Macroeconomic and Technical-Based Deep Neutral Network Forecast of USDJPY Daily Spot Rate

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CS 230: Deep Learning

Daily USDJPY exchange rates are influenced by a host of factors ranging from macroeconomic trends, expectation of monetary policies and speculative investor action based on past price actions. A deep neural network trained on current and historical information is shown to be able to predict the next-day USDJPY open rate.

Despite being a **complex and nonlinear** problem, the **set of determining factors for USDJPY rate seems to be reasonably finite**; this suggests that a well-trained neural network could be effective in predicting price movements.

Data Processing

Input variables including macroeconomic, financial, trade and monetary policies indicators are used:

- Spot daily rates of other major currencies: EURUSD, GBPUSD, USDCNY, NZDUSD and USDCHF
- Consumer price inflation rates of US and Japan
- Close price of stock indices in US and Japan: S&P 500 Index and Nikkei 225
- Yields of government bonds in US and Japan: US 13 Week Treasury Bill, US Treasury 10 Year Bond, US Treasury 30 Year Bond, Japanese Government 2 Year Bond, Japanese Government 10 Year Bond
- Export and import price indices in US and Japan
- Cross-border trading volumes between US and Japan
- CBOE volatility index (VIX)

These variables dated from 1995-03-31 to 2017-09-11 were extracted manually from FRED, Quandl, Yahoo Finance, Bloomberg and Bureau of Labor Statistics and transformed into daily frequencies. Observations on the first 5800 days, next 1200 days and last 1200 days of the above-mentioned period were placed into the training, dev and test sets (70:15:15) respectively.

Autoregressive factor of 1 is chosen based on time-series analysis. Consistent with Weak Efficient Market Hypothesis ("Markov property")

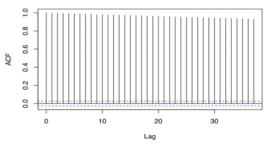

Figure 1: Autocorrelation Function

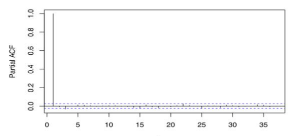

Figure 2 Partial Autocorrelation Function

References

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Model

Deep Neural Network with inclusion of previous day close price was sufficient in providing robust prediction since price contains all past relevant information. Other "memory" models like Recurrent Neural Networks (RNNs), Time-Delay Neural Networks and Long Short-Term Memory (LSTMs) were all found to perform worse during preliminary testing; probably due to inclusion of additional noise.

Mean Squared Error is used as loss function.

$$h_t^{[1]} = ReLu(W_h^{[1]}X_t + b_h^{[1]})$$

$$h_t^{[2]} = ReLu(W_h^{[2]}h_t^{[1]} + b_h^{[2]})$$

$$\hat{y_t} = ReLu(W_y h_t^{[2]} + b_y)$$

Hyperparameter tuning was conducted in 3 phases based on RMSE of dev set., starting first with 20>10>5 configuration with no regularization.

1: Number of Iterations
#Epoch: {100,500,**1000**,2500,5000}
Combinations: 5

2: Size of NN & Regularization
n1 : {**20**,40,80}
n2 : {10,20,40}
n3 : {**5**,10}
dropout_1&2 : {**0**, 0.3,0.7}
Combinations: 162

3: Fine-tune hidden layer 2 & Number of Iterations
#Epoch: {750,1000,1500,2000, 2250}
n2 : {10,20,30,40,50}
Combinations: 20

Results

Test results of tuned model demonstrates low error rate. Test RMSE of 0.235 and test MAE of 0.222 significantly outperforms devRMSE of other models.

- ReLu[20]>ReLu[50]>ReLu[5]
- No dropout regularization
- Epoch=2000
- Loss: MSE
- Adam Optimizer

Model	Train RMSE	Dev RMSE	Test RMSE
Simple linreg on covariates only	5.511	17.10	
Linreg with autoregression	0.671	0.520	
LSTM	0.084	24.35	
NN pre tuning	0.469	0.688	
NN post tuning	**0.237**	**0.163**	**0.235**

Portfolio Simulation

Investment Portfolios were generated using the test set based on 3 differing strategies:

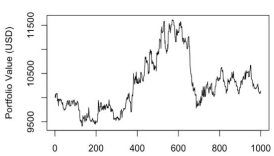

Figure 3: No leverage; No Forecast Margin

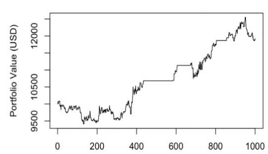

Figure 4: No leverage;
Forecast Margin > Dev_MAE = 0.25

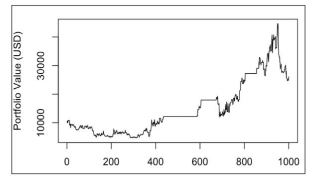

Figure 5: Fixed leverage at 10x;
Forecast Margin > Dev_MAE = 0.25

With 10x leverage and mean absolute error of dev set as margin for investment, **investor would have gained $14,853 on a $10,000 portfolio over 1000 days**. That is an annualized return of 54.2% and Sharpe ratio of 0.834.