Exercises

Machine Learning: Foundations and Applications — Paul J. Atzberger
MATH 260 — http://atzberger.org/

Can choose to complete 1 out the following 3 problems.

1. (Neural Network Universal Approximation and Activations) The Cybenko Theorem states that if a continuous activation function $g(z)$ is discriminatory on the unit cube $I_n \subset \mathbb{R}^n$ then the linear space $\mathcal{V} = \{q \mid q(\mathbf{x}) = \sum_{j=1}^{n} \alpha_j g(\mathbf{w}_j^T \mathbf{x} + b_j), n \in \mathbb{N}\}$ is dense in the space of continuous functions $\mathcal{C}(I_n)$. In other words, for any continuous function $f \in \mathcal{C}(I_n)$ and $\epsilon > 0$, there exists a $q \in \mathcal{V}$ such that $|f(\mathbf{x}) - q(\mathbf{x})| < \epsilon$ for all $\mathbf{x} \in I_n$. An activation function $g(z)$ is said to be discriminatory if for a Borel measure $\mu \in \mathcal{M}$ we have for all weights $\mathbf{w}, b$ that $\int g(\mathbf{w}^T\mathbf{x} + b) d\mu(\mathbf{x}) = 0$ then the measure must be zero $\mu \equiv 0$.

   (a) Show that the sigmoid activation function $g(z) = 1/1 + e^{-z}$ is discriminatory on $I_1 = [0, 1]$. Hint: Use that $\int g(\mathbf{w}^T\mathbf{x}+b)d\mu(\mathbf{x}) = 0$ for all $\mathbf{w}, b$ iff $\int q(\mathbf{x})d\mu(\mathbf{x}) = 0$ for all $q \in \mathcal{V}$.

   (b) Show that the ReLU activation function $g(z) = \max(z, 0)$ is discriminatory on I_1. Hint: Use that $\int g(\mathbf{w}^T\mathbf{x} + b)d\mu(\mathbf{x}) = 0$ for all $\mathbf{w}, b$ iff $\int q(\mathbf{x})d\mu(\mathbf{x}) = 0$ for all $q \in \mathcal{V}$.

   (c) Show that the linear activation function $g(z) = z$ is not discriminatory on I_1. Hint: Construct a counter-example using a measure of the form $\mu(x) = a_1\delta(x - x_1) + a_2\delta(x - x_2) + a_3\delta(x - x_3)$, where $\delta(\cdot)$ denotes here the Dirac δ-function (measure).

2. (Approximating Distributions / Variational Inference) Consider a data distribution of the form $z_i \sim \bar{\rho}$ where $\bar{\rho}(z) = (1/Z) \exp(-\beta U(z))$, where $U(z) = (1 - z^2)^2 - 4\alpha z$, $Z = \int \exp(-\beta U(z))$, $\alpha = 0.171 = 9/10 - (9/10)^3$.

   (a) Plot the distribution for the range $z \in [-3, 3]$ when $\beta = 1.5$.

   (b) Show the critical points $U'(z) = 0$ are at $z_- = -9/10$, $z_+ = \frac{1}{20}\left(9 + \sqrt{157}\right)$ and $z_0 = \frac{1}{20}\left(9 - \sqrt{157}\right)$. The $z_\pm$ give local minima of U, and consequently local maxima of $\bar{\rho}$.

   (c) Suppose as a generative model a Gaussian is used with parameter $\mu = z_+$ and $\sigma^2 = (\beta u''(z_+))^{-1}$, denote this distribution by $\tilde{\rho}$. Derive this Gaussian estimate for $\beta \gg 1$ by computing Taylor expansion of $U(z) = U(z_+) + U'(z_+)(z - z_+) + \frac{1}{2}U''(z_+)(z - z_+)^2 + \cdots + R(z, z_+)$ and substituting for U. The approximation $\tilde{\rho}$ of $\bar{\rho}$ is obtained by retaining the leading order terms in $\beta(z - z_+)^\ell$ with $\ell \leq 2$.

   (d) How well does $\tilde{\rho}$ approximate the distribution $\bar{\rho}$? For $\beta = 0.5, 1.0, 1.5, 2.0, 3.0$ compute numerical estimates of the L^1-norm error $\|\tilde{\rho} - \bar{\rho}\|_1$.

3. (Generative Models and MLE) The method of Maximum Likelihood Estimation (MLE) selects a model θ^* from data $\{\mathbf{z}_i\}_{i=1}^m$ by optimizing

$$\theta^* = \arg\min_{\theta \in \Theta} \sum_{i=1}^{m} -\log\left(\rho(\mathbf{z}_i; \theta)\right).$$

   (a) Consider estimating the mean and variance of a Gaussian using MLE. Show that the MLE estimate $\hat{\theta}$ for the variance σ^2 of a Gaussian $z_i \sim \eta(\mu, \sigma^2)$ is biased. An estimator

$\hat{\theta}$ is called biased if $\mathbb{E}\left[\hat{\theta}\right] - \sigma^2 \neq 0$, where σ^2 is the true parameter value of the data distribution.

(b) Consider using linear models for regression $\mathcal{H} = \{\mathbf{w}^T\mathbf{x} + b \mid \mathbf{w} \in \mathbb{R}^n,\ b \in \mathbb{R}\}$, where $\theta = (\mathbf{w}, b)$ and $\mathbf{z}_i = (\mathbf{x}_i, \mathbf{y}_i)$. Assume a Gaussian noise model for the data generation $y_i = f(\mathbf{x}_i) + \xi_i$ with i.i.d. $\xi_i \sim \eta(0, \sigma)$, $f \in \mathcal{H}$, and $n = 1$. Show in this case that MLE is equivalent to performing least-squares regression.

(c) Use MLE to find the estimate for $\theta = (\mu, \sigma^2)$ in the limit of an infinite number of samples (i.e. replace the MLE objective sum with $\int -\log\left(\rho(z;\theta)\right)\bar{\rho}(z)dz$). Show that for Gaussian generative models $\rho(z;\theta) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}\left(z-\mu\right)^2\right)$ the infinite sample MLE approximates $\bar{\rho}$ by selecting for $\rho(z;\theta)$ the parameters $\mu = \int z\bar{\rho}(z)dz$ and $\sigma^2 = \int (z-\mu)^2\bar{\rho}(z)dz$.