## Homework 2

Machine Learning: Foundations and Applications MATH CS 120

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1. Consider a random variable X that is non-negative satisfying the inequality  $\Pr[X > t] \le c \exp(-2mt^2)$  for all t > 0. Show that  $E[X^2] \le \log(ce)/2m$ .

Hints: Do this by using that  $E[X^2] = \int_0^\infty \Pr[X^2 > t] dt = \int_0^u \Pr[X^2 > t] dt + \int_u^\infty \Pr[X^2 > t] dt$  for any choice of u > 0. For the first term, use that probabilities are always bounded by one. Optimize the obtained bound over u.

- 2. Consider a game where we see coin flips and need to decide which of two coins A and B generated the data. Consider the case when the coins have probabilities of heads  $p_A = 1/2 + \gamma$  and  $p_B = 1/2 \gamma$  with  $\gamma = 0.1$ . Suppose we use the strategy of attributing the coin based on a sample of m flips if we saw that most were heads or most were tails. At most how many coin tosses m do we need to observe so that our strategy would identify the correct coin 99% of the time? Hint: Use Hoeffding's Inequality to get an upper bound on m so that  $\Pr[|\frac{1}{m}S_m^{(i)} p_i| \ge t] \le 2\exp(-2t^2m) < \delta = 0.01$ , where  $i \in \{A, B\}$ .
- 3. Consider a family of functions  $f^{(m)} : \mathcal{X}^m \to \mathbb{R}$  on a sample space  $\mathcal{X}$  and a sequence  $c_i$  with  $\sum_{i=1}^{\infty} c_i^2 < \infty$ . Suppose that  $f^{(m)}$  has bounded dependence on parameters in the sense

$$|f^{(m)}(x_1, \dots, x_i, \dots, x_m) - f^{(m)}(x_1, \dots, x_i^*, \dots, x_m)| \le c_i.$$
 (1)

For short-hand we denote  $f(s) = f^{(m)}(x_1, \ldots, x_i, \ldots, x_m)$ .

Consider the case when  $f^{(m)} = (1/m) \sum_{k=1}^{m} X_k$  for i.i.d random variables  $X_i \in \mathcal{X}$  with  $|X_i| \leq C$ . Show this has bounded dependence. How many samples m do we need so that the values f(S) and its mean value E[f(S)] are within the distance 0.1 and this occurs 99% of the time? In other words, establish the following bound and find for what m we have

$$\Pr[|f(S) - E[f(S)]| \ge \epsilon] \le 2 \exp\left(-2\epsilon^2 / \sum_{i=1}^m c_i^2\right) < \delta,$$
(2)

where  $\delta = 0.01$  and  $\epsilon = 0.1$ . Hint: Use McDiarmids Inequality with  $c_i = C/i$ .

- 4. Consider k Nearest Neighbor (k-NN) classifiers. Suppose the input data space has features from the unit cube in *d*-dimensional space and there are two classes we want to distinguish. Suppose that in order to capture well the classes, we need a prototype within a distance at most  $\epsilon$  of any given input  $x \in [0, 1]^d$ . Give an estimate of the number *m* of training samples (prototypes) needed to ensure this distance requirement holds. Consider here the case of the Euclidean distance. How does the number *m* of prototypes scale with dimension *d*? How many samples *m* do you need when  $\epsilon = 10^{-1}$  and d = 100 if you use the Euclidean distance?
- 5. Suppose for a data point  $x_0$  in d dimensional space the conditional probability of a neighboring data point X is distributed uniformly within the unit sphere. Compute the probability density

of  $\rho(r)$  where  $\Pr\{r_1 \leq |X - x_0| \leq r_2\} = \int_{r_1}^{r_2} \rho(r) dr$ . Show as  $d \to \infty$  for any  $\epsilon > 0$  that  $\Pr\{1 - \epsilon \leq |X - x_0| \leq 1\} \to 1$ . Give an upper bound on  $|\Pr\{1 - \epsilon \leq |X - x_0| \leq 1\} - 1|$  in terms of  $\epsilon$  and d. This result shows that when d corresponds to a high dimensional space we have that the neighboring data points tend to distribute near to the surface of the sphere. For d = 100 what is the probability that the neighbor X for  $x_0$  is within the distance  $r = 10^{-1}$ ? For  $\epsilon = 10^{-1}$  how large must d be for  $\Pr\{1 - \epsilon \leq |X - x_0| \leq 1\} = 99\%$ ? Explain briefly what implications this might have for k-NN and other methods.