Forecasting Quarterly Economic Contractions

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Introduction

Being able to predict economic contractions is crucial to the incumbents' decision on macroeconomic policy in their bid to effectively deal with the consequences of them. Through this analysis, we aim to use the given data to best identify and predict any future economic downturns. With Singapore's particular vulnerability to the US' economic developments, accurate prediction supplements businesses and relevant authorities with sufficient lead time should they feel the need to implement policy or business strategy changes to tide through said contractions. We were given the definition of economic contraction as **a quarter of negative real GDP growth,** rather than the official NBER definition. We are then motivated to attempt to predict the real GDP growth at the given the forecast horizons (Q1,2,4 of 2025). Given that the data provided is Time-series based (i.e data collected over a period of time), it helps us to predict the real GDP growth trend over time. We can classify our methods into 2 categories, the first being Continuous predictors (where we predicted the future continuous GDP values and used them to identify if there was indeed a contraction) which included methods like **Multiple Linear Regression (MLR)**, **Random Forest (RF)**, **Time Series ARIMA** and **Support Vector Regression (SVR)**, and the second being Predictive classifiers, where the likelihood of a contraction was directly predicted using the data; this comprised of **Extreme Gradient Boosting (XGBoost)**, as well as **Lasso Logit** and **Ridge Logit Models.**

Our work and in particular the choice of methods were influenced by academic work that we encountered related to time-series analysis of economic related data and prediction. In particular, we made reference to Spyridon D. Vrontos, John Galakis, Ioannis D. Vrontos' work on 'Modeling and predicting U.S. recessions using machine learning techniques (Vrontos et al., 2020). We used ideas from this in conjunction with James Chapman and Ajit Desai's 'Macroeconomic Predictions Using Payments Data and Machine Learning (Chapman et al., 2023). A key difference to note, however, is that the former paper focuses on techniques on the classification of periods as **recessions** whilst we are attempting to identify **contractions** instead**.** Inspired by the works, we continued to leverage on techniques demonstrated in both the former and latter reports mentioned, such as XGBoosting, and Logit models which were demonstrated.

A note to take however, is that some techniques, like **(MLR, RF, ARIMA, SVR)** utilised in our analysis focuses on the prediction of GDP, from which we would then conclude if the quarters displayed signs of **contraction.**

These distinctions allow us to group our methods into binary profiles for ease of presentation. 1. Continuous Predictors (MLR, ARIMA, RF, SVR) , and 2. Predictive Classifiers. (XGBoost)

Dataset

The sets of data provided to us were substantially large. First, the "Quarterly_Data" file contained data that started from the first quarter of 1959 all the way to the last quarter of 2024, with a rather comprehensive composition of different variables, containing **264 samples (excluding date)** and **246 features per sample**, spanning the period from **March 1959 onward**. This dataset includes various economic indicators, such as **GDPC1 (Real Gross Domestic Product), PCECC96 (Real Personal Consumption Expenditures), GPDIC1 (Gross Private Domestic Investment),** and **NASDAQCOM (NASDAQ Composite Index)**. The quarterly dataset serves as an assisting feature, offering a broader temporal perspective for economic analysis and forecasting.

The second dataset, "Monthly_Data" dataset similarly comprised monthly macroeconomic indicators related to economic activity, market performance, and consumer sentiment. However, it had significantly fewer features (**126 features discounting date**). It includes variables such as **industrial production (INDPRO)**, **retail sales (RETAILx)**, and **volatility index (VIXCLSx)**, among others. However this monthly dataset omits a rather large number of intuitively useful variables, some of which such as "**GDPC1 (Real Gross Domestic Product (GDP)**" and "**PCECC96 – Real Personal Consumption Expenditures**" that were present in the Quarterly Dataset. Hence, our main analysis focuses on the manipulation of the Quarterly Dataset, as we aim to predict contraction in Quarters 1, 2 and 4 of 2025. Additionally, using the Monthly dataset could lead to an overfitting of machine learning algorithms, especially since we are predicting by the quarters and analysing trends across months might produce an overfit. The Monthly dataset's lack of comprehensivity leads us to lean towards a larger focus on the Quarterly data instead.

The data provided had a significant presence of NA values which posed some issues when we attempted to run the data through the models like MLR. For instance, **CP3M** (3-Month AA Financial Commercial Paper Rate) had NA values from 1959 to the 4th Quarter of 1996, and other columns similarly posed such issues when we tried to begin our analysis. We leveraged on the "select" function of the **dplyr** package to remove rows according to index, such as the following (to name a few): CPF3MTB3Mx (col 157), MORTG10YRx(col 153), REVOLSLx(col 167), DRIWCIL (col 169), USSTHPI (col 179). This cleaned data set is then used to run our models, initially referring to ARIMA, MLR and XGBoost. Further cleaning involved the curation of lag features for the data, which was used to aid in prediction processes for techniques like RF and SVR.

Methodology

Predicting economic contractions is a time series forecasting task where historical data on GDP and its related variables is used to predict economic contractions in the future horizons. Various algorithms can be employed for this purpose, each with its own strengths and weaknesses.

MLR is a linear model used to establish multiple input features and the target variable, estimating the relationship between independent variables and the dependent variable by fitting a linear equation to the data points. **RF** is an ensemble learning algorithm that builds multiple decision trees on different random samples of the dataset and aggregates their predictions. Decision trees are highly sensitive to training data which can result in high variance and fail to generalize the data. RF uses random sampling of the data known as bootstrapping and generates decision trees from each bootstrapped data with a random selection of features. Predictions are then made through aggregating the predictions of all the random decision trees formed. RF involves the process of bootstrapping and aggregating is also known as bagging, where bootstrapping results in decreased sensitivity to data and aggregating different decision trees results in reduced correlation between features, decreasing variance.

ARIMA is a time series model used to analyze and forecast data by capturing temporal dependencies through autoregression, differencing, and moving averages. It models linear relationships within a time series by using past values and errors to predict future points. **SVR** is a regression-based machine learning model that extends Support Vector Machines to continuous outputs, fitting a function within a margin of tolerance rather than minimizing error directly. It uses kernel functions to capture complex patterns and is effective in handling high-dimensional data. **Extreme Gradient Boosting (XGBoost)** builds an ensemble of decision trees using gradient boosting, optimizing for both speed and performance. It uses a boosting technique where trees are added sequentially, correcting the mistakes of previous trees to minimize errors and improve predictive accuracy. **LSTM** networks is a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data like time series. LSTMs have memory cells that allow them to remember information over extended time periods, making them well-suited for modeling complex temporal patterns and forecasting future values in time series data.

Feature Selection Process

First we plotted the correlation matrix between all the features and identified inputs with higher correlation to the **"GDPC1"** feature (which refers to GDP). From there, we chose features that had a correlation value above 0.9 as inputs for our MLR model. The large number of variables (more than 200) meant that even when we cut the correlation threshold down to >0.9, we still had 114 features remaining.

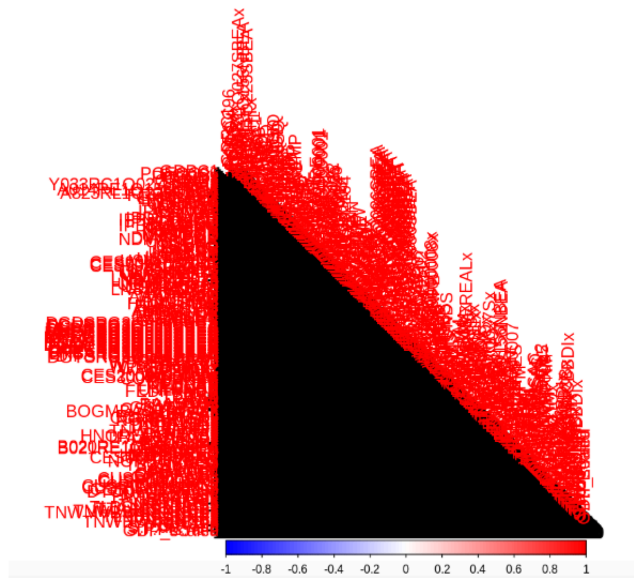

Figure 1: Correlation Matrix of features with GDPC1

We refined our analysis by streamlining this down to the top 20 most influential features.

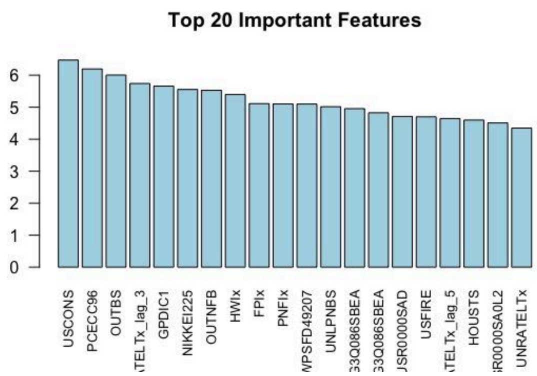

Figure 2:Top 20 important features

Modelling data: Multi-Linear Regression

After drawing out the correlation matrix and indicating the correlation threshold for the variables used. We then perform a rolling time-based data splitting procedure for time series analysis. First, we filter out missing values in the `time` column from the filtered data. Then, we apply the `sliding_period()` function to generate rolling training and testing sets, using a quarterly period with a 20-quarter lookback and a 4-quarter assessment stop. The choice of lookback and assessment stop quantities were chiefly due to the fact that we had a substantial amount of data that dated back to 1959, and our motivations to predict contractions in Q1,2, and 4 of 2025. Such splits hence made the most intuitive sense to our team. The first rolling window extracts the initial 20 quarters for training and the subsequent quarter for testing. The second rolling window shifts forward by one quarter, creating an updated training and test set.

Modelling Data: Time-Series ARIMA

Our time-series analysis with ARIMA was relatively naive and simplistic - we sought to use it as a baseline comparison to other techniques due to the perceived lack of depth when conducting this analysis. We parsed the cleaned data into the auto.arima() function, and attempted to run the model to predict the next quarters' GDP.

Modelling Data: Random Forest

Moving on, we implemented a time-series forecasting approach using a Random Forest model to predict GDP for the next six quarters based on historical economic data. Initially, the dataset is preprocessed by removing selected columns, converting the date variable, and ensuring numerical formatting for relevant features. Since RF helps to select the key features at each node to split, we left the dataset with all its variables instead of focusing on variables with correlation higher than 0.9. As mentioned previously, we also created lagged variables for selected columns to capture temporal dependencies, and missing values are removed to ensure data integrity. The lagged variables focus on macroeconomic indicators such as GDP, government spending and more as these variables tend to have a delayed impact on the economy, hence the need to analyze its changes in the periods after. A rolling forecasting strategy is then applied, where a Random Forest model is trained on the most recent 60 quarters of data, and GDP predictions are iteratively generated for six future quarters. The model's output for each quarter is fed back into the training set, simulating an autoregressive process. The predicted values were visualised using a time series plot.

Modelling Data: Support Vector Regression (SVR)

Using the cleaned data, we trained a Support Vector Regression (SVR) model with a radial kernel to forecast GDP for the next six quarters using the most recent 60 quarters of data. With the prior knowledge that GDP follows the business cycle, we used the radial kernel to do our prediction with the idea that the GDP follows a sinusoidal pattern. As mentioned above, a rolling forecasting approach is adopted, where the SVR model is trained iteratively, predicting GDP for each future quarter, incorporating predictions back into the training set to simulate an autoregressive process, similar to the RF model.

Modelling Data: XGBoost

We also modelled an XGBoost-based classification model to predict economic contractions in the next two quarters using historical GDP data. Using the cleaned dataset, we now supplement it by creating binary indicators for GDP contractions at different future horizons (one quarter, two quarters, and one year ahead). The data is then split into training and testing sets, with feature matrices prepared for model training.

The classifier is trained to predict whether GDP will contract in the next quarter, optimizing for log loss. The trained model is then used to generate predictions for the next two quarters, with contraction probabilities converted into binary classifications. A simple economic simulation adjusts GDP based on contraction predictions before making the subsequent quarter's forecast. The final output is a data frame containing the predicted probabilities and binary contraction classifications for the next two quarters.

Results and Discussions

Prediction results of contraction

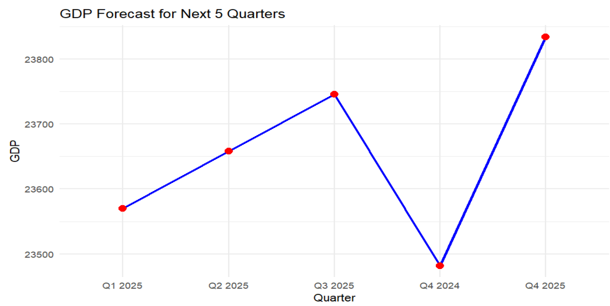

Figure 3a: Time-Series ARIMA forecasted GDP for the next 5 quarters

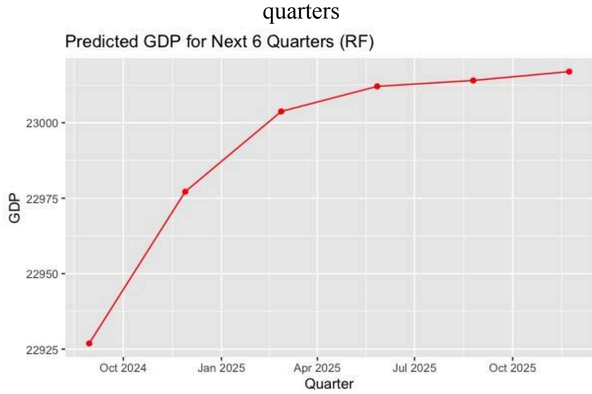

Figure 3b: Random Forest prediction of Q3 of 2024 to Q4 of 2025 GDP

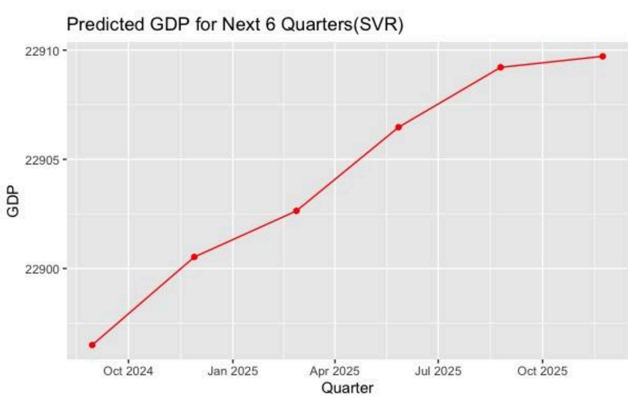

Figure 3c: SVR prediction of Q3 of 2024 to Q4 of 2025 GDP

quarter_ahead	contraction_prob	contraction_prediction
<dbl>	<dbl>	<dbl>
1	0.002283818	0
2	0.002283818	0

Figure 3d: XGBoost forecasted probability for a contraction for the next 2 quarters

Evaluation of ML/AI methods

To evaluate the different models, we make use of root mean-square error (RMSE), which provides the difference between actual and predicted GDP. To compare the accuracy of our prediction, we compared the RMSE of the GDP prediction for Q3 of 2024.

RMSE		
MLR	RF	SVR
429.60	469.0175	502.9799

Table 1: Performance of different ML/AI methods

ARIMA

While lacking in rigor, the Time-series ARIMA model that we ran on historic GDP served as a benchmark for the predicted changes in GDP in the upcoming quarters.

MLR

Although MLR achieved a relatively low RMSE on historical data, it remains too simplistic for forecasting future GDP. MLR assumes a fixed linear relationship between predictors and the target variable, but economic systems are inherently dynamic and influenced by complex, nonlinear interactions. More critically, MLR relies on future feature inputs being known in advance, which is often impractical in real-world forecasting. Without access to accurate future values of key economic indicators, the model cannot generate reliable GDP projections, highlighting its limitations for forward-looking analysis. As highlighted by the research paper " Prediction of GDP Based on the Lag Economic Indicators", forecasting of the dependent variable would require the forecasting of the independent variables as well, hence making the prediction more susceptible to errors and resulting in poor predictions (Stundziene, 2015). Hence, the MLR model would not be the best to predict the future trends in GDP.

RF

While the RMSE of the random forest predictor is high, we aimed to analyse the direction of the changes in GDP for the upcoming quarters rather than the specific GDP itself, hence by analysing Q3 of 2024 as well, the prediction of the swings in GDP do not rely on the accuracy of the prediction but rather on the analysis of the GDP trend forecasted. The limitations of random forest lie in the need for variable values in 2025 in order to make an accurate prediction for the GDPs then. Additionally, the poor prediction could also be due to noise in the data such as the sudden dip in GDP in Q1 and Q2 in 2020, potentially due to the COVID-19 pandemic. This disruption in the upwards trend during that period of time could potentially cause the random forest model to falsely predict random dips in GDP across time when realistically it is due to external factors.

This is especially so when the random forest model only takes in the last 60 quarters of data to train its model, potentially ignoring the past trends of GDP, causing the anomaly in 2020 to have a larger impact on its prediction accuracy.

From the analysis of the next 6 quarters of GDP from Q2 of 2024, it does seem to predict an expansion for Q1, Q2 and Q4 of 2025, although it does seem to suggest a cooling down in expansion as can be seen in figure 3b.

SVR

Even though SVR provided the worst prediction in comparing the RMSE, I believe SVR is a better prediction tool for GDP trends. This is because SVR can model non-linear relationships and hence account for the non-linear patterns of GDP, as supported by the research paper 'Long-term GDP forecasts and the prospects for growth' by Theodore Modis, who describes the GDP pattern of the last 80 years of the US as a 'S-shaped logistic pattern' (Modis, 2013). However, the poor prediction could be due to the relatively linear relationship of GDP across time in our dataset, which goes against our theory of the sinusoidal pattern.

Albeit the poor prediction, its analysis of the future trend in GDP aligns well with that of RF as they both predict continuous expansion over Q1, Q2 and Q4 of 2025. Similarly, it predicts a slow in growth of GDP as it approaches Q4 of 2025, simulating the peak of a sinusoidal graph as can be seen in figure 3b.

XGBoost

The XGBoost model estimated a 0.228% probability of economic contraction over the next two quarters, ultimately classifying the outcome as non-contraction. However, similar to MLR, its heavy reliance on historical data and lack of access to real-time economic indicators constrain its effectiveness. Without incorporating up-to-date information, the model's predictive power is inherently limited, reducing its reliability for forward-looking economic analysis. Additionally, tuning the hyperparameter effectively such as the depth remained a prominent issue. (Bentéjac et al., 2020)

Conclusion

Economic expansions and contractions generally follow the business cycle, hence the results of our prediction can only suggest the same flow as that. Machine learning algorithms analyse past trends and predict the future based solely on data and number. In reality, a multitude of external and unforeseen circumstances can impact the GDP of the country. Such extreme cases can be seen during the COVID-19 pandemic, which suggested deviations in GDP growth away from its predicted expansion trend. Our prediction on the expansion and contraction of the economy serve as a mere guide to the potential prospects of the US economy rather than a prophecy of the future.

While our machine learning algorithms provided poor prediction results, the analysis of the future trends in GDP aligned with each other - indicating continuous expansion of the US economy over Q1, Q2 and Q4 of 2025. Despite the lack of precision in prediction, our machine learning models are able to learn from past trends well and are able to predict the general flow of GDP trends rather than specific GDP values.

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Use of Generative AI:

Generative AI was used to refine codes used in machine learning algorithms and debugging code errors.