code_32973381

May 24, 2023

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

0.0.1 Import Libraries

[ ]:
```
!pip install surprise
```

```
Requirement already satisfied: surprise in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (0.1)
Requirement already satisfied: scikit-surprise in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (from
surprise) (1.1.3)
Requirement already satisfied: numpy>=1.17.3 in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (from
scikit-surprise->surprise) (1.22.3)
Requirement already satisfied: joblib>=1.0.0 in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (from
scikit-surprise->surprise) (1.2.0)
Requirement already satisfied: scipy>=1.3.2 in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (from
scikit-surprise->surprise) (1.10.1)

[notice] A new release of pip available: 22.1.2 -> 23.1.2
[notice] To update, run: python.exe -m pip install --upgrade pip
Requirement already satisfied: implicit in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (0.6.2)
Requirement already satisfied: tqdm>=4.27 in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (from
implicit) (4.63.1)
Requirement already satisfied: numpy in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (from
implicit) (1.22.3)
Requirement already satisfied: scipy>=0.16 in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (from
implicit) (1.10.1)
Requirement already satisfied: colorama in
c:\users\sunny\appdata\local\programs\python\python310\lib\site-packages (from
```

```
tqdm>=4.27->implicit) (0.4.4)

[notice] A new release of pip available: 22.1.2 -> 23.1.2
[notice] To update, run: python.exe -m pip install --upgrade pip
```

[ ]:
```
import os
import pandas as pd
import numpy as np
import random
import torch
import torchtext
import scipy.sparse as sparse
from multiprocessing import Pool, cpu_count
from sklearn.preprocessing import MinMaxScaler
from sklearn import metrics
from gensim.utils import simple_preprocess
from tqdm import tqdm
import matplotlib.pyplot as plt
import seaborn as sns
```

[ ]:
```
from surprise import (
    Reader,
    Dataset,
    accuracy,
    NormalPredictor,
    KNNBasic,
    KNNWithMeans,
    KNNWithZScore,
    KNNBaseline,
    SVD,
    BaselineOnly,
    SVDpp,
    NMF,
    SlopeOne,
    CoClustering
)

from surprise.model_selection import cross_validate
from surprise.accuracy import rmse
from surprise.model_selection import train_test_split
from surprise.model_selection import GridSearchCV

SEED = 1
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
```

[ ]:
```
<torch._C.Generator at 0x259f6ea3bd0>
```

[ ]:
```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
device
```

[ ]:
```
device(type='cuda')
```

0.0.2 Load data

[ ]:
```
# FolderPath = "/content/drive/MyDrive/Colab Notebooks/FIT5212/A2/Data"
FolderPath = "C:/Users/Sunny/Desktop/Master/Sem3/5212/A2/Data"

train_df = pd.read_csv(FolderPath + "/train.csv")
test_df = pd.read_csv(FolderPath + "/test.csv")
metadata_df = pd.read_csv(FolderPath + "/books_metadata.csv")
```

[ ]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 286136 entries, 0 to 286135
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   user_id    286136 non-null  int64
 1   item_id    286136 non-null  int64
 2   rating     286136 non-null  int64
 3   book_name  286136 non-null  object
dtypes: int64(3), object(1)
memory usage: 8.7+ MB
```

[ ]:
```
metadata_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1636235 entries, 0 to 1636234
Data columns (total 9 columns):
 #   Column          Non-Null Count    Dtype
---  ------          --------------    -----
 0   Name            1636235 non-null  object
 1   pagesNumber     718417 non-null   float64
 2   Publisher       1619540 non-null  object
 3   CountsOfReview  1636235 non-null  int64
 4   PublishYear     1636235 non-null  int64
 5   Language        206442 non-null   object
 6   Authors         1636235 non-null  object
 7   Rating          1636235 non-null  float64
 8   item_id         44586 non-null    float64
```

```
dtypes: float64(3), int64(2), object(4)
memory usage: 112.4+ MB
```

---

1 Memory based Algorithm comparison

[ ]:
```
reader = Reader()
data = Dataset.load_from_df(train_df[['user_id', 'item_id', 'rating']], reader)

benchmark = []
# Iterate over all algorithms
for algorithm in [SVD(), NMF(), NormalPredictor(), KNNBaseline(), KNNBasic(),␣
↪KNNWithMeans(), KNNWithZScore(), BaselineOnly()]:
    # Perform cross validation
    results = cross_validate(algorithm, data, measures=['RMSE', "MAE"], cv=5,␣
↪verbose=False)

    # Get results & append algorithm name
    tmp = pd.DataFrame.from_dict(results).mean(axis=0)
    tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],␣
↪index=['Algorithm']))
    benchmark.append(tmp)
```

```
C:\Users\Sunny\AppData\Local\Temp\ipykernel_28236\2636614995.py:12:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],
index=['Algorithm']))
C:\Users\Sunny\AppData\Local\Temp\ipykernel_28236\2636614995.py:12:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],
index=['Algorithm']))
C:\Users\Sunny\AppData\Local\Temp\ipykernel_28236\2636614995.py:12:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],
index=['Algorithm']))
```

```
Estimating biases using als…
Computing the msd similarity matrix…
Done computing similarity matrix.
Estimating biases using als…
Computing the msd similarity matrix…
Done computing similarity matrix.
Estimating biases using als…
Computing the msd similarity matrix…
```

```
Done computing similarity matrix.
Estimating biases using als…
Computing the msd similarity matrix…
Done computing similarity matrix.
Estimating biases using als…
Computing the msd similarity matrix…
Done computing similarity matrix.

C:\Users\Sunny\AppData\Local\Temp\ipykernel_28236\2636614995.py:12:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],
index=['Algorithm']))

Computing the msd similarity matrix…
Done computing similarity matrix.
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Computing the msd similarity matrix…
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C:\Users\Sunny\AppData\Local\Temp\ipykernel_28236\2636614995.py:12:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],
index=['Algorithm']))

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Done computing similarity matrix.
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Computing the msd similarity matrix…
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C:\Users\Sunny\AppData\Local\Temp\ipykernel_28236\2636614995.py:12:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],
index=['Algorithm']))

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

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

```
C:\Users\Sunny\AppData\Local\Temp\ipykernel_28236\2636614995.py:12:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],
index=['Algorithm']))
```

```
Estimating biases using als…
Estimating biases using als…
Estimating biases using als…
Estimating biases using als…
Estimating biases using als…
```

```
C:\Users\Sunny\AppData\Local\Temp\ipykernel_28236\2636614995.py:12:
FutureWarning: The series.append method is deprecated and will be removed from
pandas in a future version. Use pandas.concat instead.
  tmp = tmp.append(pd.Series([str(algorithm).split(' ')[0].split('.')[-1]],
index=['Algorithm']))
```

[ ]:
```
pd.DataFrame(benchmark).set_index('Algorithm').sort_values('test_rmse')
```

[ ]:

Algorithm	test_rmse	test_mae	fit_time	test_time
BaselineOnly	0.885800	0.706579	0.791227	0.491570
SVD	0.893184	0.708956	2.870429	0.456861
KNNBaseline	0.923082	0.726138	1.739796	3.167013
KNNWithZScore	0.951120	0.749206	1.227595	3.018960
KNNWithMeans	0.951184	0.751231	1.001780	2.885226
NMF	0.995599	0.791227	9.029701	0.450577
KNNBasic	1.000704	0.790562	0.914038	2.733662
NormalPredictor	1.341909	1.073049	0.340799	0.476726

1.0.1 Memory-based model 1 - BaselineOnly Model

[ ]:
```
reader = Reader()
data = Dataset.load_from_df(train_df[['user_id', 'item_id', 'rating']], reader)

# runing algo and get prediction results
algo = BaselineOnly()
cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=False)
trainset = data.build_full_trainset()
```

```
algo.fit(trainset)
predicted_ratings = []
for index, row in train_df.iterrows():
    user_id = row['user_id']
    item_id = row['item_id']
    prediction = algo.predict(user_id, item_id)
    predicted_ratings.append(prediction.est)
```

```
Estimating biases using als…
Estimating biases using als…
Estimating biases using als…
Estimating biases using als…
Estimating biases using als…
Estimating biases using als…
```

[ ]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 286136 entries, 0 to 286135
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype 
---  ------     --------------   ----- 
 0   user_id    286136 non-null  int64 
 1   item_id    286136 non-null  int64 
 2   rating     286136 non-null  int64 
 3   book_name  286136 non-null  object
dtypes: int64(3), object(1)
memory usage: 8.7+ MB
```

[ ]:
```
# Auxiliary function for evaluation
# Referenced: https://towardsdatascience.com/
  ↪building-and-testing-recommender-systems-with-surprise-step-by-step-d4ba702ef80b

def get_Iu(uid):
    """ return the number of items rated by given user
    args:
      uid: the id of the user
    returns:
      the number of items rated by the user
    """
    try:
        return len(trainset.ur[trainset.to_inner_uid(uid)])
    except ValueError: # user was not part of the trainset
        return 0

def get_Ui(iid):
    """ return number of users that have rated given item
    args:
```

```
      iid: the raw id of the item
    returns:
      the number of users that have rated the item.
    """
    try:
        return len(trainset.ir[trainset.to_inner_iid(iid)])
    except ValueError:
        return 0

# train_df.drop("book_name", axis = 1, inplace = True)
train_df["Prediction"] = predicted_ratings
train_df['ratings given by user'] = train_df.user_id.apply(get_Iu)
train_df['Count of ratings to item'] = train_df.item_id.apply(get_Ui)
train_df['error'] = abs(train_df.Prediction - train_df.rating)
best_predictions = train_df.sort_values(by='error')[:10]
worst_predictions = train_df.sort_values(by='error')[-10:]
```

[ ]:
```
best_predictions
```

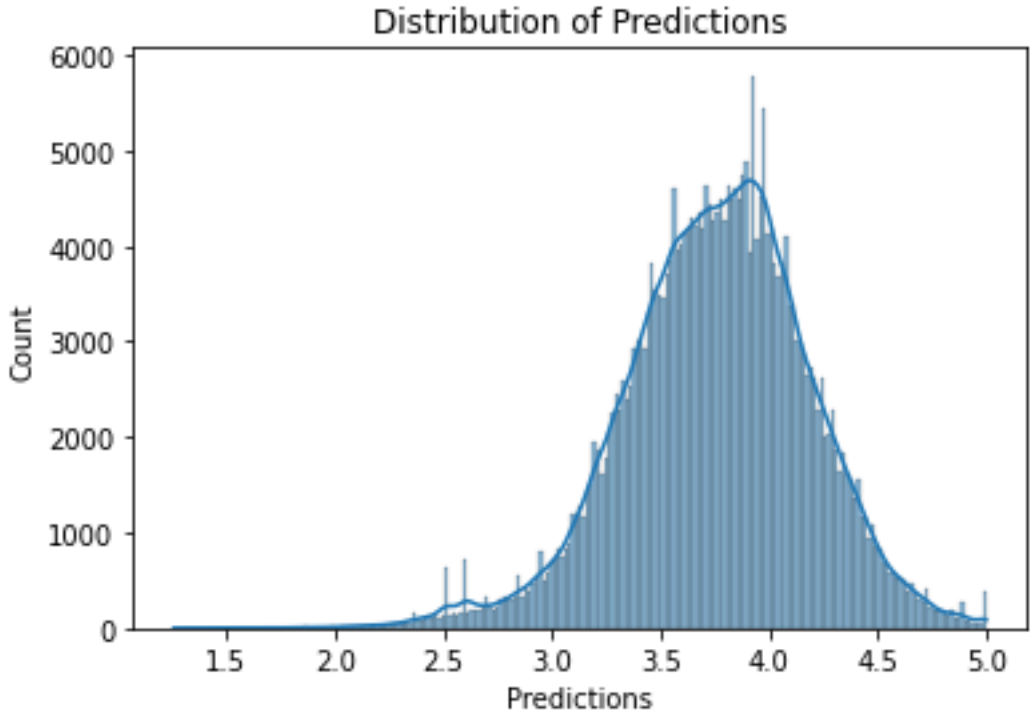
[ ]:
```
        user_id  item_id  …  Count of ratings to item  error
243416     3140    29732  …                        19    0.0
235503     2329     3318  …                        45    0.0
20357       198     8534  …                        33    0.0
20358       198       77  …                       138    0.0
20363       198     5160  …                        29    0.0
20368       198     5748  …                       108    0.0
20369       198     1856  …                        53    0.0
190756     1919     1030  …                       105    0.0
20380       198     1891  …                       410    0.0
20381       198      672  …                        36    0.0

[10 rows x 7 columns]
```

[ ]:
```
worst_predictions
```

[ ]:
```
        user_id  item_id  …  Count of ratings to item     error
191723     2671     4041  …                       141  3.516458
76300       748      153  …                       800  3.530973
173001     1812      105  …                       105  3.573162
106051     1121      242  …                       303  3.584115
198508     2027       80  …                       203  3.646298
557           4      529  …                       105  3.654988
225681     2572     7493  …                        41  3.673786
173622     1817     1282  …                       444  3.719716
88342       852    12479  …                        15  3.756892
101911     1284     1282  …                       444  3.840028
```

```
[10 rows x 7 columns]
```

[ ]:
```python
# Assuming train_df is your DataFrame with a column named "Predictions"
predictions = train_df["Prediction"]

# Plotting the distribution
sns.histplot(predictions, kde=True)
plt.title("Distribution of Predictions")
plt.xlabel("Predictions")
plt.ylabel("Count")
plt.show()
```



[ ]:
```python
predicted_ratings = []
for index, row in test_df.iterrows():
    user_id = row['user_id']
    item_id = row['item_id']
    prediction = algo.predict(user_id, item_id)
    predicted_ratings.append(prediction.est)
```

[ ]:
```python
test_df = pd.read_csv(FolderPath + "/test.csv")
test_df["rating"] = predicted_ratings
```

```
[ ]: # test_df[["ID", "rating"]].to_csv(FolderPath + "/baselineOnly.csv", index =␣
      ↪False)
```

1.0.2 SVD Model - combination of parameters

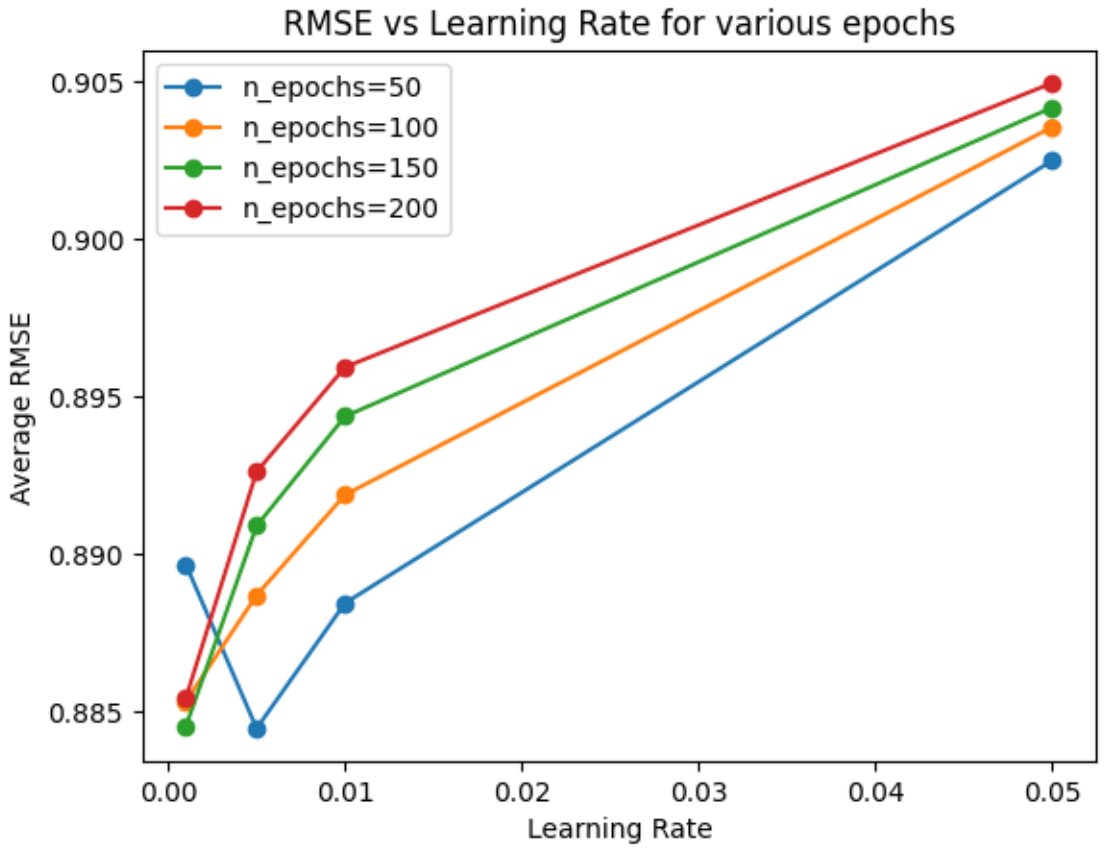
```
[ ]: # # 0.69876
     # # 0.8147 when convert to int

     # test_df.rename(columns = {"SVD_rating": "rating"}, inplace = True)
     # test_df[["ID", "rating"]].to_csv(FolderPath + "basic_200_0.001.csv", index =␣
      ↪False)
```

```
[ ]: train_df = pd.read_csv(FolderPath + "/train.csv")
     test_df = pd.read_csv(FolderPath + "/test.csv")
```

```
[ ]: reader = Reader()
     data = Dataset.load_from_df(train_df[['user_id', 'item_id', 'rating']], reader)
```

```
[ ]: import matplotlib.pyplot as plt
     from surprise import SVD, Dataset, accuracy
     from surprise.model_selection import cross_validate, KFold

     # Load your dataset here
     # data = Dataset.load_builtin('ml-100k')

     n_epochs = [50, 100, 150, 200]
     lr_all = [0.001, 0.005, 0.01, 0.05]
     reg_all = 0.1

     avg_rmses = []

     for epoch in n_epochs:
         temp_rmses = []
         for lr in lr_all:
             algo = SVD(n_epochs=epoch, lr_all=lr, reg_all=reg_all,␣
      ↪random_state=SEED)
             cv = cross_validate(algo, data, measures=['RMSE'], cv=5)
             temp_rmses.append(np.mean(cv['test_rmse']))
         avg_rmses.append(temp_rmses)

     # Plotting
     for i, rmses in enumerate(avg_rmses):
         plt.plot(lr_all, rmses, marker='o', label=f'n_epochs={n_epochs[i]}')

     plt.title('RMSE vs Learning Rate for various epochs')
     plt.xlabel('Learning Rate')
```

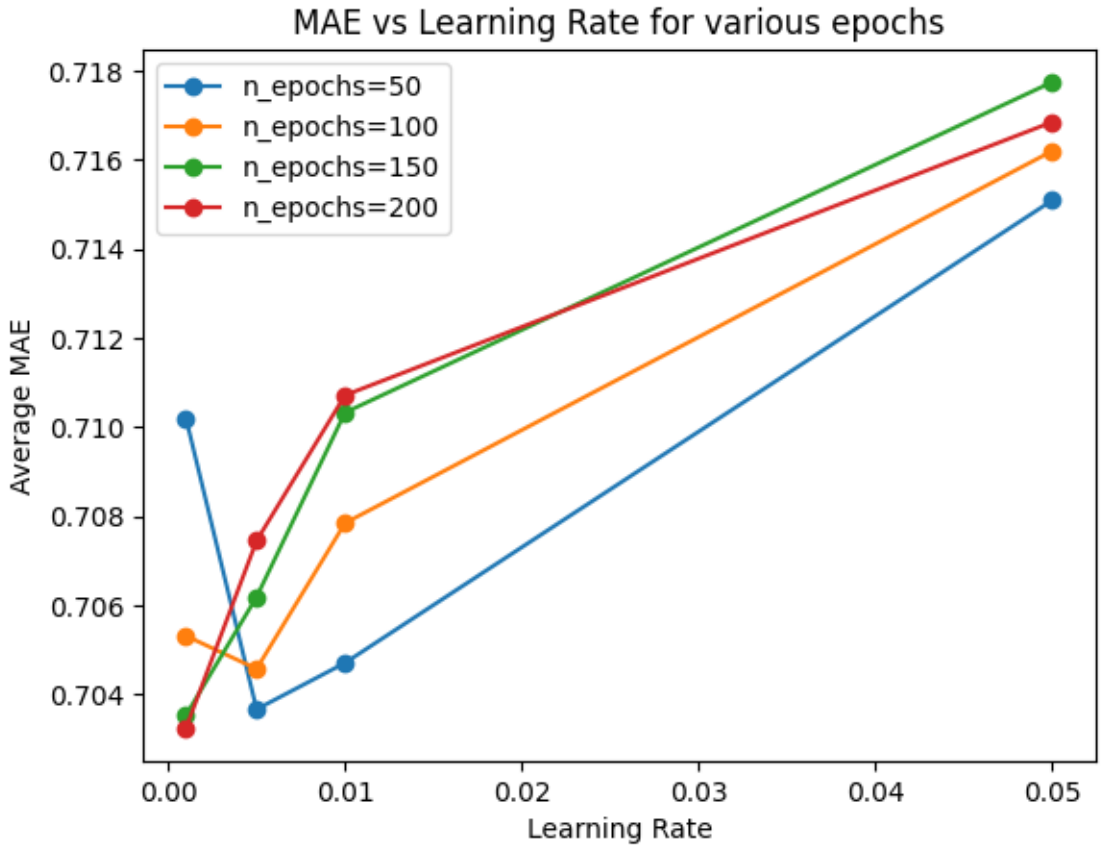
```
plt.ylabel('Average RMSE')
plt.legend()
plt.show()
```



[ ]:
```
import matplotlib.pyplot as plt
from surprise import SVD, Dataset, accuracy
from surprise.model_selection import cross_validate, KFold

# Load your dataset here
# data = Dataset.load_builtin('ml-100k')

n_epochs = [50, 100, 150, 200]
lr_all = [0.001, 0.005, 0.01, 0.05]
reg_all = 0.1
SEED = 2  # set your random state seed here

avg_maes = []

for epoch in n_epochs:
```

```
    temp_maes = []
    for lr in lr_all:
        algo = SVD(n_epochs=epoch, lr_all=lr, reg_all=reg_all,␣
↪random_state=SEED)
        cv = cross_validate(algo, data, measures=['MAE'], cv=5)
        temp_maes.append(np.mean(cv['test_mae']))
    avg_maes.append(temp_maes)
```

[ ]:
```
# Plot MAE
for i, maes in enumerate(avg_maes):
    plt.plot(lr_all, maes, marker='o', label=f'n_epochs={n_epochs[i]}')

plt.title('MAE vs Learning Rate for various epochs')
plt.xlabel('Learning Rate')
plt.ylabel('Average MAE')
plt.legend()
plt.show()
```



1.1 SVD - Best lr and epoch combinations

1.1.1 Best combination 1 - lr = 0.005, epochs = 50

[ ]:
```
n_epochs = 50
lr_all = 0.005
reg_all = 0.1

algo = SVD(n_epochs = n_epochs, lr_all = lr_all, reg_all = reg_all,␣
 ↪random_state = SEED)
cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
```

```
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8881  0.8816  0.8849  0.8868  0.8818  0.8846  0.0026
MAE (testset)     0.7053  0.6994  0.7038  0.7046  0.7027  0.7032  0.0021
Fit time          11.08   11.13   11.12   9.75    10.41   10.70   0.54
Test time         0.32    0.75    0.74    0.52    0.31    0.53    0.20
```

[ ]:
```
{'test_rmse': array([0.88813367, 0.88158909, 0.88486001, 0.88677693, 0.8817828
]),
 'test_mae': array([0.70532294, 0.69936276, 0.70378271, 0.70457476,
0.70274274]),
 'fit_time': (11.076048374176025,
  11.128887176513672,
  11.116327285766602,
  9.75194787979126,
  10.409369468688965),
 'test_time': (0.31511878967285156,
  0.7539904117584229,
  0.741586446762085,
  0.5155768394470215,
  0.3087186813354492)}
```

[ ]:
```
data = Dataset.load_from_df(train_df[['user_id', 'item_id', 'rating']], reader)
trainset = data.build_full_trainset()
algo.fit(trainset)
predicted_ratings = []
for index, row in test_df.iterrows():
    user_id = row['user_id']
    item_id = row['item_id']
    prediction = algo.predict(user_id, item_id)
    predicted_ratings.append(prediction.est)
```

[ ]:
```
test_df["SVD_rating"] = predicted_ratings
```

[ ]:
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56199 entries, 0 to 56198
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   ID          56199 non-null  int64
 1   user_id     56199 non-null  int64
 2   item_id     56199 non-null  int64
 3   book_name   56199 non-null  object
 4   SVD_rating  56199 non-null  float64
dtypes: float64(1), int64(3), object(1)
memory usage: 2.1+ MB
```

[ ]:
```
# 0.69905
test_df.rename(columns = {"SVD_rating": "rating"}, inplace = True)
test_df[["ID", "rating"]].to_csv(FolderPath + "basic_50_0.005.csv", index =␣
 ↪False)
```

1.1.2 Best combination 2 - lr = 0.001, epochs = 150

[ ]:
```
n_epochs = 150
lr_all = 0.001
reg_all = 0.1

algo = SVD(n_epochs = n_epochs, lr_all = lr_all, reg_all = reg_all,␣
 ↪random_state = SEED)
cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
```

```
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8858  0.8902  0.8830  0.8811  0.8828  0.8846  0.0032
MAE (testset)     0.7056  0.7087  0.7013  0.7002  0.7026  0.7037  0.0031
Fit time          29.40   31.80   32.59   30.16   28.68   30.53   1.46
Test time         0.30    0.83    0.34    0.65    0.31    0.49    0.22
```

[ ]:
```
{'test_rmse': array([0.88577722, 0.89023151, 0.88296002, 0.88105006,
0.88275615]),
 'test_mae': array([0.70563992, 0.70868   , 0.70133612, 0.70018968,
0.70259332]),
 'fit_time': (29.4030339717865,
  31.796489477157593,
  32.589377880096436,
  30.155160665512085,
  28.6817045211792),
 'test_time': (0.29782843589782715,
```

```
  0.8331320285797119,
  0.3444499969482422,
  0.652571439743042,
  0.31490564346313477)}
```

[ ]:
```
trainset = data.build_full_trainset()
algo.fit(trainset)
predicted_ratings = []
for index, row in test_df.iterrows():
    user_id = row['user_id']
    item_id = row['item_id']
    prediction = algo.predict(user_id, item_id)
    predicted_ratings.append(prediction.est)
```

[ ]:
```
test_df["SVD_rating"] = predicted_ratings
```

[ ]:
```
# 0.70033
test_df.rename(columns = {"SVD_rating": "rating"}, inplace = True)
test_df[["ID", "rating"]].to_csv(FolderPath + "basic_150_0.001.csv", index =␣
 ↪False)
```

1.1.3 Best combination 3 - lr = 0.001, epochs = 200

[ ]:
```
test_df = pd.read_csv(FolderPath + "/test.csv")
```

[ ]:
```
n_epochs = 200
lr_all = 0.001
reg_all = 0.1

algo = SVD(n_epochs = n_epochs, lr_all = lr_all, reg_all = reg_all,␣
 ↪random_state = SEED)
cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
```

```
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8829  0.8799  0.8868  0.8888  0.8876  0.8852  0.0033
MAE (testset)     0.7019  0.6986  0.7059  0.7067  0.7043  0.7035  0.0029
Fit time          26.30   27.25   26.70   26.33   26.27   26.57   0.38
Test time         0.57    0.59    0.57    0.57    0.57    0.57    0.01
```

[ ]:
```
{'test_rmse': array([0.88286576, 0.87985648, 0.88682733, 0.88875413,
0.88763935]),
 'test_mae': array([0.7018928 , 0.69863268, 0.70588944, 0.70672107,
0.70429611]),
 'fit_time': (26.296306848526,
```

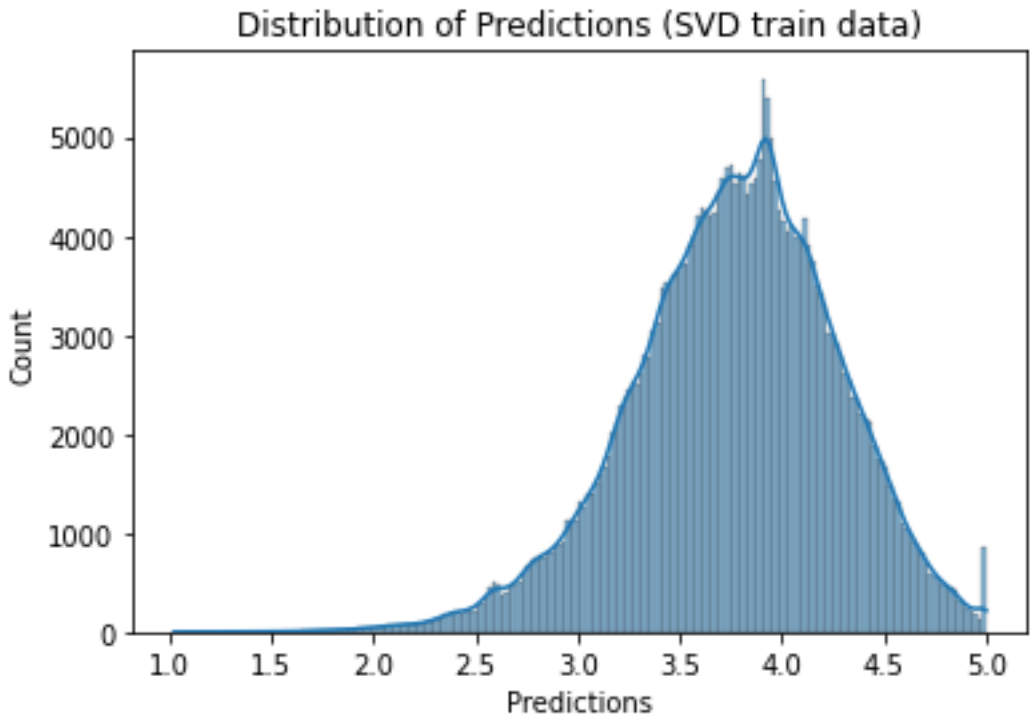
```
  27.251811504364014,
  26.70237398147583,
  26.327537059783936,
  26.268176078796387),
 'test_time': (0.571061372756958,
  0.5878851413726807,
  0.5723822116851807,
  0.5656390190124512,
  0.5664620399475098)}
```

[ ]:
```
trainset = data.build_full_trainset()
algo.fit(trainset)
```

[ ]:
```
predicted_ratings = []
for index, row in train_df.iterrows():
    user_id = row['user_id']
    item_id = row['item_id']
    prediction = algo.predict(user_id, item_id)
    predicted_ratings.append(prediction.est)
```

[ ]:
```
train_df["Prediction"] = predicted_ratings
train_df['ratings given by user'] = train_df.user_id.apply(get_Iu)
train_df['Count of ratings to item'] = train_df.item_id.apply(get_Ui)
train_df['error'] = abs(train_df.Prediction - train_df.rating)
best_predictions = train_df.sort_values(by='error')[:10]
worst_predictions = train_df.sort_values(by='error')[-10:]
```

[ ]:
```
# Plotting the distribution
sns.histplot(predicted_ratings, kde=True)
plt.title("Distribution of Predictions (SVD train data)")
plt.xlabel("Predictions")
plt.ylabel("Count")
plt.show()
```



[ ]:
```
best_predictions
```

[ ]:
```
        user_id  item_id  …  Count of ratings to item error
15007       150     4419  …                        33   0.0
270352     1908    40132  …                        10   0.0
49028       666    21937  …                        26   0.0
190433     2089     1655  …                        36   0.0
266055     3142    16775  …                        12   0.0
6237         80     4280  …                        34   0.0
76860       735    11762  …                        18   0.0
42853       555      303  …                       523   0.0
49074       666    21952  …                        14   0.0
108811     1262     7493  …                        41   0.0

[10 rows x 8 columns]
```

[ ]:
```
worst_predictions
```

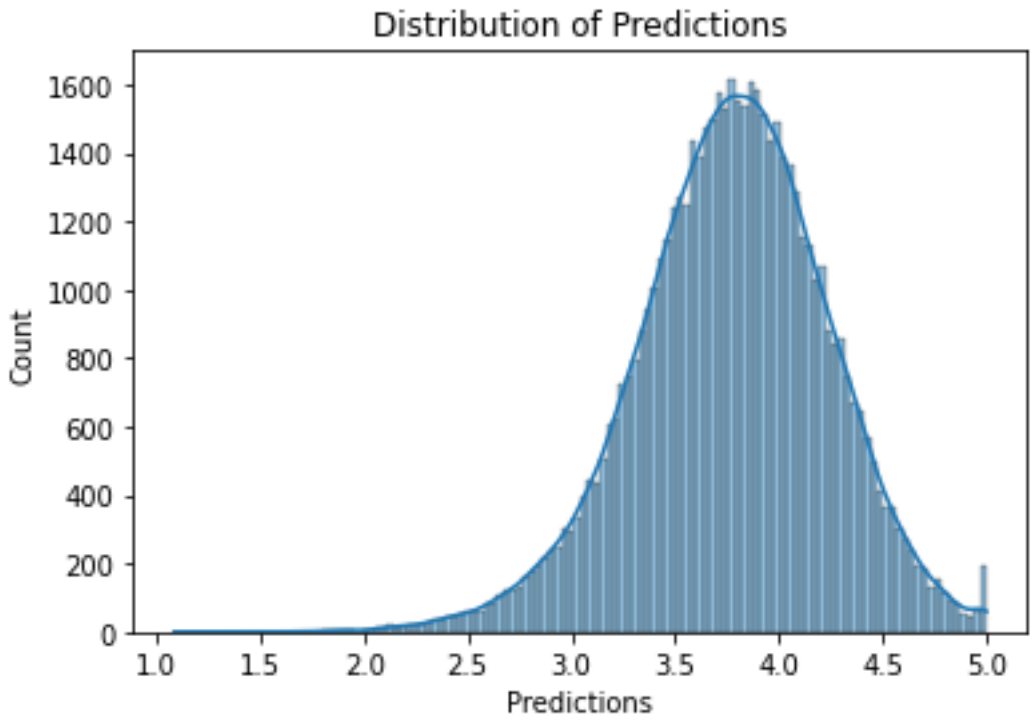
[ ]:
```
        user_id  item_id  …  Count of ratings to item     error
104661      998      602  …                       349  3.312810
37027       384      242  …                       303  3.364974
100397      998     3068  …                       215  3.375210
106712      998     1682  …                        46  3.394681
```

```
173001     1812      105  …                    105  3.406169
173622     1817     1282  …                    444  3.456504
88342       852    12479  …                     15  3.459084
557           4      529  …                    105  3.467780
198508     2027       80  …                    203  3.471670
101911     1284     1282  …                    444  3.593474

[10 rows x 8 columns]
```

[ ]:
```
predicted_ratings = []
for index, row in test_df.iterrows():
    user_id = row['user_id']
    item_id = row['item_id']
    prediction = algo.predict(user_id, item_id)
    predicted_ratings.append(prediction.est)
```

[ ]:
```
test_df["SVD_rating"] = predicted_ratings
```

[ ]:
```
# Assuming train_df is your DataFrame with a column named "Predictions"
predictions = test_df["SVD_rating"]

# Plotting the distribution
sns.histplot(predictions, kde=True)
plt.title("Distribution of Predictions")
plt.xlabel("Predictions")
plt.ylabel("Count")
plt.show()
```



---

2 Model-based collaborative filtering

2.1 Data Pre-processing (metadata)

[ ]:
```
metadata_df = metadata_df[~metadata_df["item_id"].isna()]
metadata_df.drop(["Name", "Publisher", "pagesNumber", "PublishYear"], axis = 1,␣
↪inplace = True)
```

2.1.1 Impute and preprocess Language

[ ]:
```
metadata_df.Language.value_counts()
```

[ ]:
```
eng      17494
en-US     2659
spa        669
en-GB      529
fre        302
ger        181
per         95
ita         29
por         22
```

```
mul         21
en-CA       13
rus          9
swe          7
jpn          7
nl           4
enm          4
grc          4
cat          3
zho          2
lat          2
pol          2
afr          2
gre          1
nor          1
dan          1
elx          1
gla          1
myn          1
kor          1
eus          1
frs          1
lit          1
ara          1
Name: Language, dtype: int64
```

[ ]:
```
# Grouping all english language into eng

metadata_df.loc[(metadata_df["Language"] == "en-US") | (metadata_df["Language"]
 ↪== "en-GB")| (metadata_df["Language"] == "en-CA"), "Language"] = "eng"
```

[ ]:
```
# Impute lang values given that the author is known
author_language_mapping = metadata_df[metadata_df['Language'].notna()].
 ↪groupby('Authors')['Language'].agg(pd.Series.mode).to_dict()

# author_language_mapping
```

[ ]:
```
from tqdm import tqdm

# Define a function to apply to the DataFrame
def impute_language(row):
    if pd.isnull(row['Language']) and row['Authors'] in author_language_mapping:
        return author_language_mapping[row['Authors']]
    else:
        return row['Language']

# Apply the function to the DataFrame with tqdm progress bar
```

```
def apply_impute_language(df):
    progress_bar = tqdm(total=len(df), desc="Imputing Language")
    def update_progress(*args):
        progress_bar.update()
    df['Language'] = df.apply(impute_language, axis=1)
    progress_bar.close()

# Call the function to apply the imputation with tqdm progress bar
apply_impute_language(metadata_df)
```

```
Imputing Language:   0%|          | 0/44586 [00:00<?, ?it/s]
```

[ ]:
```
# Impute rare languages
metadata_df["Language"].fillna("other", inplace = True)
# metadata_df.info()
language_counts = metadata_df['Language'].value_counts()

# If count of language is smaller than 50, impute them as "other"
rare_languages = language_counts[language_counts < 50].index
metadata_df.loc[metadata_df['Language'].isin(rare_languages), 'Language'] =␣
↪'other'
```

[ ]:
```
metadata_df.Language.value_counts()
```

[ ]:
```
eng      29832
other    13250
spa        821
fre        361
ger        216
per        106
Name: Language, dtype: int64
```

[ ]:
```
# Create a dictionary mapping each language to an integer based on its frequency
language_to_int = metadata_df['Language'].value_counts().to_dict()
language_to_int.pop('other', None)
ranked_languages = {k: rank for rank, k in enumerate(sorted(language_to_int,␣
↪key=language_to_int.get, reverse=True), 1)}

# Add 'other' to the dictionary with rank 0
ranked_languages['other'] = 0
# Map the languages in the 'Language' column to their corresponding integer
metadata_df['Language_cat'] = metadata_df['Language'].map(ranked_languages)
```

[ ]:
```
metadata_df[["Language", "Language_cat"]]
```

[ ]:
```
        Language  Language_cat
0            eng             1
1            eng             1
```

```
2             eng              1
3             eng              1
4             eng              1
…             …                …
1635748     other              0
1635934       eng              1
1635952       eng              1
1636048     other              0
1636104     other              0

[44586 rows x 2 columns]
```

2.1.2 AuthorBookCount

[ ]:
```
metadata_df['AuthorBookCount'] = metadata_df.groupby('Authors')['item_id'].
↪transform('count')
```

2.1.3 Put AuthorBookCount into category

[ ]:
```
# Create bins and put count into category corresponding to the range

quantile = 0.75
max_value = np.quantile(metadata_df.AuthorBookCount, quantile)
labels = np.arange(0,99)
value_list = np.linspace(0, int(max_value), 99).tolist()
value_list.append(np.inf)
len(labels), len(value_list)
```

[ ]:
```
(99, 100)
```

[ ]:
```
# Apply bins and label to AuthorBookCount

metadata_df["AuthorCountCat"] = pd.cut(metadata_df['AuthorBookCount'],␣
↪value_list, right=False, labels=labels)
```

2.1.4 Put CountOfReview into category

[ ]:
```
# Create bins and put count into category corresponding to the range

quantile = 0.75
max_value = np.quantile(metadata_df.CountsOfReview, quantile)
labels = np.arange(0,99)
value_list = np.linspace(0, int(max_value), 99).tolist()
value_list.append(np.inf)
```

```
len(labels), len(value_list)
```

[ ]: (99, 100)

[ ]:
```
# Apply bins and label to ReviewCountCat

metadata_df["ReviewCountCat"] = pd.cut(metadata_df['CountsOfReview'],␣
 ↪value_list, right=False, labels=labels)
```

[ ]:
```
metadata_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 44586 entries, 0 to 1636104
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CountsOfReview   44586 non-null  int64
 1   Language         44586 non-null  object
 2   Authors          44586 non-null  object
 3   Rating           44586 non-null  float64
 4   item_id          44586 non-null  float64
 5   Language_cat     44586 non-null  int64
 6   AuthorBookCount  44586 non-null  int64
 7   AuthorCountCat   44586 non-null  category
 8   ReviewCountCat   44586 non-null  category
dtypes: category(2), float64(2), int64(3), object(2)
memory usage: 2.8+ MB
```

2.1.5 Merging metadata to train df

[ ]:
```
def merge_metadata(metadata_df, other_df):
    df = pd.merge(other_df, metadata_df, how = 'left', on = "item_id")
    df["AuthorBookCount"].fillna(0, inplace = True)
    df.drop(["Authors", "Language"], axis = 1, inplace = True)
    df["Rating"].fillna(0, inplace = True)
    df["CountsOfReview"].fillna(0, inplace = True)
    df["Language_cat"].fillna(0, inplace = True)
    df.fillna(0, inplace = True)
    return df

# train_df = merge_metadata(metadata_df, train_df)
```

---

3 Implementation of basic neural network

Metadata was not applied in this model

[ ]:
```
num_users = len(train_df.user_id.unique())
num_items = len(train_df.item_id.unique())
print(num_users, num_items)

test_num_users = len(test_df.user_id.unique())
test_num_items = len(test_df.item_id.unique())
print(test_num_users, test_num_items)
```

```
4154 89030
2990 18792
```

[ ]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
```

[ ]:
```
# Basic MF NN

class MF_bias(nn.Module):
    def __init__(self, num_users, num_items, emb_size=100):
        super(MF_bias, self).__init__()
        self.user_emb = nn.Embedding(num_users, emb_size)
        self.user_bias = nn.Embedding(num_users, 1)
        self.item_emb = nn.Embedding(num_items, emb_size)
        self.item_bias = nn.Embedding(num_items, 1)
        self.user_emb.weight.data.uniform_(0,0.05)
        self.item_emb.weight.data.uniform_(0,0.05)
        self.user_bias.weight.data.uniform_(-0.01,0.01)
        self.item_bias.weight.data.uniform_(-0.01,0.01)

    def forward(self, u, v):
        U = self.user_emb(u)
        V = self.item_emb(v)
        b_u = self.user_bias(u).squeeze()
        b_v = self.item_bias(v).squeeze()
        return (U*V).sum(1) +  b_u  + b_v
```

[ ]:
```
# train loop

def train_epochs(model, train_df, epochs=10, lr=0.01, wd=0.0, unsqueeze=False):
    optimizer = torch.optim.Adam(model.parameters(), lr=lr, weight_decay=wd)
    model.train()
    for i in range(epochs):
        users = torch.LongTensor(train_df.user_id.values).cuda()
        items = torch.LongTensor(train_df.item_id.values).cuda()
        ratings = torch.FloatTensor(train_df.rating.values).cuda()
        if unsqueeze:
            ratings = ratings.unsqueeze(1)
        y_hat = model(users, items)
```

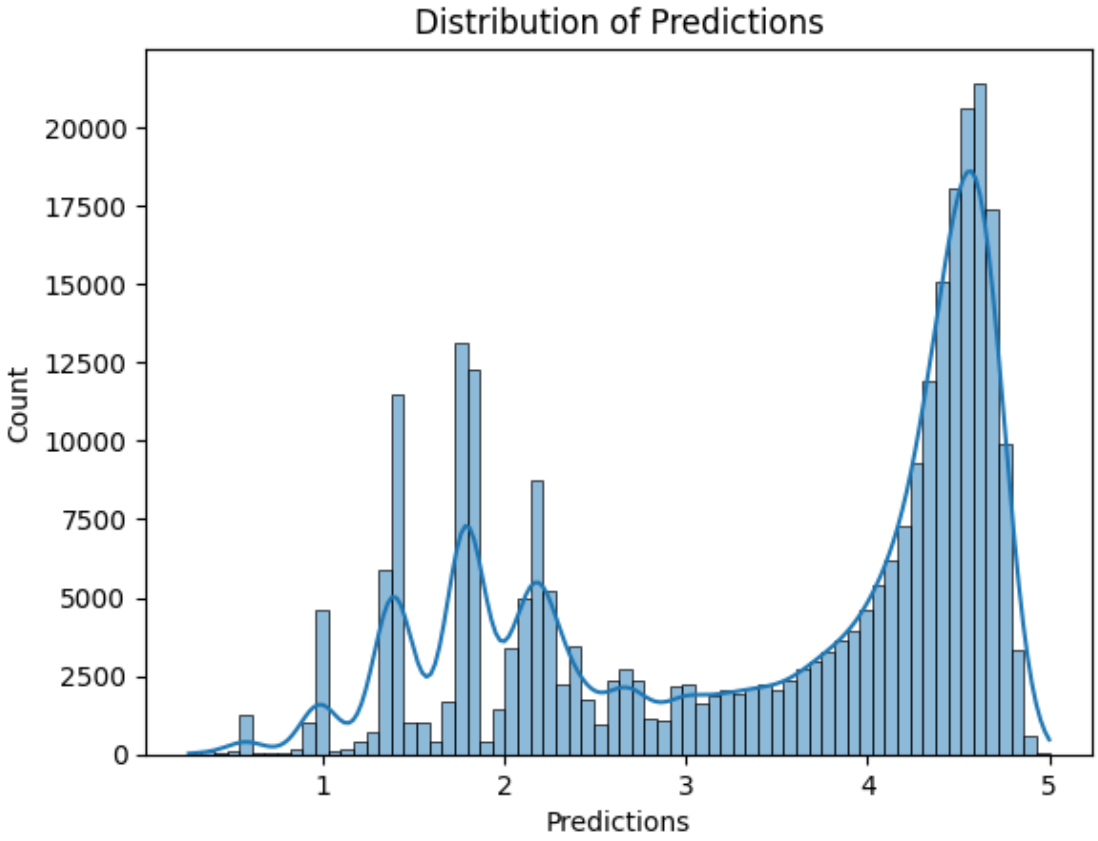
```
        loss = F.mse_loss(y_hat, ratings)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        print(f"epochs: {i+1}: loss: {round(loss.item(), 5)}")

        MAX = max(y_hat.tolist())
        MIN = min(y_hat.tolist())

        # Normalizing result back to the scale of 1 to 5
        scaled_y_hat = [value * 5 / MAX for value in y_hat]

    return scaled_y_hat

# predicted_ratings = train_epochs(model, train_df, epochs=20, lr=0.01,␣
 ↪wd=1e-5, unsqueeze=False)
```

[ ]:
```
# Initiate model and train model

model = MF_bias(num_users, num_items, emb_size=100).cuda() # if you have a GPU

predicted_ratings = train_epochs(model, train_df, epochs=20, lr=0.01, wd=5e-5,␣
 ↪unsqueeze=False)
```

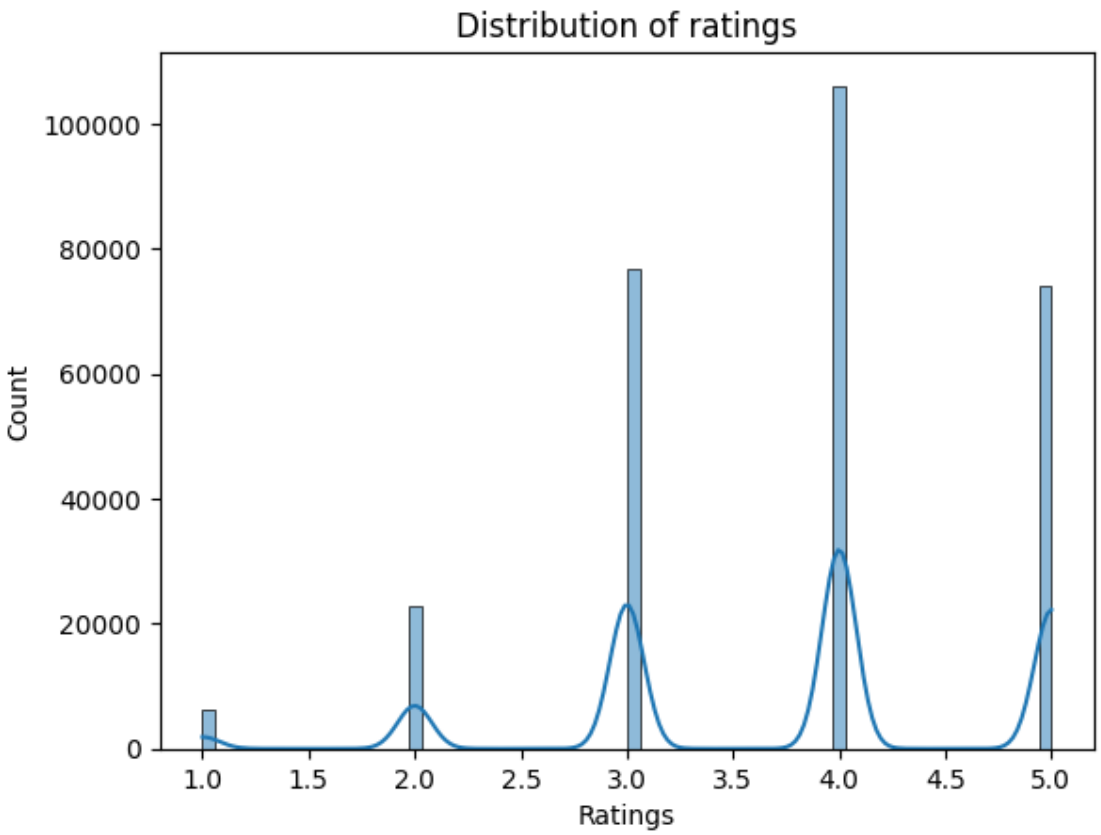
```
epochs: 1: loss: 14.69031
epochs: 2: loss: 14.19984
epochs: 3: loss: 13.60515
epochs: 4: loss: 12.9038
epochs: 5: loss: 12.09988
epochs: 6: loss: 11.20345
epochs: 7: loss: 10.23036
epochs: 8: loss: 9.20135
epochs: 9: loss: 8.14072
epochs: 10: loss: 7.07593
epochs: 11: loss: 6.03755
epochs: 12: loss: 5.05858
epochs: 13: loss: 4.17275
epochs: 14: loss: 3.41181
epochs: 15: loss: 2.80186
epochs: 16: loss: 2.35893
epochs: 17: loss: 2.08447
epochs: 18: loss: 1.96201
epochs: 19: loss: 1.95731
epochs: 20: loss: 2.02381
```

[ ]:
```
predicted_ratings_list = [tensor.item() for tensor in predicted_ratings]
# print(predicted_ratings_list)
train_df["Predictions"] = predicted_ratings_list
```

[ ]:
```
# merge result to df
predictions = train_df["Predictions"]

# Plot the distribution
sns.histplot(predictions, kde=True)
plt.title("Distribution of Predictions")
plt.xlabel("Predictions")
plt.ylabel("Count")
plt.show()
```



[ ]:
```
# Assuming train_df is your DataFrame with a column named "Predictions"
ratings = train_df["rating"]

# Plotting the distribution
sns.histplot(ratings, kde=True)
plt.title("Distribution of ratings (Ground truth)")
plt.xlabel("Ratings")
plt.ylabel("Count")
plt.show()
```



[ ]:
```python
# Test function

def test_model(model, test_data, train_data):
    model.eval()  # Set the model to evaluation mode

    # Filter test data based on available user and item IDs in training data
    valid_users = test_data.user_id.isin(train_data.user_id.unique())
    valid_items = test_data.item_id.isin(train_data.item_id.unique())
    filtered_test_data = test_data[valid_users & valid_items]

    users = torch.LongTensor(filtered_test_data.user_id.values)
    items = torch.LongTensor(filtered_test_data.item_id.values)

    with torch.no_grad():
        y_hat = model(users, items)
    MAX = max(y_hat.tolist())
    MIN = min(y_hat.tolist())

    scaled_y_hat = [value * 5 / MAX for value in y_hat]
    return scaled_y_hat
```

```
pred = test_model(model, test_df, train_df)
```

[ ]:
```
len(pred), len(test_df)
```

[ ]:
```
(56199, 56199)
```

[ ]:
```
pred_list = [tensor.item() for tensor in pred]
test_df["rating"] = pred_list
```

[ ]:
```
# Kaggle result: 1.0528

test_df[["ID", "rating"]].to_csv(FolderPath + "output.csv", index = False)
```

---

4 Implementation of Neural Network with features

Metadata was taken into consideration

[ ]:
```
train_df_ = merge_metadata(metadata_df, train_df)
test_df_ = merge_metadata(metadata_df, test_df)
```

[ ]:
```
train_df_.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 286136 entries, 0 to 286135
Data columns (total 14 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   user_id                   286136 non-null  int64
 1   item_id                   286136 non-null  int64
 2   rating                    286136 non-null  int64
 3   book_name                 286136 non-null  object
 4   Prediction                286136 non-null  float64
 5   ratings given by user     286136 non-null  int64
 6   Count of ratings to item  286136 non-null  int64
 7   error                     286136 non-null  float64
 8   CountsOfReview            286136 non-null  float64
 9   Rating                    286136 non-null  float64
 10  Language_cat              286136 non-null  float64
 11  AuthorBookCount           286136 non-null  float64
 12  AuthorCountCat            286136 non-null  category
 13  ReviewCountCat            286136 non-null  category
dtypes: category(2), float64(6), int64(5), object(1)
memory usage: 28.9+ MB
```

[ ]:
```
class MFWithFeatures(nn.Module):
    def __init__(self, num_users, num_items, num_languages,␣
 ↪num_popularity_groups, num_review_count_groups, emb_size=100):
        super(MFWithFeatures, self).__init__()
        self.user_emb = nn.Embedding(num_users, emb_size)
        self.item_emb = nn.Embedding(num_items, emb_size)
        self.language_emb = nn.Embedding(num_languages, emb_size)
        self.popularity_emb = nn.Embedding(num_popularity_groups, emb_size)
        self.review_emb = nn.Embedding(num_review_count_groups, emb_size)
        self.fc = nn.Linear(emb_size * 5, 1)

    def forward(self, u, v, lang, pop, rev):
        U = self.user_emb(u)
        V = self.item_emb(v)
        L = self.language_emb(lang)
        P = self.popularity_emb(pop)
        R = self.review_emb(rev)
        features = torch.cat([U, V, L, P, R], dim=1)
        pred = self.fc(features)
        pred = torch.sigmoid(pred) * 4 + 1
        return pred



def train_epocs(model, df, epochs=20, lr=0.01, wd=0.0, unsqueeze=False):
    optimizer = torch.optim.Adam(model.parameters(), lr=lr, weight_decay=wd)
    model.train()
    for i in range(epochs):
        users = torch.LongTensor(df.user_id.values)
        items = torch.LongTensor(df.item_id.values)
        languages = torch.LongTensor(df.Language_cat.values)
        popularity_groups = torch.LongTensor(df['AuthorCountRank'].values)
        review_count_groups = torch.LongTensor(df['ReviewCountRank'].values)
        ratings = torch.FloatTensor(df.rating.values)
        if unsqueeze:
            ratings = ratings.unsqueeze(1)
        y_hat = model(users, items, languages, popularity_groups,␣
 ↪review_count_groups)
        loss = F.mse_loss(y_hat, ratings)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
    return y_hat

def test_model(model, test_data, train_data):
    model.eval()  # Set the model to evaluation mode
```

```
    # Filter test data based on available user and item IDs in training data
    valid_users = test_data.user_id.isin(train_data.user_id.unique())
    valid_items = test_data.item_id.isin(train_data.item_id.unique())
    filtered_test_data = test_data[valid_users & valid_items]

    users = torch.LongTensor(filtered_test_data.user_id.values)  # .cuda()
    items = torch.LongTensor(filtered_test_data.item_id.values)  # .cuda()

    with torch.no_grad():
        y_hat = model(users, items)
    MAX = max(y_hat.tolist())
    MIN = min(y_hat.tolist())

    scaled_y_hat = [value * 5 / MAX for value in y_hat]
    return scaled_y_hat
```

[ ]:
```
train_df_['AuthorCountRank'] = pd.factorize(train_df_['AuthorCountCat'])[0]
train_df_['ReviewCountRank'] = pd.factorize(train_df_['ReviewCountCat'])[0]
```

[ ]:
```
num_users = len(train_df_.user_id.unique())
num_items = len(train_df_.item_id.unique())
num_languages = len(train_df_.Language_cat.unique())
num_AuthorCountRank = len(train_df_['AuthorCountRank'].unique())
num_ReviewCountRank = len(train_df_['ReviewCountRank'].unique())


print(num_users, num_items, num_languages, num_AuthorCountRank,␣
  ↪num_ReviewCountRank)
```

```
4154 89030 6 13 99
```

[ ]:
```
train_df_['Language_cat'] = train_df_['Language_cat'].astype(int)
train_df_.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 286136 entries, 0 to 286135
Data columns (total 16 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   user_id                   286136 non-null  int64
 1   item_id                   286136 non-null  int64
 2   rating                    286136 non-null  int64
 3   book_name                 286136 non-null  object
 4   Prediction                286136 non-null  float64
 5   ratings given by user     286136 non-null  int64
 6   Count of ratings to item  286136 non-null  int64
 7   error                     286136 non-null  float64
 8   CountsOfReview            286136 non-null  float64
```

```
 9   Rating                  286136 non-null  float64
 10  Language_cat            286136 non-null  int32
 11  AuthorBookCount         286136 non-null  float64
 12  AuthorCountCat          286136 non-null  category
 13  ReviewCountCat          286136 non-null  category
 14  AuthorCountRank         286136 non-null  int64
 15  ReviewCountRank         286136 non-null  int64
dtypes: category(2), float64(5), int32(1), int64(7), object(1)
memory usage: 32.2+ MB
```

[ ]:
```
model = MFWithFeatures(num_users, num_items, num_languages,␣
↪num_AuthorCountRank, num_ReviewCountRank, emb_size=100)
```

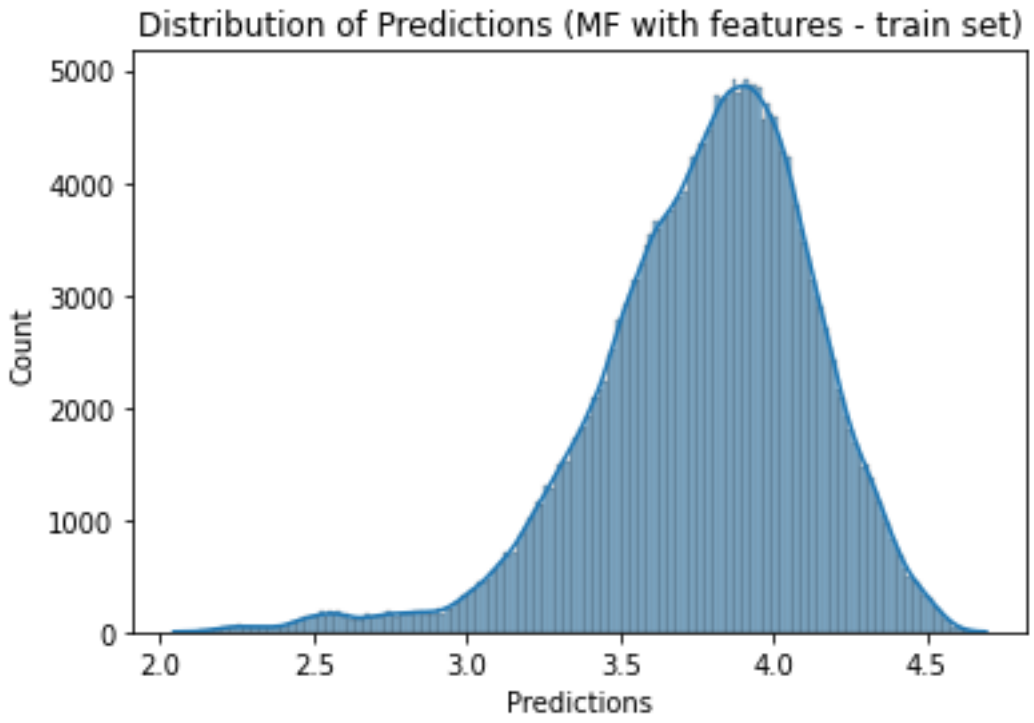
[ ]:
```
predicted_ratings = train_epocs(model, train_df_, epochs=50, lr=0.01, wd=5e-5,␣
↪unsqueeze=True)
```

[ ]:
```
train_df_["Predictions"] = predicted_ratings
```

[ ]:
```
predicted_ratings
```

[ ]:
```
tensor([[4.1282],
        [4.2137],
        [4.3225],
        …,
        [3.9676],
        [3.8570],
        [3.5859]], grad_fn=<AddBackward0>)
```

[ ]:
```
# Convert tensor into list
predictions = [tensor.item() for tensor in predicted_ratings]

# Plotting the distribution
sns.histplot(predictions, kde=True)
plt.title("Distribution of Predictions (MF with features - train set)")
plt.xlabel("Predictions")
plt.ylabel("Count")
plt.show()
```



[ ]:
```
test_df_['AuthorCountRank'] = pd.factorize(test_df_['AuthorCountCat'])[0]
test_df_['ReviewCountRank'] = pd.factorize(test_df_['ReviewCountCat'])[0]
```

[ ]:
```
def test_model(model, df, unsqueeze=False):
    model.eval()
    with torch.no_grad():
        users = torch.LongTensor(df.user_id.values)
        items = torch.LongTensor(df.item_id.values)
        languages = torch.LongTensor(df.Language_cat.values)
        popularity_groups = torch.LongTensor(df['AuthorCountRank'].values)
        review_count_groups = torch.LongTensor(df['ReviewCountRank'].values)
        if unsqueeze:
            ratings = ratings.unsqueeze(1)
        y_hat = model(users, items, languages, popularity_groups,␣
 ↪review_count_groups)
    return y_hat
```

[ ]:
```
pred = test_model(model, test_df_)
```

[ ]:
```
pred_list = [tensor.item() for tensor in pred]
```

[ ]:
```
test_df_.info()
```

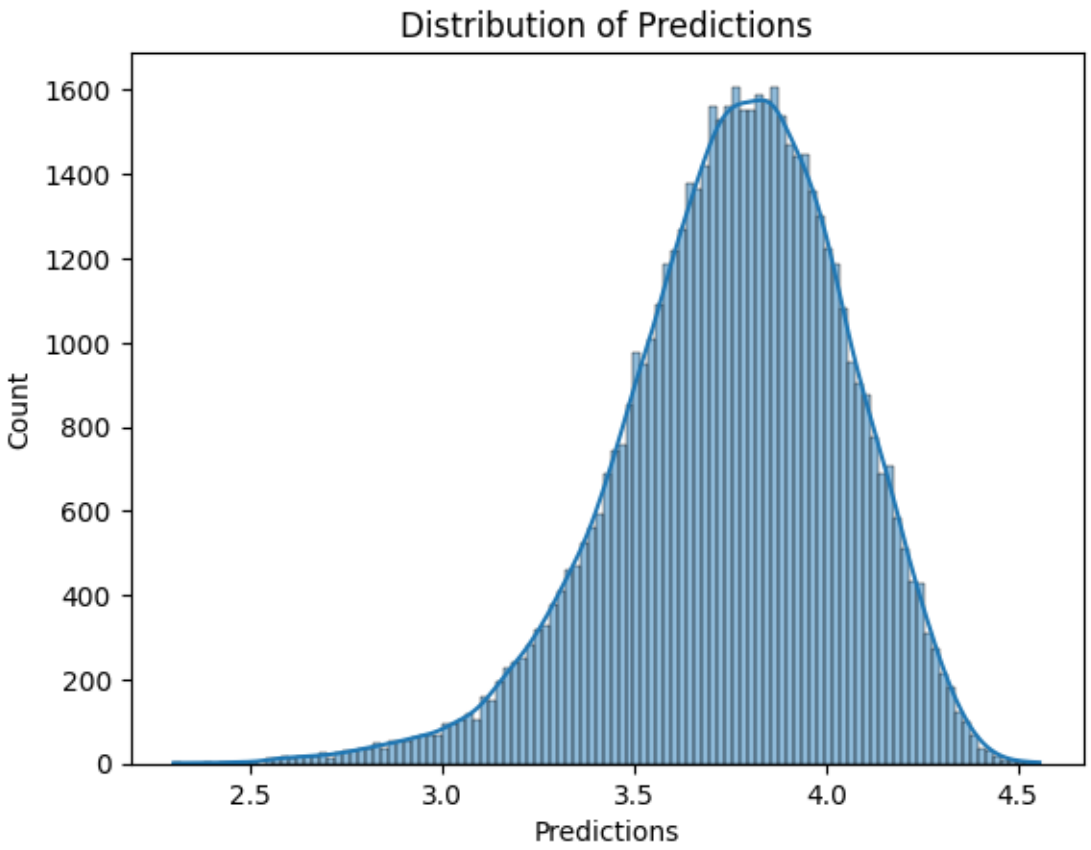
```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 56199 entries, 0 to 56198
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ID               56199 non-null  int64
 1   user_id          56199 non-null  int64
 2   item_id          56199 non-null  int64
 3   book_name        56199 non-null  object
 4   rating           56199 non-null  float64
 5   CountsOfReview   56199 non-null  float64
 6   Rating           56199 non-null  float64
 7   Language_cat     56199 non-null  float64
 8   AuthorBookCount  56199 non-null  float64
 9   AuthorCountCat   56199 non-null  category
 10  ReviewCountCat   56199 non-null  category
 11  AuthorCountRank  56199 non-null  int64
 12  ReviewCountRank  56199 non-null  int64
dtypes: category(2), float64(5), int64(5), object(1)
memory usage: 5.3+ MB
```

[ ]:
```
test_df_["rating"] = pred_list
```

[ ]:
```
# 0.77887

test_df_[["ID", "rating"]].to_csv(FolderPath + "MF_withfeatures.csv", index =␣
↪False)
```

[ ]:
```
predictions = pred_list

# Plotting the distribution of prediction result on trainset
sns.histplot(predictions, kde=True)
plt.title("Distribution of Predictions")
plt.xlabel("Predictions")
plt.ylabel("Count")
plt.show()

#
```


Distribution of Predictions
Count
Predictions
0
200
400
600
800
1000
1200
1400
1600
2.5
3.0
3.5
4.0
4.5