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Section ARTICLES

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Exploring the use of artificial intelligence in price maximisation in the tourism sector: its application in the case of Airbnb in the Valencian Community

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ABSTRACT: The use of machine learning is becoming more and more frequent in companies' search for competitiveness. Literature on the subject show us how in many cases artificial intelligence can help companies to improve their knowledge about users, optimize prices or guide buyers in their choices.
To confirm that the application of artificial intelligence models allows companies to obtain specifically better price optimisation procedures than with other traditional models, we have studied more than 10,000 Airbnb properties in the three main cities in the Valencian Community (Valencia, Alicante and Castellón), noting that the estimation process using neural networks offers significantly more satisfactory results than the use of hedonic models.

JEL Classification: O32; L83; R1.

Keywords: Machine Learning; Airbnb; tourism; hedonic prices; Valencian Region.

Explorando el uso de la inteligencia artificial en la maximización de precios para el sector turístico: su aplicación en el caso de Airbnb en la Comunidad Valenciana

RESUMEN: El empleo del aprendizaje automático es cada vez más frecuente para explicar la competitividad de las empresas. La literatura nos muestra cómo la inteligencia artificial puede ayudar a empresas a mejorar su conocimiento de los usuarios, optimizar los precios o guiar a los compradores en su proceso de elección.
Para confirmar que aplicando modelos de inteligencia artificial se permite obtener específicamente mejores procedimientos de optimización de precios respecto a otros modelos tradicionales, se estudian más 10.000 propiedades de Airbnb en las tres capitales de la Comunidad Valenciana (Valencia, Alicante y Castellón), observando que los resultados obtenidos con el modelo de redes neuronales artificiales son significativamente más satisfactorios que con el empleo de modelos hedónicos.

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Clasificación JEL: O32; L83; R1.

Palabras clave: aprendizaje automático; Airbnb; turismo; precios hedónicos; región valenciana.

1. Artificial intelligence as a way of maximizing profits and prices in the tourism sector

Autonomous and dynamic pricing in digital markets is a practice that started gaining in popularity more than a decade ago, thanks to the huge volume of past and real-time data available to many companies (Kutschinski *et al.*, 2003). Until relatively recently, as Lawrence (2003) points out, sellers could barely use their experience or intuition to price goods and services with a view to maximising results. E-commerce and increased access to data, however, has made it possible to establish an infrastructure for sellers with the potential for generating dynamic prices based on three key elements: time (temporary dynamic pricing), buyers (price differentiation) or bundling with other products or services (product differentiation).

The air transport market is a good example to look at when trying to understand this development: from an ocean of data and its management through artificial intelligence, a host of price maximization and differentiation processes can be carried out. According to Piga and Filippi (2002), Mantin and Koo (2010), Malighetti *et al.* (2010), Bachis and Piga (2011) and Moreno-Izquierdo *et al.* (2015), when dealing with the same product (seats on a flight), airlines use algorithms in which, as well as taking costs into account, they optimize the dates, the moment of purchase, the volume of sales made to date, or even specific interest in a certain destination.

This same strategy can be seen in other sectors, and not just those related to tourism, as companies are increasingly able to collect, manage and analyse data, presenting models and tools for optimising and maximising performance per user that are increasingly precise, as pointed out by Webb *et al.* (2001) or Albretch *et al.* (2007). The use of machine learning has been well studied for years; for example, in recommendations to users on goods or services in which they have shown interest (Jennings and Higuchi, 1993; Billsus and Pazzani, 1999); Alspector *et al.*, 1997), e-mail forwarding (Macskassy *et al.*, 1999), modification of means of communicating with web users (Litman and Pan, 2000) or the establishment of chatbots to speed up and improve responses to customers (Shawar and Atwell, 2007). This scientific research, however, cannot always be put into practice in companies. Although increasingly accurate artificial intelligence predictive models are being tested, according to Lang (1995) not all of these applications are profitable, since the extra profit that can be obtained from greater predictive capacity does not always exceed the investment necessary.

In the case of the tourism sector, as pointed out by Yu and Schwartz (2006) and Claveria and Torra (2015), there has been intense development in research techniques and a growing interest in artificial intelligence over the last decade in response to issues with profitability and sustainability. Ye *et al.* (2009) used comments left by tourists on websites (blogs, forums, wikis...) to conduct a sentiment analysis on seven destinations: New York, Los Angeles, Las Vegas, London, Rome, Paris and Venice. Chen and Wang (2007) and Clavería *et al.* (2016) analysed different models to contrast the predicted volume of tourist arrivals to help policymakers propose strategies and decisions to gain a competitive edge in China and Spain respectively. Meanwhile, Akın (2015) used data on the volume of tourists arriving in Turkey to try to create models for demand through different machine learning models, seeking to achieve greater profitability per foreign tourist for a country that is increasingly dependent on international arrivals. Another noteworthy example is the article by Yang *et al.* (2015), who used different machine learning algorithms to predict the success of hotel locations in the city of Beijing, identifying potentially profitable areas for the construction of new hotels based on information from existing hotels, businesses in the area, traffic density or the existence of metro stations, among other variables.

This evolution shows that, while we are talking about a relatively young field of research, Jordan and Mitchell (2007) acknowledge that it is expanding fast, and the practical applications often exceed expectations. There are, however, still many new challenges to be overcome, in particular those related to the way in which the machines themselves learn, their interaction in complex systems of various devices and within their own architecture, or the processing of public and private user data.

So how does this apply to the case at hand? At Airbnb, artificial intelligence and machine learning are essential in order to explain the development of its business model. Chang (2017), in an article published on the Airbnb website itself, details how Airbnb's algorithms have been built to determine the rental price of real estate on any given date. Approximately 150 variables are analysed, including the location (country, market, neighbourhood), the average price on each date (price of stay, extra cleaning costs), availability of the properties, or their quality (number of reviews, user ratings), among a multitude of others. In addition, in all the information that Airbnb manages, Natural Language Processing (NLP) is being used to decipher the guest comments, host descriptions, and interaction between users, as described in Laurent *et al.* (2015), in order to obtain more information with a view to optimising the platform.

Equally, Ifrach (2015) points out how Airbnb uses machine learning to detect owner preferences, not just those of tenants or users of the service. According to Webb, Pazzani and Billsus (2001), observation of user behaviour patterns can provide useful examples for training artificial intelligence systems and thus create models for predicting future user behaviour. In this case, at Airbnb we find two different types of customers (tourists and owners), with patterns that are in many cases polar opposites, which adds complexity to the task of designing algorithms. That being said, machine learning has helped to significantly improve *matches* between hosts and guests using recommendations based on the behaviour of both hosts and guests, revealing preferences that went beyond having the properties occupied for a maximum amount of time.

Following the same line, Rystad, V. *et al.* (2017) remind us how the use of machine learning allows us to improve the value proposition for customers, using Airbnb as an example of the different objectives pursued through the creation of artificial intelligence algorithms. Specifically, for the improvement of peer-2-peer interaction, customisation of user experience, co-creation of content by hosts and guests, search engine optimisation, trust between users and simplification of processes.

Having arrived at this point and with real big data and artificial intelligence applications that seem to be effective in cases such as these, different authors have begun to make comparisons between econometric and machine learning models to determine which of them have greater predictive capacity. In our case, and in addition to the previous articles such as Selim (2011), Limsombunchai *et al.* (2004) or Peterson and Flanagan (2009) that we will cite below, we will compare the results obtained through a hedonic price model with those of an artificial neural network model for a base of more than 11,000 homes offered on Airbnb in three Spanish Mediterranean destinations: Alicante, Valencia and Castellón. In determining the model, more than twenty variables have been taken into account, which include both elements specific to the property and others from the social, economic and touristic environment of the destinations studied. In order to do this, a methodological comparison will then be made and the data will be analysed on the basis of both models. The results show, as expected, that the neural network model is more robust.

2. Hedonic Price Models and Artificial Neural Networks

2.1. Hedonic prices

When determining a property's value, whether it be for rent or sale, the hedonic pricing model has been one of the most widely used methods for decades, with the understanding that pricing is based on a range of components that contribute a certain value to the final good (Rigall-I-Torrent, R. *et al.*, 2011). At first glance, it is impossible to determine all the attributes that make up a product, since not only physical or measurable factors must be taken into account, but also psychological or temporal ones, for example. The methodology of hedonic prices allows us to estimate the value contributed by each of the attributes (physical or otherwise) to a property, and to make predictions about the behaviour of the rest of the properties when any of these elements vary.

The methodology of hedonic prices is particularly useful for measuring the impact of specific elements on the value of goods or services through a multiple regression analysis. In this way, the function of the price (P) that picks up each one of the characteristics or elements can be expressed as:

$$P_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + ... + \beta_j X_{ji} + e_i,$$

where P_i is the price of good i, and each of the βX_i the characteristics defined with their corresponding regression coefficients. Finally, as is obvious, «*e*» represents the margin of error.

This method has been used to determine the value of price components since the 1930s, and in the case of the tourism sector it has been used to determine the price of hotel rooms (Espinet *et al.*, 2003; Rigall-i-Torrent *et al.*, 2011), private rental properties in holiday areas (Hamilton, 2007; Portolan, 2013), or Bed and Breakfasts (Monty and Skidmore, 2003), among others.

In recent years, it has also notably been applied to estimate the value of different attributes in price composition on the Airbnb platform, by experts like Dogru and Beijing (2017), Gibbs *et al.* (2018), Chen and Xie (2017) or Wang and Nicolau (2017), who mainly study attributes of homes such as parking facilities, washing machines, dishwashers,... but also include variables related to social reputation; others, like Ert *et al.* (2016) and Teubner *et al.* (2017), focus on issues such as the photographs that owners upload to the platform, their star rating or owner response. These studies show how the sharing of information by potential customers, in addition to direct interaction between owners and guests —without intermediation— constitute what was a non-existent value-add in the tourism sector prior to its digitalization.

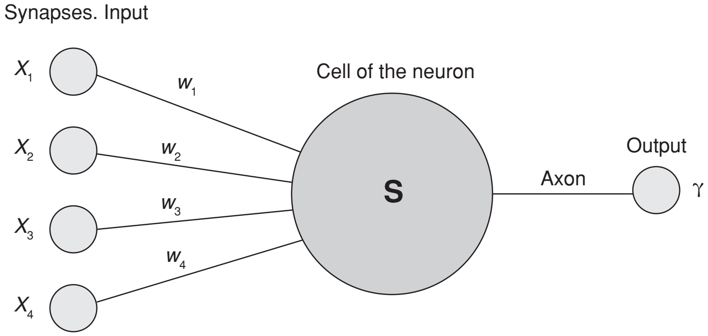
2.2. Artificial Neural Networks

The Artificial Neural Networks (ANNs) model, on the other hand, was born as part of research in the field of artificial intelligence, which was trying to model the structure of the human brain and reproduce biological nervous systems' capacity to study and correct errors. In a manner of speaking, AANs is an artificial intelligence model designed to replicate the processes of the human learning brain, generalise results and respond in the most rational way possible in cases of absence or ignorance of data (Shaw, 1992).

Neural networks make it possible to create and recognize patterns and provide the capacity to process information that incorporates random components, with the possibility of implementation in traditional statistical techniques (Otero and Trujillo, 1993). This is because distributions generated by non-linear and non-Gaussian processes are more robust, based on less strict forms of distribution and have the capacity to adapt or learn in changing environments (Lippman, 1987).

Put simply, we can represent neurons as systems formed by a branched information input structure (dendrites), the nucleus and the branch output (axon), as can be seen in Figure 1. In the structure of the brain, the axons of some neurons are connected to the dendrites of others through synapses, one neuron being activated to another from certain volumes and intensities of emitted-received signals (activation threshold). This construction founded on a large number of simple elements allows our brain to solve extremely complex problems, since each of the neurons takes a weighted sum of input signals, and in the event that the total input exceeds a certain level, it transmits the signal to new neurons.

Figure 1. Functioning of a neuron

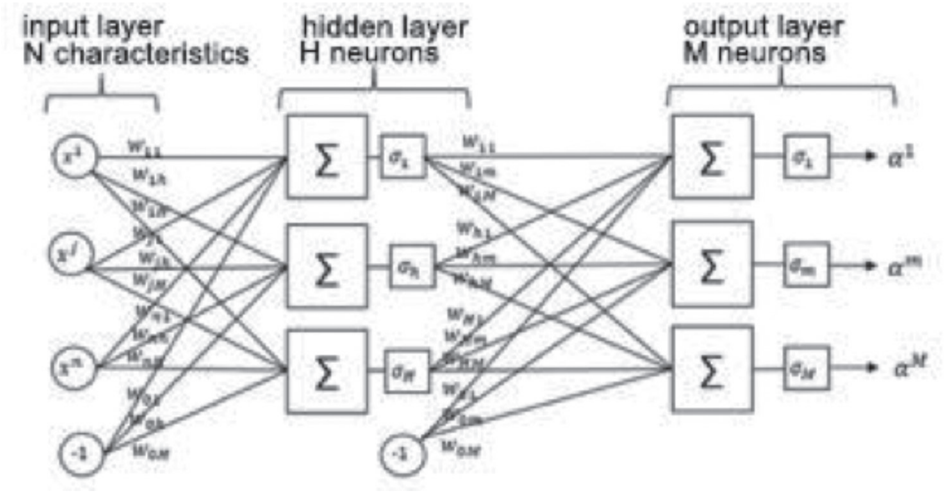


The most common neural network model, reflected in James and Carol (2000) (Figure 2), has three main components and three layers: the input data layer, the hidden layers -with the weighted summation functions and transformation function, and the output layer. These processes have a large number of interconnections between the nodes that form the layers. Through the information network, the first layer of nodes is the one that receives the data input, transferring it to all the nodes that make it up and once this information is collected by each one, it is adapted and transformed by means of a predefined function. This transformation will be the output transferred to the next layer, in turn becoming the input received by all the nodes in the second layer through all the interconnections, until it reaches the last layer, where each element receives information from the elements of the previous layers and provides an output in a non-linear process.

So, neural networks are universal function approximators, a concept used by Hornik, Stinchcombe, and White (1989), and their predictive capacity increases with the number of layers and the number of neurons in them, although generally two or three layers would be sufficient to solve the vast majority of the practical tasks of classification, regression and prediction. With this, authors such as Otero and Trujillo (1991) were able to demonstrate that neural networks can compete without significant disadvantages with the best traditional statistical model when it comes to generating multi-period predictions.

Unlike the hedonic pricing model, ANN methodology allows non-linear relationships between variables to be found and therefore can potentially provide better predictive capacity than multivariate analysis, according to Wilson *et al.* (2002). Other authors, such as Claveria and Torra (2014) showed that they have a great capacity for prediction, but that the ARIMA models surpassed them in predicting tourist demand, although they do admit that the results of neural networks can be improved through structure optimization and the incorporation of additional memory values.

Figure 2. Functional structure of the neural network model



The aim of this study is to compare the two models in order to determine which of them is the most robust in terms of predicting the value of rental properties on the Airbnb platform. This comparison exercise has already been carried out by some previous authors, such as Selim (2011) in the Turkish market for the value of properties in 2004, in which he compared the prediction results obtained between the hedonic regression and the artificial network models and demonstrated the potential of the latter to be a better alternative than the former in predicting the price of housing. A similar result was reached in the study for 200 properties in New Zealand carried out by Limsombunchai *et al.* (2004), in which the effect of factors such as the size of the property, the number of bedrooms or its location, among others, was again analysed by hedonic regression and neural networks. Peterson and Flanagan (2009) once more emphasized that artificial neural networks generated fewer errors in predicting home value prices for a sample of more than 45,000 homes in North Carolina. However, it has not been applied to date in a comparison between tourist rental properties, as is the case with Airbnb.

3. Data used for the study and results of the models

The goal of this study is to estimate rental value on Airbnb through a series of defined attributes about the apartment itself, as related to the city in which the property is located. The sample includes the apartments offered on Airbnb in the three provincial capitals of the Valencian Community (Alicante, Valencia and Castellón) during the months of May 2016 to May 2017. Valencian Community is one of the most important tourist sun-and-beach destinations in Europe, receiving more than nine million tourists per year. However, the three capitals of the region combine sun-and-beach conditions with a complete service supply (such as universities or public and private hospitals), and highly-rated cultural activities, historic monuments and famous restaurants. That implies relevant differences in the Airbnb composition with respect to those destinations completely dependent on sun-and-beach tourism: The three capitals cities have a lower seasonality of the tourism demand, and a less ratio of second homes than the average of the Region of Valencia (36%).

In all the three cities studied (specially in Alicante and Valencia) there have been a great increase of properties published in Airbnb since 2014, combining both full apartments and rooms (full and shared). However, there is a big number of these properties that have been never rented. This is a normal situation in collaborative economy markets where there is an oversupply of goods (apartmets) and full information.

Because of that, of all the homes that were offered May 2016 to May 2017 in the Valencian Community, only those that were rented for at least one day were taken into consideration, leaving out those that were inactive on Airbnb. Our dependent variable will therefore be the average rental price, taking into account only those properties that were rented for at least a day within the period being referred to.

In short, with regard to the estimation of the models, 8,096 properties in the city of Valencia, 2,988 properties in the city of Alicante and 299 properties in Castellón have been taken into consideration, each displaying significant differences. In the city of Castellón, for example, single or shared room rentals predominate over complete properties (56% compared to 44%), while in Valencia, complete properties account for 60% of the supply and in Alicante they account for 70%.

Although these total numbers may seem very high, we must remember that the collaborative economy is based on a basic assumption of «excess supply» (Moreno-Izquierdo *et al.*, 2015) and in this case it can be clearly observed by looking at the occupancy rate. In the case of Castellón, the average occupancy rate of the properties is 40%, and 30% in the case of single and shared rooms. In the case of Alicante, we see a 43% occupancy rate for the complete apartments, and 35% for the rooms. And as for Valencia, there is an occupancy rate of 48% in the case of complete buildings, and 40% in the case of room rental.

According to the data obtained from AirDNA, as well as from the statistical databases of the National Statistics Institute of Spain and the *Generalitat Valenciana*, the following variables for the study of pricing in the apartments offered on Airbnb in the three capital cities referred to (Table 1) were defined:

Table 1. Variables used for the exercise

Variable	*Meaning*	*Source*	*Mean*	*SD*
Properties	Number of properties belonging to the owner	AirDNA	7.413	18.011
Superhost	If the owner has a good reputation on Airbnb	AirDNA	0.102	0.303

Variable	*Meaning*	*Source*	*Mean*	*SD*
Population	Inhabitants in the area of the study	INE	653,316.96	216,257.03
GDPpc	GDP per capita in the study destination	GVA	14,258.17	572.87
Sec/Main	Volume of secondary properties in relation to the total number of properties	GVA	9,997	3,221
Hot/Pop	Volume of hotel beds in relation to the total population	GVA	2.029	0.107
Apt/Pop	Volume of non-hotel beds in relation to total population	GVA	0.030	0.006
Entire home	(dichotomous)	AirDNA	0.632	0.480
Private room	(dichotomous	AirDNA	0.367	0.479
Shared room	(dichotomous)	AirDNA	0.006	0.077
Bedrooms	Number of bedrooms	AirDNA	1.756	1.043
Bathrooms	Number of bathrooms	AirDNA	1.337	0.561
MinStay	Minimum authorised stay	AirDNA	4.119	119.63
BusReady	Advertised for companies	AirDNA	0.064	0.245
N.Reviews	Number of reviews left on Airbnb	AirDNA	14.125	25.800
Overall Rate	Guest ratings	AirDNA	4.520	0.555
OccRate	Occupancy rate for the property	AirDNA	0.441	0.257
T.Rented	Times the property or room has been rented	AirDNA	14.856	18.642
CancelStrict	Strict cancellation policy	AirDNA	0.355	0.478
CancelModerate	Moderate cancellation policy	AirDNA	0.294	0.455
CancelFlexible	Flexible cancellation policy	AirDNA	0.342	0.475
CancelSuperStrict	Extremely strict cancellation policy	AirDNA	0.001	0.037
N.Photos	Number of photos the owner has put on Airbnb	AirDNA	18.361	12.876

3.1. Comparing of obtained results

Once the theoretical basis of both models has been introduced, in this case study, to work the models correctly, we proceeded to divide the sample randomly: 70% of the observations are aimed at the training stage of the models, while the remaining 30% is used to test the quality of the results.

After determining the variables that form part of the estimate, two regressions of hedonic models are performed through the Ordinary Least Squares method, in the first case with Classical Standard Errors, and in the second with robust errors consistent with Heterocedasticity. The model therefore looks like this:

$$\begin{gathered} P_i = \beta_0 + \beta_1 Properties + \beta_2 Superhost + \beta_3 Population + \beta_4 GDPpc + \\ + \beta_5 Sec/Main + \beta_6 Hot/Pop + \beta_7 Apt/Pop + \beta_8 Entire\ home + \beta_9 Private\ room + \\ + \beta_{10} Bedrooms + \beta_{11} Bathrooms + \beta_{12} MinStay + \beta_{13} BusReady + \beta_{14} N.Reviews + \\ + \beta_{15} Overall\ Rate + \beta_{16} OccRate + \beta_{17} T.Rented + \beta_{18} CancelStrict + \\ + \beta_{19} CancelModerate + \beta_{20} CancelFlexible + \beta_{21} N.Photos + e_i \end{gathered}$$

with 21 variables that bring together different facts about the properties of the apartment, but also about the cities used for the study.

The results obtained by hedonic regression are shown in Table 2, with two different models depending on the robustness of the errors. Three of the five variables related to the city structure are omitted from the results of the two estimated models because of their relationship with the variable «per capita income». This indicates that the structure of tourism supply in these cities is, in turn, closely linked to the average income of their inhabitants. It is worth indicating that in subsequent tests carried out, as the number of cities in the model increased, these variables did reflect results in the model.

Table 2. Hedonic price estimation results

Variable	*Model 1:Classical Standard Errors*	*Model 2: Heterocedasticity HC1 consistent errors*
Properties	.4355309***	.4355309***
Superhost	.5838822	.5838822
Population	2.42e-06	2.42e-06
GDPpc	.0008722	.0008722
Sec/Main	(omitted)	(omitted)
Hot/Pop	(omitted)	(omitted)
Apt/Pop	(omitted)	(omitted)
Entire home	55.4549***	55.4549***
Private room	16.16067***	16.16067***
Bedrooms	11.21321***	11.21321***
Bathrooms	25.80606 ***	25.80606 ***
MinStay	–.0017646***	–.0017646***
BusReady	2.04221	2.04221
N.Reviews	–.0459272**	–.0459272**

Variable	*Model 1:Classical Standard Errors*	*Model 2: Heterocedasticity HC1 consistent errors*
Overall Rate	5.15262***	5.15262***
OccRate	–32.8399***	–32.8399***
T.Rented	–.0075623	–.0075623
CancelStrict	12.01599*	12.01599*
CancelModerate	8.743345	8.743345
CancelFlexible	8.336936	8.336936
N.Photos	.4763268***	.4763268***
N: *Adj R-squared* *F-Test*	8877 0.4957 485.65***	8877 0.4967 482.57***

*** = 99% significance (p-value less than 0.001).
** = significance at 95% (p-value less than 0.05).
* = significance at 90% (p-value less than 0.1).

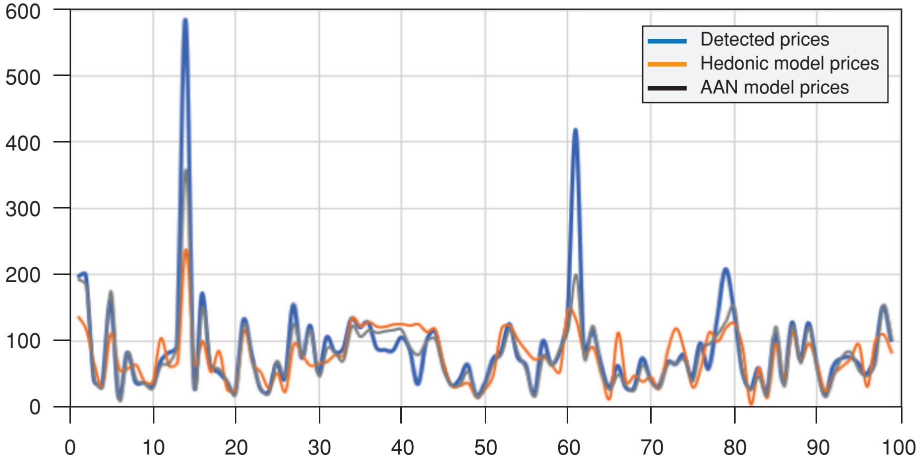
The model presented shows good accuracy, with most of the variables selected displaying a 99% significance, especially those related to the properties of the rental homes. Likewise, the F-Fisher test also performed at a confidence level of 99%. While it is true that the value of R2 is equal to 0.4967, a value below what has been obtained in articles made in similar years, this is due to the lack of significance or omission of the values of the variables that situate the context of the properties. In the case of the purchase or rental value of properties, their location or context has a high degree of explanation, and for reasons already explained our hedonic model is unable to reflect, based on the variables chosen, this relationship.

This difference in accuracy can be seen in Graph 1, where the price taken as a dependent variable is compared with the estimate under the model with robust errors. Taking 100 random values from the sample for a clear representation, we can see how there are certain properties in which the real price is much higher than the estimate, indicating this lack of explanation in the variables used in the model. In the same graph, we can also observe how the estimate made using the neural network model has better accuracy with respect to the prices used as our dependent variable.

In the process of developing our artificial neural network, a network of three layers is selected with activation functions in the neurons in sigmoid or logistic type hidden layers. This kind of neural network usually gives the best results in these types of exercises according to the literature mentioned in this article. To find the Airbnb rental price, the same set of variables that define our hedonic model are taken as inputs, and this set of data is used to train our model.

In the regularization algorithm, two phases of iterations were established for the elimination of variables with excessively small coefficients within minimums. This method involves smoothing out and eliminating variables with large regularization parameters and free construction of the model with small values. Models with small regularization parameters can be useful if we assume that the variables remaining after elimination are significant for constructing the model.

Graph 1. Comparison of real prices and estimated prices for 100 homes



Previously, we set the work areas of the neurons, which positively affects the obtaining of a more efficient model, since it does not allow the work areas to leave the data area, keeping all neurons operating.

As a result of all of the above, the neural network estimation process was found to be far more satisfactory than using the two observed hedonic models, with an accuracy of 87% versus the 46% obtained with the hedonic regression model. In addition, there was also a decrease in the mean square error, dropping to less than 2,700 with the neural network model, confirming that the application of machine learning models allows companies such as Airbnb to obtain better price optimisation procedures than with other traditional systems.

4. Conclusions

Machine learning models are making great strides in many scientific fields, but they are also making a difference on a business level. Strategies related to communication and marketing, with new gamma systems, the interpretation of user reactions or optimized pricing models, are today considered unthinkable by many companies if not coupled with artificial intelligence and big data models.

In the case of tourism, the emergence of Airbnb in recent years has provided a further example of how machine learning can optimise performance. Unlike air transport, where only one provider (the airline) acts on the basis of its demand information, Airbnb must manage millions of owners and practically the same number of tourists. In other words, they must make it their mission to optimise two key elements: price according to the qualities of the product, and utility of demand in providing the best option to the user.

Airbnb employees themselves acknowledge in various articles published on their website that without machine learning models it would be impossible to maximise performance, and this article, to some degree, gives visibility to that statement. For the data chosen —Airbnb apartments in three Spanish tourist destinations— there can be no doubt that neural networks work better than traditional regression models. This result makes us think first and foremost about relationships between variables that are not only linear, and secondly, about the greater predictability of machine learning models, which only increases with continued use, the amount of data available and the number of variables.

Unfortunately, today it is not so simple for all tourism companies to boast this type of mechanism to optimize their performance: it requires vast quantities of data and processing, as well as experts in data analysis. The tourism sector in sun-and-beach destinations

In addition, two important issues in the practical application of artificial neural networks are still the interpretability of results and the stability of the model, although the solution to these problems may be to strengthen the model by including Boosting and/or Naive Bayesian Classifier algorithms in the assembly.

In short, in the example used for apartment rental on Airbnb, neural networks have led to a considerable improvement in prediction compared to the hedonic price model. On a business level, this can mean a significant competitive advantage, provided that the benefits of its application outweigh the costs of its development.

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