Forecasting Economic Recession in Selected African Countries using Machine Learning Algorithms.

MSc Research Project
M.sc in Fintech

Adeniyi Peter Makinde
x18133681

School of Computing
National College of Ireland

Supervisor: Noel Cosgrave

National College of Ireland

MSc Project Submission Sheet – 2018/2019

School of Computing

Student Name:	Adeniyi Peter Makinde		
Student ID:	X18133681		
Programme:	M.sc in Fintech	**Year:**2019	
Module:	Msc Research Project		
Supervisor:	Noel Cosgrave		
Submission Due Date:	12/08/2019		
Project Title:	Recession Forecasting using Machine Learning		
Word Count:	…4347…… **Page Count**……18pages…		

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature:	
Date:	12th September 2019

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST

Attach a completed copy of this sheet to each project (including multiple copies)	□
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	□
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	□

Assignments that are submitted to the Programme Coordinator Office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Forecasting Economic Recession in Selected African Countries using Machine Learning Algorithms.

Adeniyi Peter Makinde
X18133681
M.sc project in Fintech

Abstract

The Author uses Machine learning approaches to classify through careful variable analysis the likelihood of a recession. Four algorithms are modelled on a data set of Financial and macro-economic variables of African economies. Results show that price level of capital stock (Stock index), real consumption plus investment, employment level, capital stocks are core variables with high predictive power of recession in African economies. Out of the four variables, Random forest outperforms with minimal misclassification error rate.

Keywords-
Recession; forecasting model; Naïve Bayes; logistic regression; random forest; probit; financial indicators.

1 Introduction

Emergence of Recessions is one of the most economic altering events for a nation. After the Great Recession 2007-2009, Scholars sort different approaches to assess various economic models and indicators to predict next economic meltdown and this remains a challenge till today (Chin, et al., 2000). This research contributes to the knowledge pool by using machine learning approaches to study the measure of fit of leading variables for forecasting recessions in economies. The National Bureau of Economic Research(NBER) (NBER, 2019) which serves as the gold standard for US business cycle expansion and contractions defined recession as *“a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales”*. This definition does not only account for real GDP but encompasses possible economic indicators that reliably date contractions(recessions), regardless, a downswing of GDP is tied to a likelihood of a recession period. Business cycle turning points have been closely associated with recession prediction by NEBER through selection of variables within Binary frameworks to classify or forecast economic events. Financial crises, followed by recessions show strong correlations between financial variables and economic activities (Edirisuriya, 2015), hence, a number of studies have tried to use various algorithms such as static and dynamic Probit model using out-of-sample performance (Estrella & Mishkin, 1996) (Nyberg, 2009) (Eric, 2012), neural network model for a flexible functional mapping between variables (Qi, 2001), Markov switching (Kim, 1994) (Lahiri &

Wang, 1994) (Levanon, 2011), random forest model (Nyman & Ormerod, 2017). These studies are vital to shaping the direction of this research.

1.1 Project Specification.

1.1.1 Research Question

Can Machine learning models identify economic variables that provide accurate measures in predicting recession.

1.1.2 Research Objectives

- To demonstrate that machine learning methods can measure and identify periods of recession
- To identify factors/variables that matter in predicting recessions in an economy
- Using selected models and accuracy ratios to determine models with best fit and misclassification errors
- To verify accuracy of results of these models using measures of performance.

In this research, we further investigate a number of models to recognize signals of recession and use a step-wise selection of variables that display strongest relationships for best fit. A Bayesian approach, Probit, Logistic regression and random forest framework to predict and classify probabilities of recession. The choice for these models is supported and further explained in subsequent sections. Models were framed in a way that is complementary and with richer and robust data points. The rest of this research is divided into the following sections; Section 2 is the related works to critically comment on significant literatures, section 3 is the research framework that guides this study, section 4 is the modelling and implementation, section 5 covers and evaluation of result and final thoughts, conclusion will be in section 7.

2 Related Work

Speculations on recession will always be made but that does not translate that all the hybrid and dynamic models can predict a recession at the exact time. If that were to be so, the number of recessions wouldn't have occurred (Marco, 2001) (Filardo, 1999). Just like stock prices, scholars always opine that, in an efficient market, it will be difficult and impossible to predict price fluctuations. It could be the same structural condition for forecasting recession given that recessions are rare events that happen once in a decade. Also, it is difficult to pinpoint the key economic relations as they are continually changing over time. This research attempts to assess these limitations by comparing a selection of tested models with vast number of economic indicators in African economies.

Several approaches have been researched to forecasting economic meltdowns. Probit models, where the renowned research work dates as far back as 1990s. (Estrella & Mishkin, 1996) used a static probit model to evaluate the importance of several variables simultaneously using lagged results. Lack of statistical approach to explanatory variable selection was a key limitation, the researcher suffered from overfitting of the model from selected variables. However, it was concluded that the yield curve and stock price index were useful financial indicators. Lagged recession dummy variables are adopted by (Dueker, 1997) whose work was heavily based on the work of Estrella & Mishkin. Dueker strengthens the position of interest rate (Yield curve) as the single best variable stating that the signals and frequency are easy to interpret. (Filardo, 1999) not only affirms the reliability of probit models, also gives credit to other models such as NEBER's composite index leading indicators(CLI), though effective, scholars have regarded it as too narrow (Diebold & Glenn, 1991), Neftci Model developed by (Neftici, 1982) refining the CLI's rule of thumb by modelling a statistical probability of recession, Stock-Watson Model developed by (Stock & Watson, 1993) which is similar to GDP forcasting model but encompasses broader measures of seven leading indicators, taking into account 10-year treasurt bond yield, labour indexes, exchange rates etc. (Filardo, 1999) work attests to the reliability of these models but also leaves the gap of continous monitoring of development of these models. Building on this, several researchers have built dynamic probit models (Kauppi & Saikkonen, 2008) (Nyberg, 2010) (Eric, 2012). These scholars takes into account the shortcomings of static model which does not take the lagged structure of binary time series into account which gives better results than static models (both in-sample and out-sample predictions). The work of (Kauppi & Saikkonen, 2008) was limited to just interest-rate spread as the only exogenous predictor.

To emphasize the position of key economic relations and changes over time, (Claveria & Torra, 2017) predicted a german recession using boosted regression trees (BRT). The movements of GDP was carefully studied which revealed a decline in the longrun. The BRT approach is useful for studying economic policies, asides that, the model is a best used to analyze the measure of fit of core indicators and allows to examine marginal effects of these indicators on the business cycle forecast. The results show that changes in importance of its leading indicator overtime was captured, there was a decrease in the comparative effect of "short-term interest rate" to "term spread" which increased overtime. (Claveria & Torra, 2017) suggested studying the effect of the stock market as the relative importance of market indexes increased overtime. The dataset used was very robust and extensive, a monthly 40 year span to measure changes overtime. (Nyman & Ormerod, 2017) carried out recession forecast using random forest by splitting dataset into training and testing constructing large number of decision trees. Random forests tend to achieve the better results in a classification model due to their ability to cope with noisy and extreme outliers, also work better with non-linear and high dimensional prediction problems (Breiman, 2001)

A recent study attempted to use Naïve bayesian(NB) approach to forecast regression, (Davig & Hall, 2019) also boast of NB model out performs other models for business cycle turning point prediction, forecasting upto 12 months ahead recessionary signals acknowledging that NB is useful for longer forecast horizon. The authors suggest that using a proven variable selector method and number of boastful lags in an optimal criterion, should achieve better results.

3 Research Methodology

For this research, The Cross Industry Standard Process for Data Mining (CRISP-DM) frame work is used. It is said to be extremely complete and documented, and because this research is a real system challenge, CRISP-DM guide researchers in practical application of its steps (Azevedo, et al., 2008). The following stages will be followed except for the last stage.
i. Business understanding, ii. Data understanding, iii. Data preparation, iv. Modelling, v. Evaluation vi. Deployment

3.1 Data description

The Dataset was gotten from Penn world productivity data[1] , Bank of Canada commodity Indices to compare and evaluate possible contagion from this index[2] and the world bank Gdp growth dataset[3]. The penn data contains relative levels of income, input, output and productivity of over 180 countries between 1950-2017. It consists of 486 rows of observations and 50 variables (49 independent and 1 dependent).

---

[1] Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer (2015), "The Next Generation of the Penn World Table" American Economic Review, 105(10), 3150-3182, available for download at www.ggdc.net/pwt

[2] www.bankofcanada.ca/rates/price-indexes/bcoi

[3] api.worldbank.org

For the purpose of this study, it was trimmed to only cover 27 selected African countries and covers a span of 18 years (2000-2017). These countries have records of slipping in and out of recessions and best for the predictive analysis where a binary outcome is to be classified.

3.2 Data preparation

Here, all tasks relating to finalizing the dataset to be utilized for implementation and evaluation was carried out. The dataset was carefully observed and cleaned. Exploratory Data analysis was carried out to fix fundamental structures, Transform, identify Missing values and fixed using the *mice* function. The stage is used over and over again and make sure the dataset is fully prepared.

3.3 Feature selection

As stated earlier, The dataset contain over 50 variables, a step-wise selection was done using machine learning. Step-wise chooses variables that have the strongest correlation which is not subject to observation by the researcher. This is further described in section 4.

4 Modelling and Implementation

The analyses that were conducted in this work were performed with R. The basic Knowledge Discovery in Databases methodology was employed. To start off the analysis in R, the basic libraries; haven, caret, naïvebayes, randomForest, dplyr, etc. which were relevant to the work were called. The data was read in. The structure of the dataset was investigated with the *str* function. A summary statistics was created.. A table of proportion indicating the ratio attributable to Recession and Expansion was generated. After investigating the absence of outliers and missing values, we proceeded with the test of multicollinearity (this indicates the correlation between regressor variables). Extreme multicollinearity is a problem in regression. Although its presence would have been irrelevant if the work was entirely predictive, we note that, it is damaging otherwise, as it renders parameters that ought to be significant to the analysis, insignificant. To check this, we deploy the *mctest* library with *omcdiag* and *imcdiag* functions.

Upon rejecting the null hypothesis of multicollinearity, we proceeded to using feature selection algorithm. This is valid as it has been proposed in numerous statistics journals that one of the solutions or remedies to multicollinearity, together with transformation of variable(s), use of factor and principal component analysis, use of orthogonal regressors, etc. is the dropping of variable(s).

To determine which variables to drop, and to not subject the selection to personal prejudice, machine learning algorithm was employed. All the variables were included in the initial model, and a stepwise regression was run on this model to remove insignificant variables from the model. Doing this saw the reduction in variable size from fifty to twelve.

The conclusion from the above implementation is that the eleven factors that are major influencers of recession in the African economy are thus:

1. emp: Number of persons engaged (in millions)
2. emp_to_pop_ratio: Ratio of Employed Persons to Total Population
3. cda: Real domestic absorption, (real consumption plus investment), at current PPPs (in mil. 2011US$)
4. cn: Capital stock at current PPPs (in mil. 2011US$)
5. ck: Capital services levels at current PPPs (USA=1)
6. ctfp: TFP level at current PPPs (USA=1)
7. pl_x: Price level of exports, price level of USA GDPo in 2011=1
8. pl_n: Price level of the capital stock, price level of USA in 2011=1
9. fish: Annual Bank of Canada commodity price index - Fish
10. total_change: Year-on-Year Percentage Change Annual Bank of Canada commodity price index - Total
11. energy_change: Year-on-Year Percentage Change Annual Bank of Canada commodity price index – Energy.

The "growthbucket" variable was recoded to a factor variable. This binary dependent variable contained "0" for "Recession" and "1" for "No Recession".

These eleven significant variables formed the base of the modelling effort, and formed a new dataset, together with the dependent variable.

A Data Quality Report (DQR) of this new dataset was generated to show that the dataset was indeed suitable for further analysis.

With this dataset, four models; logistic regression, probit, naïve Bayesian approach, and random forest, were built. Each of the model's accuracy ratio were computed and a comparison to determine the better model followed.

4.1 SELECTED MODELS DESCRIBED

4.1.1 Logistic Regression Model

The logit model is suitable for binary outcome frameworks where a classification is best predicted i.e success or fail, paid or default etc, dummy encoded which in this study are the Zeros and Ones corresponding to "Recession" and "No Recession" respectively. This model, unlike other regression models permits the regression on one more than one explanatory variable which could be dichotomous, ordinal or continuous. In cases where the categorical explanatory variable exceeds two levels, multinomial logit is used for prediction.

In this recession analysis, given the two outcomes of "No Recession and Recession, the binomial model would suffice.

An explanation of logistic regression starts with the explanation of the standard logistic function. The logistic function is a sigmoid function that takes any real input, say, t and outputs a value between 0 and 1. Logit regression is an important machine learning algorithm. The goal here is to model the probability of the random variable, Recession, being 0 or 1 given our dataset.

4.1.2 Probit Model

In statistics, a probit model is a type of regression model where the dependent/explanatory variable can take only two values, for instance, male or female. The application of the model lies in estimating the probability that an outcome with explanatory variables will be classified in one of the binary categories. Note that classifying observations based on their predicted probabilities is a type of binary classification model.
The probit model is one of the most applied specification for an ordinal or a binary response model. Thus, it treats the same set of problems as does logistic regression, using similar techniques however the major difference is in the assumption of how the error term is distributed. The error term of a probit model follows a normal distribution, hence, the model employs a probit-link function, is most often estimated using the standard maximum likelihood procedure, resulting such estimation to be known as a probit regression.

4.1.3 Naive Bayes Algorithm

Naive Bayes is a straightforward method for constructing classifiers: models that assign class labels to problem instances, depicted as vectors of characteristic values, where the class labels are samples from some population. There exists no one algorithm for training such classifiers, but a set of algorithms based on a common principle: all naive Bayes classifiers assume that the value of a feature is independent of the value of any other feature, given the class variable. Naive Bayes classifier considers each attribute to contribute independently to the probability notwithstanding of any possible correlations of features
Naive Bayes classifiers can be trained very efficiently for some type of models in a supervised learning setting. In practical scenarios, parameter estimation for naive Bayes models uses the method of maximum likelihood; thus, one can work with the naive Bayes model without accepting Bayesian probability or using any Bayesian methods.
Despite their naive design and apparently oversimplified assumptions, naive Bayes have worked quite well in many complex real-world situations.
A merit of naive Bayes is that it doesn’t require large number of data points to estimate the parameters necessary for classification.

4.1.4 Random Forest

Decision trees are common tool for a variety of machine learning tasks. Tree learning "comes closest to meeting the requirements for serving as an off-the-shelf procedure for Mining data because it is invariant under scaling and various other transformations of feature values, is robust to inclusion of irrelevant features, and produces inspectable models. However, they are seldom accurate" (Breiman, 2001).
Trees that are grown very deep tend to learn extremely irregular patterns: they overfit their training sets, i.e. have minimal bias, but very large variance. Random forests are a way of averaging multiple deep decision trees, trained on different parts of the same training set, with the goal of minimizing the variance. This comes at the expense of a little increase in the

bias and some loss of interpretability, but commonly significantly boosts the performance in the final model

.

The diagram below shows the extent of the correlation that exists amongst the dependent variables

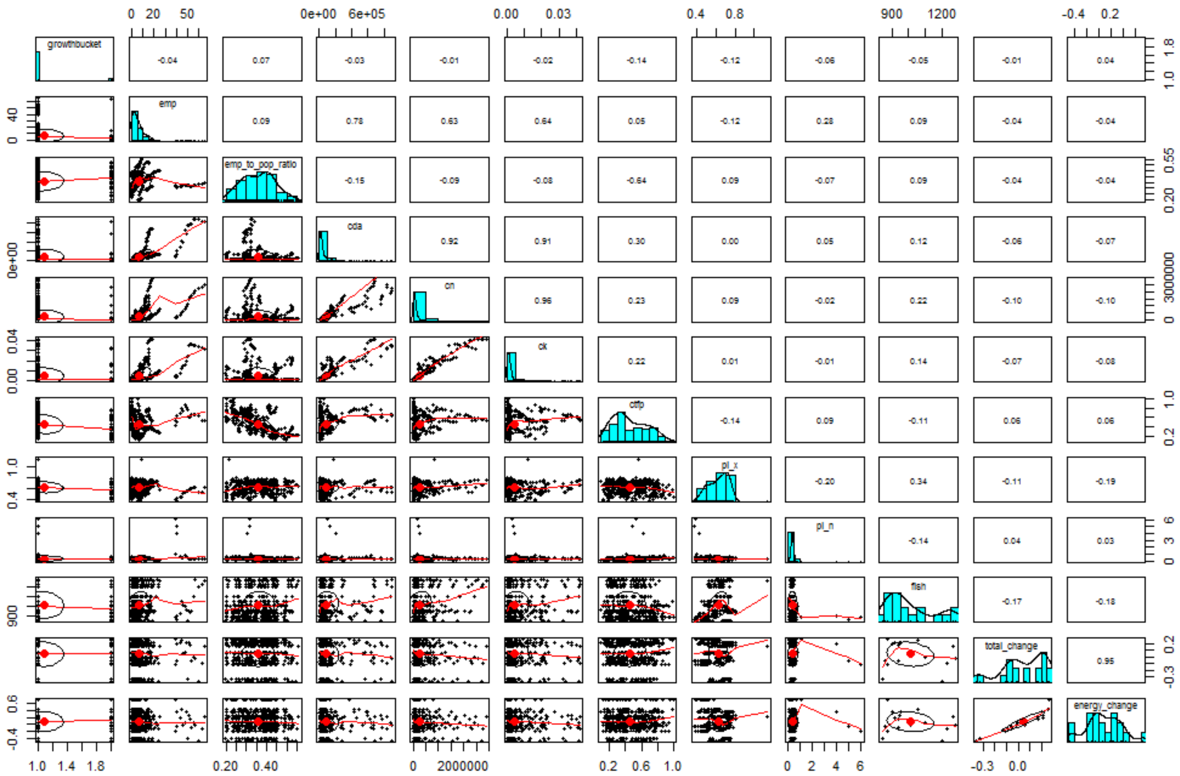

Figure 1: Correlation Matrix

5 Evaluation

In this section, we look at the outputs and their significance to the work.

Recession	No Recession
0.921811	0.07819

Fig 2: A table of Recession proportion

The dataset revealed that from 2000 to 2017, the odds of Africa being in recession was 92.18%

	Dependent variable:
	growthbucket
emp	-0.216***
	(0.074)
emp_to_pop_ratio	-6.617
	(4.404)
cda	0.00002***
	(0.00001)
cn	0.00001**
	(0.00000)
ck	-634.395***
	(169.113)
ctfp	-5.313***
	(1.986)
rkna	2.616***
	(0.929)
delta	-60.605**
	(27.146)
pl_da	24.291***
	(5.234)
csh_c	-3.736*
	(1.960)
csh_r	-8.657***
	(3.070)
pl_g	-11.453***
	(3.699)
pl_x	-14.734***
	(3.599)
pl_n	-10.189***
	(2.930)
fish	-0.009***
	(0.002)
total_change	-9.640***
	(3.292)
energy_change	6.448***
	(2.011)
Constant	20.749***
	(4.856)
Observations	486
Log Likelihood	-83.965
Akaike Inf. Crit.	203.930
Note:	*p<0.1; **p<0.05; ***p<0.01

Fig 3: table of Significant Variables.

Recession	No Recession
448	38

Fig 4: Table of recession count

Between 2000 and 2017, Africa witnessed 448 counts of downtimes. This accounts for 92.18% of the entire economic events within that timeframe. She enjoyed 38 months of boom, which accounts for 7.82% of the entire economic activities of that time.

Logit Model

	Dependent variable:
	growthbucket
emp	-0.066
	(0.048)
emp_to_pop_ratio	-0.554
	(3.469)
cda	0.00000
	(0.00001)
cn	0.00000
	(0.00000)
ck	-171.874*
	(98.581)
ctfp	-3.811**
	(1.488)
pl_x	-5.244**
	(2.216)
pl_n	-3.497*
	(1.834)
fish	-0.001
	(0.002)
total_change	-6.580**
	(2.863)
energy_change	3.895**
	(1.671)
Constant	4.785**
	(2.419)
Observations	486
Log Likelihood	-112.657
Akaike Inf. Crit.	249.314
Note:	*p<0.1; **p<0.05; ***p<0.01

Fig 5: coefficients of the logit model

From this model we see that not many of the factors are significance. As a matter of facts, we duly note that not a single one of them is significant with a probability of at least 99.99% This model gave a misclassification error of 7.41%, thus yielding an accuracy classification of 92.39%.

Probit model

	Dependent variable:
	growthbucket
emp	-0.035
	(0.024)
emp_to_pop_ratio	-0.615
	(1.690)
cda	0.00000
	(0.00000)
cn	0.00000*
	(0.00000)
ck	-80.404
	(49.721)
ctfp	-1.899***
	(0.709)
pl_x	-2.824***
	(1.094)
pl_n	-1.746*
	(0.928)
fish	-0.001
	(0.001)
total_change	-3.310**
	(1.480)
energy_change	2.007**
	(0.892)
Constant	2.481**
	(1.219)
Observations	486
Log Likelihood	-112.889
Akaike Inf. Crit.	249.778
Note:	*p<0.1; **p<0.05; ***p<0.01

Fig 6: coefficients of the probit model

The coefficients of the probit model when compared to the logit model seem to perform better and are statistically more significant. This is further explained by the misclassification error.

The error rate generated by this model is 7.41%, thus, the accuracy is approximately 92.59%.

It is true that the accuracy of the logit model is not too different from the probit model, although the latter performs 0.20 percent better than the former. This small difference only proves the underlying similarity in both models.

Naïve Bayes Algorithm

This is another tool used for binary classification and forecasting.

	Recession	No recession
Recession	432	33
No recession	16	5

Fig 7: Classification Matrix

The misclassification values are the off diagonal elements. The error in this model is 10.08%, indicating an accuracy of 89.92%

Random Forest Model

	Recession	No recession
Recession	448	0
No recession	0	38

Fig 8: Classification Matrix

The misclassification of the predicted model is 0%, implying that the model is 100% accurate.

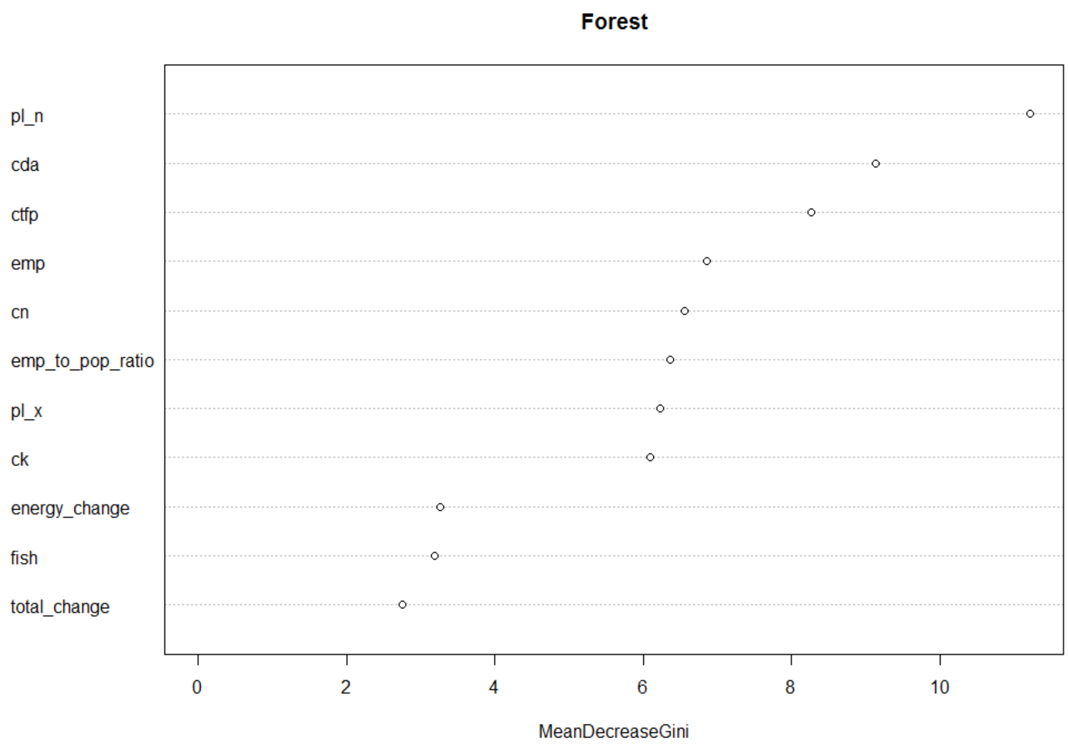

Fig 9: Plot of variables of importance

In the plot above, we notice that "Price level of the capital stock, price level of USA in 2011=1" has the highest level of importance, followed by the "real domestic absorption". The plot is in decreasing order of importance, and the order is clear cut.

Performance of predictive models.

From the foregoing, it is evident that the model that generates the smallest misclassification error, or the one with the largest accuracy be selected as the best model. In so doing, we can predict with a higher degree of certainty.

The model amongst the four with these characteristics is the Random Forest model. This model gave the higher accuracy in prediction.

6 Conclusion and Future Work

Recessions are generally not predicted before their occurrence and researchers have constantly attempted to forecast ahead, in real time with different models, sort ways to speculate and tell when a recession is going to happen. In this paper, A set of models were used to classify probability of recession in a binary framework. Four classification Models were compared to determine measures of fit. Variables were statistically selected using a stepwise approach. Random forest performed the best with an accuracy of 1. Successfully modelling and predicting the classification with little or no error. The result of the model had an error rate of 8%. The probit and naïve bayes both are strong models with accuracies of 92 and 92.5 respectively. These results cannot be relied on alone as the data set were limited from year 2000-2017. Better performances can be made if the models are fed with more data points, and other methods of selecting variable like the Principal component Analysis (PCA) can be done. Also, datasets that are monthly maintained can be used to boost the reliability of results in real time frequency.

References

Azevedo, Santos, A. I. R. L. & Filipe, M., 2008. KDD, SEMMA and CRISP-DM: a parallel overview. *ISCAP - Informática - Comunicações em eventos científicos.*

Breiman, L., 2001. Random forests. *Machine learning,* 45(1), pp. 5-32.

Chin, D., Geweke, J. & Miller, P., 2000. *Predicting Turning points,* Minneapolis: Federal Reserve Bank of Minneapolis Research Department report No 267.

Claveria, S. R. & Torra, S., 2017. Predicting recessions with boosted regression trees. *International journal of forecasting,* 33(5), pp. 745-759.

Davig, T. & Hall, A. S., 2019. Recession forecasting using Bayesian classification. *International journal of forecasting,* 35(3), pp. 848-867.

Diebold, F. & Glenn, R., 1991. Forecasting Output with the composite leading index: A Real time Analysis. *Journal of the American Statistical Association,* Volume 86, pp. 603-610.

Dueker, M., 1997. Strenghtening the case for the yield curve as a predictor of US recessions. *Federal bank of St louis Economic Review,* Volume 79, pp. 41-51.

Edirisuriya, P., 2015. The predictive power of financial Variables: New Evidence from Australia. *Australasian Accounting, Business and Finance Journal,* 9(1), pp. 57-70.

Eric, c. Y., 2012. Forecasting US recessions with various risk factors and dynamic probit models. *Journal of Macroeconomics,* 34(1), pp. 112-125.

Estrella, A. & Mishkin, F. S., 1996. Predicting US recessions: Financial Variables as leading indicators. *Review of Economics and statistics,* Volume 80, pp. 45-61.

Filardo, A. J., 1999. How reliable are recession prediction models?. *Economic Review,* Issue Q II, pp. 35-55.

Kauppi, H. & Saikkonen, P., 2008. Predicitng US recessions with binary response models. *The review of Econometrics and statistics,* 90(4), pp. 777-791.

Kim, C.-J., 1994. Dynamic Linear models with Markov-switching. *Journal of Econometrics,* 60(1-2), pp. 1-22.

Lahiri, K. & Wang, J. G., 1994. Predicting cyclical turning points with leading index in a markov switching model. *Journal of Forecasting* , 13(3), pp. 245-263.

Levanon, G., 2011. Forecasting Recession and slow-Down probabilities withh Markov witching Probabilities as Right-Hand-side Variables. *Business Economics,* 46(2), pp. 99-110.

Marco, N., 2001. Turn, Turn, Turn: predicting Turning Points in Economic Activity. *Economic Review,* Volume 86, pp. 1-12.

NBER, 2019. *The NATIONAL BUREAU of ECONOMIC RESEARCH: The NBER's Buiness Cycle Dating Committee.* [Online] Available at: https://www.nber.org/cycles/recessions.html [Accessed 3 July 2019].

Neftici, S., 1982. Optimal Prediction of Cyclical downturns. *Journal of Economic Dynamics and control,* 4(1), pp. 225-241.

Nyberg, H., 2009. Dynamic probit models and financial variables in recession forecasting. *Journal of forecasting,* 29(1-2).

Nyberg, H., 2010. Dynamic Probit models and financial Variables in recession forecasting. *Journal of Forecasting,* 29(1-2), pp. 215-230.

Nyman, R. & Ormerod, P., 2017. Predicting Economic Recessions using Machine learning algorithms. *arXiv preprint arXiv:1701.01428.*

Qi, m., 2001. Predicting US recessions with leading indicators via neural network models. *International journal of forecasting,* 17(3), pp. 383-401.

Stock, J. H. & Watson, M. W., 1993. A Proce-dure for Predicting Recessions with Leading Indicators:Econometric Issues and Recent Experience. In: J. H. Stock & M. W. Watson, eds. *Business Cycles, Indi-cators, and ForecastingBusiness Cycles, Indi-cators, and Forecasting.* Chicago: The University ofChicago Press.