```
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import math
import io
import seaborn as sns
from scipy import stats
from google.colab import files
from numpy import random
from sklearn.linear_model import LinearRegression
```

Introduction

State the bivariate data your group is going to study. Here are two examples, but you may NOT use them: height vs. weight and age vs. running distance.

The data I will study is the relationship of sales of games vs. the metacritic score of the games and sales of games vs. geographical region sales in which the games were sold.

Describe your sampling technique in detail. Use cluster, stratified, systematic, or simple random sampling (using a random number generator) sampling. Convenience sampling is NOT acceptable.

The sampling technique I will use is clustered sampling. I will use a random generator to pick the subset data which will be "Genre" and summarize the information from that clustered genre to use. The videogame data I will use has over 16,000 games.

The website from which I got the data is from a website called Kaggle. https://www.kaggle.com/rush4ratio/video-game-sales-with-ratings

This data was uploaded by Rush Kirubi's five years ago called "Video Game Sales With Ratings" to Kaggle.com. The sales data is from Vgchartz and ratings data from Metacritic. The data set contains 16 variables(columns) and 11,562 unique games(values), each of which is a game released between 1980 and 2016.

Conduct your survey. Your number of pairs must be at least 30. Print out a copy of your data.

```
video_games = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving Video Games Sales as at 22 Dec 2016.csv to Video Games Sales as at 2
```

```
vg = pd.read_csv(io.BytesIO(video_games['Video_Games_Sales_as_at_22_Dec_2016.csv']))
```

```
# Test to make sure CSV file imported correctly

vg.head()
```

	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales	EU_S
0	Wii Sports	Wii	2006.0	Sports	Nintendo	41.36	
1	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	
2	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.68	
3	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.61	
	Pokemon						

```
# Clean data of "Not a Number" (NaN)

vg.fillna(0, inplace=True)
vg.head()
```

	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales	EU_S
0	Wii Sports	Wii	2006.0	Sports	Nintendo	41.36	
1	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	
2	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.68	
3	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.61	
	Pokemon						

```
# Check the type of data to be used. Object equals categorical and float 64 equals quantitative which mea

vg.dtypes
```

```
Name                object
Platform            object
Year_of_Release    float64
Genre               object
Publisher           object
NA_Sales           float64
EU_Sales           float64
JP_Sales           float64
Other_Sales        float64
Global_Sales       float64
Critic_Score         int64
Critic_Count         int64
User_Score          object
User_Count           int64
dtype: object
```

```
# Get a summary of the quantitative data

vg.describe()
```

	Year_of_Release	NA_Sales	EU_Sales	JP_Sales	Other_Sales	G
count	16719.000000	16719.000000	16719.000000	16719.000000	16719.000000	
mean	1974.204019	0.263330	0.145025	0.077602	0.047332	
std	252.530614	0.813514	0.503283	0.308818	0.186710	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	2003.000000	0.000000	0.000000	0.000000	0.000000	
50%	2007.000000	0.080000	0.020000	0.000000	0.010000	
75%	2010.000000	0.240000	0.110000	0.040000	0.030000	
max	2020.000000	41.360000	28.960000	10.220000	10.570000	

```
# Removing Duplicates

vg.drop_duplicates()
```

	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales
0	Wii Sports	Wii	2006.0	Sports	Nintendo	41.36
1	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08
2	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.68
3	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.61
4	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27
...	...	...	...	...	...	..
16714	Samurai Warriors: Sanada Maru	PS3	2016.0	Action	Tecmo Koei	0.00
16715	LMA Manager 2007	X360	2006.0	Sports	Codemasters	0.00
16716	Haitaka no	PSV	2016.0	Adventure	Idea Factory	0.00

```
# Get unique names from genre

genre = vg['Genre']
genre = genre.unique()

genre
```

```
array(['Sports', 'Platform', 'Racing', 'Role-Playing', 'Puzzle', 'Misc',
       'Shooter', 'Simulation', 'Action', 'Fighting', 'Adventure',
       'Strategy', 0], dtype=object)
```

```
# Randomly choose what genre to use

random.choice(genre)
```

```
'Action'
```

The genre that was randomly picked is "Action" out of 'Sports', 'Platform', 'Racing', 'Role-Playing', 'Puzzle', 'Misc', 'Shooter', 'Simulation', 'Action', 'Fighting', 'Adventure', and 'Strategy'

```
# Get only "Action"  games

vg.loc[vg['Genre'] == 'Action']
```

	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales
16	Grand Theft Auto V	PS3	2013.0	Action	Take-Two Interactive	7.02
17	Grand Theft Auto: San Andreas	PS2	2004.0	Action	Take-Two Interactive	9.43
23	Grand Theft Auto V	X360	2013.0	Action	Take-Two Interactive	9.66
24	Grand Theft Auto: Vice City	PS2	2002.0	Action	Take-Two Interactive	8.41
38	Grand Theft Auto III	PS2	2001.0	Action	Take-Two Interactive	6.99
...	...	...	...	...	...	...
16696	Metal Gear Solid V: Ground Zeroes	PC	2014.0	Action	Konami Digital Entertainment	0.00

```
# Assign Action games to a varible

vg_action = vg.loc[vg['Genre'] == 'Action']

vg_action.head()
```

```
# Assign a variable for the columns to be used

meta_critic = vg_action['Critic_Score']
user_score = vg_action['User_Score']
na_sale = vg_action['NA_Sales']
eu_sale = vg_action['EU_Sales']
released = vg_action['Year_of_Release']
```

```
# Get summary of Action games

vg_action.describe()
```

	Year_of_Release	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Glob
count	3370.000000	3370.000000	3370.000000	3370.000000	3370.000000	33
mean	1971.106825	0.260834	0.154045	0.047905	0.054777	
std	269.958556	0.563271	0.403220	0.163997	0.236010	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	2005.000000	0.010000	0.000000	0.000000	0.000000	
50%	2009.000000	0.100000	0.030000	0.000000	0.010000	
75%	2012.000000	0.260000	0.140000	0.030000	0.040000	
max	2017.000000	9.660000	9.090000	3.960000	10.570000	

Grand

According to the data there is 3,370 'Action' games in the subset of Video games that have sold. I will use all pairs in the 'Action' genre for my observation.

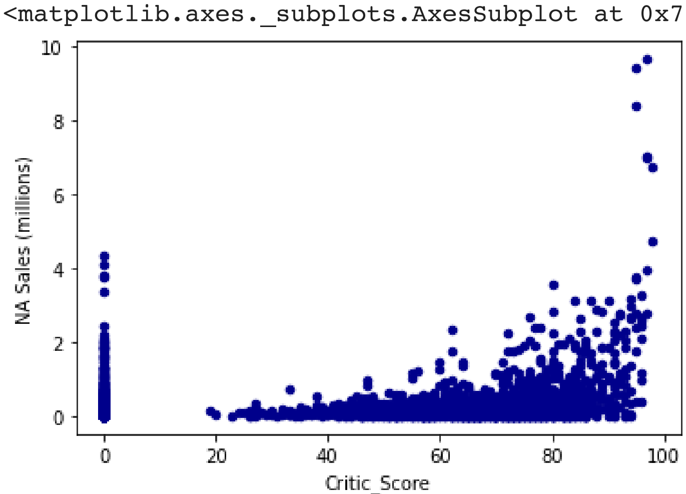
We will use "Critic Score" as the independent variable and use "NA Sales" as the dependent variable.

Analysis

On a separate sheet of paper construct a scatter plot of the data. Label and scale both axes.

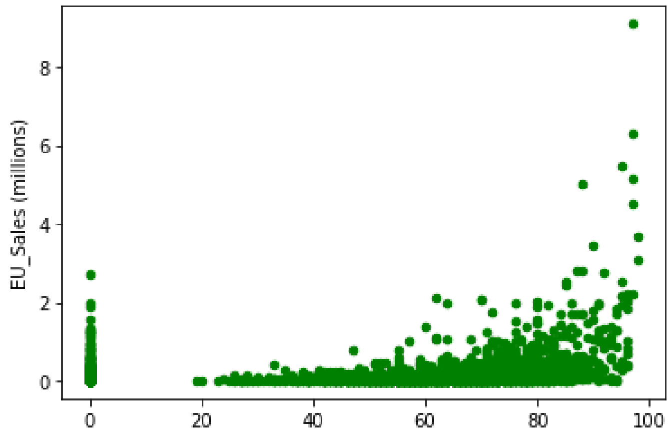
```
# This is a scatter plot of the sales in North America

vg_action.plot.scatter(x='Critic_Score', y='NA_Sales', color='darkblue', ylabel='NA Sales (millions)')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7505c88d50>
```




```
# This is a scatter plot of the sales in the European Union for comparison vesus NA Sales

vg_action.plot.scatter(x='Critic_Score', y='EU_Sales', color='green', ylabel='EU_Sales (millions)')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f7505bb82d0>



The "Critic_Score" is based on a 0 to 100 number system. The "NA_Sales" and "EU_Sales" is based on units sold in the millions.

State the least squares line and the correlation coefficient.

The process of finding the parameters for which the sum of the squares of the residuals is minimal. Linear regression for two variables is based on a linear equation with one independent variable.

y-hat = b0 + b1x

0.26083382789317217 = b0 + 1.6537045892529527(37.36765578635015)

Line of Best Fit or Least-Squares Line. has the form: y = a + bx

The best fit line always passes through the point (x-bar, y-bar). We can get x-bar by getting the mean from the "Critic Score". We get the y-bar from the mean of "NA Sales"

```
# Get the mean for X-bar. This will add up all 3,370 Critic Scores and then divide it

vg_action['Critic_Score'].mean()
```

```
37.36765578635015
```

```
# Get the mean for Y-bar. This will add up all 3,370 NA Sales and then divide it

vg_action['NA_Sales'].mean()
```

```
0.26083382789317217
```

```
# Independent variable minus the mean (X - X-bar)

critic_mean = vg_action['Critic_Score'].mean()

meta_critic - critic_mean
```

```
16        59.632344
17        57.632344
23        59.632344
24        57.632344
```

```
    38          59.632344
                   ...
    16696       42.632344
    16698      -37.367656
    16699       29.632344
    16703      -37.367656
    16714      -37.367656
    Name: Critic_Score, Length: 3370, dtype: float64
```

```
# Assign (X - X-bar) a variable. The observation from X

observed_x = meta_critic - critic_mean


# Dependent variable minus the mean (Y - Y-bar)

naSales_mean = vg_action['NA_Sales'].mean()

na_sale - naSales_mean
```

```
    16          6.759166
    17          9.169166
    23          9.399166
    24          8.149166
    38          6.729166
                   ...
    16696      -0.260834
    16698      -0.250834
    16699      -0.250834
    16703      -0.260834
    16714      -0.260834
    Name: NA_Sales, Length: 3370, dtype: float64
```

```
# Assign (Y - Y-bar) a variable. The observation from Y

observerd_y = na_sale - naSales_mean


# Square the observed X
observed_x.apply(np.sqrt)
```

```
    16          7.722198
    17          7.591597
    23          7.722198
    24          7.591597
    38          7.722198
                   ...
    16696       6.529345
    16698            NaN
    16699       5.443560
    16703            NaN
    16714            NaN
    Name: Critic_Score, Length: 3370, dtype: float64
```

```
# Square the observed  Y
observerd_y.apply(np.sqrt)
```

```
    16          2.599840
    17          3.028063
    23          3.065806
    24          2.854674
```

```
38        2.594064
             ...
16696          NaN
16698          NaN
16699          NaN
16703          NaN
16714          NaN
Name: NA_Sales, Length: 3370, dtype: float64
```

```
# Now apply (X - X-bar) times (Y - Y-bar)

observed_x * observerd_y
ob_x_times_ob_y =  observed_x * observerd_y


# Regression line is y-hat = b0 + b1x

sqrt_x = observed_x.apply(np.sqrt)
sqrt_y = observerd_y.apply(np.sqrt)

# To get the denominator for b1 sum up Sqaure root of observed_X
sum_sqrt_x = sqrt_x.sum()

# To get the numerator  for b1 sum up (X - X-bar) times (Y - Y-bar)
sum_ob_x_and_y = ob_x_times_ob_y.sum()

# B1 = numerator / denominator

b1 = sum_ob_x_and_y / sum_sqrt_x  # The slope
b1
```

```
1.6537045892529527
```

```
# To get b0 . Where y value is equal to 0.26083382789317217 =  b0 + 1.6537045892529527(37.36765578635015)

1.6537045892529527*37.36765578635015
```

```
61.79506386351189
```

```
# To get b0.   0.26083382789317217 =  b0 + 61.79506386351189

0.26083382789317217 - 61.79506386351189
```

```
-61.53423003561872
```

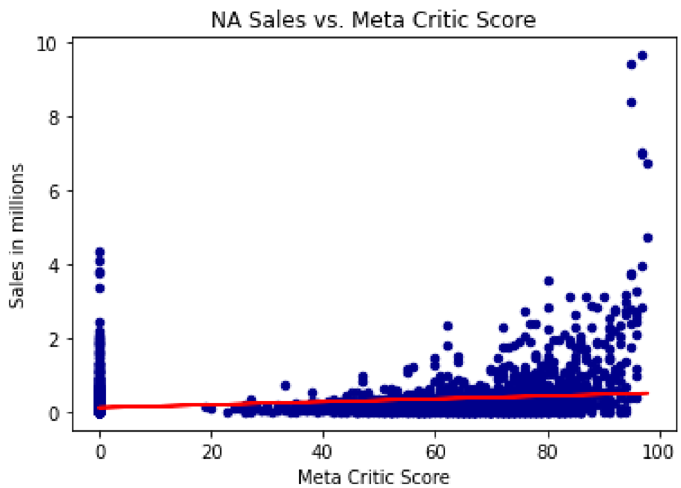
```
b0 = -61.53423003561872
```

Y-hat = 1.6537045892529527 + -61.53423003561872(X)

On your scatter plot, in a different color, construct the least squares line. Is the correlation coefficient significant? Explain and show how you determined this.

```
# Re-Assign variables to equal y=mx +b

x = vg_action['Critic_Score'] # X-Axis
y = vg_action['NA_Sales'] # Y-Axis
m, b = np.polyfit(x, y, 1)


reshaped_meta_critic = meta_critic.values.reshape(-1, 1)
reshaped_na_sale = na_sale.values.reshape(-1, 1)
lr = LinearRegression()
lr.fit(reshaped_meta_critic, reshaped_na_sale)
y_pred = lr.predict(reshaped_na_sale)


# Show the least squares line as a red line

vg_action.plot.scatter(x='Critic_Score', y='NA_Sales', color='darkblue')
plt.title('NA Sales vs. Meta Critic Score')
plt.ylabel('Sales in millions')
plt.xlabel('Meta Critic Score')
plt.plot(x, m*x+b, color='red')
```

```
[<matplotlib.lines.Line2D at 0x7f7505b34810>]
```



Interpret the slope of the linear regression line in the context of the data in your project. Relate the explanation to your data, and quantify what the slope tells you.

It is a slight positive slope. Based on the data, I can conclude that there is NOT a significant linear relationship between NA Sales and Meta Critic scores.

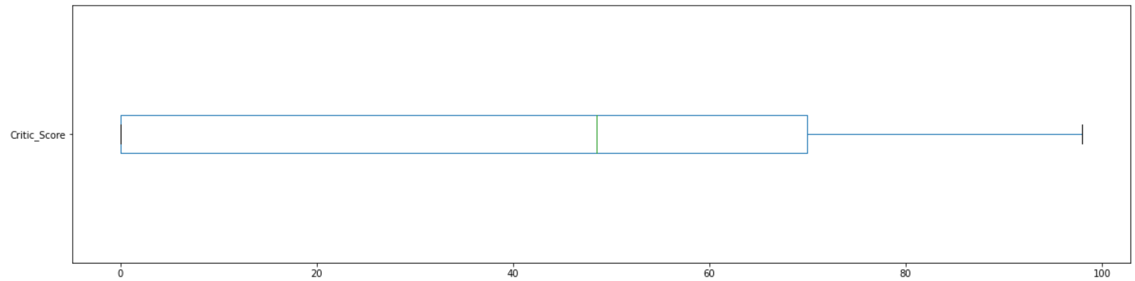
Does the regression line seem to fit the data? Why or why not? If the data does not seem to be linear, explain if any other model seems to fit the data better.

It looks like it fits but the problem is that there may be too many data points causing an "overfit" model. Therefore it can cause misleading information. Possiblely the best way to fit the data is to shrink the data to a smaller set. Also NA sales and Meta Critic Scores may not be the best selection to be applied.

Are there any outliers? If so, what are they? Show your work in how you used the potential outlier formula in the Linear Regression and Correlation chapter (since you have bivariate data) to determine whether or not any pairs might be outliers.

```
vg_action.boxplot(column='Critic_Score', grid=False, vert=False, figsize=(20,5))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7502db7450>
```




```
# To see if a data point is an outlier and check if it falls farther than three standard deviations, we c
# Q1 — 1.5 x IQR
# Q3 + 1.5 x IQR

vg_action.describe()
```

	Year_of_Release	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Glob
count	3370.000000	3370.000000	3370.000000	3370.000000	3370.000000	33
mean	1971.106825	0.260834	0.154045	0.047905	0.054777	
std	269.958556	0.563271	0.403220	0.163997	0.236010	
min	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	2005.000000	0.010000	0.000000	0.000000	0.000000	
50%	2009.000000	0.100000	0.030000	0.000000	0.010000	
75%	2012.000000	0.260000	0.140000	0.030000	0.040000	
max	2017.000000	9.660000	9.090000	3.960000	10.570000	

```
# What is the IQR for Critic score
#  Q3 - Q1 = IQR

70 - 0
```

```
70
```

```
# Q1 — 1.5 x IQR

0 - 1.5 * 70

     -105.0


# Q3 + 1.5 x IQR

70 + 1.5 * 70

     175.0
```

According to the Outlier formula any number in Critic Score passed 175 is considered an outlier.Since there was too many points of data identifying outliers can be difficult to show.