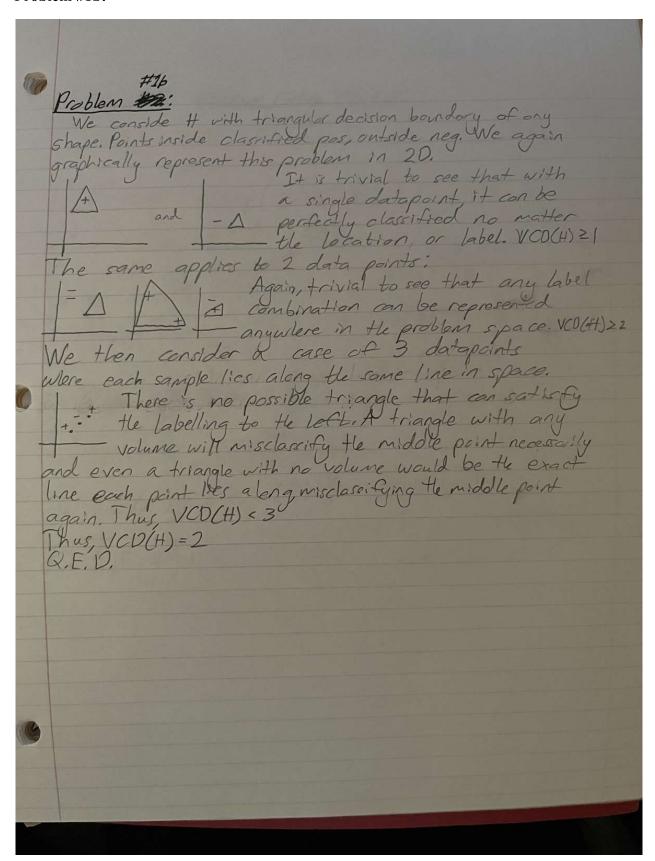
CSCI 5525: Homework #5

Noah Hendrickson

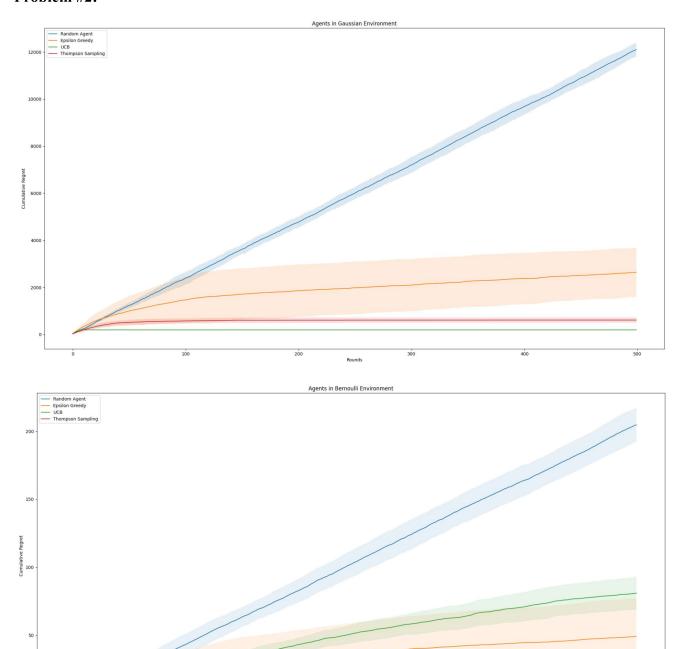
Problem #1a:

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-	CSCT SS2S: HW5
6	Noah Hendrickson
	Problem #1ai , - P Haredneld functions
11 6	We consider the class of williams
	where x is a teature and the graphic proof.
	To find the VCD, we consider a graphic proof. This problem can be represented as a 1D number. This problem can be represented as a 1D number.
	hat we consider on cons
	Case x label = 0: - x, a +
	Case x, label = 0: - a x a + tasee + hat no matter
3.3	where x, is placed, a classifies it as 0 if placed to the right and 1 if placed to the left, thus
	the right and I if placed to the leat, thus
	V()U(1) = 1.
100	Second, we consider samples x, and x2.
-	Case x, label = 0, x2 label = 1
-	- + ? We can see from the left - + ? graphic that, when x, and x2
1	with the provided labels are placed in this
750	configuration, there is no a that perfectly
	classifies both. If a were placed to the left of
	X2, X, would be misclassified. Placing a to right of
	both. Thus, VCV(H) < Z.
	Thus, VCD(H) = 1
	Q.E.D.
	Accurate 18 11
	Assumption: Both answers to a and b assume 2 data points in the same location in space will have the same label.
0	the same labor to same location in space will have
	table.
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Problem #1b:



Problem #2:



The above two plots show the average cumulative regret over 500 rounds for each of the algorithms for both gaussian and bernoulli distribution environments with the error bars being the standard deviation. Looking at the gaussian environment, we can see that the bounds are pretty similar to what was talked about in class. All of the 3 algorithms are sub-linear and random is linear as it should be. UCB just kind of hard cuts off which also follows because of the "upper confidence bound". Epsilon greedy having a bit less of a cutoff than the other two also tracks with what was mentioned in class. The bernoulli environment follows almost the same pattern. Epsilon greedy looks pretty similar to the gaussian environment, and thompson sampling takes a little bit longer

to converge. The biggest difference is UCB which has a worse curve than epsilon greedy. It's possible that this distribution is just harder to find the upper confidence bound than the gaussian distribution. Additionally, in the bernoulli environment, all of the algorithms have much higher standard deviations than in the gaussian environment, showing that they are not converging as well. The random agent is linear as it should be. From the two plots, we can conclude that how well these algorithms work depend on the underlying distribution. While they may work very well on a Gaussian distribution, they may not work as well on another distribution such as bernoulli.