VIT AP UNIVERSITY, ANDHRA PRADESH

A Project Report On

"Movie Recommendation project"

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1. Abstract

If you use Amazon, Amazon Prime, or Netflix, you're presumably aware that these services use "recommendation engines." A recommendation engine's only objective, as the name suggests, is to "propose" suitable items to consumers — whereas Amazon recommends merchandise, Prime and Netflix recommend material to users based on their past purchase or viewing history.

The main purpose of this R project is to create a recommendation system for users to watch movies. The MovieLens dataset was utilised in this study. There are 105339 ratings for over 10329 films in this database. You will develop an Item Based Collaborative Filter in this project.

The nicest thing about creating this movie recommendation engine from scratch is that it will teach you about a recommendation engine's inner workings and mechanisms.

2. Introduction

Recommended systems are one of the most important techniques used to introduce information about user needs, including related services, by analyzing user actions For the recommender system, a collaborative filtering approach is used to introduce information that will meet the needs of the user. The collaborative filtering is based on similarly tasteless users, the same choice, and the idea that users who buy in the past will buy in the future .Data production factors for the collaborative filtering process are user interest or user behavior in the form of the feature vector.

The main purpose of this document is to achieve a more effective solution than collaborative filtering. The proposed movie recommendation system is based on the Logistic regression etc. This was the first time that this method of social network analysis was used to introduce in the movie recommender system, and it is found to be very efficient. This provides the maximum accuracy with the recommender system. For performance evaluation, use MovieLens data, which is general information in movie recommendation systems. To assess the effectiveness of a MovieLens dataset, it is divided into experimental and test data that are widely used in artificial intelligence. Comparison of collaborative filtering methods using *k* nearest neighbor, to evaluate performance.

3. Objective/ Aim

Movie recommendation systems provide a mechanism to assist users in classifying users with similar interests. This makes recommender systems essentially a central part of websites and e-commerce applications. This article focuses on the movie recommendation systems whose primary objective is to suggest a recommender system through ML algorithms and artificial intelligence.

4. Proposed idea

Here we employ an Item Based Collaborative Filter. These parameters are of the default type. We utilise the cosine approach by default, but you can alternatively use the Pearson method. We will acquire the recommen model using the getModel() function. The class and dimensions of our similarity matrix, which are contained under model info, will then be determined. Finally, we will create a heatmap with the top 20 items and illustrate the similarity between them. We will compute the sum of rows and columns where the similarity of the objects is greater than 0. A distribution will be used to visualise the total of columns. We generated a top recommendations variable, which will be set to 10, indicating the amount of films recommended to each user. The predict() function will then be used to find comparable items and rank them appropriately. Each rating is treated as a weight in this case.

5. Methodology

Loading dataset

- We import datasets containing movies and ratings

```
> movie_data <- read.csv("movies.csv",stringsAsFactors=FALSE)
> rating_data <- read.csv("ratings.csv")
> head(movie_data)
  movieId                              title                                      genres
1       1                   Toy Story (1995) Adventure|Animation|Children|Comedy|Fantasy
2       2                     Jumanji (1995)                  Adventure|Children|Fantasy
3       3            Grumpier Old Men (1995)                              Comedy|Romance
4       4           Waiting to Exhale (1995)                        Comedy|Drama|Romance
5       5 Father of the Bride Part II (1995)                                      Comedy
6       6                        Heat (1995)                       Action|Crime|Thriller
> head(rating_data)
  userId movieId rating  timestamp
1      1      16    4.0 1217897793
2      1      24    1.5 1217895807
3      1      32    4.0 1217896246
4      1      47    4.0 1217896556
5      1      50    4.0 1217896523
6      1     110    4.0 1217896150
> |
```

Data Preprocessing

We can see that the userId and movieId columns are both made up of numbers. Furthermore, we must change the genres included in the movie data dataframe into a more user-friendly format. To do so, we will first develop a one-hot encoding to generate a matrix of associated genres for each of the films. We constructed a'search matrix' that will allow us to easily search the films in our list by choosing the genre. We must turn our matrix into a sparse matrix in order to receive ratings from recommenderlabs. This new matrix belongs to the'realRatingMatrix' class. Item Based Collaborative Filtering was implemented.

```
> movie_genre <- as.data.frame(movie_data$genres, stringsAsFactors=FALS
> head(movie_genre)
                              movie_data$genres
1 Adventure|Animation|Children|Comedy|Fantasy
2                Adventure|Children|Fantasy
3                            Comedy|Romance
4                      Comedy|Drama|Romance
5                                    Comedy
6                     Action|Crime|Thriller
> library(data.table)
> movie_genre2 <- as.data.frame(tstrsplit(movie_genre[,1], '[|]',
+                                         type.convert=TRUE),
+                               stringsAsFactors=FALSE)
> colnames(movie_genre2) <- c(1:10)
> list_genre <- c("Action", "Adventure", "Animation", "Children",
+                 "Comedy", "Crime","Documentary", "Drama", "Fantasy",
+                 "Film-Noir", "Horror", "Musical", "Mystery","Romance"
+                 "Sci-Fi", "Thriller", "War", "Western")
> genre_mat1 <- matrix(0,10330,18)
> genre_mat1[1,] <- list_genre
> colnames(genre_mat1) <- list_genre
> for (index in 1:nrow(movie_genre2)) {
+   for (col in 1:ncol(movie_genre2)) {
+     gen_col = which(genre_mat1[1,] == movie_genre2[index,col])
+     genre_mat1[index+1,gen_col] <- 1
+   }
+ }
>
> genre_mat2 <- as.data.frame(genre_mat1[-1,], stringsAsFactors=FALSE)
> for (col in 1:ncol(genre_mat2)) {
+   genre_mat2[,col] <- as.integer(genre_mat2[,col])
+ }
> str(genre_mat2)
'data.frame':   10329 obs. of  18 variables:
 $ Action     : int  0 0 0 0 0 1 0 0 1 1 ...
 $ Adventure  : int  1 1 0 0 0 0 0 1 0 1 ...
 $ Animation  : int  1 0 0 0 0 0 0 0 0 0 ...
 $ Children   : int  1 1 0 0 0 0 0 1 0 0 ...
 $ Comedy     : int  1 0 1 1 1 0 1 0 0 0 ...
 $ Crime      : int  0 0 0 0 0 1 0 0 0 0 ...
 $ Documentary: int  0 0 0 0 0 0 0 0 0 0 ...
 $ Drama      : int  0 0 0 1 0 0 0 0 0 0 ...
 $ Fantasy    : int  1 1 0 0 0 0 0 0 0 0 ...
 $ Film-Noir  : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Horror     : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Musical    : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Mystery    : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Romance    : int  0 0 1 1 0 0 1 0 0 0 ...
 $ Sci-Fi     : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Thriller   : int  0 0 0 0 0 1 0 0 0 1 ...
 $ War        : int  0 0 0 0 0 0 0 0 0 0 ...
 $ Western    : int  0 0 0 0 0 0 0 0 0 0 ...
```

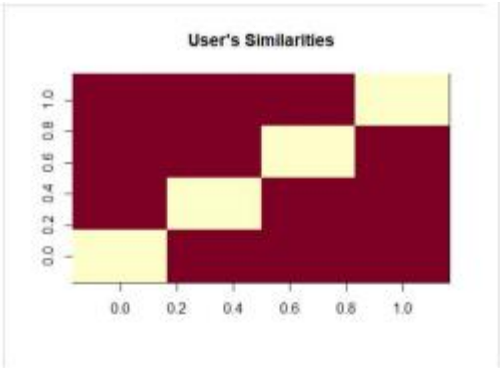
```
> head(genre_mat2)
  Action Adventure Animation Children Comedy Crime Documentary Drama Fantasy Film-Noir Horror Musical Mystery
1      0         1         1        1      1     0           0     0       1         0      0       0       0
2      0         1         0        1      0     0           0     0       1         0      0       0       0
3      0         0         0        0      1     0           0     0       0         0      0       0       0
4      0         0         0        0      1     0           0     1       0         0      0       0       0
5      0         0         0        0      1     0           0     0       0         0      0       0       0
6      1         0         0        0      0     1           0     0       0         0      0       0       0
  Romance Sci-Fi Thriller War Western
1       0      0        0   0       0
2       0      0        0   0       0
3       1      0        0   0       0
4       1      0        0   0       0
5       0      0        0   0       0
6       0      0        1   0       0
> SearchMatrix <- cbind(movie_data[,1:2], genre_mat2[])
> head(SearchMatrix)
  movieId                              title Action Adventure Animation Children Comedy Crime Documentary Drama
1       1                   Toy Story (1995)      0         1         1        1      1     0           0     0
2       2                     Jumanji (1995)      0         1         0        1      0     0           0     0
3       3            Grumpier Old Men (1995)      0         0         0        0      1     0           0     0
4       4           Waiting to Exhale (1995)      0         0         0        0      1     0           0     1
5       5 Father of the Bride Part II (1995)      0         0         0        0      1     0           0     0
6       6                        Heat (1995)      1         0         0        0      0     1           0     0
  Fantasy Film-Noir Horror Musical Mystery Romance Sci-Fi Thriller War Western
1       1         0      0       0       0       0      0        0   0       0
2       1         0      0       0       0       0      0        0   0       0
3       0         0      0       0       0       1      0        0   0       0
4       0         0      0       0       0       1      0        0   0       0
5       0         0      0       0       0       0      0        0   0       0
6       0         0      0       0       0       0      0        1   0       0
> ratingMatrix <- dcast(rating_data, userId~movieId, value.var = "rating", na.rm=FALSE)
> ratingMatrix <- as.matrix(ratingMatrix[,-1])
> ratingMatrix <- as(ratingMatrix, "realRatingMatrix")
> head(ratingMatrix)
6 x 10325 rating matrix of class 'realRatingMatrix' with 468 ratings.
> head(rating_data)
  userId movieId rating  timestamp
1      1      16    4.0 1217897793
2      1      24    1.5 1217895807
3      1      32    4.0 1217896246
4      1      47    4.0 1217896556
5      1      50    4.0 1217896523
6      1     110    4.0 1217896150
> recommendation_model <- recommenderRegistry$get_entries(dataType = "realRatingMatrix")
> names(recommendation_model)
 [1] "HYBRID_realRatingMatrix"      "ALS_realRatingMatrix"         "ALS_implicit_realRatingMatrix"
 [4] "IBCF_realRatingMatrix"        "LIBMF_realRatingMatrix"       "POPULAR_realRatingMatrix"
 [7] "RANDOM_realRatingMatrix"      "RERECOMMEND_realRatingMatrix" "SVD_realRatingMatrix"
[10] "SVDF_realRatingMatrix"        "UBCF_realRatingMatrix"
> lapply(recommendation_model, "[[", "description")
$HYBRID_realRatingMatrix
[1] "Hybrid recommender that aggegates several recommendation strategies using weighted averages."

$ALS_realRatingMatrix
```

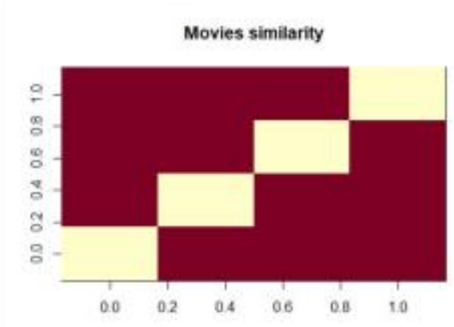
Data Exploration

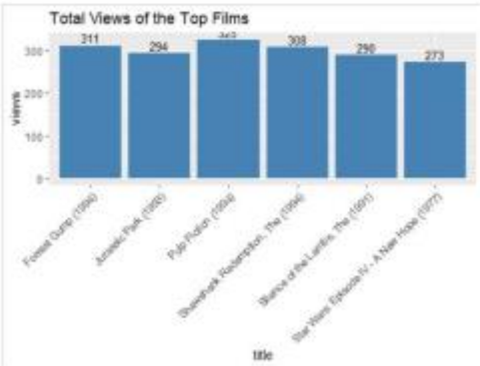
• In this step, we are able to discover the information this is contained withinside the datasets. We will use the str() function to display information about the movie_data and rating_data dataframes . We will use summary() function to summarize 2 datasets.

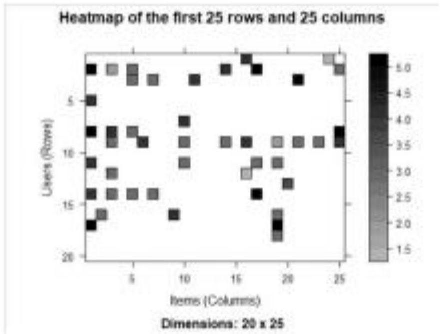
```
> str(movie_data)
'data.frame':   10329 obs. of  3 variables:
 $ movieId: int  1 2 3 4 5 6 7 8 9 10 ...
 $ title  : chr  "Toy Story (1995)" "Jumanji (1995)" "Grumpier Old Men (1995)" "Waiting to Exhale
 $ genres : chr  "Adventure|Animation|Children|Comedy|Fantasy" "Adventure|Children|Fantasy" "Comed
Drama|Romance" ...
> summary(movie_data)
    movieId           title              genres
 Min.   :     1   Length:10329       Length:10329
 1st Qu.:  3240   Class :character   Class :character
 Median :  7088   Mode  :character   Mode  :character
 Mean   : 31924
 3rd Qu.: 59900
 Max.   :149532
> str(rating_data)
'data.frame':   105339 obs. of  4 variables:
 $ userId   : int  1 1 1 1 1 1 1 1 1 1 ...
 $ movieId  : int  16 24 32 47 50 110 150 161 165 204 ...
 $ rating   : num  4 1.5 4 4 4 4 3 4 3 0.5 ...
 $ timestamp: int  1217897793 1217895807 1217896246 1217896556 1217896523 1217896150 1217895940 12
 1217895786 ...
> summary(rating_data)
     userId         movieId           rating        timestamp
 Min.   :  1.0   Min.   :     1   Min.   :0.500   Min.   :8.286e+08
 1st Qu.:192.0   1st Qu.:  1073   1st Qu.:3.000   1st Qu.:9.711e+08
 Median :383.0   Median :  2497   Median :3.500   Median :1.115e+09
 Mean   :364.9   Mean   : 13381   Mean   :3.517   Mean   :1.130e+09
 3rd Qu.:557.0   3rd Qu.:  5991   3rd Qu.:4.000   3rd Qu.:1.275e+09
 Max.   :668.0   Max.   :149532   Max.   :5.000   Max.   :1.452e+09
>
```

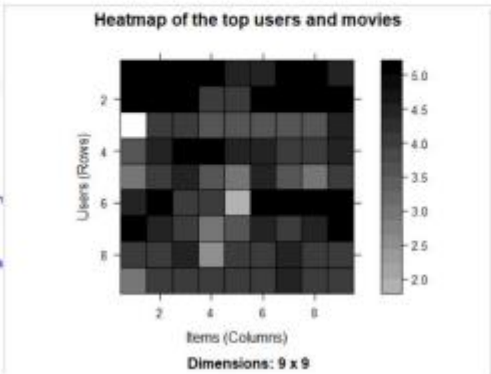
```
> similarity_mat <- similarity(ratingMatrix[1:4, ],method = "cosine",which = "users")
> as.matrix(similarity_mat)
          1         2         3         4
1 0.0000000 0.9760860 0.9641723 0.9914398
2 0.9760860 0.0000000 0.9925732 0.9374253
3 0.9641723 0.9925732 0.0000000 0.9888968
4 0.9914398 0.9374253 0.9888968 0.0000000
> image(as.matrix(similarity_mat), main = "User's Similarities")
> movie_similarity <- similarity(ratingMatrix[, 1:4], method ="cosine", which = "items")
> as.matrix(movie_similarity)
          1         2         3         4
1 0.0000000 0.9669732 0.9559341 0.9101276
2 0.9669732 0.0000000 0.9658757 0.9412416
3 0.9559341 0.9658757 0.0000000 0.9864877
4 0.9101276 0.9412416 0.9864877 0.0000000
> image(as.matrix(movie_similarity), main = "Movies similarity")
> rating_values <- as.vector(ratingMatrix@data)
> unique(rating_values)
 [1] 0.0 5.0 4.0 3.0 4.5 1.5 2.0 3.5 1.0 2.5 0.5
> Table_of_Ratings <- table(rating_values)
> Table_of_Ratings
rating_values
      0     0.5       1     1.5       2     2.5       3     3.5       4     4.5       5
6791761    1198    3258    1567    7943    5484   21729   12237   28880    8187   14856
> library(ggplot2)
> movie_views <- colCounts(ratingMatrix)
> table_views <- data.frame(movie = names(movie_views),views = movie_views)
> table_views <- table_views[order(table_views$views,decreasing = TRUE), ]
> table_views$title <- NA
> for (index in 1:10325){
+   table_views[index,3] <- as.character(subset(movie_data,movie_data$movieId == table_views[index,1])$title)
+ }
> table_views[1:6,]
    movie views                                    title
296   296   325                      Pulp Fiction (1994)
356   356   311                      Forrest Gump (1994)
318   318   308         Shawshank Redemption, The (1994)
480   480   294                     Jurassic Park (1993)
593   593   290         Silence of the Lambs, The (1991)
260   260   273 Star Wars: Episode IV - A New Hope (1977)
> ggplot(table_views[1:6, ], aes(x = title, y = views)) +
+   geom_bar(stat="identity", fill = 'steelblue') +
+   geom_text(aes(label=views), vjust=-0.3, size=3.5) +
+   theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
+   ggtitle("Total Views of the Top Films")
> image(ratingMatrix[1:20, 1:25], axes = FALSE, main = "Heatmap of the first 25 rows and 25 columns")
> movie_ratings <- ratingMatrix[rowCounts(ratingMatrix) > 50,colCounts(ratingMatrix) > 50]
> movie_ratings
420 x 447 rating matrix of class 'realRatingMatrix' with 38341 ratings.
> minimum_movies<- quantile(rowCounts(movie_ratings), 0.98)
> minimum_users <- quantile(colCounts(movie_ratings), 0.98)
> image(movie_ratings[rowCounts(movie_ratings) > minimum_movies,colCounts(movie_ratings) > minimum_users],main = "Heatmap of
> average_ratings <- rowMeans(movie_ratings)
> qplot(average_ratings, fill=I("steelblue"), col=I("red")) +ggtitle("Distribution of the average rating per user")
`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
> normalized_ratings <- normalize(movie_ratings)
> sum(rowMeans(normalized_ratings) > 0.00001)
[1] 0
> image(normalized_ratings[rowCounts(normalized_ratings) > minimum_movies,colCounts(normalized_ratings) > minimum_users],main
> binary_minimum_movies <- quantile(rowCounts(movie_ratings), 0.95)
> binary_minimum_users <- quantile(colCounts(movie_ratings), 0.95)
> good_rated_films <- binarize(movie_ratings, minRating = 3)
> image(good_rated_films[rowCounts(movie_ratings) > binary_minimum_movies,colCounts(movie_ratings) > binary_minimum_users],ma
```

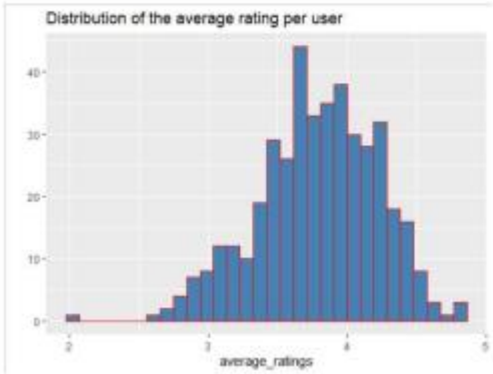

User's Similarities

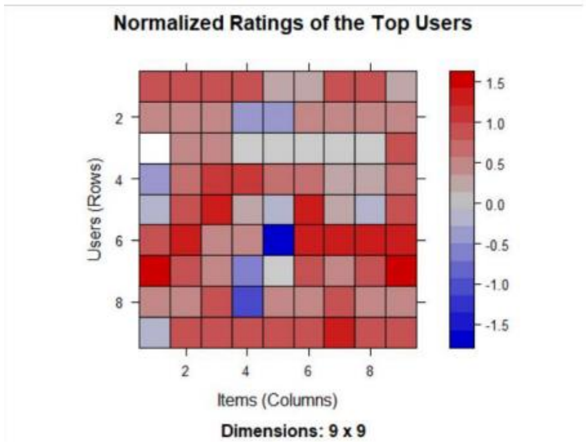

Movies similarity

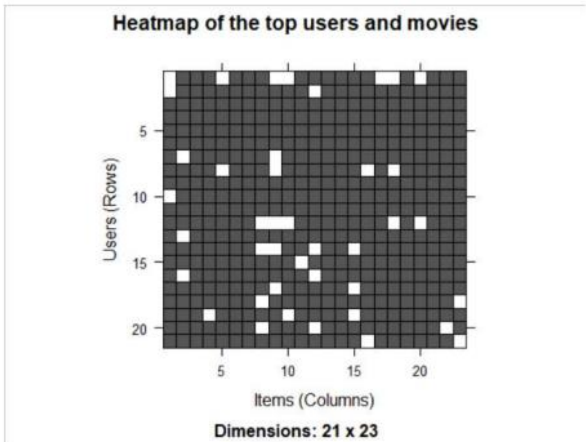

Total Views of the Top Films
views
title


Heatmap of the first 25 rows and 25 columns
Users (Rows)
Items (Columns)
Dimensions: 20 x 25


Heatmap of the top users and movies
Users (Rows)
Items (Columns)
Dimensions: 9 x 9


Distribution of the average rating per user
average_ratings


Normalized Ratings of the Top Users
Users (Rows)
Items (Columns)
Dimensions: 9 x 9

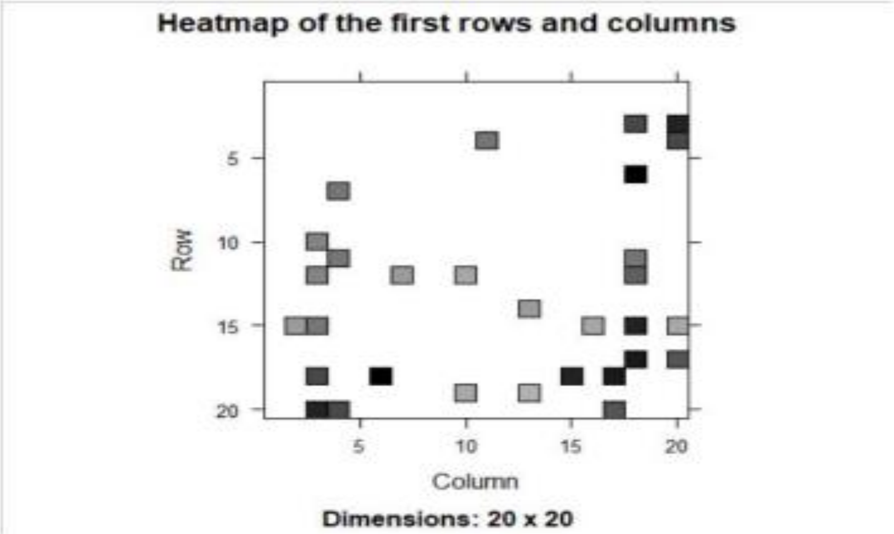

Heatmap of the top users and movies
Users (Rows)
Items (Columns)
Dimensions: 21 x 23

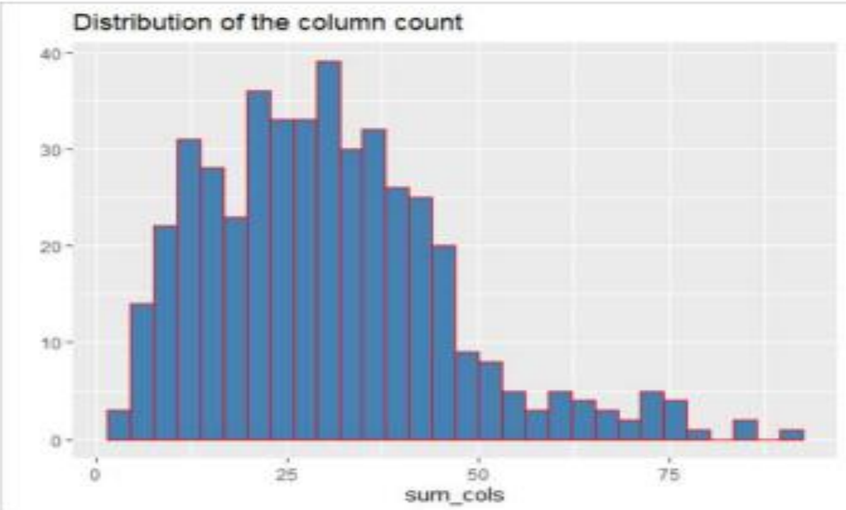
```
> df$Amount=scale(df$Amount)
> data=df[,-c(1)]
> head(data)
          V1          V2        V3         V4          V5          V6          V7          V8         V9         V10        V11         V12        V13
1 -1.3598071 -0.07278117 2.5363467  1.3781552 -0.33832077  0.46238778  0.23959855  0.09869790  0.3637870  0.09079417 -0.5515995 -0.61780086 -0.9913898
2  1.1918571  0.26615071 0.1664801  0.4481541  0.06001765 -0.08236081 -0.07880298  0.08510165 -0.2554251 -0.16697441  1.6127267  1.06523531  0.4890950
3 -1.3583541 -1.34016307 1.7732093  0.3797796 -0.50319813  1.80049938  0.79146096  0.24767579 -1.5146543  0.20764287  0.6245015  0.06608369  0.7172927
4 -0.9662717 -0.18522601 1.7929933 -0.8632913 -0.01030888  1.24720317  0.23760894  0.37743587 -1.3870241 -0.05495192 -0.2264873  0.17822823  0.5077569
5 -1.1582331  0.87773675 1.5487178  0.4030339 -0.40719338  0.09592146  0.59294075 -0.27053268  0.8177393  0.75307443 -0.8228429  0.53819555  1.3458516
6 -0.4259659  0.96052304 1.1411093 -0.1682521  0.42098688 -0.02972755  0.47620095  0.26031433 -0.5686714 -0.37140720  1.3412620  0.35989384 -0.3580907
         V14        V15        V16         V17         V18         V19         V20          V21          V22         V23         V24        V25
1 -0.3111694  1.4681770 -0.4704005  0.20797124  0.02579058  0.40399296  0.25141210 -0.018306778  0.277837576 -0.11047391  0.06692807  0.1285394
2 -0.1437723  0.6355581  0.4639170 -0.11480466 -0.18336127 -0.14578304 -0.06908314 -0.225775248 -0.638671953  0.10128802 -0.33984648  0.1671704
3 -0.1659459  2.3458649 -2.8900832  1.10996938 -0.12135931 -2.26185710  0.52497973  0.247998153  0.771679402  0.90941226 -0.68928096 -0.3276418
4 -0.2879237 -0.6314181 -1.0596472 -0.68409279  1.96577500 -1.23262197 -0.20803778 -0.108300452  0.005273597 -0.19032052 -1.17557533  0.6473760
5 -1.1196698  0.1751211 -0.4514492 -0.23703324 -0.03819479  0.80348692  0.40854236 -0.009430697  0.798278495 -0.13745808  0.14126698 -0.2060096
6 -0.1371337  0.5176168  0.4017259 -0.05813282  0.06865315 -0.03319379  0.08496767 -0.208253515 -0.559824796 -0.02639767 -0.37142658 -0.2327938
         V26          V27         V28      Amount Class
1 -0.1891148  0.133558377 -0.02105305  0.24496383     0
2  0.1258945 -0.008983099  0.01472417 -0.34247394     0
3 -0.1390966 -0.055352794 -0.05975184  1.16068389     0
4 -0.2219288  0.062722849  0.06145763  0.14053401     0
5  0.5022922  0.219422230  0.21515315 -0.07340321     0
6  0.1059148  0.253844225  0.08108026 -0.33855582     0
```

Data Modeling

• Once we have standardized the dataset, we will divide our dataset into training sets and test sets with a divide ratio of 0.80. This means that 80% of our data will be attributed to train data while 20% will be attributed to test data.

```
> sampled_data<- sample(x = c(TRUE, FALSE),size = nrow(movie_ratings),replace = TRUE,prob = c(0.8, 0.2))
> training_data <- movie_ratings[sampled_data, ]
> testing_data <- movie_ratings[!sampled_data, ]
```



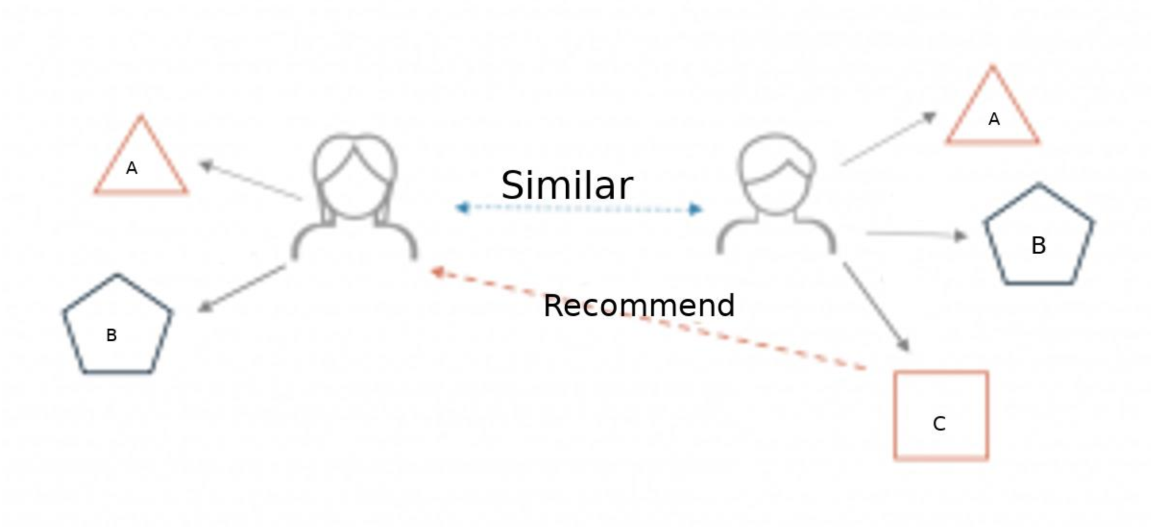


6. Experimental Framework

i. Implementation Details

A recommender system is a simple algorithm whose aim is to provide the most relevant information to a user by discovering patterns in a dataset. The algorithm rates the items and shows the user the items that they would rate highly. An example of recommendation in action is when you visit Amazon and you notice that some items are being recommended to you or when Netflix recommends certain movies to you. They are also used by Music streaming applications such as Spotify and Deezer to recommend music that you might like.

Below is a very simple illustration of how recommender systems work in the context of an e-commerce site.



Two users buy the same items A and B from an e-commerce store. When this happens the similarity index of these two users is computed. Depending on the score the system can recommend item C to the other user because it detects that those two users are similar in terms of the items they purchase.

Different types of recommendation engines

The most common types of recommendation systems are content-based and collaborative filtering recommender systems. In collaborative filtering, the behavior of a group of users is used to make recommendations to other users. The recommendation is based on the preference of other users. A simple example would be recommending a movie to a user based on the fact that their friend liked the movie. There are two types of collaborative models Memory-based methods and Model-based methods. The advantage of memory-based techniques is that they are simple to implement and the resulting recommendations are often easy to explain. They are divided into two:

User-based collaborative filtering: In this model, products are recommended to a user based on the fact that the products have been liked by users similar to the user. For example, if Derrick and Dennis like the same movies and a new movie come out that Derick like, then we can recommend that movie to Dennis because Derrick and Dennis seem to like the same movies.

Item-based collaborative filtering: These systems identify similar items based on users' previous ratings. For example, if users A, B, and C gave a 5-star rating to books X and Y then when a user D buys book Y they also get a recommendation to purchase book X because the system identifies book X and Y as similar based on the ratings of users A, B, and C.

Model-based methods are based on Matrix Factorization and are better at dealing with sparsity. They are developed using data mining, machine learning

algorithms to predict users' rating of unrated items. In this approach techniques such as dimensionality reduction are used to improve accuracy. Examples of such model-based methods include Decision trees, Rule-based Model, Bayesian Model, and latent factor models.
Content-based systems use metadata such as genre, producer, actor, musician to recommend items say movies or music. Such a recommendation would be for instance recommending Infinity War that featured Vin Diesel because someone watched and liked The Fate of the Furious. Similarly, you can get music recommendations from certain artists because you liked their music. Content-based systems are based on the idea that if you liked a certain item you are most likely to like something that is similar to it.

Datasets to use for building recommender systems

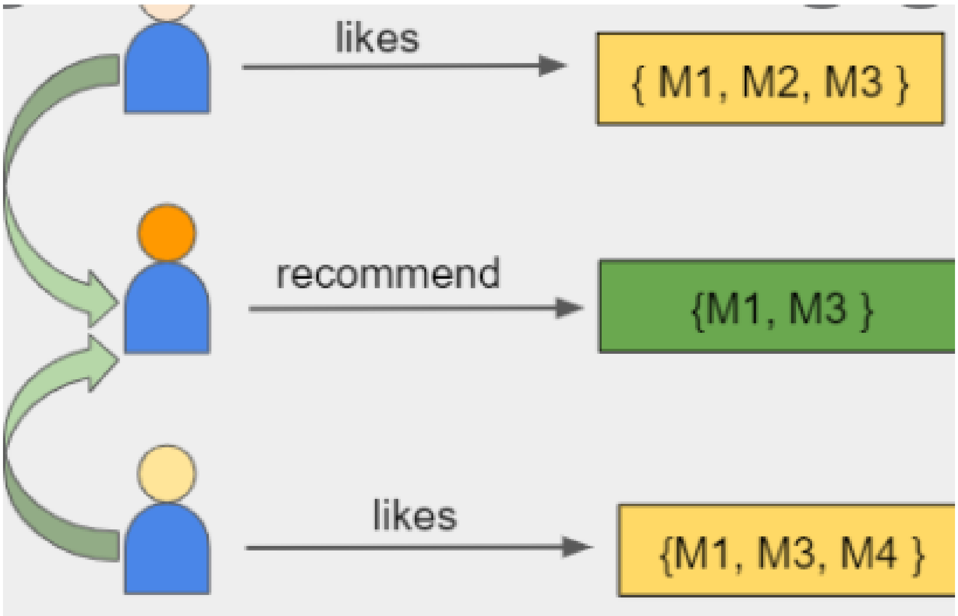
In this tutorial, we are going to use the Movie Lens Data Set. This dataset was put together by the Group lens research group at the University of Minnesota. It contains 1, 10, and 20 million ratings. Movie lens also has a website where you can sign up, contribute reviews and get movie recommendations.

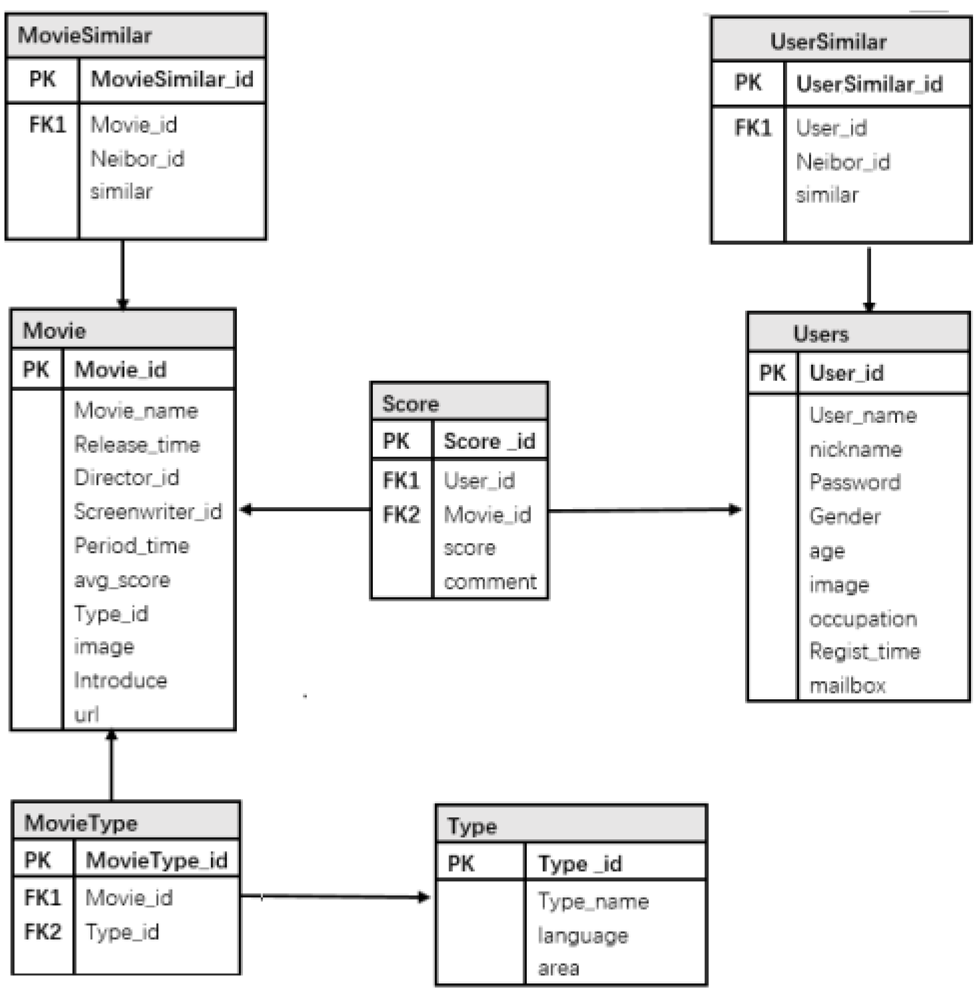
ii. Dataset Description

Here we use the Movie Lens Data Set. This dataset was put together by the Group lens research group at the University of Minnesota. It contains 1, 10, and 20 million ratings. Movie lens also has a website where you can sign up, contribute reviews and get movie recommendations.

movieId	title	genres
1	Toy Story (1995)	Adventure|Animation|Children|Comedy|Fantasy
2	Jumanji (1995)	Adventure|Children|Fantasy
3	Grumpier Old Men (1995)	Comedy|Romance
4	Waiting to Exhale (1995)	Comedy|Drama|Romance
5	Father of the Bride Part II	Comedy
6	Heat (1995)	Action|Crime|Thriller
7	Sabrina (1995)	Comedy|Romance
8	Tom and Huck (1995)	Adventure|Children
9	Sudden Death (1995)	Action
10	GoldenEye (1995)	Action|Adventure|Thriller
11	American President, The (1	Comedy|Drama|Romance
12	Dracula: Dead and Loving	Comedy|Horror
13	Balto (1995)	Adventure|Animation|Children
14	Nixon (1995)	Drama
15	Cutthroat Island (1995)	Action|Adventure|Romance

7. Flowchart / Schematic representation of your project




MovieSimilar
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FK1 Movie_id
Neibor_id
similar
UserSimilar
PK UserSimilar_id
FK1 User_id
Neibor_id
similar
Movie
PK Movie_id
Movie_name
Release_time
Director_id
Screenwriter_id
Period_time
avg_score
Type_id
image
Introduce
url
Score
PK Score _id
FK1 User_id
FK2 Movie_id
score
comment
Users
PK User_id
User_name
nickname
Password
Gender
age
image
occupation
Regist_time
mailbox
MovieType
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Type
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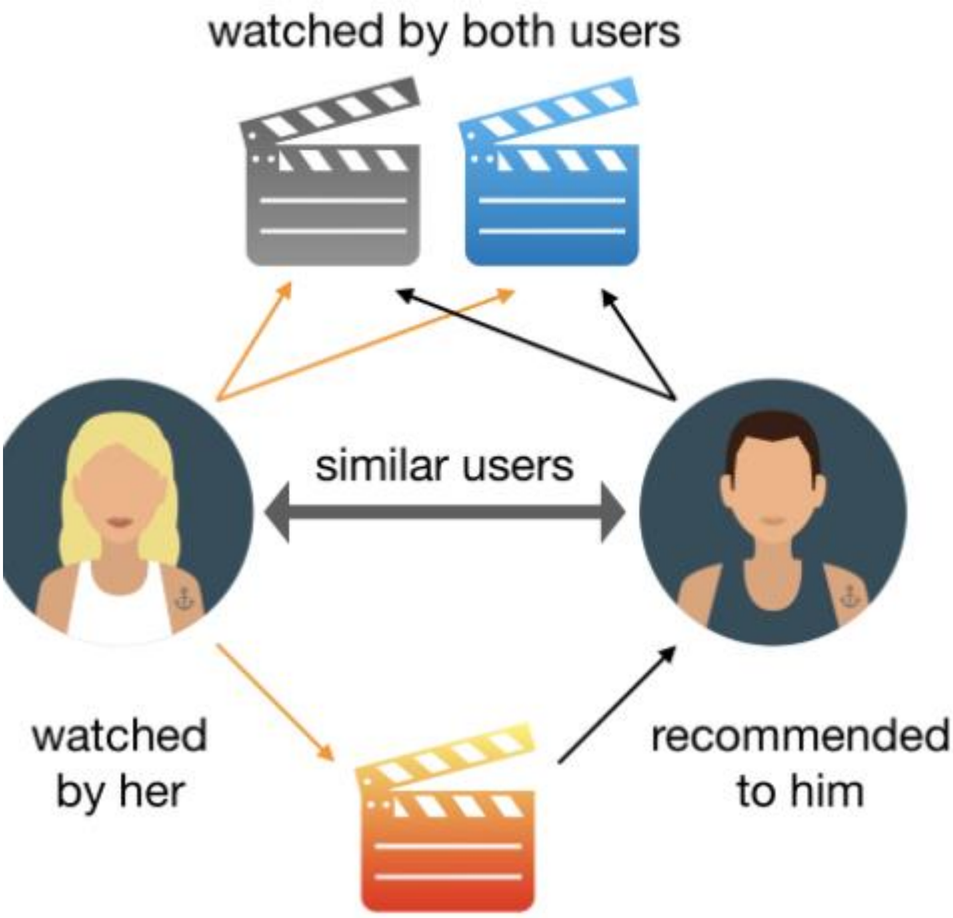
area



8. Conclusion

We implemented this model using ML algorithm and plotted some visualizations of data and predictions. We learned how to analyse and visualise data in order to recommend movies to the users

9. References

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