Yield Curve Forecast and Bond Portfolio Management

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Abstract

We noticed that the patterns of bond yields are usually three ways: level change , slope change, and curvature change. Based on this assumption, we tried to capture delta y (changes of daily yields on bonds) to design a specific strategy. In order to do so, we applied multiple machine learning models on capturing delta y as accurately as possible. To improve the accuracy of our models, we include t-1,t-2,t-3,t-4,t-5,t-6, and vix as our features, and set t+1 as target. As a result, the Lasso model performs great in terms of forecasting and generating excess return .

1. Strategy Descriptions

1.1 Yield Curve Dynamics

To determine how to profit from constantly changing yield curves, we need expected changes of the yield curves, determined by three following factors:

A. Level: the parallel shift where all yield shifts up (or down) by the same amount.
B. Slope: where the curve becomes flatter or steeper (a " twist"). It can be measured by subtracting a short-term yield from a long-term yield. If this difference increases, then the curve is steepening.
C. Slope of a curve curvature: where the curve becomes more or less curved (a "butterfly movement"). The curvature of the yield curve is measured through the butterfly spread: Butterfly spread = -(short-term yield) + (2 × medium - term yield) - long - term yield

1.2 Modeling Return

The component that matters the calculations on expected fixed-income return is expected price change due to change in benchmark yield. It is calculated from the investor's expected change in benchmark yield using the portfolio's duration and convexity:

$(-MD \times \Delta Y) + (½ \times C \times \Delta Y2)$

1.3 Yield Curve Strategies - Trades For a Dynamic Yield Curve

1.3.1 Divergent Rate Level View

An active manager can earn excess return from a bullish view that the benchmark yield curve will shift down by increasing the duration of their portfolio. Conversely, a manager with the bearish view that the yield curve will shift up would lower the duration of their portfolio.

The formula for calculating the modified duration is:

$$Modified\ Duration\ =\ \frac{\sum(C/(1+YTM/n)^{t}\times t\ /Bond\ Price)}{(1+\ YTM/n)}$$

The formula for calculating the convexity is:

$$\frac{1}{(1+Y\ \delta)^{2}}[\sum_{i=1}^{N} w_{i}t^{2}_{i}\ +\ \delta\sum_{i=1}^{N} w_{i}t_{i}]$$

$$w_{i}\ =\ \frac{\delta C_{i}Z(Y,t_{i})}{\sum_{i=1}^{N-1}\delta C_{i}Z(Y,t_{i})+(1+\delta C_{N})Z(Y,t_{N})}\ (1\ \leq i\ \leq N\ -\ 1)$$

$$w_{N}\ =\ \frac{1+\ \delta C_{N}Z(Y,t_{N})}{\sum_{i=1}^{N-1}\delta C_{i}Z(Y,t_{i})+(1+\delta C_{N})Z(Y,t_{N})}\ (1\ \leq i\ \leq N\ -\ 1)$$

1.3.2 Divergent Yield Curve Slope View

Due to the inverse relationship between rates and bond prices, an active manager that expects a change in the shape of the yield curve should buy bonds with rates that are expected to fall relative to the rest of the curve (because prices will rise) and short sell bonds with rates that are expected to rise relative to the rest of the curve (because prices will fall).

A summary of these curve changes pattern and corresponding classifications are displayed here:

Pattern Classification (Rates Change)	Pattern	Pattern Classification (change in level)	Pattern	Portfolio Duration	Short-term bonds	Long-term bonds
Bearish (level of rate rise)	Bear steepener (long-term rates rise>	Steepener (no change in level)	Bear steepener	Zero	Buy	Short sell

	short-term rates)					
	Bear flattener(short-term rates rise> long-term rates)		Bull steepener(	Negative	Buy	Short sell
Bullish(level of rates fall)	Bull steepener(short-term fall >long-term rates)	Flattener (no change in level)	Bear flattener	Positive	Buy	Short sell
	Bull flattener(long-term rates fall <short-term rates)		Bull flattener	Zero	Short sell	Buy

1.3.3 Divergent Yield Curve Shape View - Change in Curvature

If the manager believes that curvature will increase, they think that medium-term rates will rise relative to short- and long-term rates. In this scenario, the manager should short sell a medium-term bullet and buy a barbell ("short the body and long the wings").

Conversely, if the manager believes that curvature will decrease, they think that medium-term rates will fall relative to short- and long-term rates. In this scenario, the manager should buy a medium-term bullet and short sell a barbell ("long the body and short the wings").

The curvature of the yield curve can be measured through the butterfly spread:

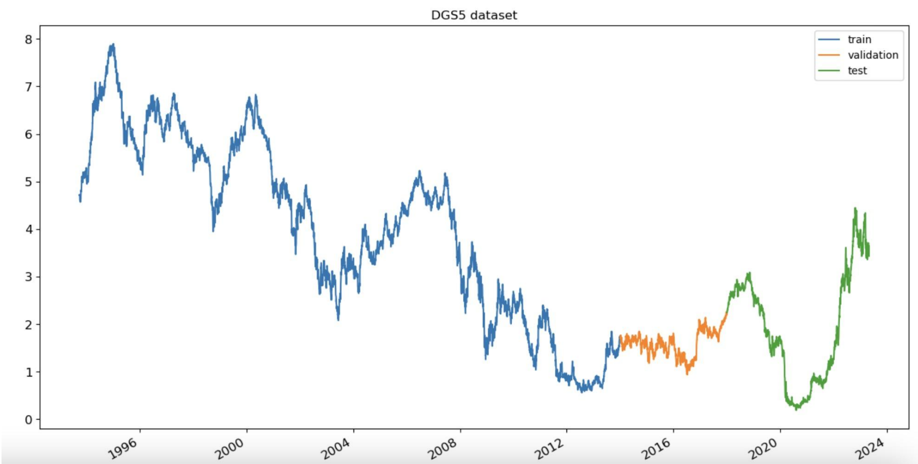
butterfly spread = –(short-term yield) + (2 × medium-term yield) – long-term yield

1.4 Logistics

In order to design appropriate strategies and generate better excess returns, we need to capture delta y as accurately as possible. Therefore, we applied various models on capturing our delta y. A more detailed description is in section 2.

2 General Preparation

First we download the Market Yield on U.S. Treasury Securities at 5Y,10Y,20Y,30Y history Yield To Maturity from Fred API. We name the five series of data as "DGS5","DGS10","DGS20","DGS30". The timeline of the dataset is from 1993-10-01 to 2023-04-11. The test set is set the same across all five models from 2018-01-09 to 2023-04-11. We evaluate each model's accuracy with metrics MSE and MAPE. The train, validation,test data look like below:

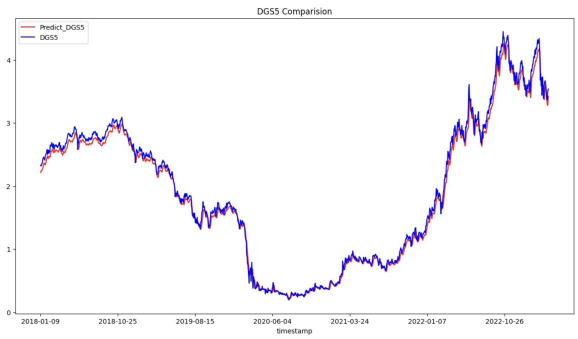


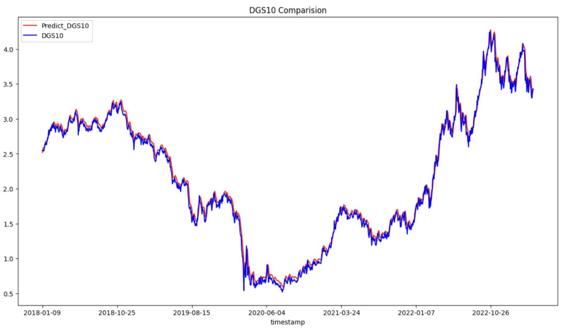
2.1 Model Implementation Logistics

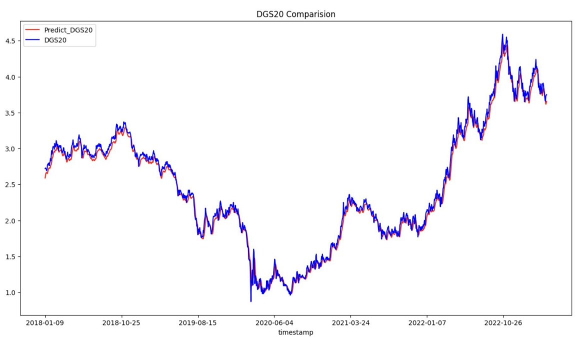
To increase our machine learning models prediction accuracy, we performed our models LSTM with sixty lagged variables(t-1,..t-60), other four models with six lagged variables (t-1,...t-6) to be features of forecast and one proceeding day(t+1) as target variable. After we train the model, we feed the model with the most recent data and make a prediction about the future data.

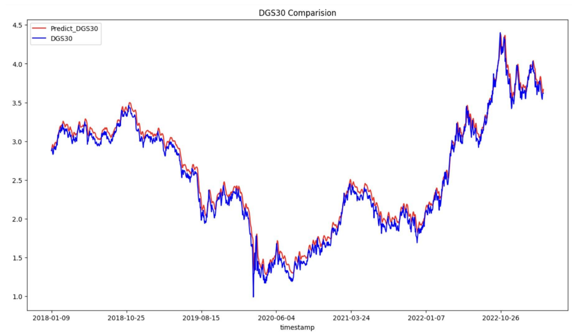
2.1.1 LSTM Model

LSTM(Long Short-Term Memory) is a type of recurrent neural network that is commonly used in financial time series data forecasting,due to its ability to capture long-term dependencies in data. We set the last 60 days data as our features to train the model. The output of the model is the predicted yield to maturity for a future point in time of the test set. Here are the testing results for DGS5, DGS10, DGS20, DGS30 with LSTM.



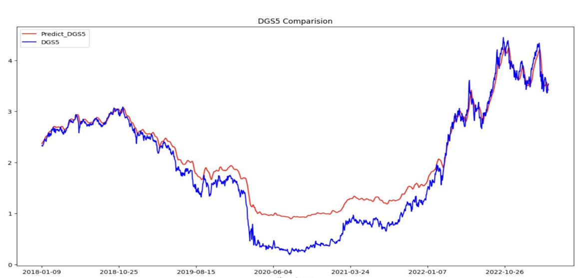


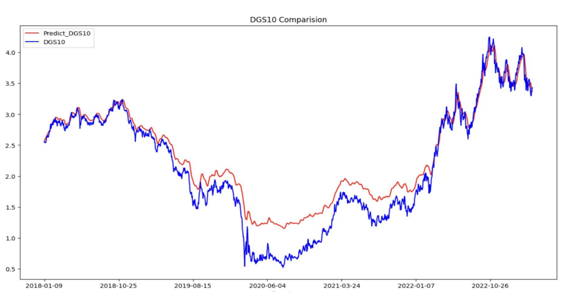


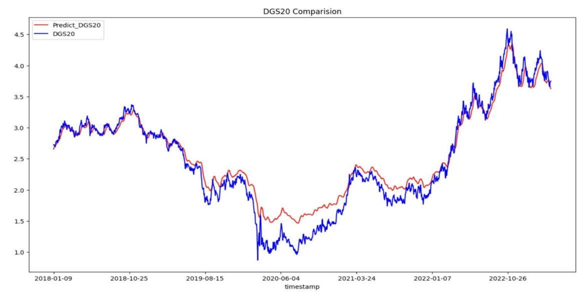


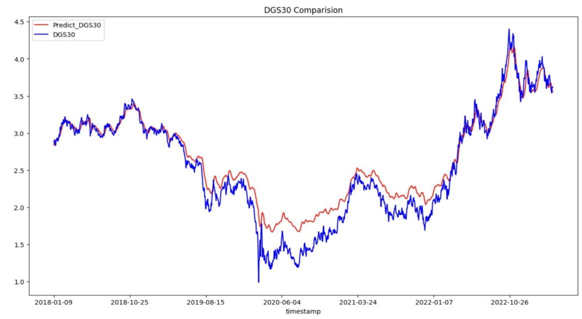
2.1.2 SVM

We set the last 6 days data as our features to train the model. The output of the model is the predicted yield to maturity for a future point in time of the test set. Here are the testing results for DGS5, DGS10, DGS20, DGS30 with SVM.



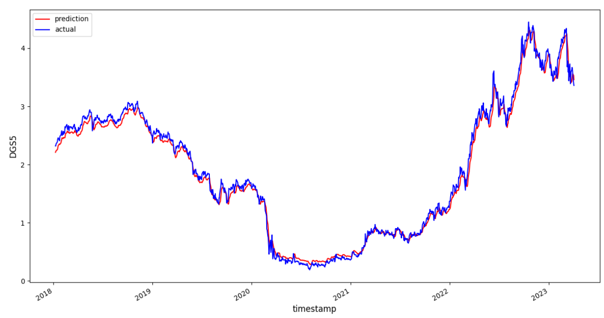


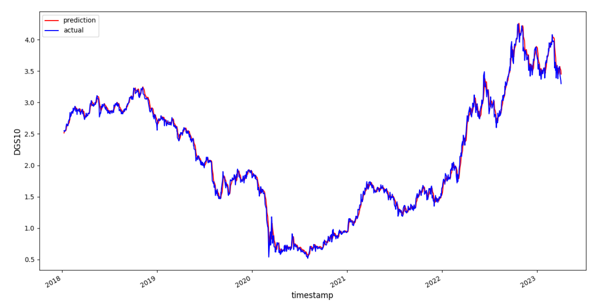


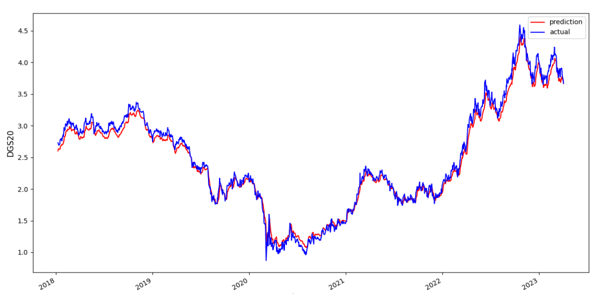


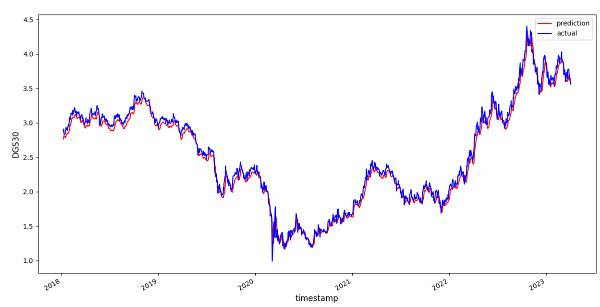
2.1.3 Neural Network

Here are the testing results for DGS5, DGS10, DGS20, DGS30 with NN.



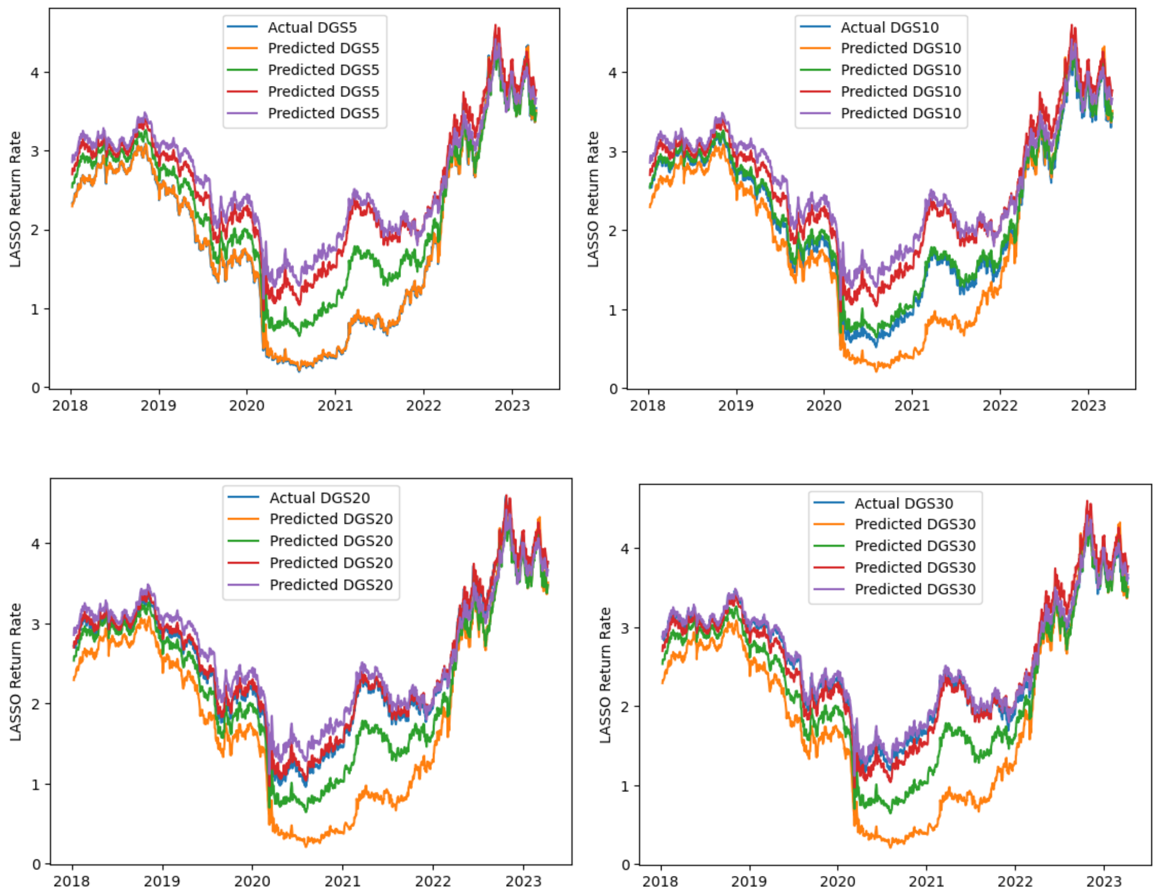






2.2.4 Lasso

Lasso (Least Absolute Shrinkage and Selection Operator) is a regularization method used in linear regression models. It adds a penalty term to the loss function and helps in shrinking the coefficients of less important features towards zero, effectively performing feature selection and reducing model complexity. It is particularly useful when dealing with high-dimensional datasets where the number of features is large compared to the number of samples. The predictions on each bond looks like below:



2.2.5 Prophet

The Prophet model is an open-source time series forecasting tool developed by Facebook. It is designed for forecasting univariate time series data that exhibit seasonal patterns, trends, and holidays. Prophet is particularly useful for forecasting data with strong seasonal effects, irregular patterns, or when domain knowledge of the data is limited. The Prophet model employs a decomposable additive model, which means it breaks down the time series into three main components: trend, seasonality, and holidays.

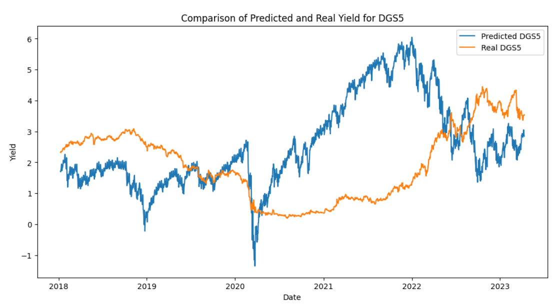
Trend: The trend component captures the overall direction of the data over time, accounting for any long-term increases or decreases. Prophet uses a piecewise linear or logistic growth model to model the trend.

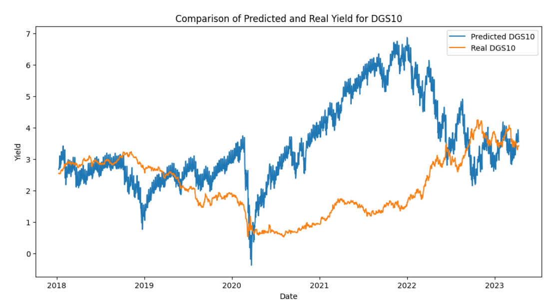
Seasonality: The seasonality component models periodic patterns that recur within a fixed time frame, like daily, weekly, or yearly seasonality. Prophet uses Fourier series to model seasonality, which allows it to capture complex seasonal patterns flexibly. Holidays: The holiday component accounts for any known events or holidays that could affect the time series.

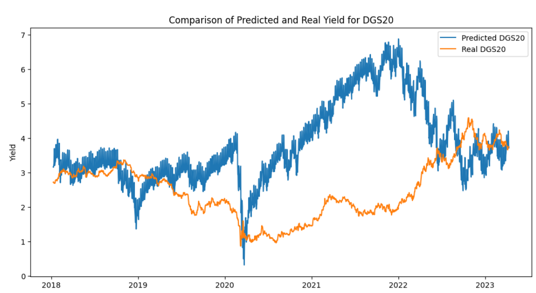
Writing down into math formula would be:

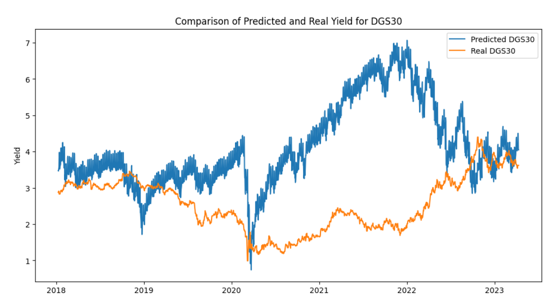
$$y_t = g(t) + s(t) + h(t) + \varepsilon_t,$$

We use Prophet mainly because of its prediction ability on the trend and the result looks like below:









Tabel 1: Model Performance Metrics Summary

Model	Bonds	Mean Absolute Percentages Error	Mean Squared Error
LSTM	DGS5	4%	
	DGS10	3%	
	DGS20	2%	
	DGS30	3%,	
SVM	DGS5	45%	
	DGS10	19%	
	DGS20	9%	
	DGS30	8%	
Neural Network	DGS5	6%	
	DGS10	3%	
	DGS20	3%	
	DGS30	3%	
Lasso	DGS5		0.9%
	DGS10		0.9%
	DGS20		0.9%
	DGS30		0.9%
Prophet	DGS5		90%
	DGS10		120%
	DGS20		79%
	DGS30		80%

3 Backtest Results

In this part, we decide to use the following index to show the performance of our strategy. The formulas look like below:

A. Average return

B. Accumulated return = $\frac{Ending\ Value - Beginning\ Value}{Beginning\ Value}$

C. Sharpe ratio = $\frac{R_p - R_f}{\sigma_p}$

D. Sortino ratio = $\frac{R_p - R_f}{DR_p}$

E. Treynor ratio = $\frac{R_p - R_f}{Beta_p}$

We also use the accumulated return's plot to show the performance of our strategy. However, only the lasso model performed fairly well. Other models performed poorly.

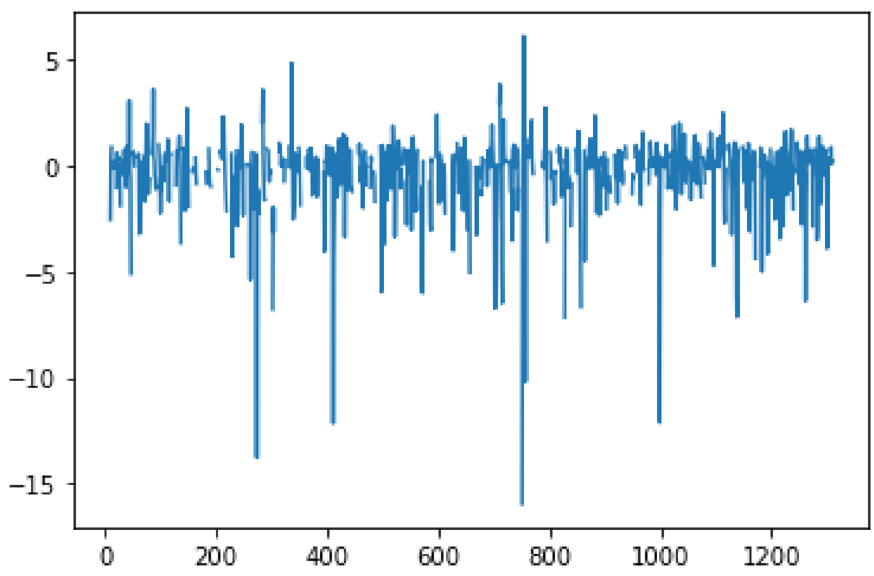


Table 2: Backtesting Results

Models	Excess Return Rate
NN	3.64%
LSTM	3.70%
SVM	2.33 %
Lasso	5%
Prophet	23.05%

We think the prophet model performs great in capturing the trends implied in time-series data, but poorly in capturing accurate changing quantities across data. That might be the reason the prophet performed excellent in generating excess return but poorly in model prediction. For the lasso model, it chooses explanatory variables to do linear regression, so it performs great in predicting and generating excess returns.

4 Conclusion

To sum up, in terms of model performance, the Lasso model gives us the best performance, giving the most accurate predictions and generating the fair excess return. The Prophet model, on the other hand, didn't give us quite accurate forecasts on yield curve change, but generated high excess returns as a compensation.

In the future, we are going to make some improvements. To be specific, we are going to Incorporate relevant macroeconomics factors (inflation, VIX) to improve model prediction accuracy. We also implement model hyperparameters tuning to improve model performance. Additionally, we tried to construct different bond trading strategies by trying different backtesting schemes to increase our strategy variety.