

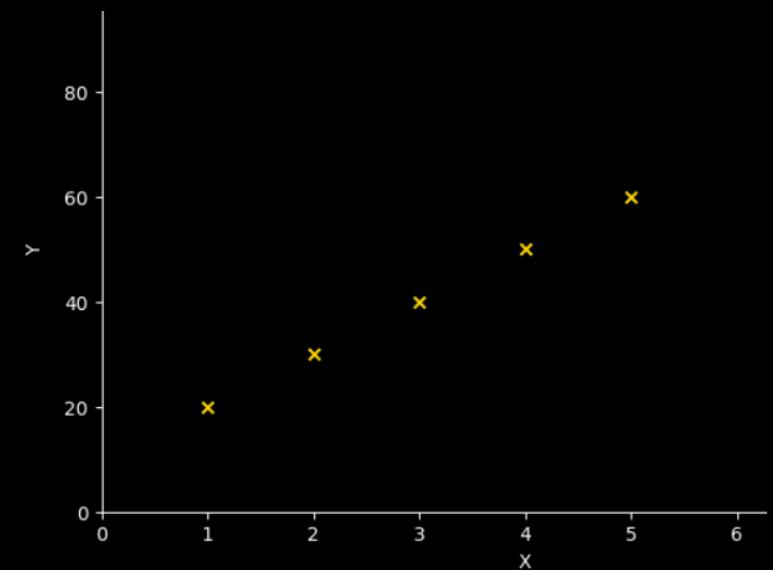
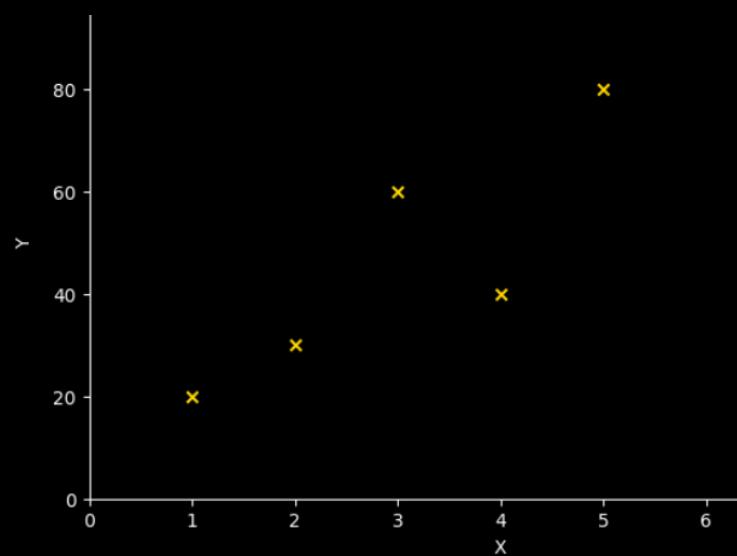
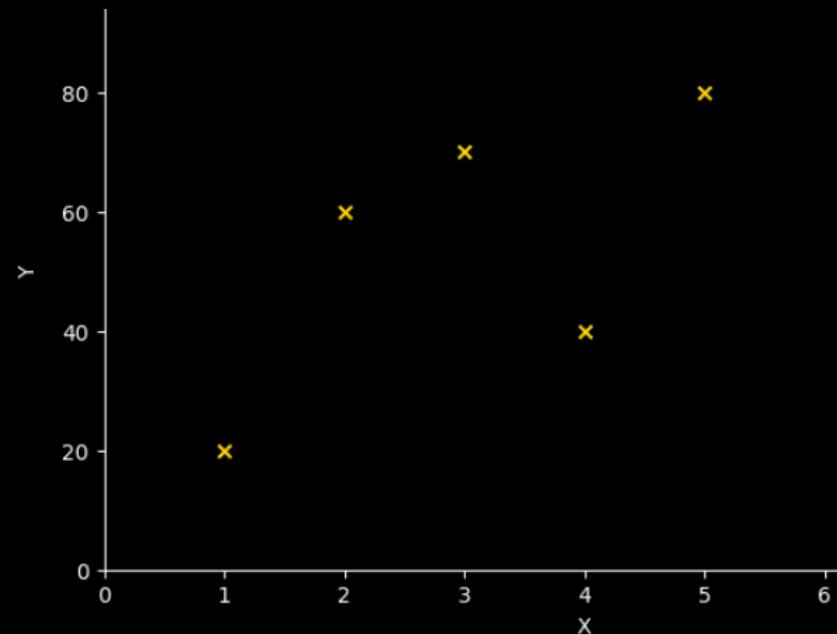
Covariance and Correlation

Problem: What type of relationship is between X and Y ? How would you measure it mathematically?

| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 20 |
| 2 | 60 |
| 3 | 70 |
| 4 | 40 |
| 5 | 80 |

| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 20 |
| 2 | 30 |
| 3 | 60 |
| 4 | 40 |
| 5 | 80 |

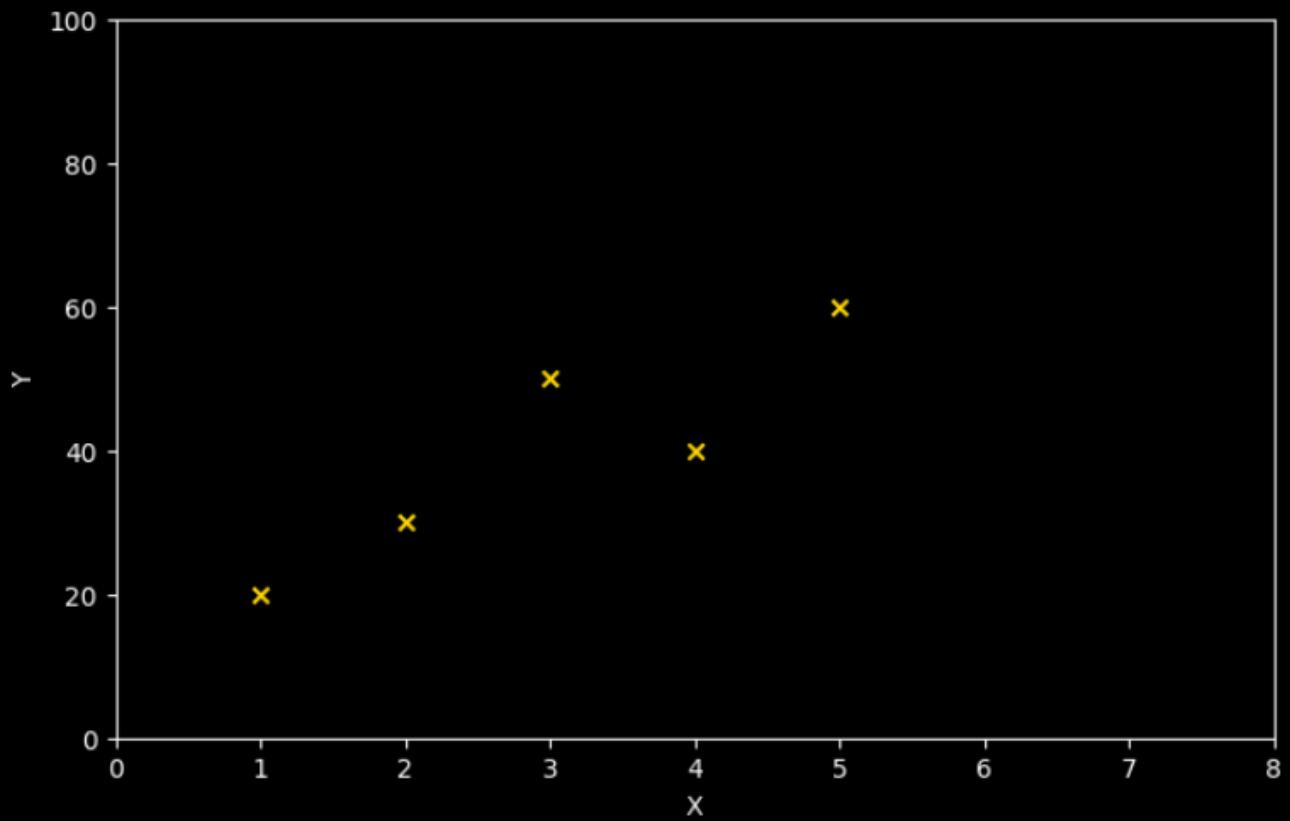
| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 20 |
| 2 | 30 |
| 3 | 40 |
| 4 | 50 |
| 5 | 60 |



Covariance

Suppose you have following data(e.g. study hours and score):

| X | Y |
|---|----|
| 1 | 20 |
| 2 | 30 |
| 3 | 50 |
| 4 | 40 |
| 5 | 60 |

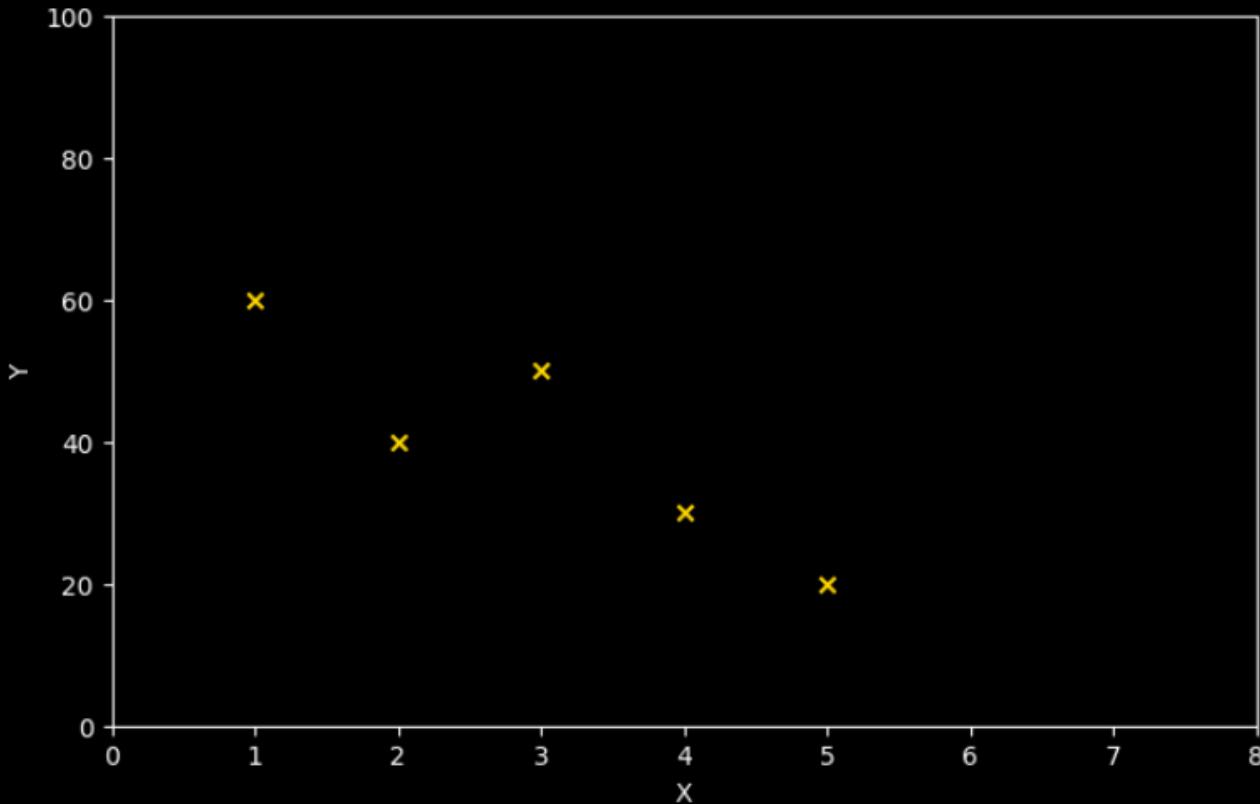


We see that as X increases, Y increases too.
Here X and Y are said to be **positively** correlated.

Covariance

Suppose you have following data (game-hours and score):

| X | Y |
|---|----|
| 1 | 60 |
| 2 | 40 |
| 3 | 50 |
| 4 | 30 |
| 5 | 20 |



We see that as X increases, Y decreases.
Here X and Y are said to be **negatively correlated**.

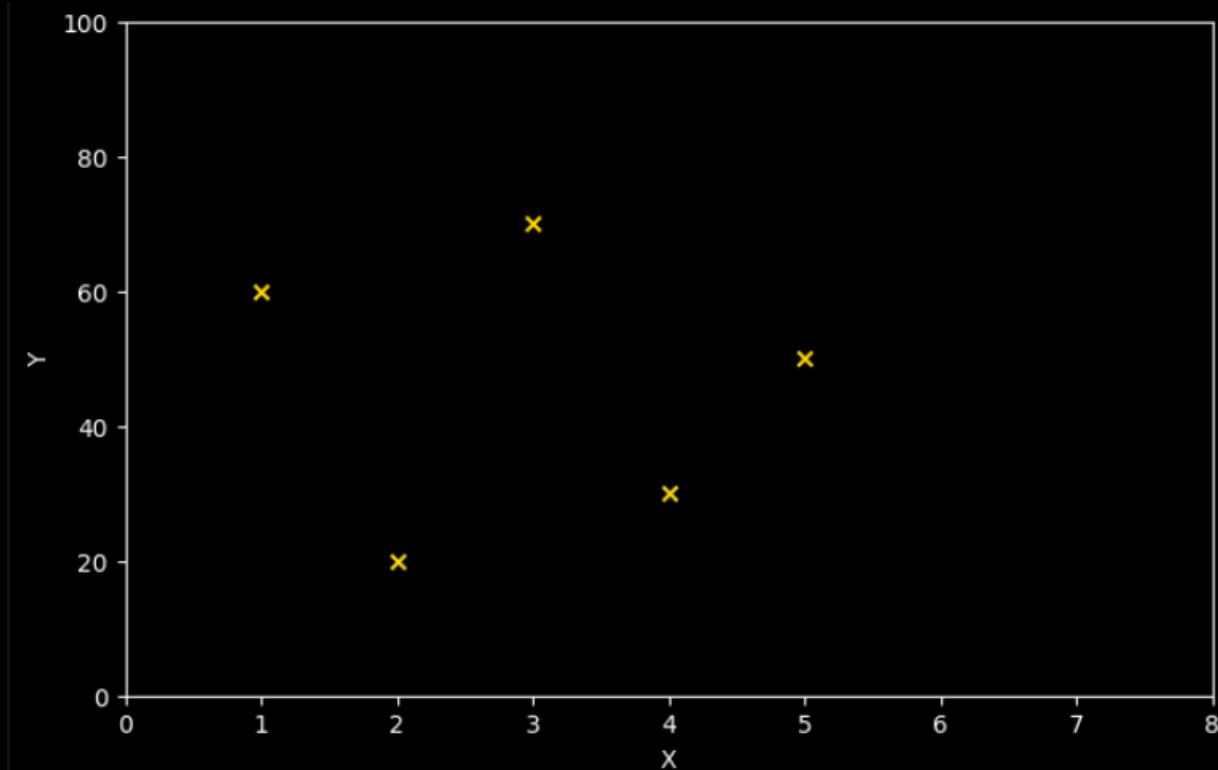


Covariance



Suppose you have following data:

| X | Y |
|---|----|
| 1 | 60 |
| 2 | 20 |
| 3 | 70 |
| 4 | 30 |
| 5 | 50 |



Here as X increases, Y has no pattern.
X and Y are said to be **not** correlated.



Covariance



We use covariance to determine the **direction** of relation between X and Y:

$$\text{Cov}(X, Y) = \frac{1}{n-1} \sum_{k=1}^n (x_k - \bar{x})(y_k - \bar{y})$$

- **Cov (X,Y) > 0**: X and Y move in same direction
- **Cov (X,Y) < 0**: X and Y move in opposite direction
- **Cov (X,Y) = 0**: X and Y are independent

Side Note: Above is the covariance of **samples**, not population. For population, $n-1 \rightarrow n$

Covariance

Example1: Find covariance between X and Y

| X | Y |
|---|----|
| 1 | 20 |
| 2 | 30 |
| 3 | 50 |
| 4 | 40 |
| 5 | 60 |

$$\text{Cov}(X, Y) = \frac{1}{n-1} \sum_{k=1}^n (x_k - \bar{x})(y_k - \bar{y})$$

$$\bar{x} = \frac{1+2+3+4+5}{5} = 3$$

$$\bar{y} = \frac{20+30+50+40+60}{5} = 40$$

$$\text{Cov}(X, Y) = \frac{1}{n-1} [(x_1 - \bar{x})(y_1 - \bar{y}) + (x_2 - \bar{x})(y_2 - \bar{y}) + \dots + (x_5 - \bar{x})(y_5 - \bar{y})]$$

$$\begin{aligned}\text{Cov}(X, Y) &= \frac{1}{(5-1)} \left[(1-3)(20-40) + (2-3)(30-40) + (3-3)(50-40) + (4-3)(40-40) + (5-3)(60-40) \right] \\ &= \frac{1}{4} [-40 + 10 + 0 + 0 + 20] \\ &= \underline{\underline{2.5}}\end{aligned}$$

Covariance

Example2: If I take same data as previous and divide Y by 10, scale it down, then $\text{COV}(X,Y) = 2.25$ (smaller by factor of 10)

| X | Y |
|---|---|
| 1 | 2 |

$$\text{Cov}(X, Y) = \frac{1}{n-1} \sum_{k=1}^n (x_k - \bar{x})(y_k - \bar{y})$$

| | |
|---|---|
| 2 | 3 |
| 3 | 5 |
| 4 | 4 |
| 5 | 6 |

$$\bar{x} = \frac{1+2+3+4+5}{5} = 3$$

$$\bar{y} = \frac{2+3+5+4+6}{5} = 4$$

$$\text{Cov}(X, Y) = \frac{1}{n-1} [(x_1 - \bar{x})(y_1 - \bar{y}) + (x_2 - \bar{x})(y_2 - \bar{y}) + \dots + (x_5 - \bar{x})(y_5 - \bar{y})]$$

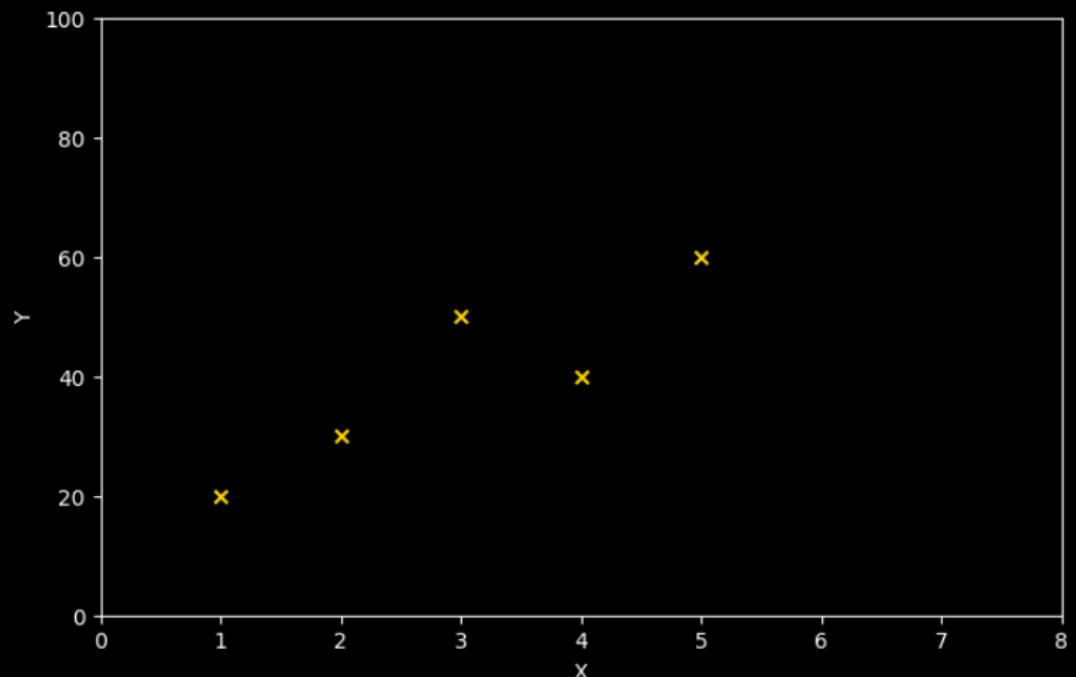
$$\begin{aligned}\text{Cov}(X, Y) &= \frac{1}{(5-1)} [(1-3)(2-4) + (2-3)(3-4) + (3-3)(5-4) + (4-3)(4-4) + (5-3)(6-4)] \\ &= \frac{1}{4} [4 + 1 + 0 + 0 + 4] \\ &= \underline{\underline{2.25}}\end{aligned}$$

Covariance

Now let's plot both these separately. Suppose in 1st figure, X is in meters and Y is in Kg, then covariance = 22.5 m-kg. In 2nd figure, X is in hours and Y is in score, and covariance = 2.25 hours-score. Numerically they are different because of different units, but visually they look identical.

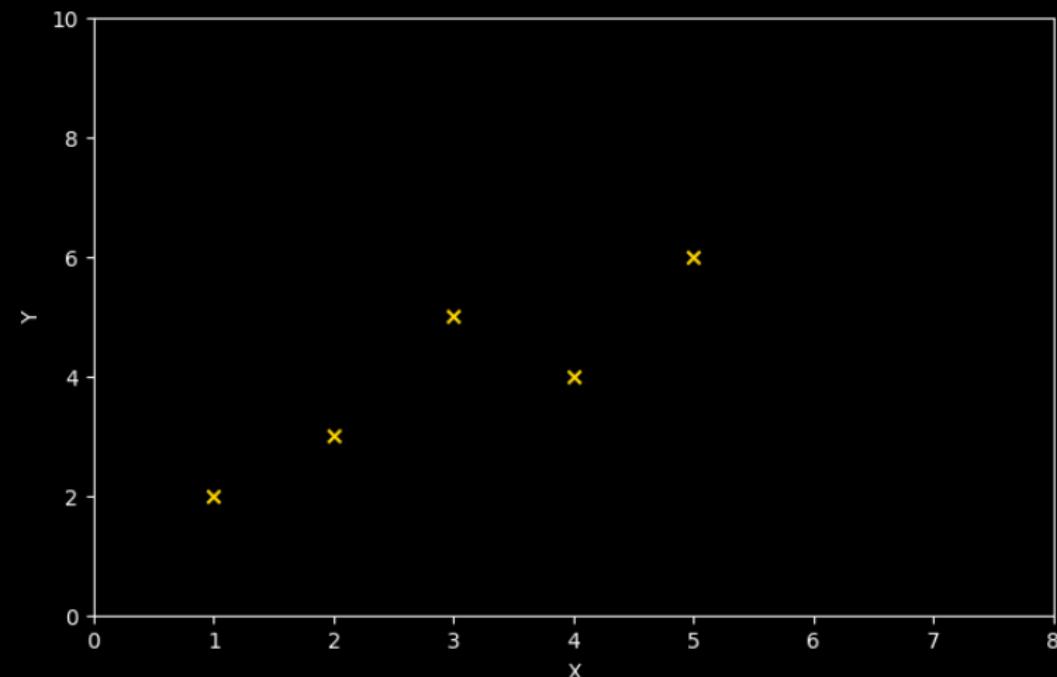
X (m) Y (Kg)

| | |
|---|----|
| 1 | 20 |
| 2 | 30 |
| 3 | 50 |
| 4 | 40 |
| 5 | 60 |



X(hr) Y (score)

| | |
|---|---|
| 1 | 2 |
| 2 | 3 |
| 3 | 5 |
| 4 | 4 |
| 5 | 6 |





Correlation



If we divide Cov(X,Y) by standard deviation (X) and standard deviation (Y), then we get **correlation**.

Correlation measures the strength of linear relationship between 2 variables.

$$r = \frac{\text{Cov}(X, Y)}{s_X s_Y}$$

$$s_X = \sqrt{\frac{\sum(x_i - \bar{X})^2}{n - 1}}$$

$$s_Y = \sqrt{\frac{\sum(y_i - \bar{Y})^2}{n - 1}}$$

Side Note: Above is for **sample**. For population, $n-1 \rightarrow n$

We use correlation over covariance because it's a **standardized** measure that is **easy to interpret and compare across different datasets**: Dataset1 could be between X in kg and Y in meter, in the Dataset2, X could be in hours and Y in score. We can still compare the datasets

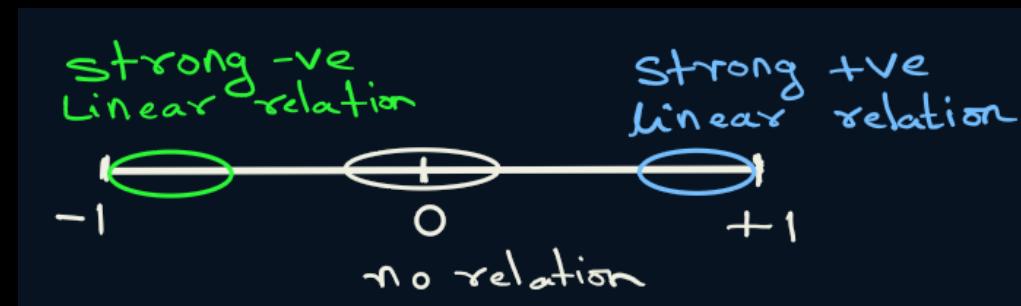
Correlation

Key properties of correlation

- It is unitless

$$r = \frac{\text{Cov}(X, Y)}{s_X s_Y}$$

- Ranges from -1 to 1



- If the values of X and/or Y are converted to a different scale, the value of r will be unchanged. (Shown in next 2 examples)

Correlation

Example: Find correlation.

| X | Y |
|---|----|
| 1 | 20 |
| 2 | 30 |
| 3 | 50 |
| 4 | 40 |
| 5 | 60 |

$$r = \frac{\text{Cov}(X, Y)}{s_X s_Y}$$

$$S_X = \sqrt{\frac{\sum(x_i - \bar{X})^2}{n - 1}}$$

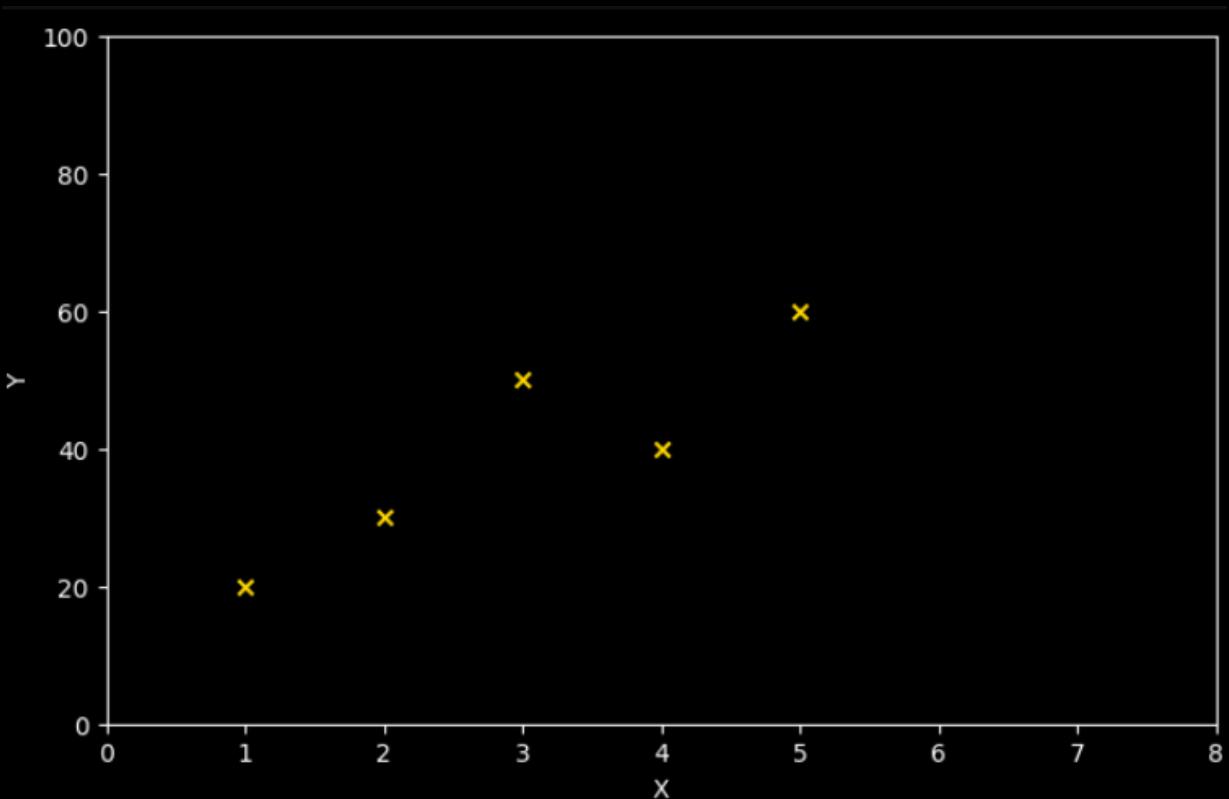
We already found $\text{Cov}(X, Y) = 22.5$

The $s_X = 1.58$, $s_Y = 15.8 \rightarrow r = \frac{22.5}{1.58 \times 15.8} = 0.9$

We already found $\text{Cov}(X, Y) = 22.5$

The $s_X = 1.58$, $s_Y = 15.8 \rightarrow$

$$r = \frac{22.5}{1.58 \times 15.8} = 0.9$$



Correlation

Example(Same data as before with Y scaled down by factor of 10): Find correlation.

| X | Y |
|---|---|
| 1 | 2 |
| 2 | 3 |
| 3 | 5 |
| 4 | 4 |
| 5 | 6 |

$$r = \frac{\text{Cov}(X, Y)}{s_X s_Y}$$

$$S_X = \sqrt{\frac{\sum(x_i - \bar{X})^2}{n - 1}}$$

$$S_Y = \sqrt{\frac{\sum(y_i - \bar{Y})^2}{n - 1}}$$

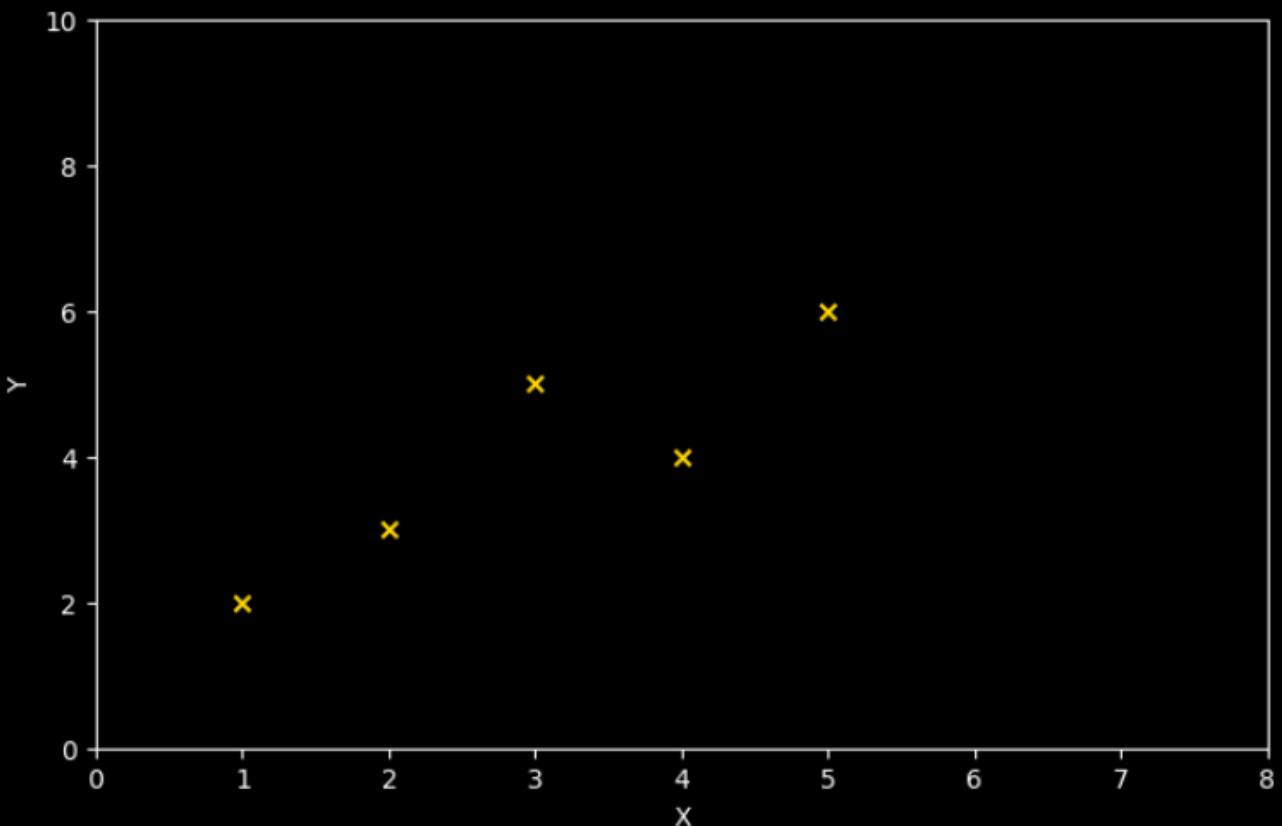
We already found $\text{Cov}(X, Y) = 2.25$

The $s_X = 1.58$, $s_Y = 1.58 \rightarrow$

$$r = \frac{2.25}{1.58 \times 1.58} = 0.9$$

The correlation is same as before.

Correlation is unaffected by scaling

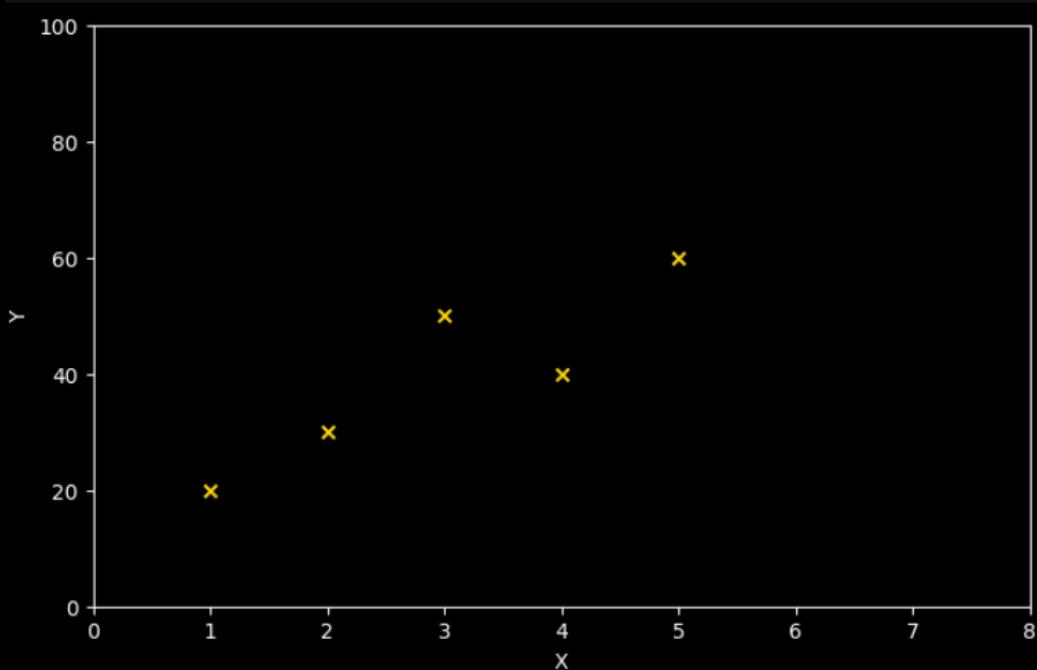




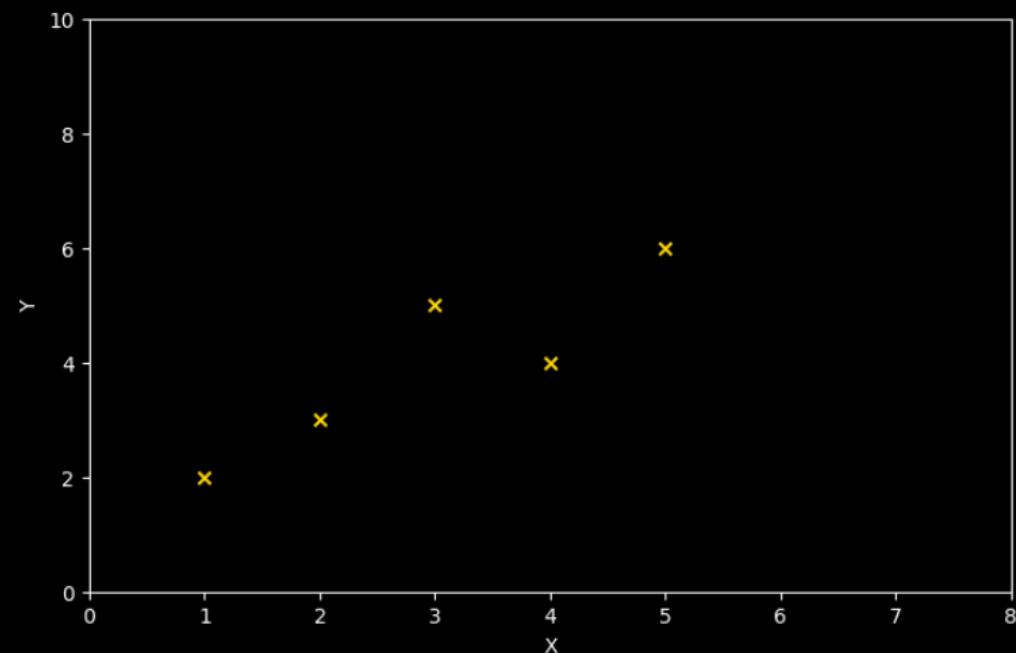
Now let's plot both these separately. The covariance is different: +22.5 -vs- +2.25.

The correlation is same: 0.9

| X | Y |
|---|----|
| 1 | 20 |
| 2 | 30 |
| 3 | 50 |
| 4 | 40 |
| 5 | 60 |



| X | Y |
|---|---|
| 1 | 2 |
| 2 | 3 |
| 3 | 5 |
| 4 | 4 |
| 5 | 6 |



Problem: Which of the following has strong linear relationship between X and Y ? How would you measure it?
Ans: Find correlation and that would tell you how strong the linear relation is between the 2 variables.

Correlation is maximum for figure with $r = +1$

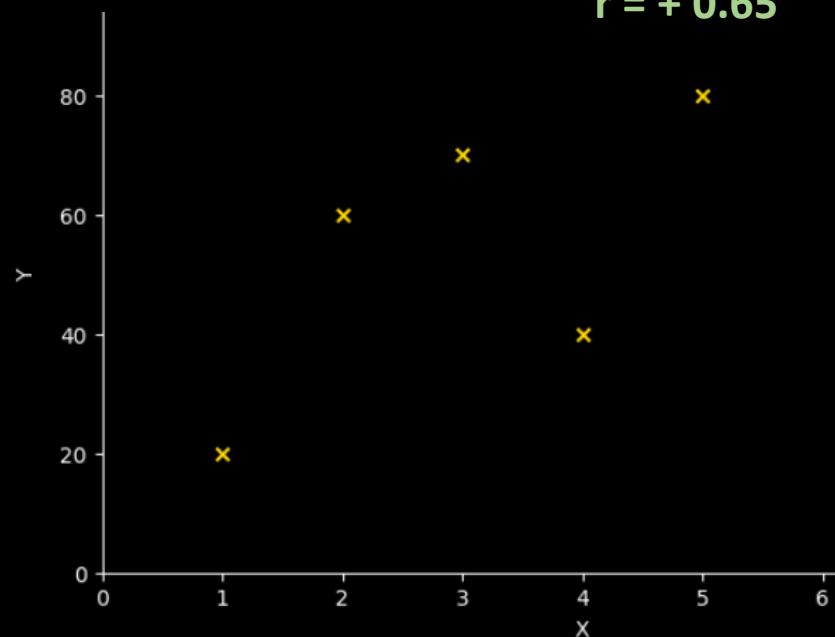


| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 20 |
| 2 | 60 |
| 3 | 70 |
| 4 | 40 |
| 5 | 80 |

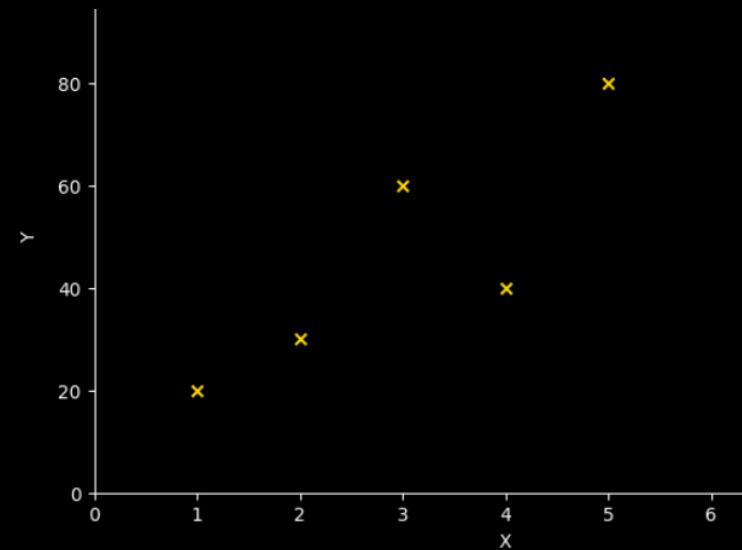
| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 20 |
| 2 | 30 |
| 3 | 60 |
| 4 | 40 |
| 5 | 80 |

| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 20 |
| 2 | 30 |
| 3 | 40 |
| 4 | 50 |
| 5 | 60 |

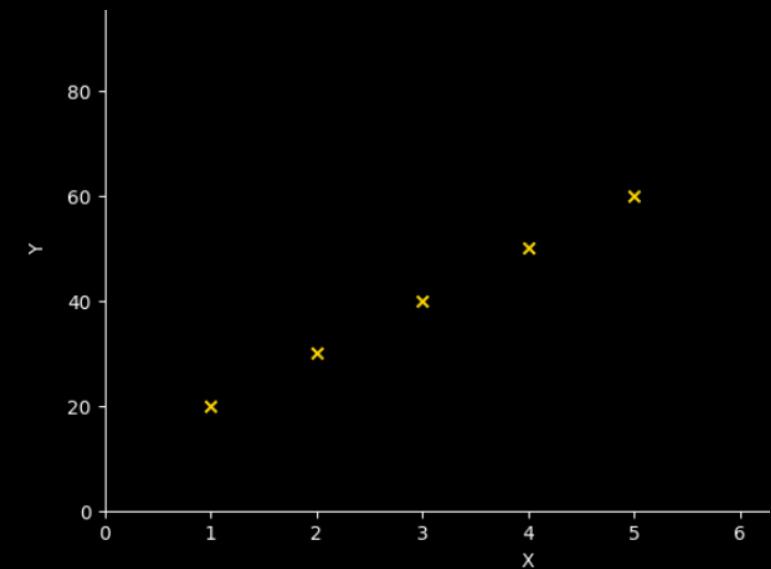
$$r = + 0.65$$



$$r = + 0.85$$



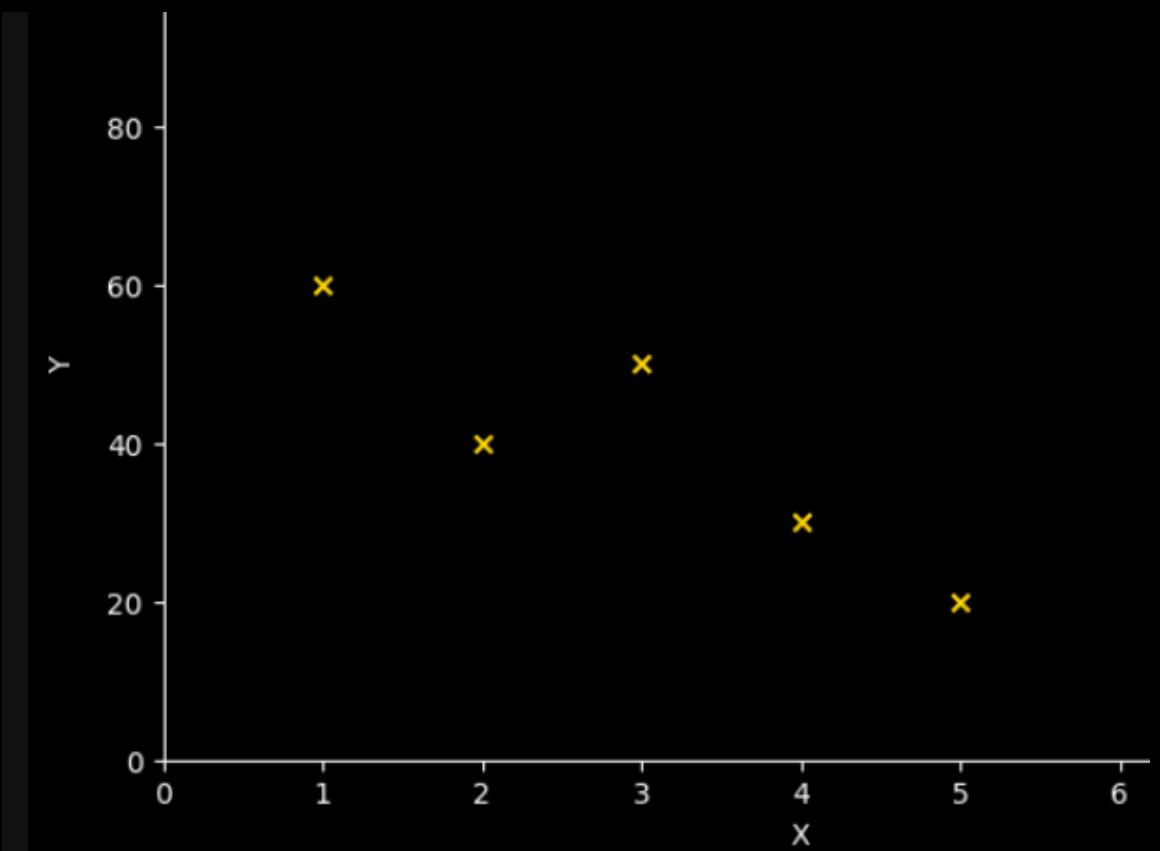
$$r = + 1$$



Example: X and Y have a strong negative correlation.

| X | Y |
|---|----|
| 1 | 60 |
| 2 | 40 |
| 3 | 50 |
| 4 | 30 |
| 5 | 20 |

$$r = -0.9$$

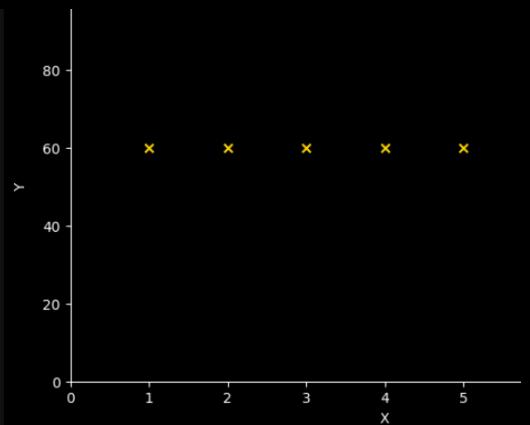
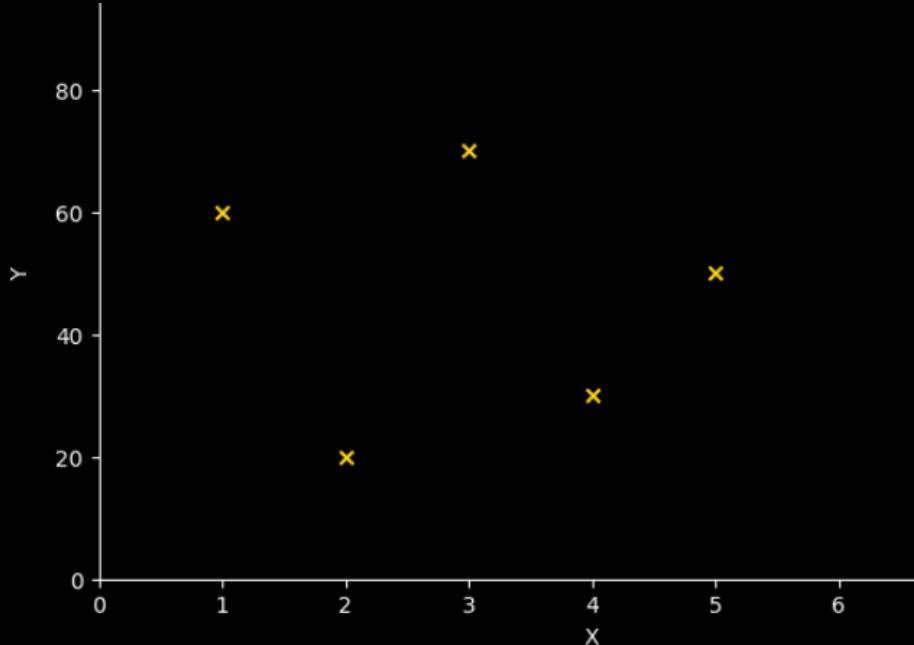




Example: X and Y have almost 0 correlation

| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 60 |
| 2 | 20 |
| 3 | 70 |
| 4 | 30 |
| 5 | 50 |

$$r = -0.07$$



Recap

$\text{Cov}(X,Y) > 0$: X and Y move in same direction

$\text{Cov}(X,Y) < 0$: X and Y move in opposite direction

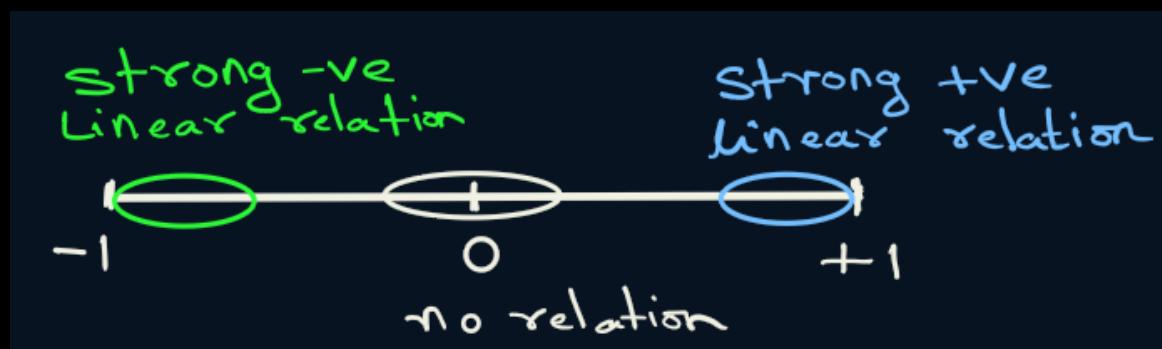
$\text{Cov}(X,Y) = 0$: X and Y are independent

Major flaw of covariance:

- It does not tell you the strength of linear relationship between X and Y.

So, we need correlation.

Correlation ranges from -1 to 1:

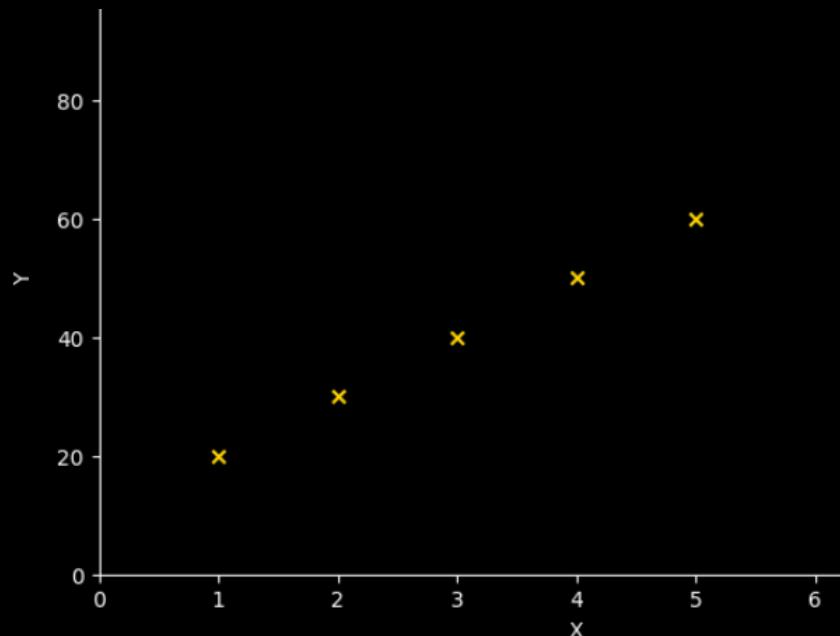


Outliers

The value of r is **sensitive to outliers** and can change dramatically if they are present in the data.

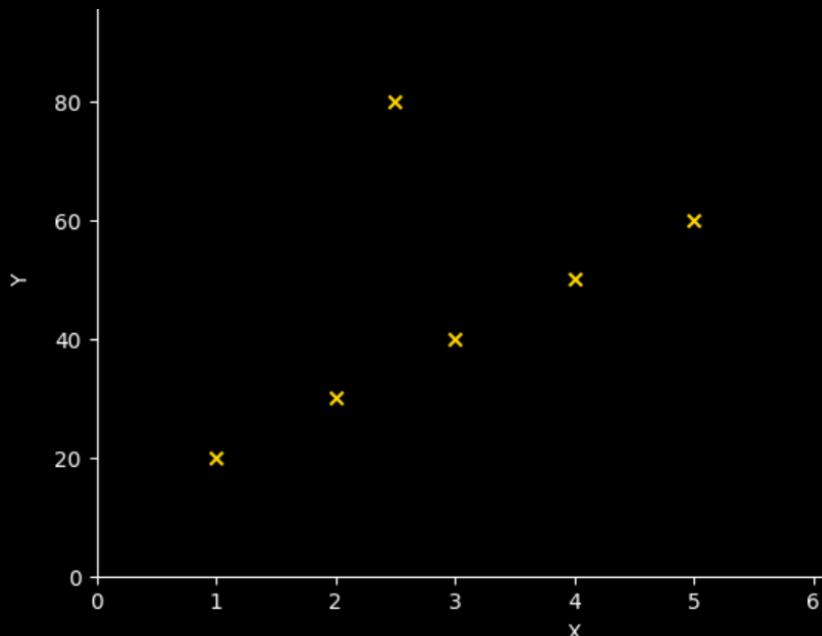
| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 20 |
| 2 | 30 |
| 3 | 40 |
| 4 | 50 |
| 5 | 60 |

$$r = +1$$



| <u>X</u> | <u>Y</u> |
|----------|----------|
| 1 | 20 |
| 2 | 30 |
| 2.5 | 80 |
| 3 | 100 |
| 4 | 50 |
| 5 | 60 |

$$r = +0.53$$



Covariance and Correlation Matrix

$$\Sigma = \begin{bmatrix} \text{Cov}(X_1, X_1) & \text{Cov}(X_1, X_2) & \cdots & \text{Cov}(X_1, X_p) \\ \text{Cov}(X_2, X_1) & \text{Cov}(X_2, X_2) & \cdots & \text{Cov}(X_2, X_p) \\ \vdots & \vdots & \ddots & \vdots \\ \text{Cov}(X_p, X_1) & \text{Cov}(X_p, X_2) & \cdots & \text{Cov}(X_p, X_p) \end{bmatrix}$$

$$R = \begin{bmatrix} 1 & r_{12} & r_{13} & \cdots & r_{1p} \\ r_{21} & 1 & r_{23} & \cdots & r_{2p} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ r_{p1} & r_{p2} & r_{p3} & \cdots & 1 \end{bmatrix} \quad r_{ij} = \frac{\text{Cov}(X_i, X_j)}{\sigma_{X_i} \sigma_{X_j}}$$

Covariance and Correlation Matrix

Printing covariance and correlation between columns x1, x2, x3 and x4 using pandas.

4 variable:

```
import pandas as pd

x1 = [1, 2, 3, 4, 5]
x2 = [2, 3, 5, 4, 6]
x3 = [6, 4, 5, 3, 2]
x4 = [6, 2, 7, 3, 5]

df = pd.DataFrame({'x1': x1,
                   'x2': x2,
                   'x3': x3,
                   'x4': x4})
)

print("\nCovariance:\n", df.cov())
print("\nCorrelation:\n", round(df.corr(),2))
```

Covariance:

| | x1 | x2 | x3 | x4 |
|----|-------|-------|-------|-------|
| x1 | 2.50 | 2.25 | -2.25 | -0.25 |
| x2 | 2.25 | 2.50 | -1.75 | 0.75 |
| x3 | -2.25 | -1.75 | 2.50 | 1.50 |
| x4 | -0.25 | 0.75 | 1.50 | 4.30 |

Correlation:

| | x1 | x2 | x3 | x4 |
|----|-------|-------|-------|-------|
| x1 | 1.00 | 0.90 | -0.90 | -0.08 |
| x2 | 0.90 | 1.00 | -0.70 | 0.23 |
| x3 | -0.90 | -0.70 | 1.00 | 0.46 |
| x4 | -0.08 | 0.23 | 0.46 | 1.00 |

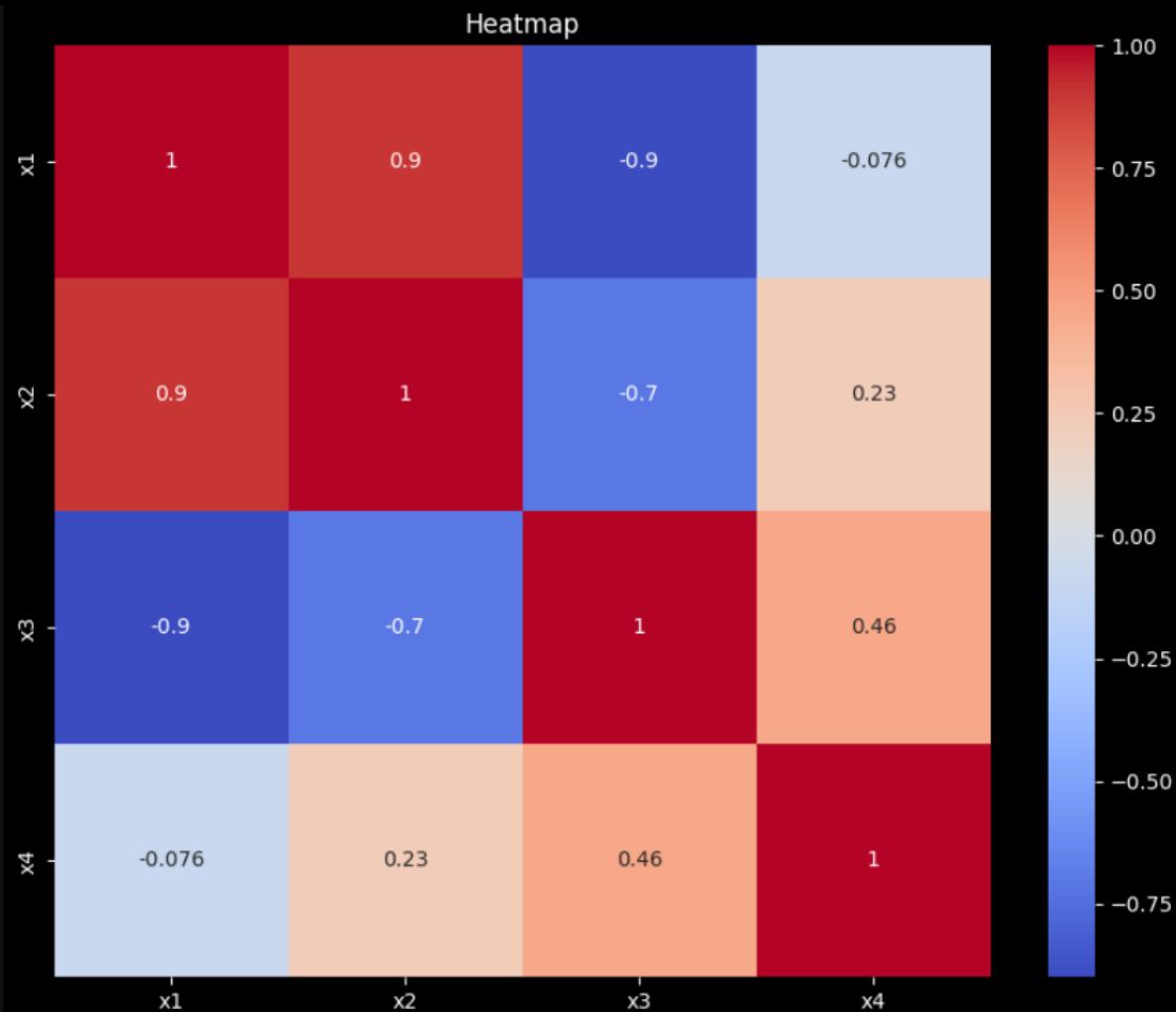
Printing covariance and correlation between columns x1, x2, x3 and x4 using pandas.

```
import matplotlib.pyplot as plt
import pandas as pd

x1 = [1, 2, 3, 4, 5]
x2 = [2, 3, 5, 4, 6]
x3 = [6, 4, 5, 3, 2]
x4 = [6, 2, 7, 3, 5]

df = pd.DataFrame({'x1': x1,
                   'x2': x2,
                   'x3': x3,
                   'x4': x4})

plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap="coolwarm")
plt.title("Heatmap")
plt.show()
```



EXTRA





Covariance-correlation



Suppose that you have samples of 2 data: X and Y. Then formula for Covariance and correlation is

$$\text{Cov}(X, Y) = \frac{1}{n-1} \sum_{k=1}^n (x_k - \bar{x})(y_k - \bar{y})$$

$$r = \frac{\text{Cov}(X, Y)}{s_X s_Y}$$

$$s_X = \sqrt{\frac{\sum(x_i - \bar{X})^2}{n-1}} \quad s_Y = \sqrt{\frac{\sum(y_i - \bar{Y})^2}{n-1}}$$

$$r_{XY} = \frac{\sum_{k=1}^n (x_k - \bar{x})(y_k - \bar{y})}{\sqrt{\sum_{k=1}^n (x_k - \bar{x})^2 \sum_{k=1}^n (y_k - \bar{y})^2}}$$

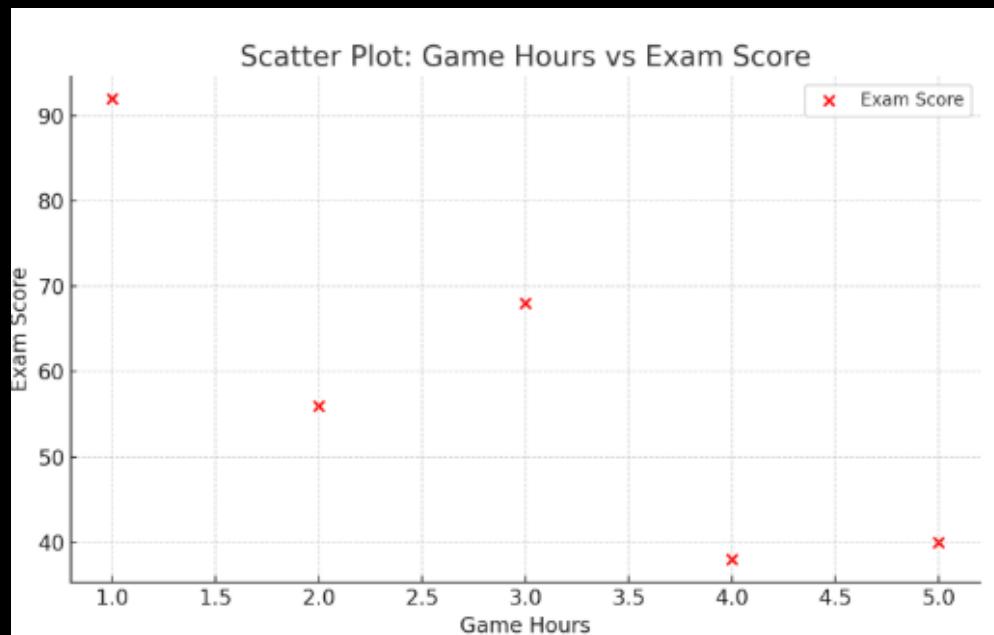
Practice: Following is sample taken from a population. What is correlation coefficient between gamehours and ExamScore ?



| <u>Student</u> | <u>GameHrs (X)</u> | <u>ExamScore (Y)</u> |
|----------------|--------------------|----------------------|
| A | 1 | 92 |
| B | 2 | 56 |
| C | 3 | 68 |
| D | 4 | 38 |
| E | 5 | 40 |

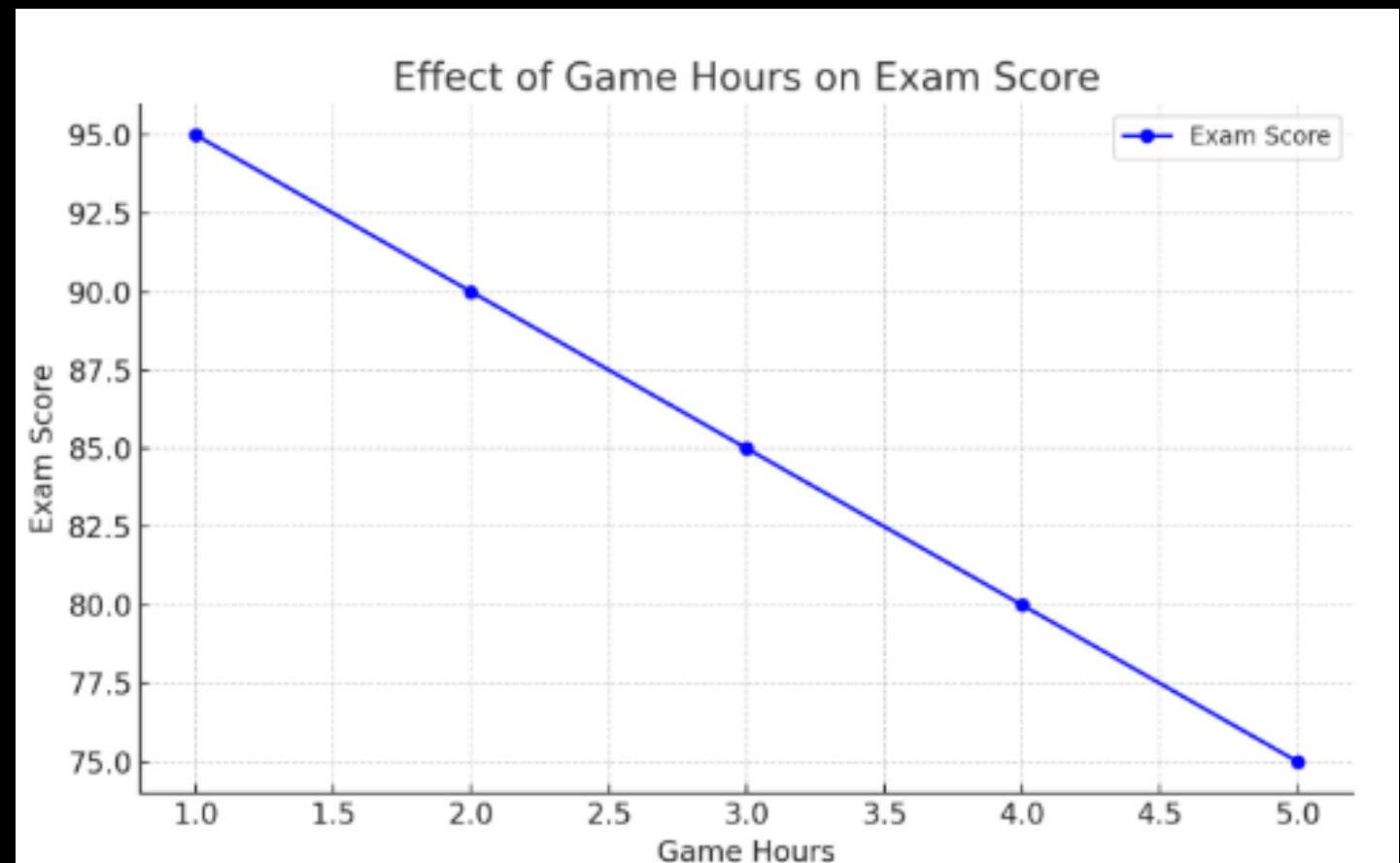
Performing the same calculation as above, we find that the mean of each is 3 and 58.8,
 $\text{Cov}(X,Y) = -24.4$

Correlation coefficient = -0.868





If we plot Gamehours versus Scores, we see following perfect linear plot. This is typical of features that have correlation coeff = 1



Covariance + correlation (p1)

Covariance measures how two variables change together—whether they increase or decrease in tandem

Population Covariance Formula

$$\text{Cov}(X, Y) = \frac{1}{n} \sum_{i=1}^n (X_i - \mu_X)(Y_i - \mu_Y)$$

Sample Covariance Formula

$$\text{Cov}(X, Y) = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})$$

Where:

- n = number of data points
- X_i, Y_i = the i -th observation of variables X and Y
- μ_X or \bar{X} = mean of X
- μ_Y or \bar{Y} = mean of Y

You will also see following formula in literature:

- The covariance matrix tells us **how features vary together**. For two features X and Y :

$$\text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$$

- In matrix form:

$$\text{Covariance matrix} = \mathbf{C} = \begin{bmatrix} \text{Var}(X_1) & \text{Cov}(X_1, X_2) & \dots \\ \text{Cov}(X_2, X_1) & \text{Var}(X_2) & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

What does this matrix represent?

1. The **diagonal elements = variances of individual features** → how much that feature spreads out.
2. The **off-diagonal elements = covariances** → how two features change together:
Negative covariance: when one increases, the other decreases.... X_1 = age and X_2 = number of pushups
Zero covariance: no linear relationship..... X_1 = your age and X_2 = neighbors income
Positive covariance: they increase together.... X_1 = your age, X_2 = income

For example X_1 could be age, X_2 could income and we may see that $\text{Cov}(X_1, X_2)$ be +ve: as age goes up, income goes up to.

Covariance + correlation EXAMPLE (jupyter n/b)

Example: Suppose we're looking at:

GameHrs: The number of hours a student plays video games per day

ExamScore: The student's exam score out of 100.

Below is a **sample** taken from a population. Find covariance and correlation coeff. between the 2 features.

| Student | GameHrs (X) | ExamScore (Y) |
|---------|-------------|---------------|
| A | 1 | 95 |
| B | 2 | 90 |
| C | 3 | 85 |
| D | 4 | 80 |
| E | 5 | 75 |

We expect that as GameHours (video games) increase, ExamScore decreases → negative covariance. Let's see if can deduce this mathematically.

Here we would use sample covariance formula.

Compute means

$$\bar{X} = (1 + 2 + 3 + 4 + 5)/5 = 3$$

$$\bar{Y} = (95 + 90 + 85 + 80 + 75)/5 = 85$$

$$\begin{aligned}\text{cov}(x, y) &= \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) \\ &= \frac{1}{4} [(x_1 - \bar{x})(y_1 - \bar{y}) + (x_2 - \bar{x})(y_2 - \bar{y}) \\ &\quad + (x_3 - \bar{x})(y_3 - \bar{y}) + (x_4 - \bar{x})(y_4 - \bar{y})] \\ &= \frac{1}{4} [(1-3)(95-85) + (2-3)(90-85) \\ &\quad + (3-3)(85-85) + (4-3)(80-85)] \\ &= \frac{1}{4} [-50] = -12.5\end{aligned}$$

| GameHrs(X) | ExamScore(Y) | (X - 3) | (Y - 85) | Product |
|------------|--------------|---------|----------|---------|
| 1 | 95 | -2 | 10 | -20 |
| 2 | 90 | -1 | 5 | -5 |
| 3 | 85 | 0 | 0 | 0 |
| 4 | 80 | 1 | -5 | -5 |
| 5 | 75 | 2 | -10 | -20 |

So the cova. is -12.5 hours - score point

Cont....

...cont

Covariance + correlation EXAMPLE (jupyter n/b)

Why do we need correlation coefficient (r) ρ ?

Covariance has units:

- Example: if X = meters, Y = seconds $\rightarrow \text{cov}(X, Y)$ is in meter·second
- This makes it hard to compare across different datasets that may have different units

The formula for correlation coefficient is

$$\text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X)} \sqrt{\text{var}(Y)}}$$

$$\text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

Key point on r :

It is dimensionless (no units) and $\in [-1, 1]$

+1 \rightarrow perfect positive linear relationship

0 \rightarrow no linear relationship

-1 \rightarrow perfect negative linear relationship



Continuing with previous example,

Std dev of X

$$\begin{aligned}\sigma_X &= \sqrt{\frac{(1 - 3)^2 + (2 - 3)^2 + (3 - 3)^2 + (4 - 3)^2 + (5 - 3)^2}{5 - 1}} \\ &= \sqrt{\frac{4 + 1 + 0 + 1 + 4}{4}} = \sqrt{\frac{10}{4}} = \sqrt{2.5} \approx 1.58\end{aligned}$$

Std dev of Y

$$\begin{aligned}\sigma_Y &= \sqrt{\frac{(95 - 85)^2 + (90 - 85)^2 + (85 - 85)^2 + (80 - 85)^2 + (75 - 85)^2}{4}} \\ &= \sqrt{\frac{100 + 25 + 0 + 25 + 100}{4}} = \sqrt{\frac{250}{4}} = \sqrt{62.5} \approx 7.91\end{aligned}$$

We already calculated:

$$\text{cov}(X, Y) = -12.5$$

Correlation coefficient

$$r = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{-12.5}{1.58 \times 7.91} = \frac{-12.5}{12.5} = -1.0$$