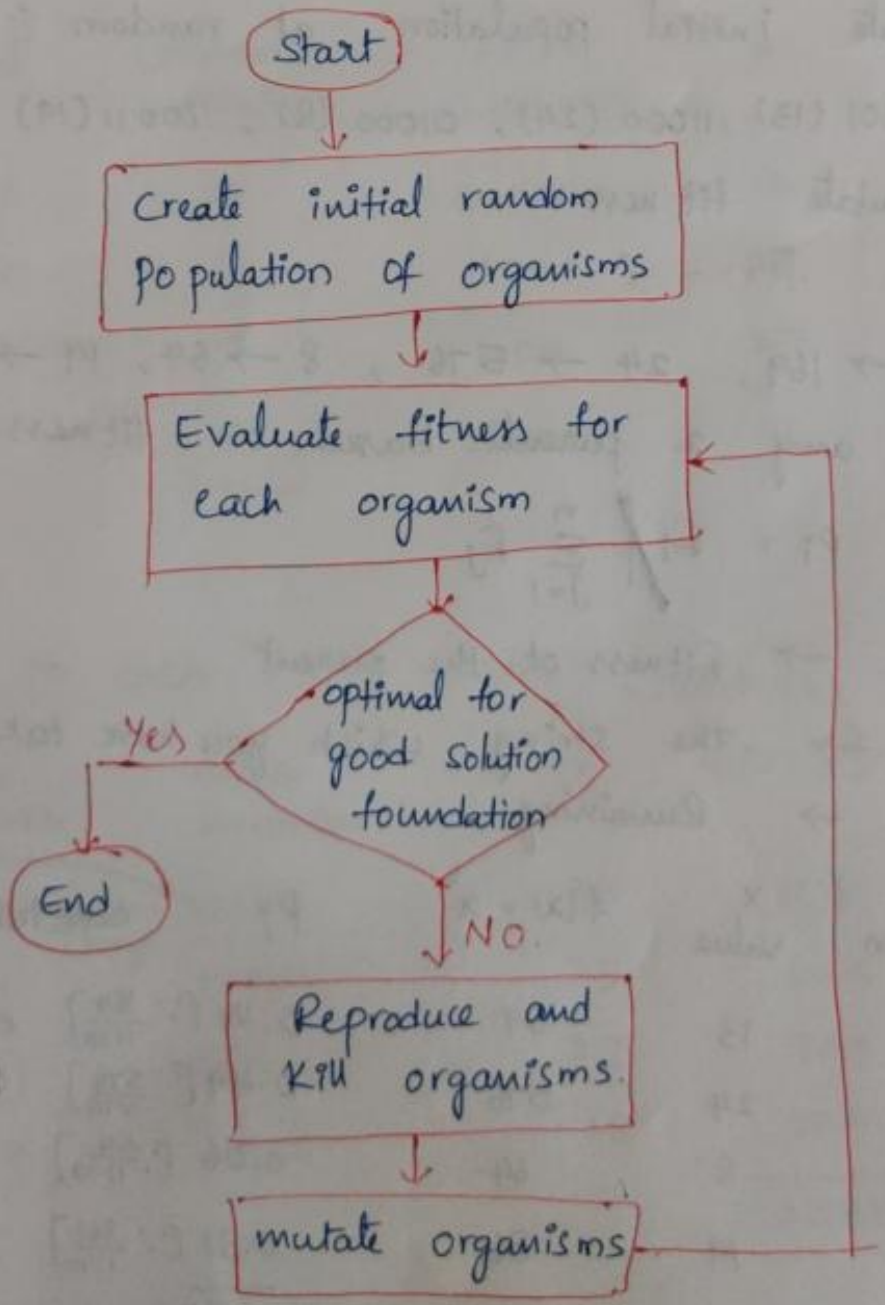
* Genetic Algorithms :-

- They belong to evolutionary Algorithms
  - Adaptive heuristic (Short cuts) search Algorithm
  - Based on genetics and natural selection
  - Used to generate high quality solution for an optimisation problem.

* Flow chart :-



* Operations of Genetic Algorithm :

1) Selection
2) Crossover
3) Mutation
4) Encoding

* Example for Genetic Algorithm :

→ $f(x) = x^2$, maximize this function with 'x' in interval [0, 31].

(1.) Generate initial population at random (Called genotypes)

01101 (13), 11000 (24), 01000 (8), 10011 (19) [No. of organisms N = 4]

(2.) Calculate fitness

$f(x) = x^2$

13 → 169, 24 → 576, 8 → 64, 19 → 361

(3.) Select any 2 parents based on fitness

$$P_i = F_i / \sum_{j=1}^{n} F_j$$

P_i → Fitness of the parent

i → The string which you have taken (13/24/8/19)

J → Remaining

NO	Initial Population	X value	$f(x) = x^2$	P_i	expected count = N x P. N = 4
1	01101	13	169	0.14 [$\because \frac{169}{1170}$]	0.56 [$\because$ 4 x 0.14]
2	11000	24	576	0.49 [$\because \frac{576}{1170}$]	1.97 [$\because$ 4 x 0.49]
3	01000	8	64	0.06 [$\because \frac{64}{1170}$]	0.22 [$\because$ 4 x 0.06] → The smallest value will be replaced with 1.97
4	10011	19	361	0.31 [$\because \frac{361}{1170}$]	1.23
			1170	1.00	4.00

→ Parent (having max. value = 1.97) selected. JV ②

④. Crossover

- Can be either one point / 2 point / n point

ex:- Let us take data as

```
100|11101        10001011
101|01011   ⇒    10111101   ] one point crossover
```

If it is two point crossover.

```
100|111|01       10001001
101|010|11   ⇒   10111111
```

NO.	Initial	Crossover point	After Crossover	x	$f(x) = x^2$
			16 8 4 2 1		
1	01101	4	01100	12	144
2	11000	4	11001	25	625
3	11000 (01000→ replaced with 11000)	2	11011	27	729
4	10011	2	10000	16	256
					1754

no change in mutation

3 bits of 0.22 lesser value

⑤. Mutation

Applied to each child after crossover.

NO.	After Crossover	After mutation	x	$f(x) = x^2$
1	01100 (random change)	11100	26	676
2	11001	11001	25	625
3	11011	11011	27	729
4	10000	10100	18	324
				2354

* Genetic Programming:

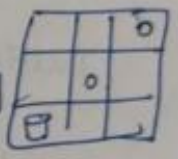
- Extension of genetic algorithms.
- Main idea - represent a Computer program as tree - used when exact solution is not known in advance

(all operations are same as genetic algorithm) - Selection, crossover, mutation & encoding

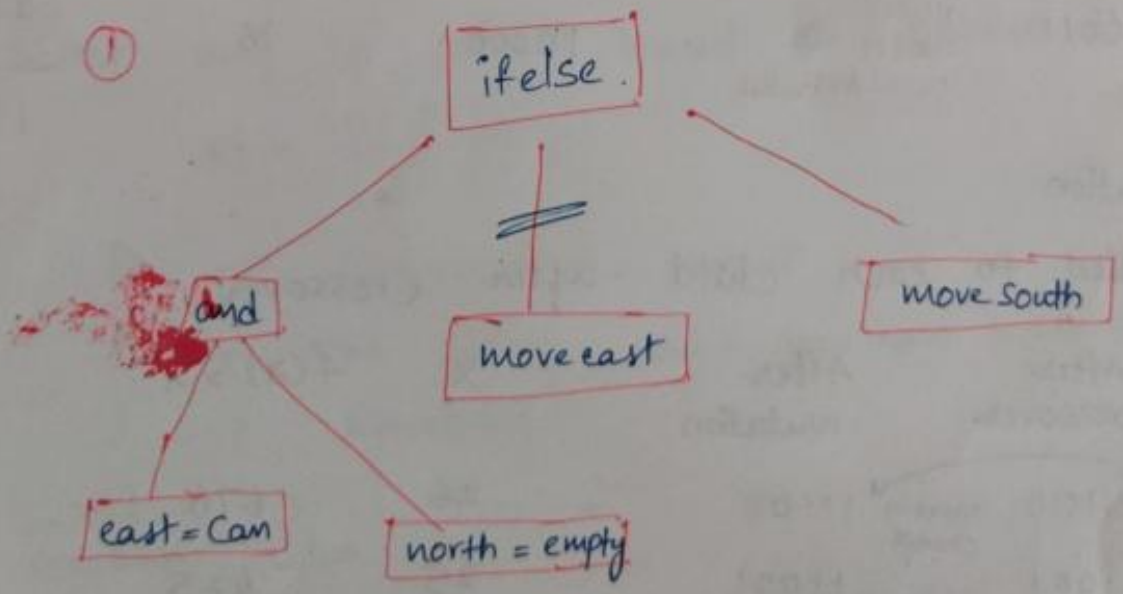
Ex: Plastic can collecting robot navigation.

```
if (east = can & north = empty)
        then move east
        else move south
```

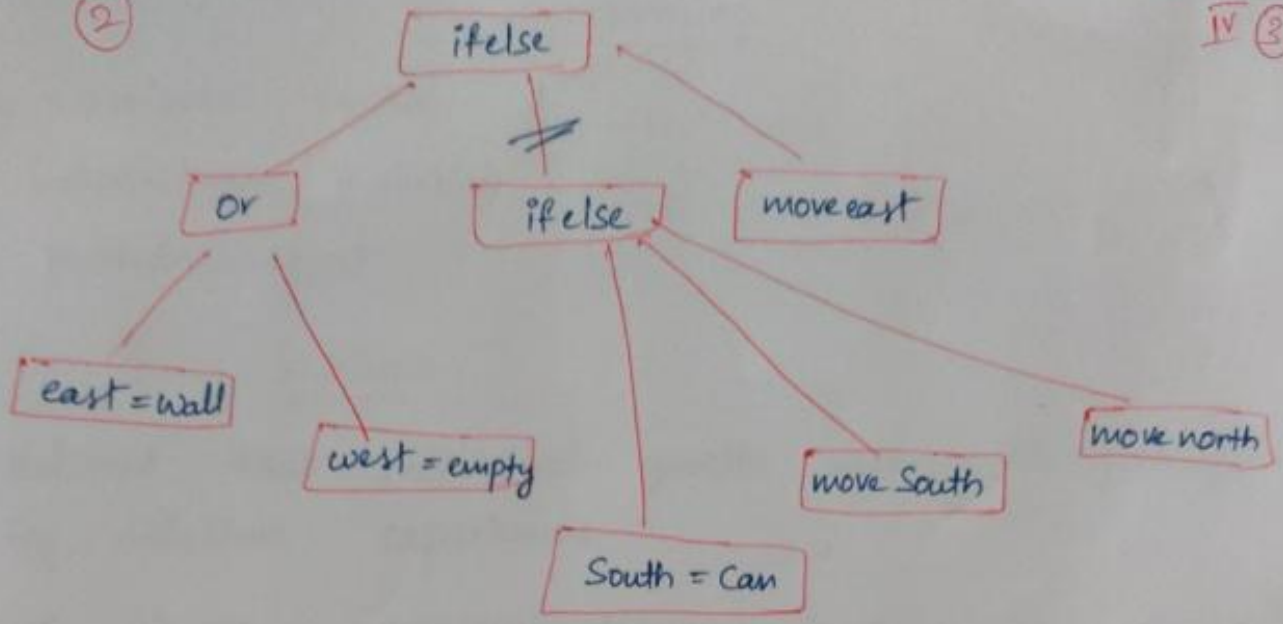
[∵ North is empty]



→ The main concept is we have to build a tree of our Computer program.



(2)



→ In order to make these two trees more efficient, we have to do the crossover operation

* Models of Evolution & Learning.

2 Evolution models.

1) Lamarckian evolution
2) Baldwin effect

* Lamarckian Evolution :

→ Believed that individual genetic makeup is changed by lifetime experiences.

i.e if an organism changes during its life to adopt to in order to adopt to the environment, then those changes are passed to its offsprings

Example : Giraffe.

* Baldwin Effect :

→ Baldwin explained about the learning behaviour of the organisms.

→ 2 things considered

1. Genotype - Genetic Code (DNA)
   - global search
2. phenotype - Your Characteristics (behaviour)
   - local search

→ Measures Cost of learning not interms of money. but interms of time and energy.

Example: Fish.

* Parallelising Genetic Algorithms :-

→ Parallel genetic algorithm uses multiple algorithms to solve a single task

2 Categories

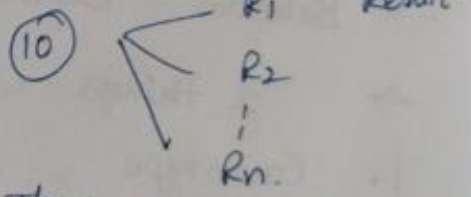
1. Fine - Grained :

Detailed description which deals with much smaller components.

2. Coarse - Grained :

Divides into fewer components (Size of component is more than that of fine - grained)

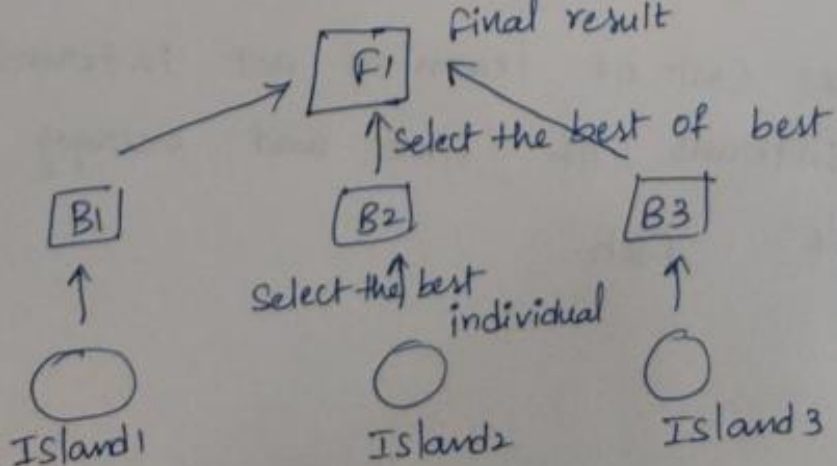
→ All the algorithms solve the same task and once they obtain solution, best one is selected.



→ Also called as island model

→ They do not depend on CPU : They can run parallelly

Advantage : Avoids problem of crowding.



* Learning Set of rules:-

IV (6).

2 ways

① way → First learn decision tree and translate that tree into rules, one rule for each leaf node.

② way → Use a genetic algorithm that encodes each rule as a bit string.

→ we have 2 types of algorithms that learn directly from set of rules.

1. First order rules
2. Sequential Covering algorithm

* Sequential Covering Algorithm:-

— It sequentially covers each and every rule
— Extracts rules from dataset directly.

It is mainly based on one of the evaluation measure — 1. Accuracy.
2. Coverage

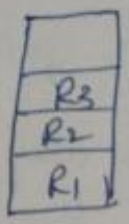
* Algorithm:

1. It creates an empty Set of decision list (R)
2. A function called "learn one rule" function is used.
   it extracts best rule for class "y"

If all training records ∈ class y ⇒ +

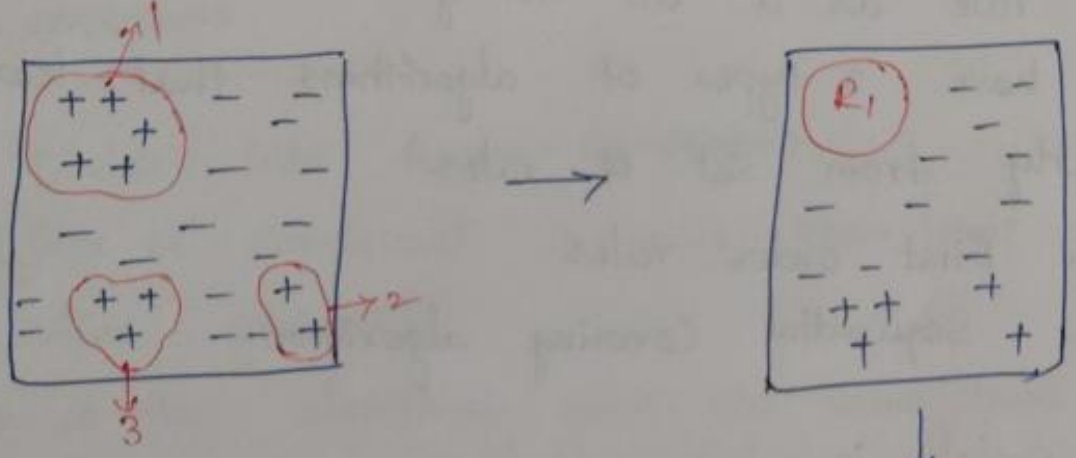
If all training records of class y ⇒ –

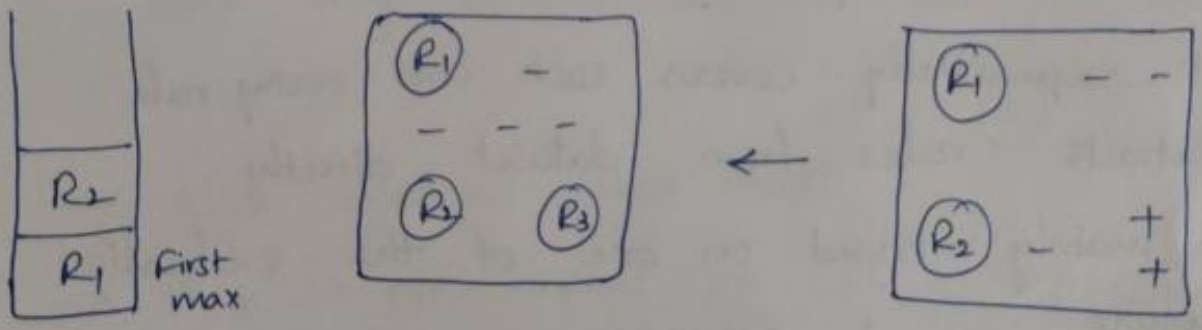
3. Get desirable values (only +ve)
4. Eliminate records (i.e the desirable ones)
5. New rule is added to bottom of R



Example :

Let us take a dataset with both +ve & –ve samples





* First order Rule learning :-

- implemented with the help of PROLOG (uses horn clauses)
- First order logic is much expressive than Propositional logic
  - It allows a finer grain of specification & reasoning

Example : daughter (x, y)

where (x, y) are {Name, Mother, Father, Male, Female}

Training examples are represented as:

(person 1, person 2, target attribute)

P1 (name 1 = Ann, mother 1 = Mary, Father 1 = Bob, male 1 = F, Female 1 = T)

P2 (name 2 = bob, mother 2 = gill, Father 2 = Joe, male 2 = T, Female 2 = F)

Target → daughter (1, 2) = T

→ with this example → only few rules

if (father 1 = Bob) ∧ (Name 2 = Bob) ∧ (Female 1 = T)

then daughter 1, 2 = T

From first order rule,

If father (y, x) ∧ Female (y) then daughter (x, y)

Terms in expressions :

Constants → Bob, 23

Variables → x, y, z

Predicate Symbols → Female, Father (only T/F)

Function Symbols → age (only const

Connectivities → (∧, ∨, →, ←)

Quantifiers → (∀, ∃) [shows the quantity whole part, some part]

* FOIL Algorithm :- (First Order Inductive Learning)

- Extension of Sequential learning (Covering)

* 1 Similarity - 1 rule at a time
* 1 Difference - only when target literal is true then only it will learn

FOIL searches its hypothesis by using 2 nested loops

* 1. Outer loop : disjunctive (∨) OR
* 2. Inner loop : Conjunction (∧) AND

(from most general to more specific).

→ Performance of FOIL Algorithm :

$$FOIL\_Gain(L, R) = t\left(\log_2 \frac{p_1}{p_1+n_1} - \log_2 \frac{p_0}{p_0+n_0}\right)$$

L - Candidate literal that is to be added to R

p_0 - No. of +ve bindings of R [R - rule set]

n_0 - No. of -ve " " R. [L - Candidate literal planning to add into R]

p_1 - " " +ve " " (R+L) (After adding L to R)

n_1 - " " -ve " " (R+L)

t - " " +ve " " R also coved by (R+L)

* REINFORCEMENT LEARNING :-

→ Learns depending on changes occuring in environment.

Goal : To achieve the best result.

Example 1 : chessboard

Goal : To win the game.

Example 2 : Agent

(2 ways fire and water)

fire - wrong choice. (-50 points)

water - Correct choice (+50 points)

whenever, choice is made (right or wrong) feedback is to agent.

Feedback - Based on this right choice is taken.

* Markov decision problem :

Examples :

Q- learning

Temporal Difference

* Q - LEARNING (Example of Reinforcement learning)

Q - Quality.

Terms Required :

1. Policy : $Q^{\pi}(S_t, a_t)$ Ex: Maze game

certain rules & limits

S - state, A - Action, t - time.

→ Policy is undertaken by agent

↓

(he observes the given state and selects best possible action)

Example: Empty road - Speed driving.

Crowdy road - Slow driving.

2. Reward: Scalar Quantity. (magnitude)

Ex:- Maze game.

Correct action → reward.

3. Penalty:- Commonly called as -ve reward

wrong action.

Ex: Parking in no parking zone.

→ Q-learning mainly depends on ② factors.

1. Q-Function
2. Q-Table.

* Q-Function:

$$Q^{\pi}(S_t, a_t) = E(R_{t+1} + \gamma R_{t+2} + \cdots \gamma^n R_{t+n} | S_t a_t)$$

↓

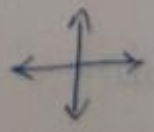
Bellman Equation

γ - Discount factor

R - Reward
S - state
a - action
t - time

* Q-Table:

→ Combination of actions & states.

Example: In a game ⇒ 

Actions: Up, down, Right, left

State: Start, end, Reward, health etc.

Steps followed :

1) Exploration : Explore (finding) all possible paths.

2). Exploitation : Best possible path is identified

3) Initialise Q table → All values '0' (Remove duplicates)

4) Choose Action

5) Perform Action

6) Measure reward.

7) Update Q - table

	↑	→	↓	←
Start				
reward				
Health				
END				

Initially all values = 0

* Temporal Difference Learning :

→ Takes advantage of both monte carlo (mc) ideas and dynamic programming (DP)

- Combination of mc and DP

* monte carlo Ideas (mc)

learns directly from raw experience i.e without model

- There is no predefined model

* Dynamic Programming (DP) :

→ It estimates based on part of learning rather than waiting for the final outcome.

→ Relation between TD, DP & mc methods are always cyclic.

more about temporal difference Learning :

- It is a model free learning.
- It has 2 important properties.

1. It does not require the model to be known in advance
2. It also can be applied for non-episodic tasks.

- Temporal difference learning (Agent's current action effects the future action) uses an update rule (Sequential) for updating the value of a state.

$$V(S_t') \leftarrow V(S_t) + \alpha \left[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)\right]$$

$V(S_t')$ ← updated value

$V(S_t)$ – value of previous state

α – learning rate (or) step size

γ – discount factor

R – Reward.

$V(S_{t+1})$ – Value of current state