Mini Project | Predicting Recessions

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Introduction

This mini-project explores predicting recessions using Machine Learning techniques. Inspired by the dataset "Dates of U.S. Recessions as Inferred by GDP-Based Recession Indicator" from the Federal Reserve Bank of St. Louis, this project investigates whether we can predict recessions based on financial indicators. Given that recession periods are labeled as 1 (recession) and 0 (no recession), we ask:

Can we develop a model to predict future recessions based on past market data?

To explore this question, we must first define key aspects of our approach.
1. What data should we use to predict recessions?
2. What method will drive our predictions?

We begin by examining the definition of a recession. According to the National Bureau of Economic Research (NBER), a recession is:

> "A significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in production, employment, real income, and other indicators."

This definition raises an important consideration: How does a decline in economic activity relate to uncertainty?

If recessions are periods of heightened uncertainty, we ask:
Can economic uncertainty itself serve as a predictor of recessions?

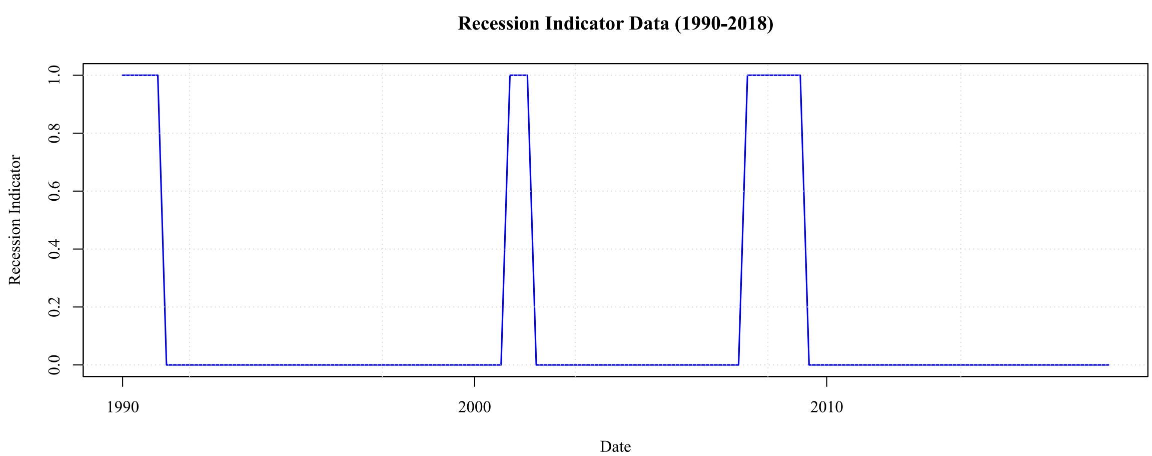
Data and Methodology

We start by choosing the period that will help us predict, defining our training dates and prediction dates. From the available data in the recession indicator dataset, we obtain data from 1990-01-02 to 2024-07-01 from FRED. It is important to note that this data is quarterly.

Next, we determine the measure of uncertainty to use. As an indicator of uncertainty, VIX is chosen due to its reliability, data availability, and daily data frequency. We obtain VIX data spanning 1990-01-02 to 2025-01-22 from FRED.

Considering these two datasets, we select our training period to be from 1990-01-02 to 2018-02-22.

The recession indicator data is depicted below:



After determining the prediction and test dates, we develop a strategy for our approach. Using VIX data, we first predict VIX values and then use them to forecast recessions.

To predict VIX values, we implemented an LSTM-based model that required several preprocessing steps to ensure data consistency and suitability for training. First, we loaded the dataset from an Excel file and formatted it by converting VIX values to float, ensuring numerical consistency by replacing commas with dots for proper interpretation. We removed missing values to maintain data integrity and normalized the VIX values to a 0 to 1 range using MinMaxScaler, which helped stabilize training and improve convergence.

To structure the data for LSTM input, we created sequences using the past 30 days' VIX values to predict the next day's value. This transformation allowed the model to learn temporal dependencies within the time series, which is essential for forecasting. The dataset was then split into training (80%) and testing (20%) sets to evaluate model performance.

LSTM Model Architecture and Training

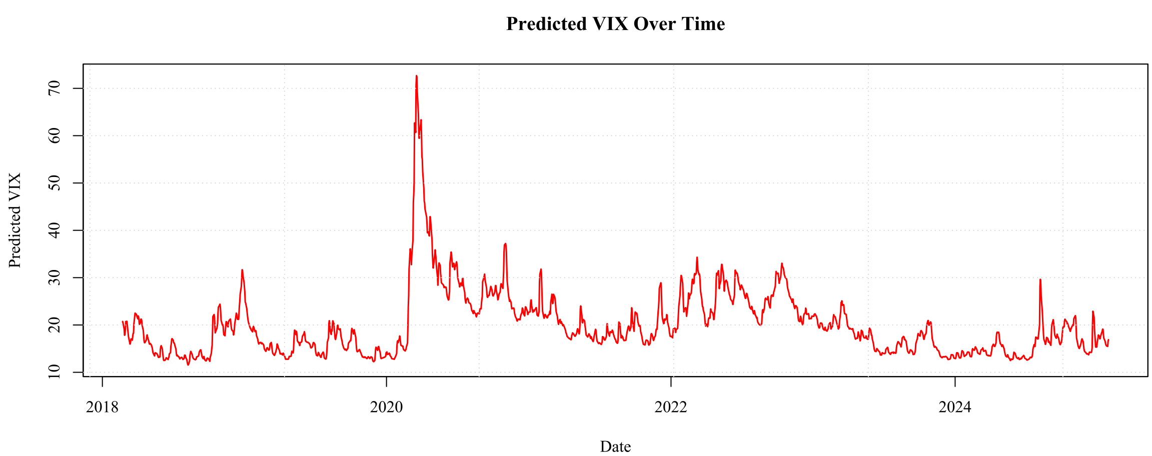
We designed a sequential LSTM network with two LSTM layers, each containing 50 units. The first LSTM layer was configured to return sequences, enabling deeper feature extraction across time steps. To mitigate overfitting, dropout layers with a dropout rate of 0.2 were introduced after each LSTM layer. The final output layer consisted of a single neuron responsible for predicting the next VIX value.

For optimization, we used the Adam optimizer with a learning rate of 0.0001, which facilitated efficient weight updates and improved convergence. The model was compiled with Mean Squared Error (MSE) as the loss function, given its suitability for regression tasks. Training was conducted over 50 epochs with a batch size of 16, incorporating a 10% validation split to monitor performance.

Once trained, the model was applied to predict the last 20% of the dataset, and the predicted values were inverse-transformed back to their original scale for interpretation. Finally, we saved the results in a CSV file and generated a visualization comparing actual and predicted VIX values, assessing the model's predictive capability.

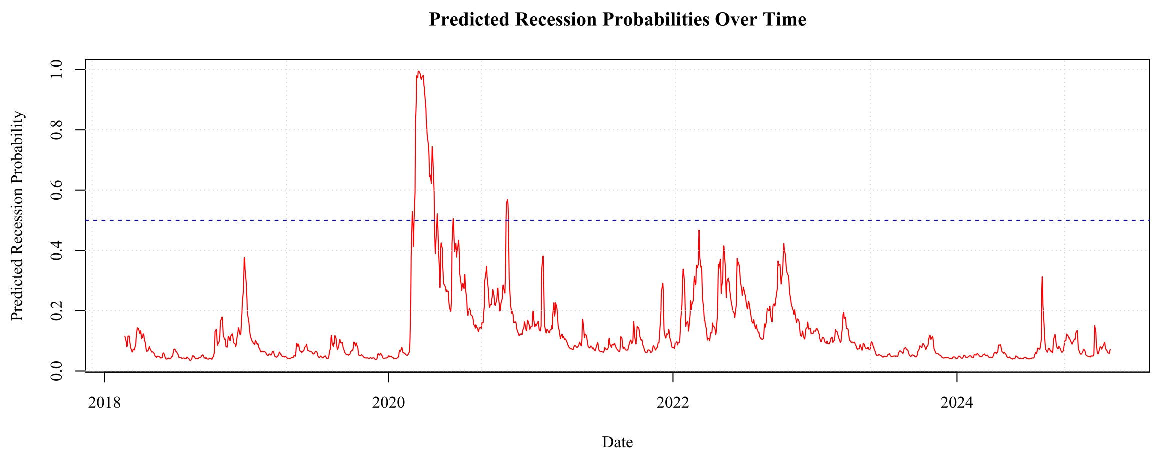
This LSTM-based approach provided a structured and data-driven method to estimate VIX values, which we subsequently used as input for our logistic regression model to predict recession probabilities.

The predicted VIX values over time are depicted below:

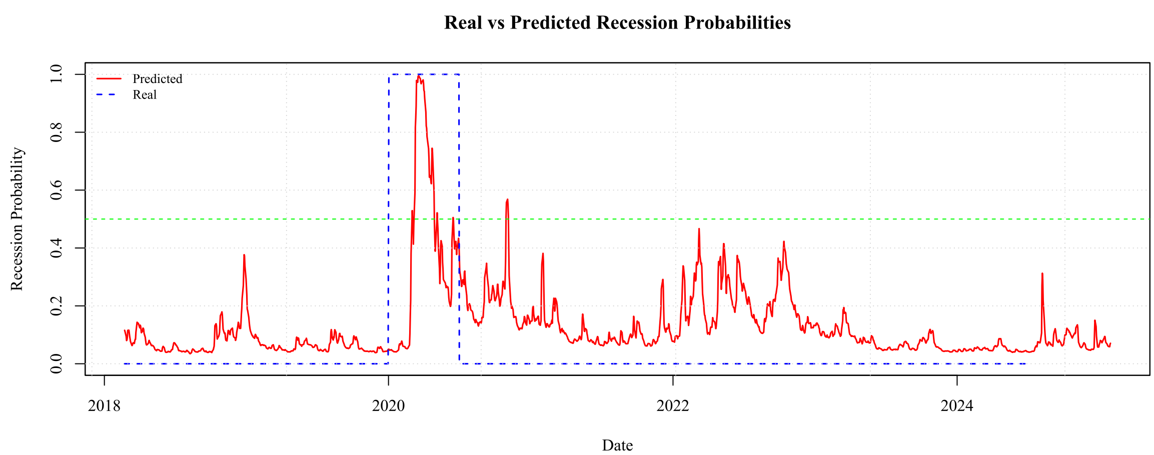


Then, we decide to use logistic regression to predict future recessions. We begin by constructing a new dataset that merges quarterly recession data with daily VIX data for the training period. To align the datasets, we apply a rolling join, ensuring that recession labels are carried forward until the next available update.

We use our fitted model to predict recessions based on the machine learning-predicted VIX during the test period. Logistic regression outputs probabilities, allowing us to visualize the predicted recession probabilities as a line plot. Additionally, we include a dashed line at the 0.5 probability threshold to indicate an arbitrary classification boundary. The depicted figure is shown below.



Given that we have the real recession labels available until July 2024, we plot them alongside the predicted probabilities to assess our model's performance:



We also include our arbitrarily defined threshold of 0.5 to observe whether the predicted recession probabilities align with actual recessions. Our model incorrectly surpasses the threshold in one additional period, suggesting that a higher threshold may have been more appropriate. However, we do not focus on classification accuracy since our primary interest lies in the continuous probabilities rather than binary classification.

Moreover, we observe that predicted recession probabilities align well with real recession periods, reinforcing the idea that our VIX-based predictions are useful as an indicator of economic downturns. This suggests that the machine learning-predicted VIX successfully captures market uncertainty, which correlates with recession risk.

We choose not to define numerical accuracy metrics such as AUC-ROC or precision-recall, as our approach involves two sequential machine learning models—one predicting VIX and the other using VIX to predict recession probabilities. Since errors compound across these models, a single accuracy metric would not fully reflect the effectiveness of our pipeline. Instead, we emphasize the interpretability of the predicted probabilities, which provide a more continuous and flexible measure of recession risk over time.

Conclusion

In this study, we explored the potential of predicting recessions using a combination of deep learning and statistical modeling. By leveraging an LSTM-based model, we first forecasted VIX values, capturing market uncertainty as a key indicator of economic downturns. These predicted VIX values were then used as input for a logistic regression model, enabling us to estimate recession probabilities over time.

Our findings suggest that predicted recession probabilities align well with actual recession periods, reinforcing the effectiveness of VIX as a recession predictor. However, the model's sensitivity to the chosen probability threshold highlights the complexity of defining recession boundaries purely based on quantitative indicators. Instead of focusing on strict classification accuracy, we emphasize the interpretability of predicted probabilities, which provide a continuous risk assessment rather than binary classifications.

This approach demonstrates the viability of integrating machine learning with traditional economic indicators to enhance recession forecasting. Future work could explore additional financial and macroeconomic variables, alternative modeling techniques, and more sophisticated uncertainty quantification methods to further refine predictions.

References

- International Monetary Fund: What is a Recession?
- Federal Reserve Economic Data (FRED):
  - GDP-Based Recession Indicator
  - CBOE Volatility Index (VIX)

- MSc. Nejat Ketrez for his guidance in machine learning.
- OpenAI's ChatGPT for writing assistance.