

Predicting Cryptocurrency Markets Using Kernel U-Net with N-Beats Kernels

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Team Members

We are a team based in Paris and Madrid, focusing on topics such as Time Series Machine Learning, Artificial Intelligence, Applied Mathematics, as well as applications in cryptocurrency and financial markets.



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Cryptocurrency Market Forecast Background (1/2)

Global Economic and Policy Context

- **Trump's Stance on Cryptocurrencies:** Donald Trump, the first U.S. presidential candidate to openly support cryptocurrencies, views them as tools to counter traditional financial systems and central bank policies. This support could drive demand for digital assets.
- **Impact on Foreign Currency Trade:** Protectionist policies under Trump, such as setting barriers to foreign currency trade, may reduce arbitrage opportunities in traditional forex markets. In response, investors might hedge assets or turn to cryptocurrencies for potential returns.

Cryptocurrency Market Forecast Background (2/2)

Market Activity and Arbitrage Opportunities

- **Policies Driving Market Volatility:** Uncertainty in political policies increases market volatility, creating more opportunities for arbitrage and trend-following strategies.
- **The Global Nature of Cryptocurrencies:** Operating beyond national monetary policies, cryptocurrencies are critical tools for investors to hedge risks. Our forecasting model leverages this increased market activity to identify trading opportunities and optimize returns.

Model Overview

- **Kernel U-Net:** A U-shaped architecture ideal for time series forecasting.
- **N-Beats Kernels:** Specialized for long-term trend and seasonal pattern decomposition.
- **Output:** Candle chart prediction for future time windows.

Kernel-U-Net: Multivariate Time Series Forecasting
using Custom Kernels

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Abstract—Three series forecasting task profiles feature models based on temporal information. Transfusion-based U-Net avoids the explicit use of temporal information, but its design requires few limitations in both experiments and applications. The model's efficiency in time series forecasting is evidenced in Thomson. To tackle these challenges, we introduce Kernel-U-Net, a flexible kernel-based model. Unlike other models, Kernel-U-Net is not limited by the number of input series. Kernel-U-Net is not separated from kernel manipulation, thereby providing the convenience of reusing customized kernels. Our method offers two primary advantages: 1) flexibility in kernel customization to adapt to various tasks, and 2) the ability to reduce the model's complexity by the Transfusion layer reduced in Thomson. Experiments on seven real-world datasets, demonstrate that Kernel-U-Net's performance outperforms or meets that of the independent studies. The source code for Kernel-U-Net will be

8. <http://www.fishbase.org>

Time series forecasting predicts future trends based on recent historical information. It allows experts to track the incoming situation and react timely in critical cases. Its applications range from different domains such as predicting the road occupancy rates from different sensors in the city [1], monitoring influenza like illness weekly patient cases [2], monitoring electricity transmission temperature in the electric

processes in deployment [31] or forecasting temperature and humidity in weather station [32] etc.

Over the past few decades, time series forecasting solutions have evolved from traditional statistical methods [33] to machine learning techniques [34] to deep learning-based models, such as recurrent neural networks (RNN) [35]. Long Short-Term Memory (LSTM) [36], Temporal Convolutional Network (TCN) [37], and Gated Recurrent Unit (GRU) [38].

Among the Transformer models applying to time series data, Inference [39], Autoformer [40], and Fedformer [41] are the best choices that increasingly improved the quality of prediction. As a recent paper [42] challenges the efficiency of Transformer-based models with a simple linear layer model NLinear, the authors in [43] argued that the degradation of performance comes from the wrong application of Transformer modules on a point-wise sequence and the ignorance of the global dependencies. To address this problem, they successfully adapted the *globalizing* modules of Transformer

We observe models that display distinct strengths depending on the dataset type. For instance, NLSAR stands out for its efficiency in handling unbalanced time series tasks, particularly with small-time windows. On the other hand, PatchTST is noteworthy for its superior performance in multivariate time series tasks, especially in scenarios where the model must highlight the uncertainty for a well-defined flexible architecture. This architecture works well to integrate various models while allowing for specific customized solutions. Such integration should not only ensure a balance between computational efficiency and expressiveness but also respond to requests for rapid model development.

The Constitutional Unit, as a classic and highly popular tool used in medical image segmentation [34], demonstrates a symmetric structure and flexible structure that is elegant and easy to design. This model's structure is particularly suited to the time series forecasting task, as both inputs and outputs in the model are sequences. The model's architecture is similar to the first NLSAR model, selected for four series forecasting tasks.

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N-BEATS: NEURAL BASIS EXPANSION ANALYSIS FOR INTERPRETABLE TIME SERIES FORECASTING

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ANTHONY

We focus on solving the *annual* time series problem forecasting problems using deep learning. We propose a deep neural architecture based on backward and forward residual links and a very deep stack of fully-connected layers. The architecture has a number of desirable properties, being interpretable, applicable to a wide range of tasks, and able to learn from a wide range of data. We use the proposed architecture on several well-known datasets, including M4, M5 and TSC+M4 competition datasets containing time series from diverse domains. We demonstrate that the proposed architecture is able to learn from all the data, and all the datasets, improving forward accuracy by 11% over a statistical benchmark and by 1% over last year's winner of the M4 competition, a domain-agnostic hand-crafted model. We also demonstrate that the proposed architecture is able to learn from the data and the time series features. The final configuration of our model does not employ any time-series-specific components and its performance on heterogeneous datasets time-series suggests that, contrary to what is often claimed, deep learning is able to learn from time series by themselves sufficient to solve a wide range of forecasting problems. Finally, we demonstrate how the proposed architecture can be augmented to provide insights on the data and the time series.

1. INTRODUCTION

These series (TS) forecasting is an important business problem and a fruitful application area for machine learning (ML). It underlies most aspects of modern business, including such critical areas as inventory control and customer management, as well as business planning arising from production and distribution in manufacturing companies. As such, it is a complex task that often costs millions of dollars in the millions of dollars for every point of forecasting accuracy gained (Jain, 2017; Kaloupek, 2017). In effect, unlike other tasks such as computer vision or natural language processing where deep learning (DL) techniques are more widely entrenched, there still exists evidence that ML and DL struggle to outperform classical statistical TS forecasting approaches (Makridakis et al., 2016b,c). For instance the rankings of the six "pure" ML methods submitted to ML competitions were 23, 37, 38, 48, 58, and 77 out of a total of 68 entries, and most of the best-ranking methods were members of classical

On the other hand, the M1 competition winner (Sneyd, 2020), was based on a hybrid between neural residual/attentional LSTM-stacks with a classical Holt-Winters statistical model (Holt, 1957, 2000; Winters, 1960) with learnable parameters. Since Sneyd's approach heavily depends on this Holt-Winters component, Malhotra et al. (2019b) further argue that "Hybrid approaches and combinations of methods are the way forward for improving the forecasting accuracy and making forecasting more valuable". In this work we aspire to challenge this conclusion by exploring the potential of deep RL architectures in the context of the TS forecasting. Moreover, in the context of the M1 competition, we have shown that the RL-based solutions are able to outperform the

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Key Advantages: Model

● Model Advantages:

- **Scalability:** Efficiently handles large and complex time series datasets.
- **Precision:** Captures intricate patterns in cryptocurrency price movements.
- **Customizability:** Flexible architecture allows integration of advanced kernels like N-Beats.
- **Efficiency:** Linear computational complexity ensures fast processing.

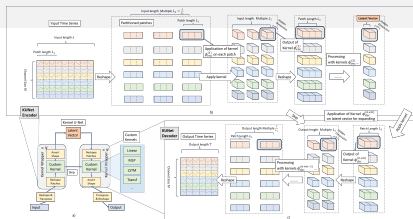


Figure: Kernel U-Net Structure

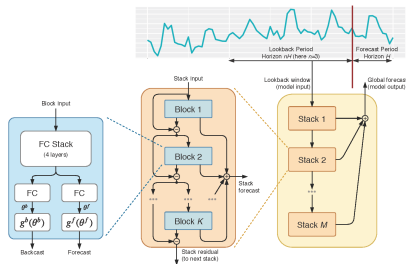


Figure: N-Beats Forecasting Diagram

Key Advantages: Team and Vision

● Team and Vision:

- **Innovation-Driven:** Inspired by the groundbreaking work of Renaissance Technologies, founded by Jim Simons.
- **Collaborative Environment:** Building a company where talented individuals can thrive, innovate, and contribute to shaping the future of financial technology.
- **Entrepreneurial Spirit:** Laying the foundation for a highly profitable company in the cryptocurrency forecasting space.
- **Join Us:** We invite like-minded individuals to collaborate and grow with us as we redefine financial prediction and market analysis.



Figure: *

Our inspiration for innovation and excellence.

Key Advantages: Surpassing Traditional Models

Limitations of Traditional Models

- **Static Rules:** Rely on historical data with the assumption that past trends remain stable.
- **Lack of Nonlinear Capability:** Unable to process complex market behaviors effectively.
- **Slow Response to Sudden Events:** Struggles to adapt to black swan events or policy changes.

Kernel U-Net with N-Beats Solutions

- Adapts dynamically to market changes and supports real-time data updates.
- Enhances the ability to predict future trends instead of merely fitting past data.
- Efficiently handles high-dimensional complex data, including sentiment analysis and blockchain activity.

Market Prospect

- **Cryptocurrency Industry:** Valued at over 2 trillion dollars and growing.
- **Demand:** Reliable prediction models are critical for institutional and retail investors.
- **Commercialization:**
 - **Potential Clients:** Hedge funds, cryptocurrency exchanges, portfolio managers.
 - **Applications:** Price forecasting, risk management, automated trading.
- **Revenue Model:** Licensing, subscription-based analytics platforms.

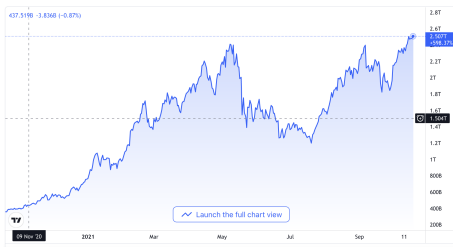
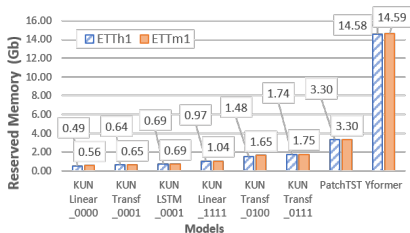


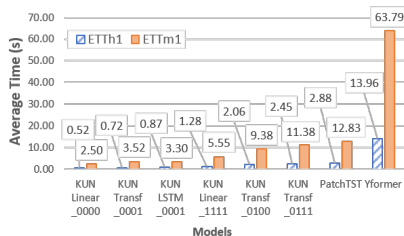
Figure: Crypto market cap breaks \$2.5T

Model Performance

- Exceeds existing benchmarks in precision for multivariate time series datasets.
- Demonstrated significant memory and computation time savings.
- Outputs clear and actionable predictions in real-time.



***Figure 1: Reserved Memory Comparison**



***Figure 2: Computation Time Comparison**

Conclusion

- Kernel U-Net with N-Beats is a cutting-edge model for cryptocurrency market forecasting.
- Combines precision, efficiency, and scalability.
- Offers substantial commercialization opportunities in a rapidly growing market.
- Ready for deployment in real-world trading and analytics platforms.

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