Final Project Submission

Please fill out:

- Student name: Abigail Campbell
- Student pace: Flex
- Scheduled project review date/time: 3:00PM EST, 9/6/23
- Instructor name: Morgan Jones
- Blog post URL: https://medium.com/@abbycampbell0/a-brief-and-incomplete-history-of-ai-468845a93b24 (https://medium.com/@abbycampbell0/a-brief-and-incomplete-history-of-ai-468845a93b24)

Setup

Import relevant packages

In [1]:
```
import sqlite3
import pandas as pd
import numpy as np
import zipfile
import scipy.stats as stats
import statsmodels.api as sm

import seaborn as sns
import matplotlib.pyplot as plt
# plt.style.use('seaborn-v0_8-whitegrid')
%matplotlib inline
```

Load and Clean Data

Movie Info

1552 entries after filtering

Remove columns: currency, writer, runtime, synopsis, dvd_date

runtime note: value = integers, but each integer is followed by 'minutes'

dates note: given as month day, year format

```
- month is in the three letter format
- day is given as 1 or 2 digits (does not put a 0 in from on single
digit days)
- year is alwasy 4 digits
```

Genres given as a list in a single string

In [2]:
```
# load data
movie_info = pd.read_csv('zippedData/rt.movie_info.tsv.gz', sep='\t', thousa

# drop columns that are irrelevent
movie_info = movie_info.drop(['currency', 'writer', 'runtime', 'synopsis', '

# remove NaN rows for genre
movie_info = movie_info.dropna(axis=0, subset=['genre'])

# separate genre into a list of genres
movie_info['genre'] = movie_info['genre'].map(lambda x: x.split('|'))
```

Reviews

40915 entries after filtering

Review format = rating/total possible

Fresh = fresh and rotten are the only two values - will probably use this as the rating metric

Date: given as month day, year format

- month is in the three letter format
- day is given as 1 or 2 digits (does not put a 0 in from on single digit days)
- year is alwasy 4 digits

In [3]:
```
# load data
reviews = pd.read_csv('zippedData/rt.reviews.tsv.gz', sep='\t', encoding='un

# convert fresh column to 0 (rotten) or 1 (fresh)
reviews['fresh_rating'] = reviews['fresh'].map(lambda x: 0 if 'rotten' in x

# remove all rows with no rating
reviews = reviews.dropna(axis=0, subset=['rating'])

reviews.info()
# reviews['fresh_rating'].value_counts()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 40915 entries, 0 to 54431
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            40915 non-null  int64 
 1   review        35379 non-null  object
 2   rating        40915 non-null  object
 3   fresh         40915 non-null  object
 4   critic        38935 non-null  object
 5   top_critic    40915 non-null  int64 
 6   publisher     40688 non-null  object
 7   date          40915 non-null  object
 8   fresh_rating  40915 non-null  int64 
dtypes: int64(3), object(6)
memory usage: 3.1+ MB
```

Budgets

5792 entries after filtering

The budget and gross columns contain a dollar sign at the beginning of the value, as well as columns to separate out thousands.

```
- remove dollar sign
- remove commas
- convert to integer
```

drop any entires with now movie title

In [4]:
```
# load data
budgets = pd.read_csv('zippedData/tn.movie_budgets.csv.gz', thousands=',')

# format the money columns to be integers, without the $ sign
budgets = budgets.drop(['id'], axis=1)
budgets['production_budget'] = budgets['production_budget'].map(lambda x: in
budgets['domestic_gross'] = budgets['domestic_gross'].map(lambda x: int(x[1:
budgets['worldwide_gross'] = budgets['worldwide_gross'].map(lambda x: int(x[

# drop any moves with no title
budgets = budgets.dropna(subset=['movie'])

budgets = budgets.rename(columns={'movie': 'title'})
# budgets = budgets.set_index('title')

# calculate roi
budgets['domestic_roi'] = budgets['domestic_gross']/budgets['production_budg
budgets['worldwide_roi'] = budgets['worldwide_gross']/budgets['production_bu
len(budgets)
```

Out[4]: 5782

SQL IMDB Database

In [5]:
```
# unzip imdb
with zipfile.ZipFile('zippedData/im.db.zip', 'r') as zip_ref:
    zip_ref.extractall('zippedData')

# create connection to the SQL database
conn = sqlite3.connect('zippedData/im.db')
```

Movie Info

140,734 entries after filtering

```
- filtered to only include moves released after 1980 (to only look a
t movies relevant to recent trends)
- filtered out any entries with no movie title or genre
```

split the genre column up into a list of individual genres, rather than a string containing all

In [6]:
```
# table containing move title, id, start_year, and genres
# remove all lines without the genre

sql_movie_basics = pd.read_sql("""
                                SELECT movie_id, original_title, start_year,
                                    FROM movie_basics
                                """, conn)

# remove movies with no title
sql_movie_basics = sql_movie_basics.dropna(subset=['original_title'])

# remove movies before 1980 (trying to stay modern)
sql_movie_basics = sql_movie_basics[sql_movie_basics['start_year'] >= 1980]

# rename title column, drop all rows with no genre information
sql_movie_basics = sql_movie_basics.rename(columns={'original_title': 'title
sql_movie_basics = sql_movie_basics.dropna(axis=0, subset=['genres'])

# split the genres string into a list of individual genres
sql_movie_basics['genres'] = sql_movie_basics['genres'].map(lambda x: x.spli
sql_movie_basics['count'] = 1
sql_movie_basics.to_csv('data/sql_movie_basics.csv')
sql_movie_basics
```

Out[6]:

	movie_id	title	start_year	genres	count
0	tt0063540	Sunghursh	2013	[Action, Crime, Drama]	1
1	tt0066787	Ashad Ka Ek Din	2019	[Biography, Drama]	1
2	tt0069049	The Other Side of the Wind	2018	[Drama]	1
3	tt0069204	Sabse Bada Sukh	2018	[Comedy, Drama]	1
4	tt0100275	La Telenovela Errante	2017	[Comedy, Drama, Fantasy]	1
...	...	...	...	...	...
146138	tt9916428	The Secret of China	2019	[Adventure, History, War]	1
146139	tt9916538	Kuambil Lagi Hatiku	2019	[Drama]	1
146140	tt9916622	Rodolpho Teóphilo - O Legado de um Pioneiro	2015	[Documentary]	1
146141	tt9916706	Dankyavar Danka	2013	[Comedy]	1
146143	tt9916754	Chico Albuquerque - Revelações	2013	[Documentary]	1

140734 rows × 5 columns

Directors

69,772 entries after filtering

```
- a movie with multiple directors will have multiple rows (one per d
irector)
```

match movie titles to their director using the person and movie ids provided in the database

only include movies/directors with more than 10 votes in their rating to ensure that we are getting movies and directors with a wider reach

In [7]:
```
# import directors of movies with more than 10 reviews (to ensure we get mov
director_table = pd.read_sql("""
    SELECT m.primary_title, p.primary_name, r.averagerating, r.numvotes
        FROM movie_basics as m
        JOIN directors as d
            ON m.movie_id = d.movie_id
        JOIN persons as p
            USING(person_id)
        JOIN movie_ratings as r
            USING(movie_id)
        WHERE numvotes > 10
    """, conn)
# drop any duplicate entires
director_table = director_table.drop_duplicates(keep='last')

# rename title column to just title - make all movie title columns univorm
director_table = director_table.rename(columns={'primary_title': 'title'})

director_table.to_csv('data/director_table.csv')
director_table
```

Out[7]:

	title	primary_name	averagerating	numvotes
1	Laiye Je Yaarian	Sukh Sanghera	8.3	31
2	Borderless	Caolan Robertson	8.9	559
3	Borderless	George Llewelyn-John	8.9	559
4	Just Inès	Marcel Grant	6.4	20
8	The Legend of Hercules	Renny Harlin	4.2	50352
...	...	...	...	...
155471	Plugged in	Richard Willett	8.6	27
155472	Caisa	Alexandru Mavrodineanu	8.1	25
155474	Code Geass: Lelouch of the Rebellion - Glorifi...	Gorô Taniguchi	7.5	24
155475	Sisters	Prachya Pinkaew	4.7	14
155476	Sathru	Naveen Nanjundan	6.3	128

69772 rows × 4 columns

Combine tables to get the specific metrics

Combine budgets table and movie info table

Create new colulmns containing the release year and the release month

Since there are several movies released under the same name, only keep the entries where the release year and the start year are within 1 year of each other. If there are still duplicate entries under the same title, drop them, since there is no way of determining which movie the budget data belongs to.

after dropping duplicates, the number of movies there is data for drops from 3473 to 2253.

In [8]:
```
s_basics = budgets.merge(sql_movie_basics, left_on='title', right_on='title'

a realase month and release year column
s_basics['release_year'] = budgets_basics['release_date'].map(lambda x: int(
s_basics['release_month'] = budgets_basics['release_date'].map(lambda x: x[0

 keep the movies that line up with their start year and release year (deal w
ets_basics_2 = budgets_basics[(budgets_basics["release_year"] - budgets_basi
s_basics.to_csv('data/budgets_basics.csv')

title column name to just title - keep all title columns uniform
s_basics = budgets_basics.set_index('title')

ve any duplicate titles - will be hard to combine with other tables when we
s_basics = budgets_basics[~budgets_basics.index.duplicated()]

len(budgets_basics))
```

2253

organize by genre

Since the genres are listed in a single string (e.g. 'Comedy, Action, Adventure'), they need to be separated into a list of individual genres the movies can be organized by the base genres.

In [9]:
```
# separate out the genre column into one row for each individual genre
split_genres = budgets_basics.explode('genres')
split_genres.to_csv('data/split_genre.csv')
```

get the sum and mean aggregations, then combine them so as to include average gross earnings and budget data as well as the total data for that genre.

add new columns calculating the domestic and worldwide ROIs

In [10]:
```
# get aggregations for genre information
genre_roi = split_genres.groupby('genres').mean()
genre_roi_sum = split_genres.groupby('genres').sum()
genre_roi['count'] = genre_roi_sum['count']
genre_roi['total_domestic_gross'] = genre_roi_sum['domestic_gross']
genre_roi['total_worldwide_gross'] = genre_roi_sum['worldwide_gross']

# recalc rois
genre_roi['domestic_roi'] = genre_roi['domestic_gross']/genre_roi['productio
genre_roi['worldwide_roi'] = genre_roi['worldwide_gross']/genre_roi['product

genre_roi.to_csv('data/genre_roi.csv')
genre_roi.describe()
```

Out[10]:

	production_budget	domestic_gross	worldwide_gross	domestic_roi	worldwide_roi	start_year
count	2.100000e+01	2.100000e+01	2.100000e+01	21.000000	21.000000	21.000000
mean	3.998325e+07	4.891433e+07	1.209342e+08	1.278929	2.957526	2013.870849
std	2.491352e+07	2.902721e+07	8.757421e+07	0.278359	0.643543	0.485888
min	1.592538e+07	2.411895e+07	4.881133e+07	0.772692	1.669083	2013.027778
25%	2.316298e+07	2.855176e+07	6.057257e+07	1.060100	2.570243	2013.590551
50%	2.743308e+07	3.332573e+07	7.198656e+07	1.270671	2.900322	2013.741935
75%	5.309025e+07	6.911474e+07	1.606471e+08	1.399047	3.337935	2014.242604
max	9.369193e+07	1.178347e+08	3.213194e+08	1.933618	4.494412	2015.187500

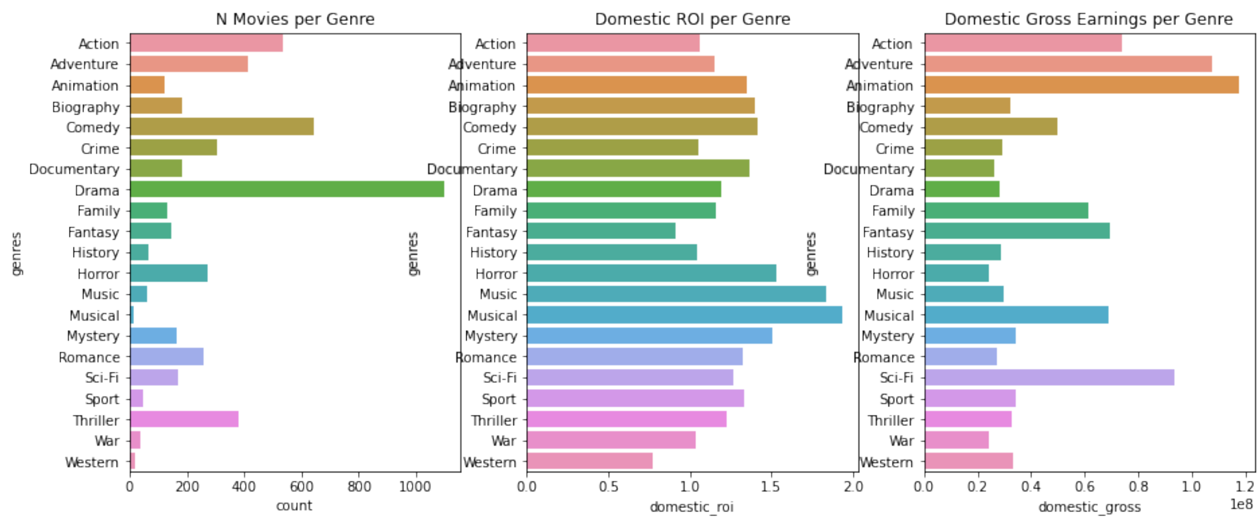
from the describe stats, we can see that the average movie make about $50M at the domestic box office with an average domestic ROI of 1.27

In [11]:
```
# reset index
genre_roi = genre_roi.reset_index()
```

Genre visualizations

plot the number of movies per genre, the average domestic ROI per month per genre, and the average domestic gross earnings per month

In [12]:
```python
# plot genre parameters
fig, axes = plt.subplots(1, 3, figsize=(15, 6))

# number of movies per genre
sns.barplot(ax=axes[0], data=genre_roi, y="genres", x="count")
axes[0].set_title('N Movies per Genre')

# domestic roi per genre
sns.barplot(ax=axes[1], data=genre_roi, y="genres", x="domestic_roi")
axes[1].set_title('Domestic ROI per Genre')

# domestic roi per genre
sns.barplot(ax=axes[2], data=genre_roi, y="genres", x="domestic_gross")
axes[2].set_title('Domestic Gross Earnings per Genre')

plt.show()
```

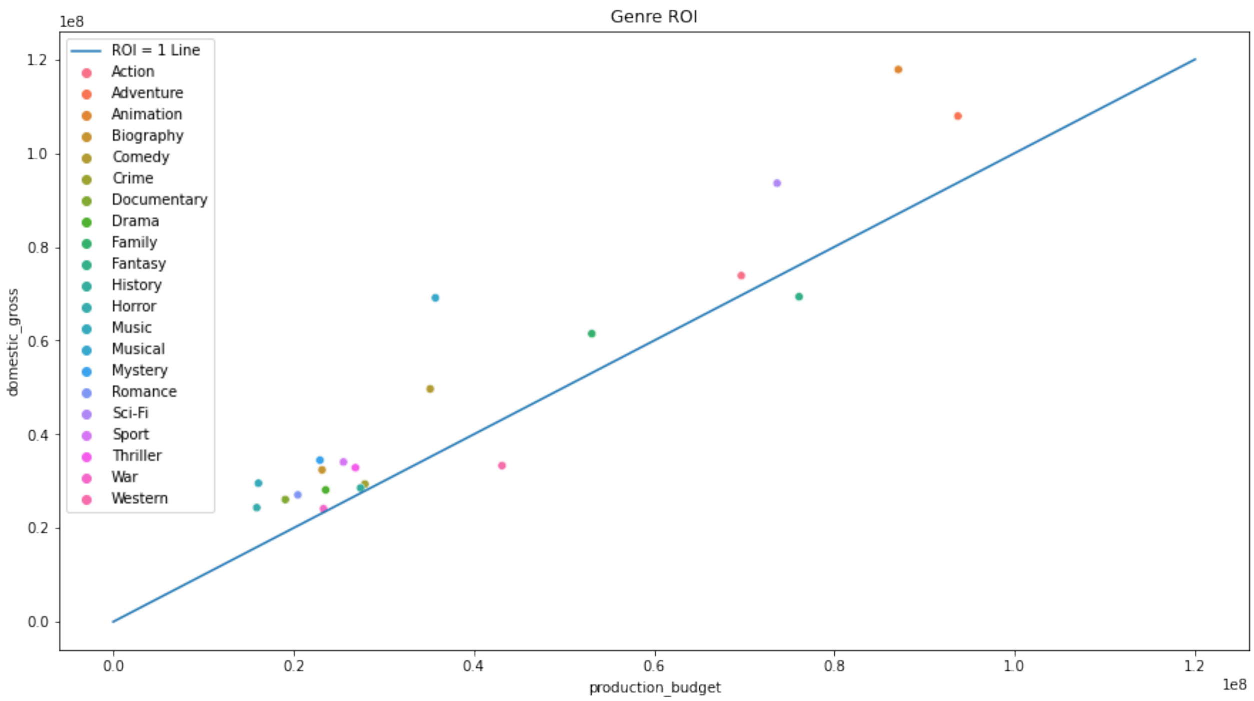


ROI plot per genre

plot the average budget on the x axis and average domestic gross earnings on the y axis include a y=x line to represent an ROI=1

In [13]:
```
# plot genre parameters
fig, axes = plt.subplots(figsize=(15, 8))

# number of movies per genre
sns.scatterplot(data=genre_roi, x="production_budget", y="domestic_gross", h
axes.set_title('Genre ROI')

# add ROI = 1 line
plt.plot([0, 120000000], [0, 120000000], '-', label='ROI = 1 Line')

plt.legend()
```

Out[13]: <matplotlib.legend.Legend at 0x7f92e9bd0910>



- high risk high reward genres: animation, sci-fi
- low risk low reward genres: sport, biography, horror
- middle ground: family, action

organize by release month

Group the data by the relase month column created during data cleaning.

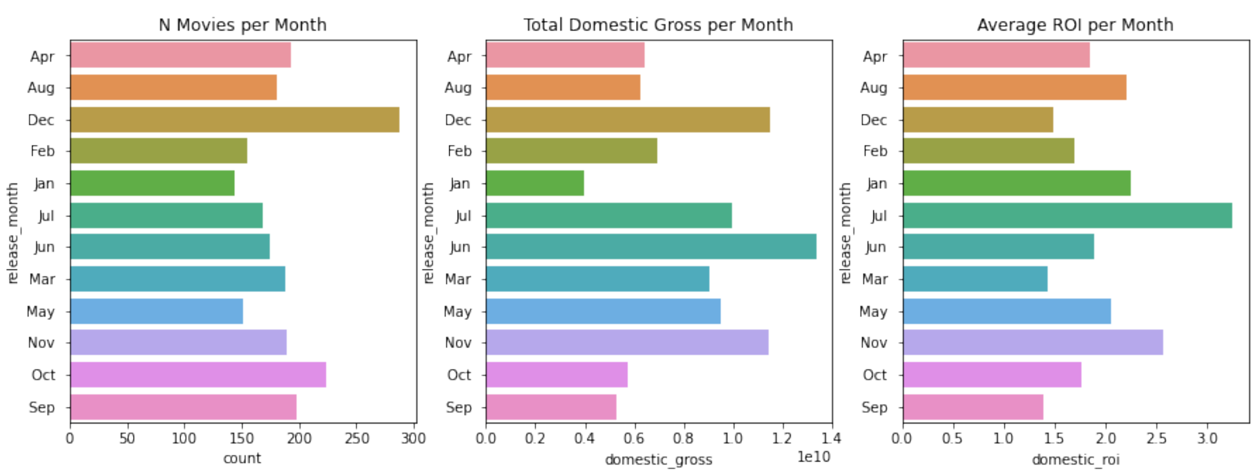
get the sum and mean aggregations, then combine them so as to include average gross earnings and budget data as well as the total data for that month.

In [14]:
```
month_sums = budgets_basics.groupby('release_month').sum()
month_sums.to_csv('data/month_sums.csv')

month_means = budgets_basics.groupby('release_month').mean()
month_means.to_csv('data/month_means.csv')

# reset index
month_sums = month_sums.reset_index()
month_means = month_means.reset_index()
```

Month visualizations

plot the number of movies per month, the average domestic ROI per month, and the average domestic gross earnings per month

In [15]:
```
# plot stats per month
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

# number of movies released per month
sns.barplot(ax = axes[0], data=month_sums, y="release_month", x="count")
axes[0].set_title('N Movies per Month')

# total domestic gross per month
sns.barplot(ax = axes[1], data=month_sums, y="release_month", x="domestic_gr
axes[1].set_title('Total Domestic Gross per Month')

# average ROI of movies released per month
sns.barplot(ax = axes[2], data=month_means, y="release_month", x="domestic_r
axes[2].set_title('Average ROI per Month')

plt.show()
```



- Month with the most movies: December
- Month with the most earings: June

Combine directors table and budgets table

Combine the directors data set and the budgets data set, using the movie title as the common column

In [16]:
```
budgets_directors = budgets.merge(director_table, left_on='title', right_on=
budgets_directors = budgets_directors.set_index('title')
budgets_directors.to_csv('data/budgets_directors.csv')
```

Group by director and get average domestic and worldwide ROI

Group the table by the directors name

get their aggregate sum, mean and count data and combine into a table to get their total numbers of movies, average and total budgets and earnings, and their average ratings

In [17]:
```
director_roi = budgets_directors.groupby('primary_name').mean()
director_roi_count = budgets_directors.groupby('primary_name').count()
director_row_sum = budgets_directors.groupby('primary_name').sum()

# combine tables
director_roi['count'] = director_roi_count['averagerating']
director_roi['total_production_budget'] = director_row_sum['production_budge
director_roi['total_domestic_gross'] = director_row_sum['domestic_gross']
director_roi['total_worldwide_gross'] = director_row_sum['worldwide_gross']


# remove rows with 0 gross earnings for bother domestic and worldwide
director_roi = director_roi[(director_roi['domestic_gross'] >= 1000000) & (d

director_roi.to_csv('data/director_roi.csv')

director_roi.head()
```

Out[17]:

	production_budget	domestic_gross	worldwide_gross	domestic_roi	worldwide_roi	avera
primary_name						
Aaron Seltzer	20000000.0	36661504.0	81424988.0	1.833075	4.071249	
Aash Aaron	3500000.0	12600000.0	12600000.0	3.600000	3.600000	
Aashiq Abu	75000000.0	14010690.0	30626690.0	0.186809	0.408356	
Abby Kohn	32000000.0	48795601.0	91553797.0	1.524863	2.861056	
Abhijit Guha	85000000.0	85900357.5	247044307.0	1.071387	3.007657	

Filter the table to only include

```
- directors with average ratings above 7 (highly rated)
- budgets between 1M and 100M (reasonable budgets)
- at least 3 movie credits (experienced)
```

In [18]:
```
# sort top to bottom by domestic roi
director_roi_sorted = director_roi.sort_values('domestic_roi', ascending=Fal

# restrict to directors with reasonable budgetes (between 1M and 100M)
director_high_budgets = director_roi_sorted[(director_roi_sorted['production
director_reasonable_budgets = director_high_budgets[(director_high_budgets['

# restrict to directors with averag ratings above 7
high_rated_directors = director_reasonable_budgets[(director_reasonable_budg

# restrict to directors with more than 2 movies, to get experienced director
experienced_directors = high_rated_directors[(high_rated_directors['count']

experienced_directors.to_csv('data/experienced_directors.csv')
```

In [19]:
```
eriienced_directors_sorted = experienced_directors.sort_values('averagerating
```

In [20]:
```
# reset index
experienced_directors_sorted = experienced_directors_sorted.reset_index()
experienced_directors_sorted.head()
```

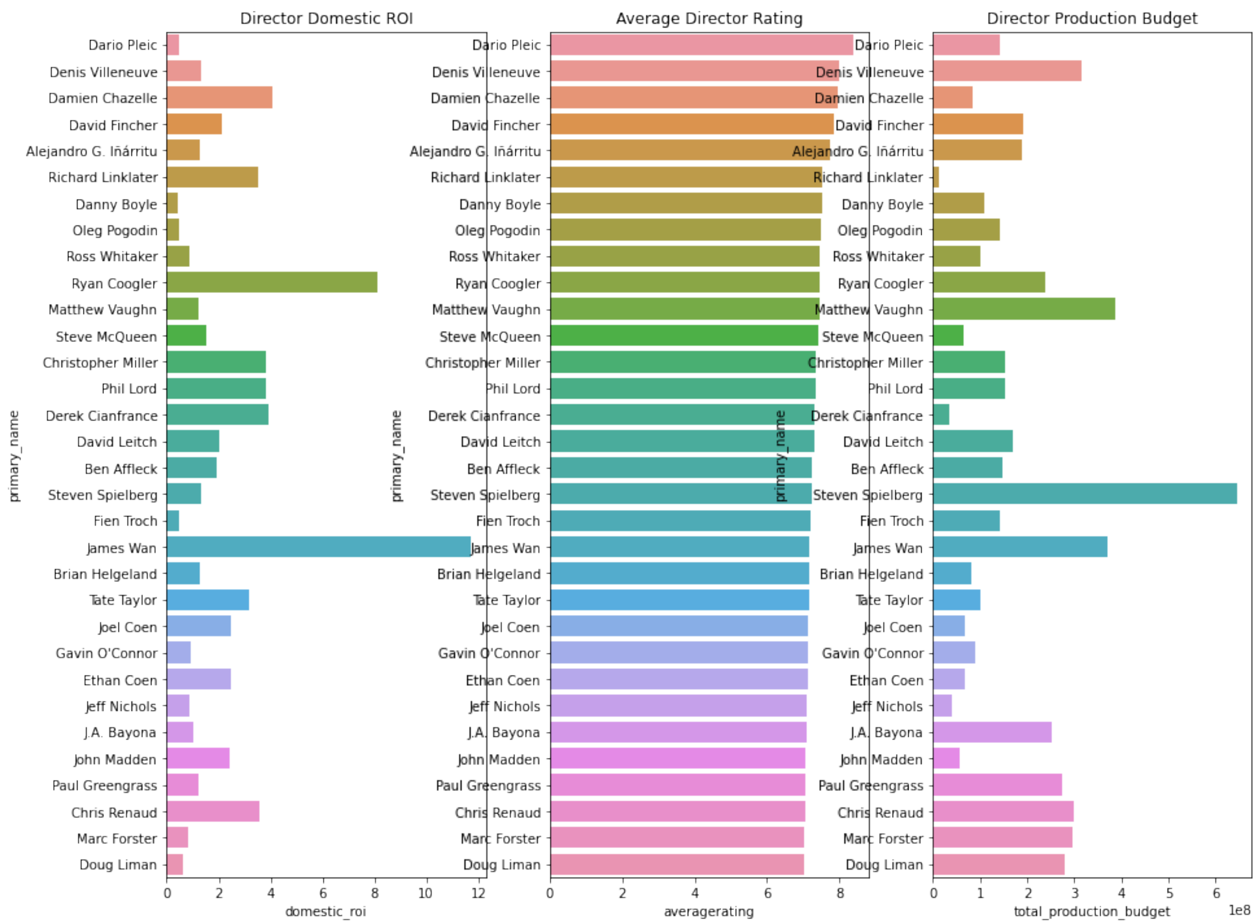
Out[20]:

	primary_name	production_budget	domestic_gross	worldwide_gross	domestic_roi	worldwide_roi	av
0	Dario Pleic	4.750000e+07	5.913765e+07	1.435970e+08	0.465154	30.851850	
1	Denis Villeneuve	6.296000e+07	6.146980e+07	1.352639e+08	1.306876	2.672155	
2	Damien Chazelle	2.776667e+07	6.971012e+07	1.901747e+08	4.090436	11.626585	
3	David Fincher	6.366667e+07	1.224152e+08	2.776211e+08	2.104471	4.774950	
4	Alejandro G. Iñárritu	6.266667e+07	7.702658e+07	2.202803e+08	1.286095	3.462407	

Director Visualizations

plot the average director domestic ROI, average directory rating, and average director produciton budget

In [21]:
```
# plot stats per month
fig, axes = plt.subplots(1, 3, figsize=(15, 12))

# number of movies released per month
sns.barplot(ax = axes[0], data=experienced_directors_sorted, y="primary_name
axes[0].set_title('Director Domestic ROI')

# average ROI of movies released per month
sns.barplot(ax = axes[1], data=experienced_directors_sorted, y="primary_name
axes[1].set_title('Average Director Rating')

# total domestic gross per month
sns.barplot(ax = axes[2], data=experienced_directors_sorted, y="primary_name
axes[2].set_title('Director Production Budget')

plt.show()
```



Damien Chazelle, Ryan Coogler, Christopher Miller & Phil Lord, and James Wan all stand out as directors that are well known, make good movies, and have a high ROI.

Linear Regression

The goal is to find genres increasing in popularity

null hypothesis: the change in domestic gross earnings is not correlated to the year

alternate hypothesis: the change in domestic gross earnings is correlated to the year (increasing or decreasing in popularity)

The following linear regressions are for the genres that show the most likelyhood to increase in popularity:

```
- Sci-Fi
- Aciton
- Fantasy
- Musical
- Sport
```

Linear regressions for genres that show the most lieklyhood to decrease in popularity are also shown:

```
- War
- Horror
- Drama
```

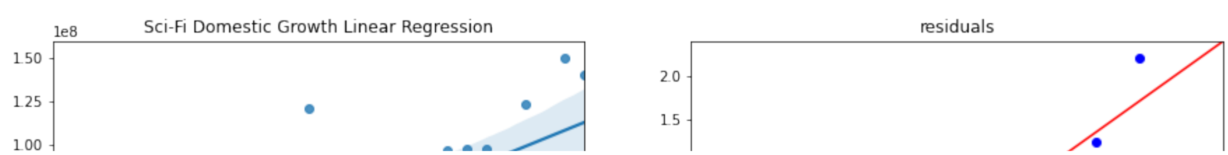
Create a function to perform the linear regression for a specific genre name and produce the visualizations.

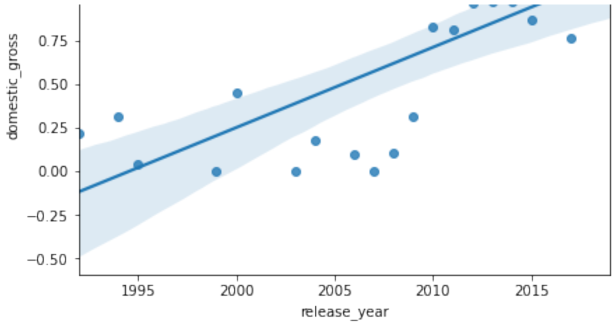
In [22]:
```
def lin_reg(genre_name):

    # isolate the data for the genre specified
    genre = split_genres[split_genres['genres'] == genre_name]
    genre = genre[genre['release_year'] >= 1990]
    genre_year = genre.groupby('release_year', as_index=False).mean()
    genre_year_sum = genre.groupby('release_year').sum()
    genre_year['count'] = genre_year_sum['count']

    # manual calculations
    rho = np.corrcoef(genre_year['release_year'], genre_year['domestic_gross
    s_y = genre_year['domestic_gross'].std()
    s_x = genre_year['release_year'].std()
    m = rho * s_y / s_x

    mean_y = genre_year['domestic_gross'].mean()
    mean_x = genre_year['release_year'].mean()
    c = mean_y - m * mean_x

    print(f"Our regression line is: y = {round(m, 5)}x + {round(c, 5)}")

    # regression with statsmodels
    model = sm.OLS(endog=genre_year.domestic_gross, exog=sm.add_constant(gen
    results = model.fit()

    # plot results
    fig, axes = plt.subplots(1, 2, figsize=(15, 5))

    sns.regplot(x='release_year', y='domestic_gross', data=genre_year, ax=ax
    axes[0].set_title(f'{genre_name} Domestic Growth Linear Regression')

    sm.graphics.qqplot(results.resid, dist=stats.norm, line='45', fit=True,
    axes[1].set_title('residuals')

    plt.show()

    return results
```

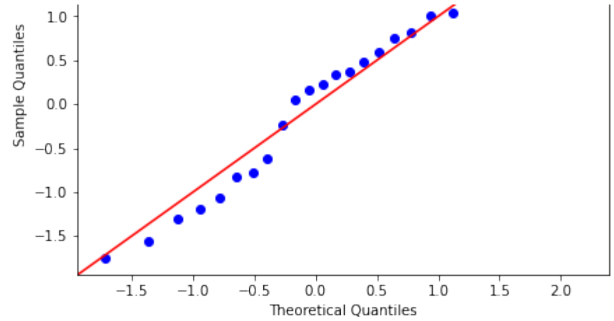
Sci-Fi Domestic Gross

In [23]:
```
sci_fi_results = lin_reg('Sci-Fi')
sci_fi_results.summary()
```

Our regression line is: y = 4619352.75155x + -9213369324.60271







Out[23]:

OLS Regression Results

Dep. Variable:	domestic_gross	**R-squared:**	0.541
Model:	OLS	**Adj. R-squared:**	0.518
Method:	Least Squares	**F-statistic:**	23.56
Date:	Tue, 05 Sep 2023	**Prob (F-statistic):**	9.62e-05
Time:	14:18:17	**Log-Likelihood:**	-412.09
No. Observations:	22	**AIC:**	828.2
Df Residuals:	20	**BIC:**	830.4
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-9.213e+09	1.91e+09	-4.823	0.000	-1.32e+10	-5.23e+09
release_year	4.619e+06	9.52e+05	4.854	0.000	2.63e+06	6.6e+06

Omnibus:	0.241	**Durbin-Watson:**	1.725
Prob(Omnibus):	0.887	**Jarque-Bera (JB):**	0.433
Skew:	0.032	**Prob(JB):**	0.806
Kurtosis:	2.316	**Cond. No.**	5.20e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.2e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Interpretation:

```
P: <<0.05 - statistically significant
Coef: 4.619e+06 increase per year
R2: 54% of variation is due to the year
F-stat: 23.56
```

Action - Domestic Gross

In [24]:
```python
action_results = lin_reg('Action')
action_results.summary()
```

```
Our regression line is: y = 2602537.69892x + -5167241401.43695
```

Out[24]:

OLS Regression Results

Dep. Variable:	domestic_gross	**R-squared:**	0.472
Model:	OLS	**Adj. R-squared:**	0.452
Method:	Least Squares	**F-statistic:**	23.27
Date:	Tue, 05 Sep 2023	**Prob (F-statistic):**	5.35e-05
Time:	14:18:21	**Log-Likelihood:**	-514.02
No. Observations:	28	**AIC:**	1032.
Df Residuals:	26	**BIC:**	1035.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**

const	-5.167e+09	1.08e+09	-4.776	0.000	-7.39e+09	-2.94e+09
release_year	2.603e+06	5.4e+05	4.824	0.000	1.49e+06	3.71e+06

Omnibus:	0.266	**Durbin-Watson:**	2.087
Prob(Omnibus):	0.875	**Jarque-Bera (JB):**	0.454
Skew:	0.116	**Prob(JB):**	0.797
Kurtosis:	2.420	**Cond. No.**	4.87e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.87e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

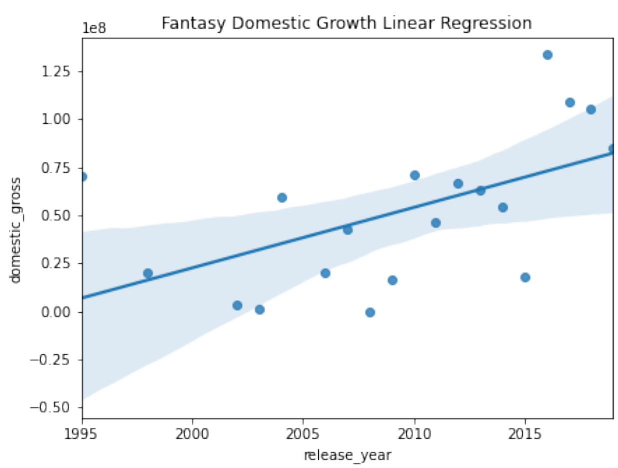
Interpretation:

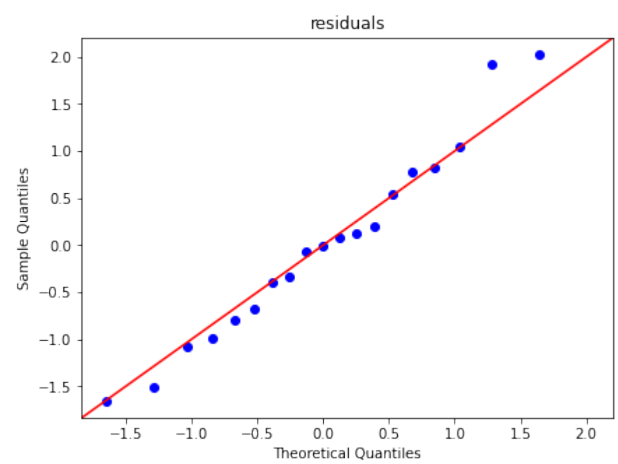
```
P: <<0.05 - statistically significant
Coef: 2.603e+06 increase per year
R2: 47% of variation is due to the year
F-stat: 23.27
```

Fantasy Domestic Gross

In [25]:
```python
fantasy_results = lin_reg('Fantasy')
fantasy_results.summary()
```

```
Our regression line is: y = 3146972.30881x + -6271392442.53548
```






```
/Users/abigailcampbell/anaconda3/envs/learn-env/lib/python3.8/site-packages
/scipy/stats/stats.py:1603: UserWarning: kurtosistest only valid for n>=20
... continuing anyway, n=19
```

```
  warnings.warn("kurtosistest only valid for n>=20 ... continuing "
```

Out[25]:

OLS Regression Results

Dep. Variable:	domestic_gross	**R-squared:**	0.302
Model:	OLS	**Adj. R-squared:**	0.261
Method:	Least Squares	**F-statistic:**	7.358
Date:	Tue, 05 Sep 2023	**Prob (F-statistic):**	0.0148
Time:	14:18:23	**Log-Likelihood:**	-355.01
No. Observations:	19	**AIC:**	714.0
Df Residuals:	17	**BIC:**	715.9
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-6.271e+09	2.33e+09	-2.690	0.015	-1.12e+10	-1.35e+09
release_year	3.147e+06	1.16e+06	2.713	0.015	6.99e+05	5.59e+06

Omnibus:	0.565	**Durbin-Watson:**	1.679
Prob(Omnibus):	0.754	**Jarque-Bera (JB):**	0.553
Skew:	0.344	**Prob(JB):**	0.758
Kurtosis:	2.526	**Cond. No.**	6.13e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.13e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Interpretation:

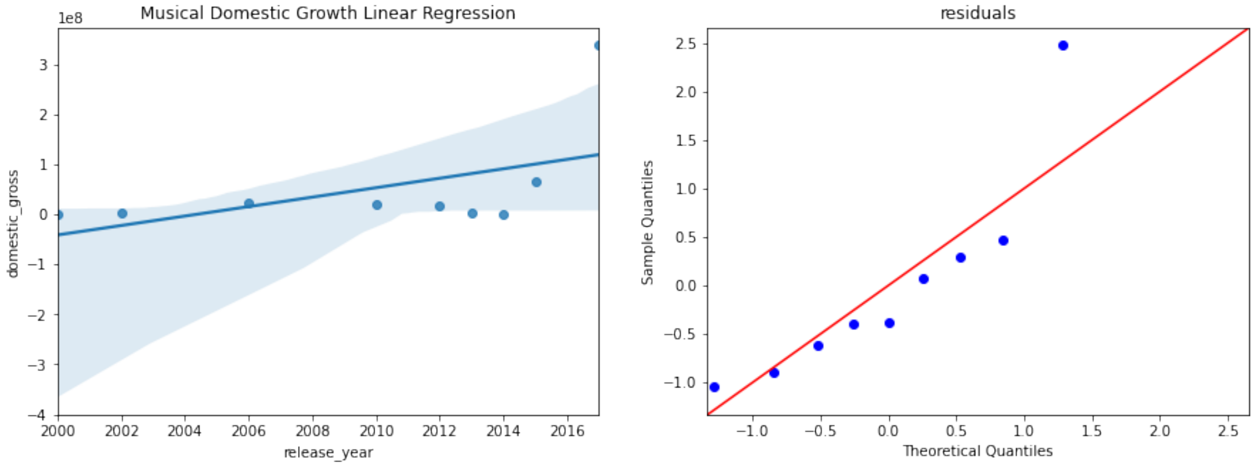
```
P: 0.015 - statistically significant (though barely)
Coef: 3.147e+06 increase per year
R2: 30% of variation is due to the year
F-stat: 7.36
```

Musical Domestic Gross

In [26]:

```
musical_results = lin_reg('Musical')
musical_results.summary()
```

```
Our regression line is: y = 9469200.52815x + -18978983944.94619
```




```
/Users/abigailcampbell/anaconda3/envs/learn-env/lib/python3.8/site-packages
/scipy/stats/stats.py:1603: UserWarning: kurtosistest only valid for n>=20
... continuing anyway, n=9
  warnings.warn("kurtosistest only valid for n>=20 ... continuing "
```

Out[26]:

OLS Regression Results

Dep. Variable:	domestic_gross	**R-squared:**	0.265
Model:	OLS	**Adj. R-squared:**	0.161
Method:	Least Squares	**F-statistic:**	2.530
Date:	Tue, 05 Sep 2023	**Prob (F-statistic):**	0.156
Time:	14:18:27	**Log-Likelihood:**	-177.44
No. Observations:	9	**AIC:**	358.9
Df Residuals:	7	**BIC:**	359.3
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-1.898e+10	1.2e+10	-1.586	0.157	-4.73e+10	9.32e+09
release_year	9.469e+06	5.95e+06	1.591	0.156	-4.61e+06	2.35e+07

Omnibus:	10.270	**Durbin-Watson:**	1.010
Prob(Omnibus):	0.006	**Jarque-Bera (JB):**	3.954
Skew:	1.462	**Prob(JB):**	0.139

Kurtosis:	4.413	**Cond. No.**	7.21e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.21e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

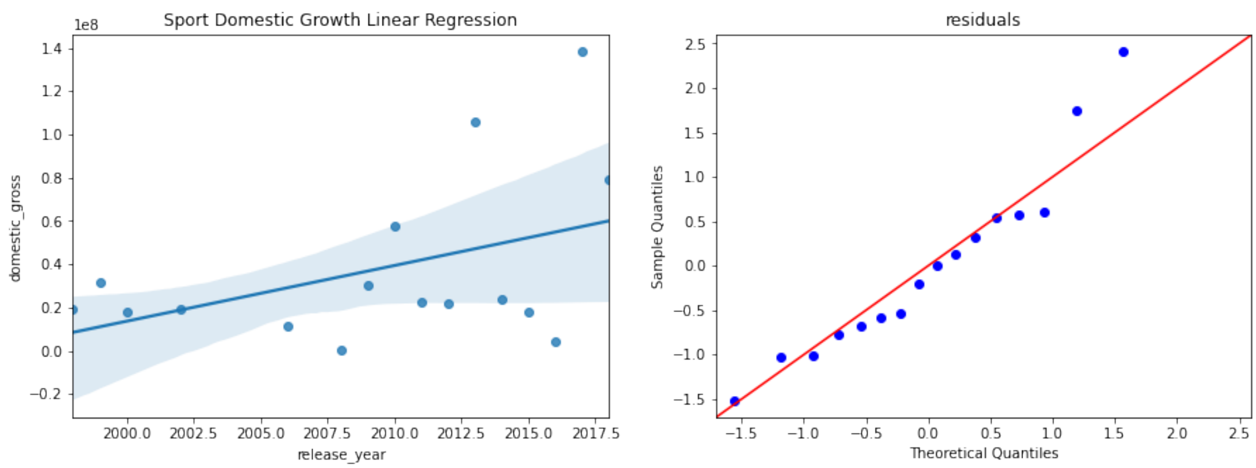
Interpretation:

```
P: 0.156 - not statistically significant
Coef: 9.469e+06 increase per year
R2: 26.5% of variation is due to the year
F-stat: 2.53
```

Sport Domestic Gross

In [27]:
```
sport_results = lin_reg('Sport')
sport_results.summary()
```

```
Our regression line is: y = 2576014.49845x + -5138391749.45988
```




```
/Users/abigailcampbell/anaconda3/envs/learn-env/lib/python3.8/site-packages
/scipy/stats/stats.py:1603: UserWarning: kurtosistest only valid for n>=20
... continuing anyway, n=16
  warnings.warn("kurtosistest only valid for n>=20 ... continuing "
```

Out[27]:

OLS Regression Results

Dep. Variable:	domestic_gross	**R-squared:**	0.192
Model:	OLS	**Adj. R-squared:**	0.134
Method:	Least Squares	**F-statistic:**	3.323

Date:	Tue, 05 Sep 2023	**Prob (F-statistic):**	0.0897
Time:	14:18:30	**Log-Likelihood:**	-299.97
No. Observations:	16	**AIC:**	603.9
Df Residuals:	14	**BIC:**	605.5
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-5.138e+09	2.84e+09	-1.810	0.092	-1.12e+10	9.52e+08
release_year	2.576e+06	1.41e+06	1.823	0.090	-4.55e+05	5.61e+06

Omnibus:	3.406	**Durbin-Watson:**	2.157
Prob(Omnibus):	0.182	**Jarque-Bera (JB):**	1.815
Skew:	0.819	**Prob(JB):**	0.404
Kurtosis:	3.196	**Cond. No.**	6.36e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.36e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

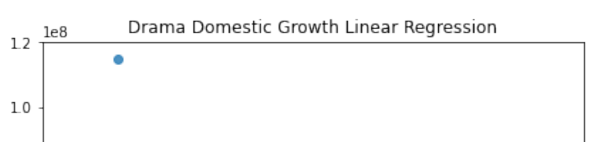
Interpretation:

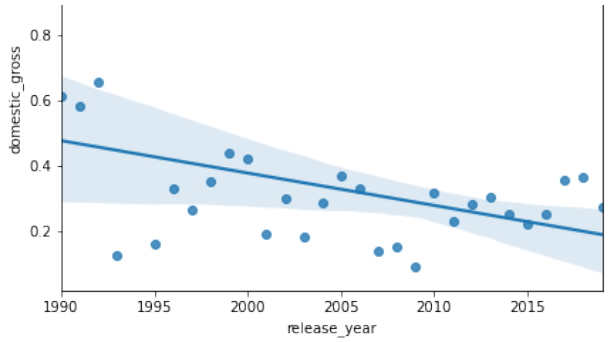
```
P: 0.092 - not statistically significant
Coef: 2.576e+06 increase per year
R2: 19.2% of variation is due to the year
F-stat: 3.32
```

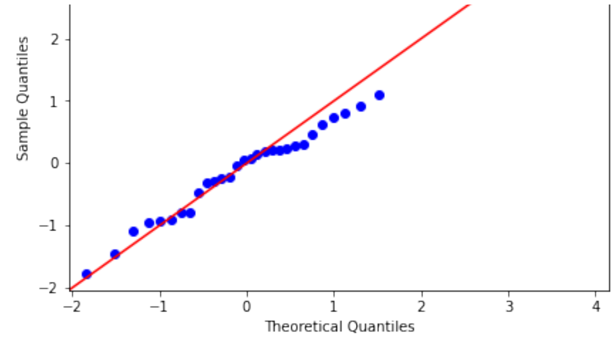
Drama Domestic Gross

In [28]:
```
drama_results = lin_reg('Drama')
drama_results.summary()
```

```
Our regression line is: y = -994884.33769x + 2027415506.61163
```







Out[28]:

OLS Regression Results

Dep. Variable:	domestic_gross	**R-squared:**	0.180
Model:	OLS	**Adj. R-squared:**	0.151
Method:	Least Squares	**F-statistic:**	6.161
Date:	Tue, 05 Sep 2023	**Prob (F-statistic):**	0.0193
Time:	14:18:33	**Log-Likelihood:**	-544.34
No. Observations:	30	**AIC:**	1093.
Df Residuals:	28	**BIC:**	1095.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	2.027e+09	8.03e+08	2.523	0.018	3.82e+08	3.67e+09
release_year	-9.949e+05	4.01e+05	-2.482	0.019	-1.82e+06	-1.74e+05

Omnibus:	23.252	**Durbin-Watson:**	2.564
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	47.213
Skew:	1.608	**Prob(JB):**	5.60e-11
Kurtosis:	8.238	**Cond. No.**	4.64e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.64e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

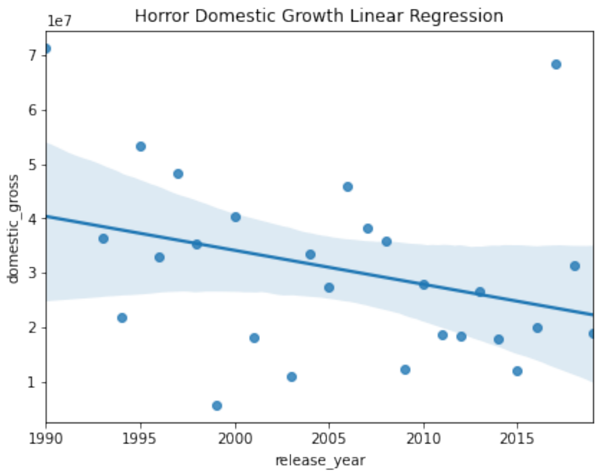
Interpretation:

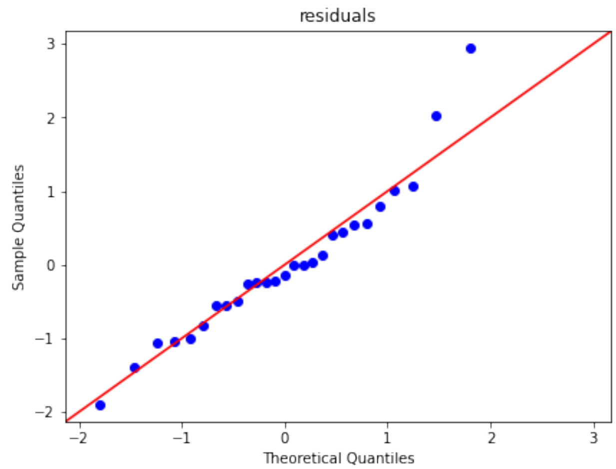
```
P: 0.018 - statistically significant, but barely
Coef: -9.949e+05 decrease per year
R2: 18% of variation is due to the year
F-stat: 6.16
```

Horror Domestic Gross

In [29]:
```
horror_results = lin_reg('Horror')
horror_results.summary()
```

```
Our regression line is: y = -622878.29095x + 1279926497.33973
```





Out[29]:

OLS Regression Results

Dep. Variable:	domestic_gross	**R-squared:**	0.104
Model:	OLS	**Adj. R-squared:**	0.068
Method:	Least Squares	**F-statistic:**	2.891
Date:	Tue, 05 Sep 2023	**Prob (F-statistic):**	0.101
Time:	14:18:36	**Log-Likelihood:**	-484.90
No. Observations:	27	**AIC:**	973.8
Df Residuals:	25	**BIC:**	976.4
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]

const	1.28e+09	7.35e+08	1.742	0.094	-2.33e+08	2.79e+09
release_year	-6.229e+05	3.66e+05	-1.700	0.101	-1.38e+06	1.32e+05

Omnibus:	6.929	**Durbin-Watson:**	1.847
Prob(Omnibus):	0.031	**Jarque-Bera (JB):**	5.008
Skew:	0.849	**Prob(JB):**	0.0818
Kurtosis:	4.252	**Cond. No.**	4.83e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.83e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

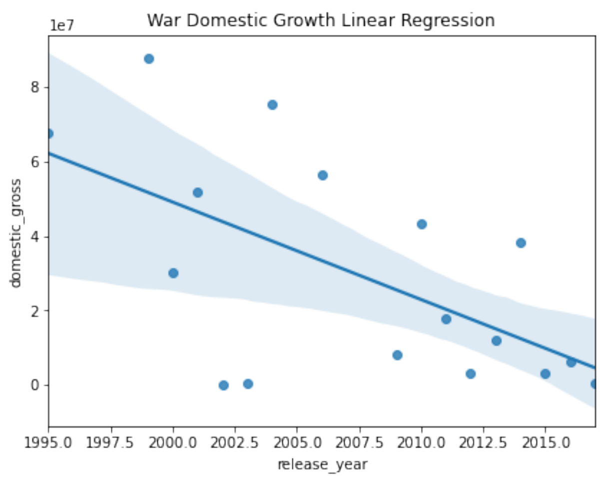
Interpretation:

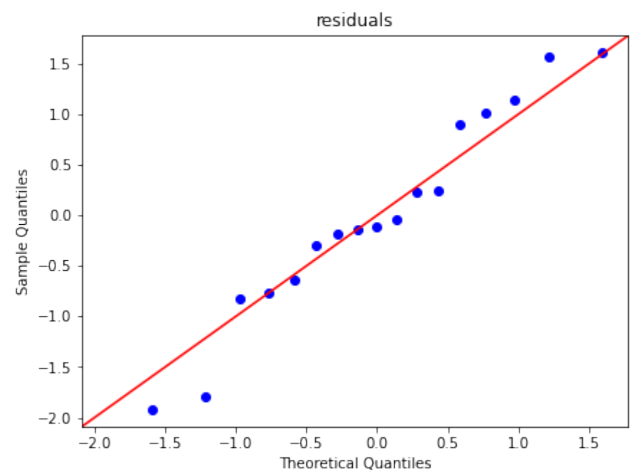
```
P: 0.094 - not statistically significant
Coef: -6.229e+06 decrease per year
R2: 10.4% of variation is due to the year
F-stat: 2.89
```

War Domestic Gross

In [30]:
```
war_results = lin_reg('War')
war_results.summary()
```

```
Our regression line is: y = -2619716.57887x + 5288569324.92254
```






```
/Users/abigailcampbell/anaconda3/envs/learn-env/lib/python3.8/site-packages
/scipy/stats/stats.py:1603: UserWarning: kurtosistest only valid for n>=20
```

```
... continuing anyway, n=17
  warnings.warn("kurtosistest only valid for n>=20 ... continuing "
```

Out[30]:

OLS Regression Results

Dep. Variable:	domestic_gross	**R-squared:**	0.359
Model:	OLS	**Adj. R-squared:**	0.317
Method:	Least Squares	**F-statistic:**	8.413
Date:	Tue, 05 Sep 2023	**Prob (F-statistic):**	0.0110
Time:	14:18:39	**Log-Likelihood:**	-312.16
No. Observations:	17	**AIC:**	628.3
Df Residuals:	15	**BIC:**	630.0
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	5.289e+09	1.81e+09	2.917	0.011	1.42e+09	9.15e+09
release_year	-2.62e+06	9.03e+05	-2.900	0.011	-4.54e+06	-6.95e+05

Omnibus:	0.149	**Durbin-Watson:**	2.142
Prob(Omnibus):	0.928	**Jarque-Bera (JB):**	0.325
Skew:	-0.165	**Prob(JB):**	0.850
Kurtosis:	2.408	**Cond. No.**	6.17e+05

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 6.17e+05. This might indicate that there are
strong multicollinearity or other numerical problems.

Interpretation:

```
P: 0.011 - statistically significant, but barely
Coef: -2.62e+06 decrease per year
R2: 35.9% of variation is due to the year
F-stat: 8.413
```