# Machine Learning

## Statistics Review

1. **Mean (Average, μ):**
   - Definition: The sum of all values divided by the number of values.
   - Formula: $\frac{Sum\ of\ all\ values}{number\ of\ values}$
   - Example: For the dataset {2, 5, 8, 10}, the mean is calculated as $\frac{(2+5+8+10)}{4} = \frac{25}{4} = 6.25$ .
2. **Median:**
   - Definition: The middle value of a dataset when arranged in ascending or descending order.
   - Formula: $\frac{n+1}{2}$
   - Example: For the dataset **{3, 1, 4, 1, 5, 9, 2, 6, 5, 3, 5}**, first, sort the values in ascending order: **{1, 1, 2, 3, 3, 4, 5, 5, 5, 6, 9}**. the median is 4, as it is the middle value. $\frac{11+1}{2} = 6 = 6^{th}$ value represents 4.
3. **Mode:**
   - Definition: The value that occurs most frequently in a dataset.
   - Example: For the dataset **{3, 1, 4, 1, 5, 9, 2, 6, 5, 3, 5}**, the mode is 5, as it appears three times, more frequently than any other value. **(5 * 3)**

**Frequency Tables:**

- Definition: Tables that show the distribution of values and their frequencies in a dataset.
- Example:

| Value (Can be like age interval) | Frequencies (number of occurrences) |
|---|---|
| 10-19 | 1 |
| 20-29 | 2 |
| 30-39 | 48 |
| 40-49 | 158 |
| 50-59 | 236 |
| 60-69 | 262 |
| 70-79 | 174 |
| 80-89 | 50 |
| 90-99 | 3 |

Relative Frequency (Percentages):

- Definition: Relative frequency means the ***number of times*** a value appears in the **data** compared to the total amount. A **percentage** is a relative frequency.
- Example: For the dataset **{2, 3, 3, 5, 5, 5}**, the relative frequency of 3 is $\left(\frac{2}{6}\right) \times\ 100\% \ =$ 33.33%. **2** Represents number of occurrences and ***6*** total number of values within a given list.
- $Relative\ Frequency\ (\%)\ =\ \left(\frac{Occurrence}{Number\ of\ values\ in\ a\ list}\right)\ \times\ 100$
- In this example: Total number of winners = **934** and frequencies values were given in the previous list. So, we use the formula of dividing the ***occurrence*** by **934**.

| Age Interval (Values) | Relative Frequency (%) |
|---|---|
| 10-19 | 0.11% |
| 20-29 | 0.21% |
| 30-39 | 5.14% |
| 40-49 | 16.92% |
| 50-59 | 25.27% |
| 60-69 | 28.05% |
| 70-79 | 18.63% |
| 80-89 | 5.35% |
| 90-99 | 0.32% |

**Cumulative Frequency:**

- Definition: Cumulative frequency counts up to a particular value.
- Example: Here are the cumulative frequencies of ages of Nobel Prize winners. Now, we can see how many winners have been younger than a certain age.

| Age | Cumulative Frequency |
|---|---|
| Younger than 20 | 1 |
| Younger than 30 | 3 |
| Younger than 40 | 51 |
| Younger than 50 | 209 |
| Younger than 60 | 445 |
| Younger than 70 | 707 |
| Younger than 80 | 881 |
| Younger than 90 | 931 |
| Younger than 100 | 934 |

**Percentiles:**

Data = {15, 16, **18**, 19, **22**, 24, **29**, 30, 34}

**Median (50th)** = **22**

**25th percentile**, since we have 10 values we can use $10\ *\ 25\ \div 100\ =$ **2.5** round that up to 3 because we have a *.5* meaning it's the 3rd value in this case **18** What about **75th percentile?** again use the formula $\frac{number\ of\ values\ in\ a\ list\ \cdot\ percentile}{100}$ in this case we end up with an **8** so that is **29** so half of the data is between **18** and **29**.

# Standard Deviation & Variance

The **standard deviation** ($\sigma$ or $\Sigma$) and **variance** are measures of how dispersed or spread out the data is.

We measure how far each datapoint is from the mean.
Let's look at our group of ages again:
`{15, 16, 18, 19, 22, 24, 29, 30, 34}`

`Mean = 23`

Let's calculate how far each value is from the mean. 15 is 8 away from the mean (since 23 **–** 15 **=** 8). Each value **-** $\mu$

Here's a list of all these distances:
`{8, 7, 5, 4, 1, 1, 6, 7, 11}`

We square these values and add them together. $\sigma^2$ **=**

$$8^2 + 7^2 + 5^2 + 4^2 + 1^2 + 1^2 + 6^2 + 7^2 + 11^2$$
$$= 64 + 49 + 25 + 16 + 1 + 1 + 36 + 49 + 121$$
$$= 362$$

We divide this value by the total number of values and that gives us the **variance**.

$\frac{\textit{sum of all values squared}}{\textit{total number of values}}$ = `362 / 9 = 40.22 # or` $\frac{362}{9}$

To get the standard deviation, we just take the square root of **this number** and get: 6.34

**$\Sigma$** = 6.34

<u>But ... there is a small change with Sample Data.</u>
Our **example** has been for a **Population** (the **9 ages** are the only ages we are interested in).

But if the data is a **<u>Sample</u>** (a selection taken from a bigger **<u>Population</u>**, say 15 instead of 9), then the calculation changes!

When you have "N" data values that are:

**The Population**: divide by N when calculating Variance (like we did).
A Sample: divide by N-1 when calculating Variance.

A **population** is the <u>entire group</u> that you want to draw conclusions about. A **sample** is the <u>specific group</u> that you will collect data from. The size of the **sample** is always less than the total size of the **population**. In research, a population doesn't always refer to people.

# Python Implementation (Pt. 1)

statisticsreview.py > ...

```python
import numpy as np

list = [2, 2, 3, 3, 8, 12, 16, 18, 20]

print(list)
print("Mean:", round(np.mean(list)))
print("Median:", round(np.median(list)))

def mode(lst):
    count_dict = {}
    max_count = 0
    mode_value = None
    mode_count = 0
    modes = []

    for value in lst:
        count_dict[value] = count_dict.get(value, 0) + 1

        if count_dict[value] > max_count:
            max_count = count_dict[value]
            mode_value = value
            mode_count = 1
            modes = [value]  # Start a new list for the new mode

        elif count_dict[value] == max_count:
            mode_count += 1
            modes.append(value)  # Add the value to the list of modes

    if mode_count == 1:
        return "Unimodal", modes
    elif mode_count == 2:
        return "Bimodal", modes
    elif mode_count == 3:
        return "Trimodal", modes
    else:
        return f"{mode_count}-modal", modes

print("Mode:", mode(list))
print("Percentile (25%):", round(np.percentile(list, 25)))
print("Percentile (75%):", round(np.percentile(list, 75)))

print("Variance:", round(np.var(list)))
print("Standard Deviation:", round(np.std(list)))
```

Output:
[2, 2, 3, 3, 8, 12, 16, 18, 20]

Mean: 9
Median: 8
Mode: ('Bimodal', [2, 3])
Percentile (25%): 3
Percentile (75%): 16
Variance: 48
Standard Deviation: 7

# Pandas

Python, a very infamous programming language, comes with handy libraries that can be used for Machine Learning.

What's cool about pandas is that you can take in data and view it as a table that's human readable, but it can also be interpreted numerically so that you can do lots of computations with it.

We call the table of data a **DataFrame**.
We need to start by importing Pandas. It's standard practice to nickname it **pd** so that it's faster to type later.

```
import pandas as pd
```

We will be working with a dataset of Titanic passengers. For each passenger, we'll have some data on them as well as whether or not they survived the crash.

Our data is stored as **CSV** (comma-separated values) file. The titanic.csv file is below. The first line is the header and then each subsequent line is the data for a single passenger.

```
Survived, Pclass, Sex, Age, Siblings/Spouses, Parents/Children, Fare
0, 3, male, 22.0, 1, 0, 7.25
1, 1, female, 38.0, 1, 0, 71.2833
1, 3, female, 26.0, 0, 0, 7.925
1, 1, female, 35.0, 1, 0, 53.1
```

We're going to pull the data into pandas so we can view it as a DataFrame.

The **read_csv** function takes a file in csv format and converts it to a Pandas DataFrame.

```
df = pd.read_csv('titanic.csv')
```

The **object df** is now our pandas dataframe with the Titanic dataset. Now we can use the **head** method to look at the data.
The **head** method returns the first 5 rows of the DataFrame.

```
print(df.head())
```

**Code:**

```
import pandas as pd
df = pd.read_csv('https://sololearn.com/uploads/files/titanic.csv')
print(df.head())
```

<u>**Summarize the Data**</u>

Usually, our data is much too big for us to be able to display it all.
Looking at the first few rows is the first step to understanding our data, but then we want to look at some summary statistics.
In pandas, we can use the **describe** method. It returns a table of statistics about the columns.

```
print(df.describe())
```

We add a line in the code below to force python to display all 6 columns. Without the line, it will abbreviate the results.

pandasDatas.py > ...

```python
import pandas as pd
pd.options.display.max_columns = 6
df = pd.read_csv("M:\Downloads\Titanic.csv")
print(df.describe())
```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

```
PS M:\Pygame> & C:/Users/iHunter/AppData/Local/Programs/Python/Python310/python.exe m:/Pygame/pandasDatas.py
       Survived    Pclass    Age  Siblings/Spouses  Parents/Children  \
count      4.00  4.000000   4.00              4.00               4.0
mean       0.75  2.000000  30.25              0.75               0.0
std        0.50  1.154701   7.50              0.50               0.0
min        0.00  1.000000  22.00              0.00               0.0
25%        0.75  1.000000  25.00              0.75               0.0
50%        1.00  2.000000  30.50              1.00               0.0
75%        1.00  3.000000  35.75              1.00               0.0
max        1.00  3.000000  38.00              1.00               0.0

            Fare
count   4.000000
mean   34.889575
std    32.389078
min     7.250000
25%     7.756250
50%    30.512500
75%    57.645825
max    71.283300
```

For each column we see a few statistics. Note that it only gives statistics for the numerical columns.

Let's review what each of these statistics means:
**Count:** This is the number of rows that have a value. In our case, every passenger has a value for each of the columns, so the value is 4 (the total number of passengers).
**Mean:** Recall that the mean is the standard average.
**Std:** This is short for standard deviation. This is a measure of how dispersed the data is.
**Min:** The smallest value
**25%:** The 25th percentile
**50%:** The 50th percentile, also known as the median.
**75%:** The 75th percentile
**Max:** The largest value

# Selecting Multiple Columns in Pandas DataFrame

Select Multiple Columns in a Pandas Dataframe
Below are the ways by which we can select multiple columns in a Pandas Dataframe:

- Using Basic Method
- Using loc[]
- Using iloc[]

Select Multiple Columns in a Pandas DataFrame using **Basic Method**

Select Name and Qualification columns:

```python
import pandas as pd

data = {
    "Name": ["John", "Peter", "Loner", "Depressed"],
    "Age": [21, 18, 23, 18],
    "Address": ["Heaven", "USA", "Hell", "Void"],
    "Qualifications": ["College Degree", "Graduated from a Bootcamp", "Failed social classes", "Passed University"]
}

df = pd.DataFrame(data)

print(df[["Name", "Qualifications"]])
```

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

```
PS M:\Pygame> & C:/Users/iHunter/AppData/Local/Programs/Python/Python310/python.exe m:/Pygame/geeksforgeeks.py
PS M:\Pygame> & C:/Users/iHunter/AppData/Local/Programs/Python/Python310/python.exe m:/Pygame/geeksforgeeks.py
        Name             Qualifications
0       John             College Degree
1      Peter  Graduated from a Bootcamp
2      Loner      Failed social classes
3  Depressed          Passed University
```

## Select Second to fourth column

```python
print(df[df.columns[1:4]])
```

**`df.columns[1:4]`** to obtain the column names at indices 1 to 3 (exclusive).
**`df[df.columns[1:4]]`** displays the columns at given indices and including their rows.

## Select Multiple Columns in a Pandas Dataframe using loc[] function

```python
df.loc[1:3, ["Name", "Qualification"]]
Another example
df.loc[0, :] # is more flexible than basic df.columns method.

# Output: first row, all columns.

# integer-based indexing.
df.iloc[:, 0:2]
# iloc[row slicing, column slicing]
df.iloc[0:2, 1:3]
```

# Reinforcement Learning

Reinforcement learning is a type of machine learning algorithm where an **agent** learns to make decisions by **interacting** with its **environment**. The **agent** then receives a **reward** after interacting with its environment. But there are 4 main aspects of this, and these include:

- **Environment (e.g., Chess):** The environment that the agent must interact with.

- **Agent:** in our example, this can be a computer that plays the chess.

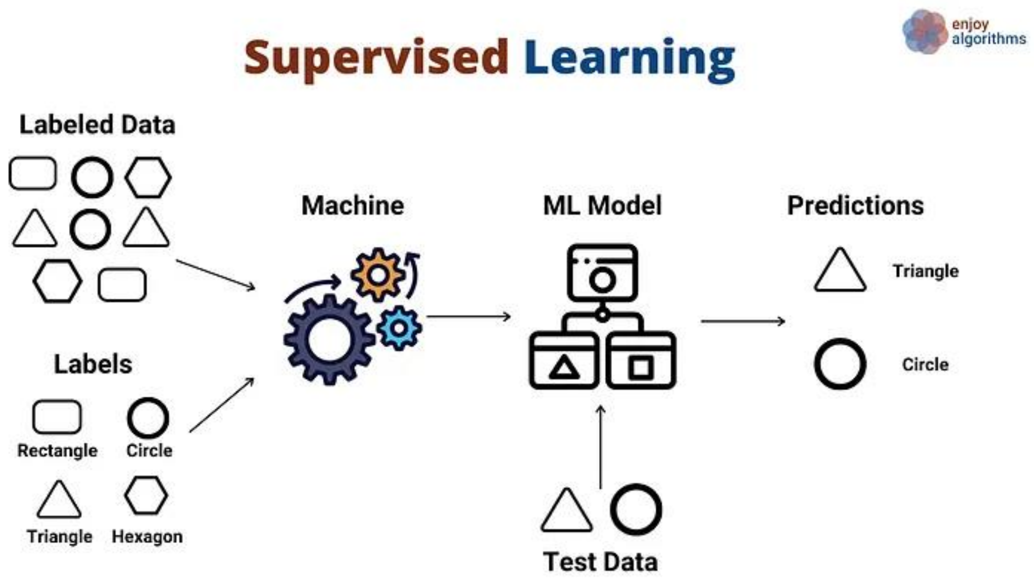
- **Action:** Playing the game, like moving the pieces.

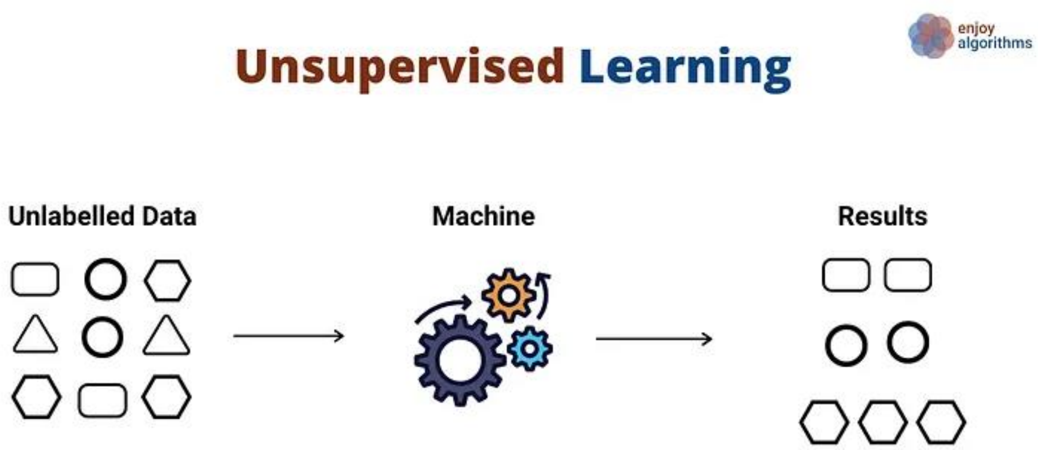
- **Reward (e.g., For winning and losing):** Feedback from the environment that describes the agent's actions. Providing positive reinforcement for desirable actions (winning), and negative reinforcement for undesirable actions (losing)

# Supervised vs Unsupervised Learning

**Supervised Learning:**
Machine Learning Algorithm makes the prediction based on labelled data. Like if we tell it, that these are pictures of shapes (Annotation), it will predict the unseen pictures before by recognizing its patterns and tries to make a prediction based on that. It's called supervise, because there is an **intervention**.

**Unsupervised Learning:**
Machine Learning Algorithm divides the data into categories since they aren't labelled, it's called unsupervised, because the machine learning algorithm tries to figure it out on its own.



# Types Of Supervised Learning

| Classification | Regression |
|---|---|
| Classification is about predicting a class or discrete values e.g.: *Male or Female; True or False.* | Regression is about predicting a quantity or continues values e.g.: Price; Salary; Age. |

**Classification:**

Let's say we have an image of a dog and a cat, and we want our machine learning model to predict those images, it will "**classify**" them by giving the output as "**dog**" or "**cat**". No integer or any other numerical values are displayed.

**Regression:**

A specific value, let's say I asked you "What's the temperature today?" You would probably give a **numerical** answer, a **value**. That is why it's called "Regression".

# Algorithms

## Classification:

1. Decision Tree Classification
2. Random Forest Classification
3. K-nearest Neighbor

## Regression:

1. Logistic Regression
2. Polynomial Regression
3. Support Vector Machines

## Types Of Unsupervised Learning

| Clustering | Association |
|---|---|
| Clustering is an unsupervised task which involves grouping the similar data points. | Association is an unsupervised task that is used to find important relationship between data points. |

**Clustering:**

Let's say a company gave us lots of data to work with we need to find which data point is associated with what. They want to us to increase their user base and revenue. Their giving us their user data, we are feeding it to a clustering algorithm, which the model would cluster into different clusters. Let's assume that the company offers fast speed internet and slow speed internet, our ML model would divide those who bought the low-speed internet plan and those who bought high internet speed in two clusters.

**Association:**

Let's say we have different customers buying different or exact items, our ML model will try to find relationship between what each customer had bought (Customer A bought milk like customer B). Now since both customer A and B bought bread, we can assume that our ML will likely predict that customer C will likely buy milk, assuming they also have bought bread too.

**Algorithms:**

1. K-Means Clustering
2. Hierarchical Clustering
3. Principal Component Analysis (PCA)
4. Apriori
5. Eclat

# <u>NumPy Basics</u>

**Numpy** is a Python package for manipulating lists and tables of numerical data. We can use it to do a lot of statistical calculations. We call the list or table of data a **numpy array.**

## Converting from a Pandas Series to a Numpy Array

We often start with our data in a Pandas DataFrame, but then want to convert it to a numpy array. The **values** attribute does this for us.

Let's convert the **Age** column to a **numpy array**.

```
df['Age']
```

Then we use the values attribute to get the values as a numpy array.

```
df['Age'].values
```

[21 18 23 18]

The result is a 1-dimensional array. You can tell since there's only one set of brackets and it only expands across the page (not down as well).

**2-dimensional numpy array**.

Recall that we can create a smaller pandas DataFrame with the following syntax.

```
df[['Age', 'Address']].values

Output:
[[21 'Heaven']
[18 'USA']
[23 'Hell']
[18 'Void']]
```

This is a 2-dimensional numpy array. You can tell because there’s two sets of brackets, and it expands both across the page and down.

Numpy Shape attribute, which returns the number of rows and columns.

```
arr = df[["Age", "Address"]].values

print(arr.shape) # (4, 2) rows and columns
```