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A Simple Neural Network Model of University Preferences: Two Algorithms and a Case Study

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Abstract: In this paper, we make use of two algorithms/methods, namely the neural networks and the multi-objective evolutionary fuzzy classifier to develop a simple model of university preferences. We use technology, teaching quality, research productivity, managerial quality, physical capital and social capital as the input variables. We first construct a neural network with a hidden layer and determine the degrees of importance of the input variables in relation to the university preferences having dichotomous values signifying the positive and negative attitudes towards the relevant higher educational institutions. With the setup and the data, it turns out the teaching quality is the most influential factor followed by the managerial quality. The second algorithm we make use of is the multi-objective evolutionary fuzzy classifier. We choose 90% of the data for training and the rest (10%) testing purposes. We obtain a 93.33% accuracy, which is quite high. In sum, machine learning algorithms turn out to be fairly successful in modeling university preferences. The classification performance of the algorithms is remarkable. In an extended framework, we can reasonably expect that the forecasting models based on machine learning algorithms would also yield high degrees of accuracy. In addition to the algorithms exemplified in this paper, algorithms such as support vector machines, random forest and bagging are likely to produce results that could be of practical significance for managerial policy makers.

Keywords: University preferences, Neural networks, Multi-objective evolutionary fuzzy classifier, Degrees of importance of input variables, Accuracy.

Introduction

Universities in modern times have been subjects of a number of works ranging from applications of artificial intelligence to higher education systems to simulations of university-related processes. Among these works are Cakit and Dağdeviren (2022), Kara (2022), Wardley et al. (2024), Kesim and Serpil (2024), which make use of machine learning/artificial intelligence to examine various issues relevant to higher education, Abramo, D'Angelo and DiCosta (2014), which deal with some issues of university-related returns to scope, Barlas & Dicker (2000) and Kara (2015, 2018, 2023), which undertake system dynamics simulations of university processes, Häyrinen-Alestalo and Peltola (2006), which examines the problem of market-oriented university, Ivanov, Markusova and Mindeli (2016), which analyzes government investments in relation to the activity of publishing. Spencer (2001) and Kara (2013) deal with some technology-and-university-related issues. Lach & Schankerman (2006) examines incentives and invention, Munoz (2016) analyzes research efficiency. Ramos-Vielba & Fernández-Esquinas (2012) and Paule-Vianez et al. (2025) analyze university-industry linkages and performance of some firms in university environment, respectively. Shin (2009) classifies higher education institutions via a performance-based approach.

Among the lines of inquiry represented by these works, which cover a wide spectrum of areas that are of theoretical and practical significance, we will contribute to a particular line making use of machine learning algorithms which have the potential of producing results that could shed some additional light on the selected complexities associated with modern universities.

In the second section, we develop a simple model of university preferences based on a number of input variables, employ two algorithms to analyze the preferences in question and give the numerical results. The concluding remarks are presented in the last section.

The Method, Model and Results

Consider a case where technology, teaching quality, research productivity, managerial quality, physical capital and social capital are the input variables underlying university preferences. University preferences are represented in the form of dichotomous values signifying the positive and negative attitudes towards the relevant higher educational institutions. The variables are measured on a scale of 1 to 7 with 1 representing the lowest value and 7 representing the highest. The dataset is based on a partly transformed subset of the data in Kara (2018) and used for a different purpose outlined in this paper and in a different framework.

In this paper, we will first construct a simple neural network model where technology, teaching quality, research productivity, managerial quality, physical capital and social capital are the input layer variables and university preference is the output layer variable. We will use the radial basis function available in SPSS so as to find degrees of importance with which input layer variables influence the output layer variable. The training and testing sets include 66.7 % (2/3) and 33.3% (1/3) of the data, respectively. The associated neural network diagram is given in Figure 1.

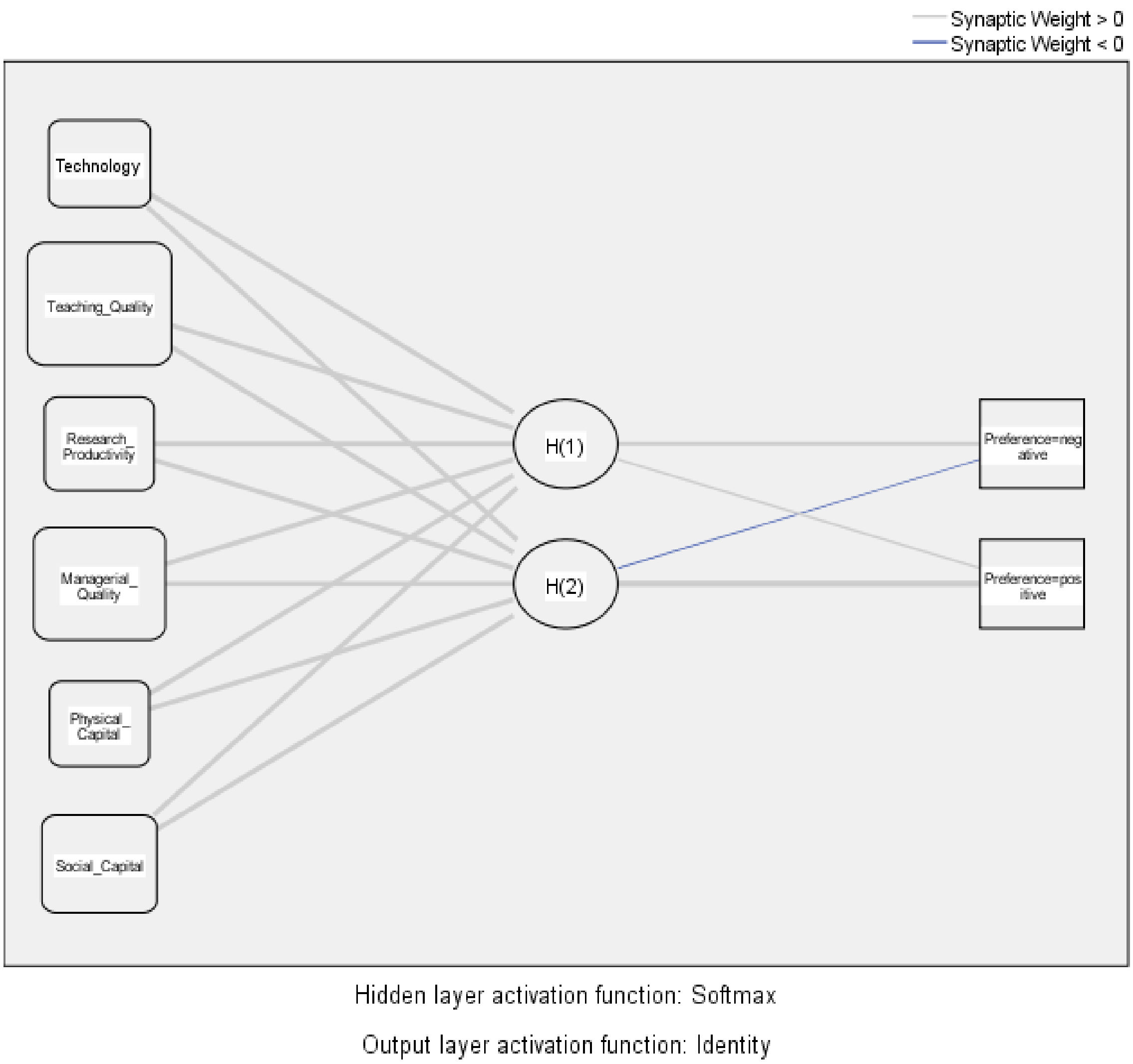

Figure 1. The neural network diagram

The degrees of importance of the input layer variables are given in Table 1 and Figure 2.

Table 1. Independent variable importance

	Importance	Normalized Importance
Technology	0.119	47.1%
Teaching Quality	0.252	100%
Research Productivity	0.143	56.9%
Managerial Quality	0.214	84.8%
Physical Capital	0.113	44.8%
Social Capital	0.160	63.6%

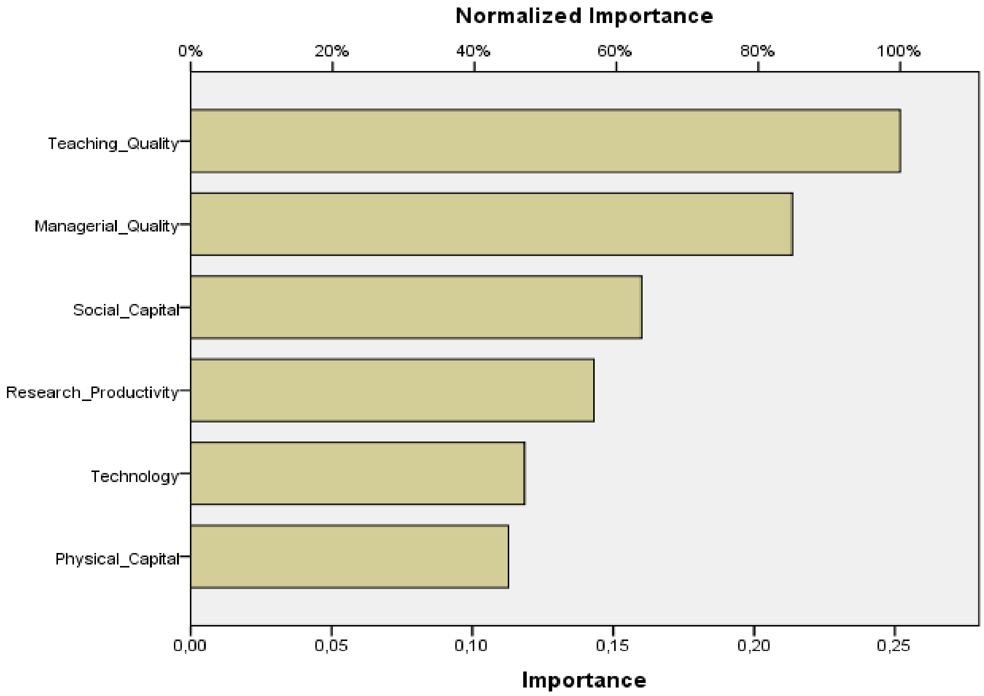

Figure 2. Normalized importance

Figure 1 and 2 and Table 1 are produced with SPSS. The results for university preferences indicate that, with the setup and the data, the teaching quality is the most influential factor followed by the managerial quality. It would be useful to take a look at the power of the relevant set of variables in predicting whether the resulting preference would be positive or negative. We will make use of a particular classification algorithm, namely multi objective evolutionary fuzzy classifier, for the purpose of classifying whether a particular set of values for technology, teaching quality, research productivity, managerial quality, physical capital and social capital yields positive or negative university preference. We will use WEKA for classification. We employ a 90%-10% percentage split for decomposing the data into the training and testing components. The results are given in Table 2 as follows:

Table 2. Classification results (produced with WEKA)

Correctly Classified Instances	14	93.3333 %
Kappa statistic		0.8649
Mean absolute error		0.0667
Root mean squared error		0.2582
Relative absolute error		13.7137
Root relative squared error		48.8467
Total Number of Instances		15

Table 3. Detailed accuracy by class

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
1,000	0,143	0,889	1,000	0,941	0,873	0,929	0,889	positive
0,857	0,000	1,000	0,857	0,923	0,873	0,929	0,924	negative
Weighted Avg.	0,933	0,076	0,941	0,933	0,933	0,873	0,929	0,905

Confusion Matrix

- a b <-- classified as
- a 8 0 | a = positive
- b 1 6 | b = negative

The confusion matrix indicates that, out of 15 observations in the testing set, 8+6=14 observations are classified correctly, yielding a 93.3 % accuracy. To state it more explicitly, based on the relevant set of variables, multi objective evolutionary fuzzy classifier classifies the resulting university preference with 93.3 % accuracy, which is quite high, demonstrating the classification success of the algorithm in question and hence of the machine learning/artificial intelligence.

Discussion, Recommendations and Concluding Remarks

This paper exemplifies the ways in which machine learning/artificial intelligence algorithms could be used for the purpose of determining the importance of technology, teaching quality, research productivity, managerial quality, physical capital and social capital in influencing the university preferences and for the purpose of classifying, with a high degree of accuracy, the categories (positive and negative preferences) on the basis of the variables in question. These results are of practical significance for educational policy making. University managers could use the independent variable importance analysis for investment decisions in various areas. Repeated classifications over time could give an idea about the patterns leading to positive and negative university preferences. Extending the analysis here with new algorithms and algorithm-incorporated simulations would be worthy of future research.

Scientific Ethics Declaration

* The author declares that the scientific ethical and legal responsibility of this article published in EPESS journal belongs to the author.

* The paper does not require any ethics committed permission.

Conflict of Interest

* The author declares that he has no conflicts of interest

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