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THE APPRAISAL OF MACHINE LEARNING TECHNIQUES FOR TOURISM DEMAND FORECASTING

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ABSTRACT

Machine learning (ML) methods are being increasingly used with forecasting purposes. This study assesses the predictive performance of several ML models in a multiple-input multiple-output (MIMO) setting that allows incorporating the cross-correlations between the inputs. We compare the forecast accuracy of a Gaussian process regression (GPR) model to that of different neural network architectures in a multi-step-ahead time series prediction experiment. We find that the radial basis function (RBF) network outperforms the GPR model, especially for long-term forecast horizons. As the memory of the models increases, the forecasting performance of the GPR improves, suggesting the convenience of designing a model selection criteria in order to estimate the optimal number of lags used for concatenation.

JEL Classification: C02, C22, C45, C63, E27, R11

Key words: Machine Learning, Multiple-input Multiple-output (MIMO), Gaussian Process Regression, Neural Networks, Forecasting

1. INTRODUCTION

Machine learning (ML) methods are being increasingly used for economic and financial forecasting (Aminian et al., 2006; Chen and Leung, 2005; Kock and Teräsvirta, 2014; Medeiros et al., 2006; Ortega and Khashanah, 2014; Stasinakis et al., 2014; Von Spreckelsen et al., 2014). International tourism is becoming one of the most important economic activities worldwide, and as result there is an increasing interest in the refinement of tourism demand forecasts. A growing body of literature finds evidence in favour of a better predictive performance of ML models with respect to traditional forecasting methods (Adya and Collopy, 1998; Cho, 2003; Xu et al., 2016).

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Statistical learning is based on the construction of computer algorithms that learn through experience. The complex nature of the data generating process of tourism demand explains the increasing use of non-linear approaches such as support vector regression (SVR) and neural network (NN) models for tourism forecasting. Akin (2015), Chen and Wang (2007), Claveria et al. (2016a) and Hong et al. (2011) all find that SVR models outperform autoregressive integrated moving average (ARIMA) models for tourism demand forecasting.

With respect to NN models, the most widely used NN feed-forward topology in tourism has been the multi-layer perceptron (MLP) network (Claveria et al., 2015a; Law, 2000; Lin et al., 2011; Molinet et al., 2015; Padhi and Aggarwal, 2011; Palmer et al., 2006; Pattie and Snyder, 1996; Teixeira and Fernandes, 2012; Tsaur et al., 2002; Uysal and El Roubi, 1999). See Athanasopoulos et al. (2011) and Song and Li (2008) for a thorough review of recent tourism demand forecasting studies.

The Radial Basis Function (RBF) network, is being increasingly used for tourism forecasting. Kon and Turner (2005) implemented a RBF NN to forecast arrivals to Singapore. More recently, Cang (2014) combined RBF, MLP and SVR forecasts of UK inbound tourist arrivals in non-linear models. Subsequently, Çuhadar et al. (2014) compared the forecasting accuracy of RBF to that of MLP networks to predict tourist demand, finding evidence in favour of RBF NNs. A complete summary on the use of NNs with forecasting purposes can be found in Zhang et al. (1998).

Originally devised for interpolation, the Gaussian Process Regression (GPR) model can be regarded as a supervised learning method based on a generalized linear regression that locally estimates forecasts by the combination of values in a kernel (Williams and Rasmussen, 1996). Gaussian process (GP) models allow to specify Bayesian priors on the data and the structure, and therefore the use of kernel analogue for ML.

Another key advantage of GPs over other statistical learning techniques is that they provide full probabilistic predictive distributions, including estimations of the uncertainty of the predictions. These features make GPR an ideal tool for forecasting purposes (Ahmed et al., 2010; Banerjee et al., 2008; Yang et al., 2013).

In spite of the fact that GPs are powerful, non-parametric tools for regression in high dimensional spaces, there are very few previous studies that use GPR for tourism forecasting (Wu et al., 2012; Claveria et al., 2016b). Wu et al. (2012) used a sparse GPR model to predict tourism demand to Hong Kong and found that its forecasting capability outperformed those of the ARMA and SVR models. Claveria et al. (2016b) compared the forecasting performance of a GPR model to that of a MLP NN, obtaining significantly better predictions with the GPR model. For a unifying description of sparse approximations for GPR see Quiñonero-Candela and Rasmussen (2005).

In order to fill this gap, we assess the forecasting performance of several ML models in a multiple-input multiple-output (MIMO) setting for multi-step-ahead time series prediction. Recently, Ben Taieb et al. (2010) presented a MIMO extension of conventional local modelling approaches that allowed to preserve the stochastic properties of the training series in multiple-step-ahead prediction. The main aim of this study is to design a MIMO framework for multi-step-ahead time series prediction with a GPR model.

To assess the forecasting performance of the presented GPR model we compare it to a RBF NN and a MLP NN used as benchmark in a MIMO setting that incorporates the cross-correlations between the inputs (international tourist arrivals to all seventeen regions of Spain) in order to generate a vector of future values (for all markets).

The study is organized as follows. The next section reviews the literature and describes the data. The third section presents the different ML methods applied in the study. Section four describes the experimental settings and reports the results of the multiple-step-ahead forecasting comparison. Finally, conclusions are drawn together with potential lines for future research.

2. BACKGROUND AND DATA

As a result of the growing importance of tourism as a key driver of socio-economic progress, there is an increasing amount of literature about the contribution of tourism to economic growth (Balaguer and Cantavella-Jordá, 2002; Chou, 2013; Durbarry, 2004; Pérez-Rodríguez et al., 2015; Sánchez et al., 2015; Schubert et al., 2011). However, due to the lack of statistical information, most of this research is conducted nationwide.

Despite the fact that most tourism demand forecasting studies are conducted at the national level, some regional studies have been published in recent years. Guizzardi and Stacchini (2015) made use of business sentiment indicators form tendency surveys for real-time forecasting of hotel arrivals at a regional level, improving the forecasting accuracy of structural time series models.

The complex data generating process of tourism demand explains the increasing use of non-linear approaches. As a result, ML methods are experiencing a growing use (Peng et al., 2014). Apart from fuzzy time series models (Tsaur and Kuo, 2011; Yu and

Schwartz, 2006), SVR and NN models are the most commonly used ML techniques for tourism demand forecasting. There is wide evidence in favour of ML methods when compared to time series models for tourism demand forecasting (Cho, 2003; Claveria and Torra, 2014; Law, 2000).

Chen and Wang (2007) forecasted tourist arrivals to China with SVR, back propagation NN and ARIMA models, obtaining the best forecasting results with SVRs. Hong et al. (2011) also obtained more accurate forecasts with SVRs than with ARIMA models. Akin (2015) compared the forecasting results of SVR to that of ARIMA and NN models to predict international tourist arrivals to Turkey, obtaining the best predictions with SVR models when the slope feature was more prominent.

There are not many studies of tourism demand forecasting at a regional level in Spain, and most of them are concentrated in two regions: the Balearic and the Canary Islands. Regarding tourism demand forecasting to the Balearic Islands, Rosselló-Nadal (2001) forecasted turning points in international visitor arrivals to the Balearic Islands using the leading indicator approach, and focusing on the two major source markets, the UK and Germany. By means of regression analysis, Rosselló et al. (2004) provided evidence of the influence of some economic variables on the seasonal distribution of tourist numbers. More recently, Álvarez-Díaz and Rosselló-Nadal (2010) forecasted British tourist arrivals using meteorological variables.

Gil-Alana (2010) analysed the degree of persistence of monthly arrivals in the Canary Islands using different time-series approaches. Gil-Alana et al. (2008) employed seasonal unit roots and seasonally fractionally integrated models to forecast tourist arrivals to the Canary Islands, and found that a simple deterministic model with seasonal dummy variables and autoregressive order one disturbances produced better results over short horizons.

The first study that implemented ML techniques for tourism demand forecasting in Spain was that of Palmer et al. (2006). The authors designed a MLP NN to forecast tourism expenditure in the Balearic Islands, finding that the network provided more accurate forecasts when data had been detrended and deseasonalized. This result coincides with that of Claveria et al. (2017) for Catalonia, who analysed the effects of data pre-processing on the forecasting performance of NN models and found that the predictive accuracy of the models improved with seasonal adjusted data. Palmer et al. (2006) also found that NNs were especially suitable for long-term forecasting, which is in line with previous research by Pattie and Snyder (1996) and Burger et al. (2001).

Medeiros et al. (2008) developed an alternative approach to analyse the demand for international tourism in the Balearic Islands. By using a NN model that incorporated time-varying conditional volatility and daily air passenger arrivals to Palma de Mallorca, Ibiza and Mahon as a proxy for international tourism demand for the Balearic Islands, the authors found that time-varying variances provided useful information regarding the risks associated with variations in international tourist arrivals.

In a recent study, Claveria et al. (2015b) designed a MIMO NN framework to generate predictions for all visitor markets to a destination simultaneously. By using monthly data of tourist arrivals to Catalonia from 2001 to 2012, the authors generated forecasts for one-month, three-months and six-months ahead with three different NN topologies and found that RBF NNs outperformed the rest of the models.

Whilst NN models have been widely used in economic modelling and forecasting, other ML techniques such as GPR have been barely applied for forecasting purposes (Ahmed et al., 2010; Andrawis et al., 2011; Chapados and Bengio, 2007). From a wide range of ML methods, Ahmed et al. (2010) found that an MLP NN and the GPR showed the best forecasting performance on the monthly M3 time series competition data. In a similar exercise, Andrawis et al. (2011) found evidence in favour of a simple average combination of NN, GPR and linear models for the NN5 competition.

GPR models can be regarded as supervised learning methods based on a generalized linear regression that locally estimates forecasts by the combination of values in a kernel (Williams and Rasmussen, 1996). The works of Smola and Barlett (2001), MacKay (2003), and Rasmussen and Williams (2006) have been key in the development of GPR models. By expressing the model in a Bayesian framework, the authors extended GPR applications beyond spatial interpolation to regression problems.

Additional refinements have been proposed by Brahim-Belhouari and Bermak (2004) and Girard et al. (2003), who respectively proposed using a non-stationary covariance function and the knowledge of the variance on inputs in order to improve the forecasting performance of the GPR model. However, up until now applications of GPR have been mostly restricted to a single-input single-output framework.

In this study, we attempt to cover this deficit by applying an extension of the GPR model for MIMO modelling, and assessing its forecasting performance at the regional level. We make use of international tourist arrivals to all seventeen regions of Spain. The MIMO GPR allows modelling the connections in tourism demand to all regions and generate a vectorial forecast. This strategy is cost-effective in computational terms, and seems particularly indicated for regional forecasting.

With this aim, we use monthly data on international tourism demand to Spain. Data are collected from the Spanish Statistical Office (National Statistics Institute – INE – www.ine.es). Our data set for the empirical experiment covers 183 monthly observations of of tourist arrivals at a regional level from 1999:01 to 2014:03. In spite of the fact that the forecasting performance of NNs improves when using deseasonalized data (Nelson et al., 1999), we use the raw data in order to analyse the forecasting accuracy of the models without using any pre-processing. In Table 1 we present the mean annual growth rates of the different regions. The regions that experience a rate of growth above the average (3.7%) are al located in coastal areas of the Mediterranean, showing the asymmetric concentration of tourism is Spain. Sarrión-Gavilán et al. (2015) found a high degree of concentration of tourism flows in the littoral area, generating a persistent imbalance between the littoral and the inland areas.

Table 1. Mean annual growth rate by region (1999:01 to 2014:03)

Region	Mean growth	**Region**	Mean growth
Andalusia	2.0%	Valencia (Community)	4.3%
Aragon	4.3%	Extremadura	2.5%
Asturias	5.1%	Galicia	5.4%
Balearic Islands	1.8%	Madrid (Community)	3.9%
Canary Islands	4.4%	Murcia (Region)	5.1%
Cantabria	3.1%	Navarra	5.7%
Castilla-Leon	2.5%	Basque Country	5.7%
Castilla-La Mancha	-0.1%	La Rioja	2.9%
Catalonia	4.8%		

3. MACHINE LEARNING METHODS

3.1. Gaussian Process Regression (GPR)

GPR was first developed by Matheron (1973) based on the geostatistic works of Krige (1951). The works of MacKay (2003) and Rasmussen and Williams (2006) have been crucial in the development of GPR, which can be conceived as a method of interpolation for which the interpolated values are modelled by a GP governed by prior covariances.

By expressing the model in a Bayesian framework, different statistical methods can be implemented in GP models. Therefore GPR applications can be extended beyond spatial interpolation to regression problems. GPR is used to estimate the weights of observed values form temporal lags and spatial points using the known covariance structures. Detailed information about GPR can be found in Rasmussen and Williams(2006).

The GPR model assumes that the inputs x_i have a joint multivariate Gaussian distribution characterized by an analytical model of the structure of the covariance matrix (Rasmussen, 1996). The key point of the GPR is the possibility of specifying the functional form of the covariance functions, which allows to introduce prior knowledge about the problem into the model. The training set $\mathbf{D} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ is assumed to be drawn from the (noisy) process:

$$y_i = f(x_i) + \varepsilon \qquad \text{with } \varepsilon \sim N(0, \sigma^2) \tag{1}$$

where x_i is an input vector in R^d and y_i is a scalar output in R^1. Therefore we have a $R^d \to R^1$ mapping. For notational convenience, we aggregate the inputs and the outputs into matrix $\mathbf{X} = [x_1, x_2, \ldots, x_n]$ and $\mathbf{y} = [y_1, y_2, \ldots, y_n]$ respectively.

The joint distribution of the variables is the conditional Gaussian distribution:

$$p(y/\mathbf{X}) \sim N(0, K(\mathbf{X}, \mathbf{X}) + \sigma^2 \mathbf{I}) \tag{2}$$

Where I is the identity matrix, and the covariance matrix $\mathbf{K}(\mathbf{X}, \mathbf{X})$ is also called the kernel matrix with elements $K_{ij}(x_i, x_j)$. The kernel function $k(x, x')$ is a measure of the distance between input vectors.

For the kernel function, a common choice is the Gaussian, or squared exponential. In this study we make use of a radial basis kernel with a linear trend to account for the trend component present in most of the time series over the training period:

$$K_{ij} = k(x_i, x_j) = \upsilon^2 \exp\left(-\frac{(x_i - x_j)^T (x_i - x_j)}{2\lambda^2} \right) + \gamma x_i^T x_j + \kappa \tag{3}$$

Where υ^2 controls the prior variance, and λ is a parameter that controls the rate of decay of the covariance by determining how far away x_i must be from x_j for f_i to be unrelated to f_j. Alternative sets of kernels are discussed in MacKay (2003). The hyperparameters $\{\upsilon, \lambda, \gamma, \kappa\}$ are estimated by maximum likelihood in:

$$\log(p(y/x)) = -\frac{1}{2} y^T \left[\mathbf{K}(\mathbf{X}, \mathbf{X}) + \sigma^2 \mathbf{I}\right]^{-1} y - \frac{1}{2} \log\left|\mathbf{K}(\mathbf{X}, \mathbf{X}) + \sigma^2 \mathbf{I}\right| - \frac{n}{2} \log 2\pi \tag{4}$$

Given the training samples (x_i, y_j) and a set of test points $X*$, the objective of GPR is to find the predictive outputs $f*$ with probabilistic confidence intervals. By making use of the Bayesian inference, the joint posterior distribution is:

$$p(f, f^*/y) = \frac{p(y/f)p(f, f^*)}{p(y/X)} \tag{5}$$

The joint prior distribution and the independent likelihood probability both follow a Gaussian distribution:

$$p(f, f^*) = N\left(0, \begin{bmatrix} K_{f,f} K_{f*,f} \\ K_{f,f*} K_{f*,f*} \end{bmatrix}\right) \tag{6}$$

$$p(y/f) = N(f, \sigma^2 I) \tag{7}$$

Where f and $f*$ are subscripts of the variables between which the covariance is computed. The Gaussian predictive distribution $p(f^*/y)$ is characterized by mean μ and variance Σ.

Therefore the GPR model specification is given by equations:

$$\mu = K(X*, X)\left[\mathbf{K}(\mathbf{X}, \mathbf{X}) + \sigma^2 I\right]^{-1} y \tag{8}$$

$$\Sigma = K(X*, X*) - K(X*, X)\left[\mathbf{K}(\mathbf{X}, \mathbf{X}) + \sigma^2 I\right]^{-1} K(X, X*) \tag{9}$$

Where μ is the predicted output, and the variance Σ can be used to estimate confidence levels.

In this study we propose an extension of the model to multiple outputs based on an analogy to radial basis functions. We use a set of univariate predictors followed by a matrix product that takes into account the cross-dependencies of the outputs in order to improve the performance of the GPR. In this case we have a $R^d \rightarrow R^M$ mapping, where M is the dimension of the output. This extension is applied by following a two-step training. First, we independently train each time series, generating supervised forecasts for each output. In the second step, by means of a regularized linear regression (Haykin, 2008), we generate forecasts for each output taking into account their correlations. This procedure is also applied to the NN models.

3.2 Neural Network models

3.2.1 Radial Basis Function (RBF)

Initially proposed by Broomhead and Lowe (1988), RBF networks are hybrid networks that combine both supervised and non-supervised learning. RBF NN are a special class of multi-layer feed-forward architecture with several layers of processing. First, an input layer, modelled as a feature vector of real numbers. Second, a hidden layer, which consists of a set of neurons, each of them computing a symmetric radial function centred each at a centroid μ_j. Finally, an output layer that consists of a set of neurons, one for each given output. The output of the network can be expressed as a scalar function of the output vector of the hidden layer:

$$
\begin{aligned}
& y_t = \beta_0 + \sum_{j=1}^{q} \beta_j g_j(x_{t-i}) \\
& g_j(x_{t-i}) = \exp\left(- \frac{\sum_{j=1}^{p} (x_{t-i} - \mu_j)^2}{2\sigma_j^2} \right) \\
& \{x_{t-i};\, i = 1, \dots, p\} \\
& \{\beta_j;\, \sigma_j;\, j = 1, \dots, q\}
\end{aligned} \tag{10}
$$

Where y_t is the output vector of the NN at time t; x_{t-i} is the input value at time $t-i$, where i stands for the number of lags that are used to introduce the context of the actual observation; g_j is the activation function, which usually has a Gaussian shape; β_j are the weights connecting the output of the neuron j at the hidden layer with the output neuron; μ_j is the centroid vector for neuron j; and the spread σ_j is a scalar that measures the width over the input space of the Gaussian function. We denote q as the number of neurons in the hidden layer, which ranges from 5 to 30, increasing for longer forecasting horizons.

3.2.2 Multi-layer Perceptron (MLP)

MLP networks consist of multiple layers of computational units interconnected in a feed-forward way. MLP networks are supervised neural networks that use as a building block a simple perceptron model. The topology consists of layers of parallel perceptrons, with optimal connections between layers:

$$
\begin{aligned}
& y_t = \beta_0 + \sum_{j=1}^{q} \beta_j g\left(\sum_{i=1}^{p} w_{ij} x_{t-i} + w_{0j} \right) \\
& \{x_{t-i};\, i = 1, \dots, p\} \\
& \{w_{ij};\, i = 1, \dots, p;\, j = 1, \cdots, q\} \\
& \{\beta_j;\, j = 1, \dots, q\}
\end{aligned} \tag{11}
$$

Where y_t is the output vector at time t; x_{t-i} is the input value at time $t-i$; β_j are the weights connecting the output of the neuron j at the hidden layer with the output neuron;. w_{ij} stand for the weights of neuron j connecting the input with the hidden layer; and g is the non-linear function of the neurons in the hidden layer. The number of neurons in the hidden layer is denoted by q, and determines the network's capacity to approximate a given function. In order to solve the problem of overfitting, the number of neurons is estimated by cross-validation.

4. FORECASTING COMPARISON

4.1. Experimental design

For an iterated multi-step-ahead forecasting comparison, the partition between train and test sets is done sequentially: as the prediction advances, past forecasts are successively incorporated to the training database. As the size of the training set increases, for each predicted value in the test database, the first element of the validation database is transferred to the training database, and the last predicted value of the test database is incorporated to the validation database in a recursive way. Thus, the first ninety-six monthly observations are selected as the initial training set, the next 33% as the validation set, and the last 15% as the test set.

Once the topology of the neural networks is decided, the parameters of the networks are estimated by means of the Levenberg-Marquardt (LM) algorithm. In order to assure a correct performance of the RBF NNs, the number of centroids and the spread of each centroid have to be selected before the training phase. In this study, the training is done by adding the centroids iteratively with the spread parameter fixed. Then a regularized linear regression is estimated to compute the connections between the hidden and the output layer. Finally, the performance of the networks is computed on the validation data set. This process is repeated until the performance on the validation database ceases to decrease.

To avoid the possibility that the search for the optimum value of the parameters finishes in a local minimum, we use a multi-starting technique that initializes the NNs several times for different initial random values and returns the best result. All models are implemented with Python.

4.2 Experimental results

To assess the performance of the GPR model, we compare its forecast accuracy to that of a RBF NN. We estimate the models and generate predictions in a recursive way for different forecast horizons (1, 3, 6 and 12 months) during the out-of-sample period. In order to summarise the results of the forecasting comparison, we compute several forecast accuracy measures.

First we obtain the Relative Mean Absolute Percentage Error (rMAPE) statistic for the GPR and the RBF NN with respect to a MLP NN model used as a benchmark (Table 2). Next, we run the Diebold-Mariano (DM) test (Diebold and Mariano, 1995) using a Newey-West type estimator (Newey and West, 1987) to analyse whether the reductions in MAPE between both models are statistically significant (Table 3). Finally, in Table 4 we compute the proportion of Periods with Lower Absolute Error (PLAE) statistic (Claveria et al., 2015b).

The results of the rMAPE for the GPR and the RBF NN models presented in Table 2 show that there are no major differences between both models when compared to a MLP NN. By regions, in the Balearic Islands, Madrid and the Canary Islands the MLP NN is rarely outperformed. Instead, in Cantabria, Castilla-Leon, Castilla-La Mancha, and the Basque Country, both the GPR model and the RBF NN outperform the MLP at all forecast horizons.

In order to test whether the differences between the two competing models are statistically significant, we calculate the DM test (Table 3). The null hypothesis of the test is that the difference between the two competing series is non-significant. A negative sign of the statistic implies that the MLP NN model has bigger forecast errors.

The results of the DM test between the GPR and the RBF NN models presented in Table 3 indicate that only in 18% of the cases we find a significant difference between the absolute forecast errors of the GPR and the RBF NN. In 58% of the cases, the RBF NN shows a significant improvement over the GPR. While in three regions (Cantabria, Catalonia and the Basque Country) the forecast errors of the RBF NN are bigger than the forecast errors of the GPR model, in the rest of the regions the results are mixed.

The improvement of the GPR model with respect to the RBF NN becomes more prominent for short-term forecast horizons (one and three-months ahead predictions). While for six and twelve-months ahead forecasts, the errors of the GPR are bigger than the ones of the RBF NN in 9 out of 17 regions (Andalusia, Aragon, the Balearic Islands, Castilla-Leon, Castilla-La Mancha, Valencia, Galicia, Murcia and La Rioja).

Table 2. Forecast accuracy. rMAPE - GPR and RBF NN vs. MLP NN

	GPR	RBF NN		GPR	RBF NN
Andalusia			**Valencia** (Community)		
h=1	0.823	0.921	h=1	0.945	1.017
h=3	1.059	0.918	h=3	0.948	0.924
h=6	0.971	0.795	h=6	0.966	0.902
h=12	1.197	0.769	h=12	0.972	0.948
Aragon			**Extremadura**		
h=1	0.820	0.935	h=1	0.991	1.106
h=3	0.911	0.976	h=3	1.228	1.307
h=6	1.041	0.928	h=6	0.898	0.741
h=12	0.866	0.850	h=12	0.921	0.961
Asturias			**Galicia**		
h=1	0.767	0.863	h=1	0.845	0.931
h=3	1.072	0.797	h=3	1.068	0.760
h=6	0.871	0.895	h=6	1.065	1.023
h=12	0.859	0.758	h=12	1.064	1.006
Balearic Islands			**Madrid** (Community)		
h=1	0.746	0.755	h=1	1.289	1.134
h=3	1.048	0.526	h=3	1.049	1.092
h=6	1.112	1.507	h=6	1.002	0.917
h=12	2.359	1.671	h=12	0.983	1.015
Canary Islands			**Murcia** (Region)		
h=1	1.148	1.123	h=1	1.061	1.121
h=3	1.002	1.003	h=3	1.073	1.001
h=6	0.933	0.957	h=6	0.920	0.845
h=12	1.055	1.031	h=12	0.919	0.836
Cantabria			**Navarra**		
h=1	0.807	0.835	h=1	0.798	0.928
h=3	0.910	0.715	h=3	1.055	0.952
h=6	0.792	1.045	h=6	1.080	1.082
h=12	0.712	0.586	h=12	0.814	0.827
Castilla-Leon			**Basque Country**		
h=1	0.761	0.966	h=1	0.871	0.914
h=3	0.841	0.797	h=3	0.909	0.914
h=6	0.935	0.933	h=6	0.924	0.945
h=12	0.913	0.818	h=12	0.894	0.954
Castilla-La Mancha			**La Rioja**		
h=1	0.592	0.862	h=1	1.026	1.058
h=3	0.736	0.838	h=3	0.769	0.613
h=6	0.916	0.911	h=6	0.976	0.677
h=12	0.872	0.696	h=12	1.079	0.852
Catalonia					
h=1	0.794	0.948			
h=3	1.063	0.996			
h=6	1.017	0.968			
h=12	0.816	0.872			

Table 3. DM test statistic - GPR and RBF vs. MLP NN

Andalusia		**Valencia** (Community)	
h=1	-2.384	h=1	-1.941
h=3	0.309	h=3	-0.207
h=6	1.619	h=6	1.784
h=12	6.426	h=12	1.138
Aragon		**Extremadura**	
h=1	-1.776	h=1	-1.755
h=3	-1.455	h=3	-1.702
h=6	2.766	h=6	1.747
h=12	0.632	h=12	-1.090
Asturias		**Galicia**	
h=1	-1.846	h=1	-2.733
h=3	0.884	h=3	0.864
h=6	-0.218	h=6	0.666
h=12	1.670	h=12	0.594
Balearic Islands		**Madrid** (Community)	
h=1	-1.941	h=1	2.334
h=3	0.668	h=3	-1.258
h=6	1.161	h=6	1.449
h=12	0.973	h=12	-0.269
Canary Islands		**Murcia** (Region)	
h=1	0.485	h=1	-0.214
h=3	-0.226	h=3	-0.029
h=6	-1.208	h=6	1.169
h=12	0.494	h=12	1.586
Cantabria		**Navarra**	
h=1	-0.437	h=1	-1.300
h=3	0.256	h=3	0.852
h=6	-0.051	h=6	-1.267
h=12	-0.460	h=12	0.788
Castilla-Leon		**Basque Country**	
h=1	-6.729	h=1	-1.626
h=3	-0.557	h=3	-0.960
h=6	1.283	h=6	-0.748
h=12	3.338	h=12	-0.899
Castilla-La Mancha		**La Rioja**	
h=1	-2.848	h=1	-0.459
h=3	-1.792	h=3	-0.325
h=6	0.660	h=6	3.425
h=12	2.325	h=12	2.616
Catalonia			
h=1	-3.758		
h=3	-0.242		
h=6	1.714		
h=12	-0.027		

Note: The 5% level critical value is 2.028

Finally, to attain a more comprehensive forecasting evaluation, we compute the PLAE statistic (Claveria et al., 2015b). The PLAE can be regarded as a variation of the Percent Better measure used in the M3-competition to compare the forecast accuracy of the models to a random walk (Makridakis and Hibon, 2000). The PLAE is a dimensionless measure based on the CJ statistic for testing market efficiency (Cowles and Jones, 1937). This accuracy measure allows us to compare the forecasting performance between two competing techniques against a benchmark model. In this study we use the MLP NN as a benchmark.

The PLAE statistic is a ratio that gives the proportion of periods in which the model under evaluation obtains lower absolute forecast errors than the benchmark model. Let us denote y_t as actual value and $\hat{y}_t$ as forecast at period $t = 1,\ldots,n$. Forecast errors can then be defined as $e_t = y_t - \hat{y}_t$. Given two competing models A and B, where A refers to the forecasting model under evaluation and B stands for benchmark model, we can then obtain the proposed statistic as follows:

$$PLAE = \frac{\sum_{t=1}^{n} \lambda_t}{n} \text{ where } \lambda_t = \begin{cases} 1 & \text{if } |e_{t,A}| < |e_{t,B}| \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

Table 4 shows the results of the PLAE statistic for the GPR and the RBF NN compared to the MLP NN. We do not find relevant differences between the GPR and the RBF NN when compared to the MLP NN. Both the GPR and the RBF NN display higher PLAE values than the MLP NN at all forecast horizons except for one-month ahead predictions, where the MLP NN shows a higher proportion of out-of-sample periods with lower absolute errors in all regions except two (the Balearic Islands and Castilla-La Mancha). Special mention should be made to the Canary Islands and the Community of Madrid, where neither model outperforms the MLP NN regardless of the forecast horizon. These results are in line with those obtained in Table 2.

Table 4. Forecast accuracy. PLAE - GPR and RBF NN vs. MLP NN

	GPR	RBF NN		GPR	RBF NN
Andalusia			**Valencia** (Community)		
h=1	0.364	0.273	h=1	0.182	0.910
h=3	0.273	0.545	h=3	0.273	0.455
h=6	0.455	0.545	h=6	0.364	0.455
h=12	0.818	0.818	h=12	0.636	0.727
Aragon			**Extremadura**		
h=1	0.273	0.273	h=1	0.182	0.182
h=3	0.545	0.727	h=3	0.273	0.727
h=6	0.727	0.545	h=6	0.727	0.818
h=12	0.636	0.727	h=12	0.909	0.818
Asturias			**Galicia**		
h=1	0.182	0.182	h=1	0.910	0.910
h=3	0.545	0.909	h=3	0.636	0.818
h=6	0.818	0.818	h=6	0.818	0.909
h=12	0.818	0.818	h=12	0.909	0.909
Balearic Islands			**Madrid** (Community)	.	
h=1	0.545	0.545	h=1	0.000	0.182
h=3	0.818	0.909	h=3	0.182	0.182
h=6	0.909	1.000	h=6	0.182	0.273
h=12	1.000	1.000	h=12	0.000	0.000
Canary Islands			**Murcia** (Region)		
h=1	0.000	0.000	h=1	0.910	0.182
h=3	0.000	0.000	h=3	0.364	0.545
h=6	0.000	0.000	h=6	0.364	0.455
h=12	0.000	0.000	h=12	0.636	0.818
Cantabria			**Navarra**		
h=1	0.364	0.364	h=1	0.182	0.910
h=3	0.818	0.909	h=3	0.545	0.818
h=6	0.818	0.909	h=6	0.636	0.727
h=12	1.000	0.909	h=12	0.727	0.636
Castilla-Leon			**Basque Country**		
h=1	0.545	0.910	h=1	0.182	0.182
h=3	0.636	0.909	h=3	0.273	0.455
h=6	0.727	0.818	h=6	0.545	0.455
h=12	0.909	0.909	h=12	0.910	0.273
Castilla-La Mancha			**La Rioja**		
h=1	0.636	0.545	h=1	0.182	0.273
h=3	0.727	0.909	h=3	0.727	0.909
h=6	0.818	0.818	h=6	0.727	0.727
h=12	0.818	0.818	h=12	0.818	0.909
Catalonia					
h=1	0.273	0.910			
h=3	0.36.4	0.545			
h=6	0.818	0.818			
h=12	0.727	0.727			

Note: The PLAE ratio measures the proportion of out-of-sample periods with lower absolute errors than the benchmark model (MLP NN model). Values below 0.5 indicate that the benchmark model displays a higher number of lower absolute forecast errors than the model under evaluation for the out-of-sample period.

In order to evaluate the effect of the memory on forecast accuracy, we repeat the experiment considering different topologies regarding the number of lags used for concatenation. In Table 5 we present the results of the rMAPE and the DM test for the GPR model comparing a one-period memory to $i=3$. We find that when additional lags are incorporated in the feature vector, the rMAPE results show that the forecasting performance of the GPR models improves in almost 70% of the cases.

Table 5. Forecast accuracy. rMAPE and DM test statistic - GPR($i=1$) vs. GPR($i=3$)

	rMAPE	DM		rMAPE	DM
Andalusia			**Valencia** (Community)		
h=1	1.264	-3.828	h=1	1.162	-1.341
h=3	1.685	-5.386	h=3	1.231	-2.429
h=6	1.151	-4.619	h=6	1.123	-3.153
h=12	1.498	-2.113	h=12	1.084	-2.744
Aragon			**Extremadura**		
h=1	0.914	-0.376	h=1	1.048	-0.685
h=3	1.200	-2.204	h=3	1.374	-1.863
h=6	1.022	-2.294	h=6	0.930	-2.259
h=12	1.089	2.192	h=12	0.827	-1.933
Asturias			**Galicia**		
h=1	0.805	-1.301	h=1	0.866	-1.536
h=3	1.569	-2.823	h=3	1.188	-3.409
h=6	1.149	-2.517	h=6	0.988	-2.314
h=12	1.108	0.660	h=12	0.759	-0.400
Balearic Islands			**Madrid** (Community)		
h=1	0.770	-1.102	h=1	1.206	0.361
h=3	1.378	-3.404	h=3	1.123	0.325
h=6	0.529	-3.553	h=6	1.066	0.950
h=12	0.964	-0.239	h=12	1.023	0.962
Canary Islands			**Murcia** (Region)		
h=1	0.960	2.768	h=1	1.208	-0.007
h=3	0.947	0.891	h=3	1.641	-3.069
h=6	1.042	0.256	h=6	1.263	-4.365
h=12	1.092	-0.898	h=12	1.088	-3.397
Cantabria			**Navarra**		
h=1	0.944	-2.499	h=1	0.767	-1.395
h=3	1.396	-3.326	h=3	1.356	-3.052
h=6	1.062	-3.798	h=6	1.021	-2.534
h=12	0.940	0.058	h=12	0.843	2.110
Castilla-Leon			**Basque Country**		
h=1	0.855	-1.948	h=1	1.049	-2.142
h=3	1.147	-4.885	h=3	1.160	-1.760
h=6	0.871	-3.150	h=6	1.066	-1.416
h=12	0.875	1.040	h=12	1.071	1.008
Castilla-La Mancha			**La Rioja**		
h=1	1.006	-2.987	h=1	0.932	-0.533
h=3	1.250	-4.548	h=3	1.246	-3.585
h=6	1.165	-3.781	h=6	1.001	-3.221
h=12	0.859	-2.239	h=12	1.276	-0.046
Catalonia					
h=1	0.887	-1.635			
h=3	1.372	-2.107			
h=6	1.055	-1.683			
h=12	1.068	2.405			

Note: The 5% level critical value is 2.028

In Table 5, we also present the results of the DM test between the GPR with a one-period memory and the GPR with a three-period memory. We find that in 54% of the cases there is a significant difference between the absolute forecasting errors of the GPR for i =1 and the GPR for i =3. In 90% of the cases, incorporating additional lags results in a significant improvement. Madrid and the Canary Islands are the only regions where there is no significant reduction in forecast errors when increasing the memory of the models. The fact that both regions are the ones with the lowest temporal concentration of tourism demand suggests that increasing the memory of the models is particularly indicated when the series present a marked seasonal component. This evidence is in line with the results obtained by Claveria et al. (2016b), who found that GPR models could not outperform naïve forecasts in the absence of seasonality regardless of the forecast horizon.

Overall, the empirical experiment shows that the forecasting performance of the different techniques improves for longer forecast horizons. For the Balearic Islands, Palmer et al. (2006) found that NNs were especially suitable for long-term forecasting, which is in line with previous research by Burger et al. (2001), Pattie and Snyder (1996) and Teräsvirta et al. (2005). However, we find that the RBF NN generates better predictions than the GPR models when compared to a MLP NN, especially for longer-term forecast horizons. This output suggests that RBF networks are better able to capture the seasonal pattern of the series than interpolation methods such as the GPR model. Cang (2014), Claveria et al. (2015a) and Çuhadar et al. (2014) also obtained better results with RBF networks than with other NN architectures for seasonal forecasting.

The GPR model only outperformed the RBF NN for short-term forecast horizons. Wu et al. (2012) obtained better forecasting results with a sparse GPR model than with ARMA and SVR models. Notwithstanding, in this study we apply a MIMO approach and use a NN model as a benchmark. Besides, due to the size of the sample, we do not apply any sparse approximation to reduce the computational complexity of the GPR model.

Overall, the forecasting performance of the different techniques improves for longer forecast horizons. Ben Taieb et al. (2010) and Claveria et al. (2015b) also found evidence that MIMO strategies for ML techniques are particularly suitable for long-term forecasting.

5. CONCLUSION

In this study we assess the forecasting performance of several ML models in a MIMO framework. We compare the out-of-sample predictive accuracy of a GPR model to that of two NN architectures (RBF and MLP) in a multiple-step-ahead forecasting comparison. The MIMO forecasting strategy allows modelling the interdependencies between the inputs in order to generate a vector of future values. By using the cross-correlations between tourist arrivals to all seventeen regions of Spain we forecast tourist demand for all markets simultaneously.

The forecasting results show that the GPR model only outperforms NN models for short-term forecasts. We find that the predictive performance of all techniques improves for the longest forecast horizons, which suggests that ML techniques are especially suitable for mid and long-term forecasting.

To evaluate the effect of an increase in the dimensionality of the input on forecast accuracy, we repeat the experiment by increasing the temporal context. As we increase the number of lags used for concatenation, we find that the forecasting performance of MIMO GPR models improves. This finding shows that the increase in the weight matrix is compensated by a more complex specification, and highlights the convenience of designing a model selection criteria to estimate the optimal number of lags when forecasting with ML methods.

The assessment of alternative kernel functions on the forecasting accuracy of GPR models is a question to be addressed in further research. Another question to be considered in future research is the effect of different sparse approximations for parameter estimation on forecast accuracy.

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