001.	Back	c-propagation networks are N	Neural	networks	С
				Feed forward	
	С	Multilayer Feed forward	D	Single layer Feed back	
002.	Durir	ng the forward pass of back-propagati	on lea	rning, is applied to the	Α
	sens	ory nodes of the network.			
	Α	Input Vector	В	Hidden Vector	
	С	Output Vector	D	Error Vector	
003.	Durir	ng the backward pass of back-propaga	ation le	earning, is propagated	D
	throu	igh the network.			
	Α	Input	В	Hidden Vector	
	С	Output	D	Error	
004.	The	perceptron learning algorithm work wi	th		Α
				linear neurons	
	С	threshold Function non-linear neurons	D	predicate logic	
005.	Multi	layer feedforward networks are trained	ed by u	using	С
				Perceptron learning Rule	
	С	Error Correlation Learning Rule	D	Delta learning rule	
006.		propagation algorithm may be viewe			D
		Hebb		Widrow-Hoff	
	С	Delta	D	LMS	
007.	Back	propagation algorithm is in r	nature.		С
	Α	Definitive	В		
	С	Stochastic	D	Obvious	
008.	In, B	ackpropagation algorithm	is	to be selected carefully to ensure that	Α
		veights quickly converge to a respons			
		Learning rate	В	Initial weights	
	С	Bias	D	Number of Input units	
009.	Multi	layer perceptron is trained by using _		Learning	Α
				Unsupervised	
		Supervised Semi-supervised	D	Reinforced	
010.	Whic	ch of the following properties is consid	ered a	s the corner stone of neural network	Α
	theo	= : : :			
	Α	Universal function approximation	В	Universal output approximation	
	С	Error minimization	D	Input generalization	
011.	Wha	t is the objective of backpropagation a	algorith	· · · · · · · · · · · · · · · · · · ·	С
	Α	to develop learning algorithm for	В	to develop learning algorithm for	
		multilayer feedforward neural network	k	single layer feedforward neural	
				network	
	С	to develop learning algorithm for	D	none of the mentioned	
		multilayer feedforward neural			
		network, so that network can be			
		trained to capture the mapping			
		implicitly			
012.	Wha	t is true regarding backpropagation ru	ıle?		В
	Α	it is a feedback neural network	В	actual output is determined by	
				computing the outputs of units for	
				each hidden layer	
	С	hidden layers output is not all	D	it is based on widrow-hoff learning	
		important, they are only meant for		rule	
		supporting input and output layers			
013.	Wha		t back	propagation is a generalized delta rule	Α
	?			- <del>-</del>	
	Α	because delta rule can be extended	В	because delta is applied to only input	
		to hidden layer units		and output layers, thus making it	

			more simple and generalized	
	C it has no significance	D	none of the mentioned	_
014.	The property that states that, a network have	_		Α
	approximate the underlying function to any			
	A Universal function approximation C Error minimization		Universal output approximation	
015		D na wh	Input generalization	С
015.	is used for increasing the rate of learni	ng wi	me maintaining stability during weight	C
	updation. A Input size	В	Learning rate	
	C Momentum	D	Bias	
016	Computational capability of a single layer p	_		Α
010.	A Nature of the Activation function	В	Nature of the input	^
	C Nature of the output	D	Choice of initial weights	
017	The LMS learning algorithm work with		Choice of miliar weights	В
<b>U</b>	A threshold logic	В	linear neurons	
	C non-linear neurons	D	predicate logic	
018.	Computational capability of a single layer p			Α
	A Lack of layered architecture	В	Nature of the input/output	
	A Lack of layered architecture C Nature of the Bias	D	Choice of initial weights	
019.	Which of the following tasks cannot be perf			D
	A pattern mapping	В	function approximation	
	C prediction	D	pattern storage	
020.	Backpropagation algorithm uses to char	nge th	e weights in the network	Α
	A error gradient for a pattern	В	some of input vectors	
	C target output	D	bias	
021.	Does backpropagation learning is based or	n grad	=	Α
	A Yes	В	No	
	C cannot be said	D	it depends on gradient descent but	
			not error surface	
022.	The backpropagation law is also known as		ralized delta rule, is it true?	Α
	A Yes	В	no	
	C cannot be said	D	it depends on input	_
023.	The backpropagation law is also known as			Α
	A generalized delta	В	extended Hebbian law	
004	C Hebbian law	D	Perceptron law	_
U <b>Z</b> 4.	Which of the following is not a limitation of			D
	A local minima problem C scaling	B D	slow convergence Poor computational capability	
025	Does back propagation learning is based o		, , , , , , , , , , , , , , , , , , , ,	Α
U <b>Z</b> J.	A Yes	В	No	^
	C cannot be said	D	it depends on gradient descent but	
	o carnot be said	0	not error surface	
026.	Multilayer Perceptron utilizes learn	ina te		Α
0_0.	A Supervised	В	Unsupervised	•
	C Semi-supervised	D	Reinforced	
027.	Introducing a bipolar signal function such a	s the		С
	a significant		31	
	A Reduction of storage space	В	Stability in the weight updation	
	• • • • • • • • • • • • • • • • • • • •		Increase in the accuracy of prediction	
028.	In a backpropagation network, hidden layer			В
	A Linear	В	Sigmoidal	
	C Circular	D	Elliptical	
029.	The error signal at the output of neuron j at			В
	Where d <sub>i</sub> (n) refers to the desired response	and y	<sub>i</sub> (n) refers to the function signal	

	appearing at the output of neuron n.			
	A $e_{i}(n) = y_{i}(n) - d_{i}(n)$	В	$e_{i}(n) = d_{i}(n) - y_{i}(n)$	
	C $e_{i}(n) = d_{i}(n) + y_{i}(n)$		$e_i(n) = d_i(n) * y_i(n)$	
030.	In sequential / pattern mode, weight updation		, , ,	Α
000.	A each training example	В	all training examples	•
	C few training examples of an epoch			
031.	In batch mode, weight updation is performe		·	В
	A each training example	В	all training examples of an epoch	
	C few training examples of an epoch			
032.	If average gradient value fall below a prese			Α
	A Terminated	В	Corrupted	
	C Extended infinitely	D	unresolvable	
033.	In order to maintain a smooth trajectory in v	veigh	t space, in the back propagation	В
	algorithm, has to be kept small.			
	A Input size	В	Learning rate	
	C Momentum	D	Bias	
034.	How can learning process be stopped in ba			C
	A there is convergence involved		no heuristic criteria exist	
	C on basis of average gradient value			
035.	In a backpropagation network, input layer n			A
	A Linear	В	Sigmoidal	
	C Circular	D	Non linear	
036.	Learning rate in the back propagation algor			Α
	order to maintain a smooth trajectory in wei	•	_	
	A Small	В	Large	
	C Average	D	Constant	_
037.	If the gradient has different signs on consec	cutive	iterations then the momentum causes	В
	in the weight space.	_	<b>5</b>	
	A Acceleration	В	Deceleration	
000	C Either Acceleration or deceleration		Cannot be determined	
038.	When neurons saturate the signal values at			Α
	A 0 or 1	В	+Ve or -Ve	
020	C Cannot be determined	D	Infinite values	_
039.	Incorrect choice of weights can lead to	В	Slower convergence	D
	<ul><li>A Faster convergence</li><li>C Network paralysis</li></ul>	D	Network saturation	
040.	'			D
U <del>4</del> U.	A Standardization	В	Normalization	ט
	C Maximization	D	Randomization	
041	Large values of momentum cause the training	_		В
<b>0</b> + 1 · ·	A Deeper global minima	B B	Deeper local minima	
	C Shallow local minima	D	Shallow global minima	
042.	Initialization of the weights of the entire net			С
•	A Faster convergence	В	Slower convergence	
	C Network paralysis	D	Network saturation	
043.	When the training data are redundant,			Α
	A Sequential	В	Batch	
	C Either sequential or batch	D	Neither sequential nor batch	
044.	During weight updation, the magnitude of the	ne mo	•	Α
	are expected to have convergent dynamics		Č	
	A Less than 1	В	Greater than 1	
	C Equal to 1	D	Greater than or equal to 1	
045.	If the gradient has same sign on consecutive	e iter		Α
	in the weight space.			

	Α	Acceleration	В	Deceleration	
	С	Either Acceleration or deceleration	D	Cannot be determined	
046.	Feed	dback connection strength are usually?			A
	A	Fixed	В	Variable	
o 4=	С	both fixed or variable type	D	set to either 1 or 0	_
047.	_	backpropagation network, output layer			В
	A C	Linear	B D	Sigmoidal Non linear	
040	_	Circular of hyperbolic tangent function comes w	_		Α
U40.		red signals extends to	/1111 111	e advantage that the range of valid	A
	A	[1 + , 1]	В	[, n ]	
	Ĉ	[n+,n]	D	[1 + , ]	
049	_	dforward networks are used for?	0	[[ + , ]	D
040.	A	Autoassociation	В	pattern storage	
	C	both autoassociation& pattern	D	pattern classification	
	Ū	storage	_	pattern diagonication	
050.		<u> </u>	numl	per of hidden layers in a multilayer	Α
		eptron with an input-output mapping the			•
	•	continuous mapping.	at pro	The or an approximate realization of	
	A	Universal approximation	В	Uniform approximation	
	C	Function approximation	D	Continuous approximation	
051.	_	dforward networks are not used for?	_	отписае аррголиналог.	D
	Α	pattern mapping	В	pattern association	
	С	pattern classification	D	Pattern Storage	
052.	Grad	dient of the pattern error is employed in	weig	<u> </u>	C
		over the entire training set.	Ū	•	
	Α	Local Error	В	Local minima	
	С	Global Error	D	Global minima	
053.	Whic	ch of the following is not a criterion for t	ermin	ating network training?	D
	Α	Compare absolute value of squared	В	use the absolute rate of change of the	
		error averaged over one epoch, with		mean squared error per epoch	
		a training tolerance			
	С	Check if Euclidean norm of the error	D	Compare the number of patterns fed	
		gradient falls below a sufficiently		into the network with a threshold	
		small threshold			
054.	_	network generalizes well if it is able to	_		В
	Α	Predict incorrect or near incorrect	В	Predict correct or near correct outputs	
	_	outputs for unseen inputs	_	for unseen inputs	
	С	Complete the training in a	D	Maximize the error gradient	
0FF	1	considerably few iterations		bidden leven evter etc	_
055.	_	network with two hidden layers, the sec			D
	A	Local features of the function	В	Features of Input Vector	
0E6	C	Features of Output Vector	D	Global features of the function	С
UOO.	_	network consists of layers.	В	Finite number	C
	A C	Single Three	D	Multiple	
057	_		_	•	D
037.	_	RBF network, the hidden nodes implen	B B	Sigmoid	ט
	A C	Square Logistic	D D	Gaussian	
<b>052</b>		RBF network, the output nodes implem	_	functions.	Α
<del>000</del> .	А	Linear Summation	B	Sigmoid	^
	Ĉ	Logistic	D	Radial Basis	
059		re-fitting process is easier with	٦	Tadiai Baoio	В
	A	One hidden layer	В	Two hidden layers	_
		,		•	

060	C	Three hidden layers	D t bidd	N hidden layers	٨
UOU.	_	network with two hidden layers, the firs			Α
	A	Local features of the function	В	Features of Input Vector	
061	C	Features of Output Vector ork saturation is a condition where	D	Global features of the function	Α
	A	Weight changes are almost negligible		Weights are set to maximum values	A
	^	over consecutive epochs.	Ь	Weights are set to maximum values	
	С	Weights are set to minimum values	D	Weights are set to fixed values	
062		ptimal learning rate reaches the error n		<del>-</del>	В
00 <u>2</u> .	A	2 learning steps	В	single learning step	
	C	Finite number of learning steps	D	Infinite number of learning steps	
063		ning rates that are larger than twice the			Α
000.	A	Diverge from the solution	В	Converge to the error minimum	, ,
	C	Converge to the global optimum	D	Take longer to converge	
064.	_	SF network, output layer is		Take lenger to converge	Α
•••		Linear	В	Non-linear	
	C	Sigmoidal	D	Either sigmoidal or linear	
065.		network contains hidden layer	er(s)	o. o.go.aa. ooa.	Α
	Α	1	В	2	
	С	3	D	N	
066.	RBF	networks are used for			С
	Α	Pattern Association	В	Pattern Storage	
	С	Pattern Classification	D	Pattern clustering	
067.	Whic	ch of the following Radial Basis Functio	ns is	not covered by Micchellis theorem?	C
	Α	Multiquadrics	В	Inverse multiquadrics	
	С	Inverse Quadratic	D	Gaussian	
068.		are very good at interpolation.			C
	Α	Single layer Perceptrons	В	Multilayer Perceptrons	
	С	RBF Networks	D	Feedback Networks	
069.	In RI	BF network, hidden layer is			В
	Α	Linear	В	Non-linear	
		Sigmoidal	D	Either sigmoidal or linear	_
070.	_	RBF network training is divided into			Α
	Α	Two	В	Three	
	С	Four	D	N(A finite number)	_
		e first stage of RBF network training, th	e we	ights from thelayer are	Α
		rmined.	_	TP The feet of	
		Input to hidden	В	Hidden to output	
070		Input to output	D	First hidden to second hidden	_
0/2.		e second stage of RBF network training	y, ine	weights from thetayer are	В
		rmined	В	Hiddon to output	
		Input to hidden	D		
072		Input to output dial basis function network requires			Ъ
073.	point		HUHL	dei di radiai basis functions for in data	ט
	A	1	В	2	
	C	3	D	N	
074	_	problem of reconstructing the hypersur	_		С
		wing condition is not satisfied.	iace	is said to be well posed ever if the	C
	A	Existence	В	Uniqueness	
	C	Linearity	D	Continuity	
075		physical phenomenon responsible for $\mathfrak g$	_	•	Α
	prob		, 01.101		, \
	•	Well posed direct	В	Well posed inverse	

076.	C In a	Ill posed direct radial basis function network, number of	D of rad	Ill posed inverse ial basis functions is number of	С
		points		<del></del>	
	Α	Less than	В	Greater than	
	С	Equal to	D	Not dependent	
077.	For	which of the following functions, the inte	erpola	ation matrix is positive definite?	В
	Α	Multiquadrics	В	Inverse multiquadrics	
	С	Inverse Quadratic	D	Either Inverse Quadratic or	
				Multiquadrics	
078.	Whi	ch of the following functions is suitable	for us		Α
	Α	Multiquadrics	В	Inverse multiquadrics	
	С	Inverse Quadratic	D	Either Inverse Quadratic or Gaussian	_
079.	_	ch of the following are the two phases of		•	Α
	A	Training and generalization	В	Training and testing	
000	С	Training and validating	, D	Testing and validating	
080.		strict interpolation, the interpolating sur			Α
	A	All the training data points		selected training data points	
004	C	All the testing data points	D	<b>U</b> 1	
UO 1.		ch of the following is the common properiquadrics functions?	BILY S	nated by Gaussian and inverse	Α
	Α	They are both localized functions	В	They are both nonlocal functions	
	С	They are both bell curve shaped	D	There dont share any common	
				property	_
082.		er surface reconstruction problem is sa			D
	Α	Existence, uniqueness and continuity	В	If any two of Existence, uniqueness	
	_	conditions are all satisfied	_	and continuity conditions are satisfied	
	С	If any one of Existence, uniqueness	D	If any one of Existence, uniqueness	
		and continuity conditions is satisfied		and continuity conditions is not satisfied	_
083.	_	can be used for solving ill posed proble		To continue the	Α
	A	Regularization	В	Transformation	
004		Translation	D	Standardization	۸
U04.	A	onov 's regularization theory involved Standard error term	ves w B	Weighted error term	Α
	C			welaniea enorienn	
085	$\mathbf{C}$	Regularized error term		•	
000.	Tikh	Regularized error term	D	Summative error term	Δ
		onov 's standard error term measu	D ures t	Summative error term he standard error between	A
	Α	onov 's standard error term measu Desired and actual response	D ures tl B	Summative error term he standard error between Input and output	Α
		onov 's standard error term measu	D ures tl B	Summative error term he standard error between Input and output Desired response and target	A
	A C	onov 's standard error term measu Desired and actual response Induced local field and target output	D ures ti B D	Summative error term he standard error between Input and output Desired response and target response	
	A C	onov 's standard error term measu Desired and actual response Induced local field and target output	D ures ti B D	Summative error term he standard error between Input and output Desired response and target response	A
	A C An i	onov 's standard error term measu Desired and actual response Induced local field and target output	D ures t B D osed	Summative error term he standard error between Input and output Desired response and target response problem via	
086.	A C An i A C	onov 's standard error term measu Desired and actual response Induced local field and target output Il posed problem can be made a well po Regularization Translation	D ures the B D osed he B D	Summative error term he standard error between Input and output Desired response and target response problem via Transformation	
086.	A C An i A C	onov 's standard error term measu Desired and actual response Induced local field and target output Il posed problem can be made a well po Regularization	D ures the B D osed he B D	Summative error term he standard error between Input and output Desired response and target response problem via Transformation	Α
086.	A C An i A C Auto	onov 's standard error term measu Desired and actual response Induced local field and target output Il posed problem can be made a well po Regularization Translation omated vehicle is an example of	D ures th B D osed h B D	Summative error term he standard error between Input and output Desired response and target response problem via Transformation Standardization	Α
086. 087.	A C Auto A C For	Desired and actual response Induced local field and target output II posed problem can be made a well posed problem can be made a we	D ures the B D osed   B D - B D erpola	Summative error term he standard error between Input and output Desired response and target response problem via Transformation Standardization  Unsupervised learning Reinforcement learning ation matrix has N-1 negative eigen	Α
086. 087.	A C Auto A C For	Desired and actual response Induced local field and target output II posed problem can be made a well posed local field and target output II posed problem can be made a well posed problem can be made a well posed problem can be made a well posed learning active learning	D ures the B D osed   B D - B D erpola	Summative error term he standard error between Input and output Desired response and target response problem via Transformation Standardization  Unsupervised learning Reinforcement learning ation matrix has N-1 negative eigen	A
086. 087.	An i A C Auto A C For value A	Desired and actual response Induced local field and target output II posed problem can be made a well posed problem can be made a we	D ures the B D osed   B D - B D erpola	Summative error term he standard error between Input and output Desired response and target response problem via Transformation Standardization  Unsupervised learning Reinforcement learning ation matrix has N-1 negative eigen	A
086. 087.	An i A C Auto A C For value	Desired and actual response Induced local field and target output II posed problem can be made a well posed problem can be made a well posed	D ures the B D osed p B D B D erpolation	Summative error term he standard error between Input and output Desired response and target response problem via Transformation Standardization  Unsupervised learning Reinforcement learning ation matrix has N-1 negative eigen it not positive definite? Inverse multiquadrics Either Inverse Quadratic or	A
086. 087. 088.	An i A C Auto A C For valu A C	Desired and actual response Induced local field and target output II posed problem can be made a well posed problem can be made a we	D ures the B D osed posed pose	Summative error term he standard error between Input and output Desired response and target response problem via Transformation Standardization  Unsupervised learning Reinforcement learning ation matrix has N-1 negative eigen it not positive definite? Inverse multiquadrics Either Inverse Quadratic or Gausssian	A A
086. 087. 088.	A C Auto A C For value A C Whi	Desired and actual response Induced local field and target output II posed problem can be made a well posed problem can be made a well posed posed posed problem can be made a well posed posed posed posed problem can be made a well posed pos	D ures the B D osed posed pose	Summative error term he standard error between Input and output Desired response and target response problem via Transformation Standardization  Unsupervised learning Reinforcement learning ation matrix has N-1 negative eigen it not positive definite? Inverse multiquadrics Either Inverse Quadratic or	A A
086. 087. 088.	An i A C Auto A C For valu A C	Desired and actual response Induced local field and target output II posed problem can be made a well posed problem can be made a well posed posed posed problem can be made a well posed posed posed posed problem can be made a well posed pos	D ures the B D osed posed pose	Summative error term he standard error between Input and output Desired response and target response problem via Transformation Standardization  Unsupervised learning Reinforcement learning ation matrix has N-1 negative eigen it not positive definite? Inverse multiquadrics Either Inverse Quadratic or Gausssian	A A

090.	Lear	ning from physical forms of data such a	as sp	eech, pictures, radar signals, viewed	D
	as a	hyper surface reconstruction problem	is	_ problem	
	Α	Well posed direct	В	Well posed inverse	
	С	III posed direct	D	III posed inverse	_
091.	-		paran	neter is assigned a value somewhere	В
	betw		_		
	A	-infinity and 0	В	0 and infinity	
000	С	-1 and 1	D	0 and 1	_
092.	_	ularization provides a practical solution			В
	A	Biaslearningrate dilemma	В	Bias-variance dilemma	
003	C	Learningrate-momentum dilemma		Learningrate-variance dilemma reted as the best approximation.	٨
093.	A	Local linear	В	Global linear	A
	C	Local non-linear	D	Global non-linear	
094	_	onov 's regularization theory involv			Α
034.	A	Regularising term	B	Weighted error term	_
	C	Regularized error term	D	Summative error term	
095.		ording to regularization theory, 0 implie		Carrinative error term	Α
	Α	The solution can be completely	В	The solution can be partially	-
		determined by the examples		determined by the examples	
	С	The solution cannot be completely	D	The examples are unreliable	
		determined by the examples		•	
096.	Acco	ording to regularization theory, implies	6		C
	Α	The solution can be completely	В	The solution can be partially	
		determined by the examples		determined by the examples	
	С	Prior smoothness constraint is	D	The examples are reliable	
		sufficient to specify the solution			
097.		proposed regularization method for so	_		С
	A	Cover	В	Powell	
000	C	Tikhonov	D	Broomhead	
098.		quantity to be minimized in regularizati			Α
	C	Tikhonov functional Regularization parameter	D D	Minimization parameter	
nga		ilarization parameter may be viewed a		•	Α
033.	A	sufficiency of the given data set as	В	sufficiency of the accuracy obtained	^
	, ,	examples that specify the solution		for given set of examples	
		F(X)		Tot given out of examples	
	С	insufficiency of the given data set as	D	insufficiency of the accuracy obtained	
	C	examples that specify the solution	D	for given set of examples	
		F(X)		for given set of examples	
100	Dogu	` '			D
100.		ularization prevents	В	Model over fitting	В
	A C	Model under fitting Both over and under fitting	D	Model over fitting Prediction error	
101	_	ber of hidden nodes in regularization F			D
101.		ng is	וו וט	etwork with it examples available for	ט
	A	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	В	2	
	C	3	D	N	
102.	_	th of the following parameters are unkr	nown		D
-	Α	Activation functions of the hidden	В	Positions of the centres of the radial	
		layer		basis functions	
	С	Norm weighting matrix associated	D	Linear weights of the output layer	
		with the hidden layer			
103.	Belln	nans curse of dimensionality tells that i	irresp	ective of the approximation techniques	Α

		loyed, if the smoothness index is maint		•	
	need A	ded for the approximating function to at Exponentially with the input	tain d B	egree of accuracy increases Linearly with the input dimensionality	
	^	dimensionality	Ь	Linearly with the input dimensionality	
	С	constantly with the input	D	Polynomially with the input	
		dimensionality		dimensionality	
104.	Whic	ch of the following is not a desirable pro	perty	of regularization network?	D
	Α	It is a Universal approximator	В	It has the best approximation property	
405	C	It computes optimal solution	D	It is expensive	_
105.	_	condition number of a matrix is defined		_	Α
	Α	Ratio of largest eigen value to the	В	Ratio of smallest eigen value to the	
	С	smallest eigen value of the matrix Ratio of largest value to the smallest	D	largest eigen value of the matrix Ratio of smallest value to the largest	
	C	value of the matrix	D	value of the matrix	
106.	Whic	ch of the following terms depend on the	geor		Α
	func		900.	manna proposition or approximation.	
	Α	Regularising term	В	Weighted error term	
	С	Regularized error term	D	Summative error term	
107.		equation defines a necessary condition	for th	ne Tikhonov functional to have an	С
	extre	emum at F(x)			
	Α	Greens function	В	Dirac delta function	
400	С	Euler-Lagrange	D	Hilbert	_
108.	_	ens function is a function	D	Linaummatria	Α
	A C	Symmetric Asymmetric	B D	Unsymmetric Null	
109	_	space of approximating functions attair	_		Α
		easingly constrained as	10010	marries newerne seconde	•
	Α	Input dimensionality m <sub>0</sub> is increased	В	Input dimensionality $\mathbf{m}_0$ is decreased	
	С	Number of hidden units are increased	D	Number of output units are increased	
110.	_	curse of dimensionality can be broken			D
	Α	Either neural networks or any other	B	Multi layerperceptrons	
		non-linear technique of similar nature			
	С	RBF networks	D	Neither neural networks nor any other	
444	۸ - ۱:		חחר	non-linear technique of similar nature	
111.	ACTIV	ation function of each hidden unit in ar Euclidean norm	B B	Distance between input vector and	Α
	A	Euclidean norm	Ь	output vector	
	С	Outer product of the input vector and	D	Inner product of the input vector and	
		the synaptic weight vector of that unit		the synaptic weight vector of that unit	
112.	Base	ed on the linear characteristics of the or	utput		В
	close	ely associated to			
	Α	Multilayer perceptron	В	Rosenblatts perceptron	
	С	Either single layer perceptron or	D	Neither single layer perceptron nor	
442	Tab	Multilayer perceptron		Multilayer perceptron	
113.		e immune to the curse of dimensionalit number of parameters.	y, an	approximating function should with	А
	A	Increase smoothness index	В	Decrease smoothness index	
	Ĉ	Increase number of training examples		Decrease number of training	
	_	i care manufacture and manufacture processing commenced	_	examples	
114.		_ method can be used to convert an ill բ	osed	•	Α
	Α	Regularization	В	Transformation	
	C	Translation	D	Standardization	_
115.	Mod	el over fitting is prevented by			В

	A C	Normalization Standardization	B D	Regularization Neutralization	
116.	The	ratio of largest eigen value to the small	est ei	gen value of the matrix is called	В
	num				
	A	Eigen	В	Condition	
	С	Singular	D	Cardinal	_
117.		gularization RBF network, the number	of hid	den nodes isthe number of	С
		nples available for training.	_		
	A	Less than	В	Greater than	
440	C	Equal to	D	No relation	_
110.		oose you are using RBF kernel in SVM	with	nigh Gamma value. What does this	В
	signi A	The model would consider even far	В	The model would consider only the	
	^	away points from hyperplane for	Ь	points close to the hyperplane for	
		modelling		modelling	
	С	The model would not be affected by	D	The model will be too constrained and	
	•	distance of points from hyperplane for		include all points of the training	
		modelling		dataset	
119.	The	cost parameter in the SVM means:			С
	Α	The number of cross-validations to be	В	The kernel to be used	
		made			
	С	The tradeoff between	D	The size of input data	
		misclassification and simplicity of the			
		model			
120.	The	effectiveness of an SVM depends upor			D
	Α	Selection of Kernel	В	Kernel Parameters	
	С	Soft Margin Parameter C	D	kernel, kernel parameters and soft	
404	16.1	and the second control of the second control of		margin parameter	_
121.		m using all features of my dataset and			С
	_	but ྂ%on validation set, what sh Underfitting	ouia i B	Nothing, the model is perfect	
	A	Overfitting	D	Increase the training samples	
122	Wha	t do you mean by a hard margin?	D	morease the training samples	Α
	A	The SVM allows very low error in	В	The SVM allows high amount of error	•
	-	classification	_	in classification	
	С	The SVM is very flexible in	D	The SVM is generalized and works	
		classification		extremely well for unseen data	
123.	The	SVMs are less effective when:		•	С
	Α	The data is linearly separable	В	The data is clean and ready to use	
	С	The data is noisy and contains	D	Datasets which have a clear	
		overlapping points		classification boundary	
124.	_	networks construct	_		D
	Α	Global approximations to linear input-	В	Local approximations to linear input-	
	_	output mapping	_	output mapping	
	С	Global approximations to non-linear	D	Local approximations to non-linear	
125	\//ha	input-output mapping	n torr	input-output mapping	В
125.	A	t do you mean by generalization error i How far the hyperplane is from the	В	How accurately the SVM can predict	D
	$\overline{}$	support vectors	U	outcomes for unseen data	
	С	The threshold amount of error in an	D	How accurately the SVM can predict	
	_	SVM	_	the class labels of test data	
126.	Supr	port vectors are the data points that lie			Α
	A	Closest to the decision surface	В	On the decision surface	-
	С	Farthest to the decision surface	D	On either side of the decision surface	

A Pattern Classification C Pattern Clustering D Pattern Storage  128. The main idea of SVM is to construct a hyperplane in such a way that the margin of separation between positive and negative examples is  A Minimized B Neutralized C Maximized D Nullified  129. SVM is an approximate implementation of the method of A structural risk maximization B structural risk minimization C standard risk nullification D standard risk minimization  130. The principle of SVM is based on the fact that generalization error rate is bounded by a term that depends on VC dimension  A inner product of training error rate and B difference between training error rate and a term that depends on VC dimension	
<ul> <li>128. The main idea of SVM is to construct a hyperplane in such a way that the margin of separation between positive and negative examples is  A Minimized B Neutralized C Maximized D Nullified</li> <li>129. SVM is an approximate implementation of the method of A structural risk maximization B structural risk minimization C standard risk nullification D standard risk minimization</li> <li>130. The principle of SVM is based on the fact that generalization error rate is bounded by  A inner product of training error rate and B difference between training error rate a term that depends on VC dimension</li> </ul>	В
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A structural risk maximization B structural risk minimization C standard risk nullification D standard risk minimization  130. The principle of SVM is based on the fact that generalization error rate is bounded by  A inner product of training error rate and B a term that depends on VC dimension and a term that depends on VC dimension	С
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A inner product of training error rate and B difference between training error rate and a term that depends on VC dimension	
a term that depends on VC dimension and a term that depends on VC dimension	е
a term that depends on VC dimension and a term that depends on VC dimension	
C access of two indices are not a condition and a towns D access and a town on the condition and a condition a	
C sum of training error rate and a term D outer product of training error rate	
that depends on VC dimension and a term that depends on VC	
dimension	
<b>131.</b> What is the consequence of increasing the complexity (or degree of polynomial of the kernel used) linear kernel which perfectly fits the data?	Α
A Increasing the complexity will overfit B Increasing the complexity will under	it
the data the data	
C Nothing will happen since the model D Increases the misclassification rate	
was already 100% accurate for training data	
132. SVM stands for	В
A Standard Vector Machine B Support Vector Machine	
C Sequential Vector Model D Structured Velocity Model	_
133. Which of the following is not an application of the SVM?	D
A Text and Hypertext Categorization B Image Classification C Clustering of News Articles D Payroll Generation	
<b>134.</b> While training an SVM, increasing the number of features in training samples causes	D
A Increased bias and variance B Decreased bias and variance	
C Increased bias and decreased D Increased variance and decreased	
variance bias	
135. Suppose you have trained an SVM with linear decision boundary after training SVM,	С
you found that the model is under fitting. Which of the following options should you	
consider for resolving the problem?	
A increase the data points  B decrease the data points	
C increase the features D reduce the features	С
<b>136.</b> Optimal hyperplane is the hyperplane for which the margin of separation is  A Minimized B Neutralized	C
C Maximized D Nullified	
137. What is/are true about kernel in SVM? 1) Kernel function maps low dimensional data	to C
high dimensional space 2) It is a similarity function	
A 1 B 2	
C 1 and 2 D Neither 1 nor 2	
<b>138.</b> In the context of using Gaussian kernel in SVM, which of the following statements	В
is/are true about feature normalization? 1) We do feature normalization so that new	
feature will dominate other 2) Sometimes, feature normalization is not feasible in case	
of categorical variables 3) Feature normalization always helps when we use Gaussian kernel in SVM	1
kernel in SVM A 1 B 1 and 2	
C 1 and 3 D 2 and 3	
<b>139.</b> For an optimal hyperplane, the optimum condition is attained by minimizing the	Α

	A C	Euclidean norm of weight vector.  Number of training examples	B D	Weight vector Number of features in a training vector	
140.	Give	n input vector x, weight vector w and b	ias b,		В
	the f	orm of hyperplane that does the separa	ation i		
	Α	$w^Tx+b<0$	В	$w^Tx+b=0$	
	С	$w^Tx+b>0$	D	$w^Tx+b>=0$	
141.	Marg	gin of separation is the separation betw	een _		Α
	Α	the hyperplane and the closest data	В	The hyperplane and the farthest data	
		point		point	
	С	any two closest data points	D	any two farthest data points	_
142.	_	e case of separable patterns, SVM pro			В
	Α	a value of zero for both generalization	В	a value of zero for generalization	
		error and the term that depends on VC dimension		error and minimizes the term that	
	С	a value of zero for generalization	D	depends on VC dimension minimum values for both	
	C	error and maximizes the term that	D	generalization error and the term that	
		depends on VC dimension		depends on VC dimension	
143.	The	support vectors consist of		aspends on ve amiension	Α
	Α	subset of training data extracted by	В	subset of testing data extracted by	
		the algorithm		the algorithm	
	С	sum of the training examples	D	sum of the testing examples	
		calculated by the algorithm		calculated by the algorithm	
144.		oort vector learning algorithm cant cons			D
	A	Polynomial learning machines	В	Radial Basis Function networks	
4 4 5	C	Two-layer Perceptrons	D bo fol	Bayesian classifiers	Р
145.	in in	e context of duality theorem, which of the context of the primal problem has an optimal	ne ioi B	If the primal problem has an optimal	В
	^	solution, the dual problem also has an		solution, the dual problem also has an	
		optimal solution, and the		optimal solution, and the	
		corresponding optimal values are not		corresponding optimal values are	
		equal.		equal.	
	С	If the primal problem has an optimal	D	If the primal problem has an optimal	
		solution, the dual problem may not		solution, the dual problem may not	
		have an optimal solution, and the		have an optimal solution, and the	
		corresponding optimal values are		corresponding optimal values are not	
		equal.		equal.	_
146.		limension of a set of separating hyperp	lanes	in a space of dimensionality m is	С
	-	al to	D	m 1	
	A C	m m+1	B D	m-1 -m	
147	_	support vector machine a structure is ir	_		С
		trainingof the weight vector w	-	od on the oot of coparating planes by	
	A	size	В	sign	
	С	Euclidean norm	D	distribution	
148.	Optin	mal hyperplane is the separating hyper	plane	with	Α
	Α	largest margin of separation	В	Smallest margin of separation	
	С	Maximized cost function	D	Maximized bias	
149.		·	-	lem is determined by the saddle point	Α
		agrangian function, which has to be min		•	
	A	w and b	В	W	
	С	b	D	w or b	

150.		dual problem has the same optimal val	ue as	the primal problem, but with	D
	•	iding the optimal solution.	Ь	Diag	
	A C	Weight Vector Weight Vector and Bias	B D	Bias	
151		constrained optimization problem is cal	_		В
101.	A	Primary Problem	пса _ В		
	C	Dual Problem	D	Prime Problem	
152.	The	constrained optimization problem may	be so		С
	Α	Gaussian Multipliers			
	С	Lagrange Multipliers	D	Bayesian Multipliers	
153.		solution to the constrained optimization	prob	lem is determined by the saddle point	C
	of	<del>.</del>			
	Α	Gaussian function Lagrangian function	В		
				Bayesian function	
154.		measure deviation of a data poin	it fron	n the ideal condition of pattern	Α
	sepa A	rability.	D	Coft margin	
		Slack variables Hard margin	B D	Soft margin Euclidean norm	
155		mization of () with respect to w is a	_		В
100.	A	convex	В	nonconvex	
	C	linear	D	polynomial	
156.	_	convex optimization problem is		p o yo.	В
	Α	NP-Hard	В	NP-Complete	
	С	NP	D	P	
157.	Supp	port vector machine is a learning metho	d for		Α
	Α	feedforward network	В	feedback network	
	C	recurrent network	D	Deep neural network	_
158.	_	h of the following cases does not cause		<del>-</del>	Α
	Α	The data point (xi, di) falls outside the			
		region of separation but on the right			
	С	side of decision surface The data point (xi, di) falls outside the		side of decision surface The data point (vi. di) falls inside the	
	C	region of separation but on the wrong	0	region of separation but on the wrong	
		side of decision surface		side of decision surface	
159.	Slac	k variables are		oldo of dociolori odridoo	В
	Α	Non-negative vectors	В	Non-negative scalars	
	С	Non-positive vectors	D	Non-positive scalars	
160.	Whic	ch of the following two statements is/are	e reas	son(s) for slower behaviour of SVM?	C
	1) Th	nere is no control over the number of da	ata po	pints selected by the learning algorithm	
		se as support vectors 2) There is no pr			
	_	ut the task at hand into the design of lea	arning	machine	
	A	1	В	2	
464	C	Both 1 and 2	D	Neither 1 nor 2	Ь
101.		set of non-separable patterns are given		•	В
	A	ning algorithm is to find an optimal hype Doesnt encounter classification errors	•	e mat Minimizes the probability of	
	A	Doesni encounter classification enois	Ь	classification errors	
	С	Maximizes the probability of	D	Either minimizes or maximizes the	
	_	classification errors	_	probability of classification errors	
162.	The	margin of separation is said to be soft i	f a da	•	D
_		for i = .1, 2,, N		, , , ,	
	Α	$di(w^{T}xi+b) > 0$	В	$di(w^Txi+b) >= 0$	
	С	$di(w^{T}xi+b) >+1$	D	$di(w^{T}xi+b) >= +1$	
		SILIT VII DI CII		WI(11 MI D) 7 - 11	

163.		Which of the following two statements is true? 1) Backpropagation algorithm minimizes <b>A</b> quadratic loss function regardless of what the learning task is. 2) SVM also minimizes			
	-	a quadratic loss function for reducing the misclassification rate.			
	Α΄	1	В	2	
	С	Both 1 and 2	D	Neither 1 nor 2	
164.	To re	educe misclassification rate, support ve	ctor I	earning algorithm minimizes number	В
		of training samples that fall inside the margin of separation. This statement is			
	approximately true because				
	Α	Indicator function is used instead of	В	slack variables are used instead of	
		slack variables		indicator function	
	С	slack variables are not used	D	Both slack variables and indicator	
				function are used	
165.	Whic	ch of the following two statements is tru	e? 1)		С
	minimizes number of training samples that fall inside the margin of separation to				
	improve accuracy of classification. 2) Backpropagation algorithm minimizes a quadr loss function regardless of what the learning task is				
	A	1	В	2	
	C	Both 1 and 2	D	Neither 1 nor 2	
166.	_	bypasses curse of dimensionality prob	_		В
	performing the constrained optimization problem.				
	A primal problem B dual problem				
	C	minimization of generalization error	D	maximization of classification	
	0	Thin in in Zation of goneralization of or		accuracy	
167	7. Which of the following are not included by SVMs?				
107.	A	Polynomial learning machine	B	RBF network	D
	C	Two-layer Perceptron	D	Single layer perceptron	
168		operates in		Olligie layer perception	Α
100.	A	Batch mode	В	Sequential mode	^
	C	Pattern mode	D	Sample mode	
160	_			•	Α
103.	SVM can be used to design a feedforward network with hidden layer(s) of units.				^
	Δ	single, nonlinear	R	multiple, nonlinear	
	C	single, linear	D	multiple, linear	
170		oort vectors are		manple, inteat	С
170.	A	not part of training data	В	subset of test data	U
	C	subset of training data	D	average values computed from	
	C	Subset of training data	D	training data	
171	<b>C</b> \/ <b>N</b> /	consists of guadratic programming pro	ahlam	•	_
171.		SVM consists of quadratic programming problem, which of the following two reason(s) <b>C</b> causes it attractive? 1) It is guaranteed to find a global extremum of the error surface 2)			
	The computation can be performed efficiently.				
		computation can be performed efficient	Ĺ	2	
	A C	Poth 1 and 2	D B		
470	_	Both 1 and 2	_	Neither 1 nor 2	Α
1/2.		By using, SVM automatically finds all the important network parameters			
		aining to that choice of a kernel	_	Manual time	
	A	Inner-product kernel	В	Kernel type	
470	C	Training data	D	Test data	_
1/3.	, , , , , , , , , , , , , , , , , , , ,				В
	Α	Size of the training sample	В	Square of the size of the training sample	
	С	Complexity of kernel	D	Number of target classes	