Recommender Systems Summative

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*Abstract*—This paper explains how recommender systems can be used in the domain of film recommendation to create personalized recommendations to active users, using both content-based and collaborative filtering approaches. These two approaches are then evaluated using MRSE and a measure to determine serendipity of the recommendations. The dataset used is the MovieLens 25 Million dataset [1].

Keywords—Recommender Systems, MovieLens Dataset, Content-Based Filtering, Collaborative Filtering

# Introduction

## Domain of the Application

The domain of this application is movie/film recommendation. In particular, providing personalised recommendations to an active user of the system.

## Purpose and Aim of the Application

Movie and film streaming is a market that is growing very quickly, with an estimated market share of 60 billion dollars worldwide, and is predicted to reach 220 billion dollars by 2028 [2]. Therefore, it is in streaming companies’ interest to improve their service in order to maximise their portion of this market share. One way in which companies can get ahead of their competitors is to provide better and more personalized recommendations to their users, as this means their users will be more inclined to stay on their platform to have access to these improved suggestions, instead of heading to a competitor platform. With the huge amount of data that companies such as Netflix and Amazon Prime Video now have on user ratings, and genres and tags for each film on their platform, their ability to provide such recommendations has increased vastly, and so recommender systems that harness this data are improving quickly.

The aim of this application is therefore to demonstrate how, using large amounts of data, recommendations can be provided to the active user, using content-based and collaborative-filtering approaches, that maximise both accuracy and serendipity.

# Methods

## Data Description

The dataset used is the MovieLens 25 Million Dataset [1]. This dataset includes 5-star rating and free-text tagging activity from MovieLens, a movie recommendation service.

The dataset includes 25000095 ratings, and 1093360 tags across 62423 movies, from 162541 different users. In order to ensure that there is enough ratings data for training the recommender systems for each user, each user in the dataset has rated at least 20 different movies. In order to hide the identity of the users, only an ID can identify each user, which has no reference to their actual identity elsewhere.

The dataset itself contains various files, namely: genome-scores, genome-tags, links, movies, ratings and tags. In this paper, the genome-scores, genome-tags, movies, ratings and tags files were used.

The dataset includes a Tag Genome. This is a data structure that contains the relevance of each tag to each movie, with each movie having a value for every tag in the genome. The tags indicate a range of features for a film, including: atmospheric, thought-provoking, realistic and more. The genome itself was calculated using a machine learning algorithm, trained upon user-contributed content such as tags, ratings and textual reviews, as described in [3]. This Tag Genome is represented by the files: genome-scores.csv and genome-tags.csv. The genome-scores.csv file contains the calculated relevance of each tag to each movie, and the genome-tags.csv file provides the description of each tag from each tag ID.

The movies file contains the title and genres associated with each movie ID.

The ratings file contains all the ratings given by users on the movies, as well as a timestamp indicating when the rating was left on the given film, represented in seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

The tags file contains all the tags given by users on films, as well as the timestamp that the user gave the tag for the corresponding film, also formatted in seconds since midnight Coordinated Universal Time (UTC) of January 1, 1970.

## Data Preparation and Feature Selection

The datasets themselves contained no missing values in their columns. No pre-processing had to be done on any of the data files.

There were 1129 tags for each movie, each with their own relevance score for each movie. All of these tags were used to train both the content-based and collaborative-filtering recommender systems. This is because the more tags, the more accurate the recommender systems can be, as they can learn from a greater volume of data to learn user preferences from. The time to making predictions for the content-based recommender is also reasonable, and the time to train the model for the collaborative-filtering model is also not too long for this many tags.

## Recommendation Algorithms

**Content-Based Filtering Approach**

In this approach, firstly the user profile is created. First, all the ratings for the active user are collected. All the IDs of the movies that this user rated are then gathered into an array. The Tag Genome relevancy scores for each of the tags for each of these movies is then collected, and a DataFrame is collected to represent this information. The average rating for the active user is then calculated. In order to determine whether a rating is positive or negative, (whether the active user liked or disliked the film given their rating of it), the average rating of the user is then subtracted from the rating given by the user for a particular film, as shown below:

Where rui represents the rating given by user u on item i, and represents the average rating of user u.

Then, the user profile is created by calculating the dot product between every tag’s relevance on every rated movie and the rating the user has given on every movie. The user profile therefore then represents the active users’ preferences for every one of the movie tags.

Then, in order to make recommendation predictions, the dot product of the user profile and the movie Tag Genome scores for each of the possible movies is calculated, and saved in a new DataFrame. The sum of all the columns for every movie is then calculated, and this represents the prediction score for each movie. These values are then scaled using Min-Max Feature Scaling, using the Sklearn MinMaxScaler [5], to ensure all the prediction values are between 0 and 1. Then, the films that the active user has seen previously are removed, so that they are not recommended movies they have already seen. The DataFrame is then sorted in descending order, off of the predicted score column, and the first 10 movies are returned, as these movies have the highest predicted scores for the active user. The prediction score is then multiplied by 100, to make the score now a percentage, and then limited to only 1 decimal place. This makes a more appealing experience for the active user.

In order to make the predictions more explainable, the 5 tags with the highest relevancy values in the user profile are displayed, as well as the 5 tags with the highest relevancy scores for each of the top 10 predictions for the active user. An example of this can be shown below in Figure 1:

This is what is displayed to the user when they choose to be recommended films by the Content-Based Filter.

**Collaborative-Filtering Approach**

In this approach, a model-based collaborative-filtering recommender system is created, based upon a Matrix-Factorisation algorithm, specifically SVD, popularized by Simon Funk in the Netflix Prize [4]. This approach works in the following way:

The predicted rating for an item i by user u, is given by the following formula:

where 𝜇 represents the average rating of all the movies in the dataset, bu represents the average rating given by user u, bi represents the average rating of item i, qi  represents the latent item vector and pu represents the latent user vector. Both the latent user and item vectors were set to 100 latent factors.

During training, the SVD minimises the following regularized squared error:

This is performed via stochastic gradient descent:

## Where eui represents the difference between the actual rating given by user u on item i, and the predicted rating by the SVD. The model in this paper was trained using the learning rate, 𝛾, of 0.005, and the regularisation term, 𝜆, of 0.02.

## Evaluation Methods

# implementation

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# Evaluation

## Evaluation Metrics’ Results

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

## RS Techniques’ Comparison

# conclusion

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