Experiment No. 5
Implement Item-based Nearest neighbor recommendation
Date of Performance:
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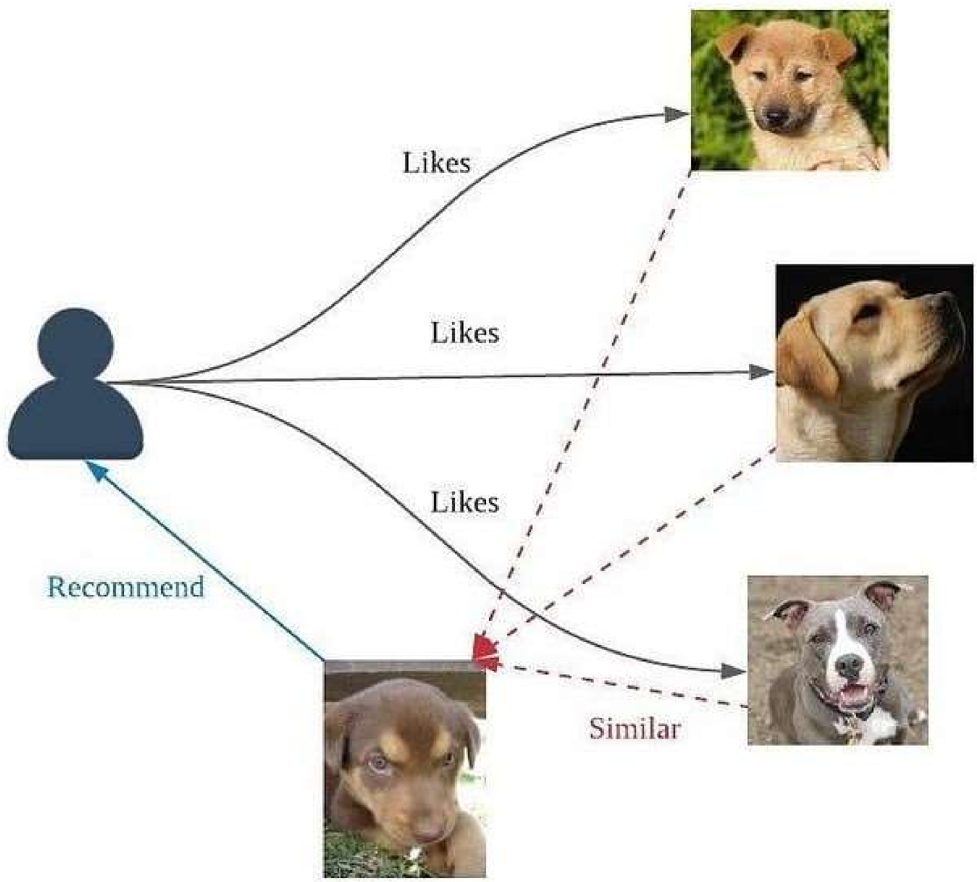
Aim: Implement Item-based Nearest neighbor recommendation.

Objective: Able to interpret and implement Item based Nearest neighbor recommendation.

Theory:

Item-based Collaborative Filtering

Item-based collaborative filtering uses the rating of co-rated item to predict the rating on specific item.



For example, we want to predict rating of user 2 on item 2.

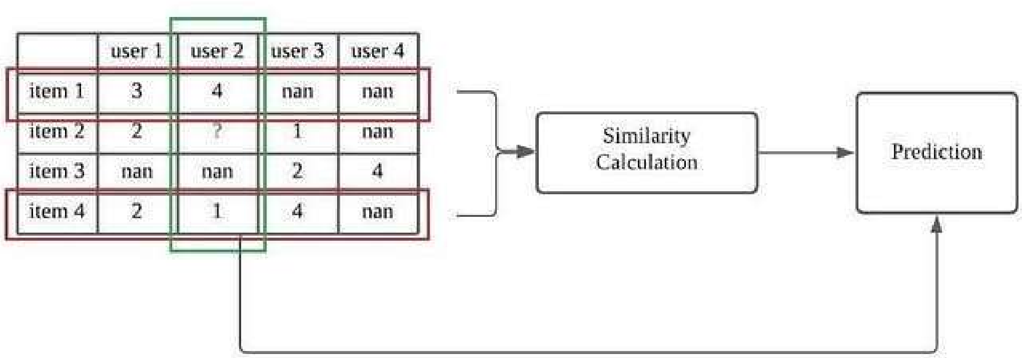
	user 1	user 2	user 3	user 4
item 1	3	4	nan	nan
item 2	2	?	1	nan
item 3	nan	nan	2	4
item 4	2	1	4	nan

To predict the rating,

1. Find the co-rated items of user 2, which is item 1 and item 4
2. Calculate the similarity between item 2 and item 1, 4
3. Calculate the prediction based on the similarity and co-rated rating, such that

$$prediction_{u,i} = \frac{\sum_n \omega_{i,n} * r_{u,n}}{\sum_n |\omega_{i,n}|}$$

where w is the similarity, and r is the rating value.



Implementation:

```
import pandas as pd
import numpy as np
df =
pd.DataFrame({'user_0':[0,3,0,5,0,0,4,5,0,2],
'user_1':[0,0,3,2,5,0,4,0,3,0],
'user_2':[3,1,0,3,5,0,0,4,0,0],
'user_3':[4,3,4,2,0,0,0,2,0,0],
                'user_4':[2,0,0,0,0,4,4,3,5,0],
'user_5':[1,0,2,4,0,0,4,0,5,0],
'user_6':[2,0,0,3,0,4,3,3,0,0],
'user_7':[0,0,0,3,0,2,4,3,4,0],
                'user_8':[5,0,0,0,5,3,0,3,0,4],
'user_9':[1,0,2,0,4,0,4,3,0,0]},
index=['movie_0','movie_1','movie_2','movie_
3','movie_4','movie_5','movie_6','movie_7','mo
vie_8','movie_9'])
df
df.values
from sklearn.neighbors import
NearestNeighbors
knn = NearestNeighbors(metric='cosine',
algorithm='brute')
knn.fit(df.values)
distances, indices = knn.kneighbors(df.values,
n_neighbors=3)
indices
distances
for title in df.index:
  index_user_likes =
df.index.tolist().index(title) # get an index for
a movie
  sim_movies =
indices[index_user_likes].tolist() # make list
for similar movies
  movie_distances =
distances[index_user_likes].tolist() # the list
for distances of similar movies
  id_movie =
sim_movies.index(index_user_likes) # get the
position of the movie itself in indices and
distances
  print('Similar Movies to
'+str(df.index[index_user_likes])+':\n')
sim_movies.remove(index_user_likes) #
remove the movie itself in indices
movie_distances.pop(id_movie) # remove the
movie itself in distances
  j = 1
  for i in sim_movies:
    print(str(j)+': '+str(df.index[i])+', the
distance with '+str(title)+':
'+str(movie_distances[j-1]))
    j = j + 1

  print('\n')

def recommend_movie(title):
index_user_likes =
df.index.tolist().index(title) # get an index for
a movie
  sim_movies =
indices[index_user_likes].tolist() # make list
for similar movies
  movie_distances =
distances[index_user_likes].tolist() # the list
for distances of similar movies
  id_movie =
sim_movies.index(index_user_likes) # get the
position of the movie itself in indices and
distances
  print('Similar Movies to
'+str(df.index[index_user_likes])+': \n')
sim_movies.remove(index_user_likes) #
remove the movie itself in indices
movie_distances.pop(id_movie) # remove the
movie itself in distances
  j = 1
  for i in sim_movies:
    print(str(j)+': '+str(df.index[i])+', the
distance with '+str(title)+':
'+str(movie_distances[j-1]))
    j = j + 1

recommend_movie('movie_3')
knn = NearestNeighbors(metric='cosine',
algorithm='brute')
knn.fit(df.values)
distances, indices = knn.kneighbors(df.values,
n_neighbors=3)
index_for_movie =
df.index.tolist().index('movie_0') # it returns 0
sim_movies =
indices[index_for_movie].tolist() # make list
for similar movies
movie_distances =
distances[index_for_movie].tolist() # the list
for distances of similar movies
```

```
id_movie =
sim_movies.index(index_for_movie) # get the
position of the movie itself in indices and
distances
sim_movies.remove(index_for_movie) #
remove the movie itself in indices
movie_distances.pop(id_movie) # remove the
movie itself in distances

print('The Nearest Movies to movie_0:',
sim_movies)
print('The Distance from movie_0:',
movie_distances)
movie_similarity = [-x+1 for x in
movie_distances] # inverse distance

predicted_rating =
(movie_similarity[0]*df.iloc[sim_movies[0],7]
+
movie_similarity[1]*df.iloc[sim_movies[1],7])
/sum(movie_similarity)
print(predicted_rating)
number_neighbors = 3
knn = NearestNeighbors(metric='cosine',
algorithm='brute')
knn.fit(df.values)
distances, indices = knn.kneighbors(df.values,
n_neighbors=number_neighbors)

# copy df
df1 = df.copy()

# convert user_name to user_index
user_index =
df.columns.tolist().index('user_4')

# t: movie_title, m: the row number of t in df
for m,t in list(enumerate(df.index)):

  # find movies without ratings by user_4
  if df.iloc[m, user_index] == 0:
  sim_movies = indices[m].tolist()
  movie_distances = distances[m].tolist()

    # Generally, this is the case: indices[3] = [3
6 7]. The movie itself is in the first place.
    # In this case, we take off 3 from the list.
Then, indices[3] == [6 7] to have the nearest
NEIGHBORS in the list.
    if m in sim_movies:
      id_movie = sim_movies.index(m)
      sim_movies.remove(m)
      movie_distances.pop(id_movie)

    # However, if the percentage of ratings in
the dataset is very low, there are too many 0s
in the dataset.
    # Some movies have all 0 ratings and the
movies with all 0s are considered the same
movies by NearestNeighbors().
    # Then,even the movie itself cannot be
included in the indices.
    # For example, indices[3] = [2 4 7] is
possible if movie_2, movie_3, movie_4, and
movie_7 have all 0s for their ratings.
    # In that case, we take off the farthest movie
in the list. Therefore, 7 is taken off from the
list, then indices[3] == [2 4].
    else:
      sim_movies =
sim_movies[:number_neighbors-1]
      movie_distances =
movie_distances[:number_neighbors-1]

    # movie_similarty = 1 - movie_distance
    movie_similarity = [1-x for x in
movie_distances]
    movie_similarity_copy =
movie_similarity.copy()
    nominator = 0

    # for each similar movie
    for s in range(0, len(movie_similarity)):

      # check if the rating of a similar movie is
zero
      if df.iloc[sim_movies[s], user_index] == 0:

        # if the rating is zero, ignore the rating
and the similarity in calculating the predicted
rating
        if len(movie_similarity_copy) ==
(number_neighbors - 1):
          movie_similarity_copy.pop(s)

        else:
          movie_similarity_copy.pop(s-
(len(movie_similarity)-
len(movie_similarity_copy)))

      # if the rating is not zero, use the rating
and similarity in the calculation
```

```
      else:
        nominator = nominator + movie_similarity[s]*df.iloc[sim_movies[s],user_index]

    # check if the number of the ratings with non-zero is positive
    if len(movie_similarity_copy) > 0:

      # check if the sum of the ratings of the similar movies is positive.
      if sum(movie_similarity_copy) > 0:
        predicted_r = nominator/sum(movie_similarity_copy)

      # Even if there are some movies for which the ratings are positive, some movies have zero similarity even though they are selected as similar movies.
      # in this case, the predicted rating becomes zero as well
      else:
        predicted_r = 0

    # if all the ratings of the similar movies are zero, then predicted rating should be zero
    else:
      predicted_r = 0

  # place the predicted rating into the copy of the original dataset
    df1.iloc[m,user_index] = predicted_r
def recommend_movies(user, num_recommended_movies):

  print('The list of the Movies {} Has Watched \n'.format(user))

  for m in df[df[user] > 0][user].index.tolist():
    print(m)

  print('\n')

  recommended_movies = []

  for m in df[df[user] == 0].index.tolist():

    index_df = df.index.tolist().index(m)
    predicted_rating = df1.iloc[index_df, df1.columns.tolist().index(user)]
    recommended_movies.append((m, predicted_rating))

  sorted_rm = sorted(recommended_movies, key=lambda x:x[1], reverse=True)

  print('The list of the Recommended Movies \n')
  rank = 1
  for recommended_movie in sorted_rm[:num_recommended_movies]:

    print('{}: {} - predicted rating:{}'.format(rank, recommended_movie[0], recommended_movie[1]))
    rank = rank + 1
recommend_movies('user_4',5)
df1 = df.copy()

def movie_recommender(user, num_neighbors, num_recommendation):

  number_neighbors = num_neighbors

  knn = NearestNeighbors(metric='cosine', algorithm='brute')
  knn.fit(df.values)
distances, indices = knn.kneighbors(df.values, n_neighbors=number_neighbors)

  user_index = df.columns.tolist().index(user)

  for m,t in list(enumerate(df.index)):
    if df.iloc[m, user_index] == 0:
      sim_movies = indices[m].tolist()
      movie_distances = distances[m].tolist()

      if m in sim_movies:
        id_movie = sim_movies.index(m)
        sim_movies.remove(m)
        movie_distances.pop(id_movie)

      else:
        sim_movies = sim_movies[:num_neighbors-1]
        movie_distances = movie_distances[:num_neighbors-1]
```

```
   movie_similarity = [1-x for x in
movie_distances]
   movie_similarity_copy =
movie_similarity.copy()
   nominator = 0

   for s in range(0, len(movie_similarity)):
    if df.iloc[sim_movies[s], user_index] ==
0:
      if len(movie_similarity_copy) ==
(number_neighbors - 1):
        movie_similarity_copy.pop(s)

      else:
        movie_similarity_copy.pop(s-
(len(movie_similarity)-
len(movie_similarity_copy)))

    else:
      nominator = nominator +
movie_similarity[s]*df.iloc[sim_movies[s],use
r_index]

   if len(movie_similarity_copy) > 0:
    if sum(movie_similarity_copy) > 0:
      predicted_r =
nominator/sum(movie_similarity_copy)

    else:
      predicted_r = 0

   else:
    predicted_r = 0

   df1.iloc[m,user_index] = predicted_r

recommend_movies(user,num_recommendatio
n)

movie_recommender('user_4', 4, 5)
ratings = pd.read_csv('ratings.csv',
usecols=['userId','movieId','rating'])
movies = pd.read_csv('movies.csv',
usecols=['movieId','title'])
ratings2 = pd.merge(ratings, movies,
how='inner', on='movieId')
df =
ratings2.pivot_table(index='title',columns='use
rId',values='rating').fillna(0)
df1 = df.copy()
```

```
def recommend_movies(user,
num_recommended_movies):

 print('The list of the Movies {} Has Watched
\n'.format(user))

 for m in df[df[user] > 0][user].index.tolist():
  print(m)

 print('\n')

 recommended_movies = []

 for m in df[df[user] == 0].index.tolist():

  index_df = df.index.tolist().index(m)
  predicted_rating = df1.iloc[index_df,
df1.columns.tolist().index(user)]
  recommended_movies.append((m,
predicted_rating))

 sorted_rm = sorted(recommended_movies,
key=lambda x:x[1], reverse=True)

 print('The list of the Recommended Movies
\n')
 rank = 1
 for recommended_movie in
sorted_rm[:num_recommended_movies]:

  print('{}: {} - predicted
rating:{}'.format(rank,
recommended_movie[0],
recommended_movie[1]))
  rank = rank + 1
def movie_recommender(user,
num_neighbors, num_recommendation):

 number_neighbors = num_neighbors

 knn = NearestNeighbors(metric='cosine',
algorithm='brute')
 knn.fit(df.values)
distances, indices =
knn.kneighbors(df.values,
n_neighbors=number_neighbors)

 user_index = df.columns.tolist().index(user)

 for m,t in list(enumerate(df.index)):
  if df.iloc[m, user_index] == 0:
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```
    sim_movies = indices[m].tolist()
    movie_distances = distances[m].tolist()

    if m in sim_movies:
      id_movie = sim_movies.index(m)
      sim_movies.remove(m)
      movie_distances.pop(id_movie)

    else:
      sim_movies =
sim_movies[:num_neighbors-1]
      movie_distances =
movie_distances[:num_neighbors-1]

    movie_similarity = [1-x for x in
movie_distances]
    movie_similarity_copy =
movie_similarity.copy()
    nominator = 0

    for s in range(0, len(movie_similarity)):
      if df.iloc[sim_movies[s], user_index] ==
0:
        if len(movie_similarity_copy) ==
(number_neighbors - 1):
          movie_similarity_copy.pop(s)
        else:
          movie_similarity_copy.pop(s-
(len(movie_similarity)-
len(movie_similarity_copy)))

      else:
        nominator = nominator +
movie_similarity[s]*df.iloc[sim_movies[s],use
r_index]

    if len(movie_similarity_copy) > 0:
      if sum(movie_similarity_copy) > 0:
        predicted_r =
nominator/sum(movie_similarity_copy)

      else:
        predicted_r = 0

    else:
      predicted_r = 0

    df1.iloc[m,user_index] = predicted_r

recommend_movies(user,num_recommendatio
n)
movie_recommender(15, 10, 10)
```

Output:

```
The list of the Movies 15 Has Watc
hed

(500) Days of Summer (2009)
10 Cloverfield Lane (2016)
101 Dalmatians (One Hundred and On
e Dalmatians) (1961)
28 Days Later (2002)
9 (2009)
A.I. Artificial Intelligence (2001
)
Adjustment Bureau, The (2011)
Aladdin (1992)
Alien (1979)
Aliens (1986)
American Beauty (1999)
American History X (1998)
American Psycho (2000)
Apocalypto (2006)
Avatar (2009)
Avengers, The (2012)
Back to the Future (1985)
Back to the Future Part II (1989)
Back to the Future Part III (1990)
Beautiful Mind, A (2001)
Bicentennial Man (1999)
Bolt (2008)
Bridge of Spies (2015)
Captain America: The Winter Soldie
r (2014)
Captain Phillips (2013)
Casper (1995)
Cast Away (2000)
Catch Me If You Can (2002)
Chappie (2015)
Children of Men (2006)
Cloudy with a Chance of Meatballs
(2009)
Dark Knight Rises, The (2012)
Dark Knight, The (2008)
Deadpool (2016)
District 9 (2009)
Django Unchained (2012)
Doctor Strange (2016)
Edge of Tomorrow (2014)
Escape from L.A. (1996)
```

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Ex Machina (2015)
Fifth Element, The (1997)
Fight Club (1999)
Finding Nemo (2003)
Flintstones, The (1994)
Forrest Gump (1994)
Frequency (2000)
Gattaca (1997)
Gladiator (2000)
Godfather, The (1972)
Gods Must Be Crazy, The (1980)
Gone Girl (2014)
Gran Torino (2008)
Grand Budapest Hotel, The (2014)
Gravity (2013)
Green Mile, The (1999)
Groundhog Day (1993)
Guardians of the Galaxy (2014)
I Am Legend (2007)
I, Robot (2004)
Inception (2010)
Incredibles, The (2004)
Independence Day (a.k.a. ID4) (199
6)
Inside Out (2015)
Interstellar (2014)
Iron Man (2008)
John Wick (2014)
Johnny Mnemonic (1995)
Junior (1994)
Kill Bill: Vol. 1 (2003)
Kill Bill: Vol. 2 (2004)
Lethal Weapon 2 (1989)
Life of Pi (2012)
Limitless (2011)
Lion King, The (1994)
Little Mermaid, The (1989)
Looper (2012)
Lord of the Rings: The Fellowship
of the Ring, The (2001)
Lord of the Rings: The Two Towers,
 The (2002)
Léon: The Professional (a.k.a. The
 Professional) (Léon) (1994)
Mad Max: Fury Road (2015)
Matrix, The (1999)
Memento (2000)
Minority Report (2002)
Misery (1990)
Monsters, Inc. (2001)
Moon (2009)
Mortal Kombat (1995)
My Neighbor Totoro (Tonari no Toto
ro) (1988)
Nightmare on Elm Street, A (1984)
Oblivion (2013)
Others, The (2001)
Passengers (2016)
Patriot, The (2000)
Pinocchio (1940)
Prestige, The (2006)
Prometheus (2012)
Pulp Fiction (1994)
Raiders of the Lost Ark (Indiana J
ones and the Raiders of the Lost A
rk) (1981)
Ratatouille (2007)
Requiem for a Dream (2000)
Road Trip (2000)
Rogue One: A Star Wars Story (2016
)
Ronin (1998)
Sausage Party (2016)
Saving Private Ryan (1998)
Schindler's List (1993)
Seven (a.k.a. Se7en) (1995)
Shawshank Redemption, The (1994)
Shrek (2001)
Shrek 2 (2004)
Sixth Sense, The (1999)
Source Code (2011)
Spirited Away (Sen to Chihiro no k
amikakushi) (2001)
Star Wars: Episode III - Revenge o
f the Sith (2005)
Star Wars: Episode IV - A New Hope
 (1977)
Star Wars: Episode V - The Empire
Strikes Back (1980)
Star Wars: Episode VI - Return of
the Jedi (1983)
Star Wars: Episode VII - The Force
 Awakens (2015)
Sully (2016)
Terminator 2: Judgment Day (1991)
Terminator, The (1984)
The Butterfly Effect (2004)
The Hunger Games (2012)
The Martian (2015)
Total Recall (1990)
Toy Story (1995)
U-571 (2000)
Unbreakable (2000)
Up (2009)
WALL·E (2008)
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What Women Want (2000)
World War Z (2013)
X-Files: Fight the Future, The (19
98)
X-Men: Apocalypse (2016)
Zootopia (2016)


The list of the Recommended Movies


1: Exorcist, The (1973) - predicte
d rating:5.000000000000001
2: Finding Forrester (2000) - pred
icted rating:5.000000000000001
3: Home Alone 2: Lost in New York
(1992) - predicted rating:5.000000
000000001
4: Master and Commander: The Far S
ide of the World (2003) - predicte
d rating:5.000000000000001
5: Speed (1994) - predicted rating
:5.000000000000001
6: Thank You for Smoking (2006) -
predicted rating:5.000000000000001
7: 2001: A Space Odyssey (1968) -
predicted rating:5.0
8: Army of Darkness (1993) - predi
cted rating:5.0
9: Beverly Hills Cop (1984) - pred
icted rating:5.0
10: Blood Diamond (2006) - predict
ed rating:5.0
```

Conclusion:

Item-based nearest neighbor recommendation systems analyze user-item interactions to suggest items similar to those a user has interacted with. By measuring item-item similarities, these systems identify patterns and recommend items that share characteristics with ones the user has liked. This approach is efficient for sparse datasets and provides personalized recommendations based on item similarities, enhancing user experience and engagement.