NEURAL NETWORK REGRESSION AND LINEAR REGRESSION IN THE ESTIMATE OF THE PRICE OF GOLD ON THE NEW YORK STOCK EXCHANGE

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Abstract

Gold has always been a very special commodity on the exchange. Throughout the history of business, it has been a generally accepted form of payment instrument (thanks to its unique characteristics, such as scarcity, divisibility, the ability of thesauration etc.). Thus, it is of great interest to today‘s traders, even though it has been completely replaced by money as a means of payment. At present, there are many tools to predict the future value of gold and other commodities. The aim of the paper is to present the two methods: statistical time series and neural networks (both as regression models) and predict the future price development of gold in the New York Stock Exchange. To carry out the analysis London Fix Price AM data was used i.e. amounts reported in the morning for a period longer than 10 years. Linear regression is carried out, using a whole range of functions, and subsequently regression via neural structures, several distributional functions are used again. Subsequently, 1000 neural networks are being generated, out of which 5 are chosen, proving the best characteristics. Results are compared on the level of an expert perspective and the evaluator´s – economist´s experience.

Key words: neural networks, time series, prediction, gold

JEL Codes: C53, C32, C45

Introduction

In antiquity gold was used for manufacturing decorative objects and jewelry. Trading in gold has a long history and the actual gold trading dates back to the 14th century. In the 19th and 20th century gold served as a monetary guarantee for the issue of banknotes. It is also associated with the emergence the first exchanges. Later, trading in gold was joined by other titles, such as commodities, stocks etc.

For trading gold on the stock market or storing gold for banking purposes, gold is calibrated per weight unit. The price of gold is expressed in USD per troy ounce (after the French city of Troyes where the unit weight was used originally). The troy unce corresponds approximately to 31.1034768 grams). Gold is differentiated according to the fineness, for our purposes we will analyze investment gold with the highest degree of fineness, 99.99, that is considered genuine gold.

Many models for predicting gold prices have been designed, e.g. the Markov chain combination method, the BP neural network model, neural networks, fuzzy logic, genetic algorithms, particle swarm optimization, simulation annealing, fractal dynamic of gold fluctuations (Auer, 2016), component wise boosting (Mittnik et al., 2015) or other boosting approaches (Pierdzioch et al., 2014). Most of the models propose linear or non-linear relationships between multiple variables and the gold price. The bid price per ounce of gold is set at London twice a day (LBMA, 2016) and is the base price for any gold transaction.

In prediction models, gold prices were often considered in relation to other factors. Malliaris & Malliaris (2009) used times series techniques and Artificial Neural Networks (ANNs) for forecasting the prices of gold, oil and Euro, and concluded that both short term and long-term relationship exists between these values. Both the time series and neural network results indicated the series‘s move though they identified slightly different relationships. Sivalingam, Mahendran & Natarajan (2016) concentrate on forecasting the future gold prices from four commodities (gold prices, silver prices, crude oil prices, Standard and Poor’s 500 stock) and propose and efficient learning algorithm. Their finding prove that ANNs are very accurate and predicts the future very well. Stehel, Vrbka & Rowland (2016) claim that networks have the ability to learn and subsequently they are able to point out strongly non-linear dependencies. They use distributed parallel processing of information and they reach a high-speed processing of huge amounts of data. Mensi et al. (2014) claim that the quantile regression method appears to be the most flexible to the dependence structure between the as it allows one to assess the responses of a variable to the external shocks with respect to its different threshold values. Kristjanpoller & Minutolo (2015) proposed a hybrid ANN–GARCH model is applied to forecast the gold price volatility (spot and future), it they applied an ANNs to the GARCH method generating an improved hybrid ANN–GARCH.

According to Arouri et al. (2012), empirical studies on precious metals can be divided into two research lines. The first line of research focuses on the macroeconomic determinants of precious metals and the second line is devoted to the modelling and forecasting of precious metals volatility. In their own findings, they assert that an ARFIMA–FIGARCH model, which captures dual long memory both in the returns and volatility, provides better out-of-sample forecast accuracy than other volatility models.

1 Data and Methodology

Analysis data is available on the New York stock exchange web pages, or perhaps on the World Bank pages (Worldbank, 2017), etc. For the analysis purpose, London Fix Price AM will be used between 3 January 2006 and 15 April 2016. Thus, there is a total of 2553 facts about gold price. The key value in determining referential price of gold is so-called London Fix Price, also referred to as London Golden Fix or only London Fix, is declared twice a day during the days of gold trading in London. Its determination happens in cooperation together with the five greatest traders in the Stock Exchange (Scotia-Mocatta, Barclays Capital, Deutsche Bank, HSBC and Société Générale) since 1919. London Fix determined twice a day, morning at 10:30 as AM and afternoon at 3:00 pm as PM of London Time.

The process of London Fix determination is the following: the presiding fixing commission suggests an opening price, which moves close to the spotting price. Consequently, the individual commission members contact their business departments dealing with who will sell and what amounts of golden ingots will be sold for the given price and who will buy them. Perhaps they slightly correct the price so, that the supply and demand for gold from these five businessmen was levelled and there would be no overhang of neither demand nor supply. Consequently, London Fix is determined. The process of London Fix determination is given in USD, GBP, and EUR per one troy Ounce (Oz, i.e. 31.1034807 grams). The greatest traders trade approximately 20 tons of gold within the given price, while the official amount is not available. Descriptive data characteristics are given in Table No. 1.

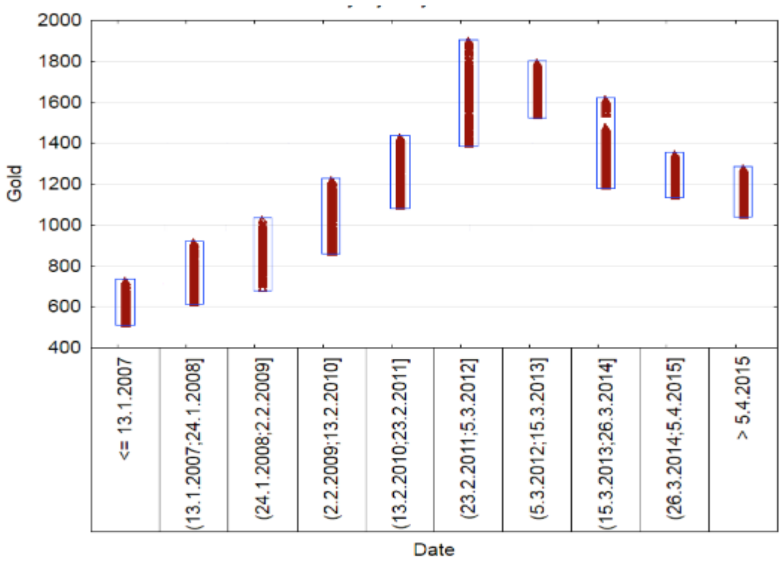
Tab. 1: Characteristics of a Data set

Descriptive Characteristics	Costs in USD
Minimal Cost	520,75
Maximal Cost	1896,5
Average Cost	1142,35
Dispersion	119225,17

Source: Author

Price development during time is interesting, of course. Fig. No. 1 determines value dispersion in individual periods of an observed time-period.

Fig. 1: Gold Price Dispersion a (London Fix AM)



Source: Author
Note: Graph of Gold dispersion Development of price for gold 2 2v*2553c.

To process the data DELL Statistica software version 12 will be used. First, linear regression will be carried out. Subsequently, neural networks will be used for regression. Linear regression will be based on the examined data sample for the following functions: Linear, Polynomial, Logarithmic, Exponential, Weighted Distance Polynomial, Negative-Exponential Smoothin Polynomial.

First of all, however, correlational coefficient will be calculated, i.e. the dependency of gold price on time. Further, we will work with significiancy level of 0.95. Then, regression will be carried out via neural structures. We will generate multi-layer perceptron networks and neural networks of the basic radial function. Time will figure as an independent variable. Gold price will be determined to figure as the dependent variable. The time line will be divided into three sets – training, testing and validation. The first set will contain 70% of input data. Based on the training data set we will generate neural structures. In the two spare data sets always 15% of input data will be left. Both groups will serve us as tools for verifying the reliability of the found neural structure, respectively found model. Time line delay will be 1. We will generate 1000 neural networks. Out of them, 5 will be preserved, proving the best characteristics[1]. In the hidden layer, there will be at least two neurons, 50 maximum. In case of radial basic function, there will be at least 21 neurons in the hidden layer, 30 maximum. The following distribution functions within the hidden and output layers will be considered for a

[1] We will be navigated by the least squares method. Network generating process will be ended if there is no improvement, i.e. decreasing of value of square sums. We will preserve those neural structures in which the sum of residues´ squares to real development of gold will be as low as possible (ideally a zero).

multilayer perceptron network: Linear, Logistic, Atanh, Exponential, Sinus. Other setting will be left as default (according to the ANNs tool – automated neural network).

Towards the end, we will compare the results of linear regression and regression via neural networks. The comparison will not be done via residues analysis (minimal, maximal values, residue dispersion, etc.), but on the level of expert view and evaluator´s, economist´s experience (the comparison itself will be performed only visually).

2 Results

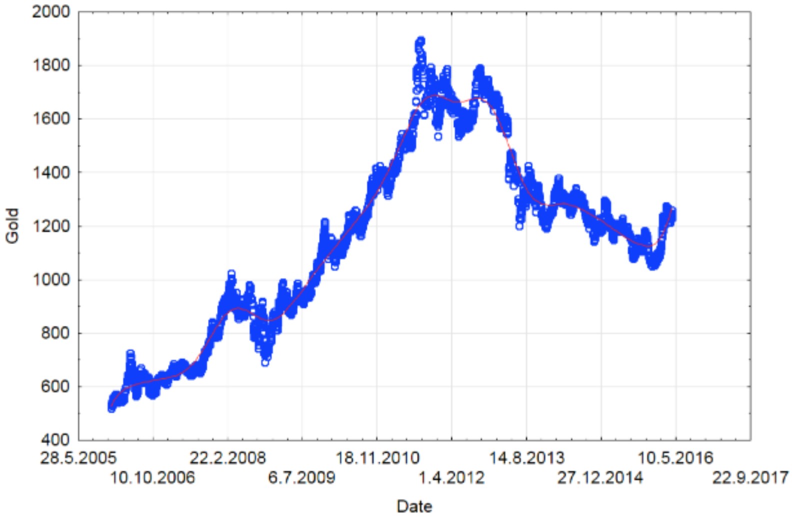
This section presents the results of linear regression analysis and neural networks analysis.

2.1 Linear Regression

Correlation coefficient is equal to 0.6824, which means a significant statistical dependency of gold on development in time.

Graphics No. 2 offers the interspacing by the last function obtained through the method of least squares negatively – by linear function, exponential smoothing. Similarly also other interspacings of point graph have been created – via polynomial function, logarithmic function, exponential function or via the function obtained through weighted distance least squares method.

Fig. 2: Point Graph of gold price interspaced by a regression curve – SSM negatively-exponential smoothing



Source: Author
Note: Point Graphics from Gold against Date Development of Gold Price 2´v°2553c Gold = Negatively-exponential Smoothing.

As it has been claimed above, correlation coefficient signifies a significant statistical dependency of the goal variable on development in time. If we were to evaluate the results only by an optical comparison of development of London Fix Price AM and the form of regression curve, and at the same time we were taking into account the simple linear regression, most certainly we could claim that the curve obtained by least squares method via negatively-exponential smoothing approaches the development the closest. Further, the curve established by least squares method, in this case via weighted distances follows. If we established imaginably a third position, this would definitely be a polynomial function. All three copy the basic development of price for gold. This becomes very rough in the case of polynomial function, which recedes minimally from the real development and reflects global extremes of such a development. On the contrary, a curve obtained via least squares method of negatively-exponential smoothing observes not only global extremes of London Fix Price AM development, but also local extremes of such a development. Optically this function then appears from the view of a possible prediction of London Fix Price AM efficient, although slightly not exact in its result. For the linear regression, we must note that the linear trend is not generally suitable for such clearly nonlinear trend.

2.2 Neural Structures

Based on the established procedure, 1000 neural networks were generated. Out of them, 5 networks were preserved, proving the best parameters. Their list is given in Table No. 2.

Tab. 2: Preserved Neural Networks

Index	Name Network	Training perform.	Test perform.	Validation perform.	Train. error	Test Error	Valid. error	Training algorithm	Error function	Activation hidden layer	Output activation function
1	MLP 1-13	0.99254	0.99235	0.99176	874.865	955.916	961.605	BFGS (Quasi-Newton)	Sum. square	Logistics	Logistics
2	MLP 1-13	0.99266	0.99238	0.9922	861.392	952.394	914.898	BFGS (Quasi-Newton)	Sum. square	Logistics	Exponen.
3	MLP 1-13	0.99237	0.99274	0.99174	895.202	907.603	967.323	BFGS (Quasi-Newton)	Sum. square	Tan.	Tan
4	MLP 1-18	0.99235	0.99236	0.99205	897.203	963.152	933.546	BFGS (Quasi-Newton)	Sum. square	Tan.	Logistics
5	MLP 1 -11	0.99259	0.99299	0.99247	869.327	876.99	880.425	BFGS (Quasi-Newton)	Sum. square	Tan.	Logistics

Source: Author

We are dealing only with multilayer perceptron networks with one hidden layer. In the output layer there is the only variable – time. Neural networks contain 11 to 18 neurons in the hidden layer. In the output layer there is logically only one neuron and only one output variable – London Fix Price. In all networks the Quasi-Newton training algorithm was applied. Mutually, artificial structures differ in the type of used activation functions in their hidden and output neuron layer (Table No. 2).

Also the training, testing and validation performance is interesting. In general, we are looking for such a network the performance of which remains in all data sets (it should be reminded that dividing data into sets was done on random) ideally the same. Error should be as minimal as possible.

Performance in individual data set sis given in the form of correlation coefficient. Values in the individual data sets according to specific neural networks are given in Table No. 3.

Tab. 3: Correlation Coefficients of individual data sets

Neural network	Correlation coefficients (development of gold prices)		
	Gold training	Gold test	Gold validation
1. MLP 1-13-1	0.992548	0.99236	0.991765
2. MLP 1-13-1	0.992663	0.99239	0.992206
3. MLP 1-13-1	0.992376	0.99274	0.991742
4. MLP 1-18-1	0.992357	0.99231	0.992059
5. MLP 1-11-1	0.992595	0.99299	0.992472

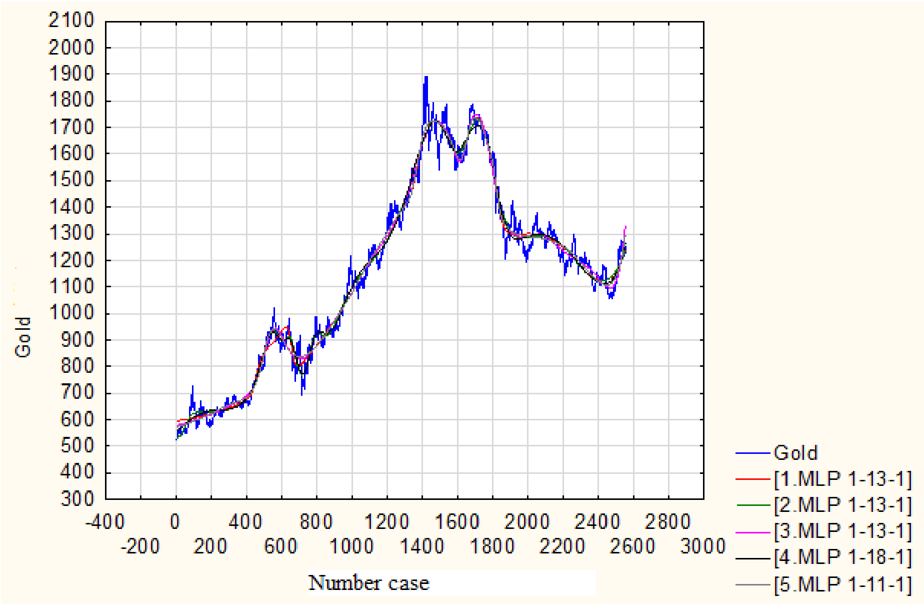
Source: Author

The table proves that the performance of all preserved neural structures is approximately identical. Insignificant changes have no influence on the performance of individual networks.

Fig. No 4 represents a line chart which suggests a real development of London Fix Price (marked as Gold in the Graphics) and at the same time, development of predictions via individual networks (they are marked by serial numbers given in Table No. 2 and numbers of neurons in individual layers).

The chart clearly proves that all neural networks predict the development of London Fix Price AM in a very similar manner (although at the first sight a deviation may be spotted, e.g. in Network No. 3. a 4. during the 600th observation). Prediction similarity in individual networks is not as important as the similarity (respectively degree of conformity) to the real development of price for gold. Even in this regard, it may be claimed that preserved neural networks look very interesting at the first sight. They respect global extremes of a curve evaluating gold price development, but they tend to register also the local extremes of this curve.

Fig. 4: Line Chart – development of price for gold predicted by neural networks in comparison to real price in the observed period.



Source: Author
Note: Prediction of Time Liners for Gold. 1 step used as inputs 1 step predicted in advance. Samples: Training, Testing, Validation.

Conclusion

The general truth is that every prediction is given by a certain amount of probability that it will come true. Once we are prediction the future development of any variable we are trying to guess the future development of this variable based on the data of previous periods. Although we are able to include most factors influencing the goal variable into the model, there is always a simplification of reality and thus we always work with a certain amount of probability that a certain predicted scenario will be fulfilled. Even in case of linear regression and regression via neural networks there is a simplification – to a significant one. As mentioned above, for a linear regression, the linear trend is not even suitable for such clearly nonlinear trend. We work with only two variables – input (time) and output (London Fix Price). Thus, we completely overlook other input variables, which definitely do influence the price of gold (national economy development, state political situation, legal environment, market obstacles, etc.). Despite this, or even because of the fact that there is an inexhaustible amount of factors influencing the price of gold, we must meditate over whether working with time lines does not simplify the development of the goal variable too much or whether on the contrary other variables are so insignificant that the input variable (time) and output variable (London Fix Price) are fully sufficient. With regard to the fact that the origin of extraordinary situations and their influence on the price of gold may not be predicted (they possibly may be in a short-time horizon, but definitely not in a long-term one), simplification and creation of a relatively simple model is definitely appropriate, and the result is useful.

Price of gold may be established on the basis of statistical methods, causal methods and intuitive methods. In this case, we were dealing with statistical methods. Nevertheless, they offered only a possible frameworks, of development of prices for gold. It is necessary to further work with information on the possible future development of economic, political or legal environment. If we are able to predict its development, we can also project it into the price for gold. At the same moment, however, the evaluator´s – economist´s personality comes in, who, based on their knowledge and experience corrects the price established via frame-statistical methods and specified on the basis of causal relations.

The aim of this contribution was to carry out a regression analysis of the development of price for gold in the New York Stock Exchange via neural structures and via linear regression and determine the most suitable one for a possible prediction of future development of price for gold in the New York Stock Exchange.

Optically, the curve obtained by least squares method via negatively-exponential smoothing appeared to be the best of linear regression. Again, however, we warn that for a linear regression, the linear trend is not even suitable for such clearly nonlinear trend. All preserved structures out of neural networks appeared to be practically useful. If we have a look at the performance from the view of correlation coefficient, only neural networks among which there is no difference remain to be used.

Of course, residue analysis might be interesting. It would help us determine the best of the preserved neural networks. This was, however, not the aim of this contribution.

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