Project: Investigate a Dataset - TMDb movie data

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Introduction

Dataset Description

As mentioned in the Choosing a Dataset notebook, I've chosen the TMDb movie data dataset. The data is pretty clean already, so there won't be much to do in terms of data hygiene, but there are quite a lot of questions we can ask regarding the data, and some of them will require us to tweak the data slightly (splitting by actors, or directors, for instance).

I couldn't find much in terms of detailed documentation regarding the dataset (other than the one provided in the project's page), so I had to make assumptions about most of the column contents. The following table summarizes each column:

Column	Type	Description
id	int	TMDb id
imdb_id	str	IMDb id
popularity	float	TMDb popularity score
budget	int	Budget in USD
revenue	int	Revenue in USD
original_title	str	Original title
cast	str	Pipe separated list of cast members
homepage	str	URL of the movie's homepage
director	str	Pipe separated list of directors
tagline	str	Movie tag line
keywords	str	Keywords associated with the movie
overview	str	Overview of the movie
runtime	int	Runtime in minutes
genres	str	Pipe separated list of genres
production_companies	str	Pipe separated list of production companies involved
release_date	str	Release date
vote_count	int	Number of votes
vote_average	float	Vote average
budget_adj	float	Budget adjusted to 2010
revenue_adj	float	Revenue adjusted to 2010

Although budget and revenue can be analyzed using the 2010 adjusted values, when presenting information regarding monitary values, it's usual to adjust those to the time reference of when the analysis was presented, so the readers have clearer picture of the amounts involved. Because of this I've decided to provide 2021 inflation adjusted values.

I could have used Python's cpi module to easily compute the adjustment, but I chose to use the Inflation, consumer prices (annual %) indicator from the World Bank, combined with the formula described in this blog post.

The following metadata (comes with the dataset) describes the indicator:

INDICATOR_CODE	INDICATOR_NAME	SOURCE_NOTE
FP.CPI.TOTL.ZG	Inflation, consumer prices (annual %)	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used.

The data itself is structured as follows:

Column	Type	Description
Country Name	string	Name of the country
Country Code	string	ISO Code of the country
Indicator Name	string	Fixed value: `"Inflation, consumer prices (annual %)"`
Indicator Code	string	Fixed value: `"FP.CPI.TOTL.ZG"`
1960...2021	float	Indicator value for the year column

In order to use this data, I'll have to filter, transpose and clean the table to produce a usable `DataFrame` .

Question(s) for Analysis

- Which genres are most popular from year to year? (taken from the Investigate a Dataset - Data Set Options)
- What kinds of properties are associated with movies that have high revenues? (taken from the Investigate a Dataset - Data Set Options)
- Is there a specific month of the year were the highest grossing films released? Is this consistent across genres?
- Of the top 5 most prolific directors, which one had the most consistently highly rated films?

In [1]:
```
import urllib.request

from pathlib import Path
from tempfile import NamedTemporaryFile
from typing import Iterator, Tuple, Type
from zipfile import ZipFile

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme(style="darkgrid")

%matplotlib inline
```

In [2]:
```
# Upgrade pandas to use dataframe.explode() function.
# !pip install --upgrade pandas==0.25.0 (commented out as the requirements'
```

Data Wrangling

General Properties

Since I wanted to make this notebook as portable as possible, instead of relying on the local filesystem to load the data, I'm going to fetch it straight from the source. I'll use `pandas` ' feature that allows me to pass a URL to most `read_*` functions, or I'll Python's `urllib.request` to fetch the packages that need pre-processing before being ingested by `pandas` .

First we fetch the *TMDb movie data* dataset straight from the URL mentioned in the Investigate a Dataset - Data Set Options page. Depending on the speed of your connection, the following cell might take a little while to evaluate.

In [3]:
```
tmdb_movie_data_df = pd.read_csv(
    "https://d17h27t6h515a5.cloudfront.net/topher/2017/October/59dd1c4c_tmdb
)
```

In [4]:
```
tmdb_movie_data_df.head()
```

Out[4]:

	id	imdb_id	popularity	budget	revenue	original_title	cast
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...

5 rows × 21 columns

In [5]:

```
tmdb_movie_data_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    10866 non-null  int64  
 1   imdb_id               10856 non-null  object 
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64  
 4   revenue               10866 non-null  int64  
 5   original_title        10866 non-null  object 
 6   cast                  10790 non-null  object 
 7   homepage              2936 non-null   object 
 8   director              10822 non-null  object 
 9   tagline               8042 non-null   object 
 10  keywords              9373 non-null   object 
 11  overview              10862 non-null  object 
 12  runtime               10866 non-null  int64  
 13  genres                10843 non-null  object 
 14  production_companies  9836 non-null   object 
 15  release_date          10866 non-null  object 
 16  vote_count            10866 non-null  int64  
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64  
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

As we can see, all the expected columns are present and accounted for. We also need to check the Python types of the columns. Since this is something that can be used later in the notebook, I'll create a function to do it.

In [6]:
```
def get_column_python_types(df: pd.DataFrame) -> Iterator[Tuple[str, Type]]:
    """Given a DataFrame, it generates the Python datatypes of the first row
    for column, value in df[~df.isna()].iloc[0, :].to_dict().items():
        yield column, type(value)
```

In [7]:
```
for column, type_ in get_column_python_types(tmdb_movie_data_df):
    print(f"{column}: {type_}")
```

```
id: <class 'int'>
imdb_id: <class 'str'>
popularity: <class 'float'>
budget: <class 'int'>
revenue: <class 'int'>
original_title: <class 'str'>
cast: <class 'str'>
homepage: <class 'str'>
director: <class 'str'>
tagline: <class 'str'>
keywords: <class 'str'>
overview: <class 'str'>
runtime: <class 'int'>
genres: <class 'str'>
production_companies: <class 'str'>
release_date: <class 'str'>
vote_count: <class 'int'>
vote_average: <class 'float'>
release_year: <class 'int'>
budget_adj: <class 'float'>
revenue_adj: <class 'float'>
```

As you can see, the `release_date` field is a string, so we will need to convert it to `datetime` so we can project on the components of the date. The rest of the fields do not require special attention, with the exception of those that contain pipe separated lists of values, but those will be handled when the need arises.

As I mentioned in the introduction I want to adjust the `budget` and `revenue` values according to inflation using this formula. In order to do that, I'm going to fetch the "Inflation, consumer prices (annual %)" indicator dataset straight from the world bank website.

Even though the data is in CSV format, it is packaged on a zip file, so I need to extract the contents before I can pass it to `pandas`' `read_csv` function.

In [8]:
```
fp_cpi_totl_zg_zip_path = Path("fp_cpi_totl_zg.zip")
```

In [9]:
```
urllib.request.urlretrieve(
    "https://api.worldbank.org/v2/en/indicator/FP.CPI.TOTL.ZG?downloadformat
    fp_cpi_totl_zg_zip_path
);
```

First, let's list the contents for the file:

In [10]:
```
with ZipFile(fp_cpi_totl_zg_zip_path) as zf:
    for zi in zf.filelist:
        print(zi.filename)
```

```
Metadata_Indicator_API_FP.CPI.TOTL.ZG_DS2_en_csv_v2_4330294.csv
API_FP.CPI.TOTL.ZG_DS2_en_csv_v2_4330294.csv
Metadata_Country_API_FP.CPI.TOTL.ZG_DS2_en_csv_v2_4330294.csv
```

The file that we're looking for is `API_FP.CPI.TOTL.ZG_DS2_en_csv_v2_4330294.csv`. The other two contain metadata that is irrelevant to the analysis. I can't open and pass this file straight to `read_csv` because there are a few informational lines at the beginning:

In [11]:
```
with ZipFile(fp_cpi_totl_zg_zip_path) as zf:
    with zf.open("API_FP.CPI.TOTL.ZG_DS2_en_csv_v2_4330294.csv", "r") as f:
        for i, line in enumerate(f.readlines()[:4], start=1):
            print(f"{i}: {line.decode('utf-8')}")
```

```
1: "Data Source","World Development Indicators",

2:

3: "Last Updated Date","2022-07-20",

4:
```

Luckily, `read_csv` has a `skiprows` argument that allow us to skip these lines:

In [12]:
```
with ZipFile(fp_cpi_totl_zg_zip_path) as zf:
    with zf.open("API_FP.CPI.TOTL.ZG_DS2_en_csv_v2_4330294.csv") as f:
        fp_cpi_totl_zg_df = pd.read_csv(f, skiprows=4)
```

In [13]:
```
fp_cpi_totl_zg_df.head(1)
```

Out[13]:

	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	...	
0	Aruba	ABW	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...	-

1 rows × 67 columns

Since this use case is common enough, I've written a Python function named `fetch_from_zip_read_csv` to automate the process:

In [14]:
```python
def fetch_from_zip_read_csv(
        uri: str,
        filename: str,
        *args,
        **kwargs
) -> pd.DataFrame:
    """Extract a DataFrame from a zip file hosted remotely"""
    with NamedTemporaryFile() as fp:
        urllib.request.urlretrieve(
            uri,
            fp.name
        )

        with ZipFile(fp.name) as zf:
            with zf.open(filename) as f:
                df = pd.read_csv(f, *args, **kwargs)

    return df
```

In [15]:
```python
fp_cpi_totl_zg_df = fetch_from_zip_read_csv(
    "https://api.worldbank.org/v2/en/indicator/FP.CPI.TOTL.ZG?downloadformat
    "API_FP.CPI.TOTL.ZG_DS2_en_csv_v2_4330294.csv",
    skiprows=4
)
```

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

Out[16]:

	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	...
0	Aruba	ABW	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...
1	Africa Eastern and Southern	AFE	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...
2	Afghanistan	AFG	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...
3	Africa Western and Central	AFW	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...
4	Angola	AGO	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...

5 rows × 67 columns

In [17]:
```
fp_cpi_totl_zg_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 266 entries, 0 to 265
Data columns (total 67 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Country Name    266 non-null    object 
 1   Country Code    266 non-null    object 
 2   Indicator Name  266 non-null    object 
 3   Indicator Code  266 non-null    object 
 4   1960            70 non-null     float64
 5   1961            72 non-null     float64
 6   1962            74 non-null     float64
 7   1963            75 non-null     float64
 8   1964            79 non-null     float64
 9   1965            86 non-null     float64
 10  1966            93 non-null     float64
 11  1967            100 non-null    float64
 12  1968            101 non-null    float64
 13  1969            102 non-null    float64
 14  1970            107 non-null    float64
 15  1971            111 non-null    float64
 16  1972            114 non-null    float64
 17  1973            117 non-null    float64
 18  1974            120 non-null    float64
 19  1975            124 non-null    float64
 20  1976            125 non-null    float64
 21  1977            129 non-null    float64
 22  1978            129 non-null    float64
 23  1979            124 non-null    float64
 24  1980            131 non-null    float64
 25  1981            146 non-null    float64
 26  1982            147 non-null    float64
 27  1983            147 non-null    float64
 28  1984            151 non-null    float64
 29  1985            152 non-null    float64
 30  1986            163 non-null    float64
 31  1987            169 non-null    float64
 32  1988            169 non-null    float64
 33  1989            172 non-null    float64
 34  1990            172 non-null    float64
 35  1991            178 non-null    float64
 36  1992            186 non-null    float64
 37  1993            192 non-null    float64
 38  1994            197 non-null    float64
 39  1995            201 non-null    float64
 40  1996            204 non-null    float64
 41  1997            204 non-null    float64
 42  1998            204 non-null    float64
 43  1999            206 non-null    float64
 44  2000            210 non-null    float64
 45  2001            215 non-null    float64
 46  2002            217 non-null    float64
 47  2003            220 non-null    float64
 48  2004            221 non-null    float64
 49  2005            224 non-null    float64
 50  2006            227 non-null    float64
 51  2007            229 non-null    float64
 52  2008            230 non-null    float64
 53  2009            233 non-null    float64
```

```
 54  2010             235 non-null    float64
 55  2011             238 non-null    float64
 56  2012             237 non-null    float64
 57  2013             235 non-null    float64
 58  2014             233 non-null    float64
 59  2015             232 non-null    float64
 60  2016             232 non-null    float64
 61  2017             227 non-null    float64
 62  2018             224 non-null    float64
 63  2019             222 non-null    float64
 64  2020             213 non-null    float64
 65  2021             192 non-null    float64
 66  Unnamed: 66      0 non-null      float64
dtypes: float64(63), object(4)
memory usage: 139.4+ KB
```

In [18]:

```
for column, type_ in get_column_python_types(fp_cpi_totl_zg_df):
    print(f"{column}: {type_}")
```

```
Country Name: <class 'str'>
Country Code: <class 'str'>
Indicator Name: <class 'str'>
Indicator Code: <class 'str'>
1960: <class 'float'>
1961: <class 'float'>
1962: <class 'float'>
1963: <class 'float'>
1964: <class 'float'>
1965: <class 'float'>
1966: <class 'float'>
1967: <class 'float'>
1968: <class 'float'>
1969: <class 'float'>
1970: <class 'float'>
1971: <class 'float'>
1972: <class 'float'>
1973: <class 'float'>
1974: <class 'float'>
1975: <class 'float'>
1976: <class 'float'>
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1980: <class 'float'>
1981: <class 'float'>
1982: <class 'float'>
1983: <class 'float'>
1984: <class 'float'>
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2002: <class 'float'>
2003: <class 'float'>
2004: <class 'float'>
2005: <class 'float'>
2006: <class 'float'>
2007: <class 'float'>
2008: <class 'float'>
2009: <class 'float'>
2010: <class 'float'>
2011: <class 'float'>
2012: <class 'float'>
2013: <class 'float'>
2014: <class 'float'>
```

```
2015: <class 'float'>
2016: <class 'float'>
2017: <class 'float'>
2018: <class 'float'>
2019: <class 'float'>
2020: <class 'float'>
2021: <class 'float'>
Unnamed: 66: <class 'float'>
```

As I mentioned in the Introduction, the dataframe is indexed on the country, with a column for each year. Before I can use this to adjust the monetary values in the `tmdb_movie_data_df` dataframe, I'll have to process the inflation dataframe to make it easier to work with, which I'll do in the next section.

Data Cleaning

Are there any duplicates in the `tmdb_movie_data_df` dataframe?

In [19]:
```
tmdb_movie_data_df.duplicated().sum()
```

Out[19]:
```
1
```

In [20]:
```
tmdb_movie_data_df[tmdb_movie_data_df.duplicated()]
```

Out[20]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepa
2090	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	N

1 rows × 21 columns

Let's get rid of the duplicates:

In [21]:
```
tmdb_movie_data_df.drop_duplicates(inplace=True)
```

In [22]:
```
tmdb_movie_data_df.duplicated().sum()
```

Out[22]:
```
0
```

Since I'm focusing on the `budget`, `revenue` both as dependent and independent variables, I need to make sure there's no missing or invalid information.

In [23]:
```
tmdb_movie_data_df[["budget", "revenue"]].describe()
```

Out[23]:

	budget	revenue
count	1.086500e+04	1.086500e+04
mean	1.462429e+07	3.982690e+07
std	3.091428e+07	1.170083e+08
min	0.000000e+00	0.000000e+00
25%	0.000000e+00	0.000000e+00
50%	0.000000e+00	0.000000e+00
75%	1.500000e+07	2.400000e+07
max	4.250000e+08	2.781506e+09

There are movies where the `budget` or the `revenue` is "0", which we'll consider missing information. Let's evaluate the extent of this case:

In [24]:
```
(tmdb_movie_data_df.budget == 0).sum(), (tmdb_movie_data_df.budget_adj == 0)
```

Out[24]:
```
(5696, 5696, 10865)
```

There are quite a lot of movies without budget info, so we can't get rid of them as we would be losing half our dataset. I'll have to filter those out when I want to do any analysis that involves this variable. Let's see what's the situation with the `revenue` :

In [25]:
```
(tmdb_movie_data_df.revenue == 0).sum(), (tmdb_movie_data_df.revenue_adj ==
```

Out[25]:
```
(6016, 6016, 10865)
```

In this case, since we're going to be using this as a dependent variable for some of the questions, we have no option but to drop those fields. Let's we how many movies have both ``budget`` or ``revenue`` at 0:

In [26]:
```
((tmdb_movie_data_df.budget == 0) & (tmdb_movie_data_df.revenue != 0)).sum()
```

Out[26]:
```
995
```

So it seems there are are some movies with a `revenue` value but not a `budget` value. I think the safest course of action, given the questions that I've formulated in the previous section, is to drop the rows without a `revenue` value, and keep those without a `budget` value, and make sure those are filtered out whenever I'm doing an analysis that involves both values.

In [27]:
```
tmdb_movie_data_df = tmdb_movie_data_df[tmdb_movie_data_df.revenue != 0]
```

In [28]:
```
(tmdb_movie_data_df.revenue == 0).sum(), (tmdb_movie_data_df.revenue_adj ==
```

Out[28]:
```
(0, 0)
```

The next step is to adjust the `budget` and `revenue` to 2021 USD values. Before we can do that, let's analyise the `fp_cpi_totl_zg_df` dataframe:

In [29]:
```
fp_cpi_totl_zg_df.head()
```

Out[29]:

	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	1964	1965	...
0	Aruba	ABW	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...
1	Africa Eastern and Southern	AFE	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...
2	Afghanistan	AFG	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...
3	Africa Western and Central	AFW	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...
4	Angola	AGO	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	NaN	NaN	NaN	NaN	NaN	NaN	...

5 rows × 67 columns

As you can see, the values are indexed on the country name, with a column for each year. The first thing we need to do is to keep only the values for the US, as (I assume) the budget and revenue values are in US dollars:

In [30]:
```
inflation_rate_df = fp_cpi_totl_zg_df[fp_cpi_totl_zg_df["Country Code"] == '
```

In [31]:
```
inflation_rate_df.head()
```

Out[31]:

	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962	1963	
251	United States	USA	Inflation, consumer prices (annual %)	FP.CPI.TOTL.ZG	1.457976	1.070724	1.198773	1.239669	1.2

1 rows × 67 columns

Now we have just the one row, but we need to drop the redundant columns:

In [32]:
```
inflation_rate_df = inflation_rate_df.drop(["Country Name", "Country Code",
```

In [33]:
```
inflation_rate_df.head()
```

Out[33]:

	1960	1961	1962	1963	1964	1965	1966	1967	1968
251	1.457976	1.070724	1.198773	1.239669	1.278912	1.585169	3.015075	2.772786	4.27179

1 rows × 63 columns

Now, we transpose the dataframe, and rename the columns, to make them easier to work with:

In [34]:
```
inflation_rate_df = inflation_rate_df\
    .T\
    .rename({251: "inflation_rate"}, axis=1)
```

In [35]:
```
inflation_rate_df.head()
```

Out[35]:

	inflation_rate
1960	1.457976
1961	1.070724
1962	1.198773
1963	1.239669
1964	1.278912

Now we check for missing values, and drop them if necessary:

In [36]:
```
inflation_rate_df.inflation_rate.isna().sum()
```

Out[36]: 1

In [37]:
```
inflation_rate_df[inflation_rate_df.inflation_rate.isna()]
```

Out[37]:

	inflation_rate
Unnamed: 66	NaN

In [38]:
```
inflation_rate_df.dropna(inplace=True)
```

In [39]:
```
inflation_rate_df.inflation_rate.isna().sum()
```

Out[39]:
```
0
```

Since we want my intention is to merge with the `tmdb_movie_data_df` dataframe on the `release_year` column, we need to convert the index of `inflation_rate_df` to `int` :

In [40]:
```
inflation_rate_df.index = inflation_rate_df.index.astype(int)
```

The last step is to compute the adjustment factor for each year. The formula for this transformation is defined in this blogpost.

In [41]:
```
inflation_rate_df["adj_factor_2021"] = inflation_rate_df.apply(
    lambda r: ((inflation_rate_df.loc[(inflation_rate_df.index >= r.name) &
    axis=1
)
```

In [42]:
```
inflation_rate_df.head()
```

Out[42]:

	inflation_rate	adj_factor_2021
1960	1.457976	9.295703
1961	1.070724	9.162122
1962	1.198773	9.065060
1963	1.239669	8.957678
1964	1.278912	8.847992

Now to adjust a value to 2021 US dollors, all I need to do is to multiply to the factor associated with the given year.

Now let's add `budget_adj_2021` and `revenue_adj_2021` columns to the `tmdb_movie_data_df` . First we merge with `inflation_rate_df` on `release_year` :

In [43]:
```
tmdb_movie_data_df = tmdb_movie_data_df.merge(
    inflation_rate_df[["adj_factor_2021"]],
    left_on="release_year",
    right_index=True,
    how="left"
)
```

In [44]:
```
tmdb_movie_data_df.head()
```

Out[44]:

	id	imdb_id	popularity	budget	revenue	original_title	cast
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...

5 rows × 22 columns

Now all wee need to do is to multiply `budget` and `revenue` by `adj_factor_2021` :

In [45]:
```
tmdb_movie_data_df["budget_adj_2021"] = tmdb_movie_data_df.apply(lambda r: r
```

In [46]:
```
tmdb_movie_data_df["revenue_adj_2021"] = tmdb_movie_data_df.apply(lambda r:
```

In [47]:
```
tmdb_movie_data_df.head()
```

Out[47]:

	id	imdb_id	popularity	budget	revenue	original_title	cast
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...

5 rows × 24 columns

I need to turn the `release_date` column into a `datetime` to make analysis on the componentes of the date much easier:

In [48]:
```
tmdb_movie_data_df["release_date"] = pd.to_datetime(tmdb_movie_data_df.relea
```

In [49]:
```
tmdb_movie_data_df[["release_date"]].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4849 entries, 0 to 10848
Data columns (total 1 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   release_date  4849 non-null   datetime64[ns]
dtypes: datetime64[ns](1)
memory usage: 75.8 KB
```

Now performing analysis on the components of the datetime much easier:

In [50]:
```
tmdb_movie_data_df.release_date.dt.year.value_counts()
```

Out[50]:
```
2013    244
2011    241
2014    228
2010    217
2012    216
2015    216
2008    206
2006    206
2009    200
2007    195
2005    184
2004    164
2002    139
2003    139
2001    128
1999    118
2000    111
1993    108
1997    107
1998    106
1996    104
1995    100
1994     87
1992     82
1988     81
1990     77
1989     77
1986     76
1987     72
1991     70
1985     67
1984     53
1983     52
1981     40
1982     40
1980     39
1979     27
1978     24
1977     24
1973     17
1974     17
1976     16
1975     15
2071     14
2067     14
2070     13
2068     12
2061     10
1972     10
2062      9
2064      8
2060      7
2063      7
2065      5
2069      5
2066      5
Name: release_date, dtype: int64
```

The last step is to split the `genres` and `director` multi-valued cells that are going to be use for analysis:

In [51]:
```
tmdb_movie_data_df["genres"] = tmdb_movie_data_df.genres.str.split("|")
```

In [52]:
```
tmdb_movie_data_df["director"] = tmdb_movie_data_df.director.str.split("|")
```

Exploratory Data Analysis

Which genres are most popular from year to year?

We're going to asume that "popular" means "Number of movies made" instead of using the `popularity` field. Before we can do any analysis on the `genre`, we need to split the values on each cell using the `DataFrame.explode` method:

In [53]:
```
tmdb_movie_data_genre_df = tmdb_movie_data_df.explode("genres")
```

In [54]:
```
tmdb_movie_data_genre_df.head()
```

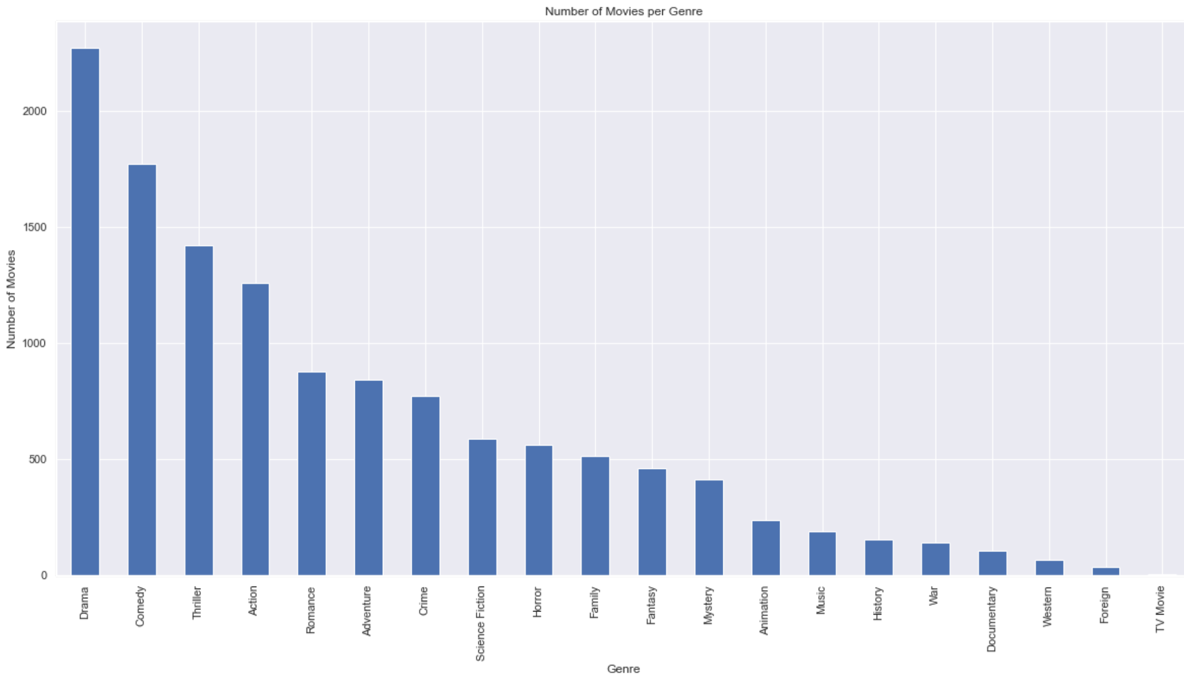
Out[54]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http:/

5 rows × 24 columns

Let's see what are the most popular genres overall:

In [55]:
```
tmdb_movie_data_genre_df\
    .genres\
    .value_counts()\
    .plot(kind="bar", figsize=(20, 10));
plt.ylabel('Number of Movies');
plt.xlabel('Genre');
plt.title('Number of Movies per Genre');
```

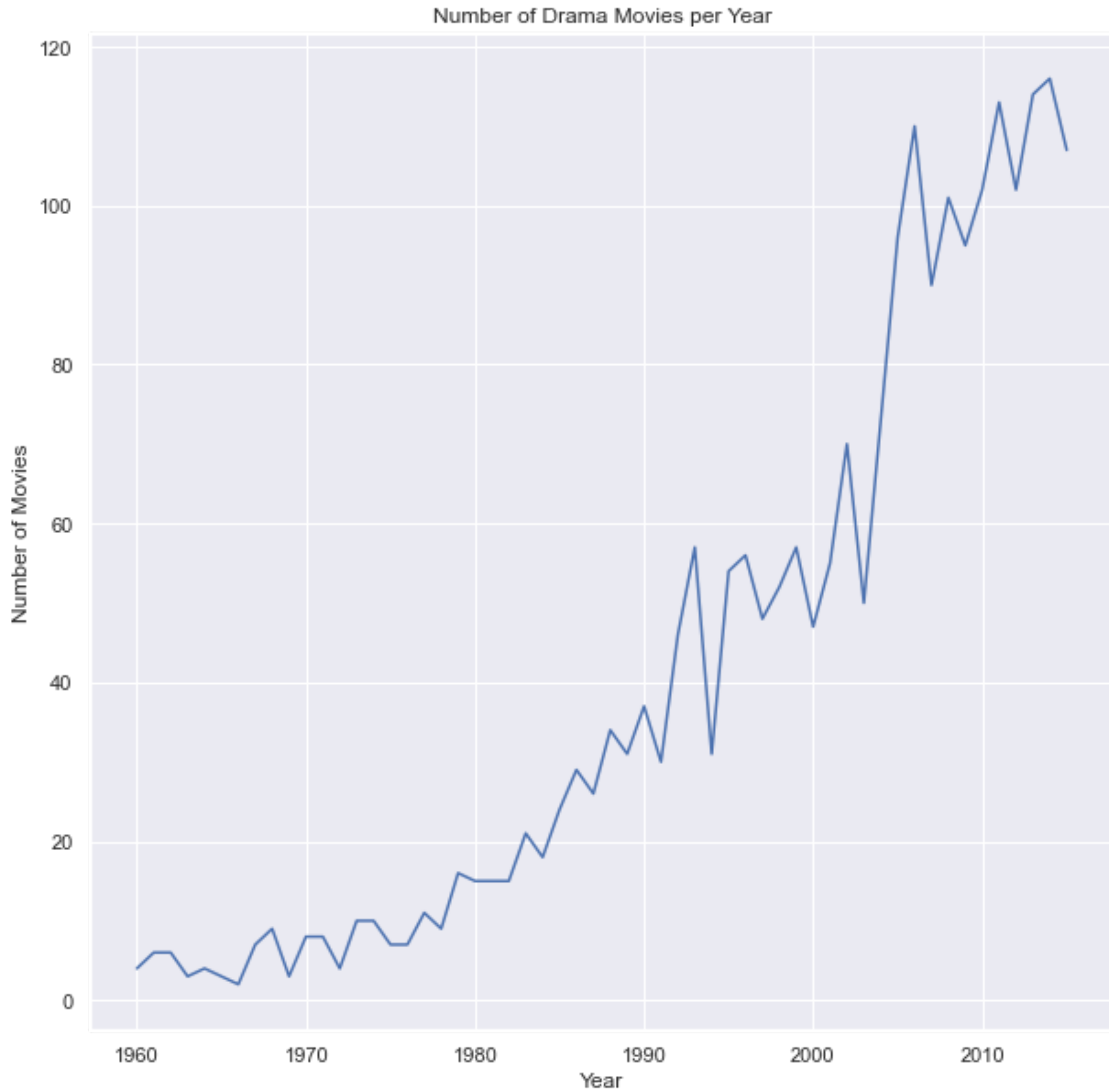


Let's see if this picture is repeated throughout the years. We're going to use the same year axis for all plots.

In [56]:
```
year_idx = tmdb_movie_data_genre_df.release_year.sort_values().unique()
```

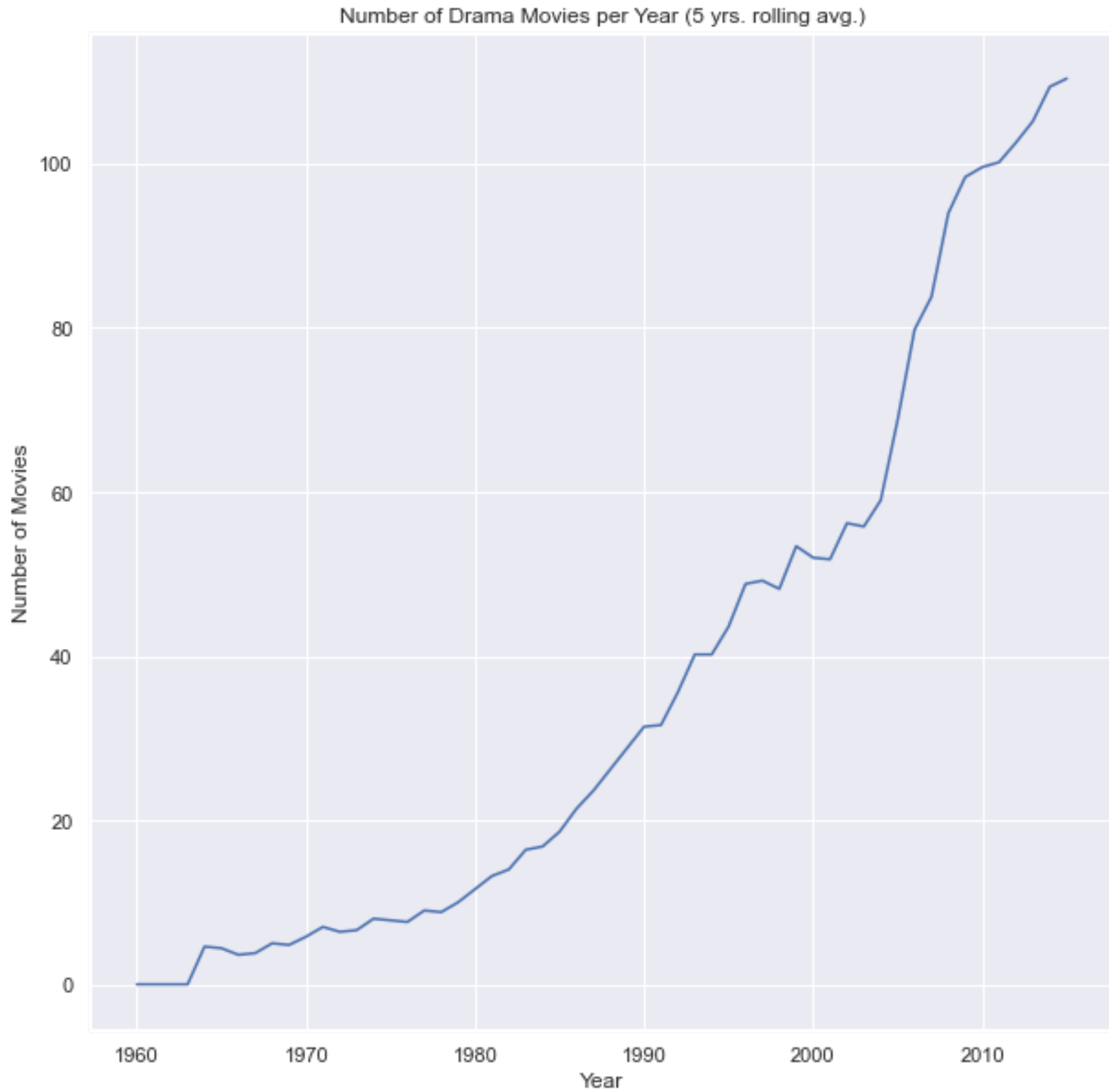
Let's plot the number of "drama" movies throughout the years:

In [57]:
```
plt.figure(figsize=(10, 10))
plt.ylabel('Number of Movies');
plt.xlabel('Year');
plt.title('Number of Drama Movies per Year');
plt.plot(
    year_idx,                                                               #
    tmdb_movie_data_genre_df[tmdb_movie_data_genre_df.genres == "Drama"]   #
        .groupby("release_year")                                            #
        .imdb_id.count()                                                    #
        .reindex(year_idx).fillna(0));                                      #
```



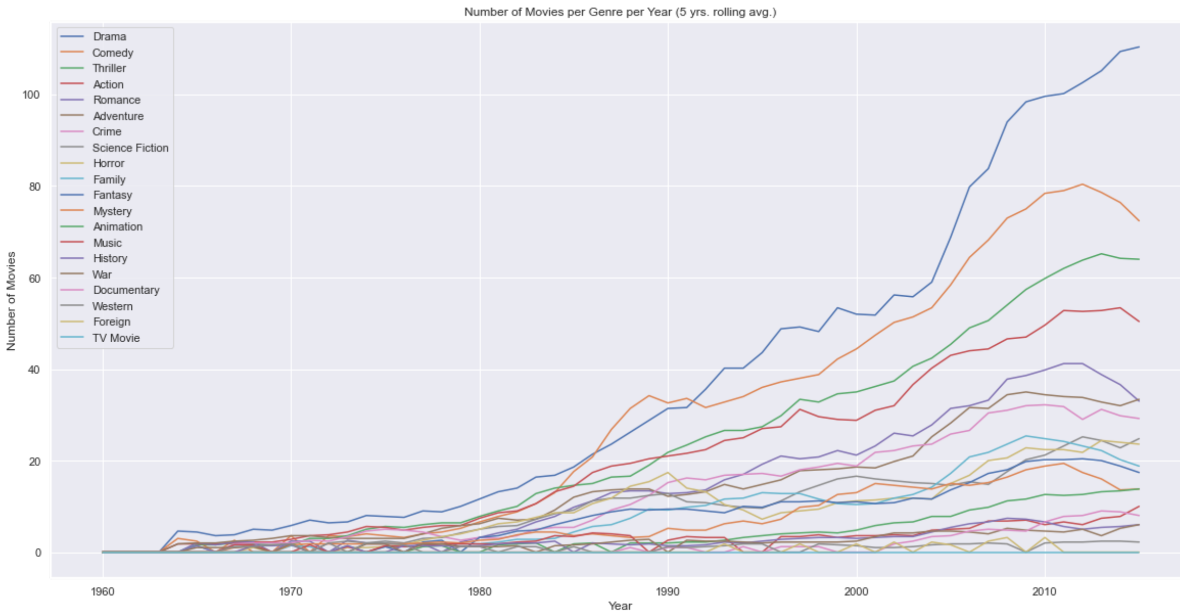
Let's try the moving averages trick to smoothout the line:

In [58]:
```
plt.figure(figsize=(10, 10))
plt.ylabel('Number of Movies');
plt.xlabel('Year');
plt.title('Number of Drama Movies per Year (5 yrs. rolling avg.)');
plt.plot(
    year_idx,                                                              #
    tmdb_movie_data_genre_df[tmdb_movie_data_genre_df.genres == "Drama"]   #
        .groupby("release_year")                                           #
        .imdb_id.count()                                                   #
        .rolling(5).mean()                                                 #
        .reindex(year_idx).fillna(0)                                       #
);
```



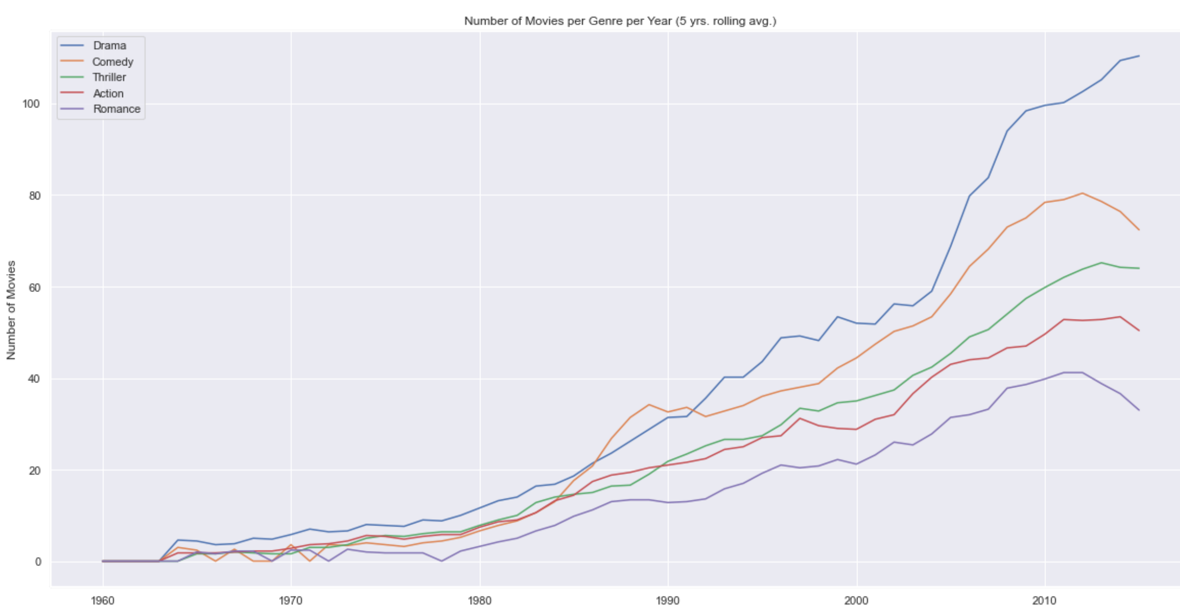
Now let's plot the progression of all genres:

In [59]:
```
plt.figure(figsize=(20, 10))
plt.ylabel('Number of Movies');
plt.xlabel('Year');
plt.title('Number of Movies per Genre per Year (5 yrs. rolling avg.)');
for genre in tmdb_movie_data_genre_df.genres.value_counts().index.to_list():
    plt.plot(
        year_idx,
        tmdb_movie_data_genre_df[tmdb_movie_data_genre_df.genres == genre]
            .groupby("release_year")
            .imdb_id.count()
            .rolling(5).mean()
            .reindex(year_idx).fillna(0),
        label=genre);
plt.legend();
```



The chart is kinda hard to parse, let's pickly only the 5 top genres:

In [60]:
```
plt.figure(figsize=(20, 10))
plt.ylabel('Number of Movies');
plt.xlabel('Year');
plt.title('Number of Movies per Genre per Year (5 yrs. rolling avg.)');
for genre in tmdb_movie_data_genre_df.genres.value_counts().index.to_list()[
    plt.plot(
        year_idx,
        tmdb_movie_data_genre_df[tmdb_movie_data_genre_df.genres == genre]\
            .groupby("release_year")\
            .imdb_id.count()\
            .rolling(5).mean()\
            .reindex(year_idx).fillna(0),
        label=genre);
plt.legend();
```

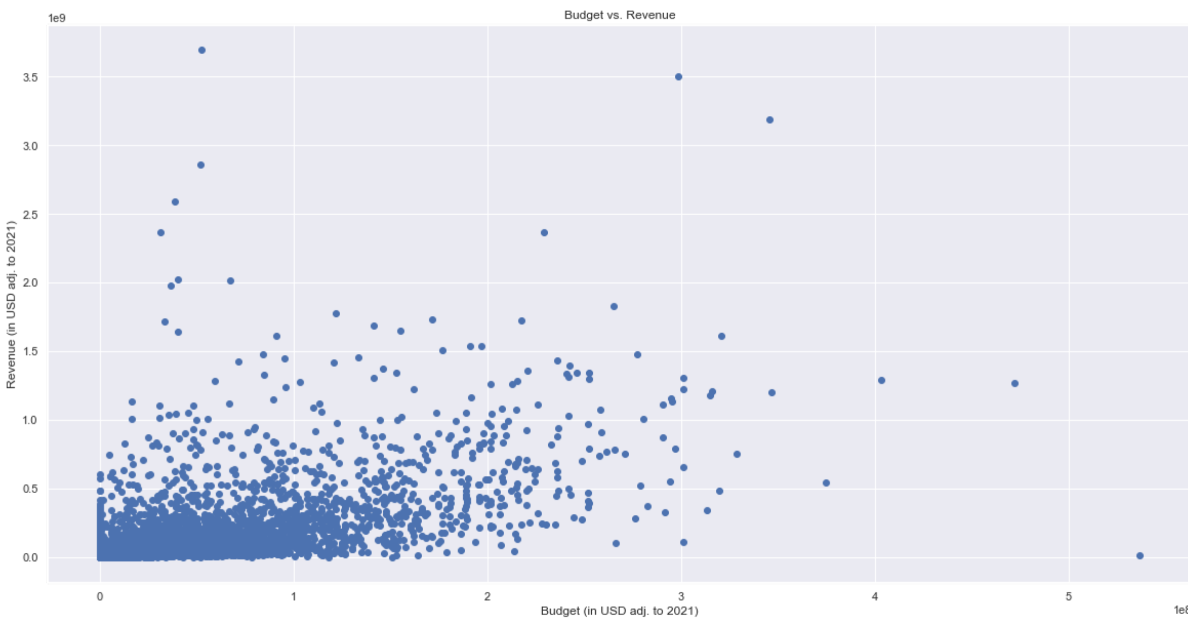


As we can see, drama movies were indeed always popular, but they were briefly surpassed by comedies in the late 90s.

What kinds of properties are associated with movies that have high revenues?

Does a higher budget lead to more revenue?

In [61]:
```
plt.figure(figsize=(20, 10))
plt.ylabel('Revenue (in USD adj. to 2021)');
plt.xlabel('Budget (in USD adj. to 2021)');
plt.title('Budget vs. Revenue');
plt.scatter(
    tmdb_movie_data_df.budget_adj_2021,   # 2021 Adjusted budget vs.
    tmdb_movie_data_df.revenue_adj_2021,  # 2021 Adjusted revenue
);
```



I can't really conclude from the chart that a higher revenue does imply a higher revenue. Let's compute the correlation factor:

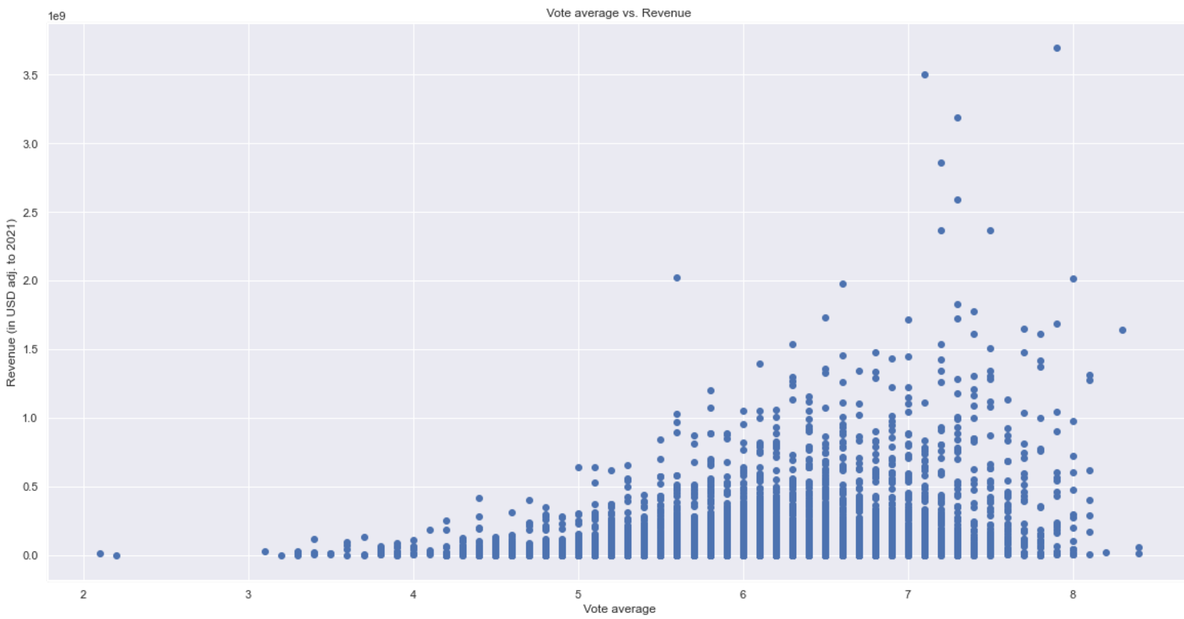
In [62]:
```
tmdb_movie_data_df.budget_adj_2021.corr(tmdb_movie_data_df.revenue_adj_2021)
```

Out[62]:
```
0.5877953736810668
```

This would imply that there is indeed a correlation between the two variables.

Are highly rated movies good performers?

In [63]:
```
plt.figure(figsize=(20, 10))
plt.ylabel('Revenue (in USD adj. to 2021)');
plt.xlabel('Vote average');
plt.title('Vote average vs. Revenue');
plt.scatter(
    tmdb_movie_data_df.vote_average,      # Vote average
    tmdb_movie_data_df.revenue_adj_2021,  # 2021 Adjusted revenue
);
```



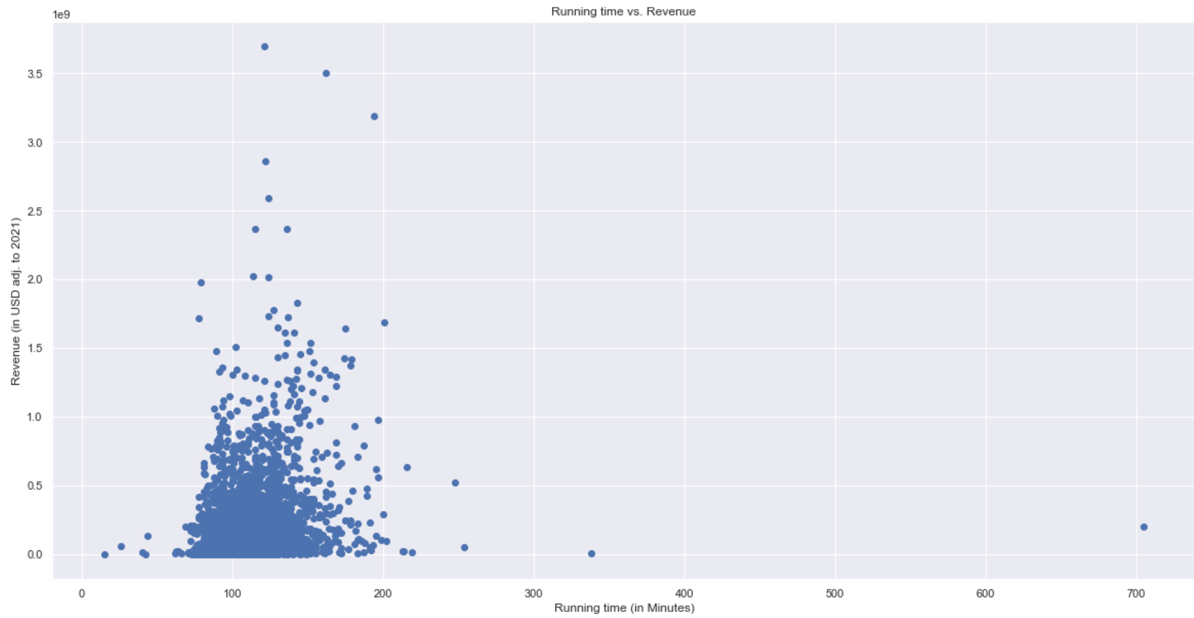
In [64]:
```
tmdb_movie_data_df.vote_average.corr(tmdb_movie_data_df.revenue_adj_2021)
```

Out[64]:
```
0.24293287516604284
```

Both the chart and the correlation factor show there's no strong correlation between the variables.

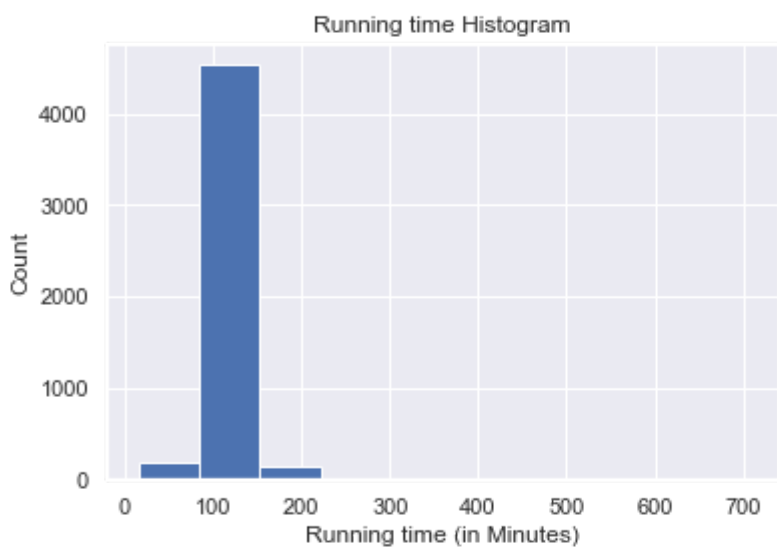
Does the running time influence the revenue?

In [65]:
```
plt.figure(figsize=(20, 10))
plt.ylabel('Revenue (in USD adj. to 2021)');
plt.xlabel('Running time (in Minutes)');
plt.title('Running time vs. Revenue');
plt.scatter(
    tmdb_movie_data_df.runtime,           # Running time
    tmdb_movie_data_df.revenue_adj_2021,  # 2021 Adjusted revenue
);
```



It's hard to take any conclusions of the chart as most samples are bunched around the 120 minute mark, and there are a few outliers.

In [66]:
```
tmdb_movie_data_df.runtime.hist();
plt.ylabel('Count');
plt.xlabel('Running time (in Minutes)');
plt.title('Running time Histogram');
```



I don't know if this distribution would allow me to extract any valuable information out of it.

In [67]:
```
tmdb_movie_data_df.runtime.corr(tmdb_movie_data_df.revenue_adj_2021)
```

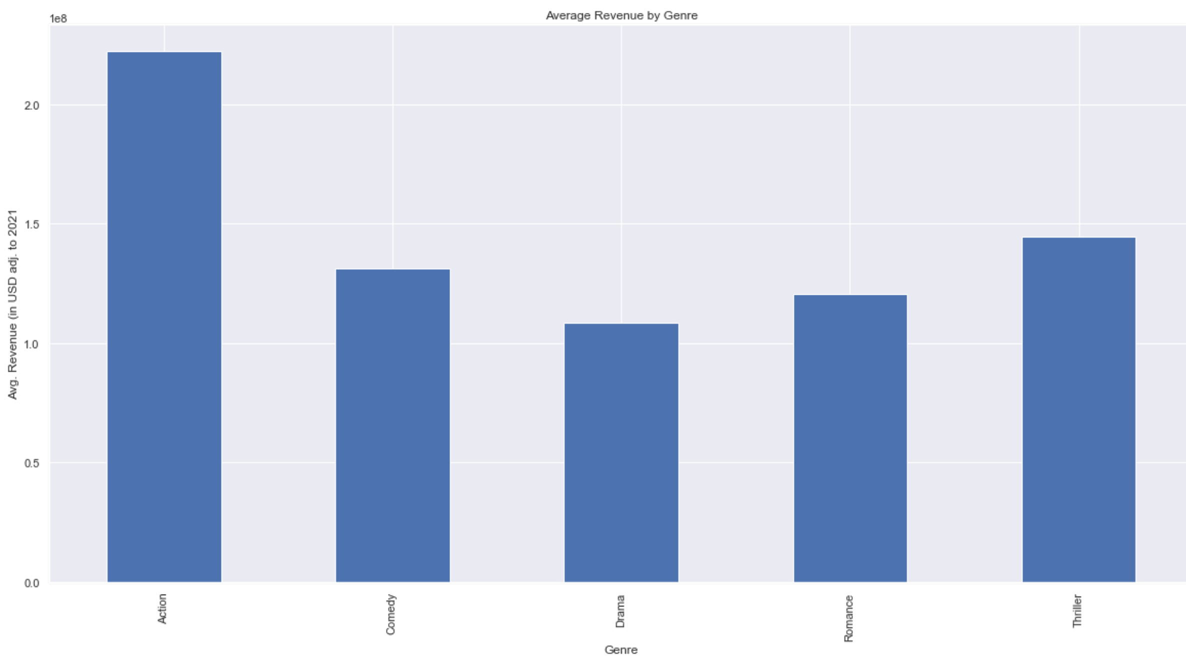
Out[67]: 0.2632592523685177

Again, not a strong correlation between the two.

Does the genre play a role on the revenue?

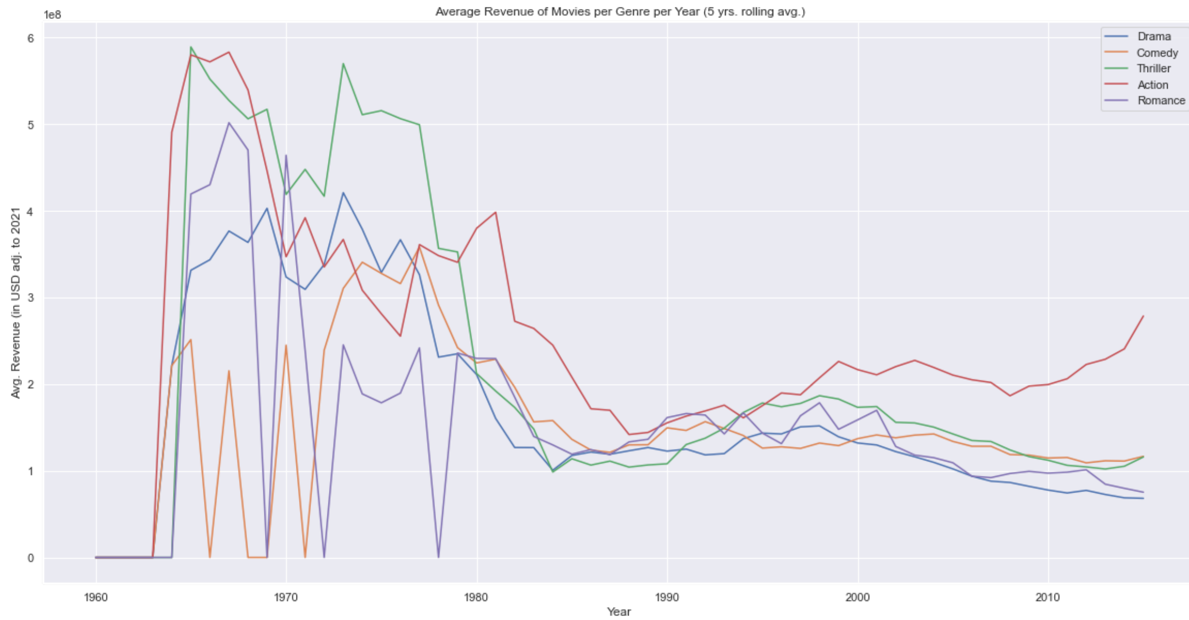
Let's take the 5 most popular genres and see if any one of them consistently outperform the others in terms of revenue.

In [68]:
```
tmdb_movie_data_genre_df[tmdb_movie_data_genre_df.genres.isin(
    tmdb_movie_data_genre_df.genres.value_counts().index.to_list()[:5]
)].groupby("genres").revenue_adj_2021.mean().plot(kind="bar", figsize=(20, 1
plt.ylabel("Avg. Revenue (in USD adj. to 2021");
plt.xlabel("Genre");
plt.title("Average Revenue by Genre");
```



Quite unsurprisingly action movies outperformed all the other genres, but was it always the case?

In [69]:
```
plt.figure(figsize=(20, 10))
plt.ylabel("Avg. Revenue (in USD adj. to 2021");
plt.xlabel('Year');
plt.title('Average Revenue of Movies per Genre per Year (5 yrs. rolling avg.
for genre in tmdb_movie_data_genre_df.genres.value_counts().index.to_list()[
    plt.plot(
        year_idx,
        tmdb_movie_data_genre_df[tmdb_movie_data_genre_df.genres == genre]
            .groupby("release_year")
            .revenue_adj_2021.mean()
            .rolling(5).mean()
            .reindex(year_idx).fillna(0),
        label=genre);
plt.legend();
```



It's no clear to see, but during the 70s, thrillers outperformed action films, so a specific genre is not a recipe for success.

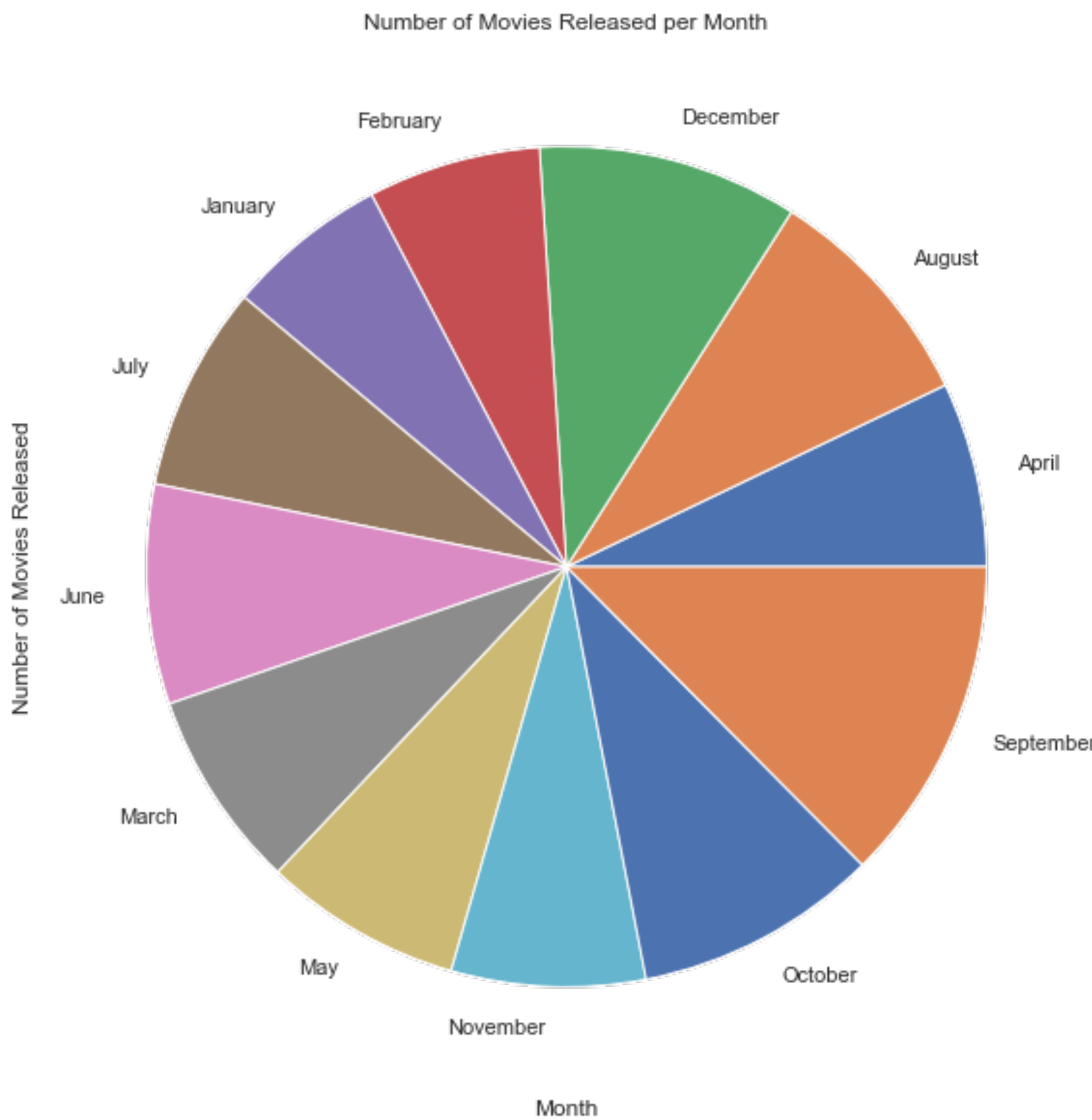
Is there a specific month of the year were the highest grossing films released? Is this consistent across genres?

Let's see how films are usually released throughout the year. First we create a new column with the release month:

In [70]:
```
tmdb_movie_data_df["release_month"] = tmdb_movie_data_df.release_date.dt.mor
```

Then we plot the amount of movies released on each month:

In [71]:
```
tmdb_movie_data_df\
    .groupby("release_month")\
    .imdb_id.count()\
    .plot(kind="pie", figsize=(20, 10));
plt.ylabel("Number of Movies Released");
plt.xlabel("Month");
plt.title("Number of Movies Released per Month");
```

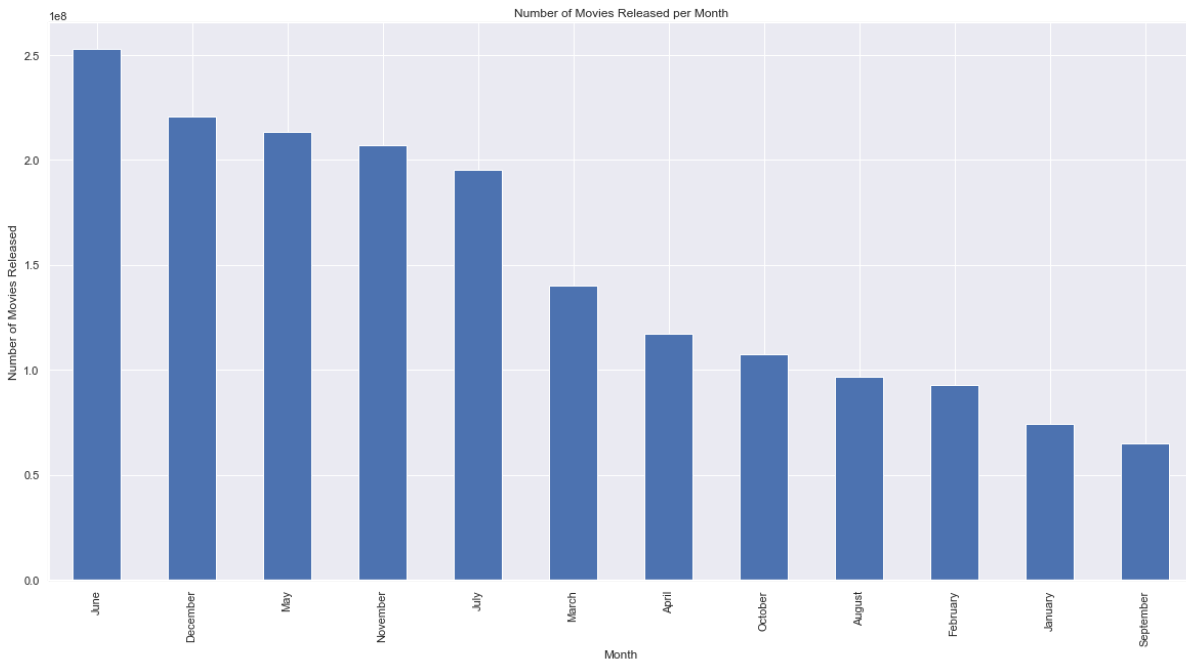


As we can see, the releases a pretty evenly distributed throughout the year. Are there any specific months were the highest grosing films are released?

In [72]:
```
tmdb_movie_data_df.groupby("release_month").revenue_adj_2021.mean()
```

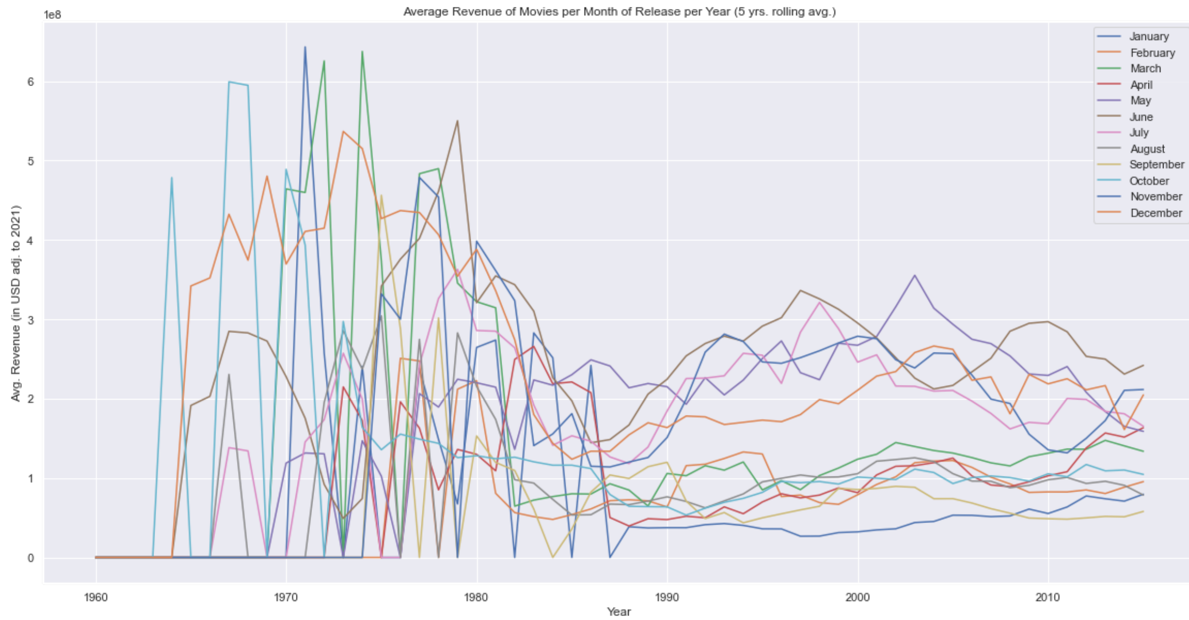
Out[72]:
```
release_month
April        1.171574e+08
August       9.662204e+07
December     2.206492e+08
February     9.275970e+07
January      7.403427e+07
July         1.953627e+08
June         2.526292e+08
March        1.402465e+08
May          2.130237e+08
November     2.067638e+08
October      1.075877e+08
September    6.475442e+07
Name: revenue_adj_2021, dtype: float64
```

In [73]:
```
tmdb_movie_data_df\
    .groupby("release_month")\
    .revenue_adj_2021.mean()\
    .sort_values(ascending=False)\
    .plot(kind="bar", figsize=(20, 10));
plt.ylabel("Number of Movies Released");
plt.xlabel("Month");
plt.title("Number of Movies Released per Month");
```



It would seem that May, June, July (beginning of summer), November and December (holiday season) are were the highest grossing films are released. Was it always like this?

In [74]:
```
plt.figure(figsize=(20, 10))
plt.ylabel("Avg. Revenue (in USD adj. to 2021)");
plt.xlabel('Year');
plt.title('Average Revenue of Movies per Month of Release per Year (5 yrs. r
for month in ["January", "February", "March", "April", "May", "June", "July"
    plt.plot(
        year_idx,                                                         # Inc
        tmdb_movie_data_df[tmdb_movie_data_df.release_month == month]  # Fil
            .groupby("release_year")                                      # Gro
            .revenue_adj_2021.mean()                                      # Rev
            .rolling(5).mean()                                            # Rol
            .reindex(year_idx).fillna(0),                                 # Fil
        label=month);
plt.legend();
```



It would seem that the monthly distribution changed over the years, but the tendencies have endured.

Of the top 5 most prolific directors, which one had the most consistently highly rated films?

First, let's look which are the most prolific directors.

In [75]:
```
tmdb_movie_data_director_df = tmdb_movie_data_df.explode("director")
```

In [76]:
```
tmdb_movie_data_director_df.head()
```

Out[76]:

	id	imdb_id	popularity	budget	revenue	original_title	cast
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...

5 rows × 25 columns

Let's use `Series.value_counts` to get the directos with the most rows:

In [77]:
```
tmdb_movie_data_director_df\
    .director\
    .value_counts()\
    .iloc[:5]
```

Out[77]:
```
Steven Spielberg    28
Clint Eastwood      26
Ridley Scott        22
Woody Allen         22
Ron Howard          18
Name: director, dtype: int64
```

Now let's see how their movies perform in terms of popularity, vote average, and revenue.

In [78]:
```
top_5_directors = tmdb_movie_data_director_df.director.value_counts().iloc[:
```

In [79]:
```
tmdb_movie_data_director_df[tmdb_movie_data_director_df.director.isin(top_5_
    .groupby("director")[["popularity", "vote_average", "revenue_adj_2021"]]
    .describe()
```

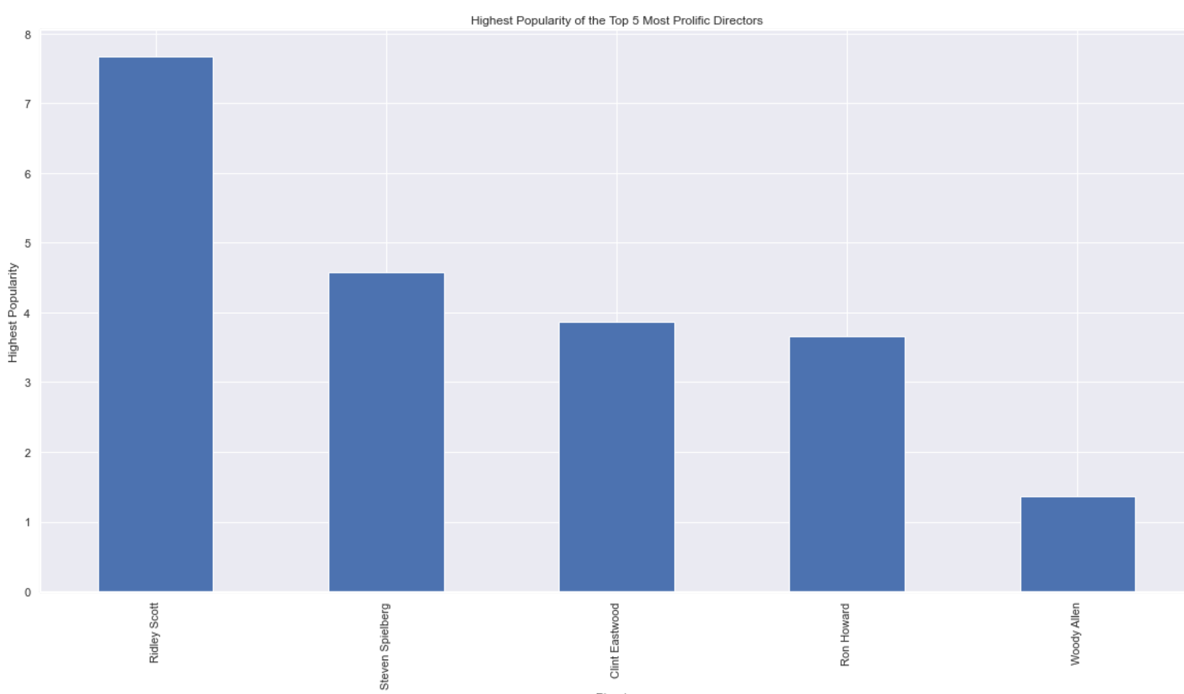
Out[79]:

	popularity								
	count	mean	std	min	25%	50%	75%	max	c
director									
Clint Eastwood	26.0	0.956933	0.732361	0.245162	0.597541	0.733779	1.088227	3.863074	
Ridley Scott	22.0	2.082423	1.927945	0.320540	0.654909	1.519517	3.389883	7.667400	
Ron Howard	18.0	1.446277	1.037013	0.309976	0.643578	0.991402	2.186163	3.655536	
Steven Spielberg	28.0	1.920691	1.170379	0.210550	0.976488	2.136865	2.647532	4.578300	
Woody Allen	22.0	0.678411	0.327162	0.133990	0.418351	0.665965	0.917104	1.367727	

5 rows × 24 columns

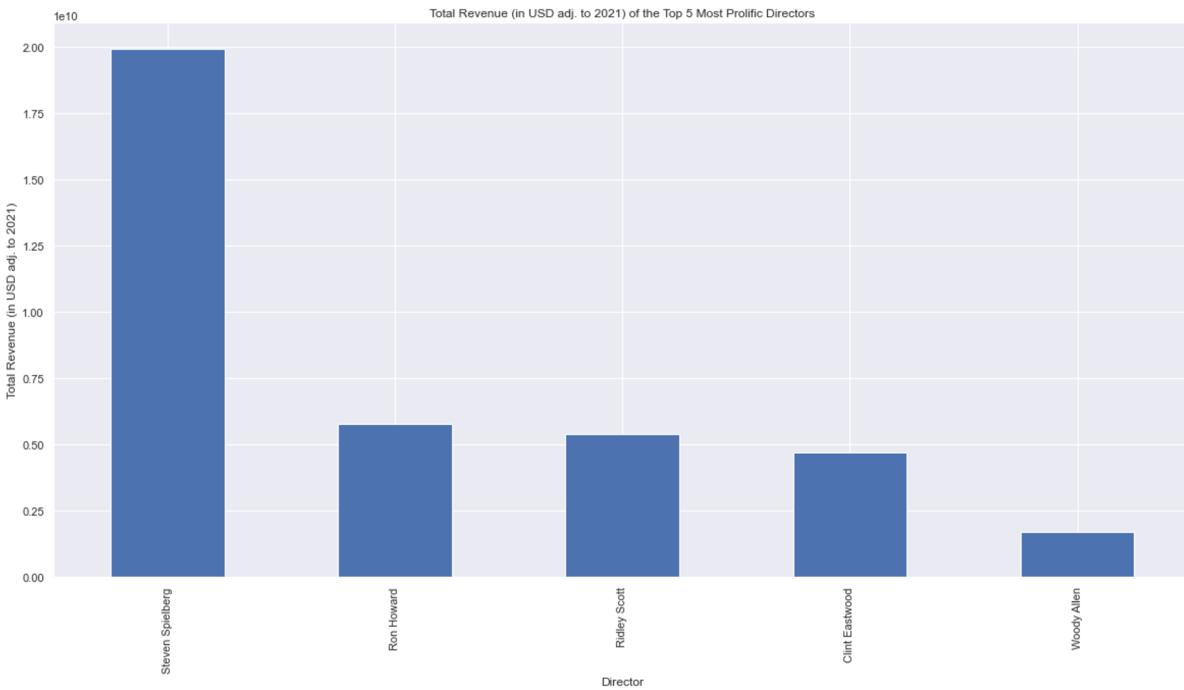
Which one of this directors has the most popular movie?

In [80]:
```
tmdb_movie_data_director_df[tmdb_movie_data_director_df.director.isin(top_5_
    .groupby("director")\
    .popularity.max()\
    .sort_values(ascending=False)\
    .plot(kind="bar", figsize=(20, 10));
plt.ylabel("Highest Popularity");
plt.xlabel("Director");
plt.title("Highest Popularity of the Top 5 Most Prolific Directors");
```



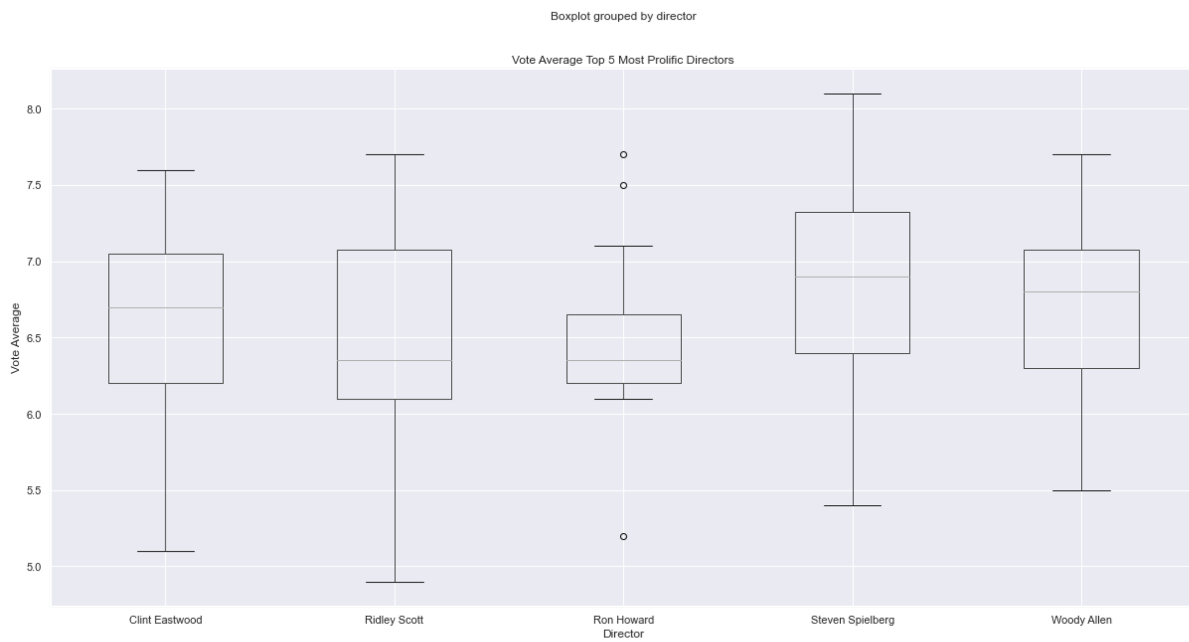
Is Ridley Scott also the highest grossing of the bunch?

In [81]:
```
tmdb_movie_data_director_df[tmdb_movie_data_director_df.director.isin(top_5_
    .groupby("director")\
    .revenue_adj_2021.sum()\
    .sort_values(ascending=False)\
    .plot(kind="bar", figsize=(20, 10));
plt.ylabel("Total Revenue (in USD adj. to 2021)");
plt.xlabel("Director");
plt.title("Total Revenue (in USD adj. to 2021) of the Top 5 Most Prolific Di
```



Unsurprising, given that Steven Spielberg is the most prolific of the bunch. But how has Spielberg's work evolved over the years?

In [82]:
```
tmdb_movie_data_director_df[tmdb_movie_data_director_df.director.isin(top_5_
    .boxplot("vote_average", by="director", figsize=(20, 10));
plt.ylabel("Vote Average");
plt.xlabel("Director");
plt.title("Vote Average Top 5 Most Prolific Directors");
```



It's pretty clear from the chart that Steven Spielberg is consistently well rated.

Conclusions

Which genres are most popular from year to year?

Before any work was done I had to make an assumption of what "popularity" means. We do have a `popularity` column, but given that it is a synthetic variable computed from multiple sources it would be hard to reach any conclusions about it. Because of this, I chose the number of movies made as a measure of popularity of the genre.

With this in mind, the charts showed somewhat clearly (after smoothing them out) that Drama is a consistent winner in terms of popularity, followed by Comedy and Thriller. Moreover, with only a few exceptions, this situation remained the same througout the years.

What kinds of properties are associated with movies that have high revenues?

I've tried a explored a few variables that might lead to a higher revenue value, but other than a higher budget and genre (Action in particular) seem to imply a higher revenue (no surprises here).

I thought a higher vote rating would lead to higher revenues, but the correlation was weak, same as with the runtime.

Is there a specific month of the year were the highest grossing films released? Is this consistent across genres?

Although this question could have been answered in the context of the previous one, I wanted to focus on the release month specifically to do a more in depth analysis.

The conclusion of this analysis is that movies released in the summer and holiday seasons seem to do better than those released throughout the year. Perhaps people have more time to go to the movies during these seasons, or maybe studios specifically wait until these times to release movies that they expect to be the highest grossing ones.

Of the top 5 most prolific directors, which one had the most consistently highly rated films?

The main conclusion here is that Steven Spielberg is a movie making machine. He's incredibly prolific, and his seem to be financial and critical successes.

Limitations

All of these conclusions are to be taken with a grain of salt as there a quite a few limitations with the dataset:

- There's not much metadata about the dataset. The kaggle page does not provide (AFAIK) explicit descriptions of each column. The TMDb website does contain documentation about their APIs, but it's not clear what was done by Kaggle to curate it.
- There's not much data available, specially for the earlier years. This makes any time-based analysis inaccurate for certain periods. This is is clearly shown in the charts over time.
- There's no actual viewership numbers that would lead to a more accurate popularity variable. I could have inferred this from the vote count, but that was an assumption I was not willing to make.