## Purdue

BME 64600-001 and ECE 60146-001
Midterm \#1, Spring 2023


## Exam instructions:

- You have 75 minutes to work the exam.
- This is a closed-book and closed-note exam. You may not use or have access to your book, notes, any supplementary reference, a calculator, or any communication device including a cell-phone or computer.
- You may not communicate with any person other than the official proctor during the exam.

To ensure Gradescope can read your exam:

- Write your full name and PUID above and on the top of every page.
- Answer all questions in the area designated for each problem.
- Write only on the front of the exam pages.
- DO NOT run over to the next question.

Name/PUID: $\qquad$
Problem 1. (32pt) Function Properties
For each of the following functions $f(x)$, check the associated box for every property that holds for the function.
a) $f(x)=\frac{1}{2} x^{2}$.

$$
\square \text { - convex }
$$

$\square$ - strictly convex
$\square$ - concave
$\square$ - strictly concave
b) $f(x)=-|x|$.
$\square$ - convex
$\square$ - strictly convex
$\square$ - concave
$\square$ - strictly concave
c) $f(x)=-x$.
$\square$ - convex
$\square$ - strictly convex
$\square$ - concave
$\square$ - strictly concave
d) $f(x)=x^{3}$.
$\square$ - convex
$\square$ - strictly convex
$\square$ - concave
$\square$ - strictly concave

Name/PUID:

## Problem 2. (15pt) Complexity of Matrix Multiplication

Consider a series of matrices $A \in \Re^{N \times 1}, B \in \Re^{1 \times N}, C \in \Re^{N \times 1}, D \in \Re^{1 \times N}$, and $E \in \Re^{N \times 1}$. Your goal is to compute the result of the following series of matrix multiples.

$$
b=A * B * C * D * E .
$$

a) What is the shape of $b$ ?

Solution: $b \in \Re^{N \times 1}$
b) Assuming that you multiple the matrices from left to right $\Rightarrow$, how many multiplies are required to compute $b$ ?

Solution: $N^{2}+N^{2}+N^{2}+N^{2}=4 N^{2}$
c) Assuming that you multiple the matrices from right to left $\Leftarrow$, how many multiplies are required to compute $b$ ?

Solution: $N+N+N+N=4 N$

Name/PUID:
Problem 3. (36pt) Convolutional Neural Networks
Consider the following convolutional neural network pictured below with a gray-scale image as both input and output. Each layer uses a ReLu activation function, a "valid" boundary condition, and denote the convolution kernels by $w_{1}$ and $w_{2}$ and the associated offsets by $b_{1}$ and $b_{2}$.

a) Calculate the value of $N_{1}$.

Solution: $N_{1}=126$
b) Calculate the value of $N_{2}$.

Solution: $N_{2}=124$
c) Calculate the shape of $w_{1}$.

Solution: $3 \times 3 \times 1 \times 16$
d) Calculate the shape of $w_{2}$.

Solution: $3 \times 3 \times 16 \times 1$
e) Calculate the shape of $b_{1}$.

Solution: 16
f) Calculate the total number of parameters in the model.

Solution: Number of parameters in each layer:

- layer1:
- filter: $3 \times 3 \times 1 \times 16=144$
- offset: 16
- layer2:
- filter: $3 \times 3 \times 16 \times 1=144$
- offset: 1

Total number of parameters:

$$
144+16+144+1=305
$$

Name/PUID:
Problem 4. (36pt) Soft Max and Cross Entropy Loss
Define the soft max function $\sigma: \Re^{M} \rightarrow \Re^{M}$ as

$$
[\sigma(z)]_{i}=\frac{\exp \left\{z_{i}\right\}}{\sum_{j=0}^{M-1} \exp \left\{z_{j}\right\}},
$$

and the cross-entropy loss function $\rho: \Re^{M \times M} \Rightarrow \Re$ as

$$
\rho(a, b)=\sum_{i=0}^{M-1}-a_{i} \log b_{i} .
$$

Furthermore, assume that

- Let $\left\{x_{n}\right\}_{n=0}^{N-1}$ be $N$ training samples where $x_{n} \in \Re^{M}$.
- Let $\theta \in \Re^{M}$ be the parameter vector where there is a component for each sample.
- Let $x_{n}$ be 1 -hot encoded, i.e., exactly one component of $x_{n}$ is non-zero and that component is equal to 1 .
- Define $N_{m}$ be the number of $x_{n}$ with class $m$.
- Define the loss function

$$
L(\theta)=\sum_{n=0}^{N-1} \rho\left(x_{n}, \sigma(\theta)\right) .
$$

a) Prove that for all $z \in \Re^{M}, p=\sigma(z)$ is in the $M$-dimensional simplex, $\mathcal{S}^{M}$.

Solution: Proof: For all $z \in \Re^{M}$, we have $[\sigma(z)]_{i}>0$ and

$$
\begin{equation*}
\sum_{i=0}^{M-1} p_{i}=\sum_{i=0}^{M-1}[\sigma(z)]_{i}=\sum_{i=0}^{M-1} \frac{\exp \left\{z_{i}\right\}}{\sum_{j=0}^{M-1} \exp \left\{z_{j}\right\}}=\frac{\sum_{i=0}^{M-1} \exp \left\{z_{i}\right\}}{\sum_{j=0}^{M-1} \exp \left\{z_{j}\right\}}=1 \tag{1}
\end{equation*}
$$

Therefore, $p=\sigma(z) \in \mathcal{S}^{M}$.
b) Prove that for all $z \in \Re^{M}, p=\sigma(z)$ is not on the boundary of $\mathcal{S}^{M}$ (i.e., it is in the interior of $\mathcal{S}^{M}$ ).

## Solution:

Proof: First, the M-dimensional simplex is defined as $\mathcal{S}^{M}=\left\{s \in \Re^{M-1}: \forall i, s_{i} \geq 0\right.$ and $\sum_{i} s_{i}=$ 1\}. A point $s \in \mathcal{S}^{M}$ is on the boundary of the simplex if there exists an $k$ such that $s_{k}=0$.
However, since

$$
p_{i}=[\sigma(z)]_{i}=\frac{\exp \left\{z_{i}\right\}}{\sum_{j=0}^{M-1} \exp \left\{z_{j}\right\}}>0
$$

Consequently, $p$ is not on the boundary of $s \in \mathcal{S}^{M}$.
c) Write an expression for $L(\theta)$ in terms of $N_{m}$.

## Solution:

First we note that

$$
N_{m}=\sum_{n=0}^{N-1} x_{n, m}
$$

Then we have that

$$
\begin{aligned}
L(\theta) & =\sum_{n=0}^{N-1} \rho\left(x_{n}, \sigma(\theta)\right) \\
& =\sum_{n=0}^{N-1} \sum_{i=0}^{M-1}\left\{-x_{n, i} \log \left(\frac{\exp \left\{\theta_{i}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}\right)\right\} \\
& =\sum_{n=0}^{N-1} \sum_{i=0}^{M-1}\left\{-x_{n, i} \log \left(\exp \left\{\theta_{i}\right\}\right)+x_{n, i} \log \left(\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}\right)\right\} \\
& =\sum_{n=0}^{N-1} \sum_{i=0}^{M-1}\left\{-x_{n, i} \theta_{i}+x_{n, i} \log \left(\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}\right)\right\} \\
& =\sum_{i=0}^{M-1} \sum_{n=0}^{N-1}\left\{-x_{n, i} \theta_{i}+x_{n, i} \log \left(\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}\right)\right\} \\
& =\sum_{i=0}^{M-1}\left[\left\{-\theta_{i}+\log \left(\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}\right)\right\} \sum_{n=0}^{N-1} x_{n, i}\right] \\
& =\sum_{i=0}^{M-1} N_{i}\left\{-\theta_{i}+\log \left(\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}\right)\right\}
\end{aligned}
$$

d) Calculate the gradient $\nabla_{\theta} L(\theta)$.

Solution:

$$
\nabla_{\theta} L(\theta)=\left[\frac{d L}{d \theta_{0}}, \frac{d L}{d \theta_{1}}, \cdots, \frac{d L}{d \theta_{M-1}}\right]
$$

where

$$
\begin{aligned}
\frac{d L}{d \theta_{m}} & =\sum_{n=0}^{N-1}\left[-x_{n, m}+\sum_{i=0}^{M-1}\left\{x_{n, i} \frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}\right\}\right] \\
& =\sum_{n=0}^{N-1} \sum_{i=0}^{M-1}-x_{n, i}\left[\delta(m-i)-\frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}\right]
\end{aligned}
$$

e) Calculate the gradient $\nabla_{\theta} L(\theta)$ in terms of $N_{m}$.

## Solution:

We have that

$$
\begin{aligned}
\frac{d L}{d \theta_{m}} & =\sum_{n=0}^{N-1} \sum_{i=0}^{M-1}-x_{n, i}\left[\delta(m-i)-\frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}\right] \\
& =\sum_{i=0}^{M-1} \sum_{n=0}^{N-1}-x_{n, i}\left[\delta(m-i)-\frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}\right] \\
& =\sum_{i=0}^{M-1}\left\{\sum_{n=0}^{N-1} x_{n, i}\right\}\left[-\delta(m-i)+\frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}\right] \\
& =\sum_{i=0}^{M-1} N_{i}\left[-\delta(m-i)+\frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}\right] \\
& =-N_{m}+\left(\sum_{i=0}^{M-1} N_{i}\right) \frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}
\end{aligned}
$$

f) Calculate an general expression for $\theta^{*}$, the value of $\theta$ that minimizes the loss $L(\theta)$.

Solution: In order to calculate $\theta^{*}$, we solve for

$$
0=\frac{d L}{d \theta_{m}}=N_{m}-\left(\sum_{i=0}^{M-1} N_{i}\right) \frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}
$$

So we have that

$$
\frac{\exp \left\{\theta_{m}\right\}}{\sum_{j=0}^{M-1} \exp \left\{\theta_{j}\right\}}=\frac{N_{m}}{\left(\sum_{i=0}^{M-1} N_{i}\right)}
$$

So that

$$
\exp \left\{\theta_{m}\right\}=\alpha N_{m}
$$

for any constant $\alpha$. Or equivalently,

$$
\theta_{m}^{*}=\beta+\log N_{m},
$$

for any constant $\beta$.

