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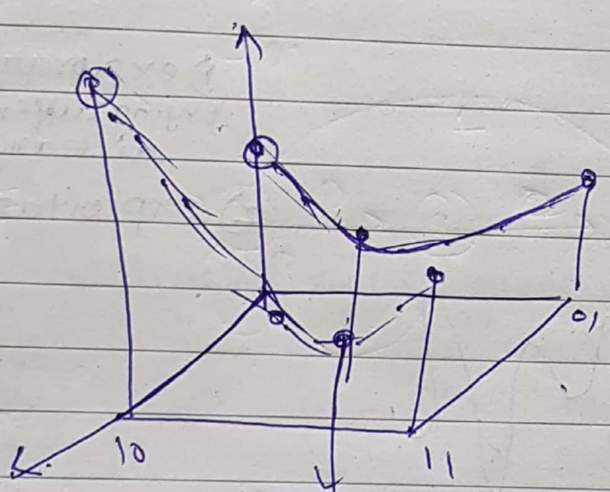
~~COMPUTER~~ SOFT COMPUTING

Von Newman architecture :

Intractible problems : Halting problem (can't be solved)

MIMD → Multiple Instructions multiple data streams
→ Homogeneous.

Array Processor = single instructions multiple data streams.



for minimisation problem best solution.

if exhaustive, all possible soln : global maxima / global minima

but in guess work - local minima / maxima. (till we find optimised soln).

Meta heuristic - part of softcomputing using approximations

1) Allow fuzziness
2) Allow approximation
3) solve meta - heuristics

GENETIC ALGORITHMS – for approximation

encoding.

chromosome → | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | (represents solution)

↳ can be int, array, binary

You need some kind of code to encode your solution.

$$f = \frac{y + \cos 32y}{x + y}$$

1) exploration: trying different x, y in search space
2) exploitation:

we go by some heuristic & not making random guesses.

we don't solve it analytically or numerically.

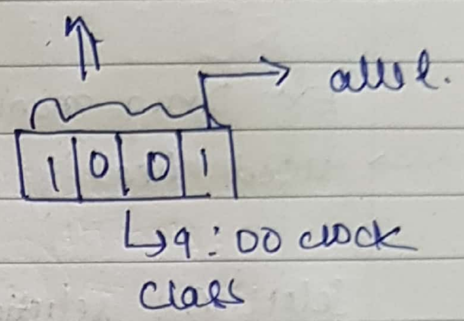
Exploration is a process of keeping on trying to make new guesses. The guesses are n't random, they are problem specific & according to nature.

stiner tree problem → Generic algorithm.

Any meta heuristic aren't applied to real time problems, generally used for design problem.

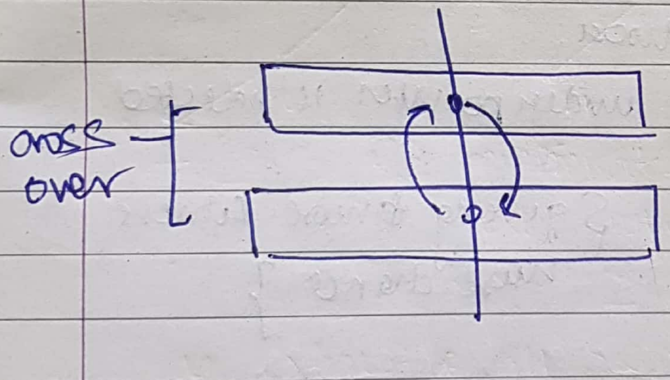
Once done, it is done.

→ Scheduling problem
→ search engine optimization
→ Resource scheduling
→ Routing on a chip
→ designing computer.



~~Genes → A group~~ gene - a group of allels which represent a feature is called gene.

A group of genes → genotype
all features genes represent - fenotype.



Find a random pt and the exchange previous ~~gene~~ chromosome & new ~~gene~~ chromosome

select two chromosome, swap them.

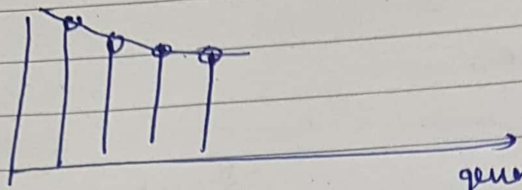
Inbreeding stops exploration, we need variety for exploration.

crossover - genetic operator, exploitation
selection - selecting two ~~do~~ individuals for cross over.

Mitchell - GS.

HIGH PERFORMANCE COMPUTING

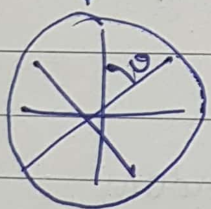
mutation - exploration.



Ex: Drug manifacture.
→ used heavily in genetics.

Selection: selection of individuals who participate it in production of next generation (crossover)

$$F = \sum_{i=1}^{N} f_i$$



rotate N times
and then choose.
Individual under pointer is selected.

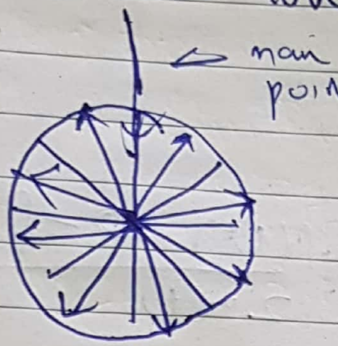
$$E[i,t] = \frac{f(i,t)}{F(t)}$$ { giving more fitness more chance }

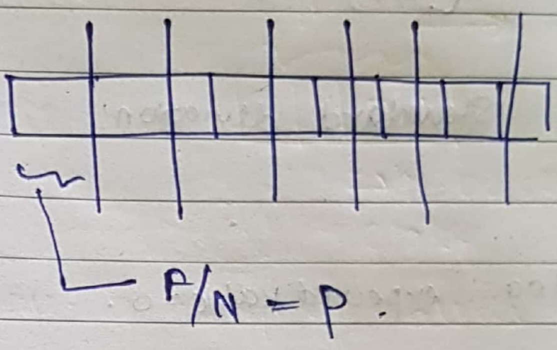
IMPLEMENTATION:
① Denote CDMA (cummulative) form
② Generate random no. b/w 1 to F
③ the keep adding till $\sum_{i=1}^{t} f_i > r$. (random no):

After a period of time, fitness remains same over a period of time & evolution converges.

Stochastic Uniform selection:

removes bias towards fitter generation.





& there is only single rotation.

IMPLEMENTATION

1. select a random no, selector = Rand()
2. {ptr := selector + i*p | i = 0 to N-1}
3. For every (individual)

```
for(i=0; i<N; i++){
    for (sum += fit(i,t); sum>=ptr ;ptr++)
        select i;
}
```

For a individual:

for selection {
minimum chance $\lfloor fit(i,t) \rfloor$
maximum chance: $\lceil fit(i,t) \rceil$

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selection pressure at moderate level
not too high not too low.

Sigma scaling
→ maintains constant selection pressure.
→ function becomes non linear.

$E[i,t] = P =$

Standard deviation: $1 + \frac{f(i,t) - f_{avg}(t)}{2\sigma(t)}$

least expected value $\doteq 0$.

Those values beyond $\sigma(t)$, they get selected & standard deviation gets low, as a result standard deviation slips life & space or less fit also gets change

Boltzmon Selection

→ make the expected value exponential
→ difference b/w minima & maxima increases with help of temporary scheduling

$$E[i,t] = \frac{e^{f(i,t)/T}}{\underbrace{\langle e^{f(i,t)/T} \rangle}_{avg}}$$

T → temperature.

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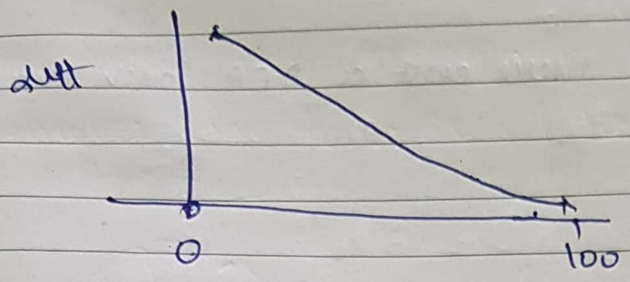
Annealing

The ~~dif~~ difference b/w maxima & minima, increase as temperature is reduced.



→ controlled by temperature
→ still low prob to select the less fit but still transition smooth & Temp. dependent

Space is distanced based.

→ selection pressure can be varied with evolution

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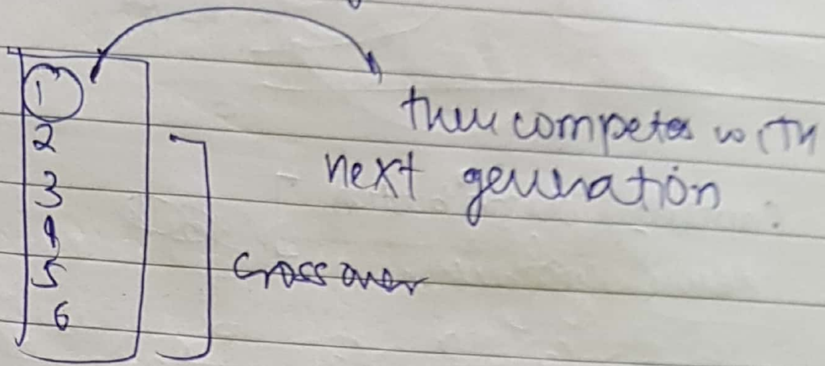
SOFT COMPUTING

→ cloning. → schema theory

(5) Elitism.

You try to retain the best or second best chromosome of this generation as well as next gen.



(6) ~~Tour~~ Rank selection.

$$\text{Expval}(i,t) = \min + (\max-\min)\frac{\text{Rank}(i,t)-1}{N-1}$$

→ Very effective method.
→ Removed direct proportionality with fitness
→ selection pressure low.

(7) Tournament selection

→ select two individuals at random, then play knockout game.
→ Let there be parameter, $k = 0.7$.
→ $r = \text{rand}(0,1)$
→ If $r > k$, then less fit or else we choose more fit.

8) Steady State Selection

→ Most fit are used to cross over with least fit

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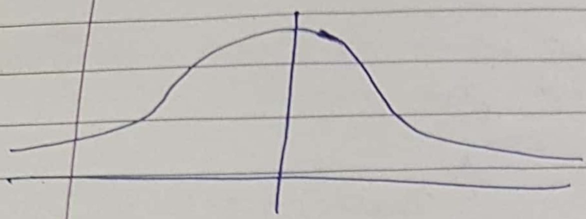
→ CUCKOO SEARCH

↳ meta heuristic



Cauchy distribution]

Lewis distribution]

MODELLING

Q. There are 50 students in a class. They have been awarded marks out of 100 in 5 different courses. Use R to visualize the data in different ways

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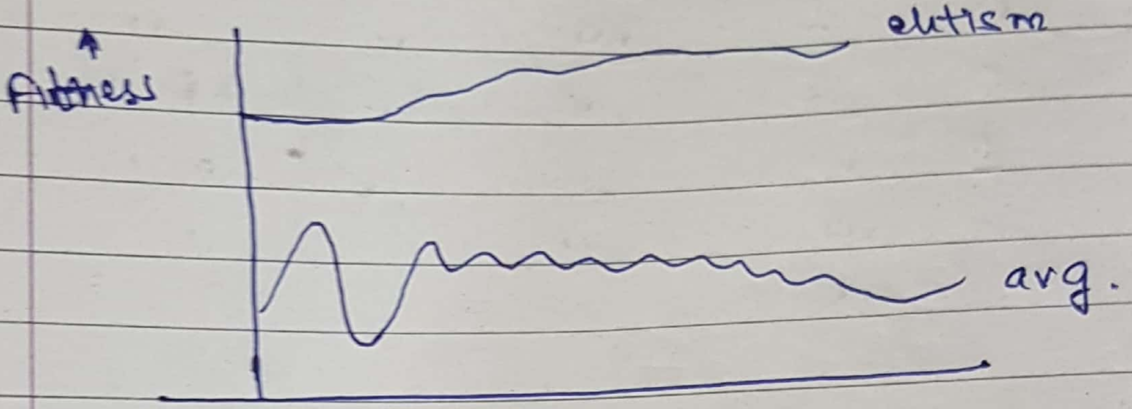
1) Calculate fitness of population and then sort the population according to the fitness.
2) selection based on elitism.
   ↳ leads to non decreasing function.

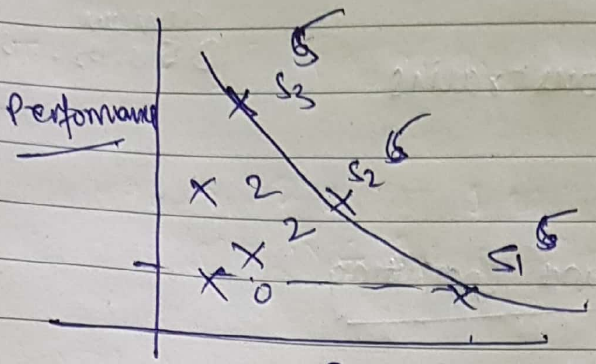


→ Cauchy distribution
→ Levy distribution

$$\boxed{OF = \frac{w_1}{\Sigma w_i} f_1 + \frac{w_2}{\Sigma w_2} f_2}$$

~~comb~~ effective obj function.

Non-inferior solutions, for these solutions you can't find a solution which is superior in ~~as~~ a aspect



Cost

efficiency

Instead of assigning wts, go for ranks ?

Rank of the solution is the ~~no. of solutions that doesn't~~ rank of superceed. ~~the soln~~

Rank of the solution ⟸ use this method.

↳ is the no. of solutions are not superior to the soln. that ~~doesn't superceed in all direction~~

Pareto optimal set → needed for rank based-selection.

↳ Rank becomes your actual fitness.

~~ACO~~

3). Ant-Colony optimization.

Two parameters

1) heuristic parameter η &

2) Pheromone τ

η → sort of local greedy search.

τ → based on experience, quality of soln, fitness function

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Combinatorial OP $< S, C, f : S \rightarrow R_0^+$

belongs to some domain $D\{v_1, v_2 .. v_n\}$

S = set of features
$S = \{x_i\}$.
C – set of constraints

High Performance Computing

PRAM
→ EREW
→ ERCW
→ CRER
→ CREW

Problem in concurrent write :

1) Priority
2) Arbitary.
3) Common
→ processor who wish to write same things.

The read has no discrepancy while the concurrent write further ~~defined~~ divided as.
→ Common: All processors are allowed to complete write if all the value written are equal. Any algorithm for this model has to make sure that this condition is satisfied. If not the algorithm is illegal and machine state is undefined.

formulate
↳ set theory, UML
pseudocode.

$S_c^* \in S_c$

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SOFT COMPUTING

$S_c \rightarrow$ feasible solⁿ.

↳ assignment of $\{x_i\}$ ~~such that~~ constrains are met.

$S_c^* \rightarrow$ reached the global optimum.

$f(\{x_i\}) : S \rightarrow R$

set of features - input
set of assigned features - output

for minimum optimal solution ←

$$\boxed{f(S_c^*) \leq f(S_c) \quad S_c^* \in S_c}$$

Initialize :

set parameters,
Initialize phenomone levels.

Loop:

Begin :

Construct Ant solutions
Synchronize. (optional)
Update phenomone

] either greedly or probabisticly

End.

till stop criterion

Probability of choosing next node :

$$P(c_{ij} | s^P) = \frac{T_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum T_{ij}^{\alpha} \eta_{ij}^{\beta}}$$

T_{ij} - phenomone level $\quad \eta_{ij}$ - distance b/w nodes.

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$\beta \propto \frac{1}{\alpha}$

τ_{ij} - experience factor
η_{ij} - local factor.

⇒ in GA there was interaction through crossover
⇒ In ACO, there may or may not be synchronisation.
{in case ant can't lift the wt of food item?}

all the ants that went through the path with fitness.

Update

$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho \sum_{S_{upd}} f(S)$

$(1-\rho)$ → evaporation rate. number b/w 0 & 1.

S_{upd} → uppermost

$\sum f(S)$ → sharing experience.

ρ - low : more weightage to past experience
& low weightage to new experience.

S_{upd} = the best so far.

$= \underset{S \in S_{iteration}}{\text{argmax}} (f(S))$

fitness of ants : inverse of length of path they traversed.

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Rough Set theory

→ A rough classifier.

U	a_1	a_2	a_3
b_1			
b_2			
b_3			

U	Age	Height	Play Volleyball
	a		c
x_1	0-10	1-3	No
x_2	0-10	3-4	Yes
x_3	10-20	4-6	Yes
x_4	10-20	4-6	No
x_5	20-30	5-6.5	Yes
x_6	20-30	5-6.5	Yes
x_7	30-40	6-7	Yes
~~x_8~~	~~20-30~~	~~5-6.5~~	~~Yes~~

$B \subseteq A$

Ind(B).

$[x]_B$

$[x]_{age}$

$\{\{x_1, x_2\}, \{x_3, x_4\}$ ...

$$\left\{ (x x') \in U^2 \;\middle|\; \forall a \in B, v_a(x) = v_a(x') \right\}$$

$X_{cj} = \{x \mid c(x) = v_{j}\}$

$X_Y = \{x_2 x_3 x_5 x_6 x_7\}$

$X_N = \{x_1 x_4\}$.

Now we define Lowerbound, Upperbound.

Lowerboundary $\underline{B}(X)$. whose equivalent classes are proper subset of classes

Want to collect all the ~~features that~~ define the equivalent classes. that surely belong Y or N.

$Y = \{\cancel{x_3}^{x_2}\, x_5\, x_6 x_7 \}$

$\underline{B}(X) = \{x \mid [x]_B \subseteq X_Y\} \Rightarrow$ Lower equivalence

↓ Yes.

Equivalence class

$C(\text{Age}, \text{Height})(x)_Y = \{x_2\, x_5\, x_6 x_7\}$

$C(\text{Age}, \text{Height})(x)_N = \{x_1\}$

$\overline{B_Y(X)} = \overline{A B}|_Y(x) = \{x_2 \cancel{x_3}\} x_4 x_5 x_6 x_7\}$

↳ part inside
part outside

upper equivalence

$\overline{B_N(X)} = \{\cancel{x_4}\}\ \{x_1 x_3 x_4\}$

$\overline{B}(X) = \{x \mid \cancel{[x]_B \subseteq X_Y \neq \phi}$
$[x]_B \cap X_Y \neq \phi\}$

$\overline{BX} = \overline{B}(X) - \underline{B}(X) \Rightarrow$ Boundary region

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$\overline{BX} = \{x_3 x_4\}$

$\overline{B^{\circ}(x)_Y} = U - \overline{B(x)_Y}$

Now only feature is Age.

$B(x)_Y = \{x_5 x_6 x_7\}$

$B(x)_N = \phi$

$\overline{B(x)_Y} = U$ {not externally defined as everything in the upper bound}

$\overline{B(x)_N} = \{x_1 x_2 x_3 x_4\}$

$\overset{\circ}{\overline{BX}}_Y = \phi$

$\overset{\circ}{\overline{BX}}_N = \{x_5 x_6 x_7\}$.

$\overline{Bx}_Y = \{x_1 x_2 x_3 x_4\}$

B(x) $\overline{BX}_N = \{\cancel{x_5 x_6 x_7}\, x_1 x_2 x_3 x_4\}$.

Rules ~~were~~ are becoming rougher ie. lower boundary is shrinking & upper boundary is expanding.

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Now feature is age, hrqW, play.

$B(x)_Y = \{x_2 x_3 x_5 x_6 x_7\}$

$\overline{B(x)}_Y = \{x_2 x_3 x_5 x_6 x_7\}$

$B^0(x)_Y = \{x_1, x_4\}$

$\overline{B x}_Y = \phi$

· Rules are crisp but decision variably not of interest as it leads to overfit.

5 classes of Rough set :

1) Roughly definable : lower boundary is not empty
upper boundary is not U.

2) $B(x)_{c_j} = \phi$ and $\overline{B}(x)_{c_j} \neq U$
Not one in it is for sure but some are present
Internally undefinable.

3) $B(x)_{c_j} \neq \phi$ and $\overline{B}(x)_{c_j} = U$
Externally undefinable.
some are definitely yes, but we can't say which are not present

4) $B(x) = \phi$ and $\overline{B}(x) = U$
Totally undefinable - i.e. all are present in boundary

5) $B(x) = \overline{B}(x)$, crisp, deterministic

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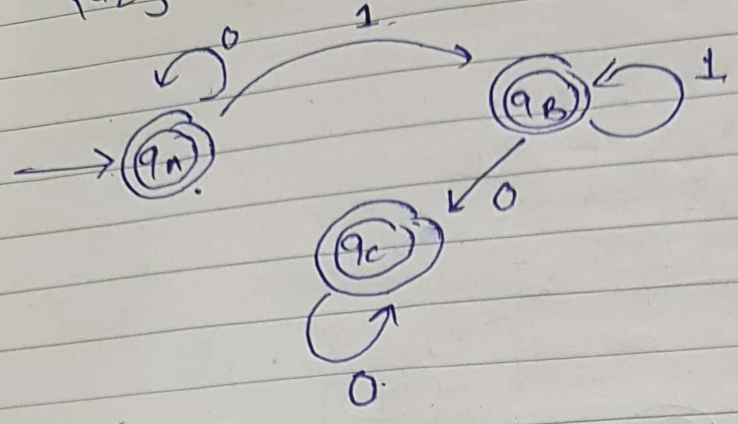
{a0 a1 a2} {a1 a2}
{a1,a2} {a2} φ.
{a2}



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U	Dep	Exp	French	Ref	Decision
x_1	MBA	Mid	Y	Excellent	Accept
x_2	MBA	Low	Y	Neutral.	Reject
x_3	MCE	Low	Y	Good	R
x_4	MSc	High	Y	Neutral.	A
x_5	MSc	Mid	Y	Neutral	R
x_6	MSc	High	Y	Excellent	A
x_7	MBA	High	N	Good	A
x_8	MCE	Low	N	Excellent	R

$X_{accept} = x_1\, x_4\, x_6\, x_7$

$X_{reject} = x_2\, x_3\, x_5\, x_8$

$X_{DEFR}: x_1\, x_4\, x_6\, x_7$

$X_{DEFR}(\text{Reject}) = x_2\, x_3\, x_5\, x_7$

$IND(DEFR) = \{x_1\}\{x_2\} \ldots \{x_8\}$

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$IND(ER) = \{x_1\}\{x_2\}\{\quad \ldots \quad \{x_8\}$

∴, reducing DEFR to ER. which reduces time.

	x_2	x_3	x_4	x_5 x_6 x_7 x_8
x_1	EUR	d, er		
x_2				
x_3				
x_4				
x_5				
x_6				
x_7				
x_8				

A : set of variables

→ define the sets

step1: $c_{ij} = \{a \in A \mid a(x_i) \neq a(x_j)\} \quad \forall (i,j) \in 1 \ldots n$

↳ set of attributes which are are different for i,j

$c_{12} = \{e, r\}$

$c_{13} = \{d, e, r\}$

$c_{14} = \{d, e, r\}$

$c_{15} = \{e, r\}$

After this, we have all the features that distinguish any two pairs.

step2: discernability function: $\wedge\{\vee c_{ij}^{*} \mid 1 \leq i, j \leq n\}$

↳ Ans: $\{e, r\}$

We need minimum no. of attributes to distinguish b/w entries.

$a(a+b)=a$

$a+ab=a.$

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SC

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
x_1	—	—	—	—	—	—		
x_2	evr	—	—	—	—	—		
x_3	evrvd	dvr	—	—	—	—		
x_4	dvevr	dve	dve vr	—	—	—		
x_5	dvr	dve	dve vr	e	—	—		
x_6	dve	dvevr	dvevr	r	evr	—		
x_7	evfvr	evfvr	dvevr	dvfvr	dve	—		
x_8	dvevf	dvfvr	fvr	dvevfvr	dvfve vr	dve vr.		

$J_D =$ (evr) (dvevr) (dvr) (dve) (e) (r) (evfvr) (dvevf) (dvfvr) (fvr) (dvev

using absorption, we get.

= er

for absorption you can use K-Map.

de \ fr	00	01	11	10
00	0	0	0	0
01	0	1	1	0
11	0	1	1	0
10	0	0	0	0

	x_1	x_4	x_6	x_7	x_2	x_3	x_5	x_8
x_1	—	—	—	—	—	—	—	—
x_4	ϕ	—	—	—	—	—	—	—
x_6	ϕ	ϕ	—	—	—	—	—	—
x_7	ϕ	ϕ	ϕ	—	—	—	—	—
x_2	$e \vee r$	$d \vee e$	$d \vee e \vee r$	$e \vee f \vee r$	—	—	—	—
x_3	$e \vee r \vee d$	$d \vee r$	$d \vee e \vee r$	$e \vee r \vee d$	ϕ	—	—	—
x_5	$d \vee r$	e	$e \vee r$	$d \vee e$	ϕ	ϕ	—	—
x_8	$d \vee e \vee f$	$d \vee e \vee f \vee r$	$d \vee e \vee f \vee r$	$d \vee e \vee r$	ϕ	ϕ	ϕ	—

$I_D = (e \vee r)(d \vee e \vee r)(d \vee r)(d \vee e \vee f)$
$(d \vee e)(e)(d \vee e \vee f \vee r)$
$(e \vee f \vee r)\, e$

$\therefore\ e(d+r)$

de \ fr	00	01	11	10
00				
01	1	1	1	
11	1	1	1	1
10		1		

$\boxed{e(d+r)}$

$ed + er$

ed - Accept equivalence class.

$\{x_1\}$ $\{x_4\ x_6\}$ $\{x_7\}$ — 3 rules

ed - Reject equivalent class

3 rules

$\{x_2\}$ $\{x_3\ x_8\}$ $\{x_5\}$

no. of rules $\Leftrightarrow$ no. of equivalent classes.

1) Make ID with respect to decision X_k 2
for each redex.

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er - Accept.
$\{x_1\}\ \{x_4\}\ \{x_6\}\ \{x_7\}$

er - Reject
$\{x_2\}\ \{x_3\}\ \{x_5\}\ \{x_8\}$

$\boxed{\text{Total rules : 14}}$

$$\sum_i \sum_K \left| Eq\left(\underset{R_i}{IND}(x_K)\right)\right| = \text{Total no of rules}$$

Total no of decision classes - ~~rank~~

$$\underset{\substack{\text{info system/}\\ \text{decision}\\ \text{system}}}{R} = (\underset{\text{Universe}}{U},\ \underset{\text{attributes}}{A} \cup \underset{\text{decision}}{\{d\}})$$

$\{a\}$: Every set is a function :,
it has a domain & range.

all possible values $d_1 d_2 \ldots d_n$ — domain

range — all values it will accept.

RA ~~rank~~ is the cardinality of ~~rank~~ image of $\{d\}$

$X_1^1\ X_1^2 \ldots\ldots X^{r(d)}$

$\{d\}' = \{v_d^1\ v_d^2 \ldots\ v_d^k \ldots\ v_d^{r(d)}\}$

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$$X_1^k = \{ x \mid d(x) = v_d^k \}$$
$x \in U$
$1 \le k \le r(d)$

no. of objects of the universe that are map to this decision

$[x]_B \leftarrow$ equivalence class of object x. w.r.t to B → attribute → decision

$IND(X^k)$

we should also have decision class.
no. of decision class = RANK.

$X(x) \rightarrow$ decision class of an object x.
$\rightarrow \{ x \mid d(x') = d(x) \}$
$x' \in U$

→ sure region.

POSITIVE REGION:
↳ union of all the lower ~~region~~ approx.

$$POS_B = BX_d^1 \cup BX_d^2 \ldots \cup BX_d^{r(d)}$$

~~[illegible]~~ which surely belong to an equivalent class

These positive regions are conservative rules.

If table is crisp then
positive region = universe.

~~Expectation~~ Expectation:- chance of occurence of the event.-

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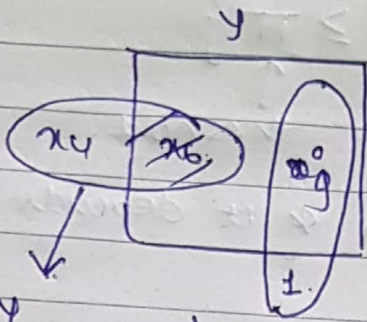

How to make it more realistic ?

Rough Membership :- degree of overlap

can be in Y or in N.

Is it okay to say that it can be in Y or N (equal prob)

$$\frac{|[X]_B \cap X|}{|[X]_B|} = \mu_X^B(x)$$

cardinality.

we say that x_4 & x_6 has probability of 50% belonging to Y.

EX:	Age	Upbringing	Like FB
1	0-10	Rural	Y
2	10-20	urban	Y
3	10-20	semi-urban	Y
4	10-20	rural	N
5	after 20	urban	N

IND. $[x]_{Age}$ = {1} {2,3,4} {5}

$\mu_Y^{Age}(x_1) = 1$ $\qquad$ $\mu_Y^{Age}(x_4) = 2/3$

$\mu_Y^{Age}(x_2) = 2/3$ $\qquad$ $\mu_Y^{Age}(x_5) = 0$

$\mu_Y^{Age}(x_3) = 2/3$

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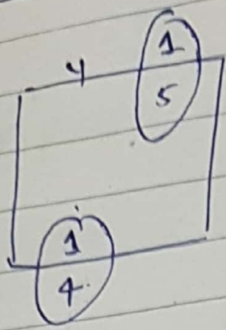
Redefine upper & lower Approximation:



Should we relax our strictness? i.e. should we redefine our threshold for lower approximation

Yes, need ed to avoid overfitting.

Lower approx: $\underline{B}(X) = \{x \mid \mu_X^B(x) \geq \pi\}$

threshold

threshold is a hyperparameter & it depends upon application.

upper approx: $\overline{B}(X) = \{x \mid \mu_X^B(x) \geq 1-\pi\}$

or π_2.

Earlier, we used threshold to be 1.

when threshold is 60 & 70 % 1.

Positive region: combination of all the lower approximation of all decision classes.

we need a metric to determine the dependency of decision on an attribute X ~~on decision~~.

Rough Dependency: what is dependency of D on C?

$$\gamma(C, D) = \frac{|POS_C(D)|}{|U|}$$

(kitna positive region mein)

attribute of C

decision per say.

set of decisions not the set of decision class

⟹ Frequently enough redux. also needs to roughness

⟹ Actual redux ⟺ that doesn't change IND

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D. threshold 1:

POS: $\{x_1\}$ ~~...~~ $\{x_5\}$

rough dependency = 2/5 = 40%

threshold 70%

~~Lower~~

~~LOWER (X)~~ = $\{x_1\}$ rough dependency = 40%

~~...~~ $\underline{B}(X)$ =

threshold 60%

rough dependency = 100% = 5/5

$C \Rightarrow D$

APPROXIMATE REDUX

So we try to look for approximate redux.

↳ GA prob / meta-heuristic

Significance of attribute:

↳ we remove ~~that~~ ~~some other~~ that attribute & how are dependency ~~on that~~ feature gets affected.

Idea to select redux among set of reduced features

$$\text{Significance} \quad \sigma_{C,D}(a) = \frac{\gamma(C,D) - \gamma(C-\{a\},D)}{\gamma(C,D)}$$

subset of features.

$$\sigma_{C,D}(B) = 1 - \frac{\gamma(C-B, D)}{\gamma(C,D)}$$

subset of features.

error

$$\varepsilon_{C,D}(B) = \frac{\gamma(C,D) - \gamma(B,D)}{\gamma(C,D)}$$

Using small radix → increases accuracy.

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We need to have error threshold to see ~~Ki to~~ it to determine error tolerance.

$\mathcal{E}_{C,D}(B)$
↓
good approximate ~~___~~ radix if within permissible limit.

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SC

Should we make cluster of ages like 0-10 or single 0,9 etc?

→ Important not loose that info that spoils my classification.

→ It can be necessary to reduce the rules. Best method to reduce rules is to form clusters.

→ We cluster in a way to ensure that we can make rules for that cluster
(use K-mean clustering)

→ clustering should be done in accordance with clustering

How to do decision related discretization of continuous functions?
(NP-hard)

U	length	breadth	buy or not?
1	1.2	2.5	Y
2	2.5	2.3	Y
3	3.2	3.1	N
4	4.1	3.5	Y
5	4.1	3.5	N
6	1.5	3.7	N

$\{q_3\}$
$\{q_1, q_3\}$
ϕ
ϕ
ϕ

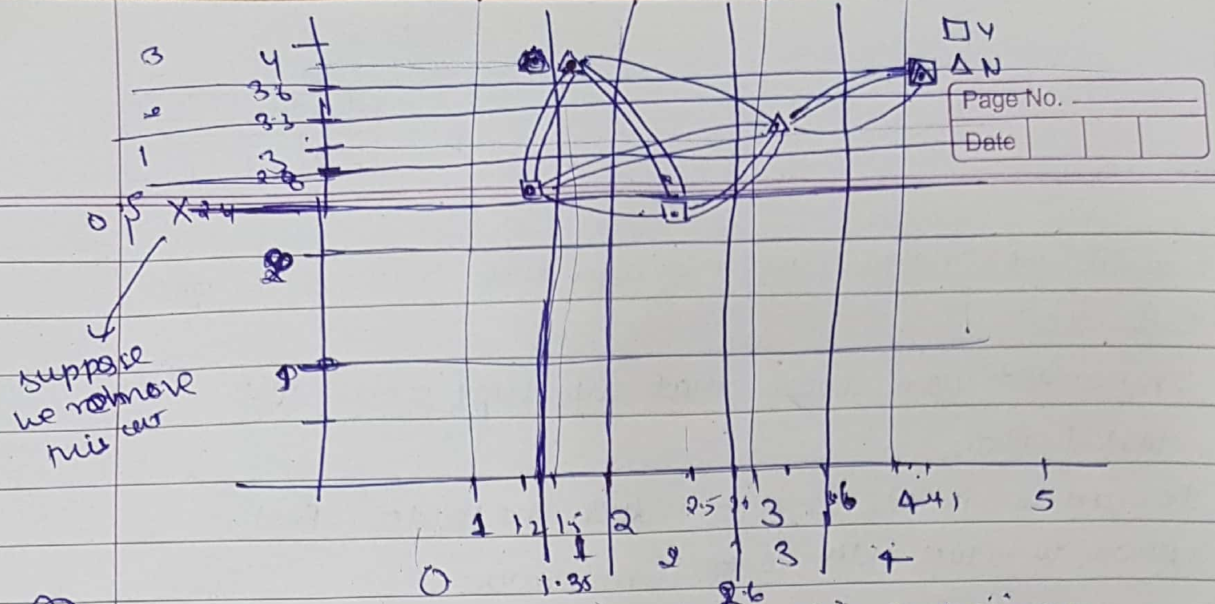
length, breadth - real valued or continuous.

We have feature space, where each pt can be considered unique.

~~Best~~ ~~we~~ We need to partition our feature space.

→ But we can't loose information

→ We need minimum no. of partitions (optimization problem)
↳ NP-hard.



(1) we adding cut at the moment irrespective of decisions

Sugar My first cut is b/w obj 1 & 2.

2 & 6

2 & 3

3 & 4.

1.2
2.5
3.7 = 1.35

breadth

1 & 2 = 2.4.

1 & 3 = 2.5

3 & 4 = 3.3

4 & 6 = 3.8

3.2
4.1
7.3 3.

2.5
3.
2.7

Make these cuts.

Do we need all the cuts?

(2) Makes edges, single line if no distinguish by cut & double line if there is distinguish by cut.

(3) All cuts through which double edge might be returned or single edge might be discarded

Now we need a heuristic to have minimum cuts.

Remove cut (breadth) b/w 1 & 2 2.4

encode

(4) Then different region & then replace continuous features values with encoded region values.

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U	length	breadth	Y/N.
1	0	0	Y
2	2	0	Y
3	3	1	N
4	4	2	N
5	4	2	Y
6	1	3	N

(6) We should express the cuts as a boolean expression.

~~we can also try empty heuristics~~

ex: (C1 || C2 || C3 || C4)

C1 or C2 or C3 or C4 can distinguish b/w 1 & 3

(7) we have maximum discernability heuristic

$P_1^{l} \rightarrow$ cut

Make relative reduxt: (use pic from phone)

	P_1^l	P_2^l	P_3^l	P_4^l	P_1^b	P_2^b	P_3^b	P_4^b
U_1U_3	1	1	1		1			
U_1U_5			1		1	1	1	
.								
.								

(1) We determine the cut / column which can distinguish maximum no. of points (P_3^b)

(2) Strike away the rows & then again select the colum.

(3) Repeat this process till you obtain the ~~maxim~~ minimum no of cuts to partition the space

$P_3^b \wedge P_3^l$

↳ Four regions.

Now we make table again.

U	l	b	Y/N
1	0	0	Y
2	0	0	Y
3	1	0	N
4	1	1	N
5	1	1	Y
6	0	1	N

(4 equivalent classes)

If value of attribute is symbol, not continuous values?

B	Y
R	N

Both these symbols are required

B	Y
B	N

B is not required.

B	Y
R	Y
G	Y
B	N

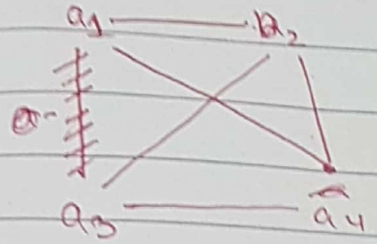
can be clubbed together.

wrong table mistake

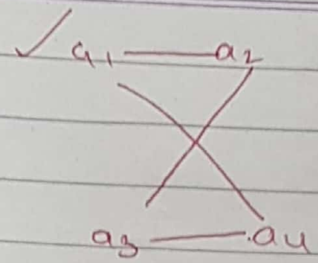
U	a	b	d	U_1	U_2	U_3	U_4
1	a_1	b_1	0				
2	a_1	b_2	0				
3	a_2	b_3	0				
4	a_3	b_1	0				
5	a_1	b_4	1	b_4^1	b_4^2	$a_1^2 b_4^3$	$a_1^3 b$
6	a_2	b_2	1	$a_2^1 b_2^1$	$a_2^1 b$	b_2^3	$a_2^3 b$
7	a_2	b_1	1	a_1^2	$a_2^1 b_1^2$	b_1^3	a_2^3
8	a_4	b_2	1	$a_4^1 b_2^1$	a_4^1	$a_4^2 b_2^3$	a_4^3
9	a_3	b_4	1	$a_3^1 b_4^1$	$a_3^2 b_4^2$	$a_3^2 b_4^3$	b_4^1
10	a_2	b_5	1	$a_2^1 b_5^1$	$a_2^1 b_5^2$	$a_3^2 b_5^3$	$a_2^3 b$

Symbol not discreminating

We can empty set ~~discn~~ heuristicto so find the different cuts



$\to$



0 $(a_1 a_3)$ 1 $(a_2 a_4)$

∴, this is one such graph but not minimised

wrong mistake

$\cancel{U_{1,5}}$ $\cancel{U_{1,5}}$

$\cancel{U_{1,6}}$ | b_4^1 | b_4^2 | $\cancel{a_1^2\, b_4^3}$ | $\cancel{a_4^3\, b_4^1}$

$\cancel{U_{1,7}}$ | $\cancel{a_2^1\, b_2^1}$ | a_2^1 | b_2^3 | $a_2^3\, b_2^1$

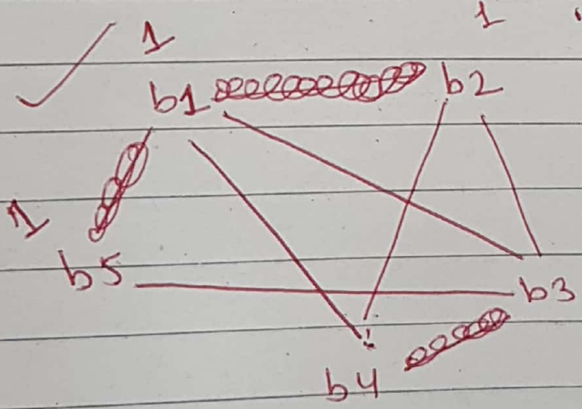
$\cancel{U_{1,8}}$ | a_1^2 | $\cancel{a_2^1\, b_1^2}$ | b_1^3 | a_2^3

$\cancel{U_{1,9}}$ | $\cancel{a_4^1\, b_2^1}$ | a_4^1 | $\cancel{a_4^2\, b_2^3}$ | $a_4^3\, b_2^1$

$\cancel{U_{1,10}}$ | $\cancel{a_3^1\, b_4^1}$ | $\cancel{a_3^2\, b_4^2}$ | $\cancel{a_3^2\, b_4^3}$ | $\cancel{b_4^1}$

| $\cancel{a_2^1\, b_5^1}$ | $\cancel{a_2^1\, b_5^2}$ | $a_3^2\, b_5^3$ | $\cancel{a_2^3\, b_5^1}$

$U_{1,5}$
$U_{1,6}$
$U_{1,7}$
$U_{1,8}$
$U_{1,9}$
$U_{1,10}$
$U_{2,5}$
$U_{2,6}$
$U_{2,7}$
U..



0
$\{b1, b2, b5\}$
$\{b3, b4\}$ 1

Now assigning the code is reduced to graph colouring problem.

U	a_0	b	D
1	0	0	0
2	0	0	0
3	1	1	0
4	0	0	0
5	0	1	1
6	1	0	1
7	1	0	1
8	0	0	1
9	0	1	1
10.	1	0	1

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