kptl-quant-challenge-rafael-celente

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1 KPTL Quant Challenge - Modelling

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1.1 Part 0: Introduction

Our goal in this challenge is to analyze and select the best classifications to execute our trading strategies based on a primary labelling model. A primary model has already been built (`side_labels.csv`), which generated long (1) and short (-1) labels. For this challenge, we shall apply different machine learning techniques to create a trading machine that performs on the sides on that have been given. Another dataset (`btc.csv`) has also been given with Bitcoin's OHLCV historic data to extract techical indicators for more features for our model.

In this notebook we will cover first a data cleaning and overall analysis. Next, we will set our performance indicators and set a baseline of our models using a Dummy Classifier and a Random Forest with only the price as our features. Finally, we will use a technical analysis library to generate technical indicators to feed more features to our model and compare against our baselines. We also use a XGBoost to compare against RF models.

1.2 Part 1: Data cleaning and normalization

Libraries and utilities import

[1]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import pandas_ta as ta
from pandas.tseries.offsets import DateOffset
import matplotlib.pyplot as plt
import matplotlib.dates as dates
import seaborn as sns
import datetime
import warnings
import plotly
import plotly.graph_objects as go
from plotly.subplots import make_subplots
from sklearn.utils import resample
from sklearn.utils import shuffle
from sklearn.tree import DecisionTreeClassifier
```

```python
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor,␣
↪BaggingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import roc_curve, auc
from sklearn.dummy import DummyClassifier
warnings.filterwarnings('ignore')
datetime.datetime.strptime
sns.set(style="darkgrid")
```

```
/home/rafa/anaconda3/lib/python3.7/site-packages/pandas/compat/_optional.py:138:
UserWarning: Pandas requires version '2.7.0' or newer of 'numexpr' (version
'2.6.9' currently installed).
  warnings.warn(msg, UserWarning)
/home/rafa/anaconda3/lib/python3.7/site-
packages/statsmodels/tools/_testing.py:19: FutureWarning: pandas.util.testing is
deprecated. Use the functions in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

Importing `side_labels.csv` dataframe.

[2]:
```python
side_labels = pd.read_csv('side_labels.csv')
side_labels['timestamp'] = pd.to_datetime(side_labels['timestamp'])
side_labels = side_labels.set_index('timestamp')
```

Importing `btc.csv` dataframe.

[3]:
```python
btc = pd.read_csv('btc.csv')
btc['timestamp'] = pd.to_datetime(btc['timestamp'])
btc = btc.set_index('timestamp')
```

[4]:
```python
side_labels.head()
```

[4]:
```
                          ret  side
timestamp
2016-09-03 19:25:00  0.011372   1.0
2016-09-03 19:40:00  0.007597   1.0
2016-09-11 19:20:00 -0.033881  -1.0
2016-09-11 19:30:00  0.009345   1.0
2016-09-11 19:35:00 -0.000545  -1.0
```

1.2.1 Part 1.1 Analyzing the dataset

First let's take a look at how our dataset behaves and map what changes should we apply to improve the model's performance.

[5]:
```
side_labels.side.value_counts()
```

[5]:
```
 1.0    11771
-1.0    10929
 0.0        1
Name: side, dtype: int64
```

Looking at the data, we see one case in which the model outputed a side 0, which is not normal since our model should be strictly binary. Let's filter this outlier and look at the metrics.

[6]:
```
side_labels = side_labels[side_labels['side'] != 0]
side_labels.side.value_counts()
```

[6]:
```
 1.0    11771
-1.0    10929
Name: side, dtype: int64
```

We can see that our classes are not strictly balanced, as we have more instances of a buy trigger than a sell trigger. Imbalaced classes may induce a bias in our classification, skewing the output towards the majority class.

[7]:
```
side_labels.side.value_counts()[1]/side_labels.side.value_counts()[-1]
```

[7]:
```
1.0770427303504437
```

However, this imbalace is very small (1.077:1). Usually, imbalace may present a problem in datasets in which classes have an imbalace ratio of 2:1 or above.

Let's also take a look at how the indexes are presented. Maybe there are a few instances in which a label is not indexed correctly or a value is null, which will influence our model.

[8]:
```
side_labels.isnull().values.any()
```

[8]:
```
False
```

[9]:
```
btc.isnull().values.any()
```

[9]:
```
True
```

Seems that a few data points on the Bitcoin dataset are missing. Let's take a further look.

[10]:
```
btc.isnull().value_counts()
```

[10]:
```
close  open   high   low    volume
False  False  False  False  False     554967
True   True   True   True   False       9801
dtype: int64
```

We have 9801 data points which have no pricing information whatsoever. Let's see if any of those points share an index with the labels.

[11]:
```
nan_values = btc.loc[btc['close'].isnull() == True]
```

[12]:
```
nan_values.index.values in side_labels.index.values
```

[12]: False

No values that return a null value are in our labels.

Let's also change our labels to 0 and 1 to facilitate handling with a few packages we will use (such as XGBoost that doesn't accept negative labels

[13]:
```
side_labels.loc[side_labels['side'] == -1, 'side'] = 0
side_labels.head(15)
```

[13]:
```
                          ret  side
timestamp
2016-09-03 19:25:00  0.011372   1.0
2016-09-03 19:40:00  0.007597   1.0
2016-09-11 19:20:00 -0.033881   0.0
2016-09-11 19:30:00  0.009345   1.0
2016-09-11 19:35:00 -0.000545   0.0
2016-09-11 20:10:00  0.008423   1.0
2016-09-21 00:00:00  0.009991   1.0
2016-09-21 00:05:00 -0.001646   0.0
2016-10-11 04:15:00 -0.007224   0.0
2016-10-22 16:20:00  0.006216   1.0
2016-10-27 01:10:00  0.005850   1.0
2016-10-29 15:45:00  0.006390   1.0
2016-10-29 21:25:00  0.006626   1.0
2016-10-30 01:40:00 -0.009225   0.0
2016-10-30 02:05:00  0.008074   1.0
```

1.2.2 Part 1.2 Modelling

In here we will apply different models, features and strategies to see their modelling performance.

Part 1.2.1 Setting a baseline (Dummy Classifier) Comparing different models takes not only definition of different performance metrics, but also setting a baseline of comparision. We can use a very simple model to serve as a baseline to compare against other complex classifiers. For this purpose, we will use DummyClassifier, which is a classifier that ignores input features. The model just returns the most frequent class label.

1.2.1.1 Model training

[14]:
```
X = btc.loc[side_labels.index, :]
y = side_labels['side']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪shuffle=False)

dummy_clf = DummyClassifier(strategy = 'prior')
dummy_clf.fit(X_train,y_train)
dummy_clf.predict(X_train)
dummy_clf.score(X_train,y_train)
```

[14]: 0.5200440528634361

1.2.1.2 Model testing and performance metrics

Performance Metrics In our classification, we can commit two types of errors: Type I and Type II. We could mislabel an operation that should've been a long as a short (false positive) and mislabel a trade that should've been a short as a long (false negative).The labels that have been correctly categorized are called our true positives and true negatives. The relationship between the ammount of these mislabellings and the ammount of true predictions is of utmost importance, since it influences how well the model's performance is.

Precision Precision is a measurement of how often our model is able to precisely predict a positive value. It computes the size of true positives against the sum of true positives and false positives.

Recall Recall (aka sensitivity or true positive rate) is a measurement of how accuretely our model is able to identify a true positive against all relevent elements. It computes de size of true positives against the sum of true positives and false negatives.

F1-Score The F1-Score is a measurment of the total test's accuracy. It computes the harmonic mean of the precision and recall, giving a standard numeric computation.

Total returns An import metric we have to look at is the total return of the model. If our model has a bad recall, it might be making bad bets too often, which could lead to negative returns even though the accuracy of the model is still over 50%.

From a financial stakeholder's perspective, minimizing risk and maximizing return is always the goal. In financial machine learning terms, minimizing risk means lowering our false positive rate, in which means lowering the probability of making a bad bet. However, since false positives and false negatives are intrinsically related in a model, lowering the false positive rate also increases the false negative rate, which increases the probability of the model not taking a bet it shouldn't have taken. This lower profit rate is a price we are willing to take to minimize the risk of the trading scheme. Therefore, we are looking to emphasize our model's recall, giving more importance to identifying true positives correctly at the expense of false positives.

With this in mind, for performance metrics, we will be looking at the model's: - Precision - Recall - F1 score - Accuracy - Total returns

To visualize the results in a complete and graphical way, we will also look at the model's ROC curve, which will give us a graphical interpretation of our model's performance. The ROC Curve is a graph that plots our Recall over the False Positive Rate. A random classifier plotted in the ROC Curve would yield a point along the diagonal line of the graph, since it has no discriminatory capability. Since we are trying to maximize our true positive rate and minimize our false positive rate, our classifier is better as closer it gets to the upper left corner of the graph.

[15]:
```
# Plotting utility function

def performance_metrics(classifier, X_test, plot = False):
    y_pred_cls = classifier.predict_proba(X_test)[:, 1]
```

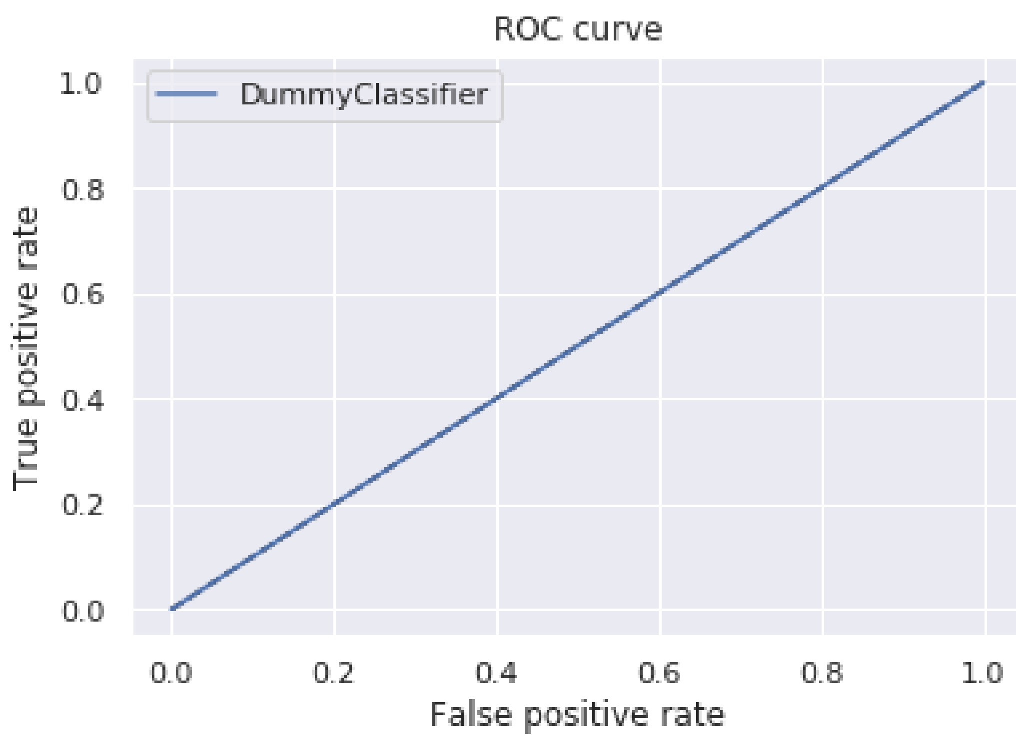
```
    y_pred = classifier.predict(X_test)
    fpr, tpr, _ = roc_curve(y_test, y_pred_cls)

    class_report = classification_report(y_test, y_pred)
    f1 = f1_score(y_test, y_pred, average='weighted')
    conf_matrix = confusion_matrix(y_test, y_pred)
    acc = accuracy_score(y_test, y_pred)

    trades = side_labels.loc[X_test.index]
    trades['predict'] = y_pred
    trades.loc[trades['side'] == 0, 'ret'] = trades['ret']*-1
    profits = trades.loc[trades['side'] == trades['predict'], 'ret'].sum()
    losses = trades.loc[trades['side'] != trades['predict'], 'ret'].sum()
    returns = profits - losses

    if plot:
        print(class_report)
        print("Confusion Matrix")
        print(conf_matrix)

        print('')
        print("Accuracy")
        print(acc)

        plt.figure(1)
        plt.plot([0, 1], [0, 1], 'k--')
        plt.plot(fpr, tpr, label=f'{classifier.__class__.__name__}')
        plt.xlabel('False positive rate')
        plt.ylabel('True positive rate')
        plt.title('ROC curve')
        plt.legend(loc='best')
        plt.show()

        print(f'Returns:  {returns}')

    return class_report, f1, conf_matrix, acc, returns
```

[16]:

```
dummy_clf.fit(X_train,y_train)
dummy_clf.predict(X_test)
dummy_clf.score(X_test,y_test)


dummy_metrics = performance_metrics(dummy_clf, X_test, plot = True)
```

```
              precision    recall  f1-score   support

         0.0       0.00      0.00      0.00      2213
         1.0       0.51      1.00      0.68      2327
```

```
    accuracy                           0.51      4540
   macro avg       0.26      0.50      0.34      4540
weighted avg       0.26      0.51      0.35      4540

Confusion Matrix
[[   0 2213]
 [   0 2327]]

Accuracy
0.5125550660792951
```




```
Returns:  2.2763690808617234
```

From the ROC curve, it is clear that this model isn't much better than a coin flip to predict our trades. Let's explore some more.

Part 1.2.2 Applying a Random Forest Classifier A Random Forest classifier was selected also to set a formal baseline of our models, since it is very reliable. For the baseline, we will apply the model to features that are readily available: price and volume. However, we expect this model to not perform much better than the Dummy Classifier because of the lack of features. Later, we will apply the RF classifier to a more complete input with more trading features.

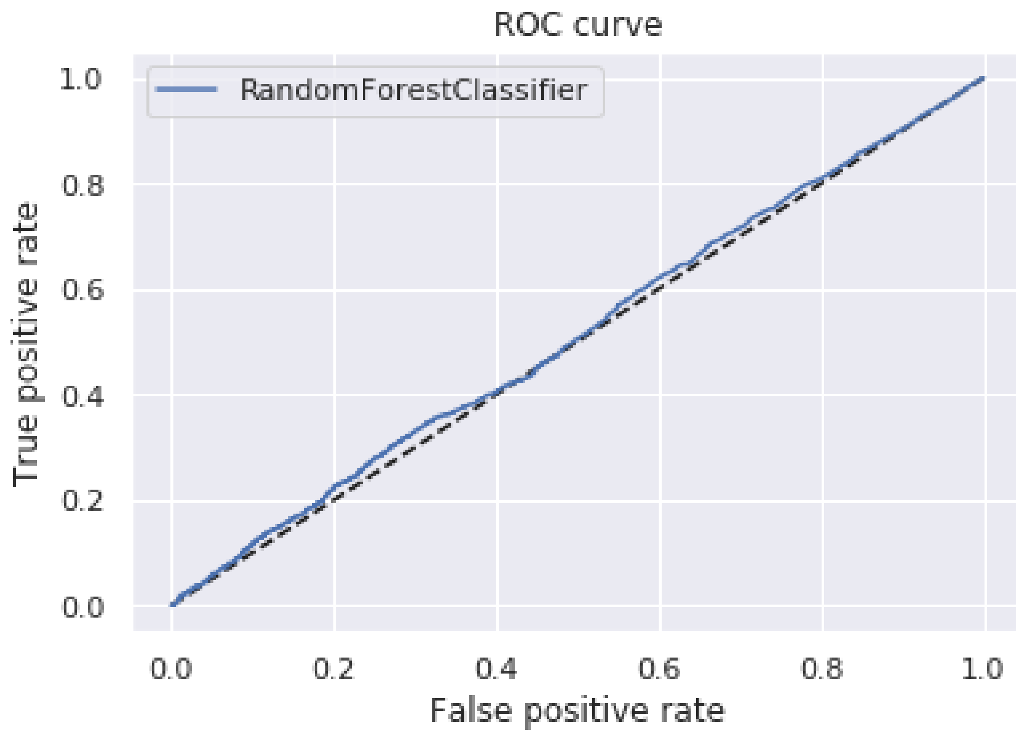
[18]:
```
# Setting random forest parameters
n_estimator = 1000
depth = 2
RANDOM_STATE = 0

rf  = RandomForestClassifier(max_depth=depth, n_estimators=n_estimator,
                             criterion='entropy',␣
 ↪class_weight='balanced_subsample',
                             random_state=RANDOM_STATE)

# Fitting our model
rf.fit(X_train, y_train)
```

[18]:
```
RandomForestClassifier(class_weight='balanced_subsample', criterion='entropy',
                       max_depth=2, n_estimators=1000, random_state=0)
```

Part 1.2.2.1 RF testing

[19]:
```
rf_metrics = performance_metrics(rf, X_test, plot = True)
```

```
              precision    recall  f1-score   support

         0.0       0.49      0.78      0.61      2213
         1.0       0.53      0.24      0.33      2327

    accuracy                           0.50      4540
   macro avg       0.51      0.51      0.47      4540
weighted avg       0.52      0.50      0.46      4540

Confusion Matrix
[[1728  485]
 [1769  558]]

Accuracy
0.5035242290748899
```




```
Returns:  1.896193007181342
```

We can see from these results that, using Bitcoin's price as the only feature, using a Random Forest classifier changed almost nothing of the model's performance compared to the Dummy Classifier. This shows that our model requires more features in order to perform better.

1.2.3 1.3 Feature extraction

For feature extraction, we shall test a few technical indications that could potentially indicate a price spike or fall. We can use the python library `pandas-ta` to easilly fetch trading indicators from our `btc.csv` dataset.

[20]:
```
import pandas_ta as ta
```

1.3.1 Technical indicators and correlation For now, let's explore these technical indicators and see how they perform with our algorithm.

- Exponential Moving Avarege (ema)
- Relative Strength Index (RSI)
- Stochastic Oscillator (stoch)
- Slope (slope)
- Moving Average Convergence Divergence (macd)
- Momemntum (mom)
- Simple Moving Average (sma)

[21]:
```
btc = pd.read_csv('btc.csv')
btc['timestamp'] = pd.to_datetime(btc['timestamp'])
btc = btc.set_index('timestamp')
btc = btc.dropna(axis=0)
```

[22]:
```
featured_btc = btc
featured_btc['ema'] = ta.ema(close = btc.close, timeperiod=7)
featured_btc['rsi'] = ta.rsi(close = btc.close)
featured_btc['slope'] = ta.slope(close = btc.close)
featured_btc['mom'] = ta.mom(close = btc.close)
featured_btc['sma'] = ta.sma(close = btc.close)
featured_btc = featured_btc.join(ta.macd(close = btc.close), on='timestamp')
featured_btc = featured_btc.join(ta.stoch(close = btc.close, high = btc.high,␣
↪low = btc.low), on='timestamp')
```

Feature Engineering

[23]:
```
featured_btc.head(40)
```

[23]:
```
                      close    open    high     low     volume         ema  \
timestamp
2016-08-24 00:00:00  582.54  582.39  582.68  582.39  20.057520         NaN
2016-08-24 00:05:00  582.49  582.68  582.68  582.47   6.698160         NaN
2016-08-24 00:10:00  582.48  582.49  582.49  582.35   4.730530         NaN
2016-08-24 00:15:00  582.28  582.45  582.49  582.28   7.149140         NaN
2016-08-24 00:20:00  582.05  582.32  582.38  582.05  13.120994         NaN
2016-08-24 00:25:00  581.63  582.04  582.20  581.52  31.566578         NaN
2016-08-24 00:30:00  581.75  581.64  581.95  581.64   3.651140         NaN
2016-08-24 00:35:00  581.20  581.70  581.89  581.12  24.184950         NaN
2016-08-24 00:40:00  581.02  581.23  581.50  580.92  27.750094         NaN
2016-08-24 00:45:00  580.74  581.06  581.11  580.55  19.917550  581.818000
2016-08-24 00:50:00  581.70  580.75  581.80  580.75  11.491563  581.796545
2016-08-24 00:55:00  581.88  581.70  582.05  581.57   5.104611  581.811719
2016-08-24 01:00:00  582.29  582.03  582.29  581.96  14.076882  581.898679
2016-08-24 01:05:00  582.24  582.29  582.38  582.18  11.504871  581.960738
2016-08-24 01:10:00  582.28  582.20  582.36  582.06   5.260700  582.018785
2016-08-24 01:15:00  582.38  582.12  582.38  582.12   1.440520  582.084461
2016-08-24 01:20:00  582.02  582.37  582.37  581.90  17.039114  582.072741
2016-08-24 01:25:00  582.11  582.03  582.38  582.03  13.359721  582.079515
2016-08-24 01:30:00  581.88  582.28  582.29  581.73  30.271788  582.043240
2016-08-24 01:35:00  581.70  582.03  582.08  581.70   8.829291  581.980832
2016-08-24 01:40:00  581.71  581.87  581.95  581.71   4.798325  581.931590
2016-08-24 01:45:00  581.70  581.77  581.77  581.69  11.887060  581.889483
2016-08-24 01:50:00  581.72  581.72  581.86  581.61   7.935560  581.858668
2016-08-24 01:55:00  581.92  581.79  581.98  581.65  11.215370  581.869819
2016-08-24 02:00:00  581.08  581.80  581.95  581.08  19.004940  581.726216
2016-08-24 02:05:00  581.18  581.19  581.19  581.16   2.126717  581.626904
2016-08-24 02:10:00  581.22  581.16  581.35  581.09  20.202160  581.552921
```

```
2016-08-24 02:15:00  581.17  581.10  581.29  581.00   2.006430  581.483299
2016-08-24 02:20:00  581.10  581.13  581.20  580.97  17.203835  581.413608
2016-08-24 02:25:00  581.23  581.08  581.23  581.04  15.544930  581.380225
2016-08-24 02:30:00  581.17  581.24  581.40  581.11   8.334052  581.342002
2016-08-24 02:35:00  581.24  581.14  581.31  581.03   6.992440  581.323456
2016-08-24 02:40:00  581.33  581.21  581.47  581.21   5.182660  581.324646
2016-08-24 02:45:00  581.58  581.32  581.58  581.16  23.293620  581.371074
2016-08-24 02:50:00  581.10  581.32  581.47  581.10   2.786672  581.321788
2016-08-24 02:55:00  581.20  581.20  581.34  581.03  10.950970  581.299645
2016-08-24 03:00:00  581.36  581.12  581.38  581.12   3.541770  581.310618
2016-08-24 03:05:00  581.00  581.33  581.34  581.00  17.401130  581.254142
2016-08-24 03:10:00  580.68  581.01  581.02  580.68  30.259504  581.149753
2016-08-24 03:15:00  580.74  580.75  580.95  580.68   4.001220  581.075252

                           rsi  slope   mom      sma  MACD_12_26_9  \
timestamp
2016-08-24 00:00:00        NaN    NaN   NaN      NaN           NaN
2016-08-24 00:05:00        NaN  -0.05   NaN      NaN           NaN
2016-08-24 00:10:00        NaN  -0.01   NaN      NaN           NaN
2016-08-24 00:15:00        NaN  -0.20   NaN      NaN           NaN
2016-08-24 00:20:00        NaN  -0.23   NaN      NaN           NaN
2016-08-24 00:25:00        NaN  -0.42   NaN      NaN           NaN
2016-08-24 00:30:00        NaN   0.12   NaN      NaN           NaN
2016-08-24 00:35:00        NaN  -0.55   NaN      NaN           NaN
2016-08-24 00:40:00        NaN  -0.18   NaN      NaN           NaN
2016-08-24 00:45:00        NaN  -0.28   NaN  581.818           NaN
2016-08-24 00:50:00        NaN   0.96 -0.84  581.734           NaN
2016-08-24 00:55:00        NaN   0.18 -0.61  581.673           NaN
2016-08-24 01:00:00        NaN   0.41 -0.19  581.654           NaN
2016-08-24 01:05:00        NaN  -0.05 -0.04  581.650           NaN
2016-08-24 01:10:00  46.467391   0.04  0.23  581.673           NaN
2016-08-24 01:15:00  47.989439   0.10  0.75  581.748           NaN
2016-08-24 01:20:00  43.224799  -0.36  0.27  581.775           NaN
2016-08-24 01:25:00  44.702924   0.09  0.91  581.866           NaN
2016-08-24 01:30:00  41.714067  -0.23  0.86  581.952           NaN
2016-08-24 01:35:00  39.488846  -0.18  0.96  582.048           NaN
2016-08-24 01:40:00  39.681357   0.01  0.01  582.049           NaN
2016-08-24 01:45:00  39.545868  -0.01 -0.18  582.031           NaN
2016-08-24 01:50:00  39.987211   0.02 -0.57  581.974           NaN
2016-08-24 01:55:00  44.361530   0.20 -0.32  581.942           NaN
2016-08-24 02:00:00  33.362408  -0.84 -1.20  581.822           NaN
2016-08-24 02:05:00  35.415394   0.10 -1.20  581.702           NaN
2016-08-24 02:10:00  36.261285   0.04 -0.80  581.622           NaN
2016-08-24 02:15:00  35.633034  -0.05 -0.94  581.528           NaN
2016-08-24 02:20:00  34.725931  -0.07 -0.78  581.450           NaN
2016-08-24 02:25:00  37.888263   0.13 -0.47  581.403           NaN
2016-08-24 02:30:00  36.997361  -0.06 -0.54  581.349           NaN
```

```
2016-08-24 02:35:00  38.805247   0.07 -0.46  581.303           NaN
2016-08-24 02:40:00  41.143729   0.09 -0.39  581.264           NaN
2016-08-24 02:45:00  47.181644   0.25 -0.34  581.230     -0.151001
2016-08-24 02:50:00  38.924918  -0.48  0.02  581.232     -0.166249
2016-08-24 02:55:00  41.232287   0.10  0.02  581.234     -0.168325
2016-08-24 03:00:00  44.824049   0.16  0.14  581.248     -0.155269
2016-08-24 03:05:00  39.042160  -0.36 -0.17  581.231     -0.171988
2016-08-24 03:10:00  34.751146  -0.32 -0.42  581.189     -0.208655
2016-08-24 03:15:00  36.167762   0.06 -0.49  581.140     -0.230218

                     MACDh_12_26_9  MACDs_12_26_9  STOCHk_14_3_3  \
timestamp
2016-08-24 00:00:00            NaN            NaN            NaN
2016-08-24 00:05:00            NaN            NaN            NaN
2016-08-24 00:10:00            NaN            NaN            NaN
2016-08-24 00:15:00            NaN            NaN            NaN
2016-08-24 00:20:00            NaN            NaN            NaN
2016-08-24 00:25:00            NaN            NaN            NaN
2016-08-24 00:30:00            NaN            NaN            NaN
2016-08-24 00:35:00            NaN            NaN            NaN
2016-08-24 00:40:00            NaN            NaN            NaN
2016-08-24 00:45:00            NaN            NaN            NaN
2016-08-24 00:50:00            NaN            NaN            NaN
2016-08-24 00:55:00            NaN            NaN            NaN
2016-08-24 01:00:00            NaN            NaN            NaN
2016-08-24 01:05:00            NaN            NaN            NaN
2016-08-24 01:10:00            NaN            NaN            NaN
2016-08-24 01:15:00            NaN            NaN      84.964426
2016-08-24 01:20:00            NaN            NaN      83.774583
2016-08-24 01:25:00            NaN            NaN      85.116331
2016-08-24 01:30:00            NaN            NaN      77.898898
2016-08-24 01:35:00            NaN            NaN      73.588342
2016-08-24 01:40:00            NaN            NaN      66.302368
2016-08-24 01:45:00            NaN            NaN      63.023679
2016-08-24 01:50:00            NaN            NaN      63.387978
2016-08-24 01:55:00            NaN            NaN      66.185032
2016-08-24 02:00:00            NaN            NaN      45.237856
2016-08-24 02:05:00            NaN            NaN      26.490483
2016-08-24 02:10:00            NaN            NaN       6.153846
2016-08-24 02:15:00            NaN            NaN      10.260126
2016-08-24 02:20:00            NaN            NaN      10.769310
2016-08-24 02:25:00            NaN            NaN      13.326138
2016-08-24 02:30:00            NaN            NaN      13.947991
2016-08-24 02:35:00            NaN            NaN      17.692886
2016-08-24 02:40:00            NaN            NaN      22.357125
2016-08-24 02:45:00      -0.011326      -0.139675      37.761006
2016-08-24 02:50:00      -0.021260      -0.144990      35.233253
```

2016-08-24 02:55:00	-0.018668	-0.149657	32.013201
2016-08-24 03:00:00	-0.004490	-0.150779	24.752475
2016-08-24 03:05:00	-0.016967	-0.155021	21.482454
2016-08-24 03:10:00	-0.042907	-0.165748	13.891695
2016-08-24 03:15:00	-0.051576	-0.178642	3.242630

	STOCHd_14_3_3
timestamp	
2016-08-24 00:00:00	NaN
2016-08-24 00:05:00	NaN
2016-08-24 00:10:00	NaN
2016-08-24 00:15:00	NaN
2016-08-24 00:20:00	NaN
2016-08-24 00:25:00	NaN
2016-08-24 00:30:00	NaN
2016-08-24 00:35:00	NaN
2016-08-24 00:40:00	NaN
2016-08-24 00:45:00	NaN
2016-08-24 00:50:00	NaN
2016-08-24 00:55:00	NaN
2016-08-24 01:00:00	NaN
2016-08-24 01:05:00	NaN
2016-08-24 01:10:00	NaN
2016-08-24 01:15:00	NaN
2016-08-24 01:20:00	NaN
2016-08-24 01:25:00	84.618447
2016-08-24 01:30:00	82.263271
2016-08-24 01:35:00	78.867857
2016-08-24 01:40:00	72.596536
2016-08-24 01:45:00	67.638130
2016-08-24 01:50:00	64.238009
2016-08-24 01:55:00	64.198897
2016-08-24 02:00:00	58.270289
2016-08-24 02:05:00	45.971124
2016-08-24 02:10:00	25.960728
2016-08-24 02:15:00	14.301485
2016-08-24 02:20:00	9.061094
2016-08-24 02:25:00	11.451858
2016-08-24 02:30:00	12.681146
2016-08-24 02:35:00	14.989005
2016-08-24 02:40:00	17.999334
2016-08-24 02:45:00	25.937006
2016-08-24 02:50:00	31.783795
2016-08-24 02:55:00	35.002487
2016-08-24 03:00:00	30.666310
2016-08-24 03:05:00	26.082710
2016-08-24 03:10:00	20.042208

```
2016-08-24 03:15:00      12.872260
```

Let's filter out the missing values.

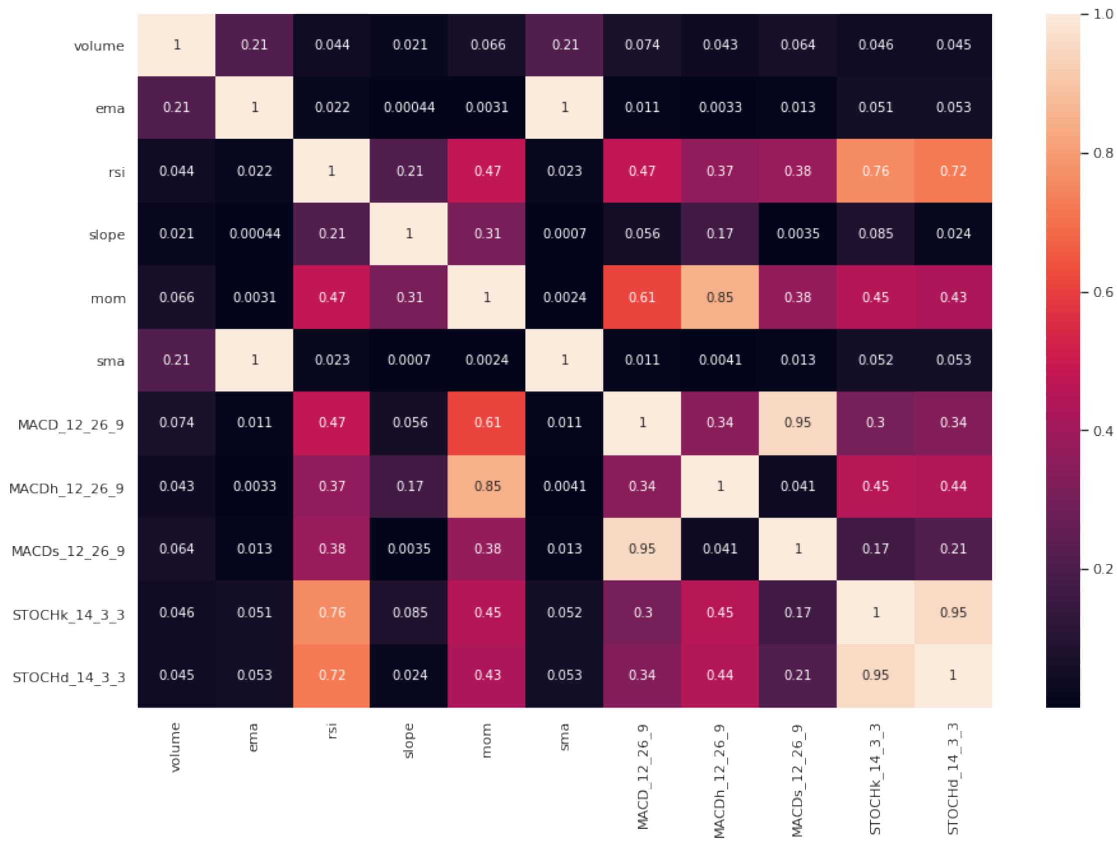
[24]:
```python
featured_btc = featured_btc.dropna()
featured_btc.head()
```

[24]:
```
                      close    open    high     low     volume         ema  \
timestamp
2016-08-24 02:45:00  581.58  581.32  581.58  581.16  23.293620  581.371074
2016-08-24 02:50:00  581.10  581.32  581.47  581.10   2.786672  581.321788
2016-08-24 02:55:00  581.20  581.20  581.34  581.03  10.950970  581.299645
2016-08-24 03:00:00  581.36  581.12  581.38  581.12   3.541770  581.310618
2016-08-24 03:05:00  581.00  581.33  581.34  581.00  17.401130  581.254142

                           rsi  slope   mom      sma  MACD_12_26_9  \
timestamp
2016-08-24 02:45:00  47.181644   0.25 -0.34  581.230     -0.151001
2016-08-24 02:50:00  38.924918  -0.48  0.02  581.232     -0.166249
2016-08-24 02:55:00  41.232287   0.10  0.02  581.234     -0.168325
2016-08-24 03:00:00  44.824049   0.16  0.14  581.248     -0.155269
2016-08-24 03:05:00  39.042160  -0.36 -0.17  581.231     -0.171988

                     MACDh_12_26_9  MACDs_12_26_9  STOCHk_14_3_3  \
timestamp
2016-08-24 02:45:00      -0.011326      -0.139675      37.761006
2016-08-24 02:50:00      -0.021260      -0.144990      35.233253
2016-08-24 02:55:00      -0.018668      -0.149657      32.013201
2016-08-24 03:00:00      -0.004490      -0.150779      24.752475
2016-08-24 03:05:00      -0.016967      -0.155021      21.482454

                     STOCHd_14_3_3
timestamp
2016-08-24 02:45:00      25.937006
2016-08-24 02:50:00      31.783795
2016-08-24 02:55:00      35.002487
2016-08-24 03:00:00      30.666310
2016-08-24 03:05:00      26.082710
```

Now let's explore the correlation of our new features.

[25]:
```python
# Correlation matrix
featured_btc = featured_btc.drop(columns=['close', 'open', 'high', 'low'])
var_corr = featured_btc.corr().abs()

plt.rcParams['figure.figsize'] = [15, 10]
sns.heatmap(var_corr, xticklabels=var_corr.columns, yticklabels=var_corr.
 ↪columns, annot=True)
```

[25]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f28d7221710>
```

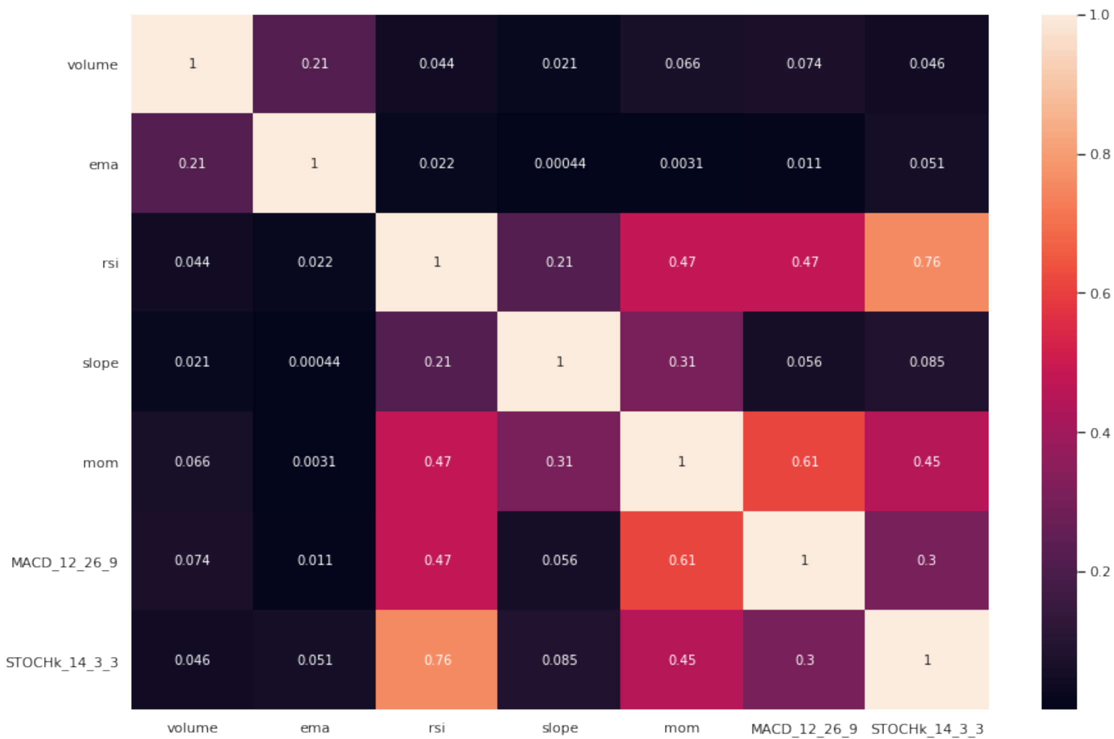


We have a pretty colorful heatmap. Some features are highly correlated, while others have next to no correlation. Let's filter the highly correlated features by some threshold to improve our model's performance.

[26]:
```
corr_threshold = 0.85
upper = var_corr.where(np.triu(np.ones(var_corr.shape), k=1).astype(np.bool))
to_drop = [column for column in upper.columns if any(upper[column] >=␣
 ↪corr_threshold)]
featured_btc.drop(to_drop, axis=1, inplace=True)
```

[27]:
```
var_corr = featured_btc.corr().abs()

plt.rcParams['figure.figsize'] = [15, 10]
sns.heatmap(var_corr, xticklabels=var_corr.columns, yticklabels=var_corr.
 ↪columns, annot=True)
```

[27]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f28d6bbf518>`



Now we have our features, let's train our model once again and see how it performs.

1.2.4 1.4 Model application

1.4.1 RF model with updated features Let's apply once again a Random Forest algorithm to our new model and track the performance.

[28]:
```
X = featured_btc.loc[side_labels.index, :]
```

[29]:
```
# Test/train split
X = featured_btc.loc[side_labels.index, :]
y = side_labels['side']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪shuffle=False)
```

[30]:
```
# Setting random forest parameters
n_estimator = 1000
depth = 2
RANDOM_STATE = 0

rf_featured = RandomForestClassifier(max_depth=depth, n_estimators=n_estimator,
                                     criterion='entropy',␣
↪class_weight='balanced_subsample',
                                     random_state=RANDOM_STATE)

# Fitting our model
```

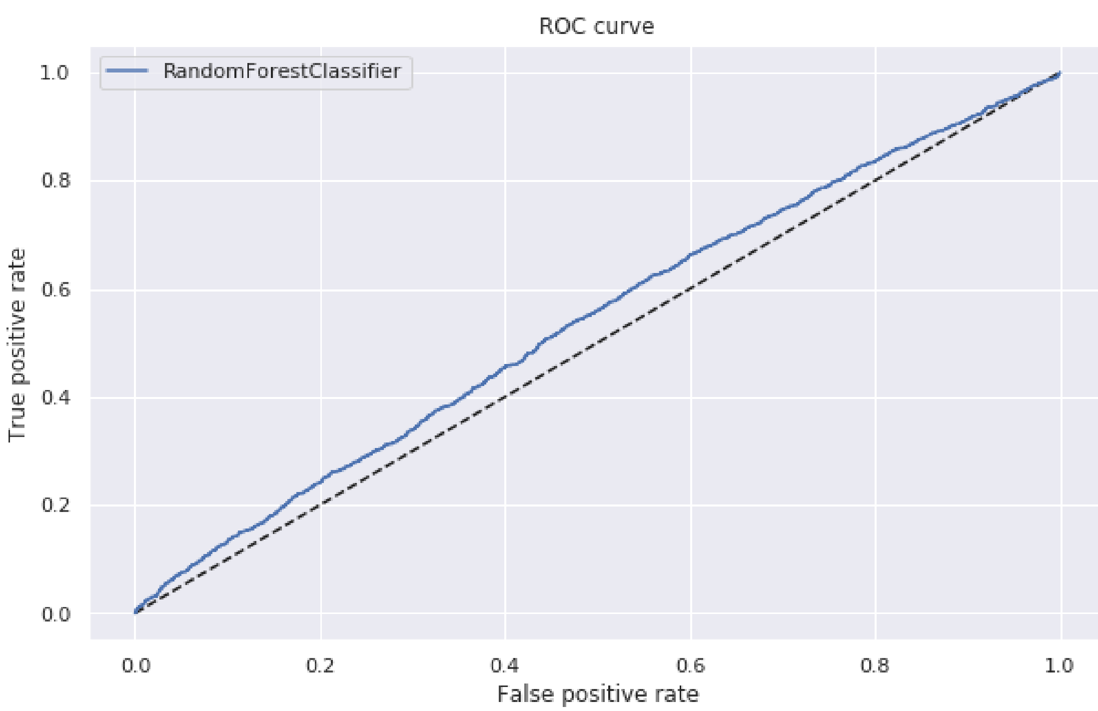
```
rf_featured.fit(X_train, y_train)
```

[30]:
```
RandomForestClassifier(class_weight='balanced_subsample', criterion='entropy',
                       max_depth=2, n_estimators=1000, random_state=0)
```

1.4.1.1 RF training

[31]:
```
plt.rcParams['figure.figsize'] = [10, 6]
featured_rf_metrics = performance_metrics(rf_featured, X_test, plot = True)
```

```
              precision    recall  f1-score   support

         0.0       0.52      0.51      0.52      2213
         1.0       0.54      0.55      0.55      2327

    accuracy                           0.53      4540
   macro avg       0.53      0.53      0.53      4540
weighted avg       0.53      0.53      0.53      4540

Confusion Matrix
[[1132 1081]
 [1047 1280]]

Accuracy
0.5312775330396475
```



```
Returns:  3.0999327741585425
```

The results already show an improvement in our model. Not only the accuracy has increased from 0.5035 to 0.5308, precision, recall and F1-score all improved. Let's see if changing our algorithm has any impact at all in our model.

1.4.2 XGBoost

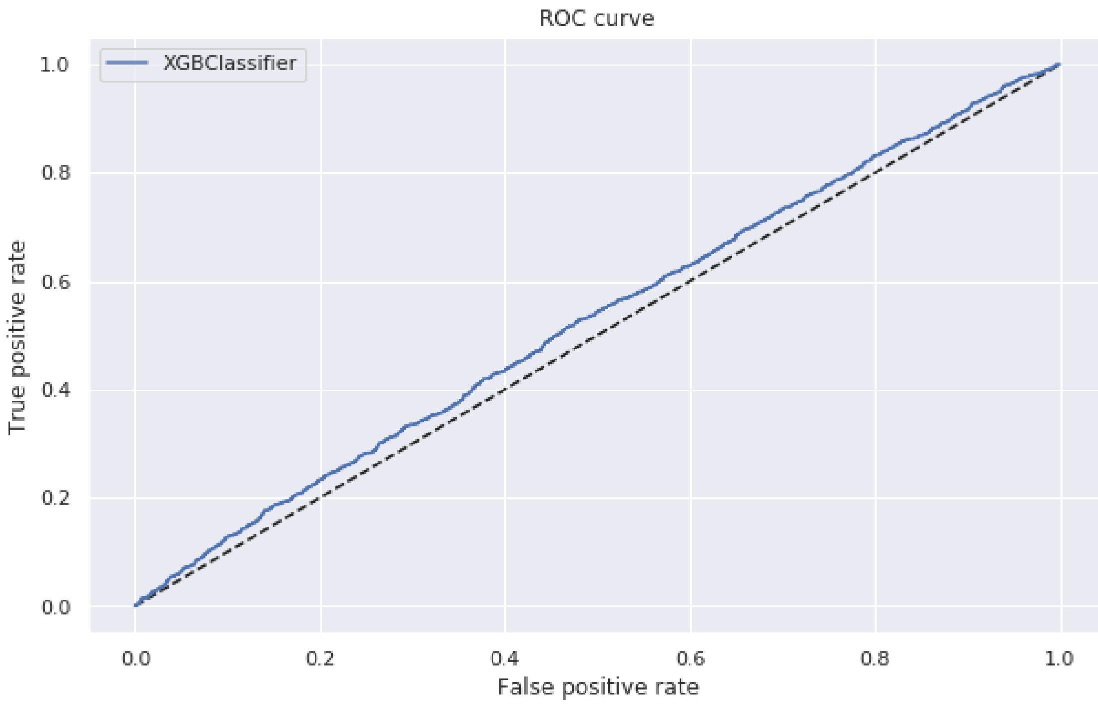
[32]:
```python
from xgboost import XGBClassifier
```

[33]:
```python
y_train = pd.DataFrame(y_train)
xgb = XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')
xgb.fit(X_train, y_train)
```

[33]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              eval_metric='mlogloss', gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=4,
              num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', use_label_encoder=False,
              validate_parameters=1, verbosity=None)
```

[34]:
```python
xgb_metrics = performance_metrics(xgb, X_test, plot = True)
```

```
              precision    recall  f1-score   support

         0.0       0.50      0.59      0.54      2213
         1.0       0.53      0.45      0.49      2327

    accuracy                           0.52      4540
   macro avg       0.52      0.52      0.51      4540
weighted avg       0.52      0.52      0.51      4540

Confusion Matrix
[[1306  907]
 [1291 1036]]

Accuracy
0.5158590308370044
```




```
Returns:  2.451157532195211
```

It seems that a XGBoost classifier gave us a worse model based on all of the metrics. This might be because of the overfitting power of the XGBoost.

1.2.5 1.5 Model comparision

Let's compare all of our models at once. (Based on https://www.imranabdullah.com/2019-06-01/Drawing-multiple-ROC-Curves-in-a-single-plot)

[35]:
```
# Test/train split
X = featured_btc.loc[side_labels.index, :]
y = side_labels['side']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪shuffle=False)
```

[44]:
```
classifiers = [LogisticRegression(random_state=1234),
               GaussianNB(),
               KNeighborsClassifier(),
               RandomForestClassifier(max_depth=2, n_estimators=1000,
                            criterion='entropy',␣
 ↪class_weight='balanced_subsample',
                            random_state=0),
               XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')]
```

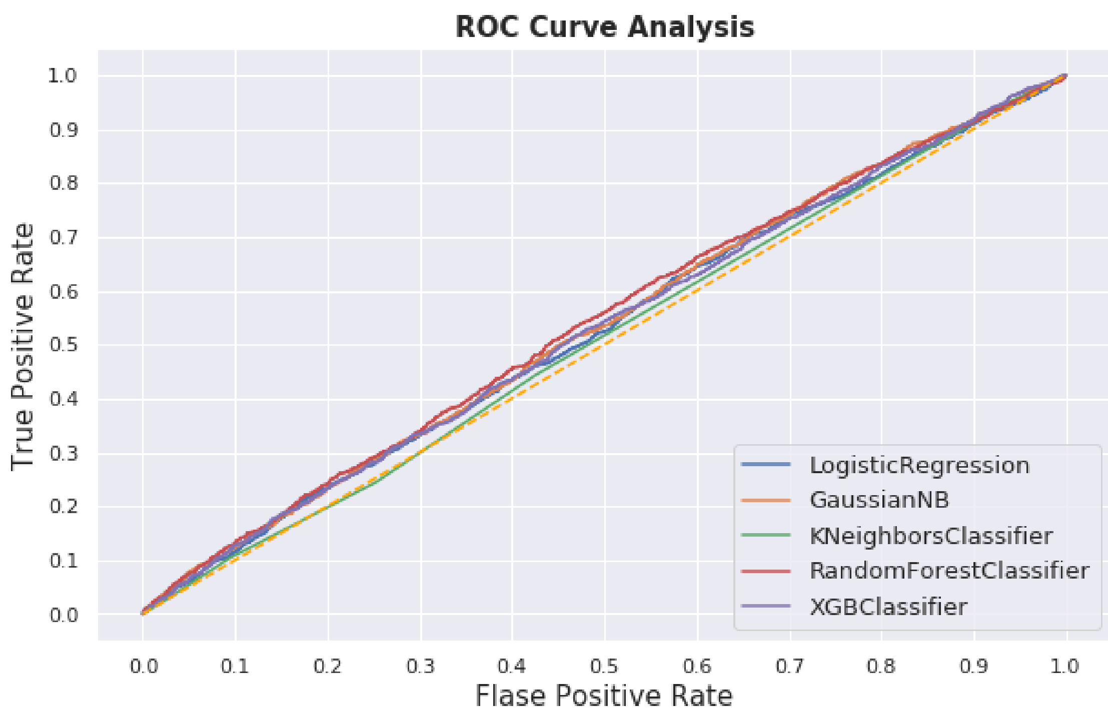
```
result_table = pd.DataFrame(columns=['classifiers', 'fpr','tpr','class_report',␣
↪'f1','conf_matrix', 'acc', 'returns'])
for cls in classifiers:
    print(f'Training {cls.__class__.__name__}')
    model = cls.fit(X_train, y_train)
    y_proba = model.predict_proba(X_test)[::,1]
    fpr, tpr, _ = roc_curve(y_test, y_proba)
    class_report, f1, conf_matrix, acc, returns = performance_metrics(cls,␣
↪X_test, plot = False)

    result_table = result_table.append({'classifiers':cls.__class__.__name__,
                                        'fpr':fpr,
                                        'tpr':tpr,
                                        'class_report':class_report,
                                        'f1':f1,
                                        'conf_matrix': conf_matrix,
                                        'acc': acc,
                                        'returns': returns}, ignore_index=True)
    print('Done\n')
result_table.set_index('classifiers', inplace=True)
```

```
Training LogisticRegression
Done

Training GaussianNB
Done

Training KNeighborsClassifier
Done

Training RandomForestClassifier
Done

Training XGBClassifier
Done
```

ROC Curve analysis.

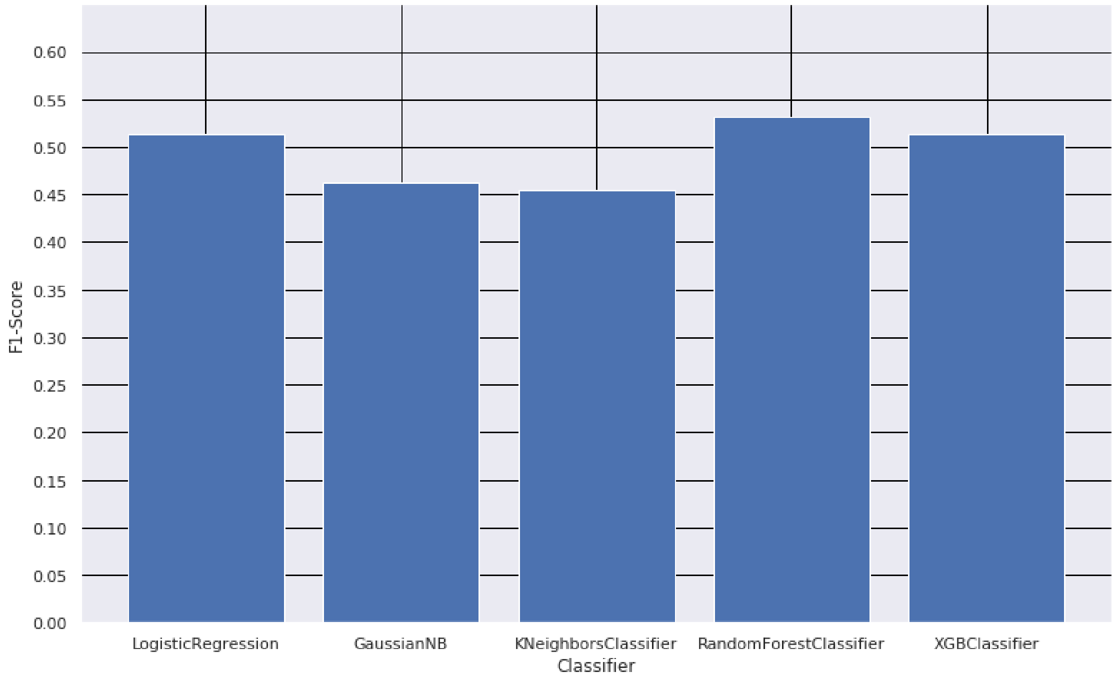
[47]:
```
fig = plt.figure(figsize=(10,6))

for i in result_table.index:
    plt.plot(result_table.loc[i]['fpr'],
             result_table.loc[i]['tpr'],
             label="{}".format(i))

plt.plot([0,1], [0,1], color='orange', linestyle='--')
```

```
plt.xticks(np.arange(0.0, 1.1, step=0.1))
plt.xlabel("Flase Positive Rate", fontsize=15)

plt.yticks(np.arange(0.0, 1.1, step=0.1))
plt.ylabel("True Positive Rate", fontsize=15)

plt.title('ROC Curve Analysis', fontweight='bold', fontsize=15)
plt.legend(prop={'size':13}, loc='lower right')

plt.show()
```

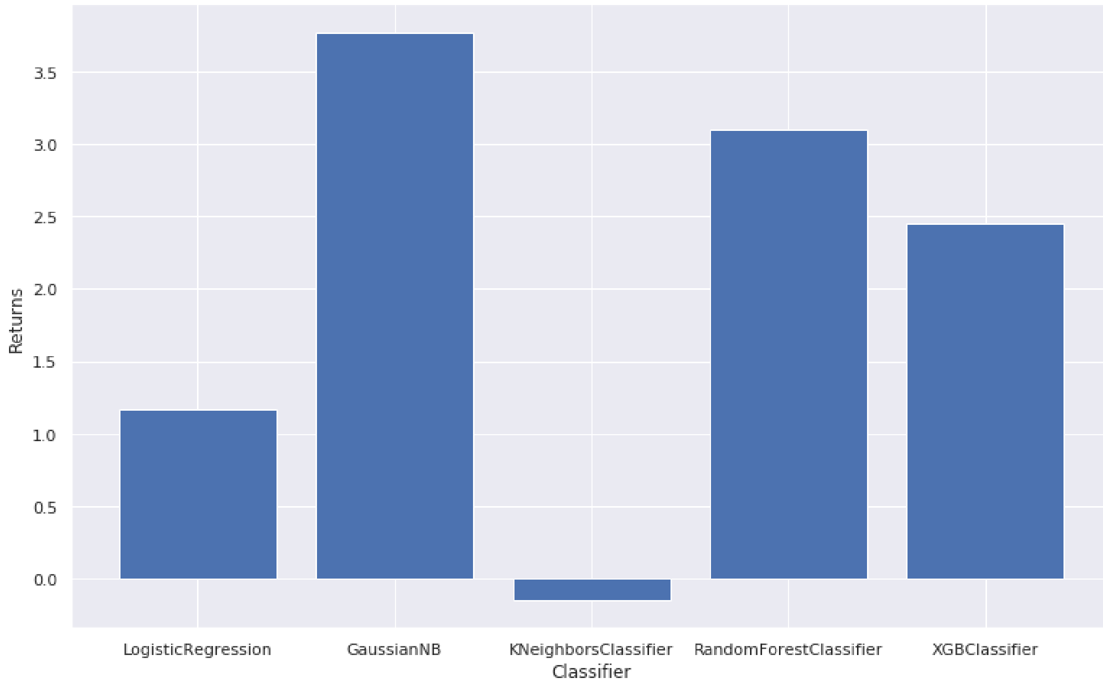


[52]:
```
fig = plt.figure(figsize=(10,6))

ax = fig.add_axes([0,0,1,1])
classifiers = result_table.index
f1 = result_table['f1']
ax.bar(classifiers, f1)

plt.grid(color = 'black')
plt.yticks(np.arange(0, 0.65, 0.05))

plt.xlabel('Classifier')
plt.ylabel('F1-Score')
plt.ylim([0,0.65])
```

```
plt.show()
```



[40]:
```
fig = plt.figure(figsize=(10,6))

ax = fig.add_axes([0,0,1,1])
classifiers = result_table.index
returns = result_table['returns']
ax.bar(classifiers, returns)
plt.xlabel('Classifier')
plt.ylabel('Returns')
plt.show()
```



From this analysis, we can see a few interesting results.

The GaussianNB had the best total returns overall in our backtest. From a naive financial stand point, this would suffice. However, this model resulted in one of the worst F1-Scores, which might be because the Gaussian Naive Bayes classifier is a simple probabilistic classifier, so it can overfit for the bullish nature of Bitcoin. This hypothesis is supported by the model's F1-score of each of the labels.

[41]:
```
print(result_table['class_report']['GaussianNB'])
```

```
              precision    recall  f1-score   support

         0.0       0.55      0.17      0.26      2213
         1.0       0.52      0.87      0.65      2327

    accuracy                           0.53      4540
   macro avg       0.54      0.52      0.46      4540
weighted avg       0.54      0.53      0.46      4540
```

This result shows that the GaussianNB is not a very good model for our shorting trades specifically for Bitcoin.

From the data performance metrics we set, the probable best model we can use is based on a Random Forest. This model had the best F1-score of the models tested and had the second best total returns. However, tuning a few more hyperparameters, I believe the XGBoost could overtake the RF model.

1.2.6 1.6 Conclusions

After all the process of data cleaning, model baseline setting, performance metrics setting, feature engineering, feature extraction, model selection and model comparision, we could conclude that for all the models here tested with the features:

- Exponential Moving Avarege (ema)
- Relative Strength Index (RSI)
- Stochastic Oscillator (stoch)
- Slope (slope)
- Moving Average Convergence Divergence (macd)
- Momemntum (mom)
- Simple Moving Average (sma)

and based on these performance metrics:

- Precision
- Recall
- F1 score
- Accuracy
- Total returns

the best overall model is an application of a Random Forest algorithm. However, the hyperparameter tuning of the XGBoost wasn't ideal. With a few tweaks, it is possible that it outperforms the RF in future results. A more thorough analysis of these hyperparameters could be beneficial before applying these models.

Also, a better primary model, based on a meta-labelling technique, could be built to further reduce the recall of the whole model. This process would yield worst total returns specially for bullish or bearish markets, but with a general application in mind, this approach would lead to a higher recall rate and better overall performance.

[ ]:

```
```