

## Lab cycle-5

This data set contains some important statistics from a large sample of movies. The data includes the movie budget and revenue from different sources as well as ratings from Rotten Tomatoes and IMDB.

```
import pandas as pd
import datetime as dt
from dateutil.parser import parse
df=pd.read_csv("/content/movies_1_.csv")
```

### preprocessing:

```
k=df[df["Release Date"].str.contains("TBD")==True]
ind=k.index
df=df.drop(ind)
for i in range(len(df)):
    df.iloc[i,5]=parse(df.iloc[i,5])
df['year'] = pd.DatetimeIndex(df['Release Date']).year
df['month'] = pd.DatetimeIndex(df['Release Date']).month
```

1 (i). Find out the no of movies released in every month of the year 1995.

```
k=df[df["year"]==1995]
g=k.groupby(["month"]).count()
g["Title"]
```

### Output:

```
month
1      3
2      2
3      3
4      5
5      6
6      7
7      8
8      7
9      4
10     8
11     7
12    13
Name: Title, dtype: int64
```

1 . ii). Find out the no. of movies released in every year from 1990 to 1998.

```
k=df[(df["year"]>=1990) & (df["year"]<=1998)]
g=k.groupby(["year"]).count()
g["Title"]
```

**Output:**

```
year
1990    28
1991    33
1992    28
1993    39
1994    52
1995    73
1996    99
1997    97
1998   144
Name: Title, dtype: int64
```

2.(i). Find no. of movies released under each genre given in the database.

```
l=df.groupby('Major Genre')['Title'].count()
|
```

**Output:**

```
Major Genre
Action          420
Adventure        274
Black Comedy     36
Comedy           675
Concert/Performance  5
Documentary      43
Drama            789
Horror           219
Musical          53
Romantic Comedy  137
Thriller/Suspense 239
Western          36
Name: Title, dtype: int64
```

2.(ii). Find the movies under each genre with 1MDB rating >7 and rotten tomatoes rating > 60.

```
d=df[(df['IMDB Rating']>7) & (df['Rotten Tomatoes Rating']>60.0)]
l=d.groupby(['Major Genre','Title'])['Title'].count()
|
```

**Output:**

```
Major Genre  Title
Action      A Bridge Too Far
1
           Aliens
1
           Apocalypse Now
1
           Avatar
1
           Batman
1
..
Western     Pale Rider
1
```

```

1           The Assassination of Jesse James by the Coward Robert Ford
1           The Ballad of Cable Hogue
1           The Wild Bunch
1           Tombstone

```

Name: Title, Length: 541, dtype: int64

3.(i). Find the movies released under each fiction with each director in the ascending order of release dates.

```

k=df.sort_values(by="Release Date")
g=k.groupby(["Creative Type","Director","Title"])["Title"].count()
g

```

Output:

Creative Type	Director	Title
Contemporary Fiction	Adam McKay	Talladega Nights: The Ballad of Ricky Bobby
1	Adam Shankman	A Walk to Remember
1		Bringing Down the House
1		Cheaper by the Dozen 2
1		The Pacifier
1		
..		
Super Hero	Tim Burton	Batman Returns
1	Tim Story	Fantastic Four
1		Fantastic Four: Rise of the Silver Surfer
1	Warren Beatty	Dick Tracy
1	Zack Snyder	Watchmen

Name: Title, Length: 1695, dtype: int64

3.(ii). Find movies released under each distributor in the order of genre and director

```

p=df.sort_values(by=['Major Genre','Director'])
q=p.groupby(['Distributor','Title'])['Title'].count()
q

```

Output:

Distributor	Title	
20th Century Fox	12 Rounds	1
	28 Weeks Later	1
	A Good Year	1
	AVP: Alien Vs. Predator	1
	Alexander's Ragtime Band	1
		..
Yash Raj Films	Veer-Zaara	1
Zeitgeist	AimÈe & Jaguar	1

```

Following 1
Nowhere in Africa 1
Travellers and Magicians 1
Name: Title, Length: 2962, dtype: int64

```

4.(i). Find the movies released world-wide and find out the revenue received world-wide other than US with their ratings.

```

df['US Gross'] = pd.to_numeric(df['US Gross'], downcast='integer', errors='coerce')
df['Worldwide Gross'] = pd.to_numeric(df['Worldwide Gross'], downcast='integer', errors='coerce')
df['res']=df['Worldwide Gross']-df['US Gross']
f=df[['Title','res','IMDB Rating']]
f

```

Output:

	Title	res	IMDB Rating
0	The Land Girls	0.0	6.1
1	First Love, Last Rites	0.0	6.9
2	I Married a Strange Person	0.0	6.8
3	Let's Talk About Sex	0.0	NaN
4	Slam	77702.0	3.4
...	...	...	...
3196	Zack and Miri Make a Porno	5398360.0	7.0
3197	Zodiac	50000000.0	NaN
3198	Zoom	516860.0	3.4
3199	The Legend of Zorro	95900000.0	5.7
3200	The Mask of Zorro	139871255.0	6.7

3194 rows × 3 columns

4.(ii). Find the movies with loss & profit released in each year with genre and ratings.

```

df["profit & loss"]=df["Worldwide Gross"]-df["Production Budget"]
k=df.groupby(["year"])
for i,j in k:
    print(i)
    print(j[["Title","Major Genre","IMDB Rating","profit & loss"]])

```

Output:

```

1929
          Title Major Genre  IMDB Rating  profit & loss
114  The Broadway Melody    Musical         6.7    3979000.0
1930
          Title Major Genre  IMDB Rating  profit & loss
404  Hell's Angels        NaN         7.9         NaN
1931
          Title Major Genre  IMDB Rating  profit & loss

```

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572	Mata Hari	NaN	2.2	342000.0
1934				
	Title	Major Genre	IMDB Rating	profit & loss
951	It Happened One Night	Romantic Comedy	8.3	2175000.0
1938				
	Title	Major Genre	IMDB Rating	profit & loss
51	Alexander's Ragtime Band	Drama	NaN	2000000.0
1050	You Can't Take It With You	NaN	8.0	2356000.0
1939				
	Title	Major Genre	IMDB Rating	profit & loss
623	Mr. Smith Goes To Washington	Drama	8.2	7500000.0
1940				
	Title	Major Genre	IMDB Rating	profit & loss
115	Boom Town	NaN	7.1	7172000.0
754	Rebecca	Drama	8.4	4712000.0
1942				
	Title	Major Genre	IMDB Rating	profit & loss
213	Casablanca	Drama	8.8	9512500.0
1944				
	Title	Major Genre	IMDB Rating	profit & loss
141	Bathing Beauty	Musical	6.2	1139000.0
1945				
	Title	Major Genre	IMDB Rating	profit & loss
548	The Lost Weekend	NaN	8.2	9750000.0
884	Spellbound	NaN	7.7	5500000.0
1004	The Valley of Decision	NaN	7.3	6972000.0
1946				
	Title	Major Genre	IMDB Rating	profit & loss
453	It's a Wonderful Life	NaN	8.7	3420000.0
661	Notorious	NaN	6.3	22464742.0
1947				
	Title	Major Genre	IMDB Rating	profit & loss
383	Gentleman's Agreement	NaN	7.4	5800000.0
1948				
	Title	Major Genre	IMDB Rating	profit & loss
710	The Pirate	NaN	7.1	-744000.0
768	Red River	NaN	7.8	6012000.0
1949				
	Title	Major Genre	IMDB Rating	profit & loss
920	Sands of Iwo Jima	NaN	7.1	6800000.0
926	She Wore a Yellow Ribbon	NaN	7.3	3800000.0
1952				
	Title	Major Genre	IMDB Rating	profit & loss
413	High Noon	NaN	8.3	7270000.0
1954				
	Title	Major Genre	IMDB Rating	profit & loss
285	The Egyptian	NaN	6.2	10000000.0
1956				
	Title	Major Genre	IMDB Rating	profit & loss
541	Love Me Tender	NaN	5.9	8000000.0
582	Moby Dick	Adventure	7.4	5900000.0
977	Trapeze	NaN	6.7	10400000.0
1034	War and Peace	NaN	6.8	6500000.0
2072				
	Title	Major Genre	IMDB Rating	\
21	1776	Drama	7.0	
244	Deep Throat	NaN	5.2	
295	Everything You Always Wanted to Know	Comedy	NaN	
352	Frenzy	NaN	7.5	
369	The Godfather	NaN	9.2	

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433	High Plains Drifter	Western	7.6
523	The Last House on the Left	NaN	6.7

	profit & loss
21	-4000000.0
244	44975000.0
295	16016290.0
352	9100000.0
369	261500000.0
433	0.0
523	3013000.0