A novel hybrid deep learning approach for tourism demand forecasting

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ABSTRACT

This paper proposes a new hybrid deep learning framework that combines search query data, autoencoders (AE) and stacked long-short term memory (staked LSTM) to enhance the accuracy of tourism demand prediction. We use data from Google Trends as an additional variable with the monthly tourist arrivals to Marrakech, Morocco. The AE is applied as a feature extraction procedure to dimension reduction, to extract valuable information and to mine the nonlinear information incorporated in data. The extracted features are fed into stacked LSTM to predict tourist arrivals. Experiments carried out to analyze performance in forecast results of proposed method compared to individual models, and different principal component analysis (PCA) based and AE based hybrid models. The experimental results show that the proposed framework outperforms other models.

Keywords: Auto encoder principal component analysis Search query data Stacked long-short term memory Tourism demand forecasting

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1. INTRODUCTION

The tourism sector is at the heart of the economic development, there has been increasing interest, among academics as well as practitioners, in the forecasting of tourism demand [1]. Considering the perishable nature of tourism industry, the necessity of accurate forecasts remains crucial [2]. The accurate forecasting of tourism demand help to decision making on tourism and policy planning [3], [4].

Nowadays, The internet contains a huge quantity of information that can be used to predict tourist volume [5], and this motivates tourism researchers to investigate new kind of data like search engine data to increase the accuracy prediction. Search engine data are a real-time daily, weekly and monthly index of the volume of queries that users submit into search engines [6]. Several studies showed that search engine can predict tourist volumes and examine travelers’ intention. For instance, [7] brings a new indicator for tourism demand forecasting created from Google Trends’ search query and discovered that Google Trends data can increase the prediction performance [8]. Used two different search engines, Google and Baidu to predict the tourist volumes to Hainan Province [9]. Forecast tourist arrivals in Hainan province from August 2008 to October 2015.

Search Engine Queries have distinct strengths over traditional data, including distinct time horizons (especially daily, weekly, and monthly) and not only ability to indicate the tendencies of the searchers’ plans for travel products but also offer predictability about their future travel behaviors [10]. As a result, researchers have employed internet data to reinforce traditional data and integrated them into prediction models.

However, when introducing the internet query data into forecasting models, extraction of the most relevant information from dataset is an important challenge for researchers. Among the most prevalent
methods to feature extraction is the dimensionality reduction method which attempts to eliminate the excess and inaptness resulting from the high-dimensional data. Since high dimensionality causes data noise, redundancy, increase the computational cost and tend to provoke overfitting and poor generalization [11]. Dimensionality reduction approaches are classified into linear and nonlinear techniques [12]. Principal component analysis (PCA) is a linear technique which has been frequently adopted in tourism demand forecasting [13]. PCA reduces the dimensions by transforming data to principal components. The concept of PCA is a data transformation method that is used to reduce the dimensionality of a dataset with various variables to a smaller number of independent variables which seize the information of the dataset by condensing the common patterns and therefore the variation of the whole dataset. Nevertheless, those approaches focus on removing linear relationship and give reduced computation time for the learning process. Nonlinear methods involve different techniques, such as kernel PCA [14], and auto-encoder [15], where learning can be performed with maintaining the nonlinear properties. Auto-encoder can provide more information from the original data set. In this paper, autoencoders (AE), a neural network technique, is trained to reconstruct its input, is applied as a non-linear mapping and to choose relevant features. Limited researches have applied autoencoder to predict tourism demand. For example, [15] used stacked autoencoder with echo-state regression (SAEN) to predict tourist flow. Empirical evidence demonstrates that SAEN performs better than the other techniques.

Apart from data, the method can hugely impact the prediction accuracy. accurate tourism demands prediction has been still an important problem for the researchers for many decades, considering its stochastic and non-linear nature. Tourism demand prediction methods is classified into the following: time series econometric and artificial intelligence (AI) models [16]. Time series techniques most frequently used as benchmarks in tourism forecasting studies. They are primarily because of the ability to predict future time series by identifying historical patterns. Econometric models try to analyze the relations between tourism demand and explanatory variables such as income and price. The principal drawback of Time series techniques and econometric models is that they cannot depict the nonlinear and stochastic nature of tourism flow [17]. They perform poorly with nonlinearity of tourism demand. Computational intelligence techniques aim to solve the complex engineering and optimization problems. The traditional machine learning forecasting methods can be adopted to find the non-linear relationship. Lately, they require manual feature extraction and selection which are complex. On top of that, they cannot handle massive quantity of data. Then, deep learning was suggested to surmount these difficulties.

Deep learning techniques have been employed as novel alternatives for tourism demand prediction. Far from artificial neural network (ANN), recurrent neural network (RNNs) contains cyclic connections. The activations pattern of the network are retained at each time step to supply a short-term memory [18]. The drawback of RNNs is the vanishing and exploding gradient problem [19]. Long short-term memory (LSTM) was designed to tackle the vanishing and exploding gradient problems of conventional RNNs. However, LSTM has evolved to be one of the most favored prediction techniques in numerous areas, particularly in resolving intricate nonlinear prediction problems. Many research has been used LSTM in tourism demand. For example, [20] used LSTM method to forecast tourism demand and found that LSTM has better prediction results [21]. Employed a deep learning approach to forecast monthly Macau tourist arrival volumes. Experimental findings showed that the deep learning approach remarkably exceeds support vector regression and artificial neural network models.

In this study, we put forward a new framework combining Internet search index, Dimensionality reduction and deep learning to forecast tourist volume. The anticipation capacity of the framework is by reason of three aspects: first, pertinent search query data immensely provide the best fit; second, autoencoder reduce the dimension of the data using the hidden layer representation and learn high-level predictive indicators from search query data (SQD); moreover, stacked LSTM can reduce time complexity and have hidden layers which able to learn the characteristic information and the relevance initiating complex dataset. Still, Limited researches have used Stacked LSTM and autoencoder to forecast tourism demand. The suggested framework is employed to forecasting Marrakech tourist arrivals. The remainder of this study is arranged as follows: in section 2, the suggested research method is introduced, while in section 3 the results and discussion are reported. In section 4 the conclusion of the study is presented.

2. RESEARCH METHOD
2.1. Methodology
This section discusses the structure of the proposed framework. Our model, that combines autoencoder and stacked LSTM for predicting the tourism demand, is highlighted in Figure 1. It consists of five steps data collection, preprocessing data, feature extraction, forecasting model and evaluation model.
2.2. Data collection

2.2.1. Historical tourism demand data

We have chosen Marrakech city, Morocco to train and test our model, and its tourism has grown at full speed. We collected the monthly tourist arrivals data for the January 2012 to August 2019 period from the official website of Tourism Observatory in Morocco. We limited the sample to 92 months.

2.2.2. Search volume data

The search queries data is generated from search engine google Trend. In this step, we identified six categories related to the destination. Categories and keywords are in the same discussed in [22]. For each category we determine the seed search keywords and subsequently convert these keywords into Arabic and French, as they are the main languages in Marrakech, Morocco using Google Translate. For each designated keyword inquired extended keywords by means of Google Trends related queries. In the end, we utilized PyTrends library to extract the keyword search volumes. We discovered 763 keywords linked to the first collection search keywords provided via Google related queries.

2.3. Preprocessing data

The collected data hold hundreds of features having the problem of noisy and missing values, which will impact the prediction of the model. So, it is required to clean and arrange data before treating it. After removing duplications and missing data extremely low volume, we normalized the data using min-max normalization algorithm. It helped to better train the proposed model. This utilized in mapping the features in the [0, 1] range.

2.4. Feature extraction

Autoencoder is a type of neural network designed for unsupervised learning method which All data is unlabeled [23]. It attempts to get its output the same as its input [24] and it is designed to reduce data dimensions by learning how to ignore the noise in the data. Figure 2 illustrates an auto encoder network.

It consists of an input, a hidden and an output layer. The input X and output layer Y are same number of nodes. The second layer is the hidden layer H with K nodes is for feature extraction. An AE consists of an encoder part and a decoder part. The encoder is usually used to reduce multidimensional data to low-dimensional data, it maps the input to a hidden layer. The process is formulated as (1):

\[ H = S_1(WX + b) \] (1)

where \( S_1 \) is an activation function (sigmoid function, rectified linear unit (ReLU), and hyperbolic tangent), \( W \) represents weight matrix, and \( b \) is a bias of encoder.

The decoder reconstructs the input from the encoded representation by minimizing by the reconstruction error. The process is presented as (2):

\[ Y = S_2(W'X + b') \] (2)

\( S_2 \) is an activation function, \( W' \) is weight matrix, and \( b' \) is a bias of decoder. Training an autoencoder aims to reduce the reconstruction loss function, which is measured using mean squared errors or cross-entropy losses.
2.5. Forecasting model

A stacked LSTM architecture defined as an LSTM model that includes multiple LSTM layers where each layer holds multiple memory cells. We stack layers to create a hierarchical feature representation of the input data. Figure 3 illustrates the architecture of three-layered stacked LSTM. The stacked LSTM was initially devised by [25]. Equally known as deep LSTM, the stacked LSTM model applies multiple LSTM layers that are stacked before the forwarding to output layer at the final output. Stacked LSTM model with one to seven hidden layers is constructed for training the tourism demand prediction model. In this paper, an RNN, ANN, and support vector regression (SVR) was adopted, as a benchmark model.

\[ MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \]  
\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \bar{y})^2} \]  
\[ R^2 = 1 - \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|^2}{\sum_{i=1}^{n} |y_i - \bar{y}|^2} \]  

where \(y_i\) and \(\hat{y}_i\) denote the actual and the predicted value, \(n\) is the number of samples.
3. **RESULTS AND DISCUSSION**

We employed a simple autoencoder, to implement this autoencoder model, our network was composed of three layers, where the input layer had 701 neurons and the hidden layer contained 150 neurons. The number of cycles epoch was selected as 5000, we opted for Adam optimization, we chose ReLU as activation function. The batch size was determined to 12. We used the cross-entropy as the loss function. The learning rate was 0.001. The loss of the autoencoder model’s training is illustrated in Figure 4.

![Figure 4. The loss of the autoencoder model during training](image)

In this study 80% of the data was set to train the models and the rest is used to test the performance of the models. The implementations are carried out employing deep learning libraries, namely, KERAS and TensorFlow using Python. We fed the extracted features into stacked LSTM for predicting the tourist arrivals in Marrakech. we constructed one to seven hidden layers stacked LSTM models. Table 1 represents R2, MSE and MAE training and testing errors of our proposed stacked LSTM architectures with the different hidden LSTM layers. it is quite clear that The LSTM network with three hidden layers has smaller MAE and RMSE; in addition, it achieves the highest R2. Therefore, the three layers is selected as the most favorable model. The different stacked LSTM models are illustrated in Figure 5 with one layer stacked LSTM in Figure 5(a), two layers in Figure 5(b), three layers in Figure 5(c), four layers in Figure 5(d), five layers in Figure 5(e), six layers in Figure 5(f) and seven layers in Figure 5(g). We plot the predicted values against actual values.

<table>
<thead>
<tr>
<th>Hidden LSTM layers</th>
<th>Training set</th>
<th>Test set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R2</td>
<td>MAE</td>
</tr>
<tr>
<td>1</td>
<td>92.18</td>
<td>0.041755</td>
</tr>
<tr>
<td>2</td>
<td>90.86</td>
<td>0.042829</td>
</tr>
<tr>
<td>3</td>
<td>97.45</td>
<td>0.021153</td>
</tr>
<tr>
<td>4</td>
<td>89.98</td>
<td>0.047321</td>
</tr>
<tr>
<td>5</td>
<td>84.91</td>
<td>0.059891</td>
</tr>
<tr>
<td>6</td>
<td>64.46</td>
<td>0.089894</td>
</tr>
<tr>
<td>7</td>
<td>63.98</td>
<td>0.089470</td>
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</table>

MAE, RMSE and R2 are used to verify the effectiveness of the proposed model. Our model is compared with other machine learning algorithms (SVR and ANN), deep learning models (RNN), different PCA based and AE based hybrid models. The findings are provided in Table 2. The results indicate that the proposed AE-3 LSTM method has shown good performance. Based on the R2, MAE and RMSE criteria, it is evident from Table 2 that the AE-3 LSTM shows improved accuracy of 97.45% than other models considered for comparison, namely RNN, LSTM, PCA–RNN, PCA–LSTM, SVR, ANN, PCA–SVR, PCA–ANN, AE–RNN and AE-3 LSTM. Then, our deep architecture. Achieves the smallest errors on MAE and RMSE criteria compared with the benchmark models. Compared to PCA, the results of the AE seem to exhibit better performance.

Figure 6 displays the forecasting curves to show the difference between the developed models. It can be noticed that prediction given by AE–3 layer LSTM model is closer to the real value. There is a great deal of deviation between true and predicted values for other models. Once more, this validates the dependability of the proposed AE–3 layer LSTM model.

**Table 1. Training and testing errors of different stacked LSTM architectures**

**Figure 6**
Figure 5. Tourism demand with: (a) 1 layer stacked LSTM in, (b) 2 layers in, (c) 3 layers in, (d) 4 layers in, (e) 5 layers in, (f) 6 layers in, and (g) 7 layers in

Table 2. Performance comparison between our model and other models

<table>
<thead>
<tr>
<th>Prediction Model</th>
<th>Train set R2</th>
<th>Train set MAE</th>
<th>Train set RMSE</th>
<th>Test set R2</th>
<th>Test set MAE</th>
<th>Test set RMSE</th>
</tr>
</thead>
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<tr>
<td>RNN</td>
<td>95.16</td>
<td>0.031904</td>
<td>0.001749</td>
<td>94.36</td>
<td>0.036290</td>
<td>0.003107</td>
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<tr>
<td>LSTM</td>
<td>96.74</td>
<td>0.025742</td>
<td>0.001035</td>
<td>95.63</td>
<td>0.027096</td>
<td>0.001379</td>
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<tr>
<td>PCA–RNN</td>
<td>89.80</td>
<td>0.047989</td>
<td>0.003989</td>
<td>88.70</td>
<td>0.051927</td>
<td>0.004183</td>
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<tr>
<td>PCA–LSTM</td>
<td>90.24</td>
<td>0.042965</td>
<td>0.003972</td>
<td>89.45</td>
<td>0.048309</td>
<td>0.004057</td>
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<tr>
<td>SVR</td>
<td>95.54</td>
<td>0.028326</td>
<td>0.001489</td>
<td>94.73</td>
<td>0.033936</td>
<td>0.002159</td>
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<tr>
<td>ANN</td>
<td>95.29</td>
<td>0.030582</td>
<td>0.001038</td>
<td>94.47</td>
<td>0.034905</td>
<td>0.002974</td>
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<tr>
<td>PCA–SVR</td>
<td>95.01</td>
<td>0.032948</td>
<td>0.001827</td>
<td>94.12</td>
<td>0.037853</td>
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<tr>
<td>PCA–ANN</td>
<td>94.43</td>
<td>0.034948</td>
<td>0.002982</td>
<td>93.68</td>
<td>0.039423</td>
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<tr>
<td>AE–RNN</td>
<td>95.37</td>
<td>0.029853</td>
<td>0.001549</td>
<td>94.58</td>
<td>0.034483</td>
<td>0.002537</td>
</tr>
<tr>
<td>AE–3 layer LSTM</td>
<td>97.45</td>
<td>0.021153</td>
<td>0.000992</td>
<td>96.52</td>
<td>0.024431</td>
<td>0.001169</td>
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</table>
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