
“A regional perspective on the accuracy of machine learning forecasts of tourism demand based on data characteristics”

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Abstract

In this work we assess the role of data characteristics in the accuracy of machine learning (ML) tourism forecasts from a spatial perspective. First, we apply a seasonal-trend decomposition procedure based on non-parametric regression to isolate the different components of the time series of international tourism demand to all Spanish regions. This approach allows us to compute a set of measures to describe the features of the data. Second, we analyse the performance of several ML models in a recursive multiple-step-ahead forecasting experiment. In a third step, we rank all seventeen regions according to their characteristics and the obtained forecasting performance, and use the rankings as the input for a multivariate analysis to evaluate the interactions between time series features and the accuracy of the predictions. By means of dimensionality reduction techniques we summarise all the information into two components and project all Spanish regions into perceptual maps. We find that entropy and dispersion show a negative relation with accuracy, while the effect of other data characteristics on forecast accuracy is heavily dependent on the forecast horizon.

JEL Classification: C45; C51; C53; C63; E27; L83.

Keywords: STL decomposition; non-parametric regression; time series features; forecast accuracy; machine learning; tourism demand; regional analysis.

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1. Introduction

The increasing weight of the tourism industry in the gross domestic product of most countries explains the growing interest in the sector from economic circles. Bilen et al. (2015), Brida et al. (2016), Chou (2013), Soukiazis and Proença (2008) and Tang and Abosedra (2016) have recently analysed the relevance of tourism in economic growth. The continuous rise of tourism demand highlights the importance of correctly anticipating the number of arrivals at the destination level. The refinement of tourism demand forecasts has led to an extensive body of research, but in most of these studies data characteristics are overlooked (Kim and Schwartz, 2013).

The main objective of this work is to fill this gap. With this aim we analyse the effect of time series features of international tourist arrivals to the different Spanish regions on the forecast accuracy derived from a multiple-step-ahead forecasting evaluation. Spain is one of the world's top tourist destinations after France and the United States. The country received more than 86 million tourist arrivals in 2017, which represents an 8.9% increase in relation to 2016 (Spanish Statistical Office – <http://www.ine.es>). As a result, Spain has become the world's second most important destination after France. The fact that regional markets present marked differences and have evolved in very diverse forms, has led us to conduct the analysis at a regional level.

The search for more accurate predictions explains that statistical learning methods based on artificial intelligence (AI) are being increasingly used with forecasting purposes. Machine learning (ML) belongs to a subfield of AI that is based on the construction of algorithms that learn through experience. The most commonly used AI-based techniques for prediction are support vector regression (SVR), which can be regarded as an extension of the support vector machine (SVM) mechanism, and neural networks (NNs). In recent years, several authors have found evidence in favour of SVRs and NNs when compared to more traditional time series models (Akin, 2015; Chen and Wang, 2007; Claveria and Torra, 2014; Hong et al., 2011; Xu et al., 2016).

In this study we compare the time series features of tourist arrivals to Spain to the forecasting performance of several ML methods. On the one hand, with the aim of assessing the role of time series features in the accuracy of ML tourism predictions, we use a seasonal-trend decomposition procedure based on non-parametric regression to isolate the different components of the time series of international tourism demand to all Spanish regions and compute a set of measures to describe the features of the data.

On the other hand, we design a recursive multiple-step-ahead forecasting experiment to evaluate the accuracy of the predictions obtained with the different techniques. Specifically, we compare the forecast accuracy obtained with a Gaussian process regression (GPR) model to that of several SVR and NN models. GPR is a statistical learning technique originally devised for spatial interpolation, which has recently been used for time series forecasting (Ben Taieb et al., 2010). Finally, by means of dimensionality reduction techniques we evaluate the interactions between data characteristics of the different regions and the obtained accuracy for different forecast horizons.

The study is organized as follows. The next section reviews the existing literature on tourism demand forecasting with ML methods. In section three, we first describe the data and compute a set of time series features, then we assess the predictive performance of the models in a multiple-step-ahead forecasting experiment in order to evaluate the role of time series features in the accuracy of the predictions by means of a multivariate analysis. Concluding remarks and the potential lines for future research are provided in the last section.

2. Literature Review

There is a growing body of literature about tourism demand forecasting. See Li et al. (2005), Peng et al. (2014), Song and Li (2008) and Witt and Witt (1995) for a thorough review of tourism demand forecasting studies. Most of this research is based on causal econometric models (Cortés-Jiménez and Blake, 2011; Gunter and Önder, 2015; Lin et al., 2015; Tsui et al., 2014), or on traditional time series models (Assaf et al., 2011; Chu, 2009; Gounopoulos et al., 2012; Li et al., 2013). However, the complex data generating process of tourism demand has fostered the use of nonlinear approaches for tourism forecasting.

In this context, ML methods are experiencing a growing use (Zhang and Zhang, 2014). The first AI-based method implemented for tourism demand forecasting were NNs. There are many NN models. The first and most commonly used NN architecture in tourism demand forecasting is the multi-layer perceptron (MLP) (Burger et al., 2001; Claveria and Torra, 2014; Hassani et al., 2015; Kon and Turner, 2005; 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).

MLP are feed-forward networks in which the information runs only in one direction, while in recurrent networks there are bidirectional data flows (Cho, 2003). A special class of feed-forward architecture with two layers of processing is the radial basis function (RBF). The first study to implement a RBF architecture for forecasting tourism demand was that of Kon and Turner (2005), who used a RBF NN to forecast arrivals to Singapore. Cang (2014) generated predictions of UK inbound tourist arrivals and combined them in nonlinear models. Çuhadar et al. (2014) compared the forecasting performance of RBF and MLP NNs to predict cruise tourist demand at the destination level (Izmir, Turkey).

The first implementations of SVMs for tourism demand forecasting were those of Pai and Hong (2005) and Hong (2006), who used SVMs to forecast tourist arrivals to Barbados. The recent extension of the SVM mechanism to regression analysis has fostered the use of SVR models for tourism prediction. Chen and Wang (2007) generated forecasts of tourist arrivals to China with SVR, back propagation NN and autoregressive integrated moving average (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, and found that SVR outperformed NNs in all cases, but ARIMA models only when the slope feature was more prominent.

The works of Smola and Barlett (2001), MacKay (2003), and Rasmussen and Williams (2006) have been key in the development of GPR, which can be regarded as a statistical learning method for interpolation. By expressing the model in a Bayesian framework, GPR applications can be extended beyond spatial interpolation to regression problems. From a wide range of ML methods, Ahmed et al. (2010) found that NN and GPR models 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.

Nevertheless, there are very few studies that implement GPR for tourism forecasting (Claveria et al., 2016a,b; Wu et al., 2012). Claveria et al. (2016b) proposed an extension of the GPR model for multiple-input multiple-output forecasting. Wu et al. (2012) used a sparse GPR model to predict tourism demand to Hong Kong, obtaining better forecasting results than with autoregressive moving average (ARMA) and SVR models.

The first attempt to use statistical learning process for tourism demand forecasting in Spain was that of Palmer et al. (2006), who applied a MLP NN to forecast tourism expenditure in the Balearic Islands. Medeiros et al. (2008) developed a NN-generalized

autoregressive conditional heteroscedasticity model to estimate demand for international tourism to the Balearic Islands. Claveria et al. (2015) compared the performance of three NN architectures in a multiple-input multiple-output setting for generating predictions of tourist arrivals to Catalonia (Spain) from all visitors markets simultaneously, finding that RBF networks provided better forecasting results than the MLP and Elman architectures.

As a result of a comprehensive meta-analysis of recent tourism studies, Kim and Schwartz (2013) have pointed out that the growing interest in refining tourism predictions has not been matched by a similar effort in analysing the effect of data characteristics on forecasting results. To cover this deficit, in this work we aim to shed some light on this issue by focusing on time series features and ML forecasts.

3. Time Series Features

In this section we describe the characteristics of the individual series on international tourism demand to each of the regions of Spain. Data is obtained from the Spanish Statistical Office (National Statistics Institute – INE – www.ine.es) and include the monthly number of tourist arrivals at a regional level over the time period 1999:01 to 2014:03. With the aim of computing time series features, we first apply the “Seasonal and Trend Decomposition using Loess” (STL) procedure proposed by Cleveland et al. (1990) to decompose the seasonal and trend components of the time series. Loess is a locally weighted polynomial regression method originally devised by Cleveland (1979).

STL presents several advantages over the classical decomposition method and X-12-ARIMA: it can handle any type of seasonality, the seasonal component is allowed to change over time, the smoothness of the trend-cycle can be controlled, and it can be robust to outliers (Bergmeir et al., 2016; Hyndman et al., 2016). Given that $Y_t = T_t + S_t + R_t$, where T_t denotes the trend component, S_t the seasonal component and R_t the residual, we can assess the strength of each component by computing:

$$\text{strength of trend} = 1 - \frac{V(R_t)}{V(Y_t - S_t)} \quad (1)$$

$$\text{strength of seasonality} = 1 - \frac{V(R_t)}{V(Y_t - T_t)} \quad (2)$$

We also compute the skewness, the kurtosis, the coefficient of variation, the first autocorrelation (r_1), and two additional statistics: the Box-Cox lambda (λ_1) and spectral entropy (H) for tourism demand to each regional market.

The lambda value indicates the power to which all data should be raised in order to be normally distributed (Box and Cox, 1964). The Box-Cox power transformation searches within the interval $[-5;5]$ until the optimal value is found in:

$$Y_t^{(\lambda)} = \begin{cases} \frac{(Y_t + \lambda_2)^{\lambda_1} - 1}{\lambda_1} & \text{if } \lambda_1 \neq 0 \\ \log(Y_t + \lambda_2) & \text{if } \lambda_1 = 0 \end{cases} \quad (3)$$

Spectral entropy describes the complexity of a system and can be used as a proxy for the predictability of a given time series. Rosselló and Sansó (2017) have recently showed the appropriateness of entropy as a new information tool for tourism seasonality analysis.

H can be computed as:

$$H = -\int_{-\pi}^{\pi} f_y(\omega) \log f_y(\omega) d\omega \quad (4)$$

Where $f_y(\omega)$ is the spectral density of Y_t . Low values of H are indicative of more signal, suggesting that a time series is easier to forecast (Hyndman et al., 2016).

In Fig. 1 we graph the evolution of tourist arrivals in each region from 1999 to 2014, including the three components obtained through STL decomposition. In Table 1 we present the descriptive analysis of the data. We can observe how the time series features notably vary across regions. The Canary Islands present the highest level of strength of trend, but the lowest in terms of the strength of seasonality, Box-Cox lambda, and spectral entropy. On the other hand, the Balearic Islands present the highest values of entropy and dispersion.

Fig. 1. International tourism demand to Spain for each CCAA – STL Decomposition

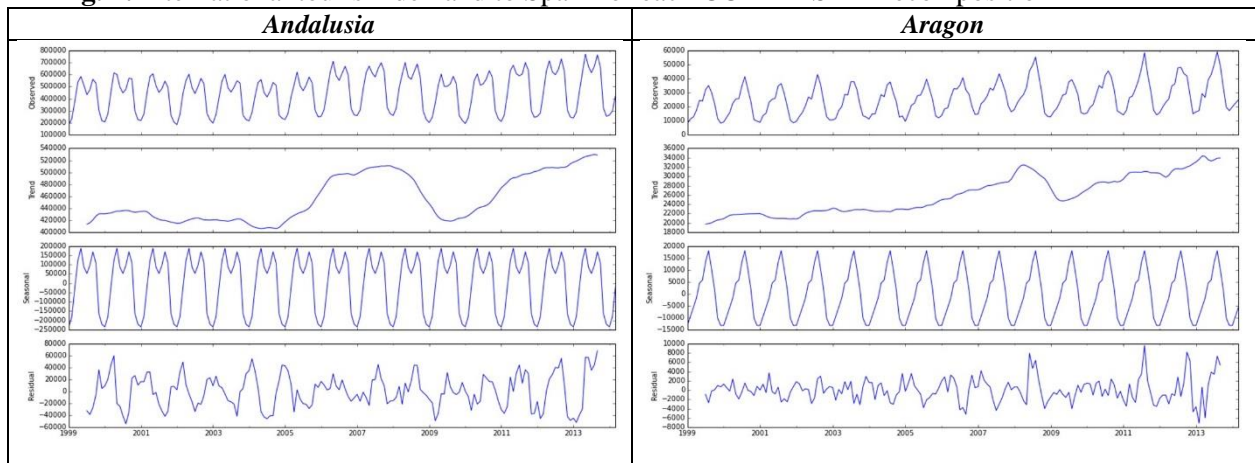


Fig. 1 (cont.). International tourism demand to Spain for each CCAA – STL Decomposition

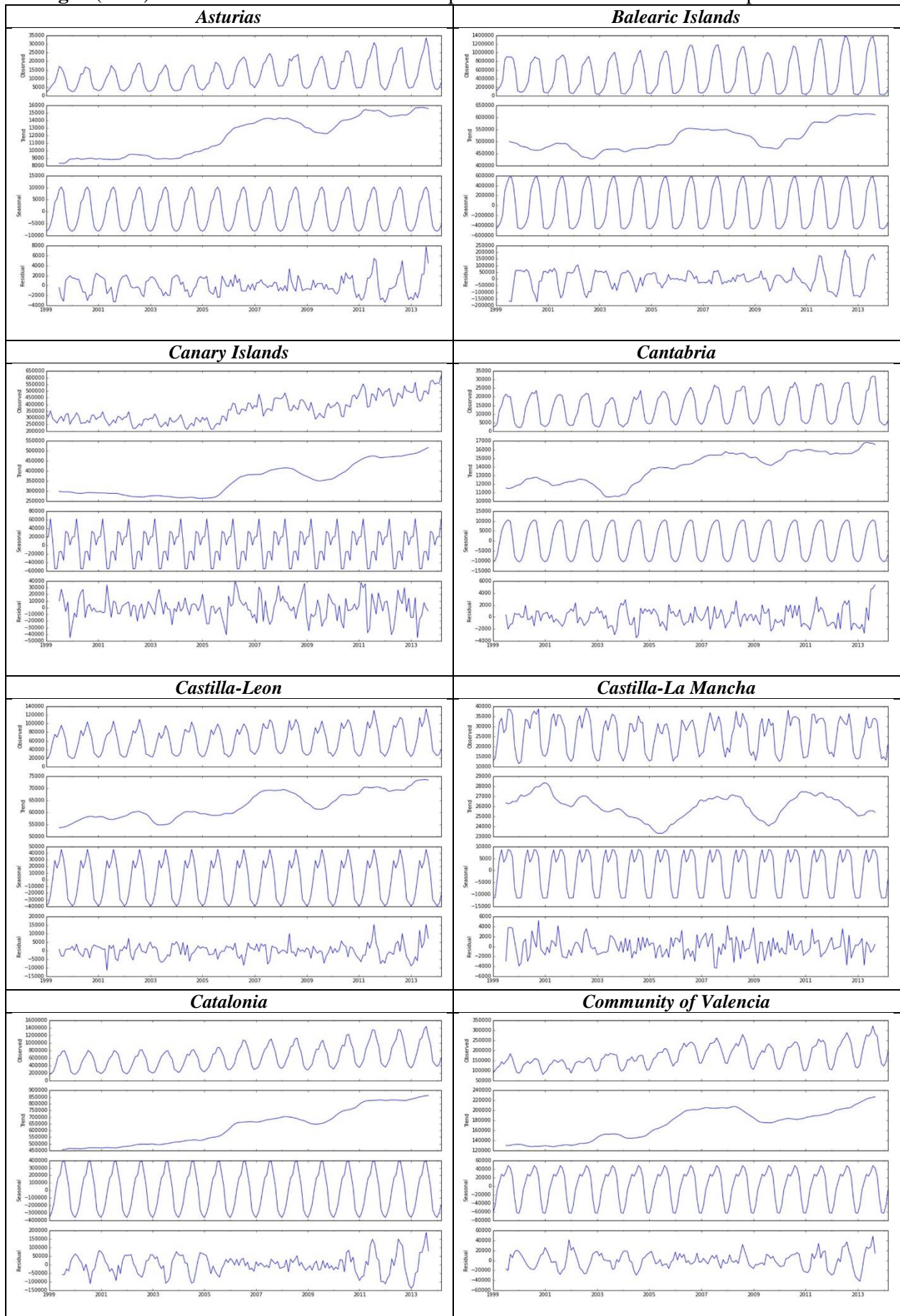


Fig. 1 (cont.). International tourism demand to Spain for each CCAA – STL Decomposition

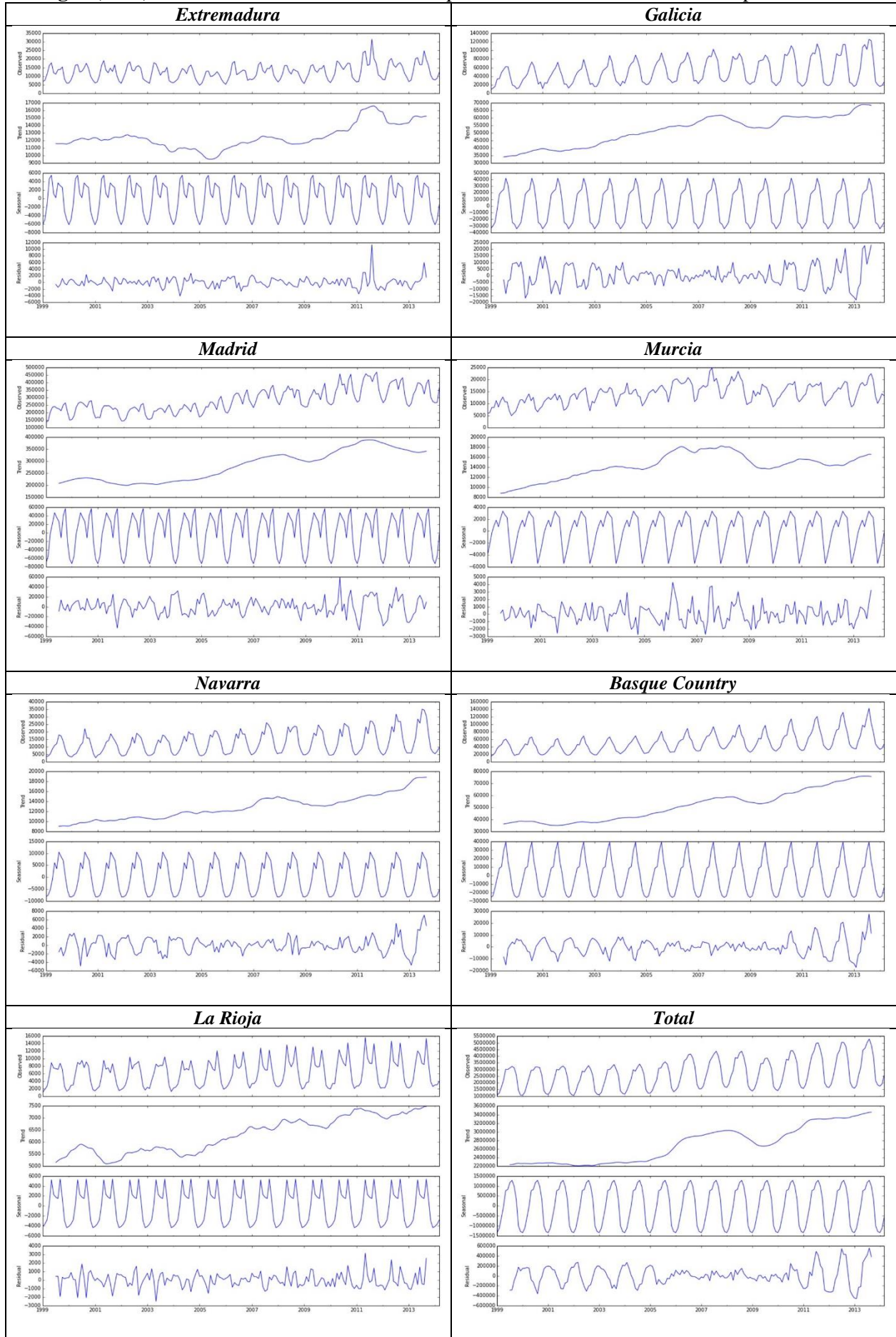


Table 1 Descriptive analysis of foreign tourist arrivals (1999:09-2013:09)

Region	Strength of trend	Strength of seasonality	Box-Cox lambda	Spectral entropy	ACF (-1)	Coeff. of variation	Skew.	Kurt.
Andalusia	0.695	0.968	0.963	0.928	0.731	35.3%	-0.167	-1.285
Aragon	0.731	0.940	0.320	1.248	0.818	44.0%	0.524	-0.290
Asturias	0.679	0.935	0.158	1.839	0.842	64.0%	0.631	-0.598
Balearic Is.	0.398	0.972	0.258	2.112	0.828	83.3%	0.347	-1.366
Canary Is.	0.957	0.808	-0.351	0.585	0.877	26.0%	0.575	-0.554
Cantabria	0.622	0.968	0.378	1.686	0.831	62.2%	0.206	-1.353
C-Leon	0.676	0.981	0.433	1.322	0.791	48.7%	0.139	-1.306
C-La Mancha	0.332	0.950	1.166	0.818	0.722	32.4%	-0.263	-1.429
Catalonia	0.851	0.957	0.333	1.378	0.862	49.1%	0.502	-0.516
Valencia	0.791	0.857	0.113	0.802	0.858	30.9%	0.446	-0.647
Extremadura	0.551	0.856	0.301	1.068	0.662	36.2%	0.634	0.909
Galicia	0.623	0.920	0.201	1.742	0.820	58.0%	0.519	-0.869
Madrid	0.934	0.868	0.212	0.667	0.844	28.1%	0.443	-0.495
Murcia	0.789	0.814	0.845	0.726	0.792	28.3%	0.063	-0.443
Navarra	0.657	0.928	0.134	1.751	0.804	58.4%	0.685	-0.300
Basque Count.	0.797	0.908	0.025	1.501	0.849	49.9%	1.050	0.961
La Rioja	0.435	0.939	0.345	1.785	0.630	56.8%	0.471	-0.548

Notes: Basque Count. stands for Basque Country, C-Leon stands for Castilla-Leon, C-La Mancha stands for Castilla-La Mancha. Coeff. of variation denotes Coefficient of variation; ACF (-1) the first autocorrelation; Skew., Skewness; and Kurt., Kurtosis.

Next, we compute the forecast accuracy of the different ML models: a GPR, a linear and a polynomial SVR, and MLP and RBF NN architectures. The theoretical foundation of the GPR model (Matheron, 1973) is based on previous geostatistic research by Krige (1951). Comprehensive information about GPR can be found in Rasmussen and Williams (2006). A GPR can be regarded as a method of interpolation based on the assumption that the inputs have a joint multivariate Gaussian distribution characterized by an analytical model of the structure of the covariance matrix (Williams and Rasmussen, 1996). As GPRs allow specifying the functional form of the covariance functions, in this experiment we use 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. Alternative sets of kernels are discussed in MacKay (2003). See Claveria et al. (2016a.,b) and Wu et al. (2012) for a detailed description of the model used in this study.

The SVR mechanism was proposed by Drucker et al. (1997) and can be regarded as an extension of SVMs to construct data-driven and nonlinear regressions. The original SVM algorithm was developed by Vapnik (1995) and Cortes and Vapnik (1995). For a comprehensive presentation of SVR models see Cristianini and Shawhe-Taylor (2000). The objective of a SVR is to define an approximation of the regression function within a tube generated by means of a set of support vectors that belong to the training data set. This

is done by introducing restrictions on the structure or curvature of the set of functions over which the estimation is done (Vapnik, 1998; Schölkopf and Smola, 2002). Any function satisfying Mercer's condition (Vapnik, 1995) can be used as the kernel function. In this experiment we use both a linear and a polynomial kernel for the estimation of the regression. See Chen and Wang (2007) and Hong et al. (2011) for a detailed description of the model.

NN models are used to identify related spatial and temporal patterns by learning from experience. A complete summary on the use of NNs with forecasting purposes can be found in Zhang et al. (1998). In this study we use two NN models: MLP and RBF. See Claveria et al. (2017a) for a detailed description of the models applied. In this experiment, we have used the Levenberg-Marquardt algorithm to estimate the parameters of the networks.

The first 52% of the observations were used as the initial training set, the next 33% as the validation set, and the last 15% as the test set. This partition is done sequentially. The estimation of the models is done recursively for different forecast horizons (1, 2, 3, 6 and 12 months) during the out-of-sample period (2013:01-2014:01). Forecast accuracy results are summarized by means of the Mean Absolute Percentage Error (MAPE). The results of the forecasting experiment are presented in Table 2.

Regarding the different models, we find that the MLP NN model shows lower MAPE values than the rest of the models in 40% of the cases. For one- and six-month ahead forecasts, this percentage goes up to 59% and 65% respectively. Nevertheless, for three-month ahead forecasts the MLP never outperforms the rest of the models, being the polynomial SVR the model that presents the lowest MAPE values in 65% of the cases.

The lowest MAPE in each region is usually obtained either with the MLP NN or the linear SVR. The exceptions are Castilla-La Mancha and La Rioja, where the GPR outperforms the rest of the models, and the Basque Country and the Canary Islands, where the RBF NN generates the forecasts with the lowest MAPE values. In the Canary Islands the RBF outperforms all the other methods for all forecast horizons.

Results of the forecasting experiment are summarized in Table 3, where we present the number regions in which each model provides the lowest MAPE. The results show that the MLP NN outperforms the rest of the models in most of the regions, and both for one- and six-month ahead forecasts.

Table 2. Forecast accuracy. MAPE (2013:01-2014:01)

Forecast horizon	Support Vector Regression models		Gaussian Proces Regression	Neural Networks models	
	SVR linear	SVR poly	GPR	RBF	MLP
Andalusia					
h=1	0.342	0.447	0.356	0.387	0.363
h=2	0.465	0.398	0.451	0.442	0.438
h=3	0.453	0.455	0.418	0.447	0.420
h=6	0.325	0.401	0.384	0.396	0.346
h=12	0.135*	0.258	0.136	0.275	0.173
Aragon					
h=1	0.385	0.331	0.361	0.303	0.295
h=2	0.440	0.433	0.412	0.370	0.364
h=3	0.366	0.352	0.370	0.367	0.388
h=6	0.291	0.321	0.270	0.298	0.224*
h=12	0.303	0.302	0.286	0.273	0.244
Asturias					
h=1	0.776	0.882	0.754	0.672	0.611
h=2	0.991	0.938	0.913	0.750	0.801
h=3	0.645	0.681	0.745	0.733	0.778
h=6	0.398	0.587	0.406	0.459	0.340
h=12	0.285*	0.374	0.289	0.420	0.318
Balearic Islands					
h=1	5.462	8.156	5.177	4.346	3.977
h=2	7.193	9.461	6.719	5.724	5.679
h=3	5.434	4.628	5.994	6.052	5.660
h=6	0.909*	2.585	0.956	3.136	1.313
h=12	1.596	2.876	1.659	2.618	1.685
Canary Islands					
h=1	0.463	0.540	0.460	0.419	0.424
h=2	0.432	0.450	0.442	0.413	0.416
h=3	0.438	0.467	0.439	0.414	0.419
h=6	0.411	0.424	0.418	0.411	0.411
h=12	0.465	0.518	0.446	0.410*	0.425
Cantabria					
h=1	1.129	1.393	1.066	0.947	1.031
h=2	1.383	1.696	1.185	0.998	1.033
h=3	1.128	0.956	1.034	1.049	1.048
h=6	0.333	0.596	0.373	0.513	0.382
h=12	0.291*	0.495	0.330	0.566	0.315
Castilla-Leon					
h=1	0.597	0.741	0.606	0.590	0.522
h=2	0.763	0.816	0.697	0.645	0.655
h=3	0.704	0.491	0.661	0.661	0.661
h=6	0.307	0.467	0.308	0.389	0.263
h=12	0.171*	0.345	0.183	0.357	0.232
Castilla-La Mancha					
h=1	0.324	0.394	0.326	0.311	0.282
h=2	0.405	0.433	0.372	0.361	0.357
h=3	0.405	0.505	0.367	0.379	0.375
h=6	0.261	0.316	0.267	0.278	0.231
h=12	0.113	0.220	0.112*	0.209	0.137
Catalonia					
h=1	0.415	0.461	0.392	0.372	0.377
h=2	0.509	0.506	0.467	0.418	0.436
h=3	0.448	0.376	0.420	0.416	0.418
h=6	0.400	0.367	0.319	0.313	0.296
h=12	0.331	0.413	0.321	0.296	0.262*

Notes: * Model with the lowest MAPE

Table 2 (cont.). Forecast accuracy. MAPE (2013:01-2014:01)

Forecast horizon	Support Vector Regression models		Gaussian Proces Regression	Neural Networks models	
	SVR linear	SVR poly	GPR	RBF	MLP
Valencia					
h=1	0.299	0.485	0.297	0.310	0.273
h=2	0.360	0.327	0.356	0.332	0.331
h=3	0.346	0.340	0.371	0.343	0.355
h=6	0.335	0.276	0.343	0.342	0.354
h=12	0.290	0.520	0.271	0.296	0.246*
Extremadura					
h=1	0.321	0.379	0.328	0.365	0.334
h=2	0.414	0.404	0.393	0.399	0.392
h=3	0.380	0.423	0.362	0.392	0.367
h=6	0.351	0.404	0.386	0.370	0.327
h=12	0.185*	0.363	0.196	0.295	0.208
Galicia					
h=1	0.859	1.014	0.848	0.764	0.723
h=2	1.074	1.068	0.982	0.869	0.889
h=3	0.815	1.054	0.884	0.895	0.918
h=6	0.525	0.747	0.546	0.628	0.458
h=12	0.347*	0.899	0.352	0.520	0.394
Madrid (Community)					
h=1	0.269	0.351	0.259	0.264	0.244
h=2	0.256	0.290	0.248	0.253	0.235
h=3	0.260	0.191	0.253	0.251	0.241
h=6	0.260	0.255	0.245	0.253	0.234*
h=12	0.238	0.424	0.243	0.253	0.245
Murcia (Region)					
h=1	0.236	0.233	0.258	0.220	0.227
h=2	0.286	0.275	0.319	0.250	0.267
h=3	0.261	0.233	0.342	0.277	0.302
h=6	0.248	0.214	0.287	0.270	0.307
h=12	0.199	0.255	0.187	0.195	0.175*
Navarra					
h=1	0.594	0.674	0.585	0.567	0.534
h=2	0.716	0.800	0.709	0.619	0.654
h=3	0.654	0.609	0.632	0.622	0.634
h=6	0.378	0.545	0.333	0.471	0.333
h=12	0.307	0.447	0.305	0.404	0.304*
Basque Country					
h=1	0.410	0.390	0.411	0.373	0.438
h=2	0.459	0.427	0.437	0.390	0.411
h=3	0.389	0.382	0.394	0.391	0.401
h=6	0.418	0.358	0.351	0.330*	0.343
h=12	0.390	0.427	0.377	0.358	0.348
La Rioja					
h=1	0.562	0.732	0.589	0.565	0.527
h=2	0.773	0.615	0.713	0.672	0.676
h=3	0.774	0.647	0.699	0.704	0.690
h=6	0.456	0.636	0.478	0.447	0.302
h=12	0.194	0.389	0.190*	0.390	0.229

Notes: * Model with the lowest MAPE

Table 3. Out-of-sample forecast accuracy. Summary

Forecast horizon	Support Vector Regression models		Gaussian Proces Regression	Neural Networks models	
	SVR linear	SVR poly	GPR	RBF	MLP
h=1	2	0	0	5	10
h=2	0	3	0	9	5
h=3	2	11	3	1	0
h=6	3	1	0	2	10
h=12	8	0	2	1	6

Summarizing, we find that:

- There are significant differences across regions regarding forecast accuracy.
- The MLP NN outperforms the rest models in most of the regions, as opposed to the GPR.
- The linear SVR relatively improves its forecasting performance for longer forecast horizons (six- and twelve-month ahead predictions), as opposed to the RBF NN.
- Regardless of the ML method, forecast accuracy improves for longer horizons. Claveria et al. (2017b) obtained similar results when comparing GPR to NN models.

With the aim of analysing the effects of data characteristics on forecast accuracy, we link the results of the two previous analysis: the time series features (Table 1) and the forecasting results (Table 2). Following the multivariate positioning approach proposed by Claveria (2016), we first rank each region according to its data characteristics and its MAPE values in increasing order. These rankings are then used as the input for an ordinal multivariate analysis that allows us to synthesise all the information in order to evaluate the effect of time series features on forecast accuracy.

Multivariate techniques for dimensionality reduction have been widely used in tourism studies. The principal components analysis (PCA) framework has been progressively extended to deal with nonlinear relationships in data and with qualitative information. Categorical principal components analysis (CATPCA) can be regarded as a development of PCA (Meulman et al., 2012). See Gifi (1990) for a historical overview, and Linting et al. (2007) for an exhaustive treatment of nonlinear PCA. In the biplot in Fig. 2 we project the two dimensions obtained with CATPCA. According to the values of the component loadings in Table 4 we labelled the first dimension as “seasonality, trend and forecast accuracy”, and the second as “predictability and dispersion”.

Table 4. Rotated component loadings

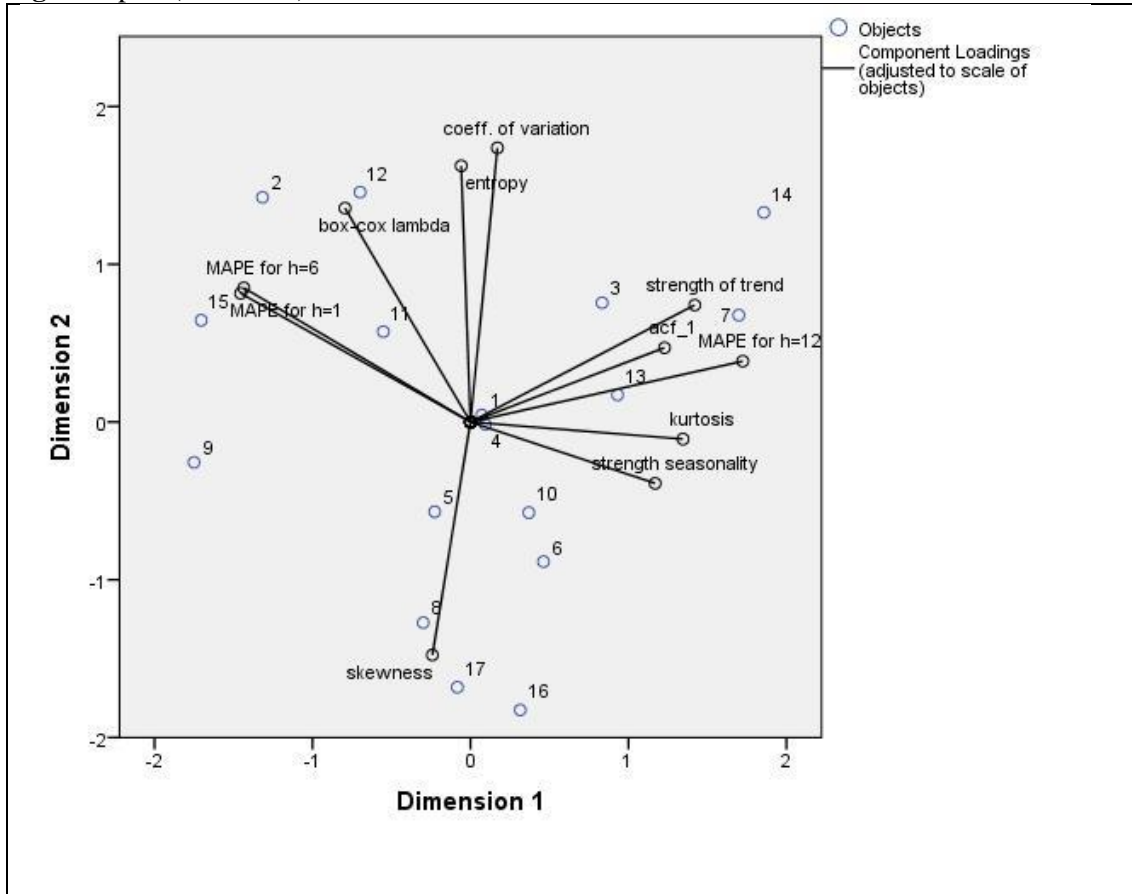
	Dimension	
	1	2
Strength of trend	0.760	0.397
Strength of seasonality	0.625	-0.208
Optimal Box-Cox transformation	-0.425	0.725
Spectral entropy	-0.031	0.869
Autocorrelation function (r1)	0.657	0.252
Coefficient of variation	0.091	0.930
Skewness	-0.129	-0.790
Kurtosis	0.720	-0.058
MAPE for h=1	-0.779	0.437
MAPE for h=6	-0.768	0.455
MAPE for h=12	0.923	0.206

Note: Component loadings indicate Pearson correlations between the quantified variables and the principal components (ranging between -1 and 1).

Along both dimensions the biplot overlaps the object scores (regions) and the rotated component loadings (Table 4). The coordinates of the end point of each vector are given by the loadings of each variable on the two components. Long vectors are indicative of a good fit. The variables that are close together in the plot, are positively related; the variables with vectors that make approximately a 180° angle with each other, are closely and negatively related; finally, non-related variables correspond with vectors making a 90° angle.

Entropy and dispersion, measured by the coefficient of variation, tend to coalesce together, indicating a close and positive relation between both rankings, but no relation with skewness, which stands apart. Entropy and dispersion clearly show a negative relation with accuracy. The same could be said for the Box-Cox lambda and accuracy for twelve-months ahead forecasts. In contrast, the power to which all data should be raised in order to be normally distributed (λ_1) is relatively close to the accuracy for h=1 and h=6. The strength of trend, the first autocorrelation, and the MAPE for h=12 also coalesce together, and are close to the strength of seasonality and kurtosis, all of which seem unrelated to the rankings regarding entropy, dispersion and skewness, and negatively related to the rankings based on the MAPE for one- and six-month ahead forecasts.

Fig. 2. Biplot (CATPCA)

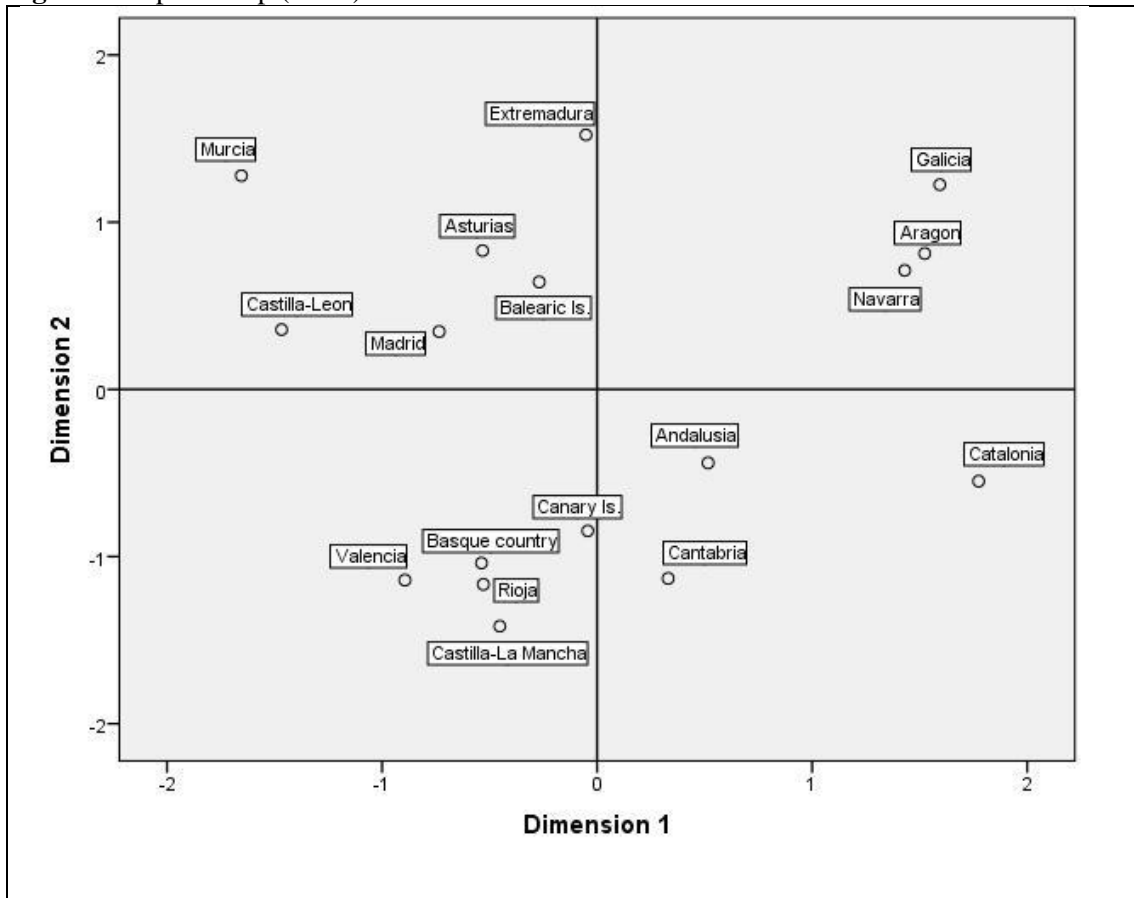


Note: Rotation Method: Varimax with Kaiser Normalization. Acf_1 denotes the first autocorrelation. For visual clarity, we have coded each region with a number: Andalusia (1), Aragon (2), Asturias (3), Balearic Islands (4), Canary Islands (5), Cantabria (6), Castilla-Leon (7), Castilla-La Mancha (8), Catalonia (9), Valencia (10), Extremadura (11), Galicia (12), Madrid (13), Murcia (14), Navarra (15), Basque Country (16), La Rioja (17).

This latter result suggests that the strength of the seasonal and the trend components have a different effect on accuracy depending on the forecast horizon. As a result, we find that the overall effect of the time series features on forecast accuracy is heavily dependent on the forecast horizon. This finding is in line with the results obtained by Hassani et al. (2017) in a recent study, who undertake a comprehensive forecasting accuracy evaluation in ten European countries and find that in order to increase forecast accuracy, model selection should be country-specific and based on the forecasting horizon.

Finally, we analyse the rankings through Multidimensional scaling (MDS) in order to group the regions according to both dimensions. MDS is also known as principal coordinates analysis (Torgerson, 1952). See Borg and Groenen (2005) for an overview of MDS, and Marcussen (2014) for a review of the literature regarding the application of MDS to tourism research. Via MDS we generate a two-dimensional projection of the results in a perceptual map, where we position the seventeen regions according to the similarity between them in terms of their time series features and forecasting results.

Fig. 3. Perceptual map (MDS)



Both techniques depict a similar positioning of the regions. In both analysis the Basque Country and La Rioja are grouped together. This result could be due to geographical proximity. Aragon and Galicia are also closely positioned. Asturias and the Balearic Islands, which are the regions that display the worse forecast accuracy for most forecast horizons, are also close together. Catalonia and Murcia are grouped apart from most of the rest of the regions.

7. Conclusions

The increasing importance of the tourism industry worldwide is fostering a growing interest in new approaches to tourism modelling and forecasting. As more accurate predictions become crucial for effective management and policy planning at the regional level, AI techniques allow forecasters to refine predictions. With this objective, we evaluate

the interrelations between time series features and the forecast accuracy of tourism demand predictions obtained with several ML methods (GRP, SVR and NN models).

Making use of international tourism demand to all seventeen regions of Spain, we first apply a seasonal-trend decomposition procedure to compute a set of time series features such as the strength of the trend and the strength of the seasonal component. In a second step, we design a multiple-step-ahead forecasting experiment. We obtain substantially different results across regions. Regarding the different techniques, NNs provide better forecasting results than the other statistical learning models based on interpolation. Finally, we combine the descriptive analysis and the forecasting results, synthesising all the information in two components labelled as “seasonality, trend and forecast accuracy”, and “predictability and dispersion”. By projecting these results on perceptual maps we find that while entropy and dispersion show a negative relation with accuracy for all forecast horizons, the effect of other time series features is heavily dependent on the horizon.

This work provides researchers and practitioners with some evidence on the effect that data characteristics may have on the accuracy of tourism predictions, as well as on the appropriateness of ML techniques for tourism forecasting depending on the forecast horizon. A question left for further research is the incorporation of additional data characteristics in the analysis. Finally, extending the analysis to regions of other destinations would allow to test if there are significant differences across countries.

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