Follow the smart money!

IBM Data Science Capstone Project
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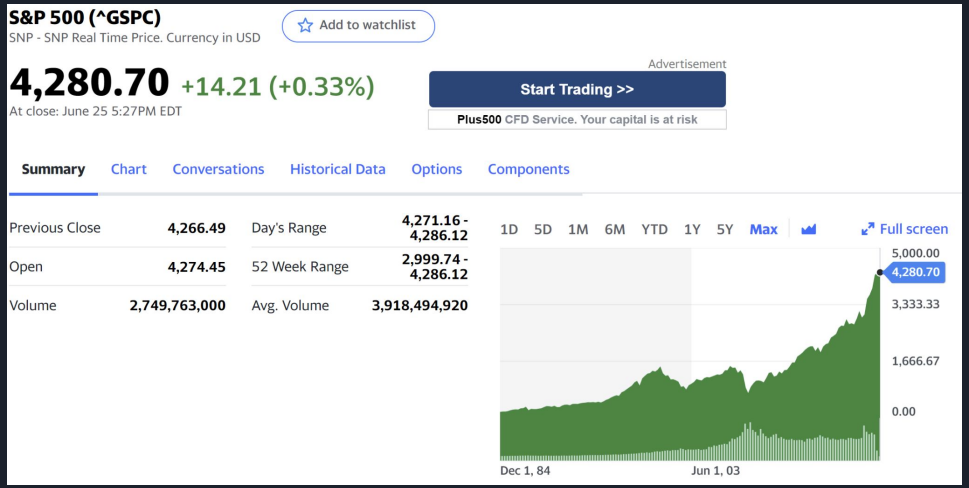
June 2021

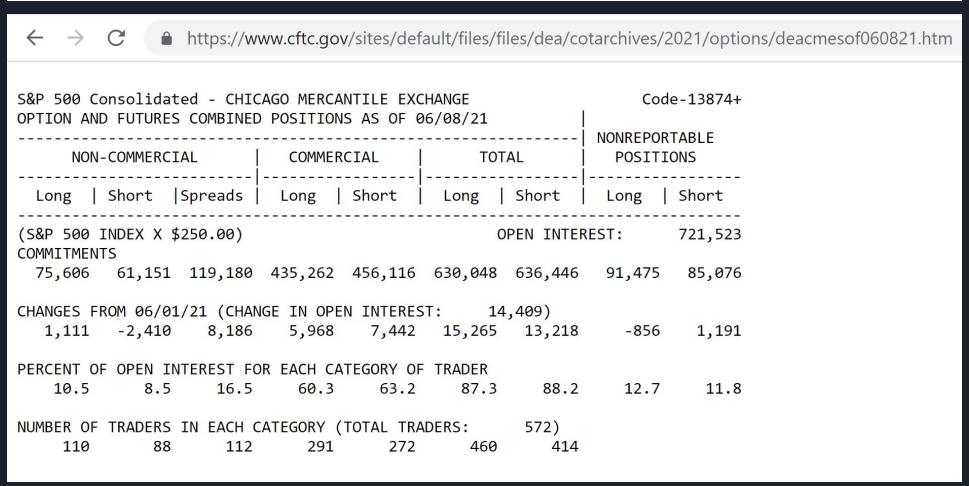
Use Case

- For many, investing in the stock market is a coin flip - *“will the market go up or down this week?”*
- Institutional investors (“smart money”) are the big hedge funds and investment banks who are able to move markets considerably.
  - Rely heavily on fundamental analysis (macro-economic landscape, political climate etc.)
  - Long-term horizon for trades (months/years)
- Retail investors (“dumb money”) are small players who are often on the losing side of a trade
  - Rely heavily on technical analysis (short term indicators, chart patterns etc.)
  - Short term horizon for trades (hours/days)
- Can we predict future stock market returns by analysing investor positioning alone?

Data Set

- S&P 500 data
  - Data: Closing prices every Tuesday from June 2010 to June 2021
  - Source: Yahoo Finance
  - Format: pandas dataframe
- Commitment of traders reports
  - Data: Long/Short Commitments for S&P 500 from June 2010 to June 2021.
  - Reports get released every Tuesday (most of the time!)
  - Source: Commodity Futures Trading Commission (CFTC) website
  - Format: static html (python web-scraping)





Data Quality Assessment

- There were some public holidays (e.g. Christmas, 4th July) on Tuesday in the USA which meant S&P 500 prices came back as *null*.
- Commitment of traders reports would also be preponed on these weeks.
- To correct for this, S&P 500 prices on the previous days were manually inserted into the dataframe. I.e. If 4th of a July was a Tuesday, the Monday 3rd of July closing price would be considered instead
    - This does not significantly affect the integrity of the data since we are considering weekly, not daily returns!
- Commitment of traders reports were also manually inputted on these exception dates.

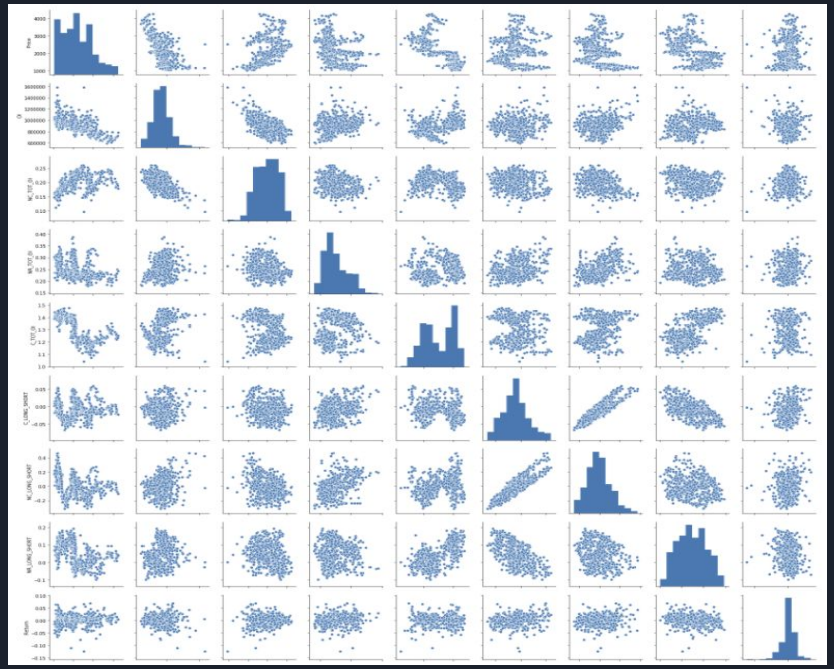
```
for date in dates:
    date_str = date.strftime('%Y/%m/%d')
    price = 0
    try:
        price=sandpclosing[date]
    except:
        print('Price Exception for '+date_str)
    url = "https://www.cftc.gov/sites/default/files/files/dea/c
    commitments = [0,0,0,0,0,0,0,0,0,0]
    try:
        page = urlopen(url)
    except:
        print('URL Exception for '+date_str)
    else:
        html = page.read().decode("utf-8")
```

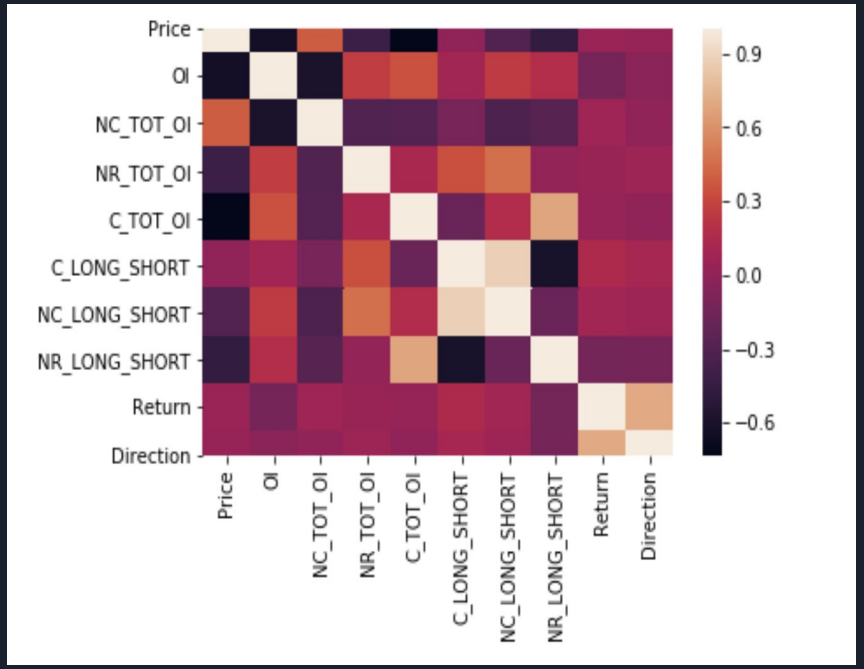
Feature Engineering

- Instead of analysing long and short positioning separately, we can engineer features for the long-to-short ratio for each investor class
- We create similar features representing how much of the open interest is accounted for by each investor class.
- For outputs, we are interested in weekly returns, along with the direction of that return

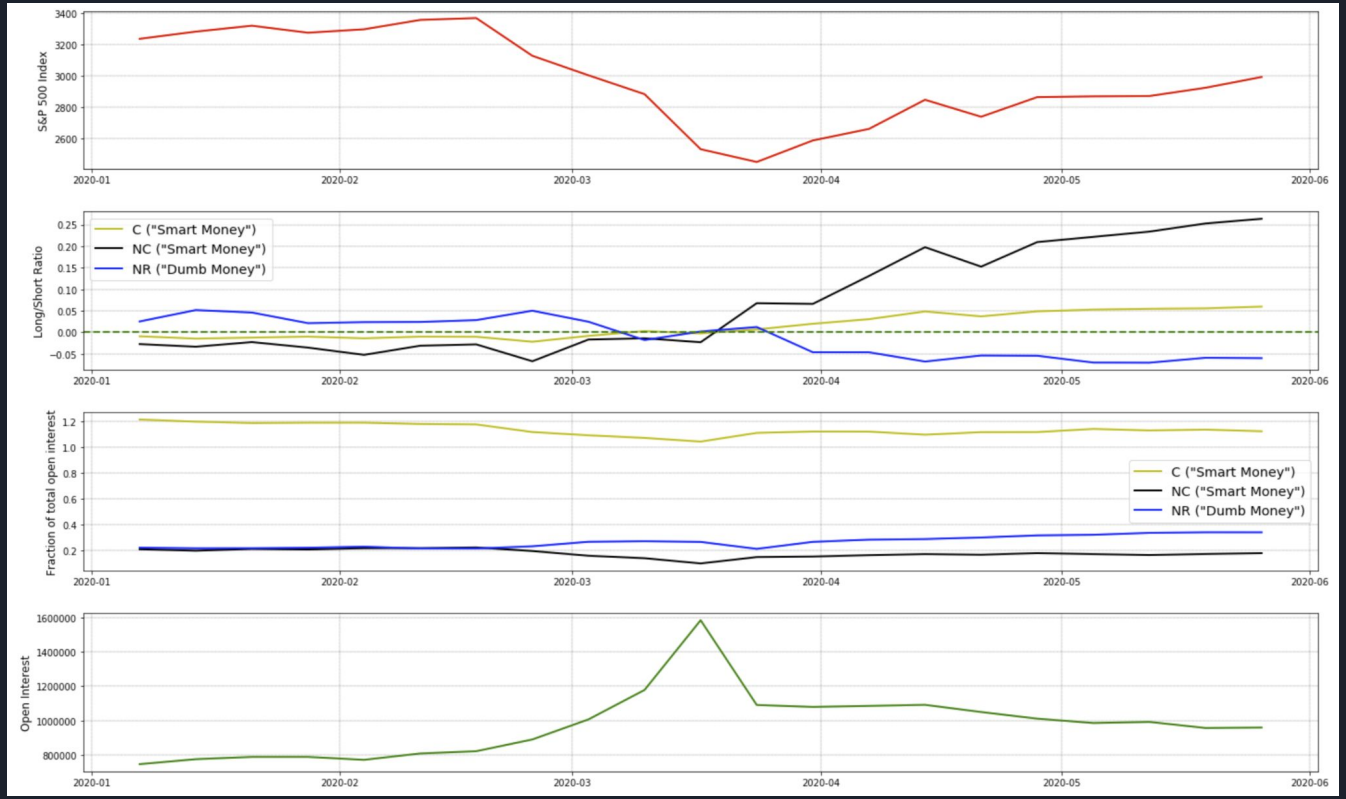
```
# - - - - - - - - - - - - - - - - - - - - - -
# DATA CLEANSING AND FEATURE ENGINEERING
# -  - - - - - - - - - - - - - - - - -  - - -

# remove unneeded columns
df.drop(columns=['NC_SPREAD','TOT_LONG','TOT_SHORT'],inplace=True)

# calculate relevant feature ratios for NC, NR, C , and remove unneeded columns
df['NC_TOT_OI'] = (df['NC_LONG']+df['NC_SHORT'])/df['OI']
df['NR_TOT_OI'] = (df['NR_LONG']+df['NR_SHORT'])/df['OI']
df['C_TOT_OI'] = (df['C_LONG']+df['C_SHORT'])/df['OI']
df['C_LONG_SHORT'] = (df['C_LONG']-df['C_SHORT'])/(df['C_LONG']+df['C_SHORT'])
df['NC_LONG_SHORT'] = (df['NC_LONG']-df['NC_SHORT'])/(df['NC_LONG']+df['NC_SHORT'])
df['NR_LONG_SHORT'] = (df['NR_LONG']-df['NR_SHORT'])/(df['NR_LONG']+df['NR_SHORT'])
df.drop(columns=['NC_SHORT','NC_LONG','NR_LONG','NR_SHORT','C_LONG','C_SHORT'],inplace=True)

# calculate weekly return as dependent variable
df['Return'] = df['Price'].pct_change()
df['Return'].iloc[0] = 0

# calculate direction of return (1 for up, 0 for down) as dependent variable
df['Direction'] = [1 if i>=0 else 0 for i in df['Return']]
```

Data Exploration





Data Visualization - COVID Crash



Data Normalization

- Due to the skew and varying magnitudes in some of the distributions seen through data exploration, features and output were normalized
- The number of outliers in the dataset is minimal, so we expect min-max normalization to yield good results.

```
# - - - - - - - - - - -
# FEATURE SCALING
# - - - - - - - - - - -

# split data into X (features) and Y (output)
X = df[['OI','NC_TOT_OI','NR_TOT_OI','C_TOT_OI','NC_LONG_SHORT','NR_LONG_SHORT','C_LONG_SHORT']]
Y = df['Return']

# normalize X data
X_normalizer = MinMaxScaler().fit(X)
X_scaled = X_normalizer.transform(X)

# normalize Y data
Y_normalizer = MinMaxScaler().fit(Y.values.reshape(-1,1))
Y_scaled = Y_normalizer.transform(Y.values.reshape(-1,1))
```

Predicting Return Direction using XGBoost

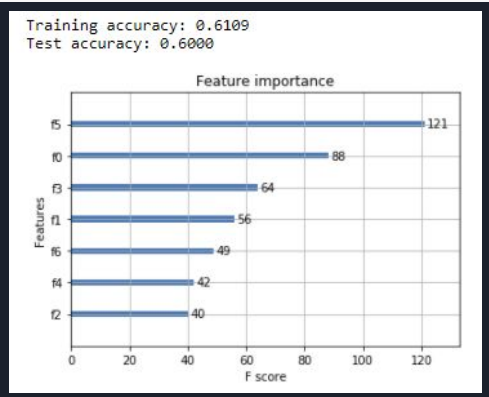
- Predict direction of this week's return using gradient boosted trees (XGBoost algorithm)
- Model justification:
  - Gradient boosted trees have the benefit of starting with a poor model and iterating multiple times.
  - XGBoost is a specific implementation which is designed to be more performant and less prone to overfitting (accuracy high for train dataset, but low for test dataset).
  - One viable alternative (there are many!) considered was a support vector machine (SVM), however it heavily relies on the correct choice of kernel (e.g. linear, RBF). Choice of kernel is not intuitive for this dataset.
- Model performance indicator:
  - Accuracy (percentage of correct "up" or "down" weeks)
  - Justification: we simply want to know if the model guesses the right direction, we are not necessarily concerned with true positives vs false positives, which would be captured by other metrics such as F1 score.

Predicting Return Direction using XGBoost

- XGBoost relies on several hyperparameters, of which 3 are tuned using *GridSearchCV* provided by scikit-learn. The cross validation splits are determined using *ShuffleSplit* which randomly partitions the train data into train and validation sets.
- The optimal XGBoost classifier is then used to predict the test data. Note the test data is arbitrarily chosen as April 2019 until June 2021.
- Training and test accuracy are around 60% - much better than a coin flip!
  - Similar accuracy values suggest model is not overfit
- Feature importance suggests the open interest (*'OI'*) and Commercial long-short ratio (*'C_LONG_SHORT'*) are the two most important features in determining the direction of return.

```
params = {
    "learning_rate" : [0.1, 0.2, 0.3],
    "max_depth" : [3, 5, 7],
    "min_child_weight" : [1, 3, 5]
}

cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)

clf = xgboost.XGBClassifier(use_label_encoder=False, objective = 'binary:logistic',eval_metric='error')
grid_search = GridSearchCV(clf, param_grid=params, scoring='accuracy', cv=cv)
grid_search.fit(X_train, Y_train)

clf = grid_search.best_estimator_
score = cross_val_score(clf, X_train, Y_train, cv=cv)

y_pred = clf.predict(X_test)
print('Training accuracy: {0:0.4f}'. format(score.mean()))
print('Test accuracy: {0:0.4f}'. format(accuracy_score(Y_test, y_pred)))

xgboost.plot_importance(clf)
plt.figure(figsize = (16, 12))
plt.show()
```

```
Training accuracy: 0.6109
Test accuracy: 0.6000
```



Predicting Future Return using LSTM

- Long Short Term Memory (LSTM) is an artificial recurrent neural network (RNN)
- Model justification:
  - Stock markets often exhibit similar patterns over time!
  - LSTM is the most appropriate RNN for time-series analysis as it can learn from past data to inform future outputs. I.e. we can analyze commitments and price patterns from previous weeks to predict future returns.
- Model performance indicator:
  - Mean squared error (MSE) and accuracy (in terms of direction) of future returns
  - Justification: We use MSE because it assigns a higher weight to larger magnitude errors. In contrast, a metric like Mean absolute error (MAE) would use linear weighting, which means it treats a difference of 5% and 10% equally. We also assess accuracy (of only return sign, not magnitude) to compare against XGBoost.

Predicting Future Return using LSTM

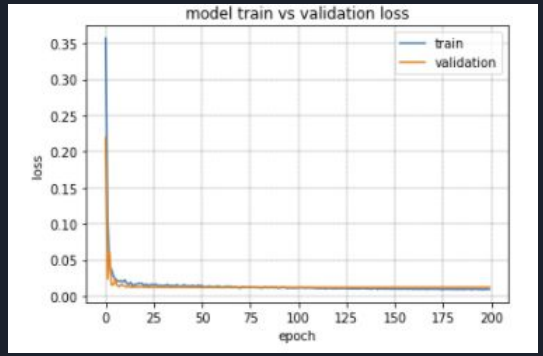
- Data is first split up into test and train sets. The training set covers June 2010 to April 2019, and test set covers April 2019 until June 2021.
- We are basing next week's return off 5 previous week's data.
- The LSTM is initialized using 1 input layer, 2 hidden layers, and 3 dropout layers (helps to minimize overfitting). Finally we have one output neuron representing the return.
- The optimizer and learning rate was chosen after trial and error
- Model fitting uses 20% validation split and we set *shuffle=False* since we need to maintain ordering of our data.

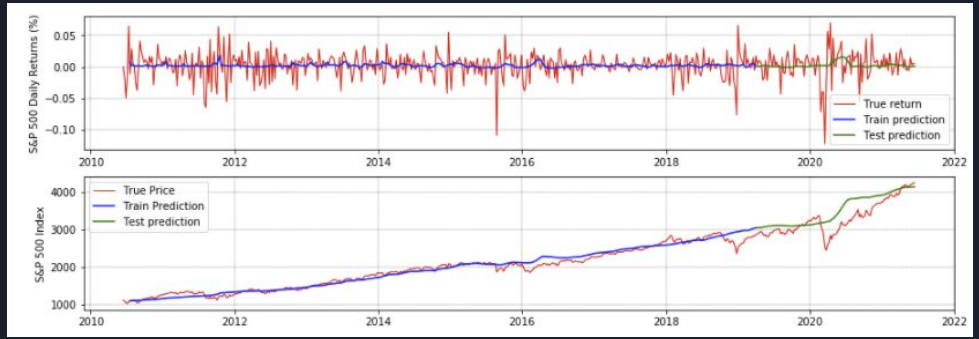
```
# - - - - - - - - - - - - - - - - - - - -
# SPLIT DATA INTO TEST/TRAIN FOR LSTM
# - - - - - - - - - - - - - - - - - - - -

# use n_past values to determine next week's return
n_future = 1
n_past = 5

X_train, Y_train, X_test, Y_test = [],[],[],[]
for i in range(n_past, len(X_scaled)-n_future+1):
    if i < test_start:
        X_train.append(X_scaled[i-n_past:i,:])
        Y_train.append(Y_scaled[i+n_future-1:i+n_future])
    else:
        X_test.append(X_scaled[i-n_past:i,:])
        Y_test.append(Y_scaled[i+n_future-1:i+n_future])

X_train, Y_train, X_test, Y_test = np.array(X_train), np.array(Y_train), np.array(X_test), np.array(Y_test)
```

```
# - - - - - - - - - - - - - - - - -
# CREATE LSTM
# - - - - - - - - - - - - - - - - -

np.random.seed(1234)
tf.random.set_seed(1234)
model = Sequential()
model.add(LSTM(64, activation='relu', input_shape=(X_train.shape[1],X_train.shape[2]), return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(32, activation='relu', return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(16, activation='relu', return_sequences=False))
model.add(Dropout(0.2))
model.add(Dense(1))

model.compile(tf.keras.optimizers.Adam(learning_rate=5e-3), loss='mse')
model.summary()

history = model.fit(X_train,Y_train,validation_split=0.2,epochs=200,batch_size=64,verbose=1,shuffle=False)
```

Predicting Future Return using LSTM

- Training performance:
  - MSE: 0.0003
  - Accuracy: 60%
- Test performance:
  - MSE: 0.0006
  - Accuracy: 67%
- Train and validation loss converge to similar values - suggests minimal overfitting.
- Predicted returns are smoothed relative to true returns since we are considering 6 weeks of past data.
- This also results in a price curve which looks similar to a moving average, however much more useful since it reflects investor sentiment rather than just price.

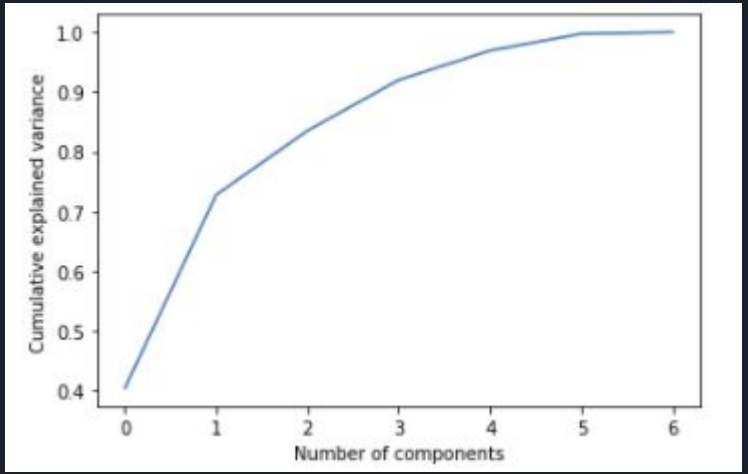




Model Iteration - PCA

- We shall use Principal Component Analysis (PCA) to extract the most important features which best determine return.
- According to PCA analysis, 4 features describe 92% of the cumulative variance.
- This suggests we can reduce our features from 7 to 4.

```
# - - - - - - - - - - - -
# PCA COMPONENT ANALYSIS
# - - - - - - - - - - - -
pca = PCA(n_components=7)
pca.fit(X_scaled)

plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('Number of components')
plt.ylabel('Cumulative explained variance')
```

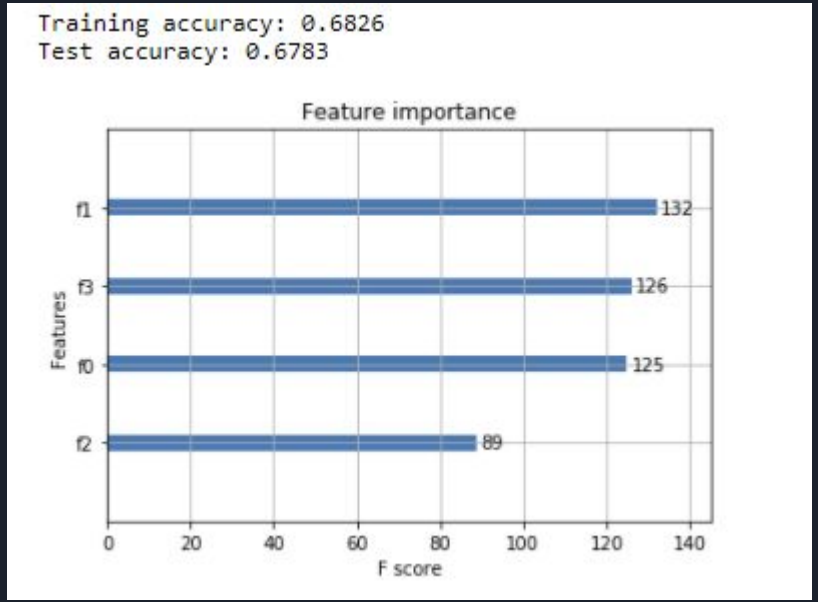


Model Iteration - Effect of PCA on XGBoost

- Training accuracy increased from 61% to 68%
- Test accuracy increased from 60% to 67%
- We can also see relative feature importance is most even compared to pre-PCA where open interest dominated.

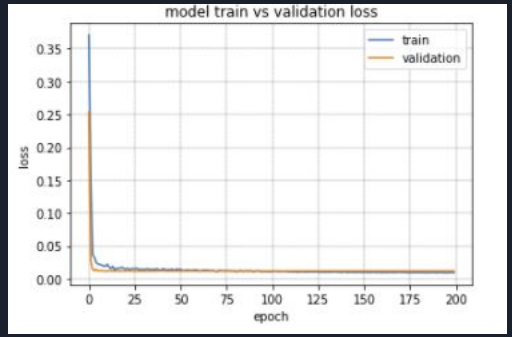
```
pca = PCA(n_components=4)
X_scaled = pca.fit_transform(X_scaled)
X_scaled = MinMaxScaler().fit_transform(X_scaled)
```

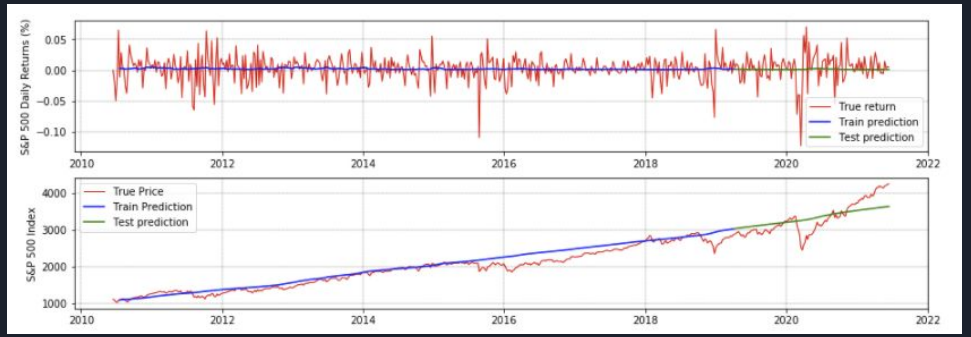
```
Training accuracy: 0.6826
Test accuracy: 0.6783
```



Model Iteration - Effect of PCA on LSTM

- Training performance:
  - MSE: 0.0004 (increased from 0.0003)
  - Accuracy: 62% (increased from 60%)
- Test performance:
  - MSE: 0.0006 (no change)
  - Accuracy: 66% (decreased from 67%)
- Effect of PCA on performance metrics is muted, with minor improvements in accuracy, but slightly increased errors for training.
- The predicted price curve attempts to make a line of best fit through the true prices, but as such is less responsive to short term volatility.





Conclusion & Future Work

- We CAN predict stock market returns using investor positioning!
- Using XGBoost, we were at least 60% and as much as 68% accurate in predicting direction of a week's returns based on that week's commitments.
- Using LSTM, we were able to achieve similar accuracy, but more importantly infer long term trends in price based purely off investor sentiment.
- Limitations:
  - Investor sentiment (particularly "smart money") is quite slow to change - they remain invested in a particular position for months/years.
  - Hence LSTM was not great at predicting short term price fluctuation, particularly when we saw large price drops.
  - Relatively small dataset (575 records)
- Future Work:
  - Incorporate technical indicators (e.g. moving average, RSI, MACD) into gain an insight into short term movements
  - Incorporate other data sources such as news articles, and social media information to better understand sentiment.