web-intelligence-pbl

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0.1 Web Intelligence PBL

0.2 Collaborative Filtering based Movie Recommendation Engine

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[1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[22]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from bs4 import BeautifulSoup
import warnings,random,requests,json,tqdm
```

[3]:
```
df = pd.read_csv('/content/drive/MyDrive/Web_Intel_PBL/IMDbRatingsByUsers.
↪csv',usecols=[1,2,3,4])
df.head()
```

[3]:

	UserID	TitleID	Rating	Date
0	ur4592644	tt0120884	10	16 January 2005
1	ur3174947	tt0118688	3	16 January 2005
2	ur3780035	tt0387887	8	16 January 2005
3	ur4592628	tt0346491	1	16 January 2005
4	ur3174947	tt0094721	8	16 January 2005

[4]:
```
df.shape
```

[4]:
```
(4669820, 4)
```

[5]:
```
df.drop_duplicates(subset=['UserID', 'TitleID'],inplace=True)
df.shape
```

[5]:
```
(4647097, 4)
```

[6]:
```
df.isnull().sum()
```

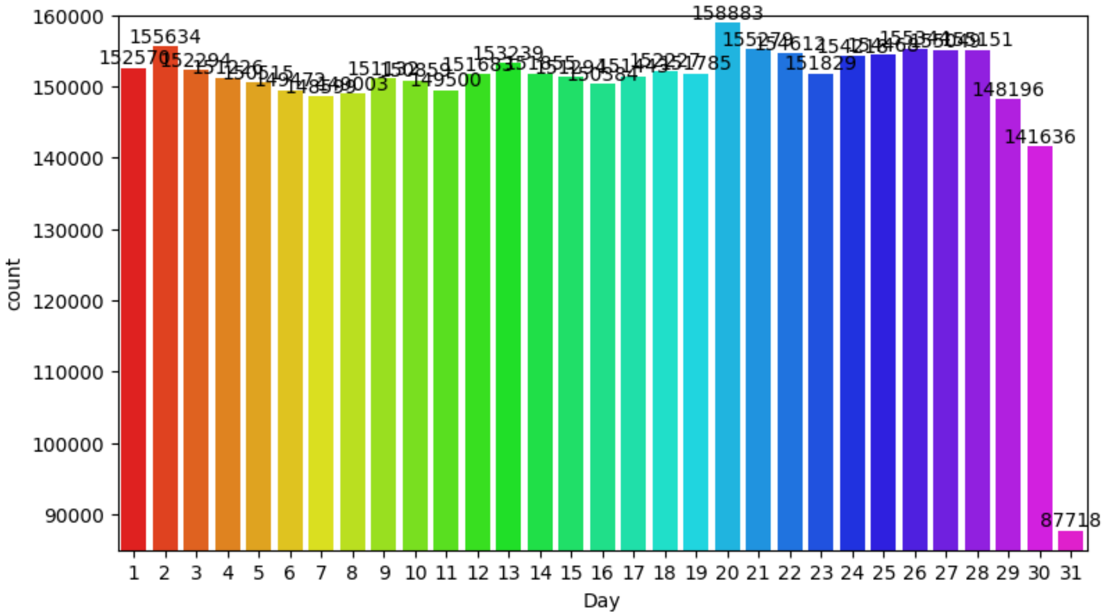
[6]:
```
UserID     0
TitleID    0
Rating     0
Date       0
dtype: int64
```

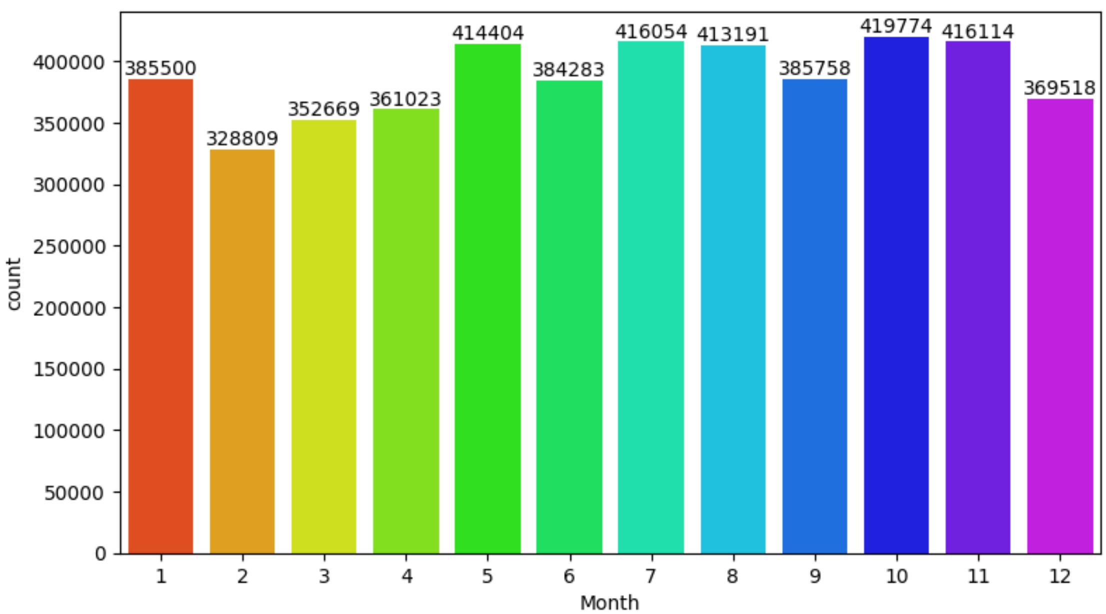
[7]:
```
df['Date'] = pd.to_datetime(df['Date'])
df['Day'] = df['Date'].dt.day
df['Month'] = df['Date'].dt.month
df['Year'] = df['Date'].dt.year
df['DayOfWeek'] = df['Date'].dt.day_name()
df.head()
```

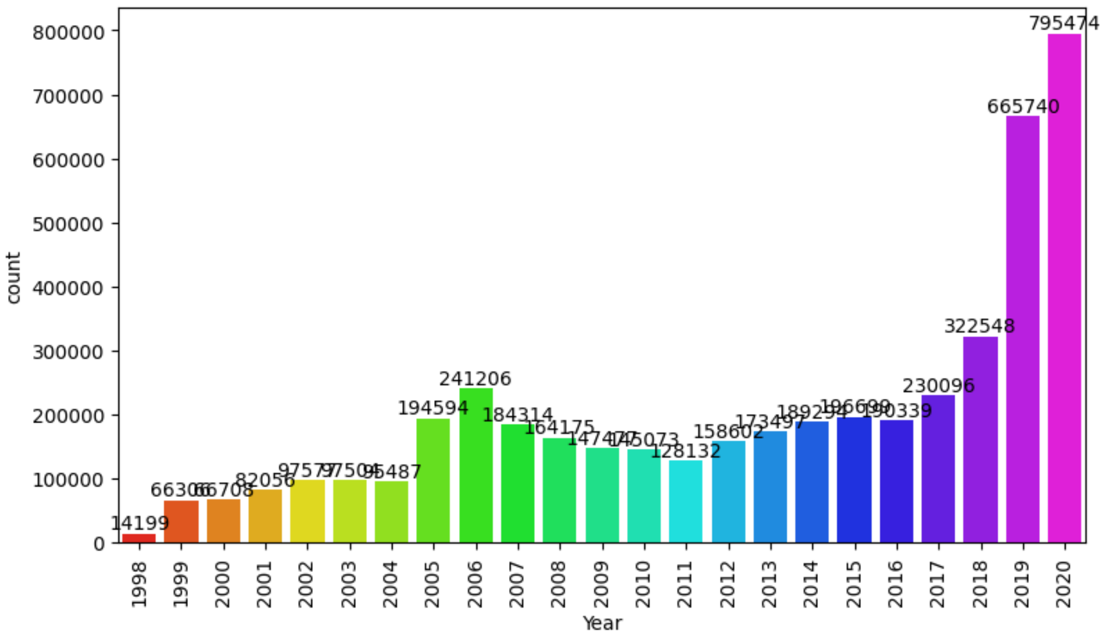
[7]:

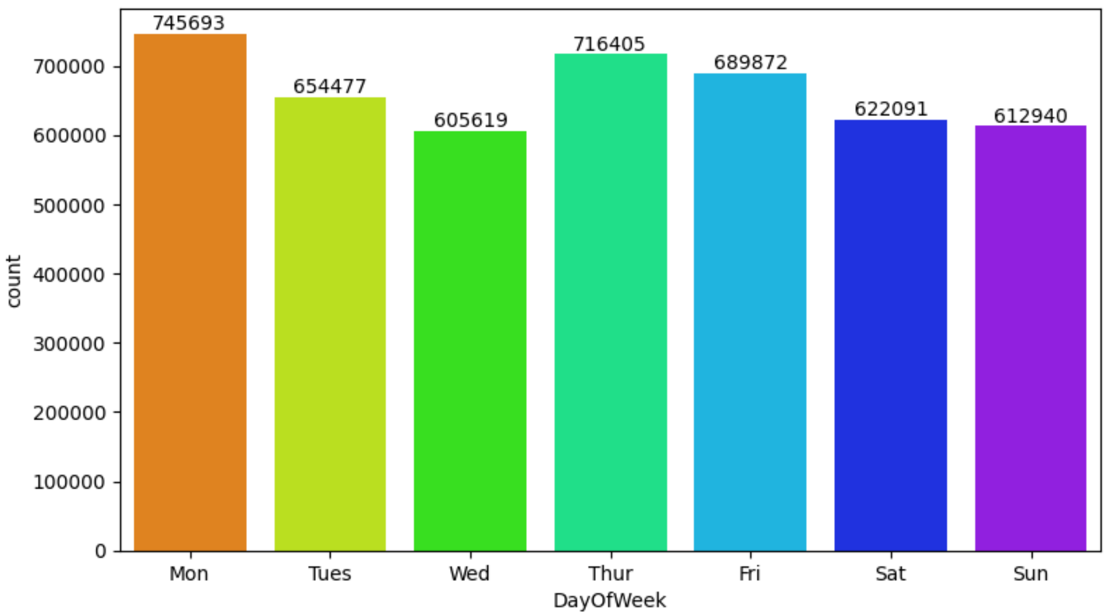
	UserID	TitleID	Rating	Date	Day	Month	Year	DayOfWeek
0	ur4592644	tt0120884	10	2005-01-16	16	1	2005	Sunday
1	ur3174947	tt0118688	3	2005-01-16	16	1	2005	Sunday
2	ur3780035	tt0387887	8	2005-01-16	16	1	2005	Sunday
3	ur4592628	tt0346491	1	2005-01-16	16	1	2005	Sunday
4	ur3174947	tt0094721	8	2005-01-16	16	1	2005	Sunday

[8]:
```
warnings.filterwarnings("ignore")
for i in ['Day','Month','Year','DayOfWeek']:
    fig, ax = plt.subplots(figsize=(9, 5))
    sns.countplot(x=i, data=df, palette='gist_rainbow', ax=ax)
    if i == 'Day':
        plt.ylim(85000,160000)
    if i == 'DayOfWeek':
        plt.
↪xticks(range(7),labels=['Mon','Tues','Wed','Thur','Fri','Sat','Sun'],rotation=0)
    if i == 'Year':
        plt.xticks(rotation=90)
    for p in ax.patches:
        ax.annotate(f'{int(p.get_height())}', (p.get_x() + p.get_width() / 2.,␣
↪p.get_height()), ha='center', va='bottom', fontsize=10)
    plt.show()
```


155634
158883
153239
149500
150384
151829
148196
141636
87718
count
Day
160000
150000
140000
130000
120000
110000
100000
90000
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31


385500
328809
352669
361023
414404
384283
416054
413191
385758
419774
416114
369518
count
Month
400000
350000
300000
250000
200000
150000
100000
50000
0
1 2 3 4 5 6 7 8 9 10 11 12





[9]:
```
df['TitleID'].value_counts()
```

[9]:
```
TitleID
tt7286456    10407
tt4154796     8695
```

```
tt8110330     7667
tt0111161     7499
tt2527338     7428
                 …
tt0384496        1
tt0390887        1
tt0416867        1
tt0136708        1
tt0174827        1
Name: count, Length: 351109, dtype: int64
```

[10]:
```
topt = list(df['TitleID'].value_counts().index)[:10]
topt
```

[10]:
```
['tt7286456',
 'tt4154796',
 'tt8110330',
 'tt0111161',
 'tt2527338',
 'tt6027920',
 'tt4154664',
 'tt0468569',
 'tt10230426',
 'tt7131622']
```

[11]:
```
df['UserID'].value_counts()
```

[11]:
```
UserID
ur2467618     24107
ur20552756    16802
ur2483625     16703
ur0482513     13206
ur2898520     12676
                  …
ur4590001         1
ur2571218         1
ur2941454         1
ur4584331         1
ur4589915         1
Name: count, Length: 1499238, dtype: int64
```

Filtering out users which gave less than or equal to 5 ratings

[12]:
```
users = df.groupby('UserID').apply(lambda x: dict(zip(x['TitleID'],␣
 ↪x['Rating']))).to_dict()
users = {user: titles for user, titles in users.items() if len(titles) > 5}
print(len(users),"Users Found!")
```

```
93744 Users Found!
```

[91]:
```python
bins = [0,10,20,50,100,200,300,500,700,1000,2000,3000,5000,10000,20000,30000]
fr = np.zeros(15)
for u,t in users.items():
    l = len(t)
    for i in range(15):
        if (i<15 and l>=bins[i] and l<bins[i+1]) or (i==15 and l>bins[i]):
            fr[i]+=1
for i in range(15):
    print(f"[{bins[i]},{bins[i+1]}] = {fr[i]} ({fr[i]/93744*100:.2f}%)")
```

```
[0,10] = 44677.0 (47.66%)
[10,20] = 28700.0 (30.62%)
[20,50] = 13520.0 (14.42%)
[50,100] = 3679.0 (3.92%)
[100,200] = 1740.0 (1.86%)
[200,300] = 530.0 (0.57%)
[300,500] = 368.0 (0.39%)
[500,700] = 184.0 (0.20%)
[700,1000] = 112.0 (0.12%)
[1000,2000] = 139.0 (0.15%)
[2000,3000] = 44.0 (0.05%)
[3000,5000] = 27.0 (0.03%)
[5000,10000] = 19.0 (0.02%)
[10000,20000] = 4.0 (0.00%)
[20000,30000] = 1.0 (0.00%)
```

[92]:
```python
histogram = go.Bar(
    x=[f"[{bins[i]}, {bins[i+1]})" for i in range(len(bins)-1)],
    y=fr,
    marker_color='royalblue'
)
fig = go.Figure(data=[histogram])
fig.update_layout(
    title='Frequency Distribution Histogram',
    xaxis=dict(title='Movies Rated'),
    yaxis=dict(title='Number of Users', type='log'),
    bargap=0.2
)
fig.show()
```

Shuffling the list of 93,744 users

[27]:
```python
items = list(users.items())
random.shuffle(items)
users2 = dict(items)
```

Picking first 10 users who have rated atleast 5 of the top 10 rated movies (topt)

[28]:
```
c = 0
usrs = []
for u,t in users2.items():
    nr = len(set(t).intersection(set(topt)))
    if nr>5:
        usrs.append(u)
        c+=1
    if c==10:
        break
```

Sampling only those ratings given by 10 Users selected earlier to top movies

[29]:
```
df2 = df[df['UserID'].isin(usrs) & df['TitleID'].isin(topt)]
df2
```

[29]:

	UserID	TitleID	Rating	Date	Day	Month	Year	DayOfWeek
709978	ur2707735	tt0468569	10	2008-07-21	21	7	2008	Monday
721320	ur2449095	tt0468569	5	2008-08-14	14	8	2008	Thursday
1030891	ur2449095	tt0111161	8	2004-03-14	14	3	2004	Sunday
1350697	ur2707735	tt0111161	10	2011-07-30	30	7	2011	Saturday
1690866	ur8462477	tt0111161	10	2013-10-17	17	10	2013	Thursday
…	…	…	…	…	…	…	…	
3731272	ur111092901	tt0468569	9	2020-01-12	12	1	2020	Sunday
3736678	ur111092901	tt4154664	7	2020-01-14	14	1	2020	Tuesday
3766709	ur4569900	tt0468569	7	2020-01-28	28	1	2020	Tuesday
3766710	ur2449095	tt2527338	7	2020-01-28	28	1	2020	Tuesday
3862702	ur4569900	tt2527338	7	2020-03-16	16	3	2020	Monday

[64 rows x 8 columns]

[30]:
```
utm = df2.pivot_table(index='UserID', columns='TitleID', values='Rating')
utm
```

[30]:

TitleID	tt0111161	tt0468569	tt2527338	tt4154664	tt4154796	tt6027920 \
UserID						
ur111092901	8.0	9.0	8.0	7.0	8.0	NaN
ur18723110	NaN	10.0	3.0	10.0	10.0	10.0
ur2449095	8.0	5.0	7.0	5.0	6.0	NaN
ur2707735	10.0	10.0	7.0	7.0	8.0	NaN
ur3670492	10.0	10.0	5.0	5.0	6.0	NaN
ur4569900	NaN	7.0	7.0	6.0	7.0	NaN
ur57691865	NaN	10.0	10.0	8.0	10.0	9.0
ur70682706	10.0	NaN	5.0	7.0	8.0	NaN
ur8462477	10.0	NaN	7.0	7.0	8.0	NaN
ur93138442	NaN	10.0	7.0	7.0	10.0	NaN

```
TitleID      tt7131622  tt7286456
UserID
ur111092901        8.0       10.0
ur18723110         NaN       10.0
ur2449095          8.0        8.0
ur2707735          7.0       10.0
ur3670492          NaN        9.0
ur4569900          6.0        6.0
ur57691865         8.0        8.0
ur70682706         8.0        8.0
ur8462477          9.0       10.0
ur93138442         9.0        9.0
```

Scraping title name from IMDb

[17]:
```
def get_title_name(tt):
    url = f'https://www.imdb.com/title/{tt}/'
    headers = {
            "User-Agent": "Mozilla/5.0 (Windows NT 10.0; Win64; x64)␣
↪AppleWebKit/537.36 (KHTML, like Gecko) Chrome/58.0.3029.110 Safari/537.3"
        }
    response = requests.get(url,headers=headers)
    soup = BeautifulSoup(response.content,'html.parser')
    script_tag = soup.find('script', {'id': '__NEXT_DATA__'})
    json_content = script_tag.contents[0]
    data = json.loads(json_content)
    tn = data["props"]["pageProps"]["aboveTheFoldData"]["titleText"]["text"]
    yr = data["props"]["pageProps"]["aboveTheFoldData"]["releaseYear"]["year"]
    tn = f"{tn} ({yr})"
    return tn
```

[18]:
```
ttn = []
for t in list(utm.columns):
    mv = get_title_name(t)
    print(mv)
    ttn.append(mv)
utm.columns = ttn
```

```
The Shawshank Redemption (1994)
The Dark Knight (2008)
Star Wars: The Rise of Skywalker (2019)
Captain Marvel (2019)
Avengers: Endgame (2019)
The Iron Throne (2019)
Once Upon a Time… in Hollywood (2019)
Joker (2019)
```

Rating Prediction using User-based CF (Only on sample of dataset (utm))

[31]:

```
utmx = np.array(utm)
nus = utmx.shape[0]
print("User-Title Ratings:")
print(utmx,'\n')
def cos_sim(v1,v2):
    mask = (v1 != 0) | (v2 != 0)
    v1,v2 = v1[mask],v2[mask]
    n1,n2 = np.linalg.norm(v1),np.linalg.norm(v2)
    if n1==0 or n2==0:
        return 0
    return np.dot(v1,v2)/(n1*n2)
sim = np.zeros((nus,nus))
for i in range(nus):
    for j in range(nus):
        rt1,rt2 = utmx[i][:],utmx[j][:]
        rt1,rt2 = rt1[~np.isnan(rt1) & ~np.isnan(rt2)], rt2[~np.isnan(rt1) &␣
 ↪~np.isnan(rt2)]
        rt1 -= np.mean(rt1)
        rt2 -= np.mean(rt2)
        sim[i][j] = cos_sim(rt1,rt2)
print('Similarity Matrix :\n',sim)
def predRat(uid,iid):
    avg = np.nanmean(np.delete(utmx, iid-1, axis=1), axis=1, keepdims=True)
    pred = avg[uid-1] + np.dot(np.nan_to_num(utmx[:,iid-1]-avg.
 ↪reshape(1,-1)),sim[uid-1,:])/(abs(sim[uid-1][:]).sum()-1)
    return pred[0]
mode = 2
if mode == 1:
    uid,iid = 2,6
    pred = predRat(uid,iid)
    print(f'\n Rating that User {uid} will give Title {iid} = {pred:.3f}')
elif mode == 2:
    rec = dict()
    for uid in range(nus):
        rs = dict()
        for iid in np.argwhere(np.isnan(utmx[uid,:])).flatten().tolist():
            pred = predRat(uid+1,iid+1)
            rs[utm.columns[iid]] = pred
        rec[utm.index[uid]] = rs
    print("Users\t\t-\tPredictions")
    rec = {user_id: dict(sorted(movies.items(), key=lambda x: x[1],␣
 ↪reverse=True)) for user_id, movies in rec.items()}
    for u,p in rec.items():
        preds = {k: round(v) for k, v in p.items()}
        print(f"{u}\t-\t{preds}")
```

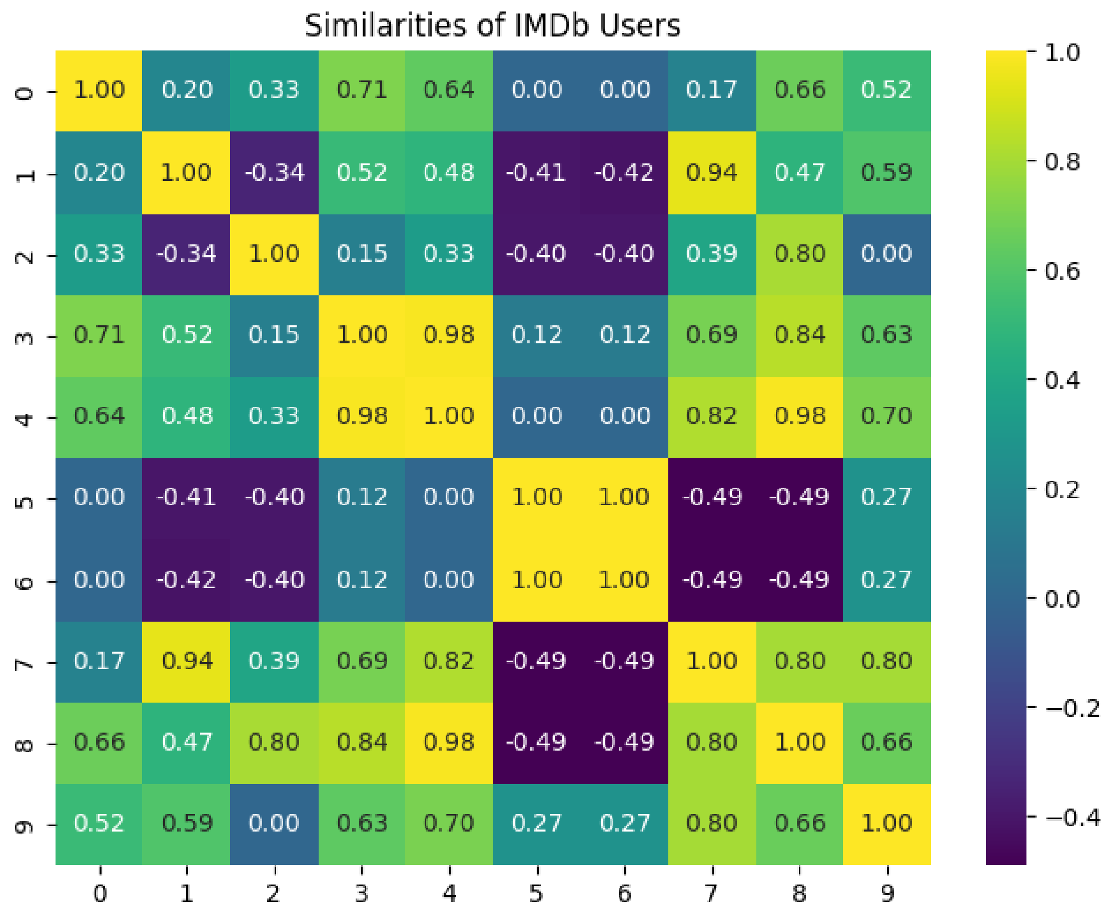
```
User-Title Ratings:
```

```
[[ 8.  9.  8.  7.  8. nan  8. 10.]
 [nan 10.  3. 10. 10. 10. nan 10.]
 [ 8.  5.  7.  5.  6. nan  8.  8.]
 [10. 10.  7.  7.  8. nan  7. 10.]
 [10. 10.  5.  5.  6. nan nan  9.]
 [nan  7.  7.  6.  7. nan  6.  6.]
 [nan 10. 10.  8. 10.  9.  8.  8.]
 [10. nan  5.  7.  8. nan  8.  8.]
 [10. nan  7.  7.  8. nan  9. 10.]
 [nan 10.  7.  7. 10. nan  9.  9.]]

Similarity Matrix :
 [[ 1.          0.19611614  0.32646431  0.71193614  0.6377928   0.
   0.          0.16609096  0.66409061  0.51970115]
 [ 0.19611614  1.         -0.34299717  0.51604685  0.47673129 -0.40824829
  -0.4152274   0.94280904  0.47140452  0.58976782]
 [ 0.32646431 -0.34299717  1.          0.14834153  0.32854123 -0.39735971
  -0.39735971  0.38729833  0.80295507  0.        ]
 [ 0.71193614  0.51604685  0.14834153  1.          0.98442507  0.12403473
   0.12403473  0.69337525  0.8378689   0.62984387]
 [ 0.6377928   0.47673129  0.32854123  0.98442507  1.          0.
   0.          0.82154192  0.98406272  0.70290195]
 [ 0.         -0.40824829 -0.39735971  0.12403473  0.          1.
   1.         -0.49009803 -0.49009803  0.26726124]
 [ 0.         -0.4152274  -0.39735971  0.12403473  0.          1.
   1.         -0.49009803 -0.49009803  0.26726124]
 [ 0.16609096  0.94280904  0.38729833  0.69337525  0.82154192 -0.49009803
  -0.49009803  1.          0.79967098  0.80032673]
 [ 0.66409061  0.47140452  0.80295507  0.8378689   0.98406272 -0.49009803
  -0.49009803  0.79967098  1.          0.65741124]
 [ 0.51970115  0.58976782  0.          0.62984387  0.70290195  0.26726124
   0.26726124  0.80032673  0.65741124  1.        ]]
Users           -       Predictions
ur111092901     -       {'tt6027920': 8}
ur18723110      -       {'tt0111161': 10, 'tt7131622': 9}
ur2449095       -       {'tt6027920': 7}
ur2707735       -       {'tt6027920': 9}
ur3670492       -       {'tt6027920': 8, 'tt7131622': 7}
ur4569900       -       {'tt6027920': 6, 'tt0111161': 6}
ur57691865      -       {'tt0111161': 8}
ur70682706      -       {'tt0468569': 9, 'tt6027920': 8}
ur8462477       -       {'tt0468569': 9, 'tt6027920': 9}
ur93138442      -       {'tt0111161': 10, 'tt6027920': 9}
```

[32]:
```
plt.figure(figsize=(8,6))
sns.heatmap(sim,cmap="viridis",annot=True,fmt=".2f")
plt.title("Similarities of IMDb Users")
```

```
plt.show()
```



[33]:
```
import plotly.graph_objects as go
import numpy as np
x, y = np.meshgrid(np.arange(sim.shape[0]), np.arange(sim.shape[1]))
fig = go.Figure(data=[go.Surface(z=sim, x=x, y=y)])
fig.update_traces(hoverinfo='x+y+z')
fig.update_layout(title='3D Similarity Matrix', autosize=False, width=600,␣
  ↪height=600)
fig.show()
```

0.6.1 Rating Prediction using CF on whole dataset

Picking a random user

[34]:
```
while True:
    rnu = random.choice(list(users.keys()))
    l = len(users[rnu])
```

```
    if l>500:
        break
mnu = np.array(list(users[rnu].values())).mean()
print(rnu,"-",len(users[rnu]),"Titles")
print("Avg Rating =",mnu)
```

```
ur40547513 - 601 Titles
Avg Rating = 7.336106489184692
```

[35]:
```
test_titles = random.sample(sorted(users[rnu]),round(0.2*l))
test = {t:r for t,r in users[rnu].items() if t in test_titles}
train = {t:r for t,r in users[rnu].items() if t not in test_titles}
mtr = np.array(list(train.values())).mean()
print("Avg Rating of Training set =",mtr)
```

```
Avg Rating of Training set = 7.345114345114345
```

Finding similar users to random user (who have rated similar titles) & computing similarity with random user

[36]:
```
rut = set(train)
c = 0
sims = dict()
for u,t in users.items():
    if u==rnu:
        continue
    ct = set(t).intersection(rut)
    if len(ct)>min(0.5*len(rut),10):
        c+=1
        print(f"{c}. Common Titles: {ct}")
        ctu1 = {t:r for t,r in users[rnu].items() if t in ct}
        ctu2 = {t:r for t,r in users[u].items() if t in ct}
        cr = np.array([[ctu1.get(title, np.nan), ctu2.get(title, np.nan)] for␣
↪title in list(ctu1.keys())],dtype=float)
        cr[:,0] -= cr[:,0].mean()
        cr[:,1] -= cr[:,1].mean()
        sim = cos_sim(cr[:,0],cr[:,1])
        print(f"Similarity b/w {rnu} & {u} = {sim:.3f}\n")
        sims[u] = sim
print("Total",c,"Similar Users Found")
```

```
1. Common Titles: {'tt1034415', 'tt8579674', 'tt7784604', 'tt6205872',
'tt7349662', 'tt6565702', 'tt1489887', 'tt3385524', 'tt4614612', 'tt4154664',
'tt8695030', 'tt5117428', 'tt7131622', 'tt1571234', 'tt5083738', 'tt2935510',
'tt5613484'}
Similarity b/w ur40547513 & ur0006042 = 0.053

2. Common Titles: {'tt0164052', 'tt4881806', 'tt8368406', 'tt4633694',
```

```
Similarity b/w ur40547513 & ur99964320 = 0.453

1363. Common Titles: {'tt2584384', 'tt8722346', 'tt7846844', 'tt6266538',
'tt10970552', 'tt4154664', 'tt7286456', 'tt7423538', 'tt8508734', 'tt5083738',
'tt0437086', 'tt2737304'}
Similarity b/w ur40547513 & ur99965244 = -0.149

Total 1363 Similar Users Found
```

[37]:
```
sims
```

[37]:
```
{'ur0006042': 0.05285164225816898,
 'ur0011762': 0.1388908726244082,
 'ur0019286': 0.03265696052517716,
 'ur0101706': 0.44345952510041453,
 'ur0102816': 0.11039815131175877,
 'ur0179626': 0.6107769209825866,
 'ur0225436': 0.01678924422599179,
 'ur0266568': 0.46513420714522313,
 'ur0277234': 0.3218960595762734,
 'ur0278527': 0.34309256121777515,
 'ur0283074': 0.6051603603638209,
 'ur0342623': 0.4934747321939812,
 'ur0345596': 0.30440824745203676,
 'ur0347711': -0.07110681947099658,
 'ur0350543': 0.3682475455538839,
 'ur0351766': 0.4689401761819642,
 'ur0442119': -0.3126526997403612,
 'ur0449021': 0.58095572057968,
 'ur0453068': 0.5863368913008201,
 'ur0453228': 0.4588377785613785,
 'ur0463200': 0.5004291786865414,
 'ur0482513': 0.36593373640431354,
 'ur0492397': 0.07962260575935998,
 'ur0503545': 0.6350999569416319,
 'ur0543054': 0.1933466813423011,
 'ur0547823': 0.31566715278397944,
 'ur0609951': 0.16589950576143966,
 'ur0629528': 0.26325132482650393,
 'ur0633574': 0.6537081739049555,
 'ur0637715': 0.2479206780724952,
 'ur0650255': 0.31661703138733127,
 'ur0651863': -0.2372054050806497,
 'ur0715302': 0.22245025558450532,
 'ur0715971': 0.4946518317664689,
 'ur0806494': 0.4807746547679025,
 'ur0865972': 0.4571607145651728,
```

```
'ur66109246': 0.38500024618063455,
'ur66111139': 0.1698339707484146,
'ur66492393': 0.323017406229672,
'ur66517869': 0.49468954096027123,
'ur66541531': 0.6997114285413195,
'ur66601046': 0.5087300484843803,
'ur66889093': 0.6492091592717517,
'ur66964206': 0.4451191997885142,
'ur66979966': -0.536995858887934,
'ur67032729': -0.15727567475697438,
'ur67073676': 0.11182939485904708,
'ur67115437': 0.1257504544881139,
'ur67260729': 0.24780723911952776,
'ur67280655': 0.11175975124542252,
'ur67325954': -0.005260851009727993,
'ur67346470': 0.5031512916999263,
'ur67394598': -0.09163242579854552,
'ur67478381': 0.4395114115544841,
'ur67595110': 0.19745042475485258,
'ur67702972': 0.5360562674188974,
'ur67826053': 0.5842330300115268,
'ur67876523': 0.11281225225643811,
'ur67902729': 0.5993857350668887,
'ur67997141': 0.6807430342773997,
…}
```

Predicting ratings for titles that random user has not rated

[38]:
```
preds = dict()
cmu = list(sims.keys())
nus = []
for t in test_titles:
    num,den = 0,0
    n = 0
    for u in cmu:
        try:
            r = users[u][t]
            s = sims[u]
            ru = list(users[u].values()) # ratings of user 'u'
            mean = (sum(ru)-r)/(len(ru)-1)
            num += s*(r-mean)
            den += abs(s)
            n+=1
        except KeyError:
            continue
    nus.append(n)
    if den>0:
```

```
        preds[t] = mtr + num/den
    else:
        test.pop(t)
```

[39]:
```
zeros = sum(1 for n in nus if n == 0)
print("No. of Titles in Test Set not rated by any SimilarUser =",zeros)
```

```
No. of Titles in Test Set not rated by any SimilarUser = 0
```

[40]:
```
preds = dict(sorted(preds.items(), key=lambda x: x[1],reverse=True))
print("Top 10 Titles Predicted for User",rnu,'\n')
tn,pr = [],[]
for t,p in list(preds.items())[:10]:
    tn.append(get_title_name(t))
    pr.append(round(p,3))
prd = pd.DataFrame({"Title Name":tn,"Score":pr})
prd.index+=1
prd
```

```
Top 10 Titles Predicted for User ur40547513
```

[40]:

	Title Name	Score
1	Dark (2017)	9.135
2	Carrie (1976)	8.989
3	Searching (2018)	8.592
4	The Wailing (2016)	8.415
5	Pájaros de verano (2018)	8.326
6	The Nightingale (2018)	8.285
7	Bone Tomahawk (2015)	8.193
8	I See You (2019)	8.122
9	Kona fer í stríð (2018)	8.106
10	Bohemian Rhapsody (2018)	8.029

[41]:
```
ae,ape,se = [],[],[]
for t in test.keys():
    true_r = test[t]
    pred_r = preds[t]
    diff = abs(pred_r-true_r)
    ae.append(diff)
    ape.append(diff/true_r*100)
    se.append(diff**2)
print(f"Mean Absolute Error (MAE) = {sum(ae)/len(ae)}")
print(f"Mean Squared Error (MSE) = {sum(se)/len(se)}")
print(f"Root Mean Squared Error (RMSE) = {(sum(se)/len(se))**0.5}")
```

```
Mean Absolute Error (MAE) = 0.8250953944244789
Mean Squared Error (MSE) = 1.0028651481197373
```

```
Root Mean Squared Error (RMSE) = 1.0014315493930364
```

[42]:
```
rats = pd.DataFrame({'True': test, 'Predicted': preds})
rats.sort_values(by='Predicted',ascending=False,inplace=True)
rats
```

[42]:

	True	Predicted
tt5753856	8	9.135035
tt0074285	8	8.989352
tt7668870	7	8.592264
tt5215952	9	8.415187
tt6386748	9	8.326440
…	…	…
tt7456312	6	4.636805
tt1255919	4	4.561334
tt7895904	6	4.507472
tt7671414	5	3.708576
tt6090044	5	3.480613

[120 rows x 2 columns]

[43]:
```
def calc_dcg(rat):
        dcg = 0
        for i in range(len(rat)):
                dcg += (2**rat[i] - 1)/(np.log2(i+2))
        return dcg
dcg = calc_dcg(rats['True'])
rats.sort_values(by='True',ascending=False,inplace=True)
dcgi = calc_dcg(rats['True'])
ndcg = dcg/dcgi
print(f"NDCG Score = {ndcg:.3f}")
```

```
NDCG Score = 0.889
```

Performance Evaluation of CF Recommender Engine

Evaluating Predictions and Rankings of All users having atleast 500 Ratings (Test Users)

[72]:
```
def predict_rating(rnu):
        user = users[rnu]

        test_titles = random.sample(sorted(user),round(0.2*len(user)))
        test = {t:r for t,r in user.items() if t in test_titles}
        train = {t:r for t,r in users[rnu].items() if t not in test_titles}
        mtr = np.array(list(train.values())).mean()

        rut = set(train)
```

```
        c = 0
        sims = dict()
        for u,t in users.items():
                if u==rnu:
                        continue
                ct = set(t).intersection(rut)
                if len(ct)>min(0.5*len(rut),10):
                        c+=1
                        ctu1 = {t:r for t,r in users[rnu].items() if t in ct}
                        ctu2 = {t:r for t,r in users[u].items() if t in ct}
                        cr = np.array([[ctu1.get(title, np.nan), ctu2.get(title, np.nan)] for title in list(ctu1.keys())],dtype=float)
                        cr[:,0] -= cr[:,0].mean()
                        cr[:,1] -= cr[:,1].mean()
                        sim = cos_sim(cr[:,0],cr[:,1])
                        sims[u] = sim

        preds = dict()
        cmu = list(sims.keys())
        nus = []
        for t in test_titles:
                num,den = 0,0
                n = 0
                for u in cmu:
                        try:
                                r = users[u][t]
                                s = sims[u]
                                ru = list(users[u].values()) # ratings of user 'u'

                                mean = (sum(ru)-r)/(len(ru)-1)
                                num += s*(r-mean)
                                den += abs(s)
                                n+=1
                        except KeyError:
                                continue
                nus.append(n)
                if den>0:
                        preds[t] = mtr + num/den
                else:
                        test.pop(t)
        return test,preds

def evaluate_user(test,preds):
        if len(test)==0:
                return 0,0,0,0
        ae,ape,se = [],[],[]
        for t in test.keys():
```

```
                true_r = test[t]
                pred_r = preds[t]
                diff = abs(pred_r-true_r)
                ae.append(diff)
                ape.append(diff/true_r*100)
                se.append(diff**2)
        mae,mse = sum(ae)/len(ae), sum(se)/len(se)
        rmse = mse**0.5

        rats = pd.DataFrame({'True': test, 'Predicted': preds})
        rats.sort_values(by='Predicted',ascending=False,inplace=True)
        def calc_dcg(rat):
                dcg = 0
                for i in range(len(rat)):
                        dcg += (2**rat[i] - 1)/(np.log2(i+2))
                return dcg
        dcg = calc_dcg(rats['True'])
        rats.sort_values(by='True',ascending=False,inplace=True)
        dcgi = calc_dcg(rats['True'])
        ndcg = dcg/dcgi
        return mae,mse,rmse,ndcg
```

[73]:
```
users500 = {u:t for u,t in users.items() if len(t)>500}
n500 = len(users500)
print("No. of users who rated more than 500 movies =",n500)
```

```
No. of users who rated more than 500 movies = 530
```

[74]:
```
MAE,MSE,RMSE,NDCG = [],[],[],[]
from tqdm import tqdm
for u in tqdm(users500):
    test,preds = predict_rating(u)
    mae,mse,rmse,ndcg = evaluate_user(test,preds)
    if mae==0 and mse==0 and rmse==0 and ndcg==0:
      print("Spam User Ignored")
      continue
    MAE.append(mae)
    MSE.append(mse)
    RMSE.append(rmse)
    NDCG.append(ndcg)
```

```
 92%|      | 488/530 [20:52<01:09,  1.66s/it]

Spam User Ignored

100%|      | 530/530 [22:12<00:00,  2.51s/it]
```

Results of CF Peformance Evaluation

[75]:
```
print(f"Average MAE for Test Users = {sum(MAE)/len(MAE):.3f}")
print(f"Average MSE for Test Users = {sum(MSE)/len(MSE):.3f}")
print(f"Average RMSE for Test Users = {sum(RMSE)/len(RMSE):.3f}")
print(f"Average NDCG for Test Users = {sum(NDCG)/len(NDCG):.3f}")
```

```
Average MAE for Test Users = 1.356
Average MSE for Test Users = 3.208
Average RMSE for Test Users = 1.727
Average NDCG for Test Users = 0.816
```