# Web Science: Assignment #6

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The goal of this project is to use the basic recommendation principles we have learned for user-collected data. You will modify the code given to you which performs movie recommendations from the MovieLense data sets. (https://github.com/arthur-e/Programming-Collective-Intelligence/blob/master/chapter2/recommendations.py) The MovieLense data sets were collected by the GroupLens Research Project at the University of Minnesota during the seven-month period from September 19th, 1997 through April 22nd, 1998. We are using the "100k dataset", available for download from:

There are three files which we will use:

http://grouplens.org/datasets/movielens/100k/

- 1. u.data: 100,000 ratings by 943 users on 1,682 movies. Each user has rated at least 20 movies. Users and items are numbered consecutively from 1. The data is randomly ordered.
- 2. u.item: Information about the 1,682 movies.
- 3. u.user: Demographic information about the users.

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

- 1. what are their top 3 favorite films?
- 2. bottom 3 least favorite films?

Based on the movie values in those 6 tables (3 users X (favorite + least)), 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").

This user is the "substitute you".

#### **SOLUTION:**

Using. following steps:

- 1. Assigned Variables, 'Age', 'Gender' and 'Occupation' as '23', 'M', 'Student' respectively.
- 2. Selected the matching users **u.user** dataset, i received 6 such users.
- 3. Selected 3 users with user ID's: 135, 33, 706

Listing 1: Assignment6\_1.py

```
from operator import itemgetter
   matchingUsers = []
   apurvAge = 23
   apurvOccupation = 'student'
   apurvGender = 'M'
   userMoviesDict = {}
   userMovieRatingDict = {}
   finalTopThree = {}
  finalBottomThree = {}
   userMovieRatingsList = []
   movieRatingsList = []
   matches = ''
   bottomCount = 0
   topCount = 0
   listSize = 0
   with open('u.user', 'r') as f1:
        for line in f1:
             userId, age, gender, occupation, zipcode = line.split(' | ')
20
             # if((int(age) < int(apurvAge) and int(age) > int((apurvAge - 3))) and (gender == apurvGen
             if((int(age) == apurvAge) and (gender == apurvGender) and (occupation == apurvOccupation))
                  matchingUsers.append(userId)
   print (matchingUsers)
   with open('u.data', 'r') as f2:
        for line in f2:
             userId, movieId, rating, mseconds = line.split('
                                                                ′)
             if (userId in matchingUsers):
                  if (userId in userMoviesDict):
                       userMoviesDict[userId] = userMoviesDict[userId] + ":" + movieId + " | " + rating
                  else:
                       userMoviesDict[userId] = movieId + "|" + rating
   print ('----')
   for key, value in userMoviesDict.items():
        # print(key,userMoviesDict[key])
        userMovieRatingsList = userMoviesDict[key].split(":")
        for movieRating in userMovieRatingsList:
             movie, rating = movieRating.split("|")
             userMovieRatingDict[movie] = rating
             # print(movie, rating)
```

```
sortedRatings = sorted(userMovieRatingDict.items(), key=lambda value: value[1])
45
        # print("Length :",len(sortedRatings))
       bottomCount = 0
       topCount = 0
       listSize = 0
       bottomMovieData = ""
50
       topMovieData = ""
        for data in sortedRatings:
            listSize = listSize + 1
             if (bottomCount < 3):</pre>
                  if (bottomMovieData == ""):
                      bottomMovieData = str(data)
                  else:
                      bottomMovieData = bottomMovieData + ":" + str(data)
                  bottomCount = bottomCount + 1
             if (listSize > len(sortedRatings) - 3):
                  if (topMovieData == ""):
                      topMovieData = str(data)
                  else:
                      topMovieData = topMovieData + ":" + str(data)
        finalBottomThree[key] = bottomMovieData
        finalTopThree[key] = topMovieData
        print ('----')
        print (finalTopThree)
       print (finalBottomThree)
        print('\n')
   print (" ****** TOP FAVORITE MOVIES ****** ")
   print ("User" + " " + "Movie Title" + " " + "Rating")
   print ("----" + " " + "-----" + " " + "----")
   for key, value in finalTopThree.items():
       movieTuple = finalTopThree[key].split(":")
        for movie in movieTuple:
            movieId, rating = str(movie).split(",")
            movieId = movieId.replace("(","").replace("'","")
            with open('u.item', 'r') as file:
80
                  for line in file:
                       mid, movieTitle = line.split("|")[0:2]
                       if (mid == movieId):
                            print (key," "+ movieTitle+" "+rating.replace(")","").replace("'",""))
   print('\n')
   print (" ****** LEAST FAVORITE MOVIES ****** ")
   print ("User" + " " + "Movie Title" + " " + "Rating")
   print ("----" + " " + "-----")
   for key, value in finalBottomThree.items():
       movieTuple = finalBottomThree[key].split(":")
        for movie in movieTuple:
            movieId, rating = str(movie).split(",")
            movieId = movieId.replace("(","").replace("'","")
95
            with open('u.item', 'r') as file:
                  for line in file:
```

The above code, will generate top favorites and least favorites movie from the selected 3 users.

		Top 3 Favorite Movie	
User		Movies	Rating
1	135	Trainspotting (1996)	4
1	135	Liar Liar (1997)	4
1	135	Silence of the Lambs, The (1991)	5
	33	Rosewood (1997)	4
	33	Titanic (1997)	5
		Silence of the Lambs, The (1991)	5
	_	Titanic (1997)	5
7	706	Edge, The (1997)	5
7	706	Silence of the Lambs, The (1991)	5
		Bottom 3 Favorite Movie	
User			Rating
User	_	Movies	Rating 1
1	135	Movies Tales from the Hood (1995)	Rating 1
1	135 135	Movies Tales from the Hood (1995) Jaws 2 (1978)	Rating 1
1	135 135 135	Movies Tales from the Hood (1995) Jaws 2 (1978) Assassins (1995)	Rating 1
1	135 135 135 33	Movies Tales from the Hood (1995) Jaws 2 (1978)	Rating 1 2 2 1 1 2 2
1	135 135 135 33 33	Movies Tales from the Hood (1995) Jaws 2 (1978) Assassins (1995) Tales from the Hood (1995)	Rating 1 2 2 2 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2
1 1	135 135 135 33 33	Movies Tales from the Hood (1995) Jaws 2 (1978) Assassins (1995) Tales from the Hood (1995) Jaws 2 (1978)	Rating 1 2 2 2 2 2 2 1 1
1 1	135 135 135 33 33 33 706	Movies Tales from the Hood (1995) Jaws 2 (1978) Assassins (1995) Tales from the Hood (1995) Jaws 2 (1978) Assassins (1995)	Rating 1 2 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Figure 1: Top 3 and Bottom 3 Favorite Movies

2. Which 5 users are most correlated to the substitute you? Which 5 users are least correlated (i.e., negative correlation)?

#### SOLUTION

I selected **33** as 'Substitute Me and pass the preferences of the 'Substitute Me' to the sim\_pearson function, to determine the nearest 5 users. The following code has been rewrited and was originally taken from Programming Collective Intelligence

Listing 2: Assignment6 2.py

```
import csv
   import math
   import operator
   import string
   from collections import Counter
   from math import sqrt
   def sim_distance(prefs, p1, p2):
        Returns a distance-based similarity score for person1 and person2.
10
        # Get the list of shared_items
        si = \{\}
        for item in prefs[p1]:
15
             if item in prefs[p2]:
                  si[item] = 1
        # If they have no ratings in common, return 0
        if len(si) == 0:
             return 0
20
        # Add up the squares of all the differences
        sum_of_squares = sum([pow(prefs[p1][item] - prefs[p2][item], 2) for item in
                                   prefs[p1] if item in prefs[p2]])
        return 1 / (1 + sqrt(sum_of_squares))
   def sim_pearson(prefs, p1, p2):
        Returns the Pearson correlation coefficient for p1 and p2.
30
        # Get the list of mutually rated items
        si = \{\}
        for item in prefs[p1]:
             if item in prefs[p2]:
35
                  si[item] = 1
        # If they are no ratings in common, return 0
        if len(si) == 0:
             return 0
        # Sum calculations
40
        n = len(si)
```

```
# Sums of all the preferences
        sum1 = sum([prefs[p1][it] for it in si])
        sum2 = sum([prefs[p2][it] for it in si])
        # Sums of the squares
        sum1Sq = sum([pow(prefs[p1][it], 2) for it in si])
        sum2Sq = sum([pow(prefs[p2][it], 2) for it in si])
        # Sum of the products
        pSum = sum([prefs[p1][it] * prefs[p2][it] for it in si])
        # Calculate r (Pearson score)
        num = pSum - sum1 * sum2 / n
        den = sqrt((sum1Sq - pow(sum1, 2) / n) * (sum2Sq - pow(sum2, 2) / n))
        if den == 0:
             return 0
        r = num / den
        return r
   def topMatches(
        prefs,
        person,
        n=5,
        similarity=sim_pearson,
   ):
        ,,,
65
        Returns the best matches for person from the prefs dictionary.
        Number of results and similarity function are optional params.
        scores = [(similarity(prefs, person, other), other) for other in prefs
70
                    if other != person]
        scores.sort()
        scores.reverse()
        return scores[0:n]
   def getRecommendations(prefs, person, similarity=sim_pearson):
        ///
        Gets recommendations for a person by using a weighted average
        of every other user's rankings
        111
        totals = {}
        simSums = {}
        for other in prefs:
85
        # Don't compare me to myself
             if other == person:
                  continue
             sim = similarity(prefs, person, other)
             # Ignore scores of zero or lower
             if sim <= 0:</pre>
                  continue
             for item in prefs[other]:
                  # Only score movies I haven't seen yet
```

```
if item not in prefs[person] or prefs[person][item] == 0:
95
                         # Similarity * Score
                        totals.setdefault(item, 0)
                         # The final score is calculated by multiplying each item by the
                             similarity and adding these products together
                         totals[item] += prefs[other][item] * sim
100
                         # Sum of similarities
                        simSums.setdefault(item, 0)
                         simSums[item] += sim
         # Create the normalized list
105
         rankings = [(total / simSums[item], item) for (item, total) in
                        totals.items()]
         # Return the sorted list
         rankings.sort()
         rankings.reverse()
110
         return rankings
    \mathbf{def} transformPrefs(prefs):
         Transform the recommendations into a mapping where persons are described
115
         with interest scores for a given title e.g. {title: person} instead of
         {person: title}.
         result = {}
120
         for person in prefs:
              for item in prefs[person]:
                   result.setdefault(item, {})
                   # Flip item and person
                   result[item][person] = prefs[person][item]
125
         return result
    \mathbf{def} calculateSimilarItems(prefs, n=10):
130
         Create a dictionary of items showing which other items they are
         most similar to.
         result = {}
135
         # Invert the preference matrix to be item-centric
         itemPrefs = transformPrefs(prefs)
         c = 0
         for item in itemPrefs:
              # Status updates for large datasets
140
              c += 1
              if c % 100 == 0:
                   print('%d / %d' % (c, len(itemPrefs)))
              # Find the most similar items to this one
              scores = topMatches(itemPrefs, item, n=n, similarity=sim_distance)
145
              result[item] = scores
         return result
```

```
def getRecommendedItems(prefs, itemMatch, user):
150
         userRatings = prefs[user]
         scores = {}
         totalSim = {}
         # Loop over items rated by this user
         for (item, rating) in userRatings.items():
155
              # Loop over items similar to this one
              for (similarity, item2) in itemMatch[item]:
                   # Ignore if this user has already rated this item
                   if item2 in userRatings:
                        continue
160
                   # Weighted sum of rating times similarity
                   scores.setdefault(item2, 0)
                   scores[item2] += similarity * rating
                   # Sum of all the similarities
                   totalSim.setdefault(item2, 0)
165
                   totalSim[item2] += similarity
         # Divide each total score by total weighting to get an average
         rankings = [(score / totalSim[item], item) for (item, score) in
                        scores.items()]
         # Return the rankings from highest to lowest
170
         rankings.sort()
         rankings.reverse()
         return rankings
175
    def loadMovieLens():
      # Get movie titles
         movies = {}
         for line in open('u.item'):
180
              (id, title) = line.split('|')[0:2]
              movies[id] = title
      # Load data
         prefs = {}
         for line in open('u.data'):
185
              (user, movieid, rating, ts) = line.split('\t')
              prefs.setdefault(user, {})
              prefs[user][movies[movieid]] = float(rating)
         return prefs
190
   prefs = loadMovieLens()
    with open('u.user') as tsv:
         for line in csv.reader(tsv, delimiter="|"):
195
            p2 = (line[0])
            p1 = '33'
            r = sim_pearson(prefs, p1, p2)
            with open ('corrlate.csv','a') as f:
                   writer=csv.writer(f)
                   writer.writerow([r,p2,p1])
```

The above code will generate **corrlate.csv**, which gives the correlation of all the users in comparison with 'Substitute Me' i.e., user **33** 

N	ega	ative Corelat	tion
Substitute Me	9	User	Corelation
	33	900	-1
	33	189	-0.981980506
	33	483	-0.866025404
	33	696	-0.866025404
	33	17	-0.755928946
F	osi	itive Corelat	ion
Substitute Me	9	User	Corelation
	33	305	0.92717265
	33	457	0.944911183
	33	288	0.948683298
	$\neg$	670	0.970725343
	33	679	0.9/0/25545

Figure 2: Negative and Positive Correlation

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 (i.e., films the substitute you is almost certain to hate).

#### SOLUTION

I made use of the **getRecommendations** function to get the recommendations for 'Substitute Me. and the results of the same is saved in to a text file **recommendedMovies.txt** The following code has been rewrited and was originally taken from **Programming Collective Intelligence** 

Listing 3: Assignment6\_3.py

```
import csv
   import math
   import operator
   import string
   from collections import Counter
   from math import sqrt
   def sim_distance(prefs, p1, p2):
10
        Returns a distance-based similarity score for person1 and person2.
        # Get the list of shared_items
15
        for item in prefs[p1]:
             if item in prefs[p2]:
                  si[item] = 1
        # If they have no ratings in common, return 0
        if len(si) == 0:
             return 0
        # Add up the squares of all the differences
        sum_of_squares = sum([pow(prefs[p1][item] - prefs[p2][item], 2) for item in
                                   prefs[p1] if item in prefs[p2]])
        return 1 / (1 + sqrt(sum_of_squares))
   def sim_pearson(prefs, p1, p2):
        Returns the Pearson correlation coefficient for p1 and p2.
30
        # Get the list of mutually rated items
        si = \{\}
        for item in prefs[p1]:
             if item in prefs[p2]:
                  si[item] = 1
        # If they are no ratings in common, return 0
        if len(si) == 0:
             return 0
40
```

```
# Sum calculations
        n = len(si)
        # Sums of all the preferences
        sum1 = sum([prefs[p1][it] for it in si])
        sum2 = sum([prefs[p2][it] for it in si])
45
        # Sums of the squares
        sum1Sq = sum([pow(prefs[p1][it], 2) for it in si])
        sum2Sq = sum([pow(prefs[p2][it], 2) for it in si])
        # Sum of the products
        pSum = sum([prefs[p1][it] * prefs[p2][it] for it in si])
50
        # Calculate r (Pearson score)
        num = pSum - sum1 * sum2 / n
        den = sqrt((sum1Sq - pow(sum1, 2) / n) * (sum2Sq - pow(sum2, 2) / n))
        if den == 0:
             return 0
55
        r = num / den
        return r
   def topMatches(prefs, person, n=5, similarity=sim_pearson,):
        Returns the best matches for person from the prefs dictionary.
        Number of results and similarity function are optional params.
        scores = [(similarity(prefs, person, other), other)] for other in prefs
                    if other != person]
        scores.sort()
        scores.reverse()
        return scores[0:n]
70
   def getRecommendations(prefs, person, similarity=sim_pearson):
        ///
        Gets recommendations for a person by using a weighted average
        of every other user's rankings
        ,,,
        totals = {}
        simSums = {}
80
        for other in prefs:
        # Don't compare me to myself
             if other == person:
                  continue
             sim = similarity(prefs, person, other)
85
             # Ignore scores of zero or lower
             if sim <= 0:
                  continue
             for item in prefs[other]:
                  # Only score movies I haven't seen yet
                  if item not in prefs[person] or prefs[person][item] == 0:
                       # Similarity * Score
                       totals.setdefault(item, 0)
```

```
# The final score is calculated by multiplying each item by the
                            similarity and adding these products together
                        totals[item] += prefs[other][item] * sim
                        # Sum of similarities
                        simSums.setdefault(item, 0)
                        simSums[item] += sim
         # Create the normalized list
100
         rankings = [(total / simSums[item], item) for (item, total) in
                        totals.items()]
         # Return the sorted list
        rankings.sort()
        rankings.reverse()
105
         return rankings
    def transformPrefs(prefs):
110
         Transform the recommendations into a mapping where persons are described
        with interest scores for a given title e.g. {title: person} instead of
         {person: title}.
115
        result = {}
         for person in prefs:
              for item in prefs[person]:
                   result.setdefault(item, {})
                   # Flip item and person
120
                   result[item][person] = prefs[person][item]
         return result
   def calculateSimilarItems(prefs, n=10):
         Create a dictionary of items showing which other items they are
        most similar to.
130
        result = {}
         # Invert the preference matrix to be item-centric
        itemPrefs = transformPrefs(prefs)
        c = 0
         for item in itemPrefs:
135
              # Status updates for large datasets
              c += 1
              if c % 100 == 0:
                   print('%d / %d' % (c, len(itemPrefs)))
              # Find the most similar items to this one
140
              scores = topMatches(itemPrefs, item, n=n, similarity=sim_distance)
              result[item] = scores
         return result
145
   def getRecommendedItems(prefs, itemMatch, user):
```

```
userRatings = prefs[user]
         scores = {}
         totalSim = {}
150
         # Loop over items rated by this user
         for (item, rating) in userRatings.items():
              # Loop over items similar to this one
              for (similarity, item2) in itemMatch[item]:
                   # Ignore if this user has already rated this item
                   if item2 in userRatings:
                        continue
                   # Weighted sum of rating times similarity
                   scores.setdefault(item2, 0)
                   scores[item2] += similarity * rating
                   # Sum of all the similarities
160
                   totalSim.setdefault(item2, 0)
                   totalSim[item2] += similarity
         # Divide each total score by total weighting to get an average
         rankings = [(score / totalSim[item], item) for (item, score) in
                        scores.items()]
165
         # Return the rankings from highest to lowest
         rankings.sort()
         rankings.reverse()
         return rankings
170
    def loadMovieLens():
      # Get movie titles
        movies = {}
175
         for line in open('u.item'):
              (id, title) = line.split(' \mid ')[0:2]
              movies[id] = title
      # Load data
180
         prefs = {}
         for line in open('u.data'):
              (user, movieid, rating, ts) = line.split('\t')
              prefs.setdefault(user, {})
              prefs[user][movies[movieid]] = float(rating)
              print prefs[user][movies[movieid]]
         return prefs
   prefs = loadMovieLens()
   userId = '33'
   r = getRecommendations(prefs, userId)
   f = open("recommendedMovies.txt", "w")
   f.write(str(r))
   f.close()
```

The above code will generate recommendations for **Substitute Me** in saves in to text file **recommended-Movies.txt**.

ı	Top 5 Recommendations
	Star Kid (1997)
	Two or Three Things I Know About Her (1966)
	Tough and Deadly (1995)
	Santa with Muscles (1996)
	Saint of Fort Washington, The (1993)
	Bottom 5 Recommendations
	3 Ninjas: High Noon At Mega Mountain (1998)
	American Strays (1996)
	Amityville 1992: It's About Time (1992)
	Amityville 3-D (1983)

Figure 3: Top 5 and Bottom 5 Recommended Movies

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?

## SOLUTION

transformPrefs function was changed to get the preferences and to get the top 5 suggestions from the topMatches function. The results for my favorite movie The Shawshank Redemption and my least favorite movie of that time Jurassic Park has been determined with positive and negative correlations. The following code has been rewrited and was originally taken from Programming Collective Intelligence

Listing 4: Assignment6 4.py

```
import csv
   import math
   import operator
   import string
   from collections import Counter
   from math import sqrt
   def sim_distance(prefs, p1, p2):
10
        Returns a distance-based similarity score for person1 and person2.
        # Get the list of shared_items
        si = \{\}
        for item in prefs[p1]:
             if item in prefs[p2]:
                  si[item] = 1
        # If they have no ratings in common, return 0
        if len(si) == 0:
             return 0
        # Add up the squares of all the differences
        sum_of_squares = sum([pow(prefs[p1][item] - prefs[p2][item], 2) for item in
                                   prefs[p1] if item in prefs[p2]])
        return 1 / (1 + sqrt(sum_of_squares))
25
   def sim_pearson(prefs, p1, p2):
        Returns the Pearson correlation coefficient for p1 and p2.
30
        # Get the list of mutually rated items
        si = \{\}
        for item in prefs[p1]:
             if item in prefs[p2]:
35
                  si[item] = 1
        # If they are no ratings in common, return 0
        if len(si) == 0:
```

```
return 0
        # Sum calculations
        n = len(si)
        # Sums of all the preferences
        sum1 = sum([prefs[p1][it] for it in si])
        sum2 = sum([prefs[p2][it] for it in si])
        # Sums of the squares
        sum1Sq = sum([pow(prefs[p1][it], 2) for it in si])
        sum2Sq = sum([pow(prefs[p2][it], 2) for it in si])
        # Sum of the products
        pSum = sum([prefs[p1][it] * prefs[p2][it] for it in si])
        # Calculate r (Pearson score)
        num = pSum - sum1 * sum2 / n
        den = sqrt((sum1Sq - pow(sum1, 2) / n) * (sum2Sq - pow(sum2, 2) / n))
        if den == 0:
             return 0
        r = num / den
55
        return r
   def topMatches(
        prefs,
60
        person,
        n=5,
        similarity=sim_pearson,
   ):
        Returns the best matches for person from the prefs dictionary.
        Number of results and similarity function are optional params.
        ,,,
        scores = [(similarity(prefs, person, other), other) for other in prefs
                    if other != person]
        scores.sort()
        # scores.reverse()
        # return scores[0:n]
        lessfavorite = scores[:n]
75
        favorite = scores[-n:]
        return (lessfavorite, favorite)
   \mathbf{def} getRecommendations (prefs, person, similarity=sim_pearson):
        Gets recommendations for a person by using a weighted average
        of every other user's rankings
        111
85
        totals = {}
        simSums = {}
        for other in prefs:
        # Don't compare me to myself
             if other == person:
90
                  continue
```

```
sim = similarity(prefs, person, other)
              # Ignore scores of zero or lower
              if sim <= 0:</pre>
                   continue
              for item in prefs[other]:
                   # Only score movies I haven't seen yet
                   if item not in prefs[person] or prefs[person][item] == 0:
                        # Similarity * Score
                        totals.setdefault(item, 0)
                        # The final score is calculated by multiplying each item by the
                            similarity and adding these products together
                        totals[item] += prefs[other][item] * sim
                        # Sum of similarities
                        simSums.setdefault(item, 0)
105
                        simSums[item] += sim
         # Create the normalized list
         rankings = [(total / simSums[item], item) for (item, total) in
                        totals.items()]
         # Return the sorted list
110
         rankings.sort()
         rankings.reverse()
         return rankings
115
   def transformPrefs(prefs):
         Transform the recommendations into a mapping where persons are described
         with interest scores for a given title e.g. {title: person} instead of
         {person: title}.
120
         ,,,
         result = {}
         for person in prefs:
125
              for item in prefs[person]:
                   result.setdefault(item, {})
                   # Flip item and person
                   result[item][person] = prefs[person][item]
         return result
130
    def calculateSimilarItems(prefs, n=10):
         Create a dictionary of items showing which other items they are
         most similar to.
135
         ,,,
         result = {}
         # Invert the preference matrix to be item-centric
         itemPrefs = transformPrefs(prefs)
140
         for item in itemPrefs:
              # Status updates for large datasets
              c += 1
```

```
if c % 100 == 0:
145
                   print('%d / %d' % (c, len(itemPrefs)))
              # Find the most similar items to this one
              scores = topMatches(itemPrefs, item, n=n, similarity=sim_distance)
              result[item] = scores
         return result
150
    def getRecommendedItems(prefs, itemMatch, user):
         userRatings = prefs[user]
155
         scores = {}
         totalSim = {}
         # Loop over items rated by this user
         for (item, rating) in userRatings.items():
              # Loop over items similar to this one
              for (similarity, item2) in itemMatch[item]:
160
                   # Ignore if this user has already rated this item
                   if item2 in userRatings:
                        continue
                   # Weighted sum of rating times similarity
                   scores.setdefault(item2, 0)
165
                   scores[item2] += similarity * rating
                   # Sum of all the similarities
                   totalSim.setdefault(item2, 0)
                   totalSim[item2] += similarity
         # Divide each total score by total weighting to get an average
170
         rankings = [(score / totalSim[item], item) for (item, score) in
                        scores.items()]
         # Return the rankings from highest to lowest
         rankings.sort()
         rankings.reverse()
175
         return rankings
    def loadMovieLens():
      # Get movie titles
180
         movies = {}
         for line in open('u.item'):
              (id, title) = line.split(' \mid ')[0:2]
              movies[id] = title
      # Load data
185
         prefs = {}
         for line in open('u.data'):
              (user, movieid, rating, ts) = line.split(' \t')
              prefs.setdefault(user, {})
              prefs[user] [movies[movieid]] = float(rating)
         return prefs
   prefs = loadMovieLens()
   prefs = transformPrefs(prefs)
   (less, high) = topMatches(prefs, 'Shawshank Redemption, The (1994)')
   f = open("moviePositiveCorrelation.txt", "w")
   f.write(str(less))
```

```
f.write('\n')
f.write(str(high))

200

(less, high) = topMatches(prefs, 'Jurassic Park (1993)')
f = open("moviepNegativeCorrelation.txt","w")
f.write(str(less))
f.write('\n')
f.write(str(high))
```

The program generates top 5 and bottom 5 recommendations for my favorite and least favorite movies and then they are saved in to **moviePositiveCorrelation.txt** and **moviepNegativeCorrelation.txt** text files respectively.

Top most Favorite Recommen	dations	Top worst/least Favorite F	ecommendations
Movies	Corelation	Movies	Corelation
Penny Serenade (1941)	1.000000003	Loch Ness (1995)	1.00000004
Newton Boys, The (1998)	1.000000033	Traveller (1997)	
Oscar & Lucinda (1997)	1.000000003	Traveller (1997)	
Wedding Gift, The (1994)	1	Vermin (1998)	
Search for One-eye Jimmy, The (1996)	1	Wedding Gift, The (1994)	
Bottom most Favorite Recomme	endations	Bottom worst/least Favorite	Recommendations
Bottom most Favorite Recomme	endations Corelation	Bottom worst/least Favorite Movies	Recommendations  Corelation
		·	Corelation
Movies	Corelation	Movies	Corelation
Movies Clean Slate (Coup de Torchon) (1981)	Corelation -1.00000004	Movies Kaspar Hauser (1993)	Corelation
Movies Clean Slate (Coup de Torchon) (1981) 1-900 (1994)	Corelation -1.00000004 -1	Movies Kaspar Hauser (1993) 1-900 (1994)	

Figure 4: Top and Bottom most and worst/least Favorite Recommendations respectively

## Conclusion

I am not in any position to make a comment on the result of the correlation because I am not sure about most of the movies here as I have not watched them, but I have watched **The Shawshank Redemption** and is one of the very best movie to watch., but the recommended movies based on this movie are obscure to me.

## References

- $1. \ \ https://github.com/arthur-e/Programming-Collective-Intelligence$
- $2. \ \ http://grouplens.org/datasets/movielens/100k/$