

UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN  
Department of Electrical and Computer Engineering

ECE 417 MULTIMEDIA SIGNAL PROCESSING  
Spring 2016

**EXAM 2**

Thursday, March 31, 2016

- This is a **CLOSED BOOK** exam. You may use one sheet (front and back) of hand-written notes.
- No calculators are permitted. You need not simplify explicit numerical expressions.
- There are 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	
Total	

Name: \_\_\_\_\_

## Possibly Useful Formulas

**Gaussian (Normal) Distribution** A Gaussian is parameterized by  $\vec{\mu}$ ,  $\Sigma$ , and  $D = \dim(\vec{\mu})$  as

$$\mathcal{N}(\vec{x}|\vec{\mu}, \Sigma) = \frac{1}{(2\pi)^{D/2}|\Sigma|^{1/2}} e^{-\frac{1}{2}(\vec{x}-\vec{\mu})^T \Sigma^{-1}(\vec{x}-\vec{\mu})}$$

**Gaussian Mixture Model (GMM)** A GMM is parameterized by  $c_k$ ,  $\vec{\mu}_k$ , and  $\Sigma_k$  for  $1 \leq k \leq K$  as

$$p_X(\vec{x}) = \sum_{k=1}^K c_k \mathcal{N}(\vec{x}|\vec{\mu}_k, \Sigma_k)$$

**Hidden Markov Model (HMM)** An HMM is parameterized by  $\lambda = \{\pi_i, a_{ij}, b_j(\vec{x})\}$ , where

$$\begin{aligned} \pi_i &= p(q_1 = i|\lambda), \quad 1 \leq i \leq N \\ a_{ij} &= p(q_{t+1} = j|q_t = i, \lambda), \quad 1 \leq i, j \leq N \\ b_j(\vec{x}) &= p(\vec{x}|q_t = j, \lambda), \quad 1 \leq j \leq N \end{aligned}$$

The acoustic model  $b_j(\vec{x})$  might be GMM, for example, in which case the HMM parameters include

$$\begin{aligned} c_{jk} &= p(g_t = k|q_t = j) \\ \vec{\mu}_{jk} &= E[\vec{x}_t|q_t = j, g_t = k] \\ \Sigma_{jk} &= E[(\vec{x}_t - \vec{\mu}_{jk})(\vec{x}_t - \vec{\mu}_{jk})^T|q_t = j, g_t = k] \end{aligned}$$

## Scaled Forward Algorithm

$$\begin{aligned} \hat{\alpha}_1(i) &= \pi_i b_i(\vec{x}_1), \quad 1 \leq i \leq N \\ g_1 &= \sum_{i=1}^N \hat{\alpha}_1(i) \\ \tilde{\alpha}_1(i) &= \frac{1}{g_1} \hat{\alpha}_1(i) \\ \hat{\alpha}_t(j) &= \sum_{i=1}^N \tilde{\alpha}_{t-1}(i) a_{ij} b_j(\vec{x}_t) \\ g_t &= \sum_{j=1}^N \hat{\alpha}_t(j) \\ \tilde{\alpha}_t(j) &= \frac{1}{g_t} \hat{\alpha}_t(j) \\ p(\vec{x}_1, \dots, \vec{x}_t|\lambda) &= \prod_{t=1}^T g_t \end{aligned}$$