Speech Recognition and Synthesis

Berkeley NLP

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UC Berkeley

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Language Models

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Noisy Channel Model: ASR

- We want to predict a sentence given acoustics:

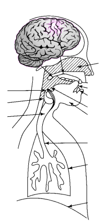
$$w^* = \arg\max_w P(w|a)$$

- The noisy-channel approach:

$$w^* = \arg\max_w P(w|a)$$
$$= \arg\max_w P(a|w)P(w)/P(a)$$
$$\propto \arg\max_w P(a|w)P(w)$$

Acoustic model: score fit between sounds and words

Language model: score plausibility of word sequences



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The Speech Signal

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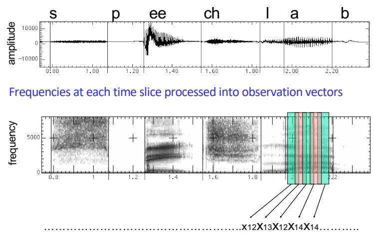
Speech in a Slide

- Frequency gives pitch; amplitude gives volume



- Frequencies at each time slice processed into observation vectors

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Articulation

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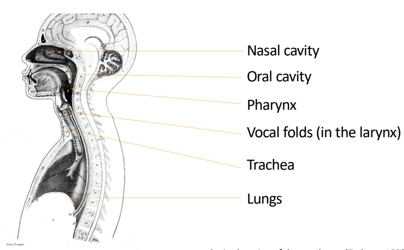
Articulatory System



Sagittal section of the vocal tract (Techmer 1880)

Text from Ohala, Sept 2001, from Sharon Rose slide

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Space of Phonemes

- Standard international phonetic alphabet (IPA) chart of consonants

	LABIAL		CORONAL				DORSAL			RADICAL		LARYNGEAL
	Bilabial	Labio-dental	Dental	Alveolar	Palato-alveolar	Retroflex	Palatal	Velar	Uvular	Pharyngeal	Epi-glottal	Glottal
Nasal	m	ɱ		n		ɳ	ɲ	ŋ	ɴ			
Plosive	p b	ȹ ȸ		t d		ʈ ɖ	c ɟ	k g	q ɢ		ʡ	ʔ
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	ʜ ʢ	h ɦ
Approximant		ʋ		ɹ		ɻ	j	ɰ				
Trill	ʙ			r					ʀ		ʁ	
Tap, Flap		ⱱ		ɾ		ɽ						
Lateral fricative				ɬ ɮ		ꞎ	ʎ̝	ʟ̝				
Lateral approximant				l		ɭ	ʎ	ʟ				
Lateral flap				ɺ		ɭ̆						

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Articulation: Place

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Places of Articulation

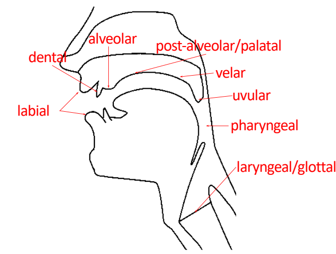

Figure thanks to Jennifer Venditti

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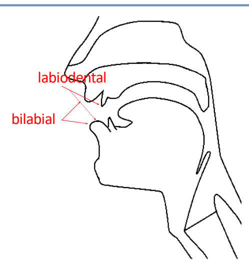
Labial place



Bilabial:
p, b, m
Labiodental:
f, v

Figure thanks to Jennifer Venditti

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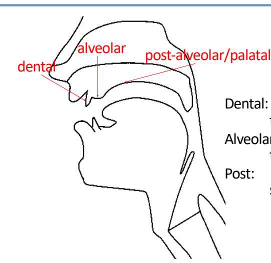
Coronal place



Dental:
th/dh
Alveolar:
t/d/s/z/l/n
Post:
sh/zh/y

Figure thanks to Jennifer Venditti

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Dorsal Place

Velar:
k/g/ng

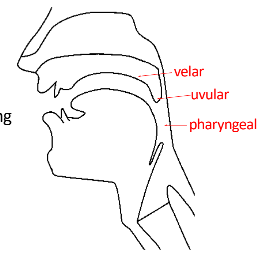

Figure thanks to Jennifer Venditti

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Plosive	p b	ȹ ȸ		t d		ʈ ɖ	c ɟ	k ɡ	q ɢ		ʡ	ʔ
Fricative	ɸ β	f v	θ ð	s z	ʃ ʒ	ʂ ʐ	ç ʝ	x ɣ	χ ʁ	ħ ʕ	ʜ ʢ	h ɦ
Approximant		ʋ		ɹ		ɻ	j	ɰ				
Trill	ʙ			r					ʀ		ᴙ	
Tap, Flap		ⱱ		ɾ		ɽ						
Lateral fricative				ɬ ɮ		ꞎ	𝼆	𝼄				
Lateral approximant				l		ɭ	ʎ	ʟ				
Lateral flap				ɺ		𝼈						

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Articulation: Manner

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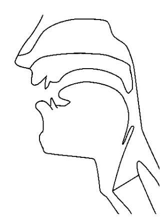
Manner of Articulation

- In addition to varying by place, sounds vary by manner
- Stop: complete closure of articulators, no air escapes via mouth
  - Oral stop: palate is raised (p, t, k, b, d, g)
  - Nasal stop: oral closure, but palate is lowered (m, n, ng)
- Fricatives: substantial closure, turbulent: (f, v, s, z)
- Approximants: slight closure, sonorant: (l, r, w)
- Vowels: no closure, sonorant: (i, e, a)



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Approximant		ʋ		ɹ		ɻ	j	ɰ				
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Lateral approximant				l		ɭ	ʎ	ʟ				
Lateral flap				ɺ		𝼈						

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Articulation: Vowels

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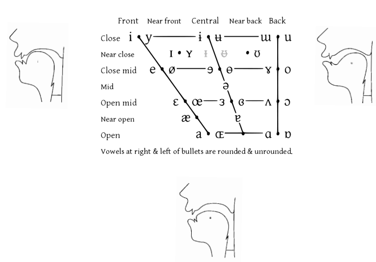
Vowel Space



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Acoustics

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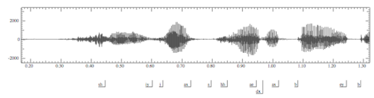
"She just had a baby"



What can we learn from a wavefile?

- No gaps between words (!)
- Vowels are voiced, long, loud
- Length in time = length in space in waveform picture
- Voicing: regular peaks in amplitude
- When stops closed: no peaks, silence
- Peaks = voicing: .46 to .58 (vowel [iy], from second .65 to .74 (vowel [ax]) and so on
- Silence of stop closure (1.06 to 1.08 for first [b], or 1.26 to 1.28 for second [b])
- Fricatives like [sh]: intense irregular pattern; see .33 to .46

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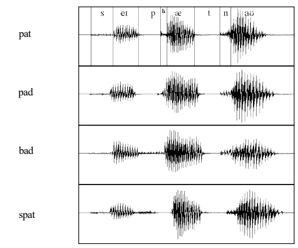
Time-Domain Information



Example from Ladefoged

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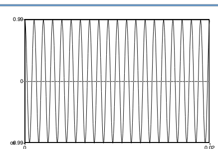
Simple Periodic Waves of Sound



- Y axis: Amplitude = amount of air pressure at that point in time
  - Zero is normal air pressure, negative is rarefaction
- X axis: Time
- Frequency = number of cycles per second
- 20 cycles in .02 seconds = 1000 cycles/second = 1000 Hz

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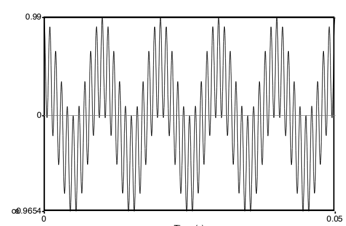
Complex Waves: 100Hz+1000Hz



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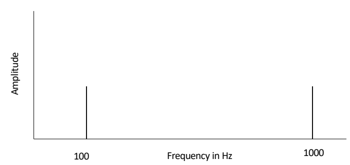
Spectrum

Frequency components (100 and 1000 Hz) on x-axis



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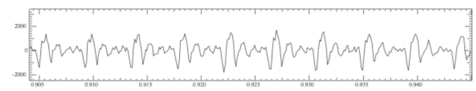
Part of [ae] waveform from "had"



- Note complex wave repeating nine times in figure
- Plus smaller waves which repeats 4 times for every large pattern
- Large wave has frequency of 250 Hz (9 times in .036 seconds)
- Small wave roughly 4 times this, or roughly 1000 Hz
- Two little tiny waves on top of peak of 1000 Hz waves

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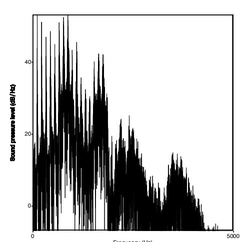
Spectrum of an Actual Soundwave



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Source / Channel

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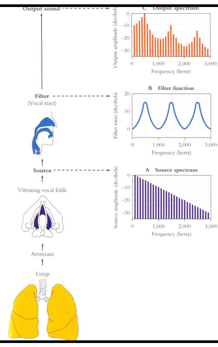
Why these Peaks?

- Articulation process:
  - The vocal cord vibrations create harmonics
  - The mouth is an amplifier
  - Depending on shape of mouth, some harmonics are amplified more than others



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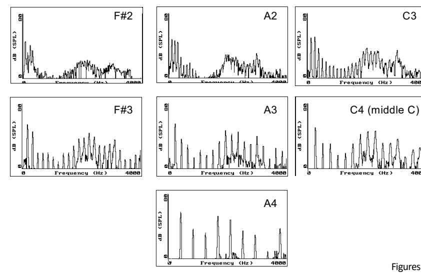
Vowel [i] at increasing pitches



Figures from Ratree Wayland

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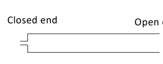
Resonances of the Vocal Tract

- The human vocal tract as an open tube:



- Air in a tube of a given length will tend to vibrate at resonance frequency of tube.
- Constraint: Pressure differential should be maximal at (closed) glottal end and minimal at (open) lip end.

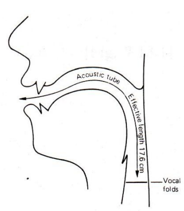


Figure from W. Barry

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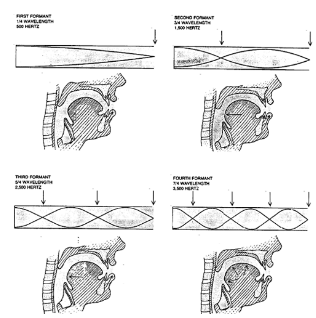

From Sundberg

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Computing the 3 Formants of Schwa

- Let the length of the tube be L
  - $F_1 = c/\lambda_1 = c/(4L) = 35{,}000/4*17.5 = 500Hz$
  - $F_2 = c/\lambda_2 = c/(4/3L) = 3c/4L = 3*35{,}000/4*17.5 = 1500Hz$
  - $F_3 = c/\lambda_3 = c/(4/5L) = 5c/4L = 5*35{,}000/4*17.5 = 2500Hz$
- So we expect a neutral vowel to have 3 resonances at 500, 1500, and 2500 Hz
- These vowel resonances are called formants

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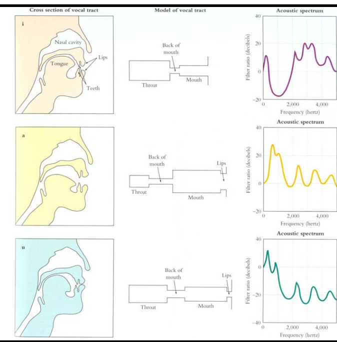

From Mark Liberman

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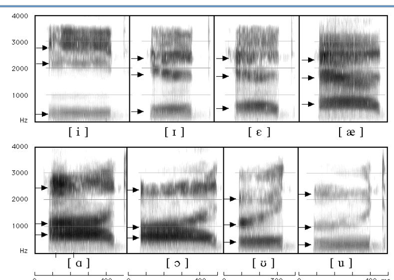
Seeing Formants: the Spectrogram



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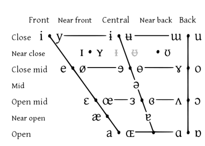
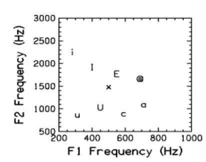
Vowel Space





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Spectrograms

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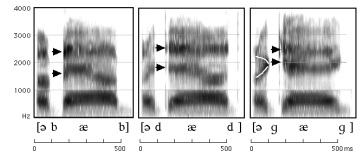
How to Read Spectrograms



- [bab]: closure of lips lowers all formants: so rapid increase in all formants at beginning of "bab"
- [dad]: first formant increases, but F2 and F3 slight fall
- [gag]: F2 and F3 come together: this is a characteristic of velars. Formant transitions take longer in velars than in alveolars or labials

From Ladefoged "A Course in Phonetics"

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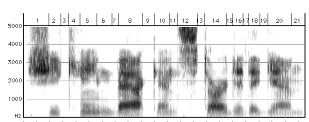
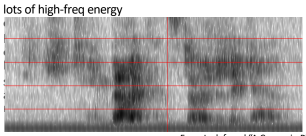
"She came back and started again"



1. lots of high-freq energy
3.
4.
5.
6.
7.
8.
9.



From Ladefoged "A Course in Phonetics"

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Speech Recognition

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Speech Recognition Architecture

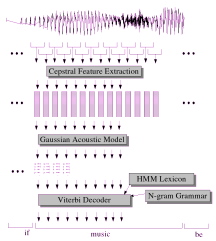

Figure: J & M

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Feature Extraction

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Digitizing Speech

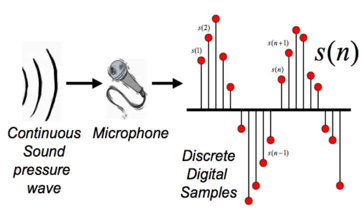

Figure: Bryan Pellom

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Frame Extraction

- A 25 ms wide frame is extracted every 10 ms

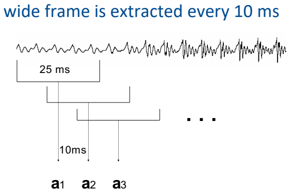

Figure: Simon Arnfield

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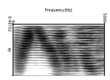
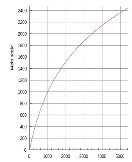
Mel Freq. Cepstral Coefficients

- Do FFT to get spectral information
  - Like the spectrogram we saw earlier
- Apply Mel scaling
  - Models human ear; more sensitivity in lower freqs
  - Approx linear below 1kHz, log above, equal samples above and below 1kHz
- Plus discrete cosine transform





[Graph: Wikipedia]

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Final Feature Vector

- 39 (real) features per 10 ms frame:
  - 12 MFCC features
  - 12 delta MFCC features
  - 12 delta-delta MFCC features
  - 1 (log) frame energy
  - 1 delta (log) frame energy
  - 1 delta-delta (log frame energy)
- So each frame is represented by a 39D vector

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Emission Model

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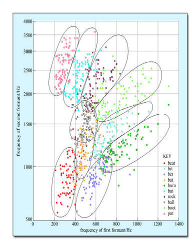
HMMs for Continuous Observations

- Solution 1: discretization
- Solution 2: continuous emission models
  - Gaussians
  - Multivariate Gaussians
  - Mixtures of multivariate Gaussians
- Solution 3: neural classifiers
- A state is progressively
  - Context independent subphone (~3 per phone)
  - Context dependent phone (triphones)
  - State tying of CD phone



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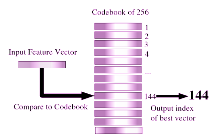
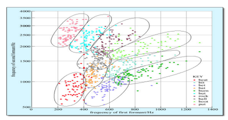
Vector Quantization

- Idea: discretization
  - Map MFCC vectors onto discrete symbols
  - Compute probabilities just by counting
- This is called vector quantization or VQ
- Not used for ASR any more
- But: useful to consider as a starting point, and for understanding neural methods





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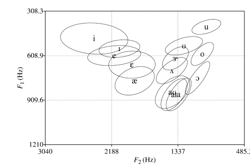
Gaussian Emissions

- VQ is insufficient for top-quality ASR
  - Hard to cover high-dimensional space with codebook
  - Moves ambiguity from the model to the preprocessing
- Instead: assume the possible values of the observation vectors are normally distributed.
  - Represent the observation likelihood function as a Gaussian?



From bartus.org/akustyk

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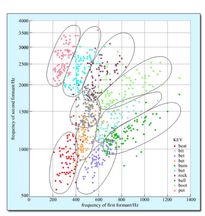
But we're not there yet

- Single Gaussians may do a bad job of modeling a complex distribution in any dimension
- Even worse for diagonal covariances
- Classic solution: mixtures of Gaussians
- Modern solution: NN-based acoustic models map feature vectors to (sub)states



From openlearn.open.ac.uk

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HMM / State Model

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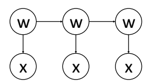
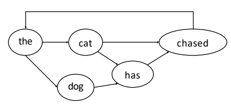
State Transition Diagrams

- Bayes Net: HMM as a Graphical Model



- State Transition Diagram: Markov Model as a Weighted FSA



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ASR Lexicon

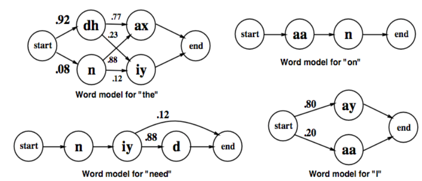

Figure: J & M

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Lexical State Structure

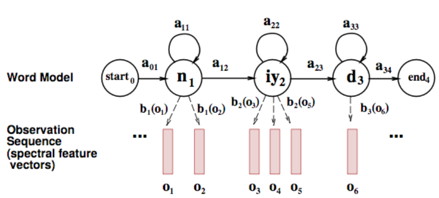

Figure: J & M

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Adding an LM

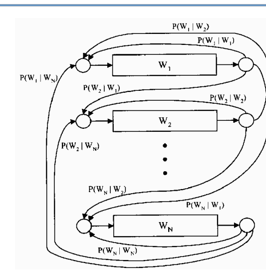

Figure from Huang et al page 618

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State Space

- State space must include
  - Current word (|V| on order of 50K+)
  - Index within current word (|L| on order of 5)
  - E.g. (lec[t]ure) (though not in orthography!)
- Acoustic probabilities only depend on (contextual) phone type
  - E.g. P(x|lec[t]ure) = P(x|t)
- From a state sequence, can read a word sequence

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State Refinement

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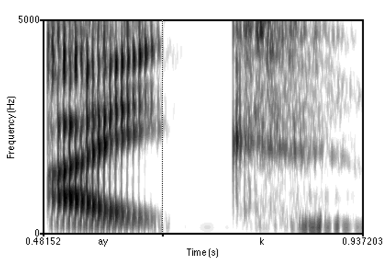
Phones Aren't Homogeneous



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Subphones

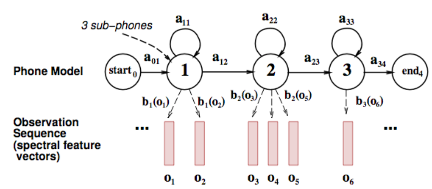

Figure: J & M

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A Word with Subphones

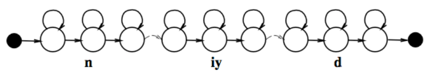

Figure: J & M

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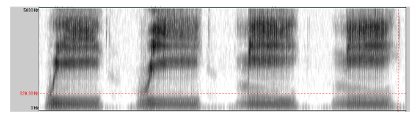
Modeling phonetic context

w iy   r iy   m iy   n iy



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"Need" with triphone models

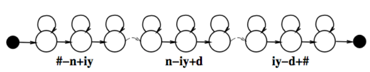

Figure: J & M

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Lots of Triphones

- Possible triphones: 50x50x50=125,000
- How many triphone types actually occur?
- 20K word WSJ Task (from Bryan Pellom)
  - Word internal models: need 14,300 triphones
  - Cross word models: need 54,400 triphones
- Need to generalize models, tie triphones

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State Tying / Clustering

- [Young, Odell, Woodland 1994]
- How do we decide which triphones to cluster together?
- Use phonetic features (or `broad phonetic classes')
  - Stop
  - Nasal
  - Fricative
  - Sibilant
  - Vowel
  - lateral

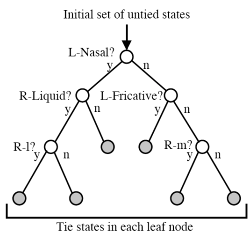

Figure: J & M

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State Space

- Full state space

  (LM context, lexicon index, subphone)

- Details:
  - LM context is the past n-1 words
  - Lexicon index is a phone position within a word (or a trie of the lexicon)
  - Subphone is begin, middle, or end
  - E.g. (after the, lec[t-mid]ure)
- Acoustic model depends on clustered phone context
  - But this doesn't grow the state space

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Learning Acoustic Models

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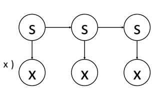
What Needs to be Learned?

- Emissions: P(x | phone class)
  - X is MFCC-valued
  - In neural methods, actually have P(phone | window around x) and then coerce those scores into P(x | phone)



- Transitions: P(state | prev state)
  - If between words, this is P(word | history)
  - If inside words, this is P(advance | phone class)
  - (Really a hierarchical model)

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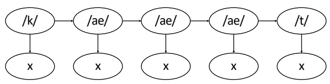
Estimation from Aligned Data

- What if each time step were labeled with its (context-dependent sub) phone?



- Can estimate P(x|/ae/) as empirical mean and (co-)variance of x's with label /ae/, or mixture, etc/
- Problem: Don't know alignment at the frame and phone level

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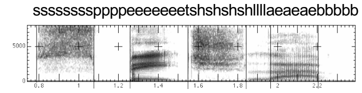
Forced Alignment

- What if the acoustic model P(x|phone) were known (or approximately known)?
  - … and also the correct sequences of words / phones
- Can predict the best alignment of frames to phones

"speech lab"

sssssssspppppeeeeeeetshshshshllllaeaeaebbbbb



- Called "forced alignment"

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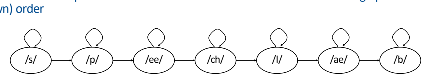
Forced Alignment

- Create a new state space that forces the hidden variables to transition through phones in the (known) order



- Still have uncertainty about durations: this key uncertainty persists in neural models (and in some ways is worse now)
- In this HMM, all the parameters are known
  - Transitions determined by known utterance
  - Emissions assumed to be known
  - Minor detail: self-loop probabilities
- Just run Viterbi (or approximations) to get the best alignment

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EM for Alignment

- Input: acoustic sequences with word-level transcriptions
- We don't know either the emission model or the frame alignments
- Expectation Maximization
  - Alternating optimization
  - Impute completions for unlabeled variables (here, the states at each time step)
  - Re-estimate model parameters (here, Gaussian means, variances, mixture ids)
  - Repeat
  - One of the earliest uses of EM for structured problems

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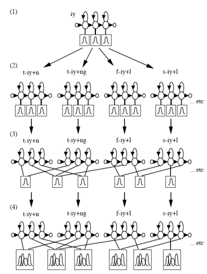
Staged Training and State Tying

- Creating CD phones:
  - Start with monophone, do EM training
  - Clone Gaussians into triphones
  - Build decision tree and cluster Gaussians
  - Clone and train mixtures (GMMs)
- General idea:
  - Introduce complexity gradually
  - Interleave constraint with flexibility



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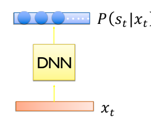
Neural Acoustic Models

- Given an input x, map to s; this score coerced into generative P(x|s) via Bayes rule (liberally ignoring terms)
  - One major advantage of the neural net is that you can look at many x's at once to capture dynamics (important!)



[Diagram from Hung-yi Li]

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Decoding

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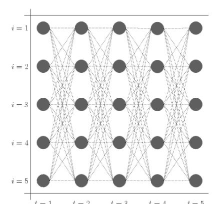
State Trellis



$$\phi_t(s_{t-1}, s_t) = P(x_t|s_t)P(s_t|s_{t-1})$$

$$P(x, s) = \prod_i P(x_i|s_i)P(s_i|s_{i-1}) = \prod_i \phi_t(s_{i-1}, s_i)$$

Figure: Enrique Benimeli

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Beam Search

- Lattice is not regular in structure! Dynamic vs static decoding
- At each time step
  - Start: Beam (collection) v_t of hypotheses s at time t
  - For each s in v_t
    - Compute all extensions s' at time t+1
    - Score s' from s
    - Put s' in v_{t+1} replacing existing s' if better
  - Advance to t+1
- Beams are priority queues of fixed size* k (e.g. 30) and retain only the top k hypotheses

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Dynamic vs Static Decoding

- Dynamic decoding
  - Build transitions on the fly based on model / grammar / etc
  - Very flexible, allows heterogeneous contexts easily (eg complex LMs)
- Static decoding
  - Compile entire subphone/vocabulary/LM into a huge weighted FST and use FST optimization methods (eg pushing, merging)
  - Much more common at scale, better eng and speed properties

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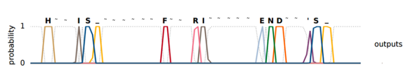
Direct Neural Decoders

- Lots of work in decoders that skip explicit / discrete alignment
  - Decode to phone, or character, or word
  - Handle alignments softly (eg attention) or discretely (eg CTC)



  - Catching up but not yet as good as structured systems

[Diagram from Graves 2014]

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Speech Synthesis

[Many slides from Dan Jurafsky]

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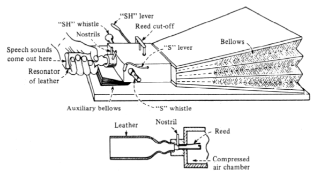
Early TTS

- Von Kempelen, 1791



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The Voder

Developed by Homer Dudley at Bell Telephone Laboratories, 1939

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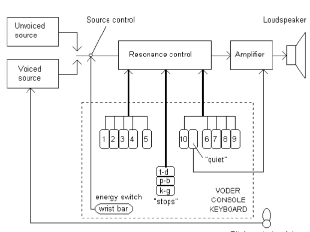
Voder Architecture

- An early hardware solution that already captured the flow of parametric synthesizers



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Modern TTS

- 1960's first full TTS: Umeda et al (1968)
- 1970's
  - Joe Olive 1977 concatenation of linear-prediction diphones
  - Speak and Spell
- 1980's
  - 1979 MIT MITalk (Allen, Hunnicut, Klatt)
- 1990's – 2000's
  - Diphone synthesis
  - Unit selection synthesis
- Recent
  - Parametric synthesis returns!

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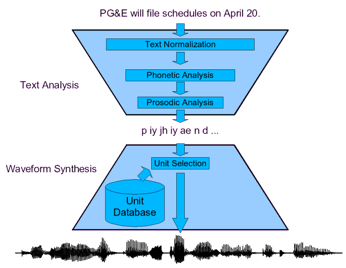
TTS Architecture



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Typical Data for TTS

- Professional voice actor
- Carefully selected material
- High-quality recordings
  - 10-100 hours @ 44kHz
  - High signal-to-noise ratio
  - Consistent audio levels
  - No vocal issues (creaky voice)
  - Anechoic-like environment
- Usually lots of post-processing (alignments, pronunciations, ...)

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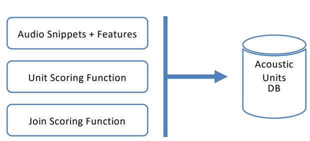
Concatenative Synthesis

- Commercially dominant (diphones, unit-selection, etc)



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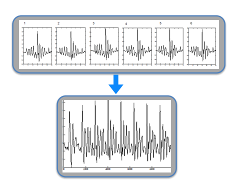
PSOLA



Time-domain Pitch-Synchronous Overlap and Add (TD-PSOLA)

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Trade-offs

"Beauty and the Beast is playing at AMC Burlington at 6:30pm, 9:30pm, and 10pm tomorrow night"

Concatenative: 1

Parametric: 2

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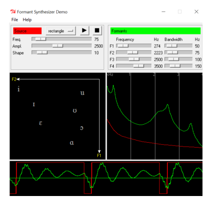
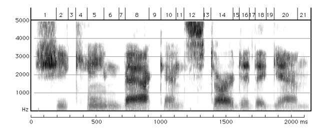
Formant Synthesis





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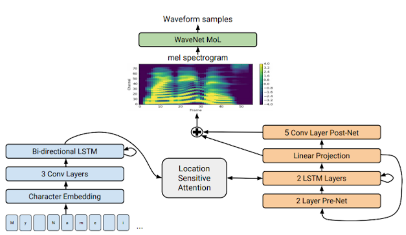
Direct-to-Wave Synthesis



https://ai.googleblog.com/2017/12/tacotron-2-generating-human-like-speech.html

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