Speech Processing and Understanding

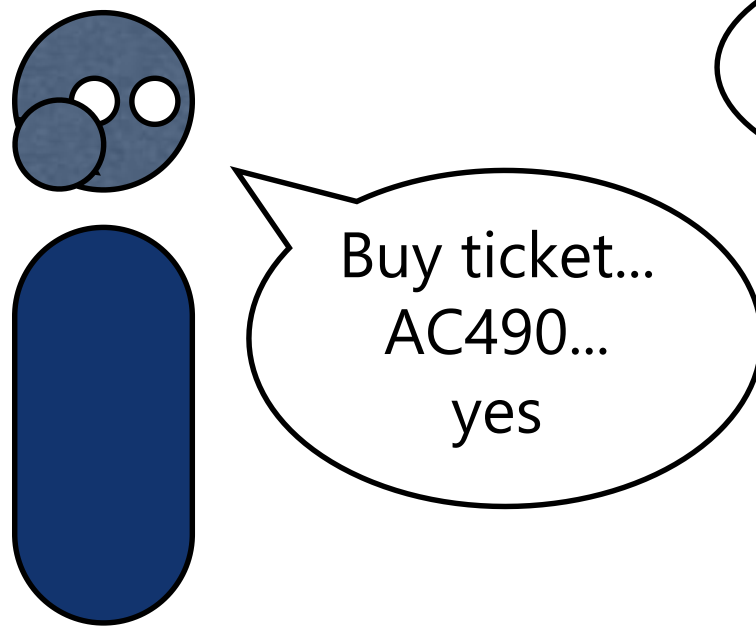
CSC401 Assignment 3

Agenda

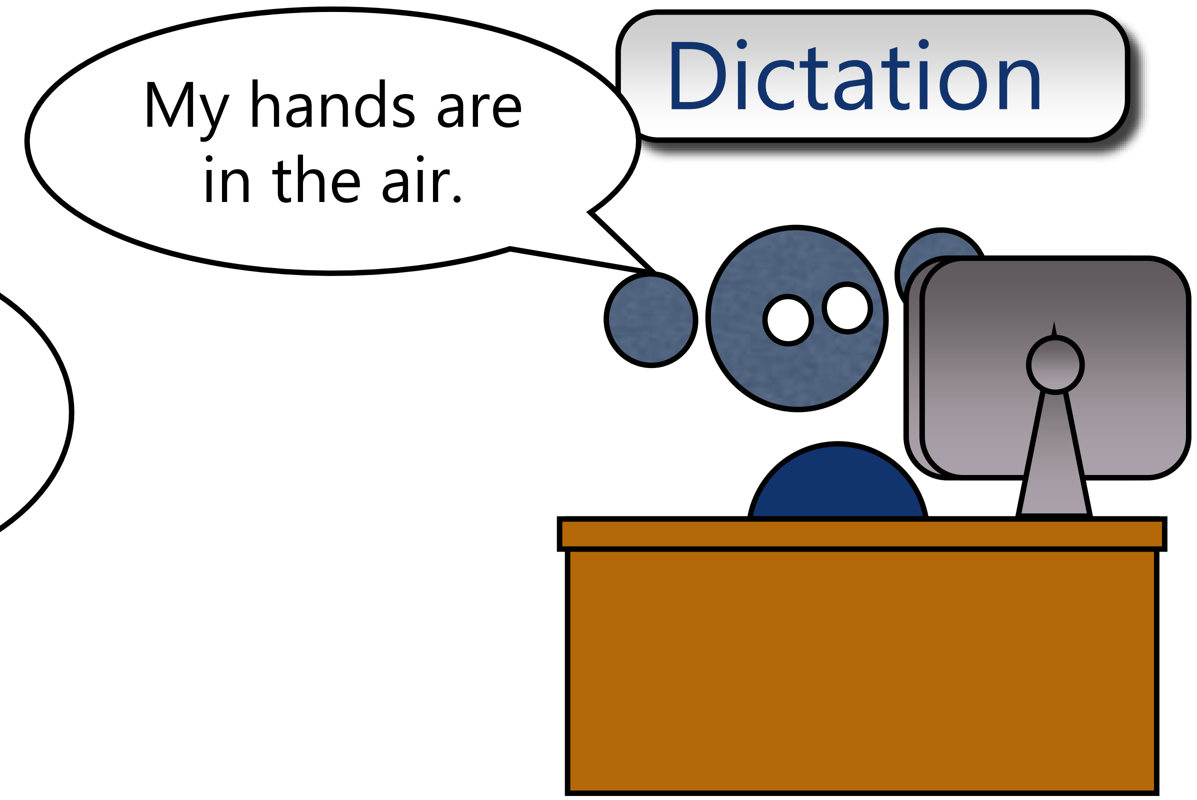
- Background
  - Speech technology, in general
  - Acoustic phonetics
- Assignment 3
  - Speaker Recognition: Gaussian mixture models
  - Speech Recognition: Word-error rates with Levenshtein distance.

Applications of Speech Technology

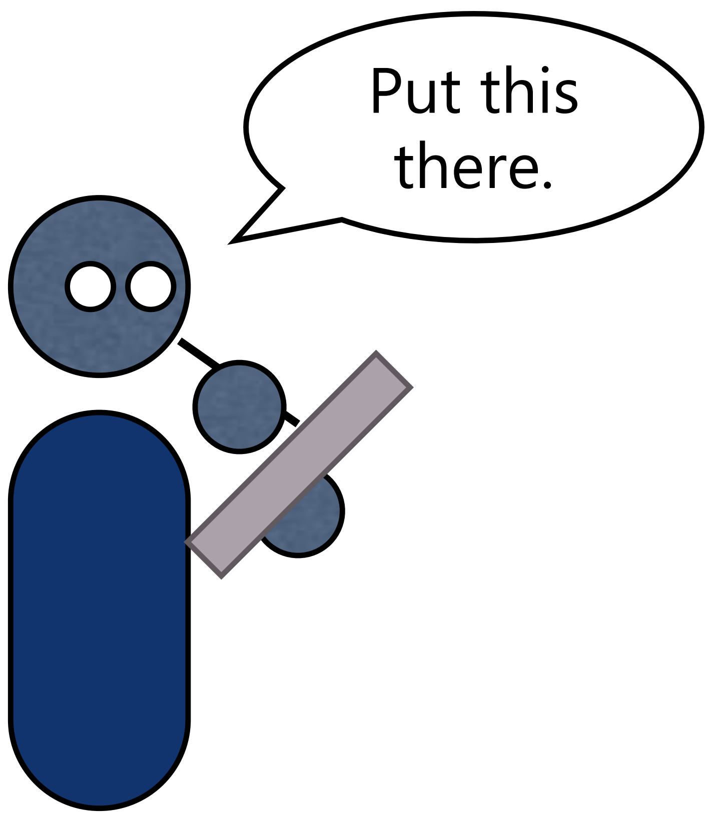
Telephony



Dictation



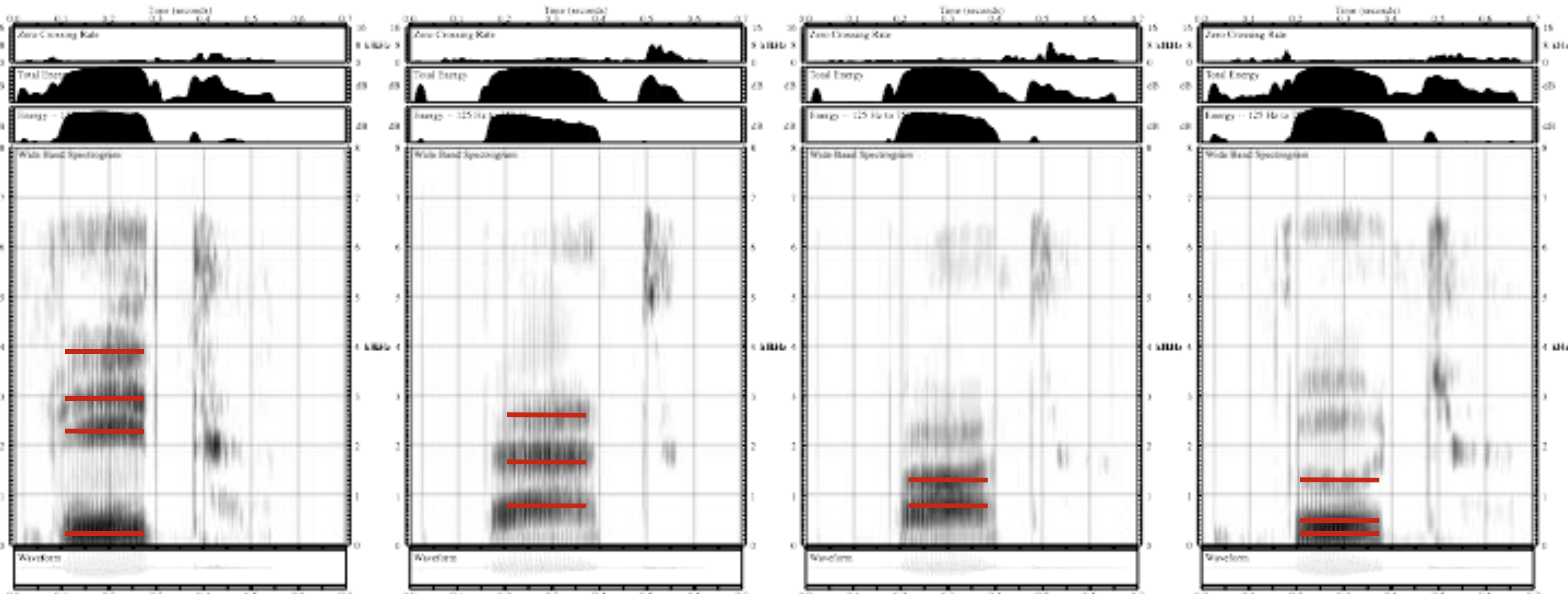
Multimodality & HCI



Emerging…

- Data mining/indexing.
- Assistive technology.
- Conversation.

Formants in sonorants

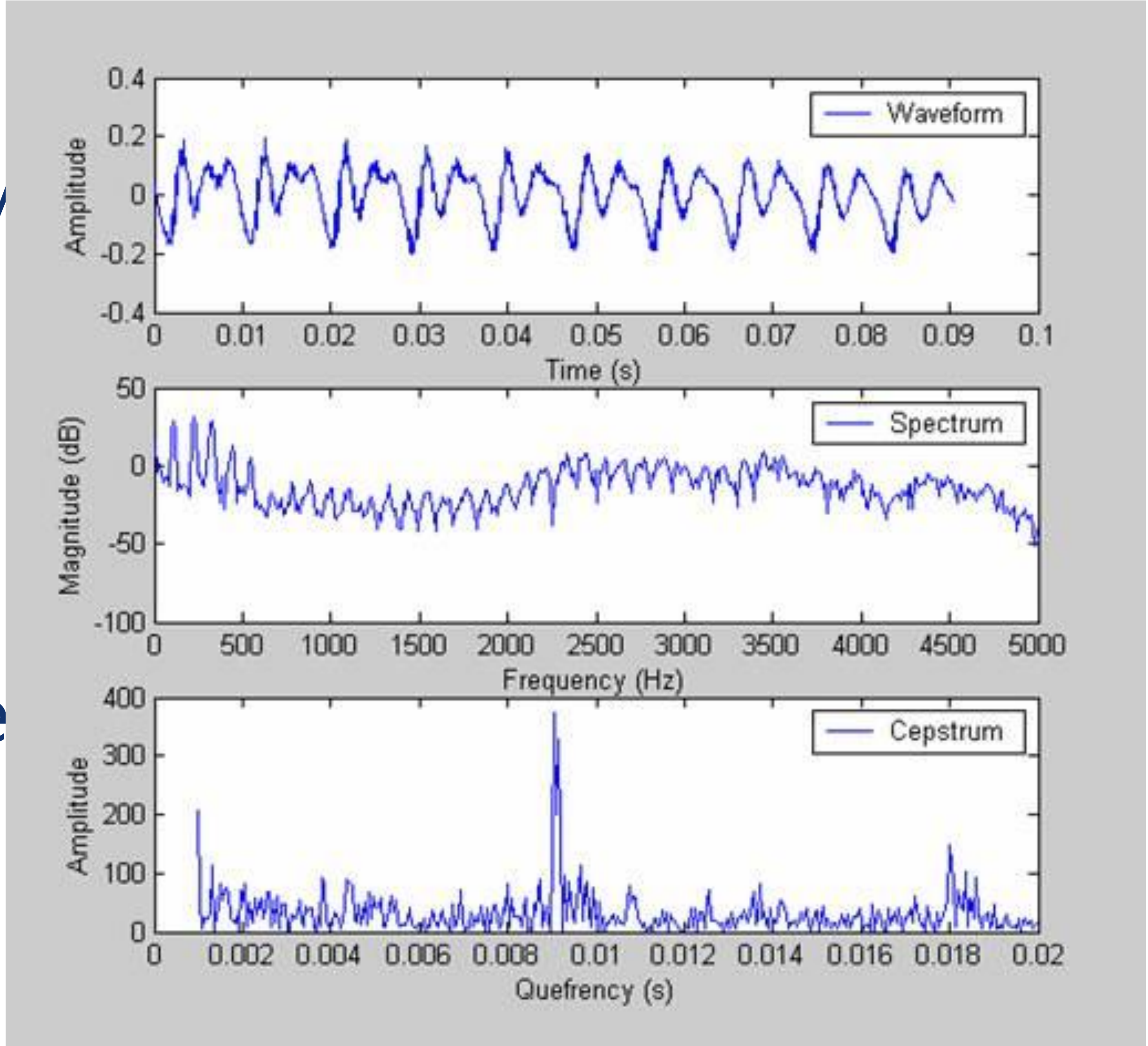


beet /biʸt/ | bat /bæt/ | bott /bat/ | boot /but/

- However, formants are insufficient features for use in speech recognition generally...

Mel-frequency cepstral coefficients

- In real speech data, the spectrogram is often transformed to a representation that more closely represents human auditory response and is more amenable to accurate classification.
- MFCCs are 'spectra of spectra'. They are the discrete cosine transform of the logarithms of the nonlinearly Mel-scaled powers of the Fourier transform of windows of the original waveform.



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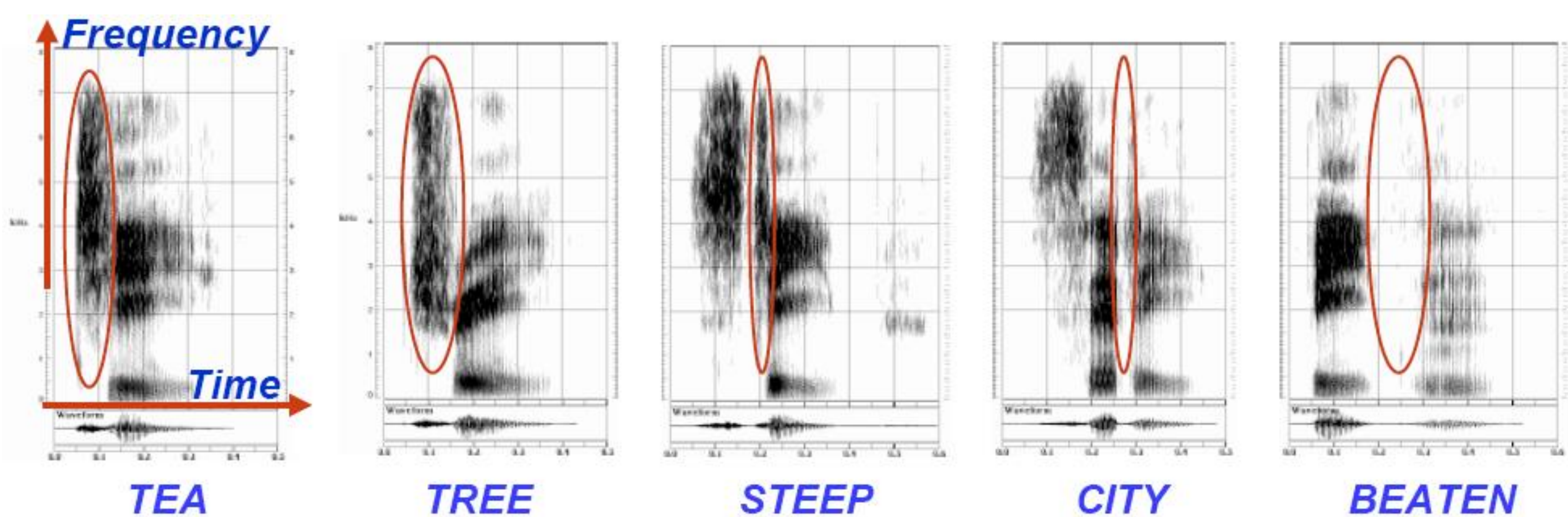
Challenges in speech data

- Co-articulation and dropped phonemes.
- (Intra-and-Inter-) Speaker variability.
- No word boundaries.
- Slurring, disfluency (e.g., ‘um’).
- Signal Noise.
- Highly dimensional.



Phonemes

- Words are formed by **phonemes** (aka 'phones'),
  e.g., 'pod' = /p aa d/

- Words have different pronunciations. and in practice we can never be certain of which phones were uttered, nor their start/stop points.

<table>
<tr><td rowspan="5">Syntactic</td><td colspan="15">Sentence</td></tr>
<tr><td colspan="15">Verb phrase</td></tr>
<tr><td colspan="4" rowspan="3">Verb</td><td colspan="11">Noun phrase</td></tr>
<tr><td colspan="2" rowspan="2">Det</td><td colspan="5">Modifier</td><td colspan="4" rowspan="2">Noun (plu)</td></tr>
<tr><td colspan="3">Noun</td><td colspan="2">Noun</td></tr>
<tr><td>Lexical</td><td colspan="4">open</td><td colspan="2">the</td><td colspan="3">pod</td><td colspan="2">bay</td><td colspan="4">doors</td></tr>
<tr><td>Phonemic</td><td>ow</td><td>p</td><td>ah</td><td>n</td><td>dh</td><td>ah</td><td>p</td><td>aa</td><td>d</td><td>b</td><td>ey</td><td>d</td><td>ao</td><td>r</td><td>z</td></tr>
</table>

Phonetic alphabets

- International Phonetic Association (IPA)
  - Can represent sounds in all languages
  - Contains non-ASCII characters
- ARPAbet
  - One of the earliest attempts at encoding English for early speech recognition.
- TIMIT/CMU
  - Very popular among modern databases for speech recognition.

Example phonetic alphabets

IPA	CMU	TIMIT	Example	IPA symbol name
[ɑ]	AA	aa	father, hot	script a
[æ]	AE	ae	had	digraph
[ə]	AH0	ax	sofa	schwa (common in unstressed syllables)
[ʌ]	AH1	ah	but	turned v
[ɔː]	AO	ao	caught	open o – Note, many speakers of Am. Eng. do not distinguish between [ɔː] and [ɑ]. If your "caught" and "cot" sound the same, you do not.
[ɛ]	EH	eh	head	epsilon
[ɪ]	IH	ih	hid	small capital I
[iː]	IY	iy	heed	lowercase i
[ʊ]	UH	uh	hood, book	upsilon
[uː]	UW	uw	boot	lowercase u
[aɪ]	AY	ay	hide	
[aʊ]	AW	aw	how	
[eɪ]	EY	ey	today	
[oʊ]	OW	ow	hoed	
[ɔɪ]	OY	oy	joy, ahoy	
[ɚ]	ER0	axr	herself	schwar (schwa changed by following r)
[ɝ]	ER1	er	bird	reverse epsilon right hook

IPA	CMU	TIMIT	Example	IPA symbol name
[ŋ]	NG	ng	sing song	eng or angma
[ʃ]	SH	sh	sheet, wish	esh or long s
[tʃ]	CH	ch	cheese	
[j]	Y	y	yellow	lowercase j
[ʒ]	ZJ	zh	vision	long z or yogh
[dʒ]	JH	jh	judge	
[ð]	DH	dh	thee, this	eth

- The other consonants are transcribed as you would expect
  - i.e., p, b, m, t, d, n, k, g, s, z, f, v, w, h

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Assignment 3

- Two parts:
  - Speaker identification: Determine which of 30 speakers an unknown test sample of speech comes from, given Gaussian mixture models you will train for each speaker.
  - Speech recognition: Compute word-error rates for speech recognition systems using Levenshtein distance.

Speaker Data

- 32 speakers (e.g., S-3C, S-5A).
- Each speaker has up to 12 training utterances.
  - e.g., `/u/csc401/A3/data/S-3C/0.wav`
- Each utterance has 3 files:
  - `*.wav` : The original wave file.
  - `*.mfcc.npy` : The MFCC features in NumPy format
  - `*.txt` : Sentence-level transcription.

Speaker Data (cont.)

- All you need to know: A speech utterance is an Nxd matrix
  - Each row represents the features of a d-dimensional point in time.
  - There are N rows in a sequence of N frames.
  - The data is in numpy arrays `*.mfcc.npy`
  - To read the files: `np.load('1.mfcc.npy')`

data dimension

time

frames

	1	2		d
1	$X_1[1]$	$X_1[2]$	…	$X_1[d]$
2	$X_2[1]$	$X_2[2]$	…	$X_2[d]$
	…	…	…	…
N	$X_N[1]$	$X_N[2]$	…	$X_N[d]$

Speaker Data (cont.)

- You are given human transcriptions in `transcripts.txt`
- You are also given Kaldi and Google transcriptions in `transcripts.*.txt`.
- Ignore any symbols that are not words.

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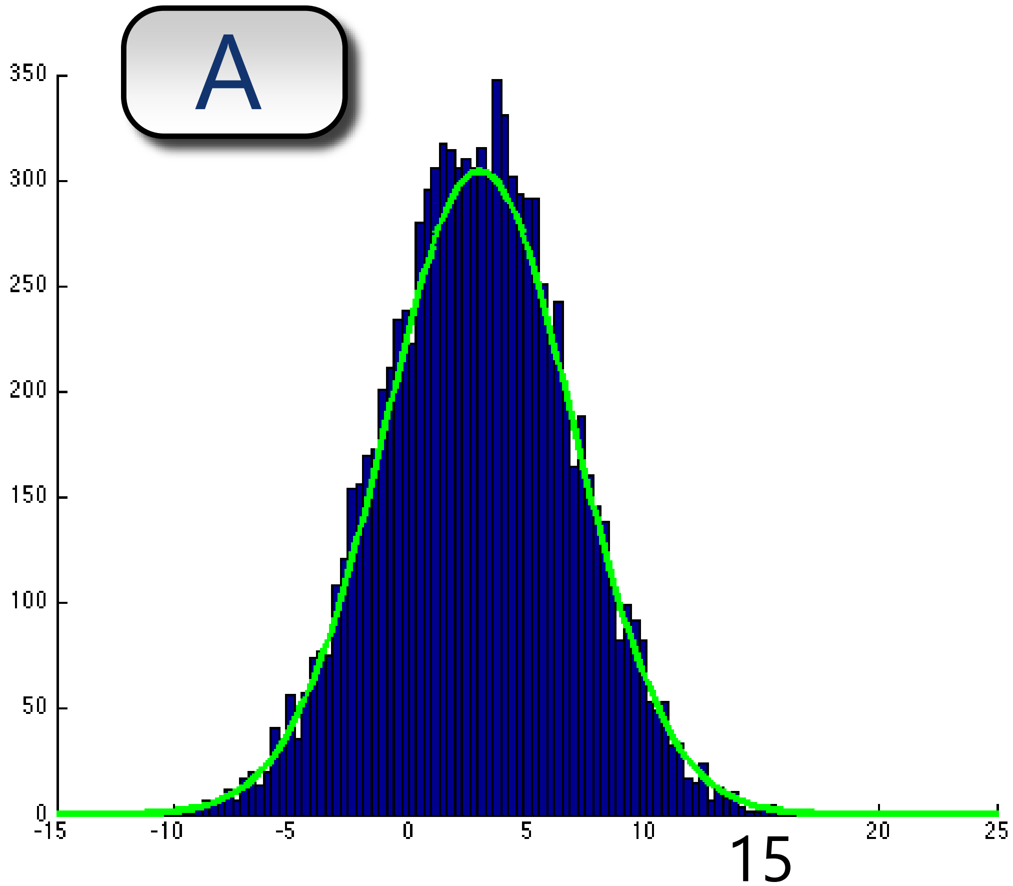
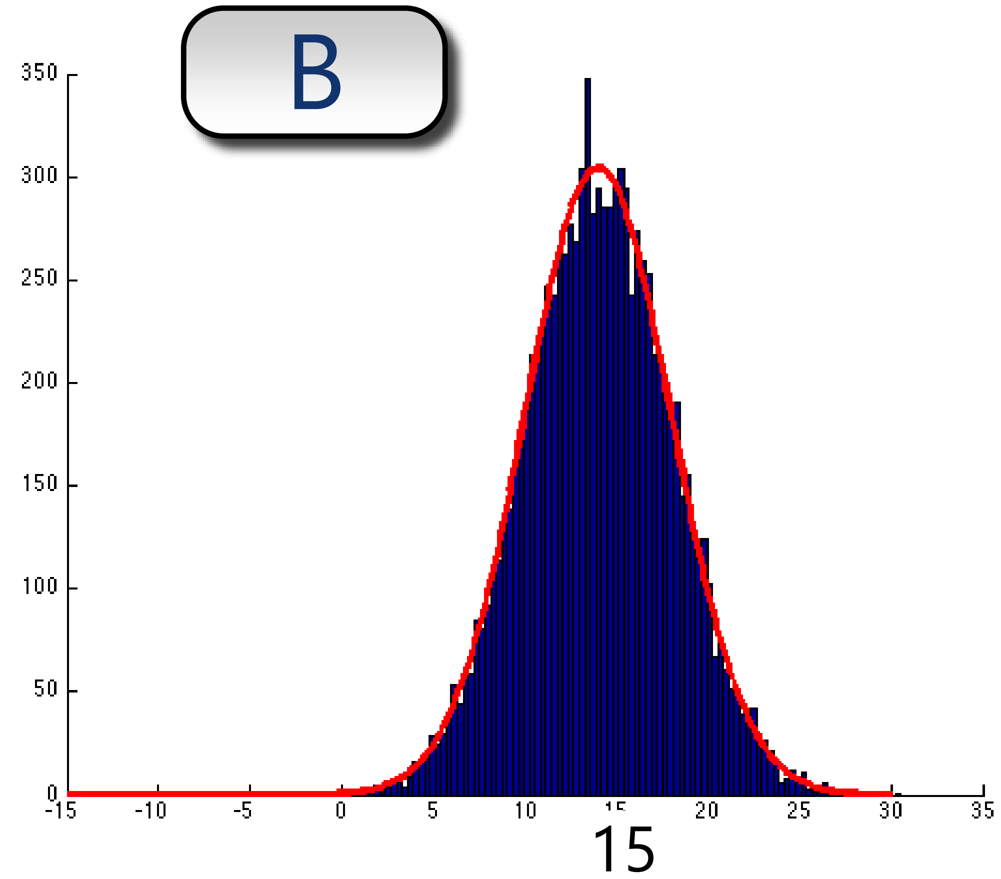
Speaker Recognition

- The data is randomly split into training and testing utterances. We don’t know which speaker produced which test utterance.
- Every speaker occupies a characteristic part of the acoustic space.
- We want to learn a probability distribution for each speaker that describes their acoustic behaviour.
  - Use those distributions to identify the speaker-dependent features of some unknown sample of speech data.

Some background: fitting to data

- Given a set of observations X of some random variable, we wish to know how X was generated.
- Here, we assume that the data was sampled from a Gaussian Distribution (validated by data).
- Given a new data point (x=15), It is more likely that x was generated by B.



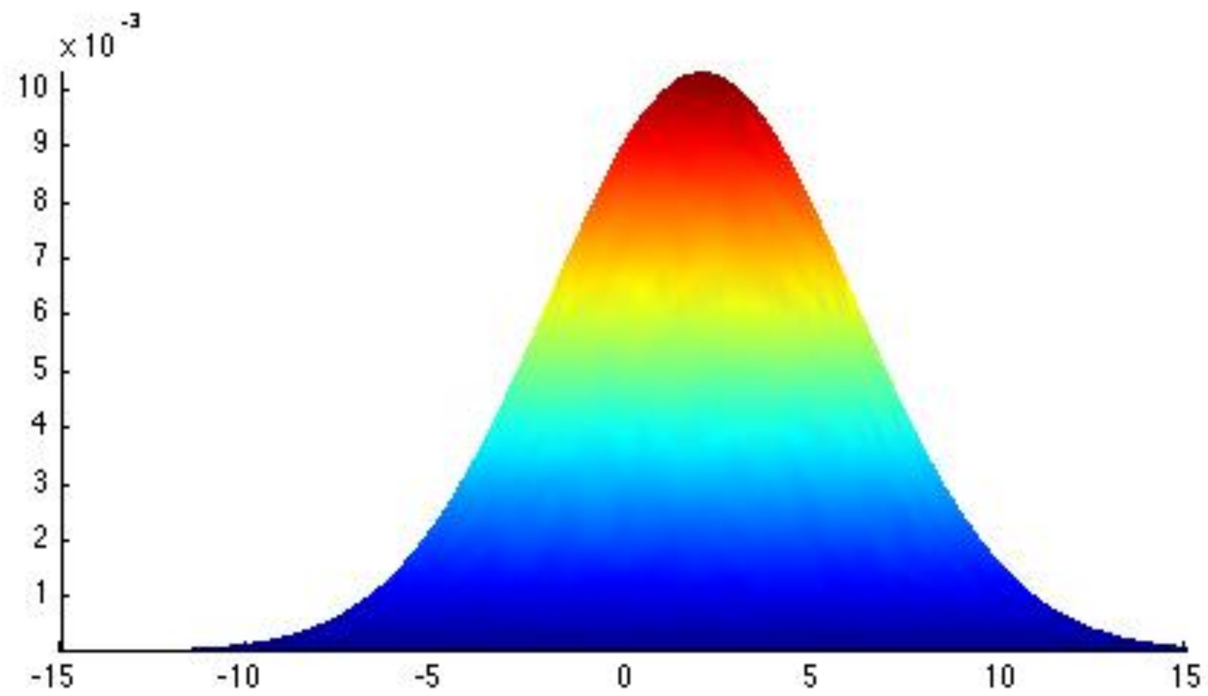


Finding parameters: 1D Gaussians

- Often called *Normal* distributions

$$p(x) = \frac{\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}{\sqrt{2\pi}\sigma}$$

$$N(\mu, \sigma)$$



$$\mu = E(x) = \int xp(x)dx$$

$$\sigma^2 = E((x-\mu)^2) = \int (x-\mu)^2 p(x)dx$$

- The parameters we can adjust to fit the data are μ and σ^2:

$$\theta = \langle \mu, \sigma \rangle$$

Maximum likelihood estimation

- Given data: $X = \{x_1, x_2, \ldots, x_n\}$
- and Parameter set: θ
- Maximum likelihood attempts to find the parameter set that maximizes the likelihood of the data.

$$L(X, \theta) = p(X \mid \theta) = p(x_1, x_2, \ldots, x_n \mid \theta) = \prod_{i=1}^{n} p(x_i \mid \theta)$$

- The likelihood function $L(X, \theta)$ provides a surface over all possible parameterizations. In order to find the Maximum Likelihood, we set the derivative to zero:

$$\frac{\partial}{\partial \theta} L(X, \theta) = 0$$

MLE - 1D Gaussian

- Estimate $\hat{\mu}$

$$L(X,\mu) = p(X \mid \mu) = \prod_{i=1}^{n} p(x_i \mid \mu) = \prod_{i=1}^{n} \frac{\exp\left(-\frac{(x_i-\mu)^2}{2\sigma^2}\right)}{\sqrt{2\pi}\sigma}$$

$$\log L(X,\mu) = -\frac{\sum_i (x_i-\mu)^2}{2\sigma^2} - n\log\sqrt{2\pi}\sigma$$

$$\frac{\partial}{\partial\mu}\log L(X,\mu) = \frac{\sum_i (x_i-\mu)}{\sigma^2} = 0$$

$$\hat{\mu} = \frac{\sum_i x_i}{n}$$

- A similar approach gives the MLE estimate of $\hat{\sigma}^2$:

$$\hat{\sigma}^2 = \frac{\sum_i (x_i-\hat{\mu})^2}{n}$$

Multidimensional Gaussians

- When your data is d-dimensional, the input variable is

$$\vec{x} = \langle x[1], x[2], \ldots, x[d] \rangle$$

the mean vector is

$$\vec{\mu} = E(\vec{x}) = \langle \mu[1], \mu[2], \ldots, \mu[d] \rangle$$

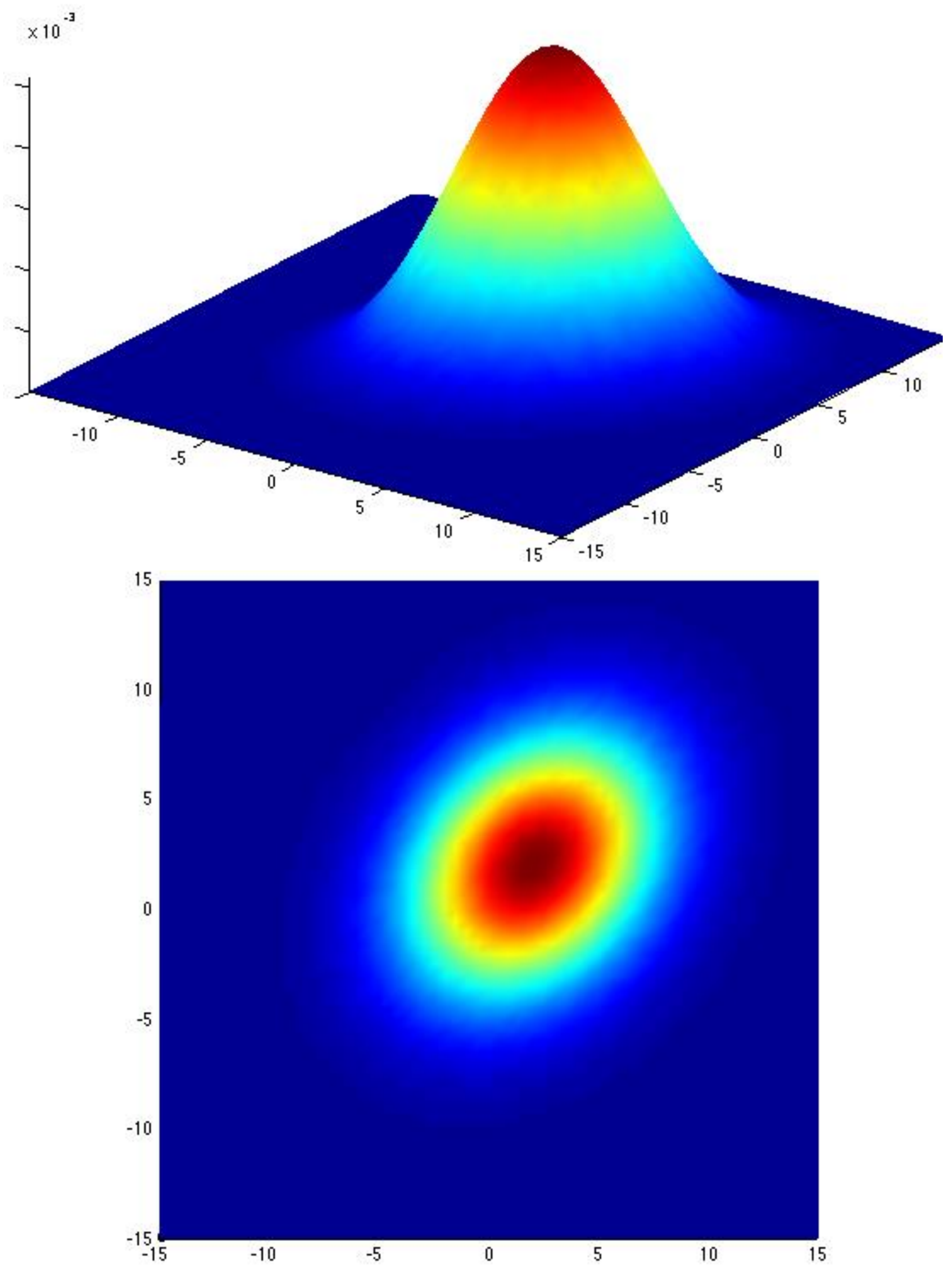
the covariance matrix is

$$\Sigma = E((\vec{x} - \vec{\mu})(\vec{x} - \vec{\mu})^T)$$

with $\Sigma[i,j] = E(x[i]x[j]) - \mu[i]\mu[j]$

and

$$p(\vec{x}) = \frac{\exp\left(-\frac{(\vec{x}-\vec{\mu})^T \Sigma^{-1} (\vec{x}-\vec{\mu})}{2}\right)}{(2\pi)^{d/2} |\Sigma|^{1/2}}$$



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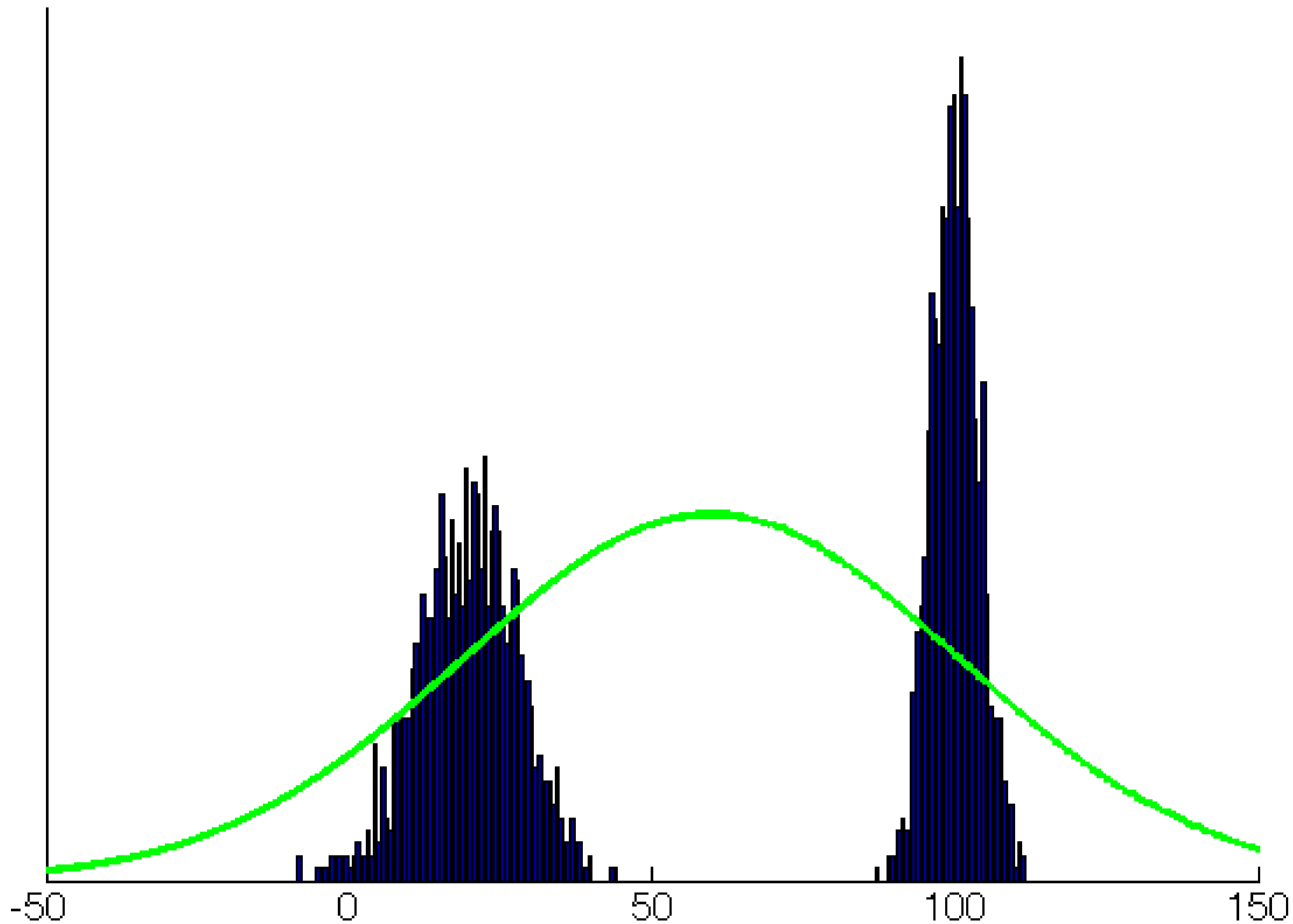
Non-Gaussian data

- Our speaker data does not behave unimodally.
  - i.e., we can't use just 1 Gaussian per speaker.
- E.g., observations below occur mostly bimodally, so fitting 1 Gaussian would not be representative.



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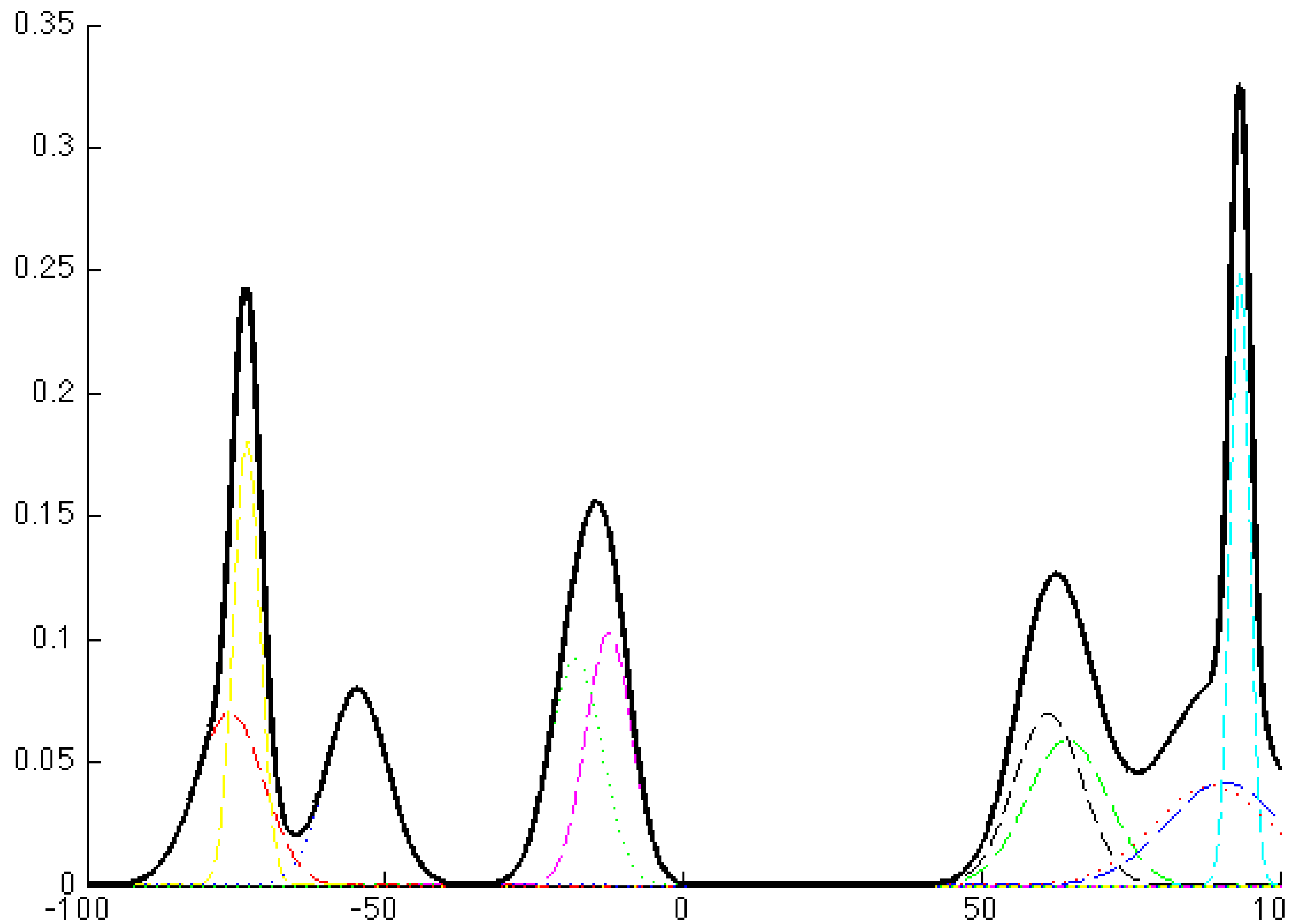
Gaussian mixtures

- Gaussian mixtures are a weighted linear combination of M component gaussians.

$$\langle \Gamma_1, \ldots, \Gamma_M \rangle$$

$$p(\vec{x}) = \sum_{j=1}^{M} p(\Gamma_j) p(\vec{x} \mid \Gamma_j)$$



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MLE for Gaussian mixtures

- For notational convenience, $\omega_m = p(\Gamma_m),\ b_m(\vec{x_t}) = p(\vec{x_t} \mid \Gamma_m)$
- So

$$p_\Theta(\vec{x_t}) = \sum_{m=1}^{M} \omega_m b_m(\vec{x_t}),\ \Theta = \langle \omega_m, \vec{\mu_m}, \Sigma_m \rangle,\ m = 1, \ldots, M$$

$$\boxed{b_m(\vec{x_t}) = \frac{\exp\left(-\frac{1}{2}\sum_{i=1}^{d}\frac{(x_t[i]-\mu_m[i])^2}{\sigma_m^2[i]}\right)}{(2\pi)^{d/2}\left(\prod_{i=1}^{d}\sigma_m^2[i]\right)^{1/2}}}$$

- To find $\hat{\Theta}$, we solve $\nabla_\Theta \log L(X, \Theta) = 0$ where

$$\log L(X, \Theta) = \sum_{t=1}^{N} \log p_\Theta(\vec{x_t}) = \sum_{t=1}^{N} \log\left(\sum_{m=1}^{M} \omega_m b_m(\vec{x_t})\right)$$

...see Appendix for more

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MLE for Gaussian mixtures (pt. 2)

- Given $$\frac{\partial \log L(X,\Theta)}{\partial \mu_m[n]} = \sum_{t=1}^{N} \frac{1}{p_\Theta(\vec{x_t})} \left[\frac{\partial}{\partial \mu_m[n]} \omega_m b_m(\vec{x_t}) \right]$$
- Since $$\frac{\partial}{\partial \mu_m[n]} b_m(\vec{x_t}) = b_m(\vec{x_t}) \frac{x_t[n] - \mu_m[n]}{\sigma_m^2[n]}$$
- We obtain $\hat{\mu_m}[n]$ by solving for $\mu_m[n]$ in :

$$\frac{\partial \log L(X,\Theta)}{\partial \mu_m[n]} = \sum_{t=1}^{N} \frac{\omega_m}{p_\Theta(\vec{x_t})} b_m(\vec{x_t}) \frac{x_t[n] - \mu_m[n]}{\sigma_m^2[n]} = 0$$

$$b_m(\vec{x_t}) = p(\vec{x_t} \mid \Gamma_m)$$
$$p(\Gamma_m \mid \vec{x_t}, \Theta) = \frac{\omega_m}{p_\Theta(\vec{x_t})} b_m(\vec{x_t})$$

and:

$$\hat{\mu_m}[n] = \frac{\sum_t p(\Gamma_m \mid \vec{x_t}, \Theta) x_t[n]}{\sum_t p(\Gamma_m \mid \vec{x_t}, \Theta)}$$

Recipe for GMM ML estimation

- Do the following for each speaker individually. Use all the frames available in their respective **Training** directories

1. **Initialize**: Guess $\Theta = \langle \omega_m, \vec{\mu_m}, \Sigma_m \rangle,\ m = 1, \ldots, M$ with M random vectors in the data, or by performing M-means clustering.
2. **Compute likelihood**: Compute $b_m(\vec{x_t})$ and $P(\Gamma_m \mid \vec{x_t}, \Theta)$
3. **Update parameters**:

$$\hat{\omega_m} = \frac{1}{T} \sum_{t=1}^{T} p(\Gamma_m \mid \vec{x_t}, \Theta)$$

$$\hat{\vec{\mu_m}} = \frac{\sum_t p(\Gamma_m \mid \vec{x_t}, \Theta) \vec{x_t}}{\sum_t p(\Gamma_m \mid \vec{x_t}, \Theta)}$$

$$\hat{\vec{\sigma}}_m^{\,2} = \frac{\sum_t p(\Gamma_m \mid \vec{x_t}, \Theta) \vec{x_t}^{\,2}}{\sum_t p(\Gamma_m \mid \vec{x_t}, \Theta)} - \hat{\vec{\mu}}_m^{\,2}$$

$$\log p(X \mid \hat{\Theta}_{i+1}) - \log p(X \mid \hat{\Theta}_i) < \epsilon$$

Repeat 2&3 until converges

Cheat sheet

$$b_m(\vec{x_t}) = p(\vec{x_t} \mid \Gamma_m)$$

$$b_m(\vec{x_t}) = \frac{\exp\left(-\frac{1}{2}\sum_{i=1}^{d}\frac{(x_t[i]-\mu_m[i])^2}{\sigma_m^2[i]}\right)}{(2\pi)^{d/2}\left(\prod_{i=1}^{d}\sigma_m^2[i]\right)^{1/2}}$$

Probability of observing x_t in the m^{th} Gaussian

$$\omega_m = p(\Gamma_m)$$

Prior probability of the m^{th} Gaussian

$$p(\Gamma_m \mid \vec{x_t}, \Theta) = \frac{\omega_m}{p_\Theta(\vec{x_t})} b_m(\vec{x_t})$$

Probability of the m^{th} Gaussian, given x_t

$$p_\Theta(\vec{x_t}) = \sum_{m=1}^{M} \omega_m b_m(\vec{x_t})$$

Probability of x_t in the GMM

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Initializing theta

$$\Theta = \langle \omega_1, \mu_1, \Sigma_1, \omega_2, \mu_2, \Sigma_2, \ldots, \omega_M, \mu_M, \Sigma_M \rangle$$

- Initialize each mu_m to a random vector from the data.
- Initialize Sigma_m to a \`random' diagonal matrix (or identity matrix).
- Initialize omega_m randomly, with these constraints:

$$0 \leq \omega_m \leq 1$$

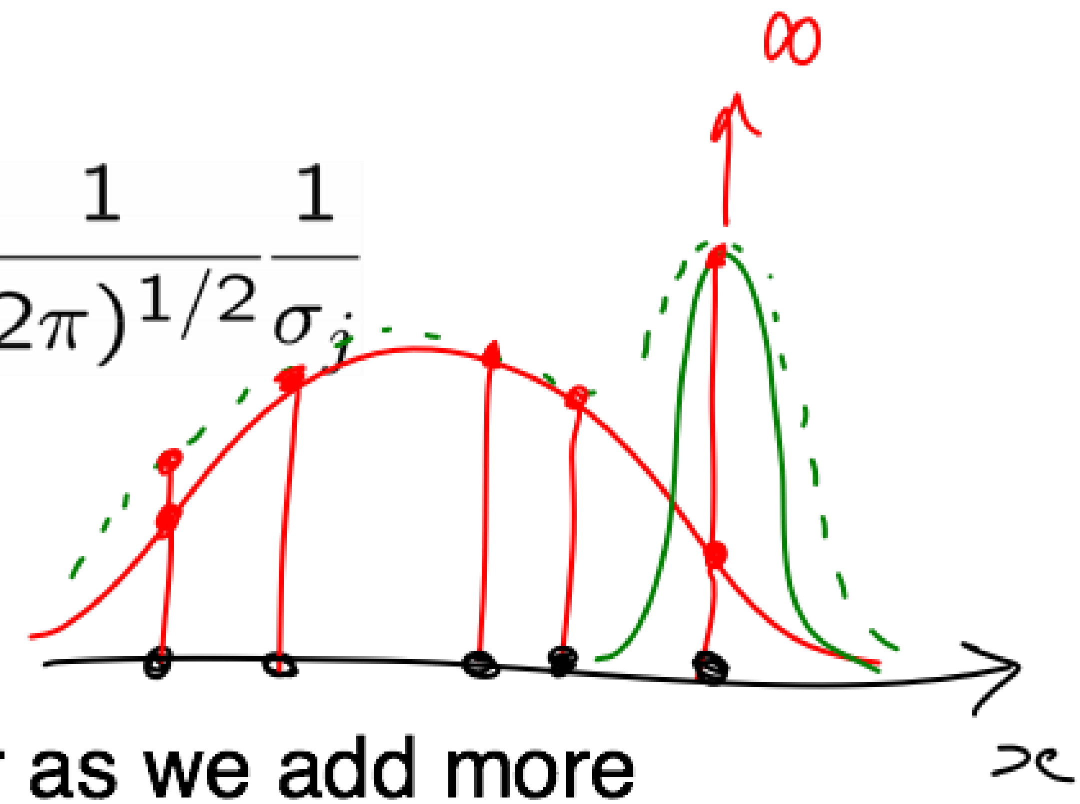
$$\sum_m \omega_m = 1$$

- A good choice would be to set omega_m to 1/M

Over-fitting in Gaussian Mixture Models

- Singularities in likelihood function when a component 'collapses' onto a data point:

$$\mathcal{N}(\mathbf{x}_n|\mathbf{x}_n, \sigma_j^2\mathbf{I}) = \frac{1}{(2\pi)^{1/2}}\frac{1}{\sigma_j}$$



then consider $\sigma_j \to 0$

- Likelihood function gets larger as we add more components (and hence parameters) to the model
  – not clear how to choose the number K of components

Solutions:

- Ensure that the variances don't get too small.
- Bayesian GMMs

* Slide borrowed from Chris Bishop's presentation

Your Task

- For each speaker, train a GMM, using the EM algorithm, assuming diagonal covariance.
- Identify the speaker of each test utterance.
- Experiment with the number of mixture elements in the models, the improvement threshold, number of possible speakers, etc.
- Comment on the results

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Practical tips for MLE of GMMs

- We assume diagonal covariance matrices. This reduces the number of parameters and can be sufficient in practice given enough components.
- Numerical Stability: Compute likelihoods in the log domain (especially when calculating the likelihood of a sequence of frames).

$$\log b_m(\vec{x_t}) = -\sum_{n=1}^{d} \frac{(\vec{x_t}[n] - \vec{\mu_m}[n])^2}{2\vec{\sigma_m}^2[n]} - \frac{d}{2}\log 2\pi - \frac{1}{2}\log \prod_{n=1}^{d} \vec{\sigma_m}^2[n]$$

- Here, $\vec{x_t}$, $\vec{\mu_m}$ and $\vec{\sigma_m}^2$ are d-dimensional vectors.

Practical tips (pt. 2)

- Efficiency: Pre-compute terms not dependent on $\vec{x_t}$

$$\log b_m(\vec{x_t}) = -\sum_{n=1}^{d}\left(\frac{1}{2}\vec{x_t}[n]^2\vec{\sigma_m}^{-2}[n] - \vec{\mu_m}[n]\vec{x_t}[n]\vec{\sigma_m}^{-2}[n]\right)$$

$$-\left(\sum_{n=1}^{d}\frac{\vec{\mu_m}[n]^2}{2\vec{\sigma_m}^{2}[n]} + \frac{d}{2}\log 2\pi + \frac{1}{2}\log\prod_{n=1}^{d}\vec{\sigma_m}^{2}[n]\right)$$

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Word-error rates

- If somebody said

  REF: how to recognize speech

  but an ASR system heard

  HYP: how to wreck a nice beach

  how do we measure the error that occurred?
- One measure is #CorrectWords/#HypothesisWords e.g., 2/6 above
- Another measure is (S+I+D)/#ReferenceWords
  - S: # Substitution errors (one word for another)
  - I: # Insertion errors (extra words)
  - D: # Deletion errors (words that are missing).

Computing Levenshtein Distance

- In the example

  REF: how to recognize speech.

  HYP: how to wreck a nice beach

  How do we count each of S, I, and D?

- If "wreck" is a substitution error, what about "a" and "nice"?

Computing Levenshtein Distance

- In the example
  REF: how to recognize speech.
  HYP: how to wreck a nice beach
  How do we count each of S, I, and D?
  If “wreck” is a substitution error, what about “a” and “nice”?

- Levenshtein distance:
  Initialize R[0,0] = 0, and R[i,j] = ∞ for all i=0 or j=0
  for i=1..n (#ReferenceWords)
  for j=1..m (#Hypothesis words)
  R[i,j] = min(R[i-1,j] + 1 (deletion)
  R[i-1,j-1] (only if words match)
  R[i-1,j-1]+1 (only if words differ)
  R[i,j-1] + 1) (insertion)
  Return 100*R(n,m)/n

Levenshtein example

		how	to	wreck	a	nice	beach
	0	∞	∞	∞	∞	∞	∞
how	∞	0	1	2	3	4	5
to	∞						
recognize	∞						
speech	∞						

Levenshtein example

		how	to	wreck	a	nice	beach
	0	∞	∞	∞	∞	∞	∞
how	∞	0	1	2	3	4	5
to	∞	1	0	1	2	3	4
recognize	∞						
speech	∞						

Levenshtein example

		how	to	wreck	a	nice	beach
	0	∞	∞	∞	∞	∞	∞
how	∞	0	1	2	3	4	5
to	∞	1	0	1	2	3	4
recognize	∞	2	1	1	2	3	4
speech	∞						

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Levenshtein example

		how	to	wreck	a	nice	beach
	0	∞	∞	∞	∞	∞	∞
how	∞	0	1	2	3	4	5
to	∞	1	0	1	2	3	4
recognize	∞	2	1	1	2	3	4
speech	∞	3	2	2	2	3	4

Word-error rate is 4/4 = 100%

2 substitutions, 2 insertions

Appendices

Multidimensional Gaussians, pt. 2

- If the i^{th} and j^{th} dimensions are statistically independent,

$$E(x[i]x[j]) = E(x[i])E(x[j])$$

and

$$\Sigma[i,j] = 0$$

- If all dimensions are statistically independent, $\Sigma[i,j] = 0, \ \forall i \neq j$ and the covariance matrix becomes diagonal, which means

$$p(\vec{x}) = \prod_{i=1}^{d} p(x[i])$$

where

$$p(x[i]) \sim N(\mu[i], \Sigma[i,i])$$
$$\Sigma[i,i] = \sigma^2[i]$$

MLE example - dD Gaussians

- The MLE estimates for parameters $\Theta = \langle \theta_1, \theta_2, \ldots, \theta_d \rangle$ given i.i.d. training data $X = \langle \vec{x_1}, \ldots, \vec{x_n} \rangle$ are obtained by maximizing the joint likelihood

$$L(X, \Theta) = p(X \mid \Theta) = p(\vec{x_1}, \ldots, \vec{x_n} \mid \Theta) = \prod_{i=1}^{n} p(\vec{x_i} \mid \Theta)$$

- To do so, we solve $\nabla_\Theta L(X, \Theta) = 0$ where

$$\nabla_\Theta = \left\langle \frac{\partial}{\partial \theta_1}, \ldots, \frac{\partial}{\partial \theta_d} \right\rangle$$

- Giving

$$\hat{\vec{\mu}} = \frac{\sum_{t=1}^{n} \vec{x_t}}{n} \qquad \hat{\Sigma} = \frac{\sum_{t=1}^{n} \left(\vec{x_t} - \hat{\vec{\mu}}\right)\left(\vec{x_t} - \hat{\vec{\mu}}\right)^T}{n}$$

MLE for Gaussian mixtures (pt1.5)

- Given $\log L(X,\Theta) = \sum_{t=1}^{N} \log p_\Theta(\vec{x_t})$ and $p_\Theta(\vec{x_t}) = \sum_{m=1}^{M} \omega_m b_m(\vec{x_t})$
  - Obtain an ML estimate, $\hat{\vec{\mu_m}}$, of the mean vector by maximizing $\log L(X, \vec{\mu_m})$ w.r.t. $\mu_m[n]$

$$\frac{\partial \log L(X,\Theta)}{\partial \mu_m[n]} = \sum_{t=1}^{N} \frac{\partial}{\partial \mu_m[n]} \log p_\Theta(\vec{x_t}) = \sum_{t=1}^{N} \frac{1}{p_\Theta(\vec{x_t})} \left[\frac{\partial}{\partial \mu_m[n]} \omega_m b_m(\vec{x_t}) \right]$$

- Why?

d of sum = sum of d

d rule for $\log_e$

d wrt μ_m is 0 for all other mixtures in the sum in $p_\Theta(\vec{x_t})$

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