Investigating The Movie Database

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Introduction ¶

The dataset I will be exploring is The Movie Database movie data, which has over 10,000 movies with 21 columns worth of information.

I will use a small set libraries for this dataset, datetime for date manipulations, pandas and numpy for data clearning and exploration. Finally seaborn and matplotlib for visualizations. The additional settings ensure plots are displayed properly, seaborn uses the ticks style, and scientific notation should not be shown.

Questions I would like answers to from the information available.

- Has the runtime of movies changed over time?

- Is there a specific time of the year or week where movies tend to perform worse?

In [1]:
```
import datetime
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

%matplotlib inline
sns.set(style='darkgrid') # set seaborn style
pd.options.display.float_format = '{:20,.2f}'.format # prevent scientific nota
tion
pd.set_option('display.max_columns', 0) # display all columns
plt.rcParams['figure.figsize'] = (12,8) # set plot size
```

Data Wrangling

Throughout this section I will perform any needed data cleaning to make working with the data easier, as well as data manipulation to assist with finding answers to the proposed questions.

General Properties

In [2]:
```
movie_database_contents = pd.read_csv("tmdb-movies.csv")
```

First we're going to import our dataset using pandas read_csv function.

In [3]:
```
movie_database_contents.head(2)
```

Out[3]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.99	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://www
1	76341	tt1392190	28.42	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www.i

With the "head(2)" function we can look at our 2 rows of information. Viewing the data I can determine that multiple columns have multiple values separated by a pipe (|), and that the release_date column may not be formated as a date.

In [4]:
```
movie_database_contents.dtypes
```

Out[4]:
```
id                        int64
imdb_id                  object
popularity              float64
budget                    int64
revenue                   int64
original_title           object
cast                     object
homepage                 object
director                 object
tagline                  object
keywords                 object
overview                 object
runtime                   int64
genres                   object
production_companies     object
release_date             object
vote_count                int64
vote_average            float64
release_year              int64
budget_adj              float64
revenue_adj             float64
dtype: object
```

Next I wanted to determine what are the data types in the columns, to help me determine if data type changes need to occur. Using pandas dtypes function, I can see release_date is a string instead of a datetime object, which I will need to change.

In [5]:
```
movie_database_contents.describe()
```

Out[5]:

	id	popularity	budget	revenue	runtime	vote_count	vote_avera
count	10,866.00	10,866.00	10,866.00	10,866.00	10,866.00	10,866.00	10,866.
mean	66,064.18	0.65	14,625,701.09	39,823,319.79	102.07	217.39	5.
std	92,130.14	1.00	30,913,213.83	117,003,486.58	31.38	575.62	0.
min	5.00	0.00	0.00	0.00	0.00	10.00	1.
25%	10,596.25	0.21	0.00	0.00	90.00	17.00	5.
50%	20,669.00	0.38	0.00	0.00	99.00	38.00	6.
75%	75,610.00	0.71	15,000,000.00	24,000,000.00	111.00	145.75	6.
max	417,859.00	32.99	425,000,000.00	2,781,505,847.00	900.00	9,767.00	9.

Using the describe function on the entire database will allow us to determine a few things.

- There is a total of 10,866 items in the dataset
- For multiple columns the minimum value is 0, which could indicate missing data
- The runtime column shows a maximum value of 900.00 which could indicate inaccurate data, or a series of movies counted as one.

Set up needed functions to clean data to make it easier to work with

Based on the information obtained so far, I want to go ahead and set up functions that I can reuse when the need arises. This will reduce the overall amount of code needed, and reduce errors by not repeating the same code multiple times and potentially injecting errors in the calculations.

In [6]:
```
movie_database_contents.head(2)
```

Out[6]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.99	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://www
1	76341	tt1392190	28.42	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www.i

We want to keep our data visible using the "head(2)" function aagain, to ensure we're creating functions that will solve our problems.

In [7]:
```
movie_database_contents = movie_database_contents[['original_title', 'cast',
'director', 'runtime', 'genres', 'release_date', 'release_year', 'budget_adj',
'revenue_adj']]
```

Based on the questions I want to find answers too, there are several columns that I will not need. By providing a list to our dataset, pandas will keep only the provided columns.

In [8]:
```
movie_database_contents = movie_database_contents.drop_duplicates()
```

To ensure that they are no duplicate values, we use pandas built in "drop_duplicates" function across the entire dataset.

In [9]:
```
movie_database_contents.shape
```

Out[9]:
```
(10865, 9)
```

Using the "shape" function, we can determine that only 1 duplicate was in the dataset.

In [10]:
```
def split_cells_by_delimiter(values):
    return str(values).split("|")
```

split_cells_by_delimiter will take a column of values and separate values on the "|" character, and create a list of values

In [11]:
```
def correct_dates(val):
    if val.year > 2015:
        val = val - pd.Timedelta(100, unit='Y') - pd.Timedelta(18, unit='H') #
- pd.Timedelta(18, units='H') ensures all our release dates have the same tim
e.
    return val
```

correct_dates will change the release_date column to a proper datetime date type. The command checks to see if the year is greater than 2015, if it is, it subtracts 100 years and 18 hours from the specific value. Otherwise, we could have date values that have years into the future. I.E. for value 1/11/66, pandas would automatically convert this to 1/11/2066 instead of the 1/11/1966

In [12]:
```
movie_database_contents['release_date'] = pd.to_datetime(movie_database_conten
ts['release_date'])
movie_database_contents['release_date'] = movie_database_contents['release_dat
e'].apply(correct_dates)
```

I used the apply function with the correct_dates fuction on the release_data column in our dataset to change the dtype of release_date from string to a actual datetime object, in case we need to do datetime calculations.

In [13]:
```
movie_database_contents[['cast', 'director', 'genres']] = movie_database_conte
nts[['cast', 'director', 'genres']].applymap(split_cells_by_delimiter)
```

I used the apply function with the split_cells_by_delimter function on the columns cast, directory, and the genres, so they can easier to work with if needed.

In [14]:
```
movie_database_contents['release_month'] = movie_database_contents['release_da
te'].dt.month_name()
movie_database_contents['release_day'] = movie_database_contents['release_dat
e'].dt.day_name()
```

To assist with determining specific times of the year for movies, I wanted two additional columns "release_month" and "release_day". Using the dt.month_name() on release date, it will create a new column with the Month as an integer. Using dt.day_name provides the day in interger format as well in our new column.

In [15]:
```
movie_database_contents[['budget_adj', 'revenue_adj']] = movie_database_conten
ts[['budget_adj', 'revenue_adj']].astype(int)
```

For consistenacy I converted all the money related columns to integers using the "astype(int)" function.

In [16]:
```
movie_database_contents.head(2)
```

Out[16]:

	original_title	cast	director	runtime	genres	release_date	release_year	budget_adj
0	Jurassic World	[Chris Pratt, Bryce Dallas Howard, Irrfan Khan...	[Colin Trevorrow]	124	[Action, Adventure, Science Fiction, Thriller]	2015-06-09	2015	137999939
1	Mad Max: Fury Road	[Tom Hardy, Charlize Theron, Hugh Keays-Byrne,...	[George Miller]	120	[Action, Adventure, Science Fiction, Thriller]	2015-05-13	2015	137999939

By viewing the first 2 rows of our dataset, I can determine that cast, director, and genres, were appropriately converted to a list of values. I can also see that our budget_adj and revenue_adj columns are now integers.

In [17]:
```
movie_database_contents.describe()
```

Out[17]:

	runtime	release_year	budget_adj	revenue_adj
count	10,865.00	10,865.00	10,865.00	10,865.00
mean	102.07	2,001.32	17,549,893.81	51,369,001.54
std	31.38	12.81	34,307,526.53	144,638,333.03
min	0.00	1,960.00	0.00	0.00
25%	90.00	1,995.00	0.00	0.00
50%	99.00	2,006.00	0.00	0.00
75%	111.00	2,011.00	20,853,251.00	33,701,729.00
max	900.00	2,015.00	425,000,000.00	2,827,123,750.00

Using the describe function again, it will allow me to further clean some of the columns that have missing or incorrect data.

In [18]:
```
movie_database_contents = movie_database_contents[(movie_database_contents['runtime'] >= 60) & (movie_database_contents['runtime'] <= 240)]
```

Using "boolean filtering" i.e. dataframe[dataframe[column] > 0] I will remove incorrect or missing values from the dataset.
Here I wanted all movies with a runtime greater than or equal to 60 minutes and less than or equal to 240 minutes.

In [19]:
```
movie_database_contents = movie_database_contents[movie_database_contents['budget_adj'] >= 10_000]
```

Using boolean filtering again, I only wanted movies with an adjusted budget of 10,000 or larger.

In [20]:
```
movie_database_contents = movie_database_contents[movie_database_contents['revenue_adj'] >= 10_000]
```

Using boolean filtering again, I only wanted movies with an adjusted revenue of 10,000 or larger.

In [21]:
```
movie_database_contents.describe()
```

Out[21]:

	runtime	release_year	budget_adj	revenue_adj
count	3,798.00	3,798.00	3,798.00	3,798.00
mean	109.30	2,001.25	44,699,196.16	138,900,275.07
std	19.34	11.29	44,776,792.48	217,035,412.37
min	62.00	1,960.00	15,775.00	10,164.00
25%	96.00	1,995.00	13,546,369.00	19,498,113.50
50%	106.00	2,004.00	30,383,599.00	63,127,971.00
75%	119.00	2,010.00	60,809,238.00	165,727,345.75
max	219.00	2,015.00	425,000,000.00	2,827,123,750.00

Using describe again, I can verify that the columns I will be using no longer have 0 as a minimum value.

In [22]:
```
movie_database_contents['adj_gains'] = movie_database_contents['revenue_adj']
- movie_database_contents['budget_adj']
```

I created a new column "adj_gains" to determine the amount of money a movie lost or made by subtracting the column budget_adj from revenue_adj.

In [23]:
```
movie_database_contents['lost_money'] = movie_database_contents['adj_gains'].a
pply(lambda x: True if x < 0 else False)
```

To make it easier to colorize plots, I wanted a simple column that used a boolean value (True or False) to represent if the movie lost money. Lambda's are simply anonymous functions without names. Here it look at value and if it's greater than 0 it places "False" as the value, and True otherwise.

In [24]:
```
def consolidate_by_time_period(dataframe, time_period):
    consolidated_dataframe = dataframe.pivot_table(values='original_title', in
dex='release_{}'.format(time_period), columns='lost_money', aggfunc='count').f
illna(0).reset_index()
    # consolidated_dataframe = dataframe.pivot_table(values='original_title',
 index=f'release_{time_period}', columns='lost_money', aggfunc='count').fillna
(0).reset_index()
    consolidated_dataframe['num_movies'] = consolidated_dataframe[True] + cons
olidated_dataframe[False]
    consolidated_dataframe['Percent Failed'] = (consolidated_dataframe[True] /
consolidated_dataframe['num_movies']) * 100
    return consolidated_dataframe
```

For analyzing my second question, I created a reusable function that takes a data frame, and time_period as parameters to return a dataframe that has had a few things done to it:

- first a pivot table is made that aggregates the dataframe by time_period and a count of movies that lost money
- a new column is created which totals the number of movies for that time_period. i.e. movies that lost money + movies that made money
- creates a new column that shows the percentage of movies that failed at the boxoffice

In [25]:
```
def top_losses(dataframe, top_values):
    top_losses_dataframe = dataframe.sort_values('Percent Failed', ascending=False).head(top_values)
    return top_losses_dataframe
```

I wanted a function that would allow me to see "Top 20" or "Top 10" loses for one of our selected time periods. The function takes in a dataframe and the number of values I would like to see. It sorts the dataframe by "Percent Failed" and the head function to return a dataframe with the only the "top values".

In [26]:
```
movie_database_contents.tail(25)
```

Out[26]:

	original_title	cast	director	runtime	genres	release_date	release_year
10724	On Her Majesty's Secret Service	[George Lazenby, Diana Rigg, Telly Savalas, Ga...	[Peter R. Hunt]	142	[Adventure, Action, Thriller]	1969-12-12	1969
10725	Butch Cassidy and the Sundance Kid	[Paul Newman, Robert Redford, Katharine Ross, ...	[George Roy Hill]	110	[History, Drama, Western, Crime]	1969-09-23	1969
10727	Midnight Cowboy	[Dustin Hoffman, Jon Voight, Sylvia Miles, Joh...	[John Schlesinger]	113	[Drama]	1969-05-25	1969
10728	The Wild Bunch	[Ernest Borgnine, William Holden, Robert Ryan,...	[Sam Peckinpah]	145	[Adventure, Western]	1969-06-17	1969
10755	Grease	[John Travolta, Olivia Newton-John, Stockard C...	[Randal Kleiser]	110	[Music]	1978-07-07	1978
10756	Jaws 2	[Roy Scheider, Lorraine Gary, Murray Hamilton,...	[Jeannot Szwarc]	116	[Horror, Thriller]	1978-06-16	1978
10757	Dawn of the Dead	[David Emge, Ken Foree, Scott H. Reiniger, Gay...	[George A. Romero]	127	[Horror]	1978-09-02	1978
10758	Superman	[Marlon Brando, Gene Hackman, Christopher Reev...	[Richard Donner]	143	[Adventure, Fantasy, Action, Science Fiction]	1978-12-14	1978
10759	Halloween	[Donald Pleasence, Jamie Lee Curtis, P.J. Sole...	[John Carpenter]	91	[Horror, Thriller]	1978-10-25	1978
10760	Animal House	[John Belushi, Tim Matheson, John Vernon, Vern...	[John Landis]	109	[Comedy]	1978-07-27	1978
10762	The Deer Hunter	[Robert De Niro, John Cazale, John Savage, Chr...	[Michael Cimino]	183	[Drama, War]	1978-12-08	1978
10770	Midnight Express	[Brad Davis, Irene Miracle, Bo Hopkins, Randy ...	[Alan Parker]	121	[Drama, Crime]	1978-10-06	1978
10771	The Lord of the Rings	[Christopher Guard, William Squire, Michael Sc...	[Ralph Bakshi]	132	[Drama, Animation, Adventure]	1978-11-15	1978

	original_title	cast	director	runtime	genres	release_date	release_year
10775	Death on the Nile	[Peter Ustinov, Mia Farrow, Simon MacCorkindal...	[John Guillermin]	140	[Mystery]	1978-10-06	1978
10778	Force 10 from Navarone	[Harrison Ford, Robert Shaw, Barbara Bach, Edw...	[Guy Hamilton]	118	[Action, Adventure, War, Thriller]	1978-11-01	1978
10779	Convoy	[Kris Kristofferson, Ali MacGraw, Ernest Borgn...	[Sam Peckinpah]	110	[Action, Comedy, Drama]	1978-06-27	1978
10780	Invasion of the Body Snatchers	[Donald Sutherland, Brooke Adams, Leonard Nimo...	[Philip Kaufman]	115	[Horror, Thriller, Science Fiction, Mystery]	1978-12-19	1978
10788	The Wiz	[Diana Ross, Michael Jackson, Nipsey Russell, ...	[Sidney Lumet]	134	[Adventure, Family, Fantasy, Music, Science Fi...	1978-10-24	1978
10791	Damien: Omen II	[William Holden, Lee Grant, Jonathan Scott-Tay...	[Don Taylor, Mike Hodges]	107	[Action, Drama, Horror, Thriller]	1978-06-09	1978
10793	Watership Down	[John Hurt, Richard Briers, Michael Graham Cox...	[Martin Rosen]	88	[Adventure, Animation, Drama]	1978-10-14	1978
10822	Who's Afraid of Virginia Woolf?	[Elizabeth Taylor, Richard Burton, George Sega...	[Mike Nichols]	131	[Drama]	1966-06-21	1966
10828	Torn Curtain	[Paul Newman, Julie Andrews, Lila Kedrova, Han...	[Alfred Hitchcock]	128	[Mystery, Thriller]	1966-07-13	1966
10829	El Dorado	[John Wayne, Robert Mitchum, James Caan, Charl...	[Howard Hawks]	120	[Action, Western]	1966-12-17	1966
10835	The Sand Pebbles	[Steve McQueen, Richard Attenborough, Richard ...	[Robert Wise]	182	[Action, Adventure, Drama, War, Romance]	1966-12-20	1966
10848	Fantastic Voyage	[Stephen Boyd, Raquel Welch, Edmond O'Brien, D...	[Richard Fleischer]	100	[Adventure, Science Fiction]	1966-08-24	1966

Finally, before I moved on to analyzing the dataset I wanted to verify that I have all the necessary columns and that they are formatted correctly so I can begin trying to find answers to my questions. Using the tail(25) function, I can see the last 25 items of the dataset, and can see that all the added columns have appropriate values.

Explorartory Data Analysis

Now that the data has been cleaned, and is more managable. I can begin exploration of the data set to try to answer my questions

- Has the runtime of movies changed over time?
- Is there a specific time of the year or week where movies tend to perform worse?

Has movie runtime changed over the years?

In [27]:
```
movie_database_contents['runtime'].describe()
```

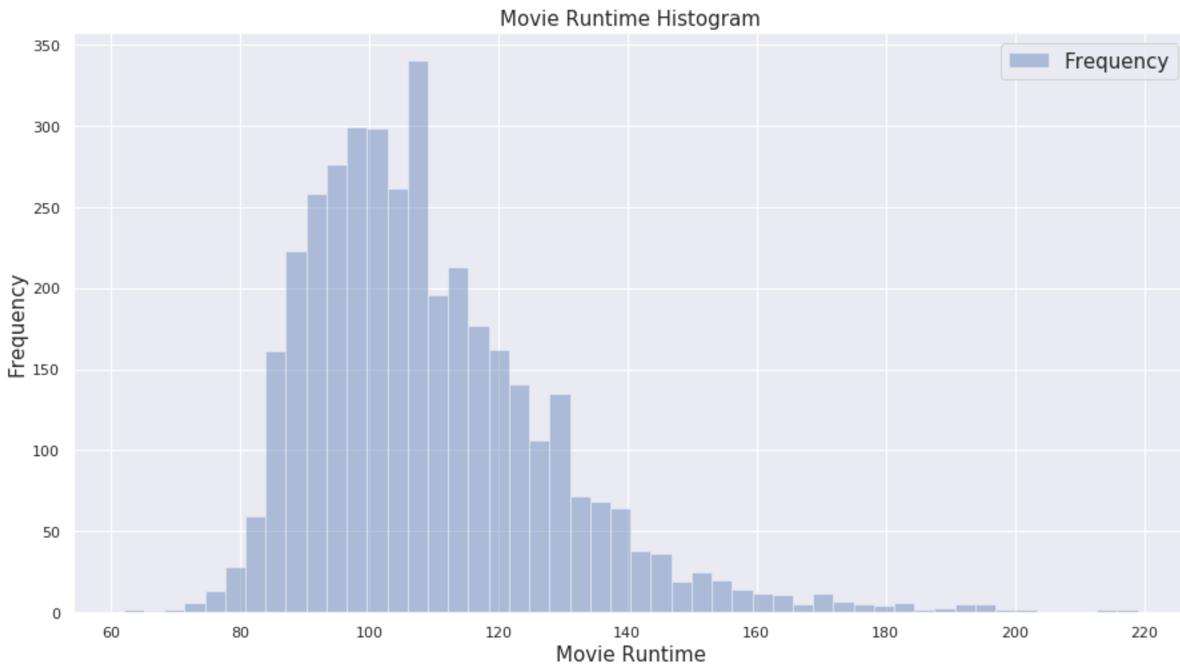
Out[27]:
```
count          3,798.00
mean             109.30
std               19.34
min               62.00
25%               96.00
50%              106.00
75%              119.00
max              219.00
Name: runtime, dtype: float64
```

Using the describe function on the runtime column we can take away a few things:

- the mean runtime of movies in the dataset is 109.30
- the max is 219
- half of the movies are under 107 minutes in length

In [28]:
```
f, ax = plt.subplots(figsize=(15, 8))
sns.distplot(movie_database_contents['runtime'], hist=True,kde=False, axlabel=
'Movie Runtime', label="Frequency")
plt.ylabel("Frequency", fontsize=15)
plt.xlabel("Movie Runtime", fontsize=15)
plt.title("Movie Runtime Histogram", fontsize=15)
plt.legend(prop={'size': 15})
```

Out[28]: <matplotlib.legend.Legend at 0x7f20ba83c9e8>



Using seaborn, I ploted a histrogram of the runtime data to see the distribution of the data. We can see that a majority of the movie runtimes are between 90 and 120 minutes.
Using plt.ylabel, xlabel, title, and label I can specify all the chart labels for easier viewing.

In [29]:
```
mdb_by_year = movie_database_contents.groupby('release_year', as_index=False).
mean()
```

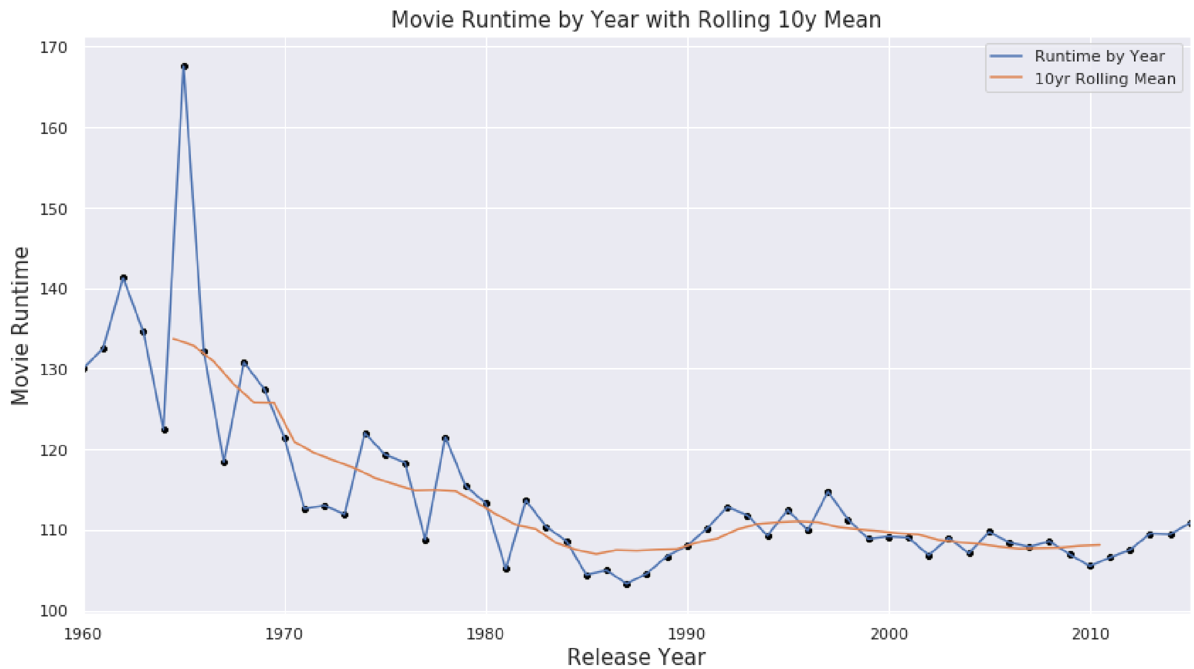
Here I group the dataframe by release year, and averaged their results. This will allow me to make a line graph showing trends over the entire time range.

In [30]:
```
f, ax1 = plt.subplots(nrows=1, ncols=1, sharex=True, sharey=True, figsize=(14,
7.5)) # make charts share x and y axis, and set the chart size
# plot the average run time by year
mdb_by_year.plot(x='release_year', y='runtime', label='Runtime by Year', ax=ax
1)

# overlap dots over the average run time by year for increased visibility
sns.scatterplot(x='release_year', y='runtime', data=mdb_by_year, color='black'
, ax=ax1)

# plot the 10 year rolling average to view trends easier
mdb_by_year.rolling(10).mean().plot(x='release_year', y='runtime', label='10yr
Rolling Mean', ax=ax1)
plt.title("Movie Runtime by Year with Rolling 10y Mean", fontsize=15)
plt.ylabel("Movie Runtime", fontsize=15)
plt.xlabel("Release Year", fontsize=15)
```

Out[30]:
```
Text(0.5, 0, 'Release Year')
```

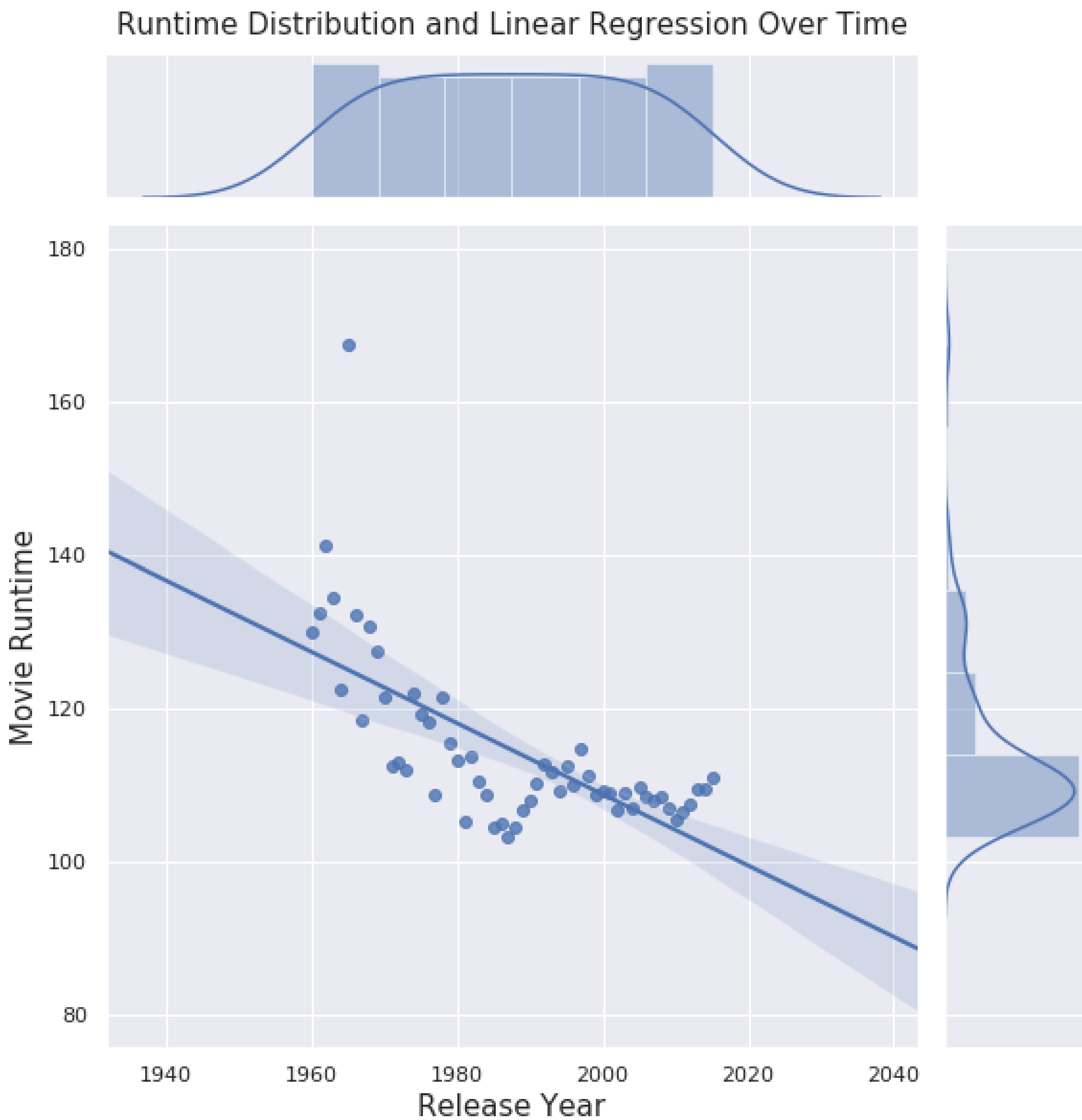


For this chart, I wanted to look at the average runtime by year and incorporate a 10 year rolling average to see the trend over time. To plot this chart I needed to:

- set parameters for matplotlib to allow multiple charts to overlap
- Create the line plot for the entire dataset by year and supply ax=ax1 to ensure it attaches to our customized matplotlib parameters
- Overlay a scatter plot on our line plot to have nice peak dots
- Used pandas "rolling(10).mean()" function on the original dataframe to overlay a 10 year rolling mean to show a trend for movie runtimes over the years.

In [31]:
```
sns.jointplot(x='release_year', y='runtime', data=mdb_by_year, kind='reg', mar
ginal_kws=dict(bins=6), height=8)
plt.title("Runtime Distribution and Linear Regression Over Time", pad=100, fon
tsize=15)
plt.ylabel("Movie Runtime", fontsize=15)
plt.xlabel("Release Year", fontsize=15)
```

Out[31]:
```
Text(0.5, 48.49999999999994, 'Release Year')
```



With a jointplot from the seaborn library, we can see that movie runtimes are between 100 and 110 minutes, and have been decreasing over the decades and equalizing around the 100 minute mark. The jointplot allow provides a linear regression indicating the same decline over the years.
To ensure our plot title was in the correct place, I had to supply "pad=100" to move it out of the center of the plot.

Is there a specific time of the year or week where movies tend to perform worse?

In [32]:
```
movie_database_contents.describe()
```

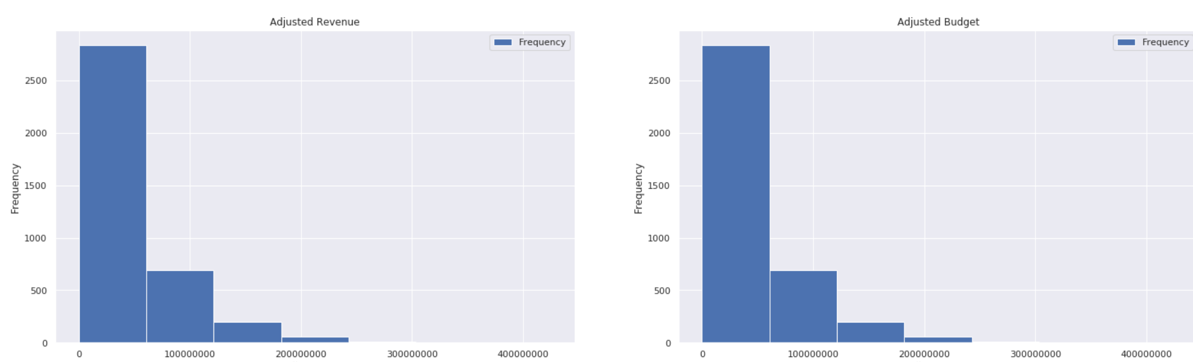
Out[32]:

	runtime	release_year	budget_adj	revenue_adj	adj_gains
count	3,798.00	3,798.00	3,798.00	3,798.00	3,798.00
mean	109.30	2,001.25	44,699,196.16	138,900,275.07	94,201,078.90
std	19.34	11.29	44,776,792.48	217,035,412.37	195,083,258.07
min	62.00	1,960.00	15,775.00	10,164.00	-413,912,431.00
25%	96.00	1,995.00	13,546,369.00	19,498,113.50	-1,356,302.50
50%	106.00	2,004.00	30,383,599.00	63,127,971.00	28,603,964.00
75%	119.00	2,010.00	60,809,238.00	165,727,345.75	109,004,230.75
max	219.00	2,015.00	425,000,000.00	2,827,123,750.00	2,750,136,651.00

Using Pandas describe function like before, I can get a summarized overview of the dataset.

In [33]:
```
fig, (ax1, ax2) = plt.subplots(nrows=1, ncols=2,figsize=(25, 7))
ax1.ticklabel_format(style='plain')
movie_database_contents['budget_adj'].plot.hist(title="Adjusted Revenue", labe
l="Frequency", bins=7, ax=ax1)
ax1.set_xlabel("Dollar Amount")
ax1.legend()
ax2.ticklabel_format(style='plain')
movie_database_contents['budget_adj'].plot.hist(title="Adjusted Budget", label
="Frequency", bins=7, ax=ax2)
ax2.set_xlabel("Dollar Amount")
ax2.legend()
```

Out[33]: <matplotlib.legend.Legend at 0x7f20ba2f4a90>



Using a histplot on both budget and revenue columns, we can see that both histograms are left skewed. To create both charts together I did:

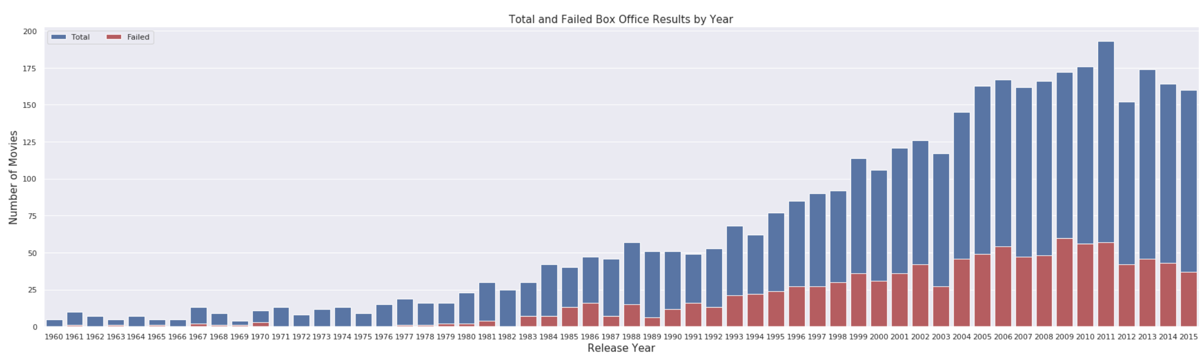
- Set matplotlib parameters nrows=1, and ncols=2 to allow 2 charts on 1 row
- To correctly format the xaxis "Dollar Amount"; I supplied the ticklabel_format style a value of "plain" to remove scientific notation
- I set both charts to show 7 bins to have an easier time viewing the content

In [34]:
```
movie_db_year = consolidate_by_time_period(movie_database_contents, "year")
```

Here I used the consolidate_by_time_period function I made earlier and supplied the original dataframe and the "year" parameter to create an aggregated count of successful, failed, and total movie counts by year.

In [35]:
```
f, ax = plt.subplots(figsize=(30, 8))
sns.barplot(y='num_movies', x='release_year', data=movie_db_year, color='b', l
abel='Total', ax=ax)
sns.barplot(y=True, x='release_year', data=movie_db_year, color='r', label='Fa
iled', ax=ax)
ax.legend(ncol=2, loc="upper left", frameon=True)
# ax.set(ylabel="Number of Movies", xlabel="Release Year")
plt.ylabel("Number of Movies", fontsize=15)
plt.xlabel("Release Year", fontsize=15)
plt.title("Total and Failed Box Office Results by Year", fontsize=15)
```

Out[35]:
```
Text(0.5, 1.0, 'Total and Failed Box Office Results by Year')
```



I wanted to see how common movies losing money has been over the years. To create the above plot I had to:

- set parameters to ensure the chart was easily readable, so our figsize was 30 wide, and 6 tall
- Created the "total" bar plot, showing how many movies were released for a given year, and provided "b" for blue for the color selection
- Created an additional barplot that shows the count of "failed" movies per year, and provided the "r" to indicate red for this barplot, to help distinguish the information
- finally I provided legend, labels, and title parameters to illustrate the plot better

In [36]:
```
top_20_fails_by_year = top_losses(movie_db_year, 20)
top_20_fails_by_year
```

Out[36]:

lost_money	release_year	False	True	num_movies	Percent Failed
34	1994	40.00	22.00	62.00	35.48
49	2009	112.00	60.00	172.00	34.88
26	1986	31.00	16.00	47.00	34.04
42	2002	84.00	42.00	126.00	33.33
31	1991	33.00	16.00	49.00	32.65
38	1998	62.00	30.00	92.00	32.61
25	1985	27.00	13.00	40.00	32.50
46	2006	113.00	54.00	167.00	32.34
50	2010	120.00	56.00	176.00	31.82
36	1996	58.00	27.00	85.00	31.76
44	2004	99.00	46.00	145.00	31.72
39	1999	78.00	36.00	114.00	31.58
35	1995	53.00	24.00	77.00	31.17
33	1993	47.00	21.00	68.00	30.88
45	2005	114.00	49.00	163.00	30.06
37	1997	63.00	27.00	90.00	30.00
41	2001	85.00	36.00	121.00	29.75
51	2011	136.00	57.00	193.00	29.53
40	2000	75.00	31.00	106.00	29.25
47	2007	115.00	47.00	162.00	29.01

Using the top_losses function I made earlier, I wanted to see which years had the worse performance. Supplying our function with the consolidated dataframe, and "20" I can see the top 20 years with the highest percentage of failures.
Using the function on the yearly dataframe, we can see that 1994 has the highest percentage of movies that lost money overall. While 2011 produced the most movies.

In [37]:
```
movie_db_month = consolidate_by_time_period(movie_database_contents, "month")
```

Next, I wanted to take a look at specific months. I used the consolidate function to make a dataframe aggregated movie counts by month.

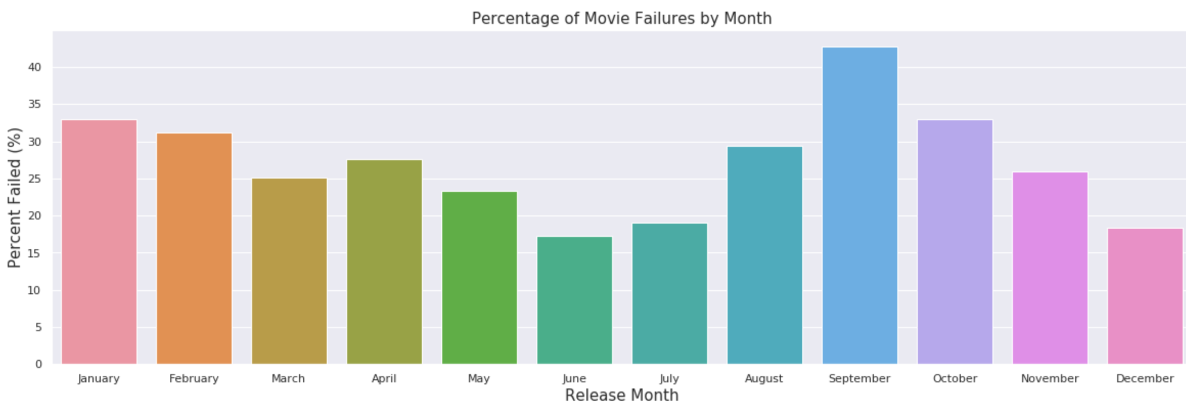
In [38]:
```
months = ["January", "February", "March", "April", "May", "June",
          "July", "August", "September", "October", "November", "December"]
movie_db_month['release_month'] = pd.Categorical(movie_db_month['release_mont
h'], categories=months, ordered=True)
```

I wanted the plots I'm going to create to be sorted correctly like a calendar; Jan to December, otherwise the months will be shown in a random fashion. To achieve this:

- I created a months list that follows a calendar progression
- To ensure our plots followed the list, I used pd.Categorical to set the release_month column to a category, and retain the order supplied to the function

In [39]:
```
f, ax = plt.subplots(figsize=(20, 6))
sns.barplot(x='release_month', y='Percent Failed', data=movie_db_month)
plt.title("Percentage of Movie Failures by Month", fontsize=15)
plt.ylabel("Percent Failed (%)", fontsize=15)
plt.xlabel("Release Month", fontsize=15)
```

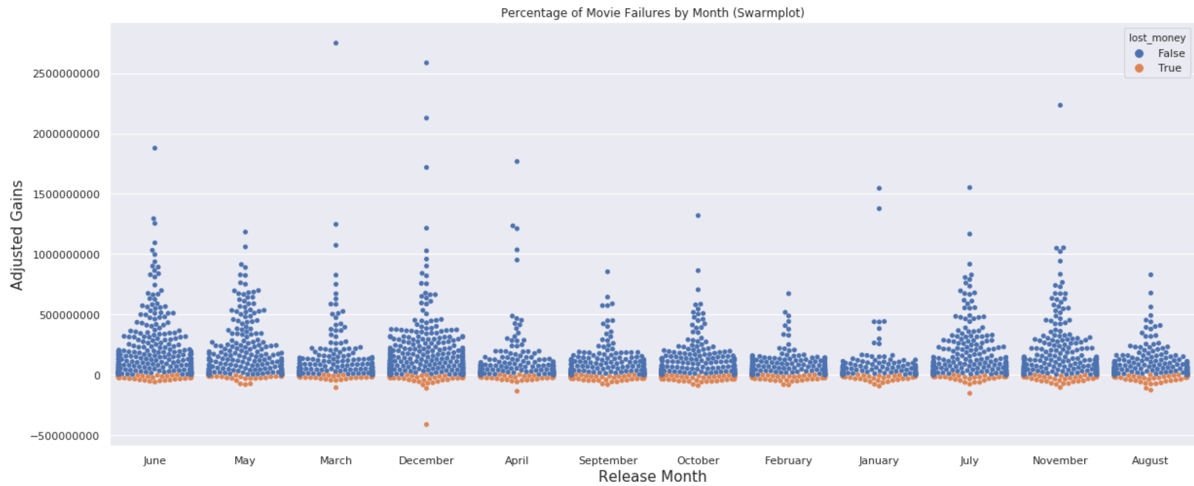
Out[39]:
```
Text(0.5, 0, 'Release Month')
```



Looking at the barplot, we can see that September is the month the where the most movies that have lost money, followed by October. Making the plot is as simple as supplying sns.barplot the x and y axis values, and the dataframe I wanted to use which was movie_db_month. plt.title() was used to supply the plot with the appropriate title.

In [40]:
```
f, ax = plt.subplots(figsize=(20, 8))
ax.ticklabel_format(style='plain')
sns.swarmplot(x='release_month', y='adj_gains',hue='lost_money', data=movie_da
tabase_contents)
plt.title("Percentage of Movie Failures by Month (Swarmplot)")
plt.ylabel("Adjusted Gains", fontsize=15)
plt.xlabel("Release Month", fontsize=15)
```

Out[40]:
```
Text(0.5, 0, 'Release Month')
```



Here I used a swarmplot to highlight the +/- box office gains, with color coding to indicate if money was lost. To create the swarmplot:

- I supplied matplotlib with the figsize=(20,8) parameters to ensure the plot was easily viewable.
- To help illustrate movies that lost money, I supplied the "hue" paremter with the "lost_money" column. On the plot, orange indicates that a movie lost money.

Using the swarmplot allow me to see additional information such as March having the best performing movie, and December having the worst performing movie.

In [41]:
```
top_losses_by_month = top_losses(movie_db_month, 12)
top_losses_by_month
```

Out[41]:

lost_money	release_month	False	True	num_movies	Percent Failed
11	September	259	194	453	42.83
4	January	146	72	218	33.03
10	October	238	117	355	32.96
3	February	172	78	250	31.20
1	August	235	98	333	29.43
0	April	191	73	264	27.65
9	November	223	78	301	25.91
7	March	205	69	274	25.18
8	May	220	67	287	23.34
5	July	255	60	315	19.05
2	December	336	76	412	18.45
6	June	278	58	336	17.26

Once again, I wanted a table summary to verify results. So I used the top_losses function again to generate the table by passing our month dataframe, and the parameter 12 to it.
September had the most movies that lost money, however it also had the most movies.

In [42]:
```
movie_db_day = consolidate_by_time_period(movie_database_contents, "day")
```

Next, I wanted to take a look at specific days. I followed the same procedure as the month views. By reusing functions, the amount of code is reduced.

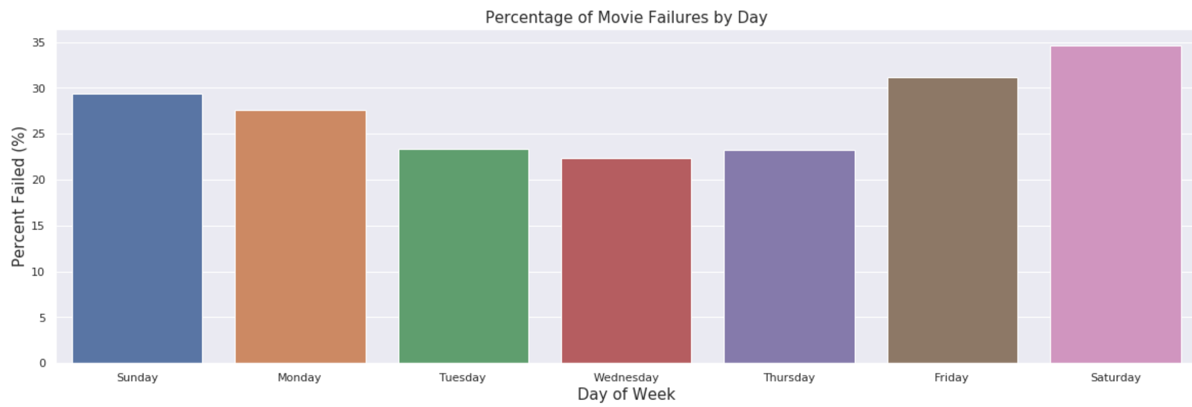
In [43]:
```
days = ["Sunday", "Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Sat
urday"]
movie_db_day['release_day'] = pd.Categorical(movie_db_day['release_day'], cate
gories=days, ordered=True)
```

I wanted the plots I'm going to create to be sorted correctly like a calendar; Sunday to Saturday, otherwise the days will be shown in a random fashion. To achieve this:

- I created a days list that follows a calendar progression
- To ensure our plots followed the list, I used pd.Categorical to set the release_day column to a category, and retain the order supplied to the function

In [44]:
```
f, ax = plt.subplots(figsize=(20, 6))
sns.barplot(x='release_day', y='Percent Failed', data=movie_db_day)
plt.title("Percentage of Movie Failures by Day", fontsize=15)
plt.ylabel("Percent Failed (%)", fontsize=15)
plt.xlabel("Day of Week", fontsize=15)
```

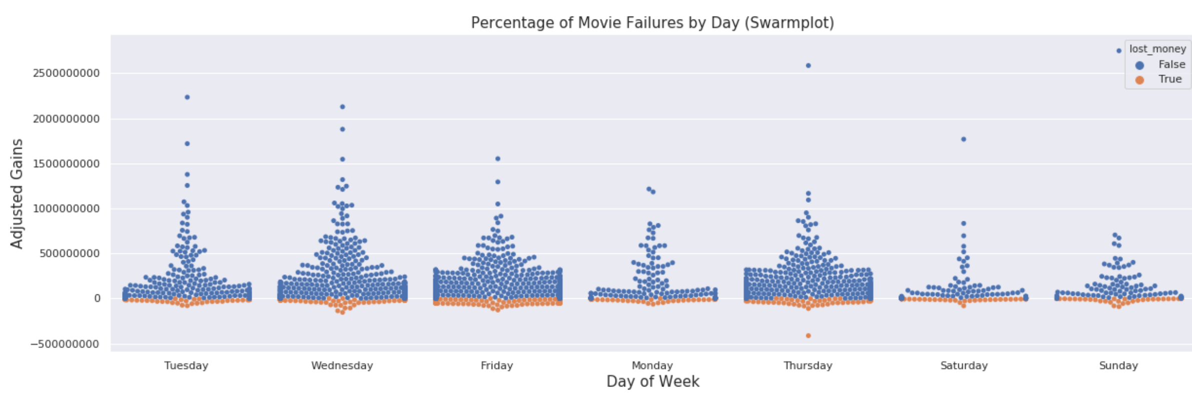
Out[44]: `Text(0.5, 0, 'Day of Week')`



From the looks of the barplot, Friday and Saturday have the highest percentage of box office failures. Creating the plot was the same steps used in the month plot.

In [45]:
```
f, ax = plt.subplots(figsize=(20, 6))
ax.ticklabel_format(style='plain')
sns.swarmplot(x='release_day', y='adj_gains',hue='lost_money', data=movie_data
base_contents)
plt.title("Percentage of Movie Failures by Day (Swarmplot)", fontsize=15)
plt.ylabel("Adjusted Gains", fontsize=15)
plt.xlabel("Day of Week", fontsize=15)
```

Out[45]: `Text(0.5, 0, 'Day of Week')`



Here I used a swarmplot to highlight the +/- box office gains, with color coding to indicate if money was lost. To create the swarmplot:

- I supplied matplotlib with the figsize=(20,8) parameters to ensure the plot was easily viewable.
- To help illustrate movies that lost money, I supplied the "hue" paremter with the "lost_money" column. On the plot, orange indicates that a movie lost money.

The benefits of using the swarmplot allow me to see additional information such as Thursday having the best and worst performing movie.

In [46]:
```
top_losses_by_day_of_week = top_losses(movie_db_day, 7)
top_losses_by_day_of_week
```

Out[46]:

lost_money	release_day	False	True	num_movies	Percent Failed
2	Saturday	98	52	150	34.67
0	Friday	1133	512	1645	31.12
3	Sunday	96	40	136	29.41
1	Monday	126	48	174	27.59
5	Tuesday	210	64	274	23.36
4	Thursday	596	180	776	23.20
6	Wednesday	499	144	643	22.40

Once again, I wanted a table summary to verify results. So I used the top_losses function again to generate the table by passing our day dataframe, and the parameter 7 to it.
Saturday had the highest percentage of movies that lost money, while Wednesday had the lowest percentage of movie failures.

Conclusions

For the Explorartory Data Analysis of The Movie Database data, I observed several interesting things.

Delving into the data to see if movie runtimes have changed over the years, was interesting and enlightening. Before and after removing outliers, more than 50% of the movies had a runtime under 107 minutes. Most of the movies with longer run times were from the 1960s, and runtimes have more or less decreased over the years finally plateauing between 110 and 100 minutes as seen in the line chart, and jointgrid plots.

Attempting to find answers to my second question proved to be more challenging. There's additional variables that cannot be accounted for such as where the film was released, a reliable popularity variable, and world events. Even though it wasn't part of my question, I still wanted to see which year had the highest percentage of movies that lost money. 1986 and 1994 had 36.07% and 34.04% of their movies loss money. At first glance it was surprising that September had the highest percentage of movie failures. However, further analysis shows that September has had the highest number of movie releases. It's curious that movies released on Saturday have the highest percentage of movie failures. I did not expect this going into the analysis.

Limitations of Dataset

After conducting analysis of the provided dataset. There are liminations that must be considered. There is clearly erroneous data in the dataset, columns such as "budget_adj" and "revenue_adj" have 0 as values. There's movies from other countries that may or may not have converted their revenue and budget to USD. There's also no clear definition of what constitues a movie, for example "Taken" released in 2002 has a run time of 877 minutes, and on imdb.com, wikipedia.com,and tv guide; it is considered a mini-series or tv show not a movie. We also do not know if world or localized events occured during a movies release that could have impacted their revenue. If I wanted to breakdown movie performance even further, such as seeing which actor/actress performed the best or worst. It would be difficult if not impossible due to not knowing if the cast column includes the entire cast, or just the most popular individuals at the time. Since we don't know how this dataset was generated and the accuracy of the data, it's not possible to state that our analysis applies to all movies.

Resources Referenced:

- https://seaborn.pydata.org/index.html (https://seaborn.pydata.org/index.html)
- https://pandas.pydata.org/pandas-docs/stable/index.html (https://pandas.pydata.org/pandas-docs/stable/index.html)
- https://www.imdb.com (https://www.imdb.com)
- https://en.wikipedia.org/ (https://en.wikipedia.org/)
- https://www.tvguide.com/ (https://www.tvguide.com/)