Mathematical Foundations of Deep Neural Networks, M1407.001200
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Homework 2 Solutions

Problem 1: *Logistic regression via SGD.* Use SGD to solve the logistic regression optimization problem

$$\underset{\theta\in\mathbb{R}^p}{\text{minimize}} \quad \frac{1}{N}\sum_{i=1}^{N}\log(1+\exp(-Y_iX_i^\intercal\theta)),$$

where $X_1,\dots,X_N\in\mathbb{R}^p$ and $Y_1,\dots,Y_N\in\{-1,1\}$. Use the data

```
N, p = 30, 20
np.random.seed(0)
X = np.random.randn(N,p)
Y= 2*np.random.randint(2, size = N)-1
```

where $X_1^\intercal,\dots,X_N^\intercal$ are the rows of `X`.

Solution. See the file `p1_sol.py`. ■

Problem 2: *SVM via SGD.* Use SGD to solve the non-differentiable SVM optimization problem

$$\underset{\theta\in\mathbb{R}^p}{\text{minimize}} \quad \frac{1}{N}\sum_{i=1}^{N}\max\{0,1-Y_iX_i^\intercal\theta\}+\lambda\|\theta\|^2,$$

where $X_1,\dots,X_N\in\mathbb{R}^p$, $Y_1,\dots,Y_N\in\{-1,1\}$, and $\lambda=0.1$. Use the data of Problem 1. Empirically, does the SGD ever encounter a point of non-differentiability?

Solution. See the file `p2_sol.py`. ■

Problem 3: Consider the data generated by the Python code

```
N=30
np.random.seed(0)
X = np.random.randn(2,N)
y = np.sign(X[0,:]**2+X[1,:]**2-0.7)
theta = 0.5
c, s = np.cos(theta), np.sin(theta)
X = np.array([[c, -s], [s, c]])@X
X = X + np.array([[1],[1]])
```

Observe (by plotting) that the data is not linearly separable. Consider the transformation

$$\phi\left(\begin{bmatrix}u\\v\end{bmatrix}\right)=\begin{bmatrix}1\\u\\u^2\\v\\v^2\end{bmatrix}.$$

Using the logistic regression or SVM, show that the data $\phi(X_1),\dots,\phi(X_N)\in\mathbb{R}^5$ with labels $Y_1,\dots,Y_N\in\{-1,+1\}$ is linearly separable. Visualize in $\mathbb{R}^2$ the data and the decision boundary.

Hint. Visualize the decision boundary given by

```
0 == w[0]+w[1]*x+w[2]*(x**2)+w[3]*y+w[4]*(y**2)
```

with the code

```
xx = np.linspace(-4, 4, 1024)
yy = np.linspace(-4, 4, 1024)
xx, yy = np.meshgrid(xx, yy)
Z = w[0] + (w[1] * xx + w[2] * xx**2) + (w[3] * yy + w[4] * yy**2)
plt.contour(xx, yy, Z, 0)
```

Remark. This is the basis of Kernel methods.

Solution. See the file `p3_sol.py`. ■

Problem 4: *Nonnegativity of KL-divergence.* A set $C \subseteq \mathbb{R}^m$ is said to be convex if

$$x_1, x_2 \in C \quad \Rightarrow \quad \eta x_1 + (1-\eta)x_2 \in C, \quad \forall \eta \in (0,1).$$

A function $\varphi \colon C \to \mathbb{R}$ is said to be convex if $C \subseteq \mathbb{R}^m$ is convex and

$$\varphi(\eta x_1 + (1-\eta)x_2) \leq \eta\varphi(x_1) + (1-\eta)\varphi(x_2), \quad \forall\, x_1, x_2 \in C,\ \eta \in (0,1).$$

Jensen's inequality [1] states that if $X \in C$ is a random variable and φ is convex, then

$$\varphi(\mathbb{E}[X]) \leq \mathbb{E}[\varphi(X)].$$

Use this to show that

$$D_{\mathrm{KL}}(p\|q) \geq 0$$

for any probability mass functions $p, q \in \mathbb{R}^n$.

Hint. First show that $-\log(x)$ is a convex function.

Solution. Let $C = \{x \in \mathbb{R} \,|\, x > 0\}$, which is clearly convex, and $x_3 = \eta x_1 + (1-\eta)x_2$. Let $\varphi = -\log$. Since $\varphi'(x) = -1/x$ is a strictly increasing function on C, we have

$$\varphi(x_2) - \varphi(x_3) = \int_{x_3}^{x_2} \varphi'(x)\, dx > \int_{x_3}^{x_2} \varphi'(x_3)\, dx = \varphi'(x_3)(x_2 - x_3)$$
$$\varphi(x_1) - \varphi(x_3) = -\int_{x_1}^{x_3} \varphi'(x)\, dx > -\int_{x_1}^{x_3} \varphi'(x_3)\, dx = \varphi'(x_3)(x_1 - x_3)$$

multyplying the first inequality by $(1-\eta)$ and the second my η and summing them gives us the strict convexity inequality. If there is an i such that $q_i = 0$ and $p_i > 0$, then $D_{\mathrm{KL}}(p\|q) = \infty$. Now now assume that $q_i > 0$ for all i such that $p_i > 0$. Then

$$D_{\mathrm{KL}}(p\|q) = \mathbb{E}_I\left[-\log(q_I/p_I)\right] \geq -\log(\mathbb{E}_I[q_I/p_I]) = -\log\left(\sum_{i=1}^{n} q_i\right) = -\log(1) = 0.$$

(The assumption is used to ensure the expectation is finite and therefore well-defined.) ■

Problem 5: *Positivity of KL-divergence.* A function $\varphi \colon C \to \mathbb{R}$ is said to be *strictly* convex if $C \subseteq \mathbb{R}^m$ is convex and

$$\varphi(\eta x_1 + (1-\eta)x_2) < \eta\varphi(x_1) + (1-\eta)\varphi(x_2), \quad \forall\, x_1, x_2 \in C,\ \eta \in (0,1).$$

Strict Jensen's inequality states that if $X \in C$ is a non-constant random variable and φ is strictly convex, then

$$\varphi(\mathbb{E}[X]) < \mathbb{E}[\varphi(X)].$$

Use this to show that

$$D_{\mathrm{KL}}(p\|q) > 0$$

for any probability mass functions $p, q \in \mathbb{R}^n$ such that $p \neq q$.

Solution. If $p \neq q$, then the random variable q_I/p_I, where I is a random index with $\mathbb{P}(I = i) = p_i$, is not constant. By the same reasoning as in the previous problem, we get $D_{\mathrm{KL}}(p\|q) > 0$. ■

Problem 6: *Differentiating 2-layer neural networks.* Consider the 2-layer neural network

$$f_\theta(x) = u^\intercal \sigma(ax+b) = \sum_{j=1}^{p} u_j \sigma(a_j x + b_j),$$

where $a, b, u \in \mathbb{R}^p$ and $\theta = (a_1, \dots, a_p, b_1, \dots, b_p, u_1, \dots, u_p) \in \mathbb{R}^{3p}$. Assume the univariate function $\sigma \colon \mathbb{R} \to \mathbb{R}$ is differentiable. The notation $\sigma(ax+b)$ means σ is applied elementwise to the vector in $\mathbb{R}^p$. Show that

$$\begin{aligned}
\nabla_u f_\theta(x) &= \sigma(ax+b) \\
\nabla_b f_\theta(x) &= \sigma'(ax+b) \odot u = \operatorname{diag}(\sigma'(ax+b))u \\
\nabla_a f_\theta(x) &= (\sigma'(ax+b) \odot u)x = \operatorname{diag}(\sigma'(ax+b))ux,
\end{aligned}$$

where $\sigma'(ax+b)$ means the univariate function σ' is applied elementwise to the vector $ax+b$, $\odot$ denotes the element-wise product, and $\operatorname{diag}(\cdot)$ denotes the diagonal matrix with the diagonal elements equal to the elements of the input vector.

Solution. By applying standard rules from vector calculus, we get

$$\begin{aligned}
\frac{\partial f_\theta(x)}{\partial u_j} &= \sigma(a_j x + b_j) \\
\frac{\partial f_\theta(x)}{\partial a_j} &= \frac{\partial f_\theta(x)}{\partial (a_j x + b_j)} \frac{\partial (a_j x + b_j)}{\partial a_j} = u_j \sigma'(a_j x + b_j) x \\
\frac{\partial f_\theta(x)}{\partial b_j} &= \frac{\partial f_\theta(x)}{\partial (a_j x + b_j)} \frac{\partial (a_j x + b_j)}{\partial b_j} = u_j \sigma'(a_j x + b_j)
\end{aligned}$$

for $j = 1, \dots, p$. Vectorizing these partial derivatives gives us the stated results. ■

Problem 7: *SGD with 2-layer neural networks.* Consider the univariate function

$$f_\star(x) = (x-2)\cos(4x).$$

Let

$$f_\theta(x) = \sum_{j=1}^{p} u_j \sigma(a_j x + b_j),$$

be the same 2-layer neural network as in the previous problem. For this problem, use the sigmoid activation function, i.e., $\sigma(x) = (1+e^{-x})^{-1}$. Given data X_i generated as IID unit Gaussians and corresponding labels $Y_i = f_\star(X_i)$ for $i = 1, \dots, N$, define loss functions

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^{N} \ell_\theta(X_i, Y_i)$$

and

$$\ell_\theta(X, Y) = \frac{1}{2}(f_\theta(X) - Y)^2.$$

Consider the minimization problem

$$\underset{\theta \in \mathbb{R}^{3p}}{\text{minimize}} \quad \mathcal{L}(\theta).$$

Without using PyTorch (so using NumPy), implement

$$\begin{aligned}
i(k) &\sim \text{Uniform}\{1, \ldots, N\} \\
\theta^{k+1} &= \theta^k - \alpha \nabla_\theta \ell_\theta(X_{i(k)}, Y_{i(k)}).
\end{aligned}$$

Use the parameters $K = 10000$, $\alpha = 0.007$, $N = 30$, and $p = 50$ and use independent initializations with distributions $a_j^0 \sim \mathcal{N}(0, 4^2)$, $b_j^0 \sim \mathcal{N}(0, 4^2)$, and $u_j^0 \sim \mathcal{N}(0, 0.05^2)$ for $j = 1, \ldots, p$. (These parameters and initializations are implemented in the starter code `twolayerSGD.py`.) Plot the final trained function with $f_{\theta^K}(x)$ as a function of x. How does it compare with $f_\star(x)$?

Remark. In order to fit the nonlinear function $f_\star$, it is essential that we use the nonlinear activation function σ; without it,

$$f_\theta(x) = \sum_{j=1}^{p} u_j(a_j x + b_j),$$

will be linear in x, and a linear function cannot approximate the nonlinear function $f_\star(x)$ well.

Solution. See the file `twolayerSGD_sol.py`. ■

References

[1] J. L. W. V. Jensen, Sur les fonctions convexes et les inégalités entre les valeurs moyennes, *Acta Mathematica*, 1906.