

# CS 5350/6350: Machine Learning Fall 2022

## Homework 1

Handed out: 6 Sep, 2022  
Due date: 11:59pm, 23 Sep, 2022

### 1 Paper Problems

1.

- (a) i. A larger hypothesis space implies higher sample complexity. Given that  $L_2$  has a smaller hypothesis space, I prefer  $L_2$ .
- ii. As the  $|H|$  term in the inequality gets larger,  $m$  increases. Although  $L_1$  and  $L_2$  are both consistent with their respective training examples, the hypothesis space of  $L_2$  is less complex. Occam's Razor states that, ceteris paribus, the simplest explanation is the best one. I think of it this way: if a hypothesis space is more complex, a learned function from that space has more degrees of freedom along which the function can be incorrect when generalized to new data.

(b)

$$\begin{aligned} |H| &= 3^{10}; \delta = 0.05; \varepsilon = 0.10 \\ m &> \frac{1}{0.10} \left( \ln(3^{10}) + \ln\left(\frac{1}{0.05}\right) \right) \\ & \qquad \qquad \qquad m > 140 \end{aligned}$$

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- 2. The key to this proof is remembering that the sum of the incorrect-example-weights and the sum of the correct-example-weights add to 1. We can substitute the sum of

these two sums in place of 1 on the 5th line.

$$\begin{aligned}
\epsilon_i &= \frac{1}{2} - \frac{1}{2} \left( \sum_{y_i=h(x_i)} D_t(i) y_i h(x_i) + \sum_{y_i \neq h(x_i)} D_t(i) y_i h(x_i) \right) \\
&= \frac{1}{2} - \frac{1}{2} \left( \sum_{y_i=h(x_i)} D_t(i)^* 1 + \sum_{y_i \neq h(x_i)} D_t(i)^* - 1 \right) \\
&= \frac{1}{2} - \frac{1}{2} \left( \sum_{y_i=h(x_i)} D_t(i) - \sum_{y_i \neq h(x_i)} D_t(i) \right) \\
&= \frac{1}{2} \left( 1 - \sum_{y_i=h(x_i)} D_t(i) + \sum_{y_i \neq h(x_i)} D_t(i) \right) \\
&= \frac{1}{2} \left( \sum_{y_i=h(x_i)} D_t(i) + \sum_{y_i \neq h(x_i)} D_t(i) - \sum_{y_i=h(x_i)} D_t(i) + \sum_{y_i \neq h(x_i)} D_t(i) \right) \\
&= \frac{1}{2} \left( 2 \sum_{y_i \neq h(x_i)} D_t(i) \right) \\
&= \sum_{y_i \neq h(x_i)} D_t(i)
\end{aligned}$$

3.

(a)

y = 1 if

$$X_1 - X_2 + X_3 \geq 2$$

(b)

y = 1 if

$$(1 - X_1) + (1 - X_2) + (1 - X_3) \geq 1$$

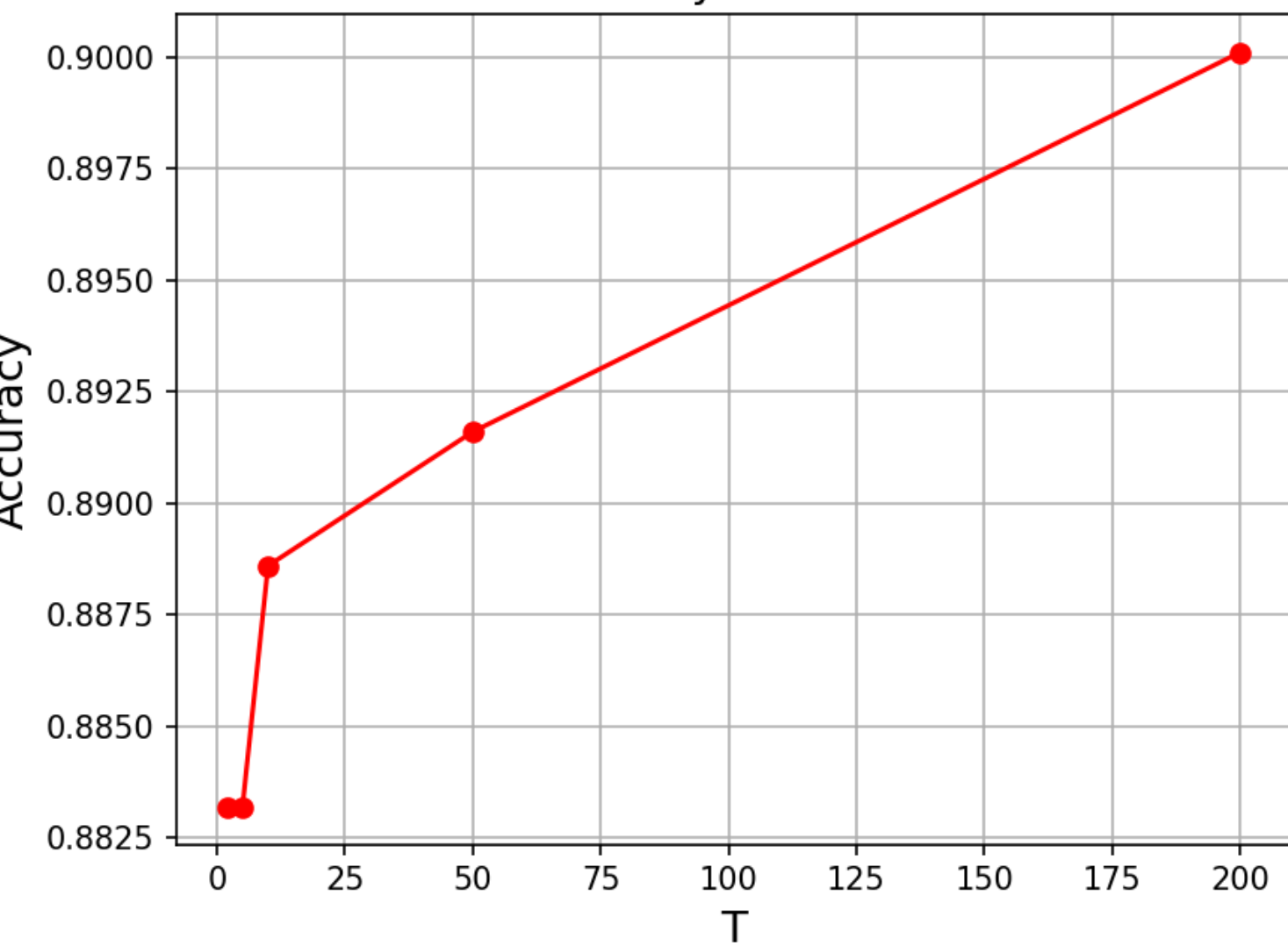
## 2 Decision Tree Practice

1. Link to repository: <https://github.com/MattMyers204453/CS-6350.git>

2.

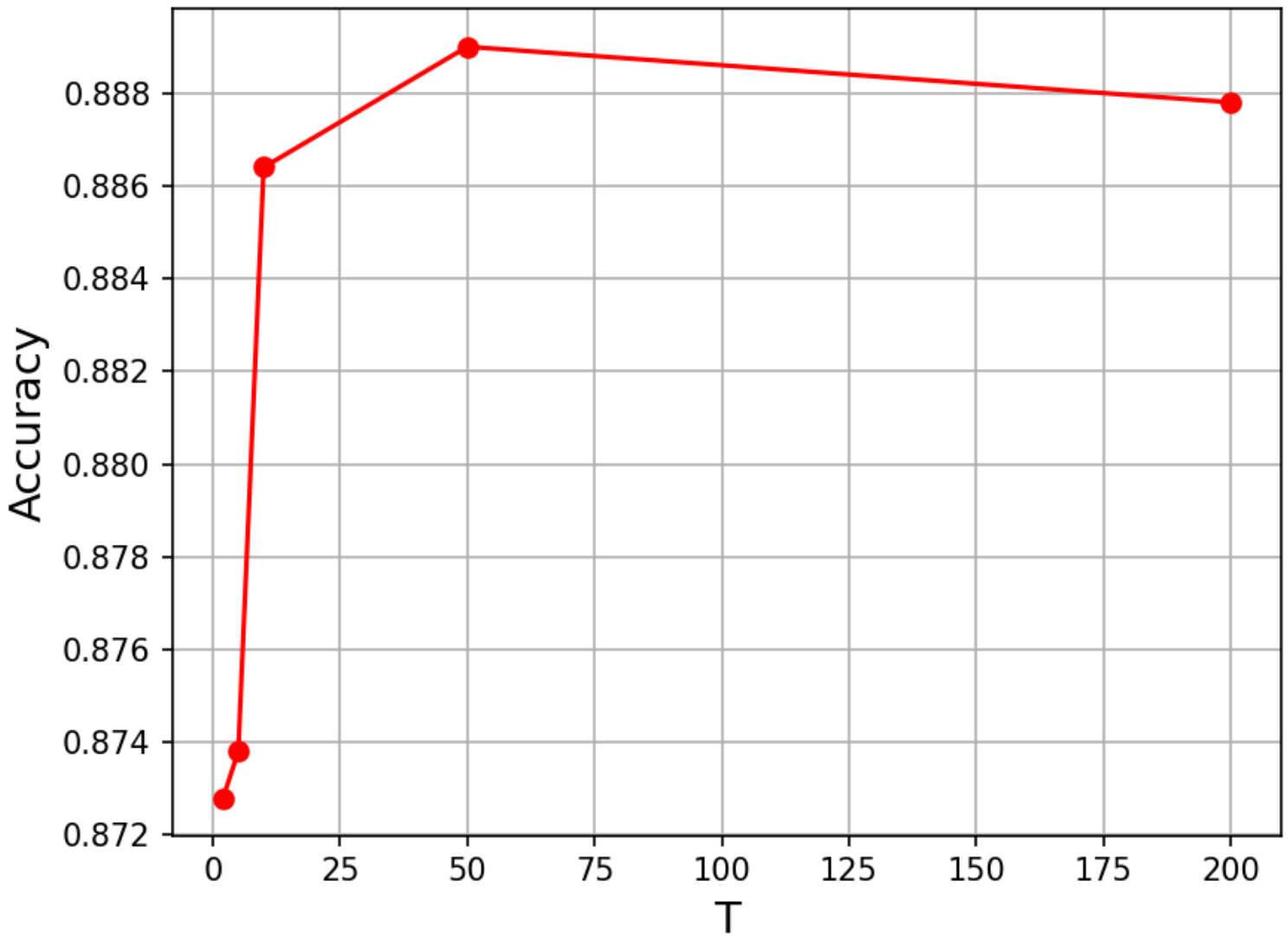
(a) My conclusion is that Adaboost, in this case, is superior for large values of T. T = 500 was too slow to test.

Accuracy for each T



- (b) My bagging algorithm seemed to stagnate past  $T = 100$ . My test sampled 1000 examples.

Accuracy for each T



- 3.
4. My Gradient Descent Algorithm found a solution with error very close to 0 with  $r = 0.5$  and  $T = 100$ .