Machine Learning Engineer Nanodegree

Capstone Proposal

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Definition

Project Overview

Mobile ad fraud is one of the biggest challenges the mobile marketing industry is currently facing. Fraud risk is everywhere, but for companies that advertise online, click fraud can happen at an overwhelming volume, resulting in misleading click data and wasted money. Ad channels can drive up costs by simply clicking on the ad at a large scale. With over 1 billion smart mobile devices in active use every month.

A new report from Juniper Research has found that advertisers will lose an estimated $19 billion to fraudulent activities next year, equivalent to $51 million per day.

The model used in the project is eXtreme Gradient Boosting, the two reason to use XGBoost are the goal of the project:

1- Execution Speed
2- Model Performance

Problem Statement

TalkingData, China's largest independent big data service platform, covers over 70% of active mobile devices nationwide. They handle 3 billion clicks per day, of which 90% are potentially fraudulent. Their current approach to prevent click fraud for app developers is to measure the journey of a user's click across their portfolio, and flag IP addresses who produce lots of clicks, but never end up installing apps. With this information, they've built an IP blacklist and device blacklist.

In this Kaggle Competition we're challenged to build an algorithm that predicts whether a user will download an app after clicking a mobile app ad. To support your modeling, they have provided a generous dataset covering approximately 200 million clicks over 4 days!

To solve this challenge, firstly I attained some basic understanding of the training data that was provided to check for characteristics such as target concept balance and distribution/importance of features.

As here, it's a classification problem, we will use XGBoost Classifier, to predict the whether the user will download the app or not.

By using XGBoost method that is fitted with the training data with all attributes to see how it performs to set a baseline expectation for the final model. At this point, having seen the technical difficulties with the engineered feature and training process, and performed parameter tuning for the classification model. Using a DMatrix that used by XGBoost which is optimized for both memory efficiency and training speed.

Lastly, I tested the final model design using its performance on the given testing data.

Metrics

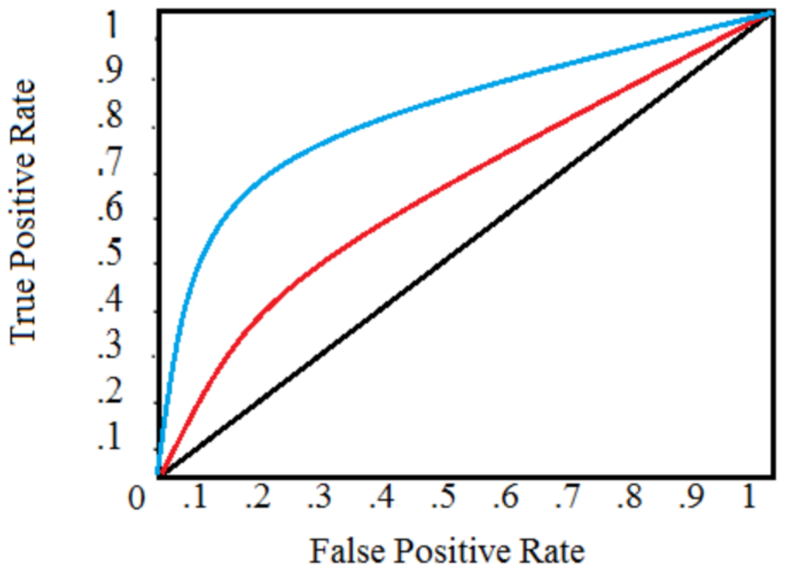
Evaluation done in the Kaggle competition based on the *area under the ROC* – Receiving Operating Characteristics – curve between the predicted probability and the observed target.

A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.

The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.

$$true\ positive\ rate = \frac{true\ positives}{true\ positives + false\ negatives} \qquad false\ positive\ rate = \frac{false\ positives}{false\ positives + true\ negatives}$$

A typical ROC curve is shown below:



Analysis

Data Exploration

The dataset provided by Talking Data on Kaggle competition includes approximately 200 million registered clicks over 4 days, split into training and testing sets. The training set contains more than 180 million rows of data, each has the timestamp of the click, number-encoded IP addresses, device numbered label code, device's operating system code, app code, channel code, whether the click resulted in a download or not, and time of download if applicable. The testing set contains about 18 million clicks with each click associated with an ID and other information excluding the download or not label and download time.

Files used:

- *train_sample.csv*, 100,000 randomly-selected rows of training data, to inspect data before downloading full se
- *test.csv*, the testing data

Data Fields:

Each row of the training data contains a click record, with the following features.

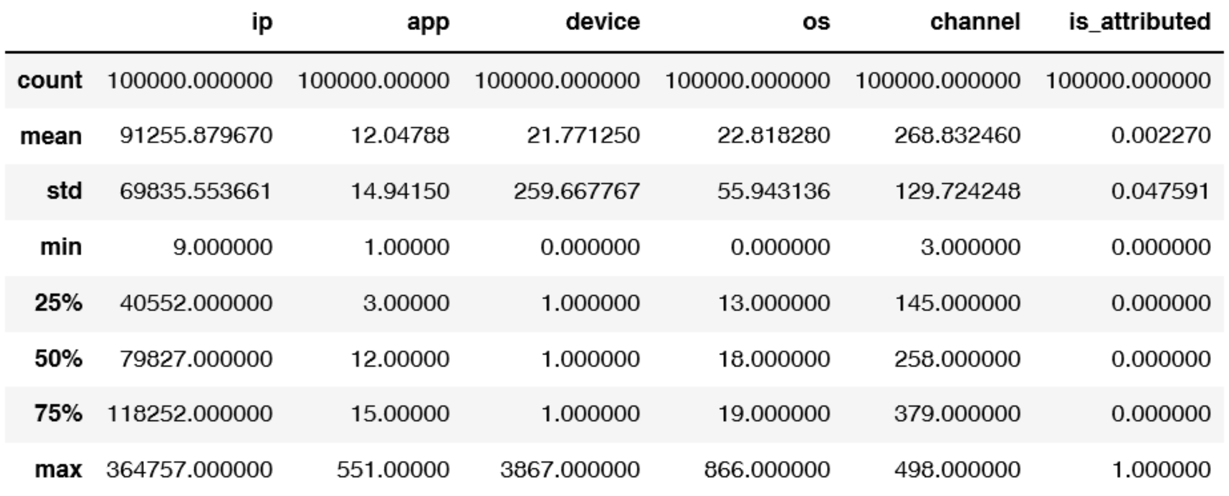
- **ip**: ip address of click.
- **app**: app id for marketing.
- **device**: device type id of user mobile phone (e.g., iphone 6 plus, iphone 7, huawei mate 7, etc.)
- **os**: os version id of user mobile phone
- **channel**: channel id of mobile ad publisher
- **click_time**: timestamp of click (UTC)
- **attributed_time**: if user download the app for after clicking an ad, this is the time of the app download
- **is_attributed**: the target that is to be predicted, indicating the app was downloaded

Note that **ip**, **app**, **device**, **os**, and **channel** are encoded.

The test data is similar, with the following differences:

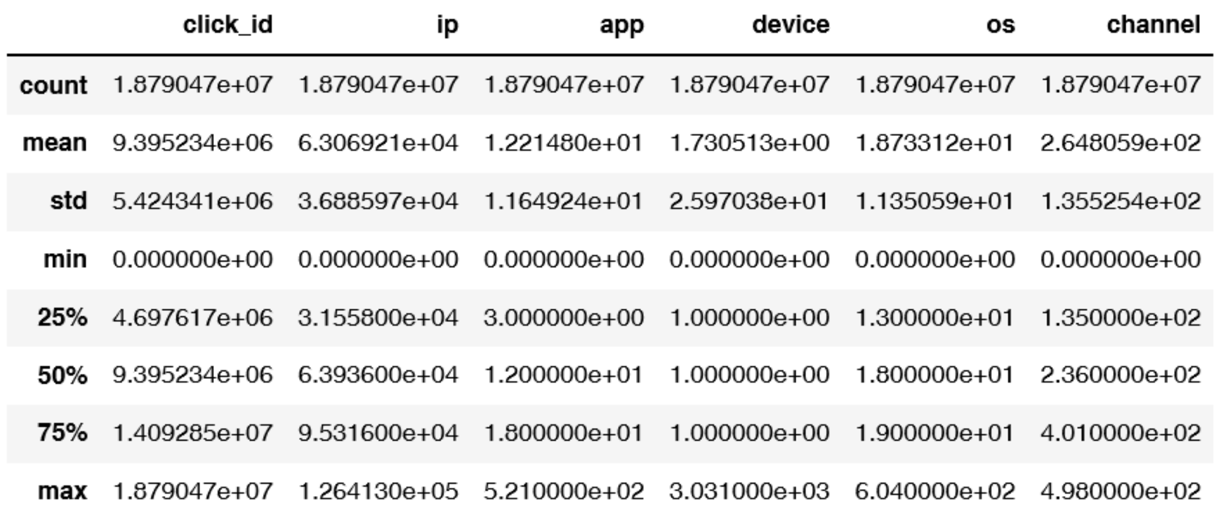
- **click_id**: reference for making predictions
- **is_attributed**: not included

Descriptive stats for the training sample dataset;



	ip	app	device	os	channel	is_attributed
count	100000.000000	100000.00000	100000.000000	100000.000000	100000.000000	100000.000000
mean	91255.879670	12.04788	21.771250	22.818280	268.832460	0.002270
std	69835.553661	14.94150	259.667767	55.943136	129.724248	0.047591
min	9.000000	1.00000	0.000000	0.000000	3.000000	0.000000
25%	40552.000000	3.00000	1.000000	13.000000	145.000000	0.000000
50%	79827.000000	12.00000	1.000000	18.000000	258.000000	0.000000
75%	118252.000000	15.00000	1.000000	19.000000	379.000000	0.000000
max	364757.000000	551.00000	3867.000000	866.000000	498.000000	1.000000

Descriptive stats for the testing dataset;



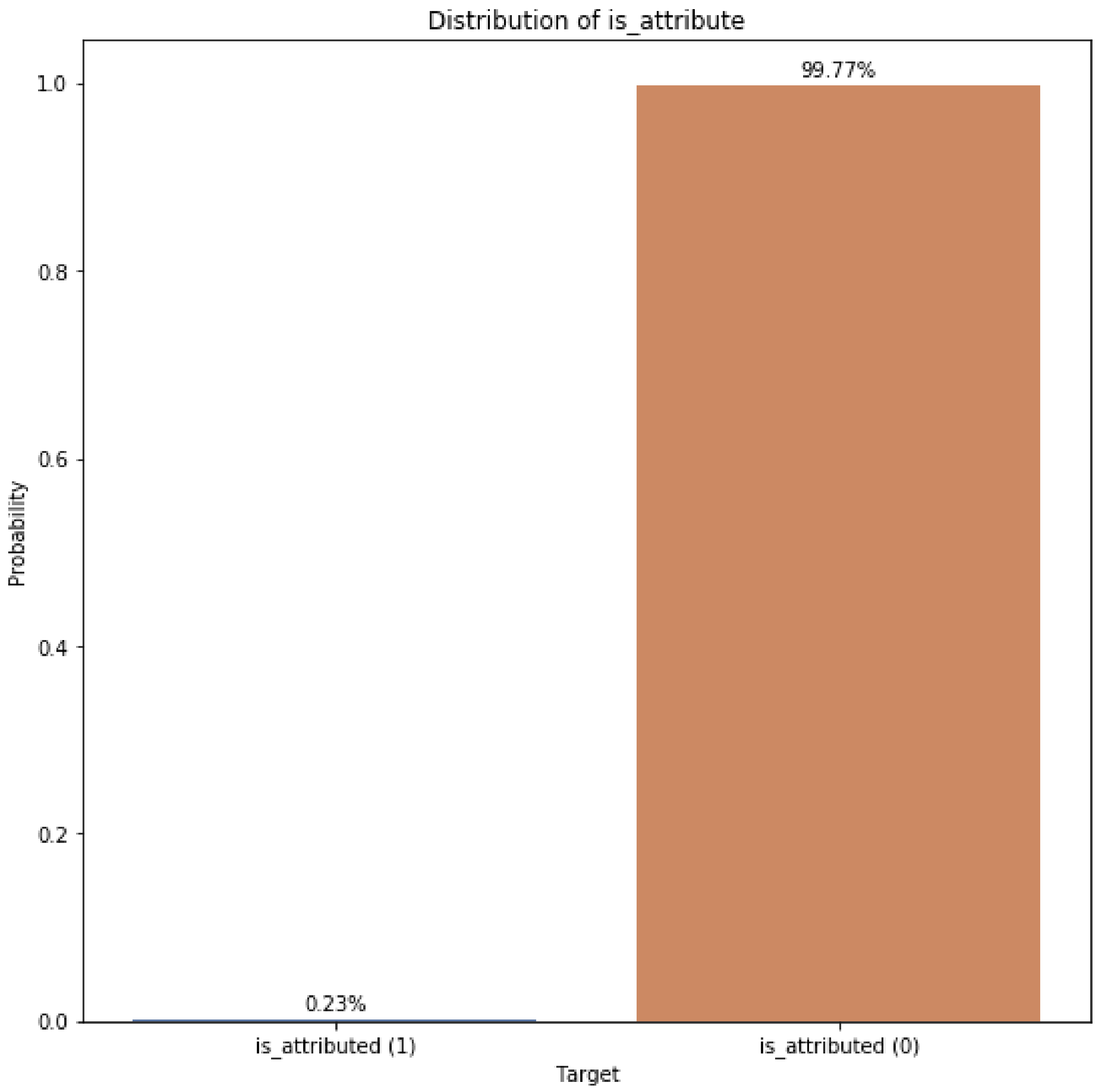
	click_id	ip	app	device	os	channel
count	1.879047e+07	1.879047e+07	1.879047e+07	1.879047e+07	1.879047e+07	1.879047e+07
mean	9.395234e+06	6.306921e+04	1.221480e+01	1.730513e+00	1.873312e+01	2.648059e+02
std	5.424341e+06	3.688597e+04	1.164924e+01	2.597038e+01	1.135059e+01	1.355254e+02
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	4.697617e+06	3.155800e+04	3.000000e+00	1.000000e+00	1.300000e+01	1.350000e+02
50%	9.395234e+06	6.393600e+04	1.200000e+01	1.000000e+00	1.800000e+01	2.360000e+02
75%	1.409285e+07	9.531600e+04	1.800000e+01	1.000000e+00	1.900000e+01	4.010000e+02
max	1.879047e+07	1.264130e+05	5.210000e+02	3.031000e+03	6.040000e+02	4.980000e+02

<u>Observation</u>

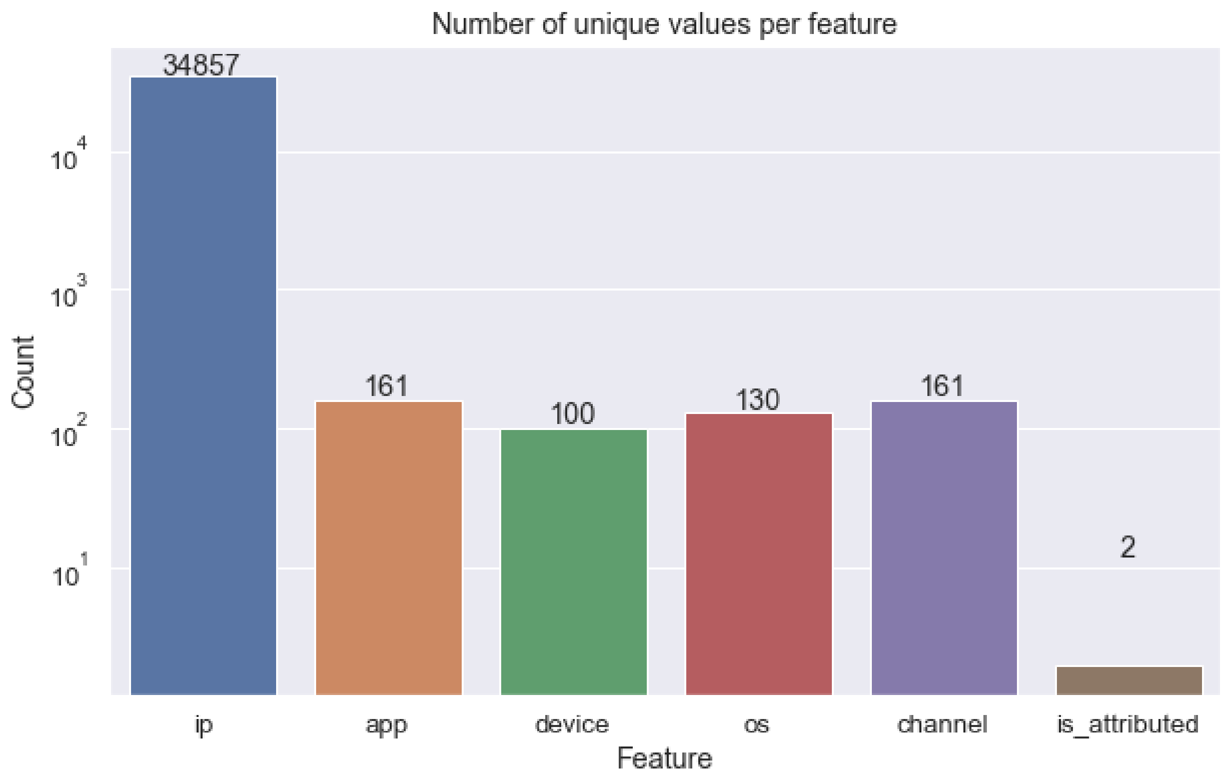
The data is strongly imbalanced with only around 0.23% positive – clicks that resulted downloads.

Exploratory Visualization

The graph below illustrates how skewed the target concept is in the sample training data set;



How many unique values our data have;

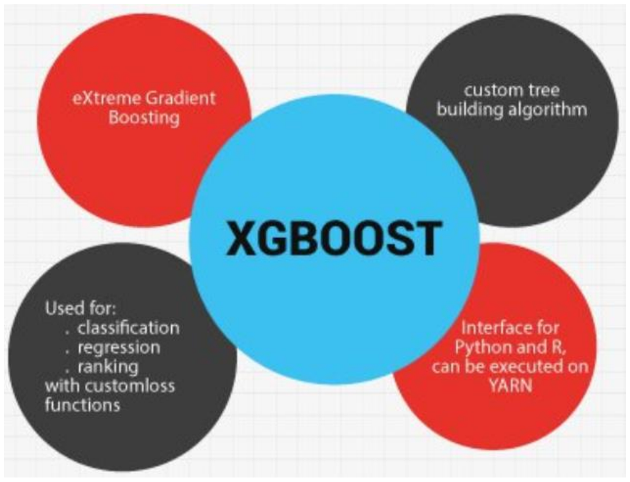


It’s interesting to see only about 34,857 IPs are responsible for millions of ad clicks! Clearly there’s some unexpected behavior.

Algorithms and Techniques

XGBoost - eXtreme Gradient Boosting - is one of the most popular machine learning algorithm these days. Regardless of the type of prediction task at hand; regression or classification.

XGBoost is well known to provide better solutions than other machine learning algorithms. In fact, since its inception, it has become the "state-of-the-art” machine learning algorithm to deal with structured data.


eXtreme Gradient Boosting
custom tree building algorithm
XGBOOST
Used for: . classification . regression . ranking with customloss functions
Interface for Python and R, can be executed on YARN

<u>XGBoost Algorithm Advantages</u>

- Speed and performance: Originally written in C++, it is comparatively faster than other ensemble classifiers.
- Core algorithm is parallelizable: Because the core XGBoost algorithm is parallelizable, it can harness the power of multi-core computers. It is also parallelizable onto GPU's and across networks of computers making it feasible to train on very large datasets as well.
- Consistently outperforms other algorithm methods: It has shown better performance on a variety of machine learning benchmark datasets.
- Wide variety of tuning parameters: XGBoost internally has parameters for cross-validation, regularization, user-defined objective functions, missing values, tree parameters, and scikit-learn compatible API etc.
  - Regularization: I believe this is the biggest advantage of xgboost. GBM has no provision for regularization. Regularization is a technique used to avoid overfitting in linear and tree-based models.

Benchmark

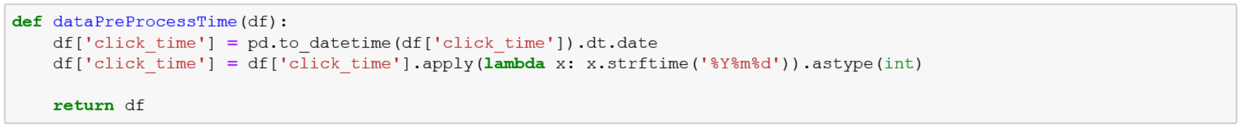
From the public leaderboard the winner has Area under Receiving Operating Characteristics Curve score equal to 0.98349 – very amazing score.

Methodology

Data Preprocessing

As previously mentioned, the given dataset had already been well-prepared and processed, all categorical features had been labelled and set to numbers, sensitive data encoded, and potentially missing data had been either filled or discarded.

Before being feed to the model, the time attributes need to be converted to a format that XGBoost can understand – year, month and day.



```
def dataPreProcessTime(df):
    df['click_time'] = pd.to_datetime(df['click_time']).dt.date
    df['click_time'] = df['click_time'].apply(lambda x: x.strftime('%Y%m%d')).astype(int)

    return df
```

Implementation

The software requirements for the implementation are as followed;

- Python => '3.6'
- Scikit-learn => '0.20.2'
- Pandas => '0.23.4'
- XGBoost => '0.82'
- Numpy => '1.16.0'
- Matplotlib => '3.0.2'

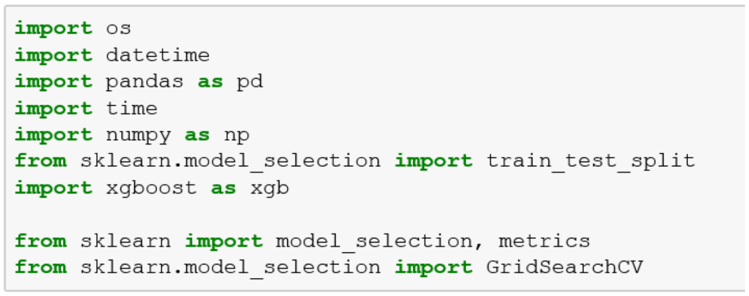
Parameters tuning used in XGBoost are as followed;

- eta – learning_rate: Step size shrinkage used in update to prevents overfitting
- max_depth: Maximum depth of a tree
- subsample: Subsample ratio of the training instances
- colsample_bytree: is the subsample ratio of columns when constructing each tree. Subsampling occurs once for every tree constructed

- colsample_bylevel: is the subsample ratio of columns for each level. Subsampling occurs once for every new depth level reached in a tree. Columns are subsampled from the set of columns chosen for the current tree
- min_child_weight: Minimum sum of instance weight (hessian) needed in a child
- alpha: L1 regularization term on weights. Increasing this value will make model more conservative
- objective [*binary:logistic*]: logistic regression for binary classification, output probability
- eval_metric [*auc*]: Evaluation metrics for validation data
- scale_pos_weight: Control the balance of positive and negative weights, useful for unbalanced classes

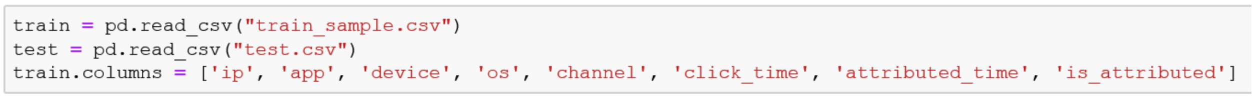
Python Implementation with code

1- import necessary libraries



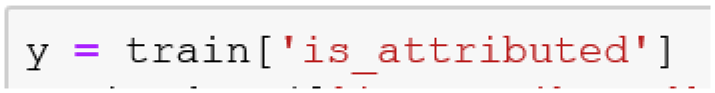
```
import os
import datetime
import pandas as pd
import time
import numpy as np
from sklearn.model_selection import train_test_split
import xgboost as xgb

from sklearn import model_selection, metrics
from sklearn.model_selection import GridSearchCV
```

2- load the dataset



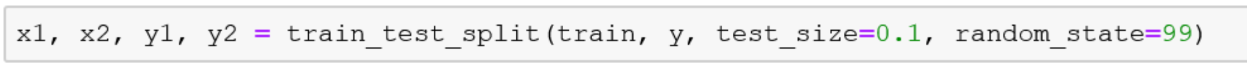
```
train = pd.read_csv("train_sample.csv")
test = pd.read_csv("test.csv")
train.columns = ['ip', 'app', 'device', 'os', 'channel', 'click_time', 'attributed_time', 'is_attributed']
```

3- Identify the target variable



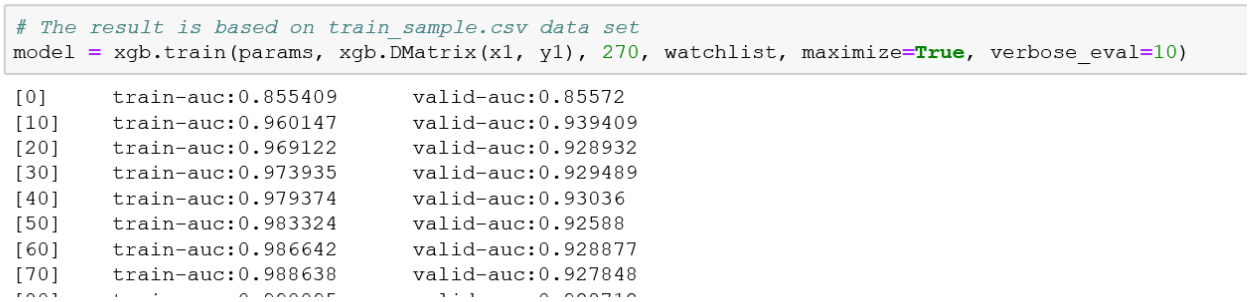
```
y = train['is_attributed']
```

4- Train test split



```
x1, x2, y1, y2 = train_test_split(train, y, test_size=0.1, random_state=99)
```

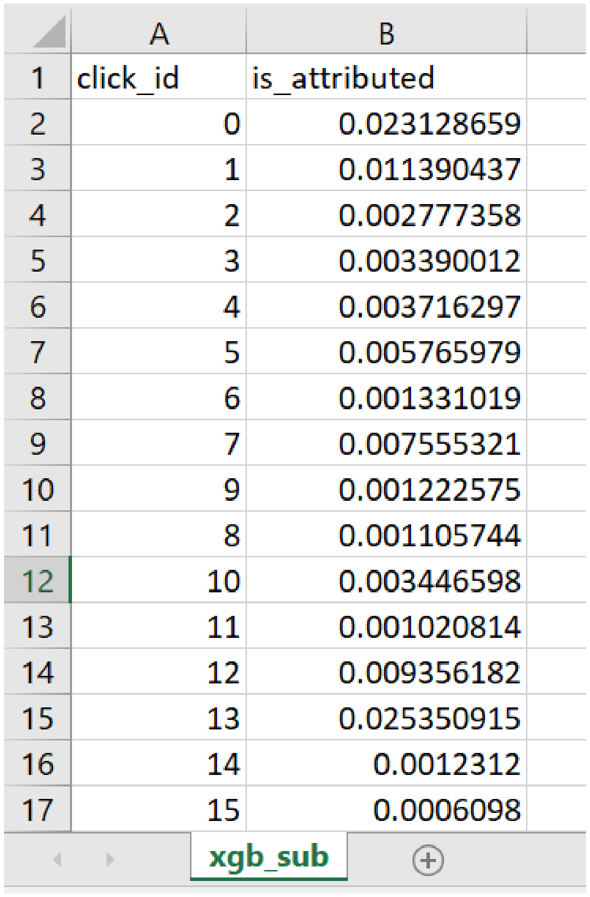
5- Training the model



```
# The result is based on train_sample.csv data set
model = xgb.train(params, xgb.DMatrix(x1, y1), 270, watchlist, maximize=True, verbose_eval=10)
```

```
[0]     train-auc:0.855409      valid-auc:0.85572
[10]    train-auc:0.960147      valid-auc:0.939409
[20]    train-auc:0.969122      valid-auc:0.928932
[30]    train-auc:0.973935      valid-auc:0.929489
[40]    train-auc:0.979374      valid-auc:0.93036
[50]    train-auc:0.983324      valid-auc:0.92588
[60]    train-auc:0.986642      valid-auc:0.928877
[70]    train-auc:0.988638      valid-auc:0.927848
```

<u>Sample of the output file as below</u>

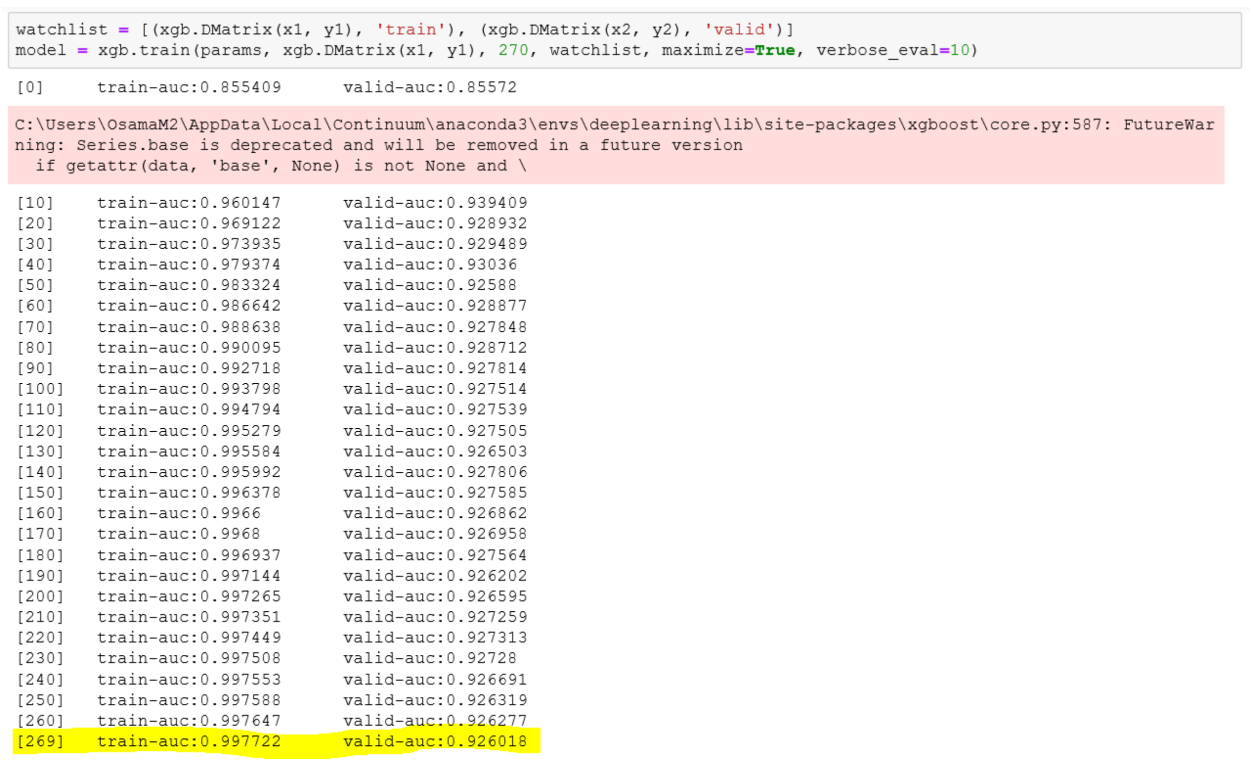


	A	B
1	click_id	is_attributed
2	0	0.023128659
3	1	0.011390437
4	2	0.002777358
5	3	0.003390012
6	4	0.003716297
7	5	0.005765979
8	6	0.001331019
9	7	0.007555321
10	9	0.001222575
11	8	0.001105744
12	10	0.003446598
13	11	0.001020814
14	12	0.009356182
15	13	0.025350915
16	14	0.0012312
17	15	0.0006098

xgb_sub

Refinement

Data Matrix used in XGBoost. DMatrix is an internal data structure that used by XGBoost which is optimized for both memory efficiency and training speed.



```
watchlist = [(xgb.DMatrix(x1, y1), 'train'), (xgb.DMatrix(x2, y2), 'valid')]
model = xgb.train(params, xgb.DMatrix(x1, y1), 270, watchlist, maximize=True, verbose_eval=10)
```

```
[0]     train-auc:0.855409      valid-auc:0.85572
```

```
C:\Users\OsamaM2\AppData\Local\Continuum\anaconda3\envs\deeplearning\lib\site-packages\xgboost\core.py:587: FutureWar
ning: Series.base is deprecated and will be removed in a future version
  if getattr(data, 'base', None) is not None and \
```

```
[10]    train-auc:0.960147      valid-auc:0.939409
[20]    train-auc:0.969122      valid-auc:0.928932
[30]    train-auc:0.973935      valid-auc:0.929489
[40]    train-auc:0.979374      valid-auc:0.93036
[50]    train-auc:0.983324      valid-auc:0.92588
[60]    train-auc:0.986642      valid-auc:0.928877
[70]    train-auc:0.988638      valid-auc:0.927848
[80]    train-auc:0.990095      valid-auc:0.928712
[90]    train-auc:0.992718      valid-auc:0.927814
[100]   train-auc:0.993798      valid-auc:0.927514
[110]   train-auc:0.994794      valid-auc:0.927539
[120]   train-auc:0.995279      valid-auc:0.927505
[130]   train-auc:0.995584      valid-auc:0.926503
[140]   train-auc:0.995992      valid-auc:0.927806
[150]   train-auc:0.996378      valid-auc:0.927585
[160]   train-auc:0.9966        valid-auc:0.926862
[170]   train-auc:0.9968        valid-auc:0.926958
[180]   train-auc:0.996937      valid-auc:0.927564
[190]   train-auc:0.997144      valid-auc:0.926202
[200]   train-auc:0.997265      valid-auc:0.926595
[210]   train-auc:0.997351      valid-auc:0.927259
[220]   train-auc:0.997449      valid-auc:0.927313
[230]   train-auc:0.997508      valid-auc:0.92728
[240]   train-auc:0.997553      valid-auc:0.926691
[250]   train-auc:0.997588      valid-auc:0.926319
[260]   train-auc:0.997647      valid-auc:0.926277
[269]   train-auc:0.997722      valid-auc:0.926018
```

Model Evaluation and Validation

By using two different approaches to estimate the ROC under the area, and find the best estimator.

For solution_1, we have used parameters tuning based on the guide for selecting parameters in XGBoost, and therefore we have achieved score as approximately as 0.99

For parameter tuning, here's some guidelines that helped me a lot,

- **learning_rate**: usually between 0.1 and 0.01. If you're focused on performance and have time in front of you, decrease incrementally the learning rate while increasing the number of trees.
- **subsample**, which is for each tree the % of rows taken to build the tree. I recommend not taking out too many rows, as performance will drop a lot. Take values from 0.8 to 1.
- **colsample_bytree**: number of columns used by each tree. In order to avoid some columns to take too much credit for the prediction (think of it like in recommender systems when you recommend the most purchased products and forget about the long tail), take out a good proportion of columns. Values from 0.3 to 0.8 if you have many

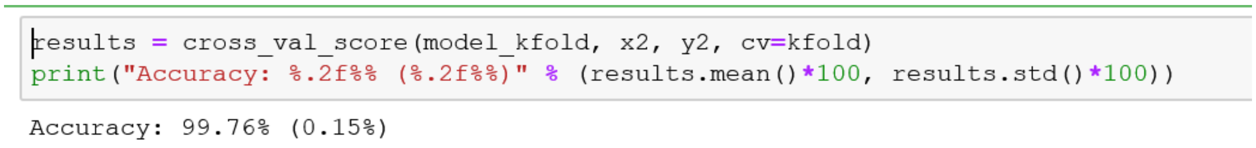
columns (especially if you did one-hot encoding), or 0.8 to 1 if you only have a few columns.

For solution_2, we have used GridSearch – is the automatic process to tune, but you can tune them manually with validation and therefore we have achieved score as approximately as 0.81

For solution_3, Evaluate XGBoost Models with k-Fold Cross Validation: Cross validation is an approach that you can use to estimate the performance of a machine learning algorithm with less variance than a single train-test set split.

It works by splitting the dataset into k-parts (e.g. k=5 or k=10). Each split of the data is called a fold. The algorithm is trained on k-1 folds with one held back and tested on the held back fold. This is repeated so that each fold of the dataset is given a chance to be the held back test set.

The below is the result for our model – using the default parameters – and k-fold CV; running this solution_3 summarizes the performance of the default model configuration on the dataset including both the mean and standard deviation classification accuracy.



```
results = cross_val_score(model_kfold, x2, y2, cv=kfold)
print("Accuracy: %.2f%% (%.2f%%)" % (results.mean()*100, results.std()*100))
```

```
Accuracy: 99.76% (0.15%)
```

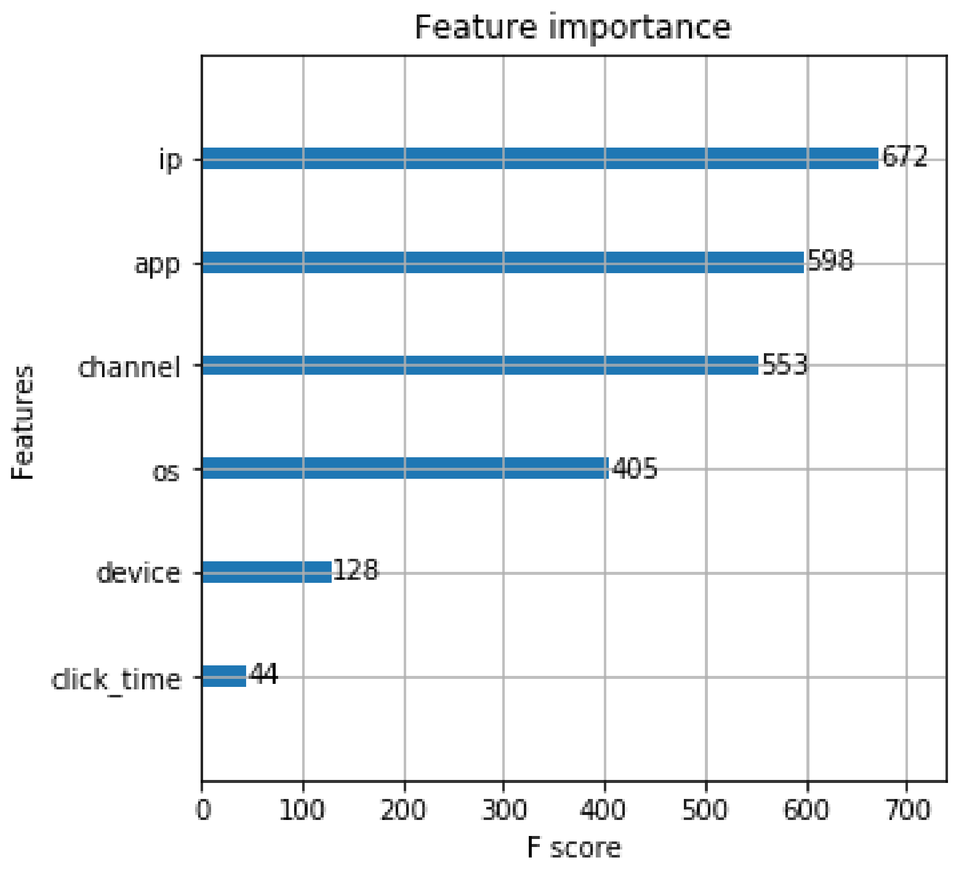
Justification

By not using the whole training dataset – *main reason is the slow internet connection and hardware limitation* – and just used the sample one (100,000 rows). In the boundaries of the competition, I can say these results are encouraging and show that the approach taken is the right direction, although there is so much to improve upon. Getting score around 0.99 is pretty motivated to use the model for the whole datasets.

Conclusion

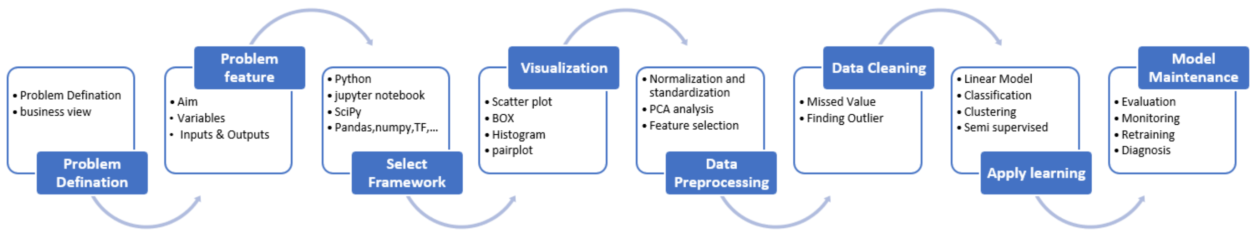
Free-Form Visualization

I fitted the data with an XGBoost classifier and used the plot_importance feature of XGBoost to see how much each feature has an impact on predicting the outcome of a click. The graph of feature importance is given below:



Reflection

You can see my reference workflow in the below image (Reference);



That helped me to understand the end-to-end ML process. The given data from TalkingData was clean, the target concept is clearly defined and the features gave me lots of room for engineering and research.

Data Matrix used in XGBoost, helped me to have optimized for both memory efficiency and training speed.

Improvement

There is so much that can be improved upon for this project, for example the same model design training on the whole dataset with all generated features present would no doubt yield a much higher performance.

My intuition is to follow the clicking patterns of individual users, and the time between the clicks has proven to be an important feature. To exploit this further, we can also generate more time-between-click features such as how much time does is it between this click and the next 2 clicks, or how much time between this click and the previous click. The reason is that for normal users, there may be cases where the user makes more than 1 click in a short amount of time due to accident or because the user realizes something after finishes reading the advertisement, and goes back to it.

These cases may be falsely identified as fake clicks, so to be able to look 2 or more clicks ahead would be helpful since it would be rare for normal users to generate repeated clicks in any case.

Similar to the time features, app and channel can be associated with individual users or "clicking sessions" by aggregating them with different groups of given identity features: [ip, device, os].