import pandas as pd import numpy as np from ast import literal eval import warnings; warnings.simplefilter('ignore') In [34]: md = pd.read csv("movies metadata.csv") print(md.head()) adult belongs to collection budget O False {'id': 10194, 'name': 'Toy Story Collection', ... 30000000 1 False 2 False {'id': 119050, 'name': 'Grumpy Old Men Collect... 3 False NaN 16000000 4 False {'id': 96871, 'name': 'Father of the Bride Col... genres \ 0 [{'id': 16, 'name': 'Animation'}, {'id': 35, '... 1 [{'id': 12, 'name': 'Adventure'}, {'id': 14, '... 2 [{'id': 10749, 'name': 'Romance'}, {'id': 35, ... 3 [{'id': 35, 'name': 'Comedy'}, {'id': 18, 'nam... [{'id': 35, 'name': 'Comedy'}] homepage id imdb id original language 862 tt0114709 0 http://toystory.disney.com/toy-story NaN 8844 tt0113497 en NaN 15602 tt0113228 3 NaN 31357 tt0114885 4 NaN 11862 tt0113041 en original title \ 0 Toy Story Jumanji 1 2 Grumpier Old Men Waiting to Exhale 4 Father of the Bride Part II overview ... release_date \ 0 Led by Woody, Andy's toys live happily in his 1995-10-30 Led by Woody, Andy's toys live mapping ...

When siblings Judy and Peter discover an encha... 1995-12-15

The ancient fend be... 1995-12-22 2 A family wedding reignites the ancient feud be... 2 A family wedding reignites the ancient feud be... ... 1995-12-22 3 Cheated on, mistreated and stepped on, the wom... ... 1995-12-22 4 Just when George Banks has recovered from his 1995-02-10 revenue runtime spoken languages \ 81.0 [{'iso_639_1': 'en', 'name': 'English'}]
104.0 [{'iso_639_1': 'en', 'name': 'English'}, {'iso...
101.0 [{'iso_639_1': 'en', 'name': 'English'}]
127.0 [{'iso_639_1': 'en', 'name': 'English'}]
106.0 [{'iso_639_1': 'en', 'name': 'English'}] 373554033.0 81.0 0 262797249.0 101.0 2 0.0 127.0 3 81452156.0 76578911.0 106.0 status tagline \ 0 Released Released Roll the dice and unleash the excitement!
Released Still Yelling. Still Fighting. Still Ready for...
Released Friends are the people who let you be yourself... 4 Released Just When His World Is Back To Normal... He's ... title video vote_average vote_count Toy Story False 7.7 5415.0 0 1 Jumanji False 6.9 2413.0 6.5 Grumpier Old Men False Waiting to Exhale False Father of the Bride Part II False 92.0 34.0 2 6.1 173.0 5.7 [5 rows x 24 columns] md.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 45466 entries, 0 to 45465 Data columns (total 24 columns): Non-Null Count Dtype # Column ----___ \cap adult 45466 non-null object belongs to collection 4494 non-null 1 object 45466 non-null object 45466 non-null object 7782 non-null object budget 3 genres 4 homepage 45466 non-null object 5 6 imdb_id 45449 non-null object 7 original_language 45455 non-null object 8 original_title 45466 non-null object 9 overview 44512 non-null object 10 popularity 45461 non-null object 11 poster_path 45080 non-null object 12 production_companies 45463 non-null object 13 production_countries 45463 non-null object 14 release date 45379 non-null object imdb id 45449 non-null object 14 release_date 45379 non-null object 15 revenue 45460 non-null float64 14 release_date
15 revenue 45460 non-null rloator
16 runtime 45203 non-null float64
17 spoken_languages 45460 non-null object
18 status 45379 non-null object
19 tagline 20412 non-null object
20 title 45460 non-null object 45460 non-null object 21 video 21 viues 22 vote_average 45460 non-null float64 23 vote count 45460 non-null float64 dtypes: float64(4), object(20) memory usage: 8.3+ MB md.describe() revenue runtime vote_average vote_count **count** 4.546000e+04 45203.000000 45460.000000 45460.000000 mean 1.120935e+07 94.128199 5.618207 109.897338 **std** 6.433225e+07 38.407810 1.924216 491.310374 **min** 0.000000e+00 0.000000 0.000000 0.000000 **25%** 0.000000e+00 85.000000 5.000000 3.000000 **50%** 0.000000e+00 95.000000 6.000000 10.000000 **75%** 0.000000e+00 107.000000 6.800000 34.000000 **max** 2.787965e+09 1256.000000 10.000000 14075.000000 md.isnull().sum() Out[37]: adult belongs to collection 40972 0 budget 0 genres 37684 homepage id imdb id 17 original language 11 original title overview 954 popularity 5 poster path 386 3 production_companies production countries 3 release date 87 revenue 6 runtime 263 spoken languages 6 87 status 25054 tagline title 6 video 6 vote average 6 6 vote count dtype: int64 mean vote = md['vote average'].mean() print(mean vote) 5.618207215133889 min vote = md['vote_count'].quantile(0.9) print(min vote) 160.0 In [40]: movies = md.copy().loc[md['vote count'] >= min vote] movies.shape (4555, 24)Out[40]: In [41]: columns with missing data = md.columns[md.isnull().any()] for col in columns with missing data: mode value = md[col].mode()[0] md[col].fillna(mode value, inplace = True) import seaborn as sns import matplotlib.pyplot as plt sns.heatmap(md.corr(), annot=True, fmt='.2f') Out[96]: <AxesSubplot:> - 1.0 id - 1.00 -0.07 -0.12 0.04 -0.17-0.06 - 0.8 1.00 0.10 -0.01 -0.070.08 0.81 revenue - 0.6 -0.120.10 1.00 -0.01 0.16 0.11 runtime - 0.4 0.04 1.00 -0.01 -0.01-0.02 -0.01 video - 0.2 -0.17 0.08 0.16 -0.021.00 0.12 vote average 0.0 -0.06 vote_count 0.81 0.11 -0.01 0.12 1.00 P video average revenue vote count sns.scatterplot(x=md['vote_count'], y=md['revenue']) Out[97]: <AxesSubplot:xlabel='vote_count', ylabel='revenue'> 2.5 2.0 revenue 1.5 1.0 0.5 0.0 14000 2000 4000 10000 12000 0 6000 8000 vote_count sns.countplot(y=md['imdb id'], order=md['imdb id'].value counts().index[0:10]) Out[98]: <AxesSubplot:xlabel='count', ylabel='imdb id'> tt1180333 tt0022879 tt1821641 ⊡, tt0022537 tt0062229 tt0499537 tt0100361 tt0067306 tt0082992 10 16 count sns.countplot(y=md['spoken_languages'], order=md['spoken_languages'].value_counts().ir <AxesSubplot:xlabel='count', ylabel='spoken languages'> [{'iso_639_1': 'en', 'name': 'English'}] [{'iso_639_1': 'fr', 'name': 'Français'}] spoken languages [{'iso_639_1': 'it', 'name': 'ltaliano'}] [{'iso_639_1': 'es', 'name': 'Español'}] [{'iso_639_1': 'ru', 'name': 'Русский'}] [{'iso_639_1': 'de', 'name': 'Deutsch'}] $\label{eq:condition} \begin{tabular}{ll} $\{'iso_639_1': 'en', 'name': 'English'\}, $\{'iso_639_1': 'fr', 'name': 'Français'\} \end{tabular}$ [{'iso_639_1': 'en', 'name': 'English'}, {'iso_639_1': 'es', 'name': 'Español'}] 5000 10000 15000 20000 count sns.distplot(x=md['vote_average']) Out[100... <AxesSubplot:ylabel='Density'> 0.5 0.4 0.3 Density 0.2 0.1 0.0 In [42]: md['genres'] = md['genres'].fillna('[]').apply(literal_eval).apply(lambda x: [i['name In [43]: vote_counts = md[md['vote_count'].notnull()]['vote_count'].astype('int') vote_averages = md[md['vote_average'].notnull()]['vote_average'].astype('int') C = vote_averages.mean() 5.24420446047596 Out[43]: In [44]: m Out[44]: 160.0 In [45]: md['year'] = pd.to datetime(md['release date'], errors='coerce').apply(lambda x: str() In [48]: qualified = md[(md['vote_count'] >= m) & (md['vote_count'].notnull()) & (md['vote_average'].notnull())][['title','year', 'vote_count', 'vote_average']. qualified['vote_count'] = qualified['vote_count'].astype('int') qualified['vote average'] = qualified['vote average'].astype('int') qualified.shape (4555, 6)Out[48]: In [49]: def weighted rating(x): voters = x['vote count'] avg vote = x['vote average'] return (voters/(voters + m) * avg_vote) + (m/(m + voters) * C) qualified['wr'] = qualified.apply(weighted rating, axis=1) qualified = qualified.sort values('wr', ascending=False).head(250) qualified.head(10) year vote_count vote_average title popularity genres wr [Comedy, Drama, 8.268054 10309 34.457024 Dilwale Dulhania Le Jayenge 1995 661 Romance] [Action, Thriller, 29.108149 15480 Inception 2010 14075 Science Fiction, 7.969025 Mystery, A... [Drama, Action, The Dark Knight 2008 123.167259 7.964524 12481 12269 Crime, Thriller] [Adventure, Interstellar 2014 Drama, Science 22879 11187 32.213481 7.961142 Fiction] 2843 Fight Club 63.869599 7.955181 1999 9678 [Drama] The Lord of the Rings: The [Adventure, 7.951290 2001 4863 8892 32.070725 Fellowship of the Ring Fantasy, Action] 292 **Pulp Fiction** 140.950236 1994 8670 [Thriller, Crime] 7.950065 The Shawshank Redemption 7.948236 314 1994 8358 51.645403 [Drama, Crime] The Lord of the Rings: The [Adventure, 7000 2003 8226 29.324358 7.947421 Return of the King Fantasy, Action] [Comedy, Drama, 7.946921 Forrest Gump 1994 48.307194 351 8147 Romance] s = md.apply(lambda x: pd.Series(x['genres']),axis=1).stack().reset_index(level=1, droperated) s.name = 'genre' gen_md = md.drop('genres', axis=1).join(s) In [54]: def genre_wise(genre, percentile=0.85): df = gen_md[gen_md['genre'] == genre] vote_counts = df[df['vote_count'].notnull()]['vote_count'].astype('int') vote_averages = df[df['vote_average'].notnull()]['vote_average'].astype('int') C = vote_averages.mean() m = vote_counts.quantile(percentile) qualified = df[(df['vote_count'] >= m) & (df['vote_count'].notnull()) & (df['vote_count']) qualified['vote count'] = qualified['vote_count'].astype('int') qualified['vote_average'] = qualified['vote_average'].astype('int') qualified['wr'] = qualified.apply(lambda x: (x['vote count']/(x['vote count']+m) qualified = qualified.sort values('wr', ascending=False).head(250) return qualified genre_wise('Romance').head(15) title vote_count vote_average year popularity wr 34.457024 8.565285 10309 Dilwale Dulhania Le Jayenge 1995 661 351 Forrest Gump 1994 8147 48.307194 7.971357 876 Vertigo 1958 18.20822 7.811667 1162 8 40251 Your Name. 2016 1030 34.461252 7.789489 11.845107 883 Some Like It Hot 1959 7.745154 835 8 Cinema Paradiso 14.177005 1132 1988 834 7.744878 19901 Paperman 2012 734 8 7.198633 7.713951 37863 Sing Street 2016 10.672862 7.689483 669 882 The Apartment 1960 498 11.994281 7.599317 8 38718 The Handmaiden 2016 16.727405 7.566166 453 3189 City Lights 1931 10.891524 7.558867 444 8 5.711274 7.331363 24886 The Way He Looks 2014 262 8 20.82178 45437 In a Heartbeat 2017 7.003959 146 8 26.88907 6.981546 1639 Titanic 1997 7770 Silver Linings Playbook 2012 19731 4840 14.488111 6.970581 genre_wise('Action').head(10) title year vote_count vote_average popularity wr 15480 Inception 2010 29.108149 7.955084 14075 12481 The Dark Knight 2008 12269 123.167259 7.948593 The Lord of the Rings: The Fellowship of the Ring 2001 8892 32.070725 7.929555 4863 8 7000 The Lord of the Rings: The Return of the King 2003 29.324358 7.924005 8226 8 The Lord of the Rings: The Two Towers 5814 2002 29.423537 7.918355 7641 8 256 Star Wars 1977 42.149697 7.908296 6778 19.470959 7.896805 1154 The Empire Strikes Back 1980 5998 8 4135 11.299673 7.801977 Scarface 1983 3017 8 9430 Oldboy 2003 2000 10.616859 7.711546 8 15.01777 7.425928 1910 1954 892 Seven Samurai links_small = pd.read_csv('links_small.csv') links_small.head() movield imdbld tmdbld 1 114709 862.0 1 2 113497 8844.0 2 3 113228 15602.0 3 4 114885 31357.0 4 5 113041 11862.0 links_small.describe() movield imdbld tmdbld 9125.000000 9.125000e+03 9112.000000 count mean 31123.291836 4.798244e+05 39104.545544 std 40782.633604 7.431774e+05 62814.519801 1.000000 4.170000e+02 2.000000 min 25% 2850.000000 8.884600e+04 9451.750000 **50%** 6290.000000 1.197780e+05 15852.000000 **75**% 56274.000000 4.284410e+05 39160.500000 **max** 164979.000000 5.794766e+06 416437.000000 links_small.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 9125 entries, 0 to 9124 Data columns (total 3 columns): # Column Non-Null Count Dtype movieId 9125 non-null 0 int64 imdbId 9125 non-null int64 2 tmdbId 9112 non-null float64 dtypes: float64(1), int64(2) memory usage: 214.0 KB links_small.isnull().sum() Out[77]: movieId 0 0 imdbId tmdbId 0 dtype: int64 mean_value = links_small['tmdbId'].mean() # Calculate the mean links_small['tmdbId'].fillna(mean_value, inplace=True) links small = links small[links small['tmdbId'].notnull()]['tmdbId'].astype('int') md = md.drop([19730, 29503, 35587])md['id'] = md['id'].astype('int') smd = md[md['id'].isin(links small)] smd.shape Out[79]: (9100, 25) smd['tagline'] = smd['tagline'].fillna('') smd['description'] = smd['overview'] + smd['tagline'] smd['description'] = smd['description'].fillna('') In [81]: from sklearn.feature extraction.text import TfidfVectorizer, CountVectorizer tf = TfidfVectorizer(analyzer='word',ngram_range=(1, 2),min_df=0, stop_words='english tfidf_matrix = tf.fit_transform(smd['description']) In [83]: tfidf_matrix.shape (9100, 269623) In [84]: from sklearn.metrics.pairwise import linear_kernel, cosine_similarity cosine_sim = linear_kernel(tfidf_matrix, tfidf_matrix) cosine_sim[1] Out[85]: array([0.00672473, 1. , 0.01531072, ..., 0.00357074, 0.00759553, 1) smd = smd.reset index() titles = smd['title'] indices = pd.Series(smd.index, index=smd['title']) def get_recommendations(title): idx = indices[title] sim_scores = list(enumerate(cosine_sim[idx])) sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True) sim_scores = sim_scores[1:31] movie indices = [i[0] for i in sim scores] return titles.iloc[movie indices] get recommendations('The Godfather').head(10) Out[88]: 973 The Godfather: Part II 8388 The Family 3509 Made 4196 Johnny Dangerously 29 Shanghai Triad 5667 American Movie 2412 1582 The Godfather: Part III 4221 8 Women 2159 Summer of Sam Name: title, dtype: object get_recommendations('The Dark Knight').head(10) 7931 The Dark Knight Rises Batman Forever 1113 Batman Returns 8228 Batman: The Dark Knight Returns, Part 2 7565 Batman: Under the Red Hood 524 Batman 7901 Batman: Year One 2579 Batman: Mask of the Phantasm 2696 Batman: The Dark Knight Returns, Part 1 Name: title, dtype: object In [94]: get_recommendations('Seven Samurai').head(10) The Magnificent Seven 4016 Shogun Assassin 7162 The Good, The Bad, The Weird Did You Hear About the Morgans? 7391 2371 The Story of Us 5705 Samurai I: Musashi Miyamoto 4619 Destry Rides Again 4136 Mr. Deeds 3605 Erik the Viking 2741 Teenage Mutant Ninja Turtles III Name: title, dtype: object