# UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN 

Department of Electrical and Computer Engineering

## ECE 544NA Pattern Recognition <br> Fall 2016

## SAMPLE EXAM 3

- This is a CLOSED BOOK exam. You may use one page, both sides, of handwritten notes.
- There are a total of 100 points in the exam. Plan your work accordingly.
- You must SHOW YOUR WORK to get full credit.

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

Name: $\qquad$
$\qquad$

## Problem 1 (20 points)

An RNN has output $\hat{y}(t)$ defined for $0 \leq t<\infty$, input $x(t)$, error $E_{t}$, network weights $a_{t}$ and $b_{t}$, and scalar nonlinearity $g(\cdot)$ related by

$$
\begin{align*}
\hat{y}(t) & =g\left(a_{t} \hat{y}(t-1)+b_{t} x(t)\right)  \tag{1}\\
E_{t} & =\frac{1}{2}(y(t)-\hat{y}(t))^{2}  \tag{2}\\
a_{0}=b_{0} & =0  \tag{3}\\
a_{t+1} & =a_{t}-0.02 \sum_{k=0}^{t} \frac{\partial E_{t}}{\partial a_{k}} \tag{4}
\end{align*}
$$

(a) Prove that, even if $E_{t}$ is bounded, $\sum_{k=0}^{t} \frac{\partial E_{t}}{\partial a_{k}}$ might grow without bound.
(b) Modify the update equation to

$$
a_{t+1}=\max \left(-a_{M A X}, \min \left(a_{M A X}, a_{t}-0.02 \sum_{k=0}^{t} \frac{\partial E_{t}}{\partial a_{k}}\right)\right)
$$

Find sufficient conditions on $a_{M A X}$ and $g(\cdot)$ such that $\sum_{k=0}^{t} \frac{\partial E_{t}}{\partial a_{k}}$ is guaranteed to remain bounded as $t \rightarrow \infty$.

## Problem 2 (10 points)

Consider a two-layer RNN, one node per layer, with input $x(t)$, hidden layer $h(t)$, output $\hat{y}(t)$, error $E_{t}$, scalar nonlinearity $g(\cdot)$, and coefficients $a, b, \alpha, \beta$ related by

$$
\begin{align*}
h(t) & =g(a h(t-1)+b x(t))  \tag{5}\\
\hat{y}(t) & =(\alpha \hat{y}(t-1)+\beta h(t))  \tag{6}\\
E_{t} & =y(t) \log (\hat{y}(t))+(1-y(t)) \log (1-\hat{y}(t)) \tag{7}
\end{align*}
$$

Find $\frac{\partial E_{t}}{\partial \beta}$ and $\frac{\partial E_{t}}{\partial b}$.

## Problem 3 (20 points)

A simplified LSTM with inputs $x(t)$ is defined by

$$
\begin{align*}
c(t) & =i(t) x(t)+m(t) c(t-1)  \tag{8}\\
i(t) & =u\left(w^{i} x(t)+b^{i}\right)  \tag{9}\\
m(t) & =u\left(w^{m} x(t)+b^{m}\right) \tag{10}
\end{align*}
$$

where $u(\cdot)$ is the unit step function, defined as $u(z)=\frac{1}{2}(\operatorname{sign}(z)+1)$.
(a) Choose $w^{i}, b^{i}, w^{m}$ and $b^{m}$ so that

$$
c(t)= \begin{cases}x(t) & x(t)>2  \tag{11}\\ c(t-1) & x(t)<2\end{cases}
$$

(b) Suppose $x(t)=s(t)+v(t)$, where $s(t)$ is the desired signal,

$$
s(t)= \begin{cases}10 & t=0 \\ 0 & \text { otherwise }\end{cases}
$$

and $v(t)$ is a random noise process with distribution given by

$$
\Phi(z)=\operatorname{Pr}\{v(t) \leq z\}=\int_{-\infty}^{z} \frac{1}{\sqrt{2 \pi}} e^{-\frac{1}{2} u^{2}} d u
$$

Define the "memory" of the network you designed in part (a) to be the expected number of time steps for which $c(t)=x(0)$. Find the memory of your network, as a function of $\Phi(z)$.

## Problem 4 (25 points)

Define $c_{t}=i$ to be the event that the $i^{\text {th }}$ coin is flipped at time $t$, where $1 \leq i \leq 3$. The possible observations are $x_{t} \in\{H, T\}$. Two of the coins are unfair; the heads probabilities of the three coins are given by $p\left(x_{t}=H \mid c_{t}=i\right)=i / 4$. Coin $c_{1}=1$ is always the first one flipped. After each coin flip, the coin is changed with probability $\frac{1}{2}$; if the coin is changed, both of the other coins are equally likely.
(a) What is $p\left(c_{1}=1, c_{2}=1, c_{3}=2\right)$ ?
(b) What is the probability of getting three heads in a row?
(c) Suppose you observe two heads in a row. You know that the first flip was coin $c_{1}=1$. Which coin was most probably the second one flipped?

## Problem 5 (15 points)

Suppose that an HMM has 6 states with transition probabilities arranged into a matrix $A$, whose $(i, j)^{\text {th }}$ element is $a_{i j}=\operatorname{Pr}\left\{s_{t}=j \mid s_{t-1}=i\right\}$. The $a_{i j}$ are initialized randomly, but because of a programming error, $a_{34}$ is accidentally set to $a_{34}=0$. New transition probabilities $\hat{a}_{i j}$ are estimated as

$$
\begin{align*}
\hat{a}_{i j} & =\frac{\sum_{t=1}^{T} \xi_{t}(i, j)}{\sum_{t=1}^{T} \sum_{j=1}^{6} \xi_{t}(i, j)}  \tag{12}\\
\xi_{t}(i, j) & =p\left(s_{t-1}=i, s_{t}=j \mid A, X\right) \tag{13}
\end{align*}
$$

where $X=\left[x_{1}, \ldots, x_{T}\right]$ is a sequence of observations whose details you do not need to know. Prove that, under these circumstances, $\hat{a}_{34}=0$.

## Problem 6 (10 points)

A NN-HMM hybrid has known observations $X=\left[x_{1}, \ldots, x_{T}\right]$, and unknown state sequence $S=\left[s_{1}, \ldots, s_{T}\right]$. Its initialization probabilities are $\pi_{i}=\operatorname{Pr}\left\{s_{1}=i\right\}$, and its transition probabilities are $a_{i j}=\operatorname{Pr}\left\{s_{t}=j \mid s_{t-1}=i\right\}$. Its observation probabilities are computed by the softmax
layer of a neural network; they are $b_{j}\left(x_{t}\right)=\operatorname{Pr}\left\{s_{t}=j \mid x_{t}\right\} / \operatorname{Pr}\left\{s_{t}=j\right\}$. Consider the following algorithm:

$$
\begin{align*}
\alpha_{1}(i) & =\pi_{i} b_{i}\left(x_{1}\right), \quad 1 \leq i \leq N  \tag{14}\\
\alpha_{t+1}(j) & =\sum_{i=1}^{N} \alpha_{t}(i) a_{i j} b_{j}\left(x_{t}\right), \quad 1 \leq i, j \leq N, \quad 1 \leq t \leq T-1  \tag{15}\\
P_{\text {final }} & =\sum_{j=1}^{N} \alpha_{T}(j) \tag{16}
\end{align*}
$$

Express $P_{\text {final }}=\ldots$, where the right-hand side of the equation contains some sort of arithmetic combination of joint, conditional, and marginal probability mass functions of the random variables $x_{t}$. No other variables should appear on the right-hand side.

