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US recession prediction using statistical and natural language processing methods

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Abstract. This study mainly predicts the recession in the United States. We build our model based on the data of more than ten recessions experienced by the United States since the mid-20th century. Our research can be divided into two parts, one part is a machine learning model constructed using econometrics theory, and the other part is a text analysis model based on natural language processing (NLP) techniques. We collected quarterly data from January 1, 1950, to September 1, 2020, to examine each historical recessionary period. We select key macroeconomic variables such as real GDP growth rate, unemployment rate, and interest rates as variables to build the machine learning model. Depending on the data type and model accuracy, we adopted three models, Support Vector Classification (SVC), Naive Bayes, and Logistic Regression, where the SVC model has the highest accuracy, above 80%. Regarding NLP models, we choose the reports based on Bank of International Settlements central bank speeches (BIS) to complete the relevant analysis. We evaluate bag-of-words and convolutional neural networks in conjunction with Epoch loss to determine how well the model's predictions match the actual data. Although we have debugged the NLP model many times, its accuracy still needs to be higher than that of the econometric model. How to effectively improve the prediction accuracy of the NLP model will be the main problem we hope to solve in the future.

Keywords: natural language processing, economic recession, future prediction.

1. Introduction

A recession will significantly negatively impact the national and even the world economy and will continue to affect economic stability for an extended period. When Gross Domestic Product (GDP) experiences negative growth for more than six months, it will be considered a signal of recession, which also means that the country's economy has fallen into a more severe crisis. Since the capital market will be severely impacted, companies will have to lay off more employees to reduce operating costs. The rapid rise in unemployment is also one of the distinguishing features of the recession. The unwillingness to spend, or the inability to repay loans, will further exacerbate economic instability as many workers lose their jobs. Besides, substantial interest rate cuts are also one of the more common phenomena in the early stage of the recession. Affected by the overall economic situation, the fall of investor confidence and thus reduced investment shares in large quantities confirms the reliability of liquidity and stock returns on forecasting withdrawals.

Due to the current COVID-19 environment and the severe global economic situation, people's lives have been affected to varying degrees, ranging from the increasing economic pressure brought aboutby rising prices to the emergence of many unstable factors, such as widespread unemployment and interest rate cuts [1]. General Public and investors are looking for ways to reduce losses during a recession. Over the past few decades, many researchers have explored recession prediction models, and machine learning models with different variables are still the mainstream. Most existing research uses market liquidity, yield curve, and the unemployment rate as the independent variables [2-4]. Recently, an increasing amount of prediction research has been embedded with the NLP method by conducting the sentiment analysis of the compression [5]. However, the effectiveness of the study is difficult to compare due to the different variables and models used directly. In this study, we will use the prediction accuracy of the traditional econometric machine learning model and the naturallanguage processing model to compare the prediction performance of the two models in different scenarios and analyze the potential factors that affect their accuracy. Through our comparative analysis, we will leverage traditional economic indicators in conjunction with Natural Language Processing techniques and formulate a framework to predict the arrival of a recession effectively and accurately assess the impact of the recession.

2. Literature Review

Economic cycles are the regular expansions and recessions of economic activity along the generaltrend of economic development [6]. Academics have recognized and studied cycles in business changes dating back to 1946 [7]. studied whether time series have specific cycles and tried to discover each cycle's start and end dates. They employed a statistical approach to describe time series. Pioneeringly, they classified macroeconomic relevant variables as lagging, consistent, and leading. The most critical transition in a business cycle is from an expansionary state to a recessionary state and vice versa. Therefore, many researchers have focused on the predictability of recessions over different periods. There are two widely accepted approaches to predicting business cycles in industry and academia. The first direction uses non-linear models to predict the state of the macroeconomy, usually using binary models, such as probit/logit models. Other studies use linear models to predict aggregate macroeconomic variables, for example, GDP growth.

Non-linear models define the state of the economy by defining a dummy variable. The purpose is to predict the state of recession in the US economic cycle. Hence, a value of "1" represents the state of recession while "0" is considered as the state of non-recession. The probit model is one of the most popular models for predicting recessions [8-11]. Besides, some researchers use the logit model to analyse recessions [11-14]. The logitmodel is similar to the probit model and is one of the most widely used models. Iterations of hardware updates have facilitated the development of machine learning. The SVM model is used in experiments [15, 16]. It is worth noting that Gogas & Chrysanthidou present a SVM model with data collected from the third quarter of 1967 to the fourth quarter of 2011 [11]. The results showed an accuracy of 66.7 percent on the test set. They constructed a logit/probit model using the same dataset, and both models' accuracy was only 50 percent. It is evident that the SVM is more effective.

The performance of the binary classifier is determined by which financial variables are chosen as predictors. An experiment utilized different financial variables to predict whether the US economy will decline in the next one to eight quarters [8]. Authors found that models using two variables, the slope of the yield (US Treasuries) curve or the term spread (US Treasury spread), were the most successful. In addition, most studies use the spread of interest rates, specifically, the spread between long-term and short-term interest rates, to predict economic activity. Researchers in the Eurozone have also used probit models to test the yield curve's predictive power [10]. The results show that yield spreads are the seemingly most leading predictor of recessions compared to other variables. Davig & Hall constructed a plain Bayesian model using variables such as payroll, S&P 500 Index, etc [17]. and showed that the model could achieve an accuracy of 72%. These empirical results provide insight intowhat variables to use to predict future economic activity in the current study.

Researcher investigated the relationship between unemployment and the Great Recession of 2008-2009 in Germany, the USA and the UK by utilizing Beveridge curve, where the result revealed that the USA possessed a slower trend in the recovery compared to previous recessions because of temporary structural problems introduced by extension of unemployment insurance to nearly two years [18]. A finding has been introduced that during the 2020 pandemic recession, females possess a seemingly higher unemployment rate than males since the majority of females' occupations focus on heavily infected sectors such as hospitals and restaurants which led to sizable repercussions for gender inequality [19]. These findings iterate the strong relationship between unemployment rate and great recession, which performs as a reliable tool to predict recessions as well as their adverse effects to the society.

Apart from non-linear models, the classical model of machine learning, the Hidden Markov Model, deals with time series, which has proved useful in forecasting financial and time series. Markov transformation models intertwine binary recession indicators with real GDP ratios to form Markov chains [20]. Other linear models are least squares regression models and Vector Autoregression (VAR). Nayman & Ormerod use the Treasury rate, US government bond yields, and the percentage of S&P 500 quarters as variables to predict GDP growth [21]. They construct least squares regression models by regressing GDP growth on the lagged values of these variables, that is, regressing GDP growth at time t on the explanatory variables at times t-1, t-2, t-3, and t-4.

Natural Language Processing (NLP) is a theoretically based collection of computational techniques for the automatic analysis and representation of human language [22]. In a connected world, the abundance of natural language text, while containing a tremendous amount of content and knowledge, has become a significant data mining challenge to extract many topics discussed. Automated natural language processing (NLP) data mining techniques are a reliable tool to solve this challenge. Since the onset of the global financial crisis in the summer of 2008, the evolution of global finance has been monitored by academics and has become one of the most popular topics among ordinary individuals. The views, opinions and feelings of all stakeholders within the impact of political as well as social events on global markets are identified as 'market sentiment indicators'. The language of finance and economics is quite similar to that of human emotions, indicating a range of emotions from fear (e.g. market anxiety) to trust (e.g. market confidence) [23]. The results of many studies demonstrate that forecasting models can be expanded by economic sentiment indicators, with significant improvements in the performance of forecasting models [24, 25]. This suggests that psychological factors govern the economic cycle to some extent. Other studies have also acknowledged the importance of psychological factors in controlling economic cycles [26, 27].

Meanwhile, randomly occurring natural disasters and epidemics also result in huge effects on the economies. Goulet et al. analyzed the most recent recession, the great recession in 2019 pandemic because of the COVID 19 [28]. They seek a representative set of hyperparameters via linear discriminant analysis (LDA), bag-of-words (BOW) and term-frequency inverse-document-frequency (tf-idf) models in order to access the keywords on every statement as well as the evolution of dominance through

COVID's adverse effects. The result iterates that LDA using BOW performs most effectively in dominant statements but the tf-idf topics balance comparison in interactions.

Referring to the suitable models applied in the prediction of huge economic recessions, researcher test whether machine learning performs as a reliable tool to catch the covid-19 recession by concentrating on UK economics [29]. They constructed a monthly large - scale macroeconomic database which contained 112 monthly macroeconomic indicators classified into 9 categories: labor, production, retail and services, consumer and retail price indices, producer price indices, international trade, money, credit and interest rate, stock market and finally sentiment and leading indicators. By testing autoregressive (AR), random walk and machine learning (ML) methods, they conclude that ML seems reliable in the great recession conditions.

3. Econometrics Model

3.1. Data

In the data we used, we leveraged four popular economic indicators: interest rate (in a unit of percentage change per annum), real GDP (percentage change from last quarter), Unemployment rate (in the percentage of the total workforce), and Recession indicator (Table 1). We collected data from the U.S.Bureau of Economic Analysis (BEA), U.S. Bureau of Labor Statistics, and International Monetary Fund (IMF) at the St. Louis Fed identifying recessions and choosing economic indicators that serve as labels and features for model training [30-32]. The BEA is a key federal statistical organization that is independent and fosters a better knowledge of the American economy by delivering economic account data that is up-to-date, pertinent, and accurate in a way that is both objective and economical. IMF is a global organization that works to achieve sustainable growth and prosperity for all of its 190 member countries.

It tries to reduce the damage that global recession brings to member countries. Thus, we collected IMF, BEA, and Labor Stats data between January 1, 1950 through September 1, 2020.

Table 1. Variables.

Variable	Type	Source	Description	Measure Format
Interest Rate	Independent	International Monetary Fund (IMF)	Interest Rates, Discount Rate for the United States	% Per annum
Real GDP Increase Rate	Independent	U.S. Bureau of Economic Analysis	The Gross Domestic Product increase rate of the United States	% Difference from last Quarter
Unemployment Rate	Independent	U.S. Bureau of Labor Statistics	The unemployment for the recent 50 years of the United States	% of Total Workforce
Recession Indicator	Dependent	?	?	0: not a recession 1: recession

Note: This table illustrated the variables, both independent and dependent, used in this research

The dataset consists of 287 quarters, roughly 72 years' worth of these economic indicators. We joined all three datasets by year and quarter (YYYYQ), resulting in a final dataset with 287 rows and 5 columns. We also aggregated recession data by timeframe (Table 2)

Table 2. Recession Length.

Recession length	Number of quarters	Recession length	Number of quarters
July 1953 – May 1954	5	July 1981 – November 1982	6
August 1957 –April 1958	3	July 1990 – March 1991	4
April 1960 –February 1961	4	March 2001 – November 2001	4
December 1969 – November 1970	5	December 2007 –June 2009	6
November 1973 – March 1975	6	February 2020 –June 2020	2
January 1980 –July 1980	3		

Note: This shows the recessions, with respective start and end months throughout history

3.2. Preprocessing

We first have to guarantee that the data set has every value for each variable in all periods. Then, certain variables have to be changed into rates instead of specific values. We have to change real GDP into a real GDP increase rate because it would most likely increase as our society is fastly developing. Furthermore, we unified the unit of times, changed the quarter unit of interest rate into the quarter, and simply combined every three-month change. Since each variable is different but similar in date length, wemade an intersection on time to get all variables' periods. Then, we add a new column that describes the under recession or not by using the recession indicator for each quarter. Lastly, we merged each single data set for each variable and finally got all combined dataset with 287 rows and 5 columns (Table 3).

Table 3. Summary Statistics of the Data.

	GDP_IR	Interest Rate	Unemployment Rate	Indicator
Count	287	287	287	287
Mean	0.015707	4.273028	5.790216	0.170732
Std	0.013139	2.837751	1.693319	0.376932
Min	-0.093000	0.250000	2.567000	0.000000
25%	0.010000	2.000000	4.633000	0.000000
50%	0.015000	4.000000	5.567000	0.000000
75%	0.021000	5.921500	6.833000	0.000000
max	0.085000	14.00000	12.967000	1.000000

3.3. Methodology

Variance Inflation Factor (VIF) is a set of multiple regression variables' which measure multicollinearity. Collinearity measures the correlation between predictor variables. The VIF for a regression model variable is mathematically equivalent to the ratio of the variance of the entire model to the variance of a model with only one independent variable. We first check the variables' tolerance factor to see if they will cause the collinearity problem.

Among the data from 1950 to 2020, there are a total of 11 recessions (Table 2) in around 70 years. The most recent downturn lasted from February 2020 through June 2020. Only 48 of the 287 quarters are recessions, which highlights the severe imbalance between recessions and expansions. As a result, imbalanced data would cause skewed class proportions in directed variables, leading to a potentially problematic model performance. Hence, the methodology we used to resolve this problem was the utilization of over-sampling. Specifically, SMOTE and ADASYN, which are two algorithms for oversampling data while the data set face the problem of imbalanced data, were being used to over-sample the data set to increase model performance.

We consider three classification algorithms: Support Vector Classification (SVC), Naive Bayes, and Logistic Regression. We split the data set into two parts, the training set and test (holdout) set, each with a percentage of 80% and 20%, respectively. We train all three models with the training set and measure the model performance measures, accuracy, recall and F-score, through the test set.

4. NLP-Based Model

4.1. Data

The data we used in training the NLP model is a collection of central bank speeches from the Bank of International Settlements (BIS) with all speeches from January 7, 1997 to March 2, 2022. All text files are in English. Each file inside the large file is named a specific date of the speech.

4.2. Preprocessing

Since the name of the files are all dates, regular Expression was used in opening up all the files, so in this case, we could walk through all the files and get speech contents. Regular expression filtered the files thatwe needed. After reading all file contexts, we save them into a data frame to represent the frequency of each word that appears in the context.

4.3. Methodology

Epoch loss is a function used to test and optimize machine learning algorithms. The interpretation of the loss depends on how well the model is performing in the two sets, which are used to calculate the loss during training and validation. It represents the total number of mistakes made for each example in the training or validation sets. The loss value denotes how well or poorly a model performs following each optimization iteration.

The performance of the algorithm is evaluated using an understandable accuracy metric. A model's accuracy is often assessed after input parameters and expressed as a percentage. It measures how closely your model's forecast matches the actual data. We split the data set into 90% training and 10% validation and trained and tested the models, using the train and test datasets to measure the model performance and the Epoch Loss.

5. Result

Table 4 shows the results of all statistical models evaluated their goodness based on the values of Accuracy, precision, recall, and F-score. The recall and accuracy are the two dimensions as the choice criteria for statistical models. The recallis calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples. The higher the recall, the more positive samples detected. Similarly, higher accuracy means better performance. As a result, not all models had equivalently precise predictions on the validation dataset. Apparently, SVC and Logistic regression models show reasonably good accuracy, with 96 test values in the validation dataset. Moreover, the SVC model had a recall of 0.76 in Adasyn and 0.79 in SMOTE, meanwhile, the logistic regression model had 0.77 in ADASYN and 0.77 in SMOTE. Among them, the SVC model had a slightly higher recall, therefore, we consider SVM to be the best performing model for the chosen statistical model.

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Table 4: Result of Econometric Models.

Model	Over-Sampling Method	Accuracy	Precision	Recall	F-score
SVC	ADASYN	0.79	0.74	0.76	0.75**
SVC	SMOTE	0.826	0.74	0.79	0.76**
Naïve Bayes	ADASYN	0.69	0.68	0.66	0.66**
Naïve Bayes	SMOTE	0.6875	0.65	0.66	0.65**
Logistic Regression	ADASYN	0.80	0.75	0.77	0.76**
Logistic Regression	SMOTE	0.79	0.75	0.76	0.75**

Note: significance level * at 0.1, ** at 0.05, and *** at 0.01

Table 5. Result of the bag of words

NLP Model	Accuracy	Epoch Loss Difference
BOW	0.6772	From 0.14604 to 0.06567

Table 6. Result of CNN

NLP Model	Accuracy	Epoch Loss Difference
CNN	0.5267	From 9.77327 to 4.76461

Table 5 and 6 shows the results of NLP models BOW and CNN individually, evaluating goodness based on the values of Accuracy and Epoch Loss Difference. As a result, the accuracy of BOW is 0.6772, and the accuracy of CNN is 0.5267, in both of the NLP models, BOW showed better and epoch loss. The large difference in results of the CNN model and BOW model might be caused by the fact that a single CNN layer doesn't fully extract the features fromthe speeches. Therefore, we ended up selecting BOW as a representative model for NLP models.

6. Conclusion

Data from many perspectives, potential influencing elements, are collected to anticipate the economic recession. This paper assessed the forecasting performance of traditional macroeconomic indicators and NLP methods for key US macroeconomic variables by focusing on every period of economic recession in history, using a specifically collected dataset of quarterly indicators from January 1, 1950 to September 1, 2020. Meanwhile, central bank statements from the Bank of International Settlements for the NLP model also perform as reliable sources in the experiment.

In this paper, Support Vector Classification, Naive Bayes, and Logistic Regression models are classified into statistical models, while NLP methods include evaluation of Bag of Words, Convolutional Neural Networks in conjunction with Epoch loss, which identifies how closely the model's forecast matches the actual data. No matter what kind of training ratio is obtained, the accuracy of traditional statistical models is better than NLP models. In general, SVM and Logistic Regression are more accurate and reliable than other models.

To improve the accuracy as well as practicability of the conclusion, models like the BERT model or Similarity algorithm must be utilized more frequently in the experiment. As for the BERT model, Bidirectional Encoder Representations from Transformer, it is a pre-trained language representation model which emphasizes that traditional one-way language models or shallow split-together of two one-way language models are no longer used for pre-training as in the past, but new masked language models (MLM) are used to generate deep bidirectional language representations. Similarity algorithms compute the similarity of record/node/data point/text pairs. Therefore, there are many kinds of similarity algorithms. For example, similarity algorithms compare the distance between two data points. There are also similarity algorithms for calculating text similarity. In our experiments, the NLP model does not perform particularly well because it contains the following shortcomings. First lack of long-term dependence, can only model to the first n-1 words; Second With the increase of N, the parameter space increases exponentially; Last, Based solely on statistical frequency, the generalization ability is poor.

It would be interesting to rerun the experiments when more statements are issued, and the data continues to update since COVID-19 is still a developing situation. This model is also applicable to other countries' economic recession predictions.

In this experiment, we employed CNN to learn financial text data. 1-dimensional convolutional kernels constructed by convolutional layers can learn sequential data, but the model only achieved an accuracy of 0.526. Therefore, temporal data like text does not fit the structure of CNN models. CNN's are mostly used to deal with image problems. Long short-term memory (LSTM) and BERT models are better to deal with textual data. They can extract semantic information more efficiently and the pre-trained BERT models have already learned semantic information from a large corpus. So, the future work is to make predictions with these models.

Combining NLP information with statistical models is a direction worth exploring, as aggregating the two approaches might yield results beyond expectations. A feasible option is to build NLP and statistical models separately and combine their prediction results using a rational voting strategy. On the other hand, sentiment analysis models can compute sentiment scores for financial documents. As illustrated in the literature review, adding sentiment scores to statistical models might enhance results.

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