PREDICTING THE SUCCESS OF NATIONS IN ASIAN GAMES USING NEURAL NETWORK

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Abstract
International success especially Asian sporting success has become increasingly important to a growing number of countries. Although an increasing number of nations invest large amounts of money in sport in order to compete against other nations, there is no clear evidence that demonstrates how sports variables can influence international sporting success. In this paper we tried to predict the success of nations in Asian Games Using Neural Network through macro- political, economic, social and cultural variables. we used the information of variables include urban population, Education Expenditures, Age Structure, GDP Real Growth Rate, GDP Per Capita, Unemployment Rate, Population, Inflation Average, current account balance, life expectancy at birth and Merchandise Trade for all of the participating countries in Asian Games from 1970 to 2006 in order to build the model and then this model was tested by the information of variables in 2010. We used WEKA software that is a popular suite of machine learning software written in Java. The prediction is based on the number of golden medals acquired each country. The value of correlation coefficient between the predicted and original ranks is 86%. One of the other results of this research is that the predicted rank of countries include China, South Korea, Iran and Uzbekistan is exactly identical with their original rank and the difference between the original rank of the first ten countries and the predicted rank of them is minimal. We tried to design the pattern that: To give the opportunity to athletes to compare themselves with athletes from the other countries in order to identify their position and plan the necessary training programs and finally, obtain the better records according to the standard templates.

Keywords: *Asian Game, Prediction, neural network, Multi-layer perceptron and Macro variable*

INTRODUCTION

A large amount of effort is spent on forecasting the outcome of sporting events. Moreover, there are large quantities of data regarding the outcomes of sporting events and the factors which are assumed to contribute to those outcomes. However, despite the 40,000 entries in JSTOR and 3700 entries in Econ Lit that refer to sports, few papers have focused exclusively on the characteristics of sports forecasts (31). In addition achieving international and especially Asian sporting success has become increasingly important to a growing number of countries. Politicians and the media count medals as a measure for international success, despite the International Asian Games Committee's protestation that the Asian Game medal table is not an order of merit (16). As a result, governments have become more willing to intervene directly in sport development by making considerable financial investments (2). From a forecasting perspective, the presence of competition introduces particular modeling challenges. These limit the applicability of standard techniques such as regression and discriminant analysis. Consequently, dedicated forecasting methods are required to accurately model the outcomes of competitive events (28).

Research on the psychological mechanisms underlying sports forecasting has been primarily focused on the forecasts of experts (5, 7, 14, 19, 26 and 27). The previous literature on sports forecasting can be divided into several groups. For example, several papers have aimed to predict the result of a particular match between two contestants (5, 8, and 25). Other papers have aimed to predict the point spread between two contestants (30), and still other papers have aimed to predict the winner of sports events involving several contestants, such as tournaments (1, 9), leagues (29), or races (4).

On the other hand are predictions or forecasts derived from statistical models more accurate than those made by experts based on informed judgment? Statistical models may yield more accurate forecasts than human judgments because they employ objective criteria that guard against bias and the idiosyncratic interpretation of data. However, sometimes statistical models cannot capture non-quantitative factors. As a result, judgmental forecasting may do a better job, not only in less routine and more uncertain situations, but also in integrating qualitative factors into the forecasting process. There have been many comparisons of the predictive abilities of judgmental and statistical forecasting methods (6, 10, 17 and 32). These comparisons have been made in diverse fields, including medicine, college success, business decision-making, weather forecasting, legal predictions, and macroeconomics. For the most part, the evidence has favored statistical model forecasts (17).

There have been a small number of studies that have examined the accuracy of the methods used to forecast the outcomes of sporting events. Andersson, Edman, and Ekman (2005) found that experts' forecasts of outcomes of the World Cup soccer games were not superior to those of non-experts. Dixon and Pope (2004) tested whether statistical forecasts were valuable in predicting the results of UK soccer games and whether the betting market was efficient.Neither study compared the relative accuracy of expert and statistical systems (13). There are, however, a number of studies that have examined this issue. Forrest and Simmons (2000) examined the accuracy of three tipsters' predictions of the outcomes of soccer games relative to that of a model. They concluded that while individual guidance is better than no guidance, the expertise that they can claim to offer is limit. Moreover, the tipsters had not incorporated information from the model into their forecasts.

Condon et al (1999) construct several models that try to predict a country's success at the Summer Olympic Games. Their data set consists of total scores for over 271 sporting events for 195 countries that were represented at the 1996 Summer Games and information they gathered on 17 independent variables. They build linear regression models and neural network models and compare the predictions of both types of models. Overall, the best neural network model outperformed the best regression model (11). Forrest et al (2010) reported in their paper the results of an exercise to forecast national team medal totals at the Beijing Olympic Games, 2008. The starting point was an established statistical model based on a regression analysis of medal totals in earlier Games, with past performance and GDP among the principal covariates. Final forecasts were successful in predicting the principal changes in medal shares relative to the 2004 Games, namely the surge in medals for China and Great Britain and the substantial fall in medals for Russia (14).

In this paper we tried to predict the success of nations in Asian Games through macro-economic, political, social and cultural variables.

Materials and Methodology

This part consists of 3 steps:
a) Economic, political, social and cultural variables that are important contributors for international sporting success were identified by a comprehensive literature review. Then the variables were given to relevant experts in order to rank them according to their importance, and then each variable was given a specific point according to its rank. At the end, the first eleven variables were selected as effective variables to predict the ranking of participating countries in Asian Games.
b) In second step, the information of selected variables for the participating countries were collected from 1974 to 2010. Additionally, the information of the countries include Uzbekistan, Kazakhstan, Tajikistan and Kyrgyzstan was given from 1994 to 2010. The countries include Afghanistan, North Korea and Iraq were removed from this research, because of the lack of their information.
c) The ranking of participating countries in Asian Games takes place in 2 methods:
1) The ranking of participating countries is based on the number of golden medals acquired each country.
2) The ranking of participating countries is based on the number of total medals acquired each country.

In this study, the prediction is based on the number of golden medals acquired each country. The number of countries in various periods participated in Asian Games is variable. Independent variables are macro economic, political, social and cultural variables and dependent variable is the success of participating countries according to the number of golden medals acquired in Asian Games.
In this research we used WEKA (Waikato Environment for Knowledge Analysis) software that is a popular suite of machine learning software written in Java, developed at the University Of Waikato, New Zealand. WEKA is free software available under the GNU General Public License. The WEKA workbench contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to this functionality. WEKA, an open source collection of data mining algorithms written in java, is a solid exploratory tool for those interested in mining their collected data (33).

RESULTS

Some of the most commonly used machine learning algorithms are Artificial Neural Networks (ANN). Artificial neural networks (ANN) is a mathematical tool, which tries to represent low-level intelligence in natural organisms and it is a flexible structure, capable of making a non-linear mapping between input and output spaces (24). ANN is now globally recognized as the most effective and appropriate AI technology for pattern recognition applicable in forecasting, process modeling, data classification and analysis. Artificial Neural Networks (ANNs) are simplified mathematical approximations of biological neural networks in terms of structure as well as function. In general, there are two aspects of ANN functioning: (1) the mechanism of information flow starting from the presynaptic neuron to postsynaptic neuron across the network, and (2) the mechanism of learning that dictates the adjustment of measures of synaptic strength to minimize a selected cost or error function Research in these areas has resulted in a wide variety of powerful ANNs based on novel formulations of the input space, neuron, type and number of synaptic connections, direction of information flow in the ANN, cost or error function, learning mechanism, output space, and various combinations of these (12).

Multi-layer perceptron trained using the error back-propagation algorithm (MLP-BP) is by far the most studied and used ANN architecture. It has been used extensively in a wide variety of applications. Yet using MLP-BP in real-time applications faces several challenges. Training of an MLP-BP network is known to be time consuming especially for large networks. This is com-pounded by the lack of clear methodology in setting up the initial topology and parameters. Topology has a significant impact on the network's computational ability to learn the target function and to generalize from training patterns to new patterns. If the network has too few free parameters (weights), training could fail to achieve the required error threshold (23). On the other hand, if the network has too many free parameters, then a large data set is needed. In this case the possibility of over-fit is higher, which impacts generalization. It is typically not possible to experiment with a large number of topologies because of the long training sessions required. As a result, heuristics have typically been used to speed the training process while preventing over-fitting (22).

An MLP is a network of simple *neurons* called *perceptrons*. The basic concept of a single perceptron was introduced by Rosenblatt in 1958. The perceptron computes a single *output* from multiple real-valued *inputs* by forming a linear combination according to its input *weights* and then possibly putting the output through some nonlinear activation function. Mathematically this can be written as

$$y = \varphi\left(\sum_{i=1}^{n} w_i x_i + b\right) = \varphi(\mathbf{w}^T\mathbf{x} +$$

where $\mathbf{w}$ denotes the vector of weights, $\mathbf{x}$ is the vector of inputs, b is the bias and φ is the activation function. A signal-flow graph of this operation is shown in Figure 1 (3, 18).
The original Rosenblatt's perceptron used a Heaviside step function as the activation function φ . Nowadays, and especially in

multilayer networks, the activation function is often chosen to be the logistic sigmoid $\mathbf{1/(1+e^{-x})}$ or the hyperbolic tangent

tanh(x). They are related by

$\frac{tanh(x)+1}{2} = \mathbf{1/(1+e^{-x})}$. These functions

are used because they are mathematically convenient and are close to linear near origin while saturating rather quickly when getting away from the origin. This allows MLP networks to model well both strongly and mildly nonlinear mappings.

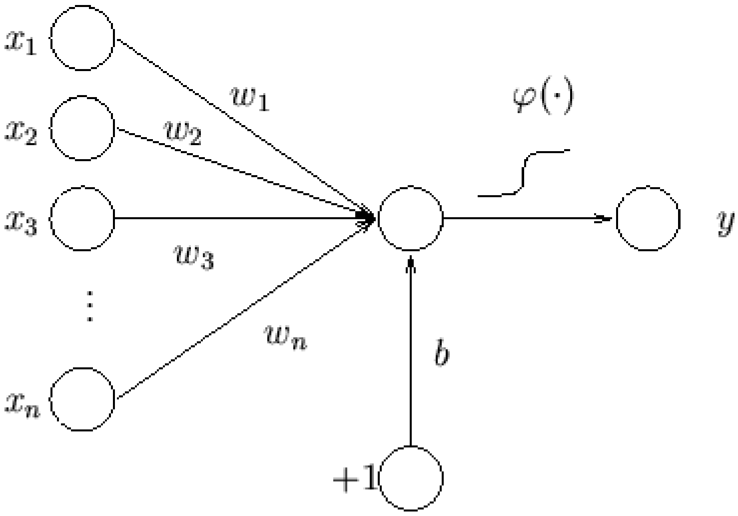

Figure 1: Signal-flow graph of the perceptron

A single perceptron is not very useful because of its limited mapping ability. No matter what activation function is used, the perceptron is only able to represent an oriented ridge-like function. The perceptrons can, however, be used as building blocks of a larger, much more practical structure. A typical *multilayer* perceptron (MLP) network consists of a set of source nodes forming the *input layer*, one or more *hidden layers* of computation nodes, and an *output layer* of nodes. The input signal propagates through the network layer-by-layer. The signal-flow of such a network with one hidden layer is shown in Figure 2 (18).

The computations performed by such a feed forward network with a single hidden layer with nonlinear activation functions and a linear output layer can be written mathematically as

X= f(s) = $\boldsymbol{B\varphi(As+a)+b}$ ***(1)***

where $\mathbf{s}$ is a vector of inputs and $\mathbf{x}$ a vector of outputs. $\mathbf{A}$ is the matrix of weights of the first layer, $\mathbf{a}$ is the bias vector of the first layer. $\mathbf{B}$ and $\mathbf{b}$ are, respectively, the weight matrix and the bias vector of the second layer. The function $\boldsymbol{\varphi}$ denotes an elementwise nonlinearity. The generalisation of the model to more hidden layers is obvious.

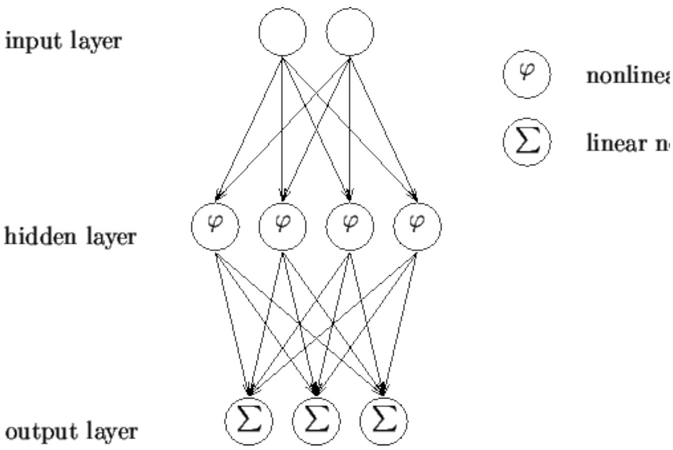

Figure 2: Signal-flow graph of an MLP

While single-layer networks composed of parallel perceptrons are rather limited in what kind of mappings they can represent, the power of an MLP network with only one hidden layer is surprisingly large. As Hornik et al. and Funahashi showed in 1989 (15, 21) , such networks, like the one in Equation (1), are capable of approximating any continuous function

$\mathbf{f} : \mathbb{R}^n \rightarrow \mathbb{R}^m$ to any given accuracy, provided that sufficiently many hidden units are available.
MLP networks are typically used in *supervised learning* problems. This means that there is a training set of input-output pairs and the network must learn to model the dependency between them. The training here means adapting all the weights and biases ***(A.B.a*** and ***b*** in Equation (1)) to their optimal values for the given pairs ***(s(t), x(t))*** . The criterion to be optimised is typically the squared reconstruction error $\sum_t \| f(s(t)) - x9t) \|^2$.

The supervised learning problem of the MLP can be solved with the *back-propagation algorithm*. The algorithm consists of two steps. In the *forward pass*, the predicted outputs corresponding to the given inputs are evaluated as in Equation (1). In the *backward pass*, partial derivatives of the cost function with respect to the different parameters are propagated back through the network. The chain rule of differentiation gives very similar computational rules for the backward pass as the ones in the forward pass. The network weights can then be adapted using any gradient-based optimisation algorithm. The whole process is iterated until the weights have converged (18).
The MLP network can also be used for unsupervised learning by using the so called *auto-associative* structure. This is done by setting the same values for both the inputs and the outputs of the network. The extracted sources emerge from the values of the hidden neurons (20). This approach is computationally rather intensive. The MLP network has to have at least three hidden layers for any reasonable representation and training such a network is a time consuming process.

Learning Rate

A constant used in error backpropagation learning and other artificial neural network learning algorithms to affect the speed of learning. The mathematics of e.g. backprop are based on *small* changes being made to the weights at each step: if the changes made to weights are too large, the algorithm may "bounce around" the error surface in a counter-productive fashion.
In this case, it is necessary to reduce the learning rate. On the other hand, the small the learning rate, the more steps it takes to get to the stopping criterion.
There are various methods to avoid the local minimum. Adding momentum is one of them and change in weight rule can be considered in a style that change in weight for nth iteration partly depends on change in weight for previous iteration.

$\Delta Wji\ (n) = \eta\ \delta j\ Xji\ +\ \alpha \Delta Wji\ (n\text{-}1)$

The value of momentum (α) should be $0 <= \alpha <= 1$.

The information of model MLP was in Table 1. Correlation coefficient between original and predicted ranks for 28 participating countries in 2010 was reported 86%.

Table1: The information of Multi Layer Perceptron for 2010 year

Correlation coefficient	0.8609
Mean absolute error	5.7624
Root mean squared error	6.6795
Relative absolute error	76.0853 %
Root relative squared error	74.5349 %
Total Number of Instances	28

The information of 28 participating countries in Asian Games in 2010 with their macro economic, political, social and cultural variables (Urban Population, Education Expenditures, Age Structure, GDP Real Growth Rate, GDP Per Capita, Unemployment Rate, Population, Inflation Average, Current Account Balance, life expectancy at birth and Merchandise Trade) was reported in table 2.The two final columns show original and predicted records.

Table2: The information of participating countries in Asian Games in 2010 with Original and predicted rank

	Urban Population	Education Expenditures (% Of GNI)	Age Structure (15-64)	GDP Real Growth Rate	GDP Per Capita (Per Person) $	Unemployment (Of Total Labor Force)	Population (Millions Person)	Inflation Average	Current Account Balance (% Of GDP)	Life Expectancy At Birth (Year)	Merchandise Trade (% Of GDP)	Original Rank	Predicted Rank
China	44	1.9	72.1	8.504	2202	4.1	1341.41	3.12	6.239	74.68	59.2	1	1
South Korea	81.7	4.2	72.3	-0.987	20329	3.3	48.91	2.9	1.607	79.05	92.27	2	2
Japan	66.6	3.7	64.3	-5.369	37555	5.145	127.471	-1.407	2.84	82.25	31.45	3	4
Iran	69	4.8	72.9	1.484	3411	12.57	75.35	8.5	2.3	70.06	46.73	4	4
Kazakhstan	58.2	4.41	70.2	1.465	6346	7.8	15.584	7.303	0.715	68.51	81.74	6	5
India	29.8	3.2	64.3	5.355	871	10.7	1215.94	13.162	-2.172	66.8	40.6	8	3
Uzbekistan	36.9	9.4	67	6.978	764	0.2	28.246	9.151	5.055	72.51	55.92	7	7
Thailand	33.7	4.9	70.5	-3.436	3577	1.39	67.653	3.245	2.496	73.6	130.86	5	9
Malaysia	71.3	4.5	63.6	-3.631	6347	3.5	28.233	2	15.379	74.12	160.71	10	11
Hong Kong	100	3.3	74.6	-3.623	29273	4.387	7.122	2	12.052	82.34	354.39	14	15
Saudi Arabia	82.3	5.7	59.5	-0.8	15886	10.476	26.106	5.2	9.1	73.12	94.03	12	21
Bahrain	83.9	2.9	70.1	3.04	14908	15	1.06	2.393	5.486	75.91	143.34	13	20
Indonesia	52.6	3.5	66	3.99	1753	7.5	134.557	4.724	1.414	70.79	51.98	19	6
Singapore	100	3.2	76.7	-3.328	33174	2.078	4.832	2.097	21.986	80.74	361.62	11	17
Qatar	95.7	3.3	76.8	11.467	34449	0.5	1.352	1.033	25.111	75.94	90.12	9	13
Kuwait	98.4	3.8	70.7	-1.51	18756	1.639	3.606	4.463	31.62	77.97	79.92	15	12
Pakistan	36.6	2.9	59.1	1.966	866	6.195	169.38	11.5	-3.824	66.53	38.11	25	16
Philippines	65.7	2.6	60.6	0.994	1499	7.2	94.013	4.953	3.492	71.83	64.82	16	10
Mongolia	57.3	5.1	67.9	0.5	1322	3	2.734	7.341	-6.641	66.57	117.07	18	14
Jordan	78.5	2	59.4	3	2707	13	6.126	5.278	-8.911	72.71	116.2	22	27
Bangladesh	27.6	2.4	61.4	5.419	436	5.1	167.671	7.385	2.088	66.15	49.31	28	19
Kyrgyzstan	36.4	6.6	64.5	1.465	589	5.57	5.431	8.428	-12.47	67.37	112.66	24	25
Vietnam	28.3	5.3	68.3	4.606	778	5	88.257	12	-6.907	74.37	158.11	17	24
Syria	54.6	4.9	59.9	3.019	1893	8.5	21.762	5.037	1.13	74.23	59.09	20	23
Tajikistan	26.5	3.5	62.1	2	465	2.2	6.536	7.039	-7.27	66.75	91.08	21	22
Laos	32	2.3	56.2	4.584	656	2.5	6.497	6.865	-10.13	64.97	44.56	26	18
Lebanon	87.1	2	67.1	7	6163	9.2	3.908	5.003	-12.79	72.05	72.47	23	26
Nepal	17.7	3.8	59.2	3.995	355	46	28.285	11.762	-2.77	66.39	37.02	27	28

Fig 3 shows MLP model with 3 Hidden Layer and (5- 10- 12) node in Layers which represents the prediction of success of participating countries in Asian Games.

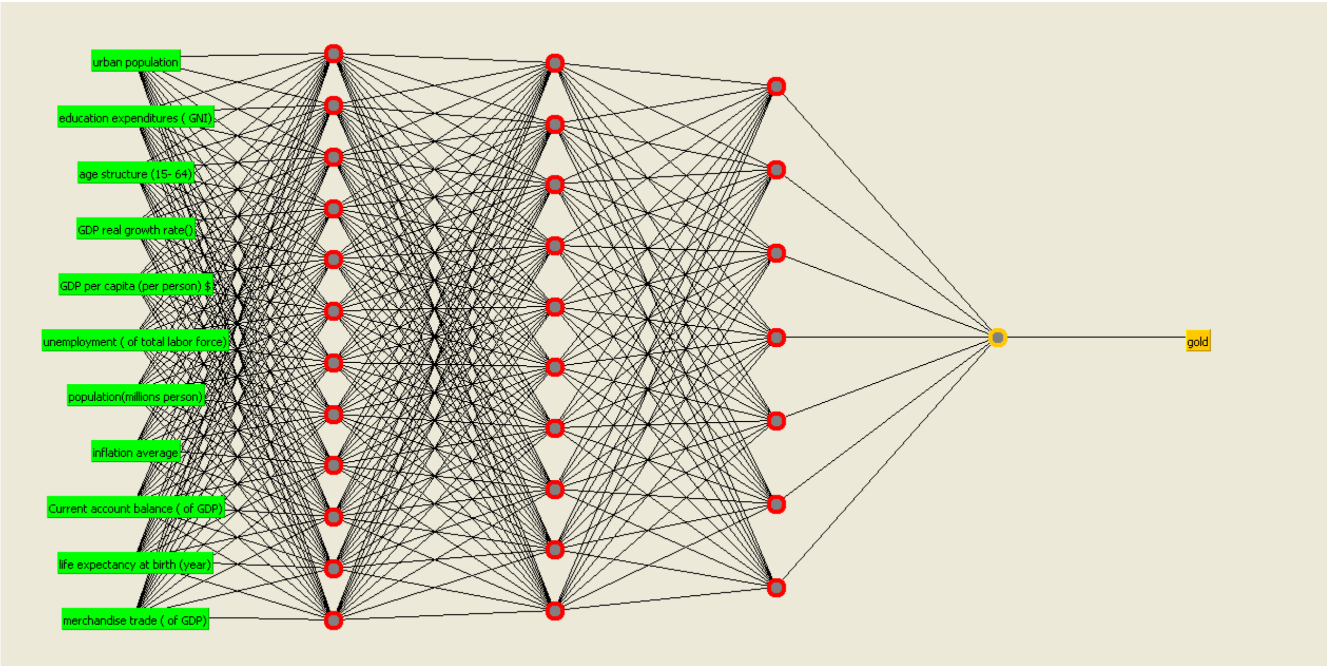

Figure 3: Neural Network with 3 Hidden Layer and (7- 10- 12) node in Layers

Table 3: Characteristics of neural network used

MLP			
Momentum	**Learning Rate**	**Iterations**	**Hidden layers**
0.08	0.3	700	3

Finally in Fig 4, the diagram of original and predicted records was reported.

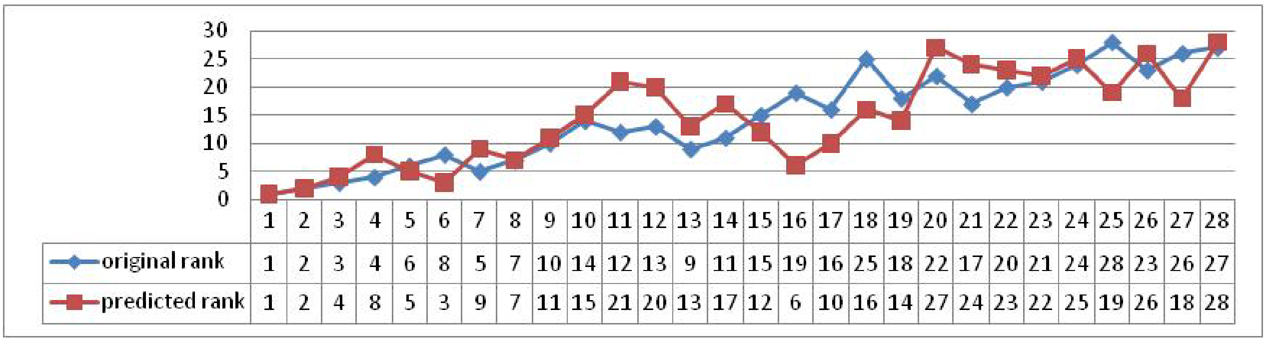

Figure 4: The diagram of original and predicted record

DISCUSSION

The purposes of this study were Predicting the success of nations in Asian Games Using Neural Network and the prediction is based on the number of golden medals acquired each country. Perceptron neural networks and especially, multi-layer Perceptron neural networks are most commonly used. These networks can do a nonlinear mapping with arbitrary precision. In this research we used a multi-layer Perceptron neural network with 3 hidden layers, and training was iterated 700 times. Good correlation results in comparison with the other common machine learning are showed. The better results can be obtained by the work on the various parameters of network. The results show the type of batch grouping of countries, it means the results show the various groups among countries on the base of their macro variables. The value of correlation coefficient between the predicted and original ranks is 86%. One of the other results of this research is that the predicted rank of countries include China, South Korea, Iran and Uzbekistan is exactly identical with their original rank and the difference between the original rank of the first ten countries and the predicted rank of them is minimal. In the situation that we encounter with political, cultural, economic and social variables and as we know one aspect of these variables is the human being factor and it is obvious that the human being is unpredictable, so it seems this percentage for correlation coefficient factor was proper.

Asian games organizing website formed 2diffrent patterns to rank the countries which have the same number of golden medals in various periods.

a. All of the countries acquired the same number of golden medals have the same rank.

b. The countries acquired the same number of golden medals have the consecutive and separated ranks although the position of all of them is same and none of them is better than the others.

In order to analyze, we should classify and change the original ranks of countries in the periods used the first pattern in Asian games site on the base of the second pattern. After that, each country has an independent and definite original rank. Because each country should have a separated original rank as it has a predicted rank. There is a possibility that in a certain period, the applied original rank of a country differs from the original rank of one. This is because of the purposeful change applied in our research and inherently the real position of each country is preserved. This factor may cause that the original rank of each country differs partially from the original rank of one on Asian games website, because the original rank of countries acquired the same number of golden medals can vary in the amplitude of their applied original ranks. This matter can cause the predicted rank of them is not exactly equal to the original one and the predicted rank is some higher or lower than the original one, it originates from the lack of stability in ranking of countries on Asian games website from 1970 to 2010.

But the reason that the predicted rank of each country differs from the original ones, originates from 2 factors:

1. In this research we only study the macro variables. To get the better results, it would rather be considered the role of micro and meso variables, and we can have an optimized pattern by the consensus of all of the variables.
2. In this research, we use the economic, political, cultural and social variables. We should consider that if the prediction of economic, political, cultural and social phenomena, because of their complexities and various parameters, is not impossible, it should be very difficult.

Finally we tried to design the pattern that:

1) To provide the atmosphere in which the expectations and demands of sports spectators, critics and experts are intellectual and realistic and so, they do not have emotional expectations on the results acquired by athletes in Games. This causes the destructive pressure and stress on athletes to decrease and they are able to do their best performance.
2) To give the opportunity to athletes to compare themselves with athletes from the other countries in order to identify their position and plan the necessary training programs and finally, obtain the better records according to the standard templates.
3) To improve sport in each country and get the better international ranks according to it's facilities, potential sources and the comparison with other countries. Managers and planners take the appropriate policies and determine long-term, medium-term and short-term goals in sport according to political, cultural, economic and social factors.

REFERENCE

1. Anderson, P., Edman, J., & Ekman, M. (2005). Predicting the World Cup 2002 in soccer: Performance and confidence of experts and non-experts. International Journal of Forecasting, 21: 565– 576.
2. Bergsgard, N. A., Houlihan, B., Mangset, P., Nodland, S. I., & Rommetveldt, H. Sport policy. A comparative analysis of stability and change. London: elsevier. 2007.
3. Bishop, C. Neural Networks for Pattern Recognition. Oxford University Press, Oxford.1995.
4. Bolton, R., & Chapman, R. (1986). Searching for positive returns at the track: a multinomial logit model for handicapping horse races. Management Science. 32: 1040– 1060.
5. Boulier, B. L., & Stekler, H. (2003). Predicting the outcomes of National Football League games. International Journal of Forecasting. 19: 257- 270.
6. Bunn, d., & Wright, G. (1991). Interaction of judgmental and statistical forecasting methods: Issues and analysis. Management Science. 37: 501–518.
7. Cantinotti, M., Ladouceur, R., & Jacques, C. (2004).Sports betting: can gamblers beat randomness? Psychology of Addictive Behaviors. 18: 143–147.
8. Caudill, S. (2003). Predicting discrete outcomes with the maximum score estimator: the case of the ncaa men's basketball tournament. International Journal of Forecasting. 19: 313– 317.
9. Clarke, S., & Dyte, D. (2000). Using official ratings to simulate major tennis tournaments. International Transactions in Operational Research, 7: 585– 594.
10. Collopy, F., Lawrence, M. J., & Wright, G. (1996). The role and validity of judgment in forecasting. International Journal of Forecasting. 12: 1-8.
11.Condon, E. M., Golden, B. L., & Wasil, E. A. (1999). Predicting the success of nations at the Summer Olympics using neural networks. 26: 1243- 1265.
12. Dastidar, S. G., & Adeli, H. (2009). A new supervised learning algorithm for multiple spiking neural networks with application in epilepsy and seizure detection. Neural Networks, 22: 1419-1431.
13. Dixon, M. J., & Pope, P. (2004). The value of statistical forecasts in the UK association football betting market. International Journal of Forecasting. 20: 697–711.
14. Forrest, D., & Simmons, R. (2000). Forecasting sports results: the behaviour and performance of football tipsters. International Journal of Forecasting. 16: 317–331.
15. Funahashi, K.-i. (1989). On the approximate realization of continuous mappings by neural networks. Neural Networks. 2 (3): 183- 192.
16. Green, M., & Houlihan, B. Elite sport development. Policy learning and political priorities. London and new York: Routledge. 2005.
17. Grove, W., Zald, D. H., Lebow, B. S., Snitz, B. E., & Nelson, C. (2000).Clinical versus mechanical prediction: A meta-analysis. Psychological Assessment. 12: 19– 30.
18. Haykin, S. Neural Networks - A Comprehensive Foundation. 2nd ed. Prentice-Hall, Englewood Cliffs. 1998.
19. Heath, C., & Gonzalez, R. (1995). Interaction with others increases decision confidence but not decision quality: evidence against information collection views of interactive decision making. Organizational Behavior and Human Decision Processes. 61: 305– 326.
20. Hochreiter, S., & Schmidhuber, J. (1999). Feature extraction through LOCOCODE. Neural Computation. 11 (3): 679-714.
21. Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. Neural Networks. 2 (5): 359-366.
22. Huang, G. B., Q.-Y. Zhu, Q. Y., & Siew, C. K. (2006). Real-time learning capability of neural networks. IEEE Transactions on Neural Networks. 17 (4): 863–878.
23. Kahramanli, H., & Allahverdi, N. (2009). Rule extraction from trained adaptive neural networks using artificial immune systems. Expert Systems with Applications. 36: 1513- 1522.
24. Kashaninejad, M., Dehghani, A. A., & Kashiri, M. (2009). Modeling of wheat soaking using two artificial neural networks (MLP and RBF). Journal of Food Engineering. 91: 602–607.
25. Klaassen, F., & Magnus, J. (2003). Forecasting the winner of a tennis match. European Journal of Operational Research. 148: 257–267.
26. Koehler, D. J. (1996). A strength model of probability judgments for tournaments. Organizational Behavior and Human Decision Processes. 66: 16–21.
27. Ladouceur, R., Giroux, I., & Jacques, C. (1998). Winning on the horses: how much strategy and knowledge are needed? The Journal of Psychology. 132: 133–142.
28. Lessmann, S., Sung, M.-C., & Johnson, J. E. (2010). Alternative methods of predicting competitive events: An application in horserace betting markets. International Journal of Forecasting. 26: 518–536.
29. Rue, H., & Salvesen, O. (2000). Prediction and retrospective analysis of soccer matches in a league. The statistician. 49 (3): 399–418.

30. Smith, T., & Schwertman, N. (1999). Can the ncaa basketball tournament seeding be used to predict margin of victory? The american statistician. 53(2): 94–98.
31. Stekler, H., Sendor, D., & Verlander, R. (2010). Issues in sports forecasting. 26: 606–621.
32. Webby, R., & O'Connor, M. (1996). Judgmental and statistical time series forecasting: A review of the literature. International Journal of Forecasting. 12: 91–118.
33. Witten, I. H., & frank, E. Data mining: Partical mashine learning tools and techniques. 2nd edition. Morgan kaufmann, sanfrancisco. 2005.

PREDIKCIJA USPJEHA NACIONALNIH TIMOVA U AZIJSKIM IGRAMA KORISTEĆI NEURALNU MREŽU

Sažetak

Međunarodni uspjeh, posebno sportski uspjeh u Aziji je postao važan sve većem broju država. Iako sve veći broj nacija ulaže velike iznose novca u sport sa ciljem takmičenja sa drugim nacijama, nema jasnih pokazatelja kako sportske varijable utiču na sportske rezultate na međunarodnom planu. U ovom radu smo pokušali da predvidimo uspjeh nacija na Azijskim igrama uz pomoć neuralne mreže kroz makropolitičke, ekonomske, društvene i kulturne varijable. Koristili smo podatke varijabli koje uključuju urbanu populaciju, izdatke za obrazovanje, starosnu strukturu, stopu rasta nacionalnog bruto dohotka, bruto dohodak po glavi stanovnika, stopu nezaposlenosti, broj populacije, stopu inflacije, kreditnu sposobnost, predvidjeni životni vijek i robnu razmjenu svih zemalja koje su učestvovale na Azijskim igrama od 1970.-te do 2006.-te sa ciljem izrade modela nakon čega je ovaj model testiran uz korišćenje vrijednosti spomenutih varijabli iz 2010.-te. Koristili smo WEKA softver koji je popularna aplikacija mašinskog učenja u Javi. Predviđanje se zasniva na broju osvojenih zlatnih medalja svake zemlje. Vrijednost odnosa između predviđenog i stvarnog rezultata je 86%. Jedan od rezultata ovog istraživanja je da su predviđeni rezultati za zemlje Kinu, Južnu Koreju, Iran i Uzbekistan identični onima postignutima, a razlika kod prvih deset zemalja između predviđenih i ostvarenih rezultata je minimalna.Trudili smo se da razvijemo šemu koja će dati sportistima priliku da se usporede sa sportistima iz drugih zemalja sa ciljem da identifikuju svoje poziciju i planiraju potrebne programe treninga I konačno, da postignu bolje rezultate u skladu sa standardnim predlošcima.

Ključne riječi: *Azijske igre, predikcija, neuralna mreža, multi-layer perceptron, macro variable*

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