Read Data and Download

!!!! Reference !!!

- collaborative-filtering
- A beginner's guide to Recommendation Systems
- LightGCN->Pytorch(From Scratch)
- Comprehensive Guide to build a Recommendation Engine from scratch (in Python)

Download the dataset movielens 100k

Upgrade system & install wget, zip

In [7]:
```
!apt-get update
!apt-get install -y zip gzip tar wget
```

```
E: Could not open lock file /var/lib/apt/lists/lock - open (13: Permission den
ied)
E: Unable to lock directory /var/lib/apt/lists/
E: Could not open lock file /var/lib/dpkg/lock-frontend - open (13: Permission
denied)
E: Unable to acquire the dpkg frontend lock (/var/lib/dpkg/lock-frontend), are
you root?
```

Using `wget` to download movielens100k

In [8]:
```
!wget https://files.grouplens.org/datasets/movielens/ml-100k.zip
```

```
--2022-12-18 11:18:11--  https://files.grouplens.org/datasets/movielens/ml-100
k.zip
Resolving files.grouplens.org (files.grouplens.org)... 128.101.65.152
Connecting to files.grouplens.org (files.grouplens.org)|128.101.65.152|:443...
connected.
HTTP request sent, awaiting response... 200 OK
Length: 4924029 (4.7M) [application/zip]
Saving to: ‘ml-100k.zip.1’

ml-100k.zip.1       100%[===================>]   4.70M  1.87MB/s    in 2.5s

2022-12-18 11:18:16 (1.87 MB/s) - ‘ml-100k.zip.1’ saved [4924029/4924029]
```

Using `zip` to unzip the `ml-100k.zip`

In [9]:
```
!unzip ml-100k.zip
```

```
Archive:  ml-100k.zip
replace ml-100k/allbut.pl? [y]es, [n]o, [A]ll, [N]one, [r]ename:
```

In [0]:
```
!pip install pandas
!pip install scikit-learn
!pip install seaborn
!pip install surprise
```

Imports

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.neighbors import NearestNeighbors

import seaborn as sns
from sklearn.metrics.pairwise import pairwise_distances
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.metrics import mean_squared_error

from surprise.model_selection import cross_validate
from surprise import Reader, Dataset, KNNBasic, accuracy

import time
```

Reading the data using pandas

In [2]:
```
col=["user","item","rating","time"]
df = pd.read_csv('ml-100k/u.data', delimiter="\t", names=col)

df
```

Out[2]:

	user	item	rating	time
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
...	...	...	...	...
99995	880	476	3	880175444
99996	716	204	5	879795543
99997	276	1090	1	874795795
99998	13	225	2	882399156
99999	12	203	3	879959583

100000 rows × 4 columns

Get the size of users and items

In [3]:
```
n_users = df['user'].unique().shape[0]
n_items = df['item'].unique().shape[0]
n_users, n_items
```

Out[3]:
```
(943, 1682)
```

Read the `u.item` data to get name of movie

In [4]:
```
movies=pd.read_csv("ml-100k/u.item",sep="\|",header= None,encoding = "ISO-8859-

movies.columns = ["item", "name"]
movies
```

```
/opt/conda/lib/python3.7/site-packages/pandas/util/_decorators.py:311: ParserW
arning: Falling back to the 'python' engine because the 'c' engine does not su
pport regex separators (separators > 1 char and different from '\s+' are inter
preted as regex); you can avoid this warning by specifying engine='python'.
  return func(*args, **kwargs)
```

Out[4]:

	item	name
0	1	Toy Story (1995)
1	2	GoldenEye (1995)
2	3	Four Rooms (1995)
3	4	Get Shorty (1995)
4	5	Copycat (1995)
...	...	...
1677	1678	Mat' i syn (1997)
1678	1679	B. Monkey (1998)
1679	1680	Sliding Doors (1998)
1680	1681	You So Crazy (1994)
1681	1682	Scream of Stone (Schrei aus Stein) (1991)

1682 rows × 2 columns

In [5]:
```
rating_train = pd.read_csv("ml-100k/ua.base",sep="\t",header= None, names=col)
rating_test = pd.read_csv("ml-100k/ua.test",sep="\t",header= None, names=col)

rating_train.shape, rating_test.shape
```

Out[5]:
```
((90570, 4), (9430, 4))
```

In [6]:
```
rating_train.head(20)
```

Out[6]:

	user	item	rating	time
0	1	1	5	874965758
1	1	2	3	876893171
2	1	3	4	878542960
3	1	4	3	876893119
4	1	5	3	889751712
5	1	6	5	887431973
6	1	7	4	875071561
7	1	8	1	875072484
8	1	9	5	878543541
9	1	10	3	875693118
10	1	11	2	875072262
11	1	12	5	878542960
12	1	13	5	875071805
13	1	14	5	874965706
14	1	15	5	875071608
15	1	16	5	878543541
16	1	17	3	875073198
17	1	18	4	887432020
18	1	19	5	875071515
19	1	21	1	878542772

In [7]:

```
rating_test.head(20)
```

Out[7]:

	user	item	rating	time
0	1	20	4	887431883
1	1	33	4	878542699
2	1	61	4	878542420
3	1	117	3	874965739
4	1	155	2	878542201
5	1	160	4	875072547
6	1	171	5	889751711
7	1	189	3	888732928
8	1	202	5	875072442
9	1	265	4	878542441
10	2	13	4	888551922
11	2	50	5	888552084
12	2	251	5	888552084
13	2	280	3	888551441
14	2	281	3	888980240
15	2	290	3	888551441
16	2	292	4	888550774
17	2	297	4	888550871
18	2	312	3	888550631
19	2	314	1	888980085

Reading movie item and its id

In [6]:
```
idx_to_movie = {}
with open('ml-100k/u.item', 'r',encoding = "ISO-8859-1")as f:
    for line in f.readlines():
        info = line.split('|')
        idx_to_movie[int(info[0])-1] = info[1]

idx_to_movie[0], idx_to_movie[1], idx_to_movie[2]
```

Out[6]: ('Toy Story (1995)', 'GoldenEye (1995)', 'Four Rooms (1995)')

In [7]:
```
movie_to_idx = {v: k for k, v in idx_to_movie.items()}
movie_to_idx['Star Wars (1977)']
```

Out[7]: 49

Exploratory Data Analysis

Adjust the dataframe to further anaysis

Associating the Movie name with item id
(Combine u.item and u.data)

In [8]:
```
merged_df = pd.merge(df,movies,on="item")
merged_df
```

Out[8]:

	user	item	rating	time	name
0	196	242	3	881250949	Kolya (1996)
1	63	242	3	875747190	Kolya (1996)
2	226	242	5	883888671	Kolya (1996)
3	154	242	3	879138235	Kolya (1996)
4	306	242	5	876503793	Kolya (1996)
...	...	...	...	...	...
99995	840	1674	4	891211682	Mamma Roma (1962)
99996	655	1640	3	888474646	Eighth Day, The (1996)
99997	655	1637	3	888984255	Girls Town (1996)
99998	655	1630	3	887428735	Silence of the Palace, The (Saimt el Qusur) (1...
99999	655	1641	3	887427810	Dadetown (1995)

100000 rows × 5 columns

We can checkout the mean value of each movie

In [9]:
```
movie_rate_mean = merged_df.groupby("name").mean()['rating']
# for k,v  in movie_rate_mean.sort_values(ascending=False).iteritems():
#     print("{:<50}{:.2}".format(k[:20] + ("..." if len(k) > 20 else "" ), v) )
movie_rate_mean.head(10)
```

Out[9]:
```
name
'Til There Was You (1997)                          2.333333
1-900 (1994)                                       2.600000
101 Dalmatians (1996)                              2.908257
12 Angry Men (1957)                                4.344000
187 (1997)                                         3.024390
2 Days in the Valley (1996)                        3.225806
20,000 Leagues Under the Sea (1954)                3.500000
2001: A Space Odyssey (1968)                       3.969112
3 Ninjas: High Noon At Mega Mountain (1998)        1.000000
39 Steps, The (1935)                               4.050847
Name: rating, dtype: float64
```

We can also count how many rating each movie has

In [10]:
```
movie_rate_count =  merged_df["name"].value_counts()

movie_id_count = df["item"].value_counts()
```

```
movie_id_count = movie_id_count.to_frame()
# for k, v in movie_rate_count.iteritems():
#     print("{:<50}{}".format(k[:20] + ("..." if len(k) > 20 else "" ), v) )
movie_rate_count.head(10)
```

Out[10]:

```
Star Wars (1977)                    583
Contact (1997)                      509
Fargo (1996)                        508
Return of the Jedi (1983)           507
Liar Liar (1997)                    485
English Patient, The (1996)         481
Scream (1996)                       478
Toy Story (1995)                    452
Air Force One (1997)                431
Independence Day (ID4) (1996)       429
Name: name, dtype: int64
```

In [11]:

```
movie_id_count.columns = ['rate_count']
movie_id_count
```

Out[11]:

	rate_count
50	583
258	509
100	508
181	507
294	485
...	...
852	1
1505	1
1653	1
1452	1
1641	1

1682 rows × 1 columns

In [12]:

```
rate_count_and_mean = pd.concat([movie_rate_count, movie_rate_mean], axis=1, ke
rate_count_and_mean
```

Out[12]:

	rate_count	mean_value
Star Wars (1977)	583	4.358491
Contact (1997)	509	3.803536
Fargo (1996)	508	4.155512
Return of the Jedi (1983)	507	4.007890
Liar Liar (1997)	485	3.156701
...	...	...
Leopard Son, The (1996)	1	1.000000
Stefano Quantestorie (1993)	1	1.000000
Quartier Mozart (1992)	1	1.000000
Reluctant Debutante, The (1958)	1	3.000000
Dadetown (1995)	1	3.000000

1664 rows × 2 columns

In [13]:

```
print(len(movie_rate_count))
print(np.count_nonzero(movie_rate_count > 100))
```

```
1664
334
```

Sorting by mean rating and filter out the movie which has rating less than 100.

In [14]:

```
RATE_COUNT_THRESHOLD = 100
rate_count_and_mean.loc[rate_count_and_mean['rate_count'] > RATE_COUNT_THRESHOL
```

Out[14]:

	rate_count	mean_value
Close Shave, A (1995)	112	4.491071
Schindler's List (1993)	298	4.466443
Wrong Trousers, The (1993)	118	4.466102
Casablanca (1942)	243	4.456790
Shawshank Redemption, The (1994)	283	4.445230
Rear Window (1954)	209	4.387560
Usual Suspects, The (1995)	267	4.385768
Star Wars (1977)	583	4.358491
12 Angry Men (1957)	125	4.344000
Citizen Kane (1941)	198	4.292929

In [15]:

```
merged_df['movie_count']= merged_df['name'].map(merged_df['name'].value_counts(
merged_df
```

Out[15]:

	user	item	rating	time	name	movie_count
0	196	242	3	881250949	Kolya (1996)	117
1	63	242	3	875747190	Kolya (1996)	117
2	226	242	5	883888671	Kolya (1996)	117
3	154	242	3	879138235	Kolya (1996)	117
4	306	242	5	876503793	Kolya (1996)	117
...	...	...	...	...	...	...
99995	840	1674	4	891211682	Mamma Roma (1962)	1
99996	655	1640	3	888474646	Eighth Day, The (1996)	1
99997	655	1637	3	888984255	Girls Town (1996)	1
99998	655	1630	3	887428735	Silence of the Palace, The (Saimt el Qusur) (1...	1
99999	655	1641	3	887427810	Dadetown (1995)	1

100000 rows × 6 columns

In [16]:

```
n=600

# count the value of item columns & get the index(user id)
top_n_item_id = df['item'].value_counts()[:n].index.tolist()

# filter out the movie that are not in the top k list
df_top_k = df[ df['item'].isin(top_n_item_id)]
df_top_k
```

Out[16]:

	user	item	rating	time
0	196	242	3	881250949
1	186	302	3	891717742
3	244	51	2	880606923
4	166	346	1	886397596
5	298	474	4	884182806
...	...	...	...	...
99993	913	209	2	881367150
99995	880	476	3	880175444
99996	716	204	5	879795543
99998	13	225	2	882399156
99999	12	203	3	879959583

83565 rows × 4 columns

Plots

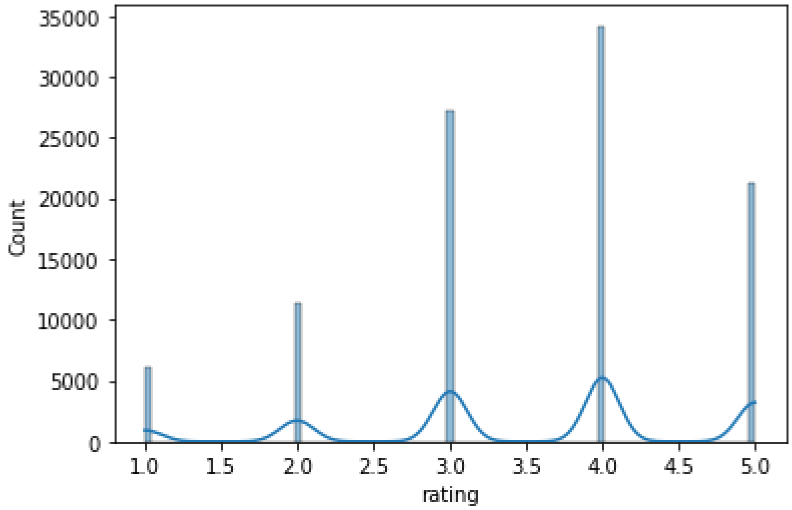
Rating Distribution

In this plot we can found out: rating 3, 4 are the most rating

In [17]:
```
sns.histplot(df["rating"], kde=True)
```

Out[17]: <AxesSubplot:xlabel='rating', ylabel='Count'>

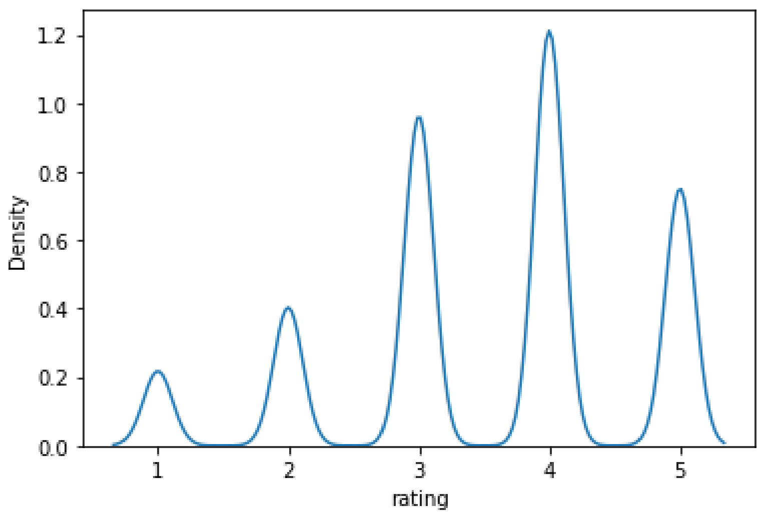
Out[17]:



In [18]:
```
sns.kdeplot(df["rating"])
```

Out[18]: <AxesSubplot:xlabel='rating', ylabel='Density'>

Out[18]:

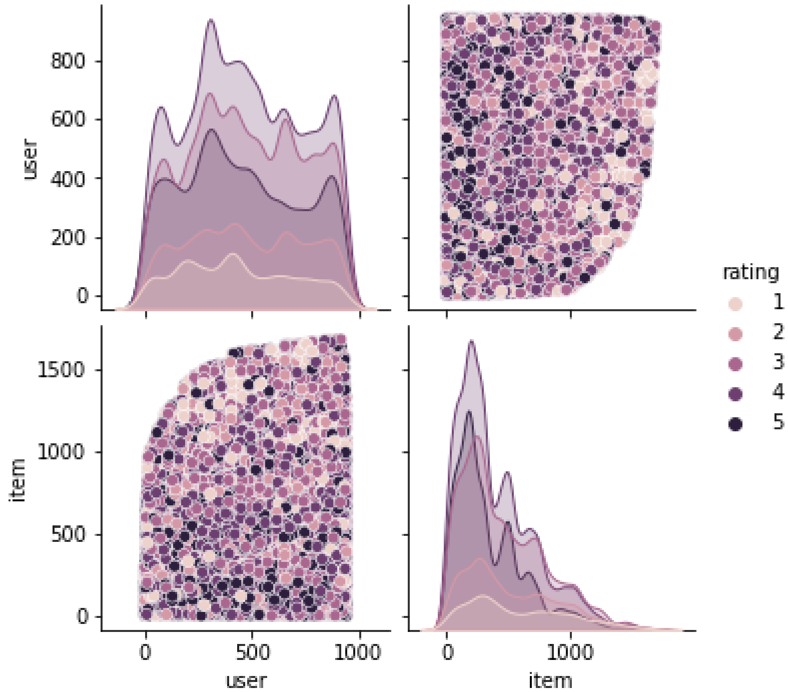


A plot to show the relation between user&item.
We can also see the distribution of rating by this.

In [19]:
```
sns.pairplot(df[['user','item', 'rating']], hue='rating')
```

Out[19]: <seaborn.axisgrid.PairGrid at 0x7f10816951d0>

Out[19]:

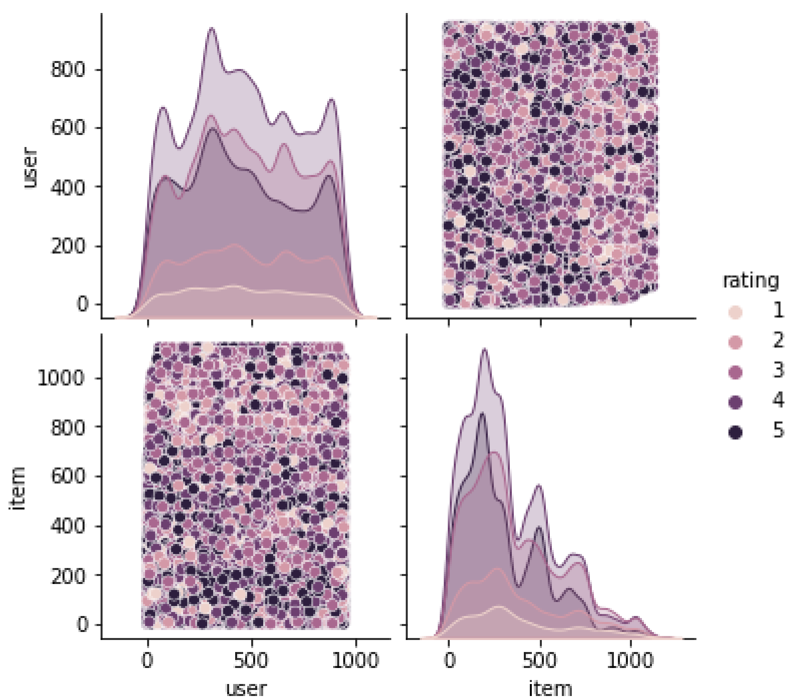


If we sort out the movie which is lack of rating, we can find a more flat a smooth slope in the distribution.

In [20]:
```
sns.pairplot(df_top_k[['user','item', 'rating']], hue='rating')
```

Out[20]: <seaborn.axisgrid.PairGrid at 0x7f107738ef90>

Out[20]:

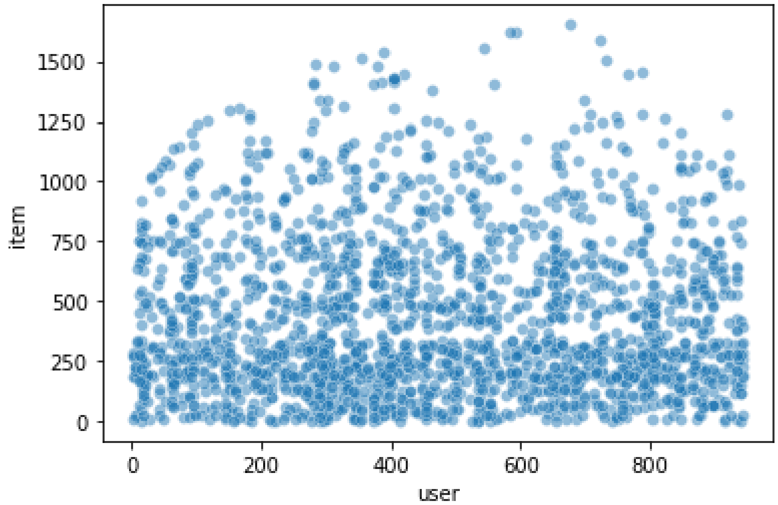


To get a idea of user-item relation, we using scatter plot here and sample some point stand for the distribution.

In [32]:
```
sns.scatterplot(x="user", y="item", data=df.sample(n=2000), alpha=0.5)
```

Out[32]: <AxesSubplot:xlabel='user', ylabel='item'>

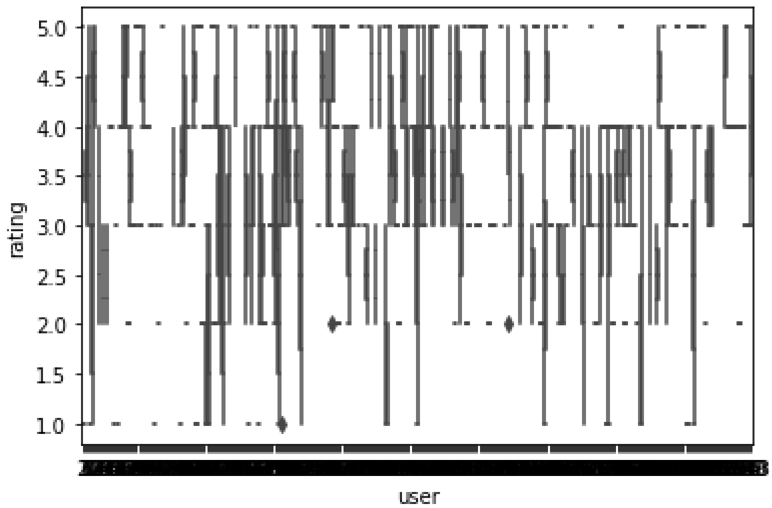
Out[32]:



In [18]:
```
sns.boxplot(x="user", y="rating", data=df.sample(n=500))
```

Out[18]: <AxesSubplot:xlabel='user', ylabel='rating'>

Out[18]:



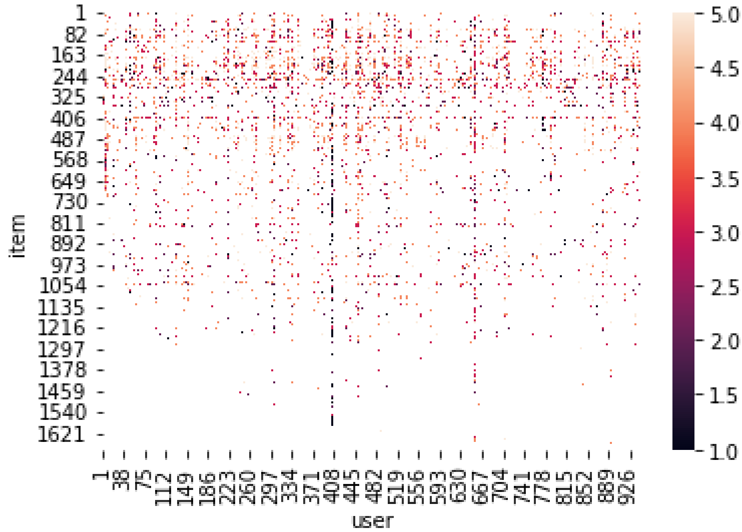
The heatmap also provide a interesting view of user-item relation.

In this figure we can see there are 2 users (408, 667) has rated a lots of movies on plots cause the 2 significant straight line. We can also learn from the line color that user 408 has a lots of rating though.
But the the user rated movie are mostly low rating (the straight line on user 408 basically black).

In [20]:
```
sns.heatmap(df.pivot_table(index="item", columns="user", values="rating"))
```

Out[20]: <AxesSubplot:xlabel='user', ylabel='item'>

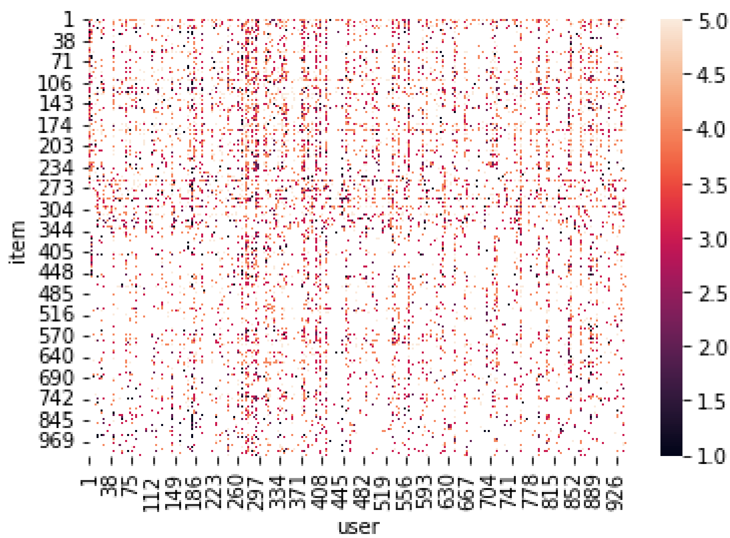
Out[20]:



In [19]:
```
sns.heatmap(df_top_k.pivot_table(index="item", columns="user", values="rating")
```

Out[19]: <AxesSubplot:xlabel='user', ylabel='item'>

Out[19]:



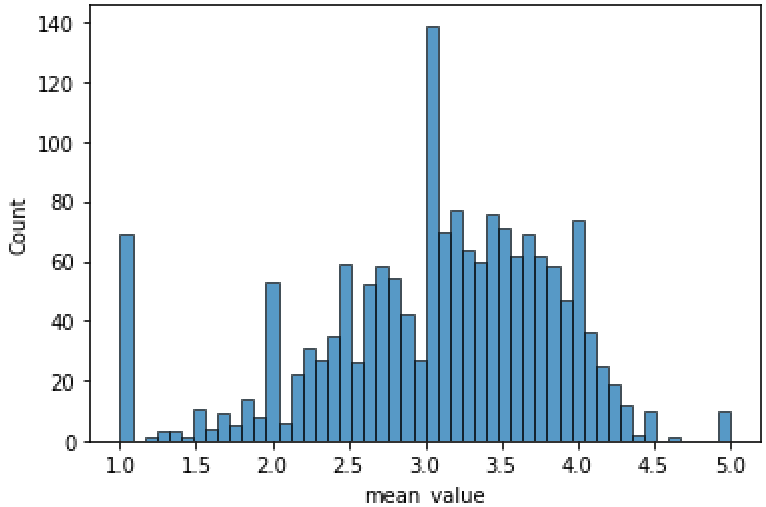
Average Rating Distribution

We can learn from this plot that the mean value 3.2 are the most movie rating belongs to.

In [29]:
```
sns.histplot(rate_count_and_mean['mean_value'], bins=50)
```

Out[29]: <AxesSubplot:xlabel='mean_value', ylabel='Count'>

Out[29]:

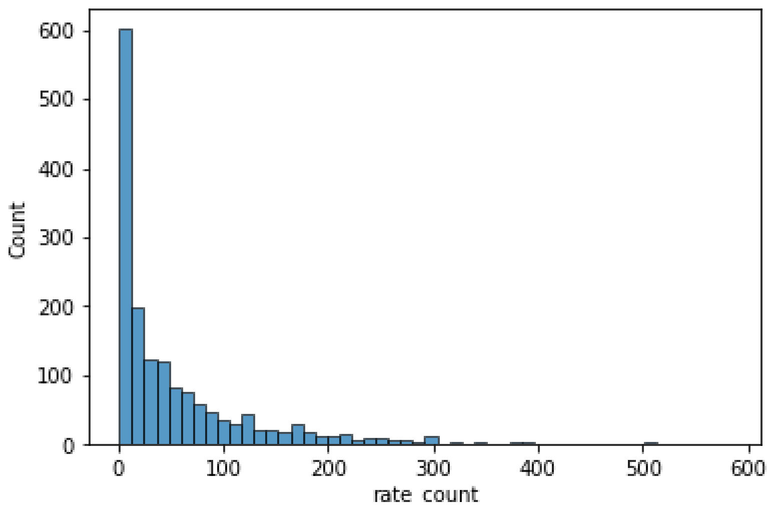


The rating count of the most of movies (above 70%) are less than 50.

In [30]:
```
sns.histplot(rate_count_and_mean['rate_count'], bins=50)
```

Out[30]: <AxesSubplot:xlabel='rate_count', ylabel='Count'>

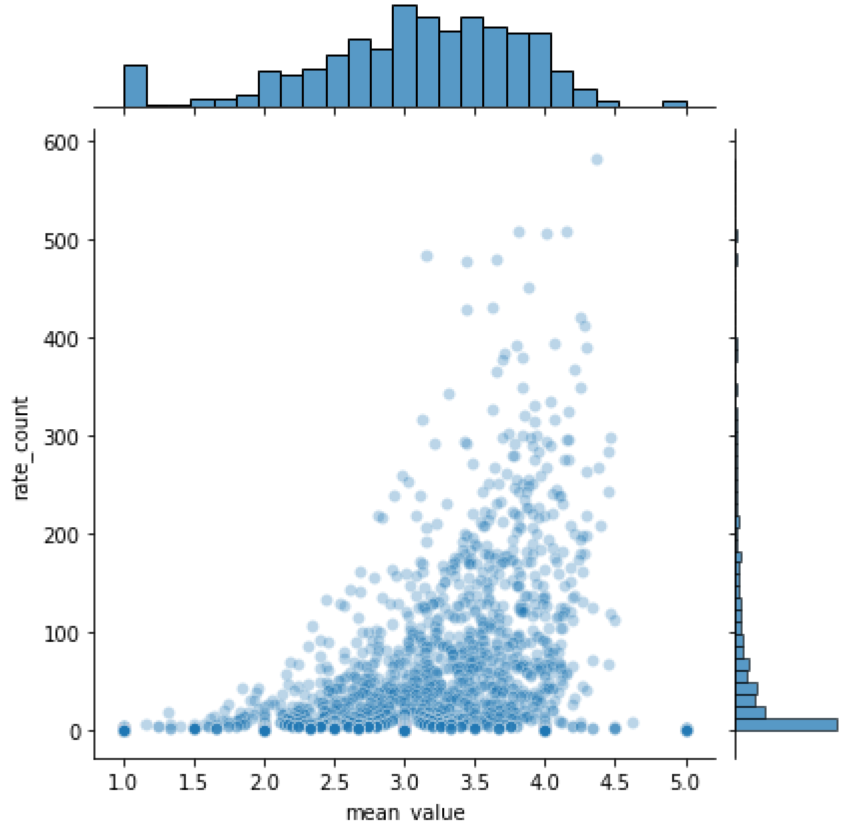
Out[30]:



In [34]:
```
sns.jointplot(x='mean_value',y='rate_count',data=rate_count_and_mean,alpha=0.3)
```

Out[34]: <seaborn.axisgrid.JointGrid at 0x7f3bc7c12dd0>

Out[34]:



User Info Distribution

In [26]:

```
col=["user_id","age","gender","occupation","zip"]
uin = pd.read_csv('ml-100k/u.user', delimiter="|", names=col)

uin
```

Out[26]:

	user_id	age	gender	occupation	zip
0	1	24	M	technician	85711
1	2	53	F	other	94043
2	3	23	M	writer	32067
3	4	24	M	technician	43537
4	5	33	F	other	15213
...	...	...	...	...	...
938	939	26	F	student	33319
939	940	32	M	administrator	02215
940	941	20	M	student	97229
941	942	48	F	librarian	78209
942	943	22	M	student	77841

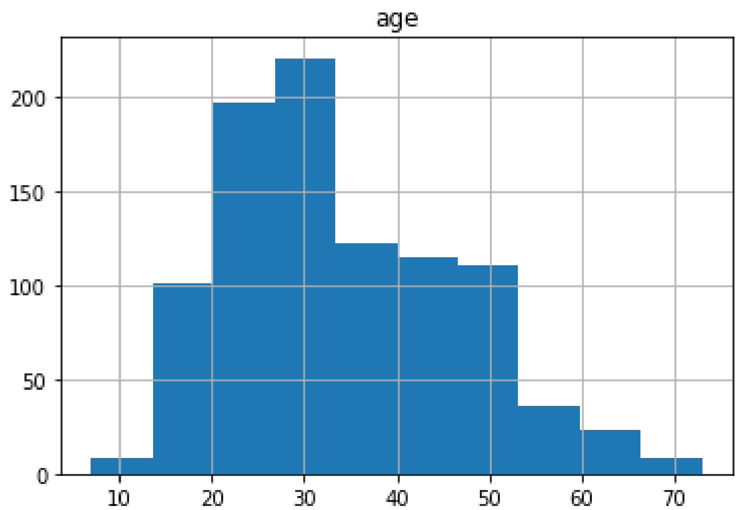
943 rows × 5 columns

Additional data analysis

In [87]:
```
uin.hist(column = "age")
#uin["age_category"] = pd.cut(uin["age"], bins = [0, 10, 20, 30, 40, 50, 60, 70
#uin["age_category"].hist()
```

Out[87]: `array([[<AxesSubplot:title={'center':'age'}>]], dtype=object)`

Out[87]:



In [69]:
```
occupation_count = uin[["user_id", "occupation"]].groupby("occupation", as_inde
uin.pie(occupation_count["size"], labels=occupation_count["occupation"])
uin.title("User's Occupation Distribution")
uin.axis("equal")
uin.show()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
/tmp/ipykernel_34916/2423833009.py in <module>
      1 occupation_count = uin[["user_id", "occupation"]].groupby("occupation"
, as_index=False).size()  # count the numbers
----> 2 uin.pie(occupation_count["size"], labels=occupation_count["occupation"
])
      3 uin.title("User's Occupation Distribution")
      4 uin.axis("equal")
      5 uin.show()

/opt/conda/lib/python3.7/site-packages/pandas/core/generic.py in __getattr__(s
elf, name)
   5485         ):
   5486             return self[name]
-> 5487         return object.__getattribute__(self, name)
   5488 
   5489     def __setattr__(self, name: str, value) -> None:

AttributeError: 'DataFrame' object has no attribute 'pie'
```

Evaluation Functions

A demo baseline model

The baseline model is if we guess all the rating is **3**

In [27]:
```
def baseline(user_id, movie_id):
    return 3.0
```

RSME & Accuracy

RMSE is Rooted Mean Square Error

Acc is 5-way classification accuracy.

In [28]:
```
def rmse(y_true,y_pred):
    return np.sqrt(mean_squared_error(y_true,y_pred))

def acc(y_true, y_pred):
    return np.sum(y_true == y_pred) / len(y_true)
```

Precision & Recall

We convert the 5-way classification problem to 2-way classification problem.
If the $\text{rating} >= 4$ we categorize it into **user like it**.
On the other hand, if the $\text{rating} < 4$ we categorize it into **user don't like it**.

Therefore, we can use it to calculate precision, recall and 2-way accuracy.
But there are another method that we can use macro precision & macro recall. Macro precision convert each rating to a binary classification problem and we would have 5 precision.
After that, we can average the 5 precision to get macro precision.

In [23]:
```
def precison_recall(y_true, y_pred):
    # size of prediction value array
    count = y_true.shape[0]

    binary_true = y_true >= 4
    binary_pred = y_pred >= 4


    TP = ( np.logical_and(binary_true, binary_pred)).sum()
    TN = ( np.logical_not( np.logical_or(binary_true, binary_pred))).sum()
    FN = (np.logical_and (binary_true ,(binary_pred == False) ) ).sum()
    FP = ( np.logical_and ((binary_true == False) ,binary_pred ) ).sum()


    return ((TP+TN)/ (count) ) ,(TP / (TP+FP)) , (TP / (TP+FN))


arr_1 = np.array([1,2,3,4,5,4,3])
arr_2 = np.array([2,3,5,3,5,1,2])
precison_recall(arr_1, arr_2)
```

Out[23]: (0.5714285714285714, 0.5, 0.3333333333333333)

Scoring a model

In [29]:
```
def predict(cf_model):
    #Construct a list of user-movie tuples from the testing dataset
    id_pairs = zip(rating_test['user'], rating_test['item'])

    #Predict the rating for every user-movie tuple
    y_pred = np.array([cf_model(user, movie) for (user, movie) in id_pairs])

    #Extract the actual ratings given by the users in the test data
    y_true = np.array(rating_test['rating'])

    return (y_true, y_pred)
```

In [32]:
```
#Function to compute the RMSE score obtained on the testing set by a model
def score(cf_model, eval_func = rmse):

    #Construct a list of user-movie tuples from the testing dataset
    id_pairs = zip(rating_test['user'], rating_test['item'])

    #Predict the rating for every user-movie tuple
    y_pred = np.array([cf_model(user, movie) for (user, movie) in id_pairs])

    #Extract the actual ratings given by the users in the test data
    y_true = np.array(rating_test['rating'])

    #Return the final RMSE score
    return eval_func(y_true, y_pred)

score(baseline)
```

Out[32]: 1.265036811170378

If we try to use dummy prediction by predicting all movie with 3 star.
We can get a RSME value with 1.26

The 5-way acc is .25 because of the data distribution.
We have more data on rating 3 and rating 4 which make the dummy model higher acc.

In [33]:
```
score(baseline, acc)
```

Out[33]: 0.25705196182396606

Recommender system with Pearson Similarity

We pandas `pivot_table()` to create User-Item Matrix.

In [34]:
```
matrix = df.pivot_table(index='user', columns='item', values='rating')
matrix
```

Out[34]:

item	1	2	3	4	5	6	7	8	9	10	...	1673	1674	1675	1676	1677
user																
1	5.0	3.0	4.0	3.0	3.0	5.0	4.0	1.0	5.0	3.0	...	NaN	NaN	NaN	NaN	NaN
2	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	2.0	...	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
5	4.0	3.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
939	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	5.0	NaN	...	NaN	NaN	NaN	NaN	NaN
940	NaN	NaN	NaN	2.0	NaN	NaN	4.0	5.0	3.0	NaN	...	NaN	NaN	NaN	NaN	NaN
941	5.0	NaN	NaN	NaN	NaN	NaN	4.0	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
942	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
943	NaN	5.0	NaN	NaN	NaN	NaN	NaN	NaN	3.0	NaN	...	NaN	NaN	NaN	NaN	NaN

943 rows × 1682 columns

Convert the movie id to movie name

In [31]:

```
matrix_with_name = merged_df.pivot_table(index= 'user', columns='name', values=
matrix_with_name
```

Out[31]:

name	'Til There Was You (1997)	1-900 (1994)	101 Dalmatians (1996)	12 Angry Men (1957)	187 (1997)	2 Days in the Valley (1996)	20,000 Leagues Under the Sea (1954)	2001: A Space Odyssey (1968)	3 Ninjas: High Noon At Mega Mountain (1998)	39 Steps, The (1935)	...
user											
1	NaN	NaN	2.0	5.0	NaN	NaN	3.0	4.0	NaN	NaN	...
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	...
3	NaN	NaN	NaN	NaN	2.0	NaN	NaN	NaN	NaN	NaN	...
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
5	NaN	NaN	2.0	NaN	NaN	NaN	NaN	4.0	NaN	NaN	...
...	...	...	...	...	...	...	...	...	...	...	...
939	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
940	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
941	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
942	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.0	NaN	3.0	...
943	NaN	NaN	NaN	NaN	NaN	2.0	NaN	NaN	NaN	NaN	...

943 rows × 1664 columns

Trying to Get Similiarty of "Star Wars (1997)"

Get the user and rating with movie "Star Wars (1997)"

In [27]:
```
matrix_with_name['Star Wars (1977)']
```

Out[27]:
```
user
1      5.0
2      5.0
3      NaN
4      5.0
5      4.0
      ...
939    NaN
940    4.0
941    NaN
942    5.0
943    4.0
Name: Star Wars (1977), Length: 943, dtype: float64
```

Using `corrwith` to calculate the similarity score.

In [28]:
```
# default correlation method is  pearson
# so we don't need to assign method here actually
similarity_starWars = matrix_with_name.corrwith(matrix_with_name['Star Wars (19
```

```
/opt/conda/lib/python3.7/site-packages/numpy/lib/function_base.py:2683: Runtim
eWarning: Degrees of freedom <= 0 for slice
  c = cov(x, y, rowvar, dtype=dtype)
/opt/conda/lib/python3.7/site-packages/numpy/lib/function_base.py:2542: Runtim
eWarning: divide by zero encountered in true_divide
  c *= np.true_divide(1, fact)
```

This is the item-item Pearson similarity

In [29]:
```
similarity_starWars
```

Out[29]:
```
name
'Til There Was You (1997)                0.872872
1-900 (1994)                            -0.645497
101 Dalmatians (1996)                    0.211132
12 Angry Men (1957)                      0.184289
187 (1997)                               0.027398
                                           ...
Young Guns II (1990)                     0.228615
Young Poisoner's Handbook, The (1995)   -0.007374
Zeus and Roxanne (1997)                  0.818182
unknown                                  0.723123
Á köldum klaka (Cold Fever) (1994)            NaN
Length: 1664, dtype: float64
```

In [30]:
```
corr_starWars = pd.DataFrame(similarity_starWars, columns=['corr'])
corr_starWars
```

Out[30]:

name	corr
'Til There Was You (1997)	0.872872
1-900 (1994)	-0.645497
101 Dalmatians (1996)	0.211132
12 Angry Men (1957)	0.184289
187 (1997)	0.027398
...	...
Young Guns II (1990)	0.228615
Young Poisoner's Handbook, The (1995)	-0.007374
Zeus and Roxanne (1997)	0.818182
unknown	0.723123
Á köldum klaka (Cold Fever) (1994)	NaN

1664 rows × 1 columns

Drop NA

In [31]:
```
corr_starWars = corr_starWars.dropna()
corr_starWars
```

Out[31]:

name	corr
'Til There Was You (1997)	0.872872
1-900 (1994)	-0.645497
101 Dalmatians (1996)	0.211132
12 Angry Men (1957)	0.184289
187 (1997)	0.027398
...	...
Young Guns (1988)	0.186377
Young Guns II (1990)	0.228615
Young Poisoner's Handbook, The (1995)	-0.007374
Zeus and Roxanne (1997)	0.818182
unknown	0.723123

1410 rows × 1 columns

In [51]:
```
corr_starWars_count = corr_starWars.join(rate_count_and_mean['rate_count'])
corr_starWars_count
```

Out[51]:

name	corr	rate_count
'Til There Was You (1997)	0.872872	9
1-900 (1994)	-0.645497	5
101 Dalmatians (1996)	0.211132	109
12 Angry Men (1957)	0.184289	125
187 (1997)	0.027398	41
...	...	...
Young Guns (1988)	0.186377	101
Young Guns II (1990)	0.228615	44
Young Poisoner's Handbook, The (1995)	-0.007374	41
Zeus and Roxanne (1997)	0.818182	6
unknown	0.723123	9

1410 rows × 2 columns

There are a lot of movies come with correlation 1.
But the rate count is too low to losing accuracy for recommender system.

In [53]:
```
corr_starWars_count.sort_values('corr', ascending=False)
```

Out[53]:

name	corr	rate_count
Hollow Reed (1996)	1.0	6
Commandments (1997)	1.0	3
Cosi (1996)	1.0	4
No Escape (1994)	1.0	5
Stripes (1981)	1.0	5
...	...	...
Roseanna's Grave (For Roseanna) (1997)	-1.0	5
For Ever Mozart (1996)	-1.0	3
American Dream (1990)	-1.0	2
Frankie Starlight (1995)	-1.0	4
Fille seule, La (A Single Girl) (1995)	-1.0	4

1410 rows × 2 columns

> `[TODO] This description need to be complete`

We can filter out some

And we can recommend these movie to people who likes "Star Wars (1977)"

In [54]:
```
corr_starWars_count[corr_starWars_count['rate_count'] > 100].sort_values('corr'
```

Out[54]:

name	corr	rate_count
Star Wars (1977)	1.000000	583
Empire Strikes Back, The (1980)	0.747981	367
Return of the Jedi (1983)	0.672556	507
Raiders of the Lost Ark (1981)	0.536117	420
Austin Powers: International Man of Mystery (1997)	0.377433	130
...	...	...
Edge, The (1997)	-0.127167	113
As Good As It Gets (1997)	-0.130466	112
Crash (1996)	-0.148507	128
G.I. Jane (1997)	-0.176734	175
First Wives Club, The (1996)	-0.194496	160

334 rows × 2 columns

A simple similarity function with item-item prediction

In [40]:
```
def get_similarity_of_movie(matrix, movie, rate_count_threshold=  100, count_df

    # get item-item similarity matrix by corrwith
    similarity_matrix = matrix.corrwith(matrix[movie])

    # convert the similarity matrix to DataFrame
    corr = pd.DataFrame(similarity_matrix, columns=['corr'])

    # Drop Nan in the DataFrame
    corr.dropna(inplace=True)

    # Join the rate_count into the DataFrame
    corr_with_count = corr.join(count_df['rate_count'])

    # Filter out the movies which has low rate count by rate_count_threshold
    similarity = corr_with_count[corr_with_count['rate_count'] > rate_count_thr

    return similarity
```

We can recommend these movie to people who likes "As Good As It Gets (1997)" with filter out low `rate_count` outliers.

In [95]:
```
get_similarity_of_movie(matrix_with_name, "As Good As It Gets (1997)").head(5)
```

```
/opt/conda/lib/python3.7/site-packages/numpy/lib/function_base.py:2683: Runtim
eWarning: Degrees of freedom <= 0 for slice
  c = cov(x, y, rowvar, dtype=dtype)
/opt/conda/lib/python3.7/site-packages/numpy/lib/function_base.py:2542: Runtim
eWarning: divide by zero encountered in true_divide
  c *= np.true_divide(1, fact)
```

Out[95]:

name	corr	rate_count
As Good As It Gets (1997)	1.000000	112
Apt Pupil (1998)	0.701931	160
Mask, The (1994)	0.618215	129
Batman Forever (1995)	0.587782	114
Glory (1989)	0.533915	171

Build the model

In [36]:
```
matrix_train = rating_train.pivot_table(index='user', columns='item', values='r
matrix_train
```

Out[36]:

item / user	1	2	3	4	5	6	7	8	9	10	...	1673	1674	1675	1676	1677
1	5.0	3.0	4.0	3.0	3.0	5.0	4.0	1.0	5.0	3.0	...	NaN	NaN	NaN	NaN	NaN
2	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	2.0	...	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
939	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	5.0	NaN	...	NaN	NaN	NaN	NaN	NaN
940	NaN	NaN	NaN	2.0	NaN	NaN	4.0	5.0	3.0	NaN	...	NaN	NaN	NaN	NaN	NaN
941	5.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
942	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
943	NaN	5.0	NaN	NaN	NaN	NaN	NaN	NaN	3.0	NaN	...	NaN	NaN	NaN	NaN	NaN

943 rows × 1680 columns

In [149…
```
get_similarity_of_movie(matrix_train, 30, 100, movie_id_count)
```

```
/opt/conda/lib/python3.7/site-packages/numpy/lib/function_base.py:2683: Runtim
eWarning: Degrees of freedom <= 0 for slice
  c = cov(x, y, rowvar, dtype=dtype)
/opt/conda/lib/python3.7/site-packages/numpy/lib/function_base.py:2542: Runtim
eWarning: divide by zero encountered in true_divide
  c *= np.true_divide(1, fact)
```

Out[149]:

item	corr	rate_count
260	1.000000	127
678	0.870388	219
303	0.851469	134
747	0.834784	102
510	0.793116	121
...	...	...
1047	-0.973329	134
326	-1.000000	175
815	-1.000000	112
926	-1.000000	101
1028	-1.000000	148

326 rows × 2 columns

Experiemnts & Evaluation

In [38]:
```
# hash table to cache our get_similarity_of_movie function
pearson_movie = {}
```

In [41]:
```
def pearson_wrapper(top_n = 30):
    def pearson_corr_model(user, item, threshold=100):

        # default value if the item is not in our train data
        if item not in matrix_train :
            return 3

        # if the item is in our hash table, we directly use the value
        #     to accelerate the algorithm
        if item in pearson_movie:
            rank_list = pearson_movie[item]
        else:

            # get filtered item-item similarity
            sim = get_similarity_of_movie(matrix_train, item, threshold, movie_

            # convert the result to a list
            rank_list = sim['corr'].keys().to_list()

            # add the item into hash table (for future use)
            pearson_movie[item] = rank_list


        iter = 0
        while iter < len(rank_list):

            # only use top_k result
```

```
            pred_movie = rank_list[iter: iter+top_n]

            # find the rate of this user with similar movie
            pred_rate = matrix_train.loc[user][pred_movie]

            # calculate the means of the rate with all similar movies
            avg = np.nanmean(pred_rate.values)

            # if the result is not nan, we round the value
            if( not np.isnan(avg)):
                rounded_avg = np.round(avg)
                return rounded_avg

            else:
                # next try if all the result is nan(not found).
                iter+=top_n
        return 3
    return pearson_corr_model
print(pearson_wrapper(30)(1, 30))
print(pearson_wrapper(30)(1,1582))
```

```
/opt/conda/lib/python3.7/site-packages/numpy/lib/function_base.py:2683: RuntimeWarning: Degrees of freedom <= 0 for slice
  c = cov(x, y, rowvar, dtype=dtype)
/opt/conda/lib/python3.7/site-packages/numpy/lib/function_base.py:2542: RuntimeWarning: divide by zero encountered in true_divide
  c *= np.true_divide(1, fact)
4.0
3
```

We can get the result of following experiments that

if we increase the k value of top_k,

the RMSE can slowing drop down but the acc is not increasing so much.

In [100…

```
score(pearson_wrapper(30)), score(pearson_wrapper(30), acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:18: RuntimeWarning: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:18: RuntimeWarning: Mean of empty slice
```

Out[100]:

```
(1.1735418289000843, 0.37147401908801697)
```

In [126…

```
score(pearson_wrapper(100)), score(pearson_wrapper(100), acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:18: RuntimeWarning: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:18: RuntimeWarning: Mean of empty slice
```

Out[126]:

```
(1.0987315543989922, 0.37857900318133614)
```

In [74]:

```
score(pearson_corr_model, acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:17: RuntimeWarning: Mean of empty slice
  app.launch_new_instance()
```

Out[74]: 0.37571580063626725

In [42]:
```
n_candidate = [2, 6, 10, 20, 30, 60, 100, 200]

item_pearson_rsme = []
item_pearson_acc = []
item_pearson_time = []
item_pearson_bin_acc = []
item_pearson_bin_precision = []
item_pearson_bin_recall = []
for n in n_candidate:

        s = time.time()

        # get RMSE
        item_pearson_rsme.append(score(pearson_wrapper(n)))
        e = time.time()

        # get 5-way Acc
        item_pearson_acc.append(score(pearson_wrapper(n), acc))
        item_pearson_time.append(e-s)

        # get binary acc & precision & recall
        APR = score(pearson_wrapper(n), precison_recall)
        item_pearson_bin_acc.append(APR[0])
        item_pearson_bin_precision.append(APR[1])
        item_pearson_bin_recall.append(APR[2])

print(item_pearson_rsme)
print(item_pearson_acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:34: RuntimeWarnin
g: Mean of empty slice
[1.3494038587928865, 1.3041657702568528, 1.2727672109528814, 1.213960853734933
3, 1.1735418289000843, 1.1223177049093167, 1.0987315543989922, 1.0847443023517
678]
[0.34432661717921526, 0.35365853658536583, 0.3604453870625663, 0.3646871686108
1657, 0.37147401908801697, 0.37688229056203604, 0.37857900318133614, 0.3774125
1325556735]
```

Recommender system with Jaccard Distance

Constuct Jaccard similarity matrix

A simple data matrix rather than DataFrame

In [50]:
```
# data matrix using train data
data_matrix = np.zeros((n_users, n_items))
for row in rating_train.itertuples():
    data_matrix[row[1]-1, row[2]-1] = row[3]

data_matrix
```

Out[50]:
```
array([[5., 3., 4., ..., 0., 0., 0.],
       [4., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [5., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 5., 0., ..., 0., 0., 0.]])
```

After we get pairwise distance, we can use $\text{similarity} = 1 - \text{distance}$

In [51]:
```
user_similiarty = 1- pairwise_distances(data_matrix, metric='jaccard')
item_similarity = 1- pairwise_distances(data_matrix.T, metric='jaccard')
user_similiarty.shape, item_similarity.shape
```

```
/opt/conda/lib/python3.7/site-packages/sklearn/metrics/pairwise.py:1875: DataC
onversionWarning: Data was converted to boolean for metric jaccard
  warnings.warn(msg, DataConversionWarning)
/opt/conda/lib/python3.7/site-packages/sklearn/metrics/pairwise.py:1875: DataC
onversionWarning: Data was converted to boolean for metric jaccard
  warnings.warn(msg, DataConversionWarning)
```

Out[51]:
```
((943, 943), (1682, 1682))
```

In [52]:
```
def get_top_k_movies( movie_idx,k=6):
    # using the item_similarity matrix to build the similiraty rank with sortin
    return [idx_to_movie[x] for x in np.argsort(item_similarity[movie_idx, :])[
```

In [53]:
```
def get_top_k_user( user_idx,k=6):
    return [x for x in np.argsort(user_similiarty[user_idx, :])[-2:-k-2:-1]]

get_top_k_user(1)
```

Out[53]:
```
[459, 930, 412, 734, 568, 767]
```

Similar movie with "Batman Forever (1995)"

In [42]:
```
get_top_k_movies( movie_to_idx["Batman Forever (1995)"])
```

Out[42]:
```
['Batman Returns (1992)',
 'Batman (1989)',
 'Die Hard: With a Vengeance (1995)',
 'Stargate (1994)',
 'Cliffhanger (1993)',
 'Crow, The (1994)']
```

Similar movie with "Star Wars (1977)"

In [43]:
```
get_top_k_movies( movie_to_idx["Star Wars (1977)"])
```

Out[43]:
```
['Return of the Jedi (1983)',
 'Raiders of the Lost Ark (1981)',
 'Empire Strikes Back, The (1980)',
 'Independence Day (ID4) (1996)',
 'Silence of the Lambs, The (1991)',
 'Toy Story (1995)']
```

Item-based Prediction model

In [54]:
```
def jaccard_wrapper(top_k=6):
    def jaccard_model(user, item):

        # Note: top_k without filter out low rate count movie
        top_k_movie_name =  get_top_k_movies(item, k=top_k)

        # Convert the names to IDs
        top_k_movie_id = [(movie_to_idx[i]+1) for i in top_k_movie_name]

        # Get rate of similar movie with specific user
        pred_rate = matrix_train.loc[user][top_k_movie_id]

        # get mean value of the prediciton rate list
        avg = np.nanmean(pred_rate.values)

        # if not nan, we round the value and return.
        if( not np.isnan(avg)):
            rounded_avg = np.round(avg)

            return rounded_avg
        else:

            # we return the default value if all the similar movies are not ava
            return 3
    return jaccard_model

print(jaccard_wrapper(6)(1, 30))
```

```
4.0
```

User-based Preditciton model

Similar the item-based Jaccard, but we find the similar user in this model

In [55]:
```
def jaccard_wrapper_user(top_k=6):
    def jaccard_model(user, item):

        # get top-k similar user by this user id
        top_k_similar_user = get_top_k_user(user-1, k=top_k)

        rating_lst = []
        for u in top_k_similar_user:
            if item not in matrix_train:
                continue

            # get rating of similar user in this movie
            rating_lst.append(matrix_train.loc[u+1][item])

        # average and ignore the nan
        avg = np.nanmean(np.array(rating_lst))

        # if we has at least one valid value, we return it.
        if(not np.isnan(avg)):
            return avg
        else:

            # otherwise, we use the default value.
            return 3

    return jaccard_model

print(jaccard_wrapper_user(1)(1, 30))
```

```
4.0
```

Evaluate

RSME & Acc on Item-based model

In this experiment, we can see as the k value increase, the RMSE climp up faster than Pearson. The Acc also has a significant improvement.

In [49]:
```
score(jaccard_wrapper(6)), score(jaccard_wrapper(6), acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:8: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:8: RuntimeWarnin
g: Mean of empty slice
```

Out[49]:
```
(1.2611748633933135, 0.30498409331919407)
```

In [123…
```
score(jaccard_wrapper(30)), score(jaccard_wrapper(30), acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:8: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:8: RuntimeWarnin
g: Mean of empty slice
```

Out[123]: (1.2026393738002403, 0.33902439024390246)

In [124…
```
score(jaccard_wrapper(100)), score(jaccard_wrapper(100), acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:8: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:8: RuntimeWarnin
g: Mean of empty slice
```

Out[124]: (1.1539043409207534, 0.3548250265111347)

In [56]:
```
score(jaccard_wrapper(200)), score(jaccard_wrapper(200), acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice
```

Out[56]: (1.1204263693811682, 0.3645811240721103)

Precision & Recall

From left to right is 2-way ACC, Precision, Recall.
We can found the acc is close to 50% which means only slightly better than random.
Higher precision means if we recommend it to user, the user usually like it.

In [57]:
```
score( jaccard_wrapper(6), precison_recall)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice
```

Out[57]: (0.5255567338282079, 0.6674520363513968, 0.3625891387822271)

Different n value on Item-based model

In [61]:
```
n_candidate = [2, 6, 10, 20, 30, 60, 100, 200]

item_jaccard_rsme = []
item_jaccard_acc = []
item_jaccard_time = []
item_jaccard_bin_acc = []
item_jaccard_bin_precision = []
item_jaccard_bin_recall = []
```

```
for n in n_candidate:

        s = time.time()

        # Jaccard RMSE
        item_jaccard_rsme.append(score(jaccard_wrapper(n)))
        e = time.time()

        item_jaccard_time.append(e-s)

        # 5-way acc
        item_jaccard_acc.append(score(jaccard_wrapper(n), acc))

        APR = (score(jaccard_wrapper(n), precison_recall))
        item_jaccard_bin_acc.append(APR[0])
        item_jaccard_bin_precision.append(APR[1])
        item_jaccard_bin_recall.append(APR[2])


print(item_jaccard_rsme)
print(item_jaccard_acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:14: RuntimeWarnin
g: Mean of empty slice
```

```
[1.2774245032924165, 1.2611748633933135, 1.2482862058637574, 1.22210117549199
6, 1.2026393738002403, 1.1792209445456534, 1.1539043409207534, 1.1204263693811
682]
[0.2846235418875928, 0.30498409331919407, 0.31208907741251324, 0.3234358430540
8274, 0.33902439024390246, 0.34517497348886533, 0.3548250265111347, 0.36458112
40721103]
```

RSME & Acc on User-based model

In [115…

```
score(jaccard_wrapper_user(60), acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:11: RuntimeWarnin
g: Mean of empty slice
  # This is added back by InteractiveShellApp.init_path()
```

Out[115]: 0.041675503711558856

Different n value on User-based model

In [86]:

```
user_jaccard_rsme = []
user_jaccard_acc = []
user_jaccard_time = []
user_jaccard_bin_acc = []
user_jaccard_bin_precision = []
user_jaccard_bin_recall = []

for n in n_candidate:
        s = time.time()
        user_jaccard_rsme.append(score(jaccard_wrapper_user(n)))
        e = time.time()

        user_jaccard_time.append(e-s)
        user_jaccard_acc.append(score(jaccard_wrapper_user(n), acc))

        APR = score(jaccard_wrapper_user(n), precison_recall)
        user_jaccard_bin_acc.append(APR[0])
        user_jaccard_bin_precision.append(APR[1])
        user_jaccard_bin_recall.append(APR[2])
print(user_jaccard_rsme)
print(user_jaccard_acc)
```

```
/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice

/opt/conda/lib/python3.7/site-packages/ipykernel_launcher.py:16: RuntimeWarnin
g: Mean of empty slice
```

```
[1.2733607139979388, 1.2218761493614894, 1.1745934114832617, 1.12839411685313
5, 1.100852518600647, 1.0700941422747379, 1.0521478872281276, 1.04005904769755
9]
[0.26373276776246024, 0.18748674443266172, 0.15196182396606575, 0.095227995758
21846, 0.06638388123011665, 0.041675503711558856, 0.02523860021208908, 0.01325
5567338282079]
```

dont use theses code (archive)

In [102…

```
mean_user_rating = data_matrix.mean(axis=1)
ratings_diff = (data_matrix - mean_user_rating[:, np.newaxis])
user_prediction = mean_user_rating[:, np.newaxis] + user_similiarty.dot(ratings
user_prediction
```

Out[102]:

```
array([[ 2.8360986 ,  1.14826266,  0.75706513, ...,  0.22532653,
          0.23281372,  0.2342726 ],
       [ 1.79489353,  0.21620436,  0.22828517, ..., -0.0468558 ,
         -0.04823227, -0.04866321],
       [ 1.10393363,  0.14131886,  0.11742525, ..., -0.05953609,
         -0.0667685 , -0.06799626],
       ...,
       [ 2.13224313,  0.17247838,  0.18682421, ..., -0.12258099,
         -0.12120784, -0.12154515],
       [ 1.88614148,  0.45625484,  0.21142362, ..., -0.05340203,
         -0.0521901 , -0.05339001],
       [ 2.60883409,  1.00418958,  0.5134546 , ..., -0.01202162,
         -0.00339989, -0.00370369]])
```

In [103…

```
item_prediction = data_matrix.dot(item_similarity) / np.array([np.abs(item_simi
```

```
item_prediction
item_prediction
```

Out[103]:
```
array([[1.62626389, 1.31606996, 1.20451096, ..., 0.03303748, 0.48350547,
        0.85628354],
       [0.38918258, 0.16190246, 0.22939773, ..., 0.07326208, 0.05310421,
        0.05897618],
       [0.13916325, 0.08279034, 0.10177364, ..., 0.2078829 , 0.06405121,
        0.01304979],
       ...,
       [0.23537419, 0.09644818, 0.12480265, ..., 0.00379743, 0.03639585,
        0.0413716 ],
       [0.53390786, 0.36510641, 0.28980048, ..., 0.06959699, 0.12691711,
        0.09855896],
       [1.04273959, 0.96721947, 0.77982691, ..., 0.        , 0.40452521,
        0.48079158]])
```

Cosine Similarity exmaple

This is just a example to calculate cosine similarity. Without actually recommend or predict the rating.

In [55]:
```
cosine_data_matrix = rating_train.pivot_table(values='rating', index='user', co
cosine_data_matrix = cosine_data_matrix.fillna(0)


cosine_sim = cosine_similarity(cosine_data_matrix, cosine_data_matrix)
cosine_sim = pd.DataFrame(cosine_sim, index=cosine_data_matrix.index, columns=c

cosine_sim.head(10)
```

Out[55]:

user	1	2	3	4	5	6	7	8	9	
user										
1	1.000000	0.146751	0.050677	0.051298	0.364836	0.412213	0.438001	0.295494	0.082464	0.
2	0.146751	1.000000	0.125808	0.117674	0.049376	0.223628	0.102842	0.086079	0.095941	0.
3	0.050677	0.125808	1.000000	0.236743	0.023378	0.072965	0.062271	0.073452	0.000000	0.
4	0.051298	0.117674	0.236743	1.000000	0.013061	0.000000	0.050802	0.154807	0.000000	0.
5	0.364836	0.049376	0.023378	0.013061	1.000000	0.232726	0.361290	0.226670	0.079715	0.
6	0.412213	0.223628	0.072965	0.000000	0.232726	1.000000	0.471841	0.153504	0.106562	0.
7	0.438001	0.102842	0.062271	0.050802	0.361290	0.471841	1.000000	0.258756	0.115554	0.
8	0.295494	0.086079	0.073452	0.154807	0.226670	0.153504	0.258756	1.000000	0.028528	0.
9	0.082464	0.095941	0.000000	0.000000	0.079715	0.106562	0.115554	0.028528	1.000000	0.
10	0.361966	0.122703	0.053468	0.017130	0.188558	0.517427	0.460518	0.197634	0.160829	1.

10 rows × 943 columns

Using KNN

Using Suprise to quickly build recommender systems

In [72]:
```
#Define a Reader object
#The Reader object helps in parsing the file or dataframe containing ratings
reader = Reader(rating_scale=(1, 5))

#Create the dataset to be used for building the filter
data = Dataset.load_from_df(rating_train[['user', 'item','rating']], reader)


trainset = data.build_full_trainset()
```

In [73]:
```
test_data = Dataset.load_from_df( rating_test[['user', 'item', 'rating']], reac
testset = data.build_full_trainset()
testset = testset.build_testset()
```

In [74]:
```
#Define the algorithm object; in this case kNN
knn = KNNBasic(40)

knn.fit(trainset)

knn_preds = knn.test(testset)
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
```

Evaluate

In [77]:
```
def surprise_acc(preds):
    y_true = []
    y_pred = []
    for p in preds:
    #     print(p.r_ui, p.est)
        y_true.append(int(p.r_ui))
        y_pred.append(round(p.est))

    five_way_acc = np.sum(np.array(y_true) == np.array(y_pred))/len(y_true)
    APR = precison_recall(np.array(y_true), np.array(y_pred))
    return five_way_acc, (*APR)
```

In [78]:
```
accuracy.rmse(knn_preds), surprise_acc(knn_preds)
```

```
RMSE: 0.7756
```

Out[78]:
```
(0.7756329024479189,
 (0.5035994258584521,
  0.8006955945677376,
  0.7975378752498552,
  0.8554682803670901))
```

In [79]:
```
knn = KNNBasic(100)
knn.fit(trainset)
```

```
knn_preds = knn.test(testset)
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
```

In [80]:
```
accuracy.rmse(knn_preds), surprise_acc(knn_preds)
```

```
RMSE: 0.8591
```

Out[80]:
```
(0.8590553243965482,
 (0.4486364138235619,
  0.7538147289389423,
  0.7573881751906475,
  0.8139502264256803))
```

In [81]:
```
knn = KNNBasic(6)
knn.fit(trainset)
knn_preds = knn.test(testset)
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
```

When the K value reduced, we can see the RMSE drop very fast and both 5-way acc and 2-way acc increase.

In [82]:
```
accuracy.rmse(knn_preds), surprise_acc(knn_preds)
```

```
RMSE: 0.5197
```

Out[82]:
```
(0.5197296838987472,
 (0.6992712818814177,
  0.9034669316550734,
  0.8952432162541049,
  0.9341161383400793))
```

Different n value

In [83]:
```
knn_rmse = []
knn_acc = []
knn_time = []
knn_bin_acc = []
knn_bin_precision = []
knn_bin_recall = []

for n in n_candidate:
    knn = KNNBasic(n)
    knn.fit(trainset)

    s = time.time()
    knn_preds = knn.test(testset)
    e = time.time()
    knn_time.append(e-s)

    knn_rmse.append(accuracy.rmse(knn_preds))

    AAPR = surprise_acc(knn_preds)
    knn_acc.append(AAPR[0])
```

```
    knn_bin_acc.append(AAPR[1])
    knn_bin_precision.append(AAPR[2])
    knn_bin_recall.append(AAPR[3])

print(knn_rmse)
print(knn_acc)
print(knn_time)
print(knn_bin_acc)
print(knn_bin_precision)
print(knn_bin_recall)
```

```
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.2992
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.5197
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.6015
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.6961
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.7442
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.8155
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.8591
Computing the msd similarity matrix...
Done computing similarity matrix.
RMSE: 0.9014
[0.29922934539168833, 0.5197296838987472, 0.6015271940551333, 0.69614625839576
73, 0.7441603983744497, 0.815535133704138, 0.8590553243965482, 0.9014215120794
002]
[0.9283979242574804, 0.6992712818814177, 0.6298222369438004, 0.558065584630672
5, 0.5245114276250414, 0.4775532737109418, 0.4486364138235619, 0.4221596555150
7123]
[5.282635927200317, 5.951030015945435, 6.437473297119141, 7.4347968101501465,
8.134795188903809, 10.001776933670044, 11.178170442581177, 11.492582321166992]
[0.9827647123771668, 0.9034669316550734, 0.8741857127084024, 0.836314452909351
9, 0.8154797394280667, 0.7797173456994589, 0.7538147289389423, 0.7291376835596
776]
[0.9826295297993412, 0.8952432162541049, 0.8649570705634844, 0.828615321205762
8, 0.8098999178430054, 0.7804407661916977, 0.7573881751906475, 0.7361426497412
799]
[0.9861539694625897, 0.9341161383400793, 0.9144391455937162, 0.886246142748366
9, 0.8691339718671102, 0.8351901574960926, 0.8139502264256803, 0.7924898809762
353]
```

Summary

How N value impact the prediction performance

In [79]:
```
print(n_candidate)
item_jaccard_rsme, item_jaccard_acc
```

```
[2, 6, 10, 20, 30, 60, 100, 200]
```

Out[79]:
```
([1.2774245032924165,
  1.2611748633933135,
  1.2482862058637574,
  1.222101175491996,
  1.2026393738002403,
  1.1792209445456534,
  1.1539043409207534,
  1.1204263693811682],
 [0.2846235418875928,
  0.30498409331919407,
  0.31208907741251324,
  0.32343584305408274,
  0.33902439024390246,
  0.34517497348886533,
  0.3548250265111347,
  0.3645811240721103,
  0.26373276776246024,
  0.18748674443266172,
  0.15196182396606575,
  0.09522799575821846,
  0.06638388123011665,
  0.041675503711558856,
  0.02523860021208908,
  0.013255567338282079])
```

RSME

As reference, our baseline model reach 1.2 RMSE.
Which means the similarity model with low K value might perform worse than baseline.
For example, Item-based Jaccard model need k value above 20 to get better result and user-based Jaccard model only need k value above 10.

It might caused by the movies and users amount are different so they perform really different on K value.
In general, the user-based Jaccard model performs the best in similarity model.

the KNN perform a little bit weird and has a really low RMSE seems to be impossible.
So we consider the **KNN part might has some calculate error in it**.

In [129…
```
sns_jaccard_rsem = pd.DataFrame(np.array([item_jaccard_rsme, user_jaccard_rsme,
sns_jaccard_rsem
```

Out[129]:

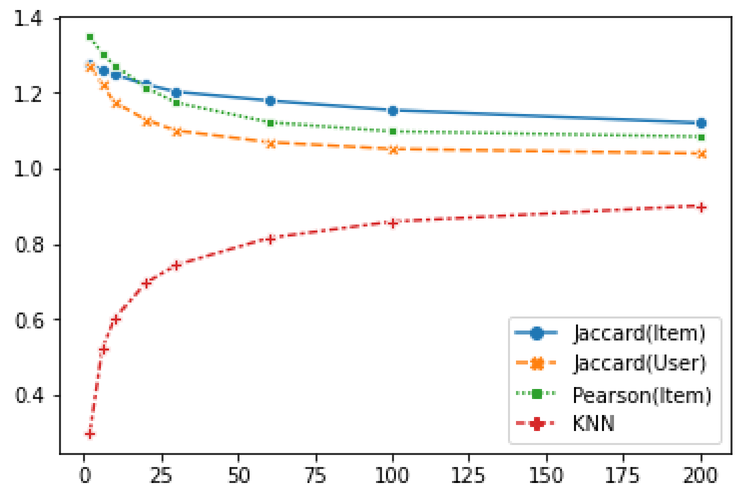
	Jaccard(Item)	Jaccard(User)	Pearson(Item)	KNN
2	1.277425	1.273361	1.349404	0.299229
6	1.261175	1.221876	1.304166	0.519730
10	1.248286	1.174593	1.272767	0.601527
20	1.222101	1.128394	1.213961	0.696146
30	1.202639	1.100853	1.173542	0.744160
60	1.179221	1.070094	1.122318	0.815535
100	1.153904	1.052148	1.098732	0.859055
200	1.120426	1.040059	1.084744	0.901422

In [130…

```
sns.lineplot(sns_jaccard_rsem, markers=True)
```

Out[130]: <AxesSubplot:>

Out[130]:



Rating Prediction Accuracy

The five-way classification acc is around 35% for item-based model.
The user-based model performs really bad for higher k might caused by the diversity of similar user.

As we said in last part, the KNN part might be lack of confidence, so we don't take the KNN acc in account.

In [131…

```
sns_acc = pd.DataFrame(np.array([item_jaccard_acc, user_jaccard_acc,item_pearso
sns_acc
```

Out[131]:

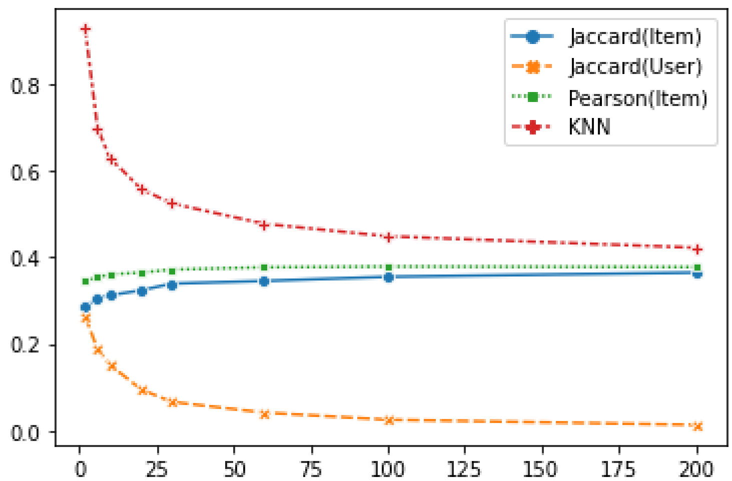
	Jaccard(Item)	Jaccard(User)	Pearson(Item)	KNN
2	0.284624	0.263733	0.344327	0.928398
6	0.304984	0.187487	0.353659	0.699271
10	0.312089	0.151962	0.360445	0.629822
20	0.323436	0.095228	0.364687	0.558066
30	0.339024	0.066384	0.371474	0.524511
60	0.345175	0.041676	0.376882	0.477553
100	0.354825	0.025239	0.378579	0.448636
200	0.364581	0.013256	0.377413	0.422160

In [132…

```
sns.lineplot(sns_acc, markers=True)
```

Out[132]: <AxesSubplot:>

Out[132]:



Recommend Result(Binary classificaiton)

2-way Acc

The acc on recommending is not well on low K in Jaccard distance.
But Acc is significant better in Pearson similarity model.

In [93]:

```
sns_bin_acc = pd.DataFrame(np.array([item_jaccard_bin_acc, user_jaccard_bin_acc
sns_bin_acc
```

Out[93]:

	Jaccard(Item)	Jaccard(User)	Pearson(Item)	KNN
2	0.487063	0.523542	0.613786	0.982765
6	0.525557	0.556734	0.619300	0.903467
10	0.540933	0.572110	0.627253	0.874186
20	0.564581	0.565642	0.634464	0.836314
30	0.582927	0.564687	0.646129	0.815480
60	0.600318	0.557794	0.652810	0.779717
100	0.614422	0.551220	0.655885	0.753815
200	0.631283	0.539873	0.651644	0.729138

Precision

User-based model leading very good precision in our experiemnt.
Which means if we want to recommend good movie for user,
using user-based model to recommending has a better chance to like the movie rather than item-based model.

In [90]:
```
sns_bin_precision = pd.DataFrame(np.array([item_jaccard_bin_precision, user_jac
sns_bin_precision
```

Out[90]:

	Jaccard(Item)	Jaccard(User)	Pearson(Item)	KNN
2	0.665618	0.680473	0.663038	0.982630
6	0.667452	0.690850	0.662628	0.895243
10	0.666862	0.709527	0.666156	0.864957
20	0.672926	0.716493	0.668951	0.828615
30	0.680028	0.733882	0.674926	0.809900
60	0.674825	0.753216	0.672644	0.780441
100	0.675340	0.765793	0.670814	0.757388
200	0.676283	0.777778	0.660872	0.736143

Recall

Item-based model especially item-based Pearson similarity has higher recall which means the result is more relevant to user no matter the user like it or not.

In [91]:
```
sns_bin_recall = pd.DataFrame(np.array([item_jaccard_bin_recall, user_jaccard_b
sns_bin_recall
```

Out[91]:

	Jaccard(Item)	Jaccard(User)	Pearson(Item)	KNN
2	0.232218	0.336442	0.679283	0.986154
6	0.362589	0.426586	0.699945	0.934116
10	0.416530	0.443957	0.716219	0.914439
20	0.484915	0.415432	0.731944	0.886246
30	0.530444	0.391296	0.752057	0.869134
60	0.599927	0.353264	0.781861	0.835190
100	0.645456	0.325837	0.798501	0.813950
200	0.698665	0.289267	0.820260	0.792490

Compare the run time on different model

The user-based jaccard model use more time than other model.
We think it might caused by
calculating each value in one time instead of numpy calculate the whole array in one time
to make it really slow on large K.

In [142…

```
sns_time = pd.DataFrame(np.array([item_jaccard_time, user_jaccard_time,item_pea
sns_time
```

Out[142]:

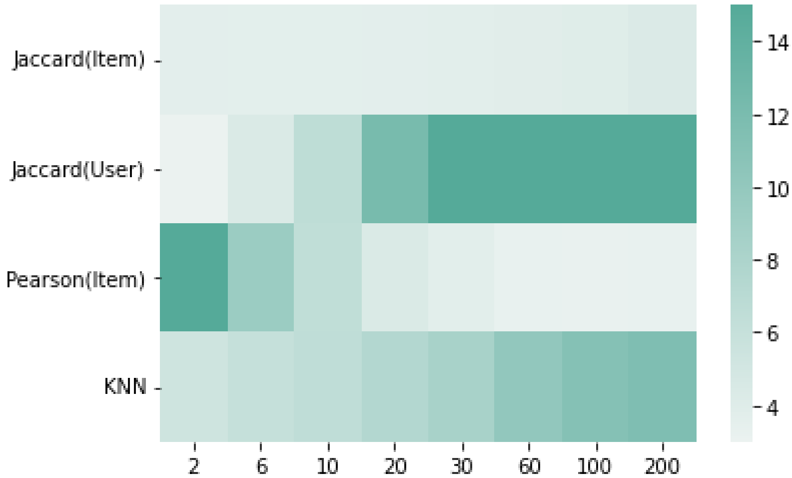
	Jaccard(Item)	Jaccard(User)	Pearson(Item)	KNN
2	3.676750	2.162182	25.631092	5.372061
6	3.621475	4.377478	9.394322	6.038865
10	3.650611	6.594064	6.466204	6.534160
20	3.679125	12.204926	4.370909	7.471330
30	3.745767	17.746416	3.795215	8.353007
60	3.831319	36.303496	3.266614	10.122386
100	3.969106	59.719915	3.178428	11.193172
200	4.328787	113.241957	3.253035	11.615518

In [155…

```
sns.heatmap(sns_time.T, vmin=3, vmax=15, cmap=sns.color_palette("light:#5A9", a
```

Out[155]: <AxesSubplot:>

Out[155]:


Jaccard(Item)
Jaccard(User)
Pearson(Item)
KNN
2
6
10
20
30
60
100
200
14
12
10
8
6
4