(!) Students have either already taken or started taking this quiz, so be careful about editing it. If you change any quiz questions in a significant way, you may want to consider regrading students who took the old version of the quiz.

		Points 6 🕑 Published
Deta	ails Questions	
	Show Question Detai	ls
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S	elect all of the statements tha	at are true below.
 r	elect all of the statements that Consider two learning sce the first scenario we can to the first scenario we will p	In are true below. In arios using the same learning algorithm L, and the same hypothesis space H. In olerate error rate of ϵ_1 , and in the second, error rate of ϵ_2 . If $\epsilon_1 < \epsilon_2$, then in probably need to train L on more examples than in the second scenario.
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·· Question	::	
	••	

1 pts

Is the class H_{disj} (all disjunctions over n variables) PAC learnable ?

swer

Yes, since $|H_{disj}| = 3^n$ and learnability depends on the log of this size, and there exists an algorithm that is consistent with an hypothesis in H_{disj} .

Quiz 7

$$\bigcirc$$
 Yes, since $\left| H_{disj}
ight| \, = \, poly \left(n
ight)$

○ No, since it is NP hard to find the smallest disjunction that is consistent with the dataset.

$$\odot$$
 No, since $|H_{disj}|=3^n$

: Question

1 pts

We want to learn a weight vector by optimizing the Soft SVM formulation. We want to use the L2 loss for optimization:

$$\min_w \left(rac{1}{2} w^T w \,+\, C\, \max \left(0, 1 - y_i w^T x_i
ight)^2
ight)$$

Assume that we have $1 > y_i w^T x_i$. If we want to use SGD to update our weight vector, which one of the following is the correct update equation?

swer

$$\begin{array}{c} & w_{t+1} = w_t \, - \, \eta w_t \, + \, 2C\eta \left(1 - y_i w_t^T x_i \right) y_i x_i \\ \\ & w_{t+1} = w_t \, + \, \eta w_t \, - \, 2C\eta \left(1 - y_i w_t^T x_i \right) y_i x_i \\ \\ & w_{t+1} = w_t \, - \, \eta w_t \, + \, 2\eta C y_i x_i \\ \\ & w_{t+1} = w_t \, + \, \eta w_t \, - \, 2\eta C y_i x_i \\ \\ & w_{t+1} = w_t \, - \, \eta \parallel w_t \parallel \, + \, 2\eta C y_i x_i \\ \\ & w_{t+1} = w_t \, + \, \eta \parallel w_t \parallel \, - \, 2\eta C y_i x_i \\ \end{array}$$

ii Question	1 pts
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Which weight vector will you obtain when you optimize according to the Hard SVM formulation

$$egin{aligned} & \mathbf{min_w}\,rac{1}{2}||\mathbf{w}||^2 \ & ext{s.t}\;y^{(i)}(\mathbf{w}\cdot\mathbf{x}^{(i)}+ heta)\geq 1, orall(\mathbf{x}^{(i)},y^{(i)})\in D \end{aligned}$$

for the following data points below?

xample x1 x2 y = Label 2 1 1 2 -1 -1 2 25 2.5 1 4 1 1 -2 -2 -1 -1 -3 -1 -1 -2 -1 -1 -3 -1 -1 -2 -1			Quiz 7	
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Positive Examples Negative Examples Negative Examples	7	1	-2	-1
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	$w^T = [0.5, -6]$	$0.5],\theta=0$		
$igcap w^T = \left[0.5, -0.5 ight], heta = 0$	$w^T = [0.5, -6]$	0.5], heta=-0.5		
$w^T = [0.5, -0.5], heta = 0$ $w^T = [0.5, -0.5], heta = -0.5$	$^{\bigcirc} w^T = [0.5, 0.5]$	[.5], heta = -0.5		
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der the hypothesis space of "origin-centered spheres", the set spheres that are centered at the origin of the three-dimensional space. The class can be formally sented as: $= \{h_r : x^2 + y^2 + z^2 = r^2 : r \in R, r > 0\}$ ach r, h_r assigns a positive or negative label based on if the point is inside or outside of the sphere. (for ple, it can assign positive a label to the point outside of the circle and vice versa.) thypothesis PAC learnable? What is the VC Dimension of the hypothesis space? (s, The hypothesis space is PAC learnable. VC(H) = 3, because we can shatter a subset of size 3 but no ubset of size 4 can be shattered.
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/es, The hypothesis space is PAC learnable. VC(H) = 3, because we can shatter a subset of size 3 but no subset of size 4 can be shattered.
/es, The hypothesis space is PAC learnable. VC(H) = 2, because we can shatter a subset of size 2 but no subset of size 3 can be shattered.
) No, The hypothesis space is PAC learnable. VC(H) = 4, because we can shatter a subset of size 3 but no subset of size 4 can be shattered.
) /es, The hypothesis space is PAC learnable. VC(H) = 3, because we can shatter a subset of size 2 but no subset of size 3 can be shattered.
) No , The hypothesis space is not PAC learnable. VC(H) = 2, because we can shatter a subset of size 2 but no subset of size 3 can be shattered.
) No , The hypothesis space is not PAC learnable. VC(H) = 3, because we can shatter a subset of size 2 but no subset of size 3 can be shattered.

