

## **TASK**

# Exploratory Data Analysis on the Automobile Data Set

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# INTRODUCTION

The dataset named 'movies.csv' includes a total of 20 columns, which are 'budget', 'genres', 'homepage', 'id', 'keywords', 'original\_language', 'original\_title', 'overview', 'popularity', 'production\_companies', 'production\_countries', 'release\_date', 'revenue', 'runtime', 'spoken\_languages', 'status', 'tagline', 'title', 'vote\_average', and 'vote\_count'. There are 4803 entries with a mixed datatype including int64, object, and float64.

Activities carried out in the exploratory project includes:

- Load the dataframe in
- Clean the data
- Remove duplicate rows
- Discard entries with a zero movie budget
- Manipulate certain columns to the correct data type
- Answer the questions about the data

# DATA PREPARATION

## **DATA CLEANING**

#### The following steps were carried out for 'data cleaning':

- 1. Identify columns that are redundant or unnecessary

  Based on the data set, it seems the following columns are not needed for the analysis
  and are removed from the data set: ['keywords', 'homepage', 'status', 'tagline',
  'original language', 'overview', 'production companies', 'original title'].
- Remove duplicate rows
   Duplicate rows were removed using .drop\_duplicates(), if any.

#### MISSING DATA

Some movies in the database have zero budget or zero revenue which implies that their values have not been recorded or some information is missing. Such entries from the dataframe were discarded, including:

For column ['budget', 'revenue'], relevant lines/records with a null value were dropped.

#### DATA TYPE AND FORMAT

In order to manipulate columns easily, it is important to make use of the python objects and make sure they are in a usable format. The following steps were carried out:

- 1. Through data set overview, it was noted that the 'release data' column is not in Date format. pd.to\_datetime() method was applied to convert the column into correct date format. A new column named 'release\_year' was also being extracted from 'release\_date' and being added in the data set.
- 2. In addition to this, columns ['budget', 'revenue'] were also converted into integer 'int64' for easier visualisation in the next steps.
- 3. Columns '['genres', 'spoken\_languages', 'production\_countries'] were in the JSON format. These have been flattened for easier interpretation in next steps for data analysis.

After the data preparation procedures, the final prepared data set include a total of 13 columns, detailed information is presented below:

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3229 entries, 0 to 4798
Data columns (total 13 columns):
# Column
                             Non-Null Count Dtype
                             3229 non-null int64
0 budget
1 genres 3229 non-null object
2 id 3229 non-null int64
3 popularity 3229 non-null float64
4 production_countries 3229 non-null object
 5 release_date 3229 non-null datetime64[ns]
    revenue 3229 non-null float64

runtime 3229 non-null float64

spoken_languages 3229 non-null object

title 3229 non-null object

mull float64
 7 runtime
9 title
10 vote_average 3229 non-null float64
                          3229 non-null int64
3229 non-null object
 11 vote count
 12 release_year
dtypes: datetime64[ns](1), float64(3), int64(4), object(5)
```

## DATA STORIES AND VISUALISATIONS

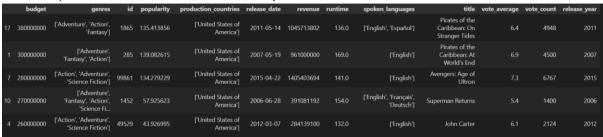
Data visualisation and story-telling were carried out by identify of relationships between variables/features.

1. Which are the 5 most expensive movies? How do the most expensive and cheapest movies compare? Exploring the most expensive movies help you

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explore if some movies are worth the money spent on them based on their performance and revenue generated.

1) Information of the 5 most expensive movies:



2) Information of the 5 cheapest movies:



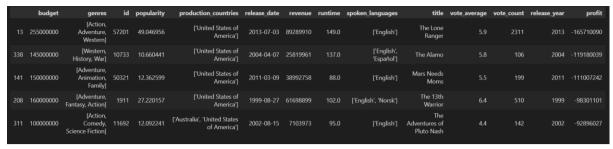
#### 3) Comparison

From above information, it seems that the most expensive movies do not always mean that they will have a vote\_average and guaranteed good return. For the top 5 most expensive movies, though they all have some profit, the overall profitability((revenue-budget)/budget) is not as good as some of the cheaper movies. Movies with lower investment could also result in a good return in profit.

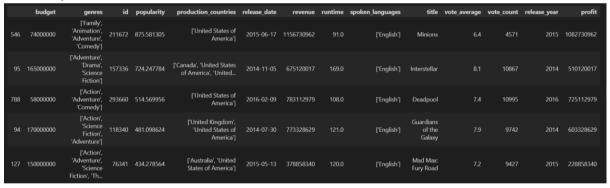
- 2. What are the top 5 most profitable movies? Compare the min and max profits. The comparison helps us identify the different approaches which failed and succeeded. Subtracting the budget from the revenue generated, will return the profit earned.
  - In order to study how profitable a movie is, a new column named ['profit']
    was generated and added into the data set.
  - 2) The top 5 most profitable movies:



3) The bottom least profitable movies:



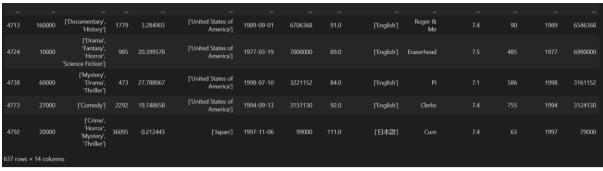
- 4) From above data, it seems that the most profitable movie(max) have very similar investment with the least profitable movie(min), which are 237,000,000 and 255,000,000. However, one has a profit of 2,550,965,087 and the other is -165,710,090. Both movies are under similar 'genres' type and very close runtime and are both available in English. It could also be told from the tables that their main differences are with columns 'popularity', 'vote\_average', and 'vote\_count'. The most profitable movie(max) has much higher values of these features compared with the least profitable movie(min).
- 3. Find the most talked about movies.
  - This is defined based on the value of 'popularity' column, using .sort\_values()
    method.
  - 2) The most talked about movies:



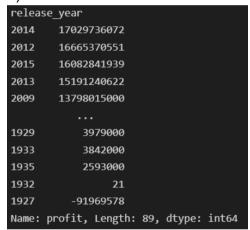
- 3) It can be seen from above table that the most talked about movie does not necessarily have the highest 'vote\_average' and 'vote\_count'. But their 'vote average' value is generally high and have positive profit.
- 4. Find movies which are rated above 7.
  - 1) Use conditional method to select movies with rating higher than 7
  - 2) Details shown below:

| <br>        | /   |       |            |  |              |            |         |                           |                             |              |            |              |            |
|-------------|---|-------|------------|--|--------------|------------|---------|---------------------------|-----------------------------|--------------|------------|--------------|------------|
| budget      | genres  | id    | popularity | production_countries                                 | release_date | revenue    | runtime | spoken_languages          | title                       | vote_average | vote_count | release_year | profit     |
| 0 237000000 | ['Action',<br>'Adventure',<br>'Fantasy',<br>'Science Fi | 19995 | 150.437577 | ['United States of<br>America', 'United<br>Kingdom'] | 2009-12-10   | 2787965087 | 162.0   | ['English',<br>'Español'] | Avatar                      | 7.2          | 11800      | 2009         | 2550965087 |
| 3 250000000 | ['Action', 'Crime',<br>'Drama',<br>'Thriller']          | 49026 | 112.312950 | ['United States of<br>America']                      | 2012-07-16   | 1084939099 | 165.0   | ['English']               | The Dark<br>Knight<br>Rises |              | 9106       | 2012         | 834939099  |
| 5 260000000 | ['Animation',<br>'Family']                              | 38757 | 48.681969  | ['United States of<br>America']                      | 2010-11-24   | 591794936  | 100.0   | ['English']               | Tangled                     | 7.4          | 3330       | 2010         | 331794936  |

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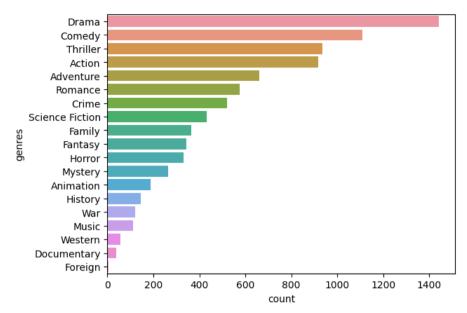


- 3) From results above, there are a total number of 637 movies with rating higher than 7 in the dataset.
- 5. Which year did we have the most profitable movies?
  - 1) Use .groupby(['release\_year']) method to sort ['profile'] columns in decreasing order.
  - 2) Results obtained is illustrated below:

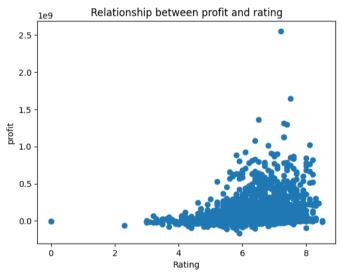


- 3) From results above, it can be told that the most successful release year is in 2014, and the year 1927 was the least successful. There are probably more insights to draw from these data if knowing what has happened in the world and what movies are released in these years and try to correlate them. However, this will not be covered in this exploratory study.
- 6. What are the most successful genres?
  - There could be multi-ways to interpret this. In this exploratory, this was explored by counting how many movies were released in total per genre type.
  - 2) A bar plot was then created:

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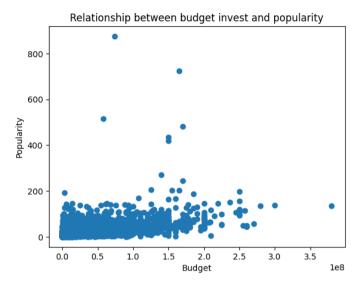


- 3) From above data, it can be found that the top 3 most successful genres are 'Drama', 'Comedy', 'Thriller' respectively.
- 7. Three more interesting visualisations.
  - 1) If the movie has high rating, is it always profitable?



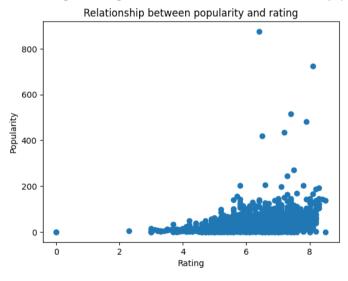
From the result, high rating may not always make the movie profitable. However, there is a trend that the higher rating the movie has, the more likely that it will be profitable. It can also be noticed from the graph that when rating is less than 4, the movie is generally not very much profitable.

2) If invest more money in a movie, will this make it to be more popular?



From the result, movie budget does not seem to have any significant influence on its popularity. Therefore, investing more money in a movie, does not mean that it will be successful.

### 3) If a movie has high rating, does this mean that it is very popular?



From the result, it seems that in general when a movie has higher rating, it is more likely to be popular. This might not be indefinite for high rating movies, but it can be noticed from the graph that movies with rating lower than 4 have very low popularity.

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