Real-world Data Wrangling

In this project, you will apply the skills you acquired in the course to gather and wrangle real-world data with two datasets of your choice.

You will retrieve and extract the data, assess the data programmatically and visually, accross elements of data quality and structure, and implement a cleaning strategy for the data. You will then store the updated data into your selected database/data store, combine the data, and answer a research question with the datasets.

Throughout the process, you are expected to:

1. Explain your decisions towards methods used for gathering, assessing, cleaning, storing, and answering the research question
2. Write code comments so your code is more readable

1. Gather data

In this section, you will extract data using two different data gathering methods and combine the data. Use at least two different types of data-gathering methods.

1.1. Problem Statement

Questions:

- Among the top 1000 movies, what percenetage of movies are horror movies?
- Whats the gross revenue of horror movies versus years? Growth rate?
- What are the factors that would affect the gross revenue of horror movies?

1.2. Gather at least two datasets using two different data gathering methods

List of data gathering methods:

- Download data manually
- Programmatically downloading files
- Gather data by accessing APIs
- Gather and extract data from HTML files using BeautifulSoup
- Extract data from a SQL database

Each dataset must have at least two variables, and have greater than 500 data samples within each dataset.

For each dataset, briefly describe why you picked the dataset and the gathering method (2-3 full sentences), including the names and significance of the variables in the dataset. Show your work (e.g., if using an API to download the data, please include a snippet of your code).

Load the dataset programmtically into this notebook.

Dataset 1: Top 1000 IMDb rated movie

This dataset collects the top 1000 IMDb rated movie

Type: CSV

Method: Gather and extract data from HTML files using BeautifulSoup

Dataset variables:

- ***name:*** Name of the movie
- ***year:*** Make Year of the movie
- ***category:*** Genre of the movie
- ***rating:*** Rating of the movie
- ***metascore:*** Metascore of the movie
- ***votes:*** Number of votes of the movie
- ***gross:*** Gross revenue of the movie

In [1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

from bs4 import BeautifulSoup
import pandas as pd
import requests
import time
import re

# IMDb "Top 1000" (Sorted by IMDb Rating Descending)
# 250 titles per url
urls = ['https://www.imdb.com/search/title/?groups=top_1000&sort=user_rating,desc&cou
       'https://www.imdb.com/search/title/?groups=top_1000&sort=user_rating,desc&coun
       'https://www.imdb.com/search/title/?groups=top_1000&sort=user_rating,desc&coun
       'https://www.imdb.com/search/title/?groups=top_1000&sort=user_rating,desc&coun
```

In [2]:
```
movie_name=[]
year_of_release=[]
category=[]
rating=[]
metascore=[]
votes=[]
gross=[]
```

In [3]:
```
for url in urls:
    response = requests.get(url)
    soup = BeautifulSoup(response.content,'html.parser')
    movie_data = soup.findAll('div',attrs={'class':'lister-item mode-advanced'})

    for i in movie_data:
        name = i.h3.a.text
        movie_name.append(name)
        year = i.h3.find('span', class_='lister-item-year text-muted unbold').text.re
        year_of_release.append(year)
        genre = i.p.find('span', class_='genre').text.replace('\n','').replace('
        category.append(genre)
        rate = i.find('div', class_ = 'inline-block ratings-imdb-rating').text.replac
        rating.append(rate)
        mscore = i.find('span', class_ = 'metascore').text.replace('        ','') if
        metascore.append(mscore)
        value = i.find_all('span', attrs ={'name':'nv'})
```

```
        votes.append(value[0].text)
        grosses=value[1].text if len(value)>1 else np.nan
        gross.append(grosses)
```

In [4]:
```
    df_top_1000 = pd.DataFrame({'name':movie_name,
                              'year':year_of_release,
                              'category': category,
                              'rating':rating,
                              'metascore':metascore,
                              'votes':votes,
                              'gross':gross
                             })
```

In [5]:
```
df_top_1000.shape
```

Out[5]:
```
(1000, 7)
```

Dataset 2 - Horror Movie Dataset

This dataset collects horrow movies info from 1920 to 2023.

Type: CSV file

Method: Download manually from Kaggle (https://www.kaggle.com/datasets/shreyanshverma27/imdb-horror-chilling-movie-dataset)

Dataset variables:

- ***Movie Title:*** Name of the movie
- ***Movie Year:*** Make Year of the movie
- ***Runtime:*** Length of the movie
- ***Genre:*** Genre of the movie
- ***Rating:*** Rating of the movie
- ***Director:*** Name of the director
- ***Votes:*** Number of votes of the movie
- ***Gross:*** Gross revenue of the movie

In [6]:
```
#FILL IN 2nd data gathering and loading method
df2_horror_movies = pd.read_csv('Horror Movies IMDb.csv')
```

In [7]:
```
df2_horror_movies.sample(10)
```

Out[7]:

	Movie Title	Movie Year	Runtime	Genre	Rating	Director	Votes	Gross
544	Victor Frankenstein	2015	110	Drama, Horror, Sci-Fi	5.9	Paul McGuigan	58,423	$5.78M
14	King Kong	1933	100	Adventure, Horror, Sci-Fi	7.9	Merian C. Cooper	88,019	$10.00M
703	The Stepford Wives	2004	93	Comedy, Horror, Sci-Fi	5.3	Frank Oz	68,040	$59.48M
151	Constantine	2005	121	Action, Fantasy, Horror	7.0	Francis Lawrence	3,59,071	$75.98M
51	Grindhouse	2007	191	Action, Horror, Thriller	7.5	Robert Rodriguez	1,87,623	$25.04M
767	Silent Hill: Revelation	2012	95	Horror, Mystery, Thriller	4.9	M.J. Bassett	65,270	$17.53M
566	Pride and Prejudice and Zombies	2016	108	Action, Comedy, Fantasy	5.8	Burr Steers	58,473	$10.91M
17	I Saw the Devil	2010	144	Action, Crime, Horror	7.8	Jee-woon Kim	1,37,559	$0.13M
749	The Haunting	1999	113	Fantasy, Horror, Mystery	5.0	Jan de Bont	78,402	$91.41M
173	Ravenous	1999	101	Adventure, Drama, Horror	6.9	Antonia Bird	41,616	$2.06M

In [8]:

```
df2_horror_movies.shape
```

Out[8]:

```
(836, 8)
```

Optional data storing step: You may save your raw dataset files to the local data store before moving to the next step.

In [9]:

```
#Optional: store the raw data in your local data store
```

2. Assess data

Assess the data according to data quality and tidiness metrics using the report below.

List **two** data quality issues and **two** tidiness issues. Assess each data issue visually **and** programmatically, then briefly describe the issue you find. **Make sure you include justifications for the methods you use for the assessment.**

Quality Issue on Dataset 1

Inspecting the dataframe visually

In [10]:

```
#FILL IN - Inspecting the dataframe visually
df_top_1000.sample(10)
```

Out[10]:

	name	year	category	rating	metascore	votes	gross
760	Coraline	2009	Animation, Drama, Family	7.7	80	253,660	$75.29M
742	The Discreet Charm of the Bourgeoisie	1972	Comedy	7.8	93	45,556	$0.20M
424	Who's Afraid of Virginia Woolf?	1966	Drama	8.0	75	78,574	NaN
858	Black Book	2006	Drama, Thriller, War	7.7	71	79,346	$4.40M
195	Vikram Vedha	2017	Action, Crime, Drama	8.2	NaN	49,130	NaN
1	The Godfather	1972	Crime, Drama	9.2	100	1,958,323	$134.97M
143	Jurassic Park	1993	Action, Adventure, Sci-Fi	8.2	68	1,038,368	$402.45M
985	The Last King of Scotland	2006	Biography, Drama, History	7.6	74	193,181	$17.61M
806	X: First Class	2011	Action, Sci-Fi	7.7	65	712,742	$146.41M
829	Fried Green Tomatoes	1991	Drama	7.7	64	79,789	$82.42M

- Missing values exist (**Completeness** issue)

Inspecting the dataframe programmatically

In [11]:
```
df_top_1000.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   name       1000 non-null   object
 1   year       1000 non-null   object
 2   category   1000 non-null   object
 3   rating     1000 non-null   object
 4   metascore  845 non-null    object
 5   votes      1000 non-null   object
 6   gross      834 non-null    object
dtypes: object(7)
memory usage: 54.8+ KB
```

- year, rating, metascore, volts, and gross should be numerical (**Validity** issue)

In [12]:
```
df_top_1000.duplicated().sum()
```

Out[12]: 0

- No **Uniquenes** issue

Quality Issue on Dataset 2

Inspecting the dataframe visually

In [13]:
```
df2_horror_movies.sample(10)
```

Out[13]:

	Movie Title	Movie Year	Runtime	Genre	Rating	Director	Votes	Gross
141	Pearl	2022	103	Drama, Horror, Thriller	7.0	Ti West	60,574	NaN
747	47 Meters Down: Uncaged	2019	90	Adventure, Drama, Horror	5.0	Johannes Roberts	28,859	$22.26M
402	Underworld: Awakening	2012	88	Action, Fantasy, Horror	6.3	Måns Mårlind	1,57,941	$62.32M
682	A Nightmare on Elm Street 2: Freddy's Revenge	1985	87	Horror	5.4	Jack Sholder	73,312	$30.00M
201	Creepshow	1982	120	Comedy, Fantasy, Horror	6.8	George A. Romero	50,496	$21.03M
289	It Chapter Two	2019	169	Drama, Fantasy, Horror	6.5	Andy Muschietti	2,81,137	$211.59M
384	Devil	2010	80	Horror, Mystery, Thriller	6.3	John Erick Dowdle	1,51,728	$33.58M
151	Constantine	2005	121	Action, Fantasy, Horror	7.0	Francis Lawrence	3,59,071	$75.98M
610	The Last Exorcism	2010	87	Horror, Mystery, Thriller	5.7	Daniel Stamm	50,953	$41.03M
187	Insidious I	2010	103	Horror, Mystery, Thriller	6.8	James Wan	3,19,707	$54.01M

- Missing values exist (**Completeness** issue)

Inspecting the dataframe programmatically

In [14]:
```
df2_horror_movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 836 entries, 0 to 835
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Movie Title  836 non-null    object 
 1   Movie Year   836 non-null    int64  
 2   Runtime      836 non-null    int64  
 3   Genre        836 non-null    object 
 4   Rating       836 non-null    float64
 5   Director     836 non-null    object 
 6   Votes        836 non-null    object 
 7   Gross        637 non-null    object 
dtypes: float64(1), int64(2), object(5)
memory usage: 52.4+ KB
```

- volts and gross should be numerical (**Validity** issue)

In [15]:
```
df2_horror_movies.duplicated().sum()
```

Out[15]: 0

- No **Uniquenes** issue

Tidiness Issue on Dataset 1:

In [16]:
```
df_top_1000.head()
```

Out[16]:

	name	year	category	rating	metascore	votes	gross
0	The Shawshank Redemption	1994	Drama	9.3	82	2,810,128	$28.34M
1	The Godfather	1972	Crime, Drama	9.2	100	1,958,323	$134.97M
2	The Dark Knight	2008	Action, Crime, Drama	9.0	84	2,791,759	$534.86M
3	Schindler's List	1993	Biography, Drama, History	9.0	95	1,412,629	$96.90M
4	The Lord of the Rings: The Return of the King	2003	Action, Adventure, Drama	9.0	94	1,923,739	$377.85M

- Category variable contains multiple values (**Data Structuring** issue)

Tidiness Issue on Dataset 2:

In [17]:
```
df2_horror_movies.head()
```

Out[17]:

	Movie Title	Movie Year	Runtime	Genre	Rating	Director	Votes	Gross
0	Alien	1979	117	Horror, Sci-Fi	8.5	Ridley Scott	9,05,275	$78.90M
1	Psycho	1960	109	Horror, Mystery, Thriller	8.5	Alfred Hitchcock	6,89,068	$32.00M
2	The Shining	1980	146	Drama, Horror	8.4	Stanley Kubrick	10,51,582	$44.02M
3	The Thing	1982	109	Horror, Mystery, Sci-Fi	8.2	John Carpenter	4,39,793	$13.78M
4	Tumbbad	2018	104	Drama, Fantasy, Horror	8.2	Rahi Anil Barve	53,297	NaN

- Genre variable contains multiple values (**Data Structuring** issue)

3. Clean data

Clean the data to solve the 4 issues corresponding to data quality and tidiness found in the assessing step. **Make sure you include justifications for your cleaning decisions.**

After the cleaning for each issue, please use **either** the visually or programatical method to validate the cleaning was succesful.

At this stage, you are also expected to remove variables that are unnecessary for your analysis and combine your datasets. Depending on your datasets, you may choose to perform variable combination and elimination before or after the cleaning stage. Your dataset must have **at least** 4 variables after combining the data.

In [18]:
```
# FILL IN - Make copies of the datasets to ensure the raw dataframes
# are not impacted

df1 = df_top_1000.copy()
df2 = df2_horror_movies.copy()
```

Quality Issue 1: FILL IN

Fixing Validity issue

years:

- Some of the year has I,II in the front
- numbers are the last four characters

In [19]:
```
df1['year'] = df1['year'].apply(lambda x: x[-4:])
df1['year'] = df1['year'].astype(int)
```

rating:

In [20]:
```
df1.rating = df1.rating.astype(float)
```

votes:

In [21]:
```
df1.votes = df1.votes.apply(lambda x: x.replace(',',''))
df1.votes = df1.votes.astype(int)
```

gross:

In [22]:
```
df1.gross = df1.gross.astype(str)
df1.gross = df1.gross.apply(lambda x: x.replace('$','').replace('M',''))
```

In [23]:
```
# There are '#' in the gross
df1.gross = df1.gross.apply(lambda x: x.replace('#','') if '#' in x else x)
```

In [24]:
```
df1['gross'] = df1['gross'].astype(float)
```

In [25]:
```
df1.rename(columns={'gross':'gross(millions)'},inplace=True)
```

In [26]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   name            1000 non-null   object 
 1   year            1000 non-null   int64  
 2   category        1000 non-null   object 
 3   rating          1000 non-null   float64
 4   metascore       845 non-null    object 
 5   votes           1000 non-null   int64  
 6   gross(millions)  834 non-null    float64
dtypes: float64(2), int64(2), object(3)
memory usage: 54.8+ KB
```

In [ ]:

Fixing Completeness issue

In [27]:
```
df1_gross = df1[~df1['gross(millions)'].isna()]
df1_gross_na = df1[df1['gross(millions)'].isna()]
```

In [28]:
```
df1_gross_na
```

Out[28]:

	name	year	category	rating	metascore	votes	gross(millions)
15	777 Charlie	2022	Adventure, Comedy, Drama	8.8	NaN	37144	NaN
22	Rocketry: The Nambi Effect	2022	Biography, Drama	8.7	NaN	55772	NaN
23	Soorarai Pottru	2020	Action, Drama	8.7	NaN	121172	NaN
36	Sita Ramam	2022	Action, Drama, Mystery	8.6	NaN	63545	NaN
59	96	2018	Drama, Romance	8.5	NaN	34577	NaN
...	...	...	...	...	...	...	...
979	Dark Waters	2019	Biography, Drama, History	7.6	73	96392	NaN
981	The Mitchells vs the Machines	2021	Animation, Action, Adventure	7.6	81	121375	NaN
982	The Invisible Man	1933	Horror, Sci-Fi	7.6	87	38624	NaN
989	Rebel Without a Cause	1955	Drama	7.6	89	95954	NaN
999	Cell 211	2009	Action, Crime, Drama	7.6	NaN	69827	NaN

166 rows × 7 columns

In [29]:
```
key = df1['category'].unique()
key = np.sort(key)
```

In [30]:
```
values = df1.groupby(by=['category'])['gross(millions)'].mean()
```

In [31]:
```
values = np.array(values)
```

In [32]:
```
Dict = dict(zip(key, values))
```

In [33]:
```
df1_gross_na['gross(millions)'] = df1_gross_na['category'].apply(lambda x:Dict[x])
df1_gross_na
```

Out[33]:

	name	year	category	rating	metascore	votes	gross(millions)
15	777 Charlie	2022	Adventure, Comedy, Drama	8.8	NaN	37144	19.380000
22	Rocketry: The Nambi Effect	2022	Biography, Drama	8.7	NaN	55772	57.683077
23	Soorarai Pottru	2020	Action, Drama	8.7	NaN	121172	124.524444
36	Sita Ramam	2022	Action, Drama, Mystery	8.6	NaN	63545	61.317500
59	96	2018	Drama, Romance	8.5	NaN	34577	62.784375
...	...	...	...	...	...	...	...
979	Dark Waters	2019	Biography, Drama, History	7.6	73	96392	56.693043
981	The Mitchells vs the Machines	2021	Animation, Action, Adventure	7.6	81	121375	130.066154
982	The Invisible Man	1933	Horror, Sci-Fi	7.6	87	38624	78.900000
989	Rebel Without a Cause	1955	Drama	7.6	89	95954	29.495395
999	Cell 211	2009	Action, Crime, Drama	7.6	NaN	69827	94.518889

166 rows × 7 columns

In [34]:
```
df1 = pd.concat([df1_gross, df1_gross_na])
```

In [35]:
```
df1[df1['gross(millions)'].isna()].sort_values(by='category')
```

Out[35]:

	name	year	category	rating	metascore	votes	gross(millions)
686	Thirteen Lives	2022	Action, Adventure, Biography	7.8	66	64164	NaN
720	Aguirre, the Wrath of God	1972	Action, Adventure, Biography	7.8	NaN	60330	NaN
87	Kaithi	2019	Action, Adventure, Crime	8.4	NaN	38409	NaN
727	To Have and Have Not	1944	Adventure, Comedy, Film-Noir	7.8	90	37264	NaN
729	The Man Who Would Be King	1975	Adventure, War	7.8	91	51125	NaN
271	A Silent Voice: The Movie	2016	Animation, Drama	8.1	78	94506	NaN
554	The Thin Man	1934	Comedy, Crime, Mystery	7.9	86	31789	NaN
493	Arsenic and Old Lace	1944	Comedy, Crime, Thriller	7.9	NaN	73707	NaN
334	The Circus	1928	Comedy, Family, Romance	8.1	90	35359	NaN
745	Duck Soup	1933	Comedy, Musical	7.8	93	61949	NaN
567	The Big Heat	1953	Crime, Film-Noir, Thriller	7.9	NaN	28288	NaN
669	The Man from Earth	2007	Drama, Fantasy, Mystery	7.8	NaN	195610	NaN
548	The Leopard	1963	Drama, History	7.9	100	28024	NaN
504	Nosferatu	1922	Fantasy, Horror	7.9	NaN	102722	NaN
701	Shadow of a Doubt	1943	Film-Noir, Thriller	7.8	94	68967	NaN

Quality Issue 2: FILL IN

In [36]:
```
df2.head()
```

Out[36]:

	Movie Title	Movie Year	Runtime	Genre	Rating	Director	Votes	Gross
0	Alien	1979	117	Horror, Sci-Fi	8.5	Ridley Scott	9,05,275	$78.90M
1	Psycho	1960	109	Horror, Mystery, Thriller	8.5	Alfred Hitchcock	6,89,068	$32.00M
2	The Shining	1980	146	Drama, Horror	8.4	Stanley Kubrick	10,51,582	$44.02M
3	The Thing	1982	109	Horror, Mystery, Sci-Fi	8.2	John Carpenter	4,39,793	$13.78M
4	Tumbbad	2018	104	Drama, Fantasy, Horror	8.2	Rahi Anil Barve	53,297	NaN

In [37]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 836 entries, 0 to 835
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Movie Title  836 non-null    object 
 1   Movie Year   836 non-null    int64  
 2   Runtime      836 non-null    int64  
 3   Genre        836 non-null    object 
 4   Rating       836 non-null    float64
 5   Director     836 non-null    object 
 6   Votes        836 non-null    object 
 7   Gross        637 non-null    object 
dtypes: float64(1), int64(2), object(5)
memory usage: 52.4+ KB
```

Fixing Validity issue

votes:

In [38]:
```
df2.Votes = df2.Votes.apply(lambda x: x.replace(',',''))
df2.Votes = df2.Votes.astype(int)
```

gross:

In [39]:
```
df2.Gross = df2.Gross.astype(str)
df2.Gross = df2.Gross.apply(lambda x: x.replace('$','').replace('M',''))
```

In [40]:
```
df2.Gross=df2.Gross.astype(float)
```

In [41]:
```
df2.rename(columns={'Gross':'Gross(millions)'},inplace=True)
```

In [42]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 836 entries, 0 to 835
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Movie Title      836 non-null    object 
 1   Movie Year       836 non-null    int64  
 2   Runtime          836 non-null    int64  
 3   Genre            836 non-null    object 
 4   Rating           836 non-null    float64
 5   Director         836 non-null    object 
 6   Votes            836 non-null    int64  
 7   Gross(millions)  637 non-null    float64
dtypes: float64(2), int64(3), object(3)
memory usage: 52.4+ KB
```

Tidiness Issue 1: FILL IN

Fixing Data Structuring issue

Dataset 1 is the collection of top 1000 movies in IMDb. We do want to keep all records and the metascore is not really important, therefore,

- 1. category into three columns: [genre_1, genre_2, genre_3]
- 2. remove the category and metascore variables
- 3. replace nan in gross by mean of the category (using group-by)

In [43]:
```
df1['genre_1'] = df1['category'].apply(lambda x:x.split(', ')[0])
df1['genre_2'] = df1['category'].apply(lambda x:x.split(', ')[1] if len(x.split(', ')
df1['genre_3'] = df1['category'].apply(lambda x:x.split(', ')[2] if len(x.split(', ')
```

In [44]:
```
arr1=df1.genre_1.unique().astype('str')
```

In [45]:
```
arr2=df1.genre_2.unique().astype('str')
```

In [46]:
```
arr3=df1.genre_3.unique().astype('str')
```

In [47]:
```
genre_all=np.concatenate([arr1,arr2,arr3])
print(np.unique(genre_all))
print(len(np.unique(genre_all)))
```

```
['Action' 'Adventure' 'Animation' 'Biography' 'Comedy' 'Crime' 'Drama'
 'Family' 'Fantasy' 'Film-Noir' 'History' 'Horror' 'Music' 'Musical'
 'Mystery' 'Romance' 'Sci-Fi' 'Sport' 'Thriller' 'War' 'Western' 'nan']
22
```

In [48]:
```
print(df1.shape)
df1.head()
```

```
(1000, 10)
```

Out[48]:

	name	year	category	rating	metascore	votes	gross(millions)	genre_1	genre
0	The Shawshank Redemption	1994	Drama	9.3	82	2810128	28.34	Drama	N
1	The Godfather	1972	Crime, Drama	9.2	100	1958323	134.97	Crime	Dra
2	The Dark Knight	2008	Action, Crime, Drama	9.0	84	2791759	534.86	Action	Cri
3	Schindler's List	1993	Biography, Drama, History	9.0	95	1412629	96.90	Biography	Dra
4	The Lord of the Rings: The Return of the King	2003	Action, Adventure, Drama	9.0	94	1923739	377.85	Action	Advent

Tidiness Issue 2: FILL IN

In [49]:
```
df2['genre_1'] = df2['Genre'].apply(lambda x:x.split(', ')[0])
df2['genre_2'] = df2['Genre'].apply(lambda x:x.split(', ')[1] if len(x.split(', '))>1
df2['genre_3'] = df2['Genre'].apply(lambda x:x.split(', ')[2] if len(x.split(', '))>2
```

In [50]:
```
df2.head()
```

Out[50]:

	Movie Title	Movie Year	Runtime	Genre	Rating	Director	Votes	Gross(millions)	genre_1	ge
0	Alien	1979	117	Horror, Sci-Fi	8.5	Ridley Scott	905275	78.90	Horror	
1	Psycho	1960	109	Horror, Mystery, Thriller	8.5	Alfred Hitchcock	689068	32.00	Horror	M
2	The Shining	1980	146	Drama, Horror	8.4	Stanley Kubrick	1051582	44.02	Drama	I
3	The Thing	1982	109	Horror, Mystery, Sci-Fi	8.2	John Carpenter	439793	13.78	Horror	M
4	Tumbbad	2018	104	Drama, Fantasy, Horror	8.2	Rahi Anil Barve	53297	NaN	Drama	Fa

Remove unnecessary variables and combine datasets

Depending on the datasets, you can also peform the combination before the cleaning steps.

In [51]:
```
df1.head()
```

Out[51]:

	name	year	category	rating	metascore	votes	gross(millions)	genre_1	genre
0	The Shawshank Redemption	1994	Drama	9.3	82	2810128	28.34	Drama	N
1	The Godfather	1972	Crime, Drama	9.2	100	1958323	134.97	Crime	Dra
2	The Dark Knight	2008	Action, Crime, Drama	9.0	84	2791759	534.86	Action	Cri
3	Schindler's List	1993	Biography, Drama, History	9.0	95	1412629	96.90	Biography	Dra
4	The Lord of the Rings: The Return of the King	2003	Action, Adventure, Drama	9.0	94	1923739	377.85	Action	Advent

Keep: name, year,rating,metascore,votes,gross,genre_1, genre_2, genre_3

Drop: category

In [52]:
```
df1.drop('category',axis=1,inplace=True)
df1
```

Out[52]:

	name	year	rating	metascore	votes	gross(millions)	genre_1	genre_2	ger
0	The Shawshank Redemption	1994	9.3	82	2810128	28.340000	Drama	NaN	
1	The Godfather	1972	9.2	100	1958323	134.970000	Crime	Drama	
2	The Dark Knight	2008	9.0	84	2791759	534.860000	Action	Crime	D
3	Schindler's List	1993	9.0	95	1412629	96.900000	Biography	Drama	Hi
4	The Lord of the Rings: The Return of the King	2003	9.0	94	1923739	377.850000	Action	Adventure	D
...	...	...	...	...	...	...	...	...	
979	Dark Waters	2019	7.6	73	96392	56.693043	Biography	Drama	Hi
981	The Mitchells vs the Machines	2021	7.6	81	121375	130.066154	Animation	Action	Adve
982	The Invisible Man	1933	7.6	87	38624	78.900000	Horror	Sci-Fi	
989	Rebel Without a Cause	1955	7.6	89	95954	29.495395	Drama	NaN	
999	Cell 211	2009	7.6	NaN	69827	94.518889	Action	Crime	D

1000 rows × 9 columns

In [53]:
```
df2.head()
```

Out[53]:

	Movie Title	Movie Year	Runtime	Genre	Rating	Director	Votes	Gross(millions)	genre_1	ge
0	Alien	1979	117	Horror, Sci-Fi	8.5	Ridley Scott	905275	78.90	Horror	
1	Psycho	1960	109	Horror, Mystery, Thriller	8.5	Alfred Hitchcock	689068	32.00	Horror	M
2	The Shining	1980	146	Drama, Horror	8.4	Stanley Kubrick	1051582	44.02	Drama	I
3	The Thing	1982	109	Horror, Mystery, Sci-Fi	8.2	John Carpenter	439793	13.78	Horror	M
4	Tumbbad	2018	104	Drama, Fantasy, Horror	8.2	Rahi Anil Barve	53297	NaN	Drama	Fa

Keep: Title, Year, Director

Drop: Runtime, Votes, Rating, Votes, Gross, genre_1, genre_2, genre_3

In [54]:
```
df2=df2.drop(['Runtime','Genre','Gross(millions)','Rating','Votes',
```

```
                    'Gross(millions)','genre_1','genre_2','genre_3'],axis=1)
df2.head()
```

Out[54]:

	Movie Title	Movie Year	Director
0	Alien	1979	Ridley Scott
1	Psycho	1960	Alfred Hitchcock
2	The Shining	1980	Stanley Kubrick
3	The Thing	1982	John Carpenter
4	Tumbbad	2018	Rahi Anil Barve

In [55]:

```
df_top1000_horror=df1.merge(df2,how='inner',left_on='name', right_on='Movie Title')
df_left=df1.merge(df2,how='left',left_on='name', right_on='Movie Title')
```

In [56]:

```
df_top1000_horror.head()
```

Out[56]:

	name	year	rating	metascore	votes	gross(millions)	genre_1	genre_2	genre_3	Movi Titl
0	Alien	1979	8.5	89	923281	78.90	Horror	Sci-Fi	NaN	Alie
1	Psycho	1960	8.5	97	701679	32.00	Horror	Mystery	Thriller	Psych
2	Psycho	1960	8.5	97	701679	32.00	Horror	Mystery	Thriller	Psych
3	The Shining	1980	8.4	66	1075121	44.02	Drama	Horror	NaN	Th Shinin
4	The Thing	1982	8.2	57	450236	13.78	Horror	Mystery	Sci-Fi	Th Thin

In [57]:

```
print(df1.shape)
print(df2.shape)
print(df_top1000_horror.shape)
```

```
(1000, 9)
(836, 3)
(40, 12)
```

In [58]:

```
df_top1000_horror.name.duplicated().sum()
```

Out[58]: 7

In [59]:

```
# Drop same name but different year
df_top1000_horror = df_top1000_horror[~(df_top1000_horror['year']!=df_top1000_horror[
```

In [60]:

```
df_top1000_horror.shape
```

Out[60]: (32, 12)

In [61]:

```
df_top1000_horror.head()
```

Out[61]:

	name	year	rating	metascore	votes	gross(millions)	genre_1	genre_2	genre_3	Mo Ti
0	Alien	1979	8.5	89	923281	78.90	Horror	Sci-Fi	NaN	Al
1	Psycho	1960	8.5	97	701679	32.00	Horror	Mystery	Thriller	Psyc
3	The Shining	1980	8.4	66	1075121	44.02	Drama	Horror	NaN	T Shini
4	The Thing	1982	8.2	57	450236	13.78	Horror	Mystery	Sci-Fi	T Thi
5	The Exorcist	1973	8.1	82	439076	232.91	Horror	NaN	NaN	T Exorc

In [62]:

```
df_top1000_horror=df_top1000_horror.drop(['Movie Title','Movie Year'],axis=1)
```

In [ ]:

4. Update your data store

Update your local database/data store with the cleaned data, following best practices for storing your cleaned data:

- Must maintain different instances / versions of data (raw and cleaned data)
- Must name the dataset files informatively
- Ensure both the raw and cleaned data is saved to your database/data store

In [63]:

```
# save the combined df
df_top1000_horror.to_csv('master_cleaned.csv')
df = pd.read_csv('master_cleaned.csv',index_col=0)
df.head()
```

Out[63]:

	name	year	rating	metascore	votes	gross(millions)	genre_1	genre_2	genre_3	Dire
0	Alien	1979	8.5	89.0	923281	78.90	Horror	Sci-Fi	NaN	R S
1	Psycho	1960	8.5	97.0	701679	32.00	Horror	Mystery	Thriller	A Hitch
3	The Shining	1980	8.4	66.0	1075121	44.02	Drama	Horror	NaN	Sta Ku
4	The Thing	1982	8.2	57.0	450236	13.78	Horror	Mystery	Sci-Fi	Carp
5	The Exorcist	1973	8.1	82.0	439076	232.91	Horror	NaN	NaN	W Frie

In [ ]:

5. Answer the research question

5.1: Define and answer the research question

Questions:

- Among the top 1000 movies, what percenetage of movies are horror movies? What's the Gross revenue of horror movies compare to other genres?
- Which Director contributes the most to the gross revenue in top 1000 movies? Does he/she also has the most number of horror movies selected in top 1000 movies?
- Is there any trend in Horror movie revenue over year in the top 1000 movies?

We will use **df1 (top 1000 movie dataset)** and **df (merged dataset)** datasets to answer those questions.

In [64]:
```
# Get movies based on specific genre
def get_genre_df1(x):
    df1_genry = df1[(df1['genre_1']==x)|(df1['genre_2']==x)|(df1['genre_3']==x)]
    return df1_genry
```

In [65]:
```
get_genre_df1('Horror').head()
```

Out[65]:

	name	year	rating	metascore	votes	gross(millions)	genre_1	genre_2	genre_3
38	Alien	1979	8.5	89	923281	78.90	Horror	Sci-Fi	NaN
46	Psycho	1960	8.5	97	701679	32.00	Horror	Mystery	Thriller
61	The Shining	1980	8.4	66	1075121	44.02	Drama	Horror	NaN
139	The Thing	1982	8.2	57	450236	13.78	Horror	Mystery	Sci-Fi
207	The Exorcist	1973	8.1	82	439076	232.91	Horror	NaN	NaN

In [66]:
```
Rate={}
Vote={}
Gross={}

for x in genre_all:
    Rate[x] = get_genre_df1(x)['rating'].mean()
    Vote[x] = get_genre_df1(x)['votes'].mean()
    Gross[x] = get_genre_df1(x)['gross(millions)'].mean()

Rate_df = pd.DataFrame.from_dict(Rate,orient='index',columns=['Rate']).transpose()
Vote_df = pd.DataFrame.from_dict(Vote,orient='index',columns=['Votes']).transpose()
Gross_df =  pd.DataFrame.from_dict(Gross,orient='index',columns=['Gross']).transpose(
```

In [67]:
```
Rate_df2 = Rate_df.transpose().reset_index()
Vote_df2 = Vote_df.transpose().reset_index()
Gross_df2 = Gross_df.transpose().reset_index()
```

In [68]:
```
test_df = Rate_df2.merge(Vote_df2, left_on='index', right_on='index').merge(Gross_df2
test_df
```

Out[68]:

	index	Rate	Votes	Gross
0	Drama	7.979783	279366.446404	52.826999
1	Crime	7.994634	348982.121951	48.126639
2	Action	7.985507	470995.985507	139.995057
3	Biography	7.973832	300433.672897	59.232987
4	Adventure	7.987634	497682.172043	166.064863
5	Animation	7.948780	325486.902439	118.471874
6	Comedy	7.914097	278807.162996	67.410298
7	Horror	7.881250	291164.843750	38.548226
8	Mystery	8.000000	341309.970000	47.128410
9	Western	8.052941	301435.411765	71.350588
10	Film-Noir	7.977273	88131.545455	8.650526
11	Family	7.932692	276293.038462	94.887320
12	Thriller	7.927857	343596.378571	67.722317
13	Fantasy	7.927869	428341.655738	132.728447
14	nan	NaN	NaN	NaN
15	Romance	7.939844	217579.281250	42.110170
16	Sci-Fi	7.990909	651795.909091	139.453030
17	War	8.056863	244113.411765	49.911875
18	Music	7.909375	194679.812500	38.894479
19	Musical	7.943750	88081.250000	17.588667
20	Sport	7.980000	272396.066667	49.866667
21	History	7.941304	232566.760870	54.054789

Among the top 1000 movies, what percenetage of movies are horror movies? What's the Gross revenue of horror movies compare to other genres?

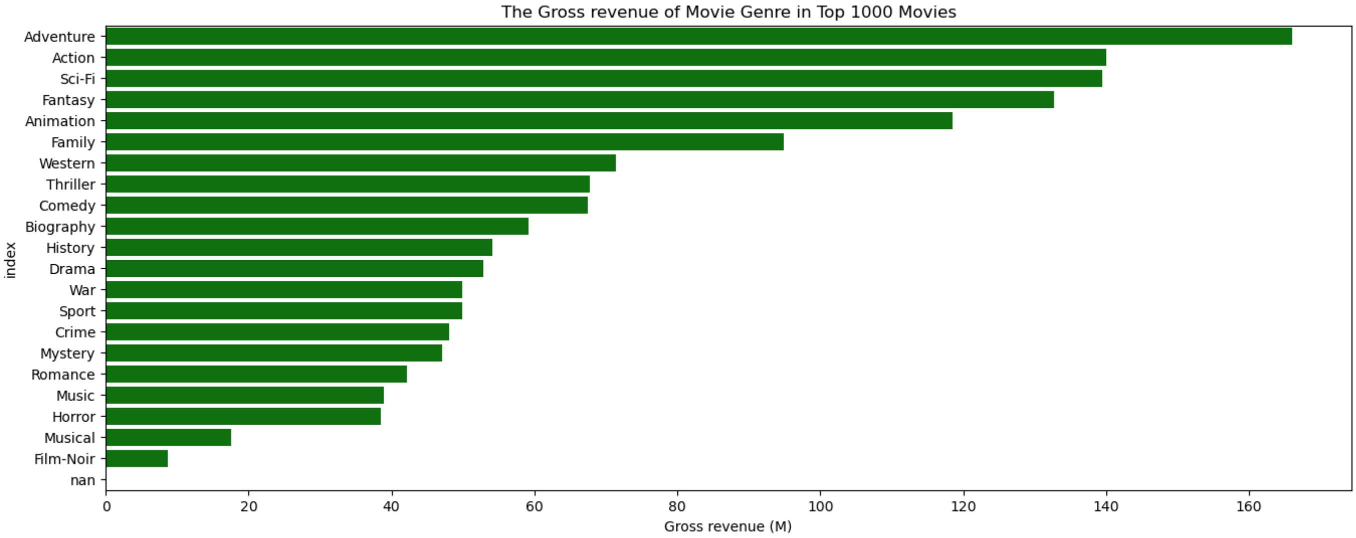
In [69]:

```
# Plot barplot for genre percentage in top 1000 movies
per_horror = get_genre_df1('Horror').shape[0]/1000*100
print('The percentage of Horror movies in top 1000 movies = {} %'.format(per_horror))
```

```
The percentage of Horror movies in top 1000 movies = 3.2 %
```

In [70]:

```
plt.figure(figsize=(16,6))
ax = sns.barplot(test_df.sort_values('Gross',ascending=False),x='Gross',y='index', or
ax.set_title('The Gross revenue of Movie Genre in Top 1000 Movies')
ax.set_xlabel('Gross revenue (M)');
```



- Among the top 1000 movies, there are **32 Horror movies (3.2%)**
- The sum revenue of top 1000 movies = **1,505 Millions** and Horror movies took over **2.56% (38.55 Millions)** of the total gross revenue.

In [ ]:

Which Director contributes the most to the gross revenue in top 1000 movies? Does he/she also has the most number of horror movies selected in top 1000 movies?

In [71]:

```
def get_genre_df(x):
    df_genry = df[(df['genre_1']==x)|(df['genre_2']==x)|(df['genre_3']==x)]
    return df_genry
```

In [72]:

```
director = get_genre_df('Horror')
director.head()
```

Out[72]:

	name	year	rating	metascore	votes	gross(millions)	genre_1	genre_2	genre_3	Dire
0	Alien	1979	8.5	89.0	923281	78.90	Horror	Sci-Fi	NaN	R
1	Psycho	1960	8.5	97.0	701679	32.00	Horror	Mystery	Thriller	A Hitch
3	The Shining	1980	8.4	66.0	1075121	44.02	Drama	Horror	NaN	St Ku
4	The Thing	1982	8.2	57.0	450236	13.78	Horror	Mystery	Sci-Fi	Carp
5	The Exorcist	1973	8.1	82.0	439076	232.91	Horror	NaN	NaN	W Frie

In [73]:

```
director_gross = get_genre_df('Horror').groupby('Director')['gross(millions)'].sum().
director_gross
```

Out[73]:
```
Director
William Friedkin          232.910
James Whale               105.670
Alejandro Amenábar         96.520
Robert Wiene               90.140
Ridley Scott               78.900
John Carpenter             60.780
John McTiernan             59.740
James Wan                  56.000
Stanley Kubrick            44.020
Alfred Hitchcock           43.400
David Cronenberg           40.460
Don Siegel                 22.410
Roman Polanski             22.325
Mary Harron                15.070
Edgar Wright               13.540
Merian C. Cooper           10.000
Sam Raimi                   5.920
George A. Romero            5.190
Robert Aldrich              4.050
Jemaine Clement             3.330
Jack Clayton                2.620
Rahi Anil Barve             2.120
Tomas Alfredson             2.120
Henri-Georges Clouzot       1.090
Tod Browning                0.630
F.W. Murnau                 0.000
Name: gross(millions), dtype: float64
```

- **William Friedkin** is the director contributed the most to gross revenue of Horror movie genre in top 1000 movies.

In [74]:
```
director[director.Director=='William Friedkin']
```

Out[74]:

	name	year	rating	metascore	votes	gross(millions)	genre_1	genre_2	genre_3	Direc
5	The Exorcist	1973	8.1	82.0	439076	232.91	Horror	NaN	NaN	Willi Fried

In [75]:
```
director.groupby('Director')['year'].count()
```

Out[75]:

```
Director
Alejandro Amenábar       1
Alfred Hitchcock         2
David Cronenberg         1
Don Siegel               1
Edgar Wright             1
F.W. Murnau              1
George A. Romero         2
Henri-Georges Clouzot    1
Jack Clayton             1
James Wan                1
James Whale              3
Jemaine Clement          1
John Carpenter           2
John McTiernan           1
Mary Harron              1
Merian C. Cooper         1
Rahi Anil Barve          1
Ridley Scott             1
Robert Aldrich           1
Robert Wiene             1
Roman Polanski           1
Sam Raimi                1
Stanley Kubrick          1
Tod Browning             1
Tomas Alfredson          1
William Friedkin         1
Name: year, dtype: int64
```

In [76]:

```
director[director.Director=='James Whale']
```

Out[76]:

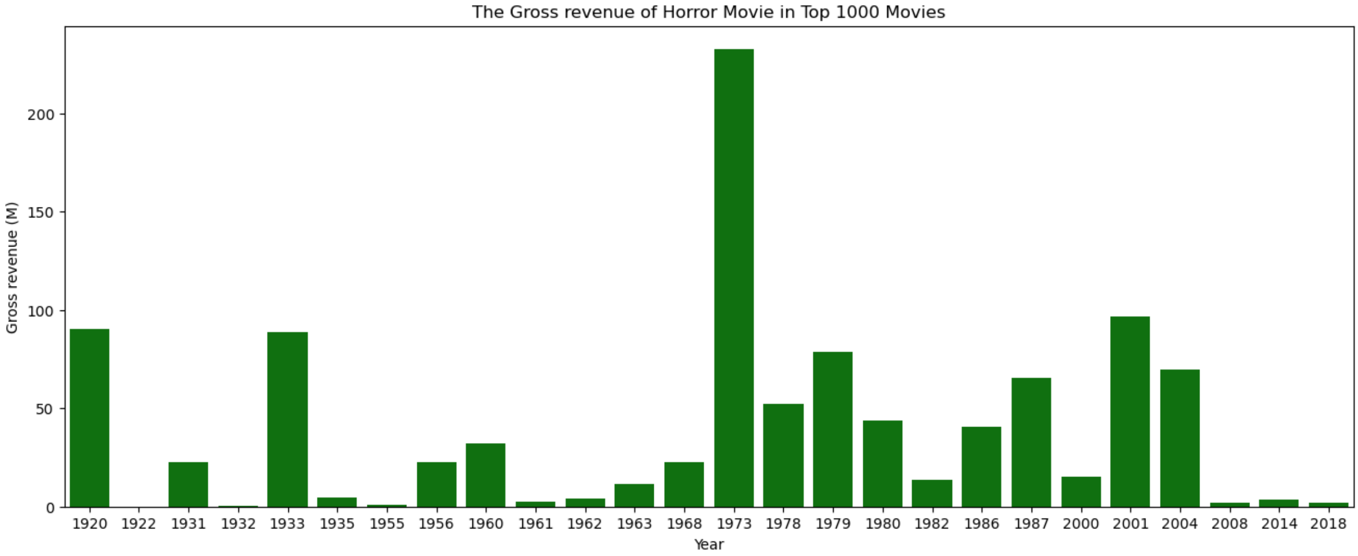
	name	year	rating	metascore	votes	gross(millions)	genre_1	genre_2	genre_3
18	The Bride of Frankenstein	1935	7.8	95.0	51581	4.36	Drama	Horror	Sci-Fi
34	Frankenstein	1931	7.8	91.0	77427	22.41	Drama	Horror	Sci-Fi
39	The Invisible Man	1933	7.6	87.0	38624	78.90	Horror	Sci-Fi	NaN

- **James Whale** is the director contributed the most number of Horror movies in top 1000 movies.

Is there any trend in Horror movie revenue over year in the top 1000 movies?

In [77]:

```
plt.figure(figsize=(16,6))
ax = sns.barplot(director.groupby('year').sum().reset_index(), x='year',y='gross(mill
ax.set_title('The Gross revenue of Horror Movie in Top 1000 Movies')
ax.set_xlabel('Year');
ax.set_ylabel('Gross revenue (M)');
```



- The gross revenue of Horror movies in top 1000 movies over year are **mostly less than 100 millions**. The only exception is at **1973**, where William Friedkin's movie **The Exorcist** make a contribution to 232 millions in single movie.

5.2: Reflection

In 2-4 sentences, if you had more time to complete the project, what actions would you take? For example, which data quality and structural issues would you look into further, and what research questions would you further explore?

If have more time, I'll:

- 1. collect more data regards to revenue and directors.
- 2. look into whether combination of genres will correlate to the gross revenues.

```
In [ ]:
```