Machine Learning Applications for Predicting Recessions

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Abstract

Modern-day business cycles consist of expansionary and recessionary periods in the economy. For economists and policymakers, it would be beneficial for the economy to generate accurate forecasts for the economy. Accurate forecasts can mitigate future risk and shape effective policy to target economic issues. This paper aims at using machine learning models such as Logistic Regression, K-Nearest Neighbors, Support Vector Machine, and Recurrent Neural Networks to generate accurate predictions for recessionary periods ranging from 1960 to 2020. Economic data was gathered from Fred such as inflation, unemployment, and business confidence to train and test these models yielding accuracy results as high as 97%. Although room for improvement, these models are a steppingstone in generating accurate recessionary forecasts using machine learning techniques.

Introduction

To be able to predict a recession it is important on how we define when the economy is in a recession. There is a slight difference in how economic recessions are defined, however, for the use of this paper and data usage we have chosen to use the National Bureau of Economic Research (NBER) as our way of classifying economic recessions. The NBER archives business cycle data to examine peaks and troughs in the economy, they classify an economic recession as the following,

The NBER's traditional definition emphasizes that a recession involves a significant decline in economic activity that is spread across the economy and lasts more than a few months[1].

Since the NBER determines an economic recession based on three criteria; depth, diffusion, and duration; there is still some room for debate within the NBER to even classify a period in the business cycle as a recession. *"That is, while each criterion needs to be met individually to some degree, extreme conditions revealed by one criterion may partially offset weaker indications from another.*[1]*"* Due to the chaotic nature social science datasets provide, there leaves plenty of differing subjective opinions and implicit bias built into how these metrics are determined. We can see problems can arise from using these types of datasets along with machine learning techniques. Training these models on a dependent feature that may contain bias has the possibility of forecasting false recessions that can negatively impact future policies.

Although we recognize this potential issue, using the same recessionary classifications as the NBER yields the highest probability of an unbiased dependent feature.

To cover extended machine learning approach on this topic, we have taken Tsao, Ueda and Vandre[2] 's paper as a ground model for the basic machine learning models. The purpose of our study is to further investigate testing result from more complex models in comparison to the models built by the previous study.

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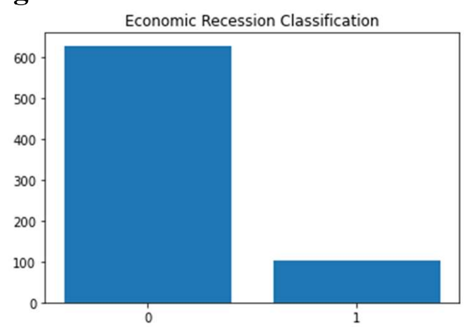
[1] https://www.nber.org/research/business-cycle-dating

[2] Shu-Chen Tsao, Kazuki Ueda, Mark Vandre. "Predicting Recessions: A Machine Learning Approach"

Data Description

For the data gathering section of this project, we decided to grab all our features using the Federal Reserve Bank of St. Louis Economic Database (FRED). We were able to use the FRED API provided by the *fredapi* package to streamline the data gathering process and generate a complete pandas data frame to build our models around. Using the FRED API, we were to grab NBER's recession data where recessions were classified with a value of 1 and 0 otherwise. One of the early challenges with using the dependent feature was the lack diversity in the dataset. Of course, this could not be altered, but the vast majority of our values are set at zero which can potentially lead to an inflated accuracy score on training and testing sets.

Figure 1: Recession Indicator Variable



Our independent features consisted of monthly economic indicators; CPI, unemployment rates, production, number of hours worked, housing projects started, personal income, 10-year treasury yields, business confidence, and M2 money stock. It should be noted that there were some transformations made to the data in the hopes of generating more robust models. CPI, production, and personal income were converted into monthly grow rates. As for the remainder of the features, we felt there was no need for any transformation due to the values already being listed as percentages (e.g. 10-year yields) or the data was already stationary (e.g. number of hours worked). Data descriptions from FRED are listed below,

- **CPI:** *A measure of the average monthly change in the price for goods and services paid by urban consumers between any two time periods.*[3]
- **Unemployment:** *Represents the number of unemployed as a percentage of the labor force. Labor force data are restricted to people 16 years of age and older, who currently reside in 1 of the 50 states or the District of Columbia.*[4]
- **Production:** *An economic indicator that measures real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities.*[5]
- **Hours:** *Weekly hours worked.*[6]
- **Housing:** *As provided by the Census, start occurs when excavation begins for the footings or foundation of a building.*[7]

[3] https://fred.stlouisfed.org/series/CPIAUCSL
[4] https://fred.stlouisfed.org/series/UNRATE
[5] https://fred.stlouisfed.org/series/INDPRO
[6] https://fred.stlouisfed.org/series/HOHWMN02USM065S
[7] https://fred.stlouisfed.org/series/HOUST

- **Personal Income:** *Billions of Chained 2012 Dollars, Seasonally Adjusted Annual Rate.*[8]
- **Yields:** *10-Year Treasury Yields.*[9]
- **Sentiment:** *OECD Business Confidence.*[10]
- **Money Supply:** *Real M2 Money Stock - Billions of 1982-84 Dollars***,** *Seasonally Adjusted*[11]

Methodology

In this paper, we have compared four machine learning techniques in forecasting recession. These algorisms include 1) Logistic regression 2) K Nearest Neighbor (KNN), 2) Logistic regression, 3) Support Vector Machine (SVM) which are imported from scikit-learn package and 4) Long short-term memory (LSTM) from the Keras library. The data set is divided into a training and testing set with proportions of 50:50 for training and evaluating models, respectively. Because LSTM works on sequence data, the first 50% of data was simply taken for the training set and the rest was for testing set. However, for logistic regression, KNN and SVM, random splitting of data should be applied since the sequence of data is not important*. This random splitting will support the model to capture the constantly changing relationship between the variables across the time period.

For training the Logistic regression, an ordinary least squares regression was used to select the features which roughly explained the pattern of recession. We used scikit-learn package for doing this model. Finally, we got the features relevant to recessions as seen in Table 1. We use those features to fit the logistic regression.

Table1: OLS regression result

Dep. Variable:	Recession	R-squared:	0.445
Model:	OLS	Adj. R-squared:	0.438
Method:	Least Squares	F-statistic:	64.19
Date:	Sun, 21 Mar 2021	Prob (F-statistic):	3.61e-86
Time:	10:45:56	Log-Likelihood:	-47.512
No. Observations:	730	AIC:	115.0
Df Residuals:	720	BIC:	161.0
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	14.1303	0.945	14.947	0.000	12.274	15.986
CPI	11.1964	4.438	2.523	0.012	2.483	19.909
Unemployment	-0.0203	0.008	-2.619	0.009	-0.036	-0.005
Production	-6.1071	1.243	-4.915	0.000	-8.547	-3.668
WorkHour	-0.1857	0.019	-9.575	0.000	-0.224	-0.148
HousingStart	-0.0002	3.53e-05	-5.336	0.000	-0.000	-0.000
PersonalIncome	-3.9001	1.115	-3.498	0.000	-6.089	-1.711
LongTermYield	-0.0087	0.005	-1.934	0.053	-0.018	0.000
BusinessConfidence	-0.0600	0.009	-6.373	0.000	-0.078	-0.042
M2	3.0197	2.441	1.237	0.216	-1.772	7.812

Omnibus:	162.058	Durbin-Watson:	0.450
Prob(Omnibus):	0.000	Jarque-Bera (JB):	342.903
Skew:	1.220	Prob(JB):	3.46e-75
Kurtosis:	5.306	Cond. No.	7.26e+05

[8] https://fred.stlouisfed.org/series/DSPIC96
[9] https://fred.stlouisfed.org/series/IRLTLT01USM156N
[10] https://fred.stlouisfed.org/series/BSCICP03USM665S
[11] https://fred.stlouisfed.org/series/M2REAL

Our K Nearest Neighbors (KNN) model used Euclidean distance as distance metric with different values of k. The k-value which gives the optimal accuracy score is 10 in our case.

Support Vector Machine was trained with different hyperparameters of c and was evaluated to select the best combination. SVM with c equal to 6 shows the lowest loss score when applying model on testing set as shown in Figure 2. Then, three different kernel types including linear, polynomial, and rbf were applied with value c of 6. The results in Figure 3 suggests the linear kernel obviously outperforms other models.

* We also applying the KNN, Logistic regression and SVM on the same testing set for LSTM (which taking sequence into account). But, as expected, the accuracy score is very low. Because the model cannot capture the current relationship between variable while information about sequence is not important in such model. We included the result in the appendix.

Figure2: Loss value from applying SVM with different C-value on testing set

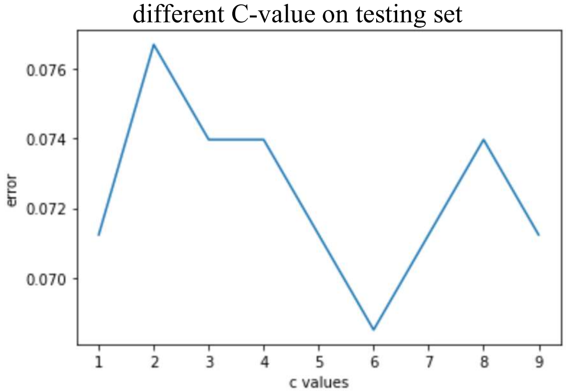
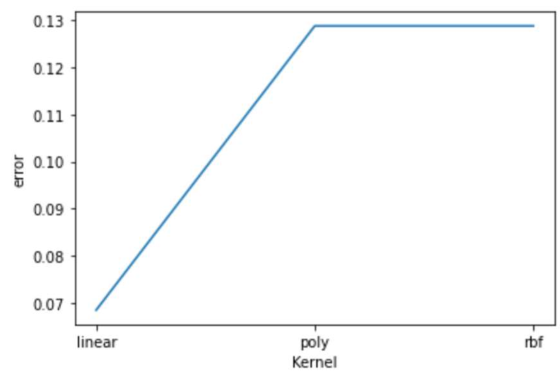


Figure3: Loss value SVM with different types of kernel



Regarding Sequence modeling, we chose Long Short-Term Memory (LSTM) model because it can store the previous information which is crucial to predict the future value. Moreover, compared to General Recurrent Neural Networks, LSTM has less problems of vanishing gradient or gradient explosion during long sequence training thanks to its addictive updates of gradient. The timestep is set to be 2. In our case, the LSTM model achieved the highest accuracy score when setting parameters as the following.

1) Hidden layers are set to 2 with the Hyperbolic Tangent Activation Function (Tanh)**. Tanh is quite similar to the sigmoid activation function and has the same S-shape. But the output range of function is (-1, 1) instead of (0,1) leading to a steeper derivative or lager updates of coefficients.

2) Units in each layer is set to 10. Moreover, to avoid overfitting problem, we randomly dropout some nodes generated by the first hidden layers, given probability of 10%.

3) Sigmoid Activation Function is adopted in the output layer because it is the classification problem. The model uses Adam as the optimizer for compiling, and the loss function is sparse categorical crossentropy and use accuracy as an additional metric; since it is easier to interpret the results. We set the epochs, batch_size to be 100 and 72, respectively.

Equation1: Sparse Categorical Cross-entropy loss function

$$CCE(p,t) = -\sum_{c=1}^{C} t_{o,c} \log\left(p_{o,c}\right)$$

The last model is a Random Walk model which assumes that in each period the dependent variable takes a random step away from its previous value. This model might work in our case because the variation in dependent variables is not high and highly influenced by previous value.

After training our models, the testing data set is used to evaluate the models. Accuracy score, recall rate and precision rate are also calculated to compare the performance of the model.

** LSTM with other combination set of hyperparameters are included in the appendix.

Results

After optimizing the four machine learning models including KNN, Logistic Regression, SVM and LSTM, the models are used to make predictions on the 365 observations of testing data. The prediction accuracy for the models is presented in Table 2 below.

Table 2: Models Accuracy, Precision and Recall Rates

Model	Accuracy	Precision [0,1]	Recall [0,1]
KNN	0.8575	[0.9591 , 0.1702]	[0.8866 , 0.3810]
Logistic Regression	0.8795	[0.9843 , 0.1702]	[0.8892 , 0.6153]
SVM	0.9315	[0.9623 , 0.7234]	[0.9592 , 0.7391]
LSTM	0.9698	[0.9813 , 0.8837]	[0.9844 , 0.8636]

As highlighted before, the three models including KNN, Logistic Regression and SVM made the prediction by treating each observation as independent data (cross-sectional data). Among these three models, the SVM evidently performed the best and produced the highest score in term of overall accuracy, precision and recall rate. This result is relatively close to the result from previous studies[12].

On the other hand, the approach of the newly developed LSTM model differs from the other models as the LSTM considers the serial correlation of the data (time-series). The LSTM proved that, by utilizing the cell state and taking into account the memorized previous data (t-1 and t-2), the model can produce a significantly better prediction in this particular problem. The accuracy from LSTM yields as high as 97% and the precision and recall of more than 98% and 86% for expansion and recession respectively.

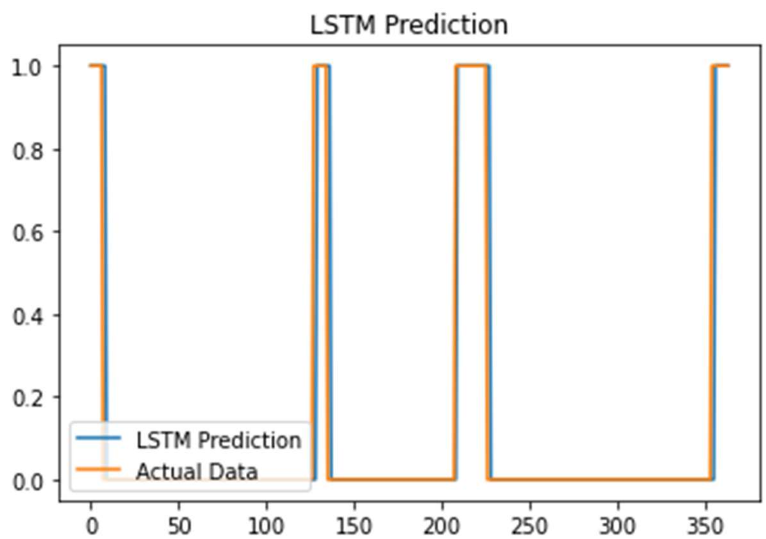
The confusion matrix from the LSTM model, shown in Table 3, indicates that the model error came from almost equally False positive and False negative. Hence, the precision and recall rates are quite similar. Upon closer inspection the prediction plot in Figure 4, it can be observed that the LSTM is usually late to detect the first period of recession and the first period of expansion (the model generates a close-to random walk prediction). This suggests that the improvement required may have to be achieved by including features that is quicker to react to recession.

[12] Shu-Chen Tsao, Kazuki Ueda, Mark Vandre. "Predicting Recessions: A Machine Learning Approach"

Table 3 : Confusion Matrix of prediction from LSTM

LSTM		Prediction	
		Expansion	**Recession**
Truth	**Expansion**	315	6
	Recession	5	38

Figure 4 : Prediction from LSTM



Conclusion

Multiple machines learning models have been built and optimized to detect the recession announcement by NBER. Three models including KNN, Logistic Regression and Support Vector Machine were trained to predict NBER announcement of any particular month given certain economic data of that month. Among the three model, the SVM produced the best result with highest prediction accuracy. However, to accomplish almost perfect prediction, the LSTM has been introduced and the model has been trained to consider the previous t-1 and t-2 data to make a prediction at time t. The LSTM achieved highest score of up to 97% accuracy and highest precision and recall rate in all categories. Although the time-series requirement limits the application of the LSTM to only 1-period forecast ahead of the latest announcement, it could be useful in some occasion to predict the future period.

Citations

Shu-Chen Tsao, Kazuki Ueda, Mark Vandre. **"Predicting Recessions: A Machine Learning Approach"**

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Statement of Contribution

Andrew Salguero: Acquired and compiled dataset, Optimized models, Prepared and edited final report, Citations

Anapat Krisdaphong: Prepared and Transformed data, Compiled codes and results, Compiled and edited Final Report

Tanaporn Sriklay: Transformed data, Prepared machine learning algorithm, Optimized models, Edited final report

Appendix I

Predictions from KNN, Logistic Regression and SVM