Assignment 3 Primer

- Assignment 3 will be based on a sample of movie rating predictions from the Netflix Prize dataset.
- It includes two pregenerated splits of 10k users for about 3k movies. So there is already a train and validation split that you will use for your experiments.
- It can be a little tricky to use predefined splits in surpise, so I will show you how to do it here.
- There are many articles available that talk about the million dollar prize and what it meant for the company. A few are:
- https://towardsdatascience.com/deep-dive-into-netflixs-recommender-system-341806ae3b48 (https://towardsdatascience.com/deep-dive-into-netflixs-recommender-system-341806ae3b48)
- https://www.thrillist.com/entertainment/nation/the-netflix-prize (https://www.thrillist.com/entertainment/nation/the-netflix-prize)
- https://analyticsindiamag.com/how-useful-was-the-netflix-prize-really/ (https://analyticsindiamag.com/how-useful-was-the-netflix-prize-really/)

In [1]:

```
import numpy as np
import pyarrow.feather as feather
import pandas as pd

# If you are on an Intel-based machine, you can also enable scikit-learn intel optin
# This does not work on an M1 / M2 Macbook, but does on older Macbooks with an Intel
# Requires ``pip install scikit-learn-intelex''
#
# from sklearnex import patch_sklearn
# patch_sklearn()
```

In [2]:

```
import pyarrow.feather as feather
import pandas as pd
from surprise import Dataset, Reader, BaselineOnly, accuracy
from surprise.model_selection import train_test_split, GridSearchCV, RandomizedSearc
from joblib import parallel_backend
from surprise import SVD
from surprise import NormalPredictor
from surprise import KNNBaseline
from surprise import CoClustering
from surprise import AlgoBase
from surprise import SlopeOne
from surprise import KNNBasic
from sklearn.metrics import average_precision_score
from sklearn.metrics import precision_score
from collections import defaultdict
from math import sqrt
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import LeaveOneOut
from tqdm import tqdm
from pandas.plotting import table
import seaborn as sns
import os, psutil
```

In [3]:

```
df_train = feather.read_feather('netflix-5k.train.feather')
df_val = feather.read_feather('netflix-5k.validation.feather')
df_titles = feather.read_feather('netflix-5k.movie_titles.feather')
df_train #321490
```

Out[3]:

	userID	movieID	rating
0	1000596	10036	4.0
1	1000596	10100	2.0
2	1000596	10209	3.0
3	1000596	10212	3.0
4	1000596	10225	3.0
...	...	...	...
1287012	99993	9683	4.0
1287013	99993	9685	4.0
1287014	99993	9800	2.0
1287015	99993	9939	5.0
1287016	99993	994	2.0

1287017 rows × 3 columns

In [4]:

```
reader = Reader(rating_scale=(0, 5))
data = Dataset.load_from_df(df_train[['userID','movieID',
                                      'rating']],reader)
datav = Dataset.load_from_df(df_val[['userID','movieID',
                                       'rating']],reader)
trainset = data.build_full_trainset()
NA,valset = train_test_split(datav, test_size=1.0)
```

In [5]:

```
def gen_anti_testset_user(valset, target_user):
  anti_testset_user = []
  fill_value = trainset.global_mean
  user_item_ratings = trainset.ur[target_user]
  user_items = [item for (item,_) in (user_item_ratings)]
  ratings = trainset.all_ratings()
  for iid in trainset.all_items():
    if iid not in user_items:
      raw_uid = trainset.to_raw_uid(target_user)
      raw_iid = trainset.to_raw_iid(iid)
      anti_testset_user.append((raw_uid,raw_iid,fill_value))
  return anti_testset_user


def algo_on_all_antisets(algo, trainset, valset, all_antisets, progress = False, k =
  scores_dict = {}
  if progress == True:
    print ('Scoring all user antisets and testset.')
    algo.fit(trainset)
    predictions = algo.test(valset)
    rmse = accuracy.rmse(predictions,verbose=False)
    mae = accuracy.mae(predictions,verbose=False)
    fcp = accuracy.fcp(predictions,verbose=False)
    mse = accuracy.mse(predictions,verbose=False)
#     print ('RMSE\tMAE\tFCP\tMSE')
#     print ('----------------------------')
#     print ('{}\t{}\t{}\t{}'.format(round(rmse,3),round(mae,3),round(fcp,3),
#                                        round(mse,3)))
    topNall = {}
    scores_dict['RMSE'] = round(rmse,3)
    scores_dict['MAE'] = round(mae, 3)
    for u,v in tqdm(all_antisets.items()):
      predictions = algo.test(v)
      pred = pd.DataFrame(predictions)
      p = pred.rename(columns={'uid':'userID','iid':'movieID'})
      pred = p.nlargest(k,['est'],keep='all')
      pred.sort_values('movieID',ascending=True,inplace=True,kind='stable')
      pred.sort_values('est',ascending=False,inplace=True,kind='stable')
      pred['pred_rank'] = pred['est'].rank(ascending=False,
                                       method='first',na_option='bottom')
      pred['pred_rank'] = pred['pred_rank'].astype(int)
      pred.reset_index(inplace=True)
      pred.drop('index',axis=1,inplace=True)
      pred['estint'] = round(pred['est'])
      pred['estint'] = round(pred['estint'].astype(float),1)
      topNall[u] = pred
    return topNall,rmse,mae,fcp,mse,scores_dict
  else:
    print ('Scoring all user antisets and testset.')
    algo.fit(trainset)
    predictions = algo.test(valset)
    rmse = accuracy.rmse(predictions,verbose=False)
    mae = accuracy.mae(predictions,verbose=False)
    fce = accuracy.fce(predictions,verbose=False)
    mse = accuracy.mse(predictions,verbose=False)
    topNall = {}
    for u,v in tqdm(all_antisets.items()):
      predictions = algo.test(v)
      pred = pd.DataFrame(predictions)
```

```
        p = pred.rename(columns={'iid':'userID','uid':'movieID'})
        pred = p.nlargest(k,['est'],keep='all')
        pred.sort_values('movieID',ascending=True,inplace=True,kind='stable')
        pred.sort_values('est',ascending=False,inplace=True,kind='stable')
        pred['pred_rank'] = pred['est'].rank(ascending=False,
                                             method='first',na_option='bottom')
        pred['pred_rank'] = pred['pred_rank'].astype(int)
        pred.reset_index(inplace=True)
        pred.drop('index',axis=1,inplace=True)
        pred['estint'] = round(pred['est'])
        pred['estint'] = round(pred['estint'].astype(float),1)
        topNall[u] = pred
    return topNall,rmse,mae,fcp,mse,scores_dict
```

In [6]:

```
def gen_r2i_map(trainset):
  inner2raw_uid = {}
  raw2inner_uid = {}
  inner2raw_iid = {}
  raw2inner_iid = {}
  for uid in tqdm(trainset.all_users()):
    rawid = trainset.to_raw_uid(uid)
    inner2raw_uid[uid] = rawid
    raw2inner_uid[rawid] = uid
  for iid in tqdm(trainset.all_items()):
    rawid = trainset.to_raw_iid(iid)
    inner2raw_iid[iid] = rawid
    raw2inner_iid[rawid] = iid
  return inner2raw_uid, raw2inner_uid,inner2raw_iid,raw2inner_iid

def gen_reference_sets(tdf, i2r_uid, r2i_iid, progress=False,k=10):
  ref = {}
  for u in i2r_uid.keys():
    udf = tdf[tdf['userID'] == i2r_uid[u]]
    ndf = udf.nlargest(k,['rating'],keep='all')
    ndf.sort_values('movieID',ascending=True,inplace=True,kind='stable')
    ndf.sort_values('rating',ascending=False,inplace=True,kind='stable')
    ndf['ref_rank'] = ndf['rating'].rank(ascending=False,method='first',
                                         na_option='bottom')
    ndf['ref_rank'] = ndf['ref_rank'].astype(int)
    ndf.reset_index(inplace=True)
    ndf.drop('index',axis=1,inplace=True)
    ref[u] = ndf
  return ref

def gen_antisets(trainset,progress=False):
  all_antisets = {}
  if progress == True:
    print ('Generating antiset for each user.')
    for uid in tqdm(trainset.all_users()):
      antitsu = gen_anti_testset_user(trainset, uid)
      all_antisets[uid] = antitsu
  else:
    for uid in trainset.all_users():
      antitsu = gen_anti_testset_user(trainset, uid)
      all_antisets[uid] = antitsu
  return all_antisets
```

In [7]:

```
i2r_uid, r2i_uid, i2r_iid, r2i_iid = gen_r2i_map(trainset)
```

```
100%|██████████| 5000/5000 [00:00<00:00, 349234.30it/s]
100%|██████████| 4334/4334 [00:00<00:00, 1079140.01it/s]
```

In [8]:

```
ref = gen_reference_sets(df_val, i2r_uid,r2i_iid, progress=False, k=10)
all_antisets = gen_antisets(trainset)
```

Data Analysis

In [9]:

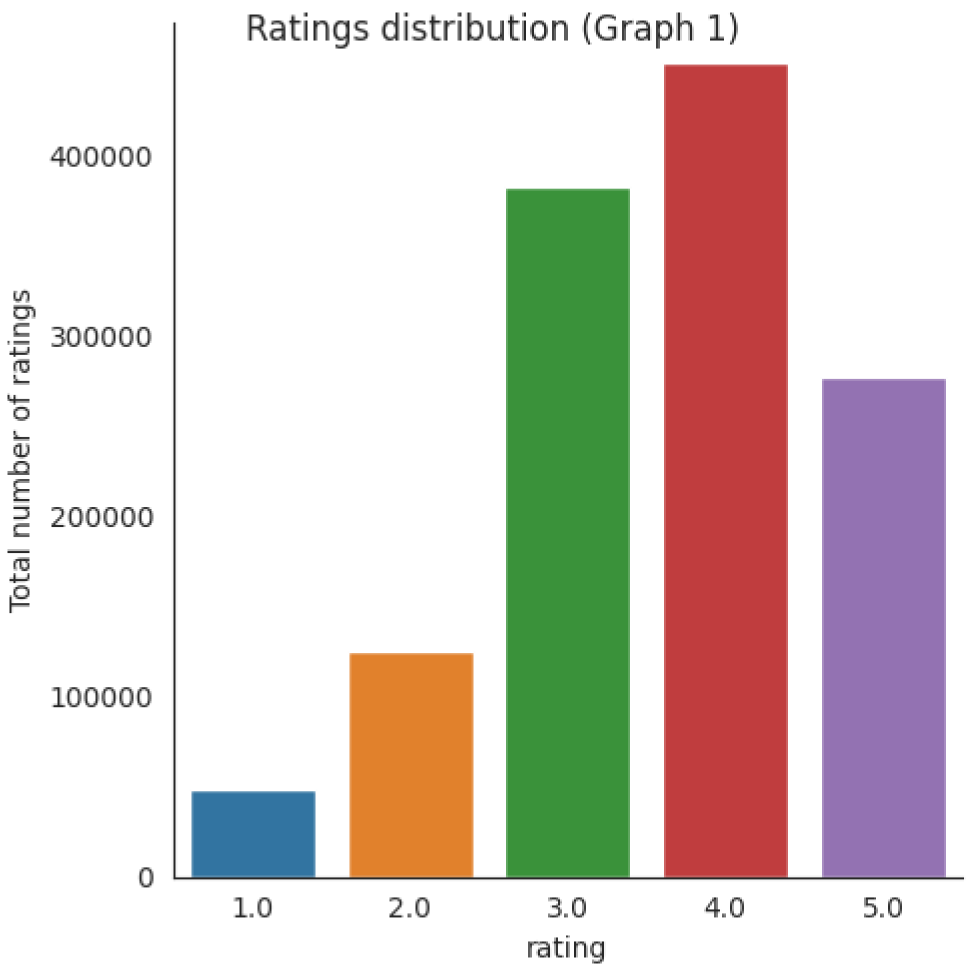
```
z = (df_train.describe()['rating'].T).to_frame()
pd.set_option('display.float_format', lambda x: '%.3f' % x)
z
```

Out[9]:

	rating
count	1287017.000
mean	3.610
std	1.045
min	1.000
25%	3.000
50%	4.000
75%	4.000
max	5.000

In [10]:

```
with sns.axes_style('white'):
    g = sns. catplot (data=df_train, x='rating', kind='count')
    g.set_ylabels("Total number of ratings")
    g.fig.suptitle("Ratings distribution (Graph 1)")
```



In [11]:

```
display(df_titles)
```

	movieID	imdb_id	imdb_date	date	title	genre
0	3	1860	1997	1997	Character	Drama
1	8	27899	2004	2004	What the #$*! Do We Know!?	Comedy|Documentary|Drama
2	16	76	1995	1996	Screamers	Action|Sci-Fi|Thriller
3	18	249	1994	1994	Immortal Beloved	Drama|Romance
4	26	7368	2004	2004	Never Die Alone	Crime|Drama|Thriller
...	...	...	...	...	...	...
4329	17761	6285	2003	2003	Levity	Drama
4330	17762	1653	1997	1997	Gattaca	Drama|Sci-Fi|Thriller
4331	17763	3813	1978	1978	Interiors	Drama
4332	17764	2396	1998	1998	Shakespeare in Love	Comedy|Drama|Romance
4333	17769	7165	2003	2003	The Company	Drama|Musical

4334 rows × 6 columns

In [12]:

```
# display(df_train)
((df_train.merge(df_titles, on='movieID')))
```

Out[12]:

	userID	movieID	rating	imdb_id	imdb_date	date	title	
0	1000596	10036	4.000	172343	2004	2004	Chris Rock: Never Scared	
1	1047019	10036	5.000	172343	2004	2004	Chris Rock: Never Scared	
2	1066990	10036	4.000	172343	2004	2004	Chris Rock: Never Scared	
3	1080891	10036	4.000	172343	2004	2004	Chris Rock: Never Scared	
4	108717	10036	5.000	172343	2004	2004	Chris Rock: Never Scared	
...	...	...	...	...	...	...	...	
1287012	611692	17379	3.000	4956	1980	1980	The Stunt Man	Action|Adventure|Comedy|Dı
1287013	659882	17379	4.000	4956	1980	1980	The Stunt Man	Action|Adventure|Comedy|Dı
1287014	668042	17379	3.000	4956	1980	1980	The Stunt Man	Action|Adventure|Comedy|Dı
1287015	798142	17379	3.000	4956	1980	1980	The Stunt Man	Action|Adventure|Comedy|Dı
1287016	923149	17379	4.000	4956	1980	1980	The Stunt Man	Action|Adventure|Comedy|Dı

1287017 rows × 8 columns

In [13]:

```
# (df_val)['userID']
pd.DataFrame((df_val)['userID']).nunique()
df_val.groupby('userID').nunique()
```

Out[13]:

	movieID	rating
userID		
785	77	5
1871	62	5
2960	73	4
3377	43	4
3826	82	5
...	...	...
2646281	66	5
2646342	43	4
2647617	88	5
2649257	89	5
2649429	40	5

5000 rows × 2 columns

Now let's look at the API documents for the 'baseline' only model in surprise: https://surprise.readthedocs.io/en/stable/prediction_algorithms.htr estimates-configuration (https://surprise.readthedocs.io/en/stable/prediction_algorithms.ht estimates-configuration)

Or after some digging, even more informative -- https://github.com/NicolasHug/Surprise/blob/master/doc/source/p (https://github.com/NicolasHug/Surprise/blob/master/doc/source/p

Note that while my attempt to tune the BaselineOnly method did not result in any noticeable performance improvements based on RMSE, that is not entirely surprising based on how this algorithm works. My goal was to show you how to tune the parameters using two different methods, so that you could more easily test and tune other algorithms from surprise.

In [14]:

```
# Print the memory usage of this process. Requires you to set n_jobs=1 and ``pip ins
# Use this to debug any memory issues you might be having.
process = psutil.Process(os.getpid())
print(process.memory_info().rss/(1024*1024))  # in MB
```

```
467.6953125
```

In [15]:

```
def predictions_to_df(p):
  df = pd.DataFrame(p, columns=['uid', 'iid', 'rui', 'est', 'details'])
  df['err'] = abs(df['rui'] - df['est'])
  return df
```

Algorithm 1: SVD

In [16]:

```
# Best parameters for SVD are {'n_epochs': 35, 'biased': 'False', 'n_factors': 50,
svd_tuned = SVD(n_factors = 225, n_epochs = 110, biased = False, init_std_dev = 0.2,
fitted_svd = svd_tuned.fit(trainset)
predictions_svd = fitted_svd.test(valset)
print('RMSE for SVD = {}'.format(round(accuracy.rmse(predictions_svd,verbose=False),
```

```
RMSE for SVD = 0.834
```

Algorithm 2: KNNBasic

In [17]:

```
# Best Score from Grid Search is  0.8566224546930907
# Best parameters for sim options are {'sim_options': {'name': 'pearson_baseline',
sim_options = {'name': 'pearson_baseline', 'user_based': False, 'shrinkage': 150, 'n
knn_basic = KNNBasic(sim_options = sim_options, min_k = 1, k = 40)
fitted_knn_basic = knn_basic.fit(trainset)
predictions_with_knn_basic = fitted_knn_basic.test(valset)
print('RMSE for KNN Basic = {}'.format(round(accuracy.rmse(predictions_with_knn_basi
```

```
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
RMSE for KNN Basic = 0.888
```

Algorithm 3: CoClustering

In [18]:

```
# Best Score from Grid Search is  0.8849491697508329
# Best parameters for SVD are {'n_epochs': 30, 'n_cltr_u': 7, n_cltr_i: 9}
coClustering = CoClustering(n_epochs=35, n_cltr_u = 7, n_cltr_i = 9 )
fitted_coClustering = coClustering.fit(trainset)
predictions_with_coClustering = fitted_coClustering.test(valset)
print('RMSE for Co-Clustering = {}'.format(round(accuracy.rmse(predictions_with_coCl
```

```
RMSE for Co-Clustering = 0.878
```

Algorithm 4: SlopeOne

In [19]:

```
slope_one = SlopeOne()
fitted_slope_one = slope_one.fit(trainset)
predictions_with_slope_one = fitted_slope_one.test(valset)
# Without Tuning: RMSE = 0.895
print('RMSE for Slope One = {}'.format(round(accuracy.rmse(predictions_with_slope_or
```

```
RMSE for Slope One = 0.895
```

Evaluation

In [20]:

```
def showMetrics(algo, trainset, valset, all_antisets):
    algo_on_all_antiset = algo_on_all_antisets(algo,trainset,valset,
                                               all_antisets,
                                               progress=True, k=10)
    topNall = algo_on_all_antiset[0]
    scores_dict = algo_on_all_antiset[5]
    hr = HitRate(topNall,ref)
    scores_dict['HitRate'] = round(hr,3)
    return scores_dict
#     print('HitRate for {} is {}'.format(algo, hr))
```

In [21]:

```
def HitRate(topNPredicted, refSet):
  hits = 0
  total = 0
  print('Computing Hitrate')
  for k,v in topNPredicted.items():
    ref = refSet[k]
    total += len(v.index)
    all_df = pd.merge(v,ref, on=['userID','movieID'])
    hits += len(all_df.index)
  return float(hits)/float(total)
```

In [22]:

```python
scores_svd = showMetrics(svd_tuned, trainset, valset, all_antisets)
print('Scores for SVD: ', scores_svd)
# Output: {'RMSE': 0.834, 'MAE': 0.655, 'HitRate': 0.08}
```

```
Scoring all user antisets and testset.

100%|██████████| 5000/5000 [04:03<00:00, 20.56it/s]

Computing Hitrate
Scores for SVD:  {'RMSE': 0.834, 'MAE': 0.655, 'HitRate': 0.079}
```

In [23]:

```python
scores_knn_basic = showMetrics(knn_basic, trainset, valset, all_antisets)
print('Scores for KNN Basic: ', scores_knn_basic)
# Output: {'RMSE': 0.888, 'MAE': 0.696, 'HitRate': 0.068}
```

```
Scoring all user antisets and testset.
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.

100%|██████████| 5000/5000 [45:20<00:00,  1.84it/s]

Computing Hitrate
Scores for KNN Basic:  {'RMSE': 0.888, 'MAE': 0.696, 'HitRate': 0.068}
```

In [24]:

```python
scores_co_clustering = showMetrics(coClustering, trainset, valset, all_antisets)
print('Scores for Co-Clustering: ', scores_co_clustering)
```

```
Scoring all user antisets and testset.

100%|██████████| 5000/5000 [03:49<00:00, 21.83it/s]

Computing Hitrate
Scores for Co-Clustering:  {'RMSE': 0.879, 'MAE': 0.688, 'HitRate': 0.
041}
```

In [25]:

```python
scores_slope_one = showMetrics(slope_one, trainset, valset, all_antisets)
print('Scores for Slope One: ', scores_slope_one)
```

```
Scoring all user antisets and testset.

100%|██████████| 5000/5000 [30:30<00:00,  2.73it/s]

Computing Hitrate
Scores for Slope One:  {'RMSE': 0.895, 'MAE': 0.703, 'HitRate': 0.016}
```

In [26]:

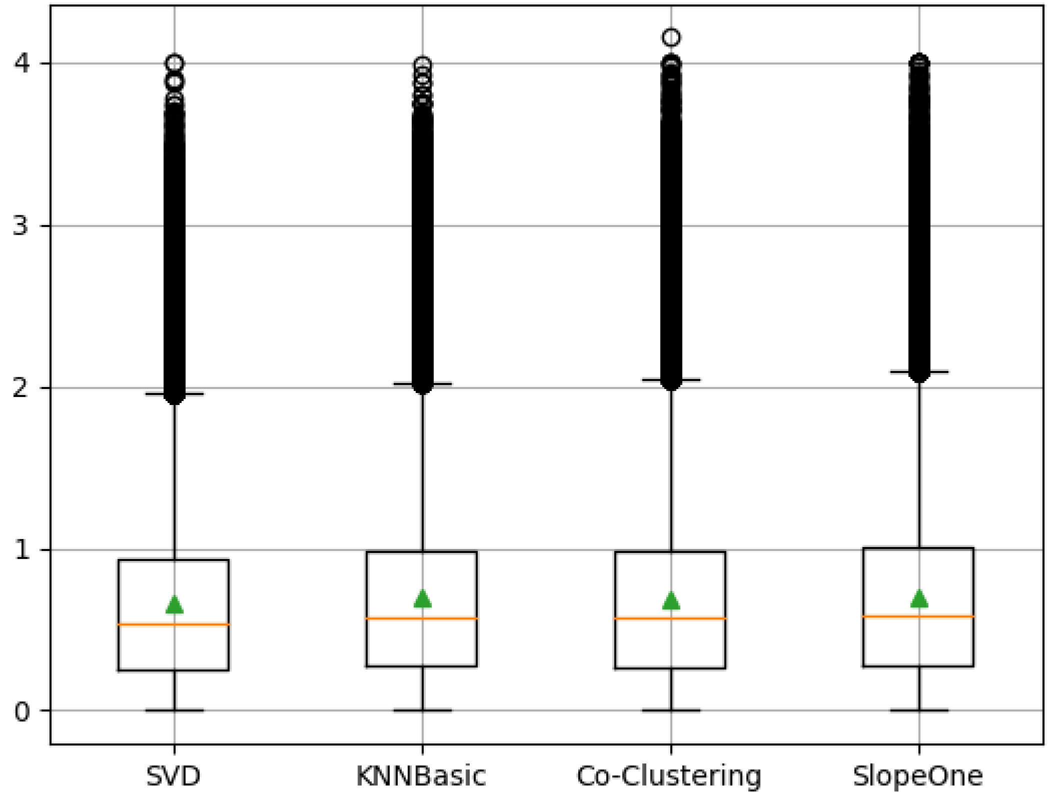
```
overall_scores = pd.DataFrame.from_dict([scores_svd, scores_knn_basic, scores_co_clu
s = pd.Series(['SVD', 'KNNBasic', 'Co-Clustering', 'SlopeOne'])
overall_scores = overall_scores.set_index([s])
overall_scores.sort_values(by=['RMSE'])
```

Out[26]:

	RMSE	MAE	HitRate
SVD	0.834	0.655	0.079
Co-Clustering	0.879	0.688	0.041
KNNBasic	0.888	0.696	0.068
SlopeOne	0.895	0.703	0.016

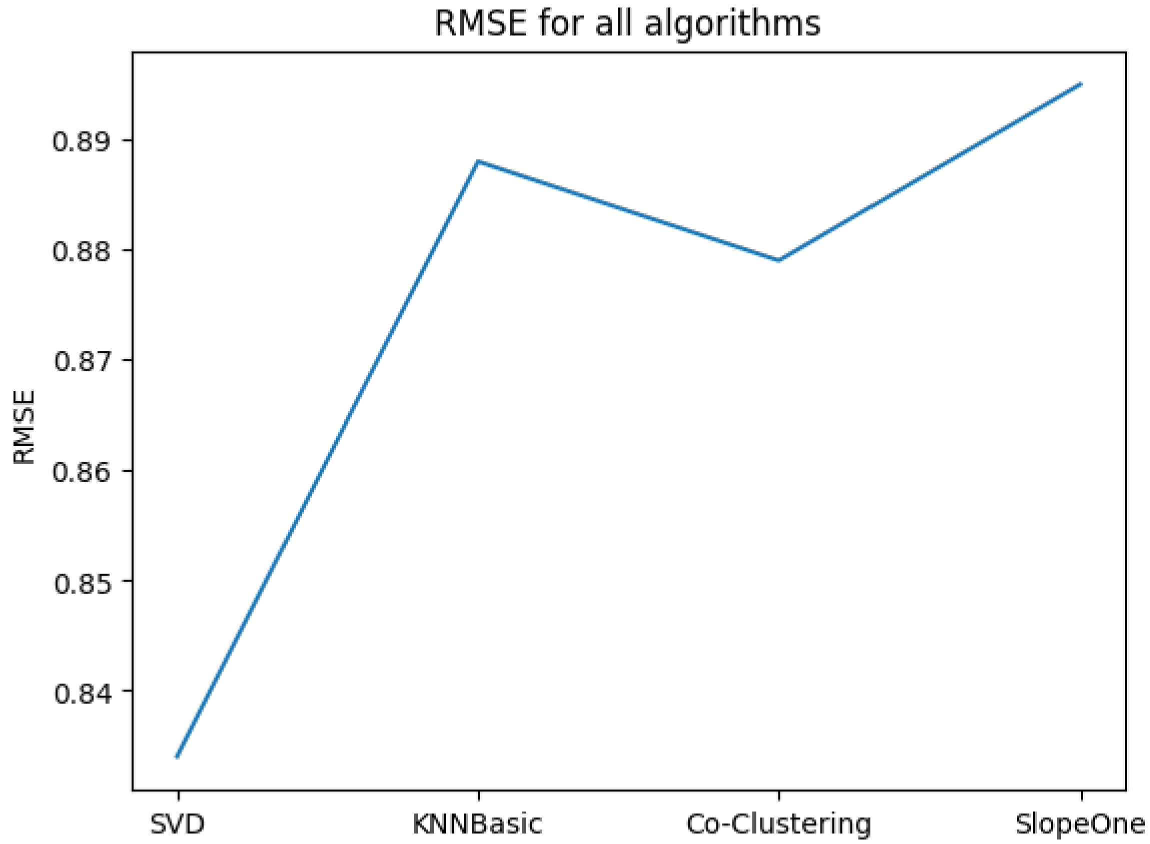
In [28]:

```
plt.grid(visible=True, which='major', axis='both')
results = [predictions_to_df(predictions_svd)['err'], predictions_to_df(predictions_
names = ['SVD', 'KNNBasic', 'Co-Clustering', 'SlopeOne']
plt.boxplot(results, labels=names, showmeans=True)
plt.show()
```



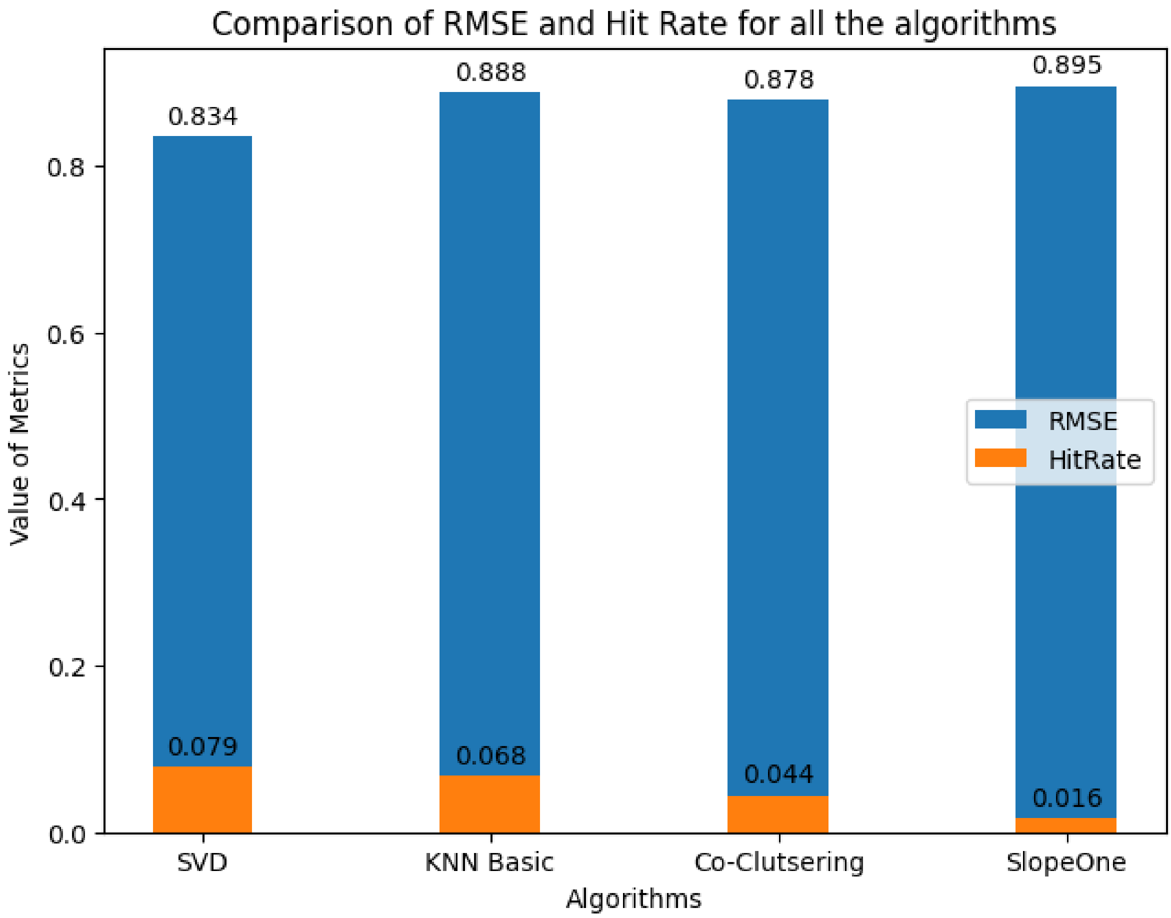
In [29]:

```
# all_rmse = {"SVD": scores_svd['RMSE'], 'KNN Basic' : scores_knn_basic['RMSE'], 'Co
g = sns.lineplot(data = overall_scores['RMSE'], sort = True).set(title='RMSE for all
```



In [31]:

```
# # all_rmse = {"SVD": scores_svd['RMSE'], 'KNN Basic' : scores_knn_basic['RMSE'],
# g = sns.barplot(data = f).set(title='RMSE for all algorithms')
labels = ['SVD', 'KNN Basic', 'Co-Clutsering', 'SlopeOne']
fig, ax = plt.subplots()
x = np.arange(len(labels))
width = 0.35
rects1 = ax.bar(labels, [0.834, 0.888, 0.878, 0.895], width=0.35, label='RMSE')
rects2 = ax.bar(labels, [0.079, 0.068, 0.044, 0.016], width=0.35,label='HitRate')
fig.tight_layout()
ax.legend()
plt.legend(loc='right')
plt.title('Comparison of RMSE and Hit Rate for all the algorithms')
plt.xlabel('Algorithms')
plt.ylabel('Value of Metrics')
ax.bar_label(rects1, padding=3)
ax.bar_label(rects2, padding=3)
plt.show()
```



In [32]:

```
# legend = ['SVD', 'KNN Basic', 'Co-Clutsering', 'SlopeOne']
g1 = sns.lineplot(data=overall_scores).set(title='Metrics for All Algorithms')
# g = g.set(xlim=(5,15))
# g.set(title = 'RMSE for top-N predictions for all algorithms')
plt.show(g1)
```