## MP2 Walkthrough HMM Speech Recognition

ECE 417 - Multimedia Signal Processing
Fall 2018

## Goal

- Implement a speech recognizer using Hidden Markov Model(HMM) to recognize certain words


## Data Corpus

- 100 different audio files:
- 4 speakers: mh, ls, dg, yx
- 5 words: "CNN", "DNN", "ASR", "TTS" and "HMM"
- 5 utterances of each word per speaker


## Overview

- Extracting audio features
- Splitting training and testing data
- Training Gaussian HMM model for speech recognizer
- Evaluating your HMM model


## Extracting audio features

- Extract the features to represent the audio recordings
- You are provided with the MFCC features for each audio recording
- BONUS POINTS! Up to $10 \%$
- New feature set other than MFCC
- Implement, report the results, and beat reference implementation accuracy results


## Splitting training and testing data

- Speaker dependent experiment
- Training: first 4 utterances of each word, from each of the 4 speakers $(4 \times 4 \times 5=80)$
- Testing: fifth utterance from each speaker ( $4 \times 5=20$ )
- Speaker independent experiment
- Training: all utterances from speakers dg, ls, and yx ( $3 \times 5 \times 5=75$ )
- Testing1: all utterances from speaker mh (5x5=25)
- Testing2: all utterances from you ( $5 \times 5=25$ )


## Training the Gaussian HMM

- Recap of HMM:
- A HMM is a statistical model for a time-varying process
- The entire model represents a probability distribution over the sequence of observations
- It has a specific probability of generating any particular sequence
- It consists of two components
- A Markov chain that specifies how many states there are, and how they can transition from one state to another
- A set of probability distributions, one for each state, which specifies the distribution of observation in that state
- HMM Parameters
- m - initial state distribution
- A - state transition matrix

$$
A=\left(\begin{array}{ccc}
0.6 & 0.4 & 0 \\
0 & 0.7 & 0.3 \\
0.5 & 0 & 0.5
\end{array}\right)
$$

- Aij is the probability that when in state $i$, the process will move to $j$
- B - observation matrix
- Probability of data produced from any state
- In this lab, model the observation matrix as Gaussian $(\mu, \sigma)$


## Training the Gaussian HMM

- Learn the HMM parameters ( $\pi, A, \mu, \sigma$ ) from observation sequences/training utterances
- Approach: forward-backward/EM algorithm to optimize the parameters
- Initialization:
- $\quad$ - uniform distribution across 5 states
- A-[0.8 $0.2000 ; 00.80 .200 ; 000.80 .20 ; 0000.80 .2$; 0000 1]
- $\mu$ - mean across the audio features for that word
- $\sigma$ - co-variance matrix across the audio features for that word


## Training the Gaussian HMM

- BONUS POINTS! Up to 10\%
- The observation matrix can also be modeled as likelihood function other than Gaussian
- Examples: GMM, KNN, NN...
- Write your own code to integrate the function with the HMM, and beat baseline
- Partial credit(8\%) possible with explanation


## Evaluating the model

- Given your trained model parameters of each word, compute the likelihood of word utterance in the test set
- Classify the utterance as the word with maximum likelihood
- Report the average classification accuracy on all the word utterances in your testing data


## Results

- Confusion matrix: a $5 \times 5$ matrix in which the $(m, n)$ th element specifies the conditional probability that the recognizer chose the nth word, given that the mth word was correct.
- Overall recognition accuracy for each of the three experiments


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Predicted word

|  |  | ASR | CNN | DNN | HMM | TTS |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | ASR | 1 | 0 | 0 | 0 | 0 |
| Ground | CNN | 0 | 1 | 0 | 0 | 0 |
| truth word | DNN | 0 | 0.25 | 0.75 | 0 | 0 |
|  | HMM | 0 | 0 | 0 | 1 | 0 |
|  | TTS | 0 | 0 | 0 | 0 | 1 |

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| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | ASR | 1 | 0 | 0 | 0 | 0 |
| Ground truth word | CNN | 0 | 1 | 0 | 0 | 0 |
|  | DNN | 0 | 0.25 | 0.75 | 0 | 0 |
|  | HMM | 0 | 0 | 0 | 1 | 0 |
|  | TTS | 0 | 0 | 0 | 0 | 1 |

## Turn In

- Report
- Include the confusion matrix and overall recognition accuracy for each of three experiments
- Include your analysis of comparisons between the outputs
- [Optional] Include your results for extra credit in the end
- File names must be <Lastname>_<Firstname>_report.pdf
- Code
- Readme file
- File names must be <Lastname>_<Firstname>_code.zip
- Do not upload the data corpus
- Submission
- Submit your report (PDF) and codes (zip) to Compass
- Teams will submit a single report but make sure that all names are included in the report

