PREDICTING TOP 20 DESTINATION FOR TOURIST RECOMMENDATION SYSTEM

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ABSTRACT

Recently, recommendation systems have become an active topic. The system also permit showing the user information about interesting attraction in more detail, which is based on analyzing information evaluations made by other users. They are collection of simple algorithms which tend to show most relevant and accurate data as per user's requirement. This paper presents a tourism recommendation system with the integration of the user review element. Based on three factors- number of reviews, rating, and sentiment, the user reviews are analyzed and then used in the recommendation of top most destination for tourists.

Key words– User Preference, Predicting, Recommendation system, Collaborative Filtering

I.INTRODUCTION

Recommendation system is defined as an information filtering system that is used to suggest the users items based on their previous history or their preferences. It has the proficiency to predict whether a particular user would prefer an item or not based on the user's profile. To develop a recommendation system first we need to be familiar with the perception of artificial intelligence and machine learning. Recommendation system has also been introduced in the tourism industry to help the tourist by delivering information related to their tourism destination. Modern technologies of classical recommender system, such as collaborative filtering are considered to be effectively adopted in the tourism domain. Collaborative filtering is a technique that can filter out items that a user might like on the basis of reactions by similar users .It works by Analyzing a large group of people and finding a smaller set of users with tastes similar to a particular user. It looks at the items they like and combines them to create a categorize list of suggestions.

II.OBJECTIVE

In the recommendation system based on collaborative filtering, the rating of a single user needs to be predicted first. However, when calculating the similarity between users or items, the traditional collaborative filtering algorithm does not consider the impact of the number of items jointly rated by users.The system incorporates two levels of recommendations as each user request undergoes two levels of recommendations. The first level involves providing the user with a set of destinations that matches her preferences (based on the preferences of similar users). The second level ranks the set of destinations based on the user preferences .

III.RELATED WORK

Ardissono,L.Goy,A.recommendation techniques, recommender systems can be classified as knowledge-based, content-based, and collaborative-based. Knowledge-based recommender systems recommend items based on the preferences and needs that the user provide. Content based recommender systems recommend items based on the user's rating history. Collaborative based recommender systems recommend items that are popular among other users with similar interests. Hybrid recommender systems aim at combining elements from two or more recommendation techniques to mitigate the weaknesses of each single one. There are different types of tourism recommendation and tour planning systems [1, 5, 11, 12, 15, 13, 6, 9].

Burguillo, J. C.Those systems provide plans based on user location or by explicitly asking the user to provide the destination she is planning to visit. Another type of tourism recommender systems provide destination recommendations [10].

Delgado, J. A., & Davidson .R uses a decision tree to build a knowledge base for each destination. The tree is built using two data source: content and ratings provided by domain experts and automatically generated ratings through text-mining of product descriptions. It also employs an incremental rating scheme to evaluate each trip based on the user response.[3]

Leal, F. proposed a system which suggests a destination to the user based on textual reviews and machine learning techniques. The system uses semantic content-based filtering to provide personalized recommendations based on Expedia crowd-sourced hotel textual reviews.[10]

J. M. Noguera & M. J. Barranco. propose a destination recommender system that uses opinion mining to build the profiles of user preferences and item opinion reputations. They also employ collaborative filtering for destination rating prediction.[14]

Sun, X ,use Flicker's public geotagged photos as well as other context information (such as weather) to extract users travel preferences and build their travel history. Then they use this profile to generate recommendations.[6]

Ji, Z., Pi, H., Wei, W., propose a hybrid recommendation model using the user ratings, reviews, and social data. A number of commercial destination recommendation tools are also available[8]
Those tools work as a destination search engine. They assign and evaluate the destinations based on a set of predefined attributes. Then they suggest destinations by finding those ones that match the user preferences. Those tools only use information explicitly given by the user and do not exploit the user's history.

IV.METHODOLOGY

WORK FLOW

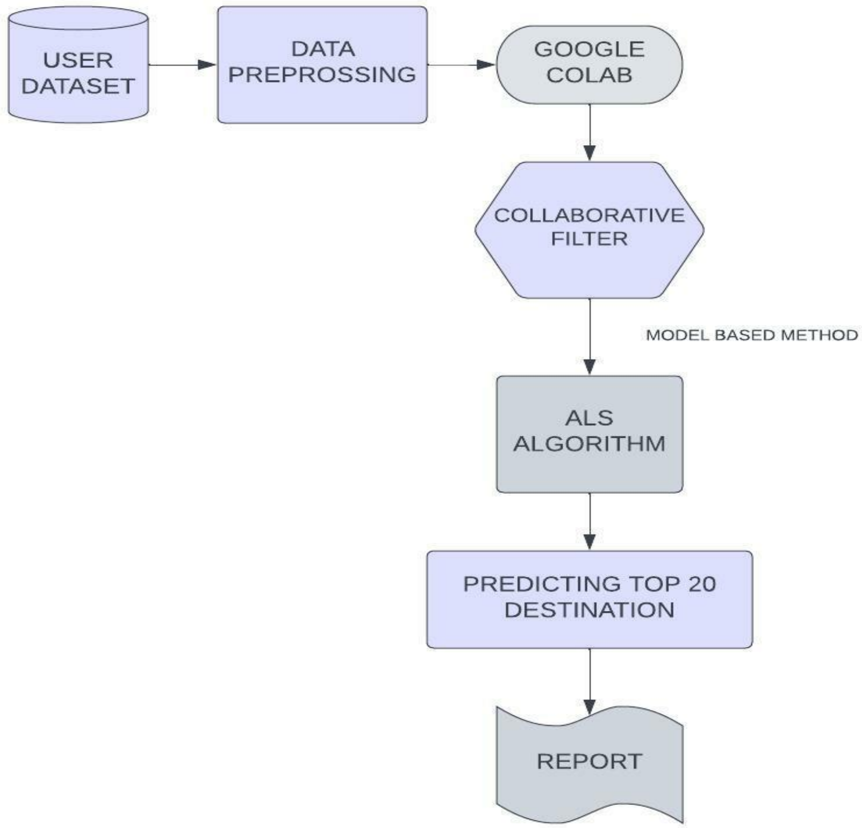

FIG 4.1

COLLABORATIVE FILTERING:

Item-item collaborative filtering is a type of recommendation system that is likeness between items calculated using the rating users have given to items. The user-user Collaborative Filter
and item-item Collaborative Filter can be achieved by two different ways, memory-based (neighbourhood approach) and model-based (latent factor model approach).

ALS ALGORITHM:

The Model- Based in Collaborative Filtering is Alternating Least Squares (ALS) matrix factorization attempts to estimate the ratings matrix R as the product of two lower-rank matrices, X and Y, i.e. X * Yt = R. Typically these approximations are called 'factor' matrices. The general approach is iterative. During each iteration, one of the factor matrices is held constant, while the other is clarify for using least squares. The newly-clarify factor matrix is then held constant while solving the other factor matrix.

IMPLEMENTATION:

Step 1: Build out an ALS model.

Step 2: Hyperparameter tuning and cross validation.

- ParamGrid Builder
- Regression Evaluator

- Cross Validator

Step 3: Check the best model parameters.

Step 4: Fit the best model and evaluate predictions.

Step 5: Make Recommendations.

V.RESULT

OUTPUT 1:

```
Out[221]: 0        4.0
          1        3.0
          2        5.0
          3        4.0
          4        3.0
                   ...
          1269     4.0
          1270     2.0
          1271     1.0
          1272     1.0
          1273     2.0
          Name: rating_float, Length: 1274, dtype: float32
```

FIG 5.1

In FIG5.1, The rating_float returns the value based on the argument or parameter value that is being passed to user items

OUTPUT 2:

	user_id	city_id	rating_float
0	0	0	4.0
1	0	0	3.0
2	0	1	5.0
3	0	2	4.0
4	0	3	3.0

FIG 5.2

In FIG5.2, The output shows the rating float with city id to predict the best destination to recommend for the user.

OUTPUT 3:

user	city	rating	prediction
11	31	4.0	4.9383407
9	28	5.0	4.0166087
9	26	4.0	3.443201
9	27	3.0	4.8522167
9	27	5.0	4.8522167
3	1	4.0	4.0169997
6	20	5.0	3.3613935
7	5	5.0	3.1133611
7	5	5.0	3.1133611
6	19	4.0	3.8444514
1	4	2.0	4.1937137
3	10	4.0	4.0438633
5	10	5.0	4.89069
9	24	3.0	4.7356796
9	24	4.0	4.7356796
10	29	5.0	4.925532
3	11	4.0	3.9556746
3	11	5.0	3.9556746
14	33	4.0	4.5550137
10	14	5.0	4.607379

only showing top 20 rows

FIG 5.3

In FIG5.3,The output shows the Prediction for top 20 cities with Rating and Prediction based on the similarity between items calculated using the rating users have given to items.

VI. CONCLUSION

The recommender system compares the collected data to similar and dissimilar data collected from others and calculates a list of recommended destination for the tourist. Collaborative filtering is considered to be memory-based and model based collaborative filtering. So as well known example of model-based approaches provided item recommendation by first developing a model of user ratings algorithm that we adopt in this paper.

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