_0	Find 80-
	7/ is a basic longelt
	learning algorithm in machine learning.
<i>i)</i>	Stard with most efecific hylothesic
	h - / d / d >
i;)	Take next example and if negative then no changes occur to hypothesis If positive and we find that own initial
	no changes occur to hypothesis
	If positive and we find that our initial
	hylothesis is too elecific then we welcote
	our current hylotheric is to a general
(v)	Refeat all steps untills we reach last
	Thy to thesis.
	d1 .
	Take an example
	Sky Tem? Humid Wind Water Forest of
	Sund Warm Normal Stewn Warm Some Yes
	Sund Wagn High Sterong Wagn Same Yes
	Rain's Cold Migh Sterong Warm Change No
	Bunno Warm Migh Sterong Cool Change you
	Now take most efecific hypothesis as he has = 200 p p p p p >
	$h_0 = 4 \phi \phi \phi \phi \phi \phi$
7	Compare with first hylothesis
	Compare with first hypothesis h. = 4 Sunny, Warm, Normal, Strong, Warm, Same >
T	Compene it with second hypothesis and do
	accordingly
	Compere it with second hypothesis and do accordingly h= 2 Sunny, Warm, P, Sterong, Warm, Same >

III Now alter compaising with third hypothosis we see had it is negative so according in algorithm we will do nothing hi = Linny, Warm? Returning, Warm, Rame ? I Compare it with fourth hypothesis as it is fasitive so do accordingly hi = Linny, Warm? Ry Strong, Ry? Dow the final hypothesis is given as he = Linny, Warm? Returning? Ry I fimitations of i) There is no way to determine if the hypothesis is consistent throughout the data ii) Inconsistent bearing got can actually misclead the find Recovide a backbracking iii) It does not provide a backbracking technique to determine the best facustle changes that could be done to improve the account hypothesis Candidate Climination of Candidate Climination of the version eface given a hypothesis eface it and a set to of examples. i) hoad the data ii) Initialize General and Sicilic 14tothesis		
Tomfare it with fourth hypothesis as it is fast tive so do accordingly hy = 2 Sunny, Warm, ?, Strong, ?, ?? Down the final hypothesis is given as he : 2 Sunny, Warm, ?, Strong, ?, ? I imilations of I here is no way to determine if the hypothesis is Consistent throughout the data ii) In consistent training set an actually misclead the find. & algorithm, since it is gnoored the negative examples iii) It does not provide a backbracking technique to determine the best facustic changes that could be done to imperore the would hypothesis. Candidate Elimination of Candidate Elimination of the version space given a hypothesis eface it and a set E of examples.	TII.	Now alter Compairing with third hylothesis
Tomfare it with fourth hypothesis as it is fast tive so do accordingly hy = 2 Sunny, Warm, ?, Strong, ?, ?? Down the final hypothesis is given as he : 2 Sunny, Warm, ?, Strong, ?, ? I imilations of I here is no way to determine if the hypothesis is Consistent throughout the data ii) In consistent training set an actually misclead the find. & algorithm, since it is gnoored the negative examples iii) It does not provide a backbracking technique to determine the best facustic changes that could be done to imperore the would hypothesis. Candidate Elimination of Candidate Elimination of the version space given a hypothesis eface it and a set E of examples.		use see that it is negative so according
Tomfare it with fourth hypothesis as it is fast tive so do accordingly hy = 2 Sunny, Warm, ?, Strong, ?, ?? Down the final hypothesis is given as he : 2 Sunny, Warm, ?, Strong, ?, ? I imilations of I here is no way to determine if the hypothesis is Consistent throughout the data ii) In consistent training set an actually misclead the find. & algorithm, since it is gnoored the negative examples iii) It does not provide a backbracking technique to determine the best facustic changes that could be done to imperore the would hypothesis. Candidate Elimination of Candidate Elimination of the version space given a hypothesis eface it and a set E of examples.		to algorithm we will do nothing
There is no way to determine if the hypothesis as it is fast tive so do accordingly Now the final hypothesis is given as he : 2 Sunny, Warm ? Stewarg ?? I imilations of I here is no way to determine if the hypothesis is consistent throughout the data ii) In consistent training get an actually mislead the find of algorithm, since it is gnoored the negative examiles iii) It does not provide a backtracking technique to determine the best facustle changes that could be done to impense the negative in the best facustle changes that could be done to impense the negative given a hypothesis Candidate Elimination of The version space given a hypothesis eface it and a set E of examples		h. = 4 Sunny Wagn ? Storing, Wagn , Same >
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i) There is no way to determine if the hypothesis is consistent throughout the data ii) In consistent training get can actually mislead the find & algorithm since it ignores the negative examiles iii) It does not provide a backtracking technique to determine the best fourble changes that could be done to imperore the wesult hypothesis Candidate Elimination of the version eface given a hypothesis eface It and a set to of examples i) hoad the data.	#	Limitation 6-
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ii) It does not favoride a backbracking technique to defermine the best favorible changes that could be done to imperove the audult hypothesis Candidate Elimination of It incomentally builds the version eface given a hypothesis eface it and a set E of examples. i) hoad the data		hylothesis is consistant throughout the data
ii) It does not favoride a backbracking technique to defermine the best favorible changes that could be done to imperove the audult hypothesis Candidate Elimination of It incomentally builds the version eface given a hypothesis eface it and a set E of examples. i) hoad the data	ii	In consistant training sets can actually
ii) It does not favoride a backbracking technique to defermine the best favorible changes that could be done to imperove the audult hypothesis Candidate Elimination of It incomentally builds the version eface given a hypothesis eface it and a set E of examples. i) hoad the data		mislead the find-s algorithm since it
technique to défermine the best fairble changes that could be done to impense the execult hypothesis. Candidate Elimination of It incomentally builds the version space given a hypothesis eface it and a set 6 of examples. i) hoad the data		ignores the regative examples
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Candidate Elimination of The version space given a hypothesis elace H and a set E of examples.	/	technique to defermine the best lawble
Candidate Elimination of It incomentally builds the version eface given a hypothesis eface H and a set E of examples. i) hoad the data.		change that Could be done to imperiore
Candidate Elimination of It incomentally builds the version eface given a hypothesis eface H and a set E of examples. i) hoad the data.		the accult hypothesis
the version eface given a hylothesis eface H and a set E of examples. i) hoad the data.		U'
the version eface given a hypothesis eface H and a set E of examples. i) hoad the data.		
the version eface given a hypothesis eface is and a set & of examples. i) hoad the data.		Condidate Elimination o
i) hoad the data.		
i) hoad the data.		the version space given a hypothesis
i) hoad the data.	· 	elace 4 and a set & of examples.
(i) Initialize General and Specific 4Hothesis	i)	
		Initialize General and Brecitic 4Hothesis

	1/6-1		
îâ	For each the toraining example if all value = hypo value: Do nothing else:		
	it alt value = hypo value.		
	Do nothing		
	else:		
	reflace altribute value with		
<i>il)</i>	else: oreflace attribute value with? Il regative example Make generalize hypothesic more efficience.		
	Marke generalie ignoment		
	Take an example		
	Sty Jam? Humid Wind Water Fromest off		
	Bunny Warmal Sterong Warm Some Yes		
	Sunn & Warm High Sterong Warm Same Yes		
=	Rainy Cold High Sterong Weern Change No		
	Sund Weem High Sterong Cool Change Yes		
<u> </u>	Initialize most general and excitic hylo.		
	Initialize most general and elecific hylo. So: 40,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,		
<u> </u>	Compare withe first tre hylothesis		
	S.: 2 Sunny, Warm, Dormal, G.: 27,7,7,7,7,7		
	Strong, Warm, Came >		
	Down, Comfare it with second tre hypothesic. Si: Lunny, Warm, ?, Sterong, Go: 4?????> Warm, Came>		
	l'élieur Wagen ? Starong Ga: 42 2 2 2 2 2		
	Wann James		
	As third hypothesis is we so do		
	accordingly.		
	G: 4 Sunny Warm, 2 G: 4 Sunny ????? Stowng Warm, Rame > 4? Warm?????		
	Sterong Warm, Rame > 27, Warm? 27, 2>		
	4/1 Normel 1/2, 4/1 ((Cool 17		
	42,7,7,7 ,1 same>		

I	Now again Comfare with last the hylo- Suic Sunny, Warm, ?, Sterong, ?, ? > Grit Sunny?????? 2?, Warm??????
	Now final hypothesis is. Gr: < Sunny, ?,??? / 2,? / 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
	Solve using KNN n(A=3, R=7) K=3 A B Label 7 7 False 9 4 Inue 1 4 True
	Now of we want to find the label from x (A=B, R=7) then take dictance from ula ax (xx.)2 + (yy.)2
	A B Pislance Label 7 7 16 False 7 4 95 False 8 4 9 Torne 1 4 18 Torne 8 7
	Now, as we know that the value of k is 3 so we have to take least three distances.

	9 18 16 are the least three distances
	10 18 16 are the least three distances
	It can easily be seen that True?s maximum time in the gresult, so we can conclude that label from x (A = S, R = 7) is force.
	Can conclude that label from
	x(A=S, R=7) is ferue.
(3) a)	Design e learning system & When we fed the
	training date to machine learning algorithm
	tening data to machine learning algorithm This algorithm will broduce a mathematica model and with helf of model the
	model and with help of model the
	machine will make a brediction and
	take a decision whome very extract
	Recognammed Ale during terring data the
	none machine will work with it more it will get experience and the more
	it will get experience and the more
	it will get experience the more efficient
	nesult is fooduced
	Teraining Leaguing Logical Outlut
	Pata Algorithm: Model Outrut
	Learn From Data
	Designing a System & According to Tom Hitchell A Confliten ferageram is said to be leasing
	A Confeden ferageran is said to be leasing
	5/12

from experience (E), with respect to some
tack (1) Thus, the fertermance measure (P)
le the lee formers of lask I which is
measured by P and it improves with
exterience E
Take an example:
Ruffore we are designing a system for
Ruffore we are designing a eyetem for Stam 6-mail Detection o Part, T: To Clarify mails into stam on Not stam
e l'enformance measure, l': Total fencent of mails being Coursetly Clausifice as being 'Sfam' on 'Not Sfam'
as being 'slam' on 'Not slam'
· Exferience, E: Set of mails with label
(Choosing Tagining Exterience)
V
(Choosing Target Function)
(Choosing Refresentation of Torget Function)
(Choosing Function Alleraximation)
V
(Final Pesign)

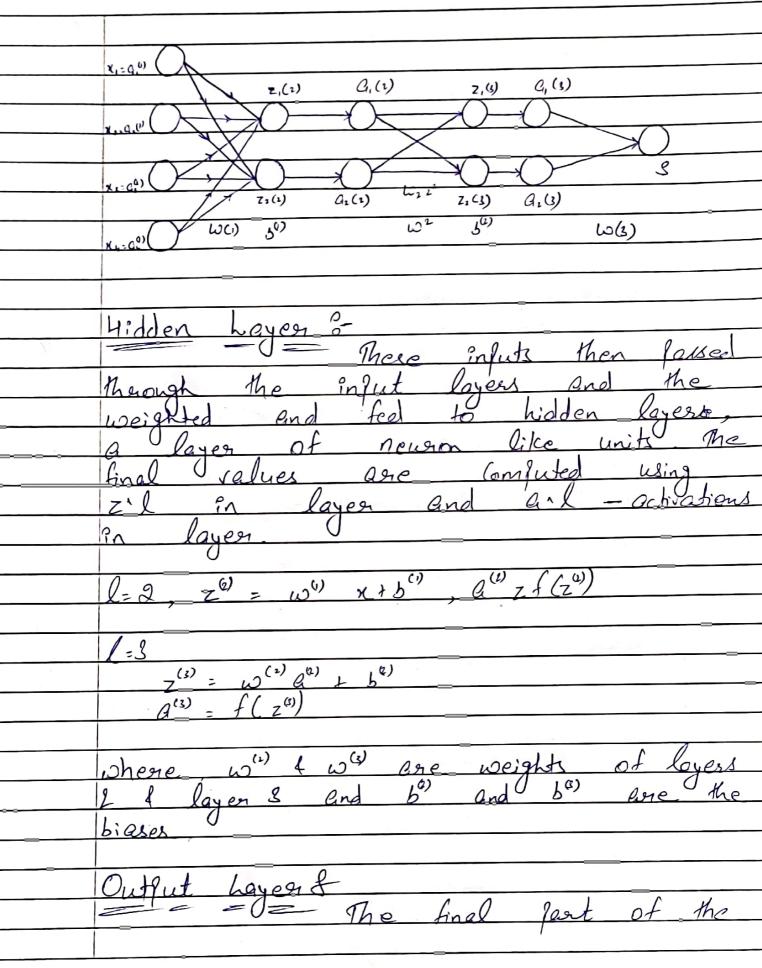
	And the second s	
	Susenvised	Unsulervised
,)	They are brained using labeled date	i) They are torained using unlabeled data
	using labeled date	using unlabeled data
	asing another away	
e.)	The Lekas dianat Sealland	(i) II does not
	TE TAKE MINEY TERMORE	leka an feellact
	19 als les de la	Take and tecapace
	It takes dinect feedback to check if it is beedicting connect output con not	
	1091 NOC	
<i>[ii)</i>	These model fredicts The outfut	iii) Thele model lines
	The output.	the hidden Yastean
	·	in data.
il)	In this, injut data	is) In this, only injust
	is provided to the	data is brovided
	model along with	,
	the outful	is) In this only infect data is provided
	the state of the s	
J)	The goal of this	Who end of this
	leagning is to teain	v) The goal of this model is to find the
	the model so that	hidden lattern and wefil
	it can legedict the	
£	putfut when it is	dalasets
	1 /	Curasers
	given new data	
.)	74 00 10 00 000	vi) It does not need
<u> √c)</u>	It needs sufervision	
	to torain the model	any suservision to train the model
		thain the model.
<u> vii)</u>	It can be categorized	in Clustering and
1	in Claufication and	in Clustering and Accordion Problem
	Reguession Peroleloms.	Accoration broken

	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
(4)	Information gain calculates the neduction
e	120 00 100 01 Or BY 131 171 111 111
	THE CONSTRUCTOR
	tree from the training datelet by
	evaluating the intermation gain of each
	variable and Collecting the variable that
	maximiles the information gain which in
	teem minimises the entropy and efficiently the dataset into grows from effective
	The dataset into grows from effective
	Clousitication
	A skewed distribution has
	low fewbability whereas a distribution
	where centre have equal to have
/	larger entroly
	Enteroly is used to
	larger entroly Entroly is used to Calculate the querity of dataset and
	IN HOSIM GATOLA YELLA (PLOS CEARS G WGY FO
	lue enteropy to calculate how a
	Change to the dataset impacts the
	Purity of the dates et
=	
•	Formula is given as.
	Enterofy(S[A9,08]) = - 90 log. (10) - 90 log. 90
	Information Gain (Sx) - E(S) - ZS. (E)
	111
	the attachetes
	the straibutes
	Now take the example

	A B	Label	10	
	al bl	No		=======================================
	01 52	Yes		
	62 63	Yes	,	
	g2 <u>52</u>	No		
	32 61	Yes		
				2 1 10
We	Can See	that it	Contains	3 tre values
and	2 negativ	ie value	<u>. </u>	
	O			
Ent	20/y PA	Blog PO	- PO log, PO	
I	/()	•		- 07
· 16(3+,2-) = -3	log. 3 -	2 log, 2 -	0.91
	<u>ک</u>	_ گ	5 5	
			<u> </u>	=
Gaic	(SA) = E(S	S) - 夕 富 ((S)	
		_ 80		
	E(s) - 2 E(<u>Sa.) - 3 6</u>	(Sa.)	
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$\mathcal{E}(\mathcal{E})$	Sa) = 1 (.	equal tu	0 4 -VP ex	an ples)
EC	Sa.) = -2 los	9 2 - 1	log.] - ()	.411
	<u></u> ک	ک ک		-
	(0, 1)	0.7 0 1	6 0 913	
(sa	in (S,A) = 0	<u>.41 - 3 x 1</u>	- <u>5</u> , 0.111	
		3		
		S.A) = O.	mias	
	1. 67 (JIN C.	<u> </u>		
	C . 10 i	1) - 5(0)	- 5 By 5(C)	
Now	, Gain (8,6	5/ - 5(3)	16 & 6, b2, b3	
- 7	L		ECSb2) - 115 E	(, (,)
	75 61	C7817 17	00392/ - 13 0	(203)

	$E(S_h) = 1$ (" equal 1ve 4 -ve examples) $E(S_h) = 1$ (" " " " " " " " " " " " " " " " " " "
(5) A)	
·)	Pencelteron Rule Delte Rule In this sule, networki) In delta sule,
	oled to the landing of the soule
	elatit its learning modification in by assigning a sympatic weight of grandom value to a node is equal to
	gandon value to a node is equal to
	each weight the multiplication of
	each weight the multiplication of errors of infut
<u> </u>	It originates serom ii) It derived from hebbian gradient de scent
	method.
iii	It stops after in It Continuous forever
	learning steps. to the solution
<i>[J)</i>	In this rule sample is In this rule
	are linearly soferable training samples are not linearly referable.
	not linearly reparable.
	It trains on the 1) It trains on un-
	The trains on the V) It toking on un-

\(\hat{i}\)	It is deriven by vi) It is deriven by binary differences blu Continuous differences (ormed and bredicted between Correct and predicted outfut. In this rule the vii) In this rule, the weight is modified by gradient descent updates.
	Rack for fagation Algorithm 3- effectively train a neural network through a method (alled chain rule This algorithm for horms learning on a multilayer feed horward neural network It iteratively learns a set of weights for bredicting a class label of tufles The multilayer feed forward neural network has these layers > infut, hidden and outfut layer Infut Layers & Infut Layers & Infut Layers & Infut is feed to units xi = aii, i \in 1, 2, 8, 4 a is a let of achivation equal to the infut values.



neueral network is outfut layer which
$S = \omega^{(s)}$
Brute Force Bayes Learning
For each hypothesis h in 4 Calculate the forterior probability.
P(hID) = P(DIh) P(h) P(D)
· Outfut the hypothesis have with the highest posterior probability
huar = Bargmax PChlD)
9(h)=1 for all h in H
$P(Dlh) = \begin{cases} 1, & \text{if } di = h(x_i) \text{ from all } di & \text{in } D \\ 0, & \text{otherwise}. \end{cases}$
To Rumnosize Rayer theorem inflier that the posterior probability 9(h/D) under our assumed P(h) and P(D/h) is
P(h D) = 1 , if h is Consistent with D [Vsup] O , Otherwise