# UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN 

Department of Electrical and Computer Engineering

## ECE 417 Multimedia Signal Processing

Fall 2018

## PRACTICE EXAM 2

Tuesday, December 11, 2018

- This is a PRACTICE exam. In the real exam, you will be permitted to use one sheet (front and back) of handwritten notes.
- In the real exam, no calculators will be permitted. You need not simplify explicit numerical expressions.
- There will be a total of 100 points in the exam. Each problem specifies its point total. Plan your work accordingly.
- You must SHOW YOUR WORK to get full credit.

| Problem | Score |
| :---: | :---: |
| 1 |  |
| 2 |  |
| 3 |  |
| 4 |  |
| 5 |  |
| 6 |  |
| Total |  |

Name: $\qquad$
$\qquad$

## Possibly Useful Formulas

## Neural Nets

$$
\begin{aligned}
a_{k} & =u_{k 0}+\sum_{j} w_{k j} x_{j} \\
y_{k} & =g\left(a_{k}\right) \\
\frac{\partial E}{\partial x_{j}} & =\sum_{k} w_{k j} g^{\prime}\left(a_{k}\right) \frac{\partial E}{\partial y_{k}}
\end{aligned}
$$

## Logistic Function

$$
\sigma(x)=\frac{1}{1+e^{-x}}, \quad \sigma^{\prime}(x)=\sigma(x)(1-\sigma(x))
$$

## Loss Functions

$$
\begin{aligned}
E_{M S E} & =\frac{1}{n} \sum_{i=1}^{n}\left\|\vec{z}_{i}-\vec{\zeta}_{i}\right\|^{2} \\
E_{C E} & =-\frac{1}{n} \sum_{i=1}^{n} \sum_{\ell=1}^{r} \zeta_{i \ell} \ln z_{i \ell} \\
E_{C E} & =-\frac{1}{n} \sum_{i=1}^{n}\left(\zeta_{i} \ln z_{i}+\left(1-\zeta_{i}\right) \ln \left(1-z_{i}\right)\right)
\end{aligned}
$$

## Affine Transform

$$
\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]=\left[\begin{array}{lll}
a & b & c \\
d & e & f \\
0 & 0 & 1
\end{array}\right]\left[\begin{array}{l}
u \\
v \\
1
\end{array}\right]
$$

Barycentric Coordinates

$$
\left[\begin{array}{c}
x_{0} \\
y_{0} \\
1
\end{array}\right]=\left[\begin{array}{ccc}
x_{1} & x_{2} & x_{3} \\
y_{1} & y_{2} & y_{3} \\
1 & 1 & 1
\end{array}\right]\left[\begin{array}{l}
\lambda_{1} \\
\lambda_{2} \\
\lambda_{3}
\end{array}\right]
$$

## LSTM

$$
\begin{aligned}
\vec{i}[n] & =\text { input gate }=\sigma\left(B_{i} \vec{x}[n]+A_{i} \vec{c}[n-1]\right) \\
\vec{o}[n] & =\text { output gate }=\sigma\left(B_{o} \vec{x}[n]+A_{o} \vec{c}[n-1]\right) \\
\vec{f}[n] & =\text { forget gate }=\sigma\left(B_{f} \vec{x}[n]+A_{f} \vec{c}[n-1]\right) \\
\vec{c}[n] & =\vec{f}[n] \odot c[n-1]+\vec{i}[n] \odot g\left(B_{c} \vec{x}[n]+A_{c} \vec{c}[n-1]\right) \\
\vec{y}[n] & =\vec{o}[n] \odot \vec{c}[n]
\end{aligned}
$$

$\qquad$

## Topics Covered in This Exam

(a) Neural Nets: logistic, softmax. MSE, Cross-entropy. Back-prop
(b) ConvNets. Back-prop through convolution, max pooling, and ReLU
(c) (Not Covered: SGD, Batch, Mini-Batch, Data Augmentation)
(d) Affine Transforms
(e) (Not Covered: Image interpolation, PWC, PWL, and sinc)
(f) Adversarial examples, adversarial training. (Not covered: autoencoder, VAE, GAN)
(g) Barycentric coordinates
(h) RNN, GRU, LSTM

## Problem 1 (16 points)

In class, we have been working with nodes in layers, but a neural net can also be defined as a fully-connected graph, with every node connected to every other node. For example, suppose there is a scalar input $x$, and

$$
\begin{aligned}
y_{0} & =x \\
a_{\ell} & =\sum_{k=0}^{\ell-1} w_{\ell k} y_{k}, \quad 1 \leq \ell \leq L \\
y_{\ell} & =\sigma\left(a_{\ell}\right), \quad 1 \leq \ell \leq L \\
E & =\frac{1}{2} \sum_{\ell=1}^{L}\left(y_{\ell}-y_{\ell}^{*}\right)^{2}
\end{aligned}
$$

Define the back-propagation error to be $\delta_{\ell}=\frac{d E}{d a_{\ell}}$. Find an algorithm that computes $\delta_{\ell}$ for all $1 \leq \ell \leq L$.

## Problem 2 (17 points)

A convolutional layer leads to convolutional back-propagation. In the neural net literature, however, convolution is sometimes replaced (without comment!) by correlation, resulting in something like the following, where $x\left[m_{1}, m_{2}\right]$ is the input and $u\left[m_{1}, m_{2}\right]$ are the network weights:

$$
a\left[n_{1}, n_{2}\right]=\sum_{m_{1}} \sum_{m_{2}} u\left[m_{1}-n_{1}, m_{2}-n_{2}\right] x\left[m_{1}, m_{2}\right]
$$

Suppose the error, $E$, is some function whose partial derivatives $\epsilon\left[n_{1}, n_{2}\right]=\frac{\partial E}{\partial a\left[n_{1}, n_{2}\right]}$ are known. Define $\delta\left[m_{1}, m_{2}\right]=\frac{\partial E}{\partial x\left[m_{1}, m_{2}\right]}$. Find $\delta\left[m_{1}, m_{2}\right]$ in terms of $\epsilon\left[n_{1}, n_{2}\right]$.

## Problem 3 (16 points)

Consider four points, $\vec{u}_{1}=\left[u_{1}, v_{1}, 1\right]^{T}, \vec{u}_{2}=\left[u_{2}, v_{2}, 1\right]^{T}, \vec{u}_{3}=\left[u_{1}+\alpha \cos \theta, v_{1}+\alpha \sin \theta, 1\right]^{T}$, and $\vec{u}_{4}=\left[u_{2}+\beta \cos \theta, v_{2}+\beta \sin \theta, 1\right]^{T}$. Notice that the slope of the line segment connecting $\overrightarrow{u_{1}}$ to $\vec{u}_{3}$ is $\frac{a \sin \theta}{a \cos \theta}=\tan \theta$, while the slope of the line segment connecting $\vec{u}_{2}$ to $\vec{u}_{4}$ is also $\frac{b \sin \theta}{b \cos \theta}=\tan \theta$. Suppose that there is an affine transform $A$ such that $\vec{x}_{1}=A \vec{u}_{1}, \vec{x}_{2}=A \vec{u}_{2}, \vec{x}_{3}=A \vec{u}_{3}$, and $\vec{x}_{4}=A \vec{u}_{4}$. Prove that, for any affine transform matrix $A$, the line segment connecting $\vec{x}_{1}$ to $\vec{x}_{3}$ is parallel to (has the same slope as) the line segment that connects $\vec{x}_{2}$ to $\vec{x}_{4}$.

## Problem 4 (17 points)

Suppose you have a dataset containing audio waveforms, $\vec{x}_{i}$, each matched with two different one-hot label vectors. The label vector $\vec{y}_{i}^{*}=\left[y_{i 1}^{*}, \ldots, y_{i q}^{*}\right]^{T}$, where $y_{i j}^{*} \in\{0,1\}$, is approximated by the network output $\vec{y}_{i}=\left[y_{i 1}, \ldots, y_{i q}\right]^{T}$, where $y_{i j} \in(0,1)$. The label vector $\vec{z}_{i}^{*}=$ $\left[z_{i 1}^{*}, \ldots, z_{i r}^{*}\right]^{T}$, where $z_{i j}^{*} \in\{0,1\}$, is approximated by the network output $\vec{z}_{i}=\left[z_{i 1}, \ldots, z_{i r}\right]^{T}$,
$\qquad$
where $z_{i j} \in(0,1)$. Both $\vec{y}_{i}$ and $\vec{z}_{i}$ are functions of a hidden nodes vector $\vec{h}_{i}$ as

$$
\begin{aligned}
\vec{h}_{i} & =g\left(W \vec{x}_{i}\right) \\
\vec{y}_{i} & =\operatorname{softmax}\left(U \vec{h}_{i}\right) \\
\vec{z}_{i} & =\operatorname{softmax}\left(V \vec{h}_{i}\right)
\end{aligned}
$$

where $U, V$ and $W$ are trainable weight matrices, and $g(\cdot)$ is some scalar nonlinearity. Find an error metric $E$ such that, by minimizing $E$, you can:

- maximize the accuracy of $\vec{y}_{i}$ as an estimate of $\vec{y}_{i}^{*}$
- minimize the accuracy of $\vec{z}_{i}$ as an estimate of $\vec{z}_{i}^{*}$


## Problem 5 (17 points)

The Barycentric coordinates of point $\vec{x}_{0}=\left[x_{0}, y_{0}, 1\right]^{T}$, as defined by the triangle $\vec{x}_{1}=$ $\left[x_{1}, y_{1}, 1\right]^{T}, \vec{x}_{2}=\left[x_{2}, y_{2}, 1\right]^{T}, \vec{x}_{3}=\left[x_{3}, y_{3}, 1\right]^{T}$, are the coordinates $\lambda_{1}, \lambda_{2}, \lambda_{3}$ such that

$$
\left[\begin{array}{c}
x_{0} \\
y_{0} \\
1
\end{array}\right]=\left[\begin{array}{ccc}
x_{1} & x_{2} & x_{3} \\
y_{1} & y_{2} & y_{3} \\
1 & 1 & 1
\end{array}\right]\left[\begin{array}{c}
\lambda_{1} \\
\lambda_{2} \\
\lambda_{3}
\end{array}\right]
$$

Provide an equation in terms of the six scalars $x_{1}, x_{2}, x_{3}, y_{1}, y_{2}, y_{3}$ specifying the conditions under which the matrix $\left[\begin{array}{ccc}x_{1} & x_{2} & x_{3} \\ y_{1} & y_{2} & y_{3} \\ 1 & 1 & 1\end{array}\right]$ is singular.

## Problem 6 (17 points)

Consider an LSTM defined by

$$
\begin{aligned}
\vec{i}[n] & =\text { input gate }=\sigma\left(B_{i} \vec{x}[n]+A_{i} \vec{c}[n-1]\right) \\
\vec{o}[n] & =\text { output gate }=\sigma\left(B_{o} \vec{x}[n]+A_{o} \vec{c}[n-1]\right) \\
\vec{f}[n] & =\text { forget gate }=\sigma\left(B_{f} \vec{x}[n]+A_{f} \vec{c}[n-1]\right) \\
\vec{c}[n] & =\vec{f}[n] \odot c[n-1]+\vec{i}[n] \odot g\left(B_{c} \vec{x}[n]+A_{c} \vec{c}[n-1]\right) \\
\vec{y}[n] & =\vec{o}[n] \odot \vec{c}[n]
\end{aligned}
$$

where the vector cell is $\vec{c}[n]=\left[c_{1}[n], \ldots, c_{p}[n]\right]^{T}$, and where $\odot$ denotes the Hadamard (array) product, e.g., $\vec{o}[n] \odot \vec{c}[n]=\left[o_{1}[n] c_{1}[n], \ldots, o_{p}[n] c_{p}[n]\right]^{T}$. Find the derivative $\frac{\partial c_{j}[n]}{\partial c_{k}[n-1]}$.

