

Machine Learning (911.236)

Exercise sheet A

Background (Probability, inequalities, ...)**Exercise 1.**

2 P.

Let X be a random variable that captures the sum of rolling a fair dice 10 times. Use Chebychev's inequality to bound

$$\mathbb{P}[|X - \mu| \geq 10]$$

Hint: Note that all dice rolls are independent. Compute the expectation of $|X|$ to obtain μ , then the variance and go on from there (this is really just a calculus exercise)!

Exercise 2.

2 P.

Consider the following problem with (binary) inputs $x_i \in \{0, 1\}$, $i = 1, \dots, 4$ and (binary) output $y \in \{0, 1\}$:

x_1	x_2	x_3	x_4	y
1	0	0	1	0
1	1	0	1	1
1	0	1	1	1
1	0	0	0	0
\vdots	\vdots	\vdots	\vdots	\vdots

Lets say our learning objective is to learn a function

$$y = f(x_1, x_2, x_3, x_4)$$

which maps our four boolean inputs to one boolean output $y \in \{0, 1\}$. To get a feeling for the (size of the) problem, we want to know how many such functions exist? When you have the solution, think about what happens for n inputs x_1, \dots, x_n ? What do you think is the big problem here? Plot the number of functions as a function of the number of inputs n .

PAC Learning**Exercise 3.**

3 P.

Let \mathcal{H} be a hypothesis class of binary classifiers. Show that (1) if \mathcal{H} is *agnostic PAC learnable*, then \mathcal{H} is *PAC learnable* and (2) if A is a successful agnostic PAC learner for \mathcal{H} , then A is also a successful PAC learner for \mathcal{H} .

Hint: In agnostic PAC learning, \mathcal{D} is a distribution over $\mathcal{X} \times \mathcal{Y}$. In PAC learning (i.e., we assume realizability), \mathcal{D} is what? Now, squeeze this into the agnostic PAC learning framework.

Exercise 4.

5 P.

Let $\mathcal{X} = \mathbb{R}^2$, $\mathcal{Y} = \{0, 1\}$ and consider hypotheses $h_r : \mathcal{X} \rightarrow \mathcal{Y}$ in \mathcal{H} of the form

$$h_r(\mathbf{x}) = 1_{\|\mathbf{x}\| \leq r}(\mathbf{x}), \text{ with } r \in \mathbb{R}_+.$$

In other words, our hypotheses are *concentric circles*. Show that this class is PAC-learnable (i.e., assume realizability) from training data of size

$$m \geq \left(\frac{1}{\epsilon}\right) \log \left(\frac{1}{\delta}\right).$$