A.I Lecture no (19 – 20)

- → Uniformed Search
- → Informed Search
- → local Search
  - hill climbing

→ One Agent

Adversial Search :- / Minimax Search :-

→ $\boxed{\text{Game theory}}$ → Multi ~~[illegible]~~ agent Environment (MAE)

→ It has more than one agent.

Agent

(helper) $\boxed{\text{Cooperative}}$ $\boxed{\text{Opponent}}$

→ Always considered moves of opponent

→ Opponent always involves "randomness" or "Unpredictable".

→ Zero Sum games :-

→ One Agent gaint is the "eauilant" loss of opponent.

~~In pubg~~

~~→ When one agent is gain and o~~

→ The loss of oppont is the eauilant gain of 1 Agent.

Game Formulation:-

- → States :- S → (Start state)
- → Player :- P → (how many Player in a game)
- → Actions :- A → (which actions will perform) (changing state is action)
- → Transition Function :- ~~SA~~ $S \times A \rightarrow S$
- → Terminal State test :- $S \rightarrow \{T, F\}$
- → Terminal Utility :- The gain of agent is utility. Every agent minimize its utility.

Utility Function:-

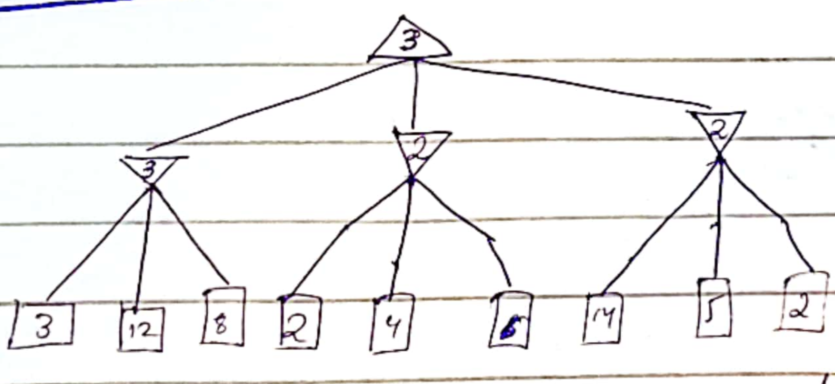
which have two agent

MAX = Me ⟶ +1/+C (+10) → value is +ve we win

Min = Opponent ⟶ −1/−C (−10) :→ value is −ve opponent win

No one ⟶ 0 :⟶ No value match draw.

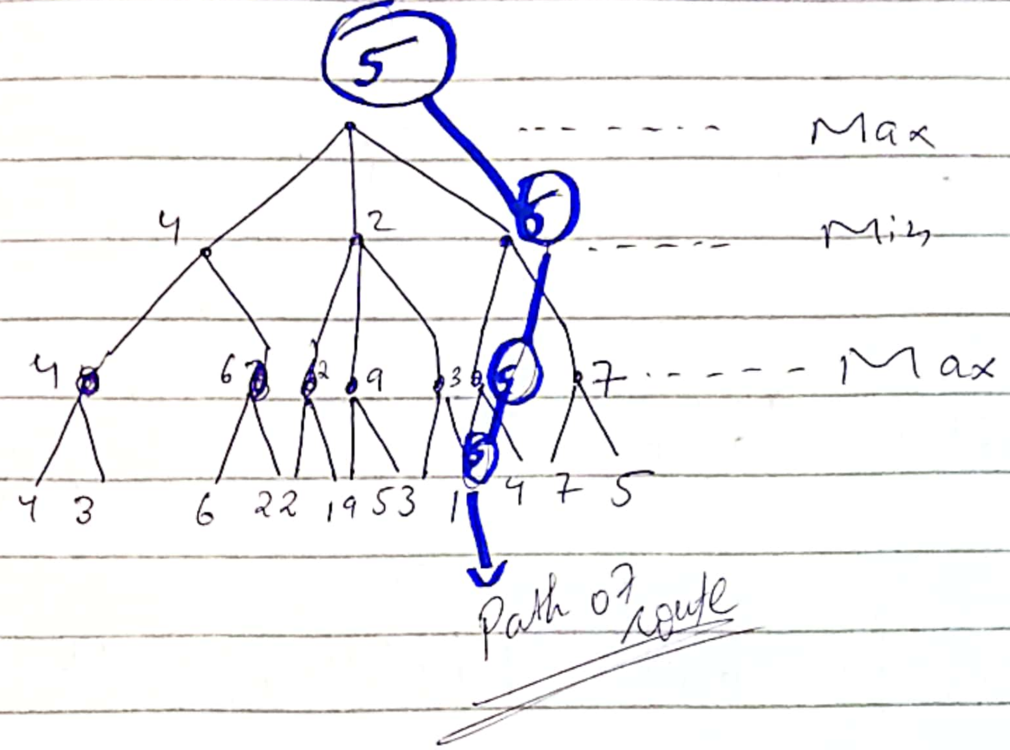
Minimax Example:-



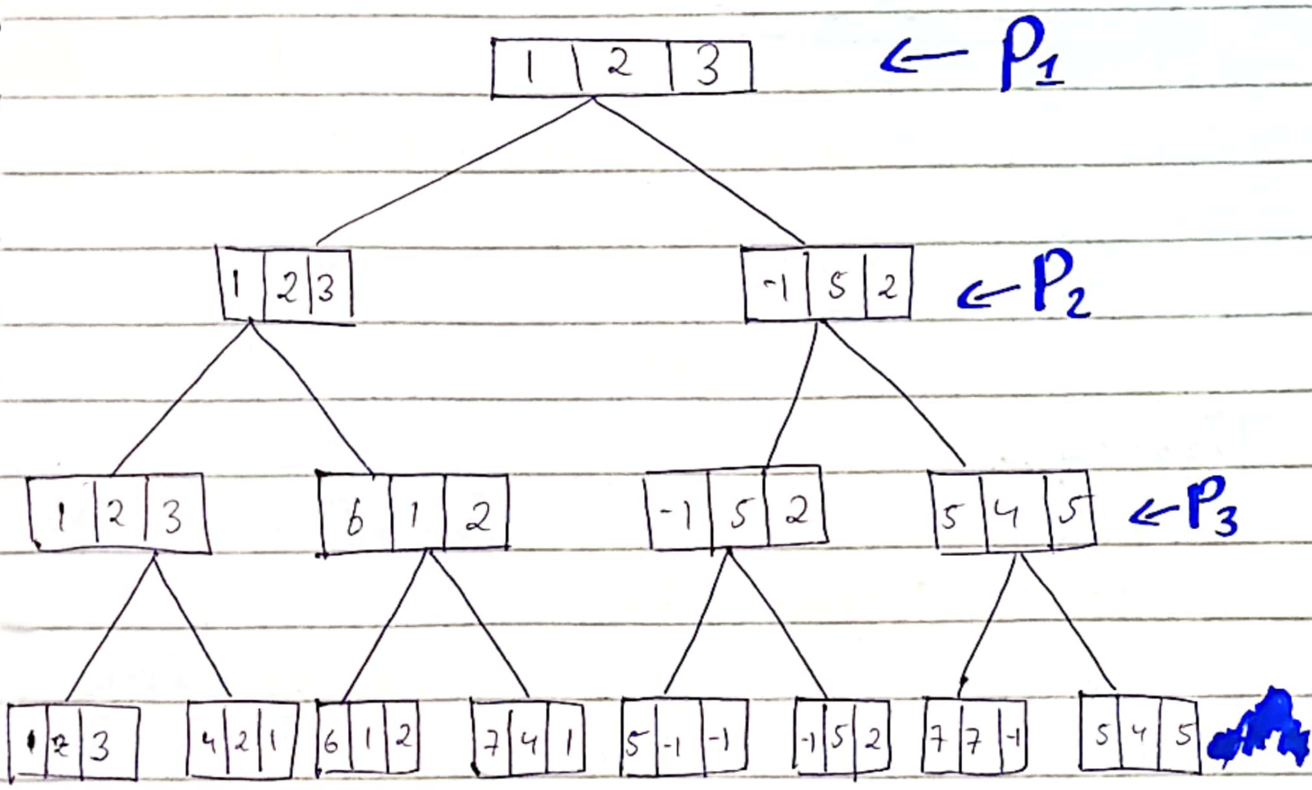
Max = $-\infty$ ✓ Max always initilize with $-\infty$ (Max denote with "α").

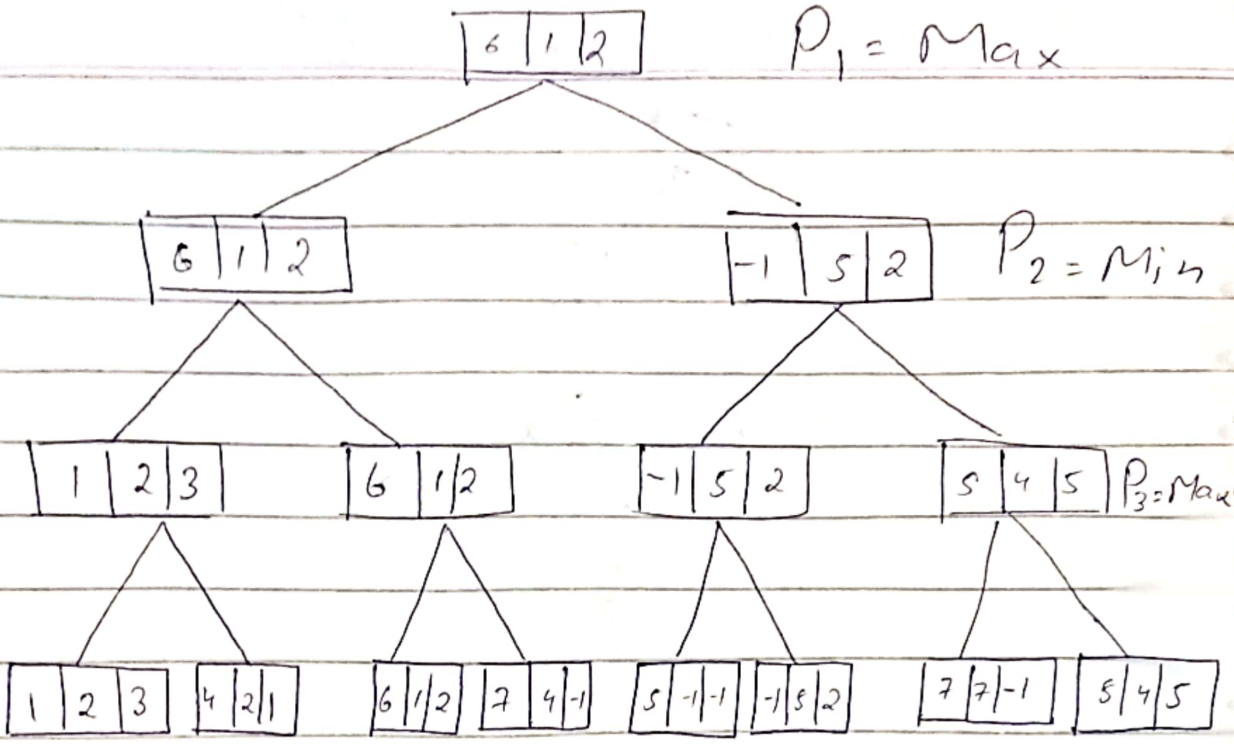
Min = $+\infty$ ✓ Min always initilize with $+\infty$ (min denote with "β")

AI- Lecture no "21"



Minimax for 3 players-





M. Imp Final

Prune condition :-

$\alpha = -\infty$

$\beta = +\infty$

→ Where value of α is grater or equal than β than the node is pruempt.

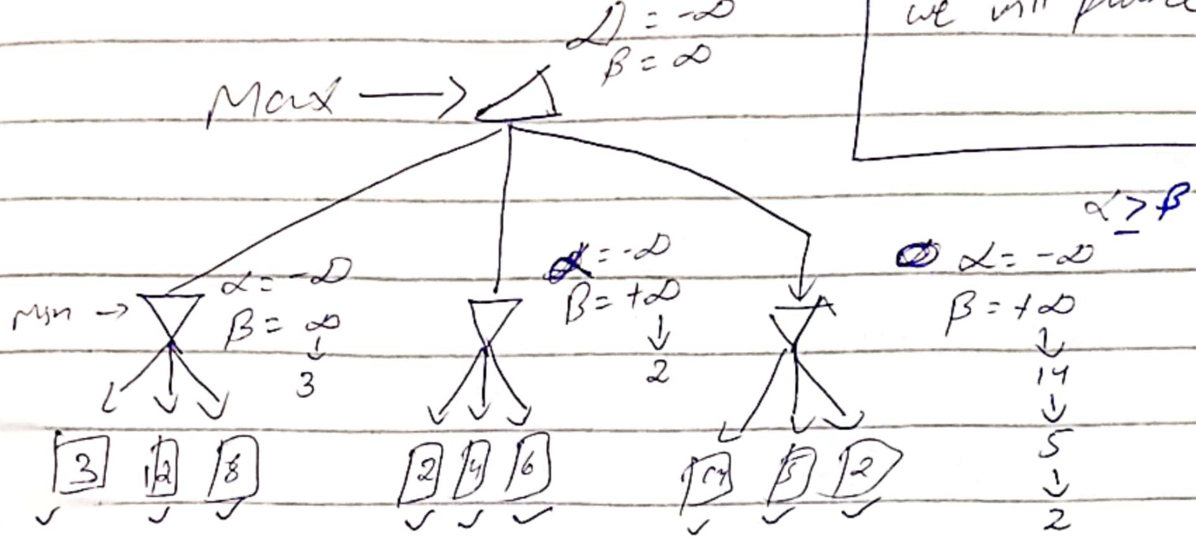
Traversing :-

→ when we move up to down we always copy the value of $\boxed{\alpha}$ and $\boxed{\beta}$.

→ whe we move down to up we always update the value if the level is "min" then only value of "β" is updated. and if level is "max" then only update the value of "α".

if $(\alpha \geq \beta)$

we will plune



AI-Lecture no "2-3"

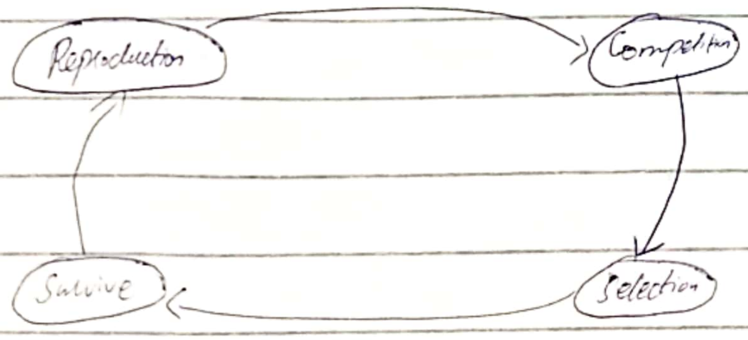
Genetic Algorithum

=> hueistic means ⟶ To caluculate Fitness
=> Competition ⟶ Suivival of fitness

Step 1) **Generate Initial Random population:-**
It has no sequence and ~~~~ if we lequire any population then we generate by randome population.

Step 2) **Caluculate fitness of Each ~~~~ chromosomes:-**
when we generate population then we also caluculate the fitness.

Step 3) **P-Select => (Parent select):-**



Step 4) **Genetic Operations:-**
(a) Crossover → 1 point crossover / multipoint crossv.
(b) Mutation (Multiple methods)

Step 5) **New Generation:-**
Fitness

New generation:-

Q:- (1) How can an individual be represented?

Q:- (2) What is fitness function?

Q:- (3) How are individuals selected?

Q:- (4) How do individuals are generated?

A:- (1) -> Every represent in number

A:- (2) -> formula given to calculate fitness.

A:- (3) -> Use rulet wheel

A:- (4) -> Apply genetic Operation

Reproduction:-

-> States are Chromosomes

-> In the form of {0, 1}

-> No of pair of chromosomes are 23 total

23 × 2 => 46

One point crossover:-

Ch:-1	1101	0100	Ch:N1 1101 1111
Ch:2	0010	1111	Ch:N2 0010 0100

Two point crossover

ch:1	11	01 01	00	Ch:N1 11000000
Ch:2	11	00 00	10	Ch:N2 11010110

31
32 16 8 4 2 1
1 1 1 1 1

Mutation:-

→ 1101 1 1001 by randome moment
choose any randome 1 and change it to 1-0 or 0-1.

→ Mutation → 1101010001

Problem:
Maximize the function $f(x)=x^2$ where x varies between "1-31".

Sol
Total population = 31

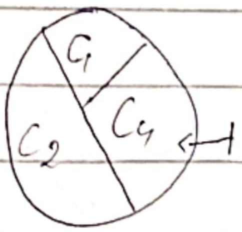
→ Generate any four (4) randome numbers.

S,no	Initial populat	x-value	$f(x)=x^2$
1	01101	13	169
2	11000	24	576
3	01000	8	64
4	10011	19	361

16 8 4 2 1
1 1 1 1 0

Sl.no	x-value	$f(x)=x^2/f_i$	P Select $= \frac{f(i)}{\Sigma f}$	Expected count $f(i)/avg$	Roulette wheel
1	13	169	0.14 = 169/1170	0.58 = 169/292.5	1
2	24	576	0.49 = 576/1170	1.97 = 576/292.5	2
3	8	64	0.06 = 64/1170	0.22 = 64/292.5	0
4	19	361	0.31 = 361/1170	1.33 = 361/292.5	1
		$\Sigma f = 1170$			

$avg = \frac{1170}{4} = 292.5$



C2	C2
C1	C4

11 00|0
01 1 0|1
C1 New (11001)
C2 New (01100)

11|000
10|011
C3 New (11011)
C4 New (10000)

$f(x)^2$
29 = 841
13 = 169
20 = 400
25 = 625

$2035 = \frac{2035}{4} = 508.75$

So our new generation is best.

Applying Mutation	New Population
11001	11101 => 29
01100	01101 => 13
11011	10100 => 20
10000	11001 => 25

$f(x) = -x^2 + 15x$

Pratice questions

		Chromosomes	fitness (f_i)		Ratio %	Roulette wheel
1)	12	=> 1100 =>	36	36/218 = 0.16	16.5%	
2)	4	=> 0100 =>	44	44/218 = 0.20	20.2	
3)	1	=> 0001 =>	14	14/216 = 0.06	6.4	
4)	14	=> 1110 =>	14	14/218 = 0.06	6.4	
5)	7	=> 0111 =>	56	56/218 = 0.25	25.7	
6)	9	=> 1001 =>	54	54/218 = 0.24	24.8	
		Σf_i : avg	218/6 = 36.3			

fi/avg	Round wheel
36/36.3 = 0.99	1
44/36.3 = 1.21	1
14/36.3 = 0.38	0
14/36.3 = 0.38	0
56/36.3 = 1.54	2
54/36.3 = 1.48	1

			R.W
5	$-(5)^2+15(5)=50$	50/48 = 1.0	1
11	$-(11)^2+15(11)=44$	44/48 = 0.9	1
5	$-(5)^2+15(5)=50$	50/48 = 1.0	1
4	$-(4)^2+15(4)=44$	44/48 = 0.9	1
5	$-(5)^2+15(5)=50$	50/48 = 1.0	1
10	$-(10)^2+15(10)=50$	50/48 = 1.0	1
	288 = 288/6 = 48		

invert	mutation

2nd bit from left

extreme change

2nd bit from right

0|11|1   1|1 0|0   0|0 0|1

0|00|1   0|1 0|0   1|1 1|0

0001   1100   0111

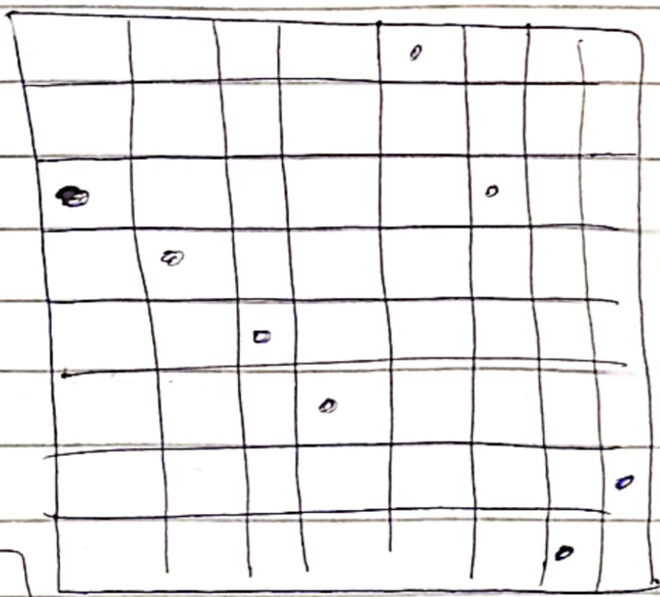
0111   0100   1000

0101   0101   0101 | 5 5 5

1011   0100   1010 | 11 4 10

8-queen Problem

6, 5, 4, 3, 8, 6, 1, 2



→ Always start with left-bottom if not given.

8 queen No. of ~~tiling~~ fitness = 28

(To see attacking always looks forward)

$Q_1 = 5$

$Q_2 = 5$

$Q_3 = 5$

$Q_4 = 3$

$Q_5 = 3$

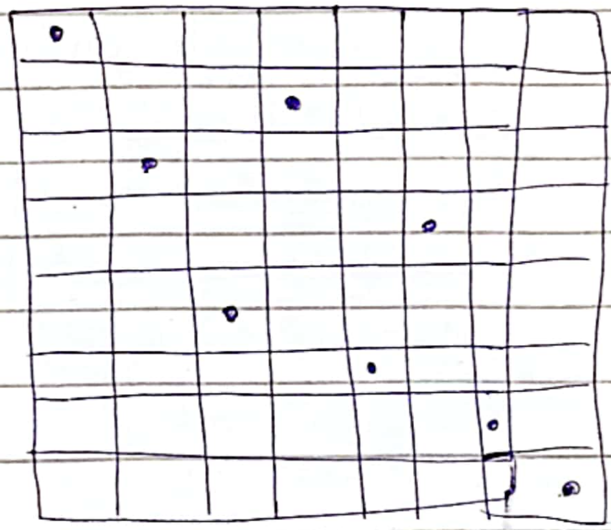
$Q_6 = 2$

$Q_7 = 0$

$Q_8 = 0$

23

fitness



Cross Overs

2 6 1	4 4 7 1	3
4 1 8	8 5 1 2	2

New chromosomes

2 6 1 8 5 1 2 3
4 1 8 4 4 7 1 2

Mutation

→ Swap any 2 in new chromosoms

~~2~~ 3 6 1 8 5 1 2 2
2 1 8 4 4 7 1 4

A-I-Lecture no "4"

Genetic Algor:-

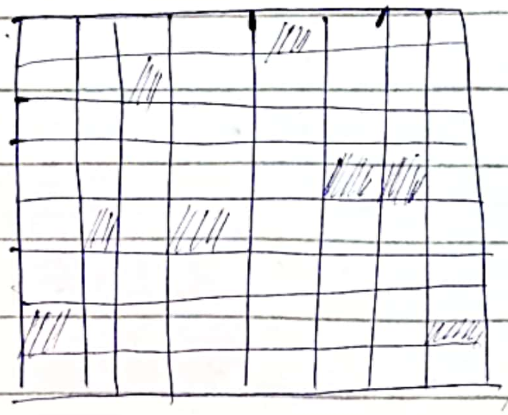
(1) IRPG

(2) Fitness

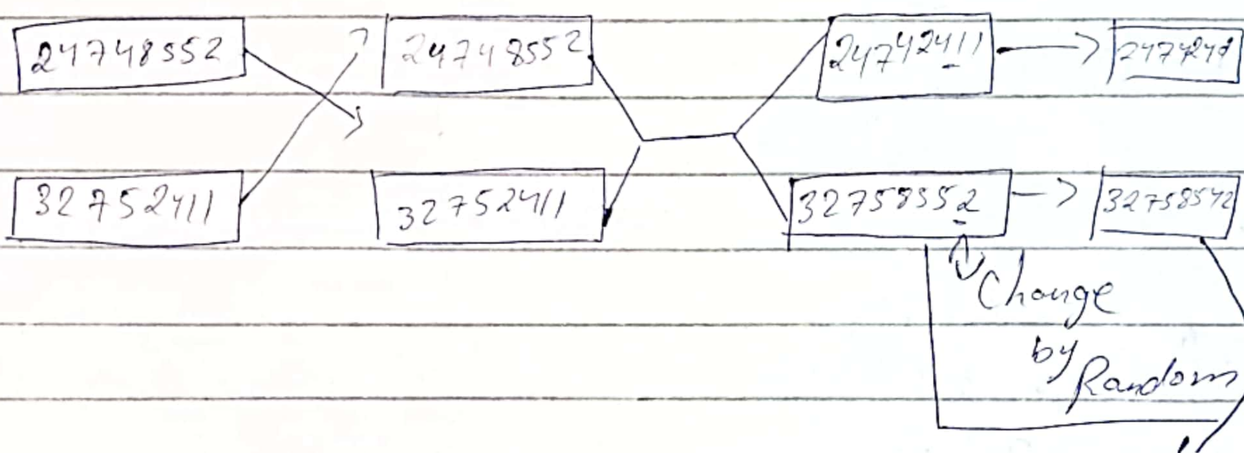
(3) P-selection

To calculate fitness:-

24748552 → Total numbers 8 draw table of 8×8



Total number of 8×8 is = 7+6+5+4+3+2+1+0=28



again calculate by 8×8 table

→ In 8-queue problem it might possible to generate more than one number.

45 $\boxed{2}$ 1 $\boxed{2}$ 5 6 7

→ In TSP (Traveling Salesman problem) we cannot visit more the one cities.

A B C D E

LHR LAR ISL QUE PES

$\boxed{0\ 1\ 2\ 3\ 4}$ → Randomness number

Always use two point crossover

P1 :- 7 4 | 1 5 3 9 | 6 | 8 2

P2 :- 3 2 | 9 4 7 1 | 8 | 5 6

1. Always write children of the ~~planent~~ parent. Childs called "Offspring" → "O".
2. Cut values in parent "1" and cancel them in parent "2".
3. ★ Always start reading from 2nd cut point in sequence.
4. To perform mutation swap the numbers.

O1: _ _ 1 5 3 9 _ _ _
O2: _ _ 9 4 7 1 _ _ _

M.I.P

P1 = 1 2 3 | 4 5 6 7 | 8 9
P2 = 4 5 2 | 1 8 7 6 | 9 3

O1 = x x x 4 5 6 7 x x => 2 1 8 4 5 6 7 9 3
O2 = x x x 1 8 7 6 x x => 3 4 5 1 8 7 6 9 2

Crossover

P1 :- 7 4 | 1 5 3 9 | 6 8 2
P2 :- 3 2 | 9 4 7 1 | 8 5 6

O1 :- 4 7 | 1 5 3 9 | 8 | 6 2
O2 :- 5 3 | 9 4 7 1 | 6 | 8 2

4 7 | ~~9 3 5 1~~ | 6 2

Mutation swap bit from 2nd and 2nd last

~~O1 :- 4 6 1 5 3 9 8 7 2~~
~~O2 :-~~

O1 = 4 7 | 2 5 3 9 8 6 7
O2 = 5 3 | 2 4 7 1 6 8 3

O1 :- 4 7 8 9 3 5 1 6 2
O2 :- 5 3 6 1 7 4 9 8 2

Knowledge Representation :- (KR) :-

- KB Knowledge base
- Resolving "OR" Reasoning
- Inference (drive)

$S_1 \Rightarrow$ It is raining

$S_2 \Rightarrow$

$\wedge$

$\vee$

$S \rightarrow B$

$S \leftrightarrow B$

$S \rightarrow B$ $S \leftarrow B$

KB = "A" father of "B"

KB = "B" and "C" brother

• infer => "A" father of "C"

Past

Experience

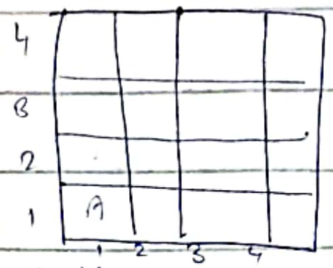
AI - "Lecture no "5 - 6"

Genetic Algo

Knap Sack

do it by yourself

Wumpus World :- (Imp)



→ 16 rooms in 4-by-4

→ There's only one monster in any of the one room.

→ In the room where is / wumpus monster is static : It can't change.

→ No diagonal movement. Only up, down.

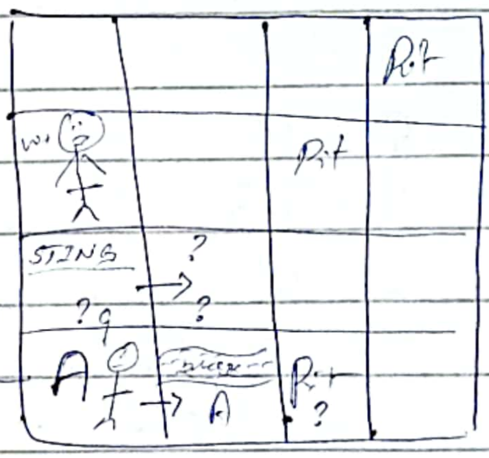
→ Stengh ~~small~~ smells available in room and agent have to identify the next room is monster.

→ The room in which $\boxed{\text{Gold}}$ avaible has $\boxed{\text{gliter}}$. Agent find the $\boxed{\text{gold}}$ and escape freely.

→ There is Pit available in multiple rows if goes then die.

→ There will be breeze available in directly connected to pit room.

→ Backtrack allows



→ Right side movement breeze found.

→ If agent move right side breeze found and agent didn't know where is pit so it back track.

→ When agent moves up in found there is sting and one of the following have monster

Fully Observable :- No

Determenestic :- Yes

Static :- Yes

Eposedic :- No

Distinct :- yes

Modus Ponens

$R_1 = \text{Clow} \rightarrow \text{Lion}$
$R_2 = \text{Clow}$
Lion

$R_1 = S1 \rightarrow S2, S1$
$R2 = S2$

$R1\ (A \vee B) \rightarrow (C \wedge D)$
$R2\ (A \vee B)$
$(C \wedge D)$

And-Elemination

$R_1 = A1 \wedge A2 \wedge A3 \wedge A7$
$R_2 = A1$
$A_3 = A2$
$R_4 = A3$
$B7$

$B\ R_1 = \text{Cat} \wedge \text{Clow} \wedge \text{doll} \wedge \text{duck}$
$R_2 = \text{Cat}$
$R_3 = \text{Clow}$
$R_4 = \text{doll}$
$R_5 = \text{duck}$

And Introduction :-

$R_1 = \text{cat}$
$R_2 = \text{doll}$
$R3 = \text{Cat} \wedge \text{doll}$

OR introduction

$R_1 = \text{Clow}$
$R_2 = \text{Clow} \vee \text{duck}$

double negation Elemination

$\neg\neg S1 = S1$

Unit resolution

$R_1 = \alpha \vee \beta \quad \neg\beta$
$R_2 = \alpha$

Supervised Learning:-

In supervised learning our data is labbeled.

If class lable is given it is called Classification:-

Unsupervised learning:-

In Unsupervised learning our data isn't labbeled.

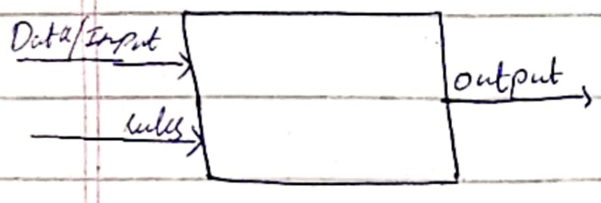
If we give some images to the Machine and it arrange in group but didn't knew the lable it is called clustering:-

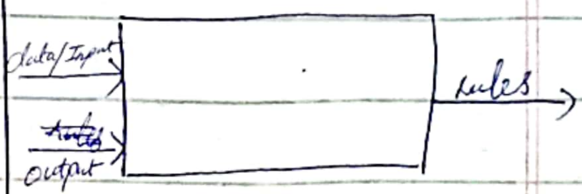
8-June-2023 "AI- Lecture no 19-20" Thursday

★ Machine Learning

- Enabling machine to learn from experience without being programmed.

→ Traditional way of developing program:- | ML Program





★ Types of Machine learning (ML):-

Classified
Regression

- Supervised learning
- Unsupervised learning
- Semisupervised learning
- Reinforcement learning

- Deep learning
- Transfer learning

Def: In supervised learning our data is labled dataset

Terms:-

Supervised learning

Unsupervised learning

Def: In unsupervised learning our data is unlable dataset.

Def: → Problem in which tells the class lable e.g. Class A

Label

- Classification (Already existing lable)
- Regression → in which we predict the value. Def:
- Clustering:- Lable didn't know but it arrange it in group.

★ Semi-Supervised learning:-

Small data → ~~learning~~ labled

large data → Unlabled

★ Reinforcement learning:-

It's contain "No Data". It learning depend on "Reward" & penalty".

★ Deep Learning:- ★★ Imp

It is also include learning but "to $\boxed{\text{mimic}}$ the human brain."

copy

★ Transfer learning:-

To train our model and learn and transfer from one information to other information.

α = learning rate

t = target variable

x_1, x_2, x_3 => Features

w = Weight

B = Bise

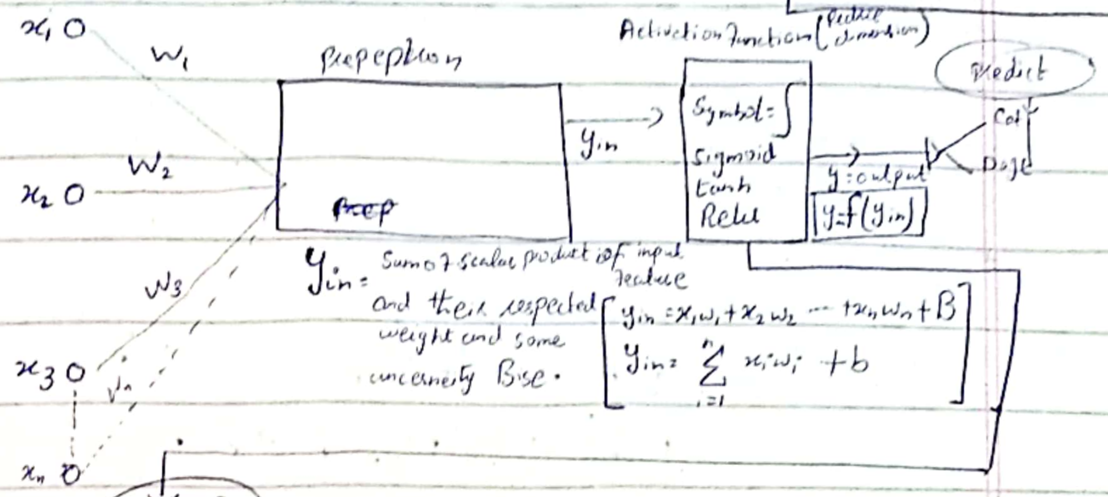
—— = Channel

y_{in} = Input

y = output

★ Perception Learning :-

input => Features



y_{in} = Sum of scalar product of input feature and their respected weight and some uncertainty Bise.

$$y_{in} = x_1 w_1 + x_2 w_2 \cdots + x_n w_n + B$$

$$y_{in} = \sum_{i=1}^{n} x_i w_i + b$$

(if value is -25000 or any (-ve) we always write "-1".)

$$y = \begin{cases} -1 & y_{in} < 0 \\ 0 & y_{in} = 0 \\ 1 & y_{in} > 0 \end{cases}$$

(when when error then then update weights and bises)

$$\boxed{W_{new} = w_{old} + \alpha t x}$$

$$\boxed{B_{new} = B_{old} + \alpha t}$$

$w_2 = w_{2}old + \alpha t x_2$

$w_2 = 0 + 1(1)(1)$

$w_2 = 0 + 1$

$\boxed{w_2 = 1}$

And Gate

A	B	t
0	0	0
0	1	0
1	0	0
1	1	1

★ Assumption/Initilization :-

$w_1 = w_2 = b = 0$

$\alpha = 1$

$B_{new} = B_{old} + \alpha t$

$= 0 + (1)(1)$

$\boxed{B_{new} = 1}$

"0" Replace with "-1"

	A (x_1)	B (x_2)	t
	-1	-1	-1
	-1	1	-1
2^{nd}	1	-1	-1
1^{st}	1	1	1

1^{st} Iteration

1 1 1

$y_{in} = x_1 w_1 + x_2 + w_2 + b$

$= 0 + 0 + 0$

$\boxed{y_{in} = 0}$

Error occurs so update

$w_{1new} = w_1 old + \alpha t x$

$= 0 + 1$

$\boxed{w_{1new} = 1}$

2^{nd} iteration

$\underset{x_1}{1}$ $\underset{x_2}{-1}$ $\underset{t}{-1}$

$y_{in} = x_1 w_1 + x_2 w_2 + b$

$y_{in} = (1)(1) + (-1)(1) + 1$

$\boxed{y_{in} = 1}$ Error so update

$w_1 new = w_1 old + \alpha t x_1$

$w_1 new = 1 + (1)(-1)(1)$

$1 + (-1)$

$\boxed{w_1 new = 0}$

$w_2 new = w_2 old + \alpha t x_2$

$= 1 + 1(-1)(-1)$

$W_2 new = 1 + 1$

$\boxed{W_2 new = 2}$

$B_{new} = B_{old} + \alpha t$

$= 1 + (1)(-1) = 1 - 1$

$\boxed{B_{new} = 0}$

A-I. Lecture no "21-23"

Naive Bayesine Classification:-

TYPES

- **Joint probability:-**

$$P(A \text{ and } B) = P(A \text{ given } B) * P(B)$$
$$P(A \wedge B) = P(A/B) * P(B)$$

Imp
- **Conditional Probability:-**

$$P(A/B) = \frac{P(B/A) * P(A)}{P(B)}$$

Example 1

* c = class
x = feature

$$P(\underset{\text{play}}{C}/\underset{\text{weather}}{x}) = \frac{P(x/c) * P(c)}{P(x)}$$

$$P(\text{Play}/\text{weather}) = \frac{P(\text{weather}/\text{play}) * P(\text{Play})}{P(\text{weather})}$$

$$P(\text{Yes}/\cancel{\text{weather}}\ \text{Sunny}) = \frac{P(\text{Sunny}/\text{yes}) * P(\text{yes})}{P(\text{Sunny})}$$

Table in slides

~~$P\left(\frac{yes}{sunny}\right) = P\left(\frac{sunny}{yes}\right)$~~

$$P\left(\frac{yes}{sunny}\right) = \frac{\left(3/9\right) * \left(9/14\right)}{\left(5/14\right)}$$

$$= \frac{(0.334) * (0.642)}{(0.357)}$$

$$\boxed{P\left(\frac{yes}{sunny}\right) = 0.6}$$

$$P\left(\frac{No}{sunny}\right) = \frac{P\left(\frac{sunny}{No}\right) * P(No)}{P(sunny)}$$

$$= \frac{P\left(2/5\right) * \cancel{P\left(5/14\right)}}{\cancel{P\left(5/14\right)}}$$

$$\boxed{P\left(No/sunny\right) = 0.4}$$

$\boxed{\text{Example 2}}$ → Table in Slide

$$P\left(\frac{\text{Gender}}{\text{Name}}\right) = \frac{P\left(\frac{\text{Name}}{\text{Gender}}\right) * P(\text{Name})}{P(\text{Gender})}$$

- $$P\left(\frac{\text{Male}}{\text{Drew}}\right) = \frac{P\left(\frac{\text{Drew}}{\text{Male}}\right) * P(\text{Male})}{P(\text{drew})}$$

- $$P\left(\frac{\text{Female}}{\text{Drew}}\right) = \frac{P\left(\frac{\text{Drew}}{\text{Female}}\right) * P(\text{Female})}{P(\text{Drew})}$$

$\boxed{\text{For Male}}$

$$P\left(\frac{\text{Male}}{\text{Drew}}\right) = \cancel{\frac{P(3/3) * P(3/8)}{}}$$

$$= \frac{P(1/3) * P(3/8)}{P(3/8)}$$

$$= P\left(\frac{1}{3}\right)$$

$$\boxed{P(\text{Male}/\text{Drew}) = 0.334}$$

$\boxed{\text{For Female}}$

$$P\left(\frac{\text{Female}}{\text{Drew}}\right) = \frac{P(2/5) * P(5/8)}{P(3/8)}$$

$$= \frac{(0.4) * (0.625)}{(0.375)}$$

$$\boxed{P\left(\frac{\text{Female}}{\text{Drew}}\right) = 0.667}$$

★ **Assumption**

In Machine learning, All the Features are considered to be independent to eachother.

Multi Input Attribute

One value which's increase called proper Probality

$$P\left(\frac{C}{x_1, x_2, x_3, x_4}\right) = P(C) * P\left(\frac{x_1}{C}\right) * P\left(\frac{x_2}{C}\right) * P\left(\frac{x_3}{C}\right) * P\left(\frac{x_4}{C}\right)$$

How to calculate problality having multiple Input attribute

$x = (\text{Sunny}, \text{cool}, \text{High}, \text{strong})$

$$P\left(\frac{yes}{Features}\right) = P(yes) * P\left(\frac{Sunny}{yes}\right) * P\left(\frac{cool}{yes}\right) * P\left(\frac{High}{yes}\right) * P\left(\frac{strong}{yes}\right)$$

$$= \left(\frac{9}{14}\right) * \left(\frac{2}{9}\right) * \left(\frac{3}{9}\right) * \left(\frac{3}{9}\right) * \left(\frac{3}{9}\right)$$

$$\boxed{P\left(\frac{yes}{Feature}\right) = 0.005}$$

$$P\left(\frac{No}{Feature}\right) = P(No) * P\left(\frac{Sunny}{No}\right) * P\left(\frac{Cool}{No}\right) * P\left(\frac{High}{No}\right) * P\left(\frac{Strong}{No}\right)$$

$$P\left(\frac{No}{Feature}\right) = P\left(\frac{5}{14}\right) * P\left(\frac{3}{5}\right) * P\left(\frac{1}{5}\right) * P\left(\frac{4}{5}\right) * P\left(\frac{3}{5}\right)$$

$$\boxed{P\left(\frac{No}{Feature}\right) = 0.02}$$

$x = (\text{Red}, \text{Domestic}, \text{SUV})$

$P(\text{yes}) *$

$P(\text{Yes}/\text{feature}) = P(\text{Red}/\text{yes}) * P(\text{SUV}/\text{yes}) * P(\text{Domestic}/\text{yes})$

$\cancel{= P(/10) * P(/10) * P(/10) * P(/10)}$

$= P(5/10) * P(3/5) * P(1/5) * P(2/5)$

$\boxed{P(\text{Yes}/\text{feature}) = 0.0214}$

$P(\text{No}/\text{feature}) = P(\text{No}) * P(\text{Red}/\text{No}) * P(\text{SUV}/\text{No}) * (\text{Domestic}/\text{No})$

$= P(5/10) * P(2/5) * (3/5) * (3/5)$

$\boxed{P(\text{No}/\text{feature}) = 0.072}$

Example 3

Insistance $= \overset{x}{2}, \overset{y}{3}, \overset{z}{4}$

$P(A/\text{feature}) = P(A) * P(2^x/A) * P(3^y/A) * P(4^z/A)$

$= P(8/15) * P(5/8) * P(2/8) * P(4/8)$

$\boxed{= 0.0416}$

$P(C/\text{feature}) = P(C) * P(2^x/C) * P(3^y/C) * P(4^z/C)$

$= P(3/15) * P(2/3) * P(2/3) * P(1/3)$

$\boxed{= 0.0148}$

$$P(B/\text{Feature}) = P(B) * P(2/B) * P(3/B) * P(4/B)$$
$$= (4/15) * P(2/4) * P(3/4) * P(2/4)$$
$$\boxed{= 0.0083}$$

(Yellow, Sweet, $\cancel{\text{Banana}}$ Long)

$\rightarrow$ $$P(\text{Mango}/\text{yellow}, S, B) = P(\text{Mango}) * P(Y/M) * P(S/M) * P(L/M)$$
$$= (650/1200) * P(350/650) * P(450/650) * P(0/650)$$
$$\boxed{P(\text{Mango}/Y, S, B) = 0}$$

$\rightarrow$ $$P(\text{Banana}/Y, S, L) = P(B) * P(Y/B) * P(S/B) * P(L/M)$$
$$= P(400/1200) * P(400/400) * P(300/400) * P(350/400)$$
$$\boxed{= 0.21875}$$

$\rightarrow$ $$P(\text{Other}/Y, S, L) = P(O) * P(Y/O) * P(S/O) * P(L/O)$$
$$= P(150/1200) * P(50/150) * P(100/150) * P(50/150)$$
$$\boxed{= 0.009}$$

A-I Lecture no "22"

KNN-Algorithm:

KNN:-

K → k is a odd number

N → Nearest N → neighbour

N → classification algo

Height (cm)	Weight (kg)	Class	Distance
167	51	Underweight	6.7
182	62	Normal	13
176	69	Normal	13.41
173	64	Normal	7.61
172	65	Normal	8.24
174	56	Underweight	4.12
169	58	Normal	1.41
173	57	Normal	3
170	55	Normal	2
Given → 170	57	?	

① X = 170 57 ; Y: 167 51

Using distance formula

$d = \sqrt{(x_2-x_1)^2+(y_2-y_1)^2}$

$d = \sqrt{(170-167)^2+(57-51)^2}$

$d = \sqrt{45} = 6.7$

② 170;57 , 182;62

$d = \sqrt{(170-182)^2+(62-57)^2}$

$d = \sqrt{(12)^2+(5)^2}$

$d = \sqrt{144+25}$

$d = \sqrt{169}$

③

Height(cm)	weight	Class	Distance	Rank
169	58	Normal	1.41	1
170	55	Normal	2	2
173	57	Normal	3	3
174	56	Underweight	4.12	4
167	51	Underweight	6.7	5
173	64	Normal	7.61	6
172	65	Normal	8.24	7
182	62	Normal	13	8
176	69	Normal	13.41	9

Brightness	Saturation	Class	Distance
40	20	Red	25
50	50	Blue	33.54
60	90	Blue	68
10	25	Red	14.14
70	70	Blue	61.03
60	10	Red	47.1
25	80	Blue	45.27
20	35	?	

Brightness	Saturation	Class	Distance	Rank
10	25	Red	14.14	1
40	20	Red	25	2
50	50	Blue	33.54	3
25	80	Blue	45.27	4
60	10	Red	47.1	5
70	70	Blue	61.03	6
60	90	Blue	68	7

→ For k=1 class Red
~~→ For k=2 class Red~~
→ For k=3 class Red
~~→ For k=4~~
→ For k=5 class Red
→ For k=7 class Blue

★
→ In case of non-numeric data we apply probality model.
→ When data is numeric we apply KNN-model

A-I

K-Mean clustering Algo:-

↳ unsupervised Learning
  ↳ Dataset
    ↓
   unlabelled

Centroid:-

Mean value of each cluster.

→ **Example:-** $\boxed{k=2}$

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8
Size:-	2	3	4	~~3~~4	2	5	7	7
Price:-	10	9	8	9	8	6	5	6

1:- Pick two any Random point and name as cluster

2:- Given in question 1st point.

	C1(3,9)	C2(7,5)	Cluster
(2,10)	1.41	7.07	C1
(3,9)	0	5.65	C1
(4,8)	1.41	4.24	C1
(4,9)	1.41	5	C1
(2,8)	1.41	5.83	C1
(5,6)	3.60	2.2	C2
(7,5)	5.65	0	C2
(7,6)	5	1	C2

$C1 = \{P_1, P_2, P_3, P_4, P_5\}$

$C2 = \{P_6, P_7, P_8\}$

* Centroid values are updated after each iteration.

$C1 = \{P_1, P_2, P_3, P_4, P_5\}$

$C2 = \{P_6, P_7, P_8\}$

* For next iteration take the mean of C1

$C1 = (3, 8.88)$

* for next itertaion take the mean of C2

$C2 = (6.33, 5.66)$

Example] Centroids:] $C1 = \{5,5\}$, $C2 = \{9,7\}$, $C3 = \{2,3\}$

x	2	3	5	8	1	7	10	9	4	8	6	4
y	2	1	7	4	6	7	2	3	4	1	3	9

		C1(5,5)	C2(9,7)	C3(2,3)	Cluster
P_1	(2, 2)	4.2	8.60	1	C3
P_2	(3,1)	4.47	8.48	2.23	C3
P_3	(5,7)	2	4	5	C1
P_4	(8,4)	3.16	3.16	6.08	C1
P_5	(1,6)	4.12	8.06	3.16	C3
P_6	(7,7)	2.82	2	6.40	C2
P_7	(10,2)	5.83	5.09	8.06	C2
P_8	(9,3)	4.47	4	7	C2
P_9	(4,4)	1.41	5.83	2.23	C1
P_{10}	(8, 1)	5	6.08	6.32	C1
P_{11}	(6, 3)	2.23	5	4	C1
P_{12}	(4,9)	4.12	5.38	6.32	C1

$C_1 = \{P_3, P_4, P_9, P_{10}, P_{11}, \ldots$

$C_2 = \{P_6, P_7, P_8\}$

$C_3 = \{P_1, P_2, P_5\}$

$UC1 = (5.83, 4.\ldots$

$UC2 = ($