3]:	SOURCE OF DATA -::learn-co-curriculum github repository Files used: 1.imdb.title.basics csv file 2.imdb.title.ratings csv file 3.bom.movie_gross csv file I chose this dataset to explore the following insights that could be achieved from this data: 1.Runtime Analysis - Explore if there are ideal runtime lengths associated with higher rating Recommend optimal target runtime. 2.Genre selection - Find the most popular genre based on the total frequency/count of that particular genre in terms of production. 3.Production studios - Find the highest grossing production studios and seek to partner with such studios. # Loading of the data df1= pd.read_csv(r'C:\Users\user.DESKTOP-OMQ89VA\OneDrive\Documents\MORINGA PHASE 1 PROJECT\imdb.title.basics.csv\title.basics.csv') df2= pd.read_csv(r'C:\Users\user.DESKTOP-OMQ89VA\OneDrive\Documents\MORINGA PHASE 1 PROJECT\imdb.title.ratings.csv\title.ratings.csv')
:]: [:]: [:]: _	df2= pd.read_csv(r'C:\Users\user.DESKTOP-OMQ89VA\OneDrive\Documents\MORINGA PHASE 1 PROJECT\imdb.title.ratings.csv\title.ratings.csv\) Checking the Data and Datatypes pd.set_option('display.max_rows', None) df2.head(5) tconst averagerating numvotes 0 ttl0356526 8.3 31
5]: 5]:	1 tt10384606 8.9 559 2 tt1042974 6.4 20 3 tt1043726 4.2 50352 4 tt1060240 6.5 21 df1.head(5) tconst primary_title original_title start_year runtime_minutes genres
7]:	0tt0063540SunghurshSunghursh2013175.0Action,Crime,Drama1tt0066787One Day Before the Rainy SeasonAshad Ka Ek Din2019114.0Biography,Drama2tt0069049The Other Side of the WindThe Other Side of the Wind2018122.0Drama3tt0069204Sabse Bada SukhSabse Bada Sukh2018NaNComedy,Drama4tt0100275The Wandering Soap OperaLa Telenovela Errante201780.0Comedy,Drama,Fantasy
]:]:]:]: []:	<pre>df2.duplicated().sum()</pre>
)]:)]: .]:	df1.isnull().sum() tconst 0 primary_title 0 original_title 21 start_year 0 runtime_minutes 31739 genres 5408 dtype: int64 df1.shape
:]: :]: :]:	(146144, 6) df2.shape (73856, 3) df2.isnull().sum() tconst 0 averagerating 0
·]: i]:	numvotes 0 dtype: int64 pd.reset_option('display.max_rows') df1.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 146144 entries, 0 to 146143 Data columns (total 6 columns): # Column Non-Null Count Dtype</class>
5]:	<pre>0 tconst 146144 non-null object 1 primary_title 146144 non-null object 2 original_title 146123 non-null object 3 start_year 146144 non-null int64 4 runtime_minutes 114405 non-null float64 5 genres</pre>
	Data columns (total 3 columns): # Column Non-Null Count Dtype
]: s]: s]:	# Dropped the original_title since it had null values and the primary_title had all the necessary rows df1 = df1.drop('original_title', axis=1) tconst primary_title start_year runtime_minutes genres 0 tt0063540 Sunghursh 2013 175.0 Action,Crime,Drama 1 tt0066787 One Day Before the Rainy Season 2019 114.0 Biography,Drama 2 tt0069049 The Other Side of the Wind 2018 122.0 Drama
	3 tt0069204 Sabse Bada Sukh 2018 NaN Comedy,Drama 4 tt0100275 The Wandering Soap Opera 2017 80.0 Comedy,Drama,Fantasy 146139 tt9916538 Kuambil Lagi Hatiku 2019 123.0 Drama 146140 tt9916622 Rodolpho Teóphilo - O Legado de um Pioneiro 2015 NaN Documentary 146141 tt9916730 Dankyavar Danka 2013 NaN Documentary 146143 tt9916754 Chico Albuquerque - Revelações 2013 NaN Documentary
0]:	# Dropped all the other rows that had null values since I had enough data to work with and it wasnt possible to get a work around for the other df1=df1.dropna() df1.shape (112233, 5)
1 2 2 _.	# Merged the two datasets using column tconst as the primary key and created df3 as the third dataframe that Id work with df3 = df1.merge(df2, on='tconst') tconst
	3 tt0100275 The Wandering Soap Opera 2017 80.0 Comedy,Drama,Fantasy 6.5 119 4 tt0137204 Joe Finds Grace 2017 83.0 Adventure,Animation,Comedy 8.1 263 65715 tt9911774 Padmavyuhathile Abhimanyu 2019 130.0 Drama 8.4 365 65716 tt9913056 Swarm Season 2019 86.0 Documentary 6.2 5 65717 tt9913084 Diabolik sono io 2019 75.0 Documentary 6.2 6 65718 tt9914286 Sokagin Çocuklari 2019 98.0 Drama,Family 8.7 136
3	65719 tt9916160 Drømmeland 2019 72.0 Documentary 6.5 11 65720 rows × 7 columns # Visualize the distribution of movie genres # Split the genres into individual categories genres_split = df3['genres'].str.split(',').explode() genres_split 0 Action
4	O Crime O Drama 1 Biography 1 Drama 65716 Documentary 65717 Documentary 65718 Drama 65718 Family 65719 Documentary Name: genres, Length: 118437, dtype: object
	# Count the frequency of each genre # Get the most popular genre by analyzing the count genre_counts = genres_split.value_counts() genre_counts Drama
	Biography 3693 Adventure 3621 Family 3231 Mystery 2889 History 2704 Sci-Fi 2048 Fantasy 1969 Music 1844 Animation 1615 Sport 1099 War 795 Musical 638 News 575
	<pre>Western</pre>
	plt.ylabel('Count') plt.xticks(rotation=90) plt.show() Genre Distribution
	20000 - 10000 - 5000 -
i	Based on the analysis of the genre data, Drama seems to be the most popular genre being produced. Id recommend to the new Microsoft studios to leverage on this by creating moin this genre to appeal to a wider audience. # Identify which genres have higher average ratings and number of votes
7	# Identify which genres have higher average ratings and number of votes # Group the data by genre and calculate average ratings and total number of votes genre_ratings_votes = df3.groupby('genres').agg({'averagerating': 'mean', 'numvotes': 'sum'}).reset_index() genre_ratings_votes Genres averagerating numvotes
	3 Action,Adventure,Animation 6.548734 3570049 4 Action,Adventure,Biography 7.105556 999592 901 Thriller 5.603727 431778 902 Thriller,War 5.650000 7166 903 Thriller,Western 6.300000 13222 904 War 5.746667 5309 905 Western 4.939063 15391
8	<pre>genre_ratings = df3.groupby('genres')['averagerating'].mean().reset_index() genre_ratings genres averagerating</pre>
	2 Action,Adventure 5.059677 3 Action,Adventure,Animation 6.548734 4 Action,Adventure,Biography 7.105556 901 Thriller, War 5.650000 903 Thriller,Western 6.300000 904 War 5.746667
9	906 rows × 2 columns # grouped the top genres based on the highest averaging rating top_10_genres = genre_ratings.nlargest(10, 'averagerating') top_10_genres genres averagerating
	442 Comedy, Documentary, Fantasy 9.4 622 Documentary, Family, Musical 9.3 824 Game-Show 9.0 668 Documentary, News, Reality-TV 8.8 670 Documentary, News, Sport 8.8 763 Drama, Short 8.8 14 Action, Adventure, Musical 8.7 185 Adventure, Crime 8.5
	Biography, History, Music 8.5 Music, Musical, Romance 8.4 Movies with the genre combination Comedy, Documentary & Fantasy have the highest average rating. Microsoft should consider producing movies in these genres as they tend to resonate with audiences. plt.figure(figsize=(12, 6)) sns.barplot(x='genres', y='averagerating', data=top_10_genres) plt.title('Top 10 Genres by Average Ratings')
	plt.xlabel('Genre') plt.ylabel('Average Ratings') plt.xticks(rotation=90) plt.show() Top 10 Genres by Average Ratings
	Average Ratings 4 - 2 -
	Documentary, Fantisy - Bocumentary, News, Reality-TV - Came-Show - Game-Show - Game-Show - Adventure, Musical - Adventure, Crime - Adventure, Musical - Music, Musical, Romance -
1 1 _.	<pre>genre_numvotes = df3.groupby('genres')['numvotes'].mean().reset_index() genre_numvotes genres</pre>
	3 Action,Adventure,Animation 22595.246835 4 Action,Adventure,Biography 55532.888889 901 Thriller 335.231366 902 Thriller,War 1791.500000 903 Thriller,Western 6611.000000 904 War 176.966667 905 Western 240.484375
2	906 rows × 2 columns #grouped the top genres based on the highest number of votes top_10_numvotes = genre_numvotes.nlargest(10, 'numvotes') top_10_numvotes genres numvotes Action,Fantasy,War 262978.000000
	17 Action,Adventure,Sci-Fi 187179.292683 257 Adventure,Mystery,Sci-Fi 135042.500000 217 Adventure,Drama,Sci-Fi 99316.950000 10 Action,Adventure,Fantasy 96588.050000 401 Biography,Drama,Thriller 88518.904762 19 Action,Adventure,Thriller 81476.152174 15 Action,Adventure,Mystery 80838.111111 69 Action,Crime,Sci-Fi 78214.125000
	Movies with the genre combination Action, Fantasy & War topped the leaderboard in number of votes, this combination is obviously a hit at the box office worldwide, make this the type of movie to produce for success. plt.figure(figsize=(12, 6)) sns.barplot(x='genres', y='numvotes', data=top_10_numvotes) plt.title('Top 10 Genres by Number of Votes') plt.xlabel('Genre') plt.ylabel('Number of Votes')
	plt.xticks(rotation=90) plt.show() Top 10 Genres by Number of Votes 250000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 200000 - 200000 - 20000000 - 2000000 - 200000 - 200000 - 200000 - 200000 - 2000000 - 2000000 - 2000000 - 2000000 - 2000000 - 20000000 - 200000000
	100000 - 500000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 500000 - 500000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50000 - 50
	Visualize with runtime minutes and averaging ratings to get which average runtime minutes have higher ratings I created bins for grouping data based on runtime minutes. These before the program of the
 4 5 	# Create runtime bins bin_edges = [0, 60, 90, 120, 150, float('inf')] bin_labels = ['<60', '60-90', '90-120', '120-150', '150+'] # Bin the data based on runtime df3['runtime_bins'] = pd.cut(df3['runtime_minutes'], bins=bin_edges, labels=bin_labels) df3['runtime_bins'] 0
6	3 60-90 4 60-90 65715 120-150 65716 60-90 65717 60-90 65718 90-120 65719 60-90 Name: runtime_bins, Length: 65720, dtype: category Categories (5, object): ['<60' < '60-90' < '90-120' < '150+'] # Calculated the average ratings for each bin
6	<pre>average_ratings_by_runtime = df3.groupby('runtime_bins')['averagerating'].mean().reset_index() runtime_bins averagerating 0</pre>
7	# Created a bar graph to visualize the average ratings by runtime plt.figure(figsize=(10, 6)) plt.bar(average_ratings_by_runtime['runtime_bins'], average_ratings_by_runtime['averagerating']) plt.xlabel('Runtime Bins') plt.ylabel('Average Ratings') plt.title('Average Ratings by Runtime') plt.show() Average Ratings by Runtime
	7 - 6 - 5 - 5 - 7 - 7 - 7 - 7 - 7 - 7 - 7 - 7
	Based on the runtime analysis, movie that had a runtime of 60 minutes and below had a higher rating. Microsoft new studio would then be adviced to create movies within that time for
1	for optimum concentration from the viewers. Analysing the data using the BOM MOVIE GROSS # Loading of the data df5 = pd.read_csv(r'C:\Users\user.DESKTOP-OMQ89VA\OneDrive\Documents\MORINGA PHASE 1 PROJECT\bom.movie_gross.csv\bom.movie_gross.csv') df5 title studio domestic_gross foreign_gross year 0 Toy Story 3 BV 415000000.0 652000000 2010
	0 Toy Story 3 BV 415000000.0 652000000 2010 1 Alice in Wonderland (2010) BV 334200000.0 691300000 2010 2 Harry Potter and the Deathly Hallows Part 1 WB 296000000.0 664300000 2010 3 Inception WB 292600000.0 535700000 2010 4 Shrek Forever After P/DW 238700000.0 513900000 2010 3382 The Quake Magn. 6200.0 NaN 2018 3383 Edward II (2018 re-release) FM 4800.0 NaN 2018
	3383 Edward II (2018 re-release) FM 4800.0 NaN 2018 3384 El Pacto Sony 2500.0 NaN 2018 3385 The Swan Synergetic 2400.0 NaN 2018 3386 An Actor Prepares Grav. 1700.0 NaN 2018 3387 rows × 5 columns Data Preprocessing df5 . shape
	<pre>(3387, 5) df5.duplicated().sum() 0 df5.info() <class 'pandas.core.frame.dataframe'=""> RangeIndex: 3387 entries, 0 to 3386</class></pre>
2	Data columns (total 5 columns): # Column Non-Null Count Dtype
	<pre>title</pre>
4	1 691300000 2 664300000 3 535700000 4 513900000 3382 NaN 3383 NaN 3384 NaN 3385 NaN 3386 NaN 3386 NaN 4 Changed the data type of the foreign_gross column to float in order to perform calculations on it
5	<pre># Changed the data type of the foreign_gross column to float in order to perform calculations on it df5['foreign_gross'] = df5['foreign_gross'].astype('float64') df5.dtypes title</pre>
6	df5.isnull().sum() title
8	555 Fireflies in the Garden NaN 70600.0 3300000.0 2011 933 Keith Lemon: The Film NaN NaN 4000000.0 2012 1862 Plot for Peace NaN 7100.0 NaN 2014 2825 Secret Superstar NaN NaN 122000000.0 2017
1	df5.shape (2007, 5) Creation of a new total gross column to find the total gross each studio was raking per movie. Eventually calculate the average total gross of each movie studio in order to find the highest grossing movie studios. # Created a new column with the total of the domestic and foreign gross columns Total_gross = df5['domestic_gross'] + df5['foreign_gross'] Total_gross
1	1
5	<pre># Added the total gross column to the Dataframe df5['Total_gross'] = df5['domestic_gross'] + df5['foreign_gross'] <ipython-input-144-eca1617685d2>:1: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy df5['Total_gross'] = df5['domestic_gross'] + df5['foreign_gross']</ipython-input-144-eca1617685d2></pre>
5	title studio domestic_gross foreign_gross year Total_gross 0 Toy Story 3 BV 415000000.0 652000000.0 2010 1.067000e+09 1 Alice in Wonderland (2010) BV 334200000.0 691300000.0 2010 1.025500e+09 2 Harry Potter and the Deathly Hallows Part 1 WB 296000000.0 535700000.0 2010 9.603000e+08 3 Inception WB 292600000.0 535700000.0 2010 8.283000e+08 4 Shrek Forever After P/DW 238700000.0 513900000.0 2010 7.526000e+08 3275 I Still See You LGF 1400.0 1500000.0 2018 1.501400e+06
6	3275 I Still See You LGF 1400.0 1500000.0 2018 1.501400e+06 3286 The Catcher Was a Spy IFC 725000.0 229000.0 2018 9.540000e+05 3309 Time Freak Grindstone 10000.0 256000.0 2018 2.660000e+05 3342 Reign of Judges: Title of Liberty - Concept Short Darin Southa 93200.0 5200.0 2018 9.840000e+04 3353 Antonio Lopez 1970: Sex Fashion & Disco FM 43200.0 30000.0 2018 7.320000e+04 2007 rows × 6 columns # Grouped the data by 'studio' and calculate the average total gross
6	# Grouped the data by 'studio' and calculate the average total gross studio_avg_gross = df5.groupby('studio')['Total_gross'].mean().reset_index() studio_avg_gross studio_Total_gross 0
	4 AR 5.805000e+07 167 WOW 4.940000e+04 168 Wein. 5.936091e+07 169 Yash 4.920575e+07 170 Zee 1.671000e+06 171 Zeit. 4.405840e+06
	# Sort the studios by average total gross in descending order studio_avg_gross_sorted = studio_avg_gross.sort_values(by='Total_gross', ascending=False) studio_avg_gross_sorted studio_Total_gross HC 8.703000e+08
6	 HC 8.703000e+08 P/DW 5.076500e+08 BV 4.249075e+08 GrtIndia 2.542000e+08 WB 2.368577e+08
6 7	 36 Darin Southa 9.840000e+04 70 ICir 7.960000e+04
6	
6	36 Darin Southa 9.840000e+04 70 ICir 7.960000e+04 73 ITL 5.290000e+04 167 WOW 4.940000e+04 33 Crnth 3.830000e+04 172 rows × 2 columns # Selected the top 10 studios based on the total gross top_10_studios = studio_avg_gross_sorted.head(10)
6	36 Darin Southa 9.840000e+04 70
6 7 7 88	