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alphanumeric journal

The Journal of Operations Research, Statistics, Econometrics and Management Information Systems

Volume 10, Issue 1, 2022

Received: May 02, 2021
Accepted: May 16, 2022
Published Online: June 30, 2022

AJ ID: 2022.10.01.STAT.01
DOI: 10.17093/alphanumeric.931652
Research Article

The Impact of Google Trends on the Tourist Arrivals: A Case of Antalya Tourism

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ABSTRACT

With the growth of the tourism industry, tourism demand forecasting has become an important research topic. Recently researches have shown that Google Trends(GT) data with the help of Google can positively affect the forecast of tourist arrivals. However, the use of this data directly can cause some errors. This article provides suggestions on how the calculation differences according to the same time at different time intervals in GT data (which is obtained on an hourly, daily, monthly and yearly basis) can be eliminated. In this study, it is aimed to examine the effect of GT data for Antalya, Turkey's favorite tourist destination by the Russians. In addition, the multivariate time series models are used to see separately and together the effects of international trade (IT), weather conditions (WC) and number of flights (FN) variables on tourism data, as well as GT data. As a result, it has been seen that the tourist arrival can be forecasted better with the GT (AGT) data, which is recommended to be used by adjusted.

Keywords: Tourism Forecast, Google Trends, Time Series, Multivariate Models, ARIMAX, MSSA

1. Introduction

Developments in the tourism industry have made tourism demand forecasting a critical research topic. Having accurate tourism demand forecasts significantly impacts the success of many businesses and industries in destinations. Reliable medium-term forecasts are needed to keep pace with changing situations, such as adapting their capacities to demand and making the right pricing policy. Many studies on this subject show that the most widely used measure of tourism demand is the number of tourists used in this study. Decision-makers have preferred the time series methods for many years to obtain future forecasts of tourist arrivals based on time. Since there is no method determined as the most accurate method among the time series methods, research is carried out on two linear and non-linear multivariate methods (ARIMAX and MSSA, respectively) in this study.

Today, the internet is the most common information source in the world. The web has many advantages for users who want to take their future decisions in advance. The search engines are utilized effectively for making these decisions. Generally, tourists search the information such as the destination, the culture, the climate, accessibility, lodging and shopping via the Internet. These search queries are collected by the search engines after they are adjusted and then published by the websites as Google Trends. Tourism forecast is examined with the help of the big data in the last researches in Literature. In this article, by using the GT data, we aim at improving the forecast accuracy.

According to the studies conducted for European countries in recent years, city tourism has increased more than country tourism (ECM & MU, 2015). Antalya is one of the most famous tourist destinations in Turkey. It also has many prominent features about tourism such as:

- High temperature, sunny days, blue flag beaches and the sea for summer tourism,
- Ancient cities and museums for cultural tourism,
- Waterfalls and caves for nature tourism,
- Golf facilities for golf tourism,
- Festivals, theater presentations and celebrations that will attract tourists.

Due to these features, mainly Russian tourists constitute the most significant share of international tourism in Antalya. In addition, the international trade and politics of the Russian Federation and Turkey make substantial contributions to tourism. According to World Bank data, about 75 percent of the Russian population uses the internet. Russians' high internet usage rates also support the use of GT data. Therefore, GT is used in this study to improve the accuracy of forecasting tourist arrivals. The article structure continues as follows: Chapter 2 presents previous work, Chapter 3 describes the data, Chapter 4 presents the methods mentioned, Chapter 5 expands on the analysis results, and the final chapter highlights implications, limitations, and suggestions for future work.

2. Literature Review

Along with the development of the Internet, users have begun to reach the data in many different ways. To this purpose, Google has provided users with the search query rate based on how it is frequently searched with the Google Trends app, and how it was starting in 2006, and providing access to data of this rate on an hourly, daily, monthly and yearly basis. The most common search queries among Google searches support various forecasts. GT data is defined to predict different topics such as automobile sales, unemployment claims, travel destination planning and consumer confidence by Choi and Varian (2012). Bangwayo-Skeete and Skeete (2015) have forecasted the tourist flows to the Caribbean from three critical countries using the data of search queries, which are based on the hotels and flights terms, in GT. Rivera (2016) has further suggested predicting hotel registrations in Puerto Rico with search query data from GT. Besides, Kim and Malek (2018) have contributed to determining GT has a predictive power to enlarge casino revenue forecasts.

According to the TURKSTAT, the tourism revenue is expected 50 million $ in 2019, although it was 10,5 million $ in 2001. This increase implies that the tourism sector has become an essential part of the Turkish economy. For this reason, most authors have examined various aspects of tourism in Turkey. Olya et al. (2017) research tourism concerning the culture in Turkey. The results of Aksu et al. (2017) could also infer from the tourist profile of golf tourism for improving future tourism strategies in Antalya. Tourism can be affected by many parameters. For instance, Balli et al. (2013) determine the number of tourists in Turkey with the impact of the Turkish soap operas and visa-free entries. Corruption is examined by Demir and Gozgor (2017) as the negative parameter on tourism of Turkey.

There are numerous studies about the inbound tourism to the favorite touristic places around the World in literature. These researches are created with the help of the different methods to forecast the tourist visits to destinations, which are the top-line countries and the cities about the tourism such as; Hadavandi et al. (2011) for Taiwan, Jackman (2010) and Greenidge (2001) for Barbados, Chu (2008) for Singapore, Gil-Alana (2005) for US, Song et al. (2010, 2011) for Hong Kong, Lim and McAleer (2001) for Australia, Shareef and McAleer (2007) for Maldives, Andrawis et al. (2011) for Egypt, Gounopoulos et al. (2012) for Greece.

The main purpose of time series analysis is to build a model to describe the structure of time-dependent data and then predict their future values. Since the future predictions obtained by time series are important, it is important to create an effective model in order to improve the forecast accuracy (Siami-Namini et al., 2018). The multivariate methods is developed for help with the modeling of the time series that cannot be explained by simple models (Chatfield, 2000). Over the years, considerable progress has been seen in the improvement of these models as it can be more accurate to obtain predictions with multivariate in the stochastic and the deterministic time series. For this purpose, the multivariate versions of many univariate methods have been improved. Because the SSA has a good theoretical structure and the ability to solve various problems, the multivariate SSA (MSSA) also emerges as a rapidly developing model. More recently, in Silva et al. (2017) it is indicated that the use of MSSA provides advantages the forecasting of demands for tourism. It's been frequently preferred by many authors for modeling economic data of the MSSA (Hassani & Mahmoudvand, 2013; Hassani et al. 2010; Patterson et al. 2011). The other implementation in multivariate time series models, the autoregressive integrated moving average with explanatory variable (ARIMAX), is employed on the tourist visits and tourist expenditure by Pang and Yang (2017). Yang et al. (2014) focus on ARIMAX model's performance for predicting the hotel demands in the shorter horizons forecast.

3. Data

3.1. Google Trends Data

GT data provide the corrected search queries between 0 and 100 depending on the topic's rate. Each of this data is calculated for the corrected process by dividing the research query's number of the selected geography and the time range by the sum of all searches. GT application can allow the data to be examined at different tabs including country, time, categories and varies search options. Google is referring that the data generation by categories section can include missing values. Therefore, the data obtained from this section can have the prediction values. In other respects, data can be displayed by different options starting from hours to years with time segmentation (Figure 1). Besides, the data, adjusted for same time point at different time intervals, do not have the equal point values, because of GT algorithm technic. Google does not explicitly declare how to process this technic . However, raw data of GT are not so feasible, because GT does not consider "trend" variable in time series model. For example; the year of 2007 should not be equal to the value of 2017, which is based on the "Antalya" keyword, if the trend of the tourist arrivals in Antalya is considered. Moreover, GT' time intervals start at 2004, but using of data between 2004 and 2007 is not so advantageous. The number of internet users is not so high between 2004 and 2007 and, because the increasing number of internet users and the tourist visits are considered, the result of this value can be biased.

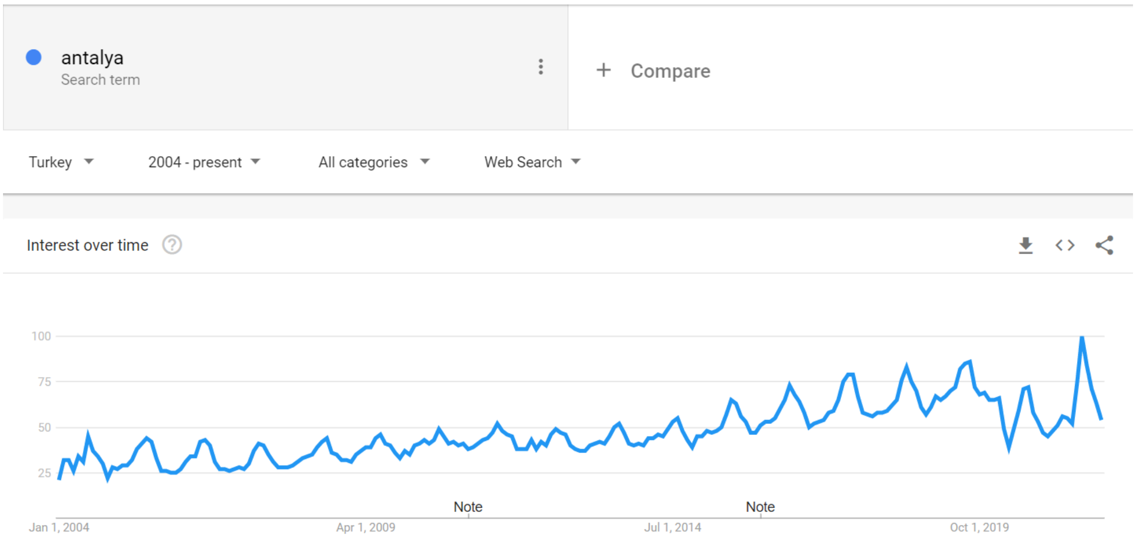

Figure 1. Google Trends website

In this article, "Antalya" keyword search queries of Russian people between 2007 and 2017 are considered in order to collect GT data. The reason is that, GT' values are multiplied by the number of internet users to diminish this bias, and improve the accuracy of forecast (The number of the internet users data is available from the World Bank (World Bank, 2019). Finally, AGT is used as an independent variable in the multivariate time series model.

3.2. The other data for Antalya tourism

Turkey has the 10th position in the World regarding the international tourist arrivals (World Travel & Tourism Council (WTTC), 2017). The total contribution of Tourism in Turkey's GDP is 11.6%. Besides, one of ten employees in Turkey works directly or indirectly to the tourism sector (World Travel & Tourism Council (WTTC), 2018). Turkey tourist visits were increasing with the positive trend until 2016. In this year, there is a vital decrease in tourist arrivals. One of the cities that were most affected by this drop is Antalya, a city that attracts the most tourists to Turkey, because, in 2016, Russia banned on the charter flights to Antalya. Therefore, Antalya tourism lost the most valuable tourist source in 2016. In light of the information, we can easily say that Russian tourist has a crucial role in Antalya economy.

In recent years, Antalya tourism has been seriously influenced by safety anxieties and political uneasiness (World Travel & Tourism Council (WTTC), 2017). The most critical sample of this influence is that Russia and Turkey was the political turmoil in 2016 (Cakar, 2018), (Poghosyan, 2018). Therefore Russia and Turkey reduced the international trade between them, especially the export. In this study, the export data is named as the international trade (IT) and is taken into account to see whether the trade relations between Turkey and Russia is an impact on tourism.

Weather conditions or the suitability of climate conditions can create fluctuations in the tourist flows in many touristic places around the world. Antalya, Florence, Izmir, Mugla, and Balearic Islands are a valid example for showing the seasonal tourist fluctuations (Álvarez-Díaz & Rosselló-Nadal, 2010; Kozak et al., 2008; Morabito et al., 2004). Antalya is one of the most famous destinations for summer tourism in Europe, therefore, the population of tourists from Russia and the weather conditions in Antalya are highly correlated. Thus, the average temperature can be a valid indicator for predicting the tourist flows to Antalya and, therefore the weather conditions (WC) function as an independent variable in multivariate time series models.

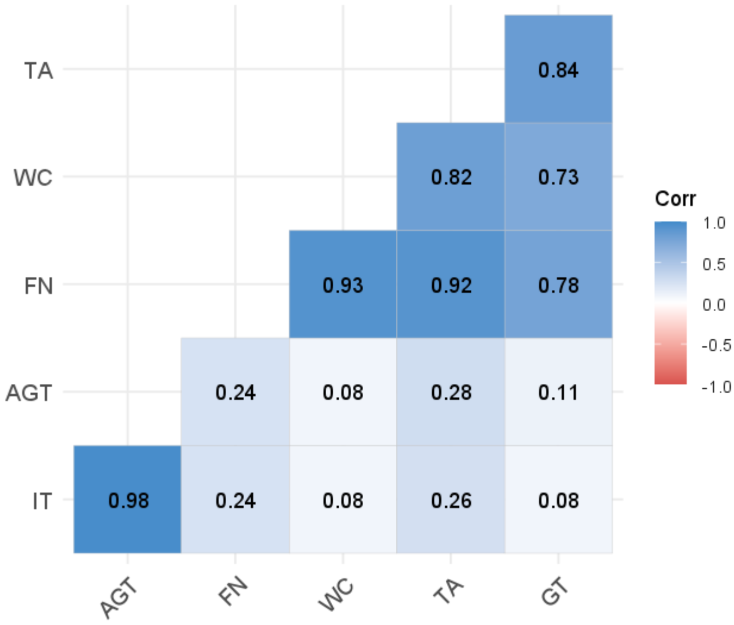

Figure 2. Correlation table

Another explanatory variable is the number for international flights to the associated airport. Tourist arrivals have a positive relationship with the number of flights to the related airport (Bieger & Wittmer, 2006; Ozdemir et al., 2012). In this study, the flights' counts from Russia to Antalya airport is attached to the data set as an independent variable. Data of tourist visits was collaterally decreasing with this variable in 2016 that the cause of Russia had banned the charter flights to Turkey. Therefore, data relating to the number of flights (FN) can explain the fluctuations in the data of tourist arrivals and, we examine the effect of the variable on the tourist arrivals.

In this study, the tourist arrivals (TA), used as the dependent variable and previously used in Cekim & Koyuncu (2021)'s paper, the international trade data between Russia and Turkey are obtained from the TURKSTAT (TURKSTAT, 2019). The data relating to the number of flights to Antalya is collected from Turkey's State Airports Administration (DHMI, 2019). Search query data is received from GT. Also, the data of weather condition in Antalya is collected from the Directorate General of Meteorology in Turkey (MGM, 2019). These data are monthly and contain the years from 2007 to 2018. The data of this study is consists of four independent variables and one dependent variable. It can be seen in Figure 2 that these variables have high correlations with each other, except for IT. Moreover, the P-value score of the Granger causality test is 0.02511, and the result has designated that all independent variables are Granger that makes the tourist arrivals variable at the P-value of 0.05. In this research, we examine the effect of independent variables on the tourist arrivals separately and in combinations.

4. Methods

The multivariate models have been dramatically improved in time series. Until today, various multivariate models have been developed because they provide efficiency in the forecast with the correct choices of the independent variables. We consider these models as ARIMAX and MSSA in this paper to see the effect of the models using the independent variables.

4.1. ARIMAX Method

The ARIMA model has been converted to ARIMAX by adding input variables (or time series) since the time series modeling was considered to increase the forecast accuracy of the joints of some variables (Anggraeni et al., 2015). For this reason, the correlations between the time series should be examined before the ARIMAX method is applied. It is preferable to include the series with high correlation. The model equation is described in the ARIMA model equation similarly (Pan & Yang, 2017):

$$\lambda_p(B)Y_t = \gamma Z_t + \mu_t \tag{1}$$

$$\theta_p(B)\mu_t = \pi_p(B)\xi_t \tag{2}$$

where Z_t is the input series (explanatory variable), μ_t is the residual series and γ is the associate correlation between the Y_t and Z_t. Though ARIMAX can explain with more than one variable, it is popular in recent studies by authors like Ihueze (2018), Jalalkamali et al. (2015), Jifri et al. (2018), Molina et al. (2018).

4.2. Multivariate Singular Spectrum Method (MSSA)

Broomhead and King (1986) proposed the multi-variable version of SSA (MSSA), which is based on classical Karhunen-Loeve spectral decomposition method, in 1986. When the MSSA is compared to the univariate SSA, it has fewer studies on the theoretical framework. The reason of this situation, it may be that the MSSA is a natural enlargement of the SSA. The primary objective of the MSSA is to take out the noise series and to achieve the estimate from data for M -variate time series with length T. Similar to the SSA, the MSSA algorithms are also performed by forecasting as the final stage after passing decomposition, reconstruction stages. Although their basic algorithms are the same, there are differences in the construction of the trajectory matrix. A one-dimensional time series Y_T into a multidimensional series $X_1, \ldots, X_K$ with vectors $X_u = [y_u, y_{u+1}, \ldots, y_{u+L-1}], u = 1, \ldots, K$, where $K = T - L + 1$ for SSA and the result of embedding is the trajectory matrix

$$X = \left(x_{u,v}\right)_{u,v=1}^{L,K} = \begin{bmatrix} y_1 & y_2 & y_3 & \cdots & y_K \\ y_2 & y_3 & y_4 & \cdots & y_{K+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ y_L & y_{L+1} & y_{L+2} & \cdots & y_T \end{bmatrix}. \tag{3}$$

This matrix is a Hankel matrix. For the MSSA, let define an M variable time series $\left(y_v^{(1)}, \ldots, y_v^{(M)}\right)$, $v = 1, \ldots, T$. Similar to the trajectory matrices $X^{(u)}$ $(u = 1, \ldots, M)$ of the one dimensional time series $\left\{y_v^{(u)}\right\}$, $(u = 1, \ldots, M)$. So, the trajectory matrix can be described as $X = \left(X^{(1)} \ldots X^{(M)}\right)$. Further, this matrix is the block Hankel matrix. Other stages are the same as the stages of the SSA (Hassani et al., 2013).

On the other hand, there are plenty of successful applications of research on the MSSA (Ghil et al., 2002; Groth & Ghil, 2011; Hassani et al., 2013; Hassani & Mahmoudvand, 2013; Oropeza & Sacchi, 2011; Yi & Xiao-feng, 2012). The choice of the variables that is added to the MSSA model is very important. In particular, the economic models are quite sensitive to adding variables.

4.3. Methods of evaluation criteria

Some authors use the whole dataset to evaluate the forecast accuracy in these models. Whereas, other authors divide the data set to reach the reliable forecast and to describe as the training data (in sample data) and the testing data (out of sample data). The use of the training data is common for estimating and the testing data to measure the validation of the model forecast. For this purpose, we consider Feb-2007 and Dec-2017 as training data and twelve months of 2018 as testing data in this manuscript.

We estimate the root mean square error (RMSE) values of the considered models in this study for the finding the best forecasting method of tourism in Antalya. The formula for RMSE is as follows: (Naim & Mahara, 2018).

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N} \left(y_t - \hat{y}_{t|t-1}\right)^2}, \tag{4}$$

where y_t and $\hat{y}_{t|t-1}$ indicate, respectively, t^{th}observation and its forecasted observation depending previous observation $(t = 1, \dots, N)$. It is not statistically correct to decide on the best forecast model only by looking at the RMSE values. Therefore, the Ratio of the RMSE (RRMSE) values are calculated as follows: (Silva et al., 2019)

$$RRMSE = \frac{RMSE_{Benchmarkmodels}}{RMSE_{Othermodels}}, \tag{5}$$

and the validity is controlled by the KSPA (or Hassani-Silva (HS)) test. After this test is introduced by Hassani and Silva in 2015, it was frequently preferred to test the statistical significance of the RRMSE values in many studies such as (Mokhtarzad et al., 2017; Ghodsi et al., 2018; Hassani et al., 2017; Silva et al., 2017; 2018; 2019). The RRMSE value shows the percentage gain that the benchmark model provides in the terms of the forecasts compared to other models.

5. Empirical Results

For any search word, GT scales data between 0 and 100. Because the number of Internet users increases over time, direct use of this data can cause errors. For this reason, more accurate the data usage in this manuscript has illustrated by the example of Antalya tourism. We use the R program for estimating the tourist arrivals. "forecastHybrid", "Rssa", "forecast" and "vars" package are practiced in the R program. The massive decrease in 2016 in tourist arrivals can be a problem for predicting the models. AGT data can prevent this problem with the use of explanatory covariates in the multivariate models.

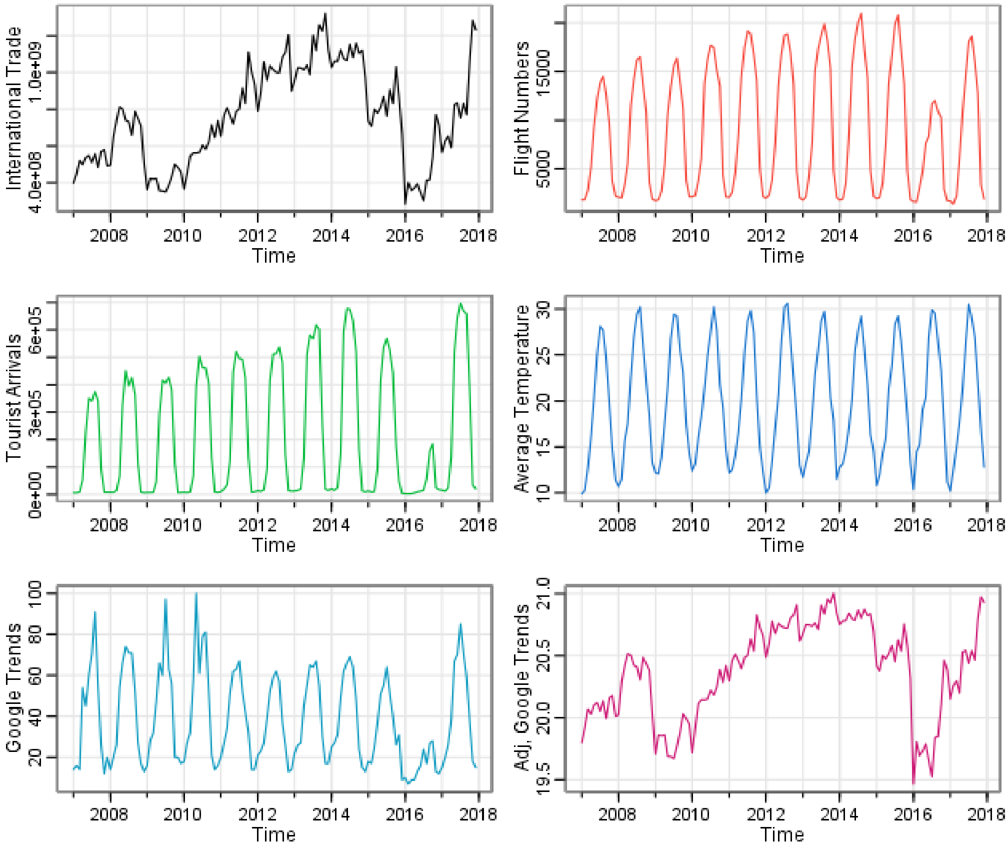

Figure 3. Time series graphs of the interested variables

The time-dependent movements of the interested series in the study are shown with the graphs in Figure 3. Before the estimation, the natural logarithm forms of all variables are utilized in this research to secure a linear functional relationship and stationarity of all variables. As we examine the stationarity of the series using the Dickey-Fuller (ADF) and the Phillips-Perron (PP), with these test results, we take the same degrees (the first differences) of integration of variables (Ihueze & Onwurah, 2018; Jalalkamali et al., 2015).

MSSA and ARIMAX, which are nonparametric and parametric multivariate methods, are applied to show the interaction of AGT with other explanatory variables. Moreover, the MSSA method is used as a benchmark model in multivariate methods. When all variables are added sequentially and in different combinations with the models, these results in Table 1 are obtained and it is given real values of TA in 2018. Also, the values shown in bold are the closest estimation values in the tables. First, AGT is added as an independent variable next to the TA dependent variable. Afterward, we utilized the binary combination of AGT with the other independent variables. When checking the prediction values of these models, the unification of the WC+AGT and IT+AGT, respectively, can explain the tourist arrivals better than the other models for ARIMAX and MSSA can.

Methods	Months	Real	AGT	IT+AGT	FN+AGT	WC+AGT	IT+FN+AGT	IT+WC+AGT	FN+WC+AGT	IT+FN+WC+AGT
ARIMAX	1	20452	22249	23359	21708	22398	22598	**21302**	21897	22762
	2	20134	19395	20477	**20176**	18945	20697	17036	19355	20048
	3	37446	29516	31754	30808	29134	**31651**	24920	30092	30678
	4	215360	161535	**175243**	146641	159802	151041	132590	142289	144246
	5	708263	524963	**549824**	485026	523713	461606	392180	477702	439613
	6	793401	637415	**670477**	586832	633792	555095	461920	573698	526531
	7	739544	669847	**718671**	580787	662457	561164	484287	559959	525227
	8	719907	901013	937953	796344	898017	733783	623101	781509	**713285**
	9	743661	939913	991723	853380	931413	794543	645489	830559	**777113**
	10	495893	429372	**437410**	408288	422778	354737	276593	394855	349325
	11	88278	46837	45696	**52199**	46376	42611	28604	51693	43470
	12	40568	26988	26210	27719	27026	22486	16466	**27789**	22761
MSSA	1	20452	51728	**51057**	51938	51720	51462	51072	51914	51453
	2	20134	37263	36089	35639	37035	**34831**	35906	35468	34687
	3	37446	**49954**	50065	50826	50579	50928	50675	51290	51384
	4	215360	**243189**	243882	250021	244384	249964	244998	250810	250717
	5	708263	834886	819450	833905	828499	821958	**814455**	829463	818329
	6	793401	728709	725329	761893	732000	759646	728806	**764074**	761902
	7	739544	**868542**	873799	885283	872962	889673	877392	887334	891285
	8	719907	847982	820786	822415	839045	**803354**	813077	815579	797260
	9	743661	689904	**698060**	688436	694291	695737	702471	692320	699568
	10	495893	393868	403257	399991	393528	**406288**	402367	399273	405252
	11	88278	38725	37905	37222	**37940**	36556	37191	36662	36041
	12	40568	20405	20621	20363	20545	20602	**20770**	20515	20756
*RRMSE($\frac{MSSA}{ARIMAX}$)			*0.707[a]	*0.623[a]	*0.666[a]	*0.692[a]	*0.577[a]	*0.408[a]	*0.630[a]	*0.514[a]

Table 1. Real tourist numbers vs predictions of tourist arrivals models with independent variables

In Table 1, multivariate methods include the triple combination of the explanatory variables to explain the tourist arrivals. The explanatory variables of the best model for ARIMAX are the triple combination of the AGT, FN and WC. Nevertheless, the best model for the MSSA has different independent variables which are AGT, IT and WC. The model with including all independent variables in the ARIMAX method has remarkably made better estimates. It is more reliable to decide which model has better prediction by looking at the RMSE values. Therefore, the RMSE values obtained are given in Table 2. Moreover, error terms in the ARIMAX method are normally distributed, and there is the white noise. Besides, the KSPA test is employed for error terms in the MSSA method in a similar way to univariate methods, and there are also normally distributed, and the white noise.

Variables in Models	**ARIMAX**	**MSSA**
AGT	109313.40	77257.95
AGT+FN	111616.76	74386.72
AGT+IT	114316.05	71272.71
AGT+WC	**109123.80**	75470.88
AGT+FN+WC	116236.68	73175.34
AGT+IT+FN	122046.11	70429.91
AGT+IT+WC	171562.86	70010.28
AGT+IT+WC+FN	135216.71	**69530.50**

Table 2. The RMSE results of the multivariate models with independent variables

Summary and Conclusions

GT is a free and easy-to-access tool for extensive search data to gain meaningful information about many fields, such as tourism. This study aims to emphasize how "Google Trends" data can contribute to the tourism area. It also determines the different models and combinations of auxiliary variables, which would be advantageous to forecast foreign tourists visiting (from Russia) Antalya.

The data that GT shares about the clicks actions on Google provides an excellent service for analysts. However, GT has a limitation for researchers. Dinis et al. (2019)'s general conclusion from the GT review study in tourism research in the literature is that these limitations reduce the applicability and reliability of the data. To get rid of this handicap, the data collection algorithm should be well explained by Google. When this algorithm is carefully examined, it is stated that it provides the adjusted rate scaled from 0 to 100, not the number of clicks. Therefore, to use the true impact of GT, it is crucial to understand the differences between years. With this study, it is seen that when the usage of search data is multiplied by the number of internet users and corrected, it is seen that more successful forecasts are obtained.

As a result of the analysis, when the independent variables for parametric tests are evaluated, WC, FN, IT variables make reasonable estimates on the number of tourists after AGT. In terms of nonparametric tests, it is observed that IT, WC and FN variables effectively predicted the number of tourists. In general, according to the RMSE values in Tables 1 and 2, the best model in the ARIMAX is the model that used the WC and AGT variables. However, for the MSSA method, the best model has all explanatory variables. According to Tables 1 and 2, the AGT variable is influential for the parametric method. In other words, the AGT variable's positive contribution in multivariate models is observed more clearly in the ARIMAX method. These results also support those better models that can be reached by using different combinations of GT data obtained by Havranek et al. (2021). In the impact of the application, it is seen that the people from Russia who searched based on the "Antalya" keyword in Google had tourist potential and came to Antalya.

Thus, this paper contributes to many aspects of the studies about the forecast of tourist arrivals with the help of the interested methods. These contributions are as follows:

i) It has guided how to eliminate differences in the calculation of GT data by the same time point at different time intervals (days, months and years).

ii) It has evaluated the performance of the AGT variable with the variables added to the multivariable models.

iii) It has provided the determination of the variables, which are a high effect on the forecast of tourist demands.

This study has various limitations from the perspective of using GT. In this research, those who searched with the keyword "Antalya" on Google were applied. Here, it is aimed to eliminate the language bias that GT can create by searching with a single special name, as in the Dergiades et al. (2018) study. More keywords can be used in future studies. Besides, the effect of those keywords can be compared with machine-learning methods. Apart from that, the data from social media sources can be implemented to increase the accuracy of tourist arrivals forecasts. The big data sources can supplement the independent variables related to tourism and this can be helped enhance the tourism forecast.

References

Aksu, A., Ucar, O., & Kilicarslan, D. (2017). Golf Tourism: A Research Profile and Security Perceptions in Belek, Antalya, Turkey. International Journal of Business and Social Research, 6(12), pp. 1-12.

Álvarez-Díaz, M., & Rosselló-Nadal, J. (2010). Forecasting British tourist arrivals in the Balearic Islands using meteorological variables. Tourism Economics, 16(1), 153-168.

Andrawis, R. R., Atiya, A. F., & El-Shishiny, H. (2011). Combination of long term and short term forecasts, with application to tourism demand forecasting. International Journal of Forecasting, 27(3), pp. 870-886.

Anggraeni, W., Vinarti, R. A., & Kurniawati, Y. D. (2015). Performance comparisons between arima and arimax method in moslem kids clothes demand forecasting: Case study. Procedia Computer Science, 72, pp. 630-637.

Balli, F., Balli, H. O., & Cebeci, K. (2013). Impacts of exported Turkish soap operas and visa-free entry on inbound tourism to Turkey. Tourism Management, 37, pp. 186-192.

Bangwayo-Skeete, P. F., & Skeete, R. W. (2015). Can Google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach, 46, pp. 454-464.

Bieger, T., & Wittmer, A. (2006). Air transport and tourism perspectives and challenges for destinations, airlines and governments. Journal of air transport management, 12(1), pp. 40-46.

Cakar, K. (2018). Critical success factors for tourist destination governance in times of crisis: a case study of Antalya, Turkey. Journal of Travel & Tourism Marketing, 35(6), pp. 786-802.

Cekim, H. O., & Koyuncu, A. Assessment of tourist arrival from Russian to Antalya using the univariate time series methods. Bitlis Eren Üniversitesi Fen Bilimleri Dergisi, 10(3), pp. 841-848.

Chatfield, C. (2000). Time-series forecasting. CRC Press.

Choi, H., & Varian, H. (2012). Predicting the present with Google Trends. Economic Record, 88, pp. 2-9.

Chu, F. L. (2008). A fractionally integrated autoregressive moving average approach to forecasting tourism demand. Tourism Management, 29(1), pp. 79-88.

Demir, E., & Gozgor, G. (2017). What about relative corruption? The impact of the relative corruption on the inbound tourism to Turkey. International Journal of Tourism Research, 19(3), pp. 358-366.

Dergiades, T., Mavragani, E., & Pan, B. (2018). Google Trends and tourists' arrivals: Emerging biases and proposed corrections. Tourism Management, 66, 108-120.

DHMI. (2019). https://www.dhmi.gov.tr/sayfalar/istatistik.aspx/. DHMI.

Dinis, G., Breda, Z., Costa, C., & Pacheco, O. (2019). Google Trends in tourism and hospitality research: a systematic literature review. Journal of Hospitality and Tourism Technology.

ECM & MU (2015). The European Cities Marketing Benchmarking Report, 11th Official Edition 2014-2015. Dijon, France: European Cities Marketing (ECM).

Ghil, M., Allen, M. R., Dettinger, M. D., Ide, K., Kondrashov, D., Mann, M. E., & Yiou, P. (2002). Advanced spectral methods for climatic time series. Reviews of geophysics, 40(1), pp. 3-1.

Ghodsi, M., Hassani, H., Rahmani, D., & Silva, E. S. (2018). Vector and recurrent singular spectrum analysis: which is better at forecasting? Journal of Applied Statistics, 45(10), pp. 1872-1899.

Gil-Alana, L. A. (2005). Modelling international monthly arrivals using seasonal univariate long-memory processes. Tourism Management, 26(6), pp. 867-878.

Gounopoulos, D., Petmezas, D., & Santamaria, D. (2012). Forecasting tourist arrivals in Greece and the impact of macroeconomic shocks from the countries of tourists' origin. Annals of Tourism Research, 39(2), pp. 641-666.

Greenidge, K. (2001). Forecasting tourism demand: An STM approach. Annals of Tourism Research, 28(1), pp. 98-112.

Groth, A., & Ghil, M. (2011). Multivariate singular spectrum analysis and the road to phase synchronization. Physical Review E, 84(3), pp. 1-12.

Hadavandi, E., Ghanbari, A., Shahanaghi, K., & Abbasian-Naghneh, S. (2011). Tourist arrival forecasting by evolutionary fuzzy systems. Tourism Management, 32(5), pp. 1196-1203.

Hassani, H., & Mahmoudvand, R. (2013). Multivariate singular spectrum analysis: A general view and new vector forecasting approach. International Journal of Energy and Statistics, 1, p. 01.

Hassani, H., & Silva, E. S. (2015). A Kolmogorov-Smirnov based test for comparing the predictive accuracy of two sets of forecasts. Econometrics, 3(3), 590-609.

Hassani, H., Heravi, S., & Zhigljavsky, A. (2013). Forecasting UK industrial production with multivariate singular spectrum analysis. Journal of Forecasting, 32(5), pp. 395-408.

Hassani, H., Silva, E. S., Antonakakis, N., Filis, G., & Gupta, R. (2017). Forecasting accuracy evaluation of tourist arrivals. Annals of Tourism Research, 63, pp. 112-127.

Hassani, H., Soofi, A. S., & Zhigljavsky, A. A. (2010). Predicting daily exchange rate with singular spectrum analysis. Nonlinear Analysis: Real World Applications, 11(3), pp. 2023-2034.

Havranek, T., & Zeynalov, A. (2021). Forecasting tourist arrivals: Google Trends meets mixed-frequency data. Tourism Economics, 27(1), 129-148.

Ihueze, C. C., & Onwurah, U. O. (2018). Road traffic accidents prediction modelling: An analysis of Anambra State, Nigeria. Accident Analysis & Prevention, 112, pp. 21-29.

Jackman, M., & Greenidge, K. (2010). Modelling and forecasting tourist flows to Barbados using structural time series models. Tourism and Hospitality Research, 10(1), pp. 1-13.

Jalalkamali, A., Moradi, M., & Moradi, N. (2015). Application of several artificial intelligence models and ARIMAX model for forecasting drought using the Standardized Precipitation Index. International journal of environmental science and technology, 12(4), pp. 1201-1210.

Jifri, M. H., Hassan, E. E., & Miswan, N. H. (2018). Investigate the forecasting technique for electricity load demand in urban area via statistical approach. Journal of Fundamental and Applied Sciences, 10(5), pp. 298-310.

Kim, W. H., & Malek, K. (2018). Forecasting casino revenue by incorporating Google trends. International Journal of Tourism Research, 20(4), pp. 424-432.

Kozak, N., Uysal, M., & Birkan, I. (2008). An analysis of cities based on tourism supply and climatic conditions in Turkey. Tourism Geographies, 10(1), pp. 81-97.

Lim, C., & McAleer, M. (2001). Forecasting tourist arrivals. Annals of Tourism Research, 28(4), pp. 965-977.

MGM. (2019). https://www.mgm.gov.tr/veridegerlendirme/sicaklik-analizi.aspx. MGM.

Mokhtarzad, M., Eskandari, F., Vanjani, N. J., & Arabasadi, A. (2017). Drought forecasting by ANN, ANFIS, and SVM and comparison of the models. Environmental Earth Sciences, 76(21), p. 729.

Molina, L. L., Angon, E., Garcia, A., Moralejo, R. H., Caballero-Villalobos, J., & Perea, J. (2018). Time series analysis of bovine venereal diseases in La Pampa, Argentina. PloS one, 13(8), pp. 1-17.

Morabito, M., Cecchi, L., Modesti, P. A., Crisci, A., Orlandini, S., Maracchi, G., & Gensini, G. F. (2004). The impact of hot weather conditions on tourism in Florence, Italy: the summer 2002-2003 experience. Advances in tourism climatology, 12, pp. 158-165.

Naim, I., & Mahara, T. (2018). Comparative Analysis of Univariate Forecasting Techniques for Industrial Natural Gas Consumption. International Journal of Image, Graphics & Signal Processing, 10(5), pp. 33-44.

Olya, H. G., Shahmirzdi, E. K., & Alipour, H. (2017). Pro-tourism and anti-tourism community groups at a world heritage site in Turkey. Current Issues in Tourism, pp. 1-23.

Oropeza, V., & Sacchi, M. (2011). Simultaneous seismic data denoising and reconstruction via multichannel singular spectrum analysis. Geophysics, 76(3), pp. V25-V32.

Ozdemir, B., Cizel, B., & Bato Cizel, R. (2012). Satisfaction with all-inclusive tourism resorts: The effects of satisfaction with destination and destination loyalty. International Journal of Hospitality & Tourism Administration, 13(2), pp. 109-130.

Pan, B., & Yang, Y. (2017). Forecasting destination weekly hotel occupancy with big data. Journal of Travel Research, 56(7), pp. 957-970.

Patterson, K., Hassani, H., Heravi, S., & Zhigljavsky, A. (2011). Multivariate singular spectrum analysis for forecasting revisions to real-time data. Journal of Applied Statistics, 38(10), pp. 2183-2211.

Poghosyan, H. (2018). The effectiveness of economic sanctions: the case of Russia sanctions against Turkey. Doctoral dissertation, Tartu Aoelikoo.

Rivera, R. (2016). A dynamic linear model to forecast hotel registrations in Puerto Rico using Google Trends data. Tourism Management, 57, pp. 12-20.

Shareef, R., & McAleer, M. (2007). Modelling the uncertainty in monthly international tourist arrivals to the Maldives. Tourism Management, 28(1), pp. 23-45.

Siami-Namini, S., Tavakoli, N., & Namin, A. S. (2018). A comparison of ARIMA and LSTM in forecasting time series. In 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA). IEEE, pp. 1394-1401.

Silva, E. S., Ghodsi, Z., Ghodsi, M., Heravi, S., & Hassani, H. (2017). Cross country relations in European tourist arrivals. Annals of Tourism Research, 63, pp. 151-168.

Silva, E. S., Hassani, H., & Heravi, S. (2018). Modeling European industrial production with multivariate singular spectrum analysis: A cross-industry analysis. Journal of Forecasting, 37(3), pp. 371-384.

Silva, E. S., Hassani, H., Heravi, S., & Huang, X. (2019). Forecasting tourism demand with denoised neural networks. Annals of Tourism, 74, 134-154.

Song, H., Li, G., Witt, S. F., & Athanasopoulos, G. (2011). Forecasting tourist arrivals using time-varying parameter structural time series models. International Journal of Forecasting, 27(3), pp. 855-869.

Song, H., Li, G., Witt, S. F., & Fei, B. (2010). Tourism demand modelling and forecasting: how should demand be measured? Tourism Economics, 16(1), pp. 63-81.

TURKSTAT. (2019). Toursim Statistics. TURKSTAT.

World Bank. (2019). https://databank.worldbank.org/data/reports.aspx?source=1147&series=IT.NET.USER. World Bank.

World Travel & Tourism Council (WTTC). (2017). City travel & tourism. World Travel & Tourism Council (WTTC). https://www.wttc.org/-/media/files/reports/special-and-periodic-reports.

World Travel & Tourism Council (WTTC). (2018). Travel & Tourism. World Travel & Tourism Council (WTTC). https://dossierturismo.files.wordpress.com/2018/03/wttc-global-economic-impact-and-issues-2018-eng.pdf

Yang, Y., Pan, B., & Song, H. (2014). Predicting hotel demand using destination marketing organization’s web traffic data. Journal of Travel Research, 53(4), pp. 433-447.

Yi, Z., & Xiao-feng, H. (2012). Research on daily exchange rate forecasting with multivariate singular spectrum analysis. In Management Science and Engineering (ICMSE), International Conference on (pp. 1365-1370). IEEE.