

I) a) Classical Planning

The agents plan to take advantage of the structure of the problem to construct complex plans of action to attain the goal. This is goal oriented planning.

The given monkey and bananas problem can be considered for classical planning with the 5 key elements.

Initial Condition, Goal, Action Schema, Precondition, effect

(more)

Initial Condition : Monkey at A, Banana at B, Bar at C, Monkey Low, Banana Low, A + B + C

The Initial Conditions gives the starting stage of problem

Goal : Monkey has Bananas, Monkey High, Banana High, monkey at B, Bar at B, Monkey on Bar

Goal indicates End of planning state

Action, Precondition and effect work together

i.e if a precondition is satisfied then the action can be mapped to effect.
This 5 elements can be seen in PDDL

Ex: To move from A to B : Action

S.J.SUDHARSHAN

Precondition : monkey at A and monkey is not at B

Effect : monkey at B and not C

b) PDDL Description of 'Monkey and Bananas Problem'

Init (AT(^A_{monkey}) ∧ AT(B, Bananas))
 ∧ AT(C, Box) ∧ Height(High, Banana)
 ∧ Height(Low, ^{Banana}_{monkey}, Box)
 ∧ notSame(A, B) ∧ notSame(B, C),
 ∧ notSame(A, C))

Goal (Poses(monkey, Bananas))

Action (Go(monkey, A, C))

~~PRECOND~~ : AT(monkey)

PRECOND : AT(A, monkey) ∧ notSame(A, C)

EFFECT : AT(C, monkey) ∧ ~AT(A, monkey)

Action (Push(monkey, box, C, B))

PRECOND : AT(C, monkey) ∧ AT(C, Box)

Height(Low, monkey, Box)

EFFECT : AT(B, monkey) ∧ AT(B, Box)

∧ Height(Low, monkey, Box)

∧ ~AT(C, monkey) ∧ ~AT(C, Box))

Action (Climb(monkey, box))

PRECOND : AT(B, monkey) ∧ AT(B, Box)

∧ AT(B, Bananas)

∧ Height(Low, ~~Box~~_{monkey}, Box)

EFFECT : add Height(High, monkey)

∧ ~Height(Low, monkey))

ACTION : Grasp (monkey, bananas)

PRECOND : At (mB, monkey) \wedge At (B, Box)
 \wedge (B, Bananas)
 \wedge Height (High, Banana, monkey)

EFFECT : Passes (monkey, Bananas)

Notation:

At (A, monkey) \rightarrow monkey is at A

At (B, Banana) \rightarrow Banana at B

At (C, Box) \rightarrow Box at C

Height (Low, monkey, Box)

Both monkey & Box is Low

Not Same (A, B) locations A & B are
 \rightarrow not same

Passes (monkey, Bananas)

\rightarrow monkey has Bananas

Grasp (monkey, A, C)

\hookrightarrow

monkey moves from A to C

Push function pushes the object
 from one location to another

Climb (monkey, box)

\rightarrow monkey climbs on box

Grasps (banana)

\rightarrow monkey grasps all
 banana

2

Given :

Decision Node : B

Choice Node : M, P

Utility Node : U

B is a) Parent of M, U, P

$$P(P|b, m) = 0.9$$

$$P(m|b) = 0.9$$

$$P(P|-b, m) = 0.5$$

$$P(m|-b) = 0.7$$

$$P(P|-b, -m) = 0.8$$

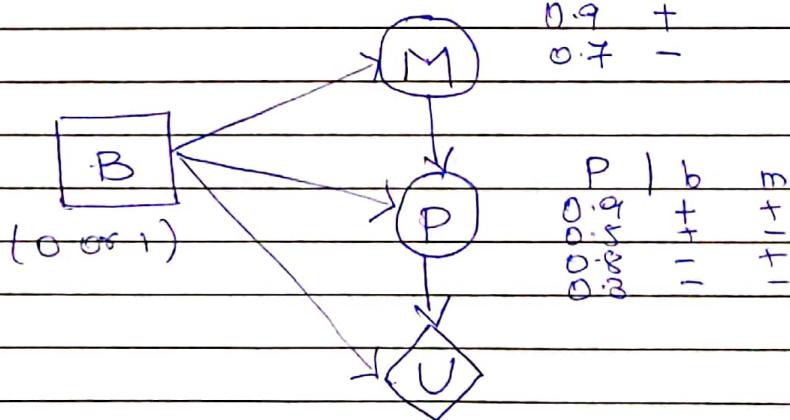
$$P(m|-b, -m) = 0.3$$

U

- 0 → Not buying the book
- 100 → Buying the book
- 2000 → Passing the course
- 0 → Not passing the course

[U depends on P, B]

a) DECISION NETWORK



b) $EU(+b)$ & $EU(-b)$

let B take $+b$ when Sam buys book
and $-b$ when he doesn't

Possible Situation for $+b$

Passing the Course After Buying and Mastering the Course

[M acts as Hidden Variable]
Not Passing the Course After Buying and Mastering the Course

$$\Rightarrow EU(+b) = \sum_p P(p|b) U(p, b)$$

$$= P(p|b) U(p, b) + P(-p|b) U(-p, b)$$

1 → ①

$P(p|b)$ we know that

$$P(p) = \sum_m P(p|m) P(m)$$

$$\Rightarrow P(p|b) = \sum_m P(p|m, b) P(m|b)$$

$$= 0.9 \times 0.9 + 0.5 \times (1 - 0.9)$$

$$= 0.86$$

$$\Rightarrow P(-p|b) = 0.14$$

$$U(p, b) = \begin{aligned} &\text{Utility of both Passing} \\ &\text{buying} \\ &= 2000 + (-100) \\ &= 1900 \end{aligned}$$

$$U(-p|b) = 0 - 100 = -100$$

Substituting all values in ① we get

$$\begin{aligned} EU(+b) &= 0.86 \times 1900 + 0.14 \times -100 \\ &= 1620 \end{aligned}$$

Possible situation for b :

→ Passing the Course without buying the book

→ Not Passing the Course without buying the book

$$\Rightarrow EU(-b) = \sum_p P(p|b) \cdot U(p, -b)$$

$$= P(p|b) \cdot U(p, -b) + P(\neg p|b) \cdot U(\neg p, -b)$$

We know that

$$P(p) = \sum_m P(pm) \cdot p(m)$$

$$\Rightarrow P(p|b) = \sum_m P(pm, b) \cdot p(m, b)$$

$$= 0.8 \times 0.7 + 0.3 \times (1 - 0.7)$$

$$= 0.65$$

$$P(\neg p|b) = 1 - 0.65 = 0.35$$

$$U(p, -b) = 2000 - 0$$

$$= 2000$$

$$U(\neg p, -b) = 0 - 0$$

$$= 0$$

Substituting all the values in above equation ②

$$EU(-b) = 0.65 \times 2000 + 0.35 \times 0$$

$$= 1300$$

Solution :

$$EU(+b) = 1620$$

$$EU(-b) = 1300$$

3.A NAIVE BAYES :

Naive Bayes algorithm is a classification technique used in Machine Learning. This algorithm is based on Bayes Theorem with the assumption that all its features are Independent and contribute equally to o/p.

This algorithm is used to Categorize data into classes

BAYES THEOREM :

→ Describes probability of occurrence of an event based on prior knowledge

FORMULA :

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$P(A|B)$ → Likelihood of A given B has happened before : POSTERIOR

$P(B|A)$ → PRIOR KNOWLEDGE

$P(B)$ → LIKELIHOOD

$P(A)$ → EVIDENCE

where B is a vector of features / Predictors

3.B

Let the probability that a person buys a PC (Yes) not be $P(\text{Yes})$ & $P(\text{No})$ respectively.

From the given Data

$$P(\text{Yes}) = 5/11 = 0.4545$$

$$P(\text{No}) = 6/11 = 0.5455$$

Let the probability that the person has a prior purchase (Yes or No) be $P(P'Y)$ and $P(P'N)$ respectively

\Rightarrow

	Yes	No	
Prior Yes ($P'Y$)	4	1	$P(P'Y) = 5/11$
Prior No ($P'N$)	1	5	$P(P'N) = 6/11$
Total	5	6	

	$P(\text{Yes})$	$P(\text{No})$
	5/11	6/11

From the above table we can calculate the probability of prior purchase, given that the user has purchased a PC?

$$P(P'Y | \text{Yes}) = 4/5 = 0.8$$

$$P(P'N | \text{Yes}) = 1/5 = 0.167$$

$$P(P'N | \text{No}) = 1/6 = 0.167$$

$$P(P'Y | \text{No}) = 5/6 = 0.833$$

Let the probability that the person has education level of High school or College be $P(H)$, $P(C)$ respectively

⇒

	Yes	No	
High school	1	3	$P(H) = \frac{1}{11} = 0.3636$
College	4	3	$P(C) = \frac{7}{11} = 0.6364$
Total	5	6	
	$P(\text{Yes})$	$P(\text{No})$	
	$\frac{5}{11}$	$\frac{6}{11}$	

From the above table we can compute the probability of a particular education given that the user has purchased a PC

$$P(H|\text{Yes}) = \frac{1}{5} = 0.2 \quad P(C|\text{Yes}) = \frac{4}{5} = 0.8$$

$$P(H|\text{No}) = \frac{3}{6} = 0.5 \quad P(C|\text{No}) = \frac{3}{6} = 0.5$$

Let the probability that the person has High, medium or low income be $P(HI)$, $P(MI)$, $P(LI)$

⇒ Yes No

High Income	3	1	$P(HI) = \frac{4}{11} = 0.3636$
Medium Income	1	2	$P(MI) = \frac{3}{11} = 0.2727$
Low Income	1	3	$P(LI) = \frac{4}{11} = 0.3636$
Total	5	6	

From the above table we can compute the probability of a particular income given the user has purchased a PC or not?

$$P(HI|\text{Yes}) = \frac{3}{5} = 0.6 \quad P(HI|\text{No}) = \frac{1}{6} = 0.167$$

$$P(MI|\text{Yes}) = \frac{1}{5} = 0.2 \quad P(MI|\text{No}) = \frac{2}{6} = 0.333$$

$$P(LI|\text{Yes}) = \frac{1}{5} = 0.2 \quad P(LI|\text{No}) = \frac{3}{6} = 0.5$$

Let the probability that the person is Young (Y), Ad Middle Age (M) and Senior (S) be $P(Y)$, $P(M)$, $P(S)$

	Yes	No	
Young Adult	3	1	$P(Y) = 4/11 = 0.3636$
Middle Age	1	3	$P(M) = 4/11 = 0.3636$
Senior	1	2	$P(S) = 3/11 = 0.2727$
Total	5	6	

From the above table we can compute the Probability of particular age group given the user has purchased a PC or not?

$$\begin{aligned} P(Y|Yes) &= 3/5 = 0.6 & P(Y|No) &= 1/6 = 0.167 \\ P(M|Yes) &= 1/5 = 0.2 & P(M|No) &= 3/6 = 0.5 \\ P(S|Yes) &= 1/5 = 0.2 & P(S|No) &= 2/6 = 0.333 \end{aligned}$$

Problem : To find

$$\begin{aligned} P(Yes | Senior, High, High School, Prior Yes) &=? \\ P(No | Senior, High, High School, Prior Yes) &=? \end{aligned}$$

Let $X = \{Senior, High, High School, Prior Yes\}$

→ According to bayes Theorem

$$P(Yes | X) = \frac{P(X | Yes) P(Yes)}{P(X)} \rightarrow (1)$$

$$P(No | X) = \frac{P(X | No) P(No)}{P(X)} \rightarrow (2)$$

$$\begin{aligned} P(X | Yes) &= P(S | Yes) P(H | Yes) P(H | Yes) P(P | Yes) \\ &= \frac{1}{5} \times \frac{1}{5} \times \frac{3}{5} \times \frac{4}{5} \\ &= 0.0192 \end{aligned}$$

$$\begin{aligned}
 P(X|No) &= P(S|No)P(H|No)P(H'|No)P(P'Y|No) \\
 &= \frac{2}{6} \times \frac{3}{6} \times \frac{1}{6} \times \frac{1}{6} \\
 &= 0.00463
 \end{aligned}$$

$$\begin{aligned}
 \Rightarrow P(X) &= P(X|Yes)P(Yes) + P(X|No)P(No) \\
 &= 0.0192 \times \frac{5}{11} + 0.00463 \times \frac{6}{11}
 \end{aligned}$$

$$P(X) = 0.01125$$

Substituting in ① and ②

$$\Rightarrow P(Yes|X) = 0.0192 \times \frac{5}{11}$$

$$0.01125$$

$$P(Yes|X) = 0.775$$

$$P(No|X) = \frac{0.00463 \times 6/11}{0.01125}$$

$$P(No|X) = 0.225$$

There is 77.5% Probability that person will buy a PC under given condition which is greater than 22.5% Probability that the person will not buy a PC.

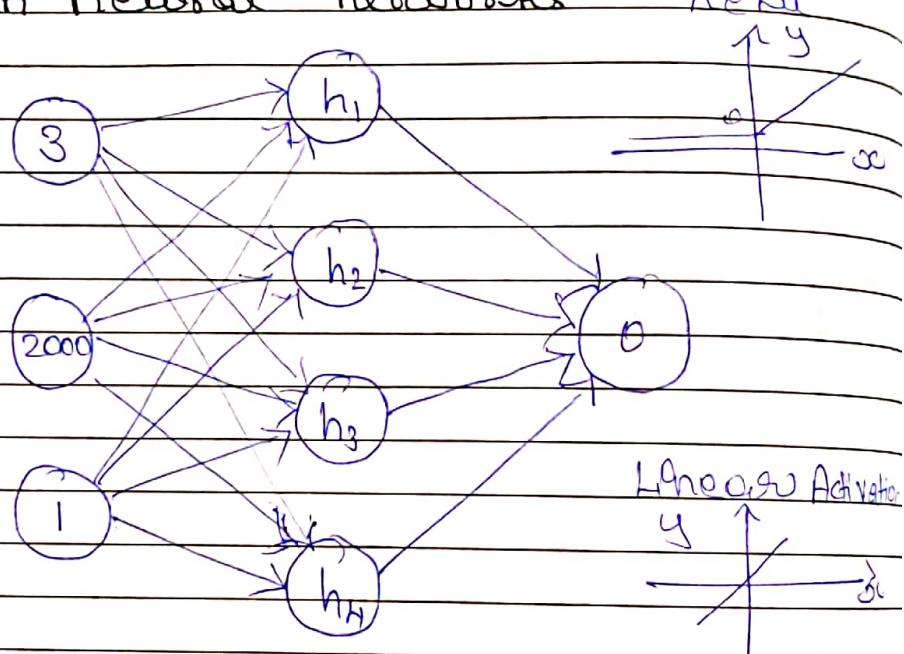
→ The Naive Bayes classifier gives Yes as O/P

Senior High High school Prior Yes \Rightarrow Yes

4) FORWARD PROPAGATION ALGORITHM.

The Data flows only in the forward direction. The Input data is fed in the forward direction and each hidden layer gets the data along with weights and biases which activates the neurons in the layers based on activation function and sends the processed data to next layer.

Given neural networks



Let us use ReLU activation function for the hidden layer

$$\Rightarrow h = \max(0, z)$$

where z is sum of weighted Inputs to h

Since all the weights = 0.1

$$\text{let } w = 0.1$$

$$z_x = w^T x$$

$$z_1 = w \times 3 + w \times 2000 + w \times 1$$

$$z_1 = 0.1(2000 + 1 + 3)$$

$$\therefore z_1 = 200.4$$

$$h_1 = \max(0, 200.4) = 200.4$$

$$z_2 = w \times 3 + w \times 2000 + w \times 1$$

$$z_2 = 0.1(3 + 2000 + 1)$$

$$\therefore z_2 = 200.4$$

$$h_2 = \max(0, 200.4) = 200.4$$

$$z_3 = w \times 3 + w \times 2000 + w \times 1$$

$$z_3 = 0.1(3 + 2000 + 1)$$

$$\therefore z_3 = 200.4$$

$$h_3 = \max(0, 200.4) = 200.4$$

$$z_4 = w \times 3 + w \times 2000 + w \times 1$$

$$z_4 = 0.1(3 + 2000 + 1)$$

$$\therefore z_4 = 200.4$$

$$h_4 = \max(0, 200.4) = 200.4$$

Now find the output Layer.

$$z_5 = w_{h_1} + w_{h_2} + w_{h_3} + w_{h_4}$$

$$\Rightarrow z_5 = 0.1(200.4 \times 4)$$

$$\therefore z_5 = 80.16$$

Output layer always uses linear activation function in Regression

$$O(z) = z \Rightarrow O = z_5 = 80.16$$

\Rightarrow The Price for given Input 80.16 Price units

5 For the given problem we have to design an algorithm that recognizes faces of people & animals, provide a count of them and identify the animal.

The algorithm starts by searching for eyes (Nally Region) and once eyes are detected detect facial regions of both human and Animal.

Now Normalize the Facial Landmarks and Extract the required Facial Features / Predictors.

Label the extracted features from the existing database to Verify and Recognize a face.

Now a face is recognized, now draw a contour around a face so we can keep track of number of faces

Now once the faces are detected perform classification to classify as Human Face or Animal Face

⇒ This algorithm is indeed a double classification

Step 1: classifies face from other parts of image

Step 2: Count faces

Step 3: Classify the faces into human face and Animal Face

Detecting Facial Features
↓

Normalizing Facial Features



Labelling Facial Features



Face Detection → Count
↓ . No
of Faces

Classify Detected Face into Human
Animal Face

6 Given :-

Robotic Arm

Goal : move from A to C and pick up a red cube.

To attain the above goal the robot has to perform 3 necessary operations.

- 1) Perception
- 2) Planning to move
- 3) moving

The robot contains 6 sensors which can be used to get data about the environment.

This data can be used by the robot to understand the environment, localize itself. The robot generates internal representation based on sensor data. This is PERCEPTION

One important part of Perception is Localization & mapping. [Finding where things are]

ALGORITHMS IN PERCEPTION

MONTECARLO LOCALIZATION

- Performed using particle filter
- Particle filter is a Recursive Bayes Filter

→ Takes Current belief and updates it based on motion information, Control Commands, bayes observation

Assumption :

Allows Arbitrary probability distribution

Particle filter uses no of Particles or Sample Considering refers to one State

Ex : Particles represent the location of Robotic Arm

So if there are 1000 particles then could be 1000 hypothesis stating where the system could be

Process :

Prediction and Correction
[of How the system evolves]

Initially random particle (with noise) is selected and uses Control Commands to Predict next state

Next Step is Correction which uses Observation from Sensors

Each particle will be assigned a weight and greater the weight greater the system to be in that state

So high weight Particles only survive

KALMAN FILTERING

- Another Localization Algorithm
- Estimate State Occurrences

Assumption : Data is Gaussian Distribution, Linear model

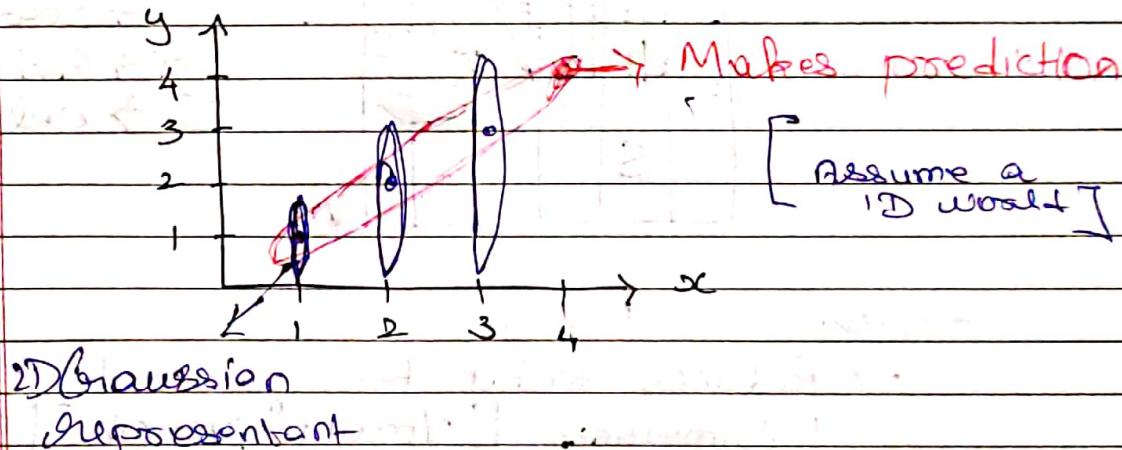
Process : 2 Steps

Loop is for new motion & observation

Step 1 : Prediction → uses Control Commands to predict the next state of robot

Step 2 : Up Corrextion → uses Observation to correct the prediction

Ex: Let us assume the robotic arm moves from (1,1), (2,2) (3,3) and will supposedly move to 4,4



Now with the availability of internal representation we can go for planning to move with a map of world

Planning occurs to move from one configuration to another in the Configuration space

ALGORITHMS FOR PLANNING TO MOVE

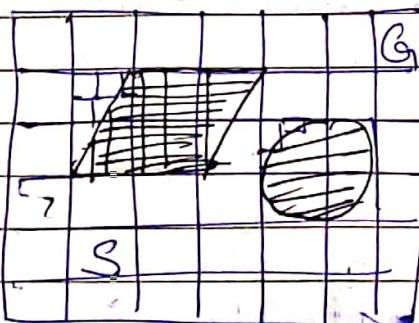
→ CELL DECOMPOSITION

→ Decomposes the free space in the Configuration Space into infinite number of contiguous regions called cells.

→ The Path Planning problem is converted to graph search as a connectivity graph is constructed ~~are based on~~ based on relation between cells

[A* can be used for shortest Path in graph]

Ex:

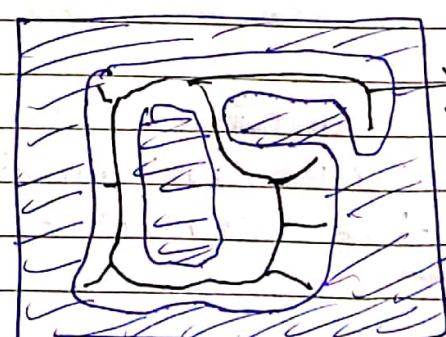
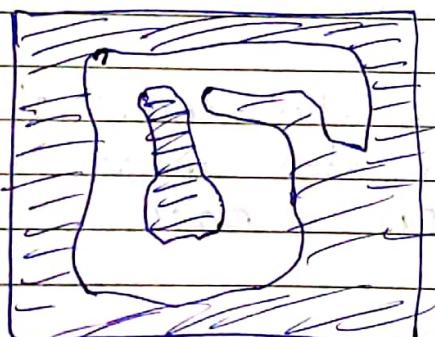


Block → Obstacle
S → Start
G → Grid
□ → cell

→ SKELETONIZATION

→ Reduces Robot free space to 1 Dimension [Voronoi graph]

Set of cell points that are equidistant from 2 obstacles



The Start and Goal points are added by connecting lines if it doesn't exist.

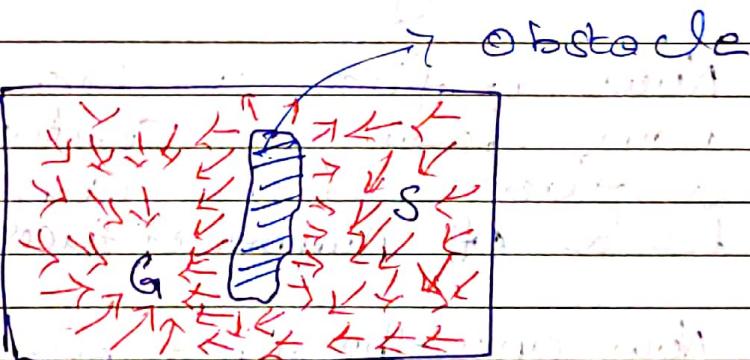
Original Path Planning is reduced to finding path on Voronoi graph

After planning the move we can move using certain Algorithms

ALGORITHM FOR MOVING

→ POTENTIAL FIELD CONTROL

- Define Attractive Force field that pulls the robot toward goal
- and Repulsive force field that repels the robot from Obstacles
- No planning is involved in generating field
- Real time Control



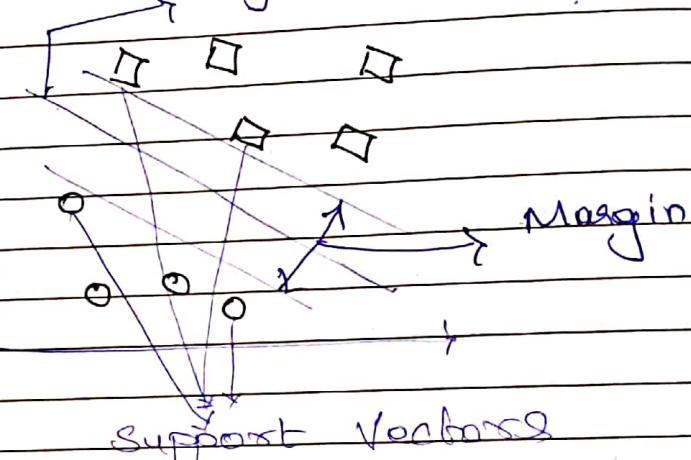
7 SUPPORT VECTOR MACHINE

→ Support Vector Machine (SVM) is a machine learning model used for Regression and classification Problem

→ Support Vectors are data points that are closer to the hyperplane and it will have an effect on location of the hyper plane

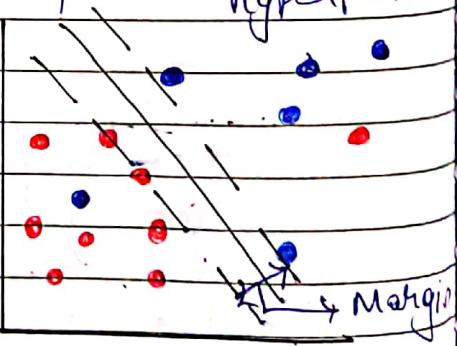
→ Hyper Planes acts as boundaries to help in making a decision

hyper plane



Data Points lying on either side of the hyperplane correspond to different classes → Classification problem

→ Support Vectors helps in generating optimal hyperplane



Possible Hyperplanes