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PREDICTING GDP WITH MACHINE LEARNING TECHNIQUE

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Abstract

This paper proposes a method for reducing model errors in regressions when modelling macroeconomic variables by using machine learning algorithms and traditional time series regression models. In this paper, machine learning models are subjected to repeated k-fold cross validation and hyperparameter tuning. The linear model uses repeated k-fold cross validation, on the other hand, the traditional time series model Mixed Data Sampling Auto Regressive Distribution Lag model is run without repeated k-fold cross validation and hyperparameter tuning. The results show that integrating repeated k-fold cross validation with hyperparameter tuning increases the overall performance of machine learning algorithms and each model records the average outcome from all folds and runs. These findings demonstrate how machine learning models outperform the traditional time series model.

Keywords

Prediction, machine learning, Real GDP, Cross Validation, Kernel Support Vector Machines, MIDAS_ARDL, Taiwan

INTRODUCTION

Policy decision-makers often make choices with uncertainty about future economic status. This is because in most cases, benchmark statistical indicators publicly released offer uncertainties about economic forecasting due to late release dates and are subject to frequent revisions. If policy makers could detect the decline in output, this would improve adjustments to monetary and fiscal policies.

Athey (2019) observed the relevance of machine learning (ML) in the era of big data, more especially in microeconomic applications. Even though there are few literatures on machine learning methods, the overall performance of these methods is very interesting. That being said, it is a common trend for machine learning models to focus on excellence in prediction without good insights on the models' overall performance in minimising root mean square errors (RMSE). Lower values of RMSE are desirable and reflect an excellent measure of accuracy in model prediction of the response. The RMSE is the most important criterion for fitting the data if the model's primary purpose is prediction.

In line with the above, ML approaches empirical analysis as algorithms that estimate and compare different alternate scenarios. This fundamentally differs from econometric analysis, where the researcher chooses a specification based on economic principles and estimates the best model. Instead, ML is based on improving and changing models dynamically because ML is data-driven. Eventually, as technology advances, researchers and policymakers have the opportunity to improve on predictions and analysis by using ML based algorithms.

The main objective of this research is to provide a framework for monitoring the economy, in econometrics, this framework is called “nowcasting”. Giannone et al. (2008) defined nowcasting as the prediction of the present, the very near future and the very recent past and is therefore particularly relevant for those variables like GDPs that albeit being critical in evaluating current economic performance are only available at low frequency, typically quarterly, and is published with significant delay, making the recent past unknown.

In order to produce early estimates of GDP, nowcasting involves exploiting the information content of indicators that, related to GDP, are available both at higher frequency and periodically. Such assessments are routinely conducted within major policy institutions that employ either judgement, or simple models let alone combination of the two to gauge insights on the current status of the economy using information contained in potentially very large sets of relevant economic variables.

This research study adheres to the following structure. First section covers the literature on machine learning models and results obtained in predicting real GDP. Data and methodology are covered in the following sections. In empirical results section, the empirical findings are explained and the focus is primarily on the MIDAS ARDL model performance, with results and overall performance of the Kernel Support Vector Machines and last section gives a conclusion.

LITERATURE REVIEW

It's fascinating to see how machine learning is being used to forecast macroeconomic variables. This chapter brings together the findings from several ML studies that have used various algorithms to forecast GDP growth even as early as 2020.

There are a wide range of traditional econometric methods available for forecasting macroeconomic variables. Two of the most common methods are called judgment-based forecast and the model-based forecast. The result of a judgment based forecast is primarily dependent on a specific forecaster's ability to observe empirical irregularities and regularities in the economy which makes it difficult for an outsider to know the model and data used as observed by Robertson and Tallman (1999). The other alternative, the model based forecast is based on a statistical approach which makes it easier to trace sampling errors and therefore the performance of the model can be evaluated. Robertson and Tallman (1999) further suggested that the challenge for governments and businesses from an economic perspective include the forecasting of real GDP growth, inflation and unemployment. According to Robertson and Tallman (1999), the model based forecast research is a vector autoregression (VAR) of six U.S. macroeconomic variables which are used to forecast real GDP growth, inflation and unemployment. The most common model based forecast is a VAR model. It is important to stress that when constructing a VAR model, one has to decide on which variables to use, and which variables to omit. Furthermore, forecasting with a VAR model is done to summarise the dynamic correlation patterns among the observed data series, and then use this observed data to forecast future values for each series.

Marcellino et al. (2003) describe the increasing importance of forecasting European economic performance with respect to the European Central Bank's inflation target rate. The increased European integration means that business and political decisions increasingly rely on the aggregate economic activity in the Euro area, which means that there is an increasing interest of forecasting these economic activities.

Krkoska and Teksoz (2007) analyse how accurate GDP forecasts have been in a sample of 25 transition countries, from 1994 to 2004. The sample includes a large part of the former Soviet Union states including the three Baltic States. Krkoska and Teksoz (2007) were interested in how the forecasts were affected by large institutional changes when only short time series for a limited number of variables were available. Krkoska and Teksoz (2007) conclude that forecasts made by the European Bank for Reconstruction and Development (EBRD) have been successful.

The large-scale dynamic factor models' approach to nowcasting is proposed by Giannone et al. (2008). Their methodology combines principal components analysis and a Kalman filter. First, they obtain the common factors from a large set of macroeconomic indicators. In the second step, they smooth these common factors using Kalman filter. Afterward, Giannone et al. (2008) use smoothed common factors as explanatory variables in a simple ordinary least squares (OLS) regression to produce nowcasts of GDP growth.

The use of SVM for time series with respect to economic prediction is not a new concept. Long (2010) trains support vector machine with a genetic algorithm (GA-SVM) as well as a Random Forest Neural Network (RBFNN) and applies it to GDP forecasting. The total GDP data collected are for Anhui province of China from 1989 to 2007. The results show that GDP prediction performance of the proposed GA-SVM is better than that of RBFNN. Recently, Tamara et al. (2020) adopt SVM model and use eighteen quarterly macroeconomic and financial market variables. Tamara et al. (2020) evaluates the performance of six popular ML algorithms, the Random forest, LASSO, Ridge regression, Elastic Net, Neural Networks, and Support Vector Machines, relating to real-time forecasting of GDP growth from 2013: Q3 to 2019: Q4 period. The RMSE, Mean Absolute Deviation, and Pearson correlation coefficient were used as measurements of forecast accuracy. The results show that the performance of all these models outperform the AR (1) benchmark model. The model that shows the best performance is the Random Forest. To gain more accurate forecast result, another regression is run using equal weighting and LASSO regression. The best model is obtained from forecast combinations using LASSO regression with selected ML models namely: Random forest, Ridge regression, Support Vector Machine, and Neural Network.

There exist several approaches in terms of nowcasting models: bridge equations, mixed data sampling (MIDAS) regressions, mixed frequency VARs, and mixed frequency dynamic factor models. Giannone et al. (2008) develops a formal forecasting model that addresses several key issues that arise when using a large number of data series that are released at alternative times and with different lags. Moreover, Giannone et al. (2008) combines the idea of ''bridging'' monthly information with the nowcast of quarterly GDP and the idea of using a large number of data releases within a single statistical framework. The framework formalises the updating of the

GDP nowcast as monthly data are released throughout the quarter. This approach can be used not only to nowcast GDP but also to evaluate the marginal impact of each new data release on the nowcast and its accuracy. The framework is a large bridge model that combines three aspects of nowcasting: (i) it uses a large number of data series, (ii) it updates nowcasts and measures of their accuracy in accordance with the real-time calendar of data releases, and (iii) it ‘‘bridges’’ monthly data releases with the nowcast of quarterly GDP. Giannone et al. (2013) nowcast China’s GDP by estimating a Dynamic Factor Model using quasi maximum likelihood. Naturally constrained by data availability, Giannone et al. (2013) estimates the model on a relatively small scale data set of monthly and quarterly indicators selected to represent the China’s economy and evaluate model performance by running a pseudo real time forecasting exercise over the period from Q1 2008 up to Q1 2013. Giannone et al. (2013) show how the model significantly gains accuracy when compared to naïve AR, and performs remarkably well when institutional and market forecasts are used as benchmarks. Due to lack of seasonally adjusted official GDP data, and contrary to standard nowcasting applications, we use as target variable the year- on-year growth rate of real GDP at quarterly frequency; this is also motivated by the fact that China did not experience negative growth at least since the early 1950’s and therefore looking at growth rates cycles is a sensible choice in this setting.

The MIDAS regression represents an alternative benchmark model, according to Ghysels et al. (2007). MIDAS method deals with mixed frequencies by employing a polynomial weighting function to link high frequency and low frequency data. Clements and Galvão (2008) compares MIDAS approach to other ways of making use of monthly data to predict quarterly output growth. The MIDAS specification used in the comparison employs a novel way of including an autoregressive term. Clements and Galvão (2008) find that the use of monthly data on the current quarter leads to significant improvement in forecasting current and next quarter output growth, and that MIDAS is an effective way of exploiting monthly data compared to alternative methods.

In contrast to the MIDAS approach and consistent with a conventional VAR model based on single frequency data, the mixed frequency (MF-VAR) model specifies the joint dynamics of monthly GDP, which are obtained from quarterly GDP by time disaggregation, and the monthly indicator. An example of an application related to the European context is in Kuzin et al. (2011) who compare MIDAS and MF-VAR for nowcasting and forecasting quarterly GDP growth in the euro area. Kuzin et al. (2011) show that the two approaches are more complementary than substitutive: MIDAS tends to perform better for shorter horizons, whereas MF-VARS is better for longer horizons.

Adopting machine learning for forecasting GDP, Richardson and Mulder (2018) examined superiority of ML algorithms in the prediction of the real GDP growth for New Zealand. Results confirmed that ML algorithms in predictions are superior to classic statistical methods. This further indicates the suitability of support vector machine (SVM), Neural Network (NN), Lasso, Boosted Tree (BT), Regularized Generalized Linear Model (GLMNET), and Ridge regression to predict GDP growth. The International Monetary Fund (IMF) published a working paper titled “An Algorithmic Crystal Ball: Forecasts-based on Machine Learning” by Jung et al. (2018), while they employ ML algorithms in particular GLMNET, Neural Network and Super Learner, they also conclude that these algorithms outperform standard classic statistical methods. Despite their findings, Richardson and Mulder (2018) and Jung et al. (2018) share an observation particularly related to parameters.

The parameters used to fit the ML models in both researches are standard thereby affecting the learning ability of the ML models. This has been proven in related research and that parameters should be carefully chosen. Therefore, the more standard the parameter choice for the model, the better is the average learning ability of the model from the dataset. Furthermore, if the prediction and forecast evaluation are only drawn on the RMSE, it is possible that one terrible prediction point will skew the metric towards underestimating any model's suitability. Moreover, Jung et al. (2018) do not provide plots of expected values versus actual values for any of the economies analysed, nor do they include a list of variables used to build the ML algorithms.

Premraj (2019) conducted a study on the following economies: Australia, Canada, the Eurozone, Germany, Spain, France, Japan, Sweden, the United Kingdom, and the United States. Premraj (2019) compares the prediction of GDP growth using machine learning algorithms and conventional time series regression models. ML algorithms in the study are the Bayesian Additive Regression Trees (BART), Elastic-Net Regularized Generalized Linear Models (GLMNET), Stochastic Gradient Boosting (GBM), and eXtreme gradient boosting (XGBoost). At the same time, Autoregressive (AR) models, Autoregressive Integrated Moving Average (ARIMA) models, and VAR models represent the traditional time-series regression methods. The results show that the multivariate VAR models outperformed the other models.

Furthermore, Premraj (2019) does an assessment of the top three variables that drives the best performing Machine Learning algorithm of XGBoost. The result shows that XGBoost chose variables which are different from the common variables that are used for forecasting GDP growth. In particular, the chosen variables by XGBoost are different for every country under study.

Qureshi et al. (2020) focused on selecting features with the AutoML function of H2O and used eXtreme gradient boosting (XGBoost). The features were introduced into XGBoost for predicting the real GDP growth rate. Qureshi et al. (2020) apply principal component analysis (PCA) in their study. The results indicate that having the train, validation, and test datasets is a better strategy to improve prediction.

Bolhuis and Rayner (2020) examined various supervised ML models, particularly Random forest, eXtreme Gradient Boost, and SVM to nowcast economic variables for Turkey. These models were also put together to form an ensemble. By combining the algorithms into a single, weighted prediction, the ensemble is expected to reduce prediction errors, however, this could be dependent on the size of the dataset. Using the benchmark Static Dynamic Model, on the other hand, resulted in low nowcast errors due to the amount of data availability, that is large enough to train and test the models. Using database of Turkey country-specific and global indicators, with 234 separate series in total. The data consist of an array of mixed-frequency (monthly and quarterly) covering the period 2012 to 2019. In conclusion, the Random forest and Gradient Boosting gained 60 percent in accuracy as compared to the traditional time series Static Dynamic Model, while the SVM decreased errors by almost 80 percent.

The contribution to the literature from this study will be two-folded and as follows. Firstly, our contribution to existing research is the use of repeated k-fold cross validation and hyper-parameter optimisation in the supervised ML models for real GDP nowcasting. Our study evaluates each model to factor in how the model capture short-term fluctuations. This is done through graphical illustration as well as use of forecast accuracy measures to thorough assess the best model(s) chosen after repeated k-fold cross validation.

Secondly, our research involves dimension reduction through feature selection from the original dataset. Having run the supervised ML models, we conduct variable selection to choose the top ten variables for each model. The selected top ten variables from the best model are compared to traditional econometric models to see whether the best ML algorithm suggest any interesting uncommon predictors.

DATA AND METHODOLOGY

In this study, we use macroeconomic data provided by the Taiwan Economic Journal database, which is a database for financial and economic variables. To validate that the input data for the models in this study is representative of the economy under study (Taiwan), we collect a wide range of macroeconomic indicators. In total, the original dataset has 60000 variables of mixed frequency, the final dataset is manually selected and has eighty-nine variables. Table 1 summarises the time series overview of the mixed frequency.

Frequency	Observation	Variable	Start	End
Monthly	440	39	1980M1	2020M6
Quarterly	146	50	1984Q1	2020Q2

Table 1: Time series overview

Variables of Interest

In this study, real GDP and all quarterly variables were imputed to monthly frequency which made it possible to run the supervised ML models. Only the traditional time series model, MIDAS ARDL use mixed frequency. We have identified the real GDP follows a ARMA(1,1) process. However, for real GDP prediction, this study adopts the supervised ML models as well as the MIDAS ARDL model for prediction.

EMPIRICAL RESULTS

This study follows Bolhuis and Rayner (2020) on machine learning models. These models Bolhuis and Rayner (2020) uses a traditional economics benchmark model, the static dynamic model. Furthermore, our study uses more observations for analysis.

This study employs hyperparameter tuning and repetitive cross validation to find an optimal combination of hyperparameters that minimises a predefined loss function, resulting in improved overall efficiency. The method for fine-tuning hyperparameters in our study is the grid search. It entails creating a model for any possible combination of the hyperparameter values given, analysing each model, and choosing the architecture that produces the best results. The challenges with hyperparameter tuning overall are time consumption and computationally expensive.

Overall Economic Volatility Prediction

While the benchmark MIDAS ARDL model Predictions are relatively stable, and all four ML approaches model major growth fluctuations better as seen in 1999, 2002-2004, and 2008–2009, and 2018- 2019. In this setting, ksvm outperforms the other supervised ML model as well as the MIDAS ARDL model.

In Figure 1, the benchmark model MIDAS ARDL prediction does not capture the up and downs of the observed real GDP. On the other hand, the four ML models outperform the benchmark model on capturing trends and patterns of the observed real GDP. This can be attributed to the repeated k- fold cross validation. Except for the

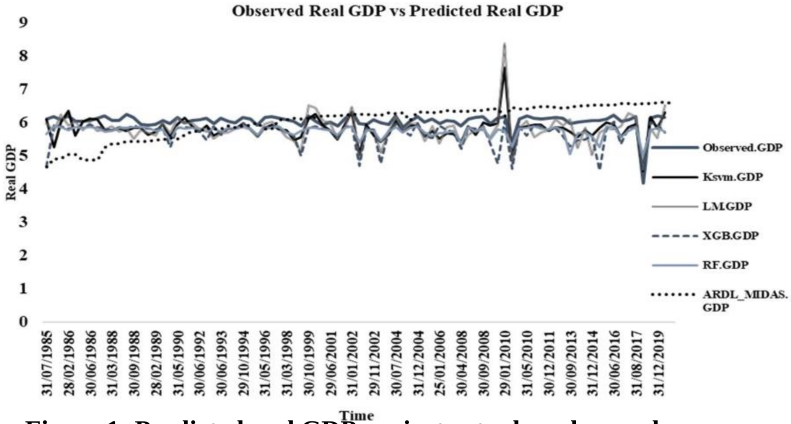

Figure 1: Predicted real GDP against actual or observed quarterly real GDP

linear model, we can also attribute the superior performance to hyperparameter tuning optimization which is adopted in the random forest model, the kernel support vector machine model and the eXtreme gradient boosting model. The trained supervised ML models learn behaviour and pattern of their dataset at each fold when predicting real GDP as compared to the benchmark model. We also observe that the kernel support vector machine model outperforms the other three supervised ML models in most quarters in the period under observation.

Model Assessment for Volatility Prediction

In Table 2, the "intercept" presents the predicted average response (5.782) from the eighty- eight explanatory variables used to predict real GDP for the kernel support vector machine model, the overall prediction in the end for real GDP is 5.22.

The top ten important variables in Table 1 are arranged in order according to the size of the effect of the variable contribution to the predicted average response. The predicted average response decreases or increases depending on the addition or subtraction sign of the variable contributions until we get the overall predicted value given by the model. The table above reflects that a large negative effect (-0.426) comes from the variable fees revenues of national treasury. This -0.426 decreases the average response to 5.356, which is found by subtracting 0.426 from 5.782. Portfolio investment assets increases the average response to 5.556.

Summing up the variable contribution for the top ten variables as well as the row labelled "+ all other factors" gives the model's predicted real GDP which is 5.22. As can be noted, the effect of the first variable is so large that it reduces the average response by a wider margin as can be compensated by the contributions of the variables with a positive effect.

In Figure 2, the ksvm model is able to capture and follow very close to projections of the observed real GDP in many points except for quarters of the years like 1985, 2002 to 2003, and 2009 up to 2010. The RMSE used to graph the ksvm model is 0.5561 from the test dataset. The ksvm model is built from eighty-nine variables of one frequency which is monthly. In this case, all the quarterly variables were imputed to monthly and all missing data were handled by the computation of the NADIA package. We get slightly similar results just like Bolhuis et al. (2020) when nowcasting real GDP.

In Bolhuis et al. (2020) paper, support vector machine model is adopted and it produced RMSE of 1.36 thereby lowering the nowcast errors by almost 80 percent than all other models used in the study including the Static Dynamic model, a traditional time series model which is used as the benchmark model. This is a study that uses Turkey's macroeconomic dataset. In our paper by adopting KSVM, the result is very impressive. We observe that the KSVM outperforms all the other models in our research and this result is similar to Bolhuis et al. (2020) paper. Out of the models in Bolhuis et al. (2020) paper, the SVM model outperformed the rest of the models in rolling out-of-sample nowcasts against actual real GDP.

Test Set Results	Variable Contribution
Intercept	5.782
Fees revenue of national treasury	-0.426
Portfolio investment assets of BOP	0.2
Portfolio investment assets	-0.175
Total net tax revenue from business	0.14
Financial derivatives in financial account	0.096
Financial derivatives assets in financial account	-0.095
Income total debit	-0.089
Tax security transaction	0.075
Gross fixed capital formation	-0.071
Exports of goods and services	0.07
+ all other factors	-0.137
Ksvm model prediction for real GDP	5.22

Table 2: Kernel support vector machine model prediction results

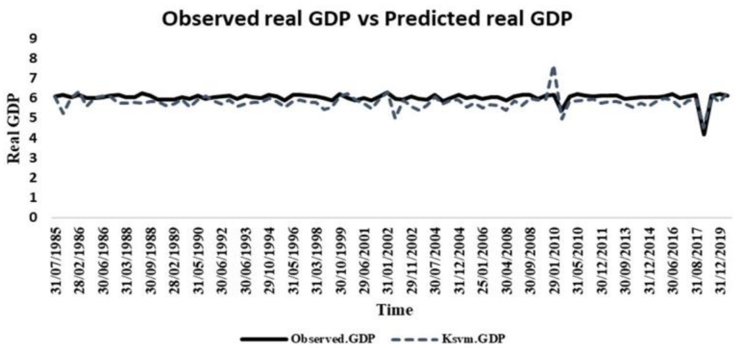

Figure 2: Kernel support vector machine Pred. real GDP vs Observed real GDP

In Table 3, the intercept represents the predicted average response which is 5.702 from the eighty-eight explanatory variables to real GDP prediction for the random forest model. The top ten important variables on the left side are arranged in order according to the size of the effect of the variable contribution to the predicted average response. The table above reflects that a large negative effect (-0.168) comes from the variable total net tax revenue from business tax. This result contradicts the result from ksvm where the same variable contributed positively but it could be attributed to the use of different models which are different in their structure and operation. The -0.168 from total net tax revenue from business decreases the average response to 5.356. Real gross domestic fixed capital formation decreases the average response further to 5.277. Summing up the variable contributions as well as the row marked "+ all other factors" gives the model's predicted real GDP which is 5.194. How we get 5.194 follows the same interpretation as in the previous chapter as we explained for the KSVM.

Test set results	Variable contribution
Intercept	5.702
Total net tax revenue from business	-0.168
Gross fixed capital formation	0.2
Gross fixed capital from private sector	-0.052
Total national Consumption	-0.074
Other investment liabilities	-0.025
Income net of BOP	-0.023
Goods trade net of BOP	0.034
Income total debit	-0.095
Consumer Price Index	-0.052
Exports of goods and services	0.013
+ all other factors	0.013
Random forest model prediction for real GDP	5.194

Table 3: Random forest model Prediction results

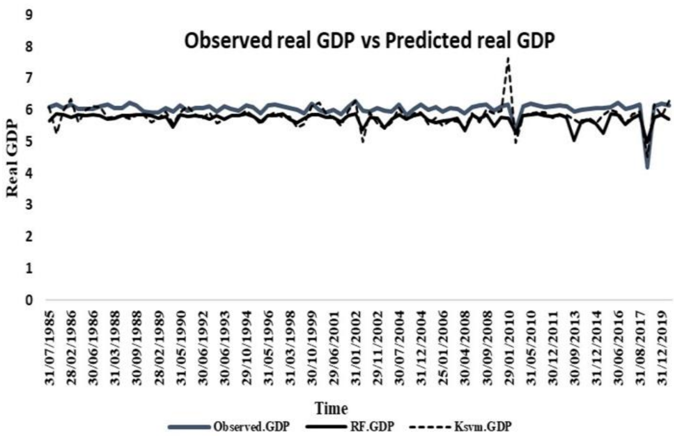

Figure 3: Ksvm Pred. real GDP, rf Pred. real GDP vs. Observed real GDP

In Figure 3, the random forest model is able to capture and follow very close to projections of the observed real GDP in many points except for quarters of the year such as in 2008 - 2010, and 2013 up to 2015. The RMSE used to graph the random forest model is 0.6191 from the test dataset. In this paper, we get different results than Bolhuis et al. (2020). In Bolhuis et al. (2020) paper, the random forest model is adopted and it produced RMSE of 1.26 and it reduced the RMSE by 24 percent than all other models used in the study including the Static Dynamic model, a traditional time series model which is used as the benchmark model.

In table 4, the intercept represents the predicted average response which is 5.599 of the eighty-eight explanatory variables used predict real GDP for the XGB model.

The top ten important variables on the left side are arranged in order according to the size of the effect of the variable contribution to the predicted average response. The graph above reflects that a large negative effect (-0.654) comes from the variable total net tax revenue from business. This result contradicts the result from ksvm where the same variable contributed positively however it is in line with the result observed for the random forest. This -0.654 decreases the average response to 4.945 which is found by subtracting 0.654 from the intercept (predicted average response) value which is 5.599. Gross fixed capital formation decreases the average response further to 4.585. Summing up the variable contributions for the top ten variables as well as the row marked "+ all other factors" gives the model's predicted real GDP which is 5.065.

Test set results	Variable contribution
Intercept	5.599
Total net tax revenue from business	-0.654
Gross fixed capital formation	-0.36
Total net tax revenue- stamp tax	-0.017
Goods trade net of BOP	0.067
Portfolio investment-liabilities- equity- securities of BOP	0.055
Exports of goods and services	-0.092
Balance on goods, services and income of BOP	-0.156
Income net of BOP	0.009
Services total credit of BOP	0.037
Real imports of goods and services	0.011
+ all other factors	0.382
eXtreme gradient boosting model prediction for real GDP	5.065

Table 4: eXtreme gradient boosting model prediction results.

In Figure 4, the eXtreme gradient boosting model is not able to capture and follow very close to projections of the observed real GDP in many points except for quarters of the year such as in 1985, 1990, 1999, 2002 to 2003, and 2009-2010, 2013 and 2015. The RMSE used to graph the eXtreme gradient boosting model is 0.6744 from the test dataset. The eXtreme gradient boosting (XGB) model is built from eighty-nine monthly variables. Bolhuis et al. (2020) used the Gradient Boosted Trees (GBT) also referred to Gradient Boosting (GBT) when nowcasting real GDP. In Bolhuis et al. (2020) paper, the GBT model produce RMSE of 1.29 and it reduced the RMSE by 22 percent than all other models used in the study using macroeconomic dataset for Turkey. In our paper we adopted the eXtreme gradient boosting, even though both XGB and GBT follows the principle of gradient boosting, they are however different in modeling details. Specifically, XGB uses a more regularized model formalization to control over-fitting, which gives it better performance.

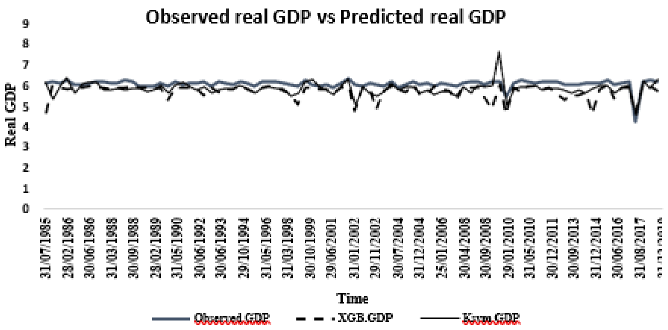

Figure 4: Ksvm Pred. real GDP, XGB Pred. real GDP vs. Observed real GDP

In Table 5, predicted average response which is represented by the intercept is 5.728 of the eighty-eight explanatory variables to real GDP prediction for the linear model. The table reflects that a large negative effect (-0.307) comes from the variable balance of goods, services and income of balance of payment. This -0.307 decreases the average response to 5.421. Portfolio investment assets decreases the average response further to 5.141. Summing up the variable contributions gives the model's predicted real GDP which is 5.009.

In Figure 5, the linear model is not able to capture and follow very close to projections of the observed real GDP particularly for quarters of 1988, 1992 to 1993, 1997 -1999, 2002, 2003, 2008 - 2011 and 2013 to 2014. The RMSE used for this graph is 0.5952.

Test set results	Variable contribution
Intercept	5.728
Balance on goods, services and income of BOP	-0.307
Portfolio investment assets	-0.28
Consumer Price Index	-0.223
Fees revenue from national treasury	-0.215
Current account	0.188
Total net tax revenue- stamp tax	-0.176
M1A	-0.164
Financial derivatives assets	-0.164
Total net tax revenue – business tax	0.162
Portfolio investment-liabilities- equity- securities of BOP	0.161
+ all other factors	0.299
Linear model prediction for real GDP	5.009

Table5: Linear model prediction results.

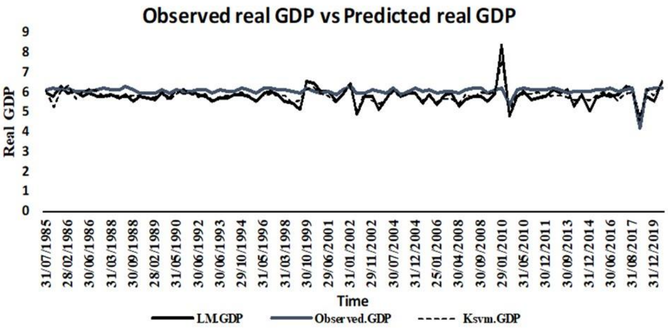

Figure 5: Ksvm Pred. real GDP, lm Pred. real GDP vs. Observed real GDP

In Figure 6, ensemble 1 is developed by combining four models which are: ksvm, random forest, eXtreme gradient boosting and linear model. It can be observed that the ensemble 1 is not able to capture and follow very close to projections of the observed real GDP in many points except for quarters of the year such as in 1986, 1988, 2005 to 2007, and 2010, 2013 and 2017 up to 2018. The RMSE used to graph the ensemble 1 model is 0.5784 from the test dataset. Bolhuis et al. (2020) observed that more complex ML methods such as SVM tend to overfit when training data is relatively limited (e.g., short time series), resulting in predictions that are sensitive to small perturbations in the leading indicators. As such, SVM acts as a counterweight against GBT and RF. In Bolhuis et al. (2020) paper, ensemble 1 is constructed from SVM, GBT and RF and gets RMSE of 1.10.

In Figure7, ensemble 2 is developed by combining four models which are: ksvm, random forest, eXtreme gradient boosting and linear model as well. However, we get the inverse of the RMSE weights for the selected models. It can be observed that the ensemble 2 slightly outperformed ensemble 1. The ensemble 2 is not able to capture and follow very close to projections of the observed real GDP in many points except for the following years: 1986, 1988, 1999, 2002, 2004 to 2007, and 2009 and 2017 up to 2018. The RMSE used to graph the ensemble 2 model is 0. 5774 from the test dataset.

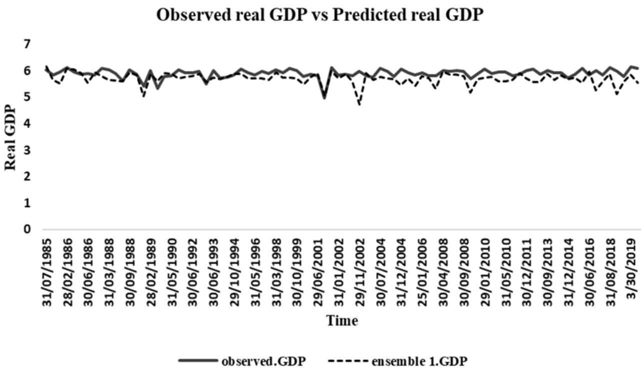

Figure 6: ensemble 1.GDP vs. Observed real GDP

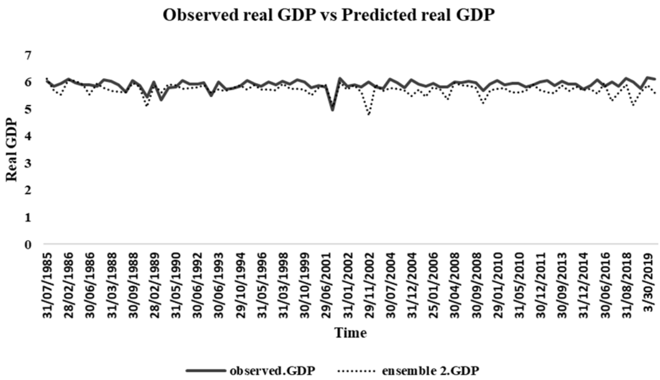

Figure 7: ensemble 2.GDP vs. Observed real GDP

Variables Assessment

The ML algorithms implemented in this paper is contrasted with existing macroeconomic theory by variables assessment. As mentioned earlier, the literature suggests that variable assessment of the model is done by Bolhuis et al. (2020) but did not detail the relevance of the selected variables to Turkish GDP.

This study finds it interesting to explore the top ten variables that contribute the most to Taiwan's real GDP prediction. In this section, top ten variables from the ksvm model are assessed because on average, ksvm has the best prediction performance. These top contributing variables are fees revenues of national treasury, portfolio investment assets, total net tax revenue from business tax, financial derivatives, financial derivatives assets of balance of payment, income total debit of balance of payment, total tax on security transaction, real gross domestic fixed capital formation and exports of goods and services. The portfolio investment assets contribute both positively and negatively and the size of the effect is very large in both instances. Financial derivatives as well as exports of goods and services contribute positively towards the overall model prediction value of real GDP.

The positive contribution from exports of goods and services is desirable considering that when exports exceed imports, the net exports figure is positive. This indicates that Taiwan has a trade surplus. A trade surplus contributes to economic growth in a country and in this case, there are high levels of output from the factories and industrial facilities in Taiwan, as well as a greater number of people that are being employed in order to keep these factories in operation. Eventually this also equates to a flow of capital into Taiwan, which stimulates consumer spending and contributes to economic growth.

The simple correlation between revenue, taxation and economic activity shows that, on average, higher economic growth leads to high tax revenues. But this correlation almost surely does not only reflect a positive effect of tax increases on output. In this study, we observe that total net tax revenue collected from business tax contributes positively to real GDP. This might be explained from the paragraph above where Taiwan has a trade surplus implying that a lot of business are producing more output which is exported and the amount of tax revenue collected equally increases from every transaction that is made on the export volume. On the other hand, we observe that total tax security transactions contribute negatively to real GDP.

The relationship between financial derivatives and real GDP is best described by identifying the channel through which the use of derivatives may impact the real economy, which in this case is international trade. This channel, specifically the imports and exports of goods and services, is perhaps the easiest to use for evaluation in this study. Derivatives are a crucial tool for any company exposed to foreign exchange or commodity price volatility. Not only do they allow exporters and importers to strengthen their financials, but they also reduce the disincentives for international trade. Given the volatility in currencies and international prices, derivatives foster an expansion of international trade in all directions (imports and exports).

In this study the financial derivatives contributed positively to real GDP prediction. However, the assets of financial derivatives contributed negatively to real GDP prediction. This is best explained by the negative contribution of income total debit of the balance of payments. To relate the two variables, investors generally use derivatives for three purposes: risk management, price discovery, and reduction of transaction costs. In a traditional banking model, a maturity mismatch between assets and liabilities exposes banks to interest rate risk. Derivatives thereby mitigate this risk, which often contributes to capital adequacy, profitability, and lowering the probability of bank failure. In addition, banks make markets in derivatives to meet the risk management needs of financial and non-financial firm customers. In the process, banks generate fees and other revenue from this trading as well as lower their cost of funding which are taxable. For non-financial firms, derivatives can assist in risk management associated with cash flow volatility arising from adverse changes in interest rates, exchange rates and commodity and equity prices. Taxes also offers incentives for hedging cash-flow volatility and income. A hedging strategy involving derivatives might alleviate underinvestment caused by insufficient cash flow and risk aversion. The insufficient cash flow affects the income total debit of the balance of payments, eventually leading to the negative contribution to real GDP prediction.

The future is uncertain, and predicting the future is thus inherently difficult. The results in this thesis indicate that machine learning models are better in predicting real GDP trends. The superior prediction abilities of the supervised ML models are highly subject to hyperparameter tuning as well as k-fold repeated cross validation.

Using the traditional time series model could also be beneficial and possibly could generate more accurate results if other techniques can be applied for instance, parameter boosting or perhaps hard thresholding as suggested in literature, which is not the focus of this study. The assumption is that using ML algorithms to predict macroeconomic variables could be more applicable and yield more appropriate results in light of high-quality data and appropriate data processing techniques, such as the optimal tuning grid search and k-fold repeated cross validation. Support vector machine model non-linear relationships between inputs and outputs, making them very useful for solving problems of non-linear nature (Suykens et al. (2001)).

Bolhuis et al. (2020) finds that the static dynamic traditional time series model gave poor performance when nowcasting real GDP growth. The performance metric of RMSE is used, the result indicate that the static dynamic traditional time series model has the highest RMSE as to compared to the three machine learning models in their study in particular the RF, GBT and SVM with macroeconomic data of Turkey covering the period from 2012 to 2019. The RMSE recorded is 1.66 which corresponded to a mean absolute deviation of about 1.2 percentage points per nowcast. In our paper, MIDAS ARDL, the traditional time series model had superior performance with RMSE of 0.0224.

Moreover, by adopting a similar approach of incorporating machine learning models with minor modifications in our paper, our results are very impressive and greatly reduces the RMSE. To be very specific, Bolhuis et al. (2020) adopted machine learning models which are RF, GBT, or SVM and found that these models reduce the RMSE by 24, 22, and 18 percent, respectively. In their paper, the models gave RMSE values ranging between 1.1 to 1.6, in comparison, in our paper, the models gave RMSE values ranging between 0.0224 to 1.21, suffice is to say that in our paper we trained more models and used data spanning over 20 years.

Qureshi et al. (2020) predicted Canadian real GDP growth using Google Trend (GT) data as well as official data from January 2004 up until March 2019. The RMSE, MSE and MAE for the benchmark forecasts of monthly real GDP growth rates are obtained from three different methods: the first-order auto-regressive model, the original boosting model, and the gradient boosting model (GBM) respectively. They found an improvement in the performance of XGBoost relative to the baseline methods even when we use GT data alone (when Official data are not available). Comparing the performance evaluation metrics, they observed a slight improvement in the RMSE, the MSE, and the MAE when both GT data and Official data are used over the case when GT data is used alone. Furthermore, they observe that when GT and Official data are used together, forecasting accuracy is further improved relative to using only GT data.

Our contributions are summarised as follows, first, the SVM model training phase under kernel improves the real GDP prediction. The SVM model achieves smaller classification errors against all other machine learning models adopted in this paper even though it did not outperform the bench mark traditional time series model. In contrast to other studies, we also plot the predictive power of ksvm out-of-sample forecast for the period January 1985 - June 2020. As is clear from Figure 1, the ksvm model provides a prediction close to the observed real GDP, tracking well both the ups and downs of the real GDP. Our findings reveal that both cross validation and hyper-parameter approaches improve the svm model's learning accuracy and prediction.

Secondly, the MIDAS ARDL which uses the unrestricted polynomial functional form does not improve prediction performance overall as seen in Figure 1. Another study by Foroni et al. (2015) showed that unrestricted functional form of the MIDAS performs better for small mixed frequency dataset with fewer variables. However, with many variables in a mixed frequency dataset, distributed lag functions outperform the unrestricted polynomial function of the MIDAS. The good performance of unrestricted MIDAS for small mixed frequency dataset is confirmed in empirical applications on nowcasting and short-term forecasting euro area and US gross domestic product growth by using monthly indicators.

CONCLUSION

Machine learning algorithms are being used solely for prediction purposes and are inherently suitable in the banking, healthcare, and retail industries. As a result, in this study, we use cutting-edge ML algorithms to predict real GDP and equate the results to standard TS regression models. We test five models to improve validity and generalization: linear model, random forest model, eXtreme gradient boosting model, kernel support vector machines model, and the MIDAS ARDL model. Furthermore, this paper has assessed the top ten variables for the kernel support vector machine, as it is the best-performing ML model that has captured the trends and patterns of the observed real GDP.

In terms of prediction accuracy, our findings show that supervised ML regression models outperform the MIDAS ARDL traditional time series model. The traditional time series model predicted real GDP is 6.062 and is higher than the predicted value of real GDP for all the models in this study. The supervised ML models capture the trends and patterns of the observed real GDP more closely as does the MIDAS ARDL. In particular, the KSVM is the model that outperforms all the other models in this study and gives a predicted real GDP value of 5.22. This answers our main objective of this study. Based on our results, one challenge for the MIDAS ARDL is that this model does not fit very well to the given dataset reflected in a low RSquared of 70.75 %. This low RSquared has greatly impacted how the MIDAS ARDL predicts real GDP in this study as seen in Figure 1. Qureshi et al. (2020) observes that ML methods are sometimes criticized as ‘black box’ models as they do not lend themselves to a good interpretation for policy-making purposes. In our paper, we encounter the same challenge.

Out of the top ten selected variables out of the eighty-nine monthly variables, based on contribution of the variable to real GDP prediction of our best model, the ksvm, four variables contribute positively. These variables are portfolio investment assets of balance of payment, total net tax revenue from business, financial derivatives and exports of goods and services. The random forest algorithm, on average, also produced higher prediction accuracy, however, it narrowly fails to outperform the ksvm model, suggesting that some minor modification to the tuning parameters would lead to preferable prediction accuracy. It can also be noted that the RF model captured different variables as compared to the ksvm model.

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