Volchek, E., Song, H., Liu, A., Law, R. and Buhalis, D., 2018, Forecasting the Demand for London Museum Visitation Using Google Trend Data, Tourism Economics, 25(3), 425–447 https://doi.org/10.1177/1354816618811558

Forecasting tourist arrivals at attractions: Search engine empowered methodologies

Abstract

Tourist decision to visit attractions is a complex process influenced by multiple factors of individual context. This study investigates how the accuracy of tourism demand forecasting can be improved at the micro-level by predicting the number of visits to London museums. The number of visits to London museums is forecasted and the predictive powers of Naïve I, seasonal Naïve, SARMA, SARMAX, SARMAX-MIDAS and artificial neural network models are compared. The empirical findings extend understanding of different types of data and forecasting algorithms to the level of specific attractions. Introducing the Google Trends index on pure time-series models enhances forecasts of the volume of arrivals to attractions. However, none of the applied models outperforms the others in all situations. Different models' forecasting accuracy varies for short- and long-term demand predictions. The application of higher-frequency search query data allows generation of weekly predictions, which are essential for attraction- and destination-level planning.

Keywords: Forecasting, Google Trends, search engine, tourist demand, attractions, artificial intelligence

Introduction

The tourism industry seeks accurate and affordable tools for marketing and management strategies to improve tourist experience (Pan et al., 2006) and increase business effectiveness (Song and Li, 2008) with a vision of enhancing destination competitiveness (Artola et al., 2015). Tourism demand forecasting can help the industry to develop more accurate and efficient strategies (Song and Li, 2008; Wu et al., 2017). The availability of real-time, high-volume and high-frequency data has revolutionised the way how tourist behaviour is monitored and forecasting reliability is achieved (Yang et al., 2014). Tourist information search data have been used widely to increase the predictive power of existing models (Park et al., 2017). Researchers in the tourism domain have proposed a range of methods to apply search queries to predict tourist arrivals at a destination level (e.g. Artola et al., 2015; Bangwayo-Skeete and Skeete, 2015; Choi and Varian, 2012; Li et al., 2017; Önder, 2017; Önder and Gunter, 2016; Park et al., 2017; Yang et al., 2015; Höpken et al., 2018; Li et al., 2018; Xiang and Pan, 2011; Antolini and Grassini, 2018; Dergiades et al., 2018). An information search index is also used to effectively forecast demand for hotels (Kadir et al., 2014; Pan et al., 2012; Yang et al., 2014; Rivera, 2016).

Despite its importance for attraction and destination management, the capability of the existing methods to accurately forecast tourist arrivals at specific attractions remains underdeveloped (Huang et al., 2017; Lei and Wang, 2017). For such forecasting, the main constraint is the availability of relevant data. First, the number of data types that can be used as explanatory variables for tourist attraction choice is limited. Most attractions do not count their arrivals by source market. The traditional factors in tourism demand theory, such as the income level of the source market and the relative price of travel between the country of origin and the destination, are thus not applicable (Wu et al., 2017). In contrast to destination choice, which is finalised before the visit, and to accommodation booking, which is arranged either before or immediately upon arrival at a destination, the choice of attractions is realised both prior to the trip (Horner and Swarbrooke, 2016) and, increasingly, during the trip (Leiper, 1990; Wang et al., 2012). While the factors of tourist context are known to be the determinants of in-destination decision-making (Choe et al., 2017; Buhalis and Foerste, 2015), the volume and the types of data that characterises visitors in the travel context is low.

Second, although tourist online search behaviour can be introduced into forecasting models, the absence of high-frequency data may limit the accuracy of these predictions. The shorter time lag between information search and actual visit to an attraction requires data of higher frequency to capture the relationships between actual demand for attractions and corresponding search queries. Currently, the most widely used data frequency in this domain is quarterly, followed by monthly and annual (Wu et al., 2017). Few studies have used data with a frequency higher than monthly (Wu et al., 2017). If most of the attraction choices are made during the trip, then monthly data frequency is too low to capture the relationship between actual demand for attractions and the corresponding search trends.

The aim of this study is to predict tourism demand for specific attractions using time series data and neutral network models. Museums are among the most popular attractions for certain types of tourists (McKercher, 2006; Recuero Virto et al., 2017). The most visited free attractions in London are the museums and art galleries (VisitLondon, 2018). Therefore, this study considers the most popular museums in London with free admission as a research context. The study is original and contributes to the field in the following ways. First, it complements the research on tourism demand forecasting by analysing the performance of forecasting techniques on individual attraction level and by comparing the accuracy of various models. Second, the study is one of the first to introduce a mixed monthly and weekly data sampling model to predict tourist demand. By relaxing the data frequency requirement, weekly information search query data can be included in the model. More importantly, with the introduction of higher frequency data, it is possible to generate weekly predictions and hence more on-time forecasts, which are essential for decision-making in destination management. The findings of this study can provide valuable information to London museums in their efforts to develop appropriate marketing strategies. Furthermore, the methodological findings may be generalised to other kinds of attractions.

This paper is organised as follows. After a brief literature review addressing the specifics of tourist behaviour and tourism demand forecasting in the next section, the following section introduces the methodologies and data used in this study. The findings and a discussion of their implications are presented in the fourth section. The fifth and final section concludes by identifying the study's limitations and by outlining future directions for research.

Literature Review

Tourist Behaviour and the Choice of Attractions

Tourist behaviour is motivated by a range of needs, including the need to relax, escape from everyday life, experience new things and develop new social relationships (Pearce, 2011). Tourist attractions have spatial and temporal characteristics that are distinct from other places in individuals' everyday lives (Leiper, 1990; Pearce, 2011). As a result, tourist attractions can draw discretionary visitors to a destination (McKercher, 2017), so that individual perceptions of the attraction's capability to satisfy visitor's needs and fulfil his or her travel motivations dictate the choice of attractions (Leiper, 1990). However, tourists usually do not have enough prior knowledge to complete all of the travel arrangements. Extensive information about tourist attractions, including their attributes, alternative options and other contextual factors, is required to support decision-making and shape expectations of future experiences (Xiang et al., 2015a; Gretzel et al., 2006; Xiang et al., 2015b).

Information search in tourism is a complex and multistage process (Hwang and Fesenmaier, 2011). Travel decision-making is often conceptualised as a linear process (e.g. need recognition, information search, evaluation of alternatives and purchase and post-purchase activities). The awareness of the travel needs and the desire to minimise the negative effect of contingencies of travel environment lead to information search and a decision-making process. To decide which attractions to visit, tourists familiarise themselves with the available options, evaluate them in terms of their capability to meet individual needs and then make decisions. The availability of the requested information, however, does not always lead to a full appraisal and a final decision. A purchase decision may be postponed due to a lack of information or to the travellers' changing situations. Also, new information may trigger a reformulation of the problem and launch a new stage of the information search process (Ho et al., 2012; Karimi et al., 2015). However, regardless of the model applied (e.g. Hyde, 2008; Gursoy and McCleary, 2004; Bargeman and van der Poel, 2006; Xiang et al., 2015a), the information search process is known to precede tourists' choice of destination, accommodations and other travel-supporting services. The search for specific topics does not guarantee a positive decision on a travel service but can nonetheless serve as a powerful predictor of purchasing behaviour.

Information search strategies for attraction selection are distinct from those for other major travel arrangements. The specific factors of the tourism context (Choe et al., 2017; Fodness and Murray, 1999) and the capabilities of the World Wide Web and personal devices (Karimi et al., 2015) have transformed the information search process into a continuous and dynamic one that occurs before, during and sometimes even after tourists experience a destination. Firstly, with exception of primary or iconic attractions, which are well-known to tourists and have the power to motivate their visit (Leiper, 1990), tourists increasingly search for information about an attraction during the actual trip (Hwang and Fesenmaier, 2011). The decision-making process for attractions is highly context-dependent. This process is shaped by tourists' personal characteristics and their travel details, such as the type, purpose, cost and length of the trip and tourists' familiarity with the destination (Hyde, 2008; Kim et al., 2015; Fodness and Murray, 1999). This decision-making process is also influenced by a range of in-destination factors, such as the tourist's location and social environment and the season, weather and time of their visit (Buhalis and Foerste, 2015). Secondly, the proliferation of information communications technologies (ICTs) has changed tourist decision-making into a more spontaneous process that is affected by the immediate situation (Choe et al., 2017; Buhalis and Foerste, 2015). While the use of printed information has dramatically decreased, interconnectivity and interoperability now enable tourists to acquire relevant digital content at any time during their customer journeys, including the in-destination phase (Xiang et al., 2015a). This access leads to a blurring of differences in information search activities before, during and after a trip (Wang, 2016). One growing trend is to postpone travel arrangements until just before tourists embark on a trip (Xiang et al., 2015a). As a result, the time lags between need recognition, an information search, the decision to visit an attraction and the actual visit all become shorter. Consequently, information search data with higher frequency may provide more accurate forecasts of tourism demand.

Tourism Demand Forecasting with Search Query Data

Forecasting Methodologies

Research has found that time series models' forecasting accuracy can be improved by including search query data. Pan et al. (2012) introduced online search query data to tourism and hotel demand forecasting. They compared various models and found that the autoregressive moving average with explanatory variables (ARMAX), which includes search query data from Google Trends, may improve the accuracy of hotel room demand forecasts. Similarly, Yang et al. (2014) used the web traffic of destination marketing organisations to predict hotel demand. The results also showed that ARMAX outperformed the autoregressive moving average (ARMA) models, which did not include data obtained from the search engine. More comprehensively, Pan and Yang (2017) incorporated both search queries and web traffic data to predict weekly hotel demand. Again, the ARMAX models outperformed the ARMA models, indicating that incorporating both indices of search query data can improve hotel demand forecasting accuracy. However, including search data does not yield superior hotel demand predictions consistently. Rivera (2016) applied a dynamic linear model to forecast hotel room demand using data from Google Trends. He found that the in-sample and 12-month forecasting accuracy of the dynamic linear model with search query data outperformed other models, whereas the exponential smoothing models were more accurate for generating 6-month forecasts. Yang et al. (2015) demonstrated the high predictive power of search query data when forecasting tourism demand, but also showed that the relevance of a search engine depends on its acceptance by target populations. For example, search queries from Baidu are more appropriate than those from Google for predicting tourism demand in China. Gunter and Önder (2016) used a Bayesian approach to forecast city arrivals with search query data. However, this approach produced no significant improvement when compared with univariate time series models in the short-run; in the long-run, combination methods, particularly the combination of other methods with the Bayesian approach, improved the forecasting accuracy significantly. Önder (2017) obtained similar findings. Thus, the application of search query data for tourism demand forecasting needs to be further developed.

Due to the complexity of tourist behaviour and the increasing technical capacity to observe this behaviour online continuously, scholars have become keen on investigating changes in tourist online search with data of different frequencies. Bangwayo-Skeete and Skeete (2015) pioneered the use of the mixed-frequency data sampling (MIDAS) model in the tourism domain. They used monthly search query data to predict quarterly tourism demand in the Caribbean, finding that the autoregressive MIDAS (AR-MIDAS) models outperformed the autoregressive (AR) models and that the seasonal autoregressive integrated moving average (SARIMA) models in reducing forecasting errors. Camacho and Pacce (2017) similarly found that the AR-MIDAS model with quarterly and monthly integreated data ourperformed the AR models in the Spanish context. However, both of these studies used the AR model as a benchmark. The ARMAX model, which has stronger predictive power when using search query data, was not included in these comparisions of forecasting accuracy. Additionally, when higher frequency data, such as monthly and weekly data, were integrated in the models, the merit of the AR-MIDAS model was not readily apparent (Hirashima et al., 2017).

The data for measuring tourism demand is typically collected less frequently than for measuring hotel demand and this has implications for research. Visitor arrivals are usually counted on a monthly basis; thus, the integration of a weekly-monitored index may generate more on-time forecasts when compared with the classic monthly or quarterly forecasts. However, previous research has only compared the forecasting accuracy of the AR-MIDAS model and the AR and ARMA models. The most competitive model, ARMAX, has not yet been included in studies of the models' relative strengths. According to Hirashima et al. (2017), the mix of monthly and weekly data does not show significant superiority over other models; thus, the MIDAS model, with its monthly and weekly data, needs to be further examined in the tourism context. By the same token, studies using search index data have normally focused on forecasting the demand for destinations, while the micro-level demand for attractions has been overlooked. One notable exception is Huang et al.'s (2017) study, which predicted tourist demand for visiting the Forbidden City in Beijing.

To address the above research gaps, this study uses the SARMAX or SARIMAX model with MIDAS (SARMAX/SARIMAX-MIDAS) models, integrating the monthly and weekly data, together with the SARMA or SARIMA family of models and artificial intelligence models, to forecast the demand for London museums and to compare the forecasting accuracy of these models. The contributions of this research are as follows. Firstly, it expands the application of search query data in tourism demand forecasting to the micro-level. Secondly, it comprehensively evaluates the forecasting accuracy of the MIDAS model, based on its integration of monthly and weekly data, with other time series and artificial intelligence models. The next section introduces the methodology and data used in this study.

Data and Method

Data

Today, tourists rely on the Internet as their major source of information and their most commonly applied planning tool (Xiang et al., 2015a). Search engines such as Google, Bing and Baidu are powerful and widely accepted intermediaries between tourists and tourism service providers, which have become the primary sources of travel-related information (Xiang and Pan, 2011; Fesenmaier et al., 2011). The Google Trends index is a ratio that reflects the popularity of a specific topic at a given moment worldwide or across topical domains and/or geographic regions (Höpken et al., 2018; Google Inc., 2017). The tool provides access to a relatively large volume of search queries submitted by its users over time.

Consumer heterogeneity (Claveria and Datzira, 2010) and the need to incorporate all variations of the search queries are challenges for the application of the Google Trends and Baidu indices (Park et al., 2017; Önder and Gunter, 2016). Another problem is the need to reduce the noise included in the index (Xiaoxuan et al., 2016). The same word or combination of words may have different meanings, adding irrelevant data to the index that can lead to significant overestimations of the results (Artola et al., 2015). Eliminating bias in language and on search engine platforms may also improve the predictive power of search query data (Dergiades et al., 2018). Therefore, there is a need to aggregate relevant search queries into one index (Höpken et al., 2018; Önder, 2017).

The straightforward collection of all of the possible word combinations, along with the elimination of irrelevant search queries, does not account for dynamic correlation between these queries (Li et al., 2017). A range of studies (e.g. Li et al., 2017; Li et al., 2018; Höpken et al., 2018) have manually developed a composite search index to account for the dynamic interrelationships between search queries. The forecasting accuracy of the models significantly improved with the benefitted of the new search index.

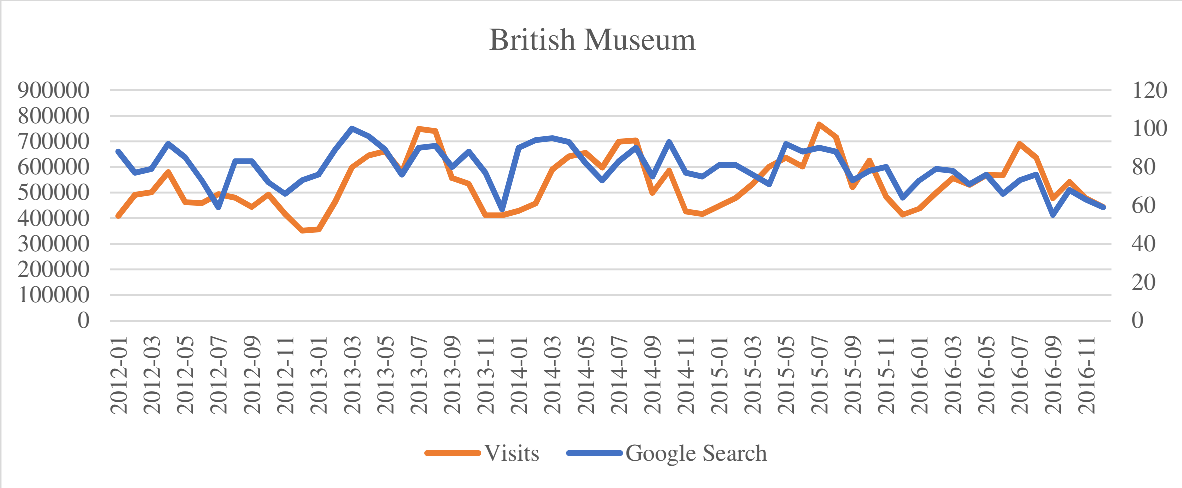
Google Trends tool recognises user queries as topics under specific categories. Google Inc. has not revealed its exact algorithm for search index aggregation, but it is widely believed that it incorporates the relevant search queries associated with the topic regardless of the exact combinations of words, the spelling or even the language used. This algorithm also eliminates irrelevant queries, such as the same words being used to describe different phenomena (Google Inc., 2017; RealGuess, 2014; Önder and Gunter, 2016). Thus, the quality of the query data is not expected to decline, while the application of the index, as aggregated by the data provider, is expected to save time.

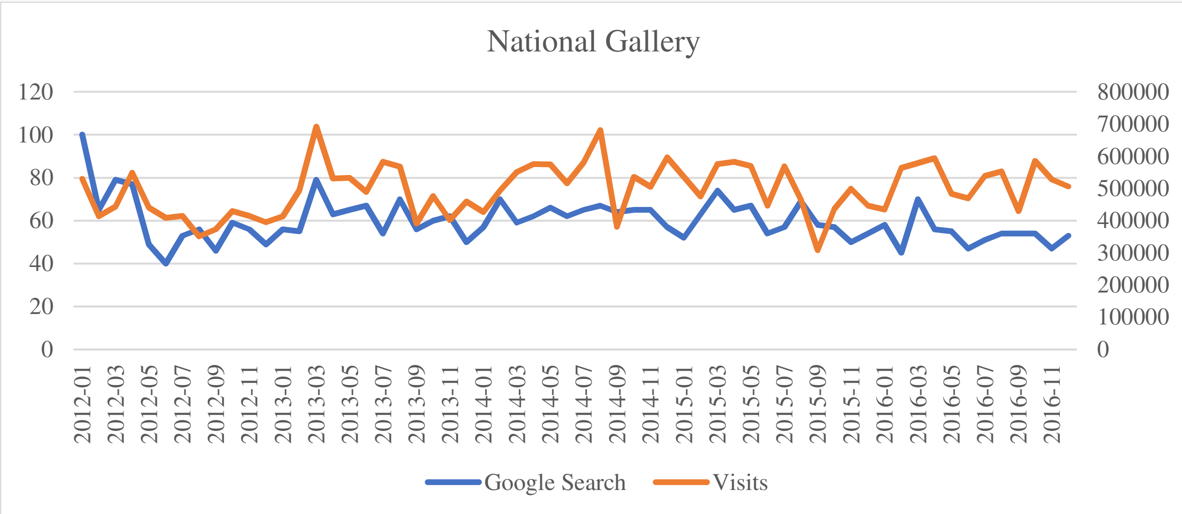
Taking into consideration the dominant role of Google search engine in the UK, and the proven importance of search query data in improving the accuracy of forecasting (e.g. Önder and Gunter, 2016; Pan et al., 2012; Yang et al., 2014), Google Trends index (Google Inc., 2017) was selected to collect the search queries for the top five most visited museums in London with free admission (VisitLondon, 2018). Rather than building the required index manually, the data on tourist online searches were obtained with the Google Trends tool by choosing the relevant category to represent each of the five museums and then applying the 'Travel' category to decrease the noise (Table 1). The applied data was collected in both monthly and weekly frequencies for the period from January 2012 to June 2017. The data on monthly visitor arrivals to these museums for the same period were acquired from the Department for Digital Culture Media & Sport, UK (2018). Figure 1 and Table 2 present data on visitor arrivals to the five museums and demonstrate the corresponding searches in Google Trends.

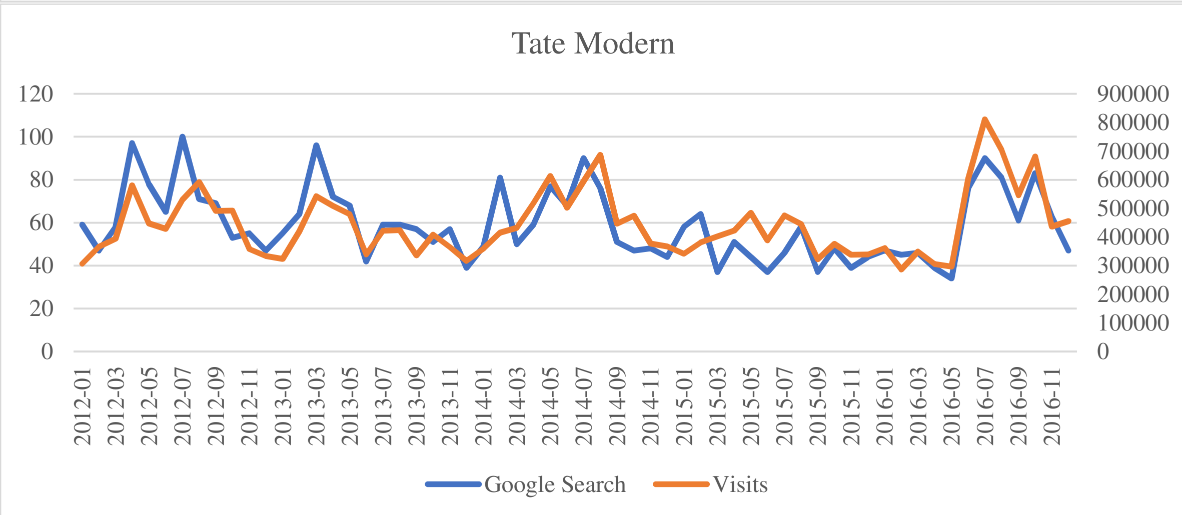
Table 1. Queries used in Google Trends

Museum	Search Query	Category	Topic

The British Museum	British Museum	Travel	Museum in London, England
The National Gallery	National Gallery	Travel	Museum in London, England
The Natural History Museum	Natural History Museum	Travel	Museum in London, England
Tate Modern	Tate Modern	Travel	Art Gallery in London, England
Science Museum	Science Museum	Travel	Museum in London, England







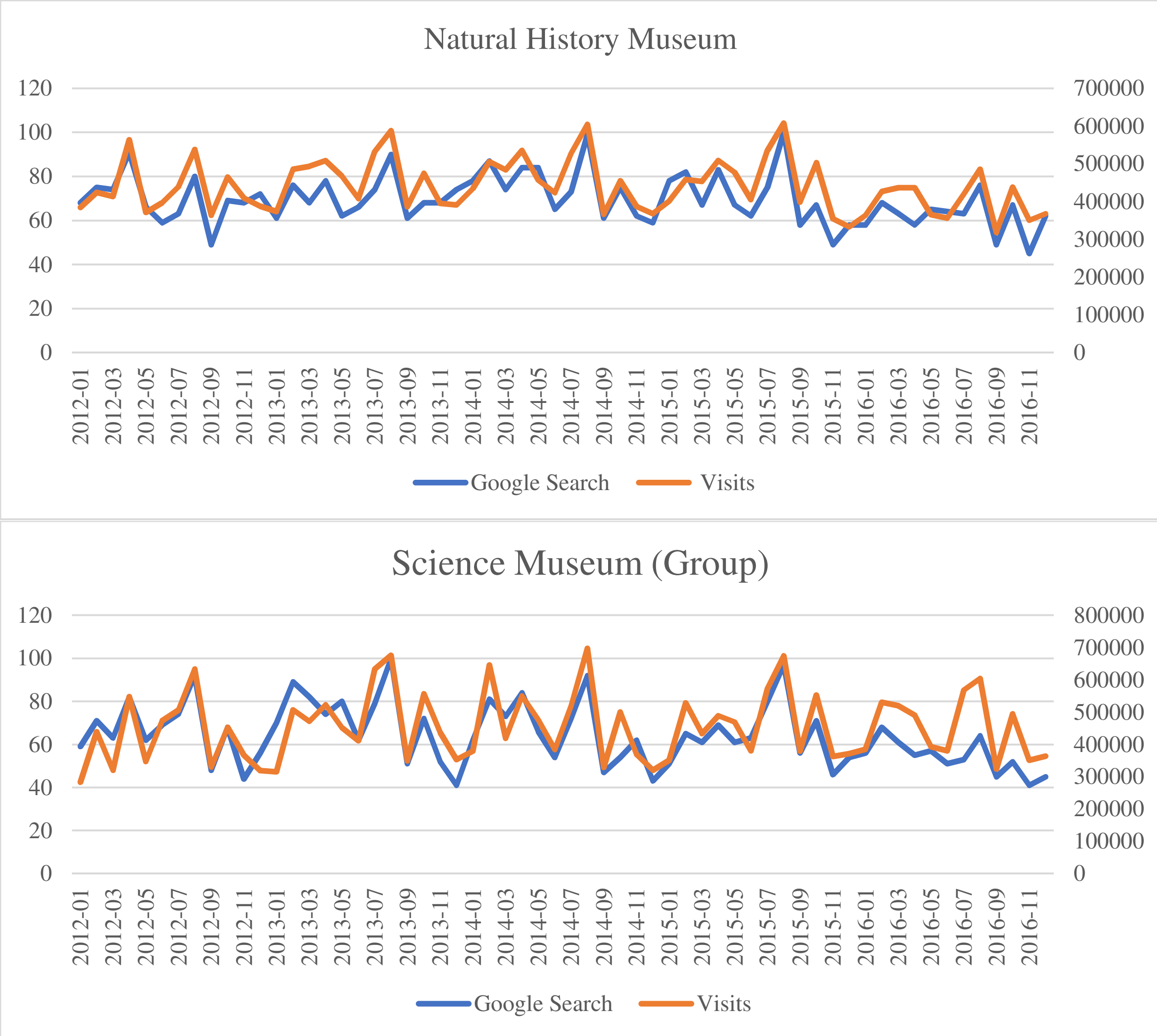


Figure 1: Absolute Number of Visits and Google Search Index for London Museums

Table 2. Descriptive Statistics for London Museums

	Mean	Median	Min	Max	Std. Dev.
British Museum Visits	536887.93	525372.50	350458.00	765877.00	101994.31
British Museum Search	79.32	78.50	55.00	100.00	10.44
National Gallery Visits	496408.58	496718.00	308832.00	692000.00	78857.65
National Gallery Search	59.82	57.50	40.00	100.00	9.92
Tate Modern Visits	442347.20	421744.00	287057.00	811162.00	112272.45
Tate Modern Search	58.88	57.00	34.00	100.00	16.52
Natural History Museum Visits	440165.78	430202.00	318413.00	607731.00	68864.12
Natural History Museum Search	69.42	68.00	45.00	100.00	11.40
Science Museum Visits	454345.05	445814.00	282802.00	697666.00	105465.13
Science Museum Search	64.20	62.00	41.00	100.00	14.48

Method

Four time series models from the Naïve I, seasonal Naïve, ARMA or ARIMA family of models, the artificial natural network (ANN) and ARMAX/ARIMAX-MIDAS were used to generate forecasts of visitor arrivals. To avoid spurious regression, unit root tests were carried out to examine the stationarity of all of the time series variables. If the time series included in the model were stationary, then level data were used in the modelling process. If non-stationary, then the data were differenced before being introduced to the models. Next, the 2012–2016 data were selected as the original training set and used to generate the ex-post forecasts from January to June 2017. The accuracy of 1-, 2-, 3- and 6-month-ahead forecasts were then compared among various models for each museum. This forecasting practice was repeated six times because the training data set extends from December 2016 to June 2017 on a rolling-monthly basis. The models used in this research are briefly introduced as follows.

Naïve I and seasonal Naïve models

Naïve I and seasonal Naïve models are usually taken as benchmarks to facilitate the improvement of newly proposed forecasting methods (Wu et al., 2017). The Naïve I model assumes the forecast of next period is equal to the observation of the last period, whereas the seasonal Naïve I model assumes that prediction of the next period equals to the observation of the same period of the previous year.

SARMA and SARIMA family models

The seasonal autoregressive moving average (SARMA) family of models, including SARMA and seasonal autoregressive moving average with explanatory variables (SARMAX) models, were used to generate forecasts if the time series in the model were stationary. A $SARMAX\ (p,q) \times (P,Q)_{12}$ is represented as Equation 1

$$\Phi(B^{12})\phi(B)\ln(Y_{j,t}) = \sum_{0}^{i}\beta_i \ln(X_{j,t-i}) + \Theta(B^{12})\theta(B)Z_{j,t}, \tag{1}$$

where

$$\Phi(B^{12}) = 1 - \Phi_1 B^{12} - \Phi_2 B^{24} - \cdots - \Phi_P B^{12P}$$

$$\phi(B) = 1 - \phi_1 B - \phi_2 B - \cdots - \phi_p B$$

$$\Theta(B^{12}) = 1 + \Theta_1 B^{12} + \Theta_2 B^{24} + \cdots + \Theta_Q B^{12Q}$$

$$\theta(B) = 1 + \theta_1 B + \theta_2 B + \cdots + \theta_q B$$

$\Phi(B^{12})$ and $\phi(B)$ are the seasonal AR and AR operators, respectively, whereas $\Theta(B^{12})$ and $\theta(B)$ are the seasonal moving average (MA) and MA operators, respectively. As monthly data were used in the models, the data frequency was set to 12. Here, $Y_{j,t}$, $X_{j,t}$ and $Z_{j,t}$ are the number of visitor arrivals, the search query data and the error term of the *j*th museum in period *t*, respectively. Also, ln is the nature logarithm operator. If $\beta_i = 0$, a SARMAX model becomes a SARMA model.

If the time series in the model have unit roots, then SARIMA and seasonal autoregressive integrated moving average with explantory variables (SARIMAX) were used. A $SARMAX\ (p, d, q) \times (P, D, Q)_{12}$ model is presented in Equation 2 as follows:

$$\Phi(B^{12})\phi(B)\Delta_{12}^{D}\Delta^{d}\ln(Y_{j,t}) = \alpha + \sum_{0}^{i}\beta_i \ln(X_{j,t-i}) + \Theta(B^{12})\theta(B)Z_{j,t}, \tag{2}$$

where Δ_{12}^{D} and Δ^{d} are seasonal difference and difference operators, respectively, and α is a drifter term. Similar to the SARMA family of models, if $\beta_i = 0$, a SARIMAX model becomes a SARIMA model. The lagged orders of P, p, Q and q and the rank of the seasonal difference (D) are determined by the Akaike information criterion (AIC), whereas the rank of difference (d) is determined by the number of the unit roots.

SARMAX/SARIMAX-MIDAS Model

Similar to Equation (1) and (2), the SARMAX/SARIMAX-MIDAS models, which apply data of different frequencies, are expressed in Equations (3) and (4), respectively.

$$\Phi(B^{12})\phi(B)\ln(Y_{j,t}) = \sum_{0}^{i}\sum_{0}^{l_i}\beta_{j,l_i}^{i}\ln X_{j,tm_i-l_i}^{i} + +\Theta(B^{12})\theta(B)Z_{j,t}, \tag{3}$$

$$\Phi(B^{12})\phi(B)\Delta_{12}^{D}\Delta^{d}\ln(Y_{j,t}) = \alpha + \sum_{0}^{i}\sum_{0}^{l_i}\beta_{j,l_i}^{i}\ln X_{j,tm_i-l_i}^{i} + \Theta(B^{12})\theta(B)Z_{j,t}, \tag{4}$$

where $X_{j,4t-l}$ is the search query data of the *j*th museum in the *(4t-l)*th week in period t. There are $p + P + q + Q + \sum_0^i \sum_0^{l_i}$ parameters that need to be estimated but which are too large for the limited number of observations; non-linear least squares (NLS) is used to estimate a restricted model with fewer parameters. Two parametric functional constraints (Exponential Almon lag polynomial and Beta (analogue of probability density function)), which are widely used in previous research (Camacho and Pacce, 2017; Gunter et al., 2018) and unconstrained MIDAS models are estimated, respectively. The model was selected by AIC. It was assumed that there are four weeks in one month to align the data with different frequencies, indicating the number of visitor arrivals in a particular month is related to a fixed set of weekly lagged search query data (Ghysels et al., 2016). More details of the estimation of the MIDAS model can be found in Ghysels et al. (2016).

ANN model

The ANN model is a type of artificial intelligence model used widely in the field of tourism and hotel demand forecasting (Song and Li., 2008; Wu et al., 2017). This model was introduced by Pattie and Snyder (1996), with subsequent development by Law and Au (1999). The ANN model is composed of an input layer, one or more hidden layer(s) and an output layer. Each layer consists of nodes that are connected to other nodes at adjacent layer(s). A weight is estimated to link each pair of the nodes. A more detailed introduction of the ANN model in the tourism research domain can be found in Law (2000). An iterative neural filter (INF) based on the common multilayer perception (MLP) method was used to select the optimal input layer for time series date based on the mean square errors (MSE). More details regarding the algorithm can be found in Crone and Kourentzes (2010).

The mean absolute percentage error (MAPE) and root mean square error (RMSE), which are the most frequently used indices to measure forecasting accuracy in the tourism and hospitality field (Peng et al., 2014), were used to evaluate the forecasting behaviour of the various models.

Findings and Discussions

Unit Root Tests of Stationarity

The Augmented Dickey-Fuller (ADF), Phillips-Perron, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests and the Canova-Hansen (CH) seasonality test are carried out to examine the stationarity of all of the variables after natural logarithm. Only constant terms are included in the ADF and KPSS tests, respectively, and dummy variables are adapted in CH test. Due to the fact that there is a different number of weeks in each year, no seasonal cycle can be observed and thus CH test is not available for weekly data. Out of caution, the stationarity of the time series is confirmed in at least three of the four tests to ensure that the same integration order is used. The results of the unit root tests are presented in Table 3. Although the KPSS test rejected the null hypothesis that the time series are stationary for a number of variables, ADF and PP tests rejected the null hypothesis that the time series has a unit root for all of the variables at a 5% significance level and the CH test cannot reject the null hypothesis that the time series is stationary for all monthly data. Thus, it can be argued that all of the data are stationary with the integration order of zero. This means that no difference is needed in the modelling process.

Table 3. Results of Unit Root Tests

Visitor Arrivals	ADF	PP	KPSS	CH	Integration Order
British Museum	-3.414***	-25.205***	0.242	1.726	I(0)
National Gallery	-4.043***	-44.595***	0.415*	1.669	I(0)
Tate Modern	-3.573***	-26.337***	0.087	1.681	I(0)
Natural History Museum	-4.538***	-54.468***	0.362*	1.653	I(0)
Science Museum	-3.573***	-61.947***	0.100	1.700	I(0)
Monthly Index					
British Museum	-3.701***	-39.054***	0.673**	1.668	I(0)
National Gallery	-4.100***	-43.962***	0.378*	1.731	I(0)
Tate Modern	-3.744***	-34.777***	0.513**	1.669	I(0)
Natural History Museum	-3.851***	-64.635***	0.603**	1.648	I(0)
Science Museum	-3.711***	-52.079***	0.685**	1.614	I(0)
Weekly Index					
British Museum	-7.768***	-232.836***	1.727**	-	I(0)
National Gallery	-8.836***	-255.754***	0.546**	-	I(0)
Tate Modern	-11.726***	-312.968***	0.281	-	I(0)
Natural History Museum	-8.693***	-210.393***	0.938**	-	I(0)
Science Museum	-8.949***	-141.777***	0.285	-	I(0)

Note: *, ** and *** represent significant at 10%, 5% and 1% significant level, respectively.

Estimation Results

Naïve I, seasonal Naïve, and SARMA $(1,0) \times (1,0)$ provides the best fit in all seven rounds of estimation for the British Museum, the National Gallery and the Tate Modern. According to AIC, SARMA $(2,0) \times (1,0)$ is the optimal model for the Natural History Museum and the January 2012 to December 2016 data for the Science Museum. For the case of the Science Museum, SARMA $(2,1) \times (1,0)$ best fits the period from January 2012 to March 2017, while SARMA $(1,1) \times (1,0)$ is more appropriate for other sample periods. When the search query data are introduced into the models, SARMAX $(1,0) \times (1,0)$ is the most fit model for the British Museum, the National Gallery, Tate Modern and six out of seven sample periods for the Natural History Museum. The data on the Natural History Museum for the period from January 2012 to February 2017 has a lower AIC with SARMAX $(0,2) \times (1,0)$. In terms of the

Science Museum, the model fits for five out of seven sample periods are best when SARMAX $(2,0) \times (1,0)$ is used, whereas the periods from January 2012 to April 2017 and from January 2012 to June 2017 fit SARMAX $(0,0) \times (1,0)$ best. In general, the AR(1) and SAR(1) terms are the most important factors for museum demand and Google Trends data in the current month is a significant explanatory variable for that demand. In the SARMAX-MIDAS family of models, NLS with Exponential Almon lag polynomial fit all of the museums best except for the National Gallery. Also, AR(1) term and the Google Trend data of the last two weeks are included in all of the NLS estimated models, whereas the Google Trends index of the second last week is dropped by AIC in the National Gallery models. In addition, the online search data of the third last week is a significant determinant of the demand for the Science Museum. In the ANN models, 11 seasonal dummies and the Google Trends data of the current month are selected by MSE in all of the models. The details of the estimation results are available upon request.

Forecasting Accuracy

The forecasting accuracy of visitor arrivals to the five museums is measured by MAPE and RMSE, which are presented in Tables 4 and 5, respectively. The prediction errors for 1-, 2-, 3- and 6-months-ahead are generated and compared among the different forecasting methods for the five museums. The figures in bold indicate the least forecasting error of the museum for each time horizon. Among the five museums, the smallest MAPE is 1.90%, which is generated by the SARMAX family of models in the two-month forecast of the Natural History Museum; whereas the largest is 50.45%, generated by the seasonal Naïve model in the two-month forecast for the Tate Modern. The most accurate and inaccurate forecast measured by RMSE are both observed in the six-month forecast of the seasonal Naïve model; the most accurate forecast is for the Science Museum (0.056) and the least accurate is for the Tate Modern (17.350).

The geometric means of the five museums' forecasting accuracy indices measured by MAPE and RMSE are presented in Tables 6 and 7, respectively. The overall MAPE of all of the methods is less than 9%, indicating good forecasting behaviour. As the forecasting horizon extends, the geometric mean of MAPE for the six methods increases, from 6.09% in the 1-month-ahead forecast to 8.95% in the 6-month-ahead forecast. Surprisingly, when the errors are measured by RMSE, the 1-month-ahead forecast (0.841) outperforms longer horizons but the 2-month-ahead forecast error is larger than the 3- and 6-month-ahead forecasts. This may be explained by the fact that the Easter Holiday in 2016 was in March but in April in 2017, so there is a significant drop in March 2017 and a sharp increase in April 2017 when compared to the same period in 2016. As RMSE is associated with fluctuations in the real data, the 2-month-ahead forecast suffered a larger error than other horizons when the forecast started from January 2017. This might also explain the dramatic forecasting error for the Tate Modern in the 2-month-ahead forecast of the seasonal Naïve I model by MAPE. In terms of each method's general performance, clear trends are observed in the errors of the ANN models, which ranged from 3.64% to 13.62% for MAPE and 0.439 to 1.786 for RMSE, respectively. The MAPE of the Naïve I model also increases from 9.67% in the 1-month-ahead forecast to 15.58% in the 6-month-ahead. The patterns of the other methods across different forecasting horizons are less clear than for the ANN and Naïve I models. The variety of forecasting behaviour across different models for different time horizons and museums supports the previous finding that no model is superior to the other models across time and contexts (Song and Li, 2008).

Table 4. MAPE of Visitor Arrivals to the Five Museums

British Museum	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**	**National Gallery**	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**
1st week						6.19%	1st week						1.48%
2nd week						7.75%	2nd week						4.78%
3rd week						4.10%	3rd week						2.78%
1-step	7.38%	5.41%	5.79%	4.27%	**4.00%**	8.05%	**1-step**	7.38%	14.65%	4.63%	5.50%	**2.83%**	5.54%
1st week						5.71%	1st week						4.58%
2nd week						10.06%	2nd week						6.73%
3rd week						9.97%	3rd week						7.35%
2-steps	8.85%	5.02%	4.34%	5.41%	**3.20%**	10.82%	**2-steps**	8.85%	16.23%	5.05%	7.03%	**2.98%**	8.49%
1st week						12.53%	1st week						9.64%
2nd week						11.75%	2nd week						11.05%
3rd week						9.21%	3rd week						11.95%
3-steps	16.93%	**4.76%**	5.27%	5.27%	8.24%	6.77%	**3-steps**	16.93%	17.58%	**4.11%**	7.91%	5.67%	12.94%
1st week						6.91%	1st week						14.60%
2nd week						6.48%	2nd week						18.81%
3rd week						6.09%	3rd week						20.76%
6-steps	26.56%	7.11%	**5.93%**	7.67%	20.39%	9.09%	**6-steps**	26.56%	29.24%	23.64%	**19.51%**	19.55%	25.19%
Natural History Museum	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**	**Tate Modern**	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**
1st week						8.74%	1st week	1st week					10.70%
2nd week						7.32%	2nd week	2nd week					9.79%
3rd week						5.96%	3rd week	3rd week					7.19%
1-step	6.22%	5.69%	7.03%	6.23%	**2.83%**	10.24%	**1-step**	12.96%	44.29%	13.74%	11.08%	**5.29%**	9.36%
1st week						9.96%	1st week						10.78%
2nd week						7.71%	2nd week						9.16%
3rd week						4.81%	3rd week						8.88%

2-steps	11.21%	7.50%	5.00%	**1.90%**	7.49%	5.87%	**2-steps**	19.37%	50.45%	24.62%	15.96%	15.26%	**8.54%**
1st week						13.40%	1st week						6.55%
2nd week						11.23%	2nd week						8.05%
3rd week						5.08%	3rd week						8.93%
3-steps	6.70%	6.87%	4.96%	**3.82%**	9.51%	4.73%	**3-steps**	15.47%	48.75%	26.19%	16.02%	**7.60%**	10.32%
1st week						11.18%	1st week						9.68%
2nd week						4.39%	2nd week						8.39%
3rd week						7.55%	3rd week						6.28%
6-steps	9.21%	3.41%	3.23%	**3.04%**	6.27%	5.48%	**6-steps**	16.84%	28.64%	14.41%	**4.22%**	13.67%	6.71%
Science Museum	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**							
1st week						13.74%							
2nd week						12.37%							
3rd week						17.66%							
1-step	19.26%	3.84%	4.66%	6.84%	**3.79%**	13.29%							
1st week						12.62%							
2nd week						12.02%							
3rd week						15.21%							
2-steps	18.53%	4.69%	8.01%	9.21%	**5.58%**	14.02%							
1st week						9.54%							
2nd week						9.55%							
3rd week						7.24%							
3-steps	13.82%	5.27%	**5.89%**	8.11%	9.61%	7.20%							
1st week						9.26%							
2nd week						9.91%							
3rd week						8.86%							
6-steps	8.38%	**4.17%**	5.54%	4.94%	13.73%	8.14%							

Table 5. RMSE of Visitor Arrivals to the Five Museums

British Museum	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**	**National Gallery**	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**
1st week						0.627	1st week						1.007
2nd week						0.560	2nd week						1.284
3rd week						0.502	3rd week						1.078
1-step	0.489	0.246	0.215	0.503	**0.118**	0.503	**1-step**	1.437	1.835	0.821	**0.741**	0.761	1.002
1st week						1.169	1st week						1.110
2nd week						1.111	2nd week						1.001
3rd week						1.173	3rd week						1.027
2-steps	1.303	0.346	0.382	1.119	**1.084**	1.119	**2-steps**	2.526	2.254	1.105	**0.834**	0.849	1.189
1st week						1.394	1st week						1.649
2nd week						1.275	2nd week						1.038
3rd week						1.268	3rd week						1.088
3-steps	2.234	**0.271**	0.315	1.294	1.385	1.294	**3-steps**	0.999	1.34	**1.057**	0.761	1.055	1.239
1st week						0.851	1st week						1.674
2nd week						0.785	2nd week						2.468
3rd week						0.842	3rd week						5.370
6-steps	2.524	0.245	**0.290**	0.828	2.227	0.828	**6-steps**	5.306	6.492	4.828	**3.567**	6.019	8.080
Natural History Museum	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**	**Tate Modern**	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**
1st week						3.181	1st week						2.563
2nd week						1.771	2nd week						2.158
3rd week						1.579	3rd week						2.036
1-step	2.621	1.746	1.514	**1.174**	1.850	1.766	**1-step**	1.295	8.151	2.108	1.273	**1.182**	2.993
1st week						1.870	1st week						2.568
2nd week						1.479	2nd week						3.079
3rd week						1.452	3rd week						2.725
2-steps	2.103	1.096	1.052	**0.554**	2.196	2.223	**2-steps**	2.927	9.389	4.091	2.159	**1.946**	3.449

1st week						2.810	1st week						4.626
2nd week						1.714	2nd week						5.096
3rd week						2.697	3rd week						4.219
3-steps	0.989	0.900	0.842	**0.788**	1.694	3.519	**3-steps**	2.441	7.364	3.434	1.716	**1.430**	4.647
1st week						3.680	1st week						2.423
2nd week						3.065	2nd week						3.254
3rd week						2.217	3rd week						2.477
6-steps	1.100	0.185	**0.166**	0.437	1.579	1.077	**6-steps**	5.583	17.350	3.012	**0.770**	1.170	2.284
Science Museum	**Naïve-1**	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**							
1st week						1.145							
2nd week						1.004							
3rd week						1.042							
1-step	2.498	0.221	0.237	0.480	**0.083**	1.074							
1st week						1.239							
2nd week						1.545							
3rd week						2.266							
2-steps	2.788	**0.191**	0.261	0.364	0.516	1.542							
1st week						1.247							
2nd week						1.040							
3rd week						1.525							
3-steps	1.492	**0.159**	0.192	0.287	0.663	2.488							
1st week						1.536							
2nd week						1.359							
3rd week						1.558							
6-steps	0.583	**0.056**	0.106	0.163	0.734	1.216							

Table 6. MAPE of the Different Models

	Naïve-1	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**	**GM**
1 month ahead	9.67%	9.48%	6.55%	6.44%	3.64%	8.93%	7.08%
2 months ahead	12.58%	10.77%	7.36%	6.39%	5.71%	9.16%	8.33%
3 months ahead	13.26%	10.81%	6.98%	7.30%	7.98%	8.40%	8.88%
6 months ahead	15.58%	9.67%	8.15%	6.24%	13.62%	9.27%	9.95%
GM	12.59%	10.16%	7.24%	6.58%	6.90%	8.94%	

Note: GM stands for geometric mean.

Table 7. RMSE of the Different Models

	Naïve-1	**Seasonal Naïve**	**SARMA**	**SARMAX**	**ANN**	**SARMAX-MIDAS**	**GM**
1 month ahead	1.429	1.073	0.669	0.639	0.439	1.234	0.841
2 months ahead	2.241	1.089	0.861	0.666	1.152	1.735	1.187
3 months ahead	1.517	0.825	0.713	0.617	1.186	2.306	1.071
6 months ahead	2.168	0.778	0.594	0.548	1.786	1.821	1.102
GM	1.802	0.931	0.703	0.616	1.017	1.732	

Note: GM stands for geometric mean.

The Figures in Tables 4 through 7 indicate that the SARMAX family of models outperformed the SARMA models in predicting visitor arrivals to London museums. Pan et al. (2012), Pan and Yang (2017) and Yang et al. (2015) found that including of search query data in the model may enhance its predictive power when forecasting tourism and hotel demand for a destination. The present study confirms this finding and shows that search query data may also improve the accuracy of forecasting demand for attractions. Thus, the incorporation of search query data is not only useful for strategic planning and for the development of destinations, but also for managers of tourist attractions, who can gain valuable insights from online data. Given the convenience and feasibility of obtaining search query data, web-based tourism demand forecasting systems (Song et al., 2013; Song and Li, 2008) are becoming increasingly important for the tourism and hotel industry.

Research has found the evidence that ANN is more accurate than the naïve models and exponential smoothing models (Law and Au, 1999; Law, 2000; Kon and Turner, 2005). Some scholars have also argued that the ARIMA family of models can outperform ANN to generate accurate forecasts of tourism demand (Claveria and Torra, 2014). The results of the present study complement the previous findings. Although the ARMAX family of models have been found to be the most accurate in general, ANN yields better results when used to forecast tourist demand for a museum in the short term. Tables 5 and 6 illustrate that the 1-month-ahead geometric means of the ANN models are 3.64% and 0.439 for MAPE and RMSE, respectively, much less than those of other methods. ANN monopolises the least error of MAPE and three out of five of RMSE for all museums in the 1-month-ahead forecast. Thus, ANNs are more appropriate for those decision-makers who focus on demand in the short term.

Given that the search query data for the SARMAX-MIDAS model is updated weekly, it is assumed that its forecasting accuracy may be higher when more recent information is used than models using only monthly data. Unfortunately, the superiority of quarterly-monthly mixed data, obtained by Bangwayo-Skeete and Skeete (2015) and Camacho and Pacce (2017), is not successfully reproduced. Nonetheless, the mixed frequency method could outperform both the Naïve models according to MAPE and the Naïve I model according to RMSE. The change of the Easter Holiday dates in 2017 caused significant fluctuation in the arrivals for March and April when compared to 2016. This may explain why SARMX-MIDAS does not outperform the seasonal Naïve I model when measured by RMSE. Data for online search behaviour have become a leading indicator of tourism demand. Larger online search data indicate that more people are interested in an attraction. However, research has yielded mixed results. Hirashima et al. (2017) found that monthly-weekly mixed data is less accurate in a prediction of tourism demand in Hawaii. Their estimation results show that the index of the last two or three weeks affects the demand of the current month. If the demand suggested by online search queries from the present month actually manifests next month, then the search data do not completely capture demand, which may lead to less accurate forecasts for the ARMAX-MIDAS model. Another issue is consumer heterogeneity, including long-term determinants such as economic factors (e.g. income level of visitors and the relative price of travel between the country of origin and the destination) and social-demographic parameters (e.g. the culture and the country of origin, family status and mode of travel), all of which affect travel planning (Buhalis and Michopoulou, 2011). For example, for the museums under discussion, the proportion of the overseas visitors, who are more likely to plan their trips in advance than domestic visitors, exceeds 50% (London & Partners, 2017). Moreover, other contextual factors, such as the presence of organised group excursions or the cancellation of roaming charges for the EU, may also shape visitors' online information search and influence the accuracy of forecasting. Although the SARMAX-MIDAS model does not outperform the others, it is more accurate than the Naïve families in general and the geometric means of the five museums' MAPEs for different forecasting horizons are all less than 10% (Table 5), indicating relatively high forecasting accuracy. Compared with the other models, SARMAX-MIDAS can provide weekly forecasts, which makes it a useful option for decision-makers who need to consider shorter-term predictions.

Conclusions

Researchers have increasingly turned to tourist online search behaviour to forecast tourism and hotel demand on the destination level. The application of search query data to predict the demand for attractions remains underdeveloped. Specifically, the forecasting accuracy of the MIDAS model with other frequently used models in tourism domain needed to be further confirmed. To address such research gaps, this study used the Naïve 1, seasonal Naïve, SARMA, SARMAX, ANN and SARMAX-MIDAS models to forecast tourism demand for the top five museums in London. MAPE and RMSE show that no model outperformed the other models in all situations. Overall, the SARMAX family of models is proved more accurate in terms of forecasting demand for museums in London, especially for the 2-, 3- and 6-month-ahead forecasts. The ANN model offers superior predictive power when forecasting demand one month ahead. The performance of the SARMAX-MIDAS model is not superior to any other model, but the overall forecasting accuracy beats the Naïve family models, which are still acceptable.

These findings indicate that different forecasting methods should be recommended to decision-makers based on their specific targets. In general, the SARMAX model, with its search trend data, is a safer choice because its overall forecasting error is less. However, if decision-making is focused on the short-term perspective, then the ANN model may be a better choice due to its merits in terms of short-run prediction. If the stakeholder needs to update forecasts frequently, such as every week, then the SARMAX-MIDAS model provides a possible solution to that problem. Given the convenience and feasibility of obtaining online search data, the imperative to develop web-based tourism demand forecasting systems should be recognised.

The main limitation of this study is its sample size. The sample period is from 2012 to 2016 and 2017 data are used to evaluate forecasting accuracy. Even when monthly data are used, the sample size remains limited. However, despite both visits and online search data being available before 2012, and despite the proliferation of the Internet and Google as the dominant search engine, Internet users still made up only 80% of the EU and UK population, which are the major markets of London tourism, as of 2016 (Google Inc., 2016). More robust results may be obtained in future studies with a larger sample size. Additionally, different types of needs motivate tourists to visit different attractions (McKercher, 2017). Due to data availability, this study considered museums with free admission. Thus, in addition to other demand-generating regions, the results of the study should be crosschecked for other types of attractions. Considering how little light has been shed on attraction-level demand forecasting, future research should expand the forecasting models used here for museums to other types of attractions, as this effort should be valuable and useful for both academia and the tourism industry.

References

Antolini F and Grassini L. (2018) Foreign arrivals nowcasting in Italy with Google Trends data. *Quality and Quantity*: 1-17.

Artola C, Pinto F and Pedraza PD. (2015) Can internet searches forecast tourism inflows? *International Journal of Manpower* 36: 103-116.

Bangwayo-Skeete PF and Skeete RW. (2015) Can Google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach. *Tourism Management* 46: 454-464.

Bargeman B and van der Poel H. (2006) The role of routines in the vacation decision-making process of Dutch vacationers. *Tourism Management* 27: 707-720.

Buhalis D and Foerste M. (2015) SoCoMo marketing for travel and tourism: Empowering co-creation of value. *Journal of Destination Marketing & Management* 4: 151-161.

Buhalis D and Michopoulou E. (2011) Information-enabled tourism destination marketing: addressing the accessibility market. *Current Issues in Tourism* 14: 145-168.

Camacho M and Pacce MJ. (2017) Forecasting travellers in Spain with Google's search volume indices. *Tourism Economics*: 1354816617737227.

Choe Y, Fesenmaier DR and Vogt C. (2017) Twenty-five years past Vogt: Assessing the changing information needs of american travellers. *Information and Communication Technologies in Tourism 2017.* Springer, 489-502.

Choi H and Varian H. (2012) Predicting the present with Google Trends. *Economic Record* 88: 2-9.

Claveria O and Datzira J. (2010) Forecasting tourism demand using consumer expectations. *Tourism Review* 65: 18-36.

Claveria O and Torra S. (2014) Forecasting tourism demand to Catalonia: Neural networks vs. time series models. *Economic Modelling* 36: 220-228.

Crone SF and Kourentzes N. (2010) Feature selection for time series prediction–A combined filter and wrapper approach for neural networks. *Neurocomputing* 73: 1923-1936.

Department for Digital Culture Media & Sport. (2018) Monthly Museums and Galleries visits. In: Sport DfDCM (ed).

Dergiades T, Mavragani E and Pan B. (2018) Google Trends and tourists arrivals: Emerging biases and proposed corrections. *Tourism Management* 66: 108-120.

Fesenmaier DR, Xiang Z, Pan B and Law R. (2011) A framework of search engine use for travel planning. *Journal of Travel Research* 50: 587-601.

Fodness D and Murray B. (1999) A model of tourist information search behavior. *Journal of Travel Research* 37: 220-230.

Ghysels E, Kvedaras V and Zemlys V. (2016) Mixed frequency data sampling regression models: the R package midasr. *Journal of statistical software* 72: 1-35.

Google Inc. (2016) *Internet users as percentage of population*. Available at: https://www.google.com.hk/publicdata/explore?ds=d5bncppjof8f9_&met_y=it_net_user_p2&idim=country:GBR:USA:CHN&hl=en&dl=en#!ctype=l&strail=false&bcs=d&nselm=h&met_y=it_net_user_p2&scale_y=lin&ind_y=false&rdim=region&idim=country:GBR:USA:FRA:DEU:ITA&ifdim=region&hl=en_US&dl=en&ind=false.

Google Inc. (2017) *Google Trends*. Available at: https://trends.google.com/.

Gretzel U, Fesenmaier DR, Formica S and O'Leary JT. (2006) Searching for the future: Challenges faced by destination marketing organizations. *Journal of Travel Research* 45: 116-126.

Gunter U and Önder I. (2016) Forecasting city arrivals with Google Analytics. *Annals of Tourism Research* 61: 199-212.

Gunter U, Önder I and Gindl S. (2018) Exploring the predictive ability of LIKES of posts on the Facebook pages of four major city DMOs in Austria. *Tourism Economics*: 1354816618793765.

Gursoy D and McCleary KW. (2004) An integrative model of tourists' information search behavoir. *Annals of Tourism Research* 31: 353-373.

Hirashima A, Jones J, Bonham CS and Fuleky P. (2017) Forecasting in a Mixed Up World: Nowcasting Hawaii Tourism. *Annals of Tourism Research* 63: 191-202.

Ho CI, Lin MH and Chen HM. (2012) Web users' behavioural patterns of tourism information search: From online to offline. *Tourism Management* 33: 1468-1482.

Höpken W, Eberle T, Fuchs M and Lexhagen M. (2018) Search Engine Traffic as Input for Predicting Tourist Arrivals. *Information and Communication Technologies in Tourism 2018.* Cham: Springer, 381-393.

Horner S and Swarbrooke J. (2016) *Consumer behaviour in tourism,* Oxford, UK: Routledge.

Huang X, Zhang L and Ding Y. (2017) The Baidu Index: Uses in predicting tourism flows –A case study of the Forbidden City. *Tourism Management* 58: 301-306.

Hwang Y-H and Fesenmaier D. (2011) Unplanned tourist attraction visits by travellers. *Tourism Geographies* 13: 398.

Hyde KF. (2008) Information processing and touring planning theory. *Annals of Tourism Research* 35: 712-731.

Kadir SN, Tahir NM, Yassin IM and Zabidi A. (2014) Malaysian tourism interest forecasting using nonlinear auto-regressive moving average (NARMA) model. *Wireless Technology and Applications (ISWTA), 2014 IEEE Symposium on.* Kota Kinabalu, Malaysia: IEEE, 193-198.

Karimi S, Papamichail KN and Holland CP. (2015) The effect of prior knowledge and decision-making style on the online purchase decision-making process: A typology of consumer shopping behaviour. *Decision Support Systems* 77: 137-147.

Kim H, Xiang Z and Fesenmaier DR. (2015) Use of the internet for trip planning: A generational analysis. *Journal of Travel & Tourism Marketing* 32: 276-289.

Kon SC and Turner LW. (2005) Neural network forecasting of tourism demand. *Tourism Economics* 11: 301-328.

Law R. (2000) Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting. *Tourism Management* 21: 331-340.

Law R and Au N. (1999) A neural network model to forecast Japanese demand for travel to Hong Kong. *Tourism Management* 20: 89-97.

Lei K and Wang X. (2017) Correlation analysis and prediction of tourist volume in tourist attraction based on network data. *Revista de la Facultad de Ingenieria* 32: 734-740.

Leiper N. (1990) Tourist attraction systems. *Annals of Tourism Research* 17: 367-384.

Li S, Chen T, Wang L and Ming C. (2018) Effective tourist volume forecasting supported by PCA and improved BPNN using Baidu index. *Tourism Management* 68: 116-126.

Li X, Pan B, Law R and Huang X. (2017) Forecasting tourism demand with composite search index. *Tourism Management* 59: 57-66.

London & Partners. (2017) London Tourism Report 2014-2015. London.

McKercher B. (2006) Are psychographics predictors of destination life cycles? *Journal of Travel & Tourism Marketing* 19: 49-55.

McKercher B. (2017) Do attractions attract tourists? A framework to assess the importance of attractions in driving demand. *International Journal of Tourism Research* 19: 120-125.

Önder I. (2017) Forecasting tourism demand with Google trends: Accuracy comparison of countries versus cities. *International Journal of Tourism Research* 19: 648-680.

Önder I and Gunter U. (2016) Forecasting tourism demand with Google Trends for a major European city destination. *Tourism analysis : an interdisciplinary journal* 21: 203-220.

Pan B, Litvin S and Goldman H. (2006) Real users, real trips, and real queries: An analysis of destination search on a search engine. *Annual Conference of Travel and Tourism Research Association (TTRA 2006), Dublin, Ireland.*

Pan B, Wu DC and Song H. (2012) Forecasting hotel room demand using search engine data. *Journal of Hospitality and Tourism Technology* 3: 196-210.

Pan B and Yang Y. (2017) Forecasting destination weekly hotel occupancy with big data. *Journal of Travel Research* 56: 957-970.

Park S, Lee J and Song W. (2017) Short-term forecasting of Japanese tourist inflow to South Korea using Google trends data. *Journal of Travel and Tourism Marketing* 34: 357-368.

Pattie DC and Snyder J. (1996) Using a neural network to forecast visitor behavior. *Annals of Tourism Research* 23: 151-164.

Pearce PL. (2011) *Tourist behaviour and the contemporary world,* Bristol [England: Channel View Publications.

Peng B, Song H and Crouch GI. (2014) A meta-analysis of international tourism demand forecasting and implications for practice. *Tourism Management* 45: 181-193.

RealGuess. (2014) *Understand Google Trends Search Term and Topic*. Available at: https://realguess.net/2014/04/27/understand-google-trends-search-term-and-topic/.
Recuero Virto N, Blasco López MF and San-Martín S. (2017) How can European museums reach sustainability? *Tourism Review* 72: 303-318.
Rivera R. (2016) A dynamic linear model to forecast hotel registrations in Puerto Rico using Google Trends data. *Tourism Management* 57: 12-20.
Song H, Gao BZ and Lin VS. (2013) Combining statistical and judgmental forecasts via a web-based tourism demand forecasting system. *International Journal of Forecasting* 29: 295-310.
Song H and Li G. (2008) Tourism demand modelling and forecasting—A review of recent research. *Tourism Management* 29: 203-220.
VisitLondon. (2018) *Top 10 London attractions*. Available at: https://www.visitlondon.com/things-to-do/sightseeing/london-attraction/top-ten-attractions.
Wang D. (2016) Smartphone use in everyday life and travel. *Journal of Travel Research* 55: 52-63.
Wang D, Fesenmaier DR and Park S. (2012) The Role of Smartphones in Mediating the Touristic Experience. *Journal of Travel Research* 51: 371-387.
Wu DC, Song H and Shen S. (2017) New developments in tourism and hotel demand modeling and forecasting. *International Journal of Contemporary Hospitality Management* 29: 507-529.
Xiang Z, Magnini VP and Fesenmaier DR. (2015a) Information technology and consumer behavior in travel and tourism: Insights from travel planning using the internet. *Journal of Retailing and Consumer Services* 22: 244-249.
Xiang Z and Pan B. (2011) Travel queries on cities in the United States: Implications for search engine marketing for tourist destinations. *Tourism Management* 32: 88-97.
Xiang Z, Wang D, O'Leary JT and Fesenmaier DR. (2015b) Adapting to the Internet: Trends in Travelers' Use of the Web for Trip Planning. *Journal of Travel Research* 54: 511-527.
Xiaoxuan L, Qi W, Geng P and Benfu L. (2016) Tourism forecasting by search engine data with noise-processing. *African Journal of Business Management* 10: 114.
Yang X, Pan B, Evans JA and Lv B. (2015) Forecasting Chinese tourist volume with search engine data. *Tourism Management* 46: 386-397.
Yang Y, Pan B and Song H. (2014) Predicting hotel demand using destination marketing organization's web traffic data. *Journal of Travel Research* 53: 433-447.