

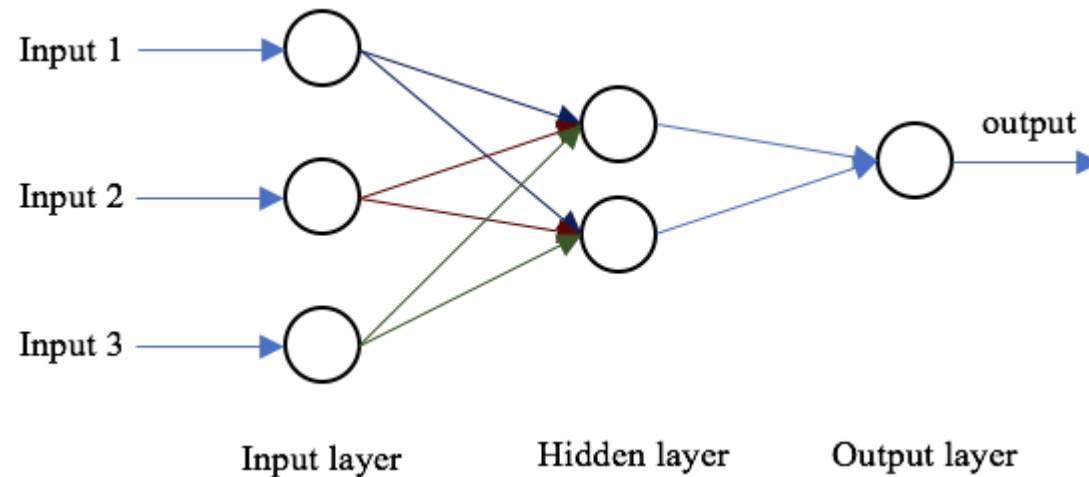
# A05: TENSORFLOW PLAYGROUND

BY OPTIC MINDS

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# NEURAL NETWORKS



Neural Networks are computerized programs that have the main purpose of learning and processing data.

Components:

- Input Layer
- Hidden Layers
- Activation Functions
- Output Layer

# TASK 1: ACTIVATION FUNCTIONS

In a neural network, the activation function plays a crucial role in converting the weighted sum of inputs from the input node into the activation of the output node.

**Simple Activation Function:** The linear activation function doesn't apply any transformation. While linear networks are straightforward to train, they struggle to learn intricate mappings.

**Non-linear Activation Functions:** These are favored to enable nodes to learn more intricate structures within the data.

**Widely Used Activation Functions:** Previously, the Sigmoid and hyperbolic tangent (Tanh) functions were commonly used; however, the Rectified Linear Unit (ReLU) is now the preferred choice.

# ReLu Activation Function

Tinker With a **Neural Network** Right Here in Your Browser.  
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Epoch  
000,291

Learning rate

0.03

Activation

ReLU

Regularization

None

Regularization rate

0

Problem type

Classification

## DATA

Which dataset do you want to use?



Ratio of training to test data: 80%

Noise: 0

Batch size: 10

REGENERATE

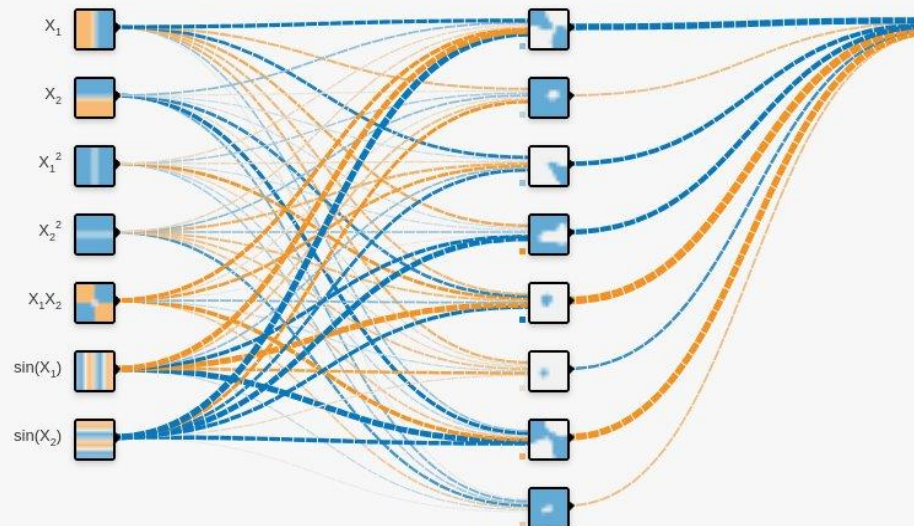
## FEATURES

Which properties do you want to feed in?

$X_1$   
 $X_2$   
 $X_1^2$   
 $X_2^2$   
 $X_1 X_2$   
 $\sin(X_1)$   
 $\sin(X_2)$

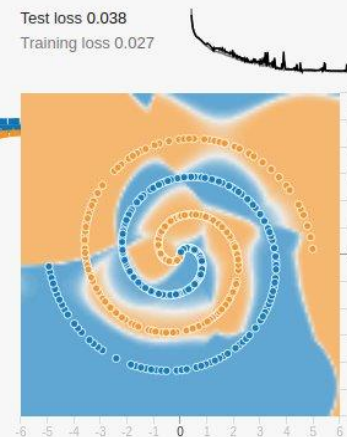
+ - 1 HIDDEN LAYER

+ -  
8 neurons

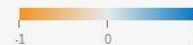


## OUTPUT

Test loss 0.038  
Training loss 0.027



Colors shows data, neuron and weight values.



☐ Show test data ☐ Discretize output



# Sigmoid Activation Function

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Epoch 000,309    Learning rate 0.03    Activation Sigmoid    Regularization None    Regularization rate 0    Problem type Classification

## DATA

Which dataset do you want to use?



Ratio of training to test data: 80%

Noise: 0

Batch size: 10

REGENERATE

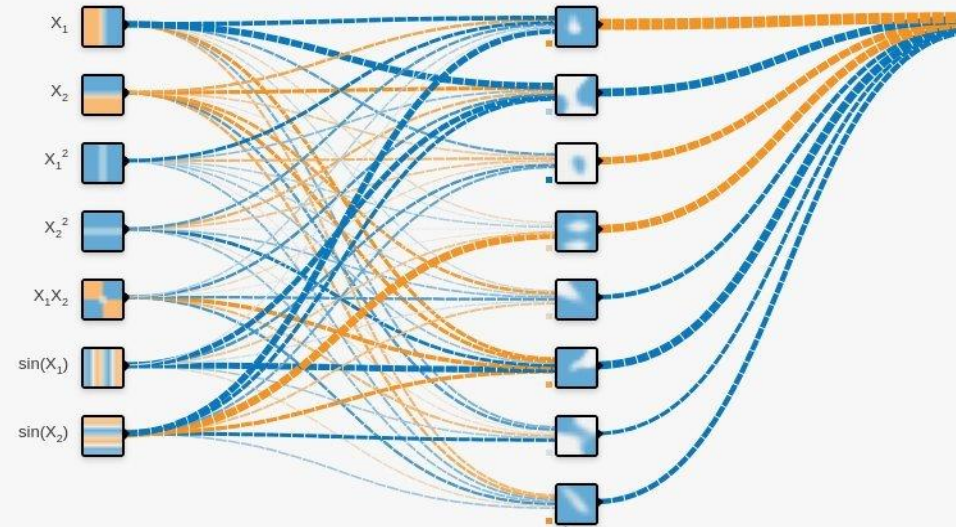
## FEATURES

Which properties do you want to feed in?

$X_1$   
 $X_2$   
 $X_1^2$   
 $X_2^2$   
 $X_1 X_2$   
 $\sin(X_1)$   
 $\sin(X_2)$

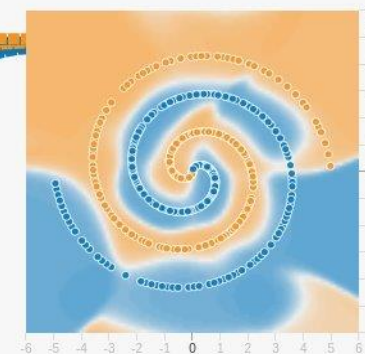
+ - 1 HIDDEN LAYER

+ -  
8 neurons



## OUTPUT

Test loss 0.055  
Training loss 0.038



Colors shows data, neuron and weight values.

☐ Show test data    ☐ Discretize output

# TanH

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Epoch  
000,264

Learning rate  
0.03

Activation  
Tanh

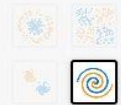
Regularization  
None

Regularization rate  
0

Problem type  
Classification

## DATA

Which dataset do you want to use?



Ratio of training to test data: 80%

Noise: 0

Batch size: 10

REGENERATE

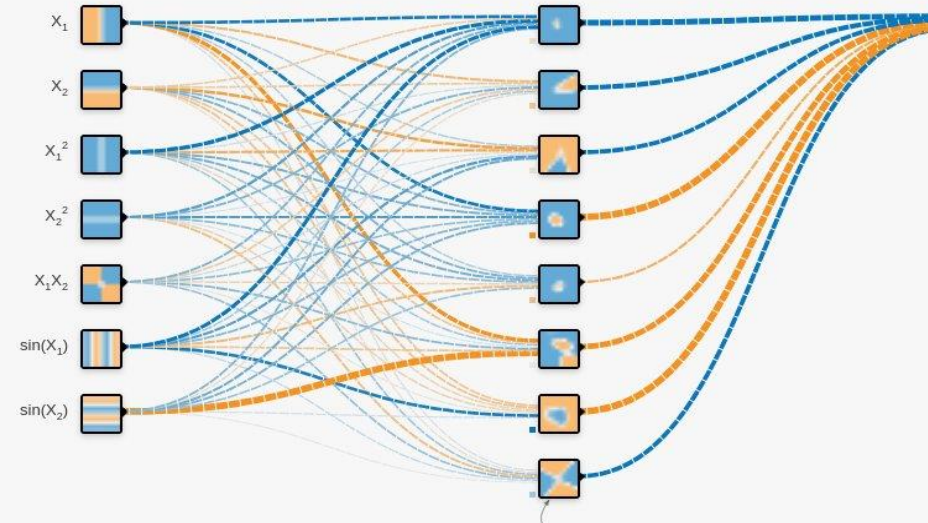
## FEATURES

Which properties do you want to feed in?

$X_1$   
 $X_2$   
 $X_1^2$   
 $X_2^2$   
 $X_1 X_2$   
 $\sin(X_1)$   
 $\sin(X_2)$

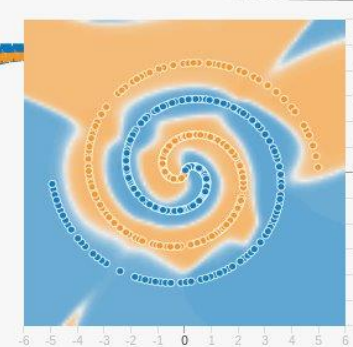
+ - 1 HIDDEN LAYER

+ -  
8 neurons



## OUTPUT

Test loss 0.016  
Training loss 0.009

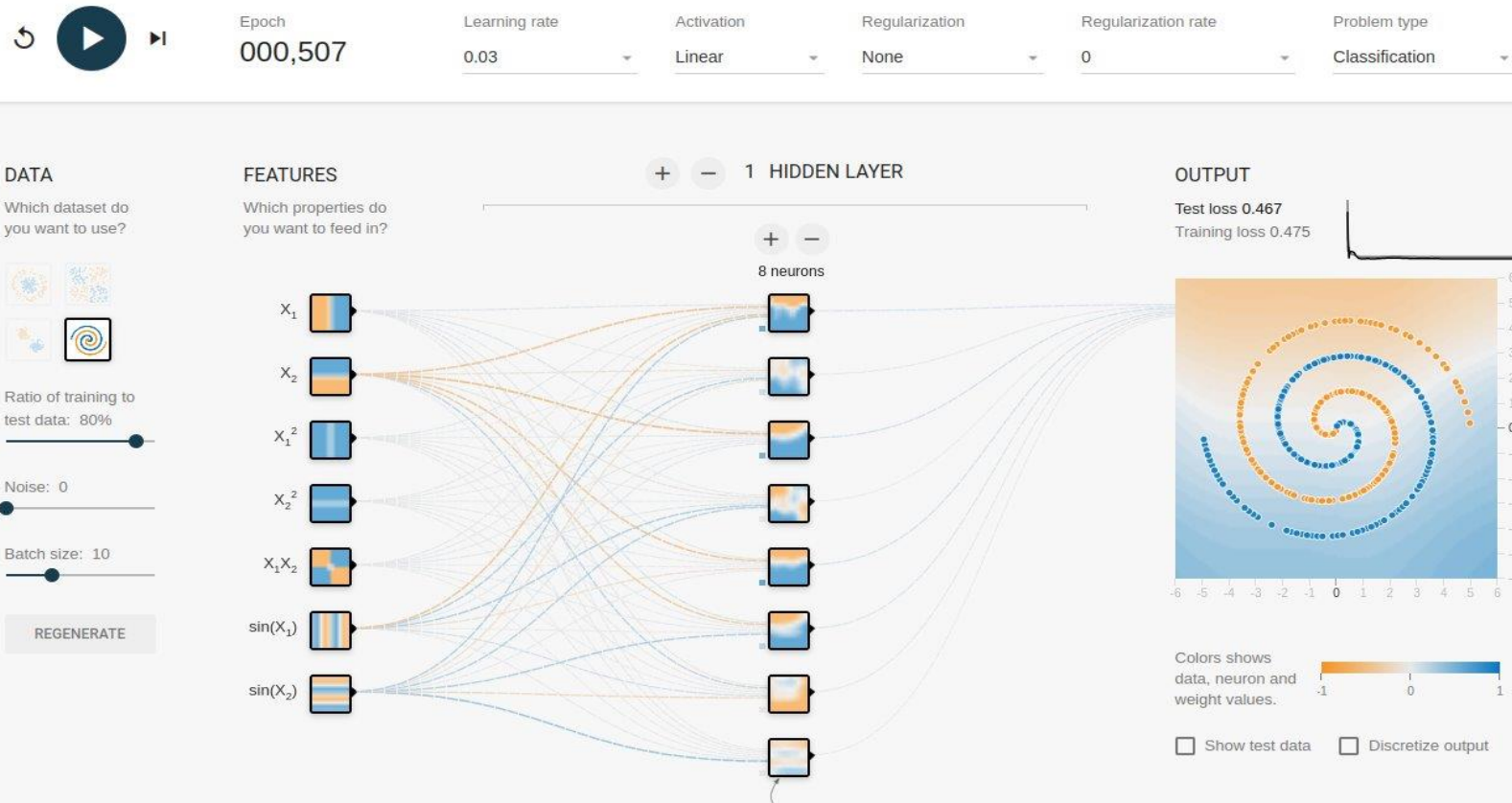


Colors shows data, neuron and weight values.

☐ Show test data ☐ Discretize output

# Linear

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# TASK 2: DOES THE QUANTITY OF HIDDEN LAYERS MAKE A DIFFERENCE?

The quantity of hidden layers in a neural network plays a crucial role in its performance and capabilities. Adding more hidden layers enhances the network's capacity to model complex relationships within the data, which is particularly advantageous for tasks involving intricate patterns and features. Deeper architectures with multiple hidden layers can better represent abstract features and hierarchical relationships within the data, enabling the network to learn more sophisticated representations. Moreover, each hidden layer extracts different levels of abstraction from the input data, allowing for the extraction of higher-level features essential for tasks like image recognition or natural language processing. However, increasing the number of hidden layers also heightens the risk of overfitting, especially if the network becomes overly complex relative to the size of the training dataset. Overfitting occurs when the model memorizes the training data instead of generalizing well to unseen data. Additionally, deeper networks with more hidden layers often require longer training times and more computational resources to converge to an optimal solution, which must be considered in the design and training process. Ultimately, the optimal number of hidden layers depends on the specific task, the complexity of the data, and various practical considerations such as computational resources and the risk of overfitting.

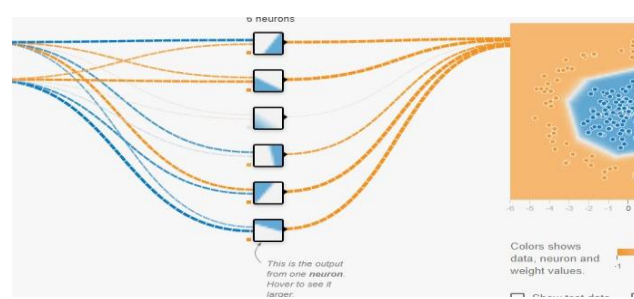
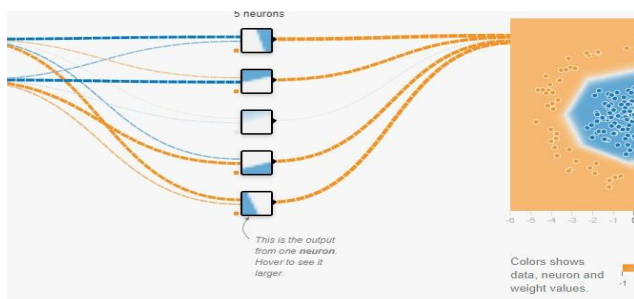
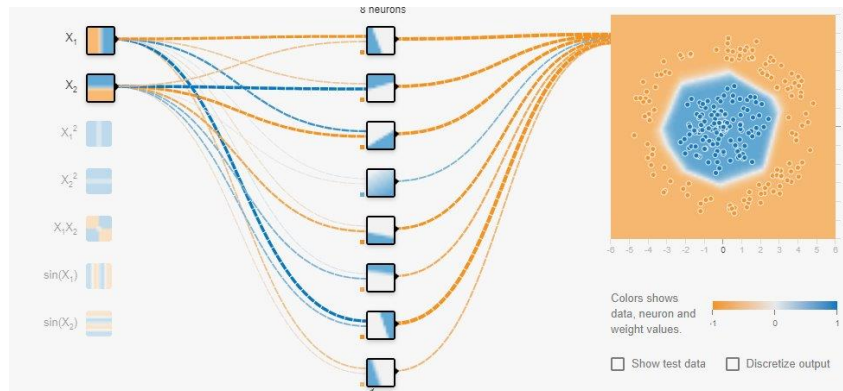
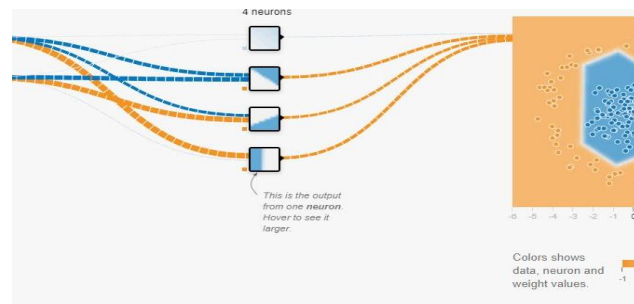
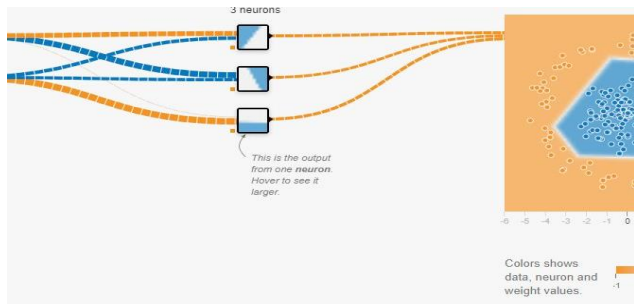
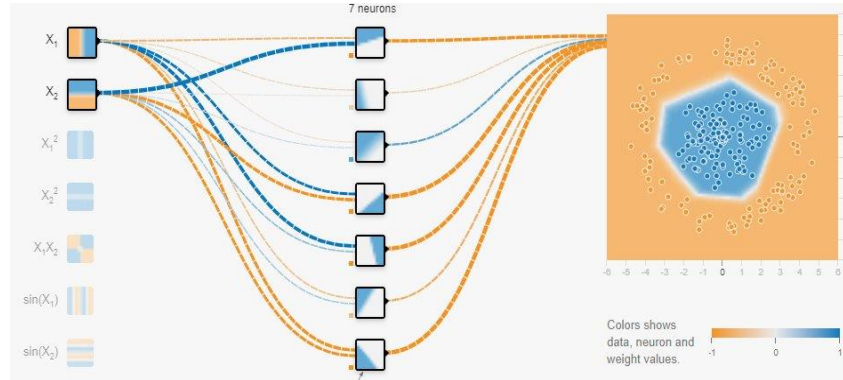
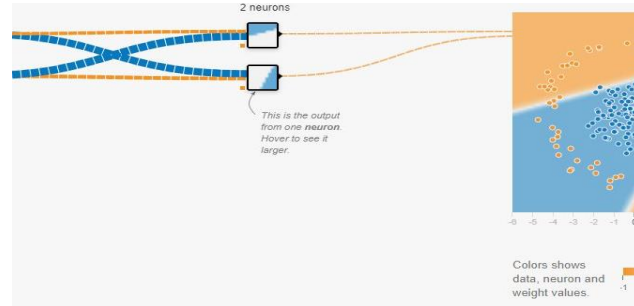
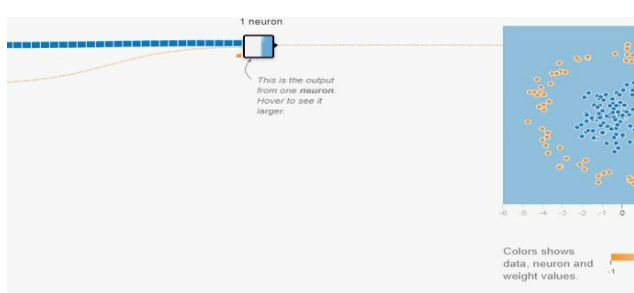


## TASK 3: NEURONS, HOW MANY IS TOO MANY?

Determining how many neurons to use in a neural network is complex. If there are too many neurons, it can cause problems like overfitting, where the network learns too much from the training data and doesn't perform well on new data. This can make the network slower and harder to understand. To find the right balance, it's important to experiment with different setups and techniques, like regularization, to prevent overfitting. Also, considering the specific needs of the problem you're working on helps determine the best number of neurons for your network.

# IMPACTS OF NEURONS

- Neurons, the foundational components of Artificial Neural Networks, intake input data, incorporate weights and biases, perform a weighted summation, and employ an activation function to generate an output.
- Illustrated by the images, including neurons within the hidden network, it expands capacity and enhances learning from input, thereby refining output accuracy.
- Through the arrangement and interconnection of multiple layers and neurons, neural networks gain the ability to capture intricate relationships, facilitating tasks like image recognition, natural language processing, speech recognition, and beyond.



# TASK 4: HOW IMPORTANT ARE THE VALUES IN THE LEARNING RATE?

- **Learning Speed:**
  - ☐ Learning Rate: 0.03 - Faster convergence during training, quicker learning from data.
  - ☐ Learning Rate: 0.01 - Slower convergence, but more stable learning process.
- **Stability:**
  - ☐ Learning Rate: 0.03 - May lead to instability, potential oscillations or divergence.
  - ☐ Learning Rate: 0.01 - Provides more stability, smoother convergence.
- **Generalization:**
  - ☐ Learning Rate: 0.03 - Risk of overfitting, model may fit training data well but generalize poorly.
  - ☐ Learning Rate: 0.01 - Helps prevent overfitting, allows for better generalization.
- **Fine-tuning:**
  - ☐ Learning Rate: 0.03 - Initial training may benefit from higher rate, followed by gradual decrease.
  - ☐ Learning Rate: 0.01 - Often used for stable and consistent training without drastic adjustments.



# TASK 5: DATA SET: WHAT ARE THEY?

VS

## Data Set Gaussian

refers to a dataset where the distribution of the data follows a Gaussian or normal distribution. In a Gaussian dataset, the data points are clustered around the mean with decreasing frequency as they move away from the mean according to the properties of the Gaussian distribution. These datasets are commonly used in statistics, machine learning, and various scientific fields for modeling and analysis due to their well-understood properties.

## Data Set Circle

Refers to a dataset where the data points are distributed in or forming a circular pattern. Each data point in this dataset may have coordinates representing its position on a two-dimensional plane, and these points are arranged in a circular manner.



# DATA EXPLORATION

- ☐ Variable identification
- ☐ Univariable analysis
- ☐ Bi-variant analysis
- ☐ Missing values treatment
- ☐ Outlier treatment
- ☐ Variable transformation
- ☐ Variable creation

# DATA EXPLORATION

Data set exploration involves a comprehensive analysis of a dataset to understand its characteristics and uncover insights. This process begins with identifying the variables within the dataset and comprehending their types and meanings. Subsequently, summary statistics are computed to describe the central tendencies and variability of the data. Visualizations such as histograms, scatter plots, and box plots are utilized to depict the distributions, relationships, and patterns present in the data. Anomalies, such as outliers, are detected to identify potential errors or unusual behavior. Additionally, the data quality is assessed by checking for missing values, inconsistencies, or errors that may require cleaning or preprocessing. Exploring relationships and correlations between variables enables the discovery of insights and patterns within the data. Overall, data set exploration serves as a critical initial step in the data analysis process, laying the groundwork for further analysis, modeling, and decision-making.

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# THANK YOU

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