HW 7 - Recommendation Systems

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Q1

Find 3 users who are closest to you in terms of age, gender, and occupation. For each of those 3 users:

- Q. What are their top 3 (favorite) films?
- Q. What are their bottom 3 (least favorite) films?

Based on the movie values in those 6 tables (3 users X (favorite + least favorite)), choose a user that you feel is most like you. Feel free to note any outliers (e.g., "I mostly identify with user 123, except I did not like "Ghost" at all"). You can investigate more than just the top 3 and bottom 3 movies to find your best match.

This user is the substitute you.

```
1 #!/usr/local/bin/python3
2 import pandas as pd
4 def funcAgeGendOccupation(item, data):
       #load movies data into variables
6
7
      movies = {}
      for line in open(str(item)):
8
9
           (id, title) = line.split('|')[0:2]
           movies[id] = title
10
       # Load data
11
      prefs = {}
12
13
      for line in open(str(data)):
14
           (user, movieid, rating, ts) = line.split('\t')
           prefs.setdefault(user, {})
15
           prefs[user] [movies[movieid]] = float(rating)
16
17
       #Load in users
18
      users = []
      for line in open('movie/u.user'):
19
           (user, age, gender, occupation, zipcode) = line.split('|')
20
```

```
21
          dictA = {'user': user, 'age':age, 'gender': gender, 'occupation
      ' :occupation }
           users.append(dictA)
22
23
      count = 1
24
      #hold 3 similar user in term of age gender and category
25
26
      similarUser =[]
      #Find all users that have things common with me
27
28
      for a in users:
           m m m
29
          passed in my age gender and occupation
30
           to find users of my age gender and occupation category.
31
           I take only 3 users
32
           m m m
33
          if a['aqe'] == '23' and a['qender'] == 'F' and a['occupation']
34
     == 'student' and count < 4 :
               similarUser.append(a['user'])
35
               count += 1
36
37
      #print user movie likes
      for a in similarUser:
38
39
40
           Based on similar users like me,
           I obtained these similar users top 3 favorite films
41
           n n n
42
43
          if a in prefs:
               #this gets the movie names, and the movie rating per user
44
               p = pd.DataFrame(list(prefs[a].items()),columns=["Movie"]
45
     Names", "Rating"])
               #this sort the users movie list based on rating in
46
     decending order
               p.sort_values("Rating", ascending=False, inplace=True)
47
               #gets the top3 films
48
49
               top3 = p.head(3)
               #gets the bottom 3 films
50
51
               bottom3 = p.tail(3)
               top3.to_csv("one/"+a+"top3.csv", index=False)
52
               bottom3.to_csv("one/"+a+"bottom.csv",index=False)
53
54 funcAgeGendOccupation('movie/u.item','movie/u.data')
```

Listing 1: one.py

Table 1: Top 3 movies for user 49

Movie Names	Rating
Monty Python and the Holy Grail (1974)	5.0
Paradise Lost: The Child Murders at Robin Hood Hills (1996)	5.0
Clockwork Orange, A (1971)	5.0

Table 2: Bottom 3 movies for user 49

Movie Names	Rating
Firm, The (1993)	1.0
Long Kiss Goodnight, The (1996)	1.0
Terminator 2: Judgment Day (1991)	1.0

Table 3: Top 3 movies for user 159

Movie Names	Rating
Grumpier Old Men (1995)	5.0
That Old Feeling (1997)	5.0
Volcano (1997)	5.0

Table 4: Bottom 3 movies for user 159

Movie Names	Rating
Grumpier Old Men (1995)	1.0
Soul Food (1997)	1.0
Ace Ventura: Pet Detective (1994)	1.0

Table 5: Top 3 movies for user 477

Movie Names	Rating
One Fine Day (1996)	5.0
Evita (1996)	5.0
Grease (1978)	5.0

Table 6: Bottom 3 movies for user 477

Movie Names	Rating
Corrina, Corrina (1994)	4.0
Black Sheep (1996)	4.0
Don Juan DeMarco (1995)	4.0

Discussion

- Q. What are their top 3 (favorite) films?
- Q. What are their bottom 3 (least favorite) films?

The users top 3 and bottom 3 films are shown in the above tables.

I created a function called funcAgeGendOccupation(), in line 4. This function takes two parameters of the location of u.item and u.data path. u.user was not going through as a parameter so it is passed directly.

From lines 6-22 the data from each file is read and stored into dictionary variables. In line 24 -36, I found users that were just as similar to me in age, gender and occupation. I limited this search to find only just 3 similar users to me on line 30. These users where stored in a list variable called similarUser. The line 26 is the variable declaration, while line 35 appends new users to the list in the created variable.

The lines 38 to 53, process the outcomes for top 3 movies and bottom 3 movies for each users found. Using a for loop to retrieve each user, parse this result to ensure that the said user is in prefs dictionary. If present, retrieve the row of the dictionary of that particular user. Using a pandas dataframe in Line 45, parse a list of the row item, so that we can easily sort the data based on values in Rating column in descending order. Retrieve the first three data using pandas .head(3) and the last three data using .tail(3). Save each result as a pandas dataFrame and convert the result to a saved csv file in one/.

My best substitute user is 159, the movies user hates I hate and the movies the user enjoys I too find them interesting.

Q2

Based on the ratings that users have given to the movies, answer the following questions:

- Q: Which 5 users are most correlated to the substitute you (i.e., which 5 users rate movies most similarly to the substitute you?)
- Q: Which 5 users are least correlated (i.e., negative correlation)?

```
1 #!/usr/local/bin/python3
```

² from math import sqrt

```
4 def sim_pearson(prefs, p1, p2):
      Returns the Pearson correlation coefficient for p1 and p2.
6
7
9 # Get the list of mutually rated items
     si = \{\}
10
11
      for item in prefs[p1]:
12
          if item in prefs[p2]:
               si[item] = 1
13
14
15 # If they are no ratings in common, return 0
     if len(si) == 0:
16
          return 0
17
18
19 # Sum calculations
n = len(si)
21
22 # Sums of all the preferences
23
      sum1 = sum([prefs[p1][it] for it in si])
24
      sum2 = sum([prefs[p2][it] for it in si])
25
26 # Sums of the squares
27
      sum1Sq = sum([pow(prefs[p1][it], 2) for it in si])
      sum2Sq = sum([pow(prefs[p2][it], 2) for it in si])
28
29
30 # Sum of the products
31
      pSum = sum([prefs[p1][it] * prefs[p2][it] for it in si])
32
33 # Calculate r (Pearson score)
34
      num = pSum - sum1 * sum2 / n
35
      den = sqrt((sum1Sq - pow(sum1, 2) / n) * (sum2Sq - pow(sum2, 2) / n
36
      ) )
37
      if den == 0:
38
          return 0
39
      r = num / den
40
      return r
41
42 def getRecommendations (prefs, person, similarity=sim_pearson):
43
       Gets recommendations for a person by using a weighted average
44
       of every other users rankings
45
      H H H
46
47
      totals = {}
48
      simSums = {}
      for other in prefs:
49
```

```
50
           if other == person:
               continue
51
           sim = similarity(prefs, person, other)
52
53
           #Ignore scores of zero or lower
           if sim <= 0:</pre>
54
55
               continue
56
           for item in prefs[other]:
               #Only score movies I havent seen yet
57
58
               if item not in prefs[person] or prefs[person][item] == 0:
59
                   # Similarity * Score
                   totals.setdefault(item, 0)
60
                   # The final score is calculated by multiplying each
61
      item by the
62
                   # similarity and adding these products together
                   totals[item] += prefs[other][item] * sim
63
                   # Sum of similarities
64
                   simSums.setdefault(item, 0)
65
                   simSums[item] += sim
66
                   # Create the normalized list
67
           rankings = [(total / simSums[item], item) for (item, total) in
68
                                totals.items()]
69
70
           # Return the sorted list
71
           rankings.sort()
72.
           rankings.reverse()
73
           return rankings
74
75 def topMatches(prefs, person, n=5, similarity=sim_pearson,):
       ///
76
77
       Returns the best matches for person from the prefs dictionary.
78
      Number of results and similarity function are optional params.
      bottomMatches
       111
79
80
       scores = [(similarity(prefs, person, other), other) for other in
81
      prefs
                 if other != person]
82
83
       scores.sort()
84
       scores.reverse()
85
       return scores[0:n]
86
87 def bottomMatches(prefs,person,n=5,similarity=sim_pearson,):
       11 11 11
88
89
       Returns the lowest matches for person from the prefs dictionary.
       Number of results and similarity function are optional params.
90
91
       scores = [(similarity(prefs, person, other), other) for other in
92
     prefs
```

```
93
       if other != person]
 94
       scores.sort()
 95
       scores.reverse()
       return scores[len(scores)-n: len(scores)]
 96
 97
 98 def transformPrefs(prefs):
       ///
 99
       Transform the recommendations into a mapping where persons are
100
      described with interest scores for a given title e.g. {title: person
       } instead of {person: title}
       111
101
102
103
       result = {}
104
       for person in prefs:
            for item in prefs[person]:
105
                result.setdefault(item, {})
106
107
                # Flip item and person
                result[item][person] = prefs[person][item]
108
109
       return result
110
111 def loadMovieLens():
112
       # Get movie titles
       movies = {}
113
       for line in open("movie/u.item"):
114
115
            (id, title) = line.split("|")[0:2]
           movies[id] = title
116
117
        # Load data
       #prefs = {}
118
119
       for line in open ("movie/u.data"):
120
            (user, movieid, rating, ts) = line.split("\t")
            prefs.setdefault(user, {})
121
122
            prefs[user] [movies[movieid]] = float(rating)
123
       #Load in users
       \#users = []
124
125
       for line in open ("movie/u.user"):
            (user, age, gender, occupation, zipcode) = line.split("|")
126
            dictA = {"user": user, "age":age, "gender": gender, "occupation
127
       " :occupation }
128
       users.append(dictA)
129
130 prefs = { }
131 users =[]
132 loadMovieLens()
134 top5 = topMatches(prefs, "159", n = 5, similarity = sim_pearson)
135 bottom5 = bottomMatches(prefs, "928", n = 5, similarity = sim_pearson)
136 print("5 users that most correlate with my substitute me ")
```

```
137 print (*top5, sep='\n')
138 print ("\n\n")
139 print ("5 users that least correlate with my substitute me ")
140 print (*bottom5, sep='\n')
141 """
142 question2:
143 (1.000000000000004, '604')
144 (1.00000000000001, '713')
145 (1.0, '914')
146 (1.0, '80')
147 (1.0, '237')
148
149 (-1.000000000000004, '760')
150 (-1.000000000000004, '547')
151 (-1.000000000000004, '432')
152 (-1.000000000000004, '317')
153 (-1.000000000000004, '112')
154 """
155 recommend = getRecommendations (prefs, "159")
156 print("\nTop 5 movies recommendations for substitute me: ")
157 print (*recommend[0:5], sep="\n")
158 print ("\nBottom 5 movies recommendations for substitute me:")
159 print (*recommend[len(recommend)], sep="\n")
160 """
161 question3:
162 (5.0, 'Unforgiven (1992)')
163 (5.0, 'Unforgettable (1996)')
164 (5.0, 'Tombstone (1993)')
165 (5.0, 'Silence of the Lambs, The (1991)')
166 (5.0, 'Net, The (1995)')
167
168 (1.0, 'Usual Suspects, The (1995)')
169 (1.0, 'Thinner (1996)')
170 (1.0, 'Natural Born Killers (1994)')
171 (1.0, 'Full Monty, The (1997)')
172 (1.0, 'Albino Alligator (1996)')
173 """
174
175 print ("\n\n")
176 movies = transformPrefs(prefs)
177 mybestmovie = "Vampire in Brooklyn (1995)"
178 topFive = topMatches(movies, mybestmovie)
179 print ("My best 5 recommended movies")
180 print (topFive)
181 print ("\n")
182 print ("My worst 5 recommended movies")
183 worstFive = bottomMatches (movies, mybestmovie)
```

Listing 2: two.py

```
5 users that most correlate with my substitute me
(1.0000000000000000, '604')
(1.0000000000000001, '713')
(1.0, '914')
(1.0, '80')
(1.0, '237')

5 users that least correlate with my substitute me
(-1.000000000000004, '760')
(-1.000000000000004, '547')
(-1.0000000000000004, '432')
(-1.0000000000000004, '317')
(-1.0000000000000004, '112')
```

Figure 1: Output for Q2

Discussion

- Q: Which 5 users are most correlated to the substitute you (i.e., which 5 users rate movies most similarly to the substitute you?)
- *Q*: Which 5 users are least correlated (i.e., negative correlation)?

The final output for the top 5 users that were most correlated to my substitute me were 604,713,914,80, and 237 with their respective correlating score of 1.00000000000004,1.00000000000001,1.0,1.0 and 1.0.

For the bottom 5 users that were most correlated to my substitute me were, 760,547,432,317,and 112. Their correlative score was the same, -1.00000000000004.

For the driver lines 130 to 159 generated the resulting output. First I loaded the u.items, u.data and u.user in this function and stored them in a dictionary, dictionary and list variables respectively. Then called the topMatches function which I passed in my substitute me user id in.

Q3

Compute ratings for all the films that the substitute you has 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 (i.e., films the substitute you is almost certain to hate).

```
Top 5 movies recommendations for substitute me:
(5.0, 'Unforgiven (1992)')
(5.0, 'Unforgettable (1996)')
(5.0, 'Tombstone (1993)')
(5.0, 'Silence of the Lambs, The (1991)')
(5.0,
     'Net, The (1995)')
Bottom 5 movies recommendations for substitute me:
(1.0, 'Usual Suspects, The (1995)')
(1.0,
      'Thinner (1996)')
(1.0,
      'Natural Born Killers (1994)')
      'Full Monty, The (1997)')
(1.0,
      'Albino Alligator (1996)')
(1.0,
```

Figure 2: Output for Q3

Discussion

Q. Provide a list of the top 5 recommendations for films that the substitute you should see. Provide a list of the bottom 5 recommendations (i.e., films the substitute you is almost certain to hate).

The question 2's two.py in Listing 2 is used to answer this question.

In line 155 to 159, function getRecommendations() was to get my substiture user recommended list, I Used *recommend[0:5] to get first 5 recommendation. This code was gotten from https://github.com/arthur-e/Programming-Collective-Intelligence/blob/master/chapter2/recommendations.py.

Top 5 movies recommendations for substitute me, Unforgiven (1992), Unforgettable (1996), Tombstone (1993), Silence of the Lambs, The (1991), Net, The (1995). Bottom 5 movies recommendations for substitute me,in line 159 *recommend[len(recommend)-5:len(recommend)] used it to extract the bottom 5 movie recommendations for substitute me Usual Suspects, The (1995), Thinner (1996), Natural Born Killers (1994), Full Monty, Albino Alligator (1996).

Q4

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.

Q: 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?

If you have not heard of the recommended movies, search for the movie's trailer on YouTube and watch it before you answer. If you do this, include the link to the trailer in your report. For example, the trailer for "Top Gun (1986)" was found by searching for "top gun 1986 trailer" on Google.

Figure 3: Output for Q4

Discussion

The question 2's two.py in Listing 2 is used to answer this question.

I first transformed the prefs dictionary to movies. I then selected my best (Vampire in Brooklyn (1995)) movie from the whole list in u.data. The function topMatches and bottomMatch handled the result of the questions 3.

Q: Based on your knowledge of the resulting films, do you agree with the results? In otherwords, do you personally like/dislike the resulting films?

Top 5 movies recommend from (Vampire in Brooklyn (1995): Young Guns II (1990) https://www.youtube.com/watch?v=r-FmfxLy7foI like this good old movie.

Reality Bites (1994) https://www.youtube.com/watch?v=xDYGoOUgIVM It seem interesting and I would watch it. Just an average movie for me.

 $Ran~(1985)~https://www.youtube.com/watch?v=YwP_kXyd-Rw~I~love~this~one~also,~war~action~my~favorite.$

Butch Cassidy and the Sundance Kid (1969) https://www.youtube.com/watch?v=YdJW2UxvSFQ I love cow boys like movies

Chinatown (1974) https://www.youtube.com/watch?v=20FfiP7g4tU Quite boring but I would enjoy the detective part to movie

Worst 5 movies recommended from (Vampire in Brooklyn (1995)

Big Night (1996) https://www.youtube.com/watch?v=Yd8gK6EgpLM It is little boring to me because its a chef movie

 $Barbarella (1968) \; \text{https://www.youtube.com/watch?v=M-fJg08wBKw} \; \textit{Very old movie and I dont find it interesting at all}$

Another Stakeout (1993) https://www.youtube.com/watch?v=Gpm41GyOVYcIlike this one action, detective kind of movies

Fathers' Day(1997) https://www.youtube.com/watch?v=xsQfKt08X1k Not an inter-

esting movie, too boring.

Devil's Own, The (1997)https://www.youtube.com/watch?v=xZiWSY2SjAM I completely love the action in this movie just the first second of seeing it. As usual war movies gets me all the time.

References

- https://github.com/arthur-e/Programming-Collective-Intelligence/blob/master/chapter2/recommendations.py
- https://www.example.com/reallyreallyreally-extra-long-URI/
- https://gis.stackexchange.com/questions/180933/how-to-slice-all-elements-in-a-list-to-a-certain-length
- https://stackoverflow.com/questions/32448414/what-does-colon-at-assignment-for-list-do-in-python/32448477
- http://www.hpc-carpentry.org/hpc-python/04-dicts/index.html
- https://www.kite.com/python/answers/how-to-append-an-elementto-a-key-in-a-dictionary-with-python