item-based

October 30, 2021

[ ]:
```python
import numpy as np
from numpy.linalg import norm
import pandas as pd
from scipy import stats
from scipy import spatial
import matplotlib.pyplot as plt
import seaborn as sb
```

0.1 Display information

[ ]:
```python
names = ['userid', 'itemid', 'rating', 'timestamp']
raw_data = pd.read_csv('./ml-100k/u.data', sep='\t', names=names)

print('Count of ratings', len(raw_data))
print('First ten rows')
print(raw_data[0:10])

# save data in a numpy array where each user ratings have their own rows
userids = sorted(list(raw_data['userid'].unique()))
itemids = sorted(list(raw_data['itemid'].unique()))

# first save in list of lists, use None values if user has not rated item
data = [[None] * len(userids) for x in range(len(itemids))]

# find ratings made by each user
for i in range(len(itemids)):
    # dict of ratings for item i+1 (key = userid, value = rating)
    item_ratings = dict(zip(raw_data.loc[raw_data['itemid'] == (i+1)].userid,␣
 ↪raw_data.loc[raw_data['itemid'] == (i+1)].rating))
    for j in range(len(userids)):
        # check if user has rated item with id j+1
        if j+1 in item_ratings:
            data[i][j] = item_ratings[j+1]

data = np.array(data)
print(data.shape)
```

```
Count of ratings 100000
```

```
First ten rows
   userid  itemid  rating  timestamp
0     196     242       3  881250949
1     186     302       3  891717742
2      22     377       1  878887116
3     244      51       2  880606923
4     166     346       1  886397596
5     298     474       4  884182806
6     115     265       2  881171488
7     253     465       5  891628467
8     305     451       3  886324817
9       6      86       3  883603013
(1682, 943)
```

[ ]:

```
# a = item a itemid, b = item b itemid, data = whole dataset
def cosine_similarity(a, b, data):
    # ratings for items a and b
    data_a = data[a-1] # indexing starts at one
    data_b = data[b-1]

    # dicts with userids and ratings
    dict_a = {u: r for u, r in enumerate(data_a, start=1) if r is not None}
    dict_b = {u: r for u, r in enumerate(data_b, start=1) if r is not None}

    # intersection between two sets
    P = list(set(dict_a).intersection(set(dict_b)))

    dict_a = {id: dict_a[id] for id in P}
    dict_b = {id: dict_b[id] for id in P}

    mean_a = np.mean(list(dict_a.values()))
    mean_b = np.mean(list(dict_b.values()))
    n = 0
    d1 = 0
    d2 = 0

    # calculate sums
    for userid in P:
        n += ((dict_a[userid] - mean_a) * (dict_b[userid] - mean_b))
        d1 += ((dict_a[userid] - mean_a) ** 2)
        d2 += ((dict_b[userid] - mean_b) ** 2)

    if n == 0:
        return 0

    sim = n / (np.sqrt(d1) * np.sqrt(d2))
```

```
    #scipy_sim = 1-spatial.distance.cosine(list(dict_a.values()), list(dict_b.
 ↪values()))
    #if np.round(sim, 10) == np.round(scipy_sim, 10):
    #    print(sim, scipy_sim)
    #    print('all ok')
    #else:
    #    print(sim, scipy_sim)
    #    print("Not okay")

    return sim
cosine_similarity(567, 123, data)
```

[ ]: -0.17518598317371087

0.1.1 Similarity matrix of all items (makes calculations faster)

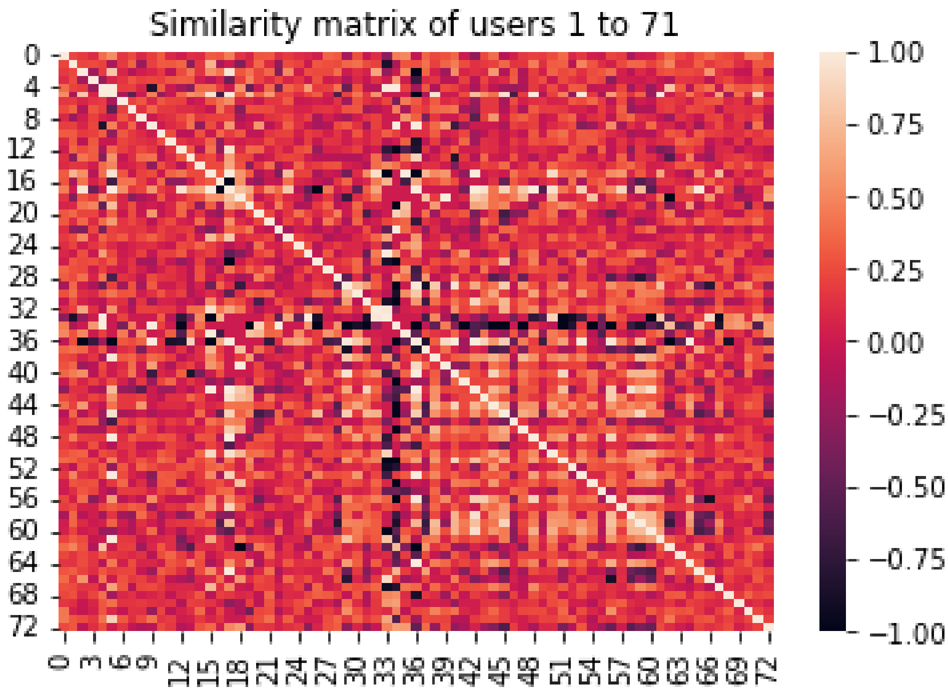
[ ]:
```
sim_matrix = [[1] * len(itemids) for x in range(len(itemids))]
for i in range(len(itemids)):
    for j in range(i+1, len(itemids)):
        sim_matrix[i][j] = sim_matrix[j][i] = cosine_similarity(i+1, j+1, data)
```

```
/home/vaino/anaconda3/envs/recommender/lib/python3.9/site-
packages/numpy/core/fromnumeric.py:3440: RuntimeWarning: Mean of empty slice.
  return _methods._mean(a, axis=axis, dtype=dtype,
/home/vaino/anaconda3/envs/recommender/lib/python3.9/site-
packages/numpy/core/_methods.py:189: RuntimeWarning: invalid value encountered
in double_scalars
  ret = ret.dtype.type(ret / rcount)
```

[ ]:
```
test_matrix = [[1] * int(len(itemids)/23) for x in range(int(len(itemids)/23))]
for i in range(int(len(itemids)/23)):
    for j in range(i+1, int(len(itemids)/23)):
        test_matrix[i][j] = test_matrix[j][i] = cosine_similarity(i+1, j+1,␣
 ↪data)

test_matrix = np.array(test_matrix)

# heatmap of the similarity matrix
sb.heatmap(test_matrix)
plt.title('Similarity matrix of users 1 to 71')
plt.show()
```




```
[ ]: # u = userid, p = itemid, data = whole data set, sim = item similarity vector,
     ↪n = number of neighbours
     def cosine_predict(u, p, data, sim_matrix, N):
         sim = sim_matrix[p-1]
         # convert similarity list to dict where key is itemid and value its
     ↪similarity with item p
         sim = {i: s for i, s in enumerate(sim, start=1)}

         # dict of items and ratings for user u
         user_rated_items = {}

         for itemid in sim:
             if data[itemid-1][u-1] != None:
                 user_rated_items[itemid] = data[itemid-1][u-1]

         for itemid in itemids:
             if itemid not in user_rated_items:
                 del sim[itemid]

         # sort similarities based on dict values and return n highest values
         sim = dict(sorted(sim.items(), key=lambda x: x[1], reverse=True))
         sim = dict(list(sim.items())[:N])

         n = 0
```

```
    d = 0

    # loop through neighbourhood
    for itemid in sim:
        n += sim[itemid] * user_rated_items[itemid]
        d += sim[itemid]

    # this happens if all values in sim are 0. This means that the N nearest␣
↪items have a similarity of zero with item p
    if n == 0:
        return 0

    return n/d
```

0.2 Recommended 20 movies for any given user

[ ]:
```
USER = 15
# neighbourhood size
N = 20

# find items the user has not rated
items = []
for itemid in range(len(itemids)):
    if data[itemid-1][USER-1] == None:
            items.append(itemid)

predictions = {}

for item in items:
    predictions[item] = cosine_predict(USER, item, data, sim_matrix, N)

# sort predictions and take 20 highest
most_relevant = dict(sorted(predictions.items(), key=lambda x: x[1],␣
↪reverse=True))
df = pd.DataFrame(list(zip(list(most_relevant.keys()), list(most_relevant.
↪values()))), columns=['itemid', 'rating pred'])[:20]
print(df)
```

```
   itemid  rating pred
0    1523     5.000000
1    1554     5.000000
2    1588     5.000000
3    1590     5.000000
4    1602     4.100095
5     861     4.000000
6    1261     4.000000
7    1463     4.000000
```

8	1472	4.000000
9	1541	4.000000
10	1622	4.000000
11	1656	4.000000
12	868	3.970689
13	1455	3.857143
14	1332	3.800000
15	610	3.795571
16	1009	3.789479
17	1127	3.767519
18	1062	3.762357
19	1600	3.748768

[ ]:
```

```