A Novel Approach to S&P 500 Stock Prediction using an Encoder and Decoder with RL to Improve the Forecast of Time-varying Volatility in Financial Time Series Data

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Abstract

For decades methods to determine the S&P 500 forecast of the stock market have been a great area of interest. The S&P 500 has been a standardized measure of the stock market over the years. Many stock investments simply follow the trends. Volatility is a measure for the level of uncertainty prevailing in financial markets. Investing decisions often follow main index trends. Investors tend to have a strong focus on risk management, optimizing trading decisions using returns weighted by risk is crucial, the main goal of most investors is to achieve the maximum revenue potential from the strategies they chose to follow. The S&P 500 Index is a widely recognized benchmark of the United States stock market, and forecasting its values remains a topic of interest for investors. Many types of Mathematical Models have been used to forecast values and algorithms are tried and tested non-stop to improve forecasting abilities. This VAE (Variational Autoencoder) project uses RL (Reinforcement Leaning) to help predict the future and train a model that will make buy, sale, and hold decisions. By leveraging both methods, models can be generated from training and tested to assess their forecasting impact.

Keywords – *VAE, S&P 500 forecast, RL*

I. Introduction

The obsession with trends in the stock market can be found in many walks of life and the desire to know what is around the corner creates the need for careful analysis that informs accurately and helps investors minimize risk. There have many mathematical models that for decades have caught the attention of investors by getting close to the prediction and outperforming strategies such as buy and hold as demonstrated by Kijewski and others [1]. The authors present an evaluation of an RNN (Recurrent Neural Network) along with traditionally used mathematical model against Buy and Hold (B&H) demonstrates the ability to leverage these methods in a forecasting scenario. Not only did they look at individual performance for each method but they tried a combination of the mathematical models with a LSTM (Long

Short-Term Memory) RNN and benchmarked the performance against traditional B&H strategies. By combining methods they saw improved results. The project looks at combining two types of AI training and testing strategies to forecast one day into the future by using a VAE coupled with RL to forecast and anticipate buying risks.

II. Related Work

Using an encoder and decoder with RL has been discussed by others Choo et al. have demonstrated effective application of this in research sponsored by the Royals Royce cooperation [2]. The robustness of combining strategies was demonstrated when Kijewski and others took the strengths of strategies and combined them with other strategies to compensate for weaknesses in each individual strategy. We can see from this the concept of working with combined methods can provide some level of improvement in performance. The sensitivity analysis from past work motivates using more robust model selection and the combination of two techniques. The World Model concept has been some recent work in this area [3], [4]. By taking advantage of the latent space and allowing RL to explore and improve outputs provides a fascinating insight into combining some traditional strategies such as VAE with the exploring abilities of RL systems.

III. Methods

This project was an attempt to find a novel approach to analyzing S&P 500 historical data and provide a one day window forecasting ability. This project focuses on stability in real-world forecasting and the concept of combining techniques is in hopes of improving forecasting performance. The original plan was to use GARCH (Generalized Autoregressive Conditional Heteroskedasticity) as data input to simulate the stock market and build a VAE that would analyze the synthetic data and produce a forecast window one day into the future. This method worked well and the ability and performance of the GARCH mathematical model was impressive[5], [6], [7]. It was determined that the availability of clean and easy to use historical S&P 500 data was available in many forms and the synthetic generation did not turn out to be a necessary step in providing historical data for training. The project originally was set up for forecasting only and though longer windows of prediction were discussed such as a 30 roughly one-month prediction or a 7 day week prediction the scope of this project was 1 day in the future. The historical data used spans more the 40 years of daily returns and gives us a great training and testing set. The data was read 6000 days at a time and then divided into mini-batches of 30 before being fed into a encoder. The encoder includes two ReLU layers in the processing of the historical S&P 500 data. This data is then compacted to a format (z) which is fed into a RL PPO (Proximal Policy Optimization) algorithm along with an output forecast from the previous run output by the decoder. The actor in the RL system determines a move buy, sale or hold for stock purchasing and then is involved again at the output of the decoder in determining a reward by checking yesterday's prediction decision in purchasing against market movement today. The decoder each run regenerates all of the input data and in addition to that a prediction of the market close one day into the future (tomorrow). Both the VAE and RL systems basically work in their own loop, and the VAE becomes an unknown environment for the actor. The critic assigns a reward for buying decision performance by the actor. The data was used in the following manner seventy-five percent of data was used to train and produce the model. The remaining was reserved for testing. The overall methods provided an interesting and effective process for forecasting with the system. The World model method became an exciting addition to the project and although it was interesting to work with GARCH and the synthetic data generation was removed.

As shown below the setup includes both VAE and RL in the structure to work on different goals and leverage combined information to inform investors.

Input (past N days)

↓

[Encoder: layers]

↓

Latent state (context vector) RL

↓

[Decoder: Layers]

↓

Predicted closing price

↓

[Reward function]

↓

RL agent updates model to reduce error

IV. Experiments

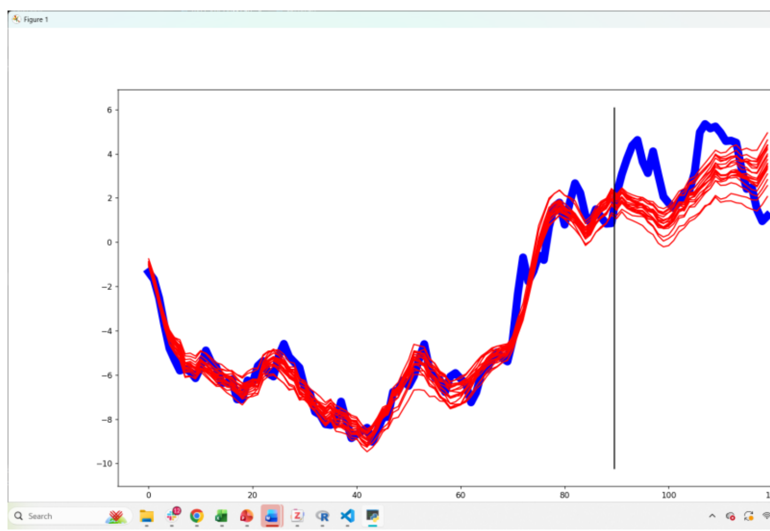
Initial research for this project involved a lot of research on the GARCH model and thought into how syntecic data could help in early development. The plan to move to S&P 500 data was always a goal but initial development included synthetic data generation this is easily turned into back on in the code by manually reinstating a portion of commented out code. In time it was determined that S&P 500 data was extremely easy to work with, and synthetic data no longer had a place in the project. As methods for working on this project and forecasting a day into the future a VAE system became the method of choice. It was really fun to set up the encoder and decoder for reading and regenerating the historical S&P 500 data. The forecasting ability was tested by the VAE before adding any other systems the results are found below in figure 1. After the VAE portion of the project was determined to be reliable and effective the RL addition was researched and planned. Early attempts to add this to the working VAE code involved the use of a DQN (Deep Q-Network) this combination of deep learning and RL allows agents to explore their environment and make decisions. These experiments went well but as that code was being finalized the world model method was discovered in the research and readings for the project. This initiated the move to a dreamer world-model approach to the design with RL working in the latent space to train and improve its decision-making abilities on the historical data.

A. Dataset description

The dataset included S&P 500 closing prices (Jan 3, 1972 – Dec 30, 2005). Training was done by loading (~6,000 days) at a time from the GARCH synthetically generated data and then later on loading (6,000 days) from the S&P 500 dataset and using 75% to train then 25% to test. Mini-batches of thirty were setup by taking 30 days until there was a remainder and getting rid of or throwing away any days in the remainder.

B. Baseline description

The historical trends of S&P 500 hundred were plotted and compared to the output generated by the VAE. A cumulative sum was used so growth over time could be displayed. A percent growth over time was looked at not a



dollar amount it was the accumulation of wealth that was the goal of the system displayed as a percentage over time. Looking at the cumulative percentage gains/losses shows wealth over time. These comparisons can be seen by looking at figure 1 with the red representing the VAE output and the blue line is plotted historical S&P 500 data. The historical S&P 500 presented a solid and historically stable method of displaying growth over time as a baseline.

C. Experimental evaluation

Different methods were tried as part of the experiment evaluation including some that ended up being removed from the project including GARCH and the DQN. There were also some experimental trial on longer forcasting periods as can be seen in figure 1 which shows comparison for 30 day of forecasting against the baseline. These types of visualizations can be found, downloaded and recreated [8] **https://linda4u.github.io/Final-Project/** where all the code for the project lives. There is code that is commented out that was used for testing the robustness of the system by injecting random noise that can be found in the S&P500.py file.

V. Conclusion and Future Work

The VAE generated a model that was trained on real historical S&P 500 data the results were incuraging and showed great potential for this type of project. The RL predictions gave a sense of how buy, hold and sell decisions could potentially be informed by a world model setup. This age-old problem continues to intrigue many as we look at how historical data can be leveraged into a system that forecast and tests its decision making processes. Future work could involve a lot of additional features including the ability to increase the forecasting window to a week or a month. The additional the ability to include tracking of a every trade and showing the investor will incur a transactional fee equivalent to a percentage or fixed amount would make the overall predictions more realistic and true to real life. These predictions and others could improve the capacity of the system but were beyond the scope of this initial project.

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