ARTIFICIAL NEURAL NETWORKS-BASED ECONOMETRIC MODELS FOR TOURISM DEMAND FORECASTING

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Abstract

Purpose – Tourism is a growing sector, playing an important role in many economies, always looking for methods to provide tourism demand forecasting and new creative ideas to develop local tourist offer.

Early prediction on the tourist inflow represents a challenge helping local economy to optimize and develop tourist income. Forecasting models for international tourism demand have usually mainly been focused on factors affecting the tourist inflow, following an approach that is time-consuming and expensive in developing econometric models.

Design – We modelled a backpropagation Artificial Neural Network (a Machine Learning Method for Decision Support and Pattern Discovery) to forecast tourists arrivals in Croatia and compared the results with those obtained with the linear regression methods.

Methodology –The accuracy of the neural network has been measured by the Mean Squared Error (MSE) and compared to MSE and R^2 obtained with the linear regression.

Approach – Our approach consists in combining ideas from Tourism Economics and Information Technology, in particular Machine Learning, with the aim of presenting creative applications of algorithms, such as the Artificial Neural Networks (ANN), to the tourism sector.

Findings – The results showed that using the neural network model to predict tourists arrivals outperforms linear regression techniques.

Originality of the research –The idea to use ANN as a Decision Making tool to improve tourist services in a proactive way or in case of unexpected events is innovative. Moreover, in our final consideration, we will also present other possible creative improvements of the method.

Keywords Artificial Neural Networks, Econometrics, Forecasting, Artificial Intelligence, Machine Learning, Prediction

INTRODUCTION

Tourism is influenced by several variables indicating the general lifestyle of a country and, moreover, also by visitors' perception about weather conditions and safety when travelling and staying at a destination.

It is important for many countries whose large part of their Gross Domestic Product (GDP) is based on tourism to be able to forecast the touristic demand (Gunter and Önder, 2015, Law, 2000). Many studies have been performed to obtain accurate forecasts (Athanasopuoulus and Hyndman, 2008; Santos and Fernandes, 2001; Peng, Song, Crouch and Witt 2014).

Generally, previsioning methods for incoming visitors are based on general and incomplete statistics (usually on number of night stays and arrivals) but communication strategies as infrastructure development strategies and tax income aimed at tourism promotion should be based on several heterogeneous data (such as terrorism index, safety, temperature, mood on the internet/social networks, GDP of the visitors' countries, degree of preservation of local natural resources, environment protection, pollution indices and so on).

In the last decades, Croatia has taken several actions to make improvements in tourism sector, especially in education, infrastructure, communication. In fact, education in several specialized university degrees in tourism is provided aimed at training young people in this key economic sector. Communication skills are also institutionally trained, to present Croatia and Croatia's tourism in an appropriate and professional way. Many efforts have been made to improve tourist infrastructure, such as public transport and a big part of GDP is devoted to environmental protection, to exploit the natural attractions and to prevent pollution. These actions, if supported by an econometric analysis could be more efficiently guided and more effective.

The main problem in forecasting tourist demand is related to the lack of data which experts need to analyse time series with the aim of obtaining efficient previsions. In fact, classical statistics need homogeneous numerical data to provide an efficient forecasting, but often, the data collected are heterogeneous and cannot easily be transformed in numerical values, as for example the analysis of moods generated by tourist communication on the social networks (Folgieri and Bait, 2014). Even if recent techniques such as the so called sentiment analysis could help in collecting this kind of data (Bait, Folgieri and Scarpello, 2015; Folgieri, Bait and Carrion, 2016;), they are rarely used in tourist demand forecasting. This is mainly due to lack of what is called cross-fertilization among disciplines, that is exchanging ideas among different subjects to find new insights in research and development of solutions. The sentiment analysis, as well as other Information Technology techniques cannot easily be used in other disciplines than Information Technology.

In this paper ideas from tourism economics and Information Technology, in particular Machine Learning are combined aimed at presenting creative applications of algorithms to tourism sector, such as the Artificial Neural Networks (ANN).

Due to their characteristics that will be described more precisely in the next paragraph, scholars are increasingly interested in applying ANN to predict tourism demand. For example, a supervised feed-forward neural network has been used to forecast Japanese tourist arrivals in Hong Kong (Law and Au, 1999) and to model and forecast tourism demand in terms of a number of overnight stays in Portugal (Fernandes and Teixeira, 2008), as well as to forecast tourism demand in Catalonia, Spain (Claveria and Torra, 2014). Most of these studies use tourist arrivals as a variable representative for tourist demand (Gunter and Önder, 2015, Law, 2000), and, in some cases, the number of overnight stays registered in hotels and guest houses is also used (Fernandes et al., 2008; Cunha and Abrantes, 2013; Teixeira and Fernandes, 2014), in this latter case representing a combination of national and international tourism.

The aim of this study is to use ANN to model and forecast tourism demand in terms of total overnight stays in Croatia, on the basis of data collected for the period 2006-2004, suggesting future improvements of the methods to obtain more accurate previsions. The accuracy of the ANN is performed by using the Mean Absolute Percentage Error (MAPE) and the Pearson correlation Coefficient (r). Therefore, in paragraph one the adopted ANN approach is shortly described; in paragraph two the results are presented and discussed; final paragraph is conclusion with considerations and ideas for further possible development.

1. THE BACKPROPAGATION ANN APPROACH

Artificial Neural Networks (ANN) are computational tools extensively used in several research fields, such as cognitive science, biology, psychology, medicine, economics, mathematics and computer science, and in solving complex real-world problems. ANNs keep inspiration by the biological neural networks (Palmer, Montaño and Sesé, 2006) and they are attractive for processing information with high parallelism, nonlinearity and especially noise tolerance, as learning and generalization characteristics (Basheer and Haimeer, 2000). As it is known, biological neurons receive signals through synapses located on the dendrites of the neuron. When the signals received surpass a certain threshold, the neuron is activated and emits a signal through the axon. This signal might be sent to another synapse or might activate other neurons. Artificial neurons (Mc Culloch and Pitts, 1943) present a highly abstract biological model: neurons consist of inputs (like synapses), multiplied by weights (representing the strength of the signals) and then computed by a mathematical function (called activation function) activating the neuron. Finally, a specific function (e.g. the identity) computes the output of the artificial neuron. ANNs consist of combination of neurons, which process information. There are several models of ANNs. Here, we briefly recall the mechanisms of ANNs learning through the backpropagation algorithm (Rumelhart and McClelland, 1986), used in our study.

The backpropagation algorithm consists in a gradient descent technique that minimizes some error criteria *E*. The descent is based on the gradient ∇E on the total training set (1):

$$\Delta w_{ij} = -\epsilon * \frac{\partial E}{\partial w_{ij}} + \alpha * \Delta w_{ij}(n-1) \tag{1}$$

Where w_{ij} is the connection strength from the unit *i* to unit *j*; E the total quadratic error on the training set; ϵ and α are, the *learning rate* and the *momentum* respectively, two nonnegative constant parameters, the first allowing to speed up training in very flat regions of the error surface suppressing weight oscillation in step valleys, the latter specifying the step width of the gradient descent.

The idea of the backpropagation algorithm is to reduce the error until the ANN learns the training data. The training starts with random weight, it is then adjusted to minimize the error. The activation function A of the artificial neurons consists in a weighted sum that is a sum of the inputs x_i multiplied by their respective weights w_{ji} as shown in formula 2:

$$A_j(\bar{x}, \bar{w}) = \sum_{i=0}^{n} x_i w_{ji} \tag{2}$$

It should be noticede that the activation depends only on the inputs and the weights. Assuming the identity as the output function means creating a linear neuron, with severe limitations. The most common output, also used in our study, is the sigmoidal function that is very close to one for large positive numbers, 0.5 at zero, and very close to zero for large negative numbers. Using a sigmoidal function allows to obtain a smooth transition from the low and the high output of the neuron.

2. ANN FOR TOURISM DEMAND FORECASTING IN CROATIA

Forecasting models usually consist of statistical regressions mainly focused on previous years tourists' inflow adding mostly monthly weather reports. The reasons for this choice are firstly lack of other kinds of data and difficulties in collecting them in a structured shape; secondly, not being familiar with other analysis tools, such as ANNs, due to distance between different disciplines which use different scientific languages; last, but not least, the difficulty to treat heterogeneous, sometimes not numeric data with statistical methods, unless reducing such data to numeric values through a too time-consuming data pre-processing.

In this study we present the results obtained by application of a backpropagation ANN applied to selected historical data to forecast prediction on the tourist inflow in Croatia. Compared to statistical ones, the advantages of adopting these methods are several, such as the computational speed, the ability to learn general solutions of presented training data, the absence of the need to develop an explicit model of a process, the ability to model parts of a process that cannot be modelled or are unidentified and particularly interesting in our case, the ability to learn from noisy and incomplete data, the adaptability to system changes from initial training model.

Moreover, we wish to recall that in some applications neural networks fits better than other models such as linear regression, and it usually occurs when there are nonlinearities involved, as in the considered topic.

Our approach consists in contaminating ideas from Tourism Economics and Information Technology, in particular Machine Learning, with the aim of presenting creative applications of algorithms, such as the ANN, to the tourism sector.

2.1. Dataset

With the aim of creating a dataset containing the most possible significant data (not always used from statistical surveys) for the purposes of our analysis, we collected data from several sources accessible on the Internet. Specifically, we accessed to statistical data from the European Union Official statistical website, the Croatian Bureau of Statistics, the ISTAT (Italian National Institute for Statistics), from Trading Economics (http://www.Tradingeconomics.com) and from the United Nations Sustainable Development Solution Network.

Considering that the cited institutions have collected data in different periods, aiming to obtain as much as possible complete statistical values, we considered monthly data for the period starting from 1st January 2007 and ending up with 31st December 2012.
The considered variables are listed and described below:

- TempC, from the Croatian Bureau of Statistics: average temperature, in degrees Celsius, monthly recorded in Croatia;
- HICP, from ISTAT: serves to measure inflation in the Euro area, measured by the MUICP (Monetary Union Index of Consumer Prices) index, as defined in the Council Regulation (EC) No 2494/95 of 23 October 1995 that is the official aggregate of the Euro Area. Initially, it included Belgium, Germany, Ireland, Spain, France, Italy, Luxembourg, The Netherlands, Austria, Portugal and Finland. Greece has been included by 1st January 2001, Slovenia from January 2007, Cyprus and Malta from 1st January 2008, Slovakia from 1st January 2009, Estonia from January 2011, Latvia from 1st January 2014, Lithuania from 1st January 2015. Change compared to the same month of previous year (%). Harmonised Indices of Consumer Prices (HICP) are designed for international comparisons of consumer price inflation. HICPs are used for the assessment of the inflation convergence criterion as required under Article 121 of the Treaty of Amsterdam and by the ECB for assessing price stability for monetary policy purposes. The ECB defines price stability on the basis of the annual rate of change of the Euro area HICP. HICPs are compiled on the basis of harmonised standards, binding for all Member States. Conceptually, the HICP is a Laspeyres-type price index and are computed as annual chain-indices allowing for weights to be changed each year. The mpst common classification for Harmonized Indices of Consumer Prices is the COICOP (Classification Of Individual COnsumption by Purpose). A version of this classification (COICOP/HICP) has been specially adapted for the HICP. Sub-indices published by Eurostat are based on this classification. HICP is produced and published using a common index reference period (2015 = 100). Growth rates are calculated from published index levels. Indices, as well as both growth rates with respect to the previous month (M/M-1) and with respect to the corresponding month of the previous year (M/M-12) are neither calendar nor seasonally adjusted.
- EORD, EUROSTAT source: percentage of contracts received by orders online, considering all the commercial activities with more than 10 employees. We decided to include this value to evaluate the general impact of the Internet on the tourism development year by year, even if the values also include non-touristic commercial activities.
- GDPEP, from EUROSTAT: Percentage of GDP (Gross Domestic Product) reserved for the environmental protection. Environmental protection expenditure is the money spent on all purposeful activities directly aimed at the prevention, reduction and elimination of pollution or any other degradation of the environment. It includes environmental investments, environmental current expenditure and environmental subsidies/transfers. Environmental investments are all outlays in a given year for machinery, equipment and land used for environmental protection purposes. Current expenditure for environmental protection includes daily operating activities aiming at the prevention or reduction of pollution. It includes, for example, expenditure for staff working on environmental issues and materials for environmental protection.

- ECUEUR, source EUROSTAT: ECU/EUR exchange rates versus national currency - 1 ECU/EUR = n units of national currency (annual average). Exchange rates are the price or value of one country's currency in relation to another. Here the exchange rates are those for Euro published by European Central Bank. Before 1999 the exchange rates are those of the ECU, as published by the European Commission.
- FTA and DTA, source Croatian Bureau of Statistics: number of Foreign Tourists Arrivals and Domestic Tourists Arrivals, respectively. Since 2010, nautical ports have no longer been considered reporting units or types of accommodation facilities in the survey on tourist arrivals and overnight stays. This happened because of the implementation of the new Sojourn Tax Act (NN, Nos. 152/08 and 59/09), which prescribes how to report sojourns on vessels. As a result of the mentioned change in methodology, determined by the implementation of new regulations on monitoring tourists, data were revised in time from 2005 to 2009 in order to make a series comparable (nautical ports have been excluded).
- GTI, source Tradingeconomics.com: Croatia Terrorism Index 2002-2015. The Global Terrorism Index (GTI) is an attempt to systematically rank the nations of the world according to terrorist activity. The index combines a number of factors associated with terrorist attacks to build an explicit picture of the impact of terrorism over a 10-year period, illustrating trends, and providing a data series for analysis by researchers and policymakers. It is a product of the Institute for Economics and Peace (IEP) and is based on data from the Global Terrorism Database (GTD) which is collected and collated by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland. The GTD has codified over 125,000 cases of terrorism.
- ROH, source United Nations Sustainable Development Solution Network: Ranking Of Happiness. The World Happiness Report is a landmark survey of the state of global happiness. The first report was published in 2012, the second in 2013, and the third in 2015. The World Happiness Report 2016 Update, which ranks 156 countries by their happiness levels, was released in Rome on the occasion of the UN World Happiness Day, March 20th 2016. Leading experts across the fields – economics, psychology, survey analysis, national statistics, health, public policy and more – describe how measurements of well-being can be used effectively to assess the progress of nations. The reports review the state of happiness in the world today and show how the new science of happiness explains personal and national variations in happiness. They reflect a new worldwide demand for more attention to happiness as a criterion for government policy.
- Overnight stays, from the Croatian Bureau of Statistics: total overnight stays in Croatian tourist accommodation sector, monthly recorded.

We built the matrix of Pearson correlations (Table 1). From that table, the variables that were more correlated with the variable to predict (number of overnight stays in accommodations structures) and less with each other were selected and tested for the input layer. We selected the variables having a significant correlation with the output variable, and not highly correlated with the others.

Table 1: **Matrix of Pearson correlation coefficient.**

	time	tempC	HICP	EORD	GDPEP	ECUEUR	FTA	DTA	GTI	RoH	nights
time	1										
tempC	0.01	1									
HICP	-0.03	-0.01	1								
EORD	0.62	-0.008	-0.41	1							
GDPEP	-0.11	0.03	0.29	-0.46	1						
ECUEUR	0.24	0.04	0.02	0.33	0.63	1					
FTA	0.06	0.87	-0.01	0.03	0.02	0.05	1				
DTA	-0.11	0.91	0.03	-0.16	-0.0008	-0.12	0.90	1			
GTI	-0.25	-0.01	-0.001	0.09	-0.86	-0.71	-0.03	0.07	1		
RoH	0.25	0.04	0.17	0.42	0.26	0.74	0.04	-0.09	-0.38	1	
nights	0.05	0.82	-0.01	0.01	0.01	0.03	0.99	0,87	-0.02	0,03	1

2.2. The ANN model and implementation

To perform the prediction of tourist arrivals, we used a backpropagation Artificial Neural Network, implemented by using the free statistical software environment R (https://www.r-project.org/).

The ANN had the following characteristics:

- 9 input nodes, corresponding to the variable tempC (average monthly temperature, in degrees Celsius), HICP (Croatian Harmonised Indices of Consumer Prices), EORD (percentage of contracts received by orders online), GDPEP (percentage of Gross Domestic Product reserved for the Environmental Protection), ECUEUR (exchange rates versus national currencies), FTA (number of monthly Foreign Tourists Arrivals), DTA (number of monthly Domestic Tourists Arrivals), GTI (Croatia Terrorism Index), RoH (Croatian Ranking Of Happiness);
- 1 hidden layers with 2 nodes;
- 1 output node, for the predictions of the number of monthly overnight stays of incoming tourists in Croatian tourist accommodation sector;
- a sigmoidal activation function in the hidden layer and a linear activation function at the output layer;
- initial random weights.

There are no fixed rules as to how many layers and neurons, but usually, one hidden layer is enough for a vast number of applications. Furthermore, for practical reasons, ANNs implementing the backpropagation algorithm do not have too many layers, since the time for training the networks grows exponentially.

The number of neurons of the hidden layer should be between the input layer size and the output layer size, it is usually between 1/2 and 2/3 of the input size. The better way to define how many neurons are needed consists in trying to find the best model fitting the data. After some trials, we verified that 2 neurons best fitted the data.

Of course, the output layer has a single output since we are doing regression.

2.3. Methods

With the aim of obtaining a monthly prediction, following the structure of the dataset, we have ran one ANN per month, and to allow the comparison, we did the same for the linear regression.

The accuracy of the neural network has been measured by the Mean Squared Error (MSE), measuring the average of the squares of the errors or deviations that is the difference between the estimator and what is estimated. It represents a measure of the quality of an estimator. It is always not negative and values closer to zero are better.

We also performed a linear regression implemented in the software environment R to compare the results obtained from the two methods.

With the aim of exploiting the generalization characteristics of the Artificial Neural Networks we also included the incomplete data to demonstrate the efficiency of the method.

Before training neural network, we needed to perform data preprocessing. We normalized the data to prevent useless results and to avoid the algorithm that will not converge before the number of maximum iterations allowed. We chose to normalize data through the min-max method and scaled the data in the interval [0,1]. Scaling in the intervals [0,1] or [-1,1] usually tends to give better results.

After normalization we also splitted the data in training-set and test-set, the first used to train the ANN and the second to test the model in the prediction phase. The training-set (composed by the 70% of the records of the initial dataset) and the test-set (composed by the remaining 30% of the records of the initial dataset) records have been randomly selected from the complete dataset.

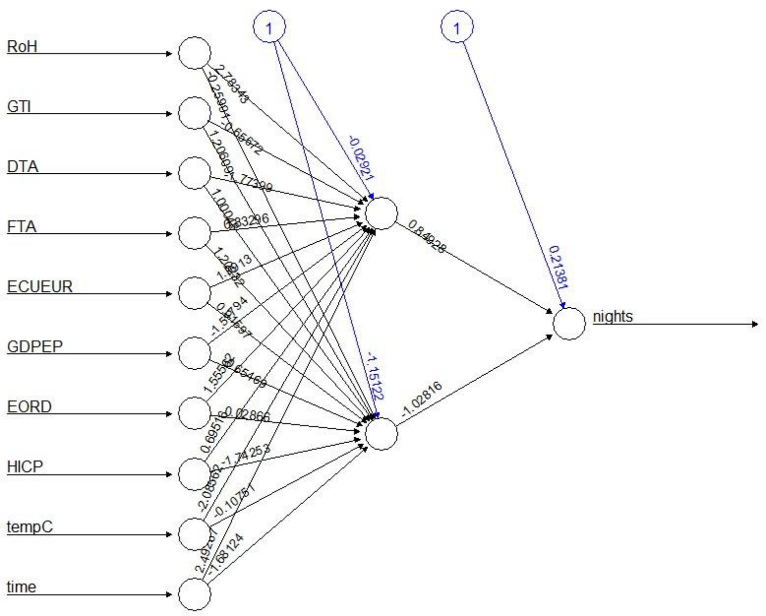
We also used a 5-fold cross validation to have a further validation of either the ANN or the linear regression. The goal of this validation technique is to define a dataset to validate the model in the training set in order to limit problems like overfitting, or for assessing how the results of the analysis generalize to the independent dataset. The reasons for using the cross-validation technique as well are relatively few records contained in the complete dataset, compared to usually larger sets of data used to perform the two prediction models. Partitioning the dataset into two sets of 70% for training and 30% for test may cause loss of significant modelling or testing capability, so the application of cross-validation method gives us an appropriate way to obtain a further proper estimation of the prediction models performance.

Furthermore, to underline the impact of different kinds of data on the forecast, compared to the simple use of the number of overnight stays and weather conditions, we also ran the same ANN model and the linear regression on the dataset reduced to these two variables, to have a further validation of the need of various and heterogeneous values.

3. RESULTS AND DISCUSSION

The error of the ANNs (one per month) performed on all the selected variables of the dataset (for the period going from 1st January 2007 to 31st December 2012) resulted in average 0.0000347.
In the following Figure 1 we show, as examples of the implemented model, the ANN resulting for the prediction for January. We also report the respective registered prediction errors.

Figure 1: **The ANN resulting for prediction of tourist arrivals in August (Error 0.000045) – dataset from 1st January 2007 to 31st December 2012.**



The result of the linear regression on the same data revealed an R^2 (comparable to the MSE of the ANNs) in average, 1 and MSE in average 0.005655. In the following Table 2, we show the comparison between the MSE (Mean Squared Error) values registered for each ANN and the R^2 for each Linear Regression performed on the same data.

Table 2: **Comparison between the MSE of the ANNs and the MSE and R^2 of the linear regressions – dataset from 1st January 2007 to 31st December 2012.**

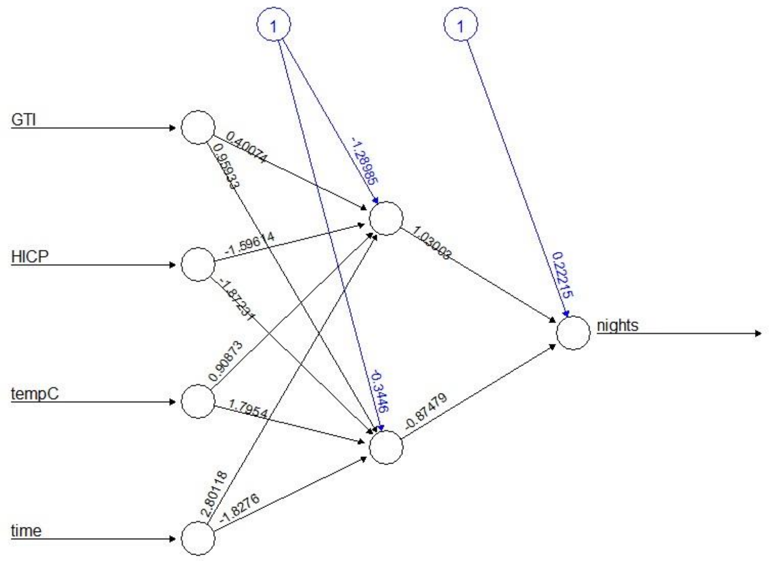
Month	**MSE ANN**	**MSE Linear Regression**	**R^2 Linear Regression**
January	0.000043	0.00567	1
February	0.000037	0.020133	1
March	0.000051	0.01902	1
April	0.00008	0.00899	1
May	0.000002	0.001034	1
June	0.000061	0.006719	1
July	0.000033	0.005042	1
August	0.000045	0.007214	1
September	0.000026	0.002708	1
October	0.000006	0.00150	1
November	0.000004	0.004329	1
December	0.000028	0.005634	1
average	**0.0000347**	**0.005655**	**1**

The results show that the neural network outperforms linear regression technique in modelling tourist arrivals.

We also trained the ANNs with 4 variables for which we have values from 2002-2014, but in this case the average error (across the monthly datasets) has been about 0.003376 that is higher than 0.0000347 obtained for the ANNs previously trained. The considered variables are tempC (average monthly temperature, in degrees Celsius), HICP (Croatian Harmonised Indices of Consumer Prices), GTI (Croatia Terrorism Index), nights (number of monthly nights spent in Croatian touristic accommodation by incoming tourists).

As an example, in the following Figure 2 we show the ANN model resulting for the prediction for August. We also report the respective registered prediction errors.

Figure 2: **The ANN resulting for prediction of tourists arrival in January on the basis of 4 variables from 2002 to 2014 (Error 0.00415)**



This means that the more information per year is collected (despite less information and more years), the more accurate the prediction will be.

Table 3: **Comparison between the MSE of the ANNs and the R^2 of the linear regressions – dataset from 1st January 2002 to 31st December 2014.**

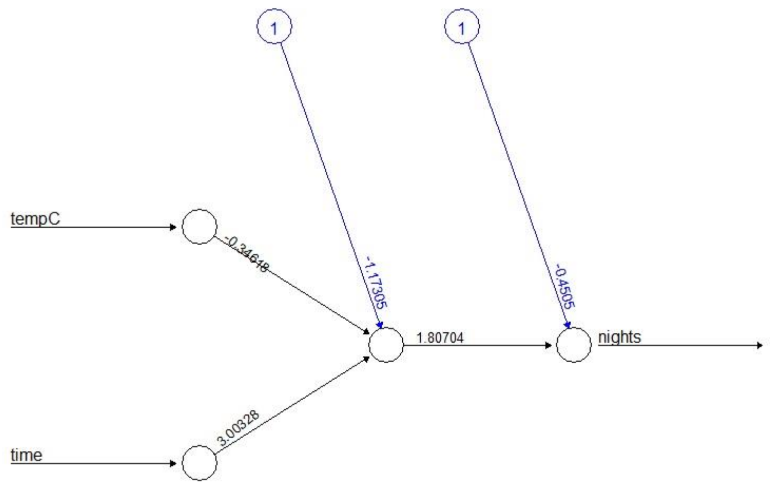
	MSE ANN	**MSE Linear Regression**	**R^2 Linear Regression**
January	0.007879	0.02177	0.284778
February	0.001824	0.0321	0.282211
March	0.003312	0.0524	0.078472
April	0.001084	0.0328	0.719963
May	0.005476	0.01245	0.203402
June	0.004134	0.03001	0.248559
July	0.000348	0.02167	0.156926
August	0.00415	0.031	0.413445
September	0.002655	0.02455	0.416213
October	0.001719	0.01401	0.472872
November	0.003555	0.0311	0.476215
December	0.004379	0.04102	0.539694
average	**0.003376**	**0.02874**	**0.357729**

We performed the linear regression on the same data and also in this case, the MSE of the ANNs resulted lower than either the MSE and the R^2 of the linear regressions, in average. In the Table 3, we show the comparison between the MSE (Mean Squared Error) values registered for each ANN and the MSE and R^2 for each Linear Regression performed on the 4-variables datasets.

Also with the 4-variables datasets, the results show that the neural network outperforms linear regression technique in modelling tourists arrivals.

Similar results were also obtained when we considered only the variables temperature and nights (evaluated in usual classical statistical simple prediction methods), even if we had values from 2002 to 2014. In this latter case (see an example of the model for January in Figure 3) the average error (across the monthly dataset) has been about 0.02, much higher than the values obtained for the ANNs previously trained, while for the linear regression we obtained an average R^2 equal to 0.9 and an average MSE equal to 0.067.

Figure 3: **The ANN resulting for prediction of tourist arrivals in January on the basis of the variable temperature and overnight stays from 2002 to 2014 (Error 0.029)**



The obtained values were also confirmed also by the 5-fold cross validation procedure.

CONCLUSION

The results showed that using the Artificial Neural Network model in predicting tourists arrivals is a robust method giving an interesting low error rate and outperforming the linear regression technique.

The paper demonstrates, through examples of application to subsets of the collected data, different in period and number of considered variables, that ANN can make long-term prediction on tourist inflow, but also, thanks to the capability of Artificial Neural Network to apply a learning process to heterogeneous sample data, a short-term analysis, useful in case of unexpected events which could influence tourism. In this last sense, ANN could operate as a Decision Making support, allowing to dispose proactive and reactive solutions to improve tourist services.

Moreover, the ANN can also consider data of various nature, such as temperature and the number of arrivals, usually used in statistical prediction.

Not only the presented ANN is creative in the sense of the innovativness of the application, but also, considering the ANN's generalization characteristics and its possible application to heterogeneous data. Data coming from a reputation analysis on the Internet, as data from sentiment analysis performed on the social networks, either for the touristic sites, in general, or also on specific accommodation structures can be included in dataset values.

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REFERENCES

Athanasopoulos, G. and Hyndman, R. (2008). "Modelling and fore-casting Australian domestic tourism". *Tourism Management*, Vol. 29, No. 1, pp.19-31. https://doi.org/10.1016/j.tourman.2007.04.009

Bait, M., Folgieri, R. andScarpello, O. (2015). "The use of agent-based models in cognitive linguistics: an approach to Chomsky's linguistics through the clarion model". *Journal of Foreign Language Teaching and Applied Linguistics*, Vol. 1, No. 3, 10.14706/JFLTAL15136

Basheer, I. and Hajmeer, M. (2000). "Artificial neural networks: Fundamentals, computing, design, and application". *Journal of Microbiological Methods*, Vol. 43, No. 1, pp. 3-31. https://doi.org/10.1016/S0167-7012(00)00201-3

Claveria, O. and Torra, S. (2014). "Forecasting tourism demand to Catalonia: Neural networks vs. time series models". *EconomicModelling*, 36, pp. 220-228. https://doi.org/10.1016/j.econmod.2013.09.024

Cunha, L. and Abrantes, A. (2013)." Introdução ao turismo", Lisboa (5th Ed.).

Fernandes, P. and Teixeira, J. (2008). "Previsão da Série Temporal Turismo com Redes Neuronais Artificiais". 5 Congresso Luso-Moçambicano de Engenharia-CLME' 2008-A Engenharia no Combate à Pobreza, pelo Desenvolvimento e Competitividade, Maputo-Moçambique.

Fernandes, P., Teixeira, J., Ferreira, J. and Azevedo, S. (2008). "Modelling tourism demand: A comparative study between artificialneural networks and the Box-Jenkins methodology". *Romanian Journal of Economic Forecasting*, 5(3), pp. 30-50.

Folgieri, R. and Bait, M. (2014, January). "The new profile of the virtual tourist- traveler: communicative perspectives and technological challenges". In *Faculty of Tourism and Hospitality Management in Opatija. Biennial International Congress. Tourism & Hospitality Industry* (p. 408). University of Rijeka, Faculty of Tourism & Hospitality Management.

Folgieri, R., Bait, M. and Carrion, J. P. M. (2016). "A Cognitive Linguistic and Sentiment Analysis of Blogs: Monterosso 2011 Flooding". In *Tourism and Culture in the Age of Innovation*, Springer International Publishing, pp. 499-522.

Gunter, U. and Önder, I. (2015). "Forecasting international city tourismdemand for Paris: Accuracy of uni- and multivariate modelsemploying monthly data". *Tourism Management*, 46, pp. 123-135. https://doi.org/10.1016/j.tourman.2014.06.017

Law, R. (2000). "Backpropagation learning in improving the accuracyof neural network-based tourism demand forecasting". *TourismManagement*, Vol. 21, No. 4. pp. 331-340. https://doi.org/10.1016/S0261-5177(99)00067-9

Law, R. and Au, N. (1999). "A neural network model to forecastJapanese demand for travel to Hong Kong". *Tourism Management*, Vol. 20, No. 1, pp. 89-97. https://doi.org/10.1016/S0261-5177(98)00094-6

Palmer, A., Montaño, J. J. and Sesé, A. (2006). "Designing an artificial neural network for forecasting tourism time series". *TourismManagement*, Vol. 27, No. 5, pp. 781-790. https://doi.org/10.1016/j.tourman.2005.05.006

Peng, B., Song, H., Crouch, G. and Witt, S. (2014)."A meta-analysisof International tourism demand elasticities". *Journal of Travel Research*, Vol. 54, No. 5, pp. 1-23. https://doi.org/10.1177/0047287514528283

Santos, N. and Fernandes, P. (2011)." Modelação e caracterizaçãoda procura turística: o caso da região Norte de Portugal". *Review of Applied Management Studies*, 9(16), pp. 118-137.

Teixeira, J. and Fernandes, P. (2014). "Tourism time series forecastwith artificial neural networks". *Tékhne Review of Applied Management Studies*, Vol. 12, No. 1-2, pp. 26-36. https://doi.org/10.1016/j.tekhne.2014.08.001

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