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

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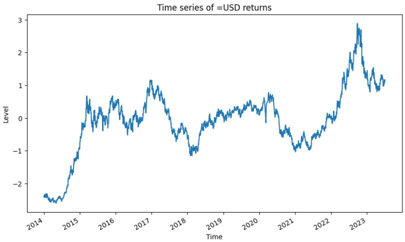
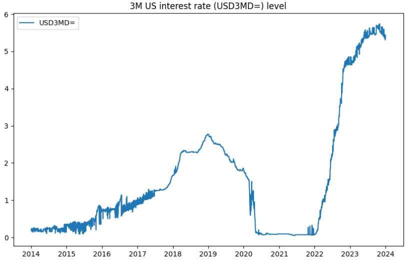
Introduction

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

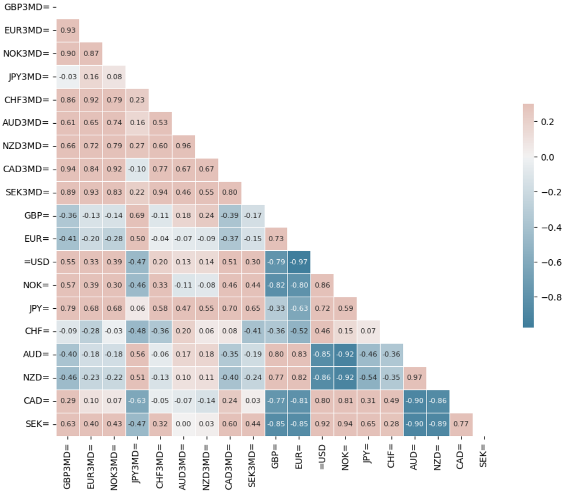
Table: Tickers and their descriptions

Data analysis of the forecasted variables





Correlation structure of assets (Z-Score)

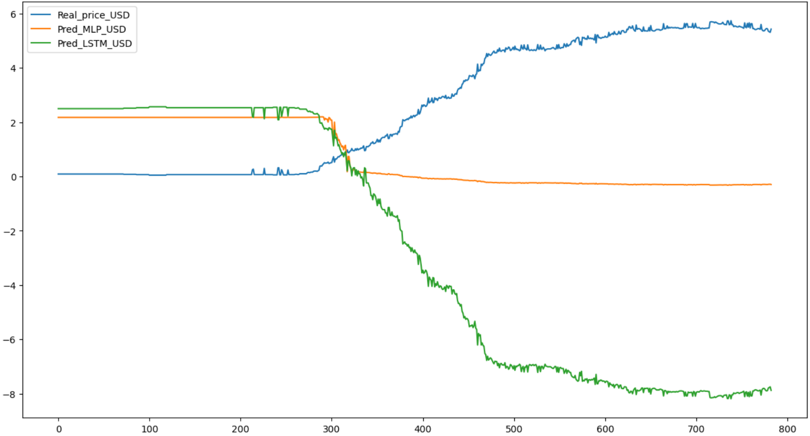


Implementation of MLP and LSTM models on 3M interest rate (USD3MD=)

We implement MLP and LSTM to capture the behavior of US 3M interest rates and USD index (underlying basket of FX labelled in USD) and enhance the forecasting with other alternative machine learning techniques to assess the forecasting accuracy and its predictive power (*):

- 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.

Machine learning analysis: MLP and LSTM on 3M interest rate (USD3MD=)

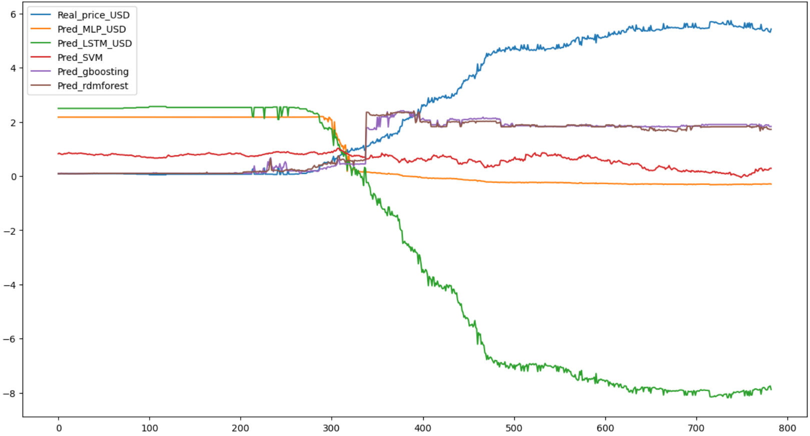


Implementation of MLP and LSTM models on 3M interest rate (USD3MD=)

The forecasting performance of the MLP and LSTM models on the 3-Month US interest rate suggests that while the models might capture the historical pattern well, they struggle with changes in the underlying data-generating process. The LSTM, in particular, seems to be vulnerable to certain features or events leading to a significant divergence in its predictions(*):

- **Divergence in prediction** (*): There is a noticeable divergence between the actual rates and the predicted values, especially apparent after the 200 time-step mark. This suggests that the models may have been well-tuned for a certain period or type of data but failed to generalize to new patterns or shifts in the interest rate trends.
- **Non stationarity**: The interest rate series often exhibits non-stationary behavior, with shifts and trends that models need to account for. The evident deviation after a certain point could be due to a structural break in the series that the models failed to anticipate.
- **Sensitivity to volatility**: The abrupt change in LSTM predictions could also reflect sensitivity to noise and volatility in the data. It's possible that the model overfit to the noise rather than underlying trends.

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

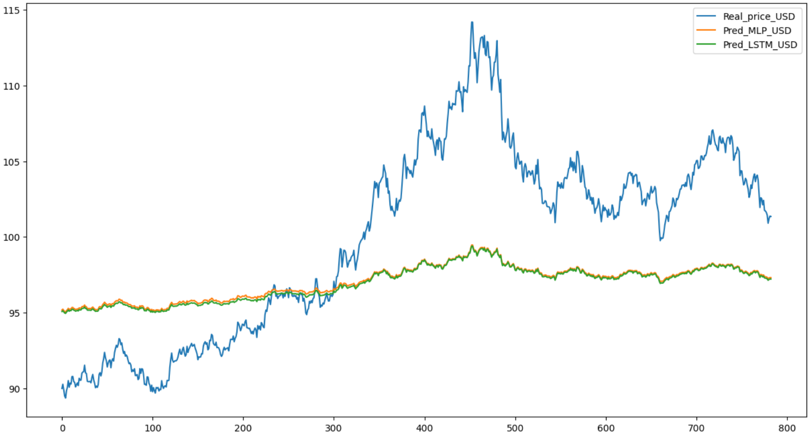


Implementation of SVM, Gradient Boost and Random Forest on USD index (=USD)

The performance of these models reflects common challenges in financial time-series forecasting. The LSTM model's relative outperformance in forecasting suggests that deep learning models, which can leverage sequential data and long-term dependencies, are well-suited for this task. However, 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, potentially a market shock or an economic event such as a policy change by the Federal Reserve (*):

- At the beginning, all models approximate the actual interest rate relatively closely. This concordance indicates that the models can capture the essence of the time series under stable conditions.
- (*) There is a sharp divergence where the actual interest rate sharply declines 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).

Machine learning analysis: MLP and LSTM

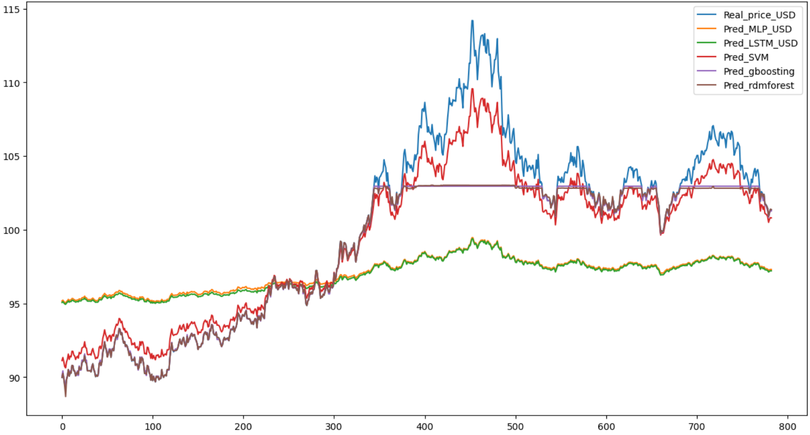


Implementation of SVM, Gradient Boost and Random Forest on USD index (=USD)

Neither model captures the full complexity of the USD index's movements. The models require further tuning, more training data, or additional relevant features that influence the USD Index to enhance predictive accuracy. The **divergence** between model predictions and actual levels might also indicate that key exogenous variables or market sentiment indicators are not being accounted for. Financial time series, like the USD Index, are notoriously difficult to predict due to their non-linear, non-stationary nature, and potential external shocks or events that models cannot anticipate:

- The MLP model produce a consistent but **flat prediction**, staying around a narrow value range and failing to track the volatility and fluctuations of the actual USD Index levels. Its relatively flat prediction line suggests that while the MLP may be capturing the average level of the index, it lacks responsiveness to market dynamics, which are crucial in financial forecasting.
- The LSTM model's predictions are more dynamic and show some responsiveness to changes in the actual index levels. This is aligned with the expected capabilities of LSTMs to capture sequential dependencies and time-based patterns. However, the LSTM also appears to underestimate the peaks and overestimate the troughs, indicative of a lagging characteristic in the model, possibly due to the historical window of data used to make the predictions.

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



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

In this analysis of the USD index forecasts under different ML techniques, we find that the LSTM and MLP models track the actual index quite well, showing their strength in handling complex patterns. The SVM model provides a smoother, less volatile forecast, which might miss some rapid changes in the market. The Gradient Boosting and Random Forest models show mixed results, with the Random Forest capturing the main shape of the USD index level. RF offers the best model on paper for this specific exercise (*):

- The simpler models (SVM) fail to capture the peaks and troughs as effectively as the more complex models (MLP and LSTM), suggesting a **trade-off** between stability and responsiveness.
- (*) RF exhibits the best performance in terms of MAE and RMSE, which suggests that this ensemble method has achieved the most accurate and stable predictions among the tested models. The Random Forest's sensitivity to noise might require tuning hyperparameters, like tree depth and the number of estimators, to generalize better.
- Incorporating additional features, such as **economic indicators**, might enhance the models' understanding of factors influencing the USD index levels.

Conclusion

- MLP and LSTM show promise in tracking and predicting financial time series such as US 3-Month interest rates and USD index levels. However, their **performance varies widely**. In some instances, models like the LSTM can closely follow the actual data, capturing trends and cyclic movements well. Yet, they may struggle with rapid market shifts or more volatile periods, highlighting a potential need for models to be trained on a wider range of data or for the inclusion of additional variables that can inform on sudden market changes.
- The Random Forest and Gradient Boosting models often perform well, but they can be **prone to overfitting**, as indicated by their sensitivity to the noise in the data. This suggests that while powerful, these methods require careful tuning and regularization to ensure that they generalize effectively to unseen data.
- SVM models appear to take a more generalized approach, resulting in **smoother prediction curves** that might miss some of the finer details in the data. This could be advantageous for capturing long-term trends but less so for short-term trading strategies.