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Lecture 23: Exam 3 Review

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University of Illinois

ECE 417: Multimedia Signal Processing











Outline



2 Topics covered

3 Sample Problems

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Overview 000 Topics covered

Sample Problems

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Wnen and Where?

- Friday, December 8
- 1:30-4:30pm
- Here (ECEB 2013)

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• Bring:

- Up to 3 sheets of notes, hand-written or $12 \mbox{pt}+$ notes on both sides
- Pencils or pens
- Don't bring:
 - Calculators, computers, tablets, phones

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Is it comprehensive?

Yes, but with an emphasis on the last third of the course.

- Total: 200 points
- About 34 points: First third of the course
- About 34 points: Second third of the course
- About 132 points: Last third of the course











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What is the "last third"?

- Covered on the exam:
 - Lecture 15: PCA
 - Lecture 17: RNN
 - Lecture 18: LSTM
- Not covered:
 - Lecture 19: Speaker verification
 - Lecture 20: AutoVC
 - Lecture 21: Transformer
 - Lecture 22: Self-supervised learning

PCA

• Symmetric positive semidefinite matrices:

$$\boldsymbol{\Sigma} = \boldsymbol{U} \boldsymbol{\Lambda} \boldsymbol{U}^{\mathsf{T}}, \quad \boldsymbol{U}^{\mathsf{T}} \boldsymbol{\Sigma} \boldsymbol{U} = \boldsymbol{\Lambda}, \quad \boldsymbol{U}^{\mathsf{T}} \boldsymbol{U} = \boldsymbol{U} \boldsymbol{U}^{\mathsf{T}} = \boldsymbol{I}$$

• Centered dataset:

$$oldsymbol{X} = [oldsymbol{x}_1 - oldsymbol{\mu}, \dots, oldsymbol{x}_M - oldsymbol{\mu}], \quad oldsymbol{\Sigma} = rac{1}{M-1}oldsymbol{X}oldsymbol{X}^{ op}, \quad oldsymbol{G} = oldsymbol{X}^{ op}oldsymbol{X}$$

• Singular value decomposition:

$$oldsymbol{X} = oldsymbol{U} \Lambda^{1/2} oldsymbol{V}^{ op}$$

 The principal components are the first K elements of y_m = U^T(x_m - μ). The amount of energy they capture is:

$$\frac{1}{M-1}\sum_{m=1}^{M}\|\boldsymbol{y}_{m}\|^{2} = \sum_{k=1}^{K}\lambda_{k}$$

RNN

• Back-Prop, in general, is just the chain rule of calculus:

$$\frac{d\mathcal{L}}{dw} = \sum_{i=0}^{N-1} \frac{d\mathcal{L}}{dh_i} \frac{\partial h_i}{\partial w}$$

- Convolutional Neural Networks are the nonlinear version of an FIR filter. Coefficients are shared across time steps.
- Recurrent Neural Networks are the nonlinear version of an IIR filter. Coefficients are shared across time steps. Error is back-propagated from every output time step to every input time step.

$$\frac{d\mathcal{L}}{dh[n]} = \frac{\partial\mathcal{L}}{\partial h[n]} + \sum_{m=1}^{M} \frac{d\mathcal{L}}{dh[n+m]} \frac{\partial h[n+m]}{\partial h[n]}$$
$$\frac{\partial\mathcal{L}}{\partial w[m]} (w[1], \dots, w[M]) = \sum_{n} \frac{d\mathcal{L}}{dh[n]} \frac{\partial h[n]}{\partial w[m]}$$

Overview 0000 Topics covered ○000● Sample Problems

Neural Network Model: LSTM



$$i[t] = \text{input gate} = \sigma(w_i \times [t] + u_i h[t-1] + b_i)$$

$$o[t] = \text{output gate} = \sigma(w_o \times [t] + u_o h[t-1] + b_o)$$

$$f[t] = \text{forget gate} = \sigma(w_f \times [t] + u_f h[t-1] + b_f)$$

$$c[t] = f[t]c[t-1] + i[t] \text{tanh} (w_c \times [t] + u_c h[t-1] + b_c)$$

$$h[t] = \text{output} = o[t] \text{tanh} (c[t])$$

Outline



2 Topics covered



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Sample Problems

- Sample problems about PCA
- Sample problems about RNN
- Sample problems about LSTM