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SCENARIO-BASED RISK MANAGEMENT WITH TEMPORAL FUSION TRANSFORMER

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ABSTRACT

Modern risk management practice often calls for Monte-Carlo simulation to visualize future realizations of portfolio assets. Many assets may have interdependent paths, however, introducing considerable complexity into the simulation. For example, stock returns of firms like Apple and Microsoft may be co-evolving given common industry factors. At present, the interdependence is often modeled in simulation via copulas, which may be suboptimal from both computational speed and stationarity assumptions. Instead of Monte-Carlo with copulas, in this paper, we propose modeling with an attention-based model known as the Temporal Fusion Transformer (TFT). We show that the TFT model can provide depth and breadth equivalent or even superlative to that of the Monte-Carlo method by simulating the assets' complex dynamics in the presence of interdependent factors and qualitative variables.

1 INTRODUCTION

Financial market inherently show non-linear and complex dynamics, which pose significant challenges to financial risk managers. To address multiple time-series variables with the non-linearity in the financial market, the Monte-Carlo simulation and Gaussian Copula are adopted as a de facto standard. This simulation process enables the generation of realistic future scenarios that preserve the dependency structure observed in historical data. However, this approach has limitations in capturing non-linear dependencies and extreme events, which are known as tail risk of financial market.

Attention-based model for multi-horizon time-series, Temporal Fusion Transformer (TFT) (Bryan Lim 2021) can overcome existing shortcomings. The attention mechanism measures the similarity between the target and the input data. The model is a neural network that assigns weights to more important inputs, and can "up-weigh" and "down-weigh" input variables based on their relevance. The model has multi-period prediction capabilities, predicting outcomes across multiple future time steps simultaneously, not a sequential single future time point.

Another advantage of TFT is its ability to combine time-varying known and unknown input data, allowing risk managers to use scenarios as input data of complex quantitative models. This allows risk managers to incorporate expected scenarios or ideas of domain experts into the model as time-varying known input to simulate the market movement. As such, TFT provides risk managers with the best of both quantitative and qualitative worlds, finally bridging the big divide between traditional scenario-based risk management and the quants.

In this study, we propose using TFT as an alternative to traditional Monte-Carlo models by using the TFT's ability to integrate co-dependence of various inputs.

2 MODEL AND FRAMEWORK

The Temporal Fusion Transformer (TFT) can be used to explore the influence of historical events on future outcomes by assigning varied weights to different time steps and inputs, revealing the intricate relationships among them over time. This approach enhances the model's ability to decode complex data dependencies, setting it apart from typical black-box deep learning models.

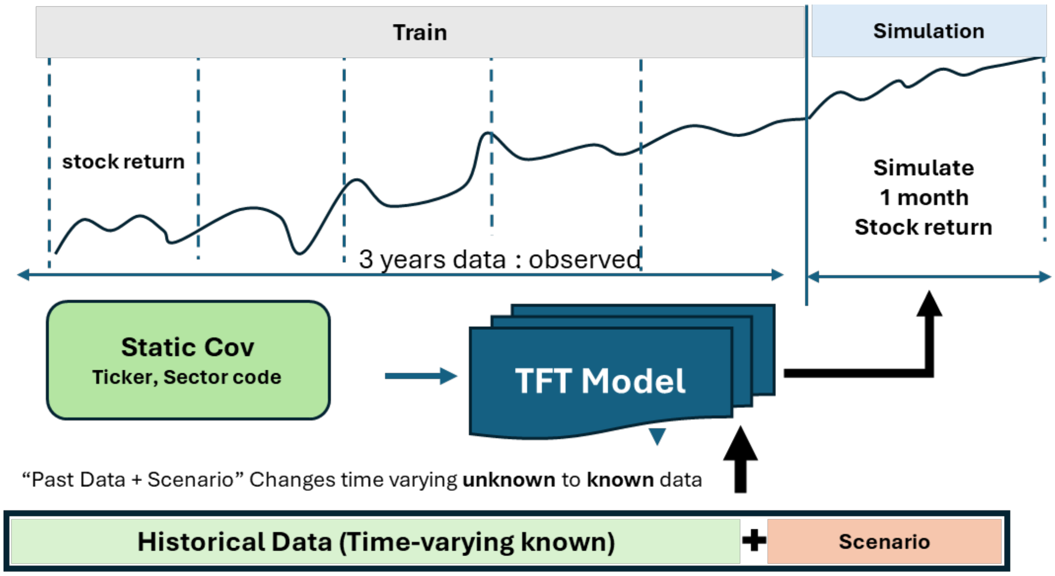

Figure 1: An illustration of the TFT performance in the Monte-Carlo-like simulation process.

Additionally, TFT's use of Variable Selection Networks (VSN) (Xin Zhang 2024) allows for dynamic evaluation and emphasis on the importance of specific input features at each time step. This capability is crucial in complex datasets where the relevance of features can change, aiding in understanding how certain variables significantly affect the model's predictions and improving the overall interpretability of the model.

To illustrate the capabilities of the model, we construct a dual-source risk management framework that sources both quantitative as well as qualitative inputs. For quantitative inputs, we use traditional prices and derived returns, including correlated time series, of the S&P 500 stocks. For qualitative variables, we rely on a Large Language Model (LLM) to generate the best, base, and worst risk scenarios for our portfolio. We incorporate all of this information and feed it to the TFT model to generate predictions for the S&P 500 for each case (best, base, and worst) 10-20 trading days ahead. (The 10-day forward-looking calculations are the current de-facto standard in the financial industry, codified by the Basel III risk management framework, while the 1-month threshold is often used in practice by investment managers).

In addition to the qualitative scenarios, we incorporate quantitative elements traditionally used in the Discounted Cash Flow (DCF) models to predict present and often future prices. Thus, our TFT process utilizes joint historical observations of treasury rates, credit spreads, costs of equity, and perpetuity growth rates to fit and predict target companies' equity values. Figure 1 illustrates our process.

We document that the Temporal Fusion Transformer (TFT) model effectively captured the dynamics and non-linearity of the stock market across realistic scenarios, demonstrating its utility in financial risk management with robust 10-day predictions. This is evidenced by metrics such as stock return, Value at Risk (VaR 95%), Conditional Value at Risk (CVaR 95%), and Maximum DrawDown (MDD) compared between actual and predicted data for July 2024.

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