1	the weights may be reduc	eed to zero.				
a	L1 and L2	(b) L1	\bigcirc	L2	d None of	the above
2 . Ba	gging is an ensemble tech	nnique that:				
(a) (b) (c) (d)	-	on different subsets of the data by iteratively updating weight				
3. W	hat is the primary purpos	e of regularization in deep lear	rning	?		
(a) (b) (c) (d)	to increase computations to reduce the number of to prevent overfitting to speed up the training	layers in a neural network				
4. W	hich of the following regu	alarization techniques adds a p	enalt	y term based on the absol	ute values of th	ne weights?
a	L1 regularization	(b) L2 regularization	\bigcirc	Dropout	d Elastic N	et
5 . In	neural networks, what do	oes L2 regularization encourag	e?			
(a) (c)	Sparse weight matrices small weight values		(b) (d)	large weight values No impact on weight val	ues	
6 . Ho	ow does dropout regulariz	ation work in a neural networ	k?			
(a) (b) (c) (d)	It randomly drops input It randomly drops entire It adds noise to the input It introduces a penalty to	layers during training t data				
7. W	hich regularization techni	que combines both L1 and L2	penal	lties?		
(a) (c)	Dropout Elastic Net		(b) (d)	Ride regression Batch Normalization		
8. W	hat is the purpose of early	stopping as a form of regular	izatio	on?		
(a) (b) (c) (d)	To prevent the model from To speed up the convergence of the convergen	cess when the model is underfi om memorizing the training da ence of the training process outliers in the training data	_			
9. W	hich of the following state	ements is true about the bias-v	arian	ce tradeoff in the context	of regularizati	on?
(a) (b) (c)	Regularization always in Regularization can help	acreases bias and decreases variance balance bias and variance	e	•		
(d)	_	npact on the bias-variance trad tworks, what does weight deca		er to?		
TA. 11	a and content of ficular fic	en orno, mriai acco weigiii acci	וטועה	C1 10.		

(a)	The gradual increase in weight values during training					
$\overline{\mathbf{b}}$	The gradual decrease in weight values during training					
\bigcirc	The removal of unnecessary weights from the network					
$\overline{\mathbf{d}}$	The introduction of noise to the weight values					
11. W	which of the following is a disadvantage of using a high	regularization strength in a neural network?				
a	Increased risk of overfitting					
$\overline{\mathbf{b}}$	Faster convergence during training					
\bigcirc	Enhanced generalization to new data					
\bigcirc	Reduced capacity to capture complex patterns					
12. W	hat is weight decay?					
	A regularization technique (such as L2 regularization) the iteration.	hat results in gradient descent shrinking the weights on every				
b	Gradual corruption of the weights in the neural netwo	rk if it's training on noisy data.				
\bigcirc	The process of gradually decreasing the learning rate of	luring training				
\bigcirc	A technique to avoid vanishing gradient by imposing a	ceiling on the values of the weights.				
13 . If	you have 10,000,000 examples, how would you split the	e train/dev/test set?				
a	98% train. 1% dev. 1% test					
b	33% train. 33% dev. 33% test					
\bigcirc	60% train. 20% dev. 20% test					
14 . Tl	he dev and test set should:					
(a)	Come from the same distribution					
$\widetilde{\mathbf{b}}$	Come from different distributions					
\bigcirc	Be identical to each other (same (x,y) pairs)					
$\overline{\mathbf{d}}$	Have the same number of examples					
	your Neural Network model seems to have high variar se all that apply)	ace, what of the following would be promising things to try?				
(a)	Make the Neural network deeper	(b) Get more training data				
$\stackrel{\smile}{(c)}$	Get more test data	d Increase the number of units in each hidden layer				
$\stackrel{\smile}{(e)}$	Add regularization					
and o		supermarket, and are building a classifier for apples, bananas ror of 0.5% and a dev set error of 7%. Which of the following k all that apply)				
(a)	Increase the regularization parameter lambda					
\widecheck{b}	decrease the regularization parameter lambda					
$\stackrel{\smile}{(c)}$	get more training data					
$\widetilde{\mathbf{d}}$	use a bigger neural network					
17 W	That hannens when you increase the regularization byp.	ernarameter lambda?				

a	Weights are pushed twoard becomi	_					
(b)							
\bigcirc	doubling lambda should roughly result in doubling the weights						
(d)	Gradient descent taking bigger step	os wi	ith each iteration	(proportional to la	mbda	n)	
18. W	ith the inverted dropout, at test tim	ie:					
a	You don't apply dropout (do not rain training	ndoı	mly eliminate uni	ts), but keep 1/kee	ep_p	rob factor in the calculations used	
b	You don't apply dropout (do not raitions usd in the training	ndon	nly eliminate unit	s) and do not keep	the 1	/keep_prob factor in the calcula	
\bigcirc	You apply dropout (randomly elimi	nate	units) but keep 1	/keep_prob facto	or in	the calculations used in training	
$\overline{\mathbf{d}}$	You apply dropout (randomly elimination)	inat	e units) and do r	not keep 1/keep_	prob	factor in the calculations used in	
19 . W	Thich of these techniques are useful	for r	reducing variance	(reduce overfitting	g)? (c	heck all that apply)	
\widehat{a}	Dropout	(b)	Gradient Checki	ng	(c)	Data augmentation	
(d)	Vanishing gradient	$\stackrel{\smile}{(e)}$	Xavier initializat		(f)	L2 regularization	
(g)	Exploding gradient					-	
\bigcirc	Thy do we normalize the inputs x ?						
_	Normalization is another word for	regu	larization–it help	s to reduce varianc	·e		
\simeq	It makes the cost function faster to	_	-				
\sim	It makes it easier to visualize the da	•					
\simeq	It makes the parameter initializatio		ster.				
21. W	hat is the role of the temperature p	aran	neter in the conte	xt of knowledge dis	stillat	tion as a form of regularization?	
_	Controls the learning rate			Ö		O	
\simeq	Adjusts the level of noise in the inp	out d	ata				
\sim	Regulates the softness of the target						
(d)	Sets the threshold for dropout during						
	the context of neural networks, wh			refer to?			
(a)	The percentage of training samples		-				
\simeq	The rate at which weight are decay						
(c)	The probability of dropping out a u		0	rs during training			
(d)	The learning rate for stochastic gra		-	8			
23. W	Thich of the following is a technique rgence in deep learning?			djustment of the le	earni	ng rate during training to improv	
(a)	Adversarial training		(b) Learning rate a	nnea	aling	
\sim	Batch Normalization			d) Feature Scaling		8	
\bigcirc	hat is the purpose of adding noise t	o th	e innut data as a f				
			_	orni or regularizati	.011;		
(a) (b)	To make the training process determ To improve model interpretability	ııııfll	SHU				
		tha :	innut data				
(c)	To reduce the impact of outliers in	me 1	шриг иата				

d To prevent the model from memorizing the training data

25 . In	the context of regulariza	tion, what does the term "shrir	nkage" refer to?					
(a)	a) Reducing the size of the input data							
$\stackrel{\smile}{(b)}$	Reducing the number of hidden layers in the network							
(c)	Constraining the magnitude of the weights in the model							
$\widetilde{\mathbf{d}}$	Eliminating unnecessary	features from the dataset						
26 . W	hich of the following stat	ements is true about the dropo	out technique?					
(a)	Dropout is more effective	e in shallow networks than dee	p networks					
$\widetilde{\mathbf{b}}$	Dropout can be applied of	only to input layers						
\bigcirc	Dropout introduces rand	om variations only during test	ing					
$\overline{\mathbf{d}}$	Dropout helps prevent co	o-adaptation of hidden units						
27. W	hat is the primary goal o	f ensemble methods in machin	e learning?					
a	To reduce the computation	onal complexity of models						
b	To increase the training t	ime of individual models						
\bigcirc	To improve the predictive	e performance of a model by c	ombining multiple models					
\bigcirc d	To decrease the diversity	among base models						
28. W	hich of the following stat	ements is true about bagging ((Bootstrap Aggregating)?					
a	It trains multiple models	sequentially.						
\bigcirc b	It trains multiple models	independently on different sul	osets of the training data.					
\bigcirc	It combines models using	g a weighted average.						
\bigcirc d	It is not suitable for high	-variance models.						
29 . W	hat is the purpose of rand	dom forests in ensemble learni	ng?					
a	To create a forest of decis	sion trees with high correlation	1					
\bigcirc b	To reduce the number of	trees in the ensemble						
\bigcirc	To introduce randomness	s by considering a random sub	set of features for each tree					
\bigcirc d	To eliminate the need for	decision trees in the ensemble						
30 . In	a boosting, how are the we	eights assigned to misclassified	l instances during training?					
a	Equally to all instances							
b	Proportional to the diffic	ulty of the instance						
\bigcirc	Sequentially, with higher	weights for misclassified insta	ances					
\bigcirc d	d Inversely proportional to the number of features							
	Which ensemble method c arned based on the perfor	-	se models by taking a weighte	ed average, where the weights				
a	Bagging	(b) Stacking	© Boosting	(d) Random Forest				
32 . W	hat is the primary advant	tage of ensemble methods over	individual base models?					
(a)	Ensemble methods are al	ways faster than individual mo	odels.					
\widecheck{b}	Ensemble methods can h	andle only linear relationships						
$\overline{\mathbf{c}}$	Ensemble methods often	generalize better and have imp	proved robustness.					
$\widetilde{\mathbf{d}}$	Ensemble methods are more prone to overfitting.							

(b)	A model that performs s	slightly better than random cl	hance	
\simeq	A model with a large nu	-		
(d)	A model that is highly o	verfit		
34 . W sor?	hich ensemble method is	known for building a sequer	nce of weak learners, each corre	ecting the errors of its predece
a	Bagging	(b) AdaBoost	© Random Forest	d Gradient Boosting
35 . W	hich ensemble method t	rains multiple models indepe	ndently on different subsets of	the training data?
a	Boosting	(b) Stacking	© Bagging	d Random Forest
36 . W	hat is bagging short for	in the context of ensemble m	ethods?	
a	Bootstrap Aggregating	(b) Boosting Algorithm	© Bagged Aggregation	d Batch Aggregation
37 . In	boosting, how are the w	reights assigned to misclassifi	ed instances during training?	
(a)	Equally to all instances			
(b)	Proportional to the diffic	culty of the instance		
_	-	r weights for misclassified in	stances	
\simeq	Randomly assigned	O		
	, ,	ambinas the predictions of b	ase models by taking a weighte	ad arrama ma?
30. W	men ensemble method c	ombines the predictions of ba	ase models by taking a weighte	a average:
\simeq	Bagging			
(b)	Stacking			
\bigcirc	Boosting			
$\left(\mathbf{d} \right)$	Random Forest			
u			£1-1	
39 . W	hich ensemble method is	s known for building a sequei	ice of weak learners, each corr	ecting the errors of its predece
39. W sor?		s known for building a sequei	ice of weak learners, each corr	ecting the errors of its predece
39. W sor?	Thich ensemble method is Bagging AdaBoost	s known for building a sequei	ice of weak learners, each corr	ecting the errors of its predece
39. W sor? (a) (b)	Bagging AdaBoost	s known for building a sequei	ice of weak learners, each corr	ecting the errors of its predece
39. W sor? a b c	Bagging AdaBoost Random Forest	s known for building a sequei	ice of weak learners, each corr	ecting the errors of its predeco
39. W sor? (a) (b) (c) (d)	Bagging AdaBoost Random Forest Gradient Boosting	s known for building a sequer		ecting the errors of its predeco
39. W sor? a b c d 40. W	Bagging AdaBoost Random Forest Gradient Boosting That is the primary advan			ecting the errors of its predec
39. W sor? a b c d 40. W	Bagging AdaBoost Random Forest Gradient Boosting hat is the primary advar	ntage of ensemble methods ov		ecting the errors of its predece
39. W sor? a b c d 40. W	Bagging AdaBoost Random Forest Gradient Boosting That is the primary advar Faster training time Improved generalization	ntage of ensemble methods ov a and robustness		ecting the errors of its predece
39. W sor? a b c d 40. W	Bagging AdaBoost Random Forest Gradient Boosting That is the primary advar Faster training time Improved generalization Lower computational con	ntage of ensemble methods ov a and robustness omplexity		ecting the errors of its predece
39. W sor? a b c d 40. W a b c d	Bagging AdaBoost Random Forest Gradient Boosting That is the primary advar Faster training time Improved generalization Lower computational con	ntage of ensemble methods ov a and robustness omplexity tliers	ver individual base models?	
39. W sor? a b c d 40. W a b 41. W	Bagging AdaBoost Random Forest Gradient Boosting That is the primary advar Faster training time Improved generalization Lower computational con	ntage of ensemble methods ov a and robustness omplexity tliers		

a	Long Short-Term Memory	b	Linear Short-Term Memo	ory
\bigcirc	Limited Short-Term Memory	\bigcirc d	Lasting Short-Term Mem	ory
43 . In	boosting, what is the purpose of the learning rate parar	nete	r?	
a	It controls the number of weak learners It adjusts the ar	noui	nt by which weights are u	pdated during each iteration
(b)	It determines the depth of decision trees			
\bigcirc	It sets the threshold for feature selection			
44 . W	hat distinguishes Random Forest from traditional baggin	ng te	echniques?	
a	Random Forest uses a single decision tree			
b	Random Forest trains models sequentially			
\bigcirc	Random Forest introduces randomness by considering a	ı ran	dom subset of features for	r each tree
\bigcirc	Random Forest assigns equal weights to all instances			
45 . H	ow does stacking differ from bagging and boosting in en	sem	ble methods?	
a	Stacking trains models independently on different subse	ets		
b	Stacking combines predictions using a weighted average	e		
\bigcirc	Stacking builds a sequence of weak learners			
\bigcirc	Stacking uses multiple base models to form a meta-mod	lel		
46 . W	hat role does the concept of "bias-variance tradeoff" pla	y in	ensemble methods?	
(a)	Ensemble methods eliminate the bias-variance tradeoff			
$\widetilde{\mathbf{b}}$	Ensemble methods intensify the bias-variance tradeoff			
\bigcirc	Ensemble methods help balance bias and variance			
\bigcirc	Ensemble methods have no impact on bias and variance	•		
47 . W	That is the primary limitation of using too many weak lea	arne	rs in boosting?	
(a)	Increased risk of overfitting	(b)	Decreased computational	l complexity
$\stackrel{\smile}{\mathbb{C}}$	Improved generalization	\bigcirc d	Faster training time	
48 . In	a bagging, how are the subsets of the training data create	d fo	each base model?	
(a)	Randomly and with replacement			
$\widetilde{\mathbf{b}}$	Randomly and without replacement			
\bigcirc	Sequentially and with replacement			
\bigcirc	Sequentially and without replacement			
49 . W	That is the primary advantage of using gradient boosting	ove	r traditional AdaBoost?	
(a)	Faster convergence	b	Better handling of outlier	rs
$\widetilde{\mathbf{c}}$	Reduced risk of overfitting	\bigcirc d	Simplicity in implementa	tion
50. V	Thich ensemble method is prone to becoming computation	onall	y expensive as the numbe	r of models increases?
a	Bagging (b) Stacking	\bigcirc	Boosting	d Random Forest
51. W	hat does the term "stacking" refer to in ensemble learning	ng?		

(a) (b)	Combining models using	a weighted average dently on different subsets		
(c)	Constructing a sequence	•		
(d)	Using multiple base mode			
\circ			ndle both linear and non-linear	relationships in the data?
a	Bagging	(b) Stacking	© Random Forest	d Gradient Boosting
53 . E	xplain the concept of "out-	-of-bag" error in the contex	t of bagging.	
(a) (b)	It is the error rate calcula It is the error rate on the			
$\stackrel{\circ}{\mathbb{C}}$			nused samples during training	
(d)		del's performance on out-of		
54. W	hat is the role of the hype	erparameter "max depth" in	decision trees within a Randor	m Forest?
a	It controls the number of	trees in the forest		
(b)		epth of individual decision t	rees	
(c)	It sets the learning rate for			
(d)	It adjusts the weights ass	igned to misclassified insta	nces	
55 . In	the context of ensemble	methods, what is "early stop	oping," and how does it contribu	ute to regularization?
a	Early stopping involves simplicity.	terminating the training p	rocess when the model is und	erfitting, contributing to model
b	Early stopping prevents of data.	overfitting by stopping the t	raining process when the mode	l starts to memorize the training
\bigcirc	Early stopping introduces	s noise to the input data du	ring training, preventing overfi	tting.
\bigcirc	Early stopping is not rela	ted to regularization in ens	emble methods.	
56. W	hat is the impact of incre	asing the number of base m	odels on the computational cor	mplexity of stacking?
a	The computational comp	lexity decreases linearly		
b	The computational comp	lexity increases linearly		
\bigcirc	The computational comp	lexity remains constant		
\bigcirc	The computational comp	lexity depends on the type	of base models used	
57 . E	xplain the concept of "adv	ersarial training" in the con	text of ensemble methods.	
(a)	Adversarial training invo	lves training models to be 1	obust against adversarial attacl	ks.
$\widetilde{\mathbf{b}}$	Adversarial training focu	ses on maximizing the accu	racy on the training set.	
\bigcirc	Adversarial training elim	inates the need for ensemb	le methods.	
\bigcirc	Adversarial training refer	rs to using adversarial exam	ples as additional training data	l.
58 . H	ow does the concept of "s	tacking with cross-validation	on" address the risk of overfitting	ng in stacking?
(a)	It eliminates the need for	cross-validation in stackin	g.	
\widecheck{b}	It uses multiple cross-val	idated models, reducing ove	erfitting.	

 $ig(\mathbf{c} ig)$ It increases the depth of individual base models.

d It has no impact on the risk of overfitting.

(a) Feature importance represents the number of times a feature is selected by a base model.
b Feature importance indicates the relevance of a feature in predicting the target variable.
© Feature importance is not applicable to ensemble methods.
d Feature importance measures the computational cost of using a specific feature.
61 . What is the role of the "n estimators" hyperparameter in ensemble methods such as Random Forest and Gradien Boosting?
(a) It controls the learning rate in boosting algorithms.
b It sets the maximum depth of individual decision trees.
c It specifies the number of base models in the ensemble.
d It determines the subset of features considered for each base model.
62 . Explain the concept of "stacking with meta-features" in the context of ensemble methods.
(a) Stacking with meta-features involves using the output of base models as features for a meta-model.
b Stacking with meta-features eliminates the need for multiple base models.
c Stacking with meta-features refers to combining models using a weighted average.
d Stacking with meta-features involves using only one type of base model in the ensemble.
63 . What is Dropout in the context of neural networks?
(a) Adding noise to input features
(b) Removing random neurons during training
© Reducing the learning rate
d Increasing the number of hidden layers
64 . What is the main purpose of Dropout in neural networks?
(a) To increase overfitting
(b) To speed up the training process
© To prevent co-adaptation of neurons
d To eliminate the need for activation functions
65 . Which of the following statements is true about the application of Dropout during training?
(a) Dropout is only applied to input layers
b Dropout is applied to all layers except the output layer
c Dropout is applied during both training and testing
d Dropout is never applied to neural networks
66 . How does Dropout contribute to regularization in neural networks?
(a) By increasing the number of parameters
b By introducing noise to the input data
© By reducing the model's capacity
d By promoting co-adaptation of neurons
8
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59. What is the primary drawback of using a high learning rate in boosting algorithms?

60. Explain the concept of "feature importance" in the context of Random Forest.

(a) Slower convergence

(c) Decreased model performance

(b) Increased risk of overfitting

d Improved generalization

6 7. II	n terms of training, what	does it mean if a neuron i	is "dropped out"?	
a	The neuron's weights a	re set to zero		
(b)	The neuron is removed	from the network tempor	arily	
\bigcirc	The neuron's activation	function is bypassed		
\bigcirc	The neuron's output is	squared		
68 . V	Vhat challenge does Drop	pout aim to address in neu	ral networks?	
a	Underfitting	(b) Overfitting	© Vanishing gradients	d Exploding gradients
69 . F	low does Dropout affect	the training time of a neur	ral network?	
(a)	Slows down the training	g process		
$\stackrel{\smile}{(b)}$	Speeds up the training p	process		
\bigcirc	No impact on training t	ime		
$\overline{\mathbf{d}}$	Depends on the type of	activation function used		
70 . V	What is the recommended	l range for Dropout rates i	in neural networks?	
a	0.0 to 0.1	(b) 0.2 to 0.5	© 0.5 to 0.8	d 0.9 to 1.0
71 . F	Iow does Dropout contril	bute to model generalizati	on?	
(a)	By memorizing the train	ning data		
$\widetilde{\mathbf{b}}$	By promoting co-adapta	ation of neurons		
\bigcirc	By reducing the sensitiv	vity of neurons to specific	input features	
\bigcirc d	By increasing the numb	er of hidden layers		
72 . V	When applying Dropout,	which phase is used for ac	ljusting the weights of the neural	network?
a	Training phase			
(b)	Testing phase			
\bigcirc	Both training and testin	ng phases		
\bigcirc	Neither training nor tes	sting phases		
73 . E	xplain the term "co-adap	tation of neurons" in the c	context of neural networks and ho	ow Dropout addresses it.
a	Co-adaptation refers to a dropping neurons durin		on each other, and Dropout breaks	these dependencies by randomly
(b)	Co-adaptation is a form	of regularization, and Dro	opout exacerbates co-adaptation b	oy introducing noise.
\bigcirc	Co-adaptation occurs w	hen neurons are independe	ent, and Dropout enforces co-adap	tation by removing dependencies
\bigcirc	Co-adaptation is unrela	ted to Dropout; Dropout o	only affects the learning rate.	
74 . F	low does the effectivenes	ss of Dropout vary with th	e size and complexity of a neural	network?
a	Dropout is more effective	ve in small and simple net	works	
b	Dropout is more effective	ve in large and complex ne	etworks	
\bigcirc	Dropout is equally effect	ctive across all network siz	zes and complexities	
\bigcirc d	Dropout is irrelevant to	network size and complex	xity	
75. V	What is the relationship b	etween Dropout and the c	concept of ensemble learning?	

a	Dropout is a type of ensemble learning						
\bigcirc b	Ensemble learning and Dropout are unrelated concepts						
\bigcirc	Dropout and ensemble learning achieve the same result in terms of model diversity						
$\overline{\mathbf{d}}$	Dropout eliminates the need for ensemble learning						
76 . Ex	76. Explain the trade-off between using a high Dropout rate and a low Dropout rate in neural networks.						
a	High Dropout rates lead to overfitting, while low Dropout rates may result in underfitting.						
\bigcirc b	High Dropout rates always improve model generalization, while low Dropout rates reduce model capacity.						
\bigcirc	There is no trade-off; the Dropout rate does not impact model performance.						
\bigcirc d	The trade-off depends on the type of activation fund	ction used in the network.					
77. H	ow does Dropout contribute to mitigating the vanish	ning gradient problem in deep ne	eural networks?				
a	a. By increasing the learning rate						
b	By preventing co-adaptation of neurons						
\bigcirc	By introducing noise to the input data						
\bigcirc	By reducing the sensitivity of neurons to specific in	put features					
78. W	That is the primary goal of data augmentation in mad	chine learning?					
a	To decrease the size of the dataset						
\bigcirc b	To increase the computational complexity						
\bigcirc	To improve model performance by increasing the d	iversity of the training data					
\bigcirc d	To eliminate the need for validation data						
79. W	which of the following is a common technique used in	n data augmentation for image d	ata?				
a	Principal Component Analysis (PCA)	b Feature scaling					
\bigcirc	Image rotation	d Lasso regularization					
80 . H	ow does data augmentation contribute to preventing	g overfitting in machine learning	models?				
a	By reducing the size of the training dataset						
b	By increasing the number of layers in the model						
\bigcirc	By introducing noise to the input data						
\bigcirc d	By providing a more diverse set of training example	es					
81 . In	81. In text data augmentation, what technique involves replacing words with their synonyms?						
a	Tokenization (b) Embedding	© Word substitution	d Lemmatization				
82. W	82. Which of the following is a disadvantage of data augmentation?						
a	Increased model generalization						
\bigcirc b	Potential introduction of unrealistic patterns						
\bigcirc	Improved model robustness						
$\stackrel{\smile}{\mathbb{d}}$	Decreased computational efficiency						
83. W	That is the purpose of random cropping in image dat	a augmentation?					

(a) To decrease the image resolution		
(b) To remove irrelevant features from the image		
(c) To create variations in the spatial location of c	objects	
d To increase the image contrast		
84. Which type of data augmentation is commonly t	used for time series data?	
(a) Image rotation (b) Time warping	© Word substitution	d Feature scaling
85. Explain the concept of "jittering" in the context of	of data augmentation.	
(a) Jittering refers to the introduction of noise to	input features	
(b) Jittering involves the random selection of a su	•	
(c) Jittering is a synonym for image rotation	-	
d Jittering is irrelevant to data augmentation		
36 . In the context of image data augmentation, what	t is the purpose of horizontal flippin	g?
(a) To rotate images clockwise	(b) To create mirror image	ges
(c) To adjust the image brightness	d To resize images	U
7. How does data augmentation differ from feature		
(a) Data augmentation focuses on creating new s		nanipulates existing features
(b) Feature engineering is limited to image data, v		
c Data augmentation involves scaling features,		
d Feature engineering and data augmentation as		
8. What is the role of dropout in the context of dat		
(a) Dropout is not related to data augmentation(b) Dropout enhances data augmentation by rand	omly removing features during train	ning
c Dropout is a type of data augmentation technic		mig
(d) Dropout prevents data augmentation from int	•	
39. Which data augmentation technique is common	_	variations in nitch?
	(b) Spectrogram augmen	-
	(d) Jittering	itation
(c) Random cropping	<u> </u>	
90 . What is the purpose of elastic deformation in im	age data augmentation?	
a To adjust the image contrast		
(b) To introduce non-linear distortions to the ima	ge	
c To resize the image		
(d) To rotate the image		
91. In natural language processing, which technic augmentation?	que involves randomly removing w	rords from sentences during dat
(a) Tokenization		
(b) Word substitution		
© Sentence splitting		
d Sentence dropout		

- 92. Explain the concept of "adversarial training" in the context of data augmentation and how it addresses robustness.
 (a) Adversarial training focuses on creating adversarial examples to test the model's robustness against unseen patterns introduced by data augmentation.
 (b) Adversarial training is irrelevant to data augmentation.
 - (c) Adversarial training involves increasing the size of the training set.
 - (d) Adversarial training enhances data augmentation by introducing adversarial noise during the augmentation process.
- 93. How does data augmentation contribute to handling class imbalance in classification tasks?
 - (a) Data augmentation exacerbates class imbalance
 - (b) Data augmentation is not related to class imbalance
- (c) Data augmentation generates additional samples for minority classes, addressing class imbalance
- (d) Data augmentation reduces the need for addressing class imbalance
- 94. What challenges might arise when applying data augmentation to non-image data types, such as tabular data?
- (a) Difficulty in implementing data augmentation for non-image data
- (b) Limited applicability of data augmentation to non-image data
- (c) The potential introduction of unrealistic patterns
- (d) No challenges; data augmentation is equally effective for all data types
- **95**. Explain the term "mixup" in the context of data augmentation and how it differs from traditional augmentation techniques.
 - (a) Mixup involves blending two or more samples, creating new synthetic samples with averaged labels.
- (b) Mixup is a synonym for image rotation.
- (c) Mixup refers to the addition of random noise to input features.
- d Mixup is irrelevant to data augmentation.
- 96. How does data augmentation impact the interpretability of machine learning models?
- (a) Data augmentation improves model interpretability by providing more diverse training examples.
- (b) Data augmentation has no impact on model interpretability.
- (c) Data augmentation reduces model interpretability due to the introduction of synthetic samples.
- (d) Data augmentation improves model interpretability by eliminating the need for validation data.
- 97. What is the role of "cutout" in image data augmentation?
 - (a) To remove random portions from images
- (b) To blur the edges of images
- (c) To rotate images
- d To resize images
- 98. In the context of data augmentation, explain how the technique of "shearing" is applied to image data.
- (a) Shearing involves adjusting the brightness of images.
- (b) Shearing is irrelevant to data augmentation.
- c Shearing introduces non-linear distortions to the image by tilting it along one of its axes.
- d Shearing is a synonym for image rotation.
- **99**. Which ensemble learning algorithm can be applied to both regression and classification tasks?

(a) Bagging	(b) AdaBoost	(c) Random Forest	(d) Stacking
100 . Ensemble learning a	algorithms can be computation	nally expensive when:	
(a) The dataset is small(c) The ensemble size		(b) The base models are s (d) The dataset is large	simple
101 . Which ensemble lea	rning algorithm can be used	to identify important features in a	dataset?
(a) Bagging	(b) AdaBoost	c Gradient Boosting	(d) Stacking

Solutions to the Exercises

- **1**.(**b**) L1
- 2.(b) Trains multiple models on different subsets of the data
- **3**.(**c**) to prevent overfitting
- 4.(a) L1 regularization
- **5**.(**c**) small weight values
- **6.(b)** It randomly drops entire layers during training
- 7.(c) Elastic Net
- 8.(b) To prevent the model from memorizing the training data
- **9**.(c) Regularization can help balance bias and variance
- 10.(b) The gradual decrease in weight values during training
- 11.(d) Reduced capacity to capture complex patterns
- 12.(a) A regularization technique (such as L2 regularization) that results in gradient descent shrinking the weights on every iteration.
- **13**.(a) 98% train. 1% dev. 1% test
- 14.(a) Come from the same distribution
- **15**.(**b**) Get more training data
- (e) Add regularization
- **16**.(a) Increase the regularization parameter lambda
- (c) get more training data
- **17**.(**a**) Weights are pushed twoard becoming smaller (closer to 0)
- **18.(b)** You don't apply dropout (do not randomly eliminate units) and do not keep the 1/keep_prob factor in the calculations usd in the training
- 19.(a) Dropout
- (c) Data augmentation
- (f) L2 regularization
- **20**.(**b**) It makes the cost function faster to optimize
- **21**.(c) Regulates the softness of the target distribution
- 22.(c) The probability of dropping out a unit in the hidden layers during training
- 23.(b) Learning rate annealing
- 24.(c) To reduce the impact of outliers in the input data
- 25.(c) Constraining the magnitude of the weights in the model
- **26**.(**d**) Dropout helps prevent co-adaptation of hidden units
- **27**.(**c**) To improve the predictive performance of a model by combining multiple models
- **28**.(b) It trains multiple models independently on different subsets of the training data.
- 29.(c) To introduce randomness by considering a random subset of features for each tree
- 30.(c) Sequentially, with higher weights for misclassified instances
- 31.(b) Stacking
- **32**.(**c**) Ensemble methods often generalize better and have improved robustness.
- **33**.(**b**) A model that performs slightly better than random chance

- 34.(b) AdaBoost
- **35**.(**c**) Bagging
- **36**.(a) Bootstrap Aggregating
- **37**.(c) Sequentially, with higher weights for misclassified instances
- 38.(b) Stacking
- 39.(b) AdaBoost
- 40.(b) Improved generalization and robustness
- 41.(c) Random Forest
- 42.(a) Long Short-Term Memory
- **43.(a)** It adjusts the amount by which weights are updated during each iteration
- **44**.(**c**) Random Forest introduces randomness by considering a random subset of features for each tree
- 45.(d) Stacking uses multiple base models to form a metamodel
- **46**.(**c**) Ensemble methods help balance bias and variance
- 47.(a) Increased risk of overfitting
- 48.(a) Randomly and with replacement
- 49.(b) Better handling of outliers
- **50**.(c) Boosting
- 51.(d) Using multiple base models to form a meta-model
- **52**.(**c**) Random Forest
- **53.(c)** It is an estimate of the test error obtained from the unused samples during training
- $\mathbf{54.(b)}$ It limits the maximum depth of individual decision trees
- **55**.(**b**) Early stopping prevents overfitting by stopping the training process when the model starts to memorize the training data.
- **56**.(**b**) The computational complexity increases linearly
- **57**.(a) Adversarial training involves training models to be robust against adversarial attacks.
- **58.(b)** It uses multiple cross-validated models, reducing overfitting.
- 59.(b) Increased risk of overfitting
- **60.(b)** Feature importance indicates the relevance of a feature in predicting the target variable.
- **61**.(c) It specifies the number of base models in the ensemble.
- **62.(a)** Stacking with meta-features involves using the output of base models as features for a meta-model.
- **63**.(**b**) Removing random neurons during training
- **64**.(c) To prevent co-adaptation of neurons
- **65**.(**b**) Dropout is applied to all layers except the output layer
- **66**.(**c**) By reducing the model's capacity
- **67**.(**b**) The neuron is removed from the network temporarily
- **68**.(**b**) Overfitting
- **69**.(a) Slows down the training process
- **70**.(**b**) 0.2 to 0.5
- 71.(c) By reducing the sensitivity of neurons to specific input features
- 72.(a) Training phase

- **73**.(a) Co-adaptation refers to neurons relying too much on each other, and Dropout breaks these dependencies by randomly dropping neurons during training.
- 74.(b) Dropout is more effective in large and complex networks
- **75.(c)** Dropout and ensemble learning achieve the same result in terms of model diversity
- **76.(a)** High Dropout rates lead to overfitting, while low Dropout rates may result in underfitting.
- 77.(c) By introducing noise to the input data
- **78**.(c) To improve model performance by increasing the diversity of the training data
- **79**.(**c**) Image rotation
- **80**.(**d**) By providing a more diverse set of training examples
- **81**.(**c**) Word substitution
- 82.(b) Potential introduction of unrealistic patterns
- 83.(c) To create variations in the spatial location of objects
- **84**.(**b**) Time warping
- 85.(a) Jittering refers to the introduction of noise to input features
- **86**.(**b**) To create mirror images
- **87**.(a) Data augmentation focuses on creating new samples, while feature engineering manipulates existing features.
- **88.(b)** Dropout enhances data augmentation by randomly removing features during training
- 89.(b) Spectrogram augmentation
- 90.(b) To introduce non-linear distortions to the image
- **91**.(**d**) Sentence dropout
- **92.(a)** Adversarial training focuses on creating adversarial examples to test the model's robustness against unseen patterns introduced by data augmentation.
- **93**.(c) Data augmentation generates additional samples for minority classes, addressing class imbalance
- 94.(c) The potential introduction of unrealistic patterns
- **95**.(a) Mixup involves blending two or more samples, creating new synthetic samples with averaged labels.
- **96.(c)** Data augmentation reduces model interpretability due to the introduction of synthetic samples.
- 97.(a) To remove random portions from images
- **98.(c)** Shearing introduces non-linear distortions to the image by tilting it along one of its axes.
- 99.(c) Random Forest
- 100.(d) The dataset is large