A Neural Network Based Forecasting Method For the Unemployment Rate Prediction Using the Search Engine Query Data

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Abstract—Unemployment rate prediction has become critically important, because it can help government to make decision and design policies. In recent years, forecast of unemployment rate attracts much attention from governments, organizations, and research institutes, and researchers. Recently, a novel method using search engine query data to forecast unemployment was proposed by scholars. In this paper, a data mining based framework using web information is introduced for unemployment rate prediction. Under the framework, a neural network method, as one of the most effective data mining tools, is developed to forecast unemployment trend using search engine query data. In the proposed method, search engine query data related with employment activities is firstly found. Secondly, feature selection models including correlation coefficient method and genetic algorithm are constructed to reduce the dimension of the query data. Thirdly, various neural networks are employed to model the relationship between unemployment rate data and query data. Fourthly, an optimal neural network is selected as the selective predictor by using the cross-validation method. Finally, the selective neural network predictor with the best feature subset is used to forecast unemployment trend. The empirical results show that the proposed method clearly outperforms the classical forecasting approaches for the unemployment rate prediction. These findings imply that data mining method, such as neural networks, together with web information, can be used as an alternative tool to forecast social/economic hotspot.

Keywords-prediction; unemployment rate; data mining; neural networks; query data

I. INTRODUCTION

Unemployment rate prediction has become critically important, in particular during economic recession, because it can not only help government to make decision and design policies, but also offer practitioners to have a better understand of the future economic trend. In recent years, forecast of unemployment rate attracts much attention from governments, organizations, and research institutes, and researchers. A great number of methods and systems methods are proposed for unemployment rate prediction. Traditional univariate time series model have been proposed for the unemployment rate prediction [3, 13, 20, 22]. For example, a time deformation model is applied to US unemployment data, and the experimental results indicate that the proposed method has better performance than other better-known models, such as the autoregressive integrated moving average (ARIMA) [22]. Similarly, autoregressive fractionally integrated moving average (ARFIMA) is offered to analyze the US unemployment trend, and the results show that ARFIMA has a better forecasting performance than threshold autoregressive (TAR) and symmetric ARFIMA model [13].

Some macroeconomic variables, such as money supply, producer price index, interest rate and gross national product (GNP), have been considered in unemployment rate prediction [10-12, 15-17, 21]. A smooth transition vector error-correction models (STVECMs) is used to forecast the unemployment rates of the four non-Euro G-7 countries in term of economic indicators [15]. Similarly, a Markov-switching vector error correction model (MS-VECM) is suggested to analyze the U.K. labor market [12]. Moreover, a univariate and multivariate functional coefficient autoregressive (FCAR) models are presented and evaluated for multi-step unemployment rate prediction [10]. A pattern recognition method is developed to analyze the specific phenomenon of fast acceleration of unemployment [11].

Since web information is regarded as a useful resource to analyze social/economic hotspot, such as influenza epidemics detection [8, 23] and finance market prediction [2, 14, 18], the unemployment rate prediction using web

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information has attracted more attention from researchers and practitioners [1, 4-7, 19]. A new method of using data on internet activity is proposed to demonstrate strong correlations between keyword searches and unemployment rates, and the experimental results show that the method used has a strong potential for the unemployment rate prediction [1]. An internet job-search indicator called Google Index (GI) is suggested as the best leading indicator to predict the US unemployment rate, and an out-of-sample comparison of other forecasting models is done to show that the GI indeed helps in predicting the US unemployment rate even after controlling for the effects of data snooping [6], while the power of a novel indicator based on job search related web queries is employed to predict quarterly unemployment rates in short samples [7]. Similarly, the popularity of web searches tracked by Google is suggested as an indicator of contemporaneous economic activity, before the official data become available and/or are revised [19]. Finally, Google Trends data is suggested to forecast the U.S. unemployment time series, and it could improve the forecasting accuracy significantly by using Google Trends [4-5].

Data mining techniques have made a significant contribution to the field of information science, management science, economics and finance for feature selection, knowledge discovery, prediction, detection and so on. Furthermore, together with web information, data mining techniques have been applied to many research topics, such as finance market prediction [18] and influenza epidemics detection [23]. However, to our knowledge, web information based data mining methods or systems are seldom been used to forecast unemployment rate. So, this paper contributes a data mining framework to forecast the unemployment rate using web information, and examines the efficiency and effectiveness of the proposed framework. Under the framework, a neural network based approach using search engine query data is offered to analyze employment trend. In the proposed method, an automated feature selection model is firstly constructed to reduce the dimension of the query data. Secondly, different neural networks (*NN*) are employed to describe the relationship between the unemployment rate data and the search engine query data. Thirdly, an optimal neural network is selected as the predictor by using the cross-validation method. Finally, the selected neural network predictor with the best feature subset is used to forecast unemployment trend.

The rest of this paper is organized as follows. The next section presents the methodology of data mining for the unemployment rate prediction using web information. For illustration the efficiency of the proposed methodology, a neural network based approach is designed to forecast the unemployment rate by using search engine query data in Section 3. Empirical analysis of unemployment trend using the proposed method is reported in Section 4. Finally, conclusions and future research directions are summarized in Section 5.

II. DATE MINING FOR UNEMPLOYMENT RATE PREDICTION

Data mining techniques together with web information, such as decision trees (DT), neural networks (NN), and support vector machines (SVM), have been successfully applied to many research topics [18, 23]. However, there are seldom data mining based methods or systems to analyze the unemployment trend using web information. So, this paper proposes a methodology of data mining for the unemployment rate prediction using web information, especially web behavior information. The framework of our proposed methodology is illustrated in Fig. 1.

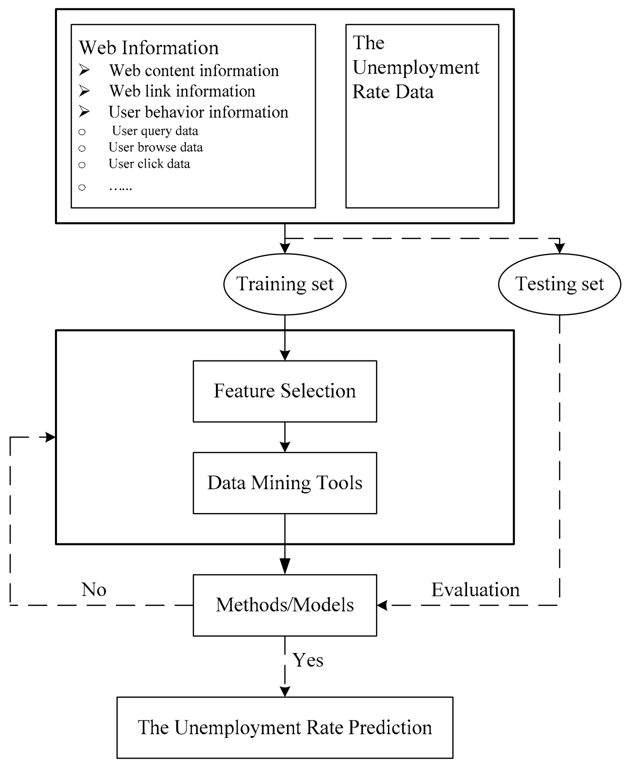

Figure 1. The framework of the unemployment rate prediction

As can be seen from Fig. 1, our proposed methodology is implemented as follows. Firstly, the web information including web content information, web link information, and user behavior information are collected and prepared for the usage. For example, user query data, one of the most important user behavior information, can be gathered from Google Search Insight. The unemployment rate data can be collected from the related websites, such as Department of Labor in USA. Secondly, feature selection methods are used to mine useful and important attributes in the given web dataset. Thirdly, data mining tools are suggested to model the relationship between the unemployment rate data and web information, and to analyze the unemployment trend. Fourthly, the designed models are gone through an iterative validation process using various evaluation methods such as cross-validation method with different evaluation criteria, until the model with best performance is selected. The selective predictor with the best feature subset and the optimal parameters is used to forecast unemployment rate.

III. NEURAL NETWORKS FOR THE UNEMPLOYMENT RATE PREDICTION USING SEARCH ENGINE QUERY DATA

In this paper, a classical data mining technique, neural networks, is employed to illustrate the effectiveness of our proposed methodology. A neural network based forecasting process using search engine query data is described in Fig. 2.

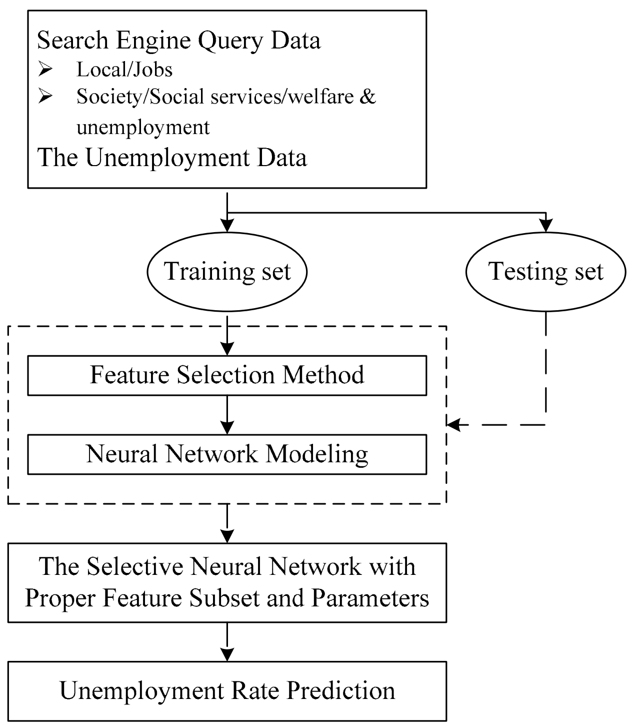

Figure 2. The process of the neural network prediction

As can be seen from Fig. 2, the main process of neural network based prediction using the search engine query data can be decomposed into the following four steps.

Step 1: Data collection. Both the search engine query data and the unemployment data are collected to help build the model. Suggested in [4], two types of the query data, “Local/Jobs” and “Society/Social Services/Welfare & Unemployment”, are supposed to be related to the unemployment queries. The weekly counts for the query data are available from 2004 to now at the Google Search Insight (http://www.google.com/insights/#) and the unemployment data is available at US Department of Labor (http://www.ows.doleta.gov/unemploy/claims.asp).

Step 2: Feature selection. The query data collected in the first step is of the low correlation with the predict target. To exclude these outliers and improve the performance of the model, a correlation coefficient method is employed as a ranking criterion to evaluate the goodness of linear fit of the selected features [9]. Through correlating the search engine query data and the unemployment data, a set of highest ranking queries will be selected. After the set of highest ranking queries is confirmed, the optimal set of the query data can be selected for the unemployment rate prediction by some heuristic algorithms, such as genetic algorithm.

Step 3: Modeling. Different architectures and learning algorithms based neural network models are tested to measure the fitness between the search engine query data and the unemployment rate data. The cross-validation method is used for validation.

Step 4: Prediction. A selective neural network model with the optimal feature subset and the proper parameters is selected by the cross-validation method. The appropriate neural network predictor is then used to forecast the unemployment trend.

IV. EMPIRICAL ANALYSIS

A. Data description and evaluation criteria

The US government only releases a monthly report of unemployment rate to the public. In order to improve the prediction performance, instead of forecasting the unemployment rate itself, the Unemployment Initial Claims (UIC) is used in our experiments. UIC is a leading indicator of US labor market to estimate the unemployment rate, which is a weekly report issued by US Department of Labor. Thus, the weekly initial claims data is collected from the website of the US Department of Labor.

On the another hand, as proposed in [4], two types of the query data, “Local/Jobs” and “Society/Social Services/Welfare & Unemployment”, are supposed to be related to the unemployment queries. The Google keyword tool (https://adwords.google.com/) is utilized to collect the query data, and 500 keywords are collected as the raw feature set based on the two types. Then the time series of weekly counts for these queries are available from Jan.2004 to Mar.2011 in the Google Search Insight, with normalized values between 0 and 100. The UIC data from Jan. 2004 to Mar. 2011 is available at US Department of Labor (http://www.ows.doleta.gov/unemploy/claims.asp).

In addition, for comparison, the indicator of Root Mean Square Error (RMSE) is used to measure the prediction results. Given n pairs of actual values (A_i) and the predictive values (P_i), the indicator can be calculated as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n}\left(A_i - P_i\right)^2 \Big/ n} \quad (1)$$

B. Experimental results

1) Experimental results in the proposed method

During the feature selection phase, the 108 highest ranking queries are selected with the correlation coefficient values greater than 0.65. The queries selected are listed in Table 1. Several *NN* learning algorithms including *NN-rp* (Resilient back propagation), *NN-gdx* (Gradient descent with momentum and adaptive learning rate back propagation), *NN-oss* (One-step secant back propagation) are applied for evaluation. To validate the efficiency of our proposed methods, 5-fold cross validation method is used.

In the NNs, the input nodes (*IN)* are suggested to use some of the *n* (*n* = 1,….., 108) highest scoring queries selected by the Pearson formula, and the number of hidden nodes (*HN*) is determined on the number of input nodes by the formula *HN* = *IN*/2. For each NN learning algorithm, the genetic algorithm is employed to mine the features, and neural networks is offered to model the relationship of the features mined and the UIC data. In the genetic algorithm, the population is set as 50, and the generation is set as 100. In addition, all the algorithms are implemented using the toolbox provided by Matlab software package.

TABLE 1 RESULTS OF THE HIGHEST SCORING QUERIES

No.	Keywords	Correlation
1	filing unemployment	0.8481
2	unemployment filing for	0.8355
3	unemployment office	0.8234
4	file for unemployment	0.8048
5	unemployment file for	0.8043
6	unemployment state	0.7976
7	state of unemployment	0.7967
8	insurance unemployment	0.7898
9	washington unemployment	0.7876
10	unemployment file	0.7876
11	unemployment insurance	0.7861
12	unemployment apply	0.7847
13	department of unemployment	0.7843
14	unemployment website	0.7791
15	unemployment application	0.7739
16	unemployment new york	0.7733
17	washington state unemployment	0.7709
18	Wisconsinunemployment benefits	0.7685
19	insurance for unemployment	0.7683
20	apply for unemployment	0.7681
21	unemployment claims	0.7673
22	unemployment apply for	0.7672
23	apply for unemployment	0.7658
24	unemployment ca	0.7645
25	unemployment services	0.7597
26	unemployment security	0.7559
27	unemployment	0.7509
28	to file unemployment	0.7481
29	unemployment benefits	0.7436
30	file for unemployment online	0.7420
31	ohio unemployment benefits	0.7401
32	unemployment file claims	0.7347
33	to file for unemployment	0.7333
34	unemployment benefits pa	0.7316
35	unemployment benefit	0.7272
36	nys dept labor	0.7270
37	state unemployment benefit	0.7242
38	connecticut unemployment benefits	0.7237
39	dept of unemployment	0.7220
40	nys dept of labor	0.7215
41	for unemployment benefits	0.7196
42	uimn.org	0.7179
43	unemployment in michigan	0.7142
44	unemployment benefit claim	0.7141
45	unemployment payment	0.7131
46	unemployment in colorado	0.7121
47	apply for unemployment online	0.7085
48	unemployment benefits insurance	0.7076
49	application for unemployment	0.7076
50	benefits unemployment insurance	0.7076
51	ohio unemployment rate	0.7071
52	unemployment ny	0.7064
53	unemployment compensation	0.7058
54	unemployment in az	0.7053
55	to apply for unemployment	0.7033
56	unemployment insurance claim	0.7019
57	unemployment department of labor	0.7011
58	department of labor unemployment	0.6998
59	labor department unemployment	0.6997
60	unemployment check	0.6996
61	unemployment for mn	0.6992
62	unemployment in indiana	0.6987
63	unemployment in california	0.6980
64	snag a job	0.6951
65	unemployment grants	0.6946
66	unemployment in pennsylvania	0.6942
67	unemployment benefit insurance	0.6941
68	claim unemployment benefit	0.6940
69	part time unemployment	0.6936
70	security jobs	0.6935
71	new york unemployment benefit	0.6925
72	unemployment insurance benefit	0.6918
73	unemployment dol	0.6900
74	unemployment info	0.6877
75	unemployment commission	0.6873
76	michigan unemployment benefits	0.6866
77	weekly unemployment insurance	0.6855

78	weekly unemployment benefits	0.6855
79	nyc unemployment benefits	0.6852
80	green jobs	0.6852
81	how to claim unemployment	0.6841
82	unemployment rate	0.6836
83	unemployment insurance benefits	0.6833
84	unemployment weekly benefits	0.6830
85	online unemployment application	0.6826
86	unemployment rate ny	0.6818
87	jobs in usa	0.6791
88	new york unemployment benefits	0.6770
89	benefits for unemployment	0.6767
90	police jobs	0.6744
91	dc unemployment	0.67408
92	unemployment in kansas	0.6731
93	mass unemployment benefits	0.6724
94	unemployment online	0.6712
95	unemployment in florida	0.6693
96	eligible for unemployment	0.6635
97	benefits of unemployment insurance	0.6628
98	unemployment eligibility	0.6611
99	construction jobs	0.6601
100	unemployment rate recession	0.6600
101	online work	0.6598
102	unemployment numbers	0.6588
103	file unemployment claim	0.6564
104	gov jobs	0.6558
105	unemployment benefits nj	0.6548
106	qualify for unemployment	0.6531
107	unemployment calculator	0.6531
108	benefit of unemployment insurance	0.6524

In the experiments, each network was trained by 10 times. The results provided by different genetic algorithm based neural network (*GA-NN*) are showed in Table 2 and Table 3.

TABLE 2 RESULTS OF GA-NN MODELS

Method	Max RMSE	Average RMSE	Min RMSE
GA-NN-rp	46008.192	39135.001	35392.997
GA-NN-gdx	79569.205	73717.636	64179.600
GA-NN-oss	33923.050	25917.995	19393.490

TABLE 3 RESULTS OF FEATURE SELECTION BY GA-NN MODELS

Methods	Feature Selection Results
GA-NN-rp	No.2, No.3, No.6, No.7, No.8, No.9, No.11, No.14, No.15, No.16, No.17, No.18, No.19, No.20, No.21, No. 24, No.25, No.27, No.28, No.29, No.30, No.33, No.37, No.39, No.40, No.41, No.43, No.44, No.45, No.50, No.52, No.53, No.54, No.55, No.57, No.60, No.70, No.73, No.75, No.79, No.80, No.82, No.83, No.88, No.90, No.92, No.96, No.97, No.100, No.101, No.102, No. 103, No.104, No.108
GA-NN-gdx	No.3, No.6, No.9, No.10, No.11, No.12, No.13, No.14, No.15, No.16, No.18, No.21, No.24, No.25, No.28, No.31, No.33, No.34, No.35, No.37, No.42, No.43, No.46, No.49, No.50, No.52, No.53, No.54, No.62, No.66, No.69, No.70, No.72, No.73, No.74, No.77, No.81, No.82, No.83, No.84, No.86, No.89, No.92, No.94, No.95, No.96, No.100, No.101, No.102, No.103, No.104, No.107, No.108
GA-NN-oss	No.5, No.6, No.7, No.10, No.13, No.16, No.18, No.19, No.23, No.24, No.25, No.26, No.29, No.30, No.31, No.35, No.37, No.38, No.39, No. 48, No.50, No.51, No.55, No.56, No.57, No.58, No.59, No.60, No.63, No.64, No.65, No.66, No.67, No.68, No.71, No.72, No.73, No.75, No.80, No.82, No.87, No.90, No.91, No.94, No.96, No.100, No.101, No.103, No.105, No.107, No.108

As can be seen from Table 2 and Table 3, the average RMSE of *GA-NN-oss* model is less than 26000 and the max RMSE is below 34000. Such result performs well since the mean of our real data about 'initial claims' is about 400000, and it outperforms significantly than the other two algorithms in terms of the RMSE level. In addition, the features including No.6, No.24, No.25, No.50, No.73, No.82, No.96, No.100, No.101, No.103 and No.108 are selected by all these methods.

2) Comparison

To compare our proposed method to the method suggested in [8, 23], some comparative experiments are done. In the experiments, three *NN* learning algorithms are also used, but the input nodes (*IN*) are suggested to use n (n = 1,…, 108) top highest scoring queries. In addition, all the algorithms are implemented using the neural network toolbox provided by Matlab software package.

The results are shown in Fig. 3 and Table 4.

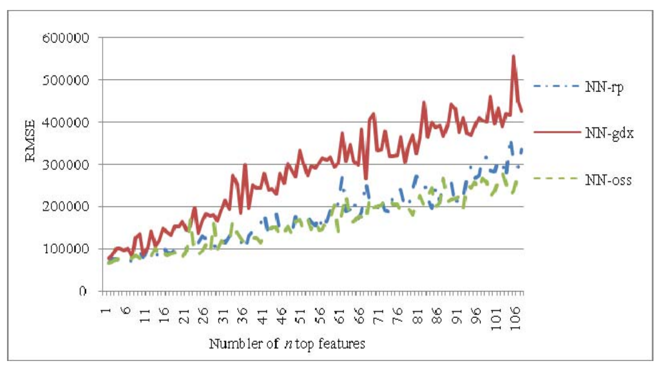

Figure 3. Results of the *NN*s models

TABLE 4 RESULTS OF NN MODELS

Method	Top n features	Max RMSE	Average RMSE	Min RMSE
NN-rp	n=6	82705.186	69063.746	59317.330
NN-gdx	n=8	100836.64	79305.305	60889.246
NN-oss	n=7	81794.821	70691.347	63136.602

As can be seen from Table 2 and Table 4, the *GA-NN*s have better performance than the traditional correlation coefficient based *NN* method.

3) Unemployment prediction by the proposed method

*GA-NN-os*s model with the most persuasive features is selected to forecast UIC in U.S. The dataset is first divided into training set and testing set. The data from Jan 4th 2004 to Sep 26th 2009 are used as the training set (300 observations), and the data from Sep 27th 2009 to Mar 12th 2011 are taken as testing set (75 observations). The number of input nodes (*IN)* is the number of features selected by the GA, and the number of hidden nodes (*HN*) is also fixed according to the number of input nodes by the formula HN = *IN*/2. The predictive values will be compared with the actual values during Sep 27th 2009 and Mar 12th 2011. In addition, the *GA-NN-oss* algorithm is implemented using the neural network toolbox provided by Matlab software package.

In the experiment, the network was trained 10 times, and the best result with lowest RMSE (89509.973) is plotted, which can be seen in Fig. 4.

Figure 4. The unemployment trend prediction

V. CONCLUSIONS

This paper presents a new data mining based framework for the unemployment rate prediction using web information. Under the framework, a genetic algorithm based neural network approach is proposed to forecast the unemployment rate using search engine query data. In the proposed method, the proper feature subset, and the optimal architecture and learning algorithm of a neural network are selected. In terms of evaluation criteria, the empirical results revealed that among different neural network models, the *GA-NN-oss* model shows dominant advantages for the unemployment rate prediction. So, it indicates that the proposed method can be used as a potential alternative to analyze the unemployment trend.

In addition, this study also has some research questions for future studies. Firstly, under our proposed framework, other data mining tools, such as SVM, and ensemble methods, can be used to forecast the unemployment trend for a more stable solution. Secondly, some other web information, including web content information and web link information, can be used to improve the forecast performance. Thirdly, an online unemployment analysis and forecast system (UAFS) can be developed to assist governments and organizations for early-warning and decision support. Finally, the proposed methodology can also be applied to other research fields, especially to society hotspot, such as real estate market, crude oil market, and foreign exchange market.

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