



# Introduction to Statistics

Data Boot Camp

Lesson 5.3



# Class Objectives

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By the end of today's lesson, you will be able to:



Calculate summary statistics, such as mean, median, mode, variance, and standard deviation, by using Python.



Plot, characterize, and quantify a normally distributed dataset by using Python.



Qualitatively and quantitatively identify potential outliers in a dataset.



Differentiate between a sample and a population in regard to a dataset.



Define and quantify correlation between two factors.



Calculate and plot a linear regression in Python.



# Instructor Demonstration

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## Summary Statistics in Python



**What is a measure of  
central tendency?**

# Measure of Central Tendency = Center of a Dataset

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The three most common measures are **mean**, **median**, and **mode**.

## Mean

Mean is the sum of all values divided by the number of elements in a dataset.

## Median

Median is the middle value in a sorted dataset.

## Mode

Mode is the most frequently occurring value(s) in a dataset.

# Measures of Central Tendency in Python

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Two packages to remember when calculating statistics: **NumPy** and **SciPy**.

Mean

Mean is calculated using **NumPy**.

Median

Median is calculated using **NumPy**.

Mode

Mode is calculated using **SciPy**.



**When new data comes along,  
you must plot it!**

# Why Plot Data?

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01

To determine if the data is normally distributed.

02

To determine if the data is multimodal.

03

To characterize clusters in the dataset.

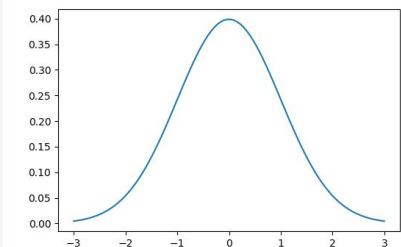


# What Is Normally Distributed Data?

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01

The distribution of data follows a bell-curve shape.



02

We can quantitatively test if a dataset is normal using SciPy.

```
stats.normaltest()
```

03

Some statistical tests assume normally distributed data.



**What are variance and  
standard deviation?**

# Variance and Standard Deviation

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Variance and standard deviation describe variability of data.



**Variance** is the measurement of how far each value is from the mean of the dataset.



**Standard deviation** is the square root of variance.



In Python, both variance and standard deviation are calculated by using the **NumPy** module.



Time to <code>



# Instructor Demonstration

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## Quantiles and Outliers in Python



**What are quantiles,  
quartiles, and outliers?**

# Quantiles, Quartiles, and Outliers

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Quantiles, quartiles, and outliers describe a dataset.

## Quantiles

Quantiles divide data into well-defined regions based on a sorted dataset.

## Quartiles

Quartiles are a specific type of quantile where a sorted dataset is split into four equal parts.

<b>Q1</b>	25% of the data
<b>Q2</b>	50% of the data
<b>Q3</b>	75% of the data

## Quartiles

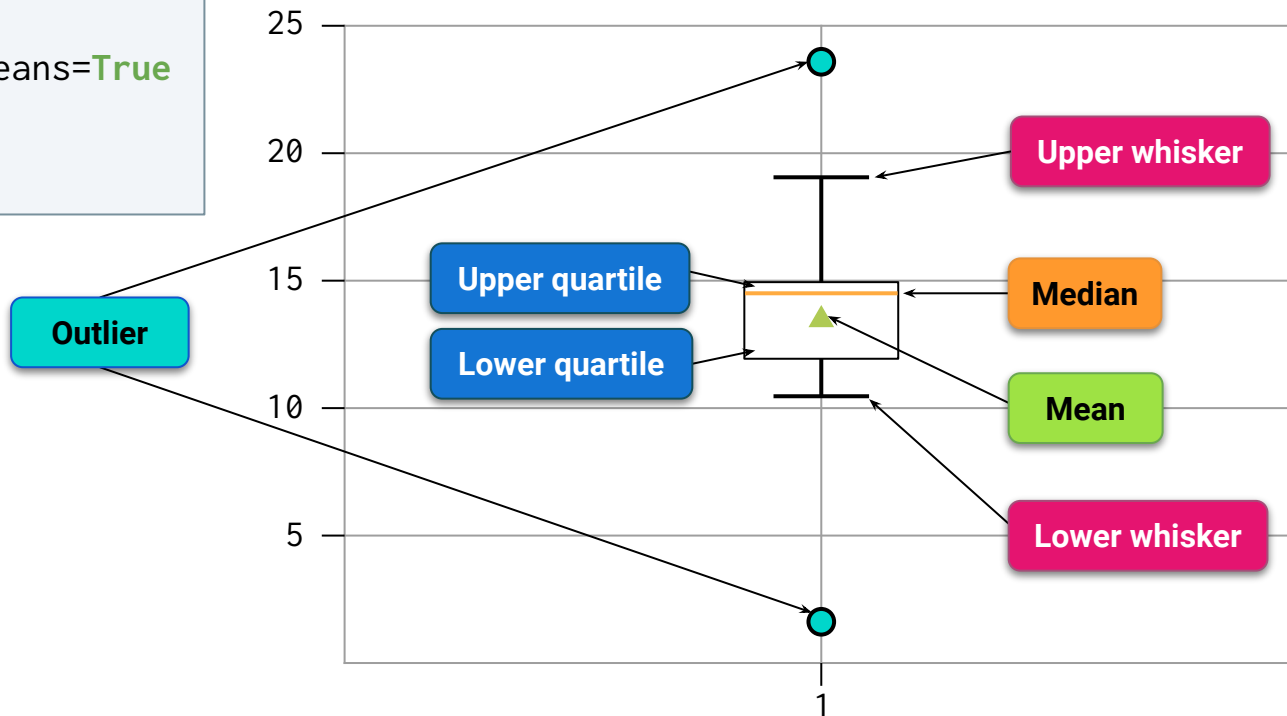
Outliers are extreme values in a dataset that can skew calculations and results.

# How to Identify Potential Outliers: Qualitatively

Use box-and-whisker plots to visually identify potential outlier data points.

```
# Create box plot
```

```
plt.boxplot(arr, showmeans=True)  
plt.grid()  
plt.show()
```





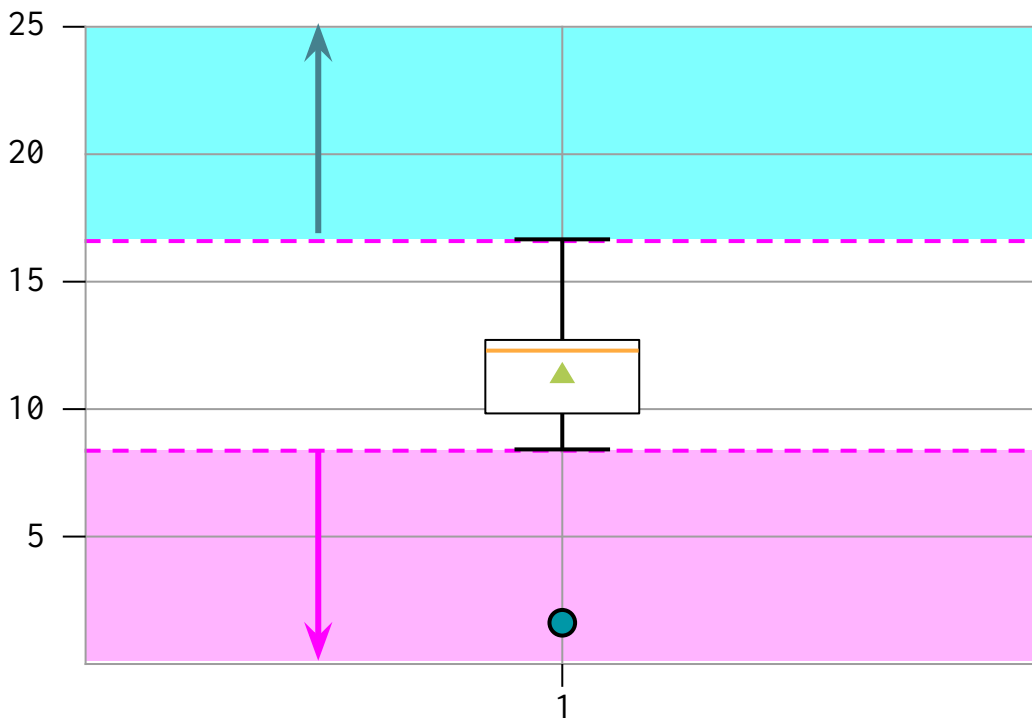
# How to Identify Potential Outliers: Quantitatively

Determine the outlier boundaries in a dataset by using the  **$1.5 \times \text{IQR}$  rule**.

The IQR is the range between the first and the third quartile.

Anything **less than, or below,** Quartile 1 –  $(1.5 \times \text{IQR})$  might be an outlier.

Anything **greater than, or above,** Quartile 3 +  $(1.5 \times \text{IQR})$  might be an outlier.

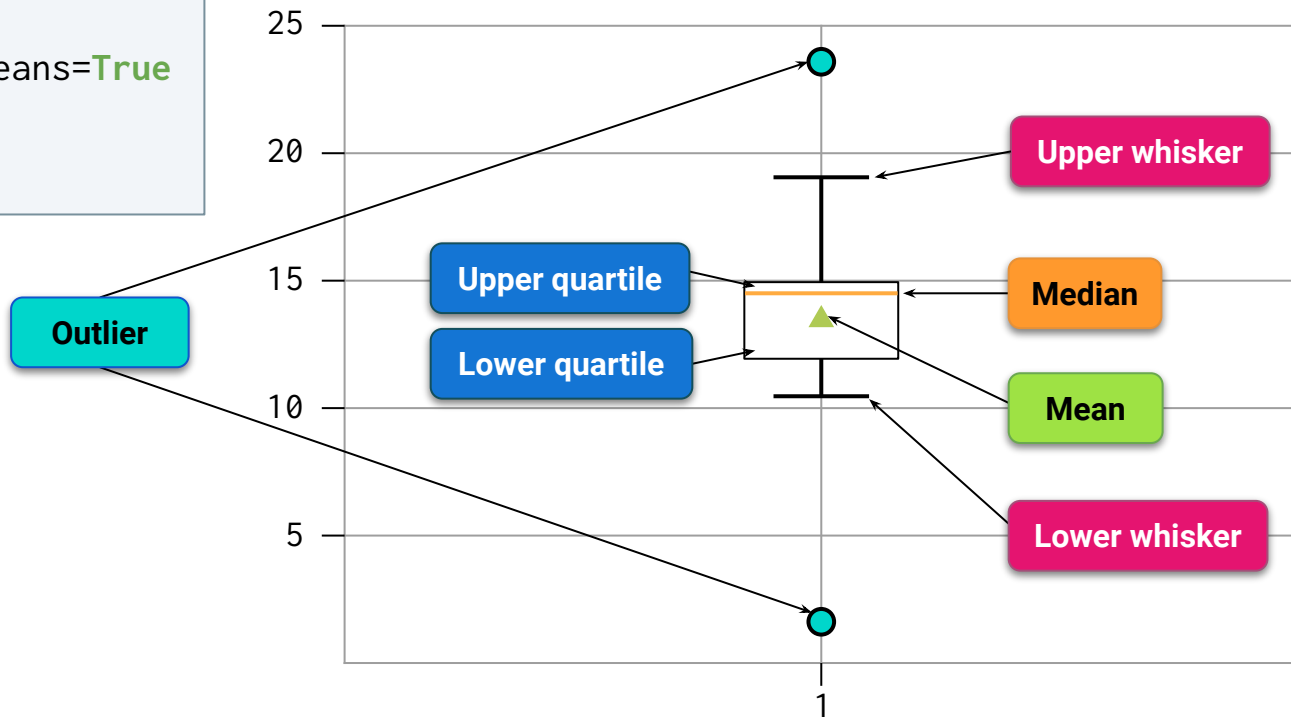


# How to Identify Potential Outliers in Python: Qualitatively

Use Matplotlib's `pyplot.boxplot` function to plot the box and whisker.

```
# Create box plot
```

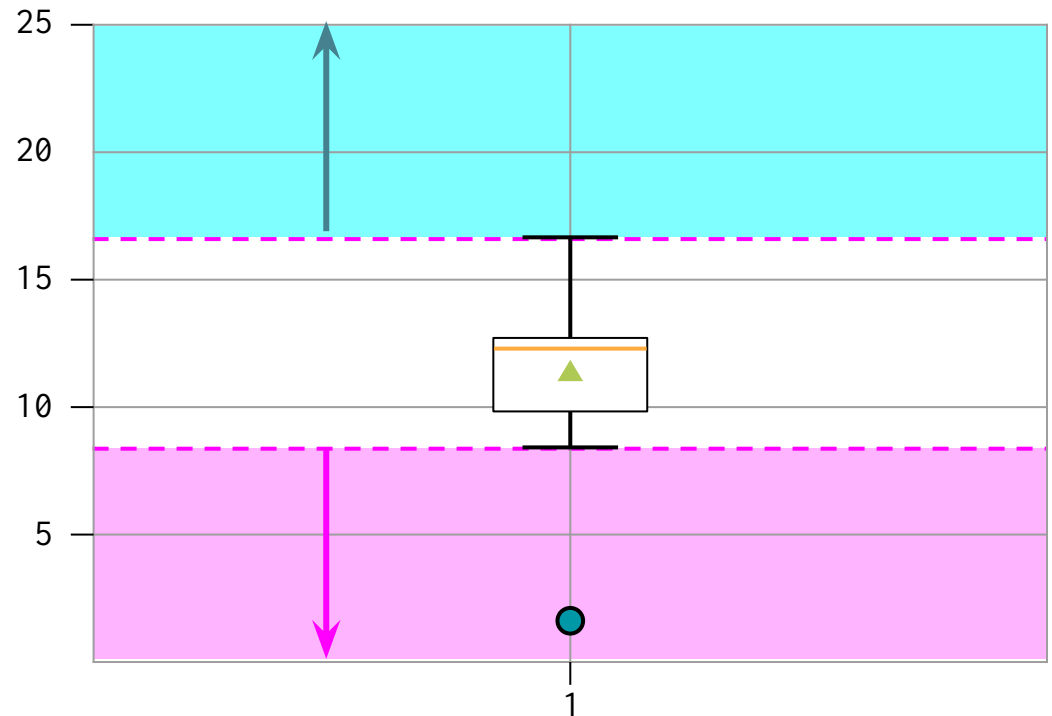
```
plt.boxplot(arr, showmeans=True)  
plt.grid()  
plt.show()
```



# How to Identify Potential Outliers in Python: Quantitatively

Use Pandas' `series.quantile` function to calculate the quantile.

Calculate the outlier boundaries.





# Activity: Summary Statistics in Python

In this activity, you will be tasked with calculating a number of summary statistics by using California housing data.

Suggested Time:

20 minutes

# Activity: Summary Statistics in Python

## Instructions

Using Pandas, import the California housing dataset from the Resources folder.

**File:** `Resources/California_Housing.csv`

Determine the most appropriate measure of central tendency to describe the population, and then calculate this value.

Is the age of houses in California normally distributed? Use both data visualization and quantitative measurement to find out.

Examine the average occupancy of housing in California, and determine if there are potential outliers in the dataset.

**Hint:** This dataset is very large.

If there are potential outliers in the average occupancy, what are the minimum and maximum median housing prices across the outliers?

## Bonus

Plot the latitude and longitude of the California housing data using Matplotlib. Color the data points using the median income of the block. Does any location seem to be an outlier?



Time's Up! **Let's Review.**



# Instructor Demonstration

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## Sample, Population, and SEM



**Let's think about  
the following scenario...**



# Predicting the City Election

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Weeks before Election Day, a local newspaper wants to predict the winner of the mayoral election. The newspaper will poll voters for their intended candidate. Consider the following:



It would be prohibitively expensive to poll all voters.



It is logistically impossible to know who will actually go out to vote on Election Day.



Therefore, the newspaper must predict the outcome of the election using data from a subset of the population.



This calls for the use of a sample dataset in place of a population dataset.



# Population Dataset vs. Sample Dataset

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## Population Dataset

- Dataset containing all possible elements of an experiment or study.
- In statistics, “population” does not mean “people.”
- Any complete set of data is a population dataset.

## Sample Dataset

- A subset of population data.
- A sample dataset can be selected randomly from the population or selected with bias.



Time's Up! **Let's Review.**



## Partner Activity: SEM and Error Bars

In this activity, you will work with a partner to characterize sample data from a California housing dataset. Make sure to compare your calculated values as you progress through the activity.

Take your time—this is an important statistical concept.  
(Instructions sent via Slack.)

Suggested Time:

25 minutes

# Partner Activity: SEM and Error Bars

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## Instructions:

- Open `samples.ipynb` in the activity folder.
- Execute the starter code to import the California housing dataset from Scikit-learn.
- Using Pandas, create a sample set of median housing prices. Be sure to create samples with at least 20 prices.
- Calculate the means and standard error for each sample.
- Create a plot displaying the means for each sample, with the standard error as error bars.
- Calculate the range of SEM values across the sample set.
- Determine which sample has the lowest standard error value.
- Compare this sample's mean to the population's mean.
- Rerun your sampling code a few times to generate new sample sets. Try changing the sample size and then re-run the sampling code.
- Discuss with your partner what changes you observe when sample size changes.



Countdown timer

**40:00**

(with alarm)

Break





Time's Up! **Let's Review.**

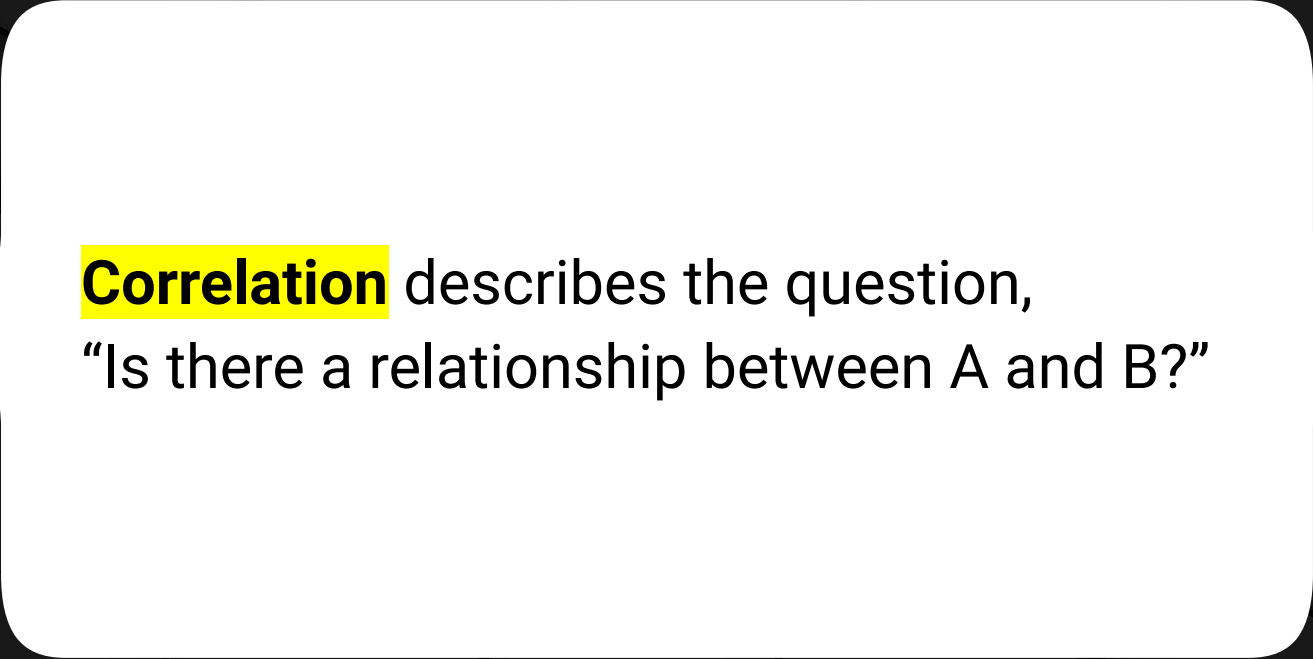


# Instructor Demonstration

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## Correlation Conundrum

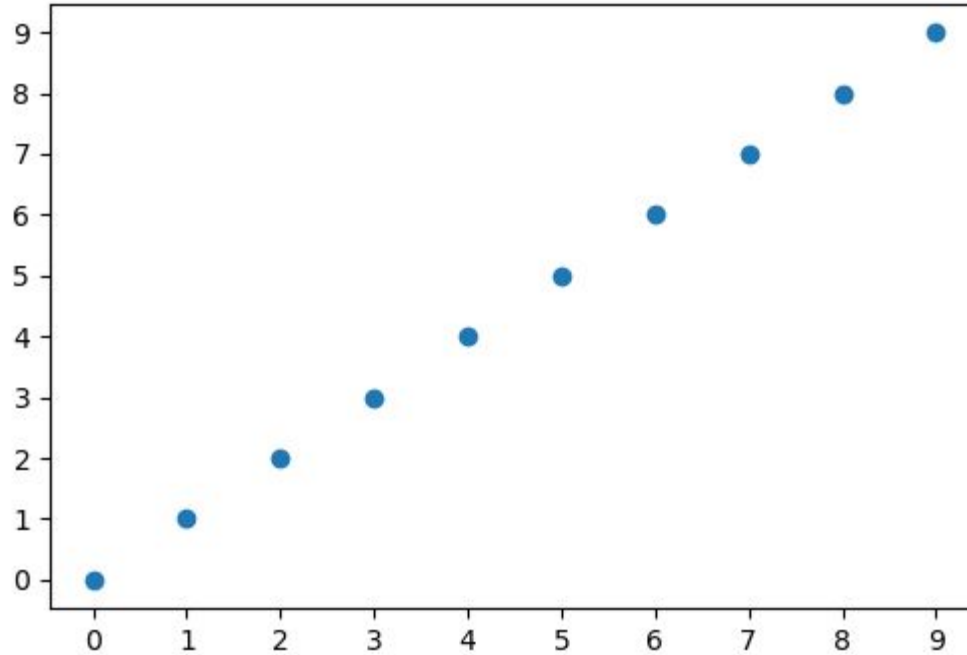




**Correlation** describes the question,  
“Is there a relationship between A and B?”

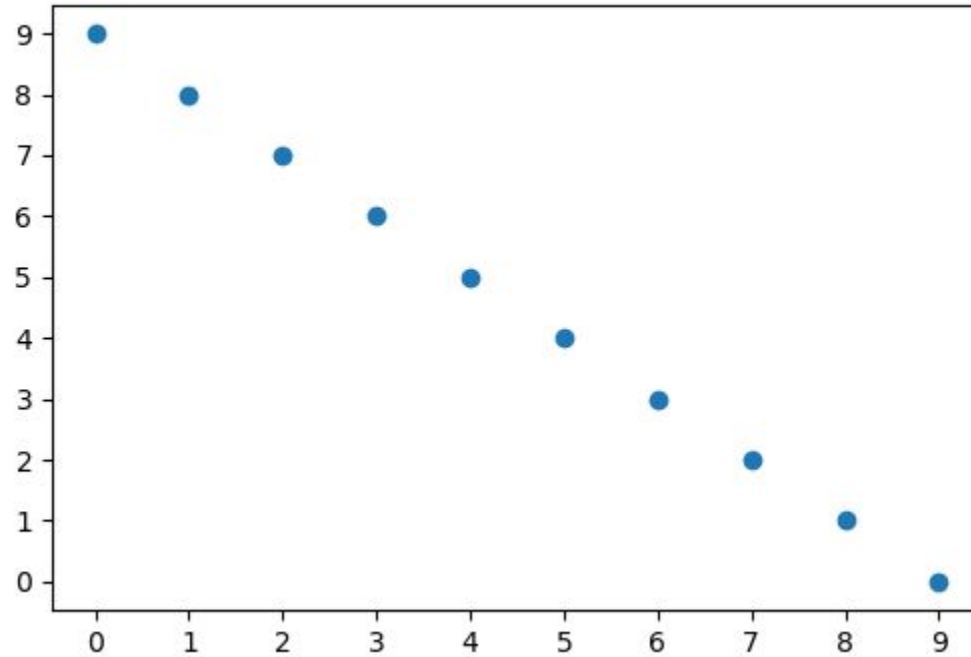
# Positive Correlation

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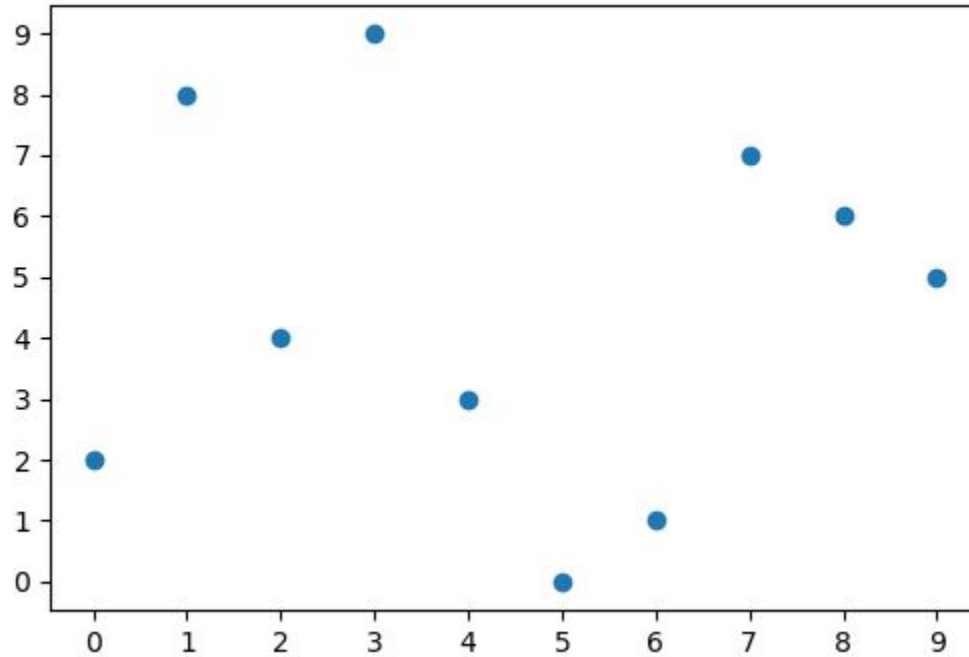
# Negative Correlation

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# No Correlation

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# Pearson Correlation Coefficient

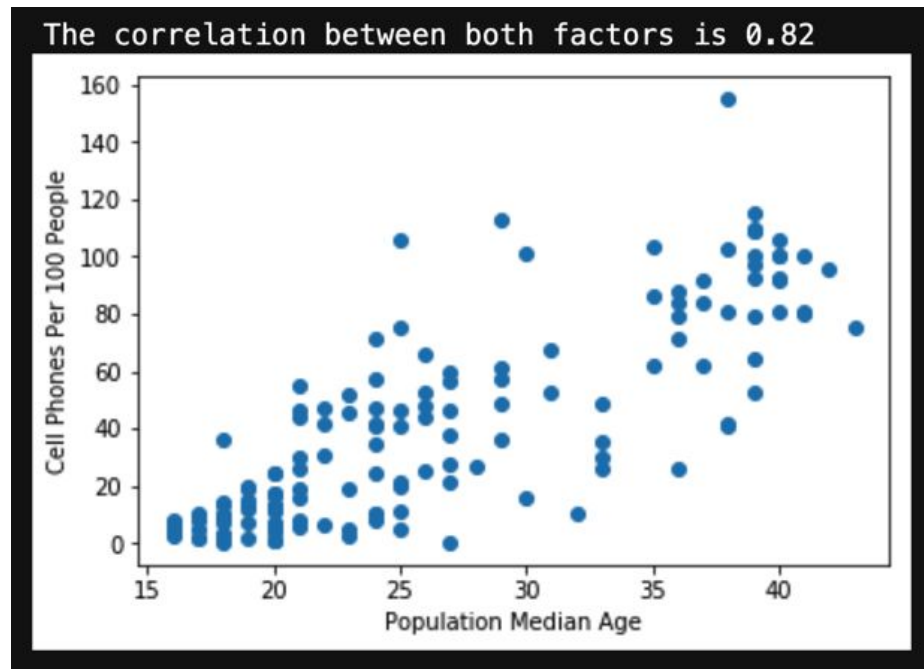
In statistics, we quantify correlation using Pearson's  $r$ .

The Pearson correlation coefficient describes the variability between two factors, denoted by the variable  $r$ .

Pearson's  $r$  is  $-1 \leq r \leq 1$

-1	Indicates perfect negative correlation.
1	Indicates perfect positive correlation.
0	Indicates no correlation.

Real-world data is never perfect.





# Activity: Correlation Conquerors

In this activity, you will examine different properties of wine to determine if wine characteristics are correlated.

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Suggested Time:

10 minutes

# Activity: Correlation Conquerors

## Instructions

Open `correlations.ipynb` in the activity folder and execute the starter code.

**Using the dataset, plot the factors flavonoids and malic acid against each other on a scatter plot.**

- Is this relationship positively correlated, negatively correlated, or not correlated?
- How strong is the correlation?

**Calculate the Pearson correlation coefficient for malic acid versus flavonoids.**

- Compare the correlation coefficient to the strength of correlation table.
- Was your prediction correct?

## Pearson's Correlation

### Absolute Value of $r$

### Strength of Correlation

$$r < 0.3$$

None or very weak

$$0.3 \leq r < 0.5$$

Weak

$$0.5 \leq r < 0.7$$

Moderate

$$r \geq 0.7$$

Strong



Time's Up! **Let's Review.**





# Instructor Demonstration

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## Fits and Regression



**What is the equation of a line?**

The equation of a line is:

$$y = mx + b$$

Diagram illustrating the components of the equation of a line:

- $y$ : Dependent variable
- $m$ : Slope
- $x$ : Independent variable
- $b$ : y-intercept

# The Equation of a Line Determines $y$ Values Given $x$

In this example:



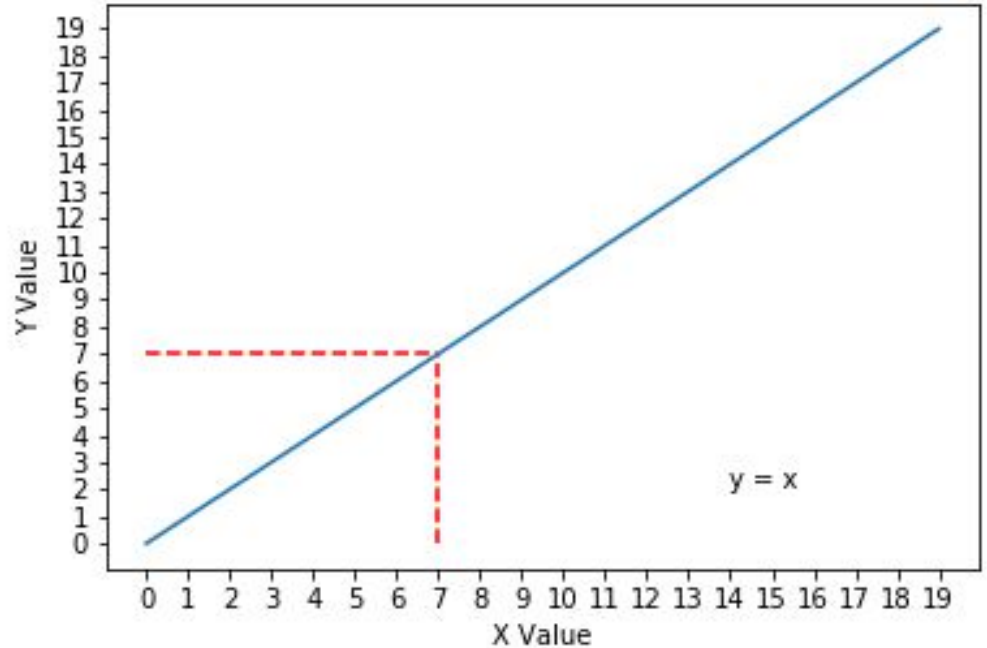
Slope = 1



$y$  intercept = 0



Whatever  $x$  is, the value of  $y$  is the same.



# The Equation of a Line Determines y Values Given x

In this example:



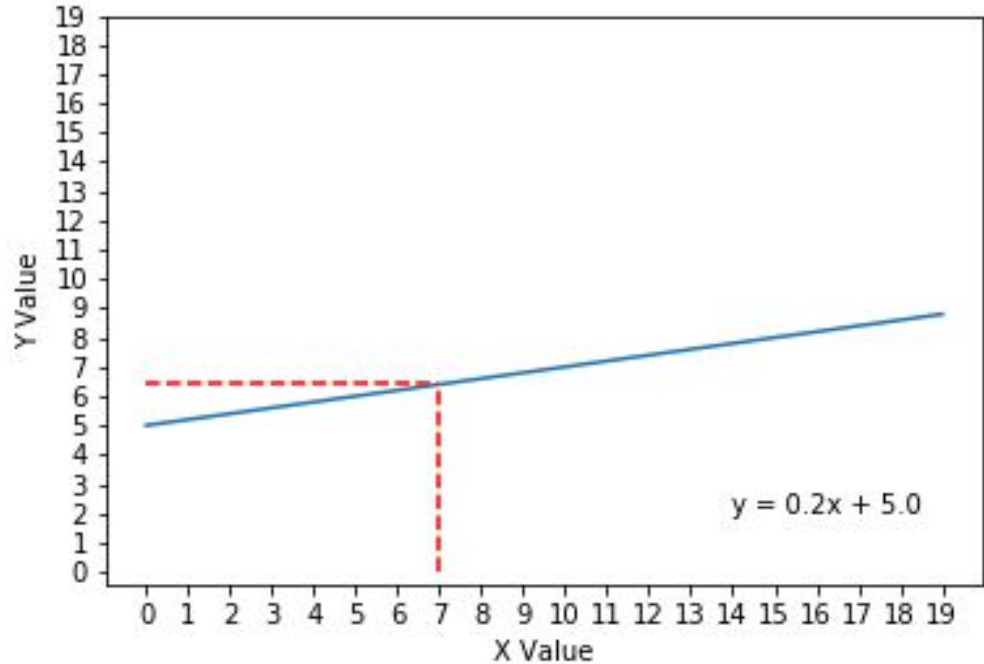
Slope = 0.2



y intercept = +5



If  $x = 7$ , then  $y = 6.4$



# Linear Regression Fits the Equation of a Line to Real-World Data

Linear regression:



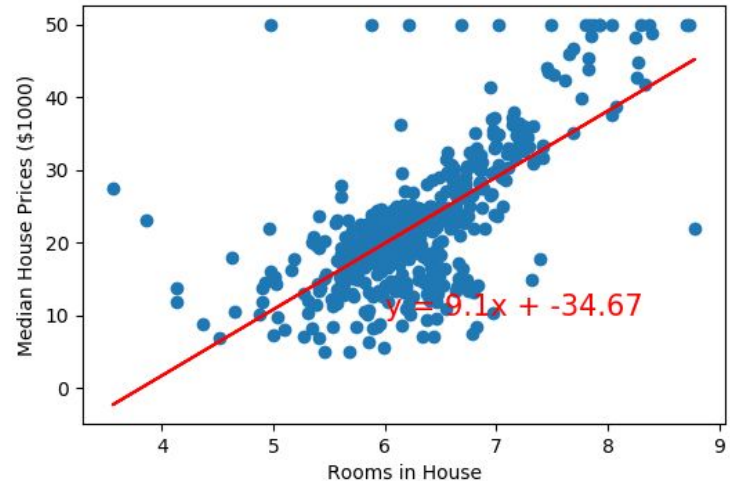
Predicts the values of factor B given values of factor A.



Estimates where unmeasured data points might end up if more data was collected.



Is used to predict housing prices, stock market, weather, etc.





# Activity: Fits and Regression

In this activity, you will predict the number of petrol-electric cars per year by using linear regression models.

Suggested Time:

15 minutes

# Activity: Fits and Regression

## Instructions

Open `vehicles.ipynb`, and execute the starter code.

Generate a scatter plot with Matplotlib using the year as the independent ( $x$ ) variable and the number of petrol-electric cars as the dependent ( $y$ ) variable.

Use `stats.linregress` to perform a linear regression with the year as the independent variable ( $x$ ) and the number of petrol-electric cars as the dependent variable ( $y$ ).

Use the information returned by `stats.linregress` to create the equation of a line from the model.

Calculate the predicted number of petrol-electric cars of the linear model using the year as the  $x$ -value.

**Plot the linear model of year versus number of petrol-electric cars on top of your scatter plot.**

- Your scatter plot and line plot share the same axis.
- To overlay plots in a notebook, the plots must be in the same code block.

Repeat the process of generating a scatter plot, calculating the linear regression model and plotting the regression line over the scatter plot for year versus petrol cars and year versus diesel cars.

## Bonus

Use `pyplot.subplots` from Matplotlib to create a new figure that displays all three pairs of variables on the same plot.





Time's Up! Let's Review.

# Questions?

