Project 04: Movielens Dataset Analysis

You don't need to limit yourself to the number of rows/cells provided. You can add additional rows in each section to add more lines of code.

Happy coding!

In [1]:

```
import os
cwd =os.chdir(r'C:\Machine_learning_datafiles\simplilearn_projects\movielens')
os.listdir(cwd)
```

Out[1]:

```
['movies.dat', 'movie_lens.csv', 'New folder', 'ratings.dat', 'users.dat']
```

In [2]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use('ggplot')
```

In [3]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [4]:

```
movie_data = pd.read_csv('movies.dat', sep='::', names=['MovieId','Title','Genre'])
ratings_data = pd.read_csv('ratings.dat', sep= '::', names=['UserId','MovieId','Rating','
TimeStamp'])
users_data = pd.read_csv('users.dat', sep='::', names=['UserId','Gender','Age','Occupatio
n','Zipcode'])
```

In [7]:

```
movie_data.columns, ratings_data.columns, users_data.columns
```

Out[7]:

```
(Index(['MovieId', 'Title', 'Genre'], dtype='object'),
 Index(['UserId', 'MovieId', 'Rating', 'TimeStamp'], dtype='object'),
 Index(['UserId', 'Gender', 'Age', 'Occupation', 'Zipcode'], dtype='object'))
```

In [8]:

```
master_data= pd.merge(ratings_data,users_data, on= 'UserId', how='left')
master_data = pd.merge(master_data,movie_data, on= 'MovieId',how='left')
```

In [5]:

```
pd.set_option('max_columns',5000)
```

In [10]:

```
master_data.to_csv('movie_lens.csv', index=False)
```

In [68]:

```
%%time
master_data= pd.read_csv('movie_lens.csv')
```

```
master_data.head()
```

Wall time: 9.72 s

Out[68]:

	UserId	MovieId	Rating	TimeStamp	Gender	Age	Occupation	Zipcode	Title	Genre
0	1	1193	5	978300760	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	Drama
1	1	661	3	978302109	F	1	10	48067	James and the Giant Peach (1996)	Animation|Children's|Musical
2	1	914	3	978301968	F	1	10	48067	My Fair Lady (1964)	Musical|Romance
3	1	3408	4	978300275	F	1	10	48067	Erin Brockovich (2000)	Drama
4	1	2355	5	978824291	F	1	10	48067	Bug's Life, A (1998)	Animation|Children's|Comedy

In [69]:

```
%%time
master_data['TimeStamp'] = master_data['TimeStamp'].apply(lambda x: pd.Timestamp(x, unit
='s'))
```

Wall time: 5.88 s

In [8]:

```
master_data.shape
```

Out[8]:

(1000209, 10)

In [9]:

```
master_data.head()
```

Out[9]:

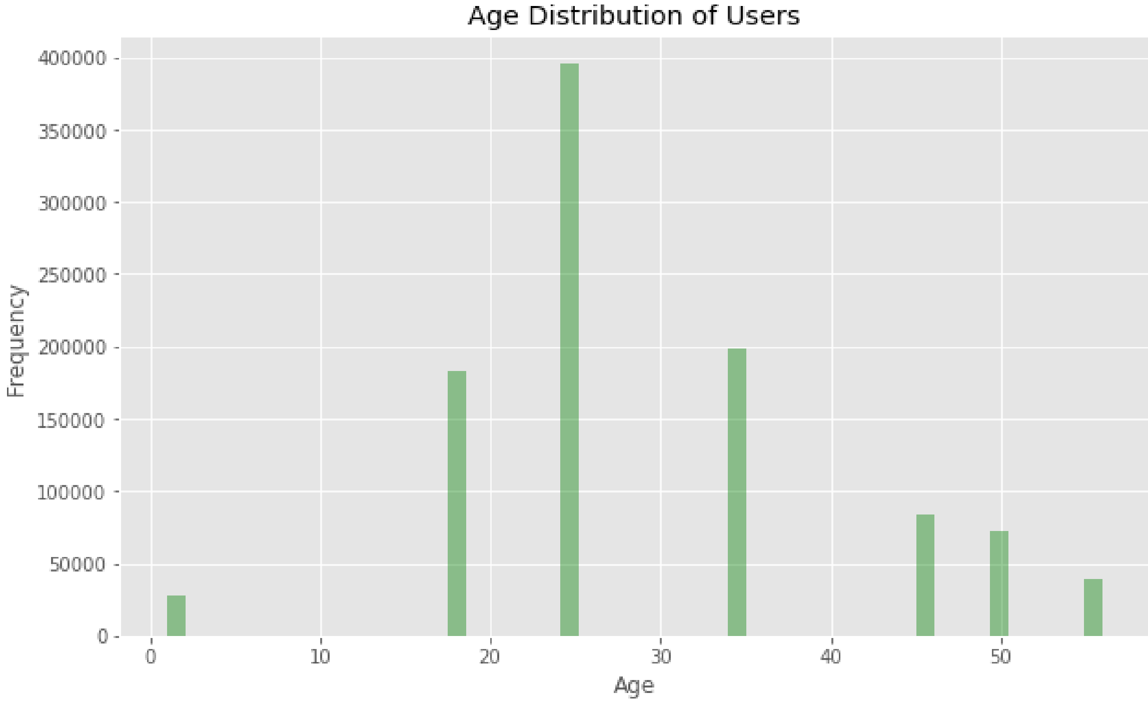
	UserId	MovieId	Rating	TimeStamp	Gender	Age	Occupation	Zipcode	Title	Genre
0	1	1193	5	2000-12-31 22:12:40	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	Drama
1	1	661	3	2000-12-31 22:35:09	F	1	10	48067	James and the Giant Peach (1996)	Animation|Children's|Musical
2	1	914	3	2000-12-31 22:32:48	F	1	10	48067	My Fair Lady (1964)	Musical|Romance
3	1	3408	4	2000-12-31 22:04:35	F	1	10	48067	Erin Brockovich (2000)	Drama
4	1	2355	5	2001-01-06 23:38:11	F	1	10	48067	Bug's Life, A (1998)	Animation|Children's|Comedy

Age Distribution

In [124]:

```
plt.figure(figsize=[10,6])
sns.distplot(master_data.Age,kde=False,color='g')
plt.title('Age Distribution of Users')
plt.ylabel('Frequency')
plt.xlabel('Age');
```

```
plt.savefig('user_age_distribution.jpg')
```



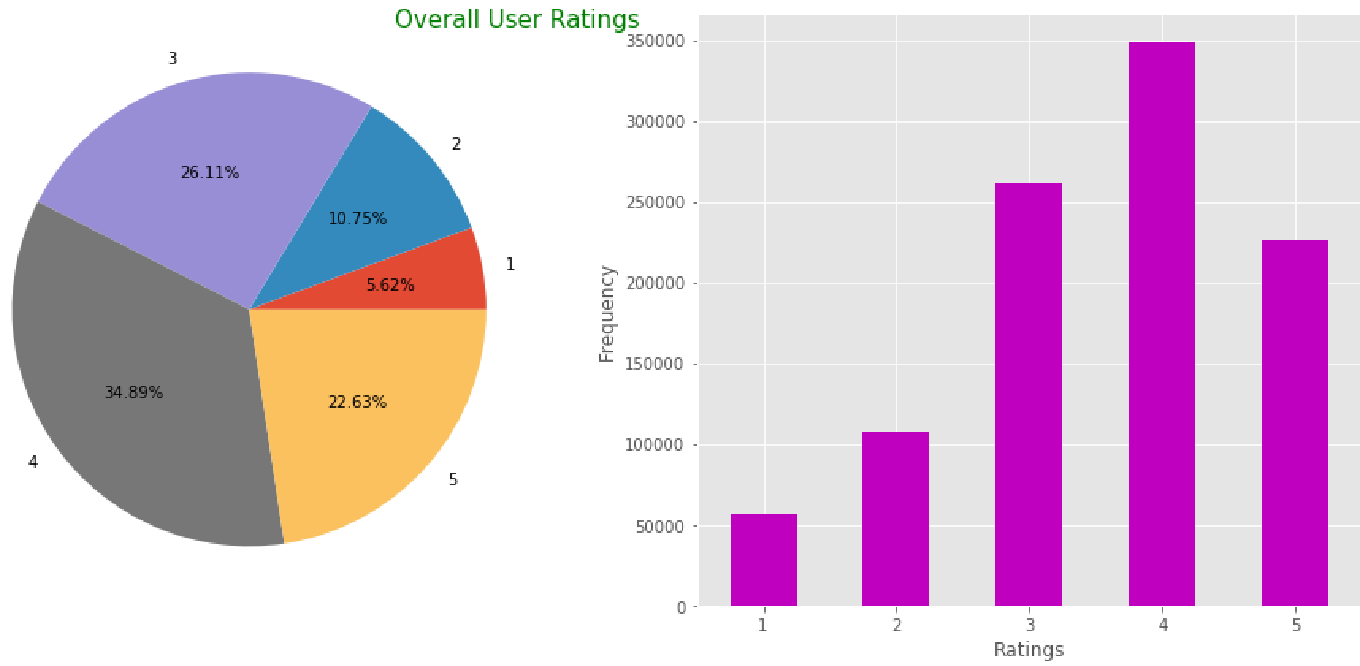
Most of the users are users between the ages of 25 and 34

Overall Rating by Users

In [153]:

```
fig,ax= plt.subplots(1,2,figsize=[13,6])
pd.value_counts(master_data.Rating).sort_index().plot.pie(autopct='%.2f%%',labels=[1,2,3
,4,5],ax=ax[0])
#ax[0].legend(title='Ratings',loc=(1.,0.29))
ax[0].set(ylabel= '')

pd.value_counts(master_data.Rating).sort_index().plot(kind='bar',color='m',rot=0,ax=ax[1
])
ax[1].set(xlabel='Ratings', ylabel='Frequency')
plt.tight_layout(pad=1.2)
fig.suptitle('Overall User Ratings',ha='right',color='g',fontsize=15);
plt.savefig('Overall_User_ratings.jpeg')
```



From the overall ratings by users, we see that most of the users rated 4 for most of the movies, followed by 3 and then 5. The least rating is 1

User rating of movie 'Toy Story'

In [17]:

```
movie_data.head() #getting the movie data
```

Out[17]:

	MovieId	Title	Genre
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama
4	5	Father of the Bride Part II (1995)	Comedy

In [18]:

```
user_toystory= master_data[master_data.MovieId.isin([1])] #getting Toy story data from th
e movie id
```

In [19]:

```
user_toystory.head()
```

Out[19]:

	UserId	MovieId	Rating	TimeStamp	Gender	Age	Occupation	Zipcode	Title	Genre
40	1	1	5	2001-01-06 23:37:48	F	1	10	48067	Toy Story (1995)	Animation|Children's|Comedy
469	6	1	4	2000-12-31 04:30:08	F	50	9	55117	Toy Story (1995)	Animation|Children's|Comedy
581	8	1	4	2000-12-31 03:31:36	M	25	12	11413	Toy Story (1995)	Animation|Children's|Comedy
711	9	1	5	2000-12-31 01:25:52	M	25	17	61614	Toy Story (1995)	Animation|Children's|Comedy
837	10	1	5	2000-12-31 01:34:34	F	35	1	95370	Toy Story (1995)	Animation|Children's|Comedy

In [20]:

```
user_toystory.Rating.value_counts().sort_index().to_frame(name='Toy Story User ratings')
```

Out[20]:

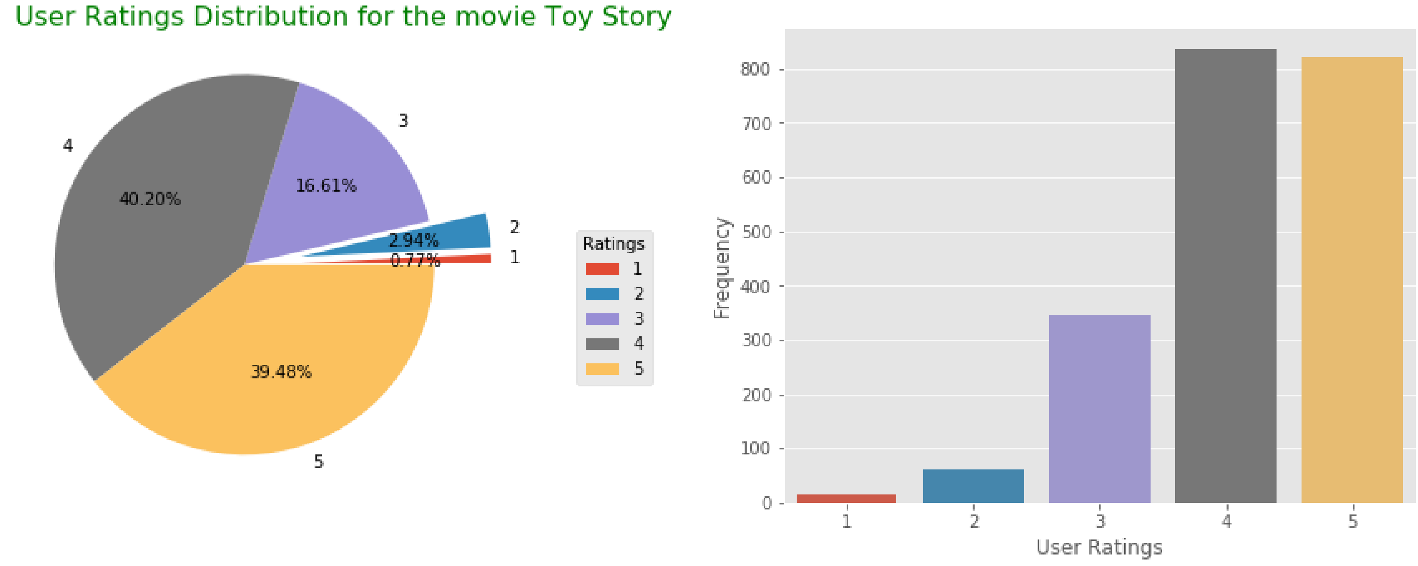
	Toy Story User ratings
1	16
2	61
3	345
4	835
5	820

In [118]:

```
fig,ax= plt.subplots(1,2,figsize=[13,5])
ax[0].pie(user_toystory.Rating.value_counts().sort_index(), autopct='%.2f%%',labels=[1,2
,3,4,5],explode=(0.3,0.3,0,0,0))
ax[0].legend(loc=[1.2,0.247],ncol=1,title='Ratings')
```

```
sns.countplot('Rating',data=user_toystory,ax=ax[1])
ax[1].set(xlabel='User Ratings', ylabel='Frequency')
fig.tight_layout(pad=2)

fig.suptitle('User Ratings Distribution for the movie Toy Story',ha='right',color='g',fon
tsize=16);
plt.savefig('user_toy_story_rating.jpeg')
```

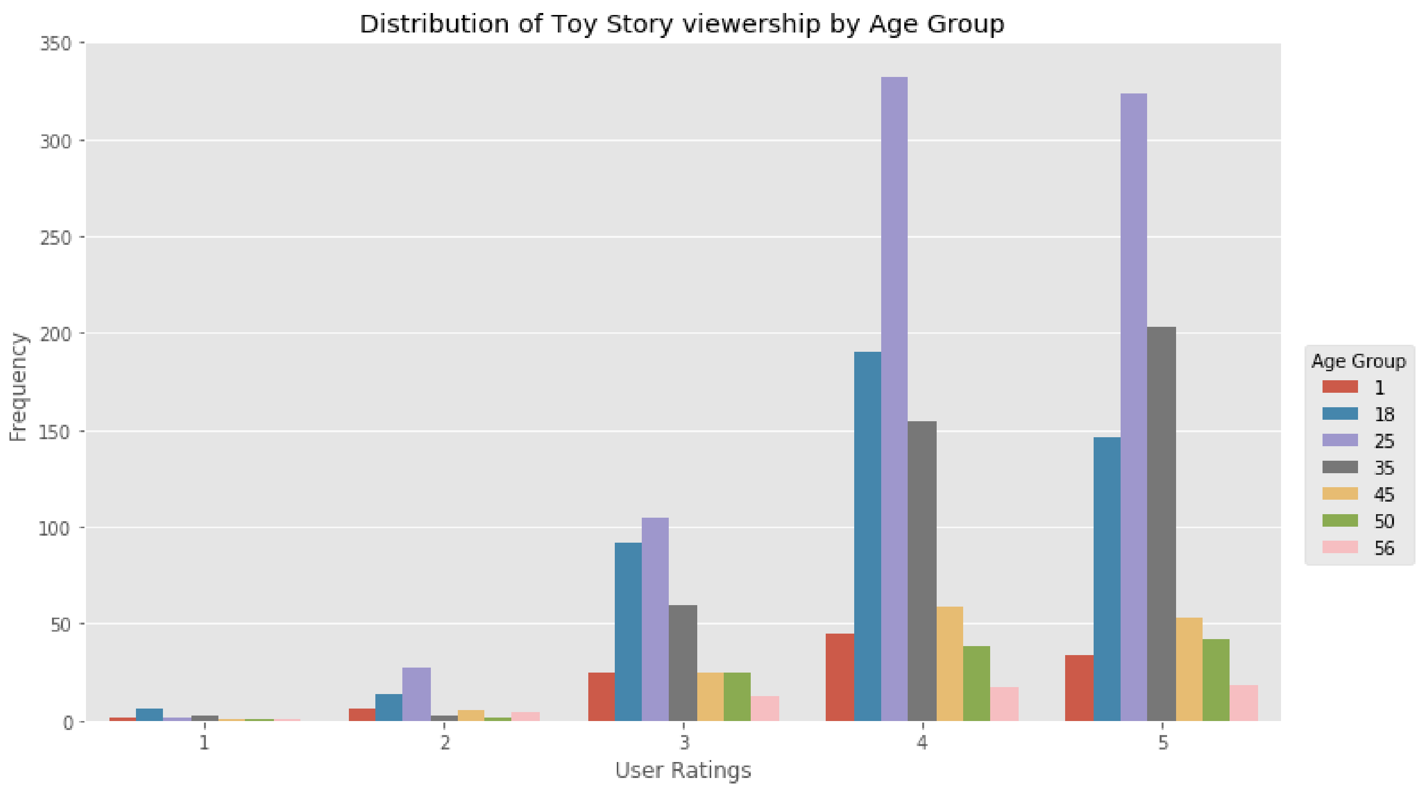


From the charts above we see that most of the users that rated Toy Story rated it as 4 or 5.

Viewership of Toy Story by Age group

In [156]:

```
plt.figure(figsize=[12,7])
sns.countplot('Rating', hue='Age', data=user_toystory)
plt.title('Distribution of Toy Story viewership by Age Group')
plt.xlabel('User Ratings')
plt.ylabel('Frequency')
plt.ylim((0,350))
plt.legend(loc=(1.02,0.23), title='Age Group');
plt.savefig('Toy_story_viewership_by_age_group.png')
```



From the chart, we see that most of the users rated the movie 'Toy Story' as 4 or 5, with most of those ratings from users between the Ages of 25 and 34.

Top 25 Movies bu viewership Ratings

In [23]:

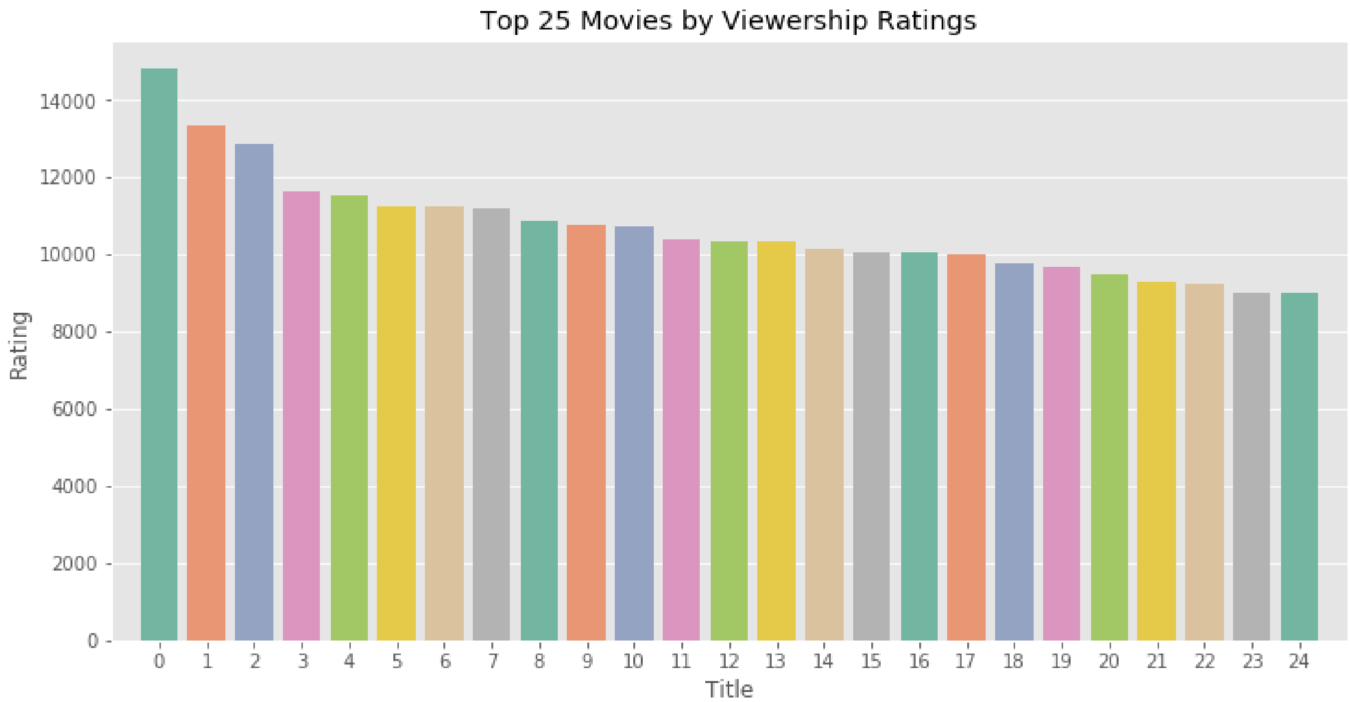
```
top_25_movies_by_user_ratings = \
master_data.groupby('Title').agg({\
                                   'Rating':'sum'\
                                  }).sort_values(by='Rating',ascending=False).reset_index
()
```

In [171]:

```
top_25_movies_by_user_ratings[:25].to_csv('top_25_movies_by_user_ratings.csv')
```

In [189]:

```
plt.figure(figsize=[12,6])
sns.barplot('Title','Rating',data=top_25_movies_by_user_ratings[:25],palette='Set2')
plt.xticks(np.arange(25),range(25))
plt.title('Top 25 Movies by Viewership Ratings')
plt.xlim((-1,25));
plt.savefig('Top_25_Movies_by_Viewership_Ratings.jpg')
```



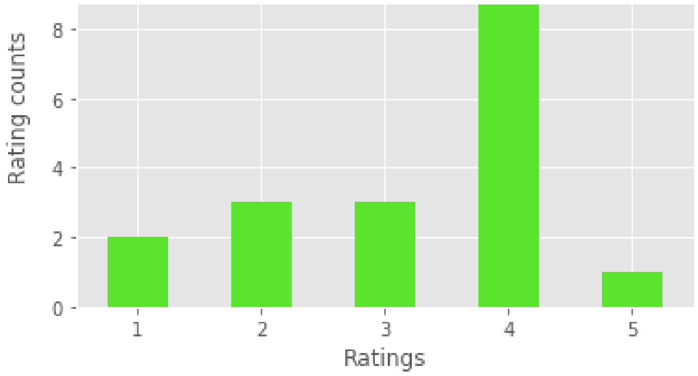
Movie rating bu userid= 2696

In [26]:

```
rating_by_user_2696 = master_data[master_data.UserId == 2696][['UserId','Rating']].reset
_index(drop=True)
```

In [190]:

```
rating_by_user_2696.Rating.value_counts().sort_index().plot.bar(rot=0,color='#5ae42d')
plt.title('Movie Ratings by Userid 2696')
plt.xlabel('Ratings')
plt.ylabel('Rating counts')
plt.savefig('Movie_Ratings_by_Userid_2696.jpg');
```



Feature Engineering

unique Genres

In [71]:

```
master_data['Genre'] = master_data.Genre.apply(lambda x: x.split('|'))
```

In [72]:

```
%%time
genre_list= []
for genres in master_data.Genre.values:
    for genre in genres:
        genre_list.append(genre)
```

```
Wall time: 608 ms
```

In [73]:

```
unique_genre = set(genre_list)
```

In [74]:

```
print('The unique Genres are: [{}]'.format(unique_genre))
```

```
The unique Genres are: [{"Children's", 'Romance', 'Action', 'Adventure', 'Sci-Fi', 'Weste
rn', 'Film-Noir', 'Documentary', 'Comedy', 'Fantasy', 'War', 'Crime', 'Horror', 'Thriller
', 'Musical', 'Drama', 'Mystery', 'Animation'}]
```

One hot encoding of unique genres

In [81]:

```
%%time
for genre in unique_genre:
    master_data[genre] = master_data.Genre.apply(lambda x: 1 if genre in x else 0)
```

```
Wall time: 9.66 s
```

In [82]:

```
master_data.head(2)
```

Out[82]:

	UserId	MovieId	Rating	TimeStamp	Gender	Age	Occupation	Zipcode	Title	Genre	Children's	Romance	Act
0	1	1193	5	2000-12-31 22:12:40	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	[Drama]	0	0	
									James and the	[Animation			

	UserId	MovieId	Rating	TimeStamp	Gender	Age	Occupation	Zipcode	Title	Genre	Children's	Romance	Act
1	1	661	3	2000-12-31 22:35:09	F	1	10	48067	and the Giant Peach (1996)	[Animation, Children's, Musical]	1	0	

Counting Genres using Counter and defaultdict

In [17]:

```
from collections import Counter, defaultdict
```

In [18]:

```
genre_count = Counter(genre_list)
```

In [19]:

```
genre_count.most_common(5) #most common genre
```

Out[19]:

```
[('Comedy', 356580),
 ('Drama', 354529),
 ('Action', 257457),
 ('Thriller', 189680),
 ('Sci-Fi', 157294)]
```

In [20]:

```
genre_dict = defaultdict(int)
for genre in genre_list:
    if genre in genre_dict:
        genre_dict[genre] +=1
    else:
        genre_dict[genre] = 1
```

In [21]:

```
genre_dict
```

Out[21]:

```
defaultdict(int,
            {'Drama': 354529,
             'Animation': 43293,
             "Children's": 72186,
             'Musical': 41533,
             'Romance': 147523,
             'Comedy': 356580,
             'Action': 257457,
             'Adventure': 133953,
             'Fantasy': 36301,
             'Sci-Fi': 157294,
             'War': 68527,
             'Thriller': 189680,
             'Crime': 79541,
             'Mystery': 40178,
             'Western': 20683,
             'Horror': 76386,
             'Film-Noir': 18261,
             'Documentary': 7910})
```

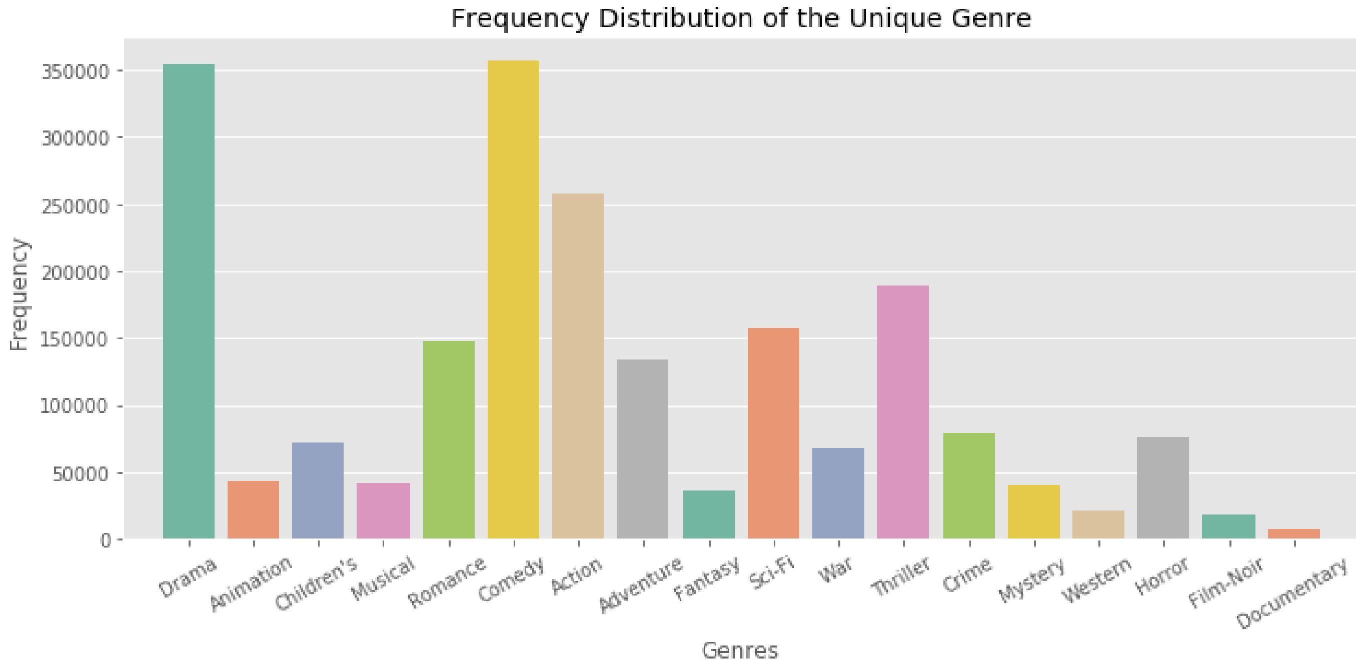
In [22]:

```
genres = pd.Series(np.array(genre_list)).to_frame(name='Genres')
```

In [23]:

```
plt.figure(figsize=[12,5])
```

```
sns.countplot('Genres',data=genres,palette='Set2')
plt.xticks(rotation=30)
plt.xlim(-1,18)
plt.title('Frequency Distribution of the Unique Genre')
plt.ylabel('Frequency');
plt.savefig('Unique_genre_Counts.png')
```



In [24]:

```
master_data.shape
```

Out[24]:

```
(1000209, 28)
```

Machine Learning

In [42]:

```
master_data.columns
```

Out[42]:

```
Index(['UserId', 'MovieId', 'Rating', 'TimeStamp', 'Gender', 'Age',
       'Occupation', 'Zipcode', 'Title', 'Genre', 'Crime', 'Western',
       'Film-Noir', 'Fantasy', 'Adventure', 'Sci-Fi', 'Romance', 'Animation',
       'Children's', 'Musical', 'Comedy', 'Thriller', 'Horror', 'Documentary',
       'War', 'Mystery', 'Action', 'Drama'],
      dtype='object')
```

In [67]:

```
master_data.head(2)
```

Out[67]:

	UserId	MovieId	Rating	TimeStamp	Gender	Age	Occupation	Zipcode	Title	Genre	Children's	Romance	Action
0	1	1193	5	2000-12-31 22:12:40	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	[Drama]	0	0	0
1	19	1193	5	2001-02-21 04:48:56	M	1	10	48073	One Flew Over the Cuckoo's Nest (1975)	[Drama]	0	0	0

master_data.groupby(['Title','MovieId','UserId'])[['Rating']].mean()

FEATURE ENGINERRING

WE WILL BE GENERATING NEW FEATURES FROM THE AVAILABLE PREDICTORS

1. **THE MEAN USER RATINGS FOR A PARTICULAR MOVIE**
2. **THE MEAN RATING BY AN AGE GROUP**
3. **THE MEAN RATING FOR A MOVIE BY A PARTICULAR AGE GROUP**

In [85]:

```
mean_user_rating_per_movie = master_data.groupby('MovieId')[['Rating']].mean()
mean_rating_by_age_group = master_data.groupby('Age')[['Rating']].mean()
mean_rating_per_movie_per_age = master_data.groupby(['MovieId','Age'])[['Rating']].mean(
)
```

In [86]:

```
master_data = pd.merge(master_data,mean_rating_by_age_group,on='Age',suffixes=['','_mean
_by_age'])
master_data = pd.merge(master_data,mean_rating_per_movie, on='MovieId',suffixes=['','_me
an_by_movieid'])
master_data = pd.merge(master_data,mean_rating_per_movie_per_age, on=['Age','MovieId'],s
uffixes=['','_mean_per_movie_by_age'])
```

For those new features generated, we will be binning them by giving a value of 1 if the rating given by a user for a particular movie is greater than any of those features and a value of 0 if rating isn't

master_data.head()

In [87]:

```
master_data['rating_greater_than_mean_age_rating']= \
(master_data.Rating >= master_data.Rating_mean_by_age).astype(int)

master_data['rating_greater_than_mean_movie_rating']=\
(master_data.Rating >= master_data.Rating_mean_by_movieid).astype(int)

master_data['rating_greater_than_mean_movie_rating_by_age']=\
(master_data.Rating >= master_data.Rating_mean_per_movie_by_age).astype(int)
```

In [88]:

```
cols_to_drop = ['UserId','MovieId','TimeStamp','Gender','Zipcode','Title','Genre','Occup
ation']
```

In [89]:

```
age_bins = {1:1,18:2,25:3,35:4,45:5,50:6,56:7}
master_data['Age'] = master_data.Age.map(age_bins)
```

In [90]:

```
master_data_copy = master_data.copy()
```

master_data_copy = pd.get_dummies(master_data_copy, columns= ['Occupation'])

In [91]:

```
master_data_copy.drop(cols_to_drop,axis=1,inplace=True)
```

In [92]:

```
master_data_copy.head()
```

Out[92]:

	Rating	Age	Children's	Romance	Action	Adventure	Sci-Fi	Western	Film-Noir	Documentary	Comedy	Fantasy	War	Crime
0	5	1	0	0	0	0	0	0	0	0	0	0	0	0
1	5	1	0	0	0	0	0	0	0	0	0	0	0	0
2	2	1	0	0	0	0	0	0	0	0	0	0	0	0
3	4	1	0	0	0	0	0	0	0	0	0	0	0	0
4	4	1	0	0	0	0	0	0	0	0	0	0	0	0

In [93]:

```
corr= master_data_copy.corr() #correlation
#creating mask
mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True
```

In [94]:

```
corr
```

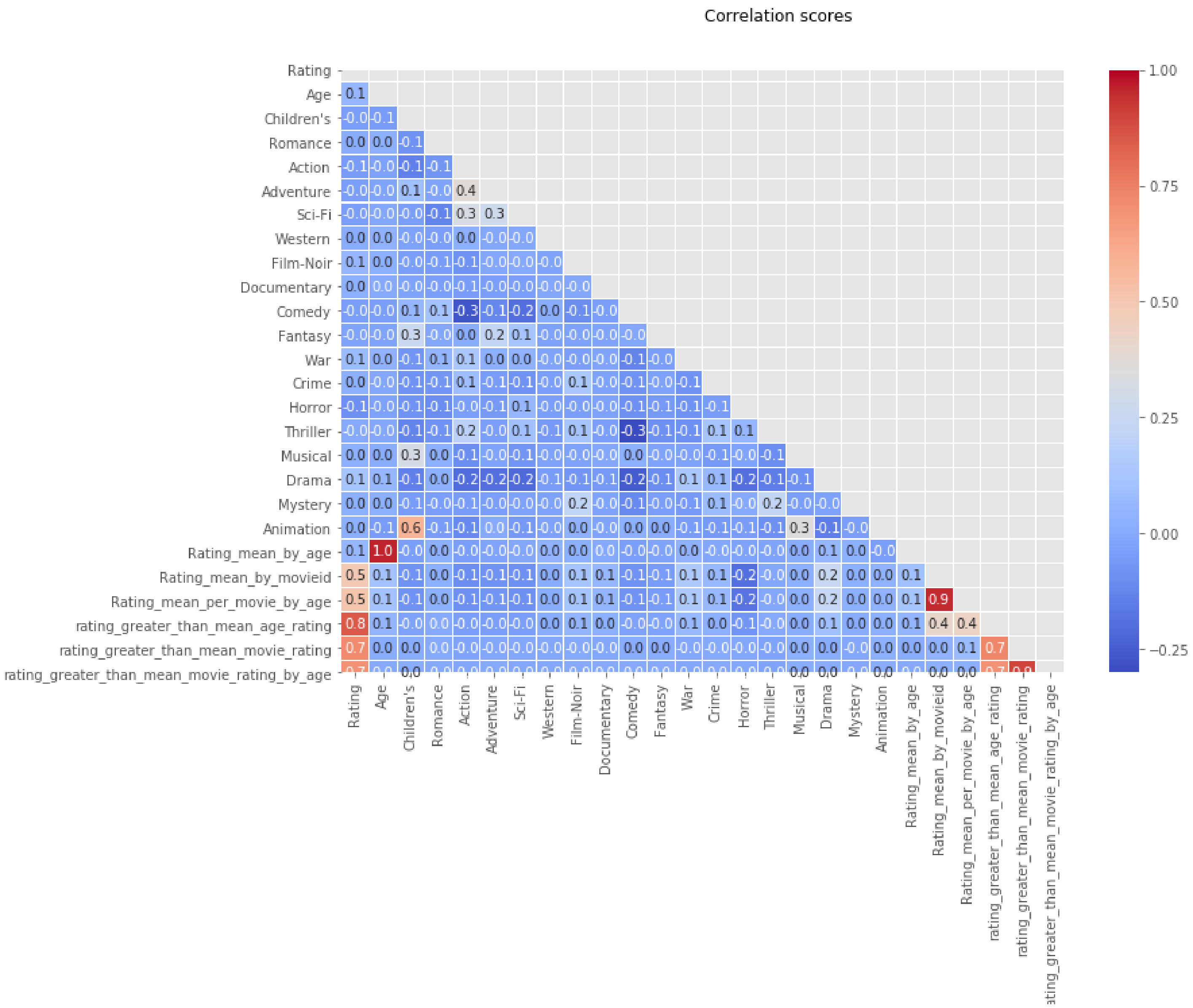
Out[94]:

	Rating	Age	Children's	Romance	Action	Adventure	Sci-Fi	Wes
Rating	1.000000	0.059047	-0.039829	0.009644	-0.047633	-0.036718	-0.044487	0.007
Age	0.059047	1.000000	-0.050375	0.017420	-0.032723	-0.017328	-0.012540	0.038
Children's	-0.039829	-0.050375	1.000000	-0.084550	-0.141314	0.098283	-0.038844	0.03
Romance	0.009644	0.017420	-0.084550	1.000000	-0.067830	-0.024389	-0.133752	0.04
Action	-0.047633	-0.032723	-0.141314	-0.067830	1.000000	0.374961	0.319117	0.02
Adventure	-0.036718	-0.017328	0.098283	-0.024389	0.374961	1.000000	0.284190	0.01
Sci-Fi	-0.044487	-0.012540	-0.038844	-0.133752	0.319117	0.284190	1.000000	0.01
Western	0.007311	0.038833	-0.031269	-0.044650	0.022242	-0.011964	-0.010935	1.00
Film-Noir	0.060259	0.034327	-0.038033	-0.047351	-0.080288	-0.014178	-0.004056	0.01
Documentary	0.028098	0.004025	-0.024901	-0.037137	-0.052565	-0.035109	-0.038568	0.01
Comedy	-0.039622	-0.043938	0.058711	0.112843	-0.268092	-0.124960	-0.187079	0.007
Fantasy	-0.023312	-0.024406	0.263280	-0.014822	0.014551	0.227046	0.121843	0.028
War	0.075688	0.039283	-0.066539	0.053347	0.135872	0.016647	0.039314	0.01
Crime	0.033446	-0.008596	-0.081977	-0.073320	0.088519	-0.045924	-0.083730	0.04
Horror	-0.094353	-0.025664	-0.077099	-0.099434	-0.042733	-0.057256	0.056505	0.04
Thriller	-0.004806	-0.014902	-0.132642	-0.081384	0.202756	-0.038423	0.102546	0.058
Musical	0.015643	0.006373	0.312567	0.023506	-0.100432	-0.022327	-0.068012	0.03

	Rating	Age	Children's	Romance	Action	Adventure	Sci-Fi	Wes
Drama	0.122561	0.064693	-0.135707	0.023552	0.202415	-0.194570	0.212747	0.04
Mystery	0.015848	0.024974	-0.052786	-0.040162	-0.054084	-0.043503	-0.028273	0.02
Animation	0.019670	-0.045272	0.576204	-0.054540	-0.110294	0.004732	-0.055526	0.03
Rating_mean_by_age	0.061349	0.962472	-0.036208	0.015512	-0.035127	-0.015667	-0.013394	0.03
Rating_mean_by_movieid	0.488549	0.105987	-0.081524	0.019740	-0.097499	-0.075157	-0.091059	0.01
Rating_mean_per_movie_by_age	0.514535	0.114758	-0.077407	0.018743	-0.092575	-0.071361	-0.086460	0.01
rating_greater_than_mean_age_rating	0.845576	0.046186	-0.033144	0.003705	-0.043084	-0.036188	-0.040404	0.00
rating_greater_than_mean_movie_rating	0.717000	0.005642	0.014023	0.000037	-0.021280	-0.008017	-0.007995	0.00
rating_greater_than_mean_movie_rating_by_age	0.700598	0.001403	0.006551	-0.002579	-0.012122	-0.002431	-0.005284	0.00

In [96]:

```
f,ax =plt.subplots(figsize=[12,8])
sns.heatmap(corr.round(2),linewidths=0.05,mask=mask,cmap="coolwarm",ax=ax,annot=True,fmt
='.1f')
f.subplots_adjust(top=0.9)
t= f.suptitle('Correlation scores', fontsize=12);
```



In [97]:

```
from custom_metrics import vif
```

In [102]:

```
vif.vif_calc(master_data_copy,['Rating','Age','Rating_mean_by_movieid'])
```

```
Children's  vif=  1.81
Romance  vif=  1.07
Action  vif=  1.57
Adventure  vif=  1.34
Sci-Fi  vif=  1.27
Western  vif=  1.03
Film-Noir  vif=  1.14
Documentary  vif=  1.05
Comedy  vif=  1.58
Fantasy  vif=  1.19
War  vif=  1.11
Crime  vif=  1.09
Horror  vif=  1.19
Thriller  vif=  1.35
Musical  vif=  1.19
Drama  vif=  1.67
Mystery  vif=  1.12
Animation  vif=  1.67
Rating_mean_by_age  vif=  1.02
Rating_mean_per_movie_by_age  vif=  1.67
rating_greater_than_mean_age_rating  vif=  3.21
rating_greater_than_mean_movie_rating  vif=  6.01
rating_greater_than_mean_movie_rating_by_age  vif=  5.83
```

For this purpose I will be dropping collinear variables with correlation coefficients equal to or above 0.85 (threshold).

From the correlation matrix, there is a very strong correlation between Age and the mean rating by age group (~0.92), so we will be dropping the age column.

In [187]:

```
X= master_data_copy.drop('Rating',axis=1)
y = master_data_copy.Rating
```

In [174]:

```
X = X.drop(['Age','Rating_mean_by_movieid'],1)
```

In [106]:

```
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.model_selection import train_test_split,cross_val_score,GridSearchCV,KFold,S
huffleSplit
from sklearn.preprocessing import StandardScaler,RobustScaler,MinMaxScaler
```

In [201]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size= 0.15, random_state=19
92)
```

In [202]:

```
X_train, X_val, y_train, y_val = train_test_split(X_train,y_train,test_size=0.1, random_
state=124)
```

In [203]:

```
X_train.shape, X_test.shape, X_val.shape
```

Out[203]:

```
((765159, 25), (150032, 25), (85018, 25))
```

In [204]:

```
predictors= X_train.columns.tolist()
```

In [205]:

```
scaler = StandardScaler()
```

In [193]:

```
from sklearn.pipeline import Pipeline
```

Linear Regression

In [206]:

```
lin_model= LinearRegression()
```

In [207]:

```
pipeline= Pipeline([('scaler',scaler),('model',lin_model)])
```

In [208]:

```
fit= pipeline.fit(X_train,y_train)
```

In [209]:

```
y_pred= pipeline.predict(X_val)
```

In [210]:

```
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
```

In [211]:

```
r2_train = r2_score(y_train, pipeline.predict(X_train))
r2_train
```

Out[211]:

```
0.8076161458823835
```

In [212]:

```
r2_val = r2_score(y_val,y_pred)
r2_val
```

Out[212]:

```
0.8067907476886027
```

In [213]:

```
train_mse = mean_squared_error(y_train, pipeline.predict(X_train))
train_mse
```

Out[213]:

```
0.2399340828307028
```

In [214]:

```
val_mse = mean_squared_error(y_val, y_pred)
val_mse
```

Out[214]:

0.24192933021228297

In [215]:

```
train_mae = mean_absolute_error(y_train, pipeline.predict(X_train))
train_mae
```

Out[215]:

0.3929323058790929

In [216]:

```
val_mae = mean_absolute_error(y_val, y_pred)
val_mae
```

Out[216]:

0.3949629434550447

In [124]:

```
coef, pred = zip(*zip(lin_model.coef_.ravel(),predictors))
```

pd.Series(coef, index=pred).sort_values().plot.barh(figsize=[10,6])

Ridge

In [217]:

```
ridge = Ridge(random_state=423)
ridge_pl = Pipeline([('scaler',scaler),('ridge',ridge)])
```

In [218]:

```
fit= ridge_pl.fit(X_train,y_train)
```

In [219]:

```
ridge_pl.score(X_val,y_val)
```

Out[219]:

0.8067907442205556

In [220]:

```
ridge_pl.score(X_train,y_train)
```

Out[220]:

0.8076161458810671

In [221]:

```
train_mse = mean_squared_error(y_train, ridge_pl.predict(X_train))
train_mse
```

Out[221]:

0.23993408283234458

In [222]:

```
val_mse = mean_squared_error(y_val, y_pred)
val_mse
```

Out[222]:

0.24192933021228297

In [223]:

```
kfold = KFold(n_splits=5,shuffle=True,random_state=3)
```

(0.2268695470626076, {'ridge__alpha': 10})

In [224]:

```
ridge_gcv= GridSearchCV(ridge_pl,
                        param_grid={
                            'ridge__alpha':[0.1,0.5,1,3,5,7.5,10,15,20,25,100]
                        },scoring= 'neg_mean_squared_error', cv=10)

ridge_gcv.fit(X_train,y_train)

-ridge_gcv.best_score_, ridge_gcv.best_params_
```

Out[224]:

```
(0.23995052140731943, {'ridge__alpha': 20})
```

In [225]:

```
ridge_gcv.cv_results_['mean_test_score']
```

Out[225]:

```
array([-0.23995052, -0.23995052, -0.23995052, -0.23995052, -0.23995052,
       -0.23995052, -0.23995052, -0.23995052, -0.23995052, -0.23995052,
       -0.23995053])
```

In [226]:

```
ridge_gcv.cv_results_['std_test_score']
```

Out[226]:

```
array([0.00116278, 0.00116278, 0.00116278, 0.00116278, 0.00116278,
       0.00116278, 0.00116278, 0.00116278, 0.00116278, 0.00116279,
       0.00116279])
```

Ridge regression seems to be underfitting the model.

In [133]:

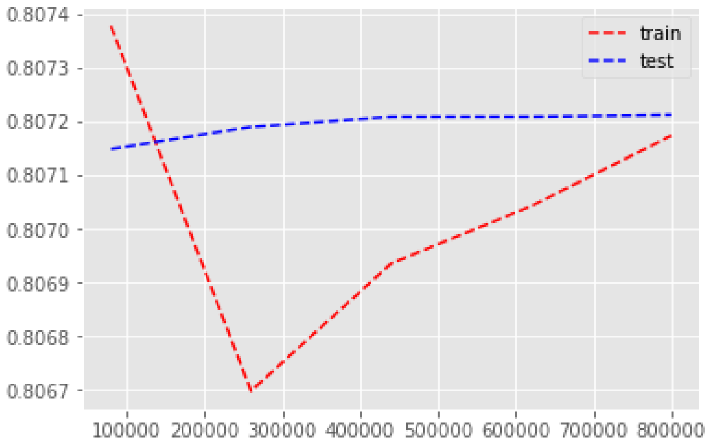
```
from sklearn.model_selection import learning_curve,validation_curve
```

In [143]:

```
train_sizes, train_scores, test_scores = learning_curve(ridge_pl, X, y, cv=kfold, scorin
g='r2',\
                                                        random_state=43, shuffle=True)
```

In [144]:

```
plt.plot(train_sizes, np.median(train_scores,1), 'r--', label='train')
plt.plot(train_sizes, np.median(test_scores,1), 'b--', label='test')
plt.legend();
```



concatenating the X_train and X_val datasets, fitting them and predicting on the X_test

In [227]:

```
X_train_ = pd.concat([X_train, X_val])
y_train_ = pd.concat([y_train, y_val])
```

In [228]:

```
ridge_model= ridge_gcv.best_estimator_.fit(X_train_, y_train_)
```

In [229]:

```
r2_score= ridge_model.score(X_test, y_test)
r2_score
```

Out[229]:

```
0.8073494787138824
```

In [230]:

```
mse = mean_squared_error(y_test, ridge_model.predict(X_test))
mse
```

Out[230]:

```
0.24068463836339005
```

Cross validation

In [231]:

```
ssplit = ShuffleSplit(n_splits=10, test_size=0.35, random_state=2991)
```

In [232]:

```
cvs = cross_val_score(ridge_gcv.best_estimator_, X, y, scoring='r2', cv=ssplit)
print(cvs)
cvs.mean()
```

```
[0.80759204 0.80792614 0.80730919 0.80822027 0.80785624 0.8080304
 0.80772101 0.80774523 0.80781624 0.80735571]
```

Out[232]:

```
0.8077572473516218
```

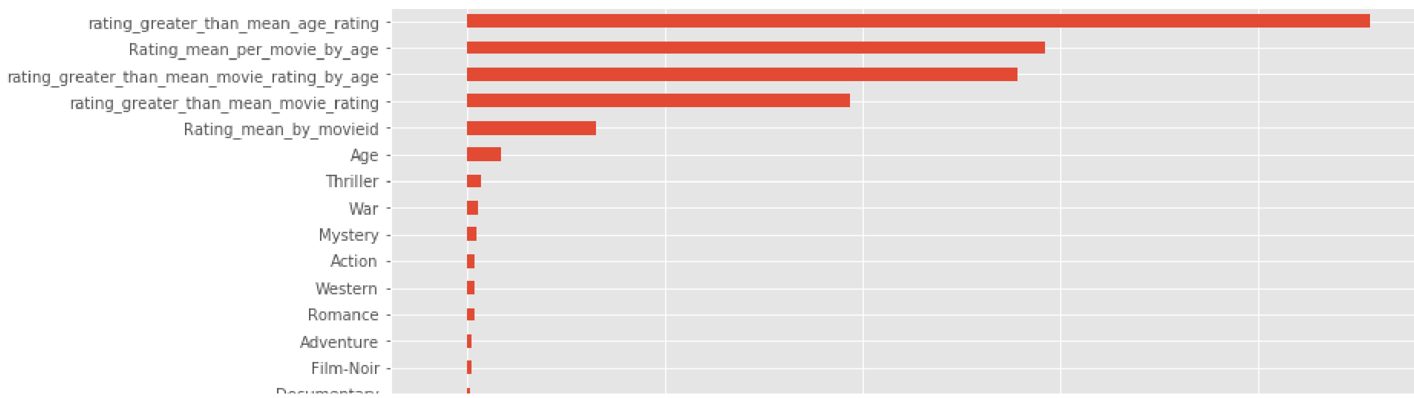
In [233]:

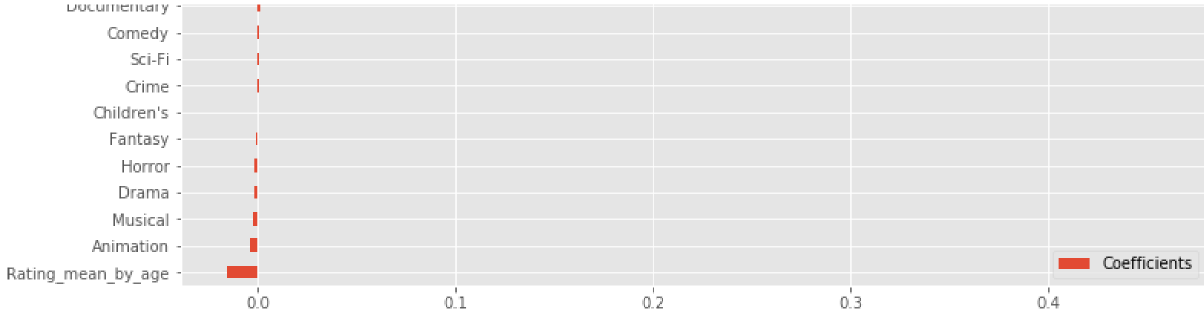
```
coef, pred = zip(*zip(ridge.coef_.ravel(),predictors))
```

pd.DataFrame(coef,index=pred,columns=['Coefficients']).sort_values(by='Coefficients')

In [234]:

```
pd.DataFrame(coef,index=pred,columns=['Coefficients']).sort_values(by='Coefficients').pl
ot.barh(figsize=[12,8]);
```





From the cross validation technique we see that our model is in line and seems to be underfitting

Non Parametric model

In [235]:

```
from sklearn.tree import DecisionTreeRegressor,ExtraTreeRegressor
```

In [236]:

```
tree= DecisionTreeRegressor(random_state=56)
```

In [237]:

```
fit = tree.fit(X_train, y_train)
```

In [238]:

```
tree.score(X_val, y_val)
```

Out[238]:

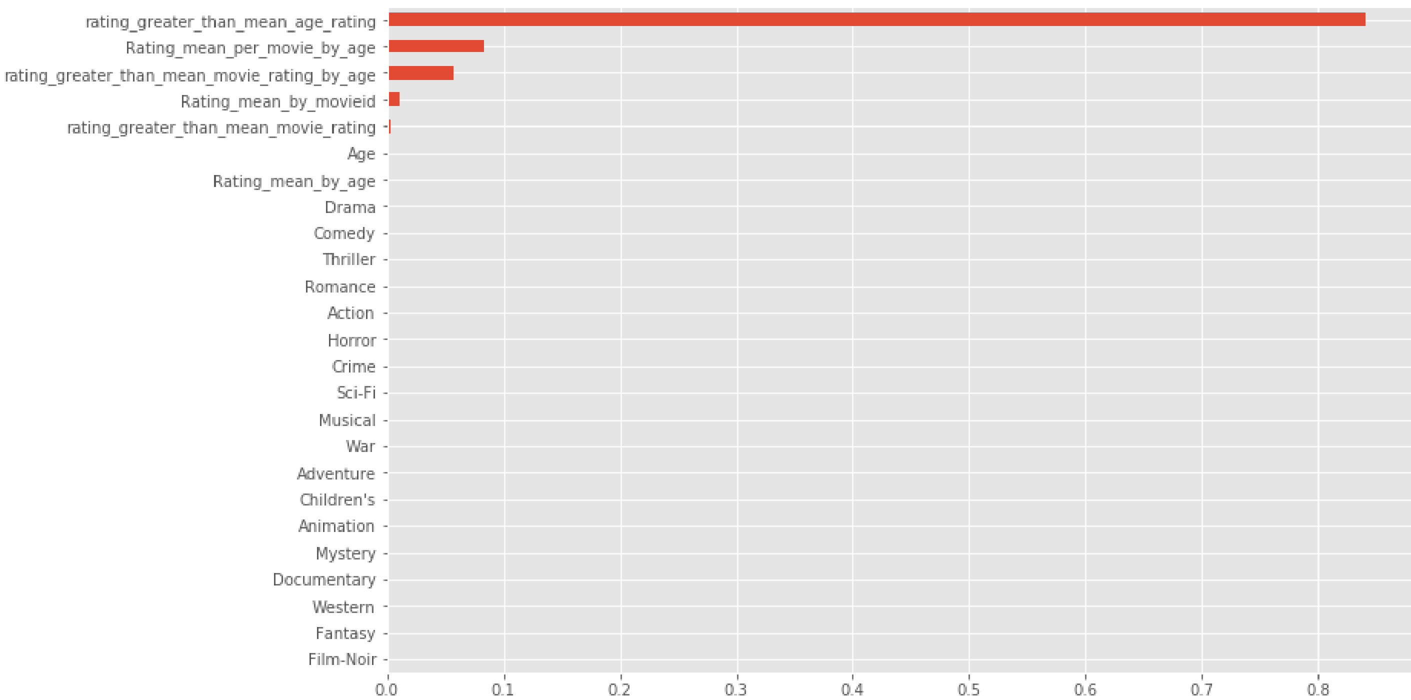
```
0.8323533877963364
```

In [239]:

```
coef, pred = zip(*zip(tree.feature_importances_,predictors))
```

In [240]:

```
pd.Series(coef,index=pred).sort_values().plot.barh(figsize=[12,8]);
```



In [241]:

```
tree.score(X_train, y_train)
```

```
tree.score(X_train, y_train)
```

Out[241]:

```
0.8511215831659009
```

In [242]:

```
train_mse = mean_squared_error(y_train, tree.predict(X_train))
train_mse
```

Out[242]:

```
0.1856756979956234
```

In [243]:

```
val_mse = mean_squared_error(y_val, tree.predict(X_val))
val_mse
```

Out[243]:

```
0.20992075750814423
```

This model is overfitting so we will use grid search to find the optimal values.

opt val = (0.862904220277267, {'max_depth': 11})

In [244]:

```
tree_gcv = GridSearchCV(tree,
                        param_grid={
                            'max_depth': [6,7,8,9,10,11,12,13,14]
                        }, scoring='r2', cv=kfold)

tree_gcv.fit(X_train, y_train)

tree_gcv.best_score_, tree_gcv.best_params_
```

Out[244]:

```
(0.8396761102990712, {'max_depth': 11})
```

In [245]:

```
tree_gcv.best_estimator_.score(X_val,y_val)
```

Out[245]:

```
0.8397475463005599
```

In [246]:

```
val_mse = mean_squared_error(y_val, tree_gcv.best_estimator_.predict(X_val))
val_mse
```

Out[246]:

```
0.20066207143069312
```

In [247]:

```
tree_gcv.best_estimator_.score(X_train,y_train)
```

Out[247]:

```
0.8406039778667973
```

In [248]:

```
train_mse = mean_squared_error(y_train, tree_gcv.best_estimator_.predict(X_train))
train_mse
```

Out[248]:

```
0.19879286935384444
```

The model seems not to be overfitting anymore

In [249]:

```
tree_model = tree_gcv.best_estimator_.fit(X_train_, y_train_)#0.8642376712418565
```

In [250]:

```
tree_model.score(X_test,y_test)
```

Out[250]:

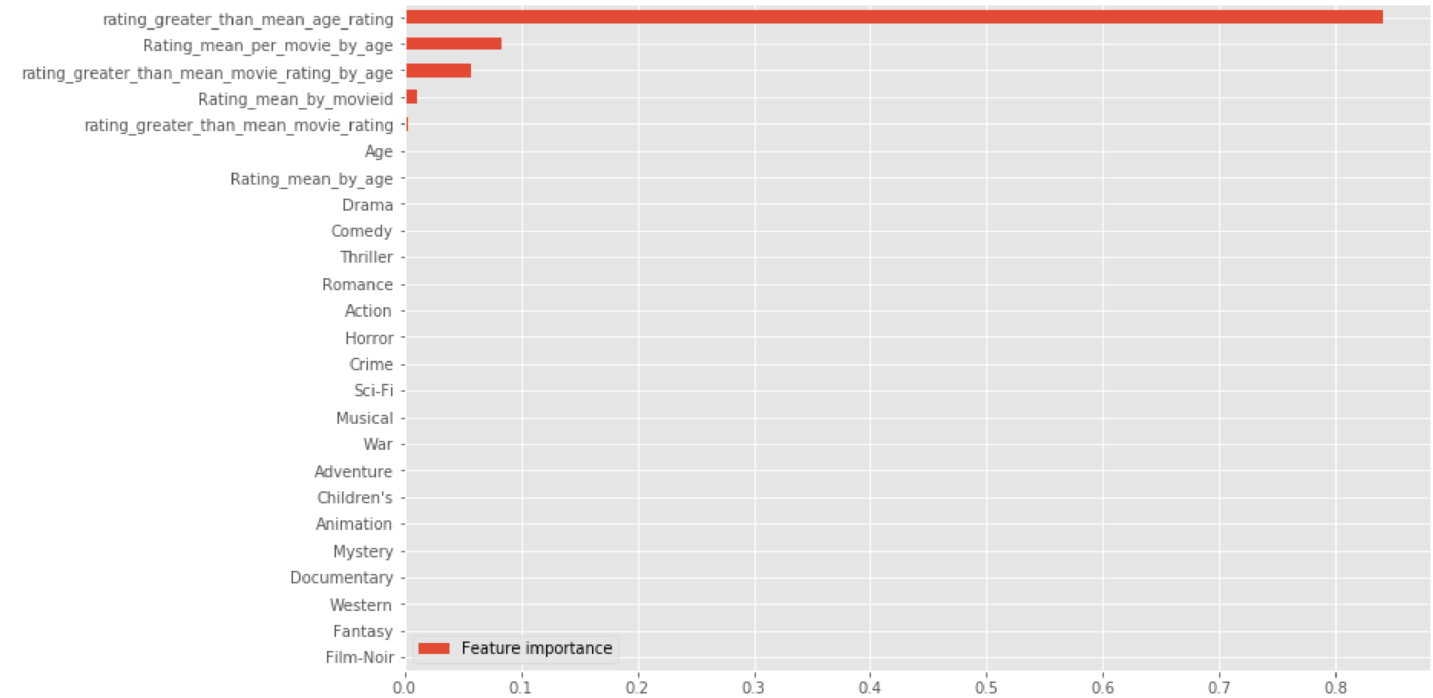
```
0.8394030828214183
```

In [251]:

```
features, importance = zip(*zip(predictors,tree.feature_importances_ ))
```

In [252]:

```
pd.DataFrame(importance, index= features, columns=['Feature importance']).sort_values(by
='Feature importance'\
                                                                                    ).
plot.barh(figsize=[12,8]);
```



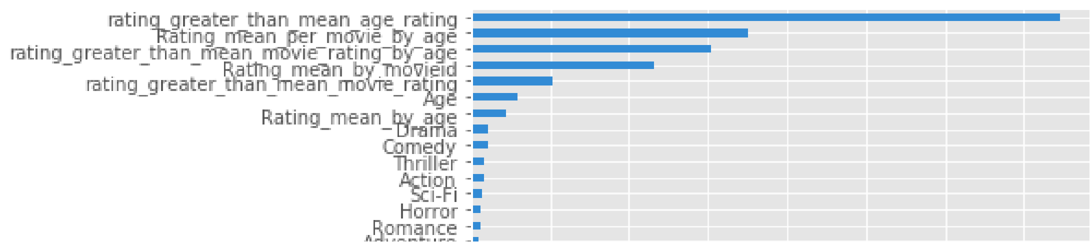
In [253]:

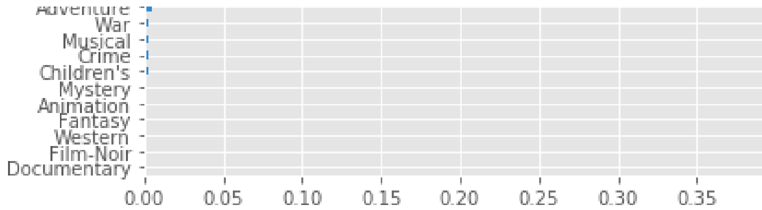
```
from skater.core.explanations import Interpretation
from skater.model import InMemoryModel
```

In [254]:

```
interpreter = Interpretation(X_val, feature_names=predictors)
model = InMemoryModel(tree.predict, examples=X_train)
plots = interpreter.feature_importance.plot_feature_importance(model, ascending=False)
```

```
[25/25] features                Time elapsed: 5 seconds
```





In [255]:

```
from eli5.sklearn import PermutationImportance
import eli5
```

In [256]:

```
perm = PermutationImportance(tree, scoring='neg_mean_squared_error',random_state=2).fit(
X_val,y_val)
eli5.show_weights(perm,feature_names=predictors)
```

Out[256]:

Weight	Feature
1.1533 ± 0.0073	rating_greater_than_mean_age_rating
0.2631 ± 0.0015	Rating_mean_per_movie_by_age
0.2504 ± 0.0018	rating_greater_than_mean_movie_rating_by_age
0.1192 ± 0.0030	Rating_mean_by_movieid
0.0506 ± 0.0012	rating_greater_than_mean_movie_rating
0.0137 ± 0.0005	Age
0.0118 ± 0.0011	Rating_mean_by_age
0.0059 ± 0.0002	Comedy
0.0059 ± 0.0006	Drama
0.0049 ± 0.0004	Action
0.0030 ± 0.0003	Sci-Fi
0.0029 ± 0.0004	Thriller
0.0023 ± 0.0005	Horror
0.0021 ± 0.0005	Adventure
0.0019 ± 0.0002	Romance
0.0012 ± 0.0003	War
0.0011 ± 0.0002	Crime
0.0009 ± 0.0002	Musical
0.0006 ± 0.0001	Children's
0.0005 ± 0.0001	Animation
	... 5 more ...

In [257]:

```
cvs= cross_val_score(tree_gcv.best_estimator_, X, y, scoring='r2', cv=ssplit)
print(cvs)
cvs.mean()
```

```
[0.83941521 0.84008844 0.83942839 0.840675   0.83953351 0.84007069
 0.83993641 0.83984111 0.83947999 0.83953986]
```

Out[257]:

```
0.8398008593408866
```

In [ ]:

In [259]:

```
extratree = ExtraTreeRegressor(random_state=426)
```

In [260]:

```
fit= extratree.fit(X_train, y_train)
```

In [261]:

```
extratree.score(X_val, y_val)
```

Out[261]:

0.8325312682051393

In [262]:

```
extratree.score(X_train, y_train)
```

Out[262]:

0.8511215831659009

In [112]:

```
extratree_gcv = GridSearchCV(extratree,
                        param_grid={
                            'max_depth': [15]
                        }, scoring='r2', cv=kfold)

extratree_gcv.fit(X_train, y_train)

extratree_gcv.best_score_, extratree_gcv.best_params_
```

Out[112]:

(0.8576987834169556, {'max_depth': 15})

In [113]:

```
extratree_gcv.cv_results_['mean_test_score']
```

Out[113]:

array([0.85769878])

In [114]:

```
extratree_gcv.best_estimator_.score(X_val,y_val)
```

```
  File "<ipython-input-114-a75fce5dadbd>", line 1
    extratree_gcv.best_estimator_.score(X_val,y_val)`
                                                    ^
SyntaxError: invalid syntax
```

In [ ]:

```
extratree_gcv.best_estimator_.score(X_train,y_train)
```

In [ ]:

```
val_mse = mean_squared_error(y_val, extratree_gcv.best_estimator_.predict(X_val))
val_mse
```

In [ ]:

```
train_mse = mean_squared_error(y_train, tree_gcv.best_estimator_.predict(X_train))
train_mse
```

In [ ]:

```
extratree_gcv.best_estimator_.score(X_test,y_test) #predicting the X_test
```

Cross validation

In [ ]:

```
cvs= cross_val_score(extratree_gcv.best_estimator_, X_train_, y_train_, scoring='r2', cv=
ssplit)
print(cvs)
cvs.mean()
```

In [266]:

```python
from sklearn.ensemble import VotingRegressor
```

In [267]:

```python
vreg = VotingRegressor([('ridge',ridge),('tree',tree),('extratree',extratree)])
```

In [268]:

```python
fit=vreg.fit(X_train, y_train)
```

In [269]:

```python
vreg.score(X_train,y_train)
```

Out[269]:

```
0.9797091511496802
```

pred,imp = zip(*zip(predictors,vreg.named_estimators_['extratree'].feature_importances_))pd.Series(imp, index=pred).sort_values().plot.barh(figsize=[12,7])

In [275]:

```python
vreg.score(X_val,y_val)
```

Out[275]:

```
0.8314070744972387
```

In [276]:

```python
from sklearn.ensemble import RandomForestRegressor
```

In [281]:

```python
rfc = RandomForestRegressor()
```

In [282]:

```python
fit= rfc.fit(X_train, y_train)
```

In [283]:

```python
rfc.score(X_train, y_train)
```

Out[283]:

```
0.9731069978140267
```

In [284]:

```python
rfc.score(X_val, y_val)
```

Out[284]:

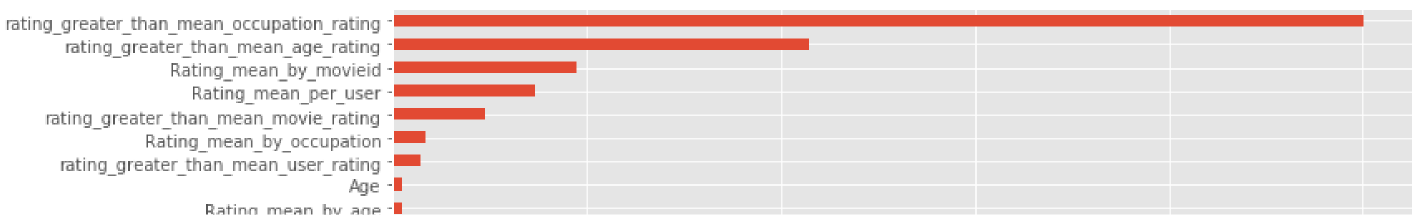
```
0.8489313896545123
```

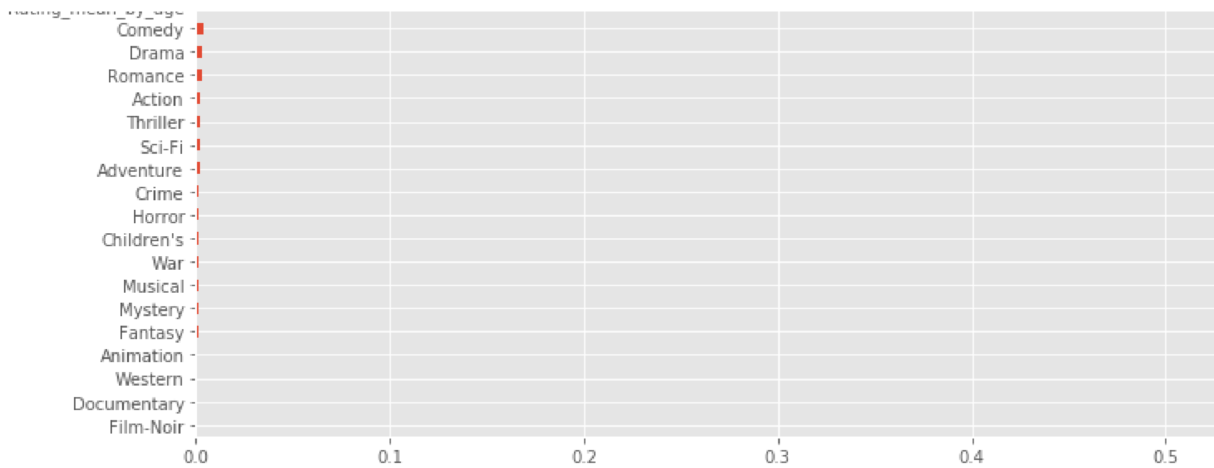
In [285]:

```python
pred, imp = zip(*zip(predictors, rfc.feature_importances_))
```

In [286]:

```python
pd.Series(imp, index=pred).sort_values().plot.barh(figsize=[11,7]);
```





In [287]:

```
from xgboost import XGBRegressor
from xgboost import plot_importance
```

In [288]:

```
xgb = XGBRegressor(random_state=53, max_depth=5)
fit= xgb.fit(X_train, y_train)
```

```
[21:23:42] WARNING: C:/Jenkins/workspace/xgboost-win64_release_0.90/src/objective/regress
ion_obj.cu:152: reg:linear is now deprecated in favor of reg:squarederror.
```

In [289]:

```
xgb.score(X_train, y_train)
```

Out[289]:

```
0.8642419228956066
```

In [290]:

```
xgb.score(X_val, y_val)
```

Out[290]:

```
0.8652332097688313
```

In [291]:

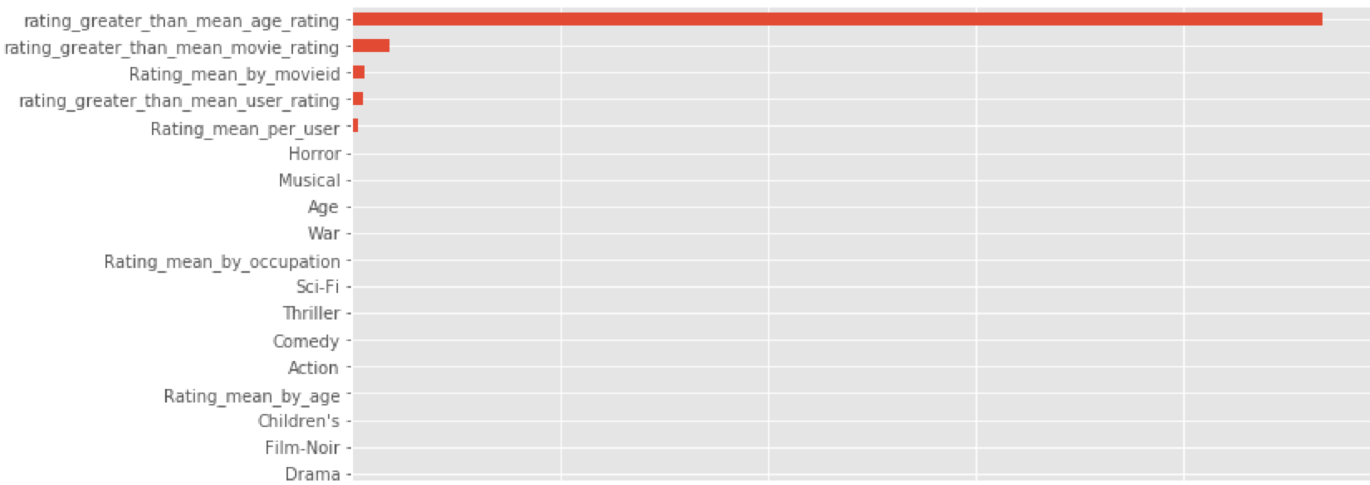
```
pred, imp = zip(*zip(predictors, xgb.feature_importances_))
```

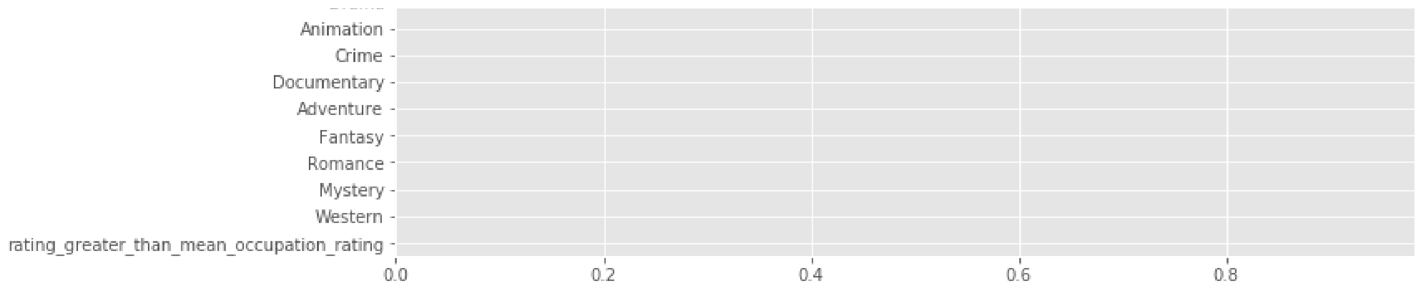
In [292]:

```
pd.Series(imp, index=pred).sort_values().plot.barh(figsize=[11,8])
```

Out[292]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xee81975208>
```





In [293]:

```
fig,ax =plt.subplots(figsize=[12,6])
plot_importance(xgb,ax=ax,)
```

Out[293]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xee816773c8>
```