Stream Max Movie Selection Modeling and Recommender Project

ADS 505 Fall 2022

Ivan Chavez

Azucena Faus

Sanjay Regi Philip

GitHub link: https://github.com/ivan-usd/business-repo

In [1]:

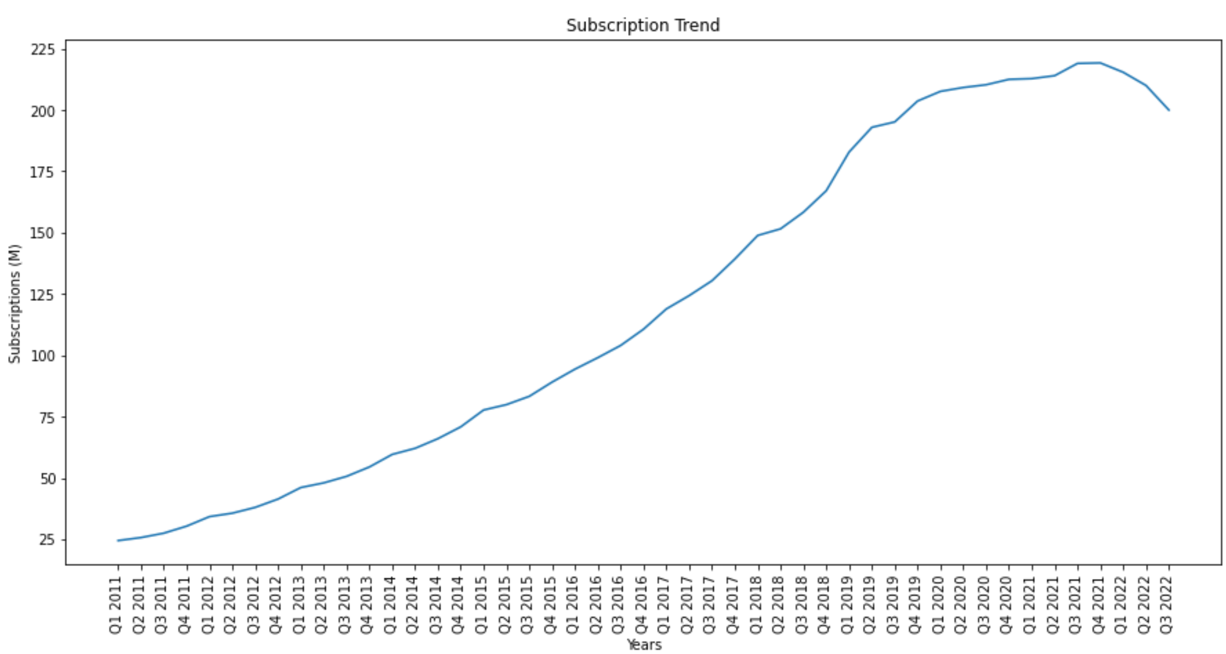
```python
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pylab as plt
import seaborn as sns
import dmba
from pathlib import Path
import functools as ft
import string
import re
import spacy
import scikitplot as skplt
import plotly.graph_objs as go


from sklearn import preprocessing
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.cluster import KMeans
from pandas.plotting import parallel_coordinates
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
from sklearn.neighbors import NearestNeighbors, KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LinearRegression
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.neural_network import MLPClassifier
from sklearn.linear_model import SGDClassifier
from plotly.offline import init_notebook_mode, plot, iplot
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules


from dmba import regressionSummary
from dmba import adjusted_r2_score, AIC_score, BIC_score
from dmba import backward_elimination, forward_selection, stepwise_selection
from plotly.offline import init_notebook_mode, plot, iplot

from dmba import plotDecisionTree, classificationSummary, regressionSummary
from scipy.spatial.distance import cosine
from sklearn.metrics.pairwise import cosine_similarity

from surprise import Dataset
from surprise import Reader
from surprise import KNNBasic

from dmba import gainsChart, liftChart
from ast import literal_eval

import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter(action='ignore', category=FutureWarning)
```

Business Problem (Hypothetical):

Business Status and Surveys:

In [952…

```python
# Subscriber trends over time:

Monthly_Subscriptions=[24.480,25.7,27.49,
                       30.36,34.24,35.64,38,41.4,46.1,47.99,50.65,54.48,
                       59.6,62.08,66.02,70.84,77.7,79.9,83.28,89.09,94.36,
                       99.04,104.02,110.64,118.9,124.34,130.42,139.26,148.86,151.56,
                       158.33,167.09,182.86,192.95,195.15,203.67,207.6,209.18,210.3,
                       212.5,212.8,214,219,219.2,215.4,210,200]
#Yearly_Subscriptions=
months=['September 2021','October 2021',
       'November 2021','December 2021','January 2022','February 2022',
       'March 2022','April 2022','May 2022','June 2022',
       'July 2022','August 2022']
years_quarters=['Q1 2011','Q2 2011','Q3 2011','Q4 2011','Q1 2012',
       'Q2 2012','Q3 2012','Q4 2012','Q1 2013','Q2 2013','Q3 2013',
       'Q4 2013','Q1 2014','Q2 2014','Q3 2014','Q4 2014','Q1 2015',
       'Q2 2015','Q3 2015','Q4 2015','Q1 2016','Q2 2016','Q3 2016',
       'Q4 2016','Q1 2017','Q2 2017','Q3 2017','Q4 2017','Q1 2018',
       'Q2 2018','Q3 2018','Q4 2018','Q1 2019','Q2 2019','Q3 2019',
       'Q4 2019','Q1 2020','Q2 2020','Q3 2020','Q4 2020','Q1 2021',
       'Q2 2021','Q3 2021','Q4 2021','Q1 2022','Q2 2022','Q3 2022']


fig, ax = plt.subplots(figsize=(15,7))

plt.title('Subscription Trend')
ax.plot(years_quarters, Monthly_Subscriptions)
plt.xlabel('Years')
plt.xticks(rotation=90)
plt.ylabel('Subscriptions (M)')
#ax.plot(x, ratings_them)
plt.show()
```



Last 3 Quarters we lost 19M subscribers

Customer Survey:

To find the possible reasons for subscriber loss

In [934…

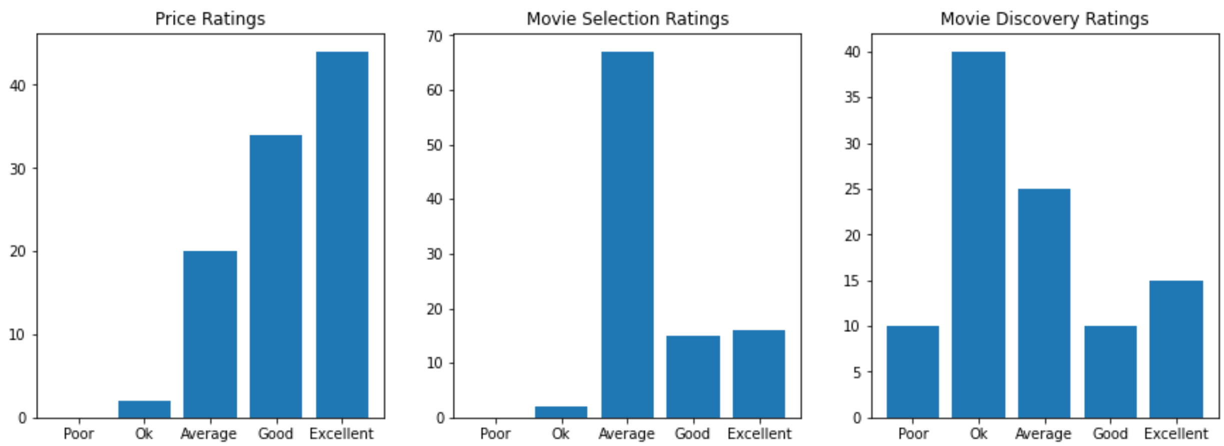
```
# Customer satisfaction:

x = [1, 2, 3, 4, 5]
ratings_us = [20, 35, 35, 5, 5]
ratings_them = [5, 10, 20, 35, 30]
Rating_Overall_Business = pd.DataFrame({'Our Ratings': [20, 35, 35, 5, 5],
                   'Our Competitor': [5, 10, 20, 35, 30]},
                  index=['Poor', 'Ok', 'Average', 'Good', 'Excellent'])

#fig, ax = plt.subplots()
Rating_Overall_Business.plot(kind='bar', stacked=True, color=['red', 'gray'],
                      figsize=(10,5))

# labels for x & y axis
plt.xlabel('Ratings')
plt.ylabel('Proportion of Customers %')

# title of plot
plt.title('Overall Customer Ratings for Movie Services')
plt.show()
```

Upon comparing our ratings from customers to their perceived rating of our competitor, it is apparent there is a problem with our ratings

Noteworthy Specifics from Survey:

In [987…

```
# Specific Survey results:

Rating_Importance = pd.DataFrame({'Price': [0, 2, 20, 34, 44],
                                  'Movie_Selection': [0, 2, 67, 15, 16],
                                  'Ease_of_finding_new_movies': [10, 40, 25, 10, 15]},
                                  index=['Poor', 'Ok', 'Average', 'Good', 'Excellent'])

fig, ax = plt.subplots(1,3,figsize=(15,5))


#plt.show()
ax[0].bar(Rating_Importance.index,Rating_Importance.Price)
ax[1].bar(Rating_Importance.index,Rating_Importance.Movie_Selection)
ax[2].bar(Rating_Importance.index,Rating_Importance.Ease_of_finding_new_movies)


ax[0].title.set_text('Price Ratings')
ax[1].title.set_text('Movie Selection Ratings')
ax[2].title.set_text('Movie Discovery Ratings')
ax=plt.show()
```



The survey questions arose from comments in the lowest ratings and was collected over the same group of customers who sent the initial results. We can see our two areas of improvement are the Movie Selection and Movie Discovery.

Results:

We see that we must improve our movie selection by choosing to add movies with higher predicted ratings than just the most recent. Also, we must have a way to help our customers discover new favorites without having to search the entire database of movies.

We will accomplish this through a movie ratings prediction algorithm that will be run on any new available selection of movies so we can only add those we are confident will be highly appreciated by our customer base, and a recommender system to use the current customer data ratings on movies already watched and recommend the top 3 or 4 movies that match with our customers' high-rated movies.

The data for movie rating prediction was based on 270,896 customer movie ratings and movie collections. The data used for the recommender system was based on 671 customer ratings for

·

Feature Engineering:

In [2]:

```
keywords_df = pd.read_csv('keywords.csv')
links_df = pd.read_csv('links.csv')
credits_df = pd.read_csv('credits.csv')
movie_meta_df = pd.read_csv('movies_metadata.csv')
movie_meta_df.sample(5)
```

Out[2]:

	adult	belongs_to_collection	budget	genres	homepage	id	im
44768	False	NaN	0	[{'id': 18, 'name': 'Drama'}]	NaN	297736	tt402
6550	False	NaN	0	[{'id': 28, 'name': 'Action'}, {'id': 35, 'nam...	NaN	22200	tt030
8242	False	{'id': 8936, 'name': 'Bridget Jones Collection...	50000000	[{'id': 35, 'name': 'Comedy'}, {'id': 10749, '...	NaN	9801	tt031
20292	False	NaN	0	[{'id': 18, 'name': 'Drama'}, {'id': 10749, 'n...	http://keepthelightsonfilm.com/	84290	tt201
38495	False	NaN	0	[{'id': 18, 'name': 'Drama'}, {'id': 10749, 'n...	NaN	97844	tt009

5 rows × 24 columns

In [123…

```
movie_meta_df.shape
```

Out[123…

```
(44838, 23)
```

In [105…

```
ratings_df = pd.read_csv('ratings.csv')
```

In [4]:

```
ratings_small_df = pd.read_csv('ratings_small.csv')
```

In [106…

```
ratings_df.tail()
```

Out[106…

	userId	movieId	rating	timestamp
26024284	270896	58559	5.0	1257031564
26024285	270896	60069	5.0	1257032032
26024286	270896	63082	4.5	1257031764
26024287	270896	64957	4.5	1257033990
26024288	270896	71878	2.0	1257031858

In [98]:

```
movie_meta_df.shape
```

Out[98]: (44838, 23)

In [99]:

```
ratings_df.shape
# 26M records, multiple
# ratings per
# 27,086 users total
```

Out[99]: (26024289, 2)

In [100…

```
ratings_small_df.shape
# about 100k records
# for 671 users with multiple
# movie ratings
```

Out[100… (100004, 4)

In [107…

```
ratings_small_df.tail()
```

Out[107…

	userId	movieId	rating	timestamp
99999	671	6268	2.5	1065579370
100000	671	6269	4.0	1065149201
100001	671	6365	4.0	1070940363
100002	671	6385	2.5	1070979663
100003	671	6565	3.5	1074784724

In [6]:

```
# dropping corrupted rows
filtered_rows = movie_meta_df[movie_meta_df['vote_count'].isnull()].index
movie_meta_df=movie_meta_df.drop(index=filtered_rows)

movie_meta_df['id'] = movie_meta_df.id.astype('int')
```

In [7]:
```
# dropping adult rated movies
filtered_rows = movie_meta_df[movie_meta_df['adult']=='True'].index
movie_meta_df = movie_meta_df.drop(index=filtered_rows)

# dropping adult column no longer needed
movie_meta_df = movie_meta_df.drop(columns='adult')
```

In [8]:
```
# dropping movies that are not already Released
filtered_rows = movie_meta_df[movie_meta_df['status']!='Released'].index
movie_meta_df = movie_meta_df.drop(index=filtered_rows)

# dropping status column no longer needed
movie_meta_df = movie_meta_df.drop(columns='status')
```

In [9]:
```
movie_meta_df['video'].unique()
```

Out[9]:
```
array([False, True], dtype=object)
```

In [10]:
```
# dropping movies that are not already Released
filtered_rows = movie_meta_df[movie_meta_df['video']==True].index
movie_meta_df = movie_meta_df.drop(index=filtered_rows)

# dropping status column no longer needed
movie_meta_df = movie_meta_df.drop(columns='video')
```

In [11]:
```
# removing appended imdb_id
movie_meta_df['imdb_id'] = movie_meta_df['imdb_id'].astype(str).str.replace('tt0', '
movie_meta_df['imdb_id'] = movie_meta_df['imdb_id'].astype(str).str.replace('tt', '')
movie_meta_df.rename(columns={'imdb_id':'imdbId'}, inplace=True)

# merging meta and links df on imdb value
filtered_rows = movie_meta_df[movie_meta_df['imdbId'] == 'nan'].index
movie_meta_df = movie_meta_df.drop(index=filtered_rows)

movie_meta_df['imdbId'] = movie_meta_df['imdbId'].astype('int64')
movie_meta_df = pd.merge(movie_meta_df,links_df,on='imdbId')
```

Cleaning JSON columns:

In [12]:
```
# merging datasets for text mining
dataframes = [keywords_df,credits_df,movie_meta_df]
text_df = ft.reduce(lambda left, right: pd.merge(left, right, on='id'), dataframes)
```

In [13]:

```
movies_df = pd.DataFrame(text_df[['movieId', 'keywords','cast', 'crew', 'genres',
                          'popularity', 'production_companies',
                          'production_countries','title', 'revenue']])

# dropping duplicates and missing values
movies_df.drop_duplicates(keep=False,inplace=True)
movies_df.dropna(inplace=True)
```

In [14]:

```
features = ['cast', 'crew', 'genres', 'keywords', 'production_companies',
            'production_countries']

movies_df = movies_df.dropna(subset=features)

for feature in features:
    movies_df[feature] = movies_df[feature].apply(literal_eval)
```

In [15]:

```
## function to get name of director from the crew field
def get_director(x):
    for i in x:
        if i['job'] == 'Director':
            return i['name']
    return np.nan

# get director
movies_df['director'] = movies_df['crew'].apply(get_director)
movies_df = movies_df.drop(columns='crew')
```

In [16]:

```
# Returns the list of top 3 elements for genres and keywords
def get_list(x):
    if isinstance(x, list):
        names = [i['name'] for i in x]
        #Check if more than 3 elements exist. If yes, return only first three. If no,
        # return entire list.
        if len(names) > 3:
            names = names[:3]
        return names

    #Return empty list in case of missing/malformed data
    return []
```

In [17]:

```
## function to get name of production company from the crew field
def get_names(x):
    for i in x:
        return i['name']
    return np.nan

# get production company names
movies_df['prod_company'] = movies_df['production_companies'].apply(get_names)
movies_df['prod_country'] = movies_df['production_countries'].apply(get_names)

movies_df = movies_df.drop(columns='production_companies')
movies_df = movies_df.drop(columns='production_countries')
```

In [18]:

```
features = ['cast', 'keywords', 'genres']

for feature in features:
    movies_df[feature] = movies_df[feature].apply(get_list)
```

In [19]:

```
filtered_rows = movies_df[movies_df['prod_country'] != 'United States of America'].in
movies_df = movies_df.drop(index=filtered_rows)
movies_df = movies_df.drop(columns='prod_country')
```

In [20]:

```
movies_df.head()
```

Out[20]:

	movieId	keywords	cast	genres	popularity	title	revenue	director	p
0	1	[jealousy, toy, boy]	[Tom Hanks, Tim Allen, Don Rickles]	[Animation, Comedy, Family]	21.946943	Toy Story	373554033.0	John Lasseter	P
1	2	[board game, disappearance, based on children'...	[Robin Williams, Jonathan Hyde, Kirsten Dunst]	[Adventure, Fantasy, Family]	17.015539	Jumanji	262797249.0	Joe Johnston	
2	3	[fishing, best friend, duringcreditsstinger]	[Walter Matthau, Jack Lemmon, Ann-Margret]	[Romance, Comedy]	11.7129	Grumpier Old Men	0.0	Howard Deutch	
3	4	[based on novel, interracial relationship, sin...	[Whitney Houston, Angela Bassett, Loretta Devine]	[Comedy, Drama, Romance]	3.859495	Waiting to Exhale	81452156.0	Forest Whitaker	
4	5	[baby, midlife crisis, confidence]	[Steve Martin, Diane Keaton, Martin Short]	[Comedy]	8.387519	Father of the Bride Part II	76578911.0	Charles Shyer	

In [86]:

```
index_TWBalloon=movies_df['title']=='The White Balloon'
movies_df[index_TWBalloon]
```

Out[86]:

movieId	keywords	cast	genres	popularity	title	revenue	director	prod_company

In [87]:

```
index_TWBalloon2=movie_meta_df['title']=='The White Balloon'
movie_meta_df[index_TWBalloon2]
```

Out[87]:

	belongs_to_collection	budget	genres	homepage	id	imdbId	original_language	original_ti
79	NaN	0	[{'id': 10751, 'name': 'Family'}, {'id': 18, '...	NaN	46785	112445	fa	بادکنک سفید

1 rows × 23 columns

EDA

In [992…

```
len(ratings_df['userId'].unique())
```

Out[992…

```
270896
```

In [991…

```
ratings_small_df['userId'].unique()
```

Out[991…

```
[1, 2, 3, 4, 5, ..., 667, 668, 669, 670, 671]
Length: 671
Categories (671, int64): [1, 2, 3, 4, ..., 668, 669, 670, 671]
```

In [525…

```
ratings_small_df.head()
```

Out[525…

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205

In [5]:

```
ratings_small_df.describe()
```

Out[5]:

	userId	movieId	rating	timestamp
count	100004.000000	100004.000000	100004.000000	1.000040e+05
mean	347.011310	12548.664363	3.543608	1.129639e+09
std	195.163838	26369.198969	1.058064	1.916858e+08
min	1.000000	1.000000	0.500000	7.896520e+08

	userId	movieId	rating	timestamp
25%	182.000000	1028.000000	3.000000	9.658478e+08
50%	367.000000	2406.500000	4.000000	1.110422e+09
75%	520.000000	5418.000000	4.000000	1.296192e+09

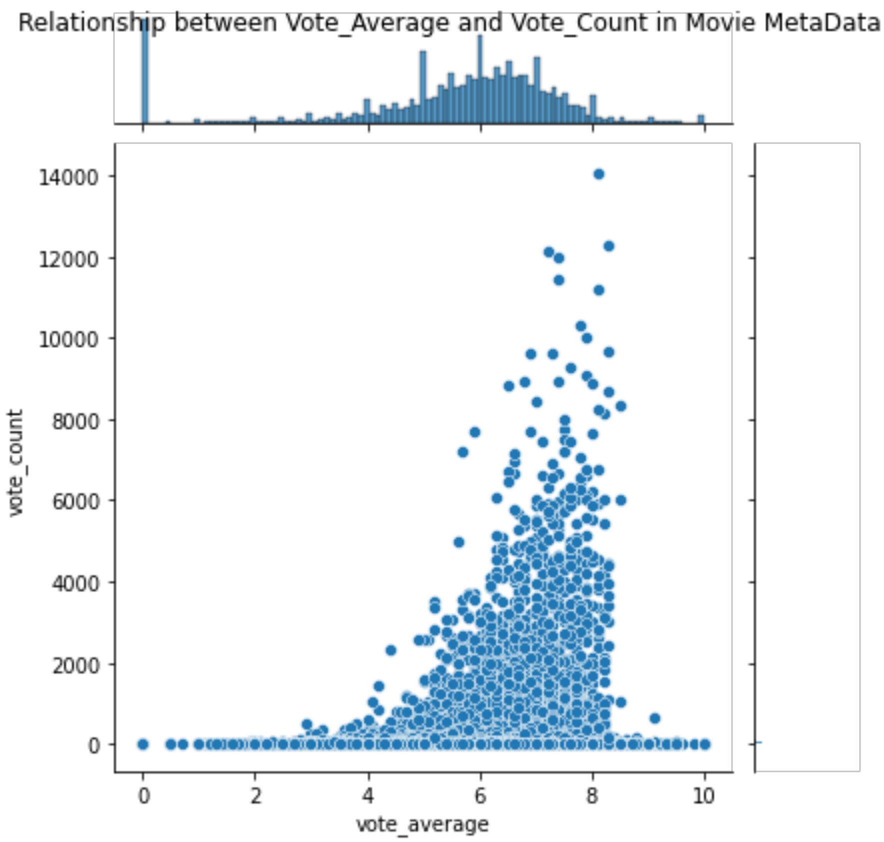
Average/Count relationships for Votes/Rates:

In [993…

```
p=sns.jointplot(x='vote_average',y='vote_count', data=movie_meta_df)
p.fig.suptitle("Relationship between Vote_Average and Vote_Count in Movie MetaData")
```

Out[993…

```
Text(0.5, 0.98, 'Relationship between Vote_Average and Vote_Count in Movie MetaData')
```



In [529…

```
# plot the rating avg vs rating count
# for our rating data:

ratings['rating_avg'] = pd.DataFrame(ratings_df.groupby('movieId')['rating'].mean())


ratings['rating_count'] = ratings_df.groupby('movieId')['rating'].count()
ratings.head()
```

Out[529…

	rating	number_of_ratings	rating_avg	rating_count
movieId				
1	3.888157	66008	3.888157	66008
2	3.236953	26060	3.236953	26060

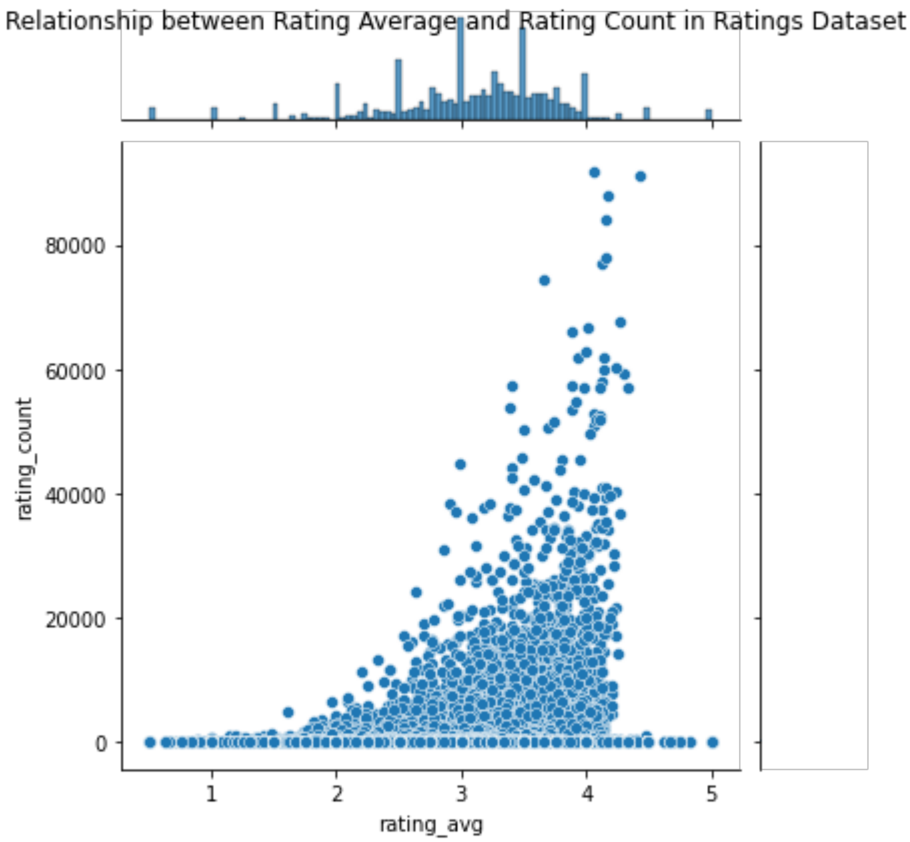
	rating	number_of_ratings	rating_avg	rating_count
movieId				
3	3.175550	15497	3.175550	15497

In [994…

```
q=sns.jointplot(x='rating_avg', y='rating_count', data=ratings)
q.fig.suptitle("Relationship between Rating Average and Rating Count in Ratings Datas
```

Out[994…

```
Text(0.5, 0.98, 'Relationship between Rating Average and Rating Count in Ratings Data
set')
```



Results:

We can see as the ratings increase, the number of people that rate the movie also increases. This is the case with both the overall movie metadata (movie_meta_df dataframe) and current customer ratings for those movies (from the ratings_df dataframe)

Move Rating Distributions:

In [115…

```
import plotly.io as pio
pio.renderers.default='notebook'
```

In [118…

```
init_notebook_mode(connected=True)
data = ratings_small_df['rating'].value_counts().sort_index(ascending=False)
trace = go.Bar(x = data.index,
               text = ['{:.1f} %'.format(val) for val in (data.values /
                                                           ratings_small_df.shape[0] *
               textposition = 'auto',
               textfont = dict(color = '#000000'),
               y = data.values,
               )
# Create layout
layout = dict(title = 'Distribution of Movie Ratings'.format(ratings_small_df.shape[0
              xaxis = dict(title = 'Rating'),
              yaxis = dict(title = 'Count'))
# Create plot
fig = go.Figure(data=[trace], layout=layout)

plot(fig)
```

Out[118… 'temp-plot.html'

In [119…

```
# Number of ratings per movie:
data = ratings_small_df.groupby('movieId')['rating'].count().clip(upper=50)

# Create trace
trace = go.Histogram(x = data.values,
                     name = 'Ratings',
                     xbins = dict(start = 0,
                                  end = 50,
                                  size = 2))
# Create layout
layout = go.Layout(title = 'Distribution Of Number of Ratings Per Movie (Clipped at 5
                   xaxis = dict(title = 'Number of Ratings Per Movie'),
                   yaxis = dict(title = 'Count'),
                   bargap = 0.2)

# Create plot
fig = go.Figure(data=[trace], layout=layout)
plot(fig)
```

Out[119… 'temp-plot.html'

In [671…

```
rating_count = ratings_small_df.groupby('movieId')['rating'].count().reset_index()
rating_count_top10=rating_count.sort_values('rating', ascending=False)[:10]
```

In [672…

```
rating_count_top10
```

Out[672…

	movieId	rating
321	356	341
266	296	324
284	318	311

	movieId	rating
525	593	304
232	260	291
427	480	274
2062	2571	259
0	1	247
472	527	244

Top 10 movie ratings:

In [683…

```
# Correlate movieId from ratings dataset
# to the imdbId in the links dataset:

top10=[]
top10_movieId=rating_count_top10['movieId'].reset_index()

for s in range(0,len(rating_count_top10)):
    index_links_top10=links_df['movieId']==top10_movieId['movieId'][s]

    top10_imdb=links_df['imdbId'][index_links_top10].astype('string')
#    top10_imdb_string=top10_imdb.values[0]
#    top10_imdb_movie= [f"tt0{top10_imdb_string}"]
    top10.append(top10_imdb.values[0])


# Find the movie title related to the
# newfound imdbId in the movie_meta_df
# dataset and add it to the top 10 rated
# movie titles:

top10_titles=[]

for i in range(0,len(top10)):

    index_movie_top10=movie_meta_df.loc[movie_meta_df['imdb_id'].str.contains(top10[
                                                                                   case=F

    top10_title=movie_meta_df['title'][index_movie_top10]
    top10_title_string=top10_title.values[0]
    top10_titles.append(top10_title_string)

rating_count_top10['movie_title']=top10_titles
```

In [684…

```
rating_count_top10
```

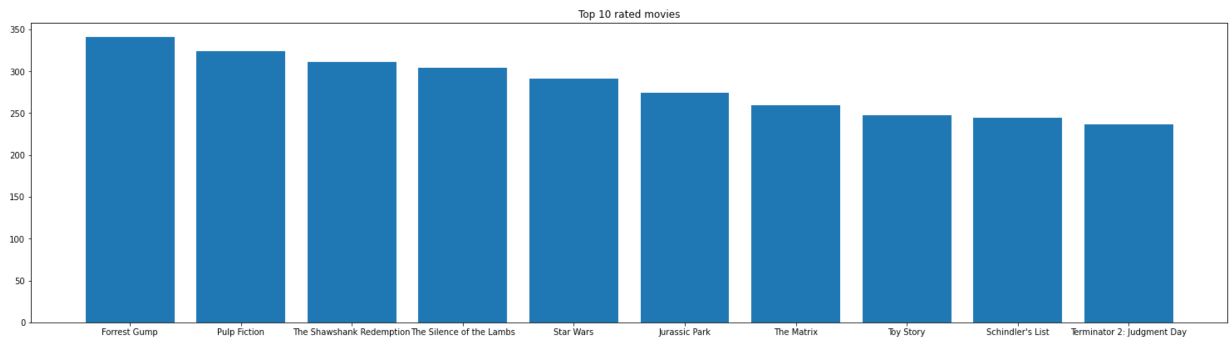
Out[684…

	movieId	rating	movie_title
321	356	341	Forrest Gump
266	296	324	Pulp Fiction
284	318	311	The Shawshank Redemption

	movieId	rating	movie_title
525	593	304	The Silence of the Lambs
232	260	291	Star Wars
427	480	274	Jurassic Park
2062	2571	259	The Matrix
0	1	247	Toy Story
472	527	244	Schindler's List

In [699…

```
fig = plt.figure(figsize=(20,5))
ax = fig.add_axes([0,0,1,1])
ax.bar(rating_count_top10['movie_title'],rating_count_top10['rating'])
plt.title('Top 10 rated movies')
plt.show()
```



Recommender

item-item collaborative filtering

Implementation as in page 365 of Data Mining for Business Analytics book

In [126…

```
ratings_small_df.head()
```

Out[126…

	userId	movieId	rating	timestamp
0	1	31	2.5	1260759144
1	1	1029	3.0	1260759179
2	1	1061	3.0	1260759182
3	1	1129	2.0	1260759185
4	1	1172	4.0	1260759205

In [128…

```
ratings_small_df.drop(columns='timestamp',inplace=True)
```

In [537…

```
movie_mod=movie_meta_df[['movieId','vote_average']]
```

In [129…

```
ratings_small_df['movieId']=ratings_small_df['movieId'].astype('category')
ratings_small_df['userId']=ratings_small_df['userId'].astype('category')
```

In [130…

```
# Split data:

ratings_train, ratings_val = train_test_split(ratings_small_df,test_size=0.20, randor
```

Generate the collaborative filter model:

In [131…

```
reader = Reader(rating_scale=(0, 6))
data = Dataset.load_from_df(ratings_train, reader)
trainset = data.build_full_trainset()

# compute cosine similarities between items
sim_options = {'name': 'cosine', 'user_based': False}
algo = KNNBasic(sim_options=sim_options)
algo.fit(trainset)
```

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

Out[131…

```
<surprise.prediction_algorithms.knns.KNNBasic at 0x1b7c7d3e5b0>
```

Predict top 4 on validation dataset:

In [144…

```
predictions = algo.test(ratings_val)

top_n = get_top_n(predictions,n=4)

#top_n
```

In [132…

```
# Automate and run on validation dataset:

movies = links_df.movieId
predictions_all2=pd.DataFrame()

for user in ratings_val['userId'].unique():

    predictions_user=pd.DataFrame(columns=['user','new_movie','predicted_rating'])

    for mov in movies:
        predictedUSER = algo.predict(user, mov).est

        if predictedUSER >= 4:
            highest_rated_indexUSER = predictedUSER
            predictions_user.loc[len(predictions_user.index)] = [user, mov,
                                                                 predictedUSER]


    top_4_USER = predictions_user.sort_values('predicted_rating', ascending=False)[:4
    predictions_all2=pd.concat([predictions_all2, top_4_USER], ignore_index=True, sor

predictions_all2.columns = ['user','new_movie','predicted_rating']
```

In [146…

```
# Automate and run on entire ratings_small_df

# Takes hours to run, was run and saved to .csv file
# in the GitHub repository

movies = links_df.movieId
predictions_all=pd.DataFrame()

for user in ratings_small_df['userId'].unique():

    predictions_user=pd.DataFrame(columns=['user','new_movie','predicted_rating'])

    for mov in movies:
        predictedUSER = algo.predict(user, mov).est

        if predictedUSER >= 4:
            highest_rated_indexUSER = predictedUSER
            predictions_user.loc[len(predictions_user.index)] = [user, mov,
                                                                 predictedUSER]


    top_4_USER = predictions_user.sort_values('predicted_rating', ascending=False)[:4
    predictions_all=pd.concat([predictions_all2, top_4_USER], ignore_index=True, sort

predictions_all.columns = ['user','new_movie','predicted_rating']
```

- predictions_all is the predictions done on the entire dataset.
- prediction_all2 are the predictions done on only the validation dataset.

In [133…

```
predictions_all2.shape
```

Out[133...

```
(2643, 3)
```

In [802...

```
predictions_user
```

Out[802...

	user	new_movie	predicted_rating
0	671.0	1.0	4.100628
1	671.0	7.0	4.011990
2	671.0	9.0	4.099485
3	671.0	10.0	4.012579
4	671.0	17.0	4.110051
...	...	...	...
3972	671.0	161918.0	4.087500
3973	671.0	161944.0	4.375000
3974	671.0	162542.0	4.500000
3975	671.0	162672.0	4.500000
3976	671.0	163949.0	4.087500

3977 rows × 3 columns

In [134...

```
predictions_all2.tail()
```

Out[134...

	user	new_movie	predicted_rating
2638	638.0	8982.0	4.5
2639	76.0	43556.0	5.0
2640	76.0	42007.0	5.0
2641	76.0	582.0	5.0
2642	76.0	563.0	5.0

In [136...

```
predictions_all2.to_csv('TopFour_MovieRecs.csv')
```

- Top4_MovieRecs.csv are all user movie recommendations
- TopFour_MovieRecs.csv are movie recommendations for validation dataset

In [812...

```
predictions_all['new_movie']=predictions_all['new_movie'].astype('int')
```

In [843...

```
predictions_all.iloc[48]
```

Out[843...

```
user                 13.0
new_movie            1133
```

```
predicted_rating     5.0
Name: 48, dtype: object
```

In [844…

```python
index_curious=links_df['movieId']==1133
links_df[index_curious]
```

Out[844…

	movieId	imdbId	tmdbId
1110	1133	111357	NaN

In [846…

```python
movie_meta_df['imdb_id']=movie_meta_df['imdb_id'].astype('string')
index_weirdi=movie_meta_df.loc[movie_meta_df['imdb_id'].str.contains('11357',
                                                                  case=False)].inc
movie_meta_df['title'][index_weirdi]
```

Out[846…

```
27946    Kristin Lavransdatter
Name: title, dtype: object
```

In [850…

```python
# correcting erroneous data in links_df
links_df['imdbId'][index_curious]='11357'
```

In [847…

```python
index_curious2=links_df['imdbId']==11357
links_df[index_curious2]
```

Out[847…

movieId	imdbId	tmdbId

In [851…

```python
links_df[index_curious]
```

Out[851…

	movieId	imdbId	tmdbId
1110	1133	11357	NaN

In [847…

```python
index_curious2=links_df['imdbId']==11357
links_df[index_curious2]
```

Out[847…

movieId	imdbId	tmdbId

In [854…

```python
predictions_all.iloc[112]
```

Out[854…

```
user                29.0
new_movie           6776
predicted_rating     5.0
Name: 112, dtype: object
```

In [855…

```python
index_curious=links_df['movieId']==6776
links_df[index_curious]
```

Out[855…

	movieId	imdbId	tmdbId

	movieId	imdbId	tmdbId

In [881…

```
movie_meta_df['imdb_id']=movie_meta_df['imdb_id'].astype('string')
index_weirdi=movie_meta_df.loc[movie_meta_df['imdb_id'].str.contains('22674',
                                                                      case=False)].in

movie_meta_df['imdb_id'][index_weirdi]
```

Out[881…

```
9360     tt0322674
20870    tt1422674
31044    tt2267454
Name: imdb_id, dtype: string
```

In [884…

```
index_curious2=links_df['imdbId']==422674
links_df[index_curious2]
```

Out[884…

	movieId	imdbId	tmdbId
9412	27639	322674	16132.0

Add movie titles:

In [885…

```
movie_meta_df['imdb_id']=movie_meta_df['imdb_id'].astype('string')

top4_movie_ALL=predictions_all['new_movie'].reset_index()
top4_titlesALL=[]

for ee in range(0,len(predictions_all)):
    #print(ee)
    index_links_top4ALL=links_df['movieId']==top4_movie_ALL['new_movie'][ee]

    top4_imdbALL=links_df['imdbId'][index_links_top4ALL].astype('string')

    top4ALL=top4_imdbALL.values[0]

    index_movie_top4ALL=movie_meta_df.loc[movie_meta_df['imdb_id'].str.contains(top4A
                                                                                case=


    if index_movie_top4ALL.empty:
        top4_titlesALL.append('NA')
    else:
        top4_titleALL=movie_meta_df['title'][index_movie_top4ALL]
        top4_title_stringALL=top4_titleALL.values[0]
        top4_titlesALL.append(top4_title_stringALL)


predictions_all['movie_title']=top4_titlesALL
```

In [140…

```
movie_meta_df['imdbId']=movie_meta_df['imdbId'].astype('string')

top4_movie_ALL2=predictions_all2['new_movie'].reset_index()
top4_titlesALL2=[]

for ee in range(0,len(predictions_all2)):
    #print(ee)
    index_links_top4ALL2=links_df['movieId']==top4_movie_ALL2['new_movie'][ee]

    top4_imdbALL2=links_df['imdbId'][index_links_top4ALL2].astype('string')

    top4ALL2=top4_imdbALL2.values[0]

    index_movie_top4ALL2=movie_meta_df.loc[movie_meta_df['imdbId'].str.contains(top4A
                                                                                case=

    if index_movie_top4ALL2.empty:
        top4_titlesALL2.append('NA')
    else:
        top4_titleALL2=movie_meta_df['title'][index_movie_top4ALL2]
        top4_title_stringALL2=top4_titleALL2.values[0]
        top4_titlesALL2.append(top4_title_stringALL2)


predictions_all2['movie_title']=top4_titlesALL2
```

Save to a csv file:

In [887…

```
predictions_all.to_csv('Top4_MovieRecs_complete.csv')
```

In [141…

```
predictions_all2.to_csv('TopFour_MovieRecs_validation.csv')
```

In [97]:

```
predictions_all_review = pd.read_csv('Top4_MovieRecs_complete.csv')
predictions_all_review.tail(12)
```

Out[97]:

	Unnamed: 0	user	new_movie	predicted_rating	movie_title
2638	2638	669.0	162672	5.000000	Mohenjo Daro
2639	2639	669.0	62115	5.000000	Six Shooter
2640	2640	669.0	71438	5.000000	Still Walking
2641	2641	669.0	71180	5.000000	Padre Padrone
2642	2642	670.0	7574	5.000000	Maborosi
2643	2643	670.0	5236	5.000000	A Tale of Springtime
2644	2644	670.0	109483	5.000000	That Awkward Moment
2645	2645	670.0	4593	5.000000	Family Business
2646	2646	671.0	134783	4.833333	Entourage
2647	2647	671.0	39416	4.833333	Kids in America

	Unnamed: 0	user	new_movie	predicted_rating	movie_title
2648	2648	671.0	5422	4.833333	The Emperor's New Clothes

In [142…

```
predictions_all_review_valid = pd.read_csv('TopFour_MovieRecs_validation.csv')
predictions_all_review_valid.tail(12)
```

Out[142…

	Unnamed: 0	user	new_movie	predicted_rating	movie_title
2631	2631	112.0	64034.0	5.0	The Boy in the Striped Pyjamas
2632	2632	112.0	51086.0	5.0	The Number 23
2633	2633	112.0	128512.0	5.0	Paper Towns
2634	2634	112.0	93422.0	5.0	Starbuck
2635	2635	638.0	160590.0	4.5	Survive and Advance
2636	2636	638.0	8167.0	4.5	Captain Blood
2637	2637	638.0	26094.0	4.5	L'eclisse
2638	2638	638.0	8982.0	4.5	I Am David
2639	2639	76.0	43556.0	5.0	Annapolis
2640	2640	76.0	42007.0	5.0	Rumor Has It...
2641	2641	76.0	582.0	5.0	Café au Lait
2642	2642	76.0	563.0	5.0	Germinal

Remove titles not found in links_df

Every user will have at least 3 recommendations, at maximum, 4

In [147…

```
index_curious3=predictions_all2['movie_title']=='NA'
index_curious4=predictions_all2[index_curious3].index
predictions_complete_all2=predictions_all2.drop(index_curious4, axis=0)
```

In [148…

```
predictions_complete_all2.to_csv('TopFour_MovieRecs_final_valid.csv')
```

In [896…

```
index_curious3=predictions_all['movie_title']=='NA'
index_curious4=predictions_all[index_curious3].index
predictions_complete_all=predictions_all.drop(index_curious4, axis=0)
```

In [100…

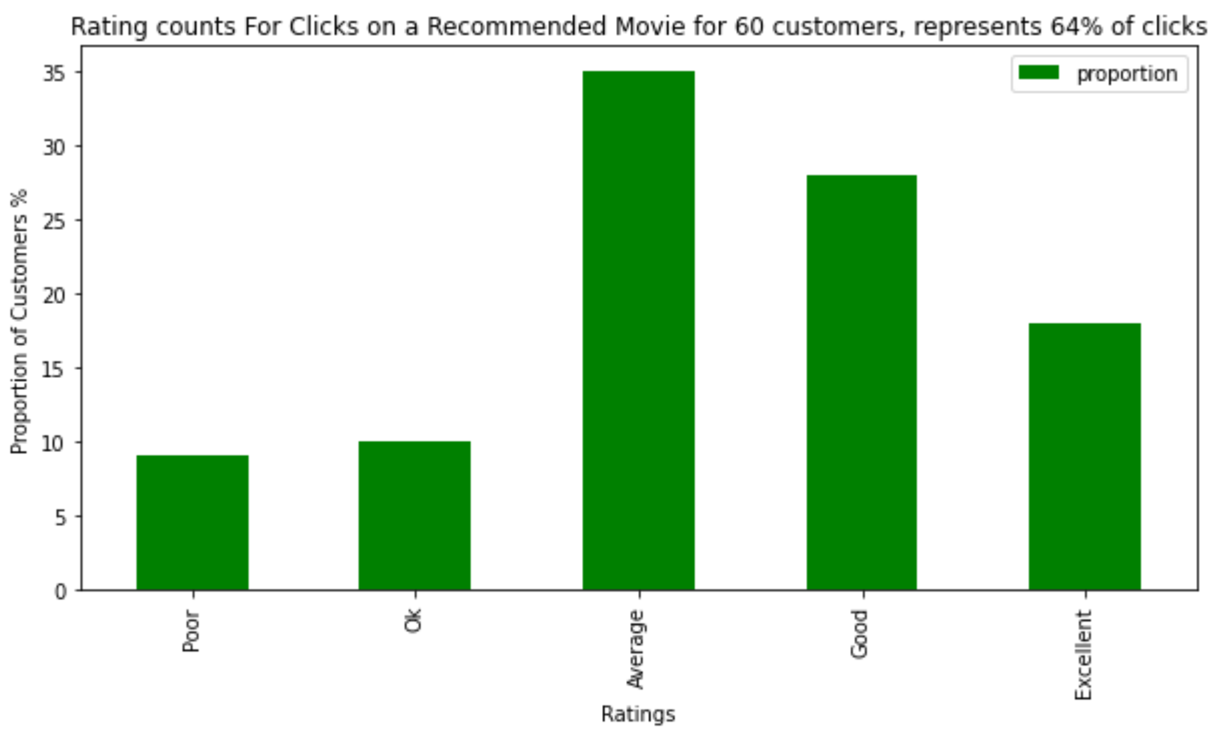
```
predictions_complete_all.to_csv('Top4_MovieRecs_final.csv')
```

Recommender Results (Hypothetical):

How was the recommender outputs received by users?

In [104…

```python
# About Half of the validation set
# 60 customers selected for soft deployment
# of the recommdner system.

# Here are the results:

#x3 = 3*np.ones(35,1)
#x4 = 4*np.ones(28,1)
#x5 = 5*np.ones(18,1)
#x2 = 2*np.ones(10,1)
#x1 = np.ones(9,1)

no_clicks_recMovies = 180 #average of 3 per user
no_clicks_Wreviews = 115 #people rated less than avg of 2/3 clicks
#ratings_per_click=['x3','x4','x5','x2','x1']
Rating_Recommended_Clicks = pd.DataFrame({'proportion': [9, 10, 35, 28, 18]},
                  index=['Poor', 'Ok', 'Average', 'Good', 'Excellent'])

#fig, ax = plt.subplots()
Rating_Recommended_Clicks.plot(kind='bar', color=['green'],
                      figsize=(10,5))

# labels for x & y axis
plt.xlabel('Ratings')
plt.ylabel('Proportion of Customers %')

# title of plot
plt.title('Rating counts For Clicks on a Recommended Movie for 60 customers, represer
plt.show()
```



Data Pre-Processing:

Use avg rating to fill for movies & prep modeling dataframe:

In [21]:
```
# averaging ratings and merging ratings to final dataframe on movie Id
ratings_df.drop(columns=['userId', 'timestamp'], inplace=True)
avg_ratings = round(ratings_df.groupby('movieId').mean(),2)
final_df = pd.merge(movies_df,avg_ratings,on='movieId')
final_df.rename(columns={'rating':'avg_rating'}, inplace=True)

# dropping null values
final_df = final_df.dropna()

# popularity clean up
final_df['popularity'] = final_df['popularity'].astype('float')
final_df['popularity'] = round(final_df['popularity'],2)

# reducing revenue to millions to mitigate large values
final_df['revenue_millions'] = round(final_df['revenue']/1000000, 3)
final_df = final_df.drop(columns='revenue')
```

Export to csv to use for modeling:

In [23]:
```
final_df.to_csv('modeling_data.csv',index=False)
```

Pre-Process for Modeling:

In [24]:
```
movies = pd.read_csv('modeling_data.csv')

features = ['keywords', 'cast', 'genres']

for feature in features:
    movies[feature] = movies[feature].apply(literal_eval)
```

In [25]:
```
movies['director'] = movies['director'].astype(str).str.replace('.', '')
movies['director'] = movies['director'].astype(str).str.replace(' ', '_')

movies['prod_company'] = movies['prod_company'].astype(str).str.replace('.', '')
movies['prod_company'] = movies['prod_company'].astype(str).str.replace(' ', '_')
```

In [26]:
```
movies['label'] = pd.cut(movies.avg_rating, bins=[0,3.4,5],labels=[0,1])
```

In [27]:
```
X = movies[['genres','cast','director','prod_company','popularity','revenue_millions
y = movies[['avg_rating','label','title']]
```

In [28]:
```
# creating dummies
genres_cat = X.genres.str.join('|').str.get_dummies().add_prefix('genres_')
X = pd.concat([X, genres_cat], axis=1)
X = X.drop(columns='genres')
```

In [29]:

```
# creating dummies
cast_cat = X.cast.str.join('|').str.get_dummies().add_prefix('cast_')
X = pd.concat([X, cast_cat], axis=1)
X = X.drop(columns='cast')
```

In [30]:

```
keyword_cat = X.director.str.get_dummies().add_prefix('director_')
X = pd.concat([X, keyword_cat], axis=1)
X = X.drop(columns='director')
```

In [31]:

```
keyword_cat = X.prod_company.str.get_dummies().add_prefix('prod_company_')
X = pd.concat([X, keyword_cat], axis=1)
X = X.drop(columns='prod_company')
```

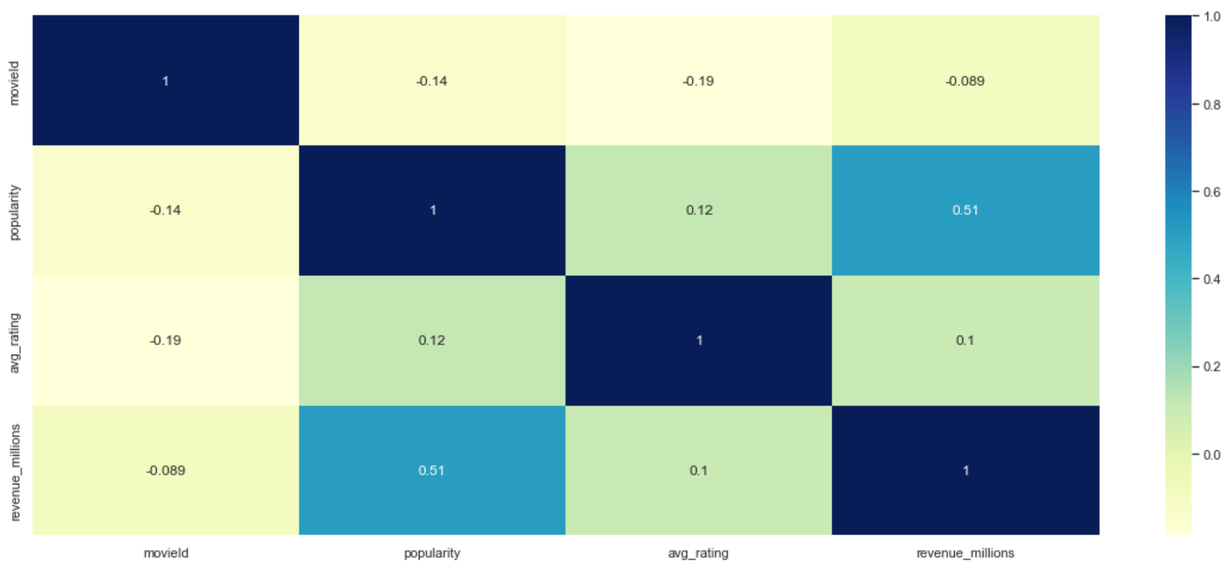
In [32]:

```
X_train, X_val, y_train, y_val = train_test_split(X, y,test_size=0.20, random_state =
```

Visualizations for Movie Characteristics:

In [108…

```
# plot the heatmap and annotation on it
#Correlation matrix
corr_matrix_movies = movies.corr()
sns.set(rc = {'figure.figsize':(20,8)})
sns.heatmap(corr_matrix_movies, cmap="YlGnBu", annot=True)
plt.show()
```



Results:

There is a moderate correlation between popularity and revenue in millions, which is obvious. Otherwise, avg rating is not related to movieId, popularity or revenue in millions

In [48]:

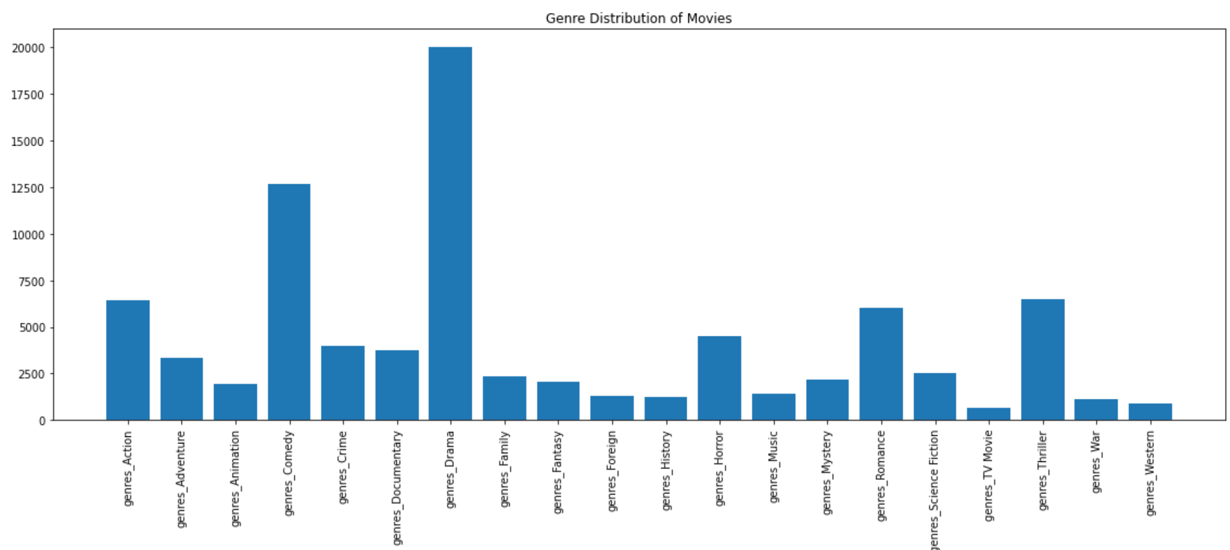
```
filter_col = [col for col in X if col.startswith('genres')]
```

In [49]:
```
X[filter_col].columns
```

Out[49]:
```
Index(['genres_Action', 'genres_Adventure', 'genres_Animation',
       'genres_Comedy', 'genres_Crime', 'genres_Documentary', 'genres_Drama',
       'genres_Family', 'genres_Fantasy', 'genres_Foreign', 'genres_History',
       'genres_Horror', 'genres_Music', 'genres_Mystery', 'genres_Romance',
       'genres_Science Fiction', 'genres_TV Movie', 'genres_Thriller',
       'genres_War', 'genres_Western'],
      dtype='object')
```

In [104…
```
X_genre_counts=X[filter_col].sum()
```

In [105…
```
fig = plt.figure(figsize=(15,5))
ax = fig.add_axes([0,0,1,1])
ax.bar(X[filter_col].columns,X[filter_col].sum())
plt.title('Genre Distribution of Movies')
plt.xticks(rotation=90)
plt.show()
```



Results:

Drama and Comedy are the largest genre represented by our movie dataset.

In [37]:
```
filter_col_cast = [col for col in X if col.startswith('cast')]
```

In [38]:
```
X[filter_col_cast].columns
```

Out[38]:
```
Index(['cast_\tRobert Osth', 'cast_ Larry Mullen Jr.',
       'cast_"Weird Al" Yankovic', 'cast_'Little Billy' Rhodes',
       'cast_50 Cent', 'cast_A Martinez', 'cast_A. Michael Baldwin',
       'cast_A.C. Abadie', 'cast_A.E. Anson', 'cast_A.J. Buckley',
       ...
       'cast_Élisabeth Vitali', 'cast_Óscar Jaenada', 'cast_Đơn Dương',
       'cast_Đỗ Thị Hải Yến', 'cast_Дэмиан Чапа', 'cast_Моррис Честнат',
       'cast_Патрик О’Нил', 'cast_Эрика Элениак', 'cast_پیمان معادی',
       'cast_杰森·莫玛'],
```

In [43]:

```
cast_counts=X[filter_col_cast].sum()
cast_counts_df=pd.DataFrame(cast_counts,columns=['count'])
```

In [44]:

```
cast_counts_df.head()
```

Out[44]:

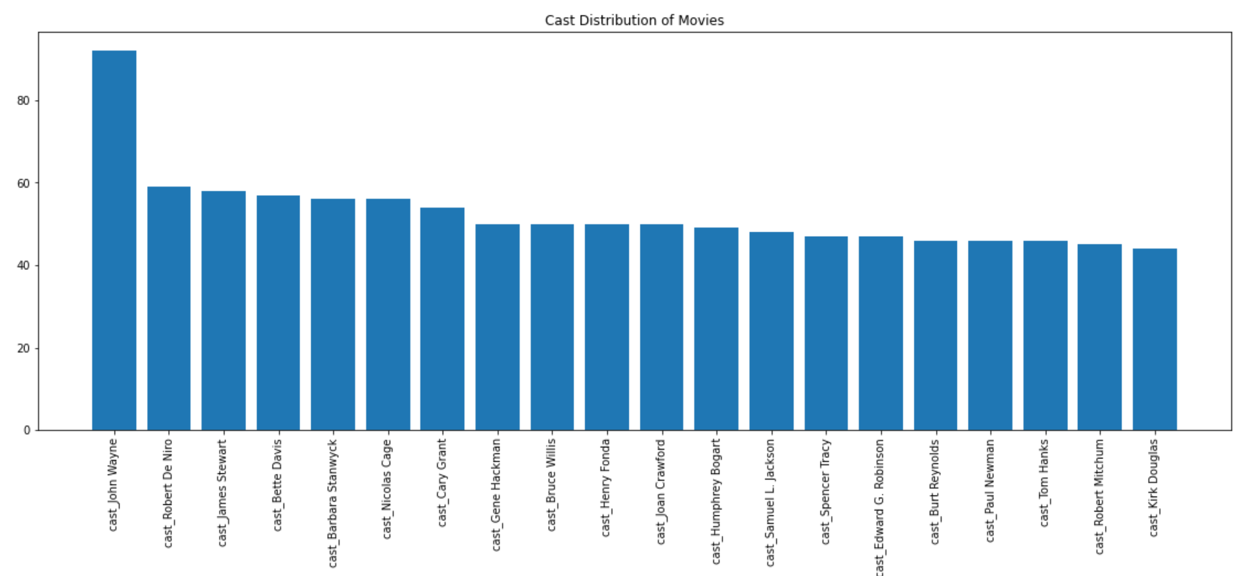
	count
cast_\tRobert Osth	1
cast_ Larry Mullen Jr.	1
cast_"Weird Al" Yankovic	1
cast_'Little Billy' Rhodes	1
cast_50 Cent	9

In [83]:

```
cast_top20=cast_counts_df.sort_values('count', ascending=False)[:20]
```

In [85]:

```
fig = plt.figure(figsize=(15,5))
ax = fig.add_axes([0,0,1,1])
ax.bar(cast_top20.index,cast_top20['count'])
plt.title('Cast Distribution of Movies')
plt.xticks(rotation=90)
plt.show()
```



Cluster movie titles by genre

In [50]:

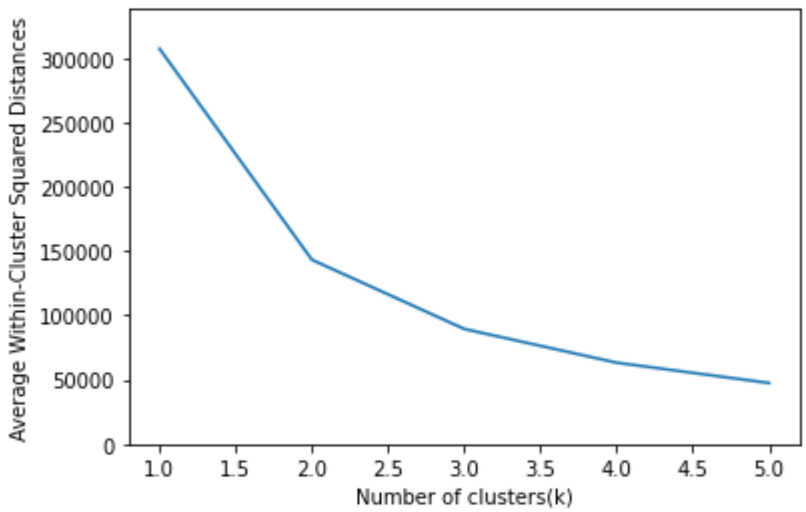
```
movie_genre_clusters_df=X[filter_col]
movie_genre_clusters_df.dropna(inplace=True)
```

In [52]:

```
movie_genre_clusters_df = movie_genre_clusters_df.apply(lambda x: x.astype('float64')

# Normalized distance
movie_genre_clusters_df_norm = movie_genre_clusters_df.apply(preprocessing.scale, ax:
```

In [53]:

```
inertia = []
for n_clusters in range(1, 6):
    kmeans = KMeans(n_clusters=n_clusters, random_state=0).fit(movie_genre_clusters_c
    inertia.append(kmeans.inertia_ / n_clusters)
inertias = pd.DataFrame({'n_clusters': range(1, 6), 'inertia': inertia})
ax = inertias.plot(x='n_clusters', y='inertia')
plt.xlabel('Number of clusters(k)')
plt.ylabel('Average Within-Cluster Squared Distances')
plt.ylim((0, 1.1 * inertias.inertia.max()))
ax.legend().set_visible(False)
plt.show()
```

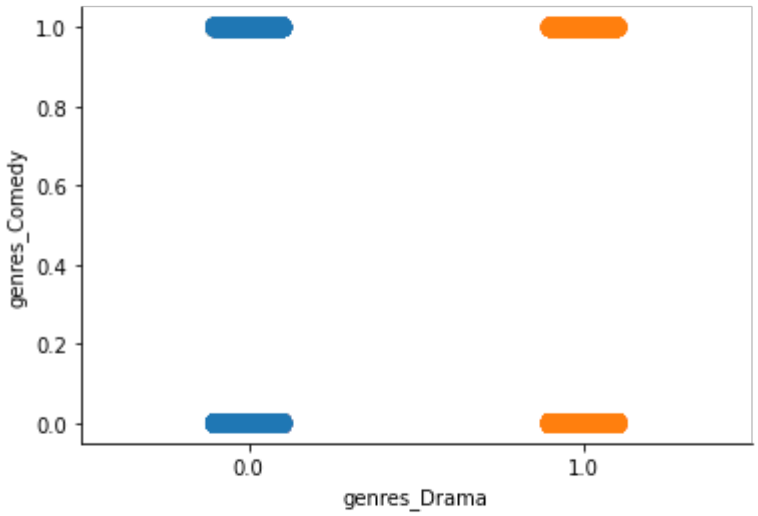


In [116…

```
# k means
kmeans_movies = KMeans(n_clusters=4, random_state=0)
movie_genre_clusters_df_norm['cluster'] = kmeans_movies.fit_predict(movie_genre_clust
# get centroids
centroids = kmeans_movies.cluster_centers_
cen_x = [i[0] for i in centroids]
cen_y = [i[1] for i in centroids]
## add to df
movie_genre_clusters_df_norm['cen_x'] = movie_genre_clusters_df_norm.cluster.map({0:c
                                                                                  1:c
                                                                                  2:c

movie_genre_clusters_df_norm['cen_y'] = movie_genre_clusters_df_norm.cluster.map({0:c
                                                                                  1:c
                                                                                  2:c

# define and map colors
colors = ['#DF2020', '#81DF20', '#2095DF']
movie_genre_clusters_df_norm['c'] = movie_genre_clusters_df_norm.cluster.map({0:colo
                                                                              1:colo
                                                                              2:colo
```

In [116…

```
sns.stripplot(x='genres_Drama',y='genres_Comedy',data=movie_genre_clusters_df,
            c=movie_genre_clusters_df_norm.c, alpha = 0.1, s=10, jitter=True)
sns.despine()
```



In [71]:

```
movie_genre_clusters_df=X[filter_col]
movie_genre_clusters_df['avg_rating']=y[['avg_rating']]
movie_genre_clusters_df.dropna(inplace=True)
```

In [56]:

```
movie_genre_clusters_df.head()
```

Out[56]:

	genres_Action	genres_Adventure	genres_Animation	genres_Comedy	genres_Crime	genres_Docum
0	0	0	1	1	0	
1	0	1	0	0	0	
2	0	0	0	1	0	
3	0	0	0	1	0	
4	0	0	0	1	0	

5 rows × 21 columns

In [57]:

```
movie_genre_clusters_df = movie_genre_clusters_df.apply(lambda x: x.astype('float64')

# Normalized distance
movie_genre_clusters_df_norm = movie_genre_clusters_df.apply(preprocessing.scale, ax
```

In [58]:

```
kmeans_movies2 = KMeans(n_clusters=4, random_state=0).fit(movie_genre_clusters_df_nor

# calculate the distances of each data point to the cluster centers
distances_movies = kmeans_movies2.transform(movie_genre_clusters_df_norm)

# reduce to the minimum squared distance of each data
# point to the cluster centers
minSquaredDistances_movies = distances_movies.min(axis=1) ** 2

# combine with cluster labels into a data frame
df_movies_cluster_centroids = pd.DataFrame({'squaredDistance': minSquaredDistances_mo
                                            'cluster': kmeans_movies2.labels_},
                                           index=movie_genre_clusters_df_norm.index)

# Group by cluster and print information
for cluster, data in df_movies_cluster_centroids.groupby('cluster'):
    count = len(data)
    withinClustSS_movies = data.squaredDistance.sum()
    print(f'Cluster {cluster} ({count} members): {withinClustSS_movies:.2f} within cl
```

```
Cluster 0 (4679 members): 53066.77 within cluster
Cluster 1 (7357 members): 160360.08 within cluster
Cluster 2 (2611 members): 43300.57 within cluster
Cluster 3 (714 members): 9706.69 within cluster
```

In [59]:

```
centroids_movies = pd.DataFrame(kmeans_movies2.cluster_centers_,
                                columns=movie_genre_clusters_df.columns)
print(centroids_movies)
```

```
   genres_Action  genres_Adventure  genres_Animation  genres_Comedy  \
0      -0.187380         -0.135687         -0.220788       1.368907
1       0.118170          0.063744         -0.220788      -0.713518
2       0.034934         -0.058410         -0.220788      -0.435346
3      -0.117422          0.445972          4.529239      -0.026713

   genres_Crime  genres_Documentary  genres_Drama  genres_Family  \
0     -0.134241           -0.189973     -0.262371       0.078787
1      0.206487            0.211350      0.455051      -0.123598
2     -0.249160           -0.207378     -0.604812      -0.237719
3     -0.336771           -0.174446     -0.757718       1.626537

   genres_Fantasy  genres_Foreign  ...  genres_Horror  genres_Music  \
0       -0.017439       -0.023121  ...      -0.372061      0.115931
1       -0.063011        0.023850  ...      -0.376331      0.004901
2        0.147466       -0.017511  ...       1.816178     -0.201375
3        0.224273       -0.030203  ...      -0.325634     -0.073815

   genres_Mystery  genres_Romance  genres_Science Fiction  genres_TV Movie  \
0       -0.153180        0.341184               -0.238760        -0.063625
1        0.056046       -0.036010               -0.265223         0.044283
2        0.179351       -0.403244                1.197782        -0.003189
3       -0.229540       -0.390208               -0.082638        -0.027676

   genres_Thriller  genres_War  genres_Western  avg_rating
0        -0.374030   -0.107167       -0.114049    0.020331
1         0.100397    0.131990        0.151196    0.211731
2         0.505771   -0.139965       -0.174473   -0.677293
```

```
3        -0.432913   -0.145889      -0.172493    0.161871

[4 rows x 21 columns]
```

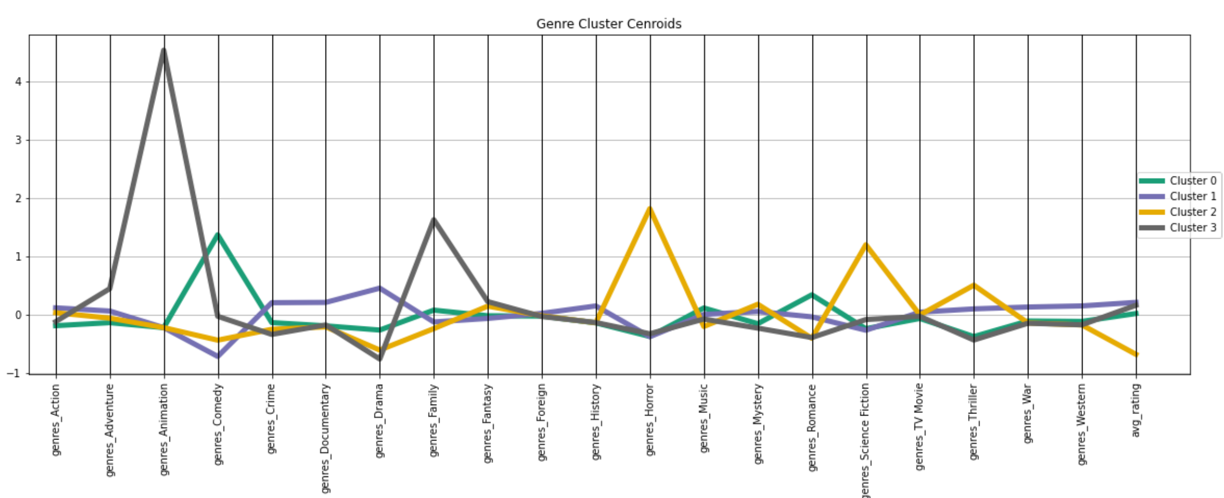
In [60]:

```python
centroids_movies['cluster'] = ['Cluster {}'.format(i) for i in centroids_movies.inde

fig, ax = plt.subplots(figsize=(20,6))
#plt.figure(figsize=(10,6))
#fig.subplots_adjust(right=3)
ax = parallel_coordinates(centroids_movies, class_column='cluster', colormap='Dark2',
                          linewidth=5)
plt.title('Genre Cluster Cenroids')
plt.legend(loc='center left', bbox_to_anchor=(0.95, 0.5))
plt.xlim(-0.5,21)
plt.xticks(rotation=90)
centroids_movies
```

Out[60]:

	genres_Action	genres_Adventure	genres_Animation	genres_Comedy	genres_Crime	genres_Docum
0	-0.187380	-0.135687	-0.220788	1.368907	-0.134241	-0.
1	0.118170	0.063744	-0.220788	-0.713518	0.206487	0.
2	0.034934	-0.058410	-0.220788	-0.435346	-0.249160	-0.
3	-0.117422	0.445972	4.529239	-0.026713	-0.336771	-0.

4 rows × 22 columns



Results:

- Cluster 0 is characterized by a peak in Comedy, and smaller peaks in Family and Romance, with small spacing, but spacing in the average rating
- Cluster 1 is characterized by small peaks in Crime, Documentary, Drama, small peak in History, and mid level in Thriller, War, Western and has similar average rating to Cluster 3.
- Cluster 2 is characterized by noticeable peaks in Horror, Science Fiction and Thriller, with a noticeable separation from the other clusters when it comes to the avg rating.

- Cluster 3 is characterized by a large peak in Animation and Family with similar avg rating as cluster 1

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from ast import literal_eval
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import recall_score, precision_score, roc_auc_score
from dmba import classificationSummary, liftChart, gainsChart

import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [3]:

```
movies = pd.read_csv('../data/iac_dataset/modeling_data.csv')

features = ['keywords', 'cast', 'genres']

for feature in features:
    movies[feature] = movies[feature].apply(literal_eval)
```

Data Preparation for Modeling

In [4]:

```
movies['director'] = movies['director'].astype(str).str.replace('.', '')
movies['director'] = movies['director'].astype(str).str.replace(' ', '_')

movies['prod_company'] = movies['prod_company'].astype(str).str.replace('.', '')
movies['prod_company'] = movies['prod_company'].astype(str).str.replace(' ', '_')
```

In [14]:

```
movies['label'] = pd.cut(movies.avg_rating, bins=[0,3.4,5],labels=[0,1])
```

In [15]:

```
X = movies[['genres','cast','director','prod_company','popularity',
            'revenue_millions']]
y = movies[['avg_rating','label','title']]
```

Generate dummy variables:

In [16]:

```
# creating dummies
genres_cat = X.genres.str.join('|').str.get_dummies().add_prefix('genres_')
X = pd.concat([X, genres_cat], axis=1)
X = X.drop(columns='genres')
```

In [17]:

```
# creating dummies
cast_cat = X.cast.str.join('|').str.get_dummies().add_prefix('cast_')
X = pd.concat([X, cast_cat], axis=1)
X = X.drop(columns='cast')
```

In [18]:

```
keyword_cat = X.director.str.get_dummies().add_prefix('director_')
X = pd.concat([X, keyword_cat], axis=1)
X = X.drop(columns='director')
```

In [19]:

```
keyword_cat = X.prod_company.str.get_dummies().add_prefix('prod_company_')
X = pd.concat([X, keyword_cat], axis=1)
X = X.drop(columns='prod_company')
```

Split data:

In [20]:

```
X_train, X_val, y_train, y_val = train_test_split(X, y,test_size=0.20,
                                                  random_state = 2020)
```

Modeling:

K-Nearest Nighbors:

Example of looping for parameter tuning done during model development:

In [5]:

```
# determining optimal number of k neighbors
# commenting out section due to long execution time
#for r in range (1, 30):
    #knn = KNeighborsClassifier(n_neighbors=r)
    #knn.fit(X_train, y_train)

    #y_pred = knn.predict(X_val)

    #print(f'neighbors: {r}')
    #print(f'accuracy: {accuracy_score(y_val, y_pred)}')
    #print(f'precision: {precision_score(y_val, y_pred, zero_division=0)}')
    #print(f'recall: {recall_score(y_val, y_pred, zero_division=1)}')
    #print('\n')
```

In [21]:

```
movie_knn = KNeighborsClassifier(n_neighbors=24, metric='cosine')
movie_knn.fit(X_train, y_train['label'])

y_pred = movie_knn.predict(X_val)

# Comparing Results
classificationSummary(y_val.label, y_pred)
print(f'precision: {precision_score(y_val.label, y_pred, zero_division=0)}')
print(f'recall: {recall_score(y_val.label, y_pred, zero_division=1)}')
```

```
Confusion Matrix (Accuracy 0.6967)

       Prediction
Actual    0    1
     0 1855  367
     1  565  286
precision: 0.43797856049004597
recall: 0.33607520564042304
```

Logistic Regression:

In [22]:

```
# Training Logistic Model
movie_log = LogisticRegression( random_state=2020, max_iter=10000)
movie_log.fit(X_train, y_train['label'])

# Predicting using training set
y_pred = movie_log.predict(X_val)

# Comparing Results
classificationSummary(y_val.label, y_pred)
print(f'precision: {precision_score(y_val.label, y_pred, zero_division=0)}')
print(f'recall: {recall_score(y_val.label, y_pred, zero_division=1)}')
```

```
Confusion Matrix (Accuracy 0.7410)

       Prediction
Actual    0    1
     0 1997  225
     1  571  280
precision: 0.5544554455445545
recall: 0.3290246768507638
```

Decision Tree Classifier:

In [23]:

```
movie_tree = DecisionTreeClassifier(random_state=2020)
movie_tree.fit(X_train, y_train['label'])
y_pred = movie_tree.predict(X_val)

# Comparing Results
classificationSummary(y_val.label, y_pred)
print(f'precision: {precision_score(y_val.label, y_pred, zero_division=0)}')
print(f'recall: {recall_score(y_val.label, y_pred, zero_division=1)}')
```

```
Confusion Matrix (Accuracy 0.7114)

       Prediction
Actual    0    1
     0 1891  331
     1  556  295
precision: 0.4712460063897764
recall: 0.34665099882491185
```

Random Forest Classifier:

In [24]:

```
movie_rf = RandomForestClassifier(random_state=2020)
movie_rf.fit(X_train, y_train['label'])
y_pred = movie_rf.predict(X_val)

# Comparing Results
classificationSummary(y_val.label, y_pred)
print(f'precision: {precision_score(y_val.label, y_pred, zero_division=0)}')
print(f'recall: {recall_score(y_val.label, y_pred, zero_division=1)}')
```

```
Confusion Matrix (Accuracy 0.7491)
```

```
        Prediction
Actual     0    1
     0  2140   82
     1   689  162
precision: 0.6639344262295082
```

Cummulative Gains Chart

In [57]:

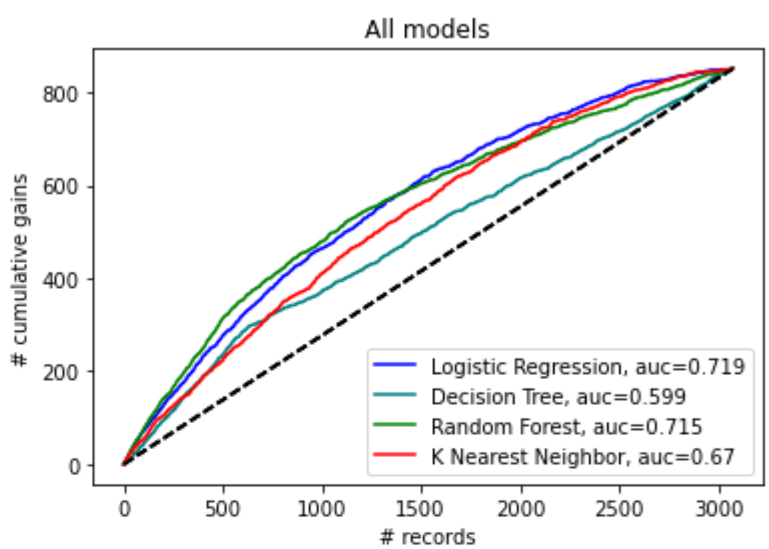
```python
def modelGainsChart(model, title, color, label, ax=None):
    result = pd.DataFrame({
        'actual': np.array(y_val['label']),
        'prob': model.predict_proba(X_val)[:, 1]
    })
    y_prob = result.prob
    result = result.sort_values(by=['prob'],
                                ascending=False).reset_index(drop=True)
    ax = gainsChart(result.actual, ax=ax, color=color, label= f'{label},
                    auc={round(roc_auc_score(y_val.label,y_prob),3)}')
    ax.set_title(title)
    return ax
```

In [58]:

```python
ax = modelGainsChart(movie_log, 'Logistic regression','blue','Logistic Regression')
modelGainsChart(movie_tree, 'Decision tree','teal','Decision Tree', ax)
modelGainsChart(movie_rf, 'Random forest','green','Random Forest', ax)
modelGainsChart(movie_knn, 'K Nearest Neighbor','red','K Nearest Neighbor', ax)
ax.legend()
ax.set_title('All models')
```

Out[58]:

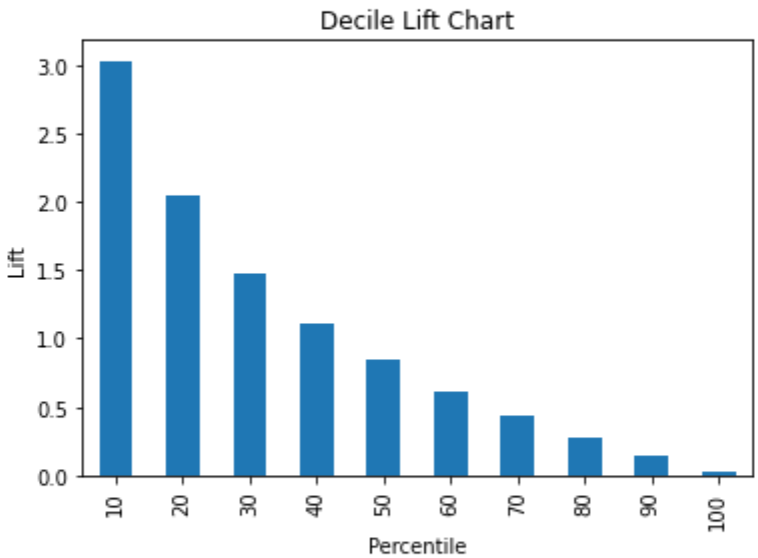
```
Text(0.5, 1.0, 'All models')
```



Lift Chart using best model: Random Forest

In [60]:

```
rf_prob = movie_rf.predict_proba(X_val)[:, 1]
rf_prob = -np.sort(-rf_prob)

ax = liftChart(pd.Series(rf_prob), labelBars=False)
ax.set_ylabel('Lift')
ax.set_title('Decile Lift Chart')
plt.show()
```



In [ ]:

```
print(f'Top 10 percent would yield about {round(len(rf_prob)*.10,)} movies that can b
print(f'Top 20 percent would yield about {round(len(rf_prob)*.20,)} movies that can b
```

Results:

- Top 10 percent would yield about 307 movies that can be added to the collection which would be 3 times as likely to be highly rated
- Top 20 percent would yield about 615 movies that can be added to the collection which would be 2 times as likely to be highly rated