

# final\_project\_submission\_suvinmajithia

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## 0.0.1 Disney Movies: A Data-Driven Exploration of Movie Revenue and Genre Dynamics

### ### Foreword

The objective of this notebook is conducting some data analysis for the Disney dataset located [here](#). Here I am analyzing the Disney dataset to scrutinize the correlation between movie revenues and their genres. Through application of Python scripts, unit tests, and the principles of reproducibility, this report offers an interesting exploration of my findings.

## 0.0.2 Introduction

### 0.0.3 Question(s) of interests

In this analysis, I will be solving a question about which movie genre has generated more gross revenue for Disney. I am also interested in finding out which genre has the most impact associated with it and which genre has more number of movies produced by Disney. This is interesting because the Disney movies are based on various themes. I would expect the 'Comedy' genre to have the most impact overall.

## 0.0.4 Dataset description

The below datasets were taken directly from this website . The Walt Disney Company, commonly known as Disney, is an American multinational mass media and entertainment conglomerate that is headquartered at the Walt Disney Studios complex in Burbank, California. The Disney dataset is composed of 5 tables, disney-characters.csv, disney-director.csv, disney-voice-actors.csv, disney\_revenue\_1991-2016.csv and disney\_movies\_total\_gross.csv that contains information about different Disney characters, Disney movies directors, Disney movie characters voice artists, annual gross revenue of the Disney company and the total gross and inflation adjusted gross revenue generated by different Disney movies. I will be using the disney\_movies\_total\_gross tables as formally described below: disney\_movies\_total\_gross.csv This file contains information on the movie title, release date, MPAA rating, genre, total gross revenue and inflation adjusted gross revenue of the Disney movies.

## 0.0.5 Methods and Results

Since I am only interested in computing the genre and its impact based on revenue and other factors, I will need to use the table that contains information on genre and inflation adjusted gross revenue. This implies that I will need to use the disney\_movies\_total\_gross table.

However, firstly, let us import the tables and do some basic visualizations.

```
[1]: # Lets import all the required libraries needed for this project analysis
import altair as alt
import pandas as pd
import numpy as np

# Import all the required 5 disney tables/files
movie_total_data = pd.read_csv("data/disney_movies_total_gross.csv")
revenue_data = pd.read_csv("data/disney_revenue_1991-2016.csv")
characters_data = pd.read_csv("data/disney-characters.csv")
director_data = pd.read_csv("data/disney-director.csv")
voice_actors_data = pd.read_csv("data/disney-voice-actors.csv")
```

Lets see what all the tables look like.

```
[2]: # Checking the first few rows of all the tables
movie_total_data.head()
```

```
[2]:
```

	movie_title	release_date	genre	MPAA_rating	\
0	Snow White and the Seven Dwarfs	Dec 21, 1937	Musical	G	
1	Pinocchio	Feb 9, 1940	Adventure	G	
2	Fantasia	Nov 13, 1940	Musical	G	
3	Song of the South	Nov 12, 1946	Adventure	G	
4	Cinderella	Feb 15, 1950	Drama	G	

  

	total_gross	inflation_adjusted_gross
0	\$184,925,485	\$5,228,953,251
1	\$84,300,000	\$2,188,229,052
2	\$83,320,000	\$2,187,090,808
3	\$65,000,000	\$1,078,510,579
4	\$85,000,000	\$920,608,730

```
[3]: revenue_data.head()
```

```
[3]:
```

	Year	Studio Entertainment[NI 1]	Disney Consumer Products[NI 2]	\
0	1991	2593.0	724.0	
1	1992	3115.0	1081.0	
2	1993	3673.4	1415.1	
3	1994	4793.0	1798.2	
4	1995	6001.5	2150.0	

  

	Disney Interactive[NI 3][Rev 1]	Walt Disney Parks and Resorts	\
0	NaN	2794.0	
1	NaN	3306.0	
2	NaN	3440.7	
3	NaN	3463.6	
4	NaN	3959.8	

	Disney Media Networks	Total
0	NaN	6111
1	NaN	7502
2	NaN	8529
3	359	10414
4	414	12525

```
[4]: characters_data.head()
```

```
[4]:
```

	movie_title	release_date	hero	villian	song
0	\nSnow White and the Seven Dwarfs	December 21, 1937	Snow White	Evil Queen	Some Day My Prince Will Come
1	\nPinocchio	February 7, 1940	Pinocchio	Stromboli	When You Wish upon a Star
2	\nFantasia	November 13, 1940	NaN	Chernabog	NaN
3	Dumbo	October 23, 1941	Dumbo	Ringmaster	Baby Mine
4	\nBambi	August 13, 1942	Bambi	Hunter	Love Is a Song

```
[5]: director_data.head()
```

```
[5]:
```

	name	director
0	Snow White and the Seven Dwarfs	David Hand
1	Pinocchio	Ben Sharpsteen
2	Fantasia	full credits
3	Dumbo	Ben Sharpsteen
4	Bambi	David Hand

```
[6]: voice_actors_data.head()
```

```
[6]:
```

	character	voice-actor	movie
0	Abby Mallard	Joan Cusack	Chicken Little
1	Abigail Gabble	Monica Evans	The Aristocats
2	Abis Mal	Jason Alexander	The Return of Jafar
3	Abu	Frank Welker	Aladdin
4	Achilles	None	The Hunchback of Notre Dame

Lets get some other information about the disney\_movies\_total\_gross.csv table.

```
[7]: movie_total_data.info()
movie_total_data['inflation_adjusted_gross'] =_
↳movie_total_data['inflation_adjusted_gross'].str.
↳replace(r'\D', '', regex=True).astype(float)
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 579 entries, 0 to 578
Data columns (total 6 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   movie_title                           579 non-null    object
1   release_date                           579 non-null    object
2   genre                                  562 non-null    object
3   MPAA_rating                           523 non-null    object
4   total_gross                           579 non-null    object
5   inflation_adjusted_gross              579 non-null    object
dtypes: object(6)
memory usage: 27.3+ KB

```

Our disney\_movies\_total\_gross has some null values in the genre column so let's explore them in detail.

```

[8]: # Some of the genre data has NA values...we need to deep dive in it
movie_total_data[movie_total_data[['genre']].isna().any(axis=1)]

```

```

[8]:
      movie_title  release_date  genre  MPAA_rating  \
20  The Many Adventures of Winnie the Pooh  Mar 11, 1977  NaN      NaN
22                Herbie Goes to Monte Carlo  Jun 24, 1977  NaN      NaN
23                The Black Hole             Dec 21, 1979  NaN      NaN
24                Midnight Madness           Feb 8, 1980  NaN      NaN
25    The Last Flight of Noah's Ark           Jun 25, 1980  NaN      NaN
26    The Devil and Max Devlin             Jan 1, 1981  NaN      NaN
121                Newsies                 Apr 8, 1992  NaN      PG
122                Passed Away             Apr 24, 1992  NaN    PG-13
128    A Gun in Betty Lou's Handbag           Aug 21, 1992  NaN    PG-13
146                Bound by Honor           Apr 16, 1993  NaN      R
155                My Boyfriend's Back           Aug 6, 1993  NaN    PG-13
156                Father Hood             Aug 27, 1993  NaN    PG-13
168                Red Rock West           Jan 28, 1994  NaN      R
251                The War at Home           Nov 20, 1996  NaN      R
304                Endurance               May 14, 1999  NaN      PG
350                High Heels and Low Lifes  Oct 26, 2001  NaN      R
355                Frank McKlusky C.I.       Jan 1, 2002  NaN     NaN

      total_gross  inflation_adjusted_gross
20              $0                  0.0
22    $28,000,000          105847527.0
23    $35,841,901          120377374.0
24    $2,900,000           9088096.0
25    $11,000,000          34472116.0
26    $16,000,000          48517980.0
121    $2,706,352           5497481.0
122    $4,030,793           8187848.0

```

128	\$3,591,460	7295423.0
146	\$4,496,583	9156084.0
155	\$3,218,882	6554384.0
156	\$3,268,203	6654819.0
168	\$2,502,551	5170709.0
251	\$34,368	65543.0
304	\$229,128	380218.0
350	\$226,792	337782.0
355	\$0	0.0

Now replacing the null values with the actual 'genre' of the movies, we can ignore the movies which have less than 10 million+ in revenue for our analysis, we will replace the null values with specified genre.

```
[9]: # Herbie Goes to Monte Carlo - Action genre
movie_total_data.loc[movie_total_data['movie_title']=='Herbie Goes to Monte_
↳ Carlo', 'genre'] = 'Action'
# The Black Hole - Action genre
movie_total_data.loc[movie_total_data['movie_title']=='The Black Hole', 'genre']_
↳ = 'Action'
# The Last Flight of Noah's Ark - Adventure genre
movie_total_data.loc[movie_total_data['movie_title']=='The Last Flight of_
↳ Noah's Ark', 'genre'] = 'Adventure'
# The Devil and Max Devlin - Comedy genre
movie_total_data.loc[movie_total_data['movie_title']=='The Devil and Max_
↳ Devlin', 'genre'] = 'Comedy'

# dropping NaN genre values from the dataframe
movie_total_data= movie_total_data.dropna(subset=['genre'])
movie_total_data = movie_total_data.reset_index()
```

Checking for more information on the disney\_movies\_total\_gross table after replacing null values with the specified values.

```
[10]: movie_total_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 566 entries, 0 to 565
Data columns (total 7 columns):
#   Column                Non-Null Count  Dtype
---  -
0   index                 566 non-null   int64
1   movie_title           566 non-null   object
2   release_date          566 non-null   object
3   genre                 566 non-null   object
4   MPAA_rating           513 non-null   object
5   total_gross           566 non-null   object
```

```

6    inflation_adjusted_gross    566 non-null    float64
dtypes: float64(1), int64(1), object(5)
memory usage: 31.1+ KB

```

We will now check which movie genre performed well for Disney movies based on the table used `disney_movies_total_gross`.

```

[11]: # Checking out which movie genre performed well for Disney
movie_total_data['inflation_adjusted_gross'] =_
    ↳movie_total_data['inflation_adjusted_gross'].astype(float)
movie_total_data['genre'] = movie_total_data['genre'].astype(str)

movie_genre_group = pd.DataFrame(movie_total_data.
    ↳groupby('genre')['inflation_adjusted_gross'].sum().
    ↳sort_values(ascending=False))

# Reset the index so we can plot using altair
movie_genre_group = movie_genre_group.reset_index()
movie_genre_group

```

```

[11]:
      genre  inflation_adjusted_gross
0    Adventure      2.459574e+10
1      Comedy      1.545804e+10
2     Musical      9.657566e+09
3       Drama      8.195804e+09
4       Action      5.725162e+09
5  Thriller/Suspense      2.151691e+09
6  Romantic Comedy      1.788873e+09
7        Western      5.167099e+08
8    Documentary      2.034884e+08
9   Black Comedy      1.567305e+08
10        Horror      1.404831e+08
11 Concert/Performance      1.148217e+08

```

Plotting the bar graph using Altair to check which genre has generated most inflation adjusted revenue.

```

[12]: # Use altair to generate a bar plot
num_parts_plot = (
    alt.Chart(movie_genre_group, width=500, height=500)
    .mark_bar()
    .encode(
        x=alt.X("genre", title="Genre"),
        y=alt.Y("inflation_adjusted_gross", title="Gross revenue in $"),
    )
    .properties(title="Genre and their revenue")
)

```

```
num_parts_plot
```

```
[12]: alt.Chart(...)
```

From the above visualization, it is shown that the 'Adventure' genre has generated the most revenue. But the picture is not over yet, let's explore further...

```
[13]: movie_genre_group.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12 entries, 0 to 11
Data columns (total 2 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   genre                                12 non-null     object
1   inflation_adjusted_gross             12 non-null     float64
dtypes: float64(1), object(1)
memory usage: 320.0+ bytes
```

Now we will plot another graph to visualize which genre has the most number of movies produced by Disney. Therefore, let us count the occurrences of different genre and creating another bar graph to represent that.

```
[14]: # Checking the count of genres in the dataset
movie_genre_count = movie_total_data.groupby('genre').count()
movie_genre_count

# Reset the index so we can plot using altair
movie_genre_count = movie_genre_count.reset_index()
movie_genre_count
```

```
[14]:
```

	genre	index	movie_title	release_date	MPAA_rating	\
0	Action	42	42	42	36	
1	Adventure	130	130	130	119	
2	Black Comedy	3	3	3	3	
3	Comedy	183	183	183	162	
4	Concert/Performance	2	2	2	2	
5	Documentary	16	16	16	16	
6	Drama	114	114	114	103	
7	Horror	6	6	6	5	
8	Musical	16	16	16	15	
9	Romantic Comedy	23	23	23	22	
10	Thriller/Suspense	24	24	24	23	
11	Western	7	7	7	7	

  

	total_gross	inflation_adjusted_gross
0	42	42

1	130	130
2	3	3
3	183	183
4	2	2
5	16	16
6	114	114
7	6	6
8	16	16
9	23	23
10	24	24
11	7	7

Plotting subsequent bar graph based on the above analysis

```
[15]: # Use Altair to generate a bar plot
genre_parts_plot = (
    alt.Chart(movie_genre_count, width=500, height=500)
    .mark_bar()
    .encode(
        x=alt.X("genre", title="Genre"),
        y=alt.Y("index", title="Count of genre"),
    )
    .properties(title="Genre and their count")
)
genre_parts_plot
```

```
[15]: alt.Chart(...)
```

The graph here shows that the 'Comedy' genre has the most movies made by Disney, with the second being 'Adventure'.

```
[16]: #Importing the custom function
import project_function as pf

final_data = pf.avg_frame(movie_genre_group, movie_genre_count)

# resetting the index
final_data = final_data.reset_index()
final_data
```

```
[16]:
```

	genre	inflation_adjusted_gross	index	avg_count
0	Adventure	2.459574e+10	130	1.891980e+08
1	Comedy	1.545804e+10	183	8.447019e+07
2	Musical	9.657566e+09	16	6.035979e+08
3	Drama	8.195804e+09	114	7.189302e+07
4	Action	5.725162e+09	42	1.363134e+08
5	Thriller/Suspense	2.151691e+09	24	8.965379e+07
6	Romantic Comedy	1.788873e+09	23	7.777708e+07



7	Western	5.167099e+08	7	7.381571e+07
8	Documentary	2.034884e+08	16	1.271803e+07
9	Black Comedy	1.567305e+08	3	5.224349e+07
10	Horror	1.404831e+08	6	2.341385e+07
11	Concert/Performance	1.148217e+08	2	5.741084e+07

The revenue numbers and the count calculated in the previous line of code have very differentiating values, therefore, getting the average of gross\_total vs count and plotting another graph to gain better insights.

```
[17]: # Use altair to generate a bar plot
avg_parts_plot = (
    alt.Chart(final_data, width=500, height=500)
    .mark_bar()
    .encode(
        x=alt.X("genre", title="Genre"),
        y=alt.Y("avg_count", title="Avg $ amount of genre"),
    )
    .properties(title="Genre and their Average $ gross revenue")
)
avg_parts_plot
```

```
[17]: alt.Chart(...)
```

Based on the graph, I encountered a rather astonishing result, that shows that the 'Musical' genre has produced the most revenue effect.

```
[18]: # Checking out the test cases

import test_function as ttf
ttf.test_custom_agg()
```

### 0.0.6 Discussions

In this work, I analyzed the Disney dataset and tried to compute which genre has the most impact in terms of revenue. I did some exploratory data analysis to find that the genre of the Disney movies that is most produced is 'Comedy', most popular amongst fans and impactful is 'Musical', and the one that has brought in the most revenue for Disney movies is 'Adventure'.

It is quite unexpected to find that the 'Musical' genre is the most popular amongst fans and has generated the highest revenue effect, as discussed earlier I had expected 'Comedy' to be the most popular genre.

Impact of such findings would be recommending Disney to make more 'Musical' genre based movies. I would like to have the data to see the original budget of the movie, to get more better insights and findings.

### **0.0.7 References**

### **0.0.8 Resources used**

#### **Data Source**

1. This Disney database used in this work was borrowed from the following website:  
<https://data.world/kgarrett/disney-character-success-00-16/workspace/data-dictionary>
2. The dataset description part involves introduction of Disney movie production borrowed from Wikipedia.