
```

```
Train on 4008025 samples, validate on 1002007 samples
Epoch 1/30
4008025/4008025 [==============================] - 55s 14us/step - loss: 0.0115 - binary_accuracy: 0.9967 - val_loss: 0.0062 -
val_binary_accuracy: 0.9980
Epoch 2/30
4008025/4008025 [==============================] - 51s 13us/step - loss: 0.0064 - binary_accuracy: 0.9980 - val_loss: 0.0061 -
val_binary_accuracy: 0.9980
Epoch 3/30
4008025/4008025 [==============================] - 34s 8us/step - loss: 0.0064 - binary_accuracy: 0.9980 - val_loss: 0.0060 - v
al_binary_accuracy: 0.9980
Epoch 4/30
4008025/4008025 [==============================] - 34s 9us/step - loss: 0.0063 - binary_accuracy: 0.9980 - val_loss: 0.0063 - v
al_binary_accuracy: 0.9980
Epoch 5/30
4008025/4008025 [==============================] - 34s 9us/step - loss: 0.0063 - binary_accuracy: 0.9980 - val_loss: 0.0059 - v
al_binary_accuracy: 0.9980
Epoch 6/30
4008025/4008025 [==============================] - 35s 9us/step - loss: 0.0064 - binary_accuracy: 0.9980 - val_loss: 0.0061 - v
al_binary_accuracy: 0.9981
Epoch 7/30
4008025/4008025 [==============================] - 34s 8us/step - loss: 0.0064 - binary_accuracy: 0.9980 - val_loss: 0.0063 - v
al_binary_accuracy: 0.9980
```

After fitting the model, our ANN runs with an accuracy of **Test Accuracy (Artificial Neural Network): 99.8039960861206%**

```
scores = ann.evaluate(x_test_ann, y_test_ann, verbose = 0)
print("Test Accuracy (Artificial Neural Network): {}%" .format(scores[1] * 100))
```

```
Test Accuracy (Artificial Neural Network): 99.8039960861206%
```

```
scores
```

```
[0.00591270173198256, 0.998039960861206]
```

Confusion Matrix for ANN:

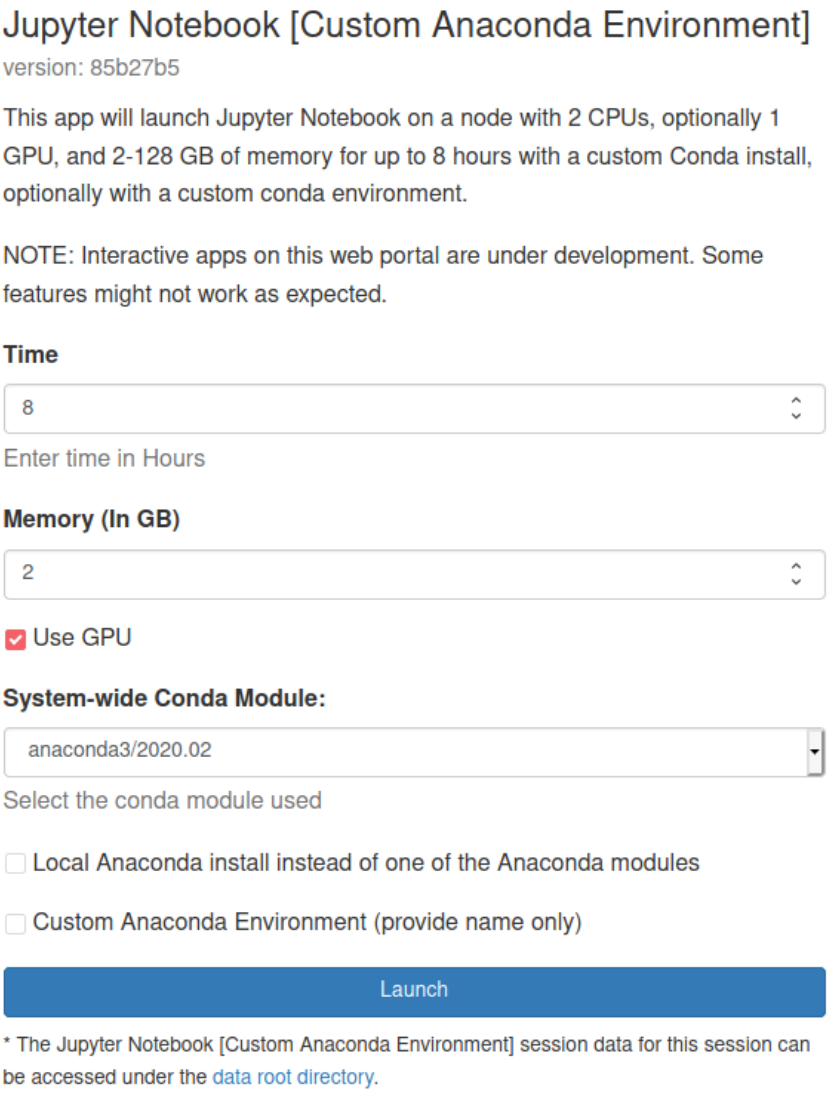
```
y_pred = ann.predict(x_test_ann)

# Compute confusion matrix
matrix = confusion_matrix(y_test_ann.argmax(axis = 1), y_pred.argmax(axis = 1)) # Building the confusion matrix
```

```
matrix
```

```
array([[1000043,       0],
       [   1964,       0]], dtype=int64)
```

Note: We also ran our Neural network using RC OpenOnDemand solution to get some performance gains on running our Jupyter Notebook by using a 1 GPU 2 CPU setup



Naïve Bayes

Fitting Naïve Bayes Algorithm to pickled Google Big Query Bitcoin dataset

```
# Fitting Naive Bayes to the Training set
nb = GaussianNB()
nb.fit(x_train, y_train)
```

```
GaussianNB(priors=None, var_smoothing=1e-09)
```

Confusion Matrix

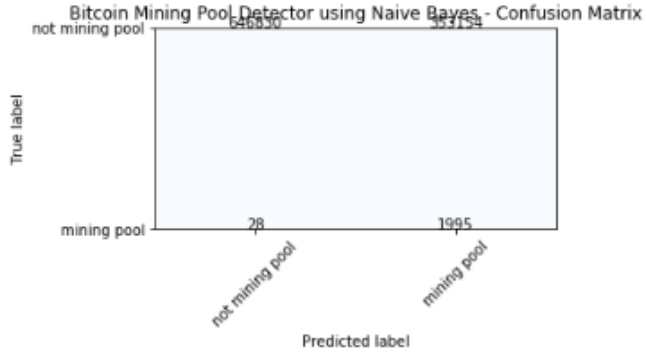
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, y_pred)
class_names = ['not mining pool', 'mining pool']
np.set_printoptions(precision = 3)

# Plot confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes = class_names, normalize = False, title = 'Bitcoin Mining Pool Detector

plt.show()
```

```
Confusion matrix, without normalization
[[646830 353154]
 [    28   1995]]

<Figure size 432x288 with 0 Axes>
```



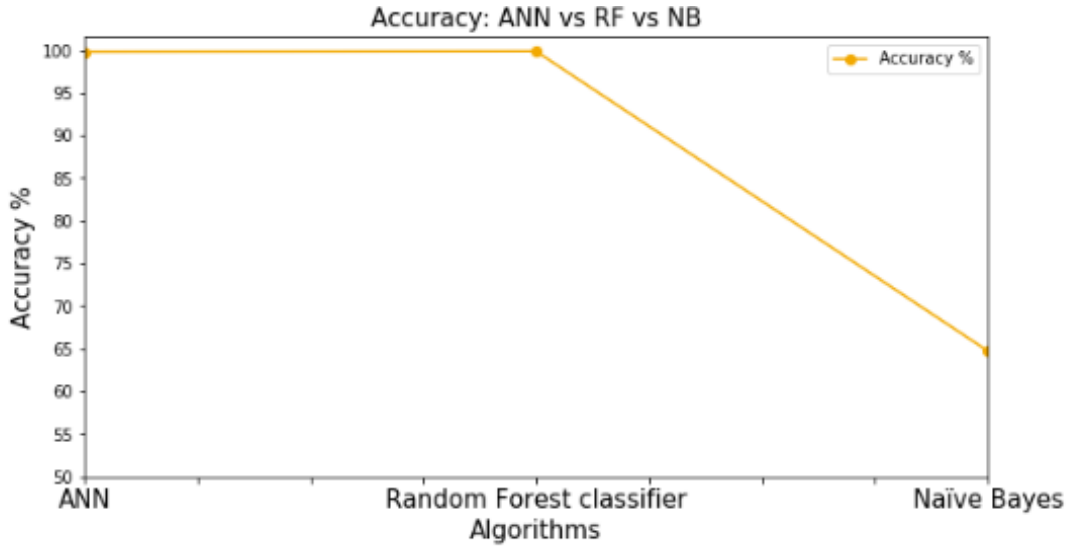
Accuracy of Naïve Bayes algorithm is : 64.75%

```
# Calculating Accuracy
acc = (cnf_matrix[0][0] + cnf_matrix[1][1]) / (cnf_matrix[0][0] + cnf_matrix[1][1] + cnf_matrix[0][1] + cnf_matrix[1][0])
print("Test Accuracy (Naive Bayes Classification): {}%" .format(acc * 100))
```

```
Test Accuracy (Naive Bayes Classification): 64.75254164891064%
```

- Post analysis, when the accuracy is compared, Random Forest Classifier performs best with our data, while ANN is very close to the accuracy of Random Forest Classifier

Algorithm	Accuracy %
ANN	99.8
Random Forest	99.86
Naïve Bayes	64.75



Model Training Parallelization

We used a Stacking Algorithm **based on 4 classifiers:**

- RidgeClassifier
- RandomForestClassifier
- LinearDiscriminantAnalysis
- GaussianNB

How Stacked Classifier Works

•The program breaks down 4 MPI processes and trains 4 ML modes on the same dataset in parallel using **classify()**

```
29  def classify(X_train, X_test, y_train, y_test):
30      # classification
31      algorithm = None
32      classification_time_start = MPI.Wtime()
33      if rank == 0:
34          algorithm = 'ridge'
35          clf0 = RidgeClassifier()
36          st.fit(clf0, X_train, y_train)
37          classification_output = st.predict(clf0, X_test)
38          pass
39      elif rank == 1:
40          algorithm = 'randomForest'
41          clf1 = RandomForestClassifier(n_estimators=10)
42          st.fit(clf1, X_train, y_train)
43          classification_output = st.predict(clf1, X_test)
44          pass
45      elif rank == 2:
46          algorithm = 'lda'
47          clf2 = LinearDiscriminantAnalysis()
48          st.fit(clf2, X_train, y_train)
49          classification_output = st.predict(clf2, X_test)
50          pass
51      elif rank == 3:
52          algorithm = 'GaussianNaiveBayes'
53          clf3 = GaussianNB()
54          st.fit(clf3, X_train, y_train)
55          classification_output = st.predict(clf3, X_test)
56          pass
57
58      classification_time_end = MPI.Wtime()
59      classification_time = classification_time_end - classification_time_start
60      print(
61          f'[TIME] Process {rank} finished classification by {algorithm} algorithm with time: {classification_time}')
62      return classification_output
63
```

- Each MPI process then provides a probabilistic prediction with **fit()**

```
    def fit(self, X_train, y_train):
        for clf in self.classifiers:
            clf.fit(X_train, y_train)
```

•Each MPI process then provides a probabilistic prediction with **predict()**

```
def predict(self, X_test):
    preds = list()
    for clf in self.classifiers:
        preds.append(clf.predict(X_test))
    aggregated_preds = self.vote(preds)
    return aggregated_preds
```

Vote Function[1]

- The Master MPI Process then receives the 4 fitted models and then for each row takes a vote on which model to use for its prediction (binary 0 or 1)

```
21      def vote(self, preds):
22          np_preds = np.array(preds).T
23          result_list = list()
24          for row in np_preds:
25              result_list.append(np.argmax(np.bincount(row)))
26          return np.array(result_list)
27
```

Improvements for Vote Function

- **np.bincount** gives you the ratio of which model voted for which outcome [0 | 4], [1 | 3], [2 | 2], [3 | 1], [0 |4]
- Unfortunately, since its an even number of models **np.argmax** defaults to the first occurrence i.e. mining_pool == False

Solution can take 2 approaches**:**

1. Numpy argmax - random tie breaking

2. Odd number of Classifiers (5 MPI Processes)

We then ran the model in 2 variations. One in **Serial** and one in **Parallel** using OpenMPI

Parallel Run Setup

- Hardware Setup on Research Computing's Discovery Cluster

(4-node CPU cluster each with 180 GB RAM)

> $ srun -p short --cpus-per-task 4 --ntasks 4 --nodes 4 --pty --export=ALL --mem=180Gb --time=08:00:00 /bin/bash

- We created a virtual anaconda environment to install our custom software

> $ conda create -n <yourenvironmentname> python=3.7 anaconda

- We used **MPI** for Python to interface the distributed memory modules of 4 separate HPC CPU nodes

> $ conda install -c anaconda mpi4py

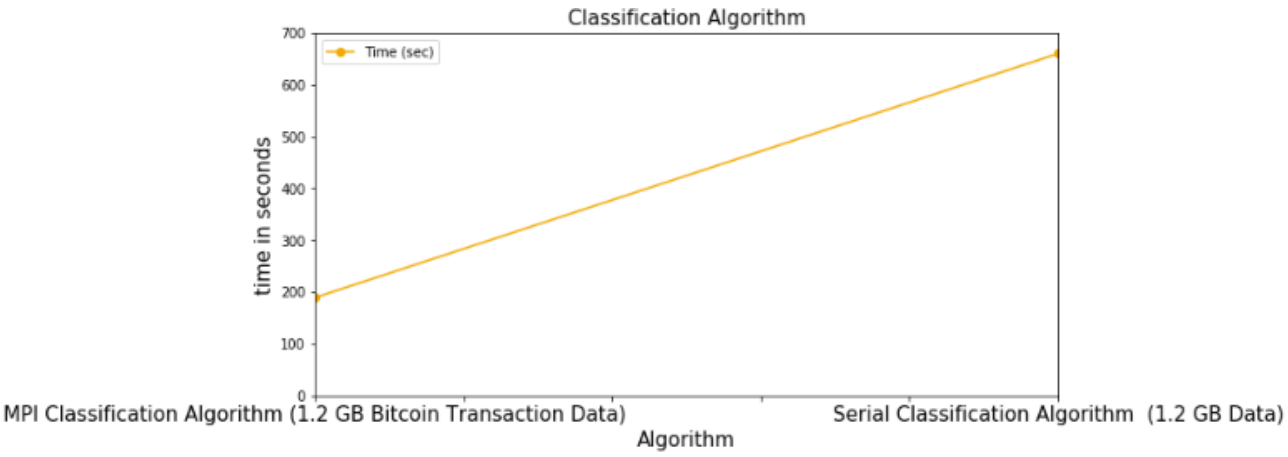
We used OpenMP version 3.1.2

> $ module load openmpi/3.1.2

Parallel Code Run

```
[INFO] Program runned in 4 processes
[INFO] Hello from process number 0
[INFO] Bcasting data from the root process (0)
[TIME] Master process (0) finished Bcasting data with time 86.51921606063843
[TIME] Process 0 finished classification by ridge algorithm with time: 24.678951025009155
[ACCURANCY] Final accurancy for test-train is 0.9983958855895836
[INFO] Stacking classifier finish work with time: 203.12623000144958
[INFO] Hello from process number 1
[TIME] Process 1 finished receive bcasted data with time 87.64578890800476
[TIME] Process 1 finished classification by randomForest algorithm with time: 98.60505700111389
[INFO] Hello from process number 3
[TIME] Process 3 finished receive bcasted data with time 88.20838403701782
[TIME] Process 3 finished classification by GaussianNaiveBayes algorithm with time: 17.277169942855835
/home/s.chakravarty/.conda/envs/parallel_flow_env/lib/python3.7/site-packages/sklearn/utils/deprecation.
py:143: FutureWarning: The sklearn.linear_model.ridge module is  deprecated in version 0.22 and will be
removed in version 0.24. The corresponding classes / functions should instead be imported from sklearn.l
inear_model. Anything that cannot be imported from sklearn.linear_model is now part of the private API.
  warnings.warn(message, FutureWarning)
[INFO] Hello from process number 2
[TIME] Process 2 finished receive bcasted data with time 87.7812020778656
[TIME] Process 2 finished classification by lda algorithm with time: 31.150506019592285
```

Performance Gains in Model Training gained with Distributed Memory Parallelization



Conclusion:

- We were able to optimize using parallelization at every step in the Data Science pipeline.
- We were able to use parallelization when saving our queried data from BigQuery using pyarrow's underlying parallelization (use_threads = True) for Parquet and Feather.
- We used the underlying Cython parallelization provided by sklearn for all our ensemble methods using (n_threads).
- Additionally, we chose the highest compression ratio when writing our raw dataset to file storage. Moreover, we chose to choose the best read/write speeds when compressing our dataset when sending between servers and HPC nodes.

- We even chose the most speediest model persistent format (job_lib) to use for future predictive work.
- Most satisfyingly, we were able to utilize MPI to parallelize model training on a single dataset to optimize and vote on the best value for each row of data.