# Artificial Neural Network for Speech Recognition

**Austin Marshall** 

March 3, 2005

2nd Annual Student Research Showcase



#### Overview

- Presenting an Artificial Neural Network to recognize and classify speech
  - Spoken digits
    - v "one","two","three", etc...
- Choosing a speech representation scheme
- Training Perceptron
- Results



## Representing Speech

#### v Problem

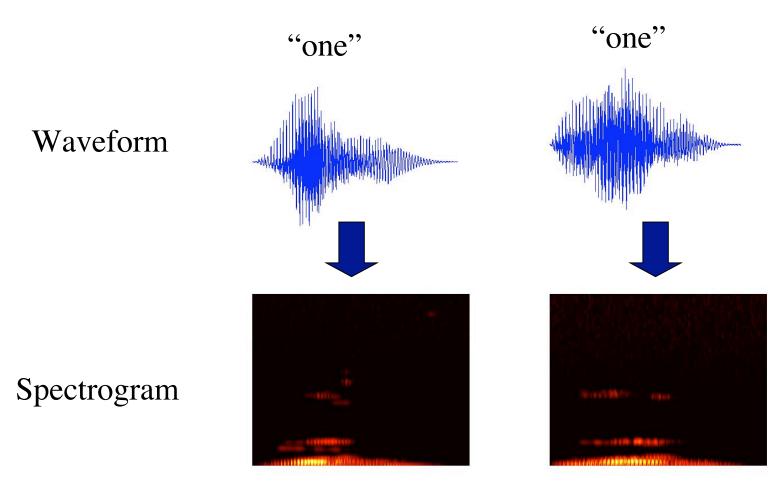
- Recording samples never produce identical waveforms
  - Length
  - Amplitude
  - v Background noise
  - Sample rate
- However, perceptual information relative to speech remains consistent

#### Solution

- Extract speech-related information
  - See: Spectrogram



# Representing Speech





## Spectrogram

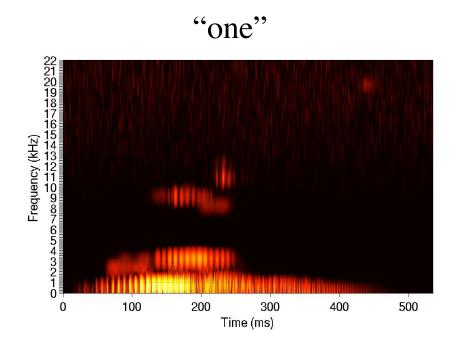
 Shows change in amplitude spectra over time

#### Three dimensions

X Axis: Time

Y Axis: Frequency

 Z axis: Color intensity represents magnitude





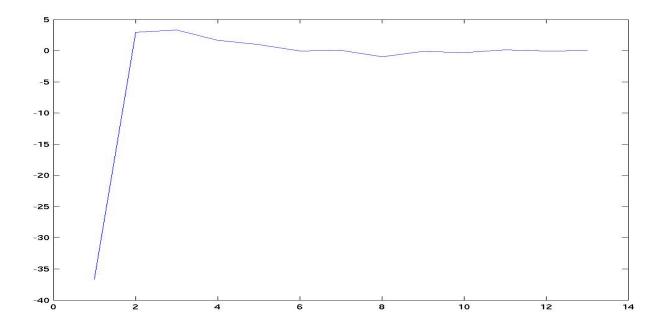
## Mel Frequency Cepstrum Coefficients

- Spectrogram provides a good visual representation of speech but still varies significantly between samples
- A cepstral analysis is a popular method for feature extraction in speech recognition applications, and can be accomplished using Mel Frequency Cepstrum Coefficient analysis (MFCC)



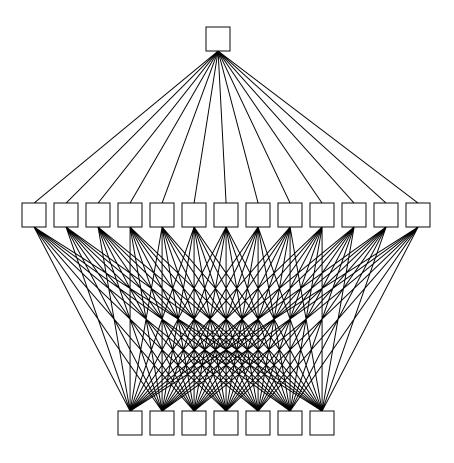
## Mel Frequency Cepstrum Coefficients

- Inverse Fourier transform of the log of the Fourier transform of a signal using the Mel Scale filterbank
- v mfcc function returns vectors of 13 dimensions





## **Network Architecture**



#### Input layer

26 Cepstral Coefficients

#### v Hidden Layer

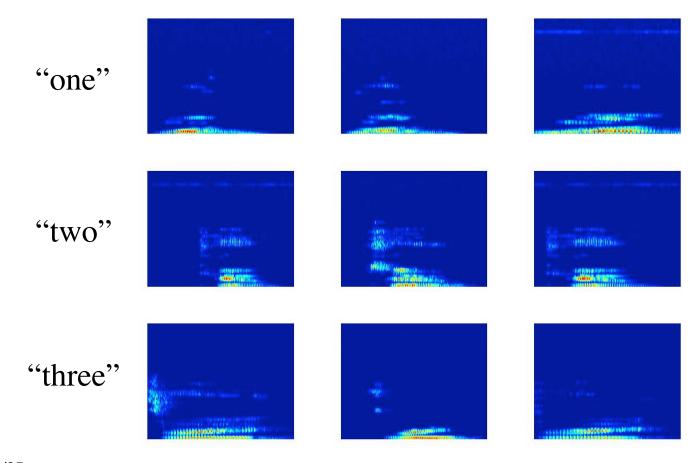
- 100 fully-connected hidden-layer units
- Weight range between -1 +1
  - Initially random
  - Remain constant

#### Output

- 1 output unit for each target
- Limited to values between 0 and +1



# Sample Training Stimuli (Spectrograms)





- Spoken digits were recorded
  - Seven samples of each digit
  - "One" through "eight" recorded
  - Total of 56 different recordings with varying lengths and environmental conditions
- Background noise was removed from each sample



- Calculate MFCC using Malcolm Slaney's Auditory Toolbox
  - c=mfcc(s,fs,fix((3\*fs)/(length(s)-256)))
  - Limits frame rate such that mfcc always produces a matrix of two vectors corresponding to the coefficients of the two halves of the sample
- Convert 13x2 matrix to 26 dimensional column vector
  - c=c(:)



- Supervised learning
  - Choose intended target and create a target vector
  - 56 dimensional target vector
- If training the network to recognize spoken "one", target has a value of +1 for each of the known "one" stimuli and 0 for everything else

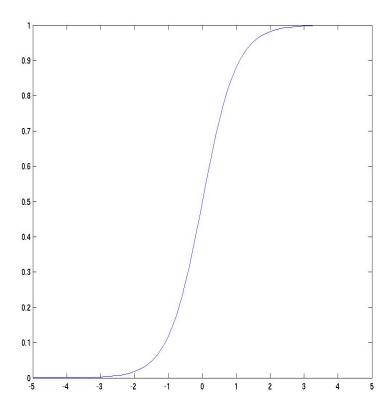


- Train a multilayer perceptron with feature vectors (simplified)
  - Select stimuli at random
  - Calculate response to stimuli
  - Calculate error
  - Update weights
  - Repeat
- In a finite amount of time, the perceptron will successfully learn to distinguish between stimuli of an intended target and not.



- Calculate response to stimuli
  - Calculate hidden layer
    - v h=sigmoid(W\*s+bias)
  - Calculate response
    - v o=sigmoid(v\*h+bias)
- Sigmoid transfer function
  - Maps values between 0 and +1

 $sigmoid(x)=1/(1+e^{-x})$ 





#### Calculate error

- For a given stimuli, error is the difference between target and response
- t-o
- t will be either 0 or 1
- o will be between 0 and +1



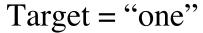
### Update weights

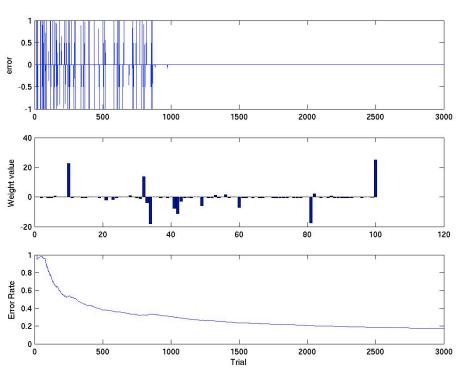
- $\mathbf{v} = \mathbf{v}_{\text{previous}} + \gamma(t-o)\mathbf{h}^{\mathsf{T}}$
- v is weight vector between hidden-layer units and output
- γ (gamma) is learning rate



### Results

- Learning rate: +1
- v Bias: -1
- 100 hidden-layer units
- 3000 iterations
- v 316 seconds to learn target







#### Results

### Response to unseen stimuli

- Stimuli produced by same voice used to train network with noise removed
- Network was tested against eight unseen stimuli corresponding to eight spoken digits
- Returned 1 (full activation) for "one" and zero for all other stimuli.
- Results were consistent across targets
  - v i.e. when trained to recognize "two", "three", etc...
- sigmoid(v\*sigmoid(w\*t1+bias)+bias) == 1



#### Results

- Response to noisy sample
  - Network returned a low, but response > 0 to a sample without noise removed
- Response to foreign speaker
  - Network responded with mixed results when presented samples from speakers different from training stimuli
- In all cases, error rate decreased and accuracy improved with more learning iterations



#### References

- Jurafsky, Daniel and Martin, James H. (2000) Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition (1st ed.). Prentice Hall
- Golden, Richard M. (1996) Mathematical Methods for Neural Network Analysis and Design (1st ed.). MIT Press
- Anderson, James A. (1995) An Introduction to Neural Networks (1st ed.).
  MIT Press
- Hosom, John-Paul, Cole, Ron, Fanty, Mark, Schalkwyk, Joham, Yan, Yonghong, Wei, Wei (1999, February 2). *Training Neural Networks for Speech Recognition* Center for Spoken Language Understanding, Oregon Graduate Institute of Science and Technology, http://speech.bme.ogi.edu/tutordemos/nnet\_training/tutorial.html
- Slaney, Malcolm Auditory Toolbox Interval Research Corporation