Contents

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Phase4 Recommender System Project
1 on 1 Review Date 8/6/2021

Buisness Problem: Recommender Systems in order to see how The PTBs requested a POC. Inte improve stickiness on the gaming site.

We are building a Recommender system for Movies from the 100KMovieLens dataset.

1 Obtain

The Data is from the MovieLens.com site. The data has over 100K rows in the ratings Sheet, over movieid, to imdb id and to the tmdbid. The movie table has over 9000 as well and the tage data ha

Contents

In [1]:

```python
import pandas as pd
ratings_df = pd.read_csv('./data/ratings.csv')
links_df = pd.read_csv('./data/links.csv')
movies_df = pd.read_csv('./data/movies.csv')
tags_df = pd.read_csv('./data/tags.csv')
ratings_df.info()
links_df.info()
movies_df.info()
tags_df.info()
```

executed in 717ms, finished 00:31:06 2021-08-06

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100836 entries, 0 to 100835
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   userId     100836 non-null  int64
 1   movieId    100836 non-null  int64
 2   rating     100836 non-null  float64
 3   timestamp  100836 non-null  int64
dtypes: float64(1), int64(3)
memory usage: 3.1 MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   movieId  9742 non-null   int64
 1   imdbId   9742 non-null   int64
 2   tmdbId   9734 non-null   float64
dtypes: float64(1), int64(2)
memory usage: 228.5 KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9742 entries, 0 to 9741
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   movieId  9742 non-null   int64
 1   title    9742 non-null   object
 2   genres   9742 non-null   object
dtypes: int64(1), object(2)
```

```
memory usage: 228.5+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3683 entries, 0 to 3682
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   userId     3683 non-null   int64
 1   movieId    3683 non-null   int64
 2   tag        3683 non-null   object
 3   timestamp  3683 non-null   int64
dtypes: int64(3), object(1)
memory usage: 115.2+ KB
```

Contents

In [2]:

```
# Drop unnecessary columns
ratings_df = ratings_df.drop(columns='timestamp')
# Drop unnecessary columns
tags_df = tags_df.drop(columns='timestamp')
```

executed in 14ms, finished 00:31:06 2021-08-06

Dropping unneeded info.

2 Scrub

#Remove Duplicates and clean up Nans.

In [3]:

```
ratings_df.isna().sum()
```

executed in 28ms, finished 00:31:06 2021-08-06

Out[3]:

```
userId     0
movieId    0
rating     0
dtype: int64
```

No Nans to clean up.

In [4]:
```
ratings_df.describe()
```
executed in 45ms, finished 00:31:06 2021-08-06

Out[4]:

	userId	movieId	rating
count	100836.000000	100836.000000	100836.000000
mean	326.127564	19435.295718	3.501557
std	182.618491	35530.987199	1.042529
min	1.000000	1.000000	0.500000
25%	177.000000	1199.000000	3.000000
50%	325.000000	2991.000000	3.500000
75%	477.000000	8122.000000	4.000000
max	610.000000	193609.000000	5.000000

Contents

3 Explore

3.0.1 Ratings Distribution

In [5]:
```
#Rating Distro
```
executed in 13ms, finished 00:31:06 2021-08-06

Contents

In [6]:

```
ratings_df['rating'].value_counts(normalize=True)
```

executed in 14ms, finished 00:31:06 2021-08-06

Out[6]:

```
4.0    0.265957
3.0    0.198808
5.0    0.131015
3.5    0.130271
4.5    0.084801
2.0    0.074884
2.5    0.055040
1.0    0.027877
1.5    0.017762
0.5    0.013586
Name: rating, dtype: float64
```

In [7]:

```
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud, STOPWORDS
%matplotlib inline
```

executed in 1.04s, finished 00:31:08 2021-08-06

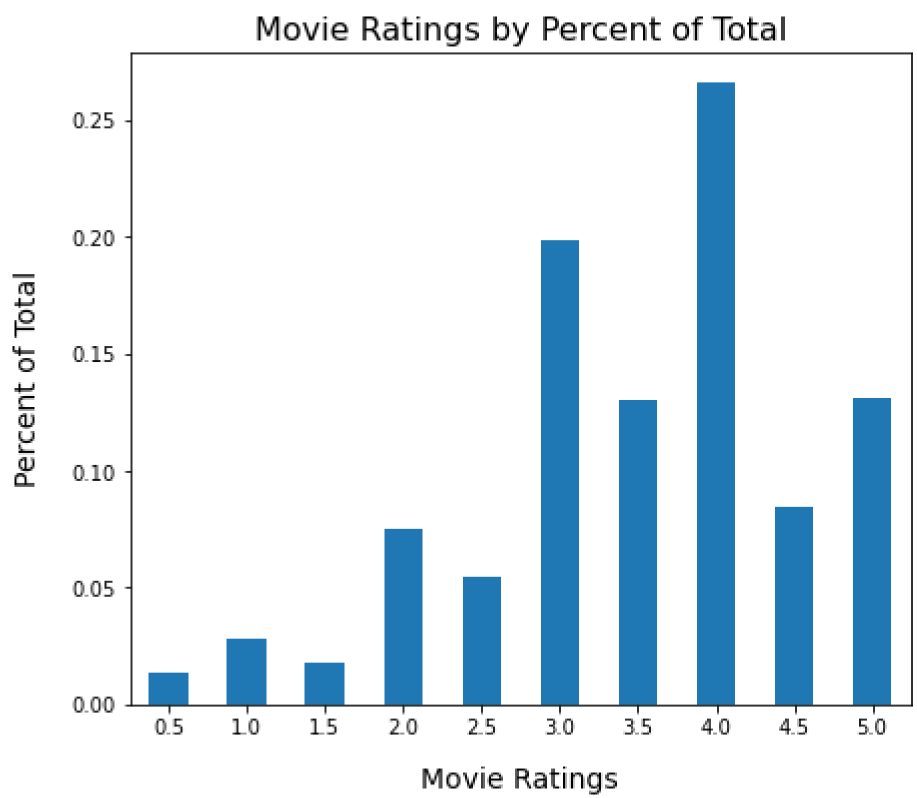
In [ ]:

executed in 31ms, finished 19:40:15 2021-08-05

In [8]:

```
ratings_df['rating'].value_counts(normalize=True,sort = False).sort_index()
plt.ylabel("Percent of Total", labelpad=14, fontsize=14)
plt.xlabel("Movie Ratings", labelpad=14,fontsize=14)
plt.title("Movie Ratings by Percent of Total", fontsize=16);
```

executed in 216ms, finished 00:31:08 2021-08-06



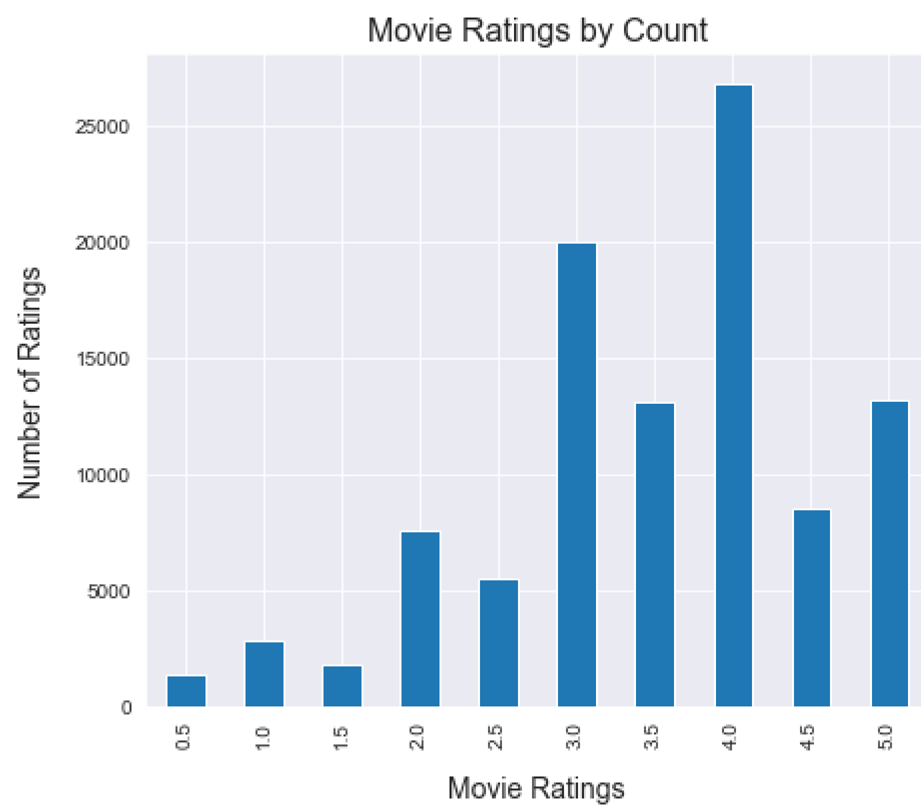
Contents

Contents

In [9]:

```
sns.set_style("darkgrid")
ratings_df['rating'].value_counts().sort_index().plot(kind='bar', figsize=(
plt.ylabel("Number of Ratings", labelpad=14, fontsize=14)
plt.xlabel("Movie Ratings", labelpad=14,fontsize=14)
plt.title("Movie Ratings by Count",fontsize=16);
```

executed in 222ms, finished 00:31:08 2021-08-06



Contents

In [10]:
```
ratings_df['rating'].agg(['mean', 'std','median'])
```
executed in 15ms, finished 00:31:08 2021-08-06

Out[10]:
```
mean      3.501557
std       1.042529
median    3.500000
Name: rating, dtype: float64
```

In [ ]:

In [11]:
```
movies_df['genres'].value_counts()
```
executed in 15ms, finished 00:31:08 2021-08-06

Out[11]:
```
Drama                                1053
Comedy                                946
Comedy|Drama                          435
Comedy|Romance                        363
Drama|Romance                         349
                                     ...
Children|Comedy|Crime|Musical           1
Children|Drama|Mystery                  1
Animation|Children|Drama|Musical        1
Horror|Romance|Thriller                 1
Action|Drama|Horror|IMAX                1
Name: genres, Length: 951, dtype: int64
```

Many mixes of Genres with Drama the singular most. We could break break the long strings up to the string.

In [12]:
```
movies_df['genres'].head()
```
executed in 13ms, finished 00:31:08 2021-08-06

Out[12]:
```
0    Adventure|Animation|Children|Comedy|Fantasy
1                     Adventure|Children|Fantasy
2                                 Comedy|Romance
3                           Comedy|Drama|Romance
4                                         Comedy
Name: genres, dtype: object
```

Contents

In [13]:
```
movies_lst = movies_df['genres'].tolist()
```
executed in 15ms, finished 00:31:08 2021-08-06

In [14]:
```
def genre_count(genres):
    count = dict()

    for entry in genres:
        for word in entry.split('|'):
            if word in count:
                count[word] += 1
            else:
                count[word] = 1
    return count
```
executed in 14ms, finished 00:31:08 2021-08-06

In [15]:
```
count = genre_count(movies_lst)
```
executed in 15ms, finished 00:31:08 2021-08-06

Contents

In [16]:

```
count
```

executed in 14ms, finished 00:31:08 2021-08-06

Out[16]:

```
{'Adventure': 1263,
 'Animation': 611,
 'Children': 664,
 'Comedy': 3756,
 'Fantasy': 779,
 'Romance': 1596,
 'Drama': 4361,
 'Action': 1828,
 'Crime': 1199,
 'Thriller': 1894,
 'Horror': 978,
 'Mystery': 573,
 'Sci-Fi': 980,
 'War': 382,
 'Musical': 334,
 'Documentary': 440,
 'IMAX': 158,
 'Western': 167,
 'Film-Noir': 87,
 '(no genres listed)': 34}
```

In [17]:

```
sortedcount=dict(sorted(count.items(), key=lambda item: item[1]))
```

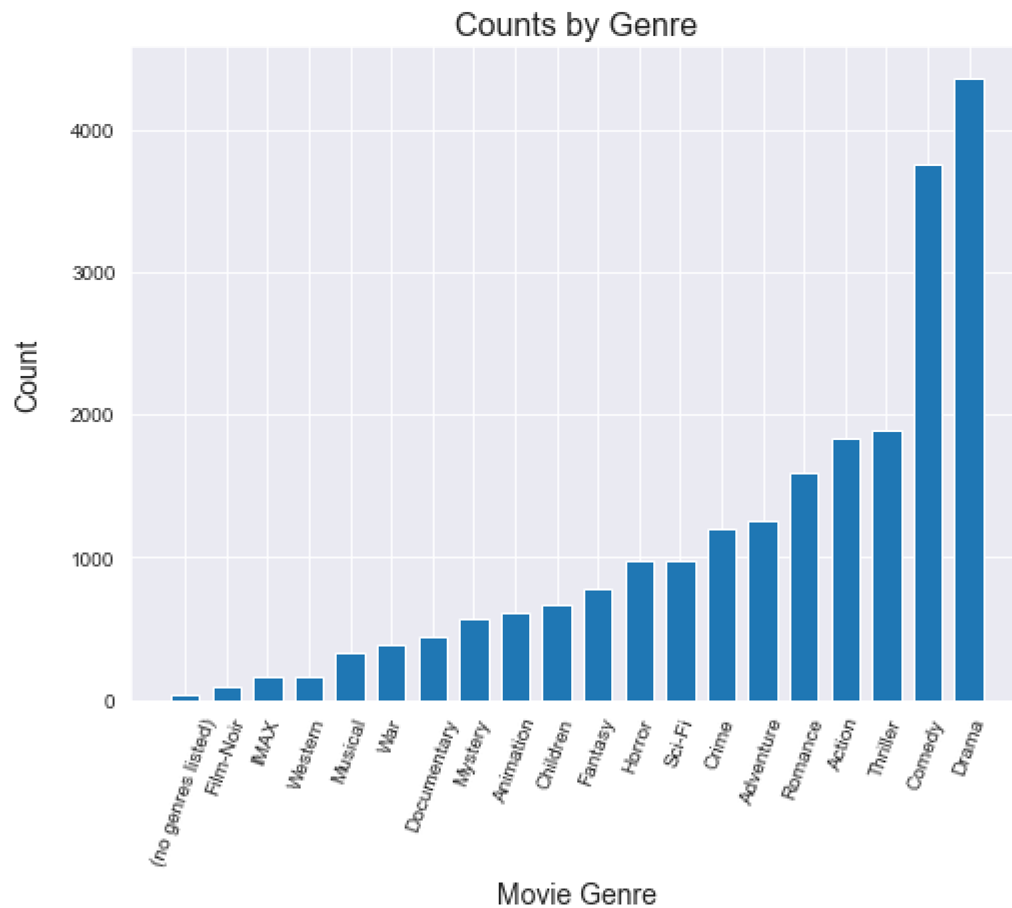
executed in 15ms, finished 00:31:08 2021-08-06

Contents

In [18]:

```
plt.figure(figsize=(8, 6))
plt.bar(list(sortedcount.keys()),list(sortedcount.values()), width=.7, )
plt.ylabel("Count", labelpad=14, fontsize=14)
plt.xlabel("Movie Genre", labelpad=7, fontsize=14)
plt.title("Counts by Genre", fontsize=16);
plt.xticks(rotation=70);
```

executed in 298ms, finished 00:31:08 2021-08-06



Contents

3.0.2 Word Cloud ON TAGS

In [19]:

```
def plot_wordcloud(data):
    removed = set(['Netflix queue','queue','Netflix']).union(STOPWORDS)
    filtered = data.loc[~data['tag'].isin(removed)]['tag']
    wc = WordCloud(stopwords = removed,background_color='white', include_nu

    plt.figure(figsize = (6, 9), facecolor = None);
    plt.imshow(wc)
    plt.axis('off')
    plt.tight_layout(pad = 0)

    plt.show;
```

executed in 15ms, finished 00:31:08 2021-08-06

Contents

In [20]:

```
plot_wordcloud(tags_df)
```

executed in 1.88s, finished 00:31:10 2021-08-06

Contents

#Lets do only from movies rated >= 4.5 and then another with movies <=1.5

In [21]:

```
result5 = ratings_df[ratings_df['rating'] <=1.5]
result5w_tag = pd.merge(result5, tags_df, left_index=True, right_index=True
```

executed in 15ms, finished 00:31:10 2021-08-06

In [22]:

```
result5w_tag
```

executed in 28ms, finished 00:31:10 2021-08-06

Out[22]:

	userId_x	movieId_x	rating	userId_y	movieId_y	tag
205	1	3176	1.0	62	60756	comedy
261	3	31	0.5	62	99114	Soundtrack
262	3	527	0.5	62	99114	western
263	3	647	0.5	62	103042	Amy Adams
264	3	688	0.5	62	103042	superhero
...	...	...	...	...	...	...
3651	21	149380	1.5	599	2959	Palahnuik
3653	21	160565	1.0	599	2959	philosophy
3654	21	160872	0.5	599	2959	postmodern
3661	21	173307	0.5	599	2959	schizophrenia
3674	22	2058	0.5	606	1948	British

249 rows × 6 columns

Contents

In [23]:

```
plot_wordcloud(result5w_tag)
```

executed in 1.67s, finished 00:31:12 2021-08-06

Contents

Contents

In [ ]:

executed in 447ms, finished 16:35:33 2021-08-05

4 Model

Surprise is a scikit package for building and analysing recommender systems maintained by Nicol

In [24]:

```
from surprise import Reader, Dataset
reader = Reader()
ratings_sp = Dataset.load_from_df(ratings_df,reader)
```

executed in 490ms, finished 00:31:12 2021-08-06

In [25]:

```
from surprise.model_selection import cross_validate, GridSearchCV
from surprise.prediction_algorithms import SVD, NMF, SlopeOne, CoClustering
from surprise.prediction_algorithms import KNNWithMeans, KNNBasic, KNNBasel
import numpy as np
```

executed in 14ms, finished 00:31:13 2021-08-06

In [ ]:

4.0.1 Cross Validate

The SVD procedure function transforms an m-by-n matrix a to the product of an m-by-n column or
matrix w, and the transpose of an n-by-n orthogonal matrix v. In other words, u, w, and v are matri

Contents

Contents

In [154]:

```
cross_validate(SVD(), ratings_sp, measures=['RMSE', 'MAE'], cv=10, verbose=
```

executed in 52.3s, finished 02:11:17 2021-08-06

```
Evaluating RMSE, MAE of algorithm SVD on 10 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Fold 6  Fold 7  F
td
RMSE (testset)    0.8775  0.8690  0.8711  0.8638  0.8623  0.8651  0.8697  0
0.0051
MAE (testset)     0.6728  0.6653  0.6703  0.6634  0.6635  0.6649  0.6672  0
0.0044
Fit time          4.73    4.74    4.86    5.49    5.16    5.22    4.90    4
0.22
Test time         0.06    0.06    0.06    0.07    0.06    0.06    0.28    0
0.07
```

Out[154]:

```
{'test_rmse': array([0.87751589, 0.86900181, 0.87114076, 0.86382491, 0.8622
        0.86514718, 0.8697337 , 0.87807446, 0.87188484, 0.86697911]),
 'test_mae': array([0.67281814, 0.66534114, 0.6703441 , 0.66341578, 0.66345
        0.66485563, 0.66722929, 0.67629267, 0.66399701, 0.66245899]),
 'fit_time': (4.730003595352173,
  4.741967439651489,
  4.858133316040039,
  5.488963603973389,
  5.16413950920105,
  5.221394777297974,
  4.901141881942749,
  4.917079925537109,
  4.888082027435303,
  4.956222057342529),
 'test_time': (0.06403565406799316,
  0.06103229522705078,
  0.0610041618347168,
  0.06999874114990234,
  0.06399989128112793,
  0.06498527526855469,
  0.2849917411804199,
  0.07300710678100586,
  0.06400084495544434,
  0.0789649486541748)}
```

Non-negative matrix factorization, another matrix factorization method where a matrix V is factoriz

W and H, with the property that all three matrices have no negative elements.

Contents

In [27]:
```
cross_validate(NMF(), ratings_sp, measures=['RMSE', 'MAE'], cv=5, verbose=T
```
executed in 27.9s, finished 00:32:04 2021-08-06

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.9208  0.9230  0.9251  0.9302  0.9124  0.9223  0.0058
MAE (testset)     0.7044  0.7072  0.7079  0.7121  0.6998  0.7063  0.0041
Fit time          5.19    5.24    5.35    5.32    5.38    5.30    0.07
Test time         0.16    0.13    0.15    0.11    0.10    0.13    0.02
```

Out[27]:
```
{'test_rmse': array([0.92081966, 0.9229778 , 0.92512711, 0.9302193 , 0.9124
 'test_mae': array([0.70438919, 0.70720189, 0.70787526, 0.71209037, 0.69976
 'fit_time': (5.192035436630249,
  5.239001035690308,
  5.353037595748901,
  5.3179991245269775,
  5.382961273193359),
 'test_time': (0.1580033302307129,
  0.12700104713439941,
  0.15399909019470215,
  0.11296463012695312,
  0.10303521156311035)}
```

SlopeOne algorithm arguably it is the simplest form of non-trivial item-based collaborative filtering

In [28]:

```
cross_validate(SlopeOne(), ratings_sp, measures=['RMSE', 'MAE'], cv=5, verb
```

executed in 53.3s, finished 00:32:57 2021-08-06

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std     
RMSE (testset)    0.8990  0.8948  0.9012  0.9022  0.9015  0.8997  0.0027  
MAE (testset)     0.6877  0.6829  0.6869  0.6892  0.6892  0.6872  0.0023  
Fit time          4.18    4.00    3.99    4.12    3.96    4.05    0.09    
Test time         6.27    6.58    6.46    6.36    6.61    6.46    0.13    
```

Out[28]:

```
{'test_rmse': array([0.89900666, 0.89477656, 0.90123851, 0.90219907, 0.9015
 'test_mae': array([0.68774964, 0.68291154, 0.68686472, 0.68920384, 0.68924
 'fit_time': (4.18496298789978,
  3.998981237411499,
  3.994962453842163,
  4.122996807098389,
  3.9559998512268066),
 'test_time': (6.267036437988281,
  6.580971717834473,
  6.456053972244263,
  6.364983320236206,
  6.613984107971191)}
```

CoClustering goal is to generate biclusters/co-clusters: a subset of rows which exhibit similar beha

Contents

In [29]:
```
cross_validate(CoClustering(), ratings_sp, measures=['RMSE', 'MAE'], cv=5,
```
executed in 15.3s, finished 00:33:12 2021-08-06

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.9401  0.9382  0.9456  0.9414  0.9445  0.9420  0.0027
MAE (testset)     0.7269  0.7305  0.7331  0.7274  0.7297  0.7295  0.0022
Fit time          2.71    2.79    2.82    2.85    2.83    2.80    0.05
Test time         0.10    0.14    0.09    0.10    0.15    0.12    0.02
```

Out[29]:
```
{'test_rmse': array([0.94005751, 0.93822905, 0.94564783, 0.94143115, 0.9444
 'test_mae': array([0.7269174 , 0.73048561, 0.73308119, 0.72738538, 0.72973
 'fit_time': (2.714000940322876,
  2.786001205444336,
  2.820998430252075,
  2.847975254058838,
  2.8259646892547607),
 'test_time': (0.10003304481506348,
  0.138016939163208,
  0.09003567695617676,
  0.09703922271728516,
  0.15003442764282227)}
```

In [ ]:
```
BaselineOnly
```

Contents

Contents

In [30]:

```python
cross_validate(BaselineOnly(), ratings_sp, measures=['RMSE', 'MAE'], cv=5,
```

executed in 2.57s, finished 00:33:15 2021-08-06

```
Estimating biases using als...
Estimating biases using als...
Estimating biases using als...
Estimating biases using als...
Estimating biases using als...
Evaluating RMSE, MAE of algorithm BaselineOnly on 5 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8777  0.8726  0.8705  0.8756  0.8661  0.8725  0.0040
MAE (testset)     0.6783  0.6741  0.6713  0.6743  0.6653  0.6727  0.0043
Fit time          0.25    0.26    0.26    0.24    0.26    0.25    0.01
Test time         0.09    0.08    0.14    0.08    0.08    0.09    0.02
```

Out[30]:

```
{'test_rmse': array([0.87774023, 0.87255962, 0.87046804, 0.87558592, 0.8661
 'test_mae': array([0.67833621, 0.67407273, 0.671319  , 0.67428522, 0.66532
 'fit_time': (0.25200390815734863,
  0.26496458053588867,
  0.25501227378845215,
  0.24395012855529785,
  0.2569546699523926),
 'test_time': (0.08999681472778320,
  0.08105039596557617,
  0.13795161247253418,
  0.08399391174316406,
  0.08003473281860352)}
```

Contents

In [63]:

```
cross_validate(KNNWithMeans(), ratings_sp, measures=['RMSE', 'MAE'], cv=10,
```

executed in 12.5s, finished 01:39:58 2021-08-06

```
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.
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.
Evaluating RMSE, MAE of algorithm KNNWithMeans on 10 split(s).

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Fold 6  Fold 7  F
td
RMSE (testset)    0.9005  0.8821  0.8874  0.8872  0.8823  0.8898  0.8941  0
0.0082
MAE (testset)     0.6839  0.6774  0.6785  0.6824  0.6755  0.6776  0.6818  0
0.0042
Fit time          0.22    0.24    0.25    0.28    0.24    0.25    0.25    0
0.01
Test time         0.92    0.83    0.85    0.90    0.81    0.83    0.84    0
0.04
```

Out[63]:

```
{'test_rmse': array([0.90046435, 0.88206995, 0.88735816, 0.8872334 , 0.8822
        0.88976637, 0.89412401, 0.90210678, 0.90803516, 0.89029125]),
 'test_mae': array([0.68387012, 0.67737693, 0.6784591 , 0.6823854 , 0.67550
        0.67755682, 0.68179216, 0.68458461, 0.69047427, 0.68279961]),
 'fit_time': (0.2200021743774414,
  0.24094700813293457,
```

Contents


```
  0.24700021743774414,
  0.27596449851989746,
  0.2389824390411377,
  0.2469625473022461,
  0.2489912509918213,
  0.2400531768798828,
  0.24301695823669434,
  0.24198436737060547),
 'test_time': (0.9230015277862549,
  0.8270382881164551,
  0.8519845008850098,
  0.9020426273345947,
  0.814000129699707,
  0.8289997577667236,
  0.838965892791748,
  0.850017786026001,
  0.7829830646514893,
  0.8400039672851562)}
```

In [61]:
```
cross_validate(KNNBasic(), ratings_sp, measures=['RMSE', 'MAE'], cv=5, verb
```
executed in 8.71s, finished 01:33:12 2021-08-06

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.9515  0.9454  0.9486  0.9439  0.9397  0.9458  0.0040
MAE (testset)     0.7274  0.7238  0.7297  0.7254  0.7207  0.7254  0.0031
Fit time          0.16    0.19    0.21    0.18    0.17    0.18    0.02
Test time         1.39    1.40    1.45    1.30    1.46    1.40    0.06
```

Out[61]:
```
{'test_rmse': array([0.9514752 , 0.94536846, 0.94855617, 0.94390515, 0.9397
 'test_mae': array([0.72738802, 0.72383563, 0.72965008, 0.72538475, 0.72065
 'fit_time': (0.15994691848754883,
  0.19300174713134766,
  0.20996737480163574,
  0.17695069313049316,
  0.1739664077758789),
 'test_time': (1.3870344161987305,
  1.4030020236968994,
  1.4450345039367676,
  1.3000402450561523,
  1.4610002040863037)}
```

Contents

In [62]:

```
cross_validate(KNNBaseline(), ratings_sp, measures=['RMSE', 'MAE'], cv=5, v
```

executed in 12.2s, finished 01:33:25 2021-08-06

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

                  Fold 1  Fold 2  Fold 3  Fold 4  Fold 5  Mean    Std
RMSE (testset)    0.8798  0.8721  0.8709  0.8659  0.8852  0.8748  0.0069
MAE (testset)     0.6740  0.6657  0.6652  0.6618  0.6763  0.6686  0.0056
Fit time          0.41    0.42    0.44    0.42    0.41    0.42    0.01
Test time         1.84    1.88    1.85    1.88    1.95    1.88    0.04
```

Out[62]:

```
{'test_rmse': array([0.87984393, 0.87210233, 0.87087456, 0.86587917, 0.8851
 'test_mae': array([0.67398099, 0.66573038, 0.66524779, 0.66176168, 0.67630
 'fit_time': (0.4089622497558594,
  0.41605186462402344,
  0.44196534156799316,
  0.418964147567749,
  0.41299629974365234),
 'test_time': (1.8420038223266602,
  1.880998134613037,
  1.8480350971221924,
  1.877035140991211,
  1.9479830265045166)}
```

4.0.2 Gridsearch SVD

4.0.2.1 Gridsearch on SVD

Contents

In [31]:
```
%%script echo skipping
params = {'n_factors': [10,25,50,75,100],
         'reg_all': [0.02, 0.04, 0.06, 0.08, 0.1]}
gs_svd = GridSearchCV(SVD,param_grid=params,n_jobs=-1)
gs_svd.fit(ratings_sp)
```
executed in 46ms, finished 00:33:15 2021-08-06

```
skipping
```

In [32]:
```
%%script echo skipping
print(gs_svd.best_score)
print(gs_svd.best_params)
```
executed in 31ms, finished 00:33:15 2021-08-06

```
skipping
```

Based off these outputs, it seems like the best performing model is the SVD model with n_factors

Gridsearch on BaselineOnly ALS

4.0.2.2 Gridsearch on BaselineOnly ALS

In [33]:
```
%%script echo skipping
params = {'bsl_options': {'method': ['als'],
                          'reg_i': [8, 9, 10, 11, 12], # Lambda 2
                          'reg_u': [3, 4, 5, 6, 7],# Lambda 3
                         }
         }
gs_bo = GridSearchCV(BaselineOnly,param_grid=params,n_jobs=-1)
gs_bo.fit(ratings_sp)
```
executed in 31ms, finished 00:33:15 2021-08-06

```
skipping
```

Contents

In [34]:

```
%%script echo skipping
print(gs_bo.best_score)
print(gs_bo.best_params)
```

executed in 31ms, finished 00:33:15 2021-08-06

```
skipping
```

4.0.2.3 Gridsearch on KNNWithMeans

In [65]:

```
params = {'n_factors': [10,25,50,75,100],
          'reg_all': [0.02, 0.04, 0.06, 0.08, 0.1]}

gs_knn = GridSearchCV(KNNWithMeans,param_grid=params,n_jobs=-1)
gs_knn.fit(ratings_sp)

print(gs_knn.best_score)
print(gs_knn.best_params)
```

executed in 1m 2.72s, finished 01:47:45 2021-08-06

```
{'rmse': 0.8959297009455709, 'mae': 0.6845950316280579}
{'rmse': {'n_factors': 10, 'reg_all': 0.02}, 'mae': {'n_factors': 10, 'reg_
```

In [ ]:

In [ ]:

4.0.3 Recommendations

4.0.3.1 Functions

For cold start ratedriver calls new_interview and movierater to ask about the top 3 genres and ask specified genres.

In [35]:

```
def new_interview(userID):
    genIds = []
    genres = { '1' :'Action' , '2' :'Adventure' , '3' :'Drama', '4' :'Comed
    top3 = []
    num = 1
    print(genres)
    while num > 0 :
        g1, g2, g3 = input('\033[1m' + 'Please enter your top 3 genres from
        genIds.append(g1)
        genIds.append(g2)
        genIds.append(g3)
        num -= 1

    for gid in genIds:
        top3.append(genres.get(gid))

    return top3
```

executed in 15ms, finished 00:33:15 2021-08-06

In [36]:

```
def rate_driver(userID):
    genres = { 1 :'Action' , 2 :'Adventure' ,3 :'Drama', 4 :'Comedy' , 5:'H
    topgenres = new_interview(userID)
    init_user_rates = []

    for genre in topgenres:
        #rate 3 movies for the genre
        init_user_rates.extend(movie_rater(userID, 3, genre))

    return init_user_rates
```

executed in 14ms, finished 00:33:15 2021-08-06

Contents

Contents

In [58]:

```
def movie_rater(movie_df, num, genre=None):
    userID = 1000
    rating_list = []
    print('\033[1m' + genre)
    print('\033[0m')

    while num > 0:

        print('###############################################################
        if genre:
            movie = movies_df[movies_df['genres'].str.contains(genre)].samp
        else:
            movie = movies_df.sample(1)
        print(movie)
        rating = input('Please rate on a scale of .5-5, press n if you have
        if rating == 'n':
            continue
        else:
            rating_one_movie = {'userId':userID,'movieId':movie['movieId'].
            rating_list.append(rating_one_movie)
            print('\n')
            num -= 1
    return rating_list
```

executed in 8ms, finished 01:04:27 2021-08-06

In [78]:

```
# return the top n recommendations using the
def recommended_movies(user_ranks,movie_title_df,n,genre=None):

    for idx, rec in enumerate(user_ranks):
        #movies = movie_title_df[movie_title_df['genres'].str.contains(

        title = movie_title_df.loc[movie_title_df['movieId'] == int(rec
        title = str(title).rpartition('\n')[0][4:]
        genre = movie_title_df.loc[movie_title_df['movieId'] == int(rec
        genre = str(genre).rpartition('\n')[0][4:]
        print('Rec# ', idx+1, ': ','\033[1m' + title + '\033[0m', genre
        n-= 1
        if n == 0:
            break
```

executed in 18ms, finished 01:52:01 2021-08-06

4.0.3.2 Recommendation PreProcess

Contents

In [39]:

```
dataset = ratings_sp.build_full_trainset()
print('Number of users: ', dataset.n_users, '\n')
print('Number of items: ', dataset.n_items)
```

executed in 79ms, finished 00:33:15 2021-08-06

```
Number of users:  610

Number of items:  9724
```

In [40]:

```
svd = SVD(n_factors= 25, reg_all=0.04)
svd.fit(dataset)
```

executed in 2.13s, finished 00:33:17 2021-08-06

Out[40]:

```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x1a15082e7f0>
```

In [41]:

```
#predict for first user and first movie
#last user first movie
svd.predict(1, 1)
```

executed in 14ms, finished 00:33:17 2021-08-06

Out[41]:

```
Prediction(uid=1, iid=1, r_ui=None, est=4.565199833435431, details={'was_im
```

In [42]:

```
### last user first movie
svd.predict(610, 1)
```

executed in 12ms, finished 00:33:17 2021-08-06

Out[42]:

```
Prediction(uid=610, iid=1, r_ui=None, est=4.06830179662995, details={'was_i
```

In [ ]:

executed in 15ms, finished 15:59:13 2021-08-05

In [ ]:

executed in 18.9s, finished 13:47:32 2021-07-29

4.0.3.3 INITIAL COLD START

3 movie rate questions for 3 top genres user_rating = rate_driver(1000)

Contents

In [146]:

```
user_rating = rate_driver(1000)
```

executed in 29.0s, finished 02:02:44 2021-08-06

```
{'1': 'Action', '2': 'Adventure', '3': 'Drama', '4': 'Comedy', '5': 'Horror
Please enter your top 3 genres from below.  Example: 2 3 5 :
2 3 4
Adventure

#####################################################################
      movieId                        title                          genres
3901     5479  K-19: The Widowmaker (2002)  Action|Adventure|Drama|Thriller
Please rate on a scale of .5-5, press n if you have not seen :
1


#####################################################################
      movieId                                  title  \
2539     3400  We're Back! A Dinosaur's Story (1993)

                                genres
2539  Adventure|Animation|Children|Fantasy
Please rate on a scale of .5-5, press n if you have not seen :
1


#####################################################################
     movieId                    title                              genres
656      849  Escape from L.A. (1996)  Action|Adventure|Sci-Fi|Thriller
Please rate on a scale of .5-5, press n if you have not seen :
1


Drama

#####################################################################
      movieId                title               genres
4186     6035  Pépé le Moko (1937)  Crime|Drama|Romance
Please rate on a scale of .5-5, press n if you have not seen :
1


#####################################################################
```

Contents

```
      movieId              title                                genres
7562    85414  Source Code (2011)  Action|Drama|Mystery|Sci-Fi|Thriller
Please rate on a scale of .5-5, press n if you have not seen :
1


###################################################################
      movieId                           title                          genr
3085     4142  Left Behind: The Movie (2000)  Action|Adventure|Drama|Thrill
Please rate on a scale of .5-5, press n if you have not seen :
1
```

Comedy

```
###################################################################
     movieId                title                genres
676      892  Twelfth Night (1996)  Comedy|Drama|Romance
Please rate on a scale of .5-5, press n if you have not seen :
1


###################################################################
      movieId                         title               genres
6836    61323  Burn After Reading (2008)  Comedy|Crime|Drama
Please rate on a scale of .5-5, press n if you have not seen :
1


###################################################################
      movieId                title        genres
4115     5900  Analyze That (2002)  Comedy|Crime
Please rate on a scale of .5-5, press n if you have not seen :
1
```

In [147]:

```
##### append the new ratings to the original ratings DataFrame
delta_ratings_df = ratings_df.append(user_rating,ignore_index=True)
delta_rating_sp = Dataset.load_from_df(delta_ratings_df,reader)
```

executed in 116ms, finished 02:02:48 2021-08-06

Contents

Contents

In [148]:

```
#%%script echo skipping
# train a model using the new combined DataFrame
svd2 = SVD(n_factors= 25, reg_all=0.04)
svd2.fit(delta_rating_sp.build_full_trainset())
```

executed in 2.31s, finished 02:02:50 2021-08-06

Out[148]:

```
<surprise.prediction_algorithms.matrix_factorization.SVD at 0x1a14f69e160>
```

In [149]:

```
%%script echo skipping
# train a model using the new combined DataFrame
knn2 = KNNWithMeans(n_factors= 10, reg_all=0.2)
knn2.fit(delta_rating_sp.build_full_trainset())
```

executed in 29ms, finished 02:02:50 2021-08-06

```
skipping
```

In [150]:

```
#make predictions for the user
#in the format (movie_id, predicted_score)
list_of_movies = []
for m_id in delta_ratings_df['movieId'].unique():
    list_of_movies.append( (m_id, svd2.predict(1000, m_id)[3]))
```

executed in 78ms, finished 02:02:50 2021-08-06

In [151]:

```
# order the predictions from highest to lowest rated
ranked_movies = sorted(list_of_movies, key=lambda x:x[1], reverse=True)
```

executed in 15ms, finished 02:02:50 2021-08-06

In [ ]:

executed in 26ms, finished 15:08:27 2021-08-05

4.0.3.4 Recommend Movies

In [152]:

```
#User id 1000
recommended_movies(ranked_movies,movies_df,5)
```

executed in 31ms, finished 02:02:50 2021-08-06

```
Rec#  1 :     Shawshank Redemption, The (1994)    Crime|Drama

Rec#  2 :     Lawrence of Arabia (1962)    Adventure|Drama|War

Rec#  3 :     Monty Python and the Holy Grail (1975)    Adventure|Comedy|Fa

Rec#  4 :     Raiders of the Lost Ark (Indiana Jones and the...    Action|A

Rec#  5 :     Pulp Fiction (1994)    Comedy|Crime|Drama|Thriller
```

Contents

In [153]:

```
delta_ratings_df.tail(20)
```

executed in 15ms, finished 02:02:50 2021-08-06

Out[153]:

	userId	movieId	rating
100825	610	161634	4
100826	610	162350	3.5
100827	610	163937	3.5
100828	610	163981	3.5
100829	610	164179	5
100830	610	166528	4
100831	610	166534	4
100832	610	168248	5
100833	610	168250	5
100834	610	168252	5
100835	610	170875	3
100836	1000	5479	1
100837	1000	3400	1
100838	1000	849	1
100839	1000	6035	1
100840	1000	85414	1
100841	1000	4142	1
100842	1000	892	1
100843	1000	61323	1
100844	1000	5900	1

In [ ]:

executed in 14ms, finished 16:46:38 2021-08-05

Contents

5 Interpret

The SVD model provides good results as opposed to the 'quirky'resutls of KNNWith Means but at
lifetime on the web. I tuned SVD down to 2 seconds with no noticible reduction in quality. To imple
Designed with layitout.com Flask (python based)and Bootstrap4 w Blueprints tying together comp
the templates(html) SQLite database and SQLAlchemy (ORM) Tested deployment on Heroku (pos

In [ ]:

Type *Markdown* and LaTeX: α^2

Contents