Machine Learning: Application of forecasting 3-month interest rate (3MUSD=) and USD FX level

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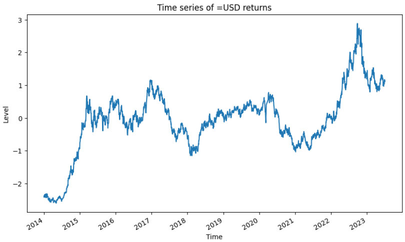
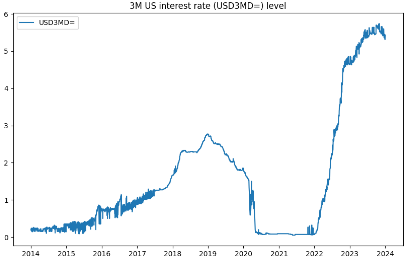
Introduction

Ticker	Description
GBP=	GBP/USD FX pair
EUR=	EURO/US DOLLAR FX SPOT RATE
=USD	USD index
NOK=	US DOLLAR/NORWEGIAN KRONE FX SPOT RATE
JPY=	US DOLLAR/JAPANESE YEN FX SPOT RATE
CHF=	US DOLLAR/SWISS FRANC FX SPOT RATE
AUD=	AUSTRALIAN DOLLAR/US DOLLAR FX SPOT RATE
NZD=	NEW ZEALAND DOLLAR/US DOLLAR FX SPOT RATE
CAD=	US DOLLAR/CANADIAN DOLLAR FX SPOT RATE
SEK=	US DOLLAR/SWEDISH KRONA FX SPOT RATE
GBP3MD=	GBP3MD 3 Month Deposit
EUR3MD=	EUR3MD 3 Month Deposit
USD3MD=	USD3MD 3 Month Deposit
NOK3MD=	NOK3MD 3 Month Deposit
JPY3MD=	JPY3MD 3 Month Deposit
CHF3MD=	CHF3MD 3 Month Deposit
AUD3MD=	AUD3MD 3 Month Deposit
NZD3MD=	NZD3MD 3 Month Deposit
CAD3MD=	CAD3MD 3 Month Deposit
SEK3MD=	SEK3MD 3 Month Deposit

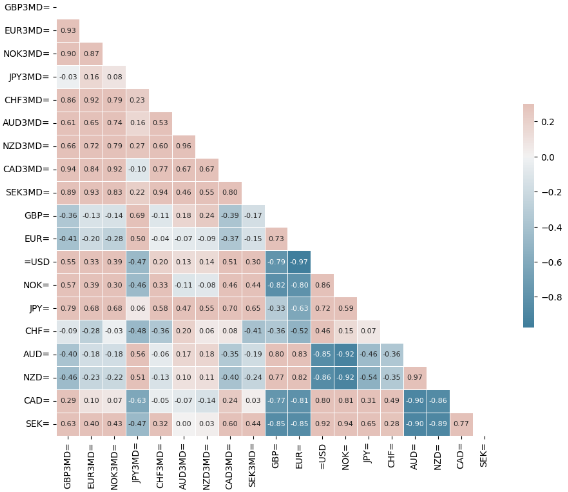
Table: Tickers and their descriptions

Data analysis of the forecasted variables





Correlation structure of assets (Z-Score)



Implementation of MLP and LSTM models on 3M interest rate (USD3MD=)

We implement different ML techniques to capture the behavior of US 3M interest rates and USD index (underlying basket of FX labelled in USD) (*):

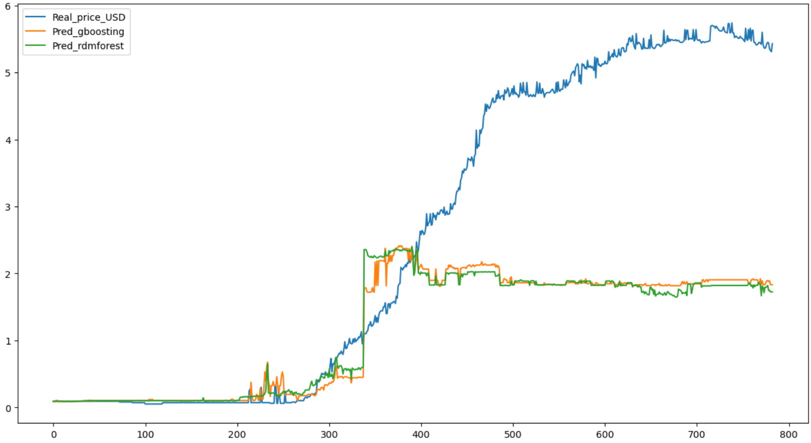
- We use a dataset of daily data capturing 2608 data points. We made sure to eliminate any missing data and applied a z_score to eliminate data above three standard deviation threshold.
- We decompose the dataset into two samples: A training period with the first 1000 observations and a testing set of the remaining observations (1608 observations).
- We implement at first Multiple Layer Perceptron (MLP) and Long-Short Term Memory (LSTM) algorithms. The (1) and (2) drops 25% of the data to preserve the model from overfitting.
- Both models will run on the training dataset ten times (epoch=10) with a batch of sixteen, meaning the model will be updated after sixteen points are processed.

Implementation of MLP and LSTM models on 3M interest rate (USD3MD=)

MLP and LSTM struggle with changes in the underlying data-generating process (*):

- **Divergence in prediction** (*): There is a noticeable divergence between the actual rates and the predicted values, especially apparent after the 200 time-step. Difficulty to model in changin rate regime shifts.
- **Non stationarity**: The interest rate series exhibits non-stationary behavior.
- **Sensitivity to volatility**: The abrupt change in LSTM predictions reflect sensitivity to noise and volatility in the data.

Implementation of SVM, Gradient Boost and Random Forest on 3M interest rate (USD3MD=)



Implementation of SVM, Gradient Boost and Random Forest on 3M interest rate (USD3M=)

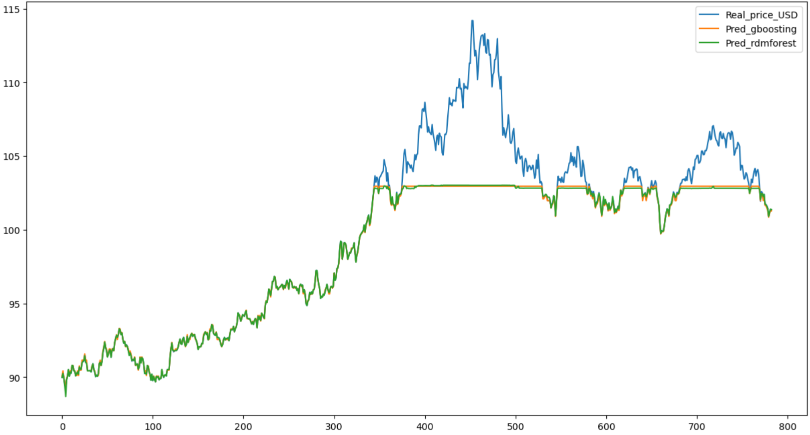
The sharp divergence of all model predictions from the actual interest rate indicates that none of the models could account for a drastic shift in the data (important policy changes by the Federal Reserve) (*):

- At the beginning, all models approximate the actual interest rate relatively closely.
- (*) There is a sharp divergence where the actual interest rate sharply increases while the model predictions do not. This period corresponds to a significant policy shift by the Federal Reserve to raise interest rates a tool to fight inflation.
- After 200 observations, the models starts to diverge significantly and fail to capture the rate dynamics (GBoost and Random Forest as the only models that capture in some way the the upward curvature of interest rate).

Implementation of SVM, Gradient Boost, and Random Forest on USD Index (USD)

Model limitations: None of the models fully capture the USD index movements, discrepancies suggest missing key variables or market sentiment indicators and financial time series like the USD index are hard to predict due to their non-linear and non-stationary nature, and external shocks.

Implementation of SVM, Gradient Boost and Random Forest on USD index (=USD)



Implementation of SVM, Gradient Boost, and Random Forest on USD Index (USD)

- Mixed results (both models show relatively close results overall).
- Random Forest (RF) captures main index shape best.
- RF achieves the best performance in terms of MAE and RMSE.
- RF requires hyperparameter tuning (tree depth, number of estimators) to generalize better.

Implementation of SVM, Gradient Boost, and Random Forest on USD Index (USD)

- **Complex vs. simple models**: Simpler models (SVM) less effective in capturing peaks and troughs. Trade-off between stability (SVM) and responsiveness (MLP, LSTM).
- **Model performance**: RF shows most accurate and stable predictions.
- **Enhancing models**: Incorporating economic indicators may improve model accuracy.

Conclusion

- **MLP & LSTM**: Show promise in predicting financial time series. Perform well in capturing trends and cycles. Struggle with rapid market shifts and volatility. Potential need for broader training data and additional variables.
- **Random Forest & Gradient Boosting**: Often perform well but prone to overfitting. Require careful tuning and regularization to generalize effectively.
- **SVM**: Produces smoother prediction curves. Better for long-term trends, less effective for short-term strategies.

Conclusion

- **Model trade-offs**: Balance between model complexity and prediction stability.
- **Overfitting concerns**: Ensemble methods (RF, Gradient Boosting) need regularization.
- **Prediction accuracy**: Additional economic indicators could enhance model performance.