Traditional Prog

data → computer → output
progrm →

1 Intro

Page No.
Date :

Intro to ML

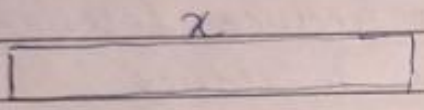
ML
Data →
Output → computer → prog

→ Machine Learning pipeline
→ Data Generation / Collection - generate, webscrape, kaggle
→ Data Cleaning / Feature Engineering
→ Algorithms to find patterns
→ Deployment

ML :- able to learn machines are without being explicitly programmed

Supervised Learning

→ learn from data (labelled)
→ generalised predictions on future data and avoid "OVERFITTING" [TRAINING]



label
- continuous → regression
  - house price prediction
  - stock price prediction
- discrete value → classification
  - is it cat or dog? 0 or 1
  - is it an apple? 0 or 1

Representation

$$x = \begin{bmatrix} x^{(1)} \\ x^{(2)} \\ \vdots \\ x^{(n)} \end{bmatrix} = \begin{bmatrix} x_1' & x_2' & x_3' & \cdots & x_n' \\ & & \vdots & & \\ & & x_j & & \end{bmatrix} \qquad y = \begin{bmatrix} \uparrow \\ y_i \\ \downarrow \end{bmatrix}$$

In regression
$f(x) \rightarrow y$
$x \in R^n$
$y \in R$

In classification
$f(x) \rightarrow y$
$x \in R^n$
$y \in$ one of the classes

Traditional Prog

data → computer → output
program →

1 Intro

Page No.
Date :

Intro to ML

ML
Data →
Output → computer → prog

→ Machine Learning pipeline
→ Data Generation / Collection - generate, webscrape, kaggle
→ Data Cleaning / Feature Engineering
→ Algorithms to find patterns
→ Deployment

ml :- machines are able to learn without being explicitly programmed

Supervised Learning

→ learn from data (labelled)
→ generalised predictions on future data and avoid "OVERFITTING"] TRAINING

x — input
y — label

label:
- continuous → regression
  - house price prediction
  - stock price prediction
- discrete value → classification
  - is it cat or dog? 0 or 1
  - is it an apple? 0 or 1

Representation

$$x = \begin{bmatrix} x^{(1)} \\ x^{(2)} \\ \vdots \\ x^{(n)} \end{bmatrix} = \begin{bmatrix} x_1' & x_2' & x_3' & \cdots & x_n' \\ & & \vdots & & \\ & & x_j & & \end{bmatrix} \qquad y = \begin{bmatrix} \uparrow \\ y_i \\ \downarrow \end{bmatrix}$$

In regression
$f(x) \rightarrow y$
$x \in R^n$
$y \in R$

In classification
$f(x) \rightarrow y$
$x \in R^n$
$y \in$ one of the classes

(1)

How algorithm works ?

Batch learning

Training Data

↓

Algorithm

↓

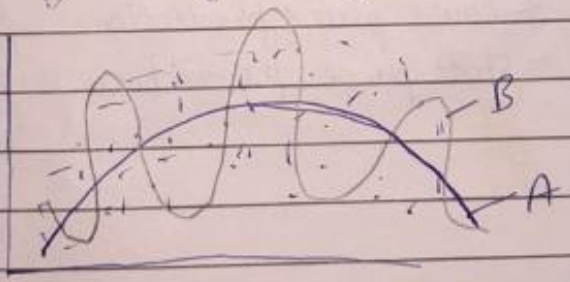
x_{Test} (unseen data) → Hypothesis → y_{test} (Prediction)

↓

function parameters

In regression our goal is to reduce loss (error)
In classification our goal is to reduce misclassifications.

Overfitting ⇒ A model that fits training data well but doesn't give good generalized predictions for example



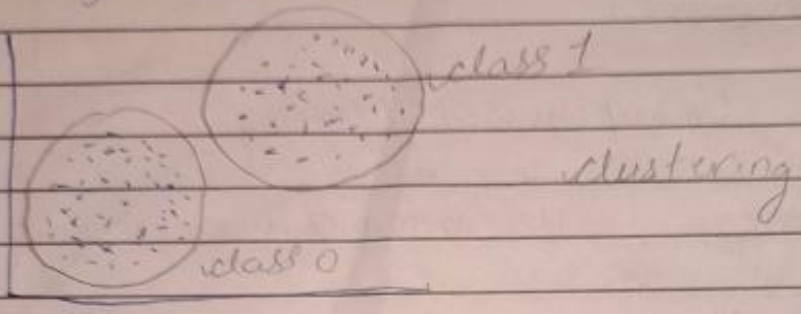
now B covers a bigger range of points so will perform well on training data, but is not suitable for predictions. whereas A is more suitable for a generalized prediction

Ex:- Spam detection, fake news prediction, document classification, NLP, image classification, sequence processing (speech, music), predictive analysis - house, stock price.

Page No.
Date :

Unsupervised Learning

- → no supervision
- → no labelled data
- → It has to find patterns on its own and group similar data points.
- → clustering is used
- → only known x values, no knowledge of y



ex:- tweet sentiment analysis, products bought together

Semi - Supervised Learning

classification ex

- → we do not have labelled data prior to use
- → we manually label the data.
- → used in object segmentation

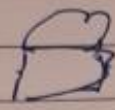
Reinforcement Learning

dog bone white example

- → Hit and trial method
- → Agent interacts with the environment.
- → environment includes everything which agent interacts with.
- → If agent reaches success there's a reward, if it fails then it gets punishment / loss through which it learns. Most like humans.

Date ..../..../.....

Batch Learning



pros - version cons - time, resources ↑

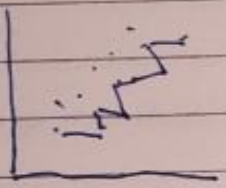
Online learning

model → new data + data → model → new data + data

pros - time ↓ cons - bad data, no version maintenance

Instance learning

lay heart learning
strict model



model based learning

logic → decision

Challenges in ML

1. Insufficient amount of data - underfitting
2. nonrepresentative data
3. poor quality of data - outliers
4. irrelevant data

Spiral