Vidyavardhini's College of Engineering and Technology Department of Artificial Intelligence & Data Science

Experiment No. 7
Implementation of a recommendation system using Hybrid approach
Date of Performance:
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Aim: Implementation of a recommendation system using Hybrid approach

Objective: Able to implement and understand the aspects of Hybrid Recommendation System.

Theory:

Hybrid recommendation systems bring the best of both worlds together. Hybrid mechanisms to predict recommendation, as the name implies, combine two or more recommendation techniques. The disadvantages of a recommendation methodology can be resolved using hybrid technology, and the benefits of various recommendation techniques can be summed up. The hybrid recommendation methodology to develop a search model for selecting the best cloud service provider. It recommended service providers close to the organization to leverage the enterprise location to boost bandwidth and eliminate latency difficulties.

In addition, this work proposes a search model, recommendation system and evaluation standard for customers based on their needs and location. According to the implementation results, cloud servers must be located close to the enterprise in order to improve bandwidth and reduce latency. This framework tracks the enterprise's location, and the recommended function recommends the closest cloud server to the enterprise. Two models are used to classify the essential factors used for the searching function: the basic and feature models. These models can make it easier for enterprises to find what they need in the system. In, the author discusses how recommendation systems play an important role in providing adequate information to users and filtering data. The various recommendation techniques, such as Collaborative Filtering, demographic-based, and knowledge-based, all have drawbacks. While opting for recommendation systems, these techniques fail to provide effective recommendations. As a result, it is necessary to optimize these techniques by identifying more distinct features. This is possible by integrating the advantages of various techniques in a hybrid manner. The author proposed an effective hybrid technique for book recommendations that uses ontology for user profiling to improve system efficiency. The results show that combination of Collaborative Filtering, knowledge-based techniques, and demographic attributes into a Hybrid technique produces the best recommendations.

A hybrid recommendation the framework uses a combination of content-based recommendation system(CBRS) and collaborative filtering recommendation systems (CFRS) to achieve precisely performance by reducing the drawbacks of the conventional recommendation techniques.

Implementation:

import pandas as pd
import numpy as np
credits = pd.read_csv ('./tmdb_5000_credits.csv')
movies_df = pd.read_csv
('./tmdb_5000_movies.csv')
print (f'Credits : {credits.shape}')
print (f'Movie Dataset : {movies_df.shape}')

print (f'Movie Dataset : {movies_df.shape}')
CSDOL8022: Recommendation Systems Lab

credits_column_renamed = credits.rename
(index=str, columns = {'movie_id' : 'id'})
movies_df_merged = movies_df.merge
(credits_column_renamed, on='id')
movies_df_merged.head ()
movies_df_merged.columns



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```
movies cleaned df = movies df merged.drop
                                                            movies scored df[['original title',
(columns = ['homepage', 'title x', 'title y', 'status',
                                                            'normalized weighted average',
'production countries'])
                                                            'normalized popularity', 'score']].head (10)
movies cleaned df.columns
                                                            movies cleaned df.head(1)['overview']
movies_cleaned_df.info()
                                                            from sklearn.feature extraction.text import
                                                            TfidfVectorizer
v = movies cleaned df.vote count
                                                            tfv = TfidfVectorizer (
m = movies cleaned df.vote count.quantile (0.7)
R = movies_cleaned_df.vote_average
                                                              \min df = 3,
C = movies cleaned df.vote average.mean ()
                                                              max features = None,
movies cleaned df['weighted average'] = ((R*v) +
                                                              strip accents = 'unicode',
(C*m)/(v+m)
                                                              analyzer = 'word',
movies sorted ranking =
                                                              token pattern = r' \setminus w\{1,\}',
movies cleaned df.sort values
                                                              ngram range = (1, 3),
('weighted average', ascending=False)
                                                              stop words = 'english'
movies_sorted_ranking[['original_title',
'vote count', 'vote average', 'weighted average',
                                                            movies cleaned df['overview'] =
                                                            movies cleaned df['overview'].fillna (")
'popularity']].head (10)
from sklearn.preprocessing import MinMaxScaler
                                                            tfv matrix = tfv.fit transform
                                                            (movies cleaned df['overview'])
scaler = MinMaxScaler ()
movie scaled df = scaler.fit transform
                                                            from sklearn.metrics.pairwise import
(movies cleaned df[['weighted average',
                                                            sigmoid kernel
'popularity']])
                                                            sig = sigmoid kernel (tfv matrix, tfv matrix)
                                                            indices = pd. Series (movies cleaned df.index,
movie normalized df = pd.DataFrame
(movie scaled df, columns=['weighted average',
                                                            index=movies cleaned df['original title']).drop du
'popularity'])
                                                            plicates()
movies cleaned df[['normalized weighted averag
                                                            def give recommendations (title, sig = sig):
e', 'normalized popularity']] =
                                                              idx = indices[title]
movie normalized df
                                                              sig scores = list (enumerate (sig[idx]))
movies cleaned df['score'] =
                                                              sig scores = sorted (sig scores, key=lambda x :
movies cleaned df['normalized weighted average'
                                                            x[1], reverse=True)
]*0.5+
                                                              sig scores = sig scores[1:11]
movies cleaned df.normalized popularity * 0.5
                                                              movie indices = [i[0]] for i in sig scores
movies scored df =
movies cleaned df.sort values (['score'],
                                                            movies_cleaned_df['original_title'].iloc[movie_indi
ascending=False)
                                                            give_recommendations ('The Dark Knight')
```

Output:

```
3
                           The Dark Knight Rises
299
                                  Batman Forever
428
                                  Batman Returns
3854
        Batman: The Dark Knight Returns, Part 2
1359
2507
                                        Slow Burn
1181
                                              JFK
119
                                    Batman Begins
205
             Sherlock Holmes: A Game of Shadows
879
                             Law Abiding Citizen
Name: original title, dtype: object
```



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Conclusion:

Hybrid recommendation systems combine collaborative filtering and content-based methods to provide diverse and accurate recommendations. By leveraging both user-item interactions and item features, these systems offer personalized suggestions, overcoming limitations of individual approaches. This hybridization enhances recommendation quality, effectively addressing the cold-start problem and improving user satisfaction. By integrating multiple techniques, hybrid systems deliver robust and versatile recommendation solutions for various domains.