Modeling Movement for Time Series Forecasting Neural Networks

Introduction

Abstract

This paper explores N-Beats, N-HiTS, and TFT models in tandem for time series forecasting, utilizing metrics like Proxy Correlation and Profit & Loss to quantify their respective performances. Having eight different assets on which the architectures were tested – Eurodollar Future CME, British Pound Futures, Vexanium-USD, Oil, Coffee, Gold, EURUSD, and VIX – the findings showcase solid underpinnings. Seeking to improve upon the outcomes from the old architecture of N-Beats, the team noted the relative strengths and weaknesses of each new model depending on the metric at hand – suggesting a more nuanced rather than general understanding of what would be the "better" architecture to use.

The Original Model (N-BEATS)

N-Beats is a neural network architecture for time series forecasting that is highly interpretable due to its design, which emphasizes learning additive components representing different aspects of the time series.

N-BEATS Interpretability Component: $\tilde{y}s, l = \sum i = 0^p \theta_{s,l,i} t^i.$

N-BEATS Seasonality Component: $\tilde{y}s, l = \sum i = 0^{\lfloor \frac{H}{2}-1 \rfloor} \theta_{s,l,i} \cos(2\pi i t) + \theta_{s,l,i+\lfloor \frac{H}{2} \rfloor} \sin(2\pi i t).$

New Model (TFT):

The architecture includes an attention mechanisms allow the model to learn the importance of different input features and time steps, while the gating layers facilitate the fusion of information from different temporal scales.

Interpretable multi-head attention: $\text{InterpretableMultiHead}(Q, K, V) = \frac{1}{H} \sum_{h=1}^{m_H} \text{Attention}(QW_Q^{(h)}, KW_K^{(h)}, VW_V),$

$$y_{t+h} = f(\mathbf{x}_t) = \mathcal{G}(\mathcal{A}(\mathcal{T}(\mathcal{P}(\mathbf{x}_t; \theta_P); \theta_T); \theta_A); \theta_G),$$

New Model (N-HiTS):

N-HiTS incorporates hierarchical interpolation which enables the model to assemble its predictions sequentially, emphasizing components with different frequencies and scales as it decomposes the input signal and synthesizes the forecast.

**N-HiTS Multirate Signal Sampling:** $y^{(p)} = \text{MaxPool}(y_{t-L:t,l}, k_l).$

N-HiTS Seasonality Component: $h_l = \text{MLP}_l(y_{t-L:t,l}^{(p)}), \theta_{fl} = \text{LINEAR}_f(h_l), \text{ and } \theta_{bl} = \text{LINEAR}_b(h_l).$

N-HiTS Hierarchical Interpolation: $|\theta_{fl}| = \lceil r_l H \rceil.$

## Model Exploration & Results

Architecture Deep-Dive (N-BEATS vs N-HiTs)

The difference in architecture allows the model to sequentially assemble its predictions and emphasize components with different frequencies and scales while decomposing the input signal and synthesizing the forecast.
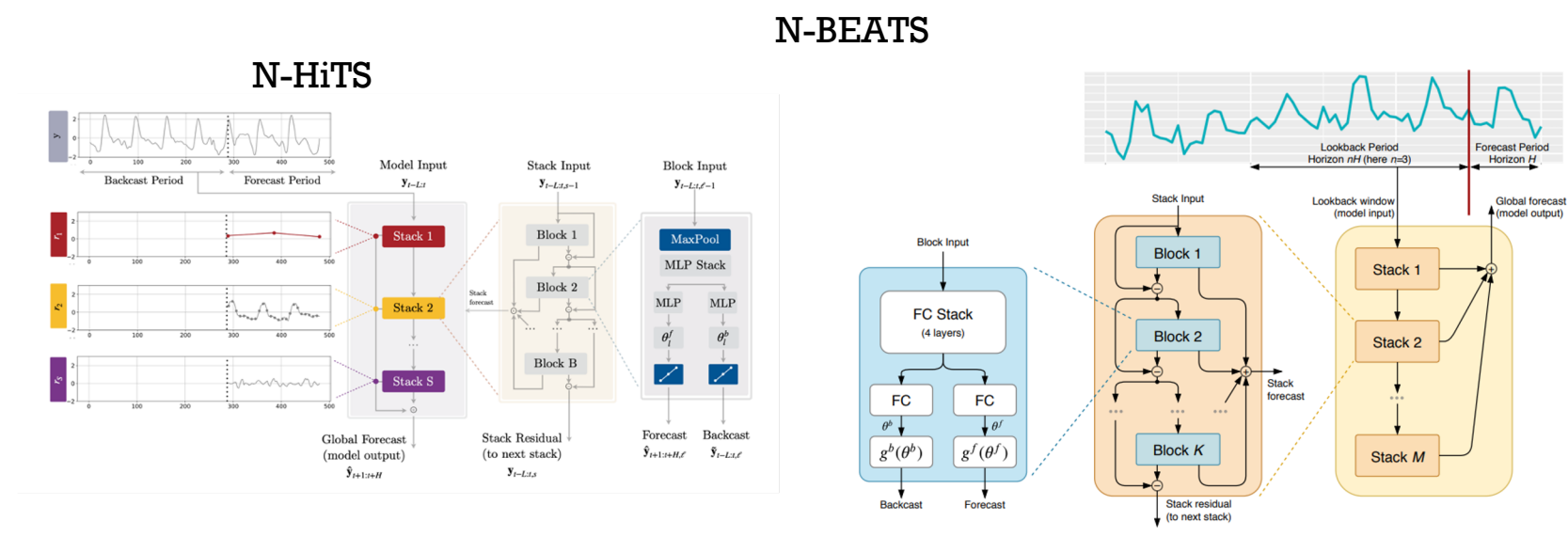

Model Exploration

A comparative analysis was conducted between N-BEATS, N-HiTS, TFT, and Prophet for Eurodollar Future CME, British Pound Futures, Vexanium-USD, Oil, Coffee, Gold, EURUSD and VIX on the same window as last year's project.
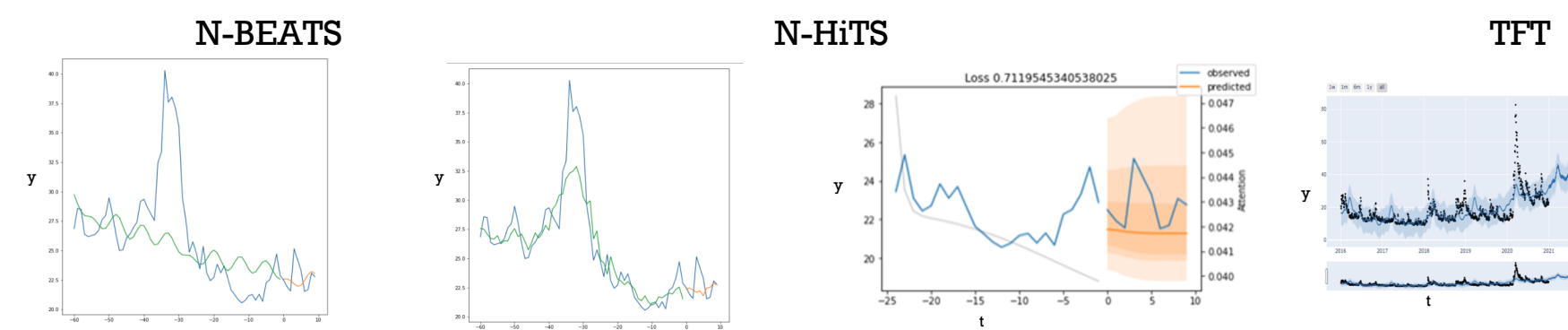
*example plots shown for VIX

Results (Sliding Window):

N-HiTS and TFT were explored further for all eight assets on a two-week sliding window, incremented by two weeks, and forecasted on two weeks.
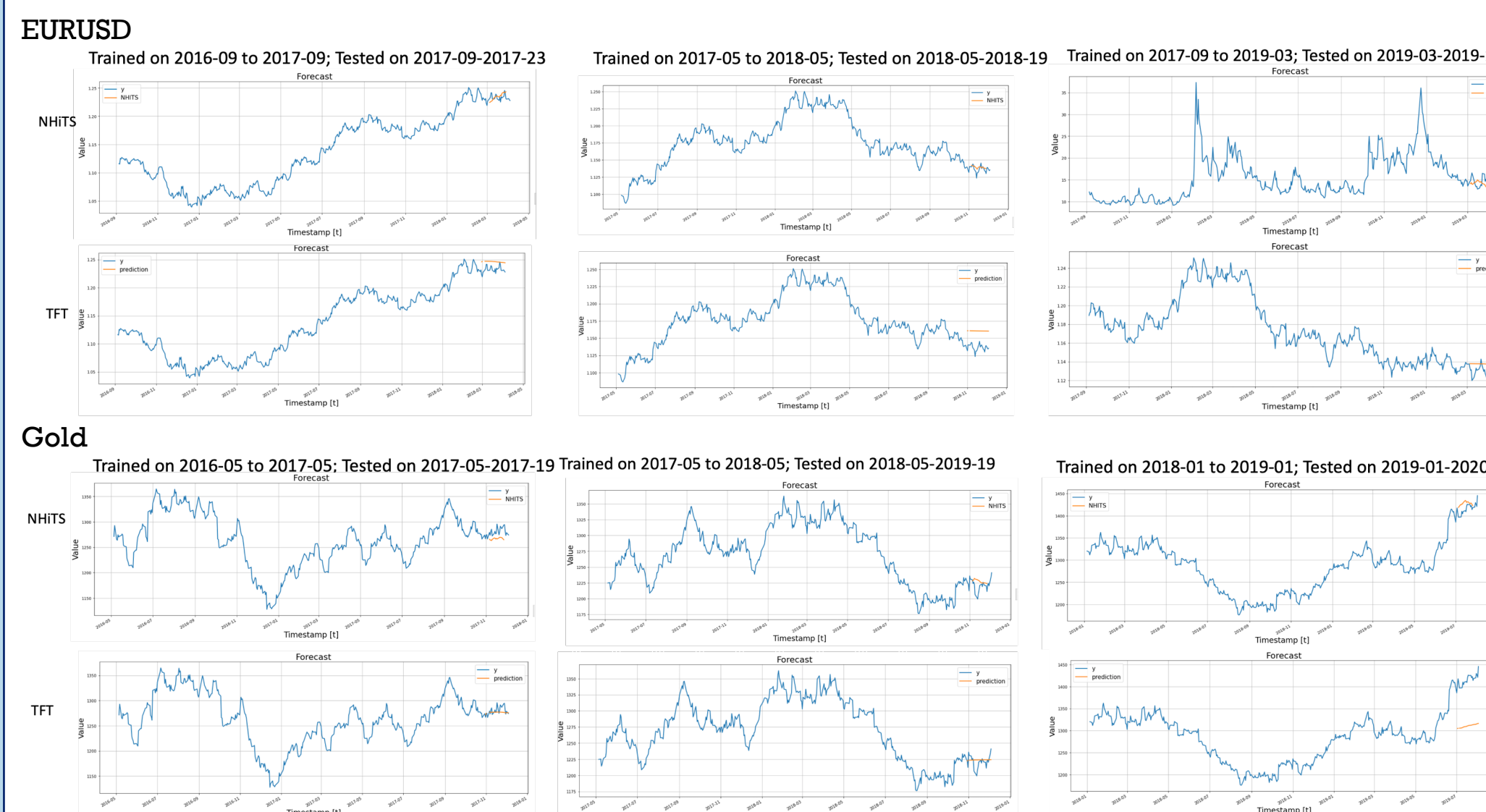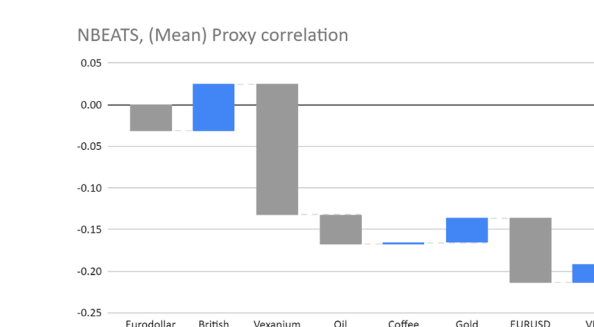

Results cont. & Further Work

Proxy Correlation (movement tracking) and Profit & Loss (aggregate returns) metrics allow us to evaluate the models more comprehensively and align our evaluations with the specific objectives of financial time series forecasting.
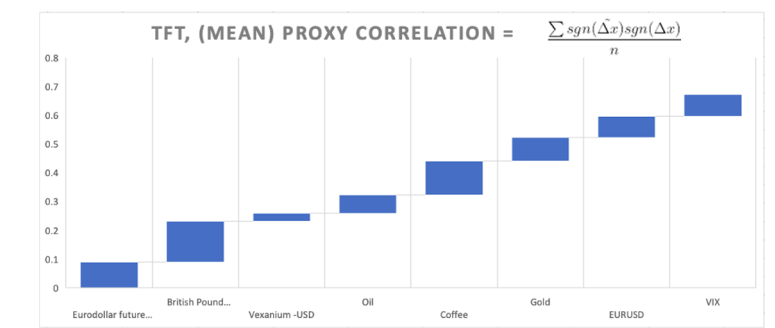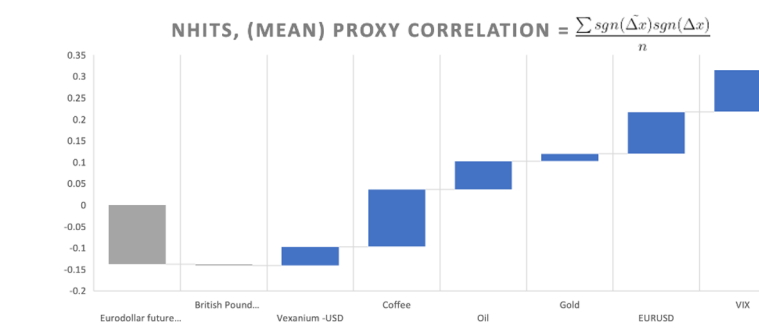
Proxy Correlation: $\frac{\sum sgn(\Delta x) sgn(\Delta x)}{n}$

Profit and Loss: $\sum_t mgn(\Delta \hat{x}_t) * (x_{t+1} - x_t)$

Results (Proxy Correlation)

*The proxy correlation results show substantial improvements of both N-HiTS and TFT of N-BEATS such that N-BEATS ended with a -1.75 aggregate while N-HiTS and TFT ended with a 0.32 and 0.73 aggregate, which that N-HiTS and TFT demonstrate strong performance for tracking the movement of assets.

Results (Profit & Loss)

*The profit and loss plots generally trended upward for both N-BEATS and N-HiTS however primarily trended downward for TFT. This shows different results from proxy correlation where although TFT performed the best tracking movement, it performed weakly in the profit and loss. Above plots were run for eight assets across the sliding window.

Conclusions and Further Work

Based on Proxy Correlation, TFT's ability to accurately forecast the direction – not magnitude – of market movement could be useful in practice where downward or upward trends are being monitored. When exact returns are considered, however, N-HiTS appears most promising. As its movement tracking is also relatively reliable, N-HiTS can be considered the "general" model of choice. Nevertheless, the right architecture to use will depend on the goal of the forecasting. An important extension would be to utilize TFT's capacity for multivariate forecasting, which is a specialty that sets it apart from the original univariate N-Beats and N-HiTS models. That is, other relevant data from categorical and quantitative variables could be incorporated to yield a more accurate prediction.

Bloomberg: Gary Kazantsev   Advisor: Professor Ali Hirsa
Group Members: Daniel Um, Richard Uzilov, Charles Xu

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The Fu Foundation School of Engineering and Applied Science