Practical Comparison of Results of Statistic Regression Analysis and Neural Network Regression Analysis

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Abstract

There are many discussions and arguments about accuracy of the results of statistic regression analysis and neural network regression analysis among experts. Of course all of them look for the best method usable in practice. The objective of the contribution is to use a case study to answer the question which of the methods provides better results. As a case study will be used time series of US Gross Domestic Product. It starts in 1966 and ends in 2014. The future development of the variable for the following 20 years will be calculated. Software Statistica 12 developed by Dell corporation will be used for both analyses. The first one will use multiple regression of the software. The second one will use data mining section with its neural networks. Generalized Regression Neural Networks, Multi-layer Perceptron Network, Radial Basis Function Neural Networks, Linear Neural Networks will by calculated. The results are two curves, the first based on statistic regression analysis. The second curve is provided by the best model of neural networks. Both the curves will describe development of the US GDP in 20 next years.

Keywords: regression analysis, neural network, gross domestic product, statistic regression

Introduction

Gross domestic product (GDP) and gross domestic income (GDI) – provide two ways to measure the value of US output. In principle, GDP should equal GDI; however, they differ in practice because each is estimated using different, and largely independent, source data Holdren (2014). The calculation of GDP for any given year rests on a host of difficult methodological decisions; resolving those methodological issues in other, equally plausible ways would result in very different final figures Lindsey (2016).

The planning process often starts with a set of assumptions about economic growth that includes forecasts for growth in real gross domestic product (GDP) in the countries or regions in which a company operates. A company might assume, as a first approximation, that demand for its products (and sales volume if market share is stable) grows with real GDP. Fry (2015) the following comparison directly does not concern US GDP, but other economic areas, where prediction was performed as the statistical regression analysis and artificial neural networks.

GDP is defined by the following formula:

$$GDP = Consumption + Investment + GovernmentSpending + NetExports\ or$$

More succinctly as:

$$GDP = C + I + G + NX$$

where consumption (C) represents private-consumption expenditures by households and non-profits, investment (I) refers to business expenditures by businesses and home purchases by households, government spending (G) denotes expenditures on goods and services by the government, and net exports (NX) represents a nation's exports minus its imports (Bondarenko 2016).

García-Plaza et al. (2013) applied both of the proposed techniques for calculating surface finish (Ra) i. e., multivariable polynomial regression, and artificial neuronal networks were good at predicting the Ra parameter, and similar results were obtained with either data validation algorithm.

During a research of a comparison of construction cost estimation using multiple regression analysis and neural network in elementary school project was concluded the artificial neural network model was found to be superior in terms of average error rate and standard distribution. Cho et al. (2013).

Shtub and Versano (1999) solved estimating the cost of steel pipe bending by using a model base of neural networks and regression analysis. Their result showed that the neural network provides a practical solution to the problem of estimating cost in a fast, inexpensive yet accurate and objective way.

Author, Cuauhtemoc (2015), looked into a predictive accuracy comparison between neural networks and statistical regression for development effort of software projects, the result clearly proved that neural network was better than for a simple linear regression at the 99% confidence level.

Using Neural networks versus Regression in task for cost Estimating model for utility rehabilitation projects averaged that the neural network model produced much more accurate results compared to the regression one. The neural network model was tested on a set of 10 projects and was able to predict the project costs by up to – 18% for 80% of projects Shehab et al. (2010).

To recognize costs estimation and sensitivity analysis on Cost Factors, according to Liu (2010), who analysed the capabilities of Taylor Kriging (regression analysis), and artificial neural networks, his conclusion is in an empirical case of cost estimation, regression analysis is shown to provide accurate results that are better than those of regression but worse than those of an ANN (artificial neural network).

Opposite view proved a study of Heiat (2002) "Comparison of artificial neural network and regression models for estimating software development effort." The article has compared the neural network estimation method to regression approach for software effort estimation. The results of this preliminary research indicate that neural network approach was competitive with regression.

The paper "Estimating the cost of vertical high-speed machining centers, a comparison between multiple regression analysis and the neural networks approach" of the authors Ciurana, Quintana and Garcia-Romeu (2008), was aimed to set a cost model for vertical high-speed machining centers based on machine characteristics. Result was based on the correlation; the best artificial neural network gave more accurate estimation results than the MRA (multiple regression analysis) model.

Wang and Gibson (2010) were dealing with problem how to solve a pre-project planning and project success using artificial neural network and regression models. This paper studies the pre-project planning of industrial and building construction projects and investigates its relationship with project success (measured by cost and schedule growth). Data collected from a total of 62 industrial and 78 building projects are used for the model development. Both models show positive relationship between PDRI (project definition rating index) score and cost/schedule growth for this particular sample of projects. The results indicate that projects with better pre-project planning are more likely to have a better project performance at completion. Modelling Blanking Process using multiple regression analysis and artificial neural networks, a paper presents the development and comparison of two models to predict the quality of the blanked edge.

According to Al-Momani et al. (2012) artificial neural network methodology consumes lesser time and gives higher accuracy. Modelling the blanking process using ANN is more effective compared with multiple regression analysis.

The aim of this paper is to compare the prediction of the future development of the GDP at current prices in the US in 2024 performed by neural networks and standard statistical time series.

Materials and Methods

The World Bank (The World Bank 2016) data on the US Gross Domestic Product in common prices will be used for calculations. The World Bank itself defines GDP in common prices as the following: (The World Bank 2016): „GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars. Dollar figures for GDP are converted from domestic currencies using single year official exchange rates. For a few countries where the official exchange rate does not reflect the rate effectively applied to actual foreign exchange transactions, an alternative conversion factor is used." Data is available for the years of 1966 to 2014. As the goal of this contribution mentions, the purpose is to create at least two models that will predict the GDP development until 2024.

The first model will work with artificial neural structures. The second model will use standard statistical models of time series (thus a model created through regression, while time will be the independent variable).

In both cases the DELL Statistica software in version 12 will be used.

To determine the statistical model, a statistical tool of multiple regression will be used. First, it is necessary to determine the dependent and the independent variable. In the first case it will be the GDP. In the second case the year will be determined. Consequently, descriptive statistics will be carried out (the average and standard deviation) and the correlational matrix. The result will be a model through which we will calculate the GDP values of 2015 to 2024.

To determine neural models, the Data Mining part of Neural Networks Tool will be used. The setting of the calculation will be as follows:

1. Choice of new analysis: Time series (regression).
2. Choice of variables:
    a. Goal continuous variable: GDP,
    b. Independent continuous variable: year.
3. Automated neural networks will be used.
4. Random sampling of networks will have the following structure:
    a. Training set of data: 70 %,
    b. Training set of data: 15 %,
    c. Testing set of data: 15 %.
5. The down-sampling method will be random. Two down-samples will be created.
6. Delay of time series at the input will be 1 maximum.
7. Delay of time series will be 1 minimum.
8. The following networks will be used for the calculation:
    a. MLP (multiple perceptron network with one hidden layer),
    b. RBF (neural network of the basic radial function) with 9 to 12 neurons in the hidden layer.
9. Hidden layers and output neurons (identical ones) will be used for the neurons as activating functions:
    a. identity,
    b. logistical function,
    c. tanh (hyperbolic tangent),

   d. exponential,
   e. sinus.
10. Weight decomposition will be performed on the 0.001 level for the hidden as well as the output layer.
11. Initialization will not be used.
12. 1000 random networks will be trained.
13. 5 best networks will be kept (determined by the method of smallest squares).

The result will thus be five models which will predict the US GDP development until 2024. It will be possible to compare predictions of individual years with the obtained regression time series.

Results

As it is assumed by the methodics, we will gain models through statistical regression and through neural networks.

Time series created through Regression

It is possible to see the basic statistics of the collection from Table No. 1.

Tab. 1: Average and standard deviation of the Data Collection

Variable/ Characteristics	Average	Standard Deviation	N
Year	1,990000E+03	1,428869E+01	49
GDP	7,054454E+12	5,206925E+12	49

Source: Author

We can characterize the data more closely looking at this table. Especially we can reach the GDP information about general prices in the US during the last 49 years. For the calculation the GDP statistics are especially interesting. The correlational matrix was generated in the next step (Table No. 2).

Tab. 2: Correlational Matrix

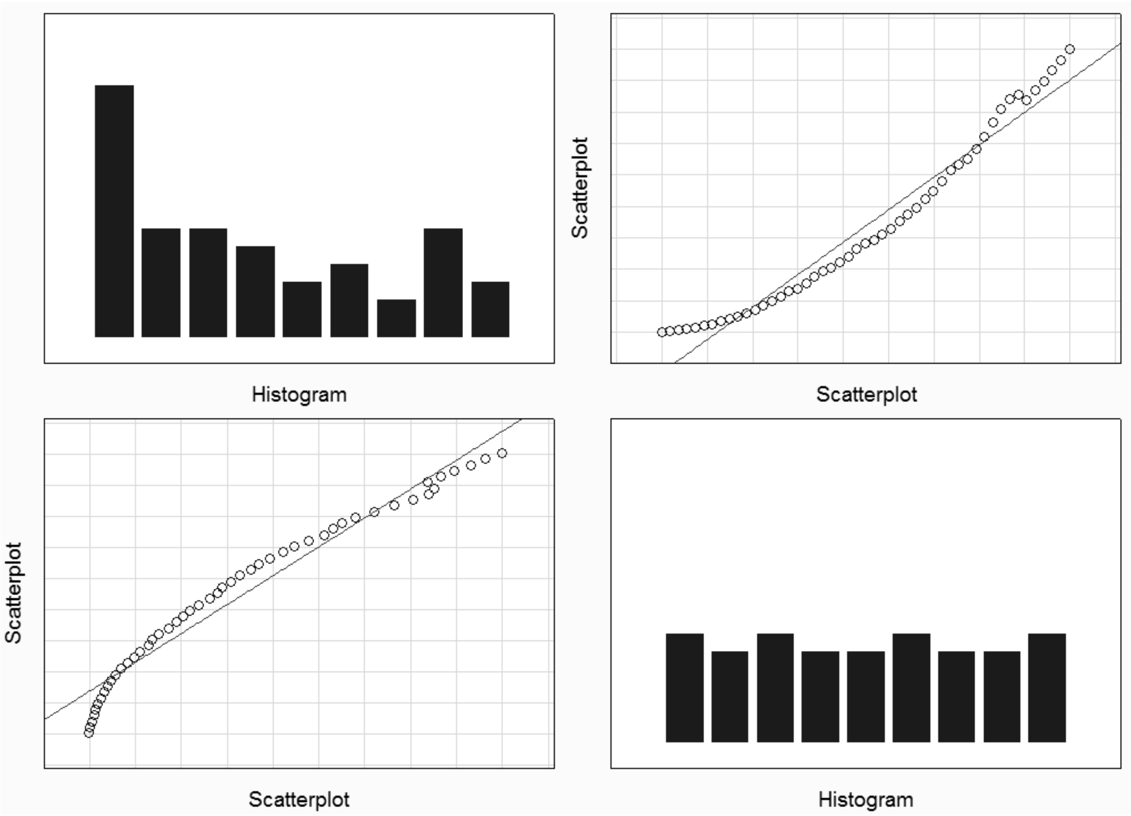
	Year	GDP in USD
Year	1,000000	0,979566
GDP in USD	0,979566	1,000000

Source: Author

It is clear from the result, that correlational coefficient between the year of observation and US GDP is very high, almost 0.98. That points to a very strong dependence between the two variables.

Data about the collection of variables has been used to create a scatter chart and histogram to create a better visualization. The result is a clear correlation of the dependent and independent variable.

Pic. 1: Variable Correlation



Source: Author

Already the histogram process suggests a huge correlation. That is, however, disproportionately clearer from scatter charts, where individual observations (GDP values) are intercut with a regression curve. Optically it is obvious that there will not be a huge data dispersion.

Consequently, a calculation of regression curve parameters calculation has been performed. A statistical sum-up of the calculation is the subject of Table No. 3.

Tab. 3: Statistical Sum-up of a Time Series Calculation

	Value
Multiple R	9,795664E-01
Multiple R2	9,595504E-01
Adapted R2	9,586898E-01
F(1,47)	1,114940E+03
P	2,160993E-34
Standard mistake of an estimate	1,058303E+12

Source: Author

Results of regression with a dependent variable are the subject of Table No. 4.

Tab. 4: Results of Regression with a dependent Variable

	b*	**Standard Mistake from b***	**b**	**Standard Mistake z b**	**t(47)**	**p-value.**
Abs. Member			-7,033013E+14	2,127458E+13	-33,0583	0,000000
Year	0,979566	0,029336	3,569627E+11	1,069047E+10	33,3907	0,000000

Source: Author

In the Column marked b there are the final parameters of a regression curve which may, for a simplification, be written as follows:

$$y = 356962700000 * x - 7{,}03301300000000$$

Where y represents the GDP value in the year observed and x the year observed.
To find out the result validity an analysis of dispersion has been carried out. Its results are stated in Table No. 5.

Tab. 5: Analysis of Variance

	Square Add-up	**Sv**	**Square Average**	**F**	**p-value**
Regress.	1,248739E+27	1	1,248739E+27	1114,940	0,000000
Resid.	5,264024E+25	47	1,120005E+24		
Total	1,301379E+27				

Source: Author

With regard to the number of observations and value volume in which the USA GDP is moving, we may state that the square add-up is not in any way huge and the result is thus acceptable.

Neural networks

Having generated 1000 random neural structures, these structures have been tested through the method of the smallest squares to keep five of the best networks. The outline of the obtained and at the same time preserved neural networks is presented in Table No. 6 and Table No. 7.

Tab. 6: Outline of Preserved Neural Networks

No	Network name	Training performance	Test performance	Valid. performance	Training error	Test error	Valid. error
1	MLP 1-20-1	0,999895	0,999695	0,999837	2,678466 E+21	3,180630 E+22	2,882701 E+21
2	RBF 1-10-1	0,999821	0,998997	0,999808	4,526701 E+21	6,038251 E+22	2,088118 E+21
3	RBF 1-11-1	0,997960	0,995470	0,999845	5,150231 E+22	4,046948 E+23	1,805968 E+21
4	MLP 1-19-1	0,999916	0,999689	0,999818	2,140256 E+21	3,216547 E+22	2,319496 E+21
5	RBF 1-11-1	0,998170	0,992277	0,999841	4,619809 E+22	6,262512 E+23	3,541035 E+21

Source: Author

Tab. 7: Outline of Preserved Neural Networks – part 2

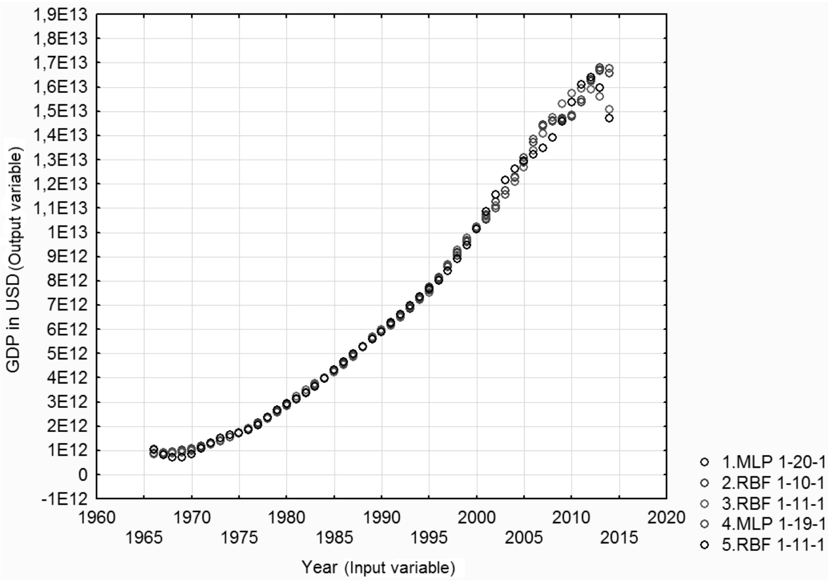
No	Network name	Training algorithm	Error function	Activation of hidden layers	Output activation function
1	MLP 1-20-1	BFGS (Quasi-Newton) 405	Sum of squares	Logistic	Logistic
2	RBF 1-10-1	RBFT	Sum of squares	Gauss	Identity
3	RBF 1-11-1	RBFT	Sum of squares	Gauss	Identity
4	MLP 1-19-1	BFGS (Quasi-Newton) 371	Sum of squares	Logistic	Logistic
5	RBF 1-11-1	RBFT	Sum of squares	Gauss	Identity

Source: Author

Especially the first two networks and the fourth network (MLP 1-20-1, RBF 1-10-1 and MLP 1-19-1) prove excellent results, i.e. maximal reliability and minimal error.

Picture No. 2 offers GDP development from 1966 to 2014 according to models of preserved neural networks.

Pic. 2: GDP Development from 1966 to 2014 according to preserved neural structures

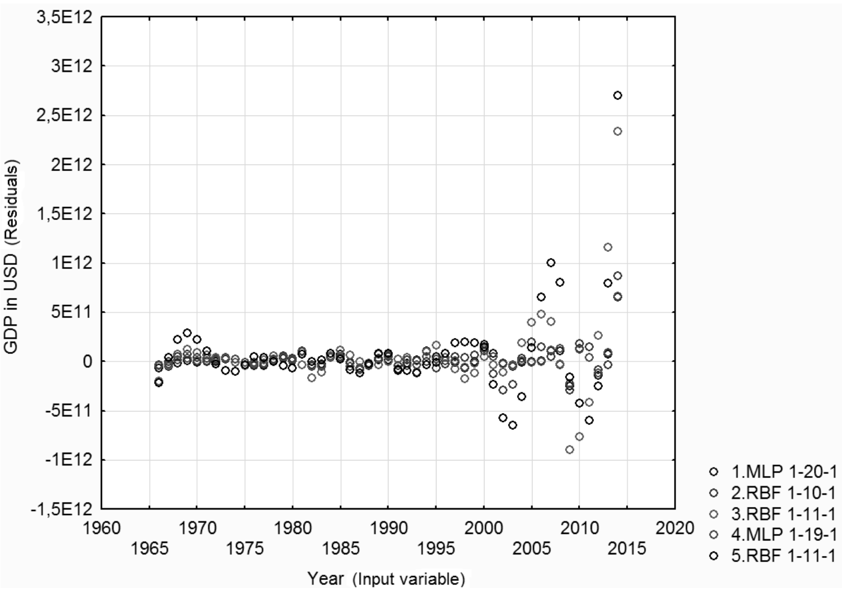


Source: Author

All networks comparatively well (meant in relation towards reality) cover the first 40 observations. Consequently, they begin to vary distinctly from each other.

Naturally, we are interested especially in the difference between individual models and reality. Picture No. 3 offers the development of residuals, i.e. the difference of GDP development according to individual preserved neural structures and the real GDP development.

Pic. 3: Development of GDP residuals in 1966 to 2014 according to preserved neural structures

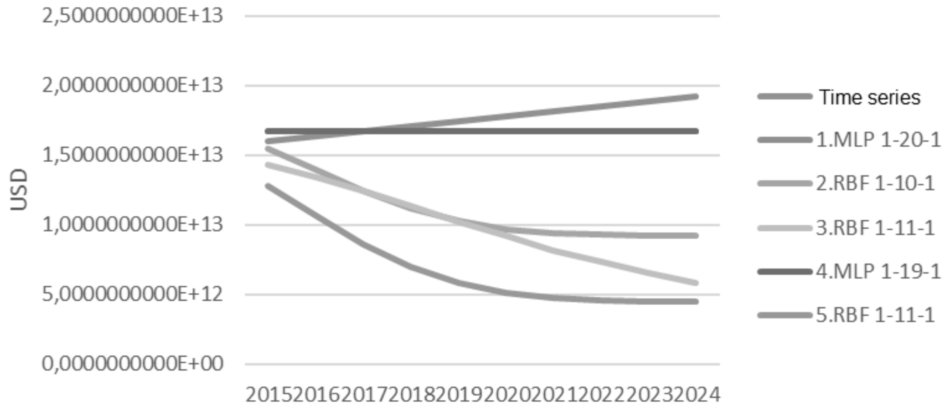


Source: Author

The best model resulting from the residual chart is the first three-layer perceptron network (MLP 1-20-1), the fourth network consequently.

The most important result in the relation towards the determined goal is given in Picture No. 4.

Pic. 4: Comparison of GDP prediction according to individual models



Source: Author

It is the US GDP development prediction in common prices (in USD) from 2015 to 2024. Optically it looks as if the picture contained only five curves instead of six. However, the MLP 1-20-1 waveform is almost equal to the MLP 1-19-1 waveform.

Discussion

From the chart and numerical results, it is clear that three models predict the GDP growth – particularly the time series and MLP 1-20-1, although in the case of neural networks the growth is only minimal, and that is for the years of 2015 and 2016. The rest of neural networks predict a GDP decline. In all three cases it is a relatively significant GDP decline, which, in the case of the second network stabilizes under the level of USD 10 trillion, and in the case of the fifth neural network it will be kept under the level of USD 5 trillion. The third neural network predicts a relatively steep fall which will not stop until 2024.

To be able to predict which prediction is the correct one we need to recourse from specific calculations to intuition and the economist´s knowledge. The amplitude of reality and models during the last years of observation is probably given by the unexpected GDP development during the world economic crisis. Thanks to that the results of individual models have been subject to amplitude too. If we have a look at the results through the eyes of the finished economic crisis, we will reach the fact that the US GDP should be growing. That means that time series and MLP 1-20-1 and MLP 1-19-1 come into consideration.

Time series assumes GDP growth of USD 16 trillion up to almost USD 20 trillion in the observed period of 2015 to 2024. Both neural networks predict a growth disproportionately smaller, specifically USD 30 trillion, respectively 40 trillion. In case of time series such a development would suppose an annual constant growth of GDP in an order slightly bigger than 2% per year. In case of the neural networks MLP 1-20-1 and MLP 1-19-1the growth would mean the order of about 2% in the years of 2015 – 2016, and stagnation subsequently.

Conclusion

It is thus clear that a classical statistical regression, respectively a time series set with its assistance has proven better results than all preserved neural structures.

The goal of this contribution has been to compare the prediction of the GDP development in common prices within the US until 2024 performed through neural networks and standard time series. Calculations have been conducted. Results have been mutually compared. The goal of this contribution has thus been fulfilled. The conclusion can be formulated as follows: **Statistical regression has proven significantly better results of the future USA GDP development in common prices than neural networks have.**

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