OPEN IIT DATA ANALYTICS

D2

Index

Introduction

"The world is a book and those who do not travel read only one page."
- by Saint Augustine

India, with its diverse cultures, rich heritage, and stunning natural beauty, holds a remarkable place in the world of tourism. According to a report by India Brand Equity Foundation (IBEF), in 2022, the travel & tourism industry's contribution to the GDP is estimated to be over US$ 215 billion; this is expected to reach US$ 488 billion by 2029. In India, the industry's direct contribution to the GDP is expected to record an annual growth rate of 7-9% between 2019 and 2030. Thus, forecasting tourist numbers is gaining significance in predicting future economic growth. The practice of forecasting tourism demand can furnish essential data for future planning and policy making endeavors. With the internet seeping deeper into our lives, internet search queries that reflect user behaviors, in addition to the government's basic visitor statistics, can be used to make tourism forecasting models more robust and scalable.

Problem Statement

Create a predictive machine learning model using Internet search index data to forecast tourist arrivals at a specific destination. The objective is to provide accurate predictions for tourism authorities and businesses to enhance resource allocation, marketing strategies, and destination management.

Dataset Description

Dataset for the Problem statement was scrapped from the tourism website of Himachal Pradesh. Search queries were scrapped from Google Search Engine and search volume for the queries was extracted from Google Trends. Dataset for forecasting number of tourist visiting Shimla is broadly classified into 3 parts:

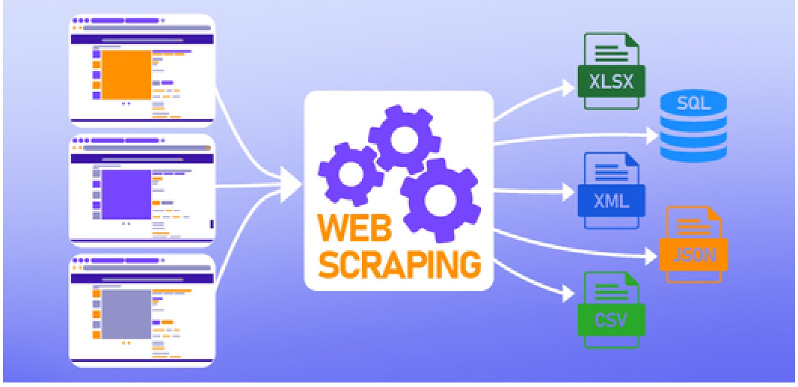
- **Timestamp**: It indicates the dates.
- **Search index data:** It indicates the search volumes of the query's searched on google search index which by a tourist. Search queries were based on all aspects of tourism planning, including travel, traffic, lodging, dining, recreation and shopping.
- **Number of Tourists:** It shows the data of monthly number of tourist both foreign and Indian visiting Shimla from 2010 to 2022.

Root mean squared error(RMSE) and mean absolute error(MAE) were employed as metrics to assess the model's accuracy and correctness.

Data Preprocessing

Web Scraping

For the prediction of tourist arrivals in the future, the monthly tourist arrival data for Himachal Pradesh has been scraped for the years ranging from 2010 to 2022. Internet search queries related to the given set of words was extracted from Google, using BeautifulSoup parsing the web pages as HTML documents, focusing on the broad domains of Tourism, Shopping, Recreation, Flights and Hotel bookings. The Search Index data relating to these queries has been scraped from Google Trends for tourists from all over the world.



Creation of training dataset

Initially, the API lists out the top 100 most-searched keywords relating to the aforementioned domains, which is further broiled down to 32 best matching searches, discarding the ones which are irrelevant to Tourism. In order to calculate the best features among these, inference has been drawn out from the Principal Component Analysis (PCA) Plots and the features exuberating a high correlation with the actual tourist numbers have been corroborated for further Model Training.

website
activities
lodging
inn
news
reviews
top
items
road
menu
perth
palace
coaltown
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best
cheap
condition
chandigarh
family
today
places
Delhi
indian
star
days
shopping
block
eat
restaurant
number
things
couples
dining
tourism
famous
luxury
recreation
market
traffic
closed
accident
hotel
time
clothes
shimla
east
itinerary
package
mall
contact
pool
visit
highway
adventure

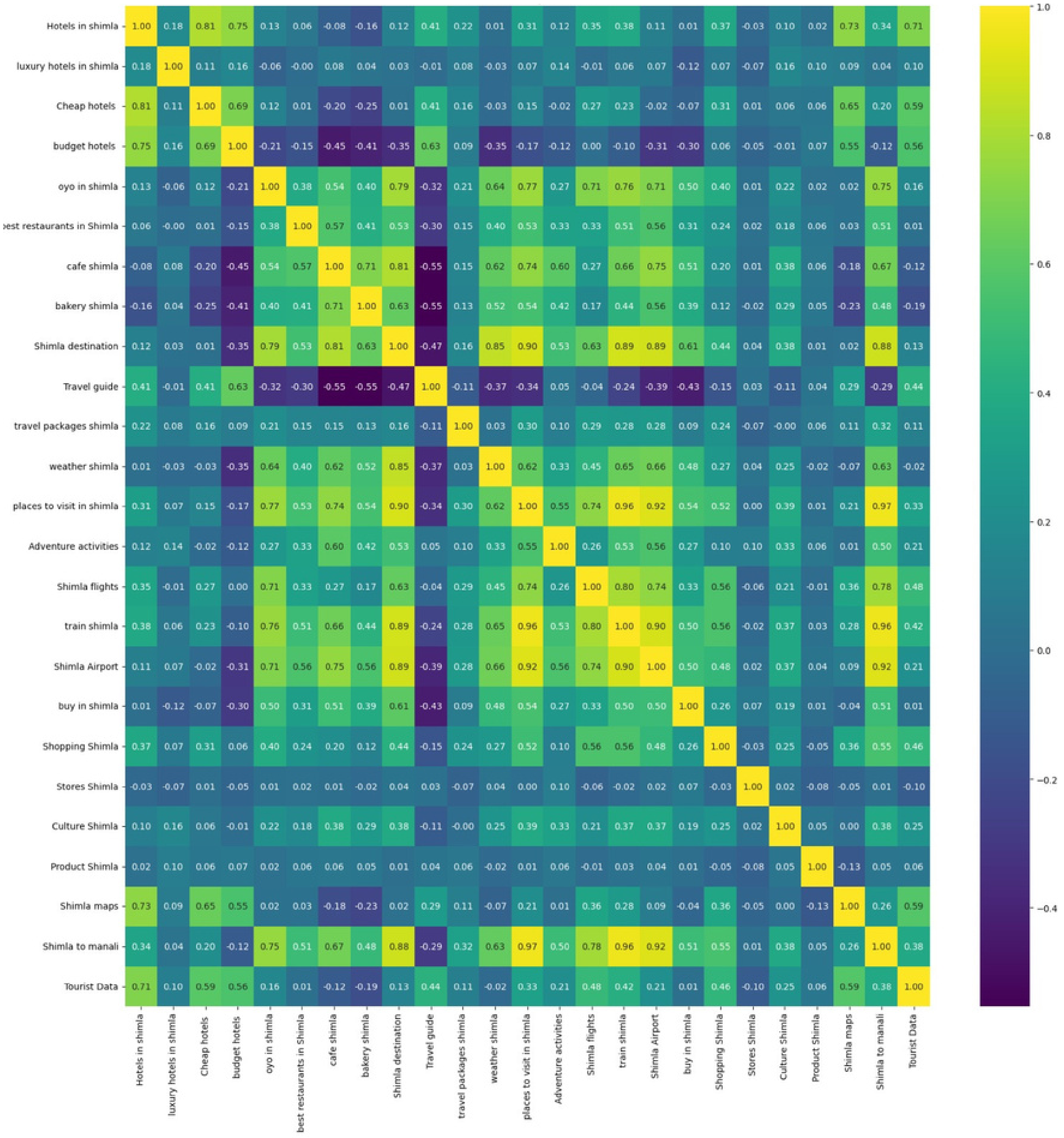
Initial search queries

oyo
road
cafe
food
Best
Airport
visit
ridge
packages
activities
Honeymoon
Traffic
weather
maps
bakery
guide
shimla
buy
Cheap
flights
luxury
near
street
places
kufri
manali
hotels
mall
train
star
Product
Stores
destination
budget
vegetarian
Shopping
Travel
Adventure
Culture
restaurants

Final search queries

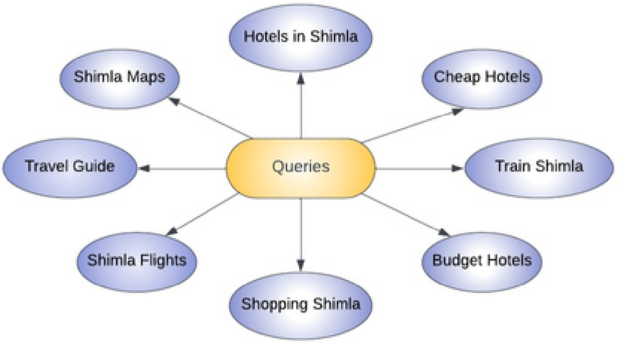
Feature Engineering

Heatmap



	Hotels in shimla	luxury hotels in shimla	Cheap hotels	budget hotels	oyo in shimla	best restaurants in Shimla	cafe shimla	bakery shimla	Shimla destination	Travel guide	travel packages shimla	weather shimla	places to visit in shimla	Adventure activities	Shimla flights	train shimla	Shimla Airport	buy in shimla	Shopping Shimla	Stores Shimla	Culture Shimla	Product Shimla	Shimla maps	Shimla to manali	Tourist Data
Hotels in shimla	1.00	0.18	0.81	0.75	0.13	0.06	-0.08	-0.16	0.12	0.41	0.22	0.01	0.31	0.12	0.35	0.38	0.11	0.01	0.37	-0.03	0.10	0.02	0.73	0.34	0.71
luxury hotels in shimla	0.18	1.00	0.11	0.16	-0.06	-0.00	0.08	0.04	0.03	-0.01	0.08	-0.03	0.07	0.14	-0.01	0.06	0.07	-0.12	0.07	-0.07	0.16	0.10	0.09	0.04	0.10
Cheap hotels	0.81	0.11	1.00	0.69	0.12	0.01	-0.20	-0.25	0.01	0.41	0.16	-0.03	0.15	-0.02	0.27	0.23	-0.02	-0.07	0.31	0.01	0.06	0.06	0.65	0.20	0.59
budget hotels	0.75	0.16	0.69	1.00	-0.21	-0.15	-0.45	-0.41	-0.35	0.63	0.09	-0.35	-0.17	-0.12	0.00	-0.10	-0.31	-0.30	0.06	-0.05	-0.01	0.07	0.55	-0.12	0.56
oyo in shimla	0.13	-0.06	0.12	-0.21	1.00	0.38	0.54	0.40	0.79	-0.32	0.21	0.64	0.77	0.27	0.71	0.76	0.71	0.50	0.40	0.01	0.22	0.02	0.02	0.75	0.16
best restaurants in Shimla	0.06	-0.00	0.01	-0.15	0.38	1.00	0.57	0.41	0.53	-0.30	0.15	0.40	0.53	0.33	0.33	0.51	0.56	0.31	0.24	0.02	0.18	0.06	0.03	0.51	0.01
cafe shimla	-0.08	0.08	-0.20	-0.45	0.54	0.57	1.00	0.71	0.81	-0.55	0.15	0.62	0.74	0.60	0.27	0.66	0.75	0.51	0.20	0.01	0.38	0.06	-0.18	0.67	-0.12
bakery shimla	-0.16	0.04	-0.25	-0.41	0.40	0.41	0.71	1.00	0.63	-0.55	0.13	0.52	0.54	0.42	0.17	0.44	0.56	0.39	0.12	-0.02	0.29	0.05	-0.23	0.48	-0.19
Shimla destination	0.12	0.03	0.01	-0.35	0.79	0.53	0.81	0.63	1.00	-0.47	0.16	0.85	0.90	0.53	0.63	0.89	0.89	0.61	0.44	0.04	0.38	0.01	0.02	0.88	0.13
Travel guide	0.41	-0.01	0.41	0.63	-0.32	-0.30	-0.55	-0.55	-0.47	1.00	-0.11	-0.37	-0.34	0.05	-0.04	-0.24	-0.39	-0.43	-0.15	0.03	-0.11	0.04	0.29	-0.29	0.44
travel packages shimla	0.22	0.08	0.16	0.09	0.21	0.15	0.15	0.13	0.16	-0.11	1.00	0.03	0.30	0.10	0.29	0.28	0.28	0.09	0.24	-0.07	-0.00	0.06	0.11	0.32	0.11
weather shimla	0.01	-0.03	-0.03	-0.35	0.64	0.40	0.62	0.52	0.85	-0.37	0.03	1.00	0.62	0.33	0.45	0.65	0.66	0.48	0.27	0.04	0.25	-0.02	-0.07	0.63	-0.02
places to visit in shimla	0.31	0.07	0.15	-0.17	0.77	0.53	0.74	0.54	0.90	-0.34	0.30	0.62	1.00	0.55	0.74	0.96	0.92	0.54	0.52	0.00	0.39	0.01	0.21	0.97	0.33
Adventure activities	0.12	0.14	-0.02	-0.12	0.27	0.33	0.60	0.42	0.53	0.05	0.10	0.33	0.55	1.00	0.26	0.53	0.56	0.27	0.10	0.10	0.33	0.06	0.01	0.50	0.21
Shimla flights	0.35	-0.01	0.27	0.00	0.71	0.33	0.27	0.17	0.63	-0.04	0.29	0.45	0.74	0.26	1.00	0.80	0.74	0.33	0.56	-0.06	0.21	-0.01	0.36	0.78	0.48
train shimla	0.38	0.06	0.23	-0.10	0.76	0.51	0.66	0.44	0.89	-0.24	0.28	0.65	0.96	0.53	0.80	1.00	0.90	0.50	0.56	-0.02	0.37	0.03	0.28	0.96	0.42
Shimla Airport	0.11	0.07	-0.02	-0.31	0.71	0.56	0.75	0.56	0.89	-0.39	0.28	0.66	0.92	0.56	0.74	0.90	1.00	0.50	0.48	0.02	0.37	0.04	0.09	0.92	0.21
buy in shimla	0.01	-0.12	-0.07	-0.30	0.50	0.31	0.51	0.39	0.61	-0.43	0.09	0.48	0.54	0.27	0.33	0.50	0.50	1.00	0.26	0.07	0.19	0.01	-0.04	0.51	0.01
Shopping Shimla	0.37	0.07	0.31	0.06	0.40	0.24	0.20	0.12	0.44	-0.15	0.24	0.27	0.52	0.10	0.56	0.56	0.48	0.26	1.00	-0.03	0.25	-0.05	0.36	0.55	0.46
Stores Shimla	-0.03	-0.07	0.01	-0.05	0.01	0.02	0.01	-0.02	0.04	0.03	-0.07	0.04	0.00	0.10	-0.06	-0.02	0.02	0.07	-0.03	1.00	0.02	-0.08	-0.05	0.01	-0.10
Culture Shimla	0.10	0.16	0.06	-0.01	0.22	0.18	0.38	0.29	0.38	-0.11	-0.00	0.25	0.39	0.33	0.21	0.37	0.37	0.19	0.25	0.02	1.00	0.05	0.00	0.38	0.25
Product Shimla	0.02	0.10	0.06	0.07	0.02	0.06	0.06	0.05	0.01	0.04	0.06	-0.02	0.01	0.06	-0.01	0.03	0.04	0.01	-0.05	-0.08	0.05	1.00	-0.13	0.05	0.06
Shimla maps	0.73	0.09	0.65	0.55	0.02	0.03	-0.18	-0.23	0.02	0.29	0.11	-0.07	0.21	0.01	0.36	0.28	0.09	-0.04	0.36	-0.05	0.00	-0.13	1.00	0.26	0.59
Shimla to manali	0.34	0.04	0.20	-0.12	0.75	0.51	0.67	0.48	0.88	-0.29	0.32	0.63	0.97	0.50	0.78	0.96	0.92	0.51	0.55	0.01	0.38	0.05	0.26	1.00	0.38
Tourist Data	0.71	0.10	0.59	0.56	0.16	0.01	-0.12	-0.19	0.13	0.44	0.11	-0.02	0.33	0.21	0.48	0.42	0.21	0.01	0.46	-0.10	0.25	0.06	0.59	0.38	1.00

The above heatmap shows the number of tourists along with the search queries from google trends. Using the heatmap we inferred that the features having PCA greater than 0.5 would have more weightage thus allowing us to identify the prominent features and sort them out. The final queries are shown on the next page.



Granger Causality Test

Granger causality is a statistical concept used to determine whether one time series can predict the future values of another time series. It measures the extent to which the past values of one variable provide valuable information for forecasting the other variable's future behavior. Granger causality helps analyze potential relationships between variables, aiding in predicting trends.

$$Y_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + u_{1t} \qquad \sum \beta_j \neq 0$$

$$X_t = \sum_{i=1}^{n} \lambda_i Y_{t-i} + \sum_{j=1}^{n} \sigma_j X_{t-j} + u_{2t} \qquad \sum \lambda_i \neq 0$$

A variable Y is causal for another variable X if knowledge of the past history of Y is useful for predicting the future state of X over and above knowledge of the past history of X itself. So if the prediction of X is improved by including Y as a predictor, then Y is said to be Granger causal for X.

For the Tourist data we performed Granger causality test of overall search index data from Google Trends with Tourist Volume and we got the following results:

Number of lags(monthly)	F Value	P Value
0	5.7846	0.0174
1	3.0911	0.0484
2	2.4792	0.0635
3	2.2582	0.0658

For lags= 0 and 1 Granger causality test gave positive results, the p value for these lags were less than 0.05 but from lags =2 the p value was greater than 0.05 showing that up-till 1 month lag data of search trends data can be used to forecast number of Tourist.

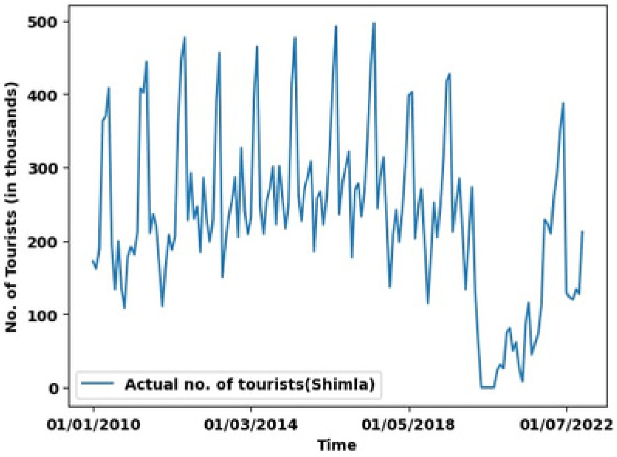
Data Visualisation

Actual No. of Tourists vs Timestamp:

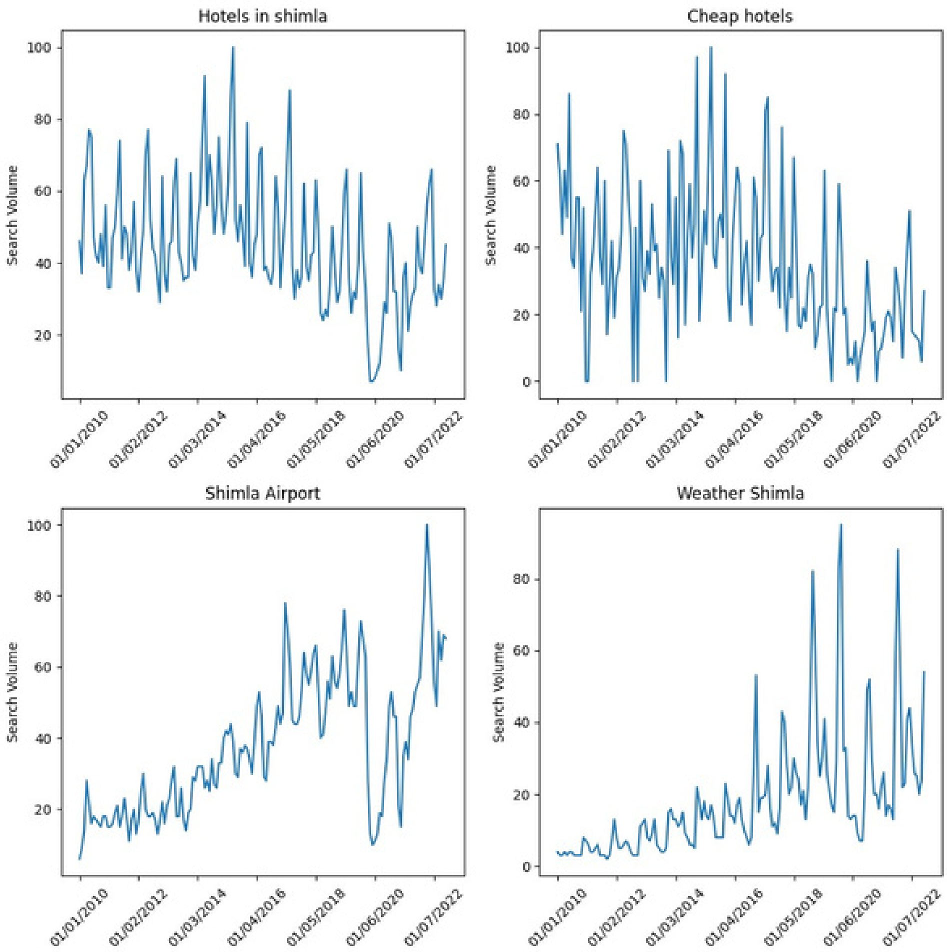
We plot the total actual no. of tourists vs the timestamp. The peaks in the plot denotes the rise in no. of tourists.

By observing the plot, we can infer that-

- In general, the no. of tourists is affected by seasonality (denoted by the peaks in the graph).
- There has been a significant dip in the no. of tourists visiting from 2020-2021 due to the effect of COVID-19.
- After 2021, the industry of tourism, although has not reached the pre-Covid trends, is at its growing stage.

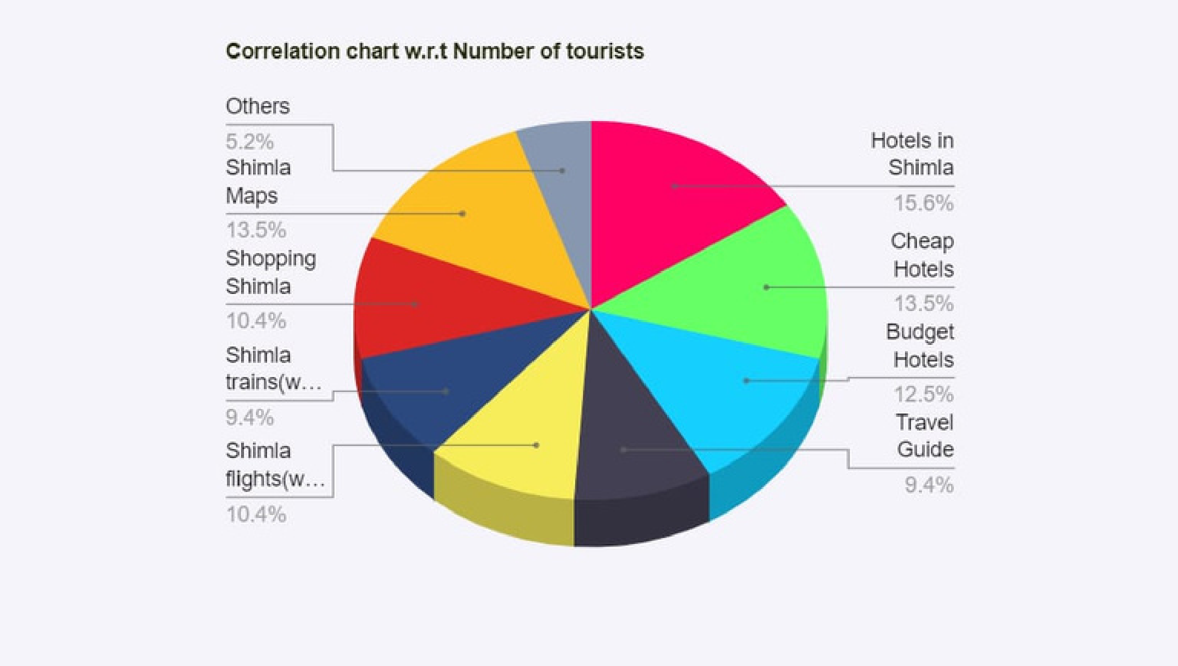


Search Trends of highly correlated queries(with tourist data):



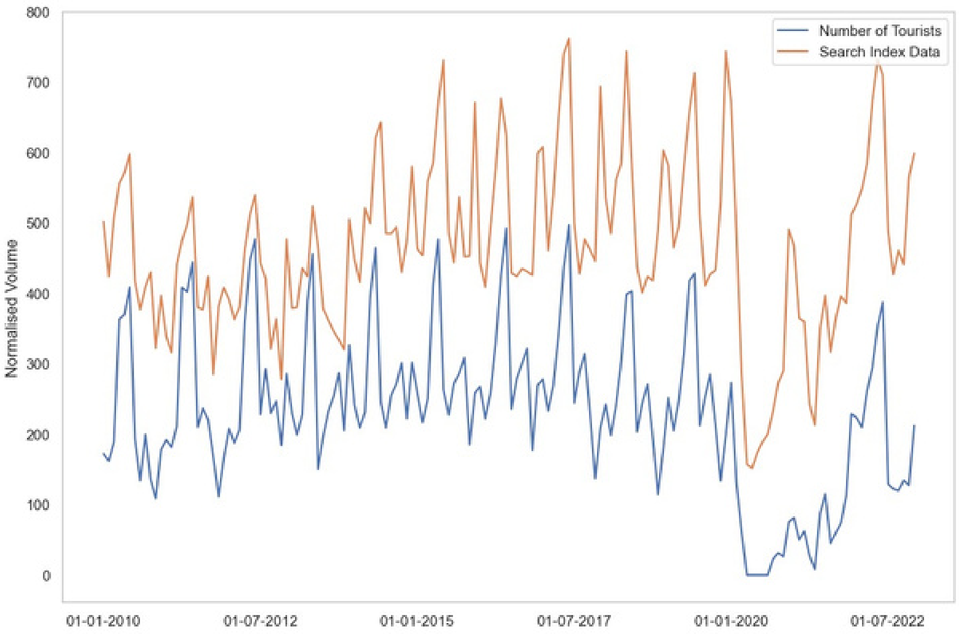
- These are the plots of search trends of best correlated features with the number of tourists .
- From the above plots, we can infer that the trends of these features match with the trends of the number of tourists visiting Shimla.

Correlation chart w.r.t Number of Tourists



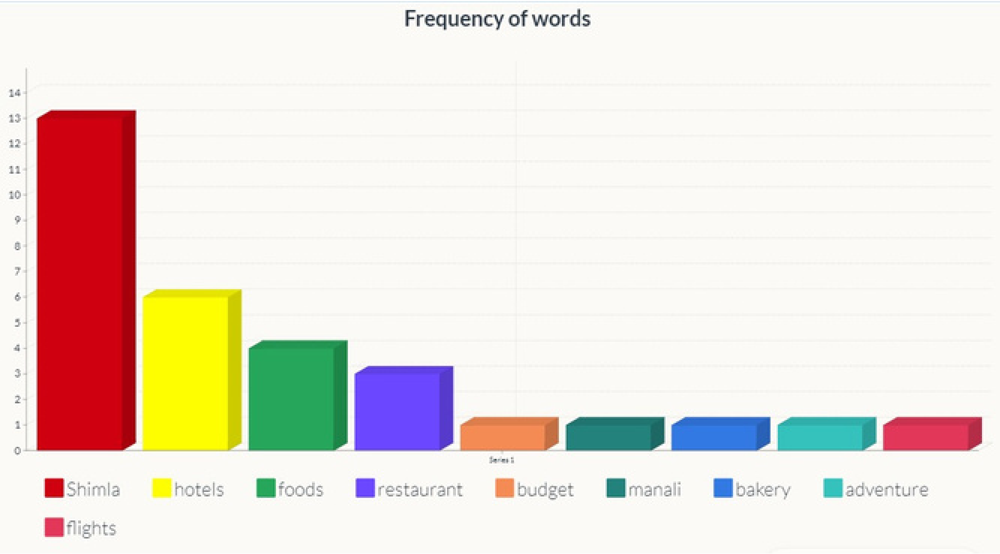
- Above Pie-plot shows how good trends of search query related with the number of tourists visiting Shimla.
- The higher the area of the sector it the more that search trend is converting into volume of tourist.

Plot of search Index and Tourists volume data

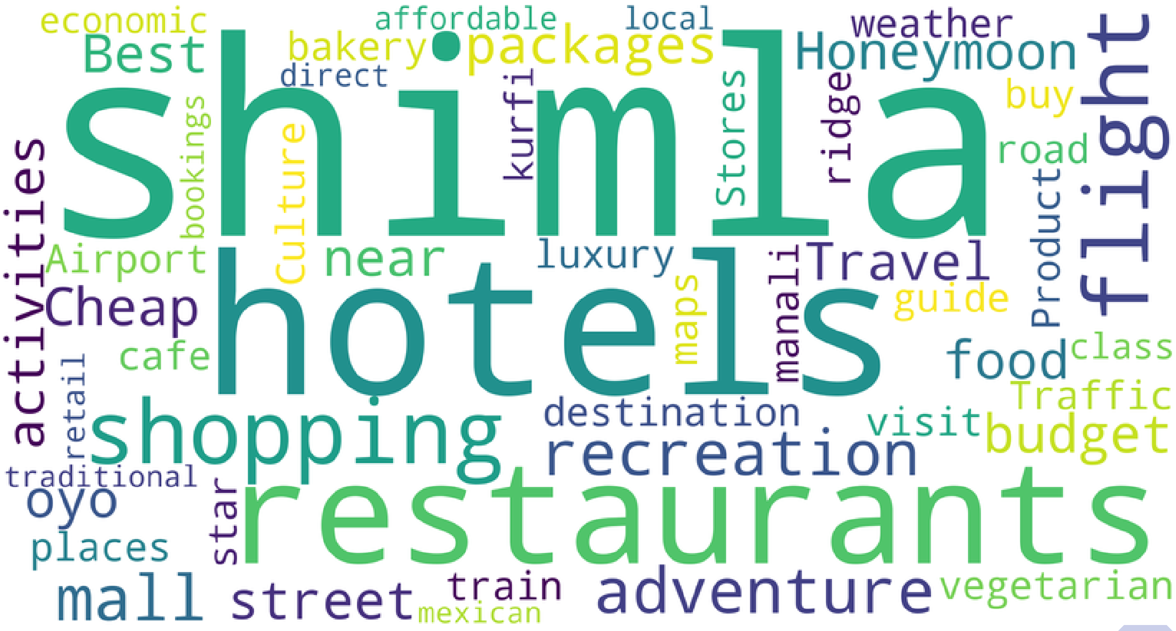


- From the plot of total volume of search trends data of best correlated words and tourists volume data it can be inferred that search trend can be used to predict the number of tourist.
- The plot clearly shows a good correlation between the search trend data and actual tourist volume data.
- An offset between the peaks of search trend data and normalised volume of tourist can be seen showing showing that people search for that place atleast one month before reaching there.

Frequency of words in search queries:



- Above bar-graph show’s the most commonly occurring words in the best search query.
- Shimla is the most commonly occurring word followed by hotels, foods etc. in the search query.
- This words cover’s all the parameters for predicting volume of tourists including Tourism, Lodging, Dining, Recreation and Shopping.



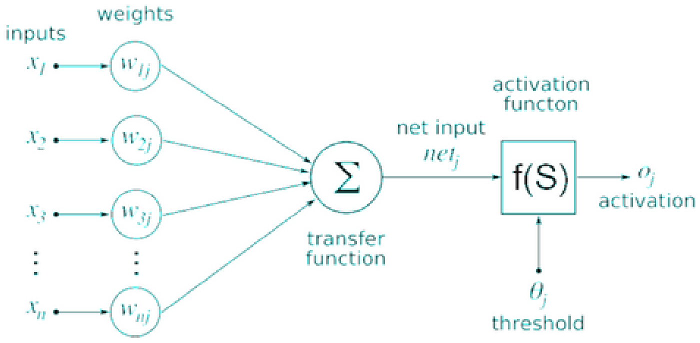
Models and Approach

1. Artificial Neural Network (ANN)

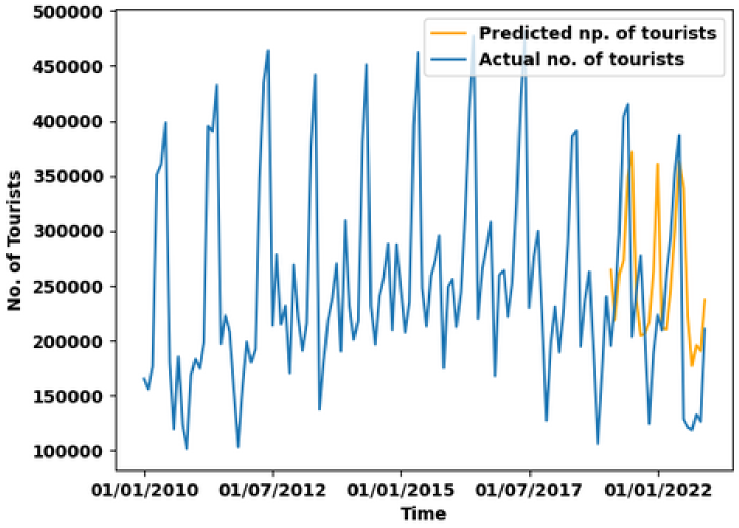
Artificial neural network (ANN) is a deep learning method that arose from the concept of the human brain biological networks. ANNs are built in a way to mimic the network of neurons in a human brain by a computer. Even though they work in an extremely similar manner, they are not identical.

The basic architecture of ANN consists of 3 layers:

- Input layer : which accepts numeric and structured data.
- Hidden layer(s) : which extracts some of the most relevant patterns from the inputs and sends them on to the next layer for further analysis.
- Output layer : which gives the final result that we are looking for.



For our problem the preprocessed vectorized dataset (containing the features including number of hotels in Shimla, flights, trains etc.) was given as an input to the ANN and the number of tourists were provided as the output.



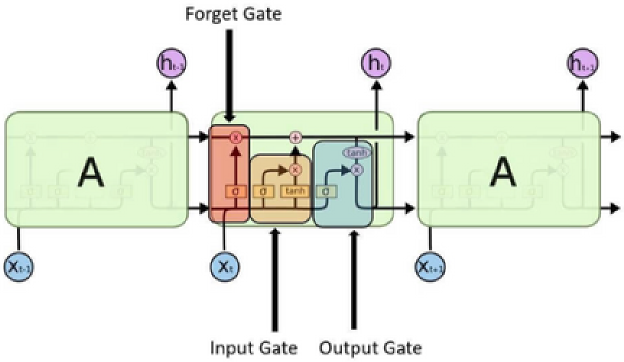
Input	RMSE	MAE
Tourist + Search Index	6.31	4.72

2. Long Short Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks represent a significant advancement in the realm of recurrent neural network (RNN) architectures, purpose-built for the intricacies of sequence and time series data. In contrast to conventional RNNs, LSTMs possess a remarkable capability to capture long-range dependencies within data sequences while dealing with the notorious vanishing gradient problem. They achieve this through deployment of three gates:

- Input gate
- Forget gate
- Output gate

These gates collaboratively exert fine control over information flow within network. The result is an architecture that can selectively remember or discard information, rendering LSTMs exceptionally well-suited for the task of time series forecasting and an array of other sequence-related tasks.



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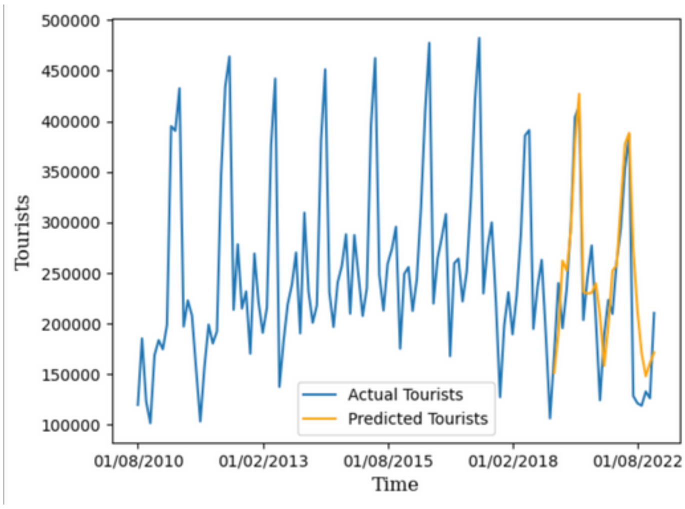


Input	RMSE	MAE
Tourist + search Index	4.8	3.7

3. SARIMA

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is a time series forecasting model which extends ARIMA, by incorporating seasonal components to handle seasonality which may be present in our time series dataset.

Components of the SARIMA model:

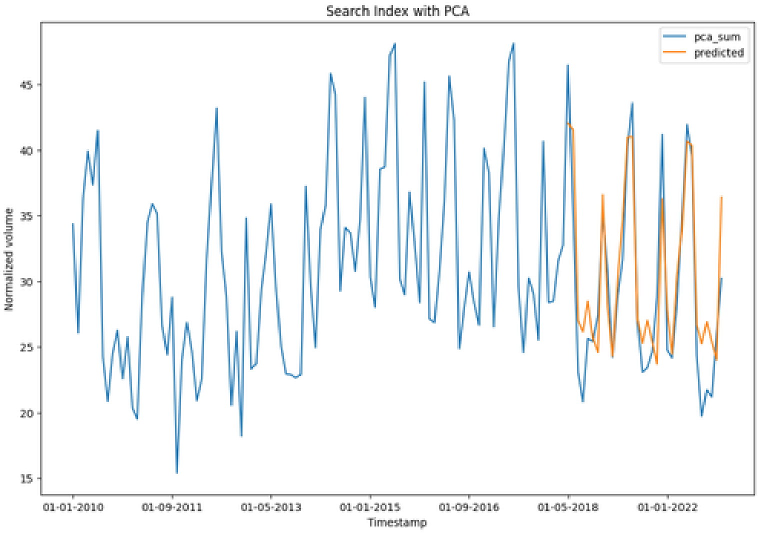
Sarima consists of Seasonal Autoregressive (SAR) and Seasonal Moving Average (SMA) terms, which are denoted as SARIMA(p,d,q)(P,D,Q,s).

Here (p,d,q) represent the non-seasonal Autoregressive (AR), Differencing and Moving Average (MA) parameters respectively, while (P,D,Q) represent the seasonal counterparts. s denotes the seasonality, representing the number of steps in a seasonal cycle which we have chosen as 12. By plotting the ACF and PACF plots we chose the values of p and q as 2 and 3 respectively.

$$SARIMA\underbrace{(p,d,q)}_{non-seasonal}\underbrace{(P,D,Q)_m}_{seasonal}$$

We also observe that if we use PCA to reduce dimensionality of the model replacing the less correlated columns by using column transformation, RMSE and MAE are reduced, thus improving our model.

Results:



Input	RMSE	MAE
No. of Tourists	6.31	4.72
Tourist + Search Index	3.98	3.38
Tourists + Search Index with PCA	3.34	2.77

4. SARIMAX

SARIMAX extends SARIMA by including external variables for improved forecasting of time series data with additional influences. It regroups AR, MA, differencing, and seasonal effects. On top of that, it adds the X: external variables.

Equation :

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t$$

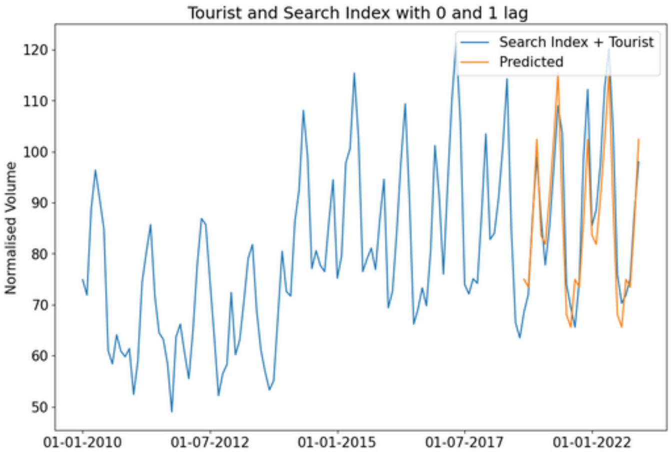
Model Parameters:

Sarimax(p,d,q)(P, D, Q, M) is our model where parameters are obtained by acf and pacf plots, where P and Q are the highest significant lag in pacf plot and acf plot respectively . by our observation best-suited values of p,q ranges between 0 to 2 and d and D are the number of steps used in differencing is generally 0 or 1.

Most Suited Approach:

We applied the rolling mean function on some of the features to get smoother and better plots. We got the best plot (tourist vs search) by adding the features (one with the best plot) and their lagged value(lag=1). Below is the plot of Number of Tourist and Summation of the features and their lagged(lag=1) values .

Results:

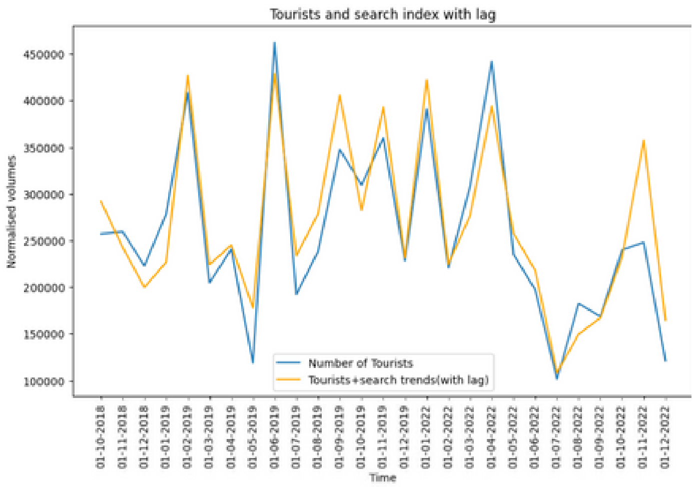


Input	RMSE	MAE
No. of Tourists	6.08	5.31
Tourist + Search Index	7.83	6.48
Search Index with Lag	6.85	5.72

5. CATBOOST

CatBoost is a gradient boosting algorithm designed for supervised machine learning tasks, such as classification and regression. It is known for its efficient handling of categorical features and its impressive performance on tabular data. It is designed to be efficient and can train models relatively quickly. It employs various optimization techniques like ordered boosting and data partitioning that help speed up the training process.

Results:

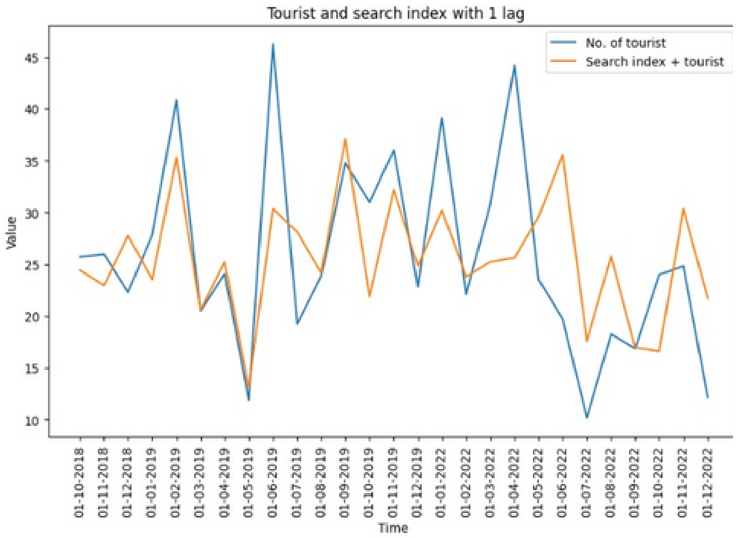


Input	RMSE	MAE
No. of Tourists	3.69	2.87
Tourist + Search Index	3.86	3.10
Search Index with Lag	3.78	3.02

6. k-Nearest Neighbours(k-NN)

k-Nearest Neighbors (k-NN) is a simple, non-parametric machine learning algorithm for classification and regression. It makes predictions by finding the majority class or averaging near data points. k represents the number of neighbours to consider.

Results:



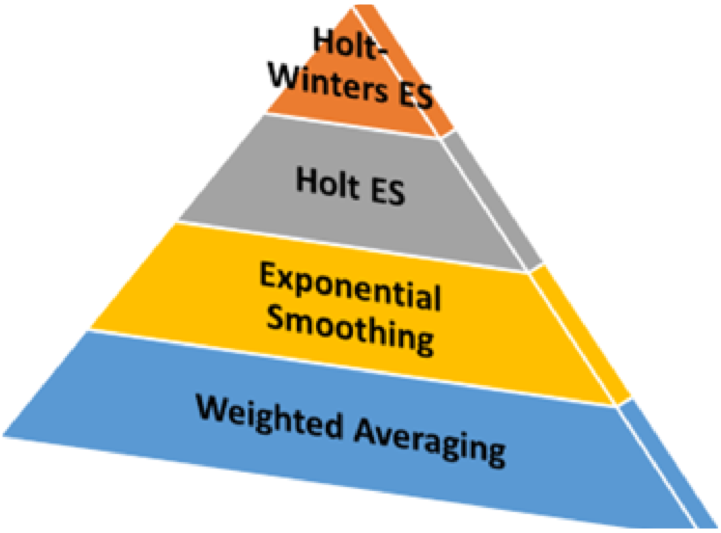
Input	RMSE	MAE
No. of Tourists	7.18	9.10
Tourist + Search Index	6.81	8.851
Search Index with Lag	6.001	7.87

7. Exponential Smoothing

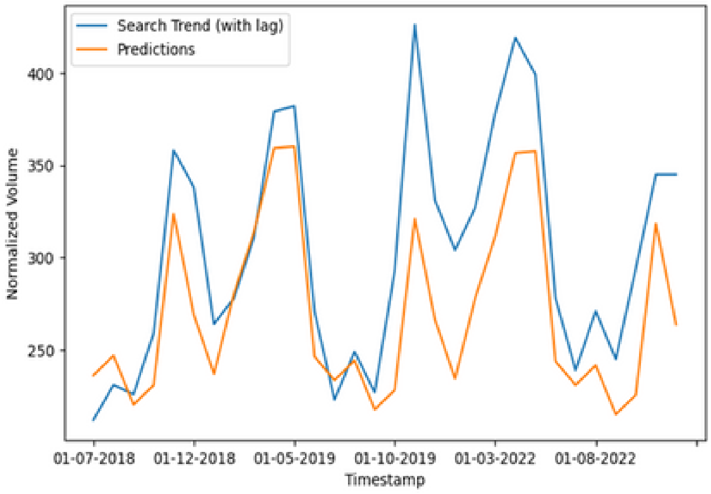
Exponential Smoothing is a time series forecasting model that is widely used in various fields. It is designed to capture and forecast time series data with trends and seasonality. Here, new observations receive greater weight than older ones, giving more importance to recent data.
The Exponential Smoothing Model calculates forecast by updating the level, trend and seasonal components based on historical data. The prediction for the next period is generated using the updated components.

Model Parameters:

Exponential Smoothing models involve parameters like the smoothing level (α), smoothing trend (β), smoothing seasonality (γ), and seasonal period (m). These parameters are estimated from historical data and can affect the forecasting accuracy.



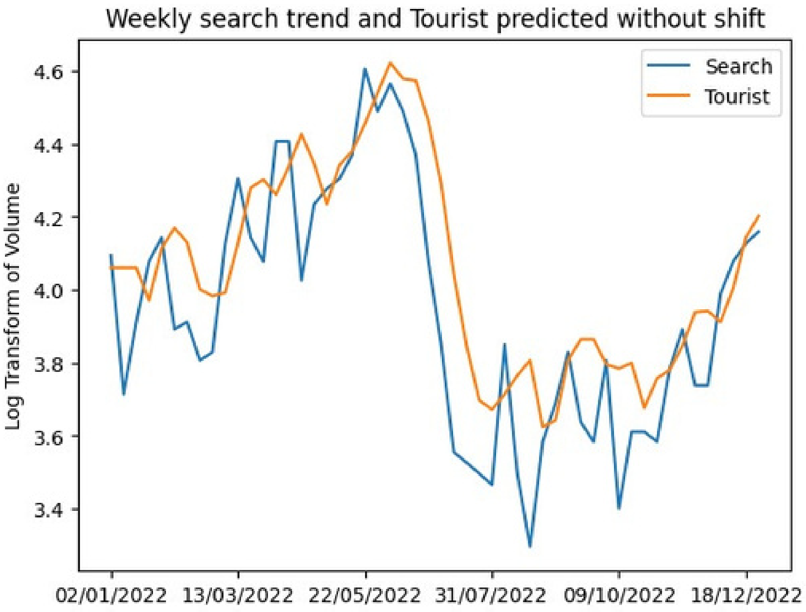
Results:

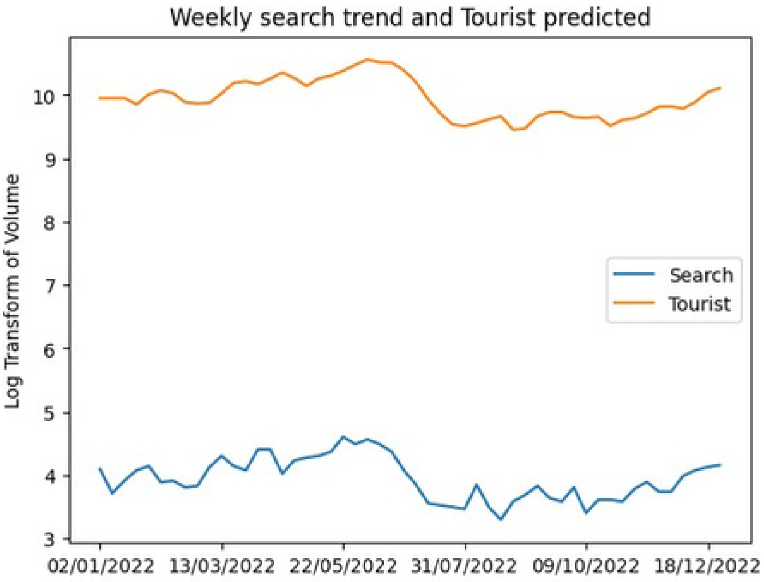


Input	RMSE	MAE
No. of Tourists	6.44	7.92
Tourist + Search Index	9.44	11.64
Search Index with Lag	3.60	4.46

Weekly Interpolation Approximation

- The time series analysis of search trend data and actual tourist numbers in Shimla demonstrates remarkable similarities in their patterns, with identical seasonality and peak occurrences.
- The observed one-month offset between search data and tourist data implies that individuals tend to search for related information both prior to and after their visit to Shimla.
- It can be concluded that the number of tourists is nothing but the summation of search trend and the shift in the graph along Y-axis(due to difference in scaling).
- Granger-causality tests conducted on monthly data have established that a one-month lag significantly influences the estimation of current-month tourist numbers.
- This derived monthly equation can be extended to weekly data by applying a weighted mean of the search trend from the previous three weeks and integrating the shift parameter from the monthly data to obtain precise weekly tourist figures.





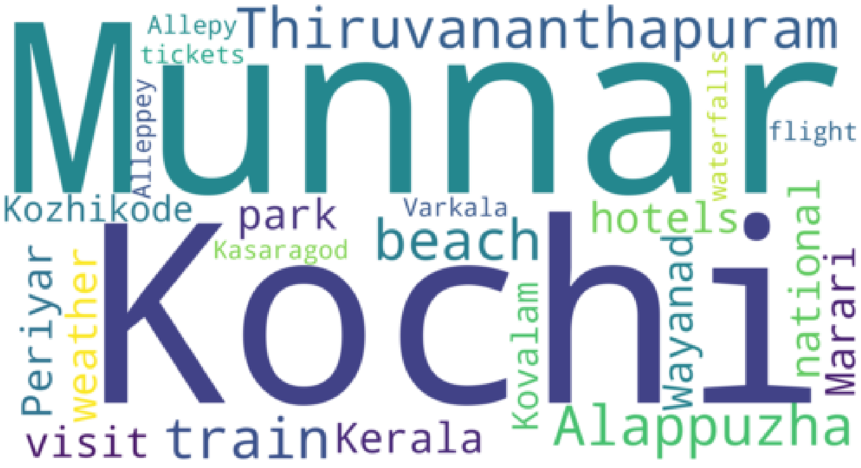
Results and Conclusion

MODELS	RMSE	MAE
ANN	6.31	4.72
Sarima	3.34	2.77
Sarimax	6.85	5.72
Exponential Smoothing	4.46	3.60
XG Boost	6.54	5.02
CatBoost	3.78	3.02
LSTM	4.8	3.7
KNN	6.00	7.87

- After deploying various Time series Forecasting model we found that integrating search trend with the normal statics of tourist helps in increasing the accuracy of the model and facilitate with better forecasting.
- The search trend data for model were selected for the queries whose search trend gave highest correlation with tourist data and granger causality test was used to find the number of lags which can be integrated with tourist volume data.
- Finally models were trained and tested and we found that models gave high accuracy when integrated with search volume data apart from forecasting with only tourist volume.

Robustness and Scalability

- Our scraping model gives the set of queries related to lodging, food, recreational activities, transport and traffic for the specified place. These search queries are fed to Google trends API which gives the search trend data and out of these queries best queries are selected based on best PCA scores and lags was find out by Granger Causality test. Finally any Forecasting model can be deployed integrating search data with tourist data to predict future tourist. For Kerala, our scraping model gave the following word cloud with best PCA scores.



Annexure

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