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Research on Economic Recession Prediction Model From the Multiple Behavioral Features Perspective

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ABSTRACT Considering the disadvantages of conventional economic recession methods, such as low efficiency and low generalization, we construct an economic recession prediction model based on the neighborhood rough set (NRS) and support vectors machine (SVM). NRS is first introduced to reduce multiple behavioral features (consumer behavior, work behavior, and residential behavior) of economic recession. The proposed model is examined by the U.S. monthly datasets from January 1959 to December 2016. The results demonstrate that the NRS-SVM model has a high out-of-sample performance than the SVM, probit approach and the overall improvement is 13.65% and 18.79%. Meanwhile, the result shows that the measure of consumer sentiment, work behavior, and residential behavior all have a dynamic impact on the future of economic recession.

INDEX TERMS Recession forecasting, behavioral features, neighborhood rough set, support machine vector.

I. INTRODUCTION

How to accurately forecast troughs and peaks at the business cycle, especially the coming recession, is an essential challenge to investors and policymakers. Prior studies have examined that macroeconomic and financial variables have the ability to forecast future U.S. recessions. Most prominently, Bernard and Gerlach [1] find that the term structure has the ability to predict a recession in several countries. Nyberg [2] show that the financial variables, such as stock price, can play a useful role in predicting whether or not the economy will be in a recession. Other indicators that also have been examined as leading recession variable, including labor market activity, interest rate, crude oil price [3]–[7]. Considering all the above, the previous studies mostly focused on macroeconomic variables or financial indicators. However, it has been thought that human behavior associated with economic fluctuations [8]. Christiansen *et al.* [9] find that consumer sentiment variable has vast predictive ability for US recession. Furthermore, the new private housing units also were introduced to add in the leading economic indicators and express residential behavior [10]. In the recent paper, average weekly hours in manufactures has the power to predict the peaks and valleys of the business cycle, reflecting the enthusiasm of workers' work behavior [11]. Thus, this paper constructs an intelligent model to predict the US economic recession from the perspective of multiple behavioral features.

Various approaches have been developed to forecasting recession. The probit model has been commonly popular with the economic recession studies since the 1990s [1], [12]. Kauppi and Saikkonen [13] applied a dynamic binary probit model to forecast the economic recession, mainly using the term spread as the independent variables. Fossati [14] also employed dynamic factors estimated from panels of macroeconomic variables to forecast economic recession by probit models. Due to many independent variables, these models can't fully capture dynamic nonlinearities in the connection between the recession probability and these factors well. Nevertheless, with the development of machine learning methods in recently, many application of intelligent methods to economics are employed in energy markets [15],

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forecasting stock market crisis [16], population structure [17] and short-term demand prediction [18]. Among these machine learning methods, support machine vector(SVM) is the most popular methodology which is based on the statistical learning method [19]. The classical intelligent methods just use the empirical risk minimization to minimize sample errors. However, the SVM theory applies the structural risk minimization rule to minimize the sampling error and the upper bound of the generalization errors, which make sure the generalization of the model.

When using SVM, it is essential to note that the selection of an optimal combination of input variables and selection of optimal parameters for establishing predictive models with higher prediction accuracy and stability. It is an important issue that selecting representative features in the classification model. It aims to identify important relevant features and reject unrelated features to establish a good learning model. For instance, Lei [20] proposed an hybrid prediction method based on rough set(RS) and wavelet neural network(WNN), the results demonstrate that the proposed model is better than other neural network, SVM, WNN. Zhu *et al.* [21] proposed a fault diagnosis approach base on SVM and quantum genetic algorithm(QGA) to optimize SVM parameters, the results show that combined methods have higher accuracy than classical SVM. Wang *et al.* [22] proposed a novel risk-forecasting method by using rough set theory and artificial neural networks, and the experiment's results examined that the new method provides higher accuracy than logistic regression, neural network.

From those studies mentioned above, our research will focus on reducing input features and optimizing the parameters for a better economic recession model. Therefore, this paper proposes a novel method for the U.S. economic recession forecasting, which mainly includes the following contributions: Firstly, in order to find what leading variables can have predictive power for the economic recession, the Neighborhood Rough Set is employed to reduce the input features. Next, the quantum genetic algorithm(QGA) is used to optimize the SVM parameters. Thirdly, according to the characteristics of economic recession, those behavior features with potential predictive content and other classical indicators are all considered, including consumer sentiment, working hours, new private housing permits, interest rate, term spread, stock price indexes and so on. Finally, in order to show the advantages of the NRS-SVM model in the recession forecast, frequently applied models- probit, SVM are adapted to compare. The result of an out-of-sample predicting experiment shows that the proposed model has a high predicting effect among others approaches.

The rest of this study is structured as follows: Part 2 introduces the basic methodology, Part 3 describes the data and forecasting model, Part 4 represents the empirical results, and Part 5 summarizes the conclusion and future research directions of this study. Table 1 lists the symbols that appear in the following description of the proposed model.

TABLE 1. List of symbols.

Symbol	Description
U	the universe: finite and non-empty sets
C	condition attribute set
V	the domain of attribute
f	a mapping function
δ	a neighborhood parameter
Δ	a distance function
N	a neighborhood relation
$\underline{N}X$	the lower approximation of X
$\overline{N}X$	the upper approximation of X
BNX	the boundary region of X in the approximation space
$BN(D)$	the decision boundary region of D
$Pos_B(D)$	the positive region
$\gamma_B(D)$	the dependency degree of the decision set D with respect to the attribute set B
w	the vector of weight coefficient
$\varphi(\mathbf{x})$	the nonlinear mapping function
C	a penalty value
ξ_i	the positive slack variable
$\kappa(\mathbf{x}_i, \mathbf{x}_j)$	the kernel function

II. METHODOLOGY

A. THE BASIC CONCEPTS OF NEIGHBORHOOD ROUGH SET

Rough sets theory, proposed by Pawlak [23], has been proved as an intelligent technique for dealing with uncertainty and incompleteness. The classical rough set employ equivalence relations to generate the upper and lower approximation notion of a set. However, this tool just applicable to handle nominal attributes. Aiming at the problem that traditional rough set is difficult to process numerical attribute datasets, the neighborhood rough set is proposed [24]. The advantages of neighborhood rough set is that there is no need to discrete the data, so the original properties of the data are not changed. Thus, the neighborhood rough set is used as a feature selection tool to reduce redundant attributes and choose a relatively important leading indicator. Here we show the main concepts in the neighborhood rough sets.

1) NEIGHBORHOOD INFORMATION SYSTEMS

In the neighborhood rough set theory, neighborhood information systems are employed to stand for knowledge. In this paper, the information system is represented by $\langle U, A, V, f, \delta \rangle$, where $U = \{x_1, x_2, \ldots, x_n\}$ are finite and non-empty sets which stand for the universe, $A = \{C \cup D\}$ is a set of attribute that consists of condition attribute set C and decision attribute set D, $V = \underset{a \in A}{\cup} V_a$ is the domain of an attribute of $a, f : U \times A \to V_a$ is a mapping function, δ is a neighborhood parameter$(0 \leq \delta \leq 1)$.

For an arbitrary $x_i \in U$ and $B \subseteq C$, the neighborhood relation $\delta_B(x_i)$ is defined as:

$$\delta_B(x_i) = \{x_j | x_j \in U, \Delta^B(x_i, x_j) \leq \delta\} \tag{1}$$

The Δ is a distance function, which satisfies:
(1) $\Delta(x_i, x_j) \geq 0$, $\Delta(x_i, x_j) = 0$ if and if $x_i = x_j$;
(2) $\Delta(x_i, x_j) = \Delta(x_j, x_i)$;
(3) $\Delta(x_i, x_k) \leq \Delta(x_i, x_j) + \Delta(x_j, x_k)$.

In this paper, we consider Manhattan distance as our metric functions, which defined as:

$$\Delta(x_1, x_2) = \sum_{i=1}^{N} |f(x_1, a_i) - f(x_2, a_i)| \tag{2}$$

where x_1, x_2 are two objects in an N-dimensional space $A = \{a_1, a_2, .., a_N\}$, $f(x_1, a_i)$ and $f(x_2, a_i)$ represents the value of objects x_1, x_2 in the i dimension a_i.

2) NEIGHBORHOOD ROUGH SETS APPROXIMATION

In the neighborhood rough set theory, the lower and approximations are two basic operations. Suppose a set of objects U and a neighborhood relation N over U, $\langle U, N\rangle$ are defined as neighborhood approximation space. Therefore, the lower and upper approximation of any $X \subseteq U$ in $\langle U, N\rangle$ is defined as:

$$\underline{N}X = \{x_i|\delta(x_i) \subseteq U, x_i \in U\} \tag{3}$$

$$\overline{N}X = \{x_i|\delta(x_i) \cap X \neq \emptyset, x_i \in U\} \tag{4}$$

And the boundary region of X in the approximation space is represented as:

$$BNX = \overline{N}X - \underline{N}X \tag{5}$$

3) NEIGHBORHOOD DECISION SYSTEMS

Suppose a neighborhood decision system $NDS = \langle U, A, N\rangle$, $A = C \cup D$ and $U/D = \{X_1, X_2, \ldots, X_N\}$ be equivalence classes generated by decision attributes D. for $\forall B \subseteq C$, the lower and upper approximation of X is defined as follows:

$$\underline{N_B}D = \cup_{i=1}^{N} \underline{N_B}X_i \tag{6}$$

$$\overline{N_B}D = \cup_{i=1}^{N} \overline{N_B}X_i \tag{7}$$

So, the decision boundary region of D is defined as:

$$BN(D) = \overline{N_B}D - \underline{N_B}D \tag{8}$$

We used the dependency as the measure of the discrimination power of attribute subset B [29], which is defined as:

$$\gamma_B(D) = \frac{|Pos_B(D)|}{|U|}, \quad 0 \leq \gamma_B(D) \leq 1 \tag{9}$$

where $Pos_B(D)$ is defined as the positive region, which is calculated by $Pos_B(D) = \underline{N_B}D$ and $|U|$ is denoted the cardinality of the universe U. In the neighborhood information system, it is easy to know $0 \leq \gamma_B(D) \leq 1$. If $\gamma_B(D) = 1$, we concluded that D depends entirely on attribute subset B, and $\gamma_B(D) = 0$ indicates that both of them are independent of each other. Meanwhile, if $\gamma_M(D) = \gamma_N(D)$ means that the attribute subset M, N has the same classification ability.

B. SVM

SVM is a supervised learning method for predictive analysis and pattern recognition [19]. It has been proven that has good generalization performance in dealing with classification problems. Therefore, we make an attempt on exploring the availability of the SVM in forecasting recession.

Consider a training set $(\mathbf{x}_i, y_i), i = 1, 2, ..n$, consisting of n samples with $\mathbf{x}_i \in R^d$ and $y_i \in \{-1, 1\}$,where $\mathbf{x}_i \in R^d$ are input data and y_i are classified labels. we define a hyperplane as $w^T\phi(\mathbf{x}) + b = 0$, where w is the vector of weight coefficient, $\phi(\mathbf{x})$ is the nonlinear mapping function and b is the bias.

The optimal hyper is chosen as a decision boundary that the margin of separation from both classes is maximized and classifies each data vector into the correct labels. The method of finding the optimal hyper to solve the following problems:

$$\min_{w,b} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \tag{10}$$

Subject to:

$$y_i(w^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \tag{11}$$

where C is a penalty value which is introduced to deal with misclassification of cross-border points, and ξ_i is the positive slack variable which is introduced to allow misclassification of the noisy data.

The Lagrange type dual form of this problem is defined as follows:

$$L_p = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j \varphi(\mathbf{x}_i)\varphi(\mathbf{x}_j) \tag{12}$$

So that:

$$\sum_{i=1}^{n}\alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C \tag{13}$$

The solution of the above model provides the location of the optimal hyper that defined by:

$$\widehat{w} = \sum_{i=1}^{N} a_i y_i \varphi(\mathbf{x}_i) \tag{14}$$

$$\widehat{b} = \sum_{i=1}^{n} y_i \alpha_i \kappa(\mathbf{x}_i, \mathbf{x}_j) - y_i \tag{15}$$

where $\kappa(\mathbf{x}_i, \mathbf{x}_j) = \varphi(\mathbf{x}_i)^T\varphi(\mathbf{x}_j)$ is the kernel function. There are many popular kernel functions in SVM, such as linear kernel function, polynomial kernel function, and Gaussian kernel function (radial basis function, RBF). In this paper, the RBF is used by the reasons for the relatively best performance in most situations [15]:

$$\kappa(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{2\sigma^2}) \tag{16}$$

where σ is the parameter controlling the width of RBF.

III. DATA AND EMPIRICAL DESIGN

A. DATA

Our analysis is based on monthly U.S. data and our sample the period starts in January 1978 and ends in December 2016. Consistent with most previous studies, the NBER defined business cycle data is used to determine independency variable of recessions [5], [9], [25]. The NBER committee takes into many economic variables to access whether the recession and expansion accrued in real economic activity, which has been considered as the benchmark for the U.S. business cycle. In this paper, if the business cycle in recession, the predictive labels assign the value one and zero if in the expansion. In particular, the first recession month is defined as the first month following a peak month and the last recession month is defined as the last month of through.

Based on prior research, our dependent variables mainly are taken from the Federal Reserve Economic Database(FRED) and we consider the following list of leading predictor variables [26]. First, we add some interest rates and spreads. The yield spread has a higher predictive power since the yield curve contains useful information about financial markets' expectations of future economic activity [27], [28]. A flat curve indicates weak growth, whereas a steep curve will follow a stronger growth. Our spread measures consist of 10-Year Treasury Constant Maturity Minus Federal Funds Rate, 5-Year Treasury Constant Maturity Minus Federal Funds Rate, 1-Year Treasury Constant Maturity Minus Federal Funds Rate, 6-Month Treasury Constant Maturity Minus Federal Funds Rate, 3-Month Treasury Constant Maturity Minus Federal Funds Rate, 3-Month Commercial Paper minus Federal Funds Rate. In addition, we hold that the default spread is a predictor of actual growth. So the spread between Moody's Baa corporate bonds and federal funds rate are considered as predictors.

As well as interest rates, changes in monetary aggregates have the potential to affect real activity in the short term. This means that money flows provide potential information for future economic activity [5]. So, we selected the real M2 money stock to imply changes in monetary aggregates.

Since stock prices reflect the expected discounted value of future earnings, stock returns should provide useful information for forecasting returns to predict the future economic recession. And their volatility is also considered, which indicate stock market confidence. Moreover, the commodity prices are also employed as leading indicators, so we add crude oil prices(spliced WTI and cushing). This measure is motivated by the facts that the recession of the 1970s and early 1980s, associated with a sharp rise in oil prices, which is considered to be the root cause of these declines.

The next group of variables of real economy indicators, such as labor market variables, prices and unfilled orders. Generally, unfilled orders indicate the decline of domestic and international demand. Today's unfilled orders will result in less production in the future, providing useful information for the recession. What's more, labor market indicators(the average working hour, civilian unemployment rate, the number of employees and vacancies) may also be associated with the economic recession. Further, we consider the industrial production index, real personal income and capacity utilization(manufacturing).

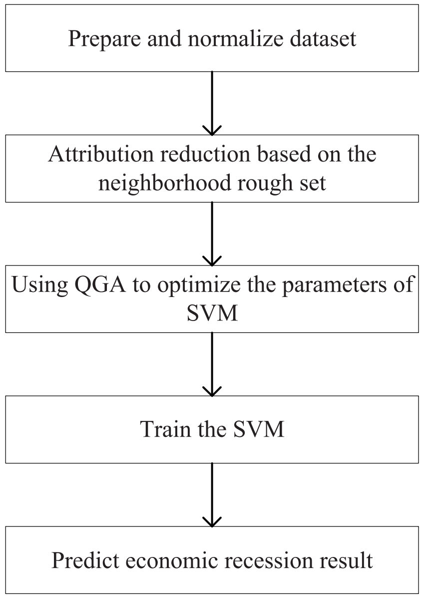

FIGURE 1. Process of the proposed NRS-SVM algorithm.

Finally, we consider potential behaviors features. These individual factors consist of: average weekly hours, new private housing permits, consumer sentiment index [9]. These indicators have been examined for their ability to reflect the peaks and troughs of the business cycle [10].

These variables that we considered are represented in Table 2 with the description, source, and transformations that are employed to keep the indicators stationary.

B. THE NRS-SVM FORECASTING MODEL

The economic recession method based on NRS-SVM is shown in Fig. 1, and its steps are as follows: (1) The parameters reduction algorithm based no neighborhood rough sets is used to select the economic recession leading predictors.
(2) Based on the reduced data set. SVM is introduced to verify the prediction effect of the leading predictors. The RBF kernel function is applied as the kernel function of SVM, and the optimal parameters of SVM model are obtained by the quantum genetic algorithm.
(3) the economic recession forecasting using trained SVM.

1) FEATURE SELECTION

Selecting different types of indicators as research indicators have a vast influence on the predictive power of the model and the reliability of indicators. This step's goal is to search a reduced set of features which has the similarity quality of classification as the not-reduced indexes and has noted any redundant attribute.

As mentioned previously, suppose the information system $\langle U, C \cup D, V, f, \delta \rangle$, B is the subset of condition attributes, $B \subset C$. If $a \in B$, then the importance of the attribute relative to a and B is calculated as: $SIG(a, B, D) = \gamma_{B \cup a}(D) - \gamma_B(D)$ [24], [29]. Using $SIG(a, B, D)$, we can able to measure the increment of dependency, that is if we increase

TABLE 2. The pool of key indicators.

Label	Indicators name	Source	Transformation
D	Recession phases	NBER	None
C_1	Help-Wanted Index for the US	FRED	Monthly difference
C_2	Ratio of Help Wanted/No. Unemployed	FRED	Monthly difference
C_3	Civilian Unemployment Rate	FRED	Monthly difference
C_4	Civilian Unemployment-15 Weeks&Over	FRED	Monthly log difference
C_5	Civilian Unemployment for 15-26 Weeks	FRED	Monthly log difference
C_6	All Employees: Total non-farm	FRED	Monthly log difference
C_7	All Employees: Goods-Producing Industries	FRED	Monthly log difference
C_8	All Employees: Construction	FRED	Monthly log difference
C_9	All Employees: Manufacturing	FRED	Monthly log difference
C_{10}	All Employees: Durable goods	FRED	Monthly log difference
C_{11}	All Employees: Nondurable goods	FRED	Monthly log difference
C_{12}	All Employees: Service-Providing Industries	FRED	Monthly log difference
C_{13}	All Employees: Trade,Transportation&Utilities	FRED	Monthly log difference
C_{14}	All Employees: Wholesale Trade	FRED	Monthly log difference
C_{15}	All Employees: Retail Trade	FRED	Monthly log difference
C_{16}	Avg Weekly Hours: Goods-Production	FRED	None
C_{17}	Avg Weekly Hours:Manufacturing	FRED	None
C_{18}	Housing Starts: Total New Privately Owned	FRED	Log of the series
C_{19}	Housing Permits	FRED	Log of the series
C_{20}	Housing Permits, Midwest	FRED	Log of the series
C_{21}	Housing Permits, South	FRED	Log of the series
C_{22}	Housing Permits, West	FRED	Log of the series
C_{23}	S&P's 500: Composite	FRED	Monthly log difference
C_{24}	S&P's 500: Dividend Yield	FRED	Monthly difference
C_{25}	Crude Oil, spliced WTI and Cushing	FRED	Monthly log second difference
C_{26}	Effective Fed	FRED	Monthly difference
C_{27}	3-m AA Financial Commercial Paper Rate	FRED	Monthly difference
C_{28}	3-m Treasury Bill	FRED	Monthly difference
C_{29}	3-m Commercial Paper Minus EFF Rate	FRED	None
C_{30}	3m- EFF spreads	FRED	None
C_{31}	6m-EFF spreads	FRED	None
C_{32}	1y-EFF spreads	FRED	None
C_{33}	5y-EFFspreads	FRED	None
C_{34}	10y-EFF spreads	FRED	None
C_{35}	Moodyąŕs Baa Corporate Bond Minus EFF Rate	FRED	None
C_{36}	Real Personal Income	FRED	Monthly log difference
C_{37}	IP index	FRED	Monthly log difference
C_{38}	IP : Final Products and Nonindustrial Supplies	FRED	Monthly log difference
C_{39}	IP: Final Products(Market Group)	FRED	Monthly log difference
C_{40}	IP: Business Equipment	FRED	Monthly log difference
C_{41}	IP: Materials	FERD	Monthly log difference
C_{42}	IP: Durable Materials	FERD	Monthly log difference
C_{43}	IP: Nondurable Materials	FERD	Monthly log difference
C_{44}	IP: Manufacturing	FERD	Monthly log difference
C_{45}	Capacity Utilization: Manufacturing	FERD	Monthly difference
C_{46}	Real M2 Money Stock	FERD	Monthly log difference
C_{47}	Consumer Sentiment Index	FERD	Monthly difference
C_{48}	Unfilled Orders for Durable Goods	FERD	Monthly log difference
C_{49}	CBOE S&P 100 Volatility Index	FERD	Monthly difference

the attribute a to the B, the increment of the positive area is the importance of the attribute a. Especially, If the $SIG(a, B, D) = 0$,which denoted the attribute a is redundant for B to approximate D.

The algorithm flow of feature selection is given below:

Step 1: Calculate the neighborhood relation for $\forall a \in A$ (red is the pool containing the selected features)

Step 2: Initialize the $red = \phi, B = A - red$

Step 3: For each $a_i \in B$: calculate $SIG(a_i, red, D) = \gamma_{red \cup a}(D) - \gamma_{red}(D)$

Step 4: Choose a_k if $SIG(a_k, red, D)$ has a maximum value

Step 5: If $SIG(a_k, red, D) > \delta$:

$red \leftarrow red \cup \{a_k\}$;
$B \leftarrow B - red$;
Go back to step 2
Else:
Return red, end.

2) FIND OPTIMAL PARAMETERS

Besides of the feature selection, the way of finding model's optimal parameters can greatly enhance the performance of SVM forecast [30]. Therefore, the quantum genetic algorithm(QGA) and 10-fold cross-validation are adopted to investigate the optimal parameter of NRS-SVM. Compared with the classical genetic algorithm, the QGA can improve

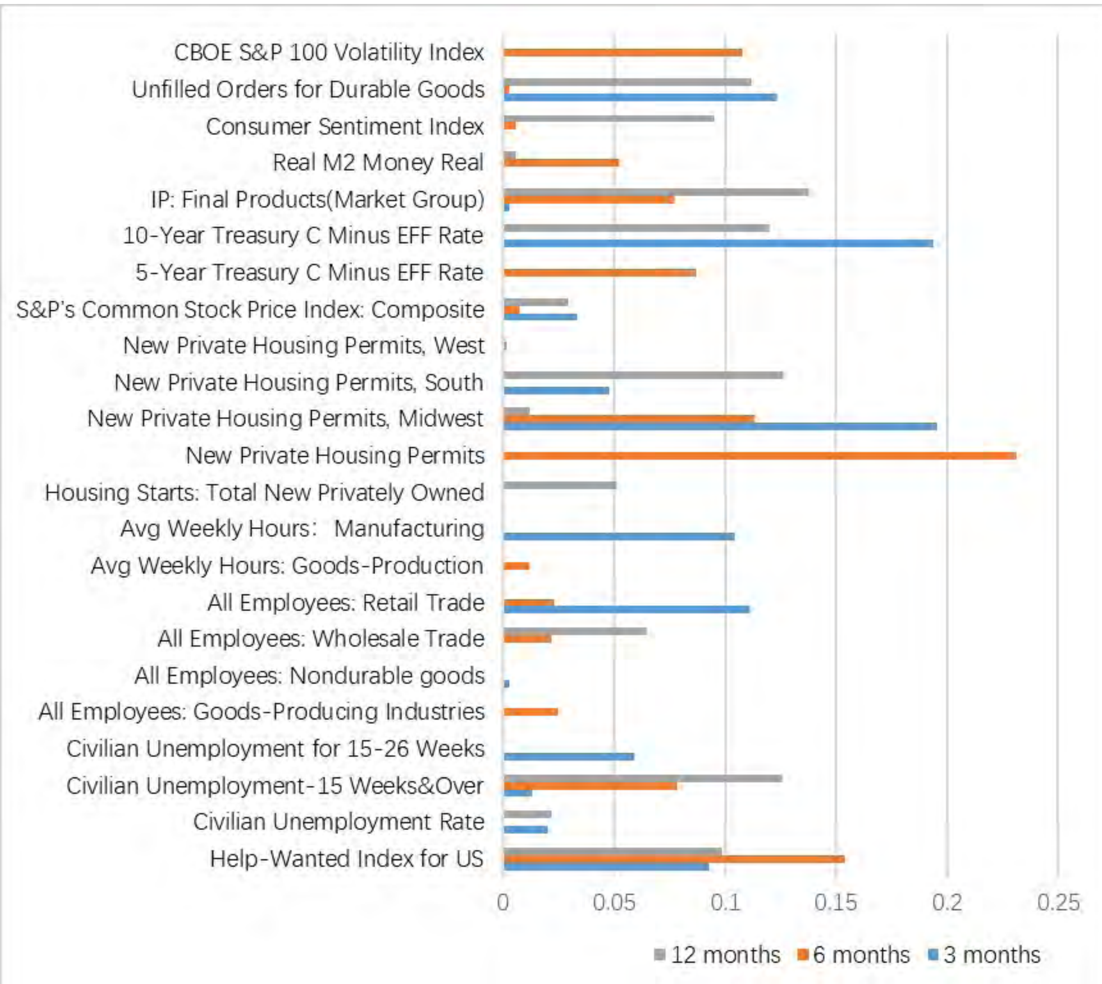

FIGURE 2. Relative importance of selected variables.

TABLE 3. Features selected with neighborhood rough set.

Time horizons	Features selected	Number	Extracted percent
3 months	$C_1, C_3, C_4, C_5, C_{11}, C_{15}, C_{17}, C_{20}, C_{21}, C_{23}, C_{34}, C_{39}, C_{48}$	13	13/50
6 months	$C_1, C_4, C_7, C_{14}, C_{15}, C_{16}, C_{19}, C_{20}, C_{22}, C_{23}, C_{33}, C_{39}, C_{46}, C_{47}, C_{48}, C_{49}$	16	16/50
12 months	$C_1, C_3, C_4, C_{15}, C_{18}, C_{20}, C_{21}, C_{23}, C_{34}, C_{39}, C_{46}, C_{47}, C_{48},$	13	13/50

both convergence speed and global optimization ability by the quantum computing concept [21]. Then the optimal parameter set is employed to build the recession forecasting model for training samples.

The algorithm flow of the parameters optimization is given below:

Step 1: Drop useless variable by neighborhood rough set and rebuild the data set.

Step 2: Choose the RBF kernel as for kernel function which is considered the most suitable for predicting financial variable [15].

Step 3: Consider the pair of parameters (C, γ) with $C \in (0.01, 100)$ and $\gamma \in (0.0001, 32)$ as the solution space. Then the initialization of population of quantum chromosomes are randomly initialized to estimate the fitness of the individuals in the population. The individual's fitness is calculated by the classification accuracy.

TABLE 4. AUROC of different methods.

Forecast horizon	3 months	6 months	12 months
SVM	0.8992	0.6938	0.5558
Probit model	0.7212	0.6715	0.6655
NRS-SVM	0.9402	0.7735	0.7310

Step 4: Recode of the best individual and fitness value and update the chromosome by quantum rotation operator.

Step 5: Continue until the condition of algorithm is met.

IV. EMPIRICAL AND ANALYSIS

A. RELATIVE IMPORTANCE OF SELECTED VARIABLE

For a large number of leading indicators is difficult for the further investigate, the feature selection by the neighborhood rough set is required. We also calculated the relative importance of a leading indicator by the increment of dependency (Figure 2,Table 3).

TABLE 5. The ranking of indicators in 3-month-ahead forecast horizon.

Condition attribute		C_{22}	C_9	C_{20}	C_{34}	C_{48}	C_1	C_{14}	C_5	C_{23}	C_3	C_{39}	C_4	C_{11}
	2000-2005	6	2	4	10	1	12	3	8	5	9	13	11	7
Rank	2006-2010	6	4	3	2	1	10	8	9	12	11	5	7	13
	2011-2016	4	7	1	2	12	10	11	13	5	8	6	9	3

TABLE 6. The ranking of indicators in 6-month-ahead forecast horizon.

Condition attribute		C_{16}	C_{33}	C_{19}	C_1	C_{20}	C_{49}	C_4	C_{39}	C_{46}	C_{14}	C_{15}	C_7	C_{23}	C_{47}	C_{22}	C_{48}
	2000-2005	2	10	15	8	1	16	5	7	11	14	13	9	3	4	12	6
Rank	2006-2010	6	1	13	11	16	10	2	8	9	14	4	7	5	15	3	12
	2011-2016	15	10	2	12	13	11	16	14	8	6	5	9	4	7	3	1

TABLE 7. The ranking of indicators in 12-month-ahead forecast horizon.

Condition attribute		C_{18}	C_{34}	C_{22}	C_4	C_{48}	C_1	C_{39}	C_{47}	C_{14}	C_{23}	C_3	C_{20}	C_{46}
	2000-2005	5	2	1	13	3	9	12	11	4	8	7	10	6
Rank	2006-2010	2	12	5	8	6	13	3	11	9	1	10	7	4
	2011-2016	12	3	7	6	4	11	9	13	1	2	10	5	8

According to the result calculated by the neighborhood rough set, the term spread between the 10-year government bonds and the effective federal funds, the new private housing permits, and help-wanted index are among the most influential factors. While the term spread and help-wanted index are comparatively more significance for 3-month-ahead forecast horizon. The new private housing permits index is more important for 12-month-ahead forecast horizon (especially the south of new private housing permits). The civilian unemployment rate also has the importance index between 5% and 10% and unfilled orders for durable goods still have an influence on the recession for different forecast horizon. Importantly, the relative importance of the consumer sentiment variable is about 10%, which is examined that behavior features imply information about future economic activity fluctuations.

B. ACCURACY ASSESSMENT OF RECESSION FORECAST BY THE PROPOSED HYBRID MODEL

To capture possible structural changes in the economic activity, we conduct the following experiments. First, the proposed model is estimated using data from 1978:M1 to 1999:M12. Then the estimated parameters are used to predict the recession for 2000:M1 to 2016:M12, which covers two recessions.

In order to access the property of the different models, we employ the receiver operating characteristics curve (ROC) [9]. When the cutoff value changes, the ROC curve plots all possible combinations of the true positive and false positive. We make use of the AUROC statistic to summarizes the performance, which is the area under the ROC curve. For a perfect recession classifier, $AUROC = 1$. For a recession classifier that randomly assigns observations to labels, $AUROC = 0.5$.

We calculated the AUROC for the thousand simulated samples of the out-of-sample forecasts, then used a probit model to the same out-of-sample forecasts. The result of our proposed model, SVM with unreduced feature and the probit model are represented in Table 4. This experiment is organized by the three different forecast horizons.

As the three-month-ahead horizon, the probit method gains AUROC of 0.7212, which is slightly greater than a random recession classifier. While the way of reducing the redundant related variables and parameters optimization improves the predictive power of the NRS-SVM model. Turning to the 6-month-ahead forecast horizon, the proposed hybrid model's AUROC is 0.7735, which is marginally below than at the three-month-ahead horizons. But they are still significantly better than the probit model. The result of 12-month-ahead forecast horizon indicates the prediction ability reaches 73.1%, which is still higher than other approaches, thereby verifying the validity and practicality of the proposed model in the recession forecast.

Although the result reported in the previous subsection indicate the importance of various indicators in the entire forecasting periods, it is not present information about how the relevance of different indicators changes over time. This study adopts recursive feature elimination(RFE) to rank the variables by the weight magnitude in three subperiods:2000:M1-2005:M12, 2006:M1-2010:M12, and 2011:M1-2016:M12.

The Table 5 show the change in the ranking of the various indicators since 2000. From Table 5, the relative importance of various indicators tends to change in different period. For instance, at the three-month forecast horizon, 'Unfilled Orders for Durable Goods' ranked No.1 in the 2000:M1-2005:M12 and 2006:M1-2010:M12 sub-periods. However 'New Private Housing Permits' take its place in the 2011:M1-2016:M12. So even at the same forecasting horizon, the most important indicators are rarely the same during three sub-periods.

The Table 6 also presents the change in the ranking of the various indicators at the six-month horizons. the finding show that the best indicators of the economic recessions changed in different forecast horizons. Furthermore, the relatively importance of 'New Private Housing Permits(Midwest)' has declined in recent years, this decline indicates the housing permits are less cyclical today than it was. The importance of stock market price index basically ranks high in all three sub-periods.

Similar patterns are observed with table 7 where the ranking of the twelve-month forecasts horizons are reported. In addition, the importance of stock market price index has increased slightly in all three sub-periods. From all those three tables, even at the same sub-periods, the importance rankings of various indicators are dynamically change during the different forecast horizon.

V. CONCLUSION

Economic crisis forecasting is of great significance to policymakers and investors. Because of the thorough understanding of the interaction after the recession, it can greatly help the adjustment of corporate policies and the formulation of government emergency plans. The objective of this paper constructs an economic recession prediction model based on the neighborhood rough set-support machine vector(NRS-SVM) from the perspective of multiple behavioral features (consumer behavior, work behavior, and residential behavior). So, we select the multiple behavioral features variables and finds the relative importance of the selected indicator, which can be used to predict the recession effectively. Meanwhile, we provide a hybrid method that can capture the nonlinear and dynamic linkage between the selected indicators and the probability of recession. Finally, our empirical results examined that the proposed method based on the neighborhood rough set and SVM have better out-of-sample predictive performance in different time horizons, which complements the widely-used probit approach to forecast the recession.

The experiment suggests that the possibility of an economic downturn has related to multiple behavioral features, indicating the consumer sentiment, work behavior and residential behavior are all important leading variables to forecast US recession. Especially, the shorter of the leading horizon time, the greater importance of new private housing permits in Midwest. In further study, it will be interesting to investigate the role of the other investor behavior's index using NRS-SVM methods or some intelligent methods. It is also valuable to study the behavior variables and macroeconomic to predict other countries recession.

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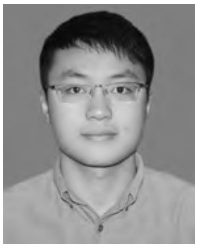

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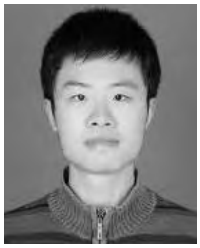

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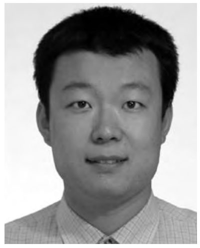

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