

APPENDIX

CODE

```
118 import pandas as pd
119 import numpy as np
120 import math
121
122 class CF:
123
124     def ExplodeRatingSet(data):
125         return data.split(',')
126
127     def ExplodeGenre(data):
128         return data.split('|')
129
130     def CountAverageRating(data):
131         DataRate = []
132
133         for i in range(len(data)):
134             DataTemp = [CF.ExplodeRatingSet(data[i][0])[1],
135                         CF.ExplodeRatingSet(data[i][0])[3],
136                         str(CF.ExplodeRatingSet(data[i][0])[2]),
137                         CF.ExplodeRatingSet(data[i][0])[4]]
138             count = 0
139
140             for a in range(len(DataRate)):
141                 if DataRate[a][0] == DataTemp[0] and DataRate[a][1] != []:
142                     Ratings = str(DataRate[a][1]) + ',' + str(DataTemp[1])
143                     DataTemp = [DataTemp[0], Ratings, DataTemp[2], DataTemp[3]]
144                     DataRate[a] = DataTemp
145                     count = 1
146
147             if count == 0:
148                 DataRate.append(DataTemp)
149                 #print('Data Appendedd')
150
151         return DataRate
152
153     def CosineSimilarity(id, data):
154         Ranking = []
155
156         #Get Movie Average
157         for a in range(len(data)):
158             if data[a][0] == id:
159                 Movie = data[a]
160                 break
161
162         MovieAverage = CF.ExplodeRatingSet(Movie[1])
163
164         #Scoring Ranking With Cosine Similarity
165         for a in data:
```

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165         OtherMovie = CF.ExplodeRatingSet(a[1])
166         B = 1
167         Pb = 0
168         C = 1
169         Pc = 0
170
171         #Hitung B
172         for b in MovieAverage:
173             B = float(B) * float(b)
174             Pb = float(Pb) + float(b)**2
175
176         for c in OtherMovie:
177             C = float(C) * float(c)
178             Pc = float(Pc) + float(c)**2
179
180         Pb = round(math.sqrt(Pb), 3)
181         Pc = round(math.sqrt(Pc), 3)
182
183         BxC = round(B + C, 3)
184         BC = round(Pb * Pc, 3)
185
186         Score = round(BxC / BC, 3)
187
188         Score = round(Score / 1000, 2)
189
190         Ranking.append([a[0], a[1], a[2], Score, a[3]])
191
192
193     return Ranking
194
195     def sortingRanking(val):
196         return val[3]
197
198     def printScore(data, limit):
199         print('\n-----Movie Ranking-----')
200         for i in range(limit):
201             print('\nTitle : ', data[i][2], ' Genres : ', data[i][4])
202
203     def CountValidation(ScoreValue, DataActual):
204
205         MSE = 0
206         for count in range(len(ScoreValue)):
207             rates = CF.ExplodeRatingSet(ScoreValue[count][1])
208             AverageRating = 0
209             for value in rates:
210                 AverageRating += float(value)
211             AverageRating = AverageRating/len(rates)
212             ActualRating = CF.ExplodeRatingSet(DataActual[count][0])
213             MSE += pow((AverageRating-float(ActualRating[1])), 2)
214
215         MSE = 1/len(ScoreValue) * float(MSE)
216         print('\n MSE Score : ', round(MSE, 3))
217         print('\n RMSE Score : ', round(math.sqrt(MSE), 3))
218
219
220 class NB:

```

```

221 def ExplodeRatingSet(data):
222     return data.split(',')
223
224 def SplittingData(data, seperator):
225     return data.split(seperator)
226
227 def PreprocessingData(data):
228     MovieData = []
229     UserData = []
230
231     CountCoba = 0
232
233     for value in data:
234         value = NB.SplittingData(value[0], ',')
235         #print('\nValue : ', value)
236
237         conditionMovie = 0
238         for countMovie in range(len(MovieData)):
239
240             if MovieData[countMovie][0] == value[1]:
241                 MovieData[countMovie][1].append([value[0], value[2]])
242                 MovieData[countMovie][2] = round((MovieData[countMovie][2]
float(value[2])) / 2, 3) +
243                 conditionMovie = 1
244                 CountCoba += 1
245
246             if conditionMovie == 0:
247                 MovieData.append( [ value[1], [[value[0], value[2] ]], float(value[2]), value[3] ] )
248
249             conditionUser = 0
250             for countUser in range(len(UserData)):
251
252                 if UserData[countUser][0] == value[0]:
253                     UserData[countUser][1].append([value[1], value[2]])
254                     conditionUser = 1
255
256                 if conditionUser == 0:
257                     UserData.append([value[0], [ [value[1], value[2] ] ] ])
258
259             print('\n Count : ', CountCoba)
260
261         return MovieData, UserData
262
263 def NaiveBayes(MovieData, UserData):
264     result = []
265     tempAtas = 1.0
266     tempBawah = 1.0
267     #print('\nNaive Bayes')
268
269     SumValueRating = 0
270     for movie in MovieData:
271         #print('\nRating Luar : ', movie[1])
272         for rating in movie[1]:
273
274             SumValueRating += float(rating[1])
275

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276     for MovieValue in MovieData:
277
278         MovieId = MovieValue[0]
279
280         SumMovieRating = 0
281         for Rating in MovieValue[1]:
282             SumMovieRating += float(Rating[1])
283
284         tempAtas = 1.0
285         tempBawah = 1.0
286
287         for Rating in MovieValue[1]:
288
289             UserId = Rating[0]
290
291             TotalUserRating = 0
292             for UserValue in UserData:
293
294                 if UserValue[0] == UserId:
295
296                     for UserRating in UserValue[1]:
297
298                         TotalUserRating += float(UserRating[1])
299
300                 tempAtas = tempAtas * (SumMovieRating/SumValueRating)
301
302                 total = round(tempAtas/tempBawah, 3)
303
304                 result.append([MovieId, total, MovieValue[2], MovieValue[3]])
305
306     return result
307
308 def CountValidation(NaiveBayes, DataActual):
309     MSE = 0
310
311     for count in range(len(NaiveBayes)):
312
313         MSE += pow(float(NaiveBayes[count][2]) - float(
314 NB.ExplodeRatingSet(DataActual[count][0])[1] ), 2)
315
316     MSE = 1/len(NaiveBayes) * MSE
317     RMSE = math.sqrt(MSE)
318
319     print("\nMSE Score : ', MSE)
320     print("\nRMSE Score : ', RMSE)
321
322     return
323
324 # Raw Data
325
326 nRows = 10000
327 RatingSet = pd.read_csv("ratings_movies.csv",delimiter=";", nrows=nRows)
328 RatingSet = RatingSet.values
329
330

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331
332 # Actual Data
333 DataActual = pd.read_csv("ranking.csv",delimiter=";", nrows=nRows)
334 DataActual = np.array(DataActual)
335 print('\nData Actual :', DataActual[1][0])
336
337
338 # Collaborative Filtering
339
340 Average = CF.CountAverageRating(RatingSet)
341 pd.set_option('display.max_columns', None)
342 print('\nAverage : ', pd.DataFrame(Average).head())
343
344 Ranking = CF.CosineSimilarity('16', Average)
345
346 Ranking = np.array(Ranking)
347 print('\n\nRanking :\n',Ranking)
348 Ranking = Ranking[np.argsort(Ranking[:, 3])]
349
350 CF.printScore(Ranking, 10)
351
352 CF.CountValidation(Ranking, DataActual)
353
354
355 # Naive Bayes
356 MovieData, UserData = NB.PreprocessingData(RatingSet)
357 pd.set_option('display.max_columns', None)
358 print('\nMovie Data : \n ', pd.DataFrame(MovieData).head(10))
359 print('\nUser Data : \n ', pd.DataFrame(UserData).head(10))
360 print('\n Movie Data : ', MovieData[1])
361
362 NaiveBayes = NB.NaiveBayes(MovieData, UserData)
363 NaiveBayes = np.array(NaiveBayes)
364 NaiveBayes = NaiveBayes[np.argsort(NaiveBayes[:, 1])]
365 print('\nOutPut Naive Bayes :\n', pd.DataFrame(NaiveBayes).tail(100))
366
367 NB.CountValidation(NaiveBayes, DataActual)
368
369
370 # Comparing Ranking Movies
371
372 for count in range(10):
373
374     print('\nCF : ', Ranking[count][2], ' NB : ', NaiveBayes[count][3], ' Actual : ',
NB.ExplodeRatingSet(DataActual[count][0])[2] )
375

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APPROXIMATELY

Report #14327927

1. CHAPTER 1 INTRODUCTION Background Movies have become our daily needs in terms of entertainment. It's no secret that several well-known platforms such as Netflix, Youtube, Disney+ Hotstar, and others have more or fewer millions and even tens of millions of films on each of these platforms. Therefore, the recommendation engine is at the heart of various movie provider platforms. The number of these films is what causes a new problem, namely what film to watch next. Almost all platforms must collect data on movies watched by their users, the problem is if a platform still doesn't have data from that user or a new user. Then what are the movie recommendations that should be presented to the new user if a platform still doesn't have viewing data from that user or still has very little data from that user. Of course, users from each platform want to get movie recommendations that they think are most suitable for them, if not, then it's likely that these users will not use the platform anymore. However, this