CS532S19: Assignment #6

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Nwala, Alexander C

Giridharan Ganeshkumar

Question 1

Find 3 users who are closest to you in terms of age, gender, and occupation. For each of those 3 users: what are their top 3 favorite films? bottom 3 least favorite films? Based on the movie values in those choose a user that you feel is most like you.

- 1. The first step is to identify the user closest in terms of age, gender, and occupation.
- 2. In order to do this we read through the u.user file and check against the defined values based on the if condition
- 3. The initial thought was to include values for myself on the u.user but after the discussion in the class we decided to just go with the simple conditional check as we did not want to include new records to the record set
- 4. The next step is to find the top and bottom 3 favorite movies for each of the user identifies as closest
- 5. In order to find the top movies, we use the getTopMoviesForTheUser method. The method sorts the movies by ratings and returns both the top and bottom 3 in the result set.
- 6. The getTopMoviesForTheUser method is called within the loop to get the top and bottom 3 for all the identified users.
- 7. Looking through the result I mostly identify myself to the user with user id 350. 350 is the substitute user.

```
Closest to me in terms of age, gender, and occupation with user id: 350

Top 3 favorite films for user 350:

[['Raiders of the Lost Ark (1981)', 5.0], ['Manchurian Candidate, The (1962)', 5.0], ['Wild Bunch, The (1969)', 5.0]]

Bottom 3 least favorite films for user 350:

[['Starship Troopers (1997)', 3.0], ['M*A*S*H (1970)', 2.0], ['Hunt for Red October, The (1990)', 2.0]]

Closest to me in terms of age, gender, and occupation with user id: 560

[['Contact (1997)', 5.0], ['Citizen Kane (1941)', 5.0], ['Chinatown (1974)', 5.0]]

Bottom 3 least favorite films for user 560:

[['Kids in the Hall: Brain Candy (1996)', 1.0], ['Event Horizon (1997)', 1.0], ['Bed of Roses (1996)', 1.0]]

Closest to me in terms of age, gender, and occupation with user id: 890

Top 3 favorite films for user 890:

[['Empire Strikes Back, The (1980)', 5.0], ['To Kill a Mockingbird (1962)', 5.0], ['2001: A Space Odyssey (1968)', 5.0]]

Bottom 3 least favorite films for user 890:

[['Star Trek: The Motion Picture (1979)', 1.0], ['Ref, The (1994)', 1.0], ['Batman (1989)', 1.0]]

""""

I mostly identify with user with user id 350

""""

I mostly identify with user with user id 350
```

Question 2

Which 5 users are most correlated to the substitute you? Which 5 users are least correlated?

- 1. In order to find the most correlated to the substitute you we call the topMatches with user parameter as 350 and n as 5 and similarity as sim pearson
- 2. In order to find the least correlated to the substitute you we call the topMatchesReversed with

user parameter as 350 and n as 5 and similarity as sim pearson

3. topMatchesReversed is a method modified from the original topMatches method but the order just reversed using the sort method.

```
[(1.0000000000004, '544'), (1.0, '939'), (1.0, '915'), (1.0, '904'), (1.0, '888')]

[(-1.0000000000000004, '133'), (-1.0, '166'), (-1.0, '17'), (-1.0, '172'), (-1.0, '190')]
```

Question 3

Compute ratings for all the films that the substitute you have not seen. Provide a list of the top 5 recommendations for films that the substitute you should see. Provide a list of the bottom 5 recommendations

- 1. In order to Provide a list of the top 5 recommendations for films that the substitute you should see we call the getRecommendations with user parameter as 350 and similarity as sim pearson
- 2. The result is stored in topMoviesForGivenUser and we get the top 5 and bottom 5 from the set which will be the top and least recommendations for the user.

```
Top 5 Recommendations for user 350:
[(5.0, 'They Made Me a Criminal (1939)'), (5.0, 'The Deadly Cure (1996)'), (5.0, "Someone Else's America (1995)"), (5.0, 'Santa with Muscles (1996)'), (5.0, 'Prefontaine (1997)')]

Bottom 5 Recommendations for user 350:
[(1.0, 'B*A*P*S (1997)'), (1.0, 'Amityville: Dollhouse (1996)'), (1.0, 'Amityville: A New Generation (1993)'), (1.0, "Amityville 1992: It's About Time (1992)"), (1.0, '3 Ninjas: High Noon At Mega Mountain (1998)')]
```

Question 4

Choose your the real you, not the substitute you favorite and least favorite film from the data. For each film, generate a list of the top 5 most correlated and bottom 5 least correlated films. Based on your knowledge of the resulting films, do you agree with the results? In other words, do you personally like dislike the resulting films?

- 1. To get the required, we modify the calculateSimilarItems and name it calculateSimilarItems-ByMovies.
- 2. Inside the calculateSimilarItemsByMovies we call both the topMatches and topMatchesReversed both and we get the top 5 correlated and least correlated for all.
- 3. The results are read and looped through and checked for favorite film in my case is the The Silence of the Lambs
- 4. The result included Witness, The Deadly Cure, Substance of Fire, The, Spanish Prisoner and Wonderland. All the movies does seem to be related, i have not watched all the in the results After reading the synopsis I might still watch some of the movies not all. The recommendation is based on the movie and not based on the user, so it is definitely close to the movie given. In order to get more accurate results it would be better to see how i rated the movies so that the recommendations are a little more accurate than just based on movies.
- 5. The results from the least favorite movie is also similar to what is explained above.

```
Favorite Movie: Silence of the Lambs, The (1991)

[(1.0, 'Wonderland (1997)'), (1.0, 'Witness (1985)'), (1.0, 'The Deadly Cure (1996)'), (1.0, 'Substance of Fire, The (1996)'), (1.0, 'Spanish Prisoner, The (1997)')]

[(0, 'American Strays (1996)'), (0, 'August (1996)'), (0, 'B. Monkey (1998)'), (0, 'Big Bang Theory, The (1994)'), (0, 'Bird of Prey (1996)')]

Least Favorite Movie: Addams Family Values (1993)

[(1.0, 'You So Crazy (1994)'), (1.0, 'World of Apu, The (Apur Sansar) (1959)'), (1.0, 'Wild America (1997)'), (1.0, 'When Night Is Falling (1995)'), (1.0, 'War Room, The (1993)')]

[(0, "'Til There Was You (1997)'), (0, 'A Ninjas: High Noon At Mega Mountain (1998)'), (0, 'A Chef in Love (1996)'), (0, 'Afterglow (1997)'), (0, 'Aiqing wansui (1994)')]
```

Listing 1: Python Script

```
#!/usr/bin/env python
  # coding: utf-8
  # In [7]:
6
  #!/usr/bin/python
7
  \# -*- coding: utf-8 -*-
8
  from math import sqrt
  import csv
  # A dictionary of movie critics and their ratings of a small set of movies
11
   critics = {
12
       'Lisa Rose': {
13
            'Lady in the Water': 2.5,
14
            'Snakes on a Plane': 3.5,
15
            'Just My Luck': 3.0,
16
            'Superman Returns': 3.5,
17
            'You, Me and Dupree': 2.5,
18
            'The Night Listener': 3.0,
19
20
        Gene Seymour': {
21
            'Lady in the Water': 3.0,
22
            'Snakes on a Plane': 3.5,
23
            'Just My Luck': 1.5,
24
            'Superman Returns': 5.0,
25
            'The Night Listener': 3.0,
26
            'You, Me and Dupree': 3.5,
27
28
        Michael Phillips': {
29
            'Lady in the Water': 2.5,
30
            'Snakes on a Plane': 3.0,
31
            'Superman Returns': 3.5,
32
            'The Night Listener': 4.0,
33
34
        'Claudia Puig': {
35
            'Snakes on a Plane': 3.5,
36
             Just My Luck': 3.0,
37
            'The Night Listener': 4.5,
38
            'Superman Returns': 4.0,
39
            'You, Me and Dupree': 2.5,
40
41
        Mick LaSalle': {
42
            'Lady in the Water': 3.0,
43
            'Snakes on a Plane': 4.0,
44
            'Just My Luck': 2.0,
45
```

```
'Superman Returns': 3.0,
46
            'The Night Listener': 3.0,
47
            'You, Me and Dupree': 2.0,
48
49
        Jack Matthews': {
50
            'Lady in the Water': 3.0,
51
            'Snakes on a Plane': 4.0,
52
            'The Night Listener': 3.0,
53
            'Superman Returns': 5.0,
54
            'You, Me and Dupree': 3.5,
55
56
        Toby': {'Snakes on a Plane': 4.5, 'You, Me and Dupree': 1.0,
57
                  'Superman Returns': 4.0},
58
59
60
61
   def sim_distance(prefs, p1, p2):
62
63
       Returns a distance-based similarity score for person1 and person2.
64
65
66
       # Get the list of shared_items
67
       si = \{\}
68
       for item in prefs[p1]:
69
            if item in prefs[p2]:
70
                si[item] = 1
71
       # If they have no ratings in common, return 0
72
       if len(si) == 0:
73
            return 0
74
       # Add up the squares of all the differences
75
       sum\_of\_squares = sum([pow(prefs[p1][item] - prefs[p2][item], 2) for
                               prefs[p1] if item in prefs[p2]])
77
       return 1 / (1 + sqrt(sum_of_squares))
78
79
80
   def sim_pearson(prefs, p1, p2):
81
82
       Returns the Pearson correlation coefficient for p1 and p2.
83
84
85
       # Get the list of mutually rated items
86
       si = \{\}
87
       for item in prefs[p1]:
88
            if item in prefs[p2]:
89
                si[item] = 1
90
       # If they are no ratings in common, return 0
91
       if len(si) == 0:
92
            return 0
93
       # Sum calculations
94
       n = len(si)
95
       # Sums of all the preferences
96
       sum1 = sum([prefs[p1][it] for it in si])
97
       sum2 = sum([prefs[p2][it] for it in si])
       # Sums of the squares
99
       sum1Sq = sum([pow(prefs[p1][it], 2) for it in si])
100
```

```
sum2Sq = sum([pow(prefs[p2][it], 2) for it in si])
101
        # Sum of the products
102
        pSum = sum([prefs[p1][it] * prefs[p2][it] for it in si])
103
        # Calculate r (Pearson score)
104
       num = pSum - sum1 * sum2 / n
105
        den = sqrt((sum1Sq - pow(sum1, 2) / n) * (sum2Sq - pow(sum2, 2) / n))
106
        if den == 0:
107
            return 0
108
        r = num / den
109
        return r
110
111
112
   def topMatches(
113
        prefs.
114
        person,
115
        n=5,
        similarity=sim_pearson,
117
   ):
118
119
        Returns the best matches for person from the prefs dictionary.
120
        Number of results and similarity function are optional params.
121
122
123
        scores = [(similarity(prefs, person, other), other) for other in prefs
124
                   if other != person]
125
        scores.sort()
126
        scores.reverse()
127
        return scores[0:n]
128
129
   def topMatchesReversed(
130
        prefs,
131
        person,
132
        n = 5,
133
        similarity=sim_pearson,
134
135
136
        Returns the best matches for person from the prefs dictionary.
137
        Number of results and similarity function are optional params.
138
139
140
        scores = [(similarity(prefs, person, other), other) for other in prefs
141
                   if other != person]
142
        scores.sort()
143
        return scores[0:n]
144
145
   def getRecommendations(prefs, person, similarity=sim_pearson):
147
        Gets recommendations for a person by using a weighted average
148
        of every other user's rankings
149
150
151
        totals = \{\}
152
        simSums = {}
153
        for other in prefs:
        # Don't compare me to myself
155
            if other == person:
156
```

```
continue
157
            sim = similarity(prefs, person, other)
158
            # Ignore scores of zero or lower
159
            if sim <= 0:
160
                 continue
161
            for item in prefs [other]:
162
                 # Only score movies I haven't seen yet
163
                 if item not in prefs[person] or prefs[person][item] == 0:
164
                     # Similarity * Score
165
                     totals.setdefault(item, 0)
166
                     # The final score is calculated by multiplying each item by
167
                          similarity and adding these products together
168
                     totals[item] += prefs[other][item] * sim
169
                     # Sum of similarities
170
                     simSums.setdefault(item, 0)
171
                     simSums[item] += sim
172
        # Create the normalized list
173
        rankings = [(total / simSums[item], item) for (item, total) in
174
                     totals.items()]
175
        # Return the sorted list
176
        rankings.sort()
177
        rankings.reverse()
178
        return rankings
179
180
181
   def transformPrefs(prefs):
182
183
        Transform the recommendations into a mapping where persons are
184
           described
        with interest scores for a given title e.g. {title: person} instead of
        {person: title }.
186
187
188
        result = \{\}
189
        for person in prefs:
190
            for item in prefs[person]:
191
                 result.setdefault(item, {})
192
                 # Flip item and person
193
                 result[item][person] = prefs[person][item]
194
        return result
195
196
197
   def calculateSimilarItems(prefs, n=10):
198
199
        Create a dictionary of items showing which other items they are
200
        most similar to.
201
202
203
        result = \{\}
204
        # Invert the preference matrix to be item-centric
205
        itemPrefs = transformPrefs(prefs)
206
        \mathbf{c} = 0
207
        for item in itemPrefs:
208
            # Status updates for large datasets
209
            c += 1
210
```

```
if c % 100 == 0:
211
                print('%d / %d' % (c, len(itemPrefs)))
212
            # Find the most similar items to this one
213
            scores = topMatches(itemPrefs, item, n=n, similarity=sim_distance)
214
            result[item] = scores
215
        return result
216
217
   def calculateSimilarItemsByMovies(prefs, n=10):
218
219
        Create a dictionary of items showing which other items they are
220
       most similar to.
221
222
223
        result = \{\}
224
        resultReveresed = {}
225
       # Invert the preference matrix to be item-centric
226
       itemPrefs = transformPrefs(prefs)
227
       c = 0
228
        for item in itemPrefs:
229
            # Status updates for large datasets
230
            c += 1
231
            if c % 100 == 0:
232
                print('%d / %d' % (c, len(itemPrefs)))
233
            # Find the most similar items to this one
234
            scores = topMatches(itemPrefs, item, n=n, similarity=sim_distance)
235
            scoresReversed = topMatchesReversed(itemPrefs, item, n=n,
236
                similarity = sim_distance)
            result[item] = scores
237
            resultReveresed[item] = scoresReversed
238
        return result, resultReveresed
239
   def getRecommendedItems(prefs, itemMatch, user):
241
       userRatings = prefs[user]
242
        scores = \{\}
243
        totalSim = {}
244
       # Loop over items rated by this user
245
        for (item, rating) in userRatings.items():
246
            # Loop over items similar to this one
247
            for (similarity , item2) in itemMatch[item]:
248
                # Ignore if this user has already rated this item
249
                if item2 in userRatings:
250
                     continue
                # Weighted sum of rating times similarity
252
                scores.setdefault(item2, 0)
253
                scores[item2] += similarity * rating
254
                # Sum of all the similarities
255
                totalSim.setdefault(item2, 0)
256
                totalSim[item2] += similarity
257
       # Divide each total score by total weighting to get an average
258
       rankings = [(score / totalSim[item], item) for (item, score) in
259
                     scores.items()]
260
       # Return the rankings from highest to lowest
261
       rankings.sort()
262
        rankings.reverse()
        return rankings
264
265
```

```
def getRecommendedItemsByMovies(prefs, itemMatch):
266
       userRatings = prefs
267
       scores = {}
268
       totalSim = {}
269
       # Loop over items rated by this user
270
       for (item, rating) in userRatings.items():
271
            # Loop over items similar to this one
272
            for (similarity , item2) in itemMatch[item]:
273
                if item2 in userRatings:
274
                    continue
275
                # Weighted sum of rating times similarity
276
                scores.setdefault(item2, 0)
                scores[item2] += similarity * rating
278
                # Sum of all the similarities
279
                totalSim.setdefault(item2, 0)
280
                totalSim[item2] += similarity
281
       # Divide each total score by total weighting to get an average
282
       rankings = [(score / totalSim[item], item) for (item, score) in
283
                    scores.items()]
       # Return the rankings from highest to lowest
285
       rankings.sort()
286
       rankings.reverse()
287
       return rankings
288
289
290
   arrayofpref = []
291
   def loadMovieLens():
292
     # Get movie titles
293
       movies = {}
294
       for line in open("C:\\6\\u.item"):
295
            (id, title) = line.split('|')[0:2]
296
            movies | id | = title
297
     # Load data
298
       prefs = {}
299
       for line in open("C:\\6\\u.data"):
300
            (user, movieid, rating, ts) = line.split('\t')
301
            prefs.setdefault(user, {})
302
            prefs[user][movies[movieid]] = float(rating)
303
       return prefs
304
305
   #def getCurrentUserRatings(pref, userid):
306
307
   def getTopMoviesForTheUSer(prefs, person):
308
       currentUserMovieRating = []
309
       for other in prefs:
310
       # Don't compare me to myself
311
            if other == person:
312
                    for item in prefs[other]:
313
                         currentUserMovieRating.append([item, prefs[person][item
314
                            ]])
315
       currentUserMovieRating = sorted(currentUserMovieRating, key = lambda x
316
            return currentUserMovieRating[:3], currentUserMovieRating[-3:]
318
319
```

```
pref = loadMovieLens()
320
321
  with open("C:\\6\\u.user") as csv_file:
322
      csv_reader = csv.reader(csv_file, delimiter='|')
323
      line_count = 0
324
      for row in csv_reader:
325
          if line_count == 0:
326
             line_count += 1
327
          else:
328
             if row[1] == "32" and row[2] == "M" and row[3] == "student":
329
                #Find 3 users who are closest to you in terms of age,
330
                    gender, and occupation. For each of those 3 users:
                 print('
331
                    _____
                 print("Closest to me in terms of age, gender, and
332
                   occupation with user id: ", row[0])
                 print("
333
                    _____
                    ")
                 #what are their top 3 favorite films?
334
                 currentUserMovieRatingTop3 , currentUserMovieRatingBottom3 =
335
                    getTopMoviesForTheUSer(pref, row[0])
                 print("Top 3 favorite films for user ",row[0],":\n",
336
                   currentUserMovieRatingTop3)
                 #What are bottom 3 least favorite films?
337
                 print("Bottom 3 least favorite films for user ",row[0],":\n
338
                    ,currentUserMovieRatingBottom3)
339
340
  print("
     ")
  print("
342
     ______
  print("I mostly identify with user with user id 350")
343
  print(
344
     ")
  print("
345
     ")
346
347
  #Which 5 users are most correlated to the substitute you?
348
  print(topMatches(pref, "350", n=5, similarity=sim_pearson,))
349
  print(
350
     ______
     ")
351
  #Which 5 users are least correlated (i.e., negative correlation)?
352
  print(topMatchesReversed(pref, "350", n=5, similarity=sim_pearson,))
353
  print(
     ______
     ")
```

```
355
   #Compute ratings for all the films that the substitute you have not seen.
356
      Provide a list of the top 5 recommendations for films
   #that the substitute you should see. Provide a list of the bottom 5
      recommendations
   topMoviesForGivenUser = getRecommendations(pref, "350", similarity =
358
      sim_pearson)
   print("Top 5 Recommendations for user ",350,":\n", topMoviesForGivenUser
359
      [:5])
   #What are bottom 3 least favorite films?
360
   print("Bottom 5 Recommendations for user ",350,":\n",topMoviesForGivenUser
361
      [-5:]
362
363
364
   #Choose your (the real you, not the substitute you) favorite and least
365
      favorite film from the data. For each film, generate a list
   #of the top 5 most correlated and bottom 5 least correlated films. Based on
366
       your knowledge of the resulting films, do you agree with
   #the results? In other words, do you personally like / dislike the
      resulting films?
368
   \#Favorite\ 98|Silence\ of\ the\ Lambs,\ The\ (1991)|01-Jan-1991||http://us.imdb.
369
      com/M/title -exact? Silence %20 of %20 the %20 Lambs, %20 The %20 (1991)
      10101010101010101110101010101010111010
   #Least favorite 386|Addams Family Values (1993)|01-Jan-1993||http://us.imdb
370
      .com/M/title -exact?Addams%20Family%20Values%20(1993)
      |0|0|0|0|0|1|0|0|0|0|0|0|0|0|0|0|0|0
371
   itemsim, itemsimreversed = calculateSimilarItemsByMovies(pref,5)
372
373
374
375
   print("Favorite Movie : Silence of the Lambs, The (1991)")
376
   print("
377
      ______
   for line in itemsim:
378
       if (line == "Silence of the Lambs, The (1991)"):
379
           print(itemsim[line])
380
   for line in itemsimreversed:
381
       if(line == "Silence of the Lambs, The (1991)"):
382
           print (itemsimreversed [line])
383
384
   print("Least Favorite Movie :Addams Family Values (1993)")
385
   print (
      ______
      ")
387
   for line in itemsim:
388
       if(line == "Addams Family Values (1993)"):
389
           print(itemsim[line])
390
   for line in itemsimreversed:
391
       if (line == "Addams Family Values (1993)"):
392
           print(itemsimreversed[line])
393
```