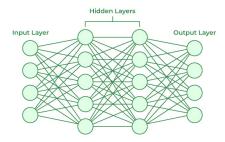
AGGIE DATA SCIENCE CLUB

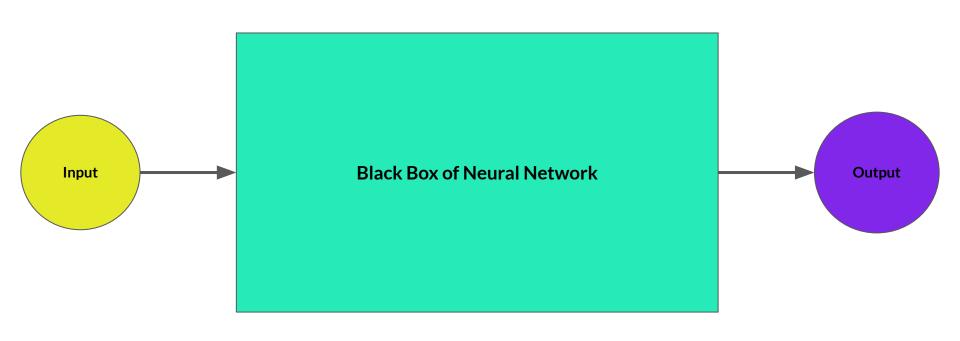


Spring 2024 Neural Networks

- www.aggiedatascience.com
- in
 - Aggie Data Science Club
- 0
- aggiedatascience

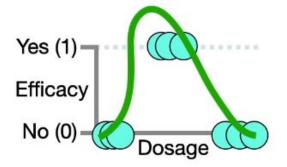
Quick Recap On Neural Networks

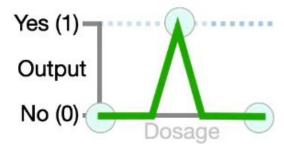




Why are NNs good?

- Approximate ANY curve
- Learn hidden features
 - Find underlying patterns in the data that are too complex for other models (non-linearity)
- Very good results
 - Because of the ability to fit very well

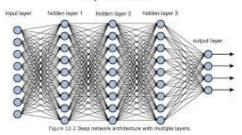


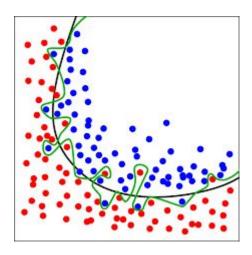


Risks of NNs

- Need a LOT of data
- Lots of time/money/computing power to train
 - More parameters = more computations = more time
- Hyperparameter tuning is not easy
 - o many different options
- Uninterpretable
 - Bias and fairness implications in hidden features (black box)
- Prone to overfitting
 - You can continue training all the way to the exact dataset
 - The squiggle can get very, very complicated...

Deep Neural Network





Overall Steps in a Neural Network Model



Feed Data

Making Predictions / Forward Propagation

Computations are performed on each layer of the neural network to make predictions. This process is often called a "black box" because the process in finding these outputs is complex and not completely known. Activation functions like ReLU (Rectified Linear Unit) or sigmoid are used to understand more complex relationships in the data. The output of each layer, after applying the activation function, is then passed to the next layer.

Back Propagation

Calculates gradients using chain rule, contains the partial derivatives of the loss function with respect to each weight and bias (∂L/∂w and ∂L/∂b). These partial derivatives indicate how much a small change in each parameter will affect the loss.

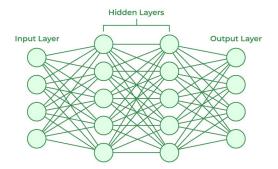
Gradient Descent

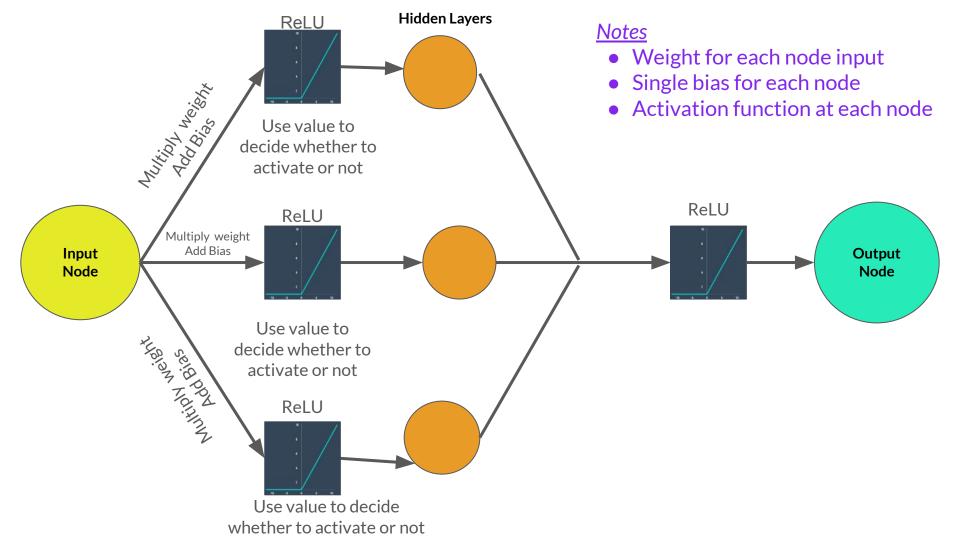
Once you have these calculated gradients from back propagation, we use gradient descent to determine learning rates and adjust weights and biases respectively

Repeat

04

05





Activation Functions

There are many activation functions, but these are just a couple. Activation functions take the value calculated with the weight and bias from the previous node to decide whether a neuron should be activated or not. It helps us understand more complex

relationships in data, which brings in the idea of non-linearity.



ReLU

- Commonly used
- Negative -> 0
- If result is positive, neuron is activated



Sigmoid

- Binary classification
- Think of it as 0 -> false, 1 -> true
- Drawback: vanishing gradient

Gradient Descent

Gradient Descent is a more effective way of minimizing loss functions to optimize values in the neural network such as weights and biases. The ultimate goal is to adjust the parameters so that the difference between target values and predicted values is smaller and therefore makes the model more accurate. We can understand the learning rate in order to more accurately and efficiently predict the curve.

Example of a Common Loss Function:

 $SSR = \sum (Observed - Predicted) ^2$

Backpropagation

- Starts at the output note and goes backwards and calculates the gradients
- Iteratively updates weights across all layers using gradient descent (and chain rule)
- Consists of continuous forward prediction and backward error propagation to predict values and update weights

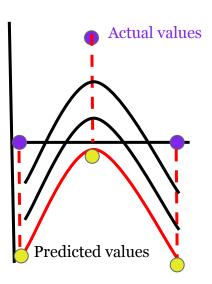
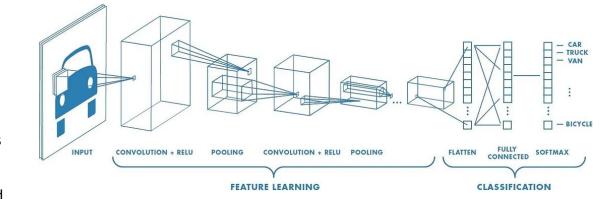


Image Detection and Classification with Convolutional Neural Network (CNN)

CNN Introduction

- ConvNet/CNN is a Deep Learning algorithm.
- Input Handling: It takes an input image to process.
- Functionality:
 - Assigns Importance: Applies learnable weights and biases to different parts of the image.
 - Object Differentiation: Differentiates between various aspects or objects within the image.
- Purpose: The network learns to recognize and differentiate elements within images, making it useful for tasks like image classification, object detection, and more.



CNN Use Cases

Use Cases

Object Detection

Image Segmentation

Create Images

Video Analytics

Natural Language Processing

Autonomous Systems

Classifying fruit

Segmenting brain regions into different classes

Generate images given a prompt

Tracking objects in a video

Text classification

Self driving cars and lane detection



CNN Input layer

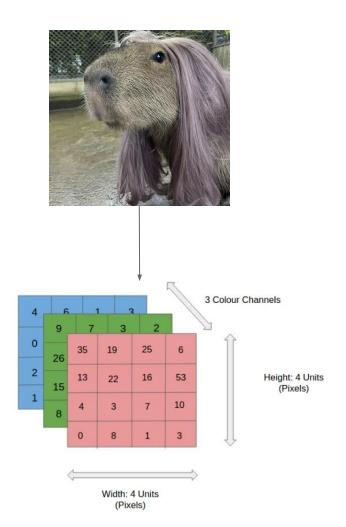
Input are typically

- RGB
- Grayscale

But can be

HSV, CMYK, etc.

Converting the input into a matrix of these values makes it easier to compress and extract important features



CNN Kernel Layers

Image

• Height x Width x # of channels

Sliding kernel

Matrix of weight

Stride

How much the kernel will move

$$n_{out} = \left\lfloor \frac{n_{in} + 2p - k}{s} \right\rfloor + 1$$

n_{in}: number of input features
n_{out}: number of output features
k: convolution kernel size
p: convolution padding size
s: convolution stride size

1,	1,0	1,	0	0
0,0	1,	1,0	1	0
0,1	0,0	1,	1	1
0	0	1	1	0
0	1	1	0	0

Image

Convolved Feature

0	0	0	0	0	0	•••
0	156	155	156	158	158	
0	153	154	157	159	159	
0	149	151	155	158	159	
0	146	146	149	153	158	
0	145	143	143	148	158	

0	0	0	0	0	0	
0	167	166	167	169	169	
0	164	165	168	170	170	
0	160	162	166	169	170	
0	156	156	159	163	168	
0	155	153	153	158	168	

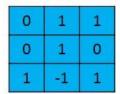
0	0	0	0	0	0	
0	163	162	163	165	165	
0	160	161	164	166	166	
0	156	158	162	165	166	
0	155	155	158	162	167	
0	154	152	152	157	167	

Input Channel #1 (Red)

Input Channel #2 (Green)

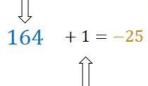
Input Channel #3 (Blue)

-1	-1	1
0	1	-1
0	1	1



Kernel Channel #1



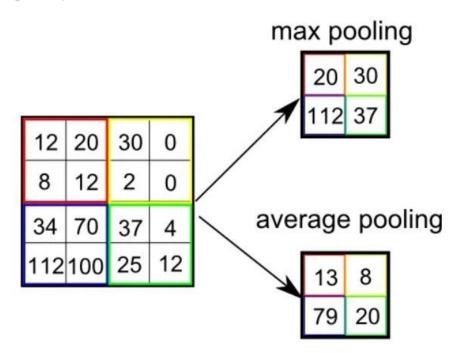


	☆		
	Ш		
	П		
Bia	as	=	1

Output					
-25					
				5505	

CNN Pooling Layer

- Further reduced dimensions
 - More aggressive extractions
 - Better fit into next layer
- Max Pooling and Average Pooling



CNN Pooling Layer

Max Pooling

Strengths

- Finds the most prominent features
- More robust to noise
- Sharp edges

Weaknesses

More focused

Average Pooling

Strengths

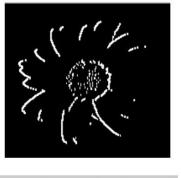
- Distributes importance
- Prevents overfitting

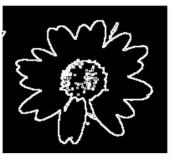
Weaknesses

Sensitive to noise





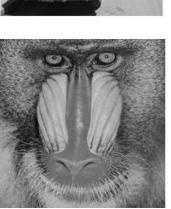




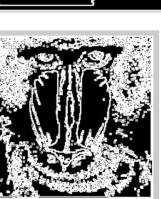






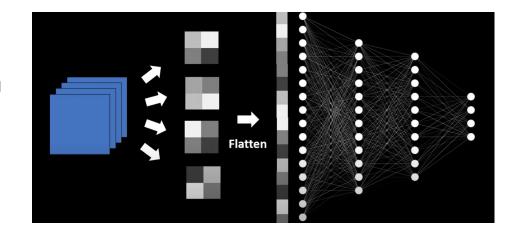




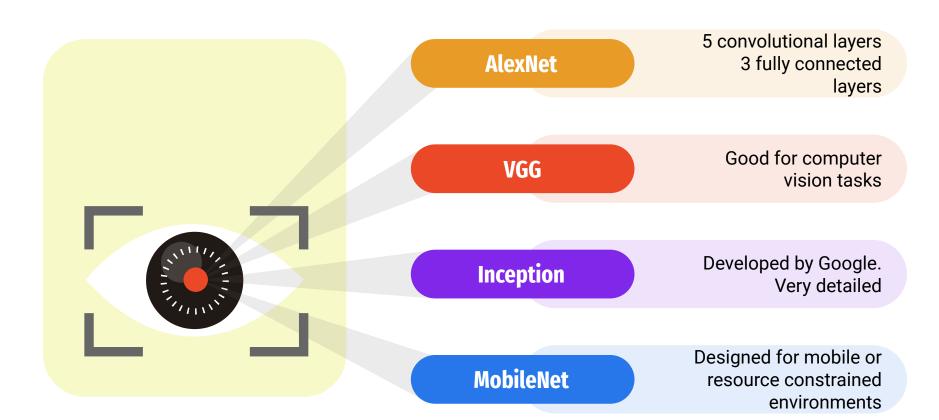


CNN Fully Connected Layer

- Previous layers process the inputs
- FC layer will make a decision based off the inputs
- Applied after convolutional and pooling layers
- Flatten the input into a column vector to be used as input
 - After weights and biases are updated
 - Fed into the activation function



Premade CNNs



Sequential Data Processing with Recurrent Neural Networks (RNN)

RNN Use Cases

Use Cases

Speech Recognition

Language Modeling

Image Summarization

Text Summarization

Time Series

Video Tagging

Audio Processing

Detecting different voices

Generating text given a prompt

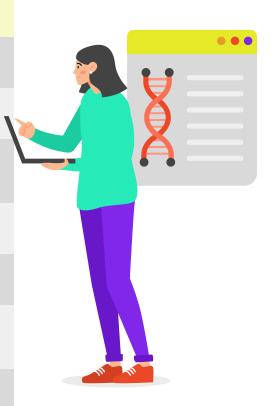
Generate image descriptions / tags given a prompt

Summarizing a block of text

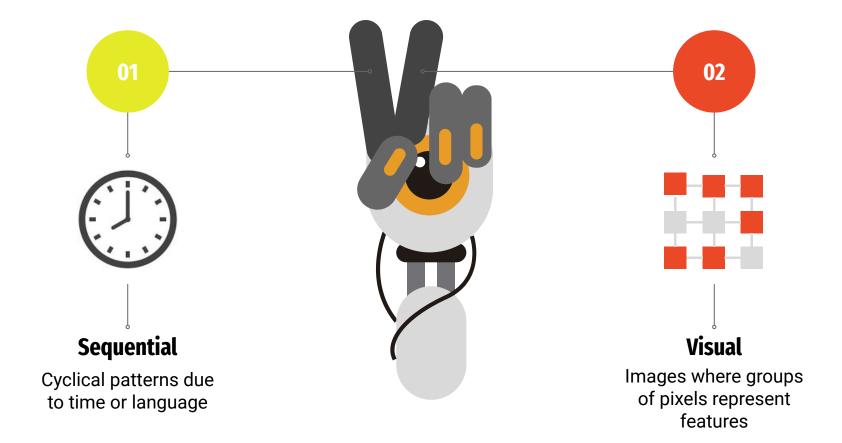
Predicting which stocks will do well

Generates hashtags given a video or tiktok

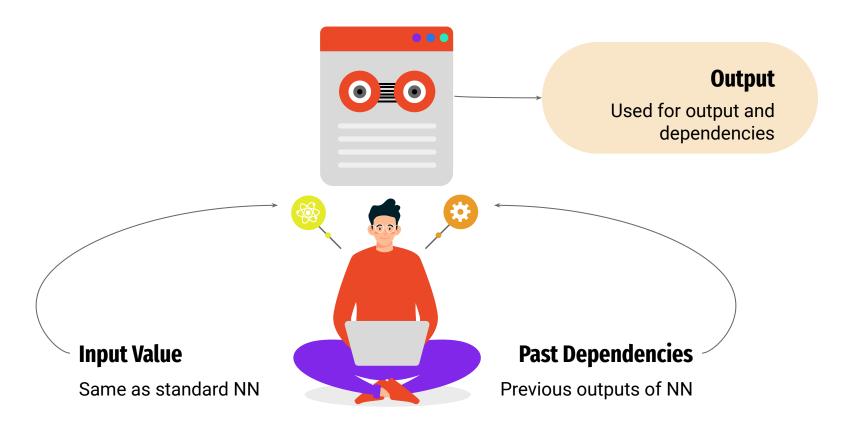
Recognize patterns in music or voice recordings based on context



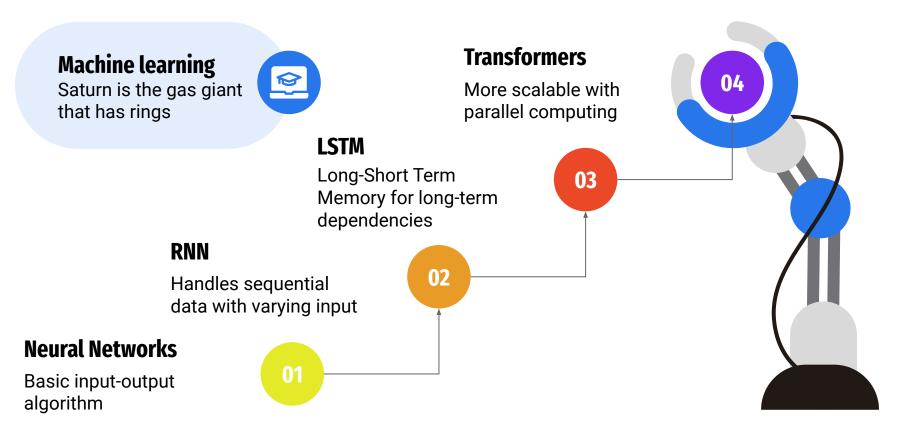
How do we deal with complex forms of data?

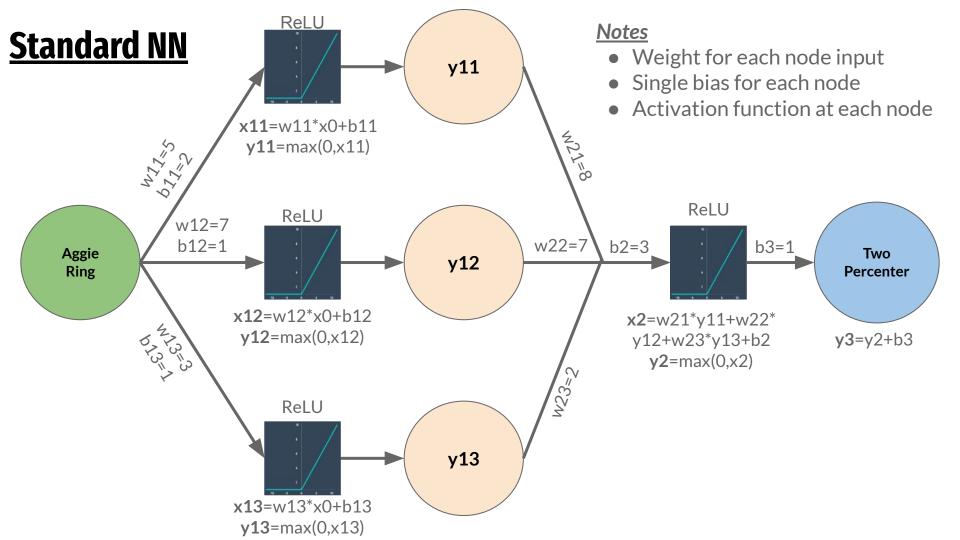


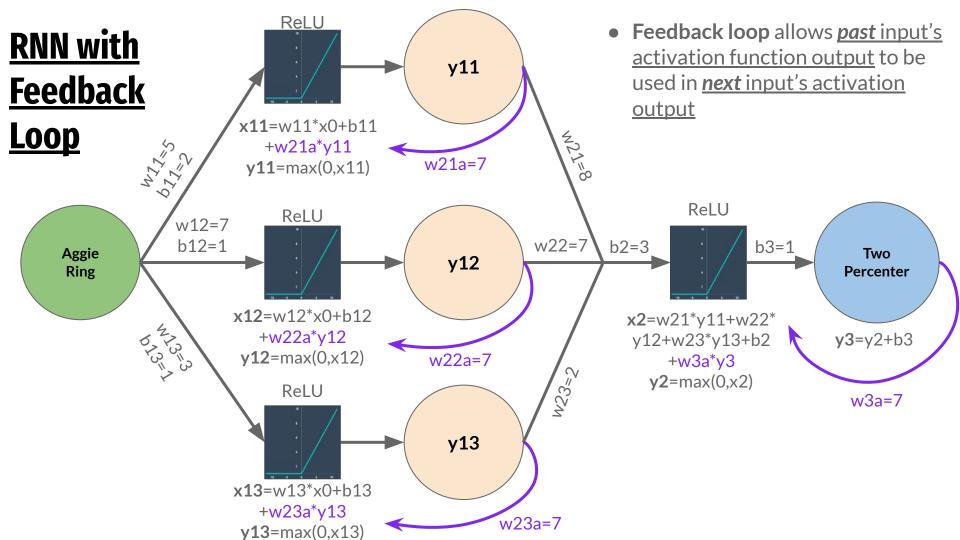
Unlike NNs, Recurrent NNs use multiple inputs



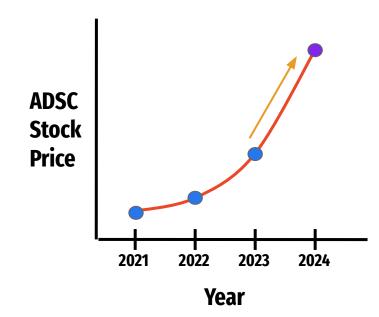
Hierarchy of Sequential Data ML



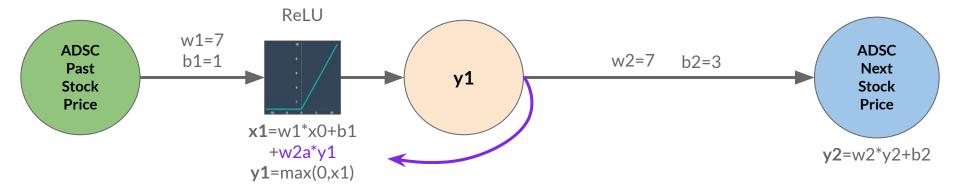




Simplifying RNN with Stock Example

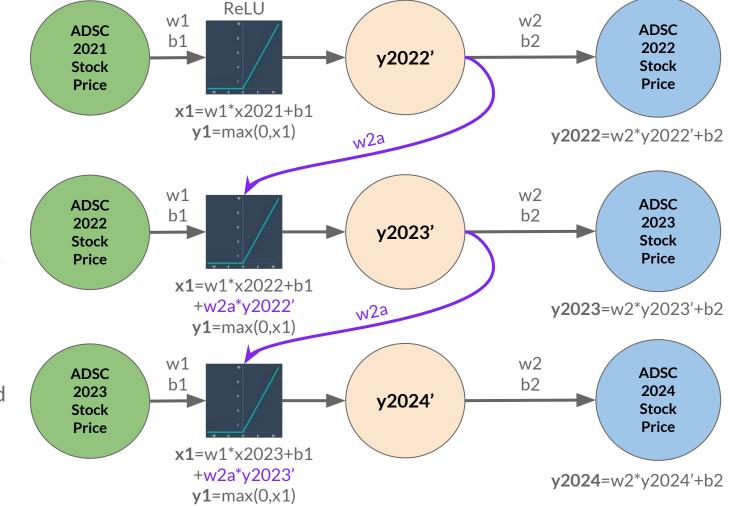


- ADSC stock price has been steadily increasing over the past 3 years
- Based on the context, we can assume the stock price will continue to increase next year
- Data points are <u>not</u> <u>independent</u> of each other



Unrolling RNN with ADSC Stock ✓

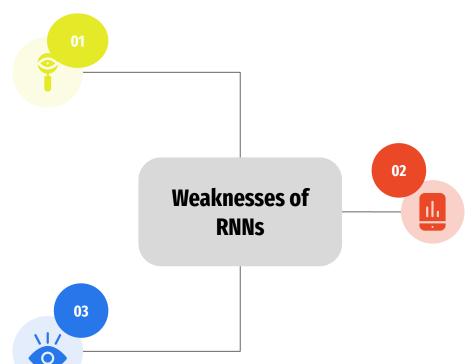
- Previous year's output is used in calculation of current year's output
- Past outputs funneled into summations
- Notice that the same weight is used for each feedback loop



Why are basic RNNs not used very often?

Vanishing Gradient

The more we unroll, the harder it is to train the NN if the weights are large (Input * 0.5²)



Exploding Gradient

The more we unroll, the harder it is to train the NN if the weights are small (Input * 2²)

Loses Long-Term Dependencies

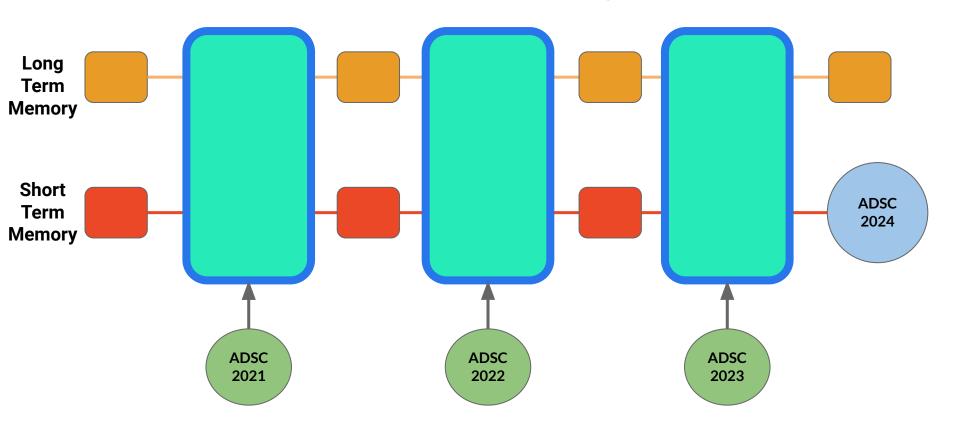
The more we unroll, the more context we lose

Long-Short Term Memory (LSTM)

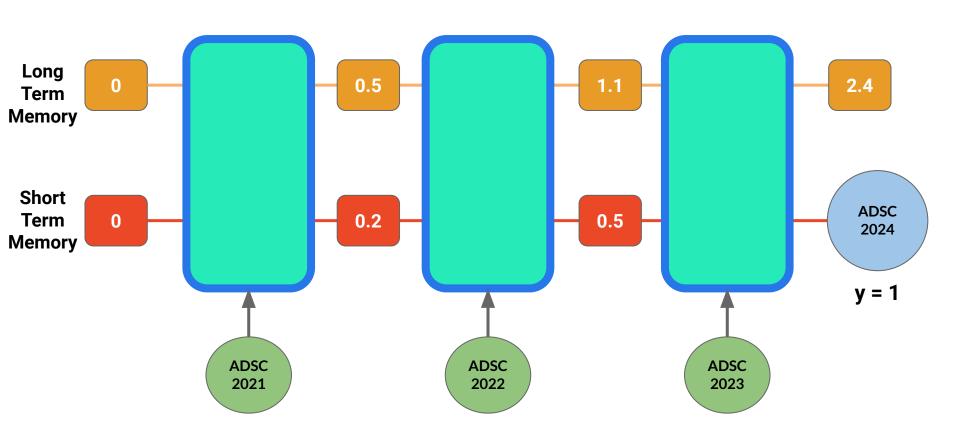


LSTM for ADSC Stock

- Next data point relies not only on last data point (ST) but also on all data points (LT)
- Only uses sigmoid and hyperbolic tangent activation functions to represent memory retention



Runthrough Example LSTM for ADSC Stock



Transformers!!!

Long Range Dependencies

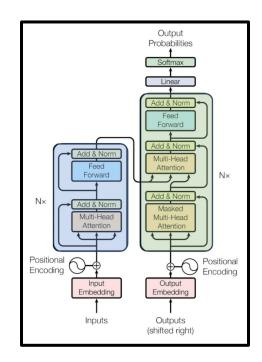
Ensures that all inputs are considered from beginning to end



Interpretable Attention

Relates different positions of a single sequence to compute a representation of the same sequence





02

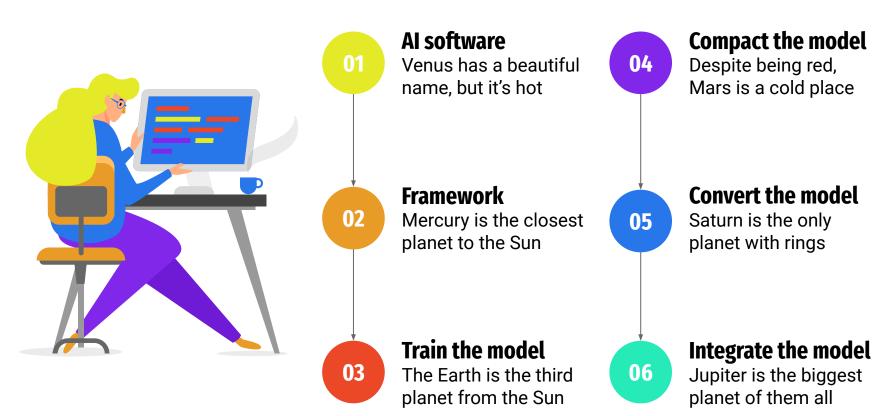
Parallel Processing

Computations are completed far more efficiently

Machine Learning Infographics

Models Artificial neural networks The Earth is the planet we live on **Decision trees** Mercury is the smallest planet **Support-vector machines** Despite being red, Mars is a cold place **Regression analysis** Jupiter is the biggest planet of them all **Bayesian networks** Venus has a beautiful name **Genetic algorithms** Pluto is considered a dwarf planet

TEMPLATE STARTS





Artificial Intelligence

- Computers act on their own
- They act according to environment
- Systems display cognitive ability
- Computers make decisions

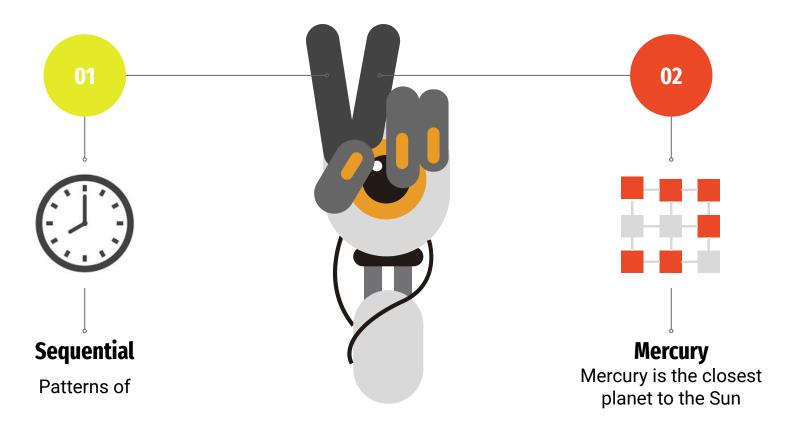


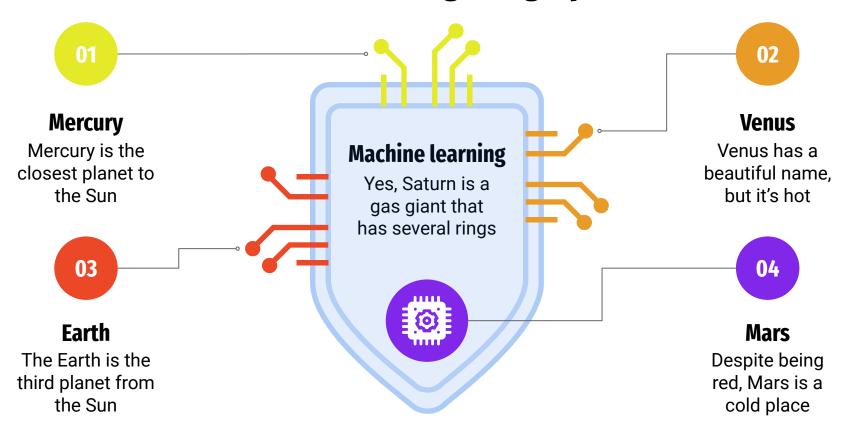
Machine learning

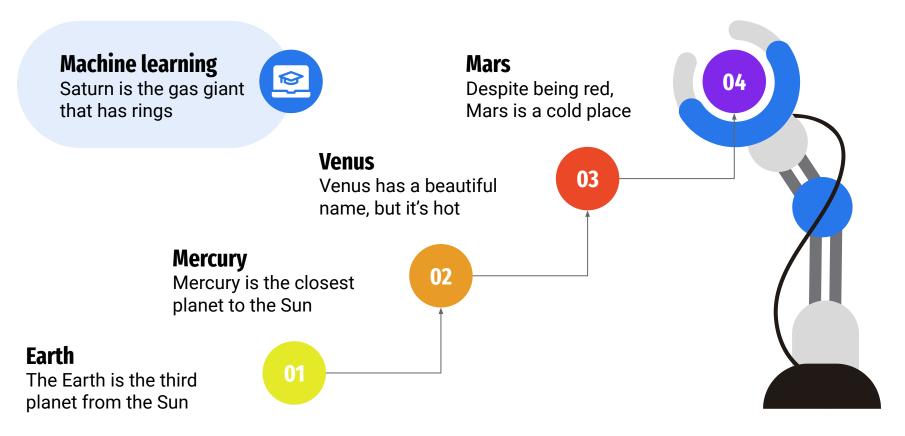
- It's an application of Al
- Computers observe and analyze
- Predict based on previous patterns
- Pre-programmed algorithms

Vs

How do we deal with complex forms of data?







01 Power

Mercury is the closest planet to the Sun

03 Memory

Jupiter is a gas giant and the biggest planet

05 Security

Venus has a beautiful name, but it's hot

07 MCU

The Earth is the third planet from the Sun





Memory 02

Neptune is the farthest planet from the Sun

Mars 04

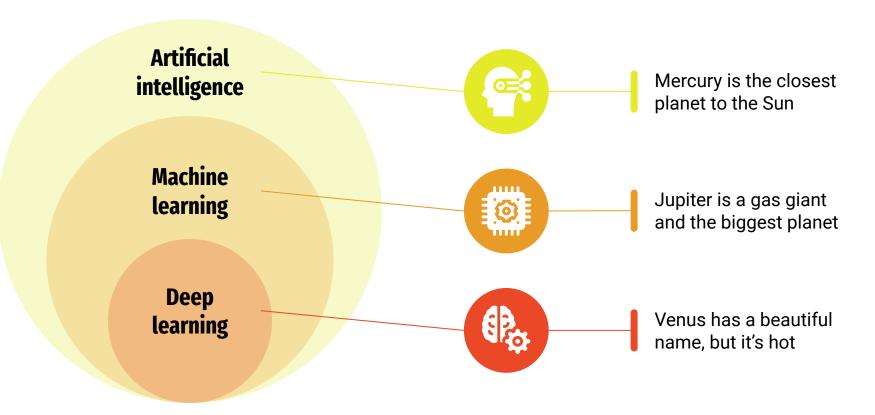
Despite being red, Mars is a cold place

FPGA 06

Pluto is considered a dwarf planet

Wireless 08

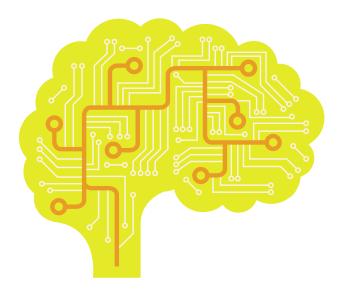
Ceres is located in the main asteroid belt

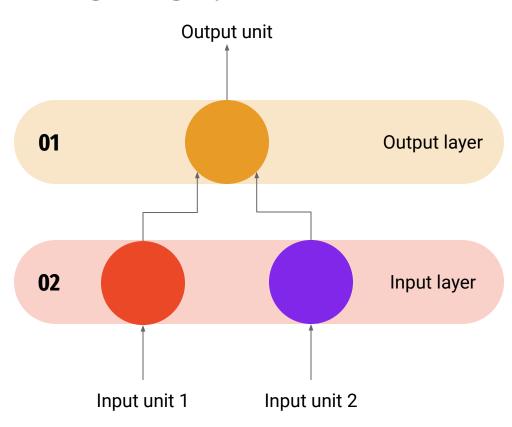


Neural network

Yes, Saturn is a gas giant that has rings







02 01 03 04 1950s 1970s 1980s 1960s Simple Al winter caused **Bayesian Resurgence in** algorithms methods by pessimism ML research Mercury is the Venus has a Jupiter is a gas Mercury is the closest planet to giant and the beautiful name. closest planet to the Sun biggest planet but it's very hot the Sun 05 06 1990s 2000s **2010s Data-driven Deep learning Support-Vector Clustering** popularity approach The Earth is the Ceres is located Venus has a third planet from in the main beautiful name, the Sun asteroid belt but it's very hot

Continuous improvement

Despite being red, Mars is a cold place

Data acquisition

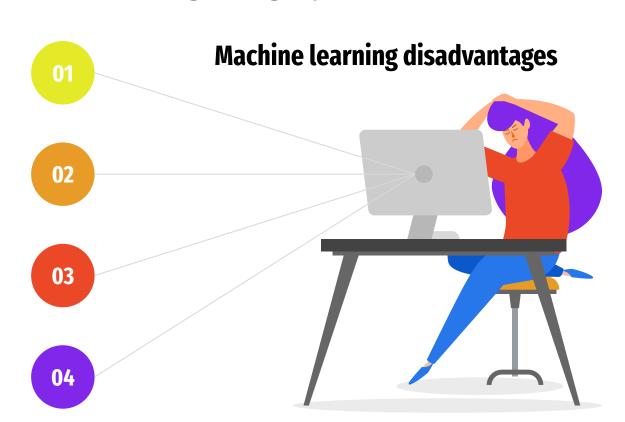
Venus has a beautiful name, but it's hot

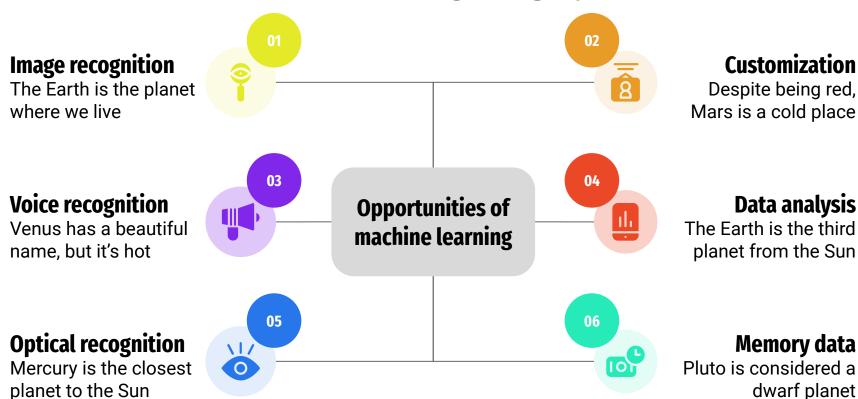
Patterns identification

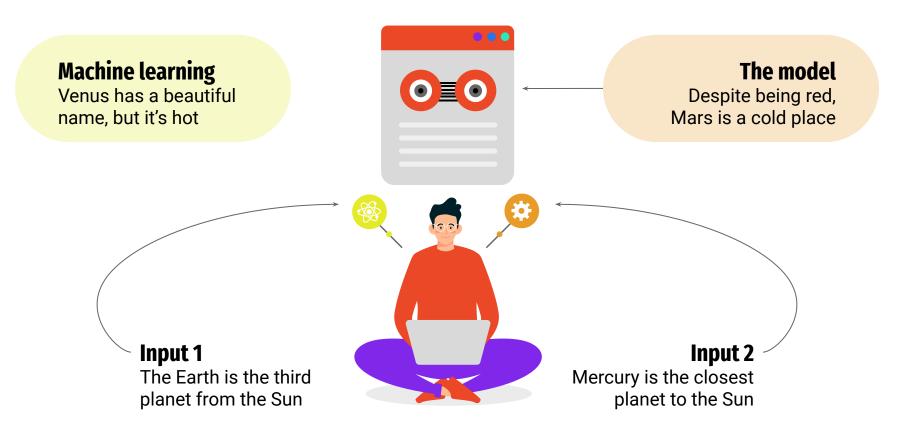
Mercury is the closest planet to the Sun

Time and resources

The Earth is the third planet from the Sun







O1 Supervised learning

Venus has a beautiful name, but it's hot

02 Unsupervised learning

Despite being red, Mars is a cold place

03 Semi-supervised learning

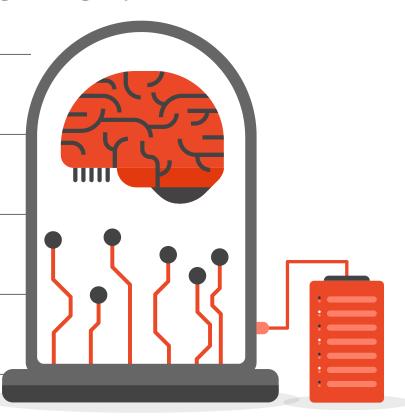
The Earth is the third planet from the Sun

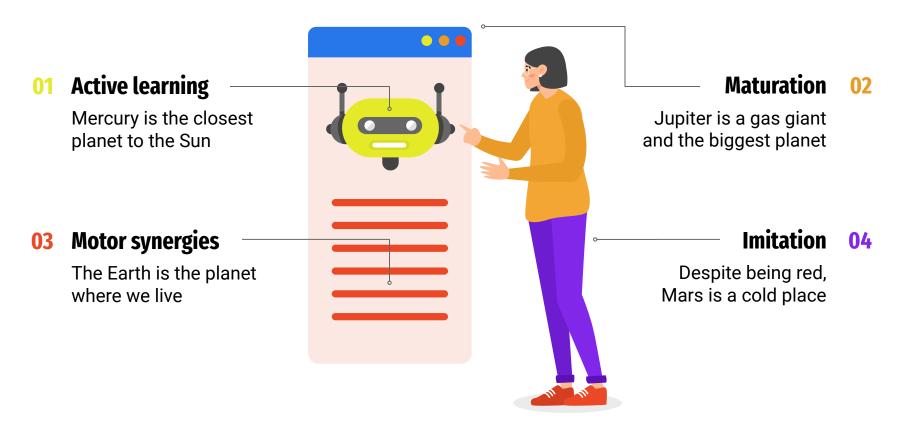
04 Reinforcement learning

Mercury is the closest planet to the Sun

05 Dimensionality reduction

Pluto is considered a dwarf planet





45%

Data mining

The Earth is the third planet from the Sun

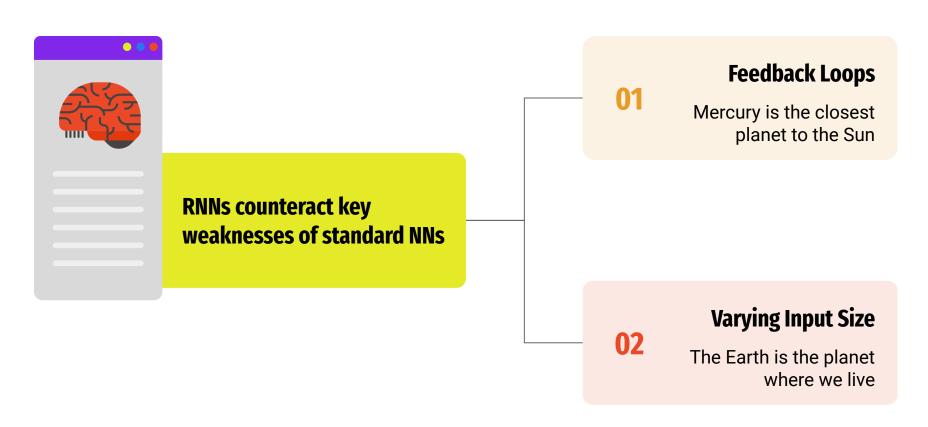
35%

Continuous production

Despite being red, Mars is a very cold place



Follow the link in the graph to modify its data and then paste the new one here. For more info, click here



01 Active learning

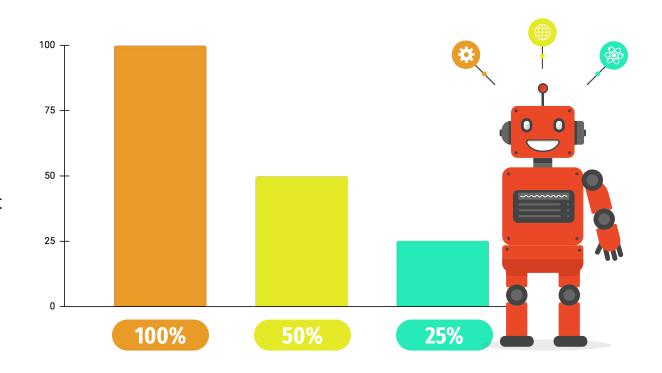
Mercury is the closest planet to the Sun

02 Maturation

Jupiter is a gas giant and the biggest planet

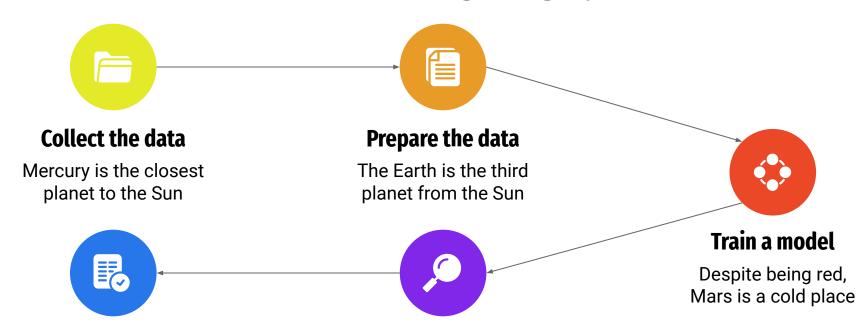
03 Motor synergies

Neptune is very far away from the Sun



Follow the link in the graph to modify its data and then paste the new one here. For more info, click here

Models Artificial neural networks The Earth is the planet we live on **Decision trees** Mercury is the smallest planet **Support-vector machines** Despite being red, Mars is a cold place **Regression analysis** Jupiter is the biggest planet of them all **Bayesian networks** Venus has a beautiful name **Genetic algorithms** Pluto is considered a dwarf planet



Improve

Pluto is considered a dwarf planet

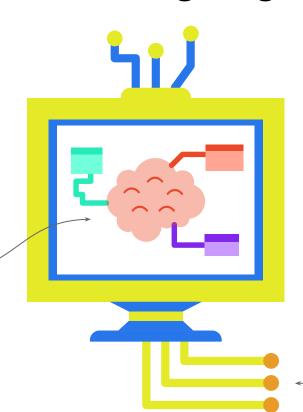
Evaluate the model

Jupiter is the biggest planet of them all

Inputs

Mercury is the closest planet to the Sun

- Input 1
- Input 2
- Input 3



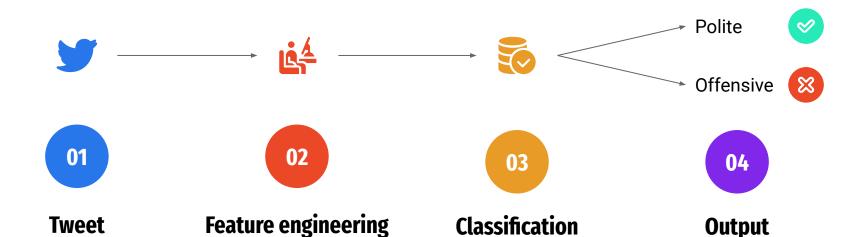
Outputs

Jupiter is a gas giant and the biggest planet

- Output 1
- Output 2
- Output 3



Machine learning application example



The Earth is the third

planet from the Sun

Despite being red,

Mars is a cold place

Venus has a beautiful

name, but it's hot

Mercury is the closest planet to the Sun

10%

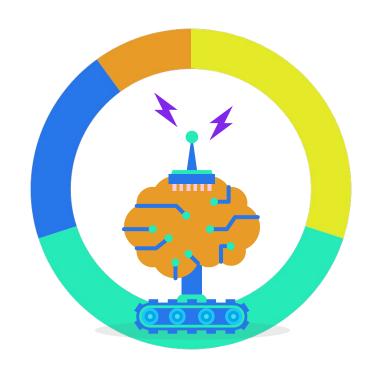
Mercury

Mercury is the closest planet to the Sun

20%

Neptune

It's the farthest planet from the Sun



30%

Jupiter

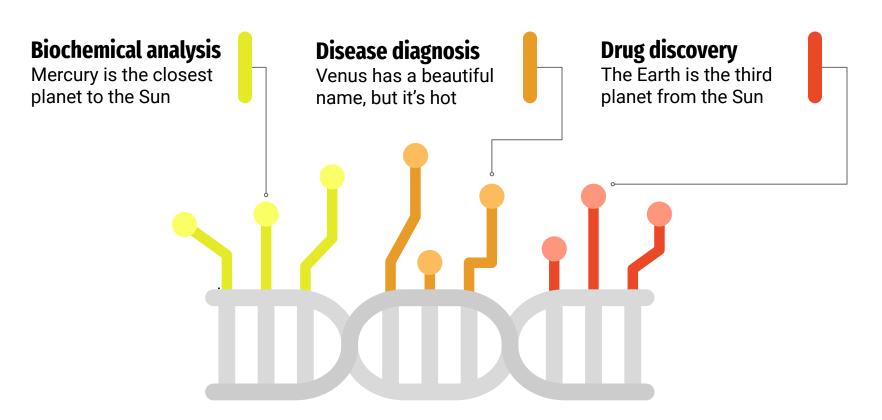
Jupiter is a gas giant and the biggest planet

40%

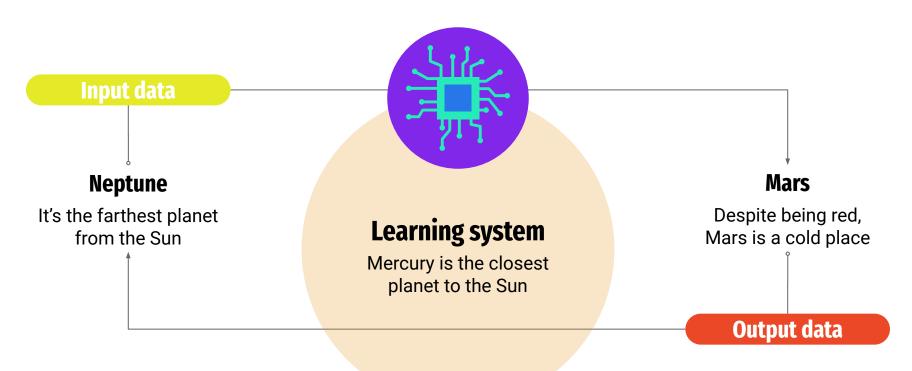
Mars

Despite being red, Mars is a cold place

Follow the link in the graph to modify its data and then paste the new one here. For more info, click here



	Common Uses for Machine Learning	
01	Chatbot systems	Venus has a beautiful name, but it's hot
02	Decision support	Mercury is the closest planet to the Sun
03	Customer recommendation engines	The Earth is the third planet from the Sun
04	Customer churn modeling	Despite being red, Mars is a cold place
05	Pricing strategies	Neptune is the farthest planet from the Sun
06	Customer segmentation	Jupiter is the biggest planet of them all
07	Image classification	Pluto is now considered a dwarf planet



Machine learning advantages vs disadvantages



Advantages

- Efficiency data managing
- Continuous improvement
- Lots of applications
- Trend identification
- Pattern identification



Disadvantages

- Data acquisition
- Time and space
- Time-consuming
- High error possibilities
- Algorithm selection



01

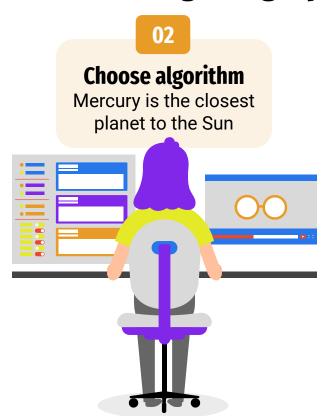
Identify data

Venus has a beautiful name, but it's hot

04

Train the model

Jupiter is the biggest planet of them all



03

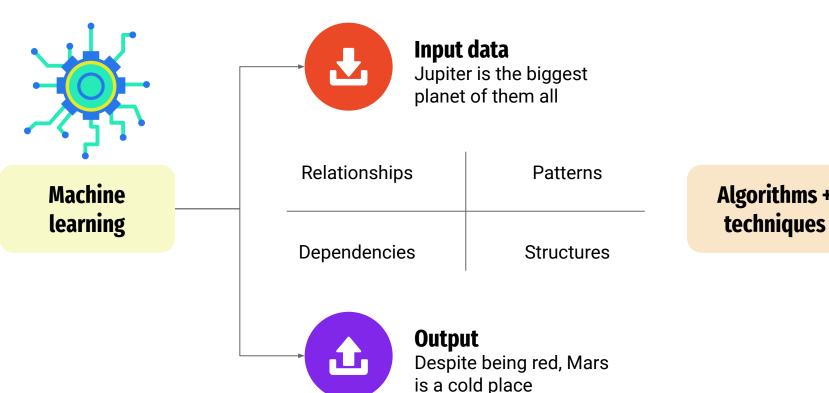
Analytical model

Despite being red, Mars is a cold place

05

Run the model

Neptune is very far away from the Sun



Algorithms +

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 + Ctrl V or Cmd C + Cmd V in Mac.
- Select one of the parts and **ungroup** it by right-clicking and choosing "Ungroup".
- Change the color by clicking on the paint bucket.
- Then resize the element by clicking and dragging one of the square-shaped points of its bounding box (the cursor should look like a double-headed arrow).
 Remember to hold Shift while dragging to keep the proportions.
- **Group** the elements again by selecting them, right-clicking and choosing "Group".
- Repeat the steps above with the other parts and when you're done editing, copy the end result and paste it into your presentation.
- Remember to choose the "Keep source formatting" option so that it keeps the design. For more info, please visit Slidesgo School.

