

MACHINE LEARNING - UI

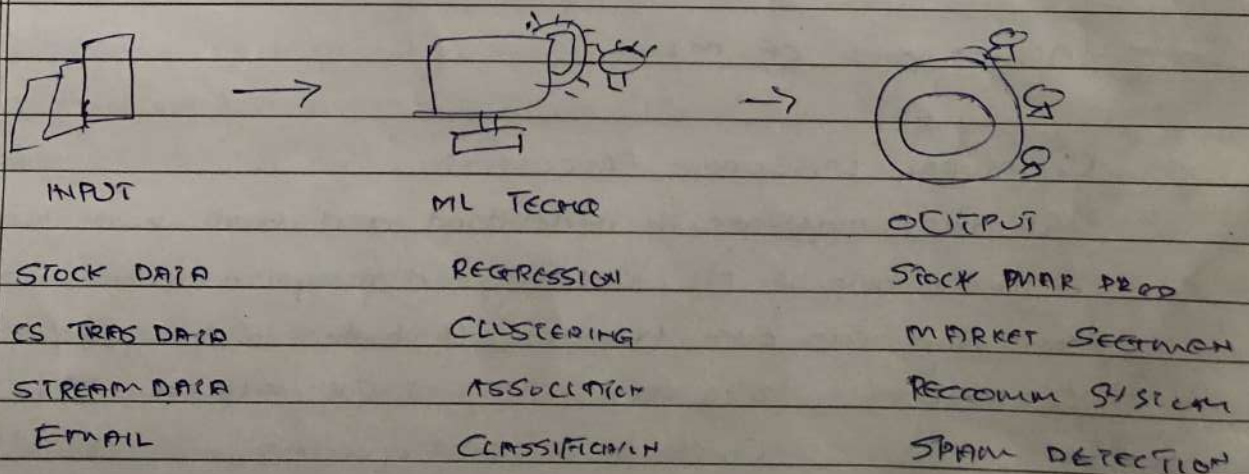
Q. Machine Learning & Its Concepts

Ans. Machine Learning is a branch of Artificial Intelligence that allows computers to learn from data and improve their performance on a task ^{over} time, without being explicitly program with step by step rules.

It focuses on teaching computers to learn from data instead of following fixed instructions. Instead of programming everything we feed the computer with large amount of information and let it find its own pattern. Over the time, the computer improves its ability to make predictions or decisions when it sees new data. This makes machine learning powerful for solving problems where writing exact rules would be complex.

Machine Learning finds its applications in diverse fields such as image and speech recognition, natural language processing, recommendation system and automating tasks also recognizing faces or predicting customer behaviour.

WORKING OF ML



TYPES OF ML

(I) SUPERVISED

A type of machine learning where the model is trained on the labeled data (both the input and correct output are provided). It learns by mapping between them to make predictions on new data.

Ex: Predicting house prices using past data of houses with their actual prices.

(II) UNSUPERVISED

A type of machine learning where the model is trained on unlabeled data with no pre-defined outputs. It finds the hidden patterns, groups or structure in the data.

(III) REINFORCEMENT

A type of machine learning where an agent learns by itself interacting with an environment and receiving awards and penalties. It aims to find the best strategy for long term success.

APPLICATIONS OF ML.

(I) NATURAL LANGUAGE PROCESSING

NLP helps machines to understand and work with human language. With the help of ML, systems can recognize speech, understand text and can even translate it between languages.

Ex includes: Voice assistant → Siri, Alexa

Chatbots for customer queries

Google Translate for language conversion

⑪ FRAUD DETECTION

Machine learning is broadly used in finance to spot unusual or suspicious activities. By studying millions of past transactions, ML models can flag patterns that look like fraud.

Ex: A sudden large withdrawal from a foreign location on your credit card. This helps banks and companies protect customers and reduce losses.

⑫ RECOMMENDATION SYSTEM

Recommendation System uses ML to suggest items as per user might like, based on their past choices and behaviour.

Ex: Netflix recommends you movies that you might enjoy.

Amazon suggests you products similar to what you've bought.
Youtube suggest videos based on your viewing history.

These systems keep on improving as they keep on learning.

Q. Classification VS Regression in Machine Learning

Ans: Classification and Regression are two main tasks in supervised machine learning, which means both use labelled data (inputs with correct answers) to learn. The key difference is the type of results they give.

- Classification is used when the output is a category or class.

Ex: Predicting whether the Email is spam or not or whether the fruit is Apple or banana. The model's goal is to draw boundaries that separate different groups.

- Regression is used when the output is a continuous number.

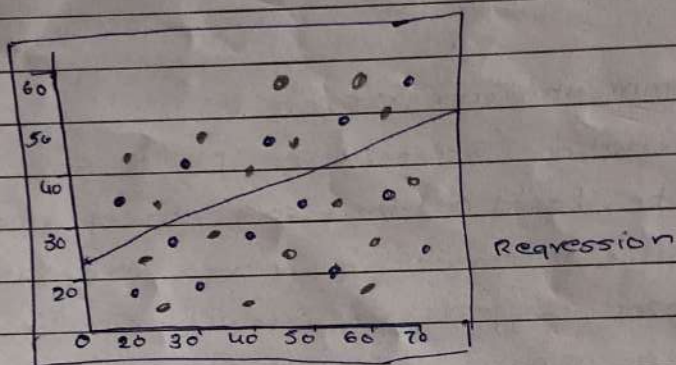
Ex: Predicting the price of a house or the temperature of tomorrow. The model's goal is to find best path / fit that can estimate

the value.

• REGRESSION IN ML

Regression is used when we want to predict a number or continuous value based on the input data.

Ex: Predicting a person's salary from their years of experience, estimating house prices from size and location or forecasting the chance of rain, all these are used to ^{fit} straight ^{fit} the line



Types of Regression

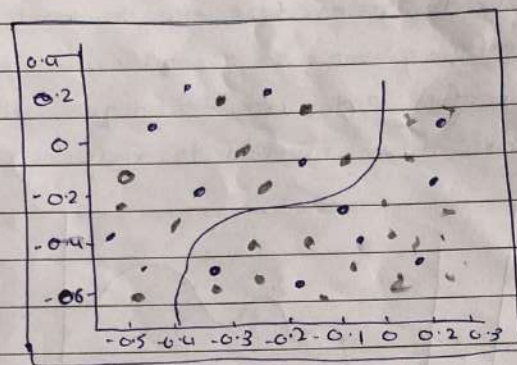
- ① Simple Regression - Uses a straight line to show the relationship between one input and one output
- ② Multiple Linear Reg - Uses multiple input and ~~multiple output~~ to predict single output
- ③ Polynomial Reg - Fits a curve when the relationship is not a straight line

• CLASSIFICATION IN ML

Classification is used when we want to ~~use~~ put data into categories or groups instead of predicting numbers

Ex: Classifying whether the email is spam or not spam or predicting if a patient has a disease based on symptoms. These models learn from labelled data examples and then assign new data

- to the correct class



Types of Classification

- (i) Decision Tree - which splits data into categories
- (ii) Random Forest - which uses many trees together for higher accuracy.
- (iii) KNN - K-Nearest neighbor, which classifies data based on closest similar example.

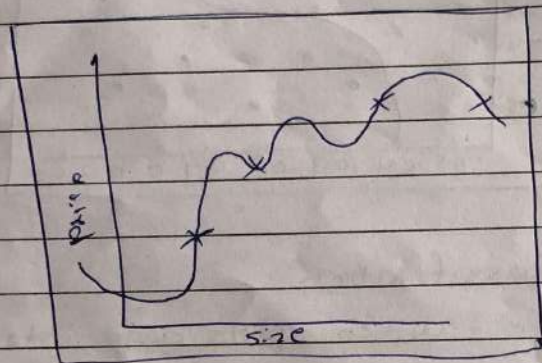
Q. Overfitting VS Underfitting

Ans. Overfitting

Overfitting occurs when a machine learning model learns data too closely, including its random noise, errors or small details, while this makes the model perform extremely well on the training datasets, it struggles to make accurate prediction on new or unseen data.

Overfitting happens mostly when the data model becomes too complex, such as having too many decision rules or parameters, instead of focusing on the general trend or relationship in the

data, it tries to memorize every detail. This makes the model lose its ability to generalize to real-world cases. It's to prevent overfitting we can simplify the model, collect more training and useful data, use techniques like cross-validation or apply regularization method to reduce complexity.



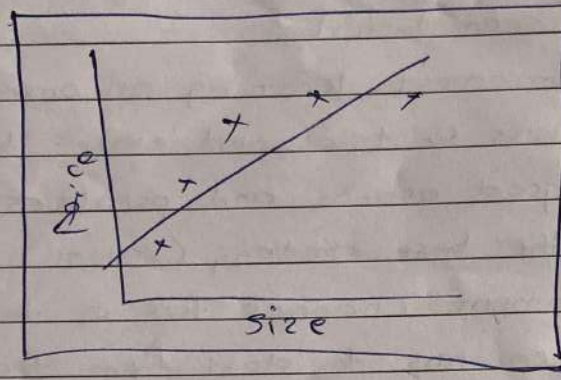
Ex: Imagine a model training to recognize cats in photos. If the training photos mostly have cats on green grass, the model may wrongly assume that "green background" always means "cat". When ~~cat~~ shown ~~as~~ a cat indoors on a red carpet, it may fail to recognize it because it memorized details of training set instead of learning general features of cat like ears, tail.

• UNDERFITTING:

Underfitting occurs when a machine learning algorithm/model is too simple to capture the underlying patterns in the data. It performs poorly not only on new data but also on the training data itself, showing that it has not learned enough.

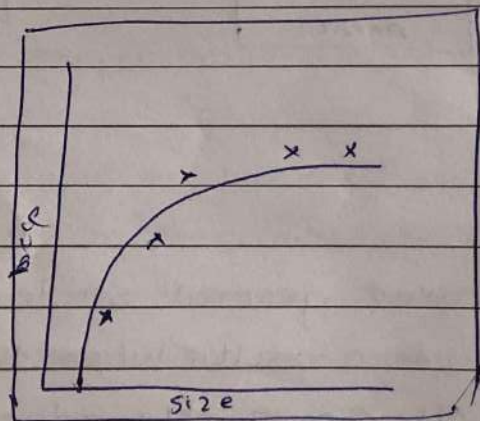
This usually occurs when the model lacks with complexity, or when it hasn't been trained enough times. It fails to capture the important relationships in the datasets and ends up making

Weak predictions. To fix underfitting, we can make the model more complex, like add more features or layers, increase training time, or reduce restrictions on the model.



Ex: Suppose we want to predict house price not only use "Size of the house" as input, ignoring other important factors like location, number of bedrooms or condition. The model will be too simple and make poor predictions because it cannot capture all necessary details that affects the price.

To overcome overfitting and underfitting, we need to train the model in Goodfitting.



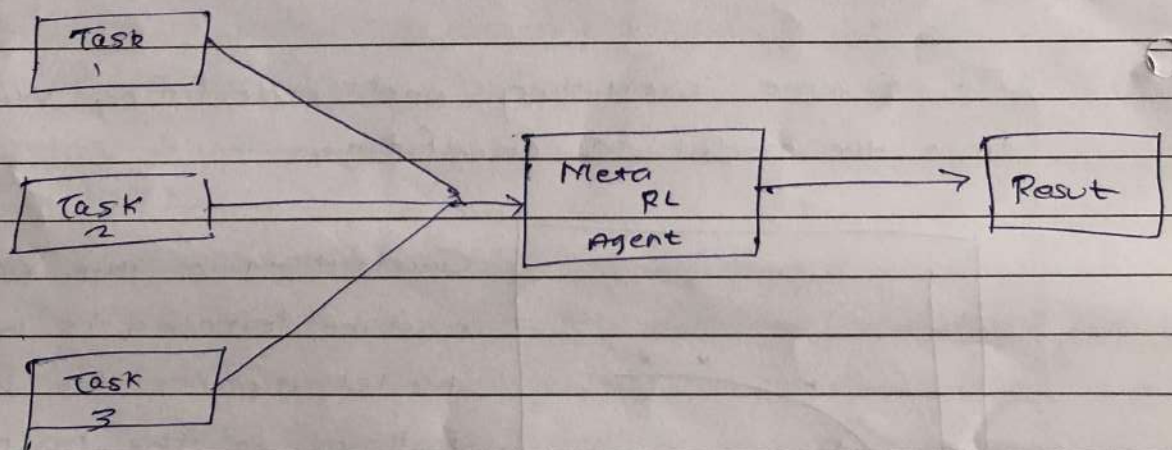
Goodfitting or the right fit in machine learning is when the model captures the important patterns in the training data without memorizing noise or being too simple.

Q. Meta Learning and Re-Inforcement Learning.

ANS: Meta Reinforcement Learning is an advanced form of the reinforcement learning where an agent learns how to quickly adapt new tasks by using experience from similar tasks it has seen before.

In normal reinforcement learning an agent learns how to perform one task by trial and error - it tries actions, gets rewards for good actions and penalties for bad ones, and over time the best strategy (called Policy). However, if the environment changes or the tasks changes, the agent often has to start from the scratch, which takes a lot of time and data.

Meta-RL solves this problem by combining reinforcement learning with the idea of meta-learning (learning to learn). Instead of training the data only for 1 task, it is trained on many different but related tasks.



By doing this, the agent learns general strategies and patterns of learning itself. As a result, when the agent faces any brand new tasks, it can quickly adapt and perform.

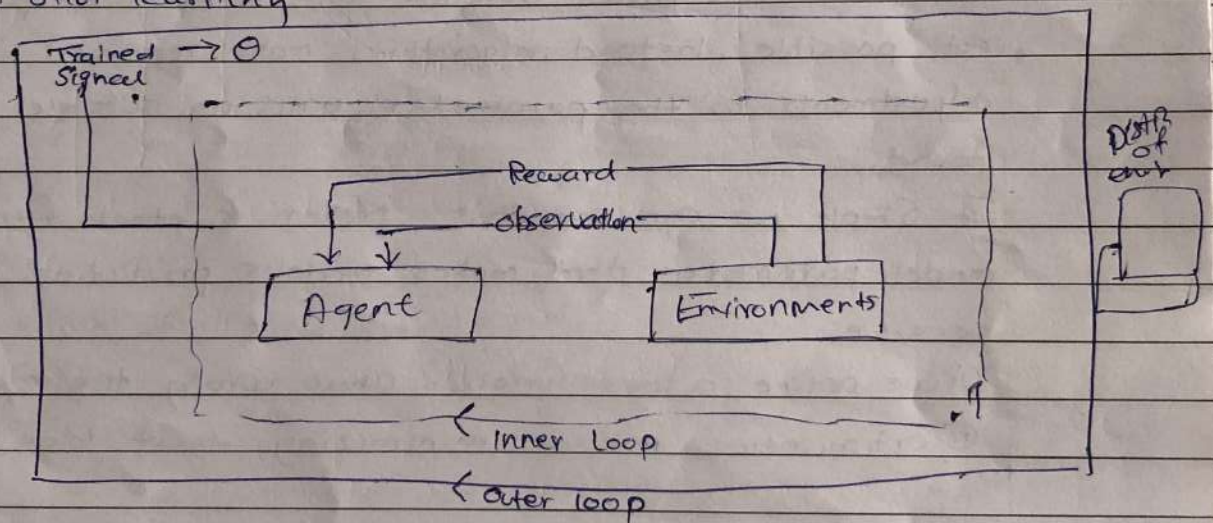
well without needing a lot of extra training or learning the models.

The Typical Meta-RL Involves 2 phases

(1) Meta Training phase: The agent experiences a variety of tasks drawn from a tasks distribution

(2) Meta Testing Phase: The agent is evaluated on new, unseen tasks and should quickly adapt using minimal data.

This process helps Meta-RL agents learn new tasks faster sometime after just few tries. The agent know a few-shot learning



Ex: Imagine training a robot with regular reinforcement learning to walk on flat ground. It learns very well but struggles when asked to walk on sand or climb stairs because it hasn't seen those situation before. With Meta-RL the robot is trained on many terrains - flat grounds, sand, slopes and stairs overtime, it doesn't just learn how to walk in each environments but also learns the process of adapting its walking style. So, when faced with a brand-new surface like gravel it can quickly adjust without needing to relearn everything from scratch.

Q. Numerical Optimization Methods.

Ans.

Numerical optimization is a core component of machine learning, serving as the process by which the model "learns" from data. It is a collection of mathematical techniques used to find the minimum of a function, known as a loss function or cost function. By minimizing the loss, a machine learning model iteratively improves its parameters (weights & biases) to make more accurate predictions.

The need for numerical optimization arises because for many complex models, particularly deep learning/neural networks, a direct analytical solution for the optimal parameters is not possible. Instead, algorithms make repeated, incremental adjustments to the parameters until a suitable solution is found.

In simple terms, we can say that N.O.M is about finding the best model parameters that make the model's prediction as accurate as possible.

(i) We define a loss function (how wrong the model is)

(ii) Optimization means minimizing that loss

Gradient Descent is the most common optimization method used in machine learning. Its goal is to minimize the error (loss) of a model by adjusting its parameters step by step. You can think of it like finding the lowest point in a valley: at each step, you look at the slope of the ground under your feet (the gradient), and then take a small step downhill. In this way, the slope tells us how the error changes if we tweak the parameters. By repeatedly moving in the opposite direction of the

slope, the model gradually learns better parameters and reduces its error. The size of each step is controlled by a number called the learning rate, if it's too big, you might overshoot the minimum, and if it is too small, learning will be very slow.



Ex: Minimizing $f(x) = x^2$
 $f(x) = x^2$

Derivative of slope is $f'(x) = 2x$

Formula: $x_{\text{new}} = x_{\text{old}} - \eta \cdot f'(x_{\text{old}})$

Steps with learning rate $\eta = 0.1$, starting at $x = 5$

S1: Gradient $= 2(5) = 10$

update $x = 5 - 0.1(10) = 4$

S2: Gradient $= 2(4) = 8$

update $x = 4 - 0.1(8) = 3.2$

S3: Gradient $= 2(3.2) = 6.4$

update $x = 3.2 - 0.1(6.4) = 2.56$

By this way each step
 moves x closer to 0
 which is the minimum
 of $f(x) = x^2$