Abstract

In view of today's global economy, countries around the world are getting more connected and linked to each other via trade, technically known as import and export activities. To allow a monetary transaction to take place during a trading process in a systematic and coherent manner, exchange rate plays a prominent role. However, due to the uncertainty and volatility in the world's economy, the participants of such trading activities are vulnerable and exposed to risk. Therefore, the ability to accurately forecast the exchange rate offers a solution to mitigate this risk. In this project, we attempt to forecast the exchange rate for US Dollar expressed in terms of the British pound (GBP), the Euro (EUR), and the Japanese Yen (JPY) through sign prediction and trading strategy backtesting. The exchange rate forecasting is conducted by a number of machine learning techniques. The backtesting results of our trading strategy suggest that in this research, Random Forest approach is a more suitable forecasting method to predict the exchange rate for a short period of time.

1 Introduction

The foreign exchange market is the largest and most liquid financial market in the world. In 2016, the trading in foreign exchange markets averaged $5.09 trillion per day. Foreign exchange trading can influence the purchase of foreign goods and services and investment abroad on the individual, corporate, and even government level. Therefore, exchange rate forecasting is very important to examine the returns and risks attached to the international business environment.

Unlike other financial assets, current exchange rate forecasts face its own great challenges. Meese and Rogoff [6] have pointed out that even the simplest random walk model can defeat complex structural econometric models in foreign exchange forecasting. In the past decades, researchers have tried various combinations of economic variables and econometric methods to challenge Meese and Rogoffs finding. There have been some impressive advances, but most results are fragile due to the nonlinearity and noise of the foreign exchange data, which makes foreign exchange forecasting an impossible mission. With the development of the computation and machine learning techniques, we are curious about whether we can address the impossible mission with the help of modern machine learning methods, and whether some certain methods can generate systematically superior forecasting performance.

In essence, machine learning methods are used to produce the best out-of-sample forecast of a quantity/category of interest based on given conditioning information, which justifies the suitability of machine learning methodologies for financial asset return forecasting [3]. Recently, most studies apply machine learning techniques in stock return and bond risk premia prediction, but few literatures analyze the application of machine learning in foreign exchange forecasting. In this project, we will fill in this gap by extensively testing both classical and advanced machine learning techniques.

In the first stage of this project, we try to do sign prediction, which is a binary classification of whether or not the stock price is going to increase. In the second stage, we switch to predict log return values directly. Based on the predicted value of the returns, we formulate some practicable trading strategies and backtest them based on real data to see if some forecasting method can significantly bring economic values.
2 Related Work

Machine learning techniques have been applied for financial asset forecasting and empirical asset pricing decades ago. With the fast development in computation and learning techniques, machine learning methods began to gain more attention in finance research in recent few years. Most of the recent research use machine learning techniques in stock return prediction, bond premia prediction, and housing prices prediction. Specifically, [3] conduct a comparison of machine learning methods for predicting the panel of individual US stock returns. [7] and follows a similar approach as [3] to predict stock returns with neural networks.

However, compared to other financial assets, little literature has been applying machine learning methods for foreign exchange forecasting. [4] investigate the out-of-sample forecasting ability of feed forward and recurrent neural networks based on empirical foreign exchange rate and find that some networks have significant market timing ability and lower out-of-sample prediction error relative to the random walk model. [9] find that, Random Forest performs better than Support Vector machine when training with empirical commodity price data. By the inspiration of current literature in foreign exchange forecasting using ML techniques, we would do a tentative experiment on the forecasting power of ML techniques in foreign exchange assets.

3 Dataset and Features

3.1 Dataset

We use the daily closed price of the foreign exchange rate of three major currency pairs, US Dollar to British pound (GBP/USD), US Dollar to Euro (USD/EUR), and US Dollar to Japanese Yen (USD/JPY) from January 2001 to December 2018. Our data source is from Bloomberg Terminal. Figure 1 shows the main trend of the foreign exchange rate of the three currency pairs.

For the classical time-series models, the models are only fed with the exchange rate changing history. This is based on our assumption that it might be possible to predict the exchange rate by looking at the previous pattern only. For other models, we incorporate more macro-economic and financial features including the S&P 500 index, the S&P 100 index, the Nasdaq index, the Dow Jones Industrial Average, the rate of change in consumer price index, the federal funds, the NBER based recession indicator and the federal debt. The economic and financial data above are obtained from Center for Research in Security Prices.

We split the data and features to training, validation and test set by the ratio of 0.8:0.1:0.1.

3.2 Features

Feature Selection is one of the core concepts which hugely impacts the performance of our models.

In our initial design of the sign prediction experiment, we fed seven features into the model, including the log return of the current day, the log return of the last day, and simple moving averages of the log return of today (the past 5, 10, 20, 60, and 120 days). During the training process, we found the seven features only were not sufficient to provide enough predicting power for our three currency pairs, so we extensively constructed and tested more engineered features out of our exchange rate data to assist our forecasting and avoid under-fitting. As a result, we figured out some empirically helpful features, such as the logarithm of the closing prices and its moving averages to our model, and we ended up accumulating 15 features to our feature library, which additionally includes the log of the actual exchange rate value, its square, its cube, and its simple moving averages (the past 5, 10, 20, 60, and 220 days).

For the trading strategy backtesting part, we directly
forecast the values of the log returns of each currency pair. In an attempt to extract more information from the economic environment and financial markets, we also considered some economic and financial factors into our forecasting problem and ended up incorporating several US market based economic and financial factors to our feature library. Detailed description of our economic and financial features is in Section 3.1.

4 Methods

We extensively tested different kinds of machine learning techniques in the application of foreign exchange forecasting. The machine learning techniques we applied includes Random Forest, Support Vector Machine, Multi-layer Perceptron, Lasso, and Ridge. We use the validation set to select our models and we use the test set for our backtest (described below).

4.1 Random Forest

Random Forest is a method that evolves from decision trees [5]. It is capable of both classification and regression. It uses multiple decision trees and bagging to do prediction. The basic idea the following. First, for each decision tree, we acquire a group of sample from the original data with replacement (bagging). Second, we get the result from all decision trees and take the majority (classification) or average (regression). In the random forest model we use, the number of trees in the forest is 1000 and the maximum depth of each tree is 100.

4.2 Support Vector Machine

The basic idea of the SVM is to find a maximum margin that separates a training set into the positive and negative classes, based on a discriminant function that maximizes the geometric margin. In the paper of [1], they focus on employing SVM for USD/EUR exchange prediction using the Mackey-Glass dataset and yield an range of appropriate parameters for the SVM.

4.3 Multi-layer Perceptron

Multilayer perceptions is a type of neural networks, which is most commonly used in the literature of artificial intelligence. In 2011, [2] introduced a time-delayed multilayer perceptron neural network with gold price as external factor to predict the exchange rate of EUR/USD, GBP/USD, and USD/JPY. In general, a multilayer perceptron with two hidden layers can be illustrated as

$$ o_k = f\left(\sum_j w_{kj}g\left(\sum_i w_{ij}x_i\right)\right) $$

(1)

4.4 Lasso & Ridge

Ridge and Lasso regression are some of the simple techniques to reduce model complexity and prevent over-fitting which may result from simple linear regression.

Ridge Regression: In ridge regression, the cost function is altered by adding a penalty equivalent to square of the magnitude of the coefficients.

$$ \sum_{i=1}^{M} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{M} (y_i - \sum_{j=0}^{p} w_j x_{ij})^2 + \lambda \sum_{j=0}^{p} w_j^2 $$

(2)

Lasso Regression: The cost function for Lasso (least absolute shrinkage and selection operator) regression can be written as

$$ \sum_{i=1}^{M} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{M} (y_i - \sum_{j=0}^{p} w_j x_{ij})^2 + \lambda \sum_{j=0}^{p} |w_j| $$

(3)

5 Experiments

5.1 Sign Prediction (classification)

In the finance world, sign prediction can yield important information for financial decisions such as market timing. We will compare out-of-sample forecasting ability between these models as well as these models’ losses on some metrics. These metrics include Normalized Mean Square Error (NMSE), Mean Absolute Error (MAE), Directional Symmetry (DS), Correct Up trend (CU) and Correct Down trend (CD).

For sign prediction, We plan to use several machine learning techniques including logistic regression, Lasso
and Ridge, SVM with kernel $[8]$, Random Forest, Neural Networks such as CNN.

5.2 Profit Simulation Experiment (regression)

We also designed an experiment to see if the random forest model can help us make money. We are using the actual predicted exchange rate return values instead of sign in this experiment. We assume that we have 100 dollars. All the exchange rates here are USD/other currencies. Our test set for EUR starts are March 3rd, 2017 and our tests set for GBP and JPY start at March 7th, 2017. They all end at November 30th, 2018. When we are doing this experiment, we assume our start date to be March 3rd, 2017 and for the first couple days we only consider EUR. The way we do this experiment is the following.

First, for one day, we collect all the predicted return values on our exchange rate. The predicted return at time $t$ is:

$$\text{return}_t = \frac{\text{ExchangeRate}_{t+1}}{\text{ExchangeRate}_t}$$

Second, if all return values are larger than 1, then we do nothing; if there are some return values lower than 1, then we "switch" to the currency that has lowest exchange rate return with USD for one day and "switch" back. For example, if USD/GBP is 1.0, USD/EUR is 1.02, and USD/JPY is 0.95, then we will use our 100$ to "buy" some JPY, and then "buy" USD back at the end of the day, so at the end of the day we will have 105.26 USD (100/0.95). This is because if the return is lower than one, the value of USD is decreasing with respect to the other currency.

During this experiment, we only take into account exchange rates that are available. Different places have different holidays, so at some days not all three exchange rates is available. For example, if for one day, EUR is not available, then we only use the data for JPY and GBP; if for one day, all three exchange rates are not available, we skip this day.

6 Results and Discussion

6.1 Sign Prediction

Table 1 shows the result of our preliminary experiments with different machine learning models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Acc.</th>
<th>NMSE</th>
<th>MAE</th>
<th>DS</th>
<th>CU</th>
<th>CD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lasso</td>
<td>0.52</td>
<td>1.90</td>
<td>0.95</td>
<td>0.52</td>
<td>0.47</td>
<td>0.58</td>
</tr>
<tr>
<td>Ridge</td>
<td>0.55</td>
<td>1.81</td>
<td>0.91</td>
<td>0.55</td>
<td>0.58</td>
<td>0.51</td>
</tr>
<tr>
<td>Logistic</td>
<td>0.51</td>
<td>1.97</td>
<td>0.98</td>
<td>0.51</td>
<td>0.45</td>
<td>0.57</td>
</tr>
<tr>
<td>SVM $rbf$</td>
<td>0.51</td>
<td>1.95</td>
<td>0.97</td>
<td>0.51</td>
<td>0.57</td>
<td>0.52</td>
</tr>
<tr>
<td>Random Forest</td>
<td>0.53</td>
<td>2.03</td>
<td>1.02</td>
<td>0.49</td>
<td>0.44</td>
<td>0.49</td>
</tr>
<tr>
<td>MLP</td>
<td>0.52</td>
<td>1.92</td>
<td>0.96</td>
<td>0.52</td>
<td>0.54</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Table 1: Comparison in predicting the sign of exchange rate among different machine learning techniques

All these values were the average values of the 3 currencies (British pound (GBP), the Euro(EUR), and the Japanese Yen (JPY)) with respect to US dollar. As we can see, the accuracy values based on the models are all around 50%. In fact, although the prediction accuracy is not very satisfactory, the result is in accordance with our expectations; currency exchange rate prediction is currently one of the most challenging topics in the field of economy and it is considered almost impossible to many experts. Therefore, aside from attempting to accurately predict the actual sign of return values, we are more interested in testing if our model can help us maximize profit in currency trade within a period of time.

6.2 Trading Strategy Backtesting Experiment

6.2.1 Model Selection

We use the coefficient of determination, $R^2$, of the prediction to measure our model and we averaged the scores for all three exchange rates. According to Scikit-learn, the best possible score is 1.0 and it can be negative and a constant model that always predicts the expected value of $y$, disregarding the input features, would get a $R^2$ score of 0. The definition of $R^2$ is:

$$R^2 = 1 - \frac{u}{v}$$
\[ u = SUM((y_{true} - y_{pred})^2) \quad (6) \]

\[ v = SUM((y_{true} - mean(y_{true}))^2) \quad (7) \]

Table 2 shows the scores for each model. According to this table, we select Random forest as our model.

<table>
<thead>
<tr>
<th></th>
<th>RF</th>
<th>MLP</th>
<th>SVM_rbf</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R^2 )</td>
<td>0.74</td>
<td>-inf</td>
<td>0.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>SVM_poly</th>
<th>Lasso</th>
<th>Ridge</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R^2 )</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Table 2: Coefficient of determination for each model

It is interesting to see that although the Random Forest model performs poorly in the sign prediction experiment, it turns out to be a good model to adopt in the profit simulation experiment. One possible explanation for this is that the RF method, as we can see in Table 1, has a relatively high score in the matrices NMSE and MAE, which measure the difference between the true exchange rate and the value our models predict. Although the RF method cannot make an accurate prediction of the signs of future exchange rate, it will give a predicted value relatively close to the true value each time. Therefore, the RF method is more flexible than other models and less likely to make major mistakes when conducting the profit simulation experiment. We believe the RF model can be used as a good reference while doing profit prediction in a short period of time.

### 6.2.2 Prediction result

Figure 2 shows the results of our RF model for all three exchange rates. The X axis is days (March 3rd, 2017 to November 30th, 2018) and the Y axis is the log of the return of exchange rates. The blue points are the predicted log returns and the green points are the actual log returns. Just by looking at these plots, the results (log return) are not that precise. It is also hard to judge if our models are useful by only looking at this figure. In the world of finance, what we care about is if we can make money. The result of the experiment (next section) is more meaningful.

### 6.2.3 Trading strategy Backtesting Result

Table 3 below shows the final amount of money we have for each different currency combinations. Here if the column is “JPY”, then we only consider JPY for all dates; if the column is “GBP+JPY”, then we are considering GBP and JPY but not EUR for all dates.

<table>
<thead>
<tr>
<th></th>
<th>GBP</th>
<th>JPY</th>
<th>EUR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Final</td>
<td>104.40</td>
<td>104.44</td>
<td>110.5</td>
</tr>
<tr>
<td>GBP+JPY</td>
<td>100.33</td>
<td>109.46</td>
<td>104.88</td>
</tr>
<tr>
<td>GBP+JPY+EUR</td>
<td>Final 101.30</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3: Final cash in the experiment for all cases

Figure 3 shows the variation of our cash. The first one is when taking all three exchange rates into account (JPY, GBP, and EUR). As we can see in this plot, our portfolio value peaks around 112$ at about March 2018, but eventually drops to 101.30$. The starting time is March 3rd, 2017, and the end time is November 30th, 2018. This means that our model works well in trading signal prediction during March 2017 and March 2018, but fails to adjust to the regime change after March 2018 when we take all three exchange rates into account. The second, third, and fourth plot are for only portfolios only considering GBP/USD, USD/JPY, and EUR/USD respectively.
As we can see, different currencies have different experiment results. We can notice that the portfolios trading exclusively in GBP/USD and EUR/USD also experience such plunge of portfolio values after March 2018. We investigated thoroughly about the reasons for the failure of our trading strategy. We found that, Trump’s government started to impose tariffs on steel and aluminum imports from all suppliers since March 2018, which signifies the overturing of the trade war between China and the U.S. We know that the balance of trade between 2 countries influences foreign exchange rate through the its effect on the supply and demand for foreign exchange. Therefore, the declaration of the "trade war" might have changed the regime of the foreign exchange rate dynamics of the three currency pairs we considered. Since our parameters for the trading strategy were predetermined before the testing set, we are not able to adjust the generating of our trading signals, which might have led to a huge loss after the change of the market environment.

Table 4 shows the coefficient of determination, $R^2$, of the prediction for our random forest model. These scores are calculated using the test set.

<table>
<thead>
<tr>
<th></th>
<th>GBP</th>
<th>JPY</th>
<th>EUR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.70</td>
<td>0.74</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Table 4: $R^2$ for all three exchange rates (Random Forest)

7 Conclusion/Future Work

In conclusion, with our models selected above, it is very hard to get high accuracy trying to predict the sign of log exchange rate return (or if the return is larger of smaller than 1). However, the random forest model can help us make money sometimes. In different periods and for different currencies, the model has different performance. The next step will be to further investigate into this issue. We expect to consider more economic and financial market factors to capture the regime changes in foreign exchange markets. Another applicable change in our predicting method is to shorten the forecasting window of our models and retrain the prediction model with a shorter period.

We can also try to adopt recurrent neural networks which work better with information hidden in time series, including LSTM, gated recurrent units, simple recurrent units, etc. Also, expanding our factor library with more diversified economic factors should also generate better prediction power.

8 Contributions

Team members:

Jiequan Zhang: Writing code to run models, plotting, designing and implementing the experiment.

Jiahao Zhang: Data collecting, data preprocessing, models, report setup, poster setup, experiment design

Jialu Sun: Literature Review, Data collecting, Traditional Econometric models

9 Github Link

https://github.com/Jiequannnnnnnnn/CS29_Exchangge_rate

References


