Descriptive Statistics with Python

Feb 28, 2024

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Link: https://www.loom.com/share/4ea7751dddf94c82 sid=1f8872cd-c5b9-491f-8a60-025d3be92810

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as stats
import random
```

1) Outlier Identification and Handling: In this task, you will work with a real-world dataset to identify and handle outliers. Choose a dataset (e.g., from Kaggle, UCI Machine Learning Repository) from the list of "Repositories for Finding Suitable Datasets," located in Class Resources, that exhibits outliers or extreme values. Write a Python script that identifies and handles the outliers using at least two methods (e.g., z-score, interquartile range). Use visualization techniques to demonstrate the impact of the outliers on measures of central tendency and variability.

In [2]:

```
fire = pd.read_csv('/Users/zanderbonnet/Desktop/GCU/DSC_510/DataSets/top_20_CA_w
fire
```

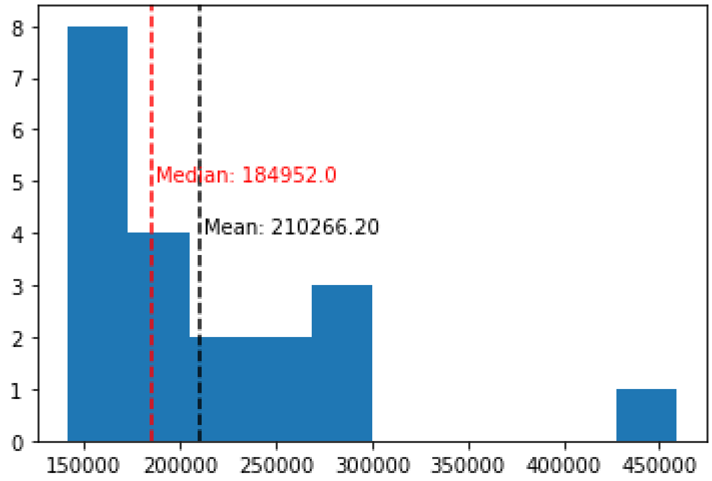
Out[2]:

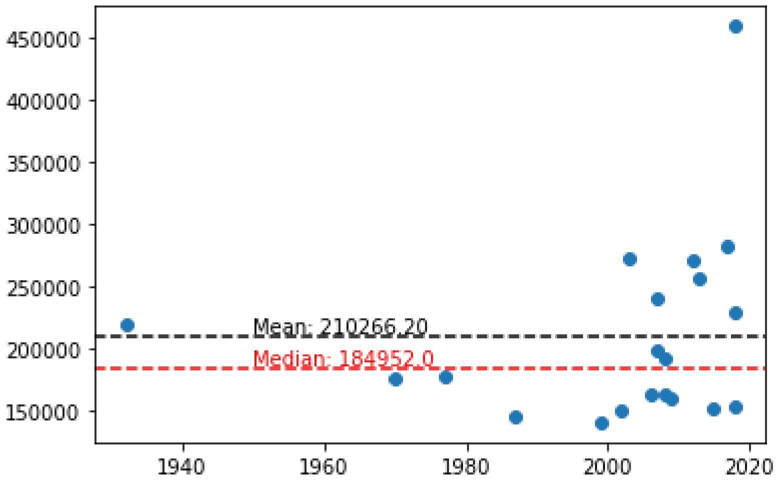
	fire_name	cause	month	year	county	acres	structures	deaths
0	Mendocino Complex	Under Investigation	July	2018	Colusa County, Lake County, Mendocino County &...	459123	280	1
1	Thomas	Powerlines	December	2017	Ventura & Santa Barbara	281893	1063	2
2	Cedar	Human Related	October	2003	San Diego	273246	2820	15
3	Rush	Lightning	August	2012	Lassen	271911	0	0
4	Rim	Human Related	August	2013	Tuolumne	257314	112	0
5	Zaca	Human Related	July	2007	Santa Barbara	240207	1	0

	fire_name	cause	month	year	county	acres	structures	deaths
6	Carr	Human Related	July	2018	Shasta County,Trinity County	229651	1614	8
7	Matilija	Undetermined	September	1932	Ventura	220000	0	0
8	Witch	Powerlines	October	2007	San Diego	197990	1650	2
9	Klamath Theater Complex	Lightning	June	2008	Siskiyou	192038	0	2
10	Marble Cone	Lightning	July	1977	Monterey	177866	0	0
11	Laguna	Powerlines	September	1970	San Diego	175425	382	5
12	Basin Complex	Lightning	June	2008	Monterey	162818	58	0
13	Day Fire	Human Related	September	2006	Ventura	162702	11	0
14	Station	Human Related	August	2009	Los Angeles	160557	209	2
15	Camp Fire	Powerlines	November	2018	Butte	153336	18804	85
16	Rough	Lightning	July	2015	Fresno	151623	4	0
17	Mcnally	Human Related	July	2002	Tulare	150696	17	0
18	Stanislaus Complex	Lightning	August	1987	Tuolumne	145980	28	1
19	Big Bar Complex	Lightning	August	1999	Trinity	140948	0	0

In [3]:

```
# Make histogram
plt.hist(fire['acres'])
plt.axvline(fire['acres'].mean(), color = 'black', linestyle = 'dashed')
plt.text(fire['acres'].mean() * 1.01, 4, 'Mean: {:.2f}'.format(fire['acres'].mea

plt.axvline(np.median(fire['acres']), color = 'red', linestyle = 'dashed')
plt.text(np.median(fire['acres'] * 1.01),5, 'Median: {}'.format(np.median(fire['

plt.show()

#Make Scatter Plot
plt.scatter(fire['year'], fire['acres'])
plt.axhline(fire['acres'].mean(), color = 'black', linestyle = 'dashed')
plt.text(1950, fire['acres'].mean() * 1.01,  'Mean: {:.2f}'.format(fire['acres']

plt.axhline(np.median(fire['acres']), color = 'red', linestyle = 'dashed')
plt.text(1950,np.median(fire['acres'] * 1.01), 'Median: {}'.format(np.median(fir

plt.show()

#Find standard deviation
sd = np.round(np.std(fire['acres']), 2)
```





In [4]:

```
#IQR method to remove outliers
q3 = np.percentile(fire['acres'], 75)
q1 = np.percentile(fire['acres'], 25)
iqr = q3-q1
upthresh = q3 + (1.5*iqr)
botthresh = q1 - (1.5*iqr)
trimiqr = fire[(fire['acres'] < upthresh) & (fire['acres'] > botthresh)]
trimiqr
```

Out[4]:

	fire_name	cause	month	year	county	acres	structures	deaths
1	Thomas	Powerlines	December	2017	Ventura & Santa Barbara	281893	1063	2
2	Cedar	Human Related	October	2003	San Diego	273246	2820	15
3	Rush	Lightning	August	2012	Lassen	271911	0	0
4	Rim	Human Related	August	2013	Tuolumne	257314	112	0
5	Zaca	Human Related	July	2007	Santa Barbara	240207	1	0
6	Carr	Human Related	July	2018	Shasta County,Trinity County	229651	1614	8

	fire_name	cause	month	year	county	acres	structures	deaths
7	Matilija	Undetermined	September	1932	Ventura	220000	0	0
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9	Klamath Theater Complex	Lightning	June	2008	Siskiyou	192038	0	2
10	Marble Cone	Lightning	July	1977	Monterey	177866	0	0
11	Laguna	Powerlines	September	1970	San Diego	175425	382	5
12	Basin Complex	Lightning	June	2008	Monterey	162818	58	0
13	Day Fire	Human Related	September	2006	Ventura	162702	11	0
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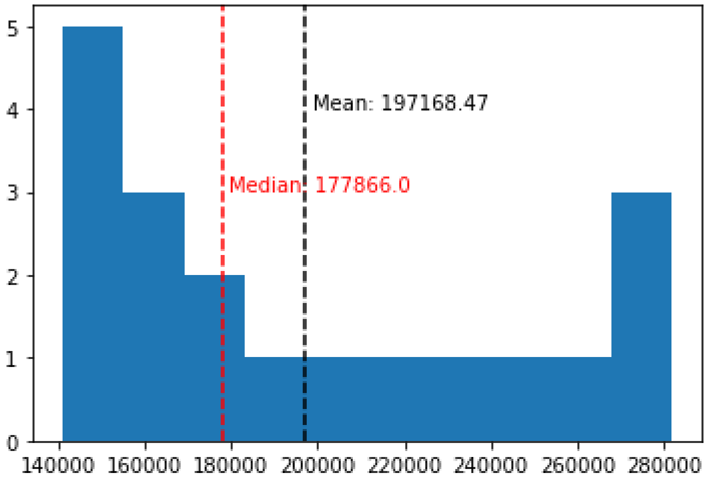
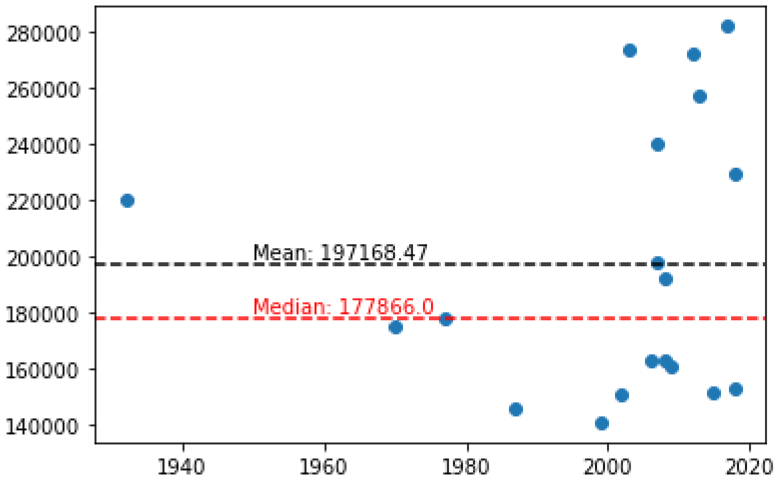
15	Camp Fire	Powerlines	November	2018	Butte	153336	18804	85
16	Rough	Lightning	July	2015	Fresno	151623	4	0
17	Mcnally	Human Related	July	2002	Tulare	150696	17	0
18	Stanislaus Complex	Lightning	August	1987	Tuolumne	145980	28	1
19	Big Bar Complex	Lightning	August	1999	Trinity	140948	0	0

In [5]:

```
#Make Histogram
plt.hist(trimiqr['acres'])
plt.axvline(trimiqr['acres'].mean(), color = 'black', linestyle = 'dashed')
plt.text(trimiqr['acres'].mean() * 1.01, 4, 'Mean: {:.2f}'.format(trimiqr['acres

plt.axvline(np.median(trimiqr['acres']), color = 'red', linestyle = 'dashed')
plt.text(np.median(trimiqr['acres'] * 1.01),3, 'Median: {}'.format(np.median(tri

plt.show()

#Make Scatter Plot
plt.scatter(trimiqr['year'], trimiqr['acres'])
plt.axhline(trimiqr['acres'].mean(), color = 'black', linestyle = 'dashed')
plt.text(1950, trimiqr['acres'].mean() * 1.01,  'Mean: {:.2f}'.format(trimiqr['a

plt.axhline(np.median(trimiqr['acres']), color = 'red', linestyle = 'dashed')
plt.text(1950,np.median(trimiqr['acres'] * 1.01), 'Median: {}'.format(np.median(

plt.show()

#Find Standard Deviation
sdiqr = np.round(np.std(trimiqr['acres']), 2)
```





In [6]:

```
#Z-Score method to remove outliers
zs = np.abs(stats.zscore(fire['acres']))
out_ind = np.where(zs > 3)[0]
trimzs = fire.drop(out_ind)
trimzs
```

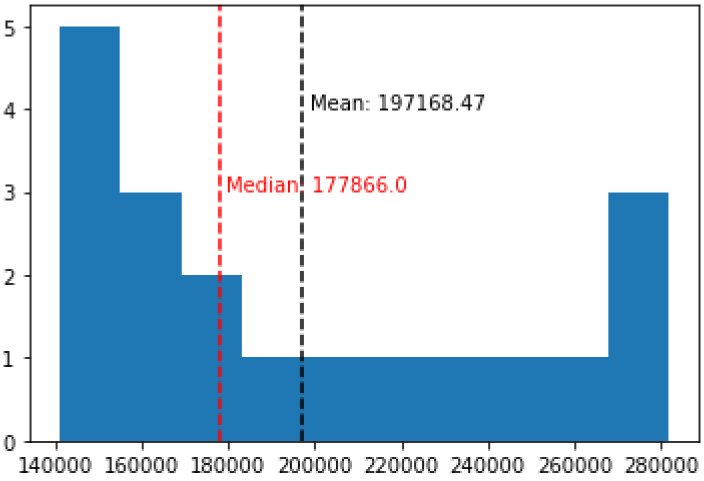
Out[6]:

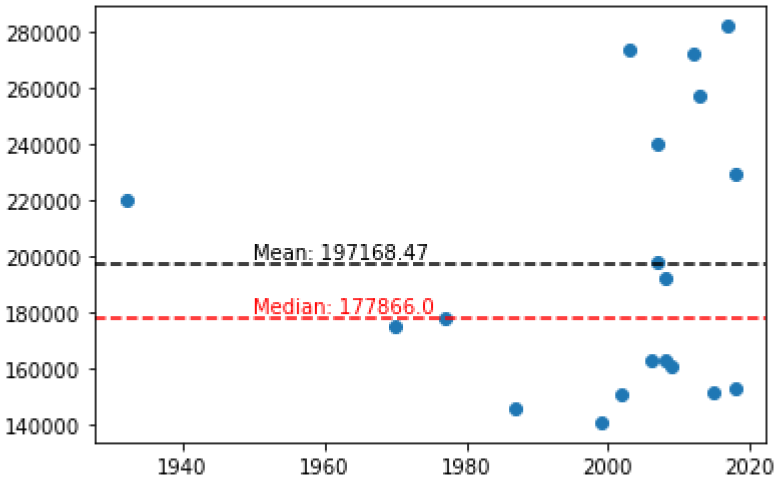
	fire_name	cause	month	year	county	acres	structures	deaths
1	Thomas	Powerlines	December	2017	Ventura & Santa Barbara	281893	1063	2
2	Cedar	Human Related	October	2003	San Diego	273246	2820	15
3	Rush	Lightning	August	2012	Lassen	271911	0	0
4	Rim	Human Related	August	2013	Tuolumne	257314	112	0
5	Zaca	Human Related	July	2007	Santa Barbara	240207	1	0
6	Carr	Human Related	July	2018	Shasta County,Trinity County	229651	1614	8
7	Matilija	Undetermined	September	1932	Ventura	220000	0	0
8	Witch	Powerlines	October	2007	San Diego	197990	1650	2

	fire_name	cause	month	year	county	acres	structures	deaths
9	Klamath Theater Complex	Lightning	June	2008	Siskiyou	192038	0	2
10	Marble Cone	Lightning	July	1977	Monterey	177866	0	0
11	Laguna	Powerlines	September	1970	San Diego	175425	382	5
12	Basin Complex	Lightning	June	2008	Monterey	162818	58	0
13	Day Fire	Human Related	September	2006	Ventura	162702	11	0
14	Station	Human Related	August	2009	Los Angeles	160557	209	2
15	Camp Fire	Powerlines	November	2018	Butte	153336	18804	85
16	Rough	Lightning	July	2015	Fresno	151623	4	0
17	Mcnally	Human Related	July	2002	Tulare	150696	17	0
18	Stanislaus Complex	Lightning	August	1987	Tuolumne	145980	28	1
19	Big Bar Complex	Lightning	August	1999	Trinity	140948	0	0

In [7]:

```
#Make histogram
plt.hist(trimzs['acres'])
plt.axvline(trimzs['acres'].mean(), color = 'black', linestyle = 'dashed')
plt.text(trimzs['acres'].mean() * 1.01, 4, 'Mean: {:.2f}'.format(trimzs['acres']

plt.axvline(np.median(trimzs['acres']), color = 'red', linestyle = 'dashed')
plt.text(np.median(trimzs['acres'] * 1.01),3, 'Median: {}'.format(np.median(trim

plt.show()

#make scatter plot
plt.scatter(trimzs['year'], trimzs['acres'])
plt.axhline(trimzs['acres'].mean(), color = 'black', linestyle = 'dashed')
plt.text(1950, trimzs['acres'].mean() * 1.01,  'Mean: {:.2f}'.format(trimzs['acr

plt.axhline(np.median(trimzs['acres']), color = 'red', linestyle = 'dashed')
plt.text(1950,np.median(trimzs['acres'] * 1.01), 'Median: {}'.format(np.median(t

plt.show()

#find standard deviation
sdzs = np.round(np.std(trimzs['acres']), 2)
```





In [8]:

```
#Show change in standard deviation
sdframe = pd.DataFrame({'Original': sd, 'IQR': sdiqr, 'Z-Score': sdzs}, index =
sdframe
```

Out[8]:

	Original	IQR	Z-Score
SD	73247.82	47080.95	47080.95

2) Bias and Confounding Variables Identification: Identify potential sources of bias or confounding variables in the dataset selected in Task 1 above and discuss how they might impact the analysis.

The potential bias of this dataset is that it only contains the top 20 largest fires in California based on acerage. So if we were to try and run analysis on other factors we would be biased towards large fires. There is also a possible location bias as this data only looks as California fires, so we could not generalize this data to other parts of the world.

There are possible confounding variables in the data set such as population and building densities in the location and time of the fires when trying to analyze the deaths and structures variables.

3) Handling Missing Data: Develop and justify an appropriate statistical method to handle missing data in the dataset selected in Task 1.

In [9]:

```python
#Picks 3 random acres to become a missing value
firena = fire.copy()
ran = random.choices(range(0,20), k = 3)
for x in ran:
    firena.loc[x, 'acres'] = np.nan
firena
```

Out[9]:

	fire_name	cause	month	year	county	acres	structures	deaths
0	Mendocino Complex	Under Investigation	July	2018	Colusa County, Lake County, Mendocino County &...	NaN	280	1
1	Thomas	Powerlines	December	2017	Ventura & Santa Barbara	281893.0	1063	2
2	Cedar	Human Related	October	2003	San Diego	273246.0	2820	15
3	Rush	Lightning	August	2012	Lassen	271911.0	0	0
4	Rim	Human Related	August	2013	Tuolumne	257314.0	112	0
5	Zaca	Human Related	July	2007	Santa Barbara	240207.0	1	0
6	Carr	Human Related	July	2018	Shasta County,Trinity County	NaN	1614	8
7	Matilija	Undetermined	September	1932	Ventura	220000.0	0	0
8	Witch	Powerlines	October	2007	San Diego	197990.0	1650	2
9	Klamath Theater Complex	Lightning	June	2008	Siskiyou	192038.0	0	2
10	Marble Cone	Lightning	July	1977	Monterey	177866.0	0	0
11	Laguna	Powerlines	September	1970	San Diego	175425.0	382	5
12	Basin Complex	Lightning	June	2008	Monterey	NaN	58	0
13	Day Fire	Human Related	September	2006	Ventura	162702.0	11	0
14	Station	Human Related	August	2009	Los Angeles	160557.0	209	2
15	Camp Fire	Powerlines	November	2018	Butte	153336.0	18804	85
16	Rough	Lightning	July	2015	Fresno	151623.0	4	0
17	Mcnally	Human Related	July	2002	Tulare	150696.0	17	0
18	Stanislaus Complex	Lightning	August	1987	Tuolumne	145980.0	28	1
19	Big Bar Complex	Lightning	August	1999	Trinity	140948.0	0	0

In this case using the interpolate method to fill missing values would be benificicial becasue our data is already sorted by acres, so using the linear method would fill values accuratly. This method assumes there is an equal distance between points and picks the midpoint to fill the missing value

In [10]:

```
firena['acres'].interpolate(method= 'linear', inplace = True, limit_direction =
firena
```

Out[10]:

	fire_name	cause	month	year	county	acres	structures	deaths
0	Mendocino Complex	Under Investigation	July	2018	Colusa County, Lake County, Mendocino County &...	281893.0	280	1
1	Thomas	Powerlines	December	2017	Ventura & Santa Barbara	281893.0	1063	2
2	Cedar	Human Related	October	2003	San Diego	273246.0	2820	15
3	Rush	Lightning	August	2012	Lassen	271911.0	0	0
4	Rim	Human Related	August	2013	Tuolumne	257314.0	112	0
5	Zaca	Human Related	July	2007	Santa Barbara	240207.0	1	0
6	Carr	Human Related	July	2018	Shasta County,Trinity County	230103.5	1614	8
7	Matilija	Undetermined	September	1932	Ventura	220000.0	0	0
8	Witch	Powerlines	October	2007	San Diego	197990.0	1650	2
9	Klamath Theater Complex	Lightning	June	2008	Siskiyou	192038.0	0	2
10	Marble Cone	Lightning	July	1977	Monterey	177866.0	0	0
11	Laguna	Powerlines	September	1970	San Diego	175425.0	382	5
12	Basin Complex	Lightning	June	2008	Monterey	169063.5	58	0
13	Day Fire	Human Related	September	2006	Ventura	162702.0	11	0
14	Station	Human Related	August	2009	Los Angeles	160557.0	209	2
15	Camp Fire	Powerlines	November	2018	Butte	153336.0	18804	85
16	Rough	Lightning	July	2015	Fresno	151623.0	4	0
17	Mcnally	Human Related	July	2002	Tulare	150696.0	17	0
18	Stanislaus Complex	Lightning	August	1987	Tuolumne	145980.0	28	1

	fire_name	cause	month	year	county	acres	structures	deaths
19	Big Bar Complex	Lightning	August	1999	Trinity	140948.0	0	0

In [11]:

```python
#Picks 3 random acres to become a missing value
firena = fire.copy()
ran = random.choices(range(0,20), k = 3)
for x in ran:
    firena.loc[x, 'acres'] = np.nan
firena
```

Out[11]:

	fire_name	cause	month	year	county	acres	structures	deaths
0	Mendocino Complex	Under Investigation	July	2018	Colusa County, Lake County, Mendocino County &...	459123.0	280	1
1	Thomas	Powerlines	December	2017	Ventura & Santa Barbara	281893.0	1063	2
2	Cedar	Human Related	October	2003	San Diego	273246.0	2820	15
3	Rush	Lightning	August	2012	Lassen	271911.0	0	0
4	Rim	Human Related	August	2013	Tuolumne	257314.0	112	0
5	Zaca	Human Related	July	2007	Santa Barbara	240207.0	1	0
6	Carr	Human Related	July	2018	Shasta County,Trinity County	229651.0	1614	8
7	Matilija	Undetermined	September	1932	Ventura	NaN	0	0
8	Witch	Powerlines	October	2007	San Diego	197990.0	1650	2
9	Klamath Theater Complex	Lightning	June	2008	Siskiyou	192038.0	0	2
10	Marble Cone	Lightning	July	1977	Monterey	177866.0	0	0
11	Laguna	Powerlines	September	1970	San Diego	175425.0	382	5
12	Basin Complex	Lightning	June	2008	Monterey	NaN	58	0
13	Day Fire	Human Related	September	2006	Ventura	162702.0	11	0
14	Station	Human Related	August	2009	Los Angeles	160557.0	209	2
15	Camp Fire	Powerlines	November	2018	Butte	NaN	18804	85
16	Rough	Lightning	July	2015	Fresno	151623.0	4	0
17	Mcnally	Human Related	July	2002	Tulare	150696.0	17	0

	fire_name	cause	month	year	county	acres	structures	deaths
18	Stanislaus Complex	Lightning	August	1987	Tuolumne	145980.0	28	1
19	Big Bar Complex	Lightning	August	1999	Trinity	140948.0	0	0

If the missing values were not sorted I would use mean inputation to fill the values. If I had more data in the dataset I might have elected to use a regression model to fill in the missing values.

In [12]:

```python
firena.fillna(firena['acres'].mean())
```

Out[12]:

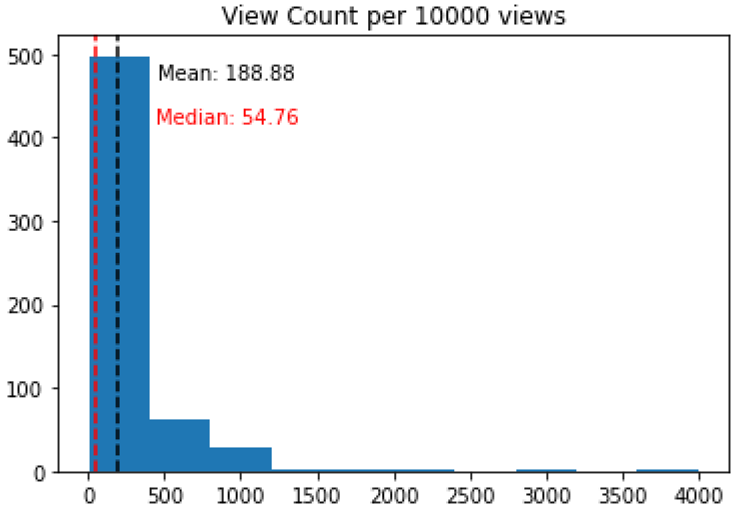
	fire_name	cause	month	year	county	acres	structures	deaths
0	Mendocino Complex	Under Investigation	July	2018	Colusa County, Lake County, Mendocino County &...	459123.000000	280	1
1	Thomas	Powerlines	December	2017	Ventura & Santa Barbara	281893.000000	1063	2
2	Cedar	Human Related	October	2003	San Diego	273246.000000	2820	15
3	Rush	Lightning	August	2012	Lassen	271911.000000	0	0
4	Rim	Human Related	August	2013	Tuolumne	257314.000000	112	0
5	Zaca	Human Related	July	2007	Santa Barbara	240207.000000	1	0
6	Carr	Human Related	July	2018	Shasta County,Trinity County	229651.000000	1614	8
7	Matilija	Undetermined	September	1932	Ventura	215833.529412	0	0
8	Witch	Powerlines	October	2007	San Diego	197990.000000	1650	2
9	Klamath Theater Complex	Lightning	June	2008	Siskiyou	192038.000000	0	2
10	Marble Cone	Lightning	July	1977	Monterey	177866.000000	0	0
11	Laguna	Powerlines	September	1970	San Diego	175425.000000	382	5
12	Basin Complex	Lightning	June	2008	Monterey	215833.529412	58	0
13	Day Fire	Human Related	September	2006	Ventura	162702.000000	11	0
14	Station	Human Related	August	2009	Los Angeles	160557.000000	209	2
15	Camp Fire	Powerlines	November	2018	Butte	215833.529412	18804	85
16	Rough	Lightning	July	2015	Fresno	151623.000000	4	0

	fire_name	cause	month	year	county	acres	structures	deaths
17	Mcnally	Human Related	July	2002	Tulare	150696.000000	17	0
18	Stanislaus Complex	Lightning	August	1987	Tuolumne	145980.000000	28	1
19	Big Bar Complex	Lightning	August	1999	Trinity	140948.000000	0	0

4) Analysis of Mean and Median Values: In this task, you will analyze a dataset to understand the difference between mean and median values. Choose a dataset from the list of "Repositories for Finding Suitable Datasets," located in Class Resources, where the mean and median values differ significantly. Write a Python script to calculate and visualize the mean and median values of the dataset. Interpret the results and provide insights into what the difference means for the dataset. Propose solutions to handle this discrepancy and implement them using Python. Compare and contrast the effectiveness of four different measures of central tendency and variability in capturing the characteristics of the data.

In [13]:

```
vids = pd.read_csv('/Users/zanderbonnet/Desktop/GCU/DSC_510/DataSets/most_watche
#makes histogram
plt.hist(vids['view_count']/10000)
plmin, plmax = plt.ylim()
plt.title('View Count per 10000 views')
plt.axvline((vids['view_count']/10000).mean(), color = 'black', linestyle = 'das
plt.text((vids['view_count']/10000).mean() * 2.4, plmax *.9,
         'Mean: {:.2f}'.format((vids['view_count']/10000).mean()))

plt.axvline(np.median(vids['view_count']/10000), color = 'red', linestyle = 'das
plt.text(np.median(vids['view_count']/10000) * 8, plmax *.8,
         'Median: {:.2f}'.format(np.median(vids['view_count']/10000)), color = '
plt.show()
```



The plot shows that there is a large right skew of the data. This is shown by how there is a elongated tail to the right of the graph as well as the mean is significanly larger than the median. To handle this problem there are a couple solutions. We could choose to find outliers and remove them, or we could take those outliers and replace their values with existing values.

These possible values could be the mean, median, mode, largest nonoutlier value if it is a large outlier, or replace with the smallest nonoutlier value if it is a small outlier.

I chose to replace the upper outliers with the largest nonoutlier value as this will still preserve the shape of the data, and it will bring the mean and variance down. If I were to have removed the outliers it would have shrunk my dataset by about 100 values, so I thought it would be more benifical to keep them in the dataset.

In [14]:

```
x#uses iqr to replace outlier values with max nonoutlier
q1 = np.percentile(vids['view_count'],25)
q3 = np.percentile(vids['view_count'],75)
iqr = q3-q1
up_thresh = q3 + (3*iqr)
low_thresh = q1 - (3*iqr)
rep = vids[(vids['view_count'] > low_thresh) & (vids['view_count'] < up_thresh)]
rep['view_count'].max()
trim = vids.copy()
trim.loc[trim['view_count'] > rep['view_count'].max(), 'view_count'] = rep['view
trim
```

Out[14]:

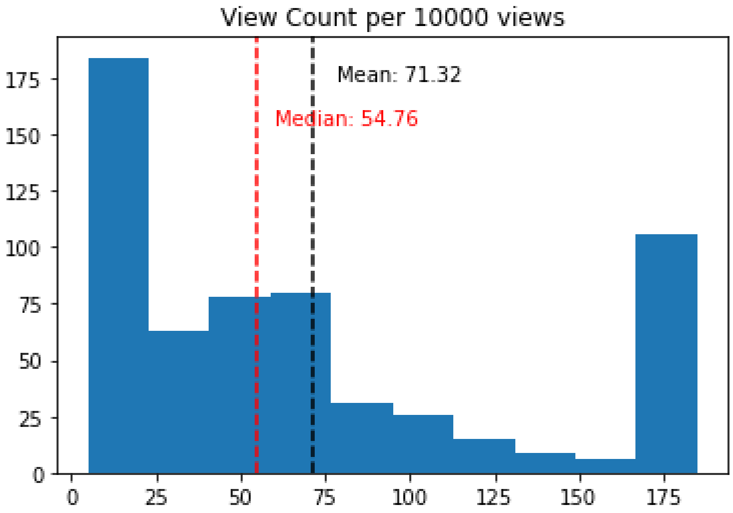
	title	published_at	duration	view_count	like_
0	Se Libró del ATAQUE de un Cocodrilo ❌🐊	2024-01-27T19:16:13Z	PT25S	1849258	114
1	#Sareedrapping#pregnancydrapping#babyshower#sh...	2024-02-11T14:43:07Z	PT37S	1849258	1239
2	Majburi Insaan Se Kuch Bhi Karva Deti Hai | PA...	2024-01-24T05:17:00Z	PT1M1S	1849258	93
3	Tom 🍓 Jerry (Soumya&Ammu)Real End Twist😍🎈 #sho...	2024-01-17T14:14:43Z	PT58S	1849258	43
4	The success of people depends on their life co...	2024-01-24T09:00:30Z	PT56S	1849258	34
...	...	...	...	...	
593	కేసీఆర్ ఏం చేయబోతున్నడు..ముందే చెప్పేసిన మల్లన...	2024-02-20T06:23:10Z	PT7M14S	109855	1
594	The BEST feeling in the World!! I know I’ll mi...	2024-02-19T18:12:55Z	PT7S	54557	4
595	Chinese burger with chicken and bamboo shoots ...	2024-02-20T03:16:24Z	PT59S	63345	1
596	АЛЁНА, БЛИН про Ксению Собчак и Дину Саеву / ...	2024-02-19T20:04:58Z	PT58S	52786	1
597	Week 15 living off homegrown and wild food! 🙂 ...	2024-02-19T17:04:55Z	PT58S	49143	6

598 rows × 6 columns

In [15]:

```
#makes histogram
plt.hist(trim['view_count']/10000)
plmin, plmax = plt.ylim()
```

```
plt.title('View Count per 10000 views')
plt.axvline((trim['view_count']/10000).mean(), color = 'black', linestyle = 'das
plt.text((trim['view_count']/10000).mean() * 1.1, plmax *.9,
         'Mean: {:.2f}'.format((trim['view_count']/10000).mean()))

plt.axvline(np.median(trim['view_count']/10000), color = 'red', linestyle = 'das
plt.text(np.median(trim['view_count']/10000) * 1.1, plmax *.8,
         'Median: {:.2f}'.format(np.median(trim['view_count']/10000)), color = "
plt.show()
```



In [16]:

```
print('Mean: {:.2f}'.format(trim['view_count'].mean()))
print('Std: {:.2f}'.format(np.std(trim['view_count'])))
print('Median: {}'.format(np.median(trim['view_count'])))
print('Mode: {}'.format(stats.mode(trim['view_count'])))
```

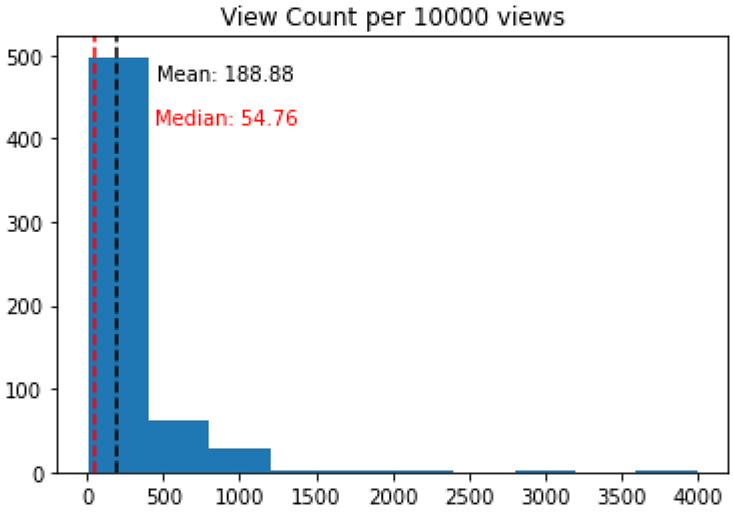
```
Mean: 713211.02
Std: 614205.55
Median: 547645.0
Mode: ModeResult(mode=array([1849258]), count=array([101]))
```

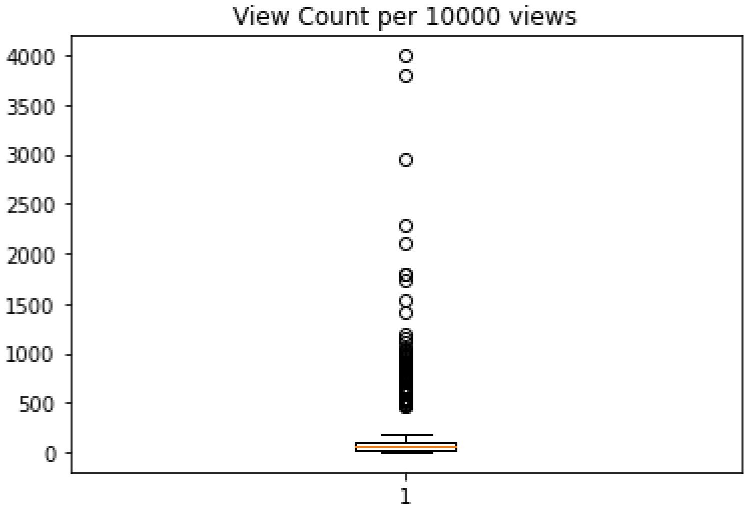
The most effective way to utilze the mean and median is to comapare them to analyze the skew in the data. From this we can see any possible shift depending on what way the mean leans. If the mean is shifted to the right from the median we can see that there is a right skew and if its to the left there is a left skew. Another effective meassure is the standard deviation/varriance, these measures allow us to see the spread of the data and know how compact our data points are. If we have lots of data points in a small range adn hen just a couple outside of that range we will see that the standard deviation will be smaller than if they were all spread out. Another measure of tendancy is the mode. In examples like this the mode isn't the most useful as the data is very spread out, but in data sets where there may only be a couple possible values it is very helpful to see the most common result.

5) Data Visualization: In this task, you will use Python to create visualizations that effectively communicate data distribution. Choose a dataset from the list of "Repositories for Finding Suitable Datasets," located in Class Resources, and create basic plots to visualize the data distribution (e.g., histogram, boxplot). Analyze the plots to gain insights into the data distribution and interpret the results.

In [17]:

```
#makes histogram
plt.hist(vids['view_count']/10000)
plmin, plmax = plt.ylim()
plt.title('View Count per 10000 views')
plt.axvline((vids['view_count']/10000).mean(), color = 'black', linestyle = 'das
plt.text((vids['view_count']/10000).mean() * 2.4, plmax *.9,
         'Mean: {:.2f}'.format((vids['view_count']/10000).mean()))

plt.axvline(np.median(vids['view_count']/10000), color = 'red', linestyle = 'das
plt.text(np.median(vids['view_count']/10000) * 8, plmax *.8,
         'Median: {:.2f}'.format(np.median(vids['view_count']/10000)), color = '
plt.show()

#makes boxplot
plt.boxplot(vids['view_count']/10000)
plt.title('View Count per 10000 views')
plt.show()
```





In these plots we can see the skew, frequency, and spread of the data.

The histogram is great at showing the frequency of data. It also shows us any skew in the data. In this example we can see that there is a large skew to the right and there is a much larger concentration of data in the 250 and under bar.

The boxplot is great at showing the spread of the data. It shows us the quantiles and any possible outliers we may have in the data. You can also see skew in this plot by looking at the size of the individual boxes, and where the outliers are located. In this example we can see there are a large amount of possible outliers as well as a very tight spread of nonoutlier values.

6) Measures of Central Tendency and Variability: In this task, you will calculate and interpret measures of central tendency and variability using Python. Choose a dataset from the list of "Repositories for Finding Suitable Datasets," located in Class Resources, and write a Python script to calculate the mean, median, mode, range, variance, and standard deviation of the dataset. Interpret the results and discuss how the measures of central tendency and variability relate to the data distribution.

In [18]:

```
print('Mean: {:.2f}'.format(fire['acres'].mean()))
print('Median: {}'.format(np.median(fire['acres'])))
print('Mode: {}'.format(stats.mode(fire['acres'])))
print('Range: {}'.format(fire['acres'].max() - fire['acres'].min()))
print('Std: {:.2f}'.format(np.std(fire['acres'])))
print('Var: {:.2f}'.format(np.var(fire['acres'])))
```

```
Mean: 210266.20
Median: 184952.0
Mode: ModeResult(mode=array([140948]), count=array([1]))
Range: 318175
Std: 73247.82
Var: 5365242992.96
```

In our results we can see that the data has a right skew with a fairly large spread. We can see that there is a large std and var in relation to the range so the data must be spread out or there are large outliers.

The measures of central tendancy and variabilty can show us the possible shape of the data, if there are a large amount of one data point, and how spread out the data is.

7) Data Cleaning: In this task, you will use Python to clean a dataset and prepare it for analysis. Choose a messy dataset (e.g., missing values, inconsistent formatting) from the list of "Repositories for Finding Suitable Datasets," located in Class Resources, and write a Python script to clean the dataset. Use appropriate methods to handle missing values, remove duplicates, and convert data types. Visualize the cleaned dataset to demonstrate the impact of the cleaning process.

In [19]:

```
movies = pd.read_csv('/Users/zanderbonnet/Desktop/GCU/DSC_510/DataSets/movies.cs
movies
```

Out[19]:

	MOVIES	YEAR	GENRE	RATING	ONE-LINE	STARS	VOTES	RunTim
0	Blood Red Sky	(2021)	\nAction, Horror, Thriller	6.1	\nA woman with a mysterious illness is forced ...	\n Director:\nPeter Thorwarth\n| \n Star...	21,062	121.

	MOVIES	YEAR	GENRE	RATING	ONE-LINE	STARS	VOTES	RunTim
1	Masters of the Universe: Revelation	(2021–)	\nAnimation, Action, Adventure	5.0	\nThe war for Eternia begins again in what may...	\n \n Stars:\nChris Wood, \nSara...	17,870	25.
2	The Walking Dead	(2010–2022)	\nDrama, Horror, Thriller	8.2	\nSheriff Deputy Rick Grimes wakes up from a c...	\n \n Stars:\nAndrew Lincoln, \n...	885,805	44.
3	Rick and Morty	(2013–)	\nAnimation, Adventure, Comedy	9.2	\nAn animated series that follows the exploits...	\n \n Stars:\nJustin Roiland, \n...	414,849	23.
4	Army of Thieves	(2021)	\nAction, Crime, Horror	NaN	\nA prequel, set before the events of Army of ...	\n Director:\nMatthias Schweighöfer\n| \n ...	NaN	Nal
...	...	...	...	...	...	...	...	.
9994	The Imperfects	(2021–)	\nAdventure, Drama, Fantasy	NaN	\nAdd a Plot\n	\n \n Stars:\nMorgan Taylor Camp...	NaN	Nal
9995	Arcane	(2021–)	\nAnimation, Action, Adventure	NaN	\nAdd a Plot\n	\n	NaN	Nal
9996	Heart of Invictus	(2022–)	\nDocumentary, Sport	NaN	\nAdd a Plot\n	\n Director:\nOrlando von Einsiedel\n| \n ...	NaN	Nal
9997	The Imperfects	(2021–)	\nAdventure, Drama, Fantasy	NaN	\nAdd a Plot\n	\n Director:\nJovanka Vuckovic\n| \n Sta...	NaN	Nal
9998	The Imperfects	(2021–)	\nAdventure, Drama, Fantasy	NaN	\nAdd a Plot\n	\n Director:\nJovanka Vuckovic\n| \n Sta...	NaN	Nal

9999 rows × 9 columns

In [20]:

```
movies = movies.dropna().reset_index(drop= True)
movies.drop_duplicates(inplace = True)
movies = movies.convert_dtypes()
#puts years in format to be an int
for x in range(0,len(movies['YEAR'])):
    word = movies.loc[x,'YEAR']
    dig = ''
    for l in word:
            if l.isdigit():
                dig += l
        int(dig)
        movies.loc[x,'YEAR'] = dig
movies['YEAR'] = movies['YEAR'].astype('int64')

#puts votes in format to be an int
for x in range(0,len(movies['VOTES'])):
    word = movies.loc[x,'VOTES']
    dig = ''
    for l in word:
        if l.isdigit():
            dig += l
    int(dig)
    movies.loc[x,'VOTES'] = dig
movies['VOTES'] = movies['VOTES'].astype('int64')

#puts gross in format to be a float
for x in range(0,len(movies['Gross'])):
    movies.loc[x,'Gross'] = movies.loc[x,'Gross'].replace('$','').replace('M', '
movies['Gross'] = movies['Gross'].astype('Float64')

print(movies.dtypes)
movies
```

```
MOVIES       string
YEAR          int64
GENRE        string
RATING      Float64
ONE-LINE     string
STARS        string
VOTES         int64
RunTime       Int64
Gross       Float64
dtype: object
```

Out[20]:

	MOVIES	YEAR	GENRE	RATING	ONE-LINE	STARS	VOTES	RunTime	
0	The Hitman's Bodyguard	2017	Action, Comedy, Crime	6.9	The world's top bodyguard gets a new client, ...	Director: Patrick Hughes | Stars: Ry...	205979	118	75470
1	Jurassic Park	1993	Action, Adventure, Sci-Fi	8.1	A pragmatic paleontologist visiting an almost...	Director: Steven Spielberg | Stars: ...	897444	127	402450
2	Don't Breathe	2016	Crime, Horror, Thriller	7.1	Hoping to walk away with a massive fortune, a...	Director: Fede Alvarez | Stars: Step...	237601	88	89220
3	The Lord of the Rings: The Fellowship of the Ring	2001	Action, Adventure, Drama	8.8	A meek Hobbit from the Shire and eight compan...	Director: Peter Jackson | Stars: Eli...	1713028	178	315540
4	Escape Room	2019	Action, Adventure,	6.4	Six strangers find	Director: Adam	99351	99	57010

	MOVIES	YEAR	GENRE	RATING	ONE-LINE	STARS	VOTES	RunTime	
			Horror		themselves in a maze of de...	Robitel | Stars: Tayl...			
...	...	...	...	...	...	...	...	...	
455	Vidal Sassoon: The Movie	2010	Documentary	6.5	Vidal Sassoon is more than just a hairdresser...	Director: Craig Teper | Stars: Bever...	245	90	90
456	Men at Lunch	2012	Documentary, Mystery	6.3	The story of "Lunch atop a Skyscraper," the i...	Director: Seán Ó Cualáin | Stars: Fi...	331	75	
457	Decoding Deepak	2012	Documentary	5.5	Deepak Chopra's son, Gotham, spends a year tr...	Director: Gotham Chopra | Stars: Dee...	124	83	10
458	Theo Who Lived	2016	Documentary	6.8	A documentary on American journalist Theo Pad...	Director: David Schisgall | Star: Th...	111	86	10
459	Southern Justice	2006	Action, Adventure, Thriller	3.1	M.D. Selig's feature thriller, SOUTHERN JUSTI...	Director: M.D. Selig | Stars: M.D. S...	126	96	140

460 rows × 9 columns

In [21]:

```
#if any 0 or negative values replace with the median of that category
movies.loc[movies['Gross'] <= 0, 'Gross'] = int(movies['Gross'].median())
movies.loc[movies['RATING'] <= 0, 'RATING'] = int(movies['RATING'].median())
movies.loc[movies['VOTES'] <= 0, 'VOTES'] = int(movies['VOTES'].median())
movies.loc[movies['RunTime'] <= 0, 'RunTime'] = int(movies['RunTime'].median())
movies
```

Out[21]:

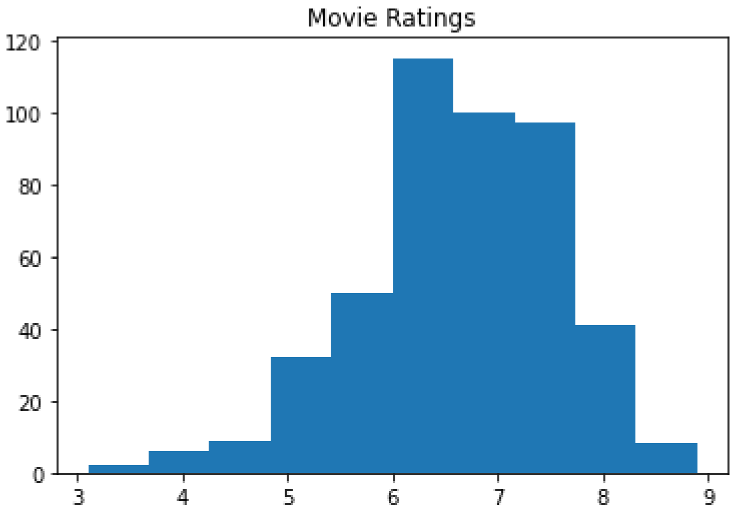
	MOVIES	YEAR	GENRE	RATING	ONE-LINE	STARS	VOTES	RunTime	
0	The Hitman's Bodyguard	2017	Action, Comedy, Crime	6.9	The world's top bodyguard gets a new client, ...	Director: Patrick Hughes | Stars: Ry...	205979	118	75470
1	Jurassic Park	1993	Action, Adventure, Sci-Fi	8.1	A pragmatic paleontologist visiting an almost...	Director: Steven Spielberg | Stars: ...	897444	127	402450
2	Don't Breathe	2016	Crime, Horror, Thriller	7.1	Hoping to walk away with a	Director: Fede Alvarez |	237601	88	89220

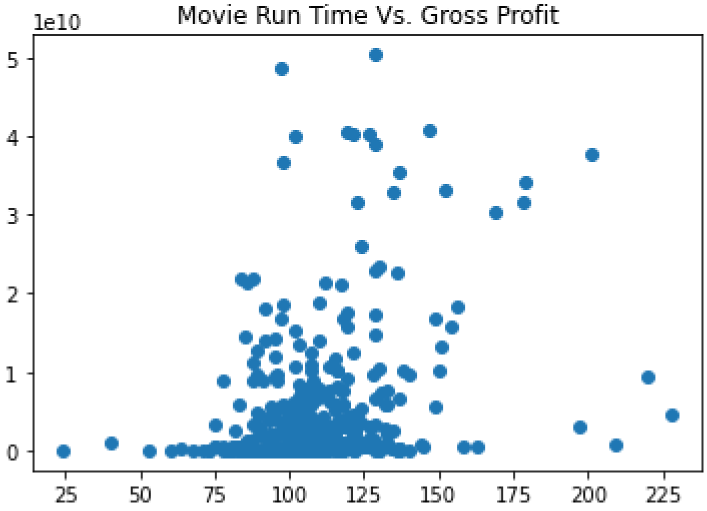
	MOVIES	YEAR	GENRE	RATING	ONE-LINE	STARS	VOTES	RunTime	
					massive fortune, a...	Stars: Step...			
3	The Lord of the Rings: The Fellowship of the Ring	2001	Action, Adventure, Drama	8.8	A meek Hobbit from the Shire and eight compan...	Director: Peter Jackson | Stars: Eli...	1713028	178	315540
4	Escape Room	2019	Action, Adventure, Horror	6.4	Six strangers find themselves in a maze of de...	Director: Adam Robitel | Stars: Tayl...	99351	99	57010
...	...	...	...	...	...	...	...	...	
455	Vidal Sassoon: The Movie	2010	Documentary	6.5	Vidal Sassoon is more than just a hairdresser...	Director: Craig Teper | Stars: Bever...	245	90	90
456	Men at Lunch	2012	Documentary, Mystery	6.3	The story of "Lunch atop a Skyscraper," the i...	Director: Seán Ó Cualáin | Stars: Fi...	331	75	6145
457	Decoding Deepak	2012	Documentary	5.5	Deepak Chopra's son, Gotham, spends a year tr...	Director: Gotham Chopra | Stars: Dee...	124	83	10
458	Theo Who Lived	2016	Documentary	6.8	A documentary on American journalist Theo Pad...	Director: David Schisgall | Star: Th...	111	86	10
459	Southern Justice	2006	Action, Adventure, Thriller	3.1	M.D. Selig's feature thriller, SOUTHERN JUSTI...	Director: M.D. Selig | Stars: M.D. S...	126	96	140

460 rows × 9 columns

In [22]:

```
#makes histogram
plt.hist(movies["RATING"])
plt.title('Movie Ratings')
plt.show()
#makes scatter plot
plt.scatter(movies['RunTime'], movies['Gross'])
plt.title('Movie Run Time Vs. Gross Profit')
plt.show()
```





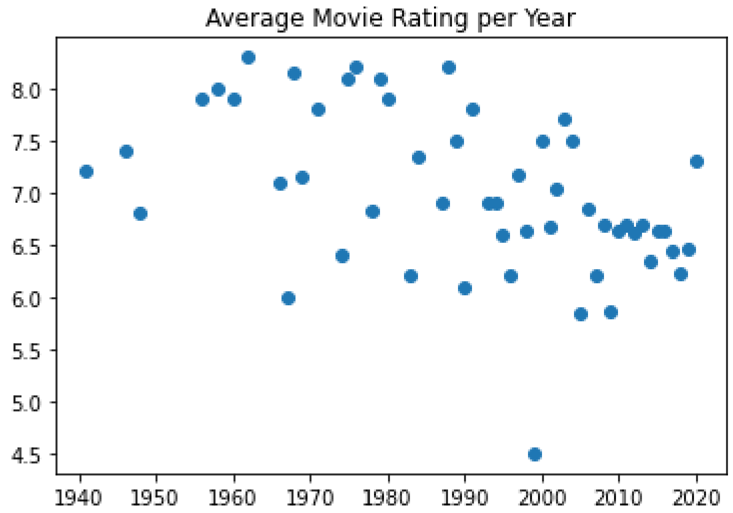
By cleaning the data we are now able to conduct graphical analysis on the data. Before it thought these values were strings so we would have not been able to plot them. We also droped many missing values so we are able to get an accurate representation of the complete data. As well as we corrected any data that was wrong with a median value of its category.

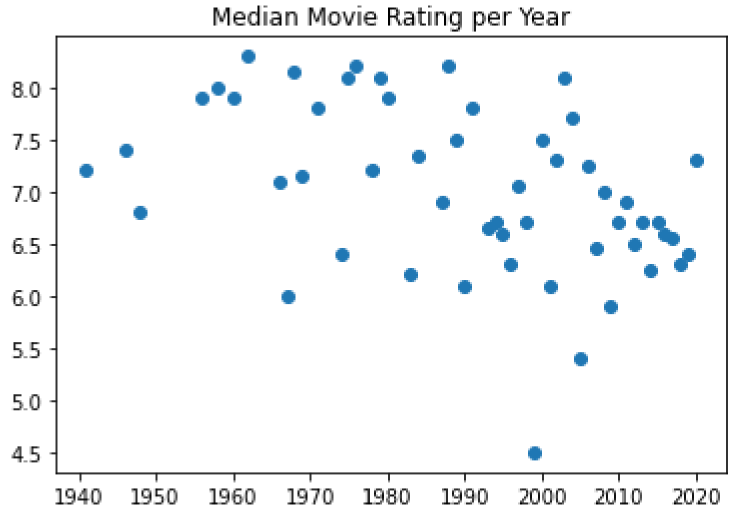
8) Group Analysis: In this task, you will use Python to conduct group analysis on a dataset. Choose a dataset from the list of "Repositories for Finding Suitable Datasets," located in Class Resources, and write a Python script to group the data by a categorical variable (e.g., gender, age group). Calculate measures of central tendency and variability for each group and visualize the results using appropriate plots. Interpret the results and discuss any differences between the groups.

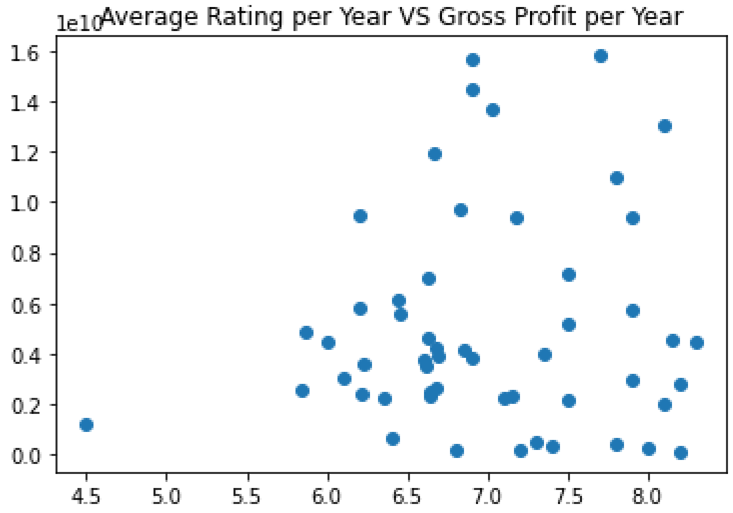
In [23]:

```
yearmeans = movies.groupby(movies['YEAR']).mean()
yearmed = movies.groupby(movies['YEAR']).median()
yearsd = movies.groupby(movies['YEAR']).agg(np.std)
yearvar = movies.groupby(movies['YEAR']).agg(np.var)
yearmode = movies.groupby(movies['YEAR']).agg(stats.mode)

years = sorted(movies['YEAR'].unique())
#makes scatter plot
plt.scatter(years, yearmeans['RATING'])
plt.title('Average Movie Rating per Year')
plt.show()
```

```
#makes scatter plot
plt.scatter(years, yearmed['RATING'])
plt.title('Median Movie Rating per Year')
plt.show()

#makes scatter plot
plt.scatter(yearmeans['RATING'], yearmeans['Gross'])
plt.title('Average Rating per Year VS Gross Profit per Year')
plt.show()
```







In conducting this analysis we can see differences in values per year across all the numerical data points. We can then use this data to plot and make assumptions about general trends over time. We can see that in the average and median movie ratings the ratings have been trending down since about the 1980's.

References:

Top 20 Largest California Wildfires. (2020).Kaggle [Dataset]. https://www.kaggle.com/datasets/annieichen/top-20-largest-california-wildfires.

2024's Most-Watched YouTube Videos. (2024). Kaggle [Dataset}. https://www.kaggle.com/datasets/kanchana1990/2024s-most-watched-youtube-videos.

MOVIES DATASET FOR FEATURE EXTRACION ,PREDICTION. (2021).Kaggle [Dataset]. https://www.kaggle.com/datasets/bharatnatrayn/movies-dataset-for-feature-extracion-prediction?select=movies.csv

Rogel-Salazar, J. (2023). Statistics and Data Visualization with Python. CRC Press.