Speech Recognition

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Today's ASR Topics

- Spoken language processing
- Speech production
- Signal representation
- Probabilistic formulation for ASR
- Lexicons, language models, acoustic models
- Search space representation via FSTs
- Corpora, evaluations, progress over time

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Virtues of Spoken Language

- Natural – No special training
- Flexible – Hands/eye free interaction
- Efficient – High input rate

Ideal for information access and management:

- Broad, complex information space
- Technically naïve users

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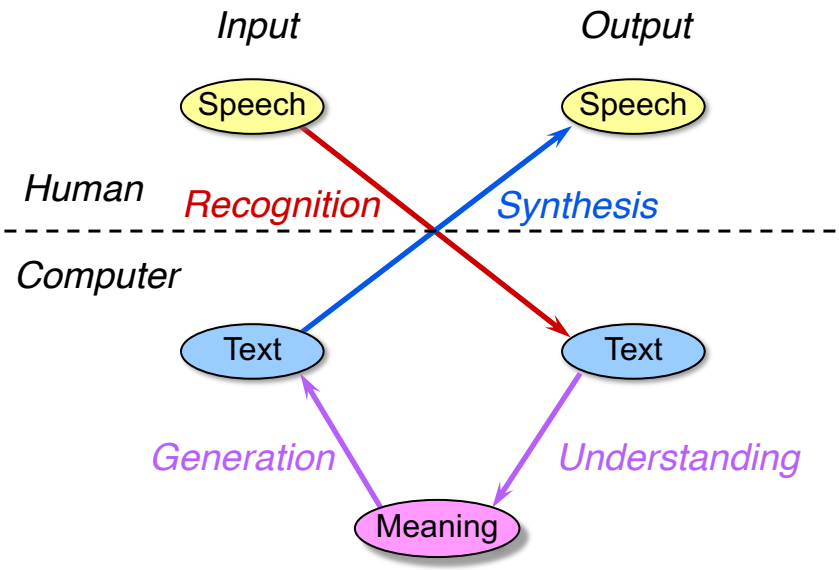
Spoken Communication w. Machines



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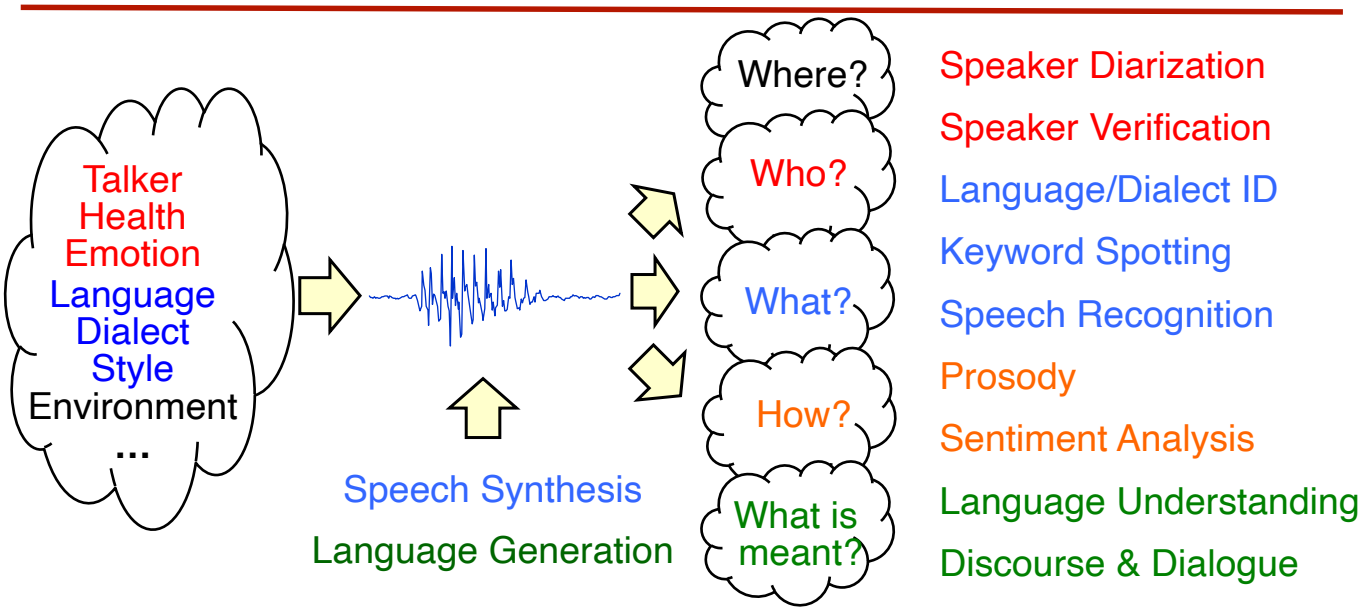
Spoken Language Processing



- For interfaces, content, language learning, health, …

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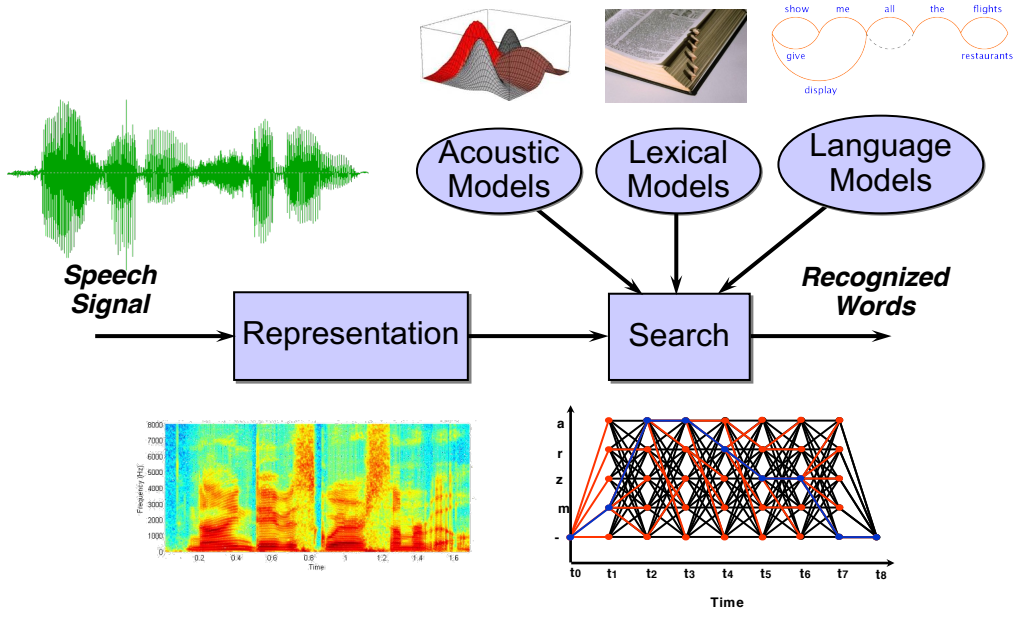
Speech Recognition Architecture



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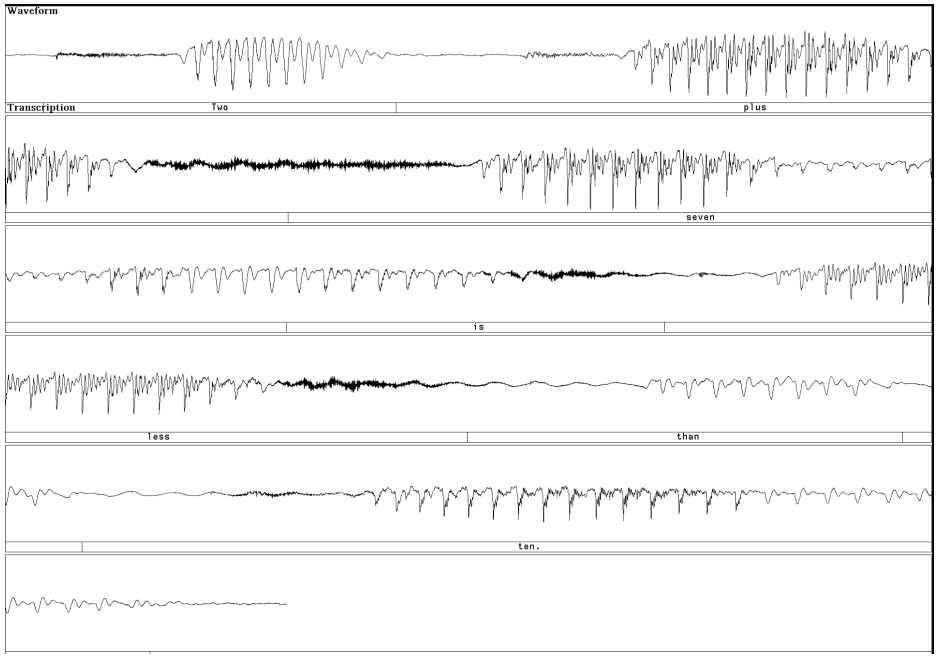
A Speech Waveform



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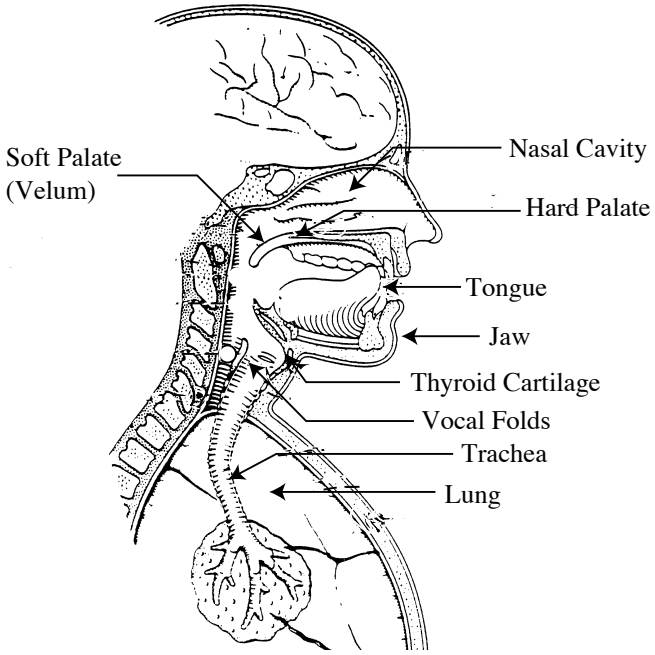
Anatomical Structures for Speech Production



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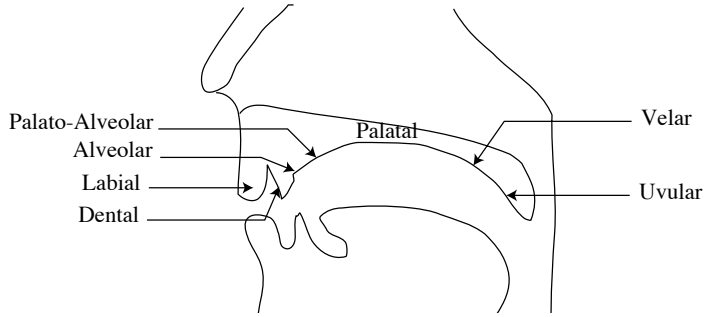
Manner and Places of Articulation



- Speech articulation characterized by manner and place
  - Vowels: No significant constriction in the vocal tract; usually voiced
  - Fricatives: turbulence produced at a narrow constriction
  - Stops: complete closure in the vocal tract; pressure build up
  - Nasals: velum lowering results in airflow through nasal cavity
  - Semivowels: constriction in vocal tract, no turbulence

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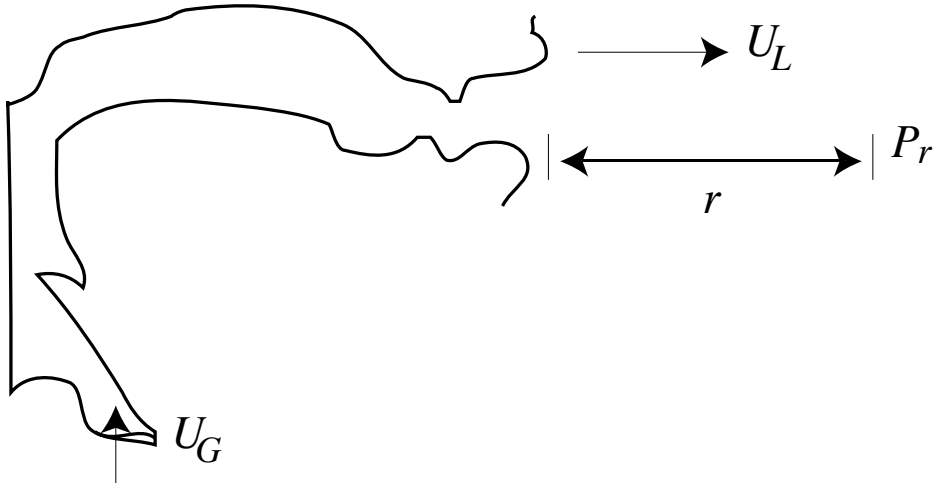
Acoustic Theory of Speech Production



- Speech produced via coordinated movement of articulators
- Spectral characteristics of speech influenced by source, vocal tract shape, and radiation characteristics

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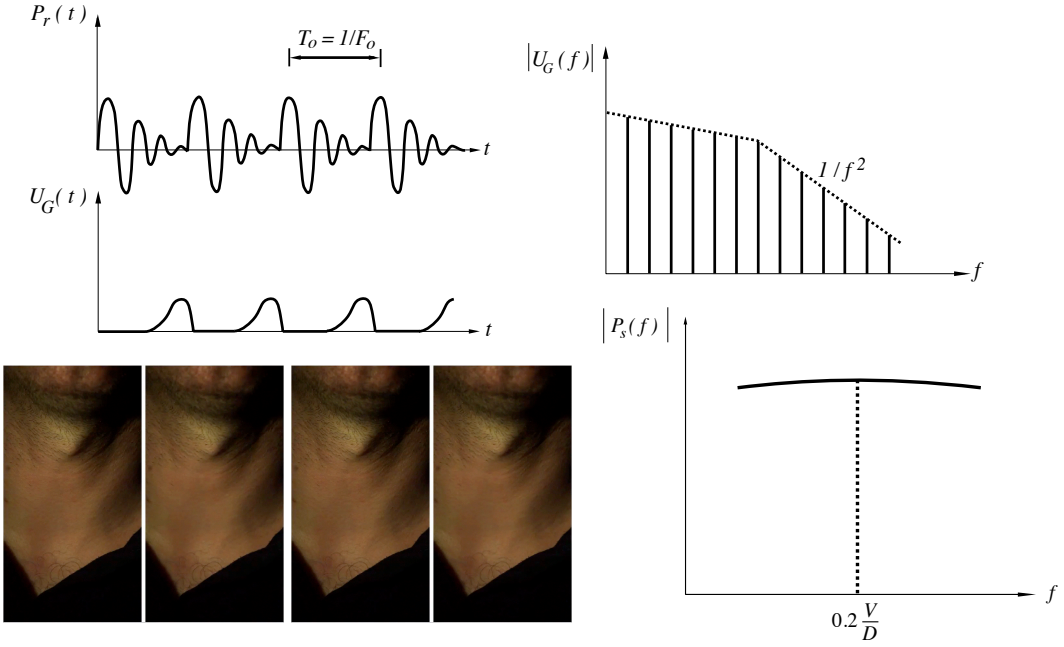
Vocal Fold Vibration & Turbulence



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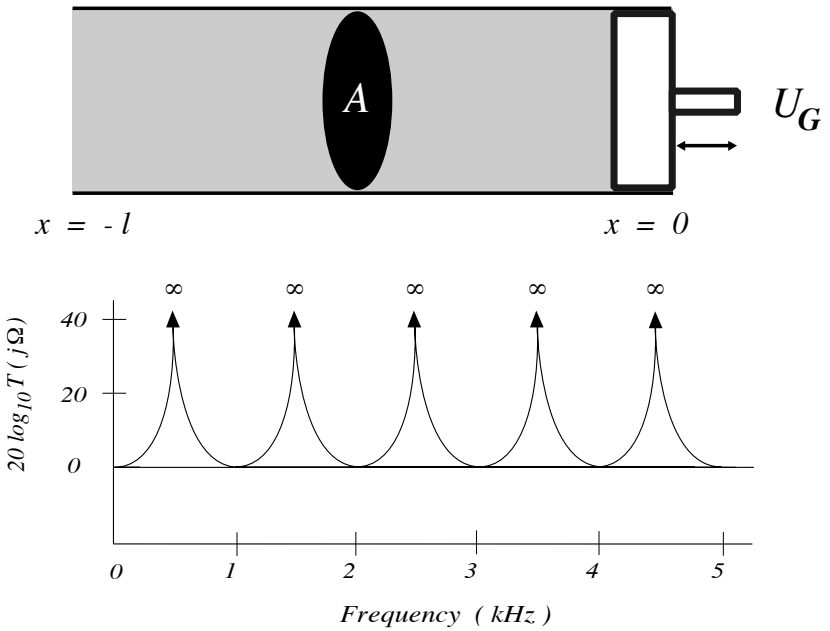
Propagation of Sound in a Uniform Tube



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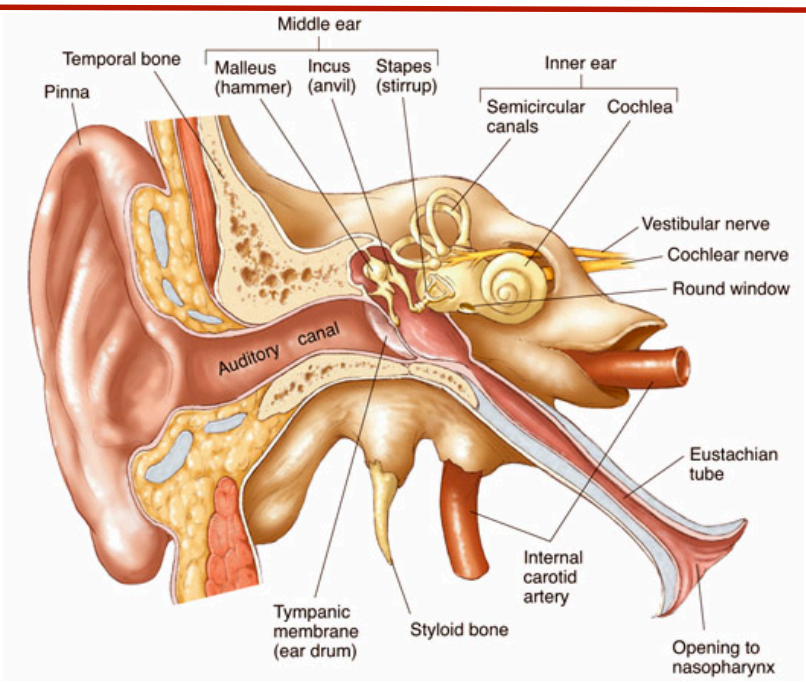
Anatomy of the Human Ear



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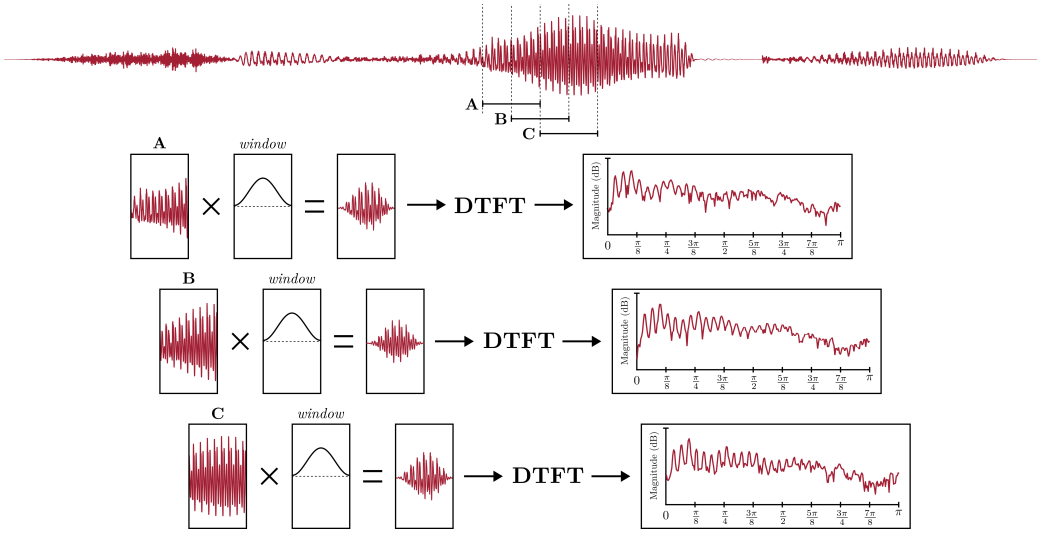
Digital Speech Processing

- Speech is typically represented by a sequence of Discrete-Time Fourier Transforms computed over a windowed snippet of speech



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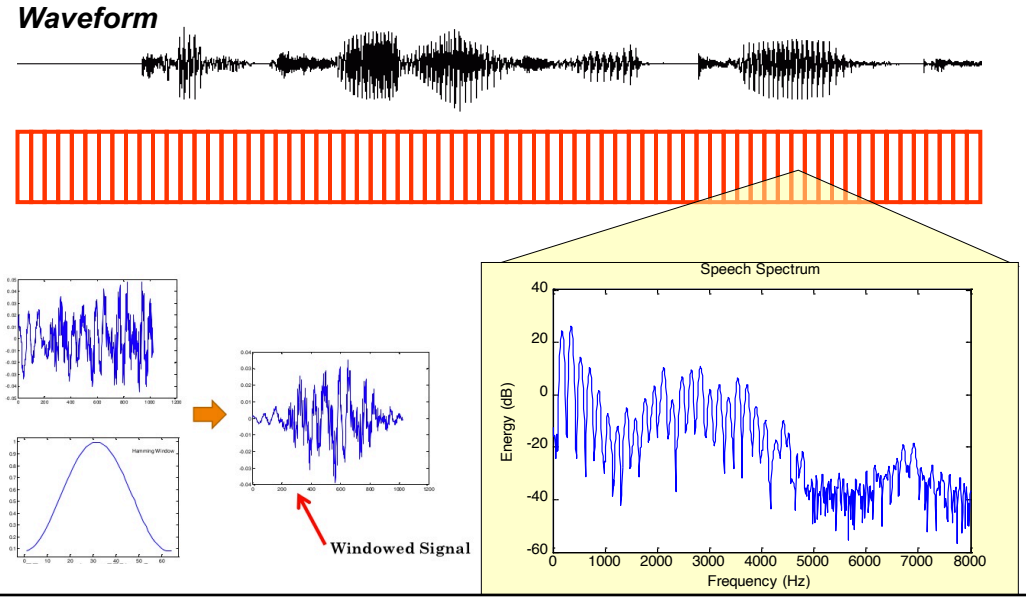
Speech Processing

Spectral energies (frames) are typically computed at regular (e.g., 10ms) intervals



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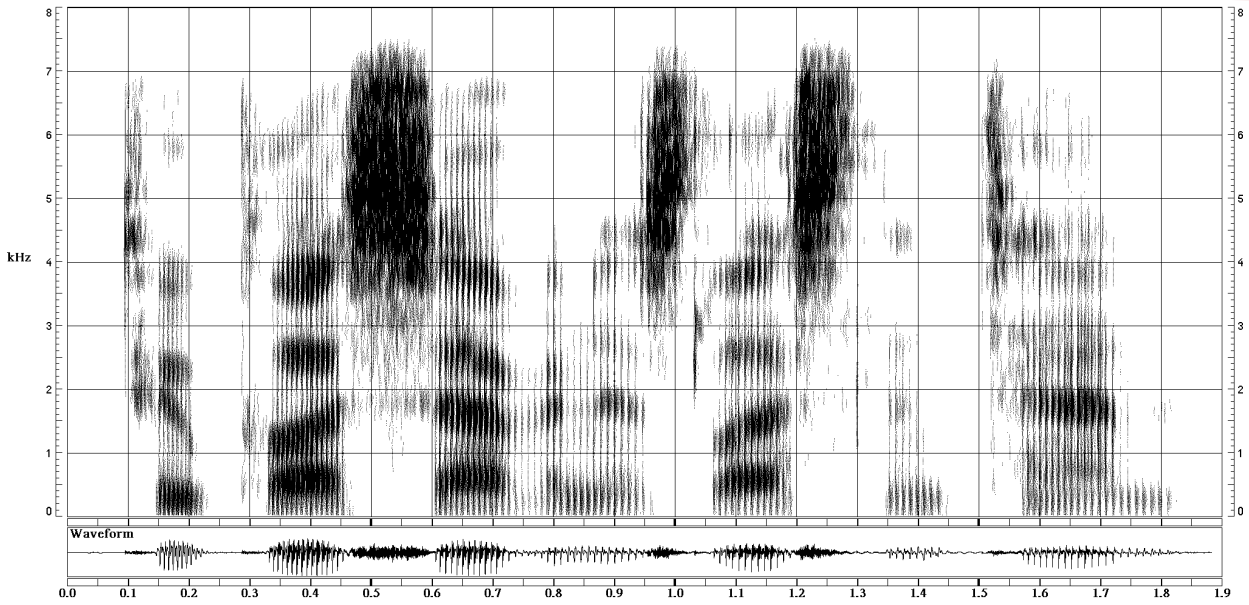
The Speech Spectrogram



Spectrograms visualize spectral-temporal characteristics of speech

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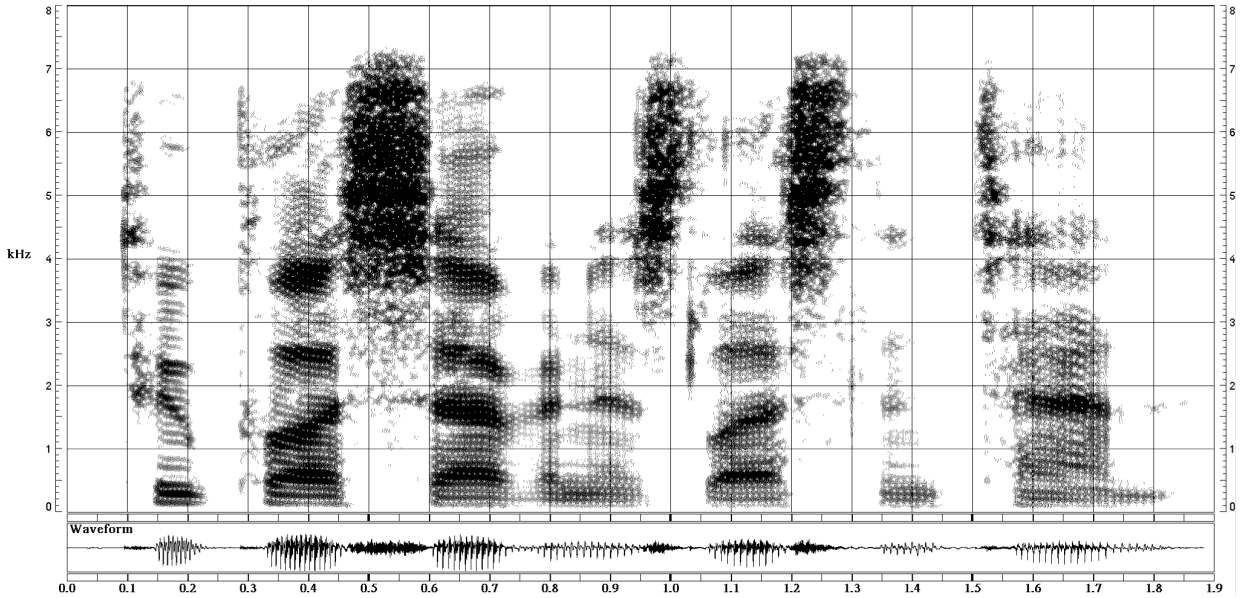
A Narrowband Spectrogram



ASR spectra are typically computed with a ~25ms Hamming window

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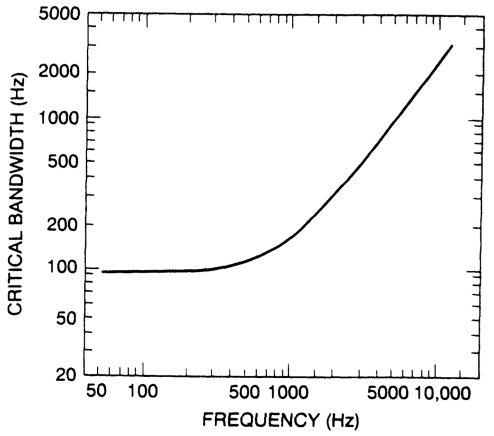
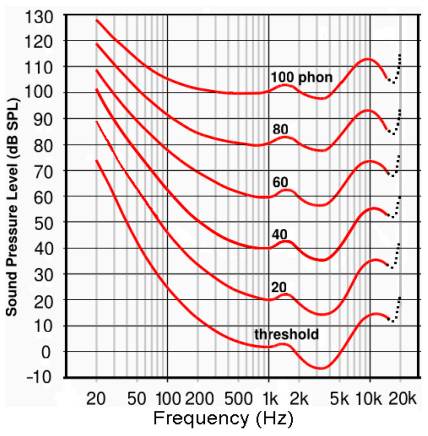
Auditory Representations

- Perceptually relevant properties of the human auditory system can be incorporated into the spectral estimation process





- A variety of models have been explored in the past but simple models based on Mel-frequency warping have worked well

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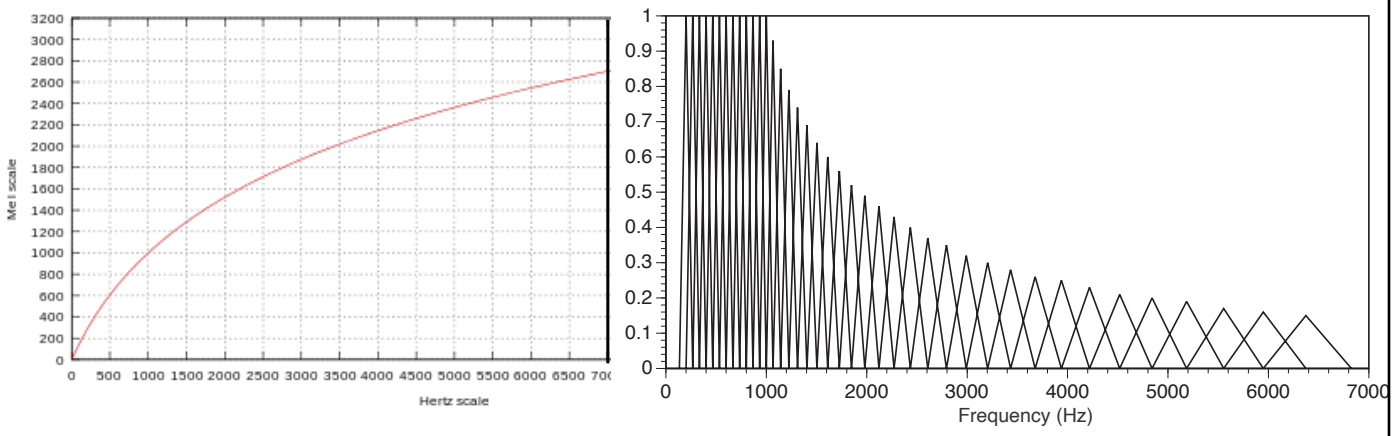
Mel-Frequency Spectral Coefficients (MFSCs)

- Mel-frequency scale originally based on pitch perception
  - Spectral filters are spaced evenly on Mel-scale



- Mel-frequency cepstral coefficients (MFCCs) are popular for ASR
  - MFCCs are typically computed via the discrete cosine transform

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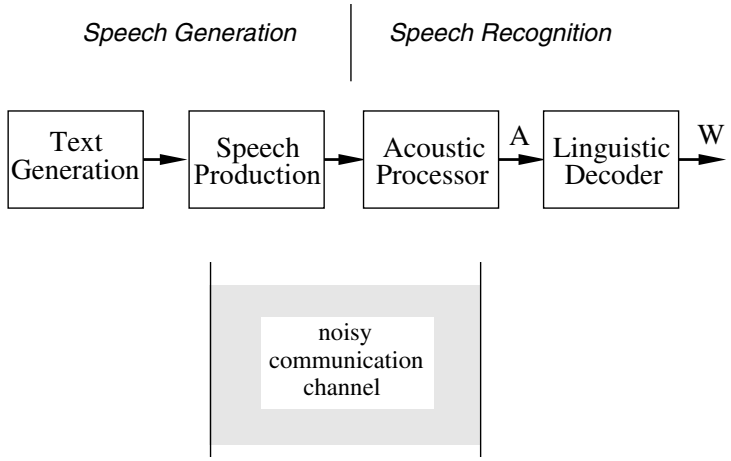
Information Theoretic Formulation of ASR



$$W^* = \arg\max_W P(W \mid A) \qquad P(W \mid A) = \frac{P(A \mid W)P(W)}{P(A)}$$

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Probabilistic ASR Formulation

- A full search considers all possible segmentations, *S*, and units, *U*, for each hypothesized word sequence, *W*

$$W^* = \arg\max_W P(W \mid A) = \arg\max_W \sum_S \sum_U P(WUS \mid A)$$

- Can seek best path to simplify search using dynamic programming (e.g., Viterbi) or graph-searches (e.g., *A**)

$$W^*, U^*, S^* \approx \arg\max_{W,U,S} P(WUS \mid A)$$

- The modified Bayes decomposition has four terms:

$$P(WUS \mid A) = \frac{P(A \mid SUW)P(S \mid UW)P(U \mid W)P(W)}{P(A)}$$

acoustic model | duration model | lexical model | language model

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Lexical Modeling

- Pronunciation dictionaries are typically used to describe the realizations of words in terms of sub-word units
  - English is comprised of ~40 phonemes
  - Pronunciations and phonological rules can be supplied or learned from data
- For languages with regular letter-to-sound transformations, *graphemic* approaches are effective
  - Many end-to-end neural network-based ASR models output letter sequences

a	(ax | ey)
...	
beach	b iy ch
...	
nice	n (iy | ay) s
...	
recognize	r eh k ax gd n ay z
...	
speech	s p- iy ch
...	
stata	s t- (ey | aa) tf ax
...	
tomato	t ax m (ey | aa) tf ow
...	
wreck	r eh kd
...	

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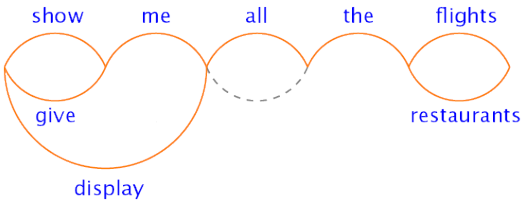
Language Modeling



- ASR systems constrain possible word combinations by way of simple, but powerful, language models
  - Trigram is the dominant language model for ASR:

$$P(w_i | w_{i-2}, w_{i-1})$$

  - Much effort has gone into smoothing techniques for sparse data
- RNN-based LMs have shown improved performance
  - Generally used as a post-process to re-rank ASR hypotheses
- Task difficulty is measured by perplexity

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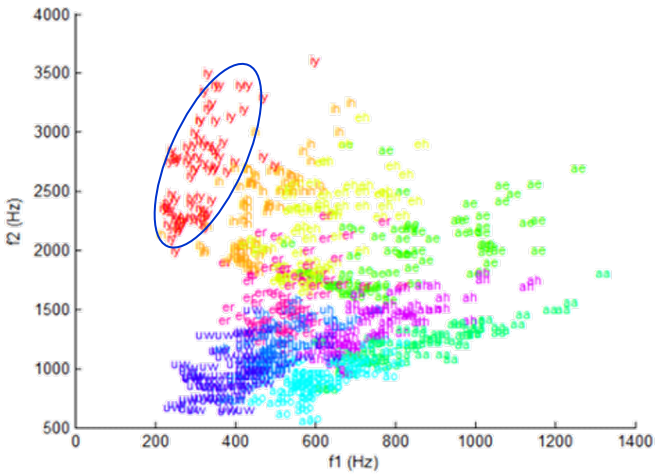
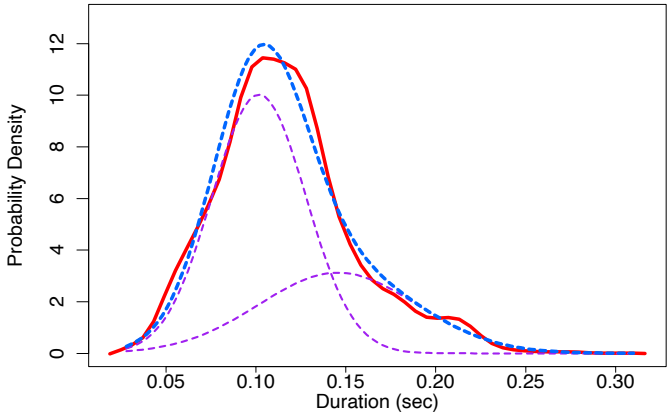
Acoustic Modeling





Acoustic models must capture the variation in the physical realization of an underlying linguistic unit due to speaker, style, environmental factors etc.

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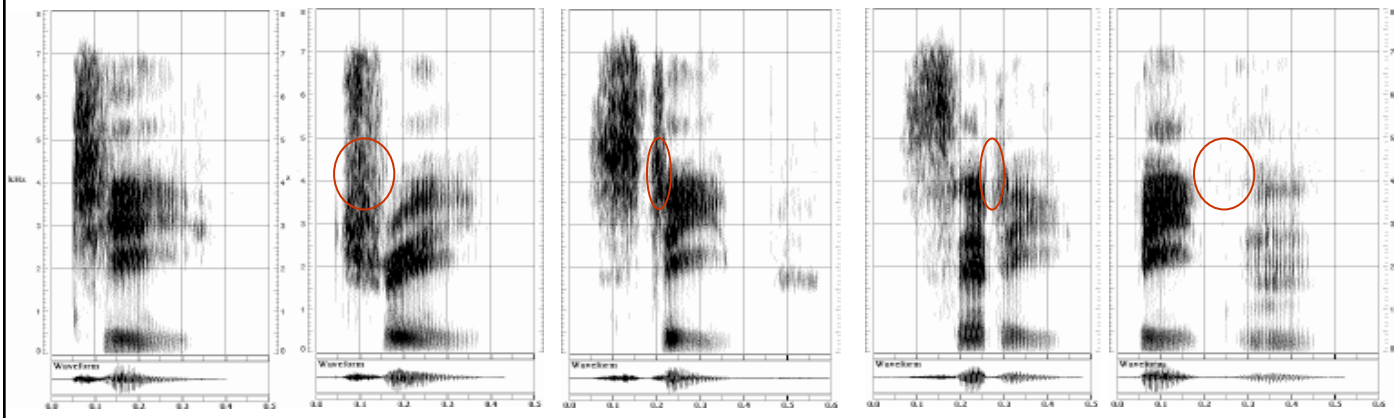
Coarticulation and Phonological Variation

- The acoustic realization of a phoneme depends strongly on context
- Context-dependent models are often used to model coarticulation



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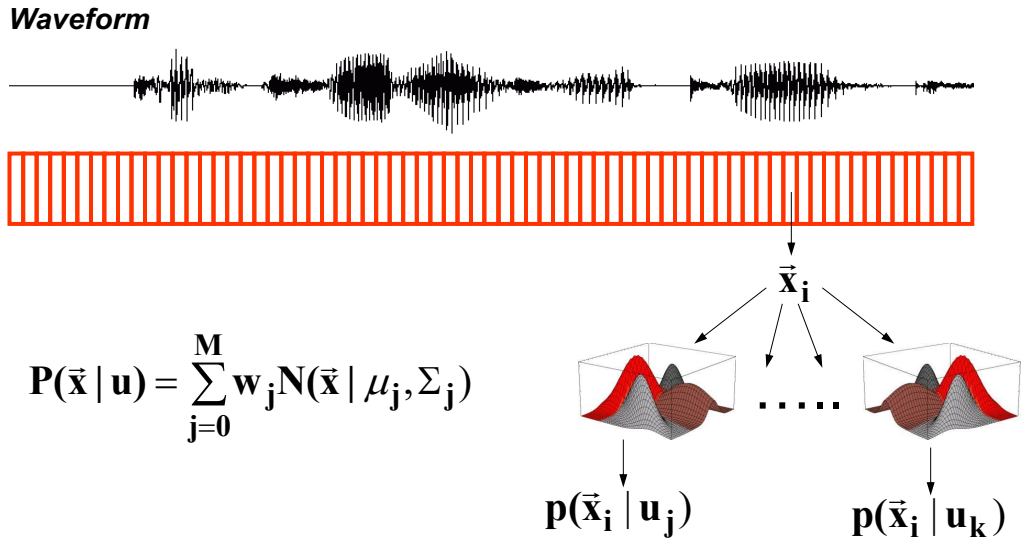
Frame-based Acoustic Modeling

Acoustic models (e.g., GMMs, ANNs) are typically applied to each spectral frame



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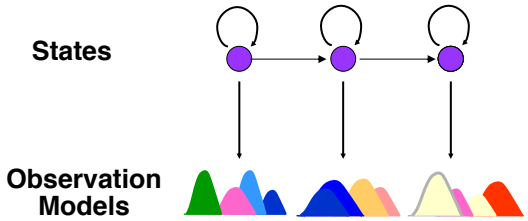
Hidden Markov Models (HMMs)

- Dominant modeling framework used for speech recognition
- Generative model that predicts likelihood of observation sequence being generated by an underlying state sequence
  - Either discrete or continuous observation models can be used



- HMMs can model words or sub-words (e.g., phones)
  - Sub-word HMMs concatenated to create larger word-based HMMs

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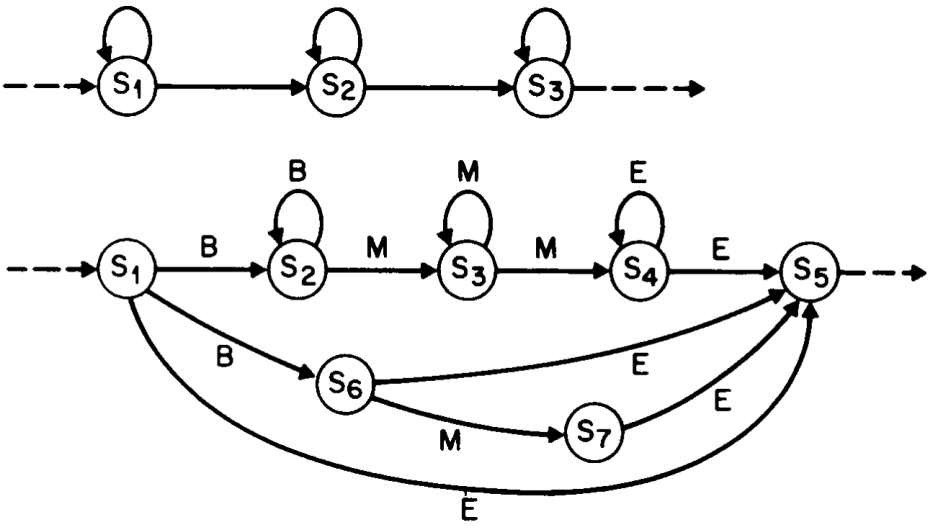
HMM Sub-Word Topologies



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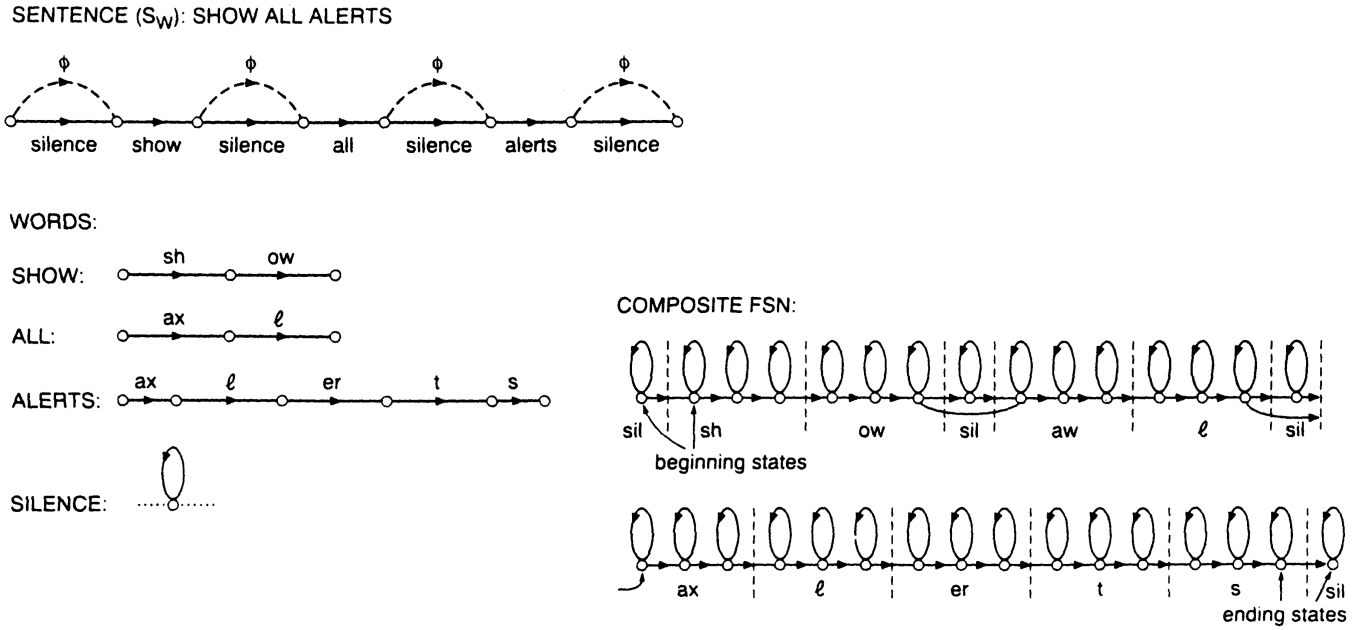
HMM ASR Formulation



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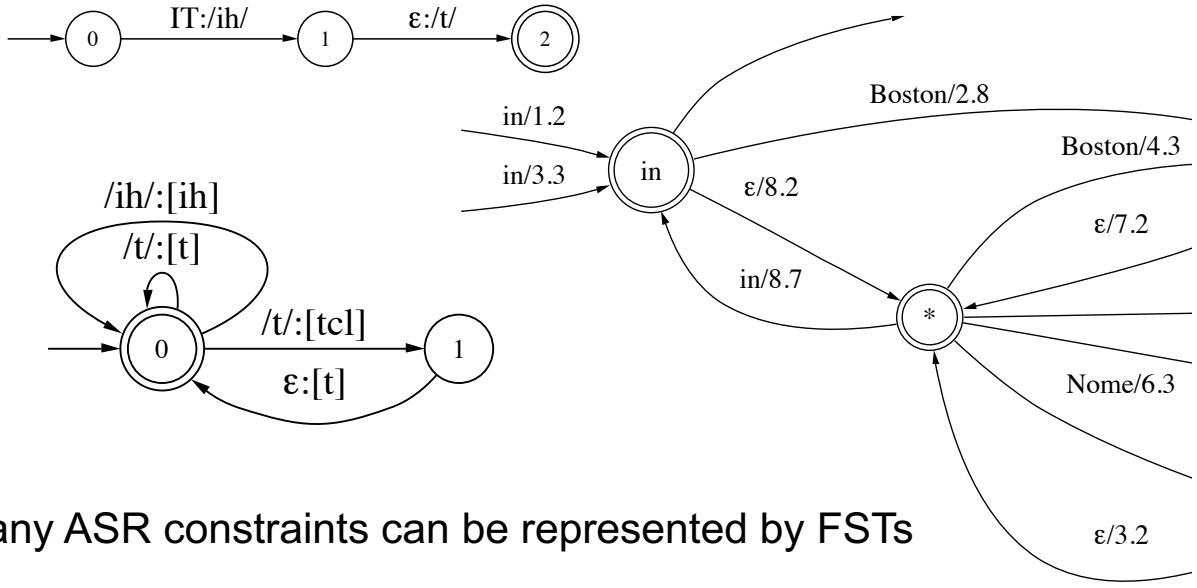
Finite State Transducer Representations for ASR



Many ASR constraints can be represented by FSTs

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Speech Recognition as Cascade of FSTs

- ASR as a cascade of FSTs:
  $$O \circ (M \circ P \circ L \circ G)$$
  - G: language model (weighted words ← words)
  - L: lexicon (phonemes ← words)
  - P: phonological rule application (phones ← phonemes)
  - M: model topology (e.g., HMM) (states ← phones)
  - O: observations with acoustic model scores
- (M ∘ P ∘ L ∘ G) is *single* FST seen by search
- Viterbi search performs composition of O with (M ∘ P ∘ L ∘ G)
- Gives great flexibility in how components are combined

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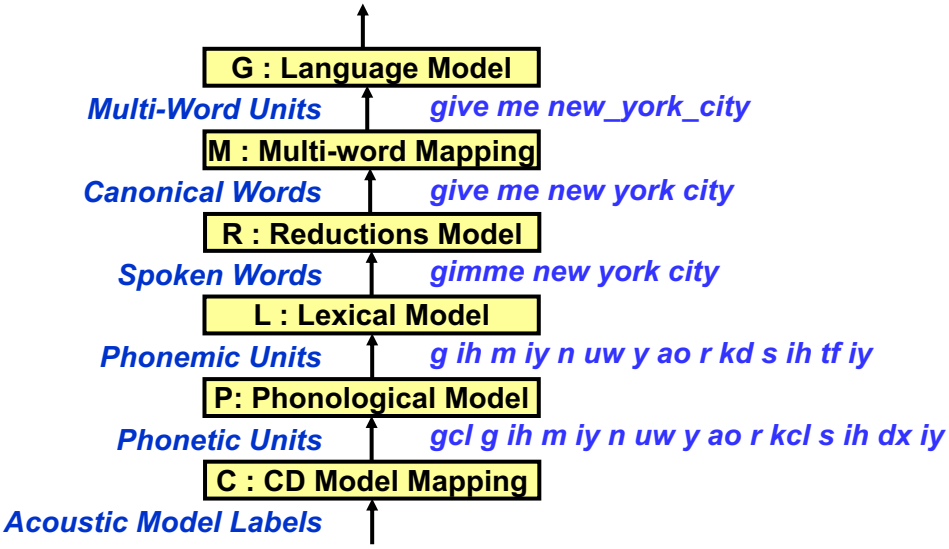
Expanded FST Representation

- FST representation can be expanded for more efficient representation of lexical variation



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Evaluating Speech Recognition

- The standard evaluation metric for ASR is word error rate (WER)
  - Based on a string alignment between hypothesis and reference text
  - Errors can include insertions, deletions, and substitutions

REF:	i	***	**	UM	the	PHONE	IS		i	LEFT	THE	portable	****	PHONE	UPSTAIRS	last	night
HYP:	i	GOT	IT	TO	the	*****	FULLEST		i	LOVE	TO	portable	FORM	OF	STORES	last	night
Eval:		I	I	S		D	S			S	S		I	S	S		

$$WER = 100 \text{ x } \frac{Insertions + Substitutions + Deletions}{Total\ Words\ in\ Correct\ Transcript}$$

- The same metric can be applied to character error rate (CER) etc.
- String edit distance tends to underestimate errors at high WERs
- Standard NIST software (sclite) is available to measure WERs

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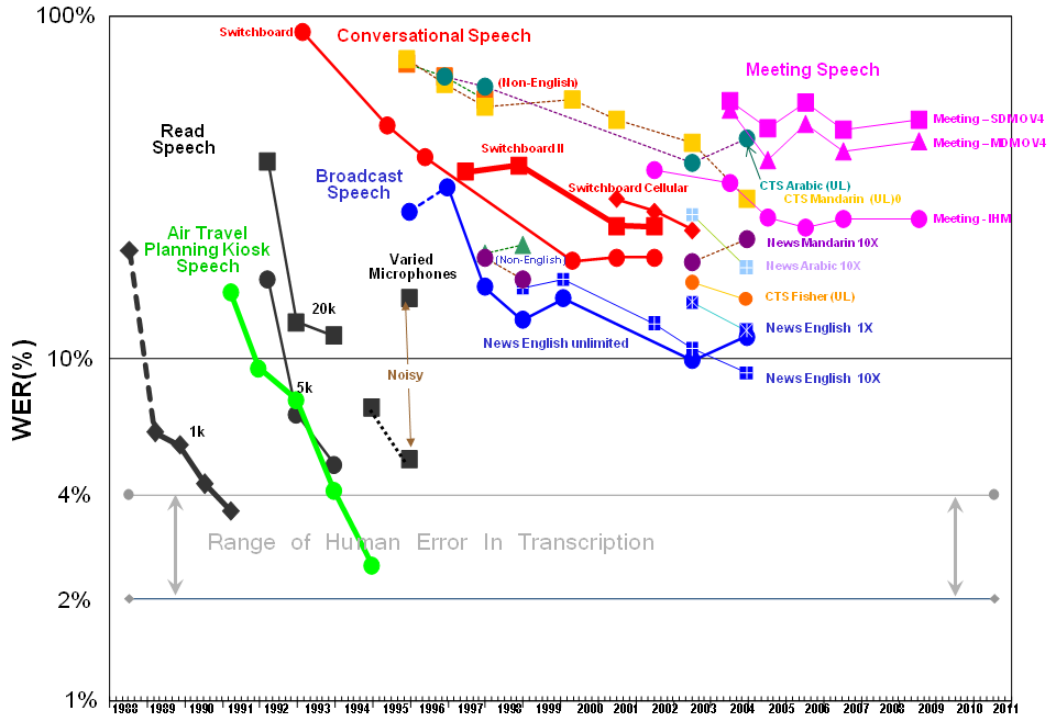

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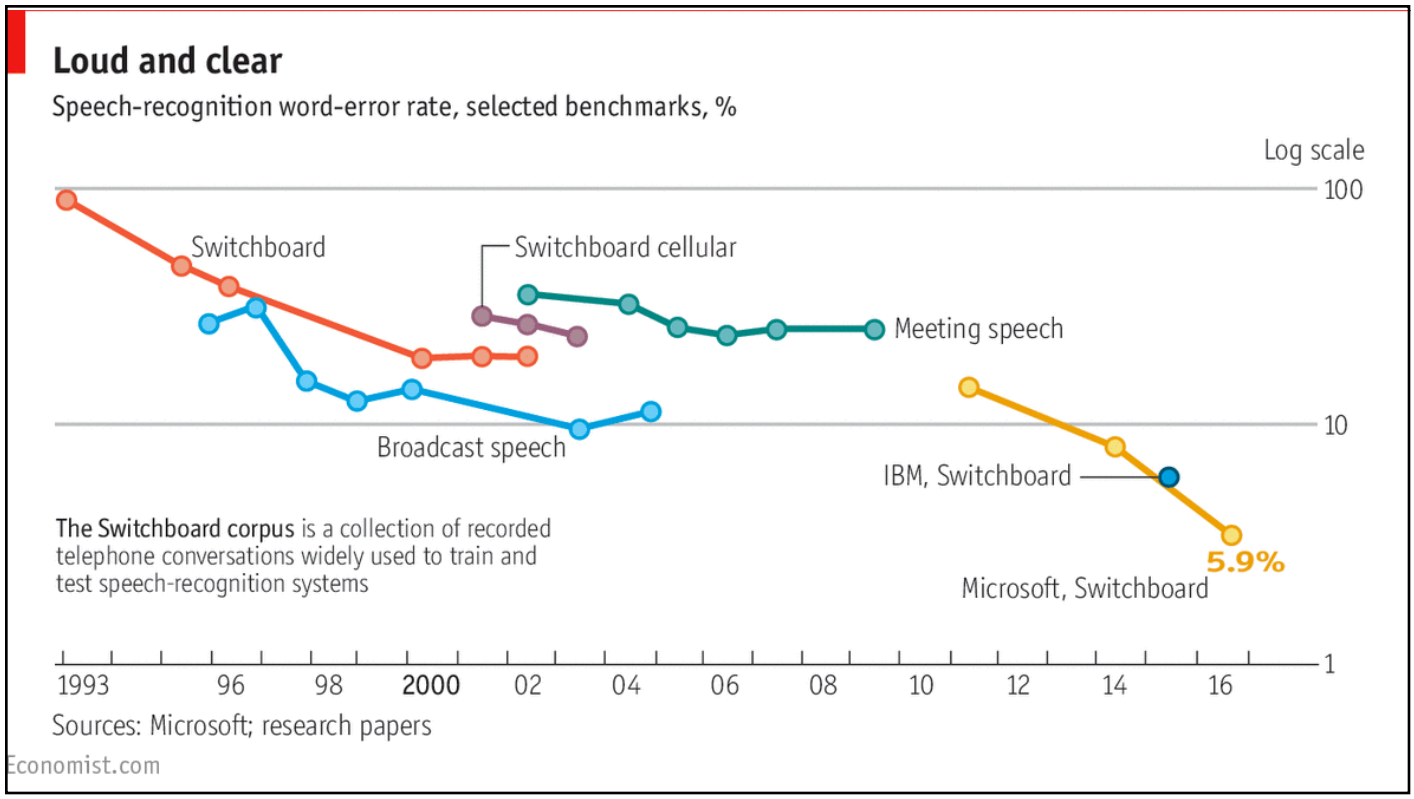

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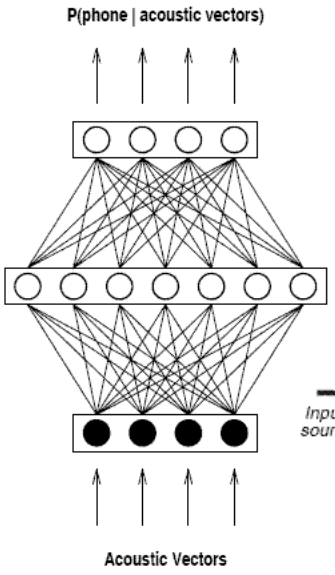
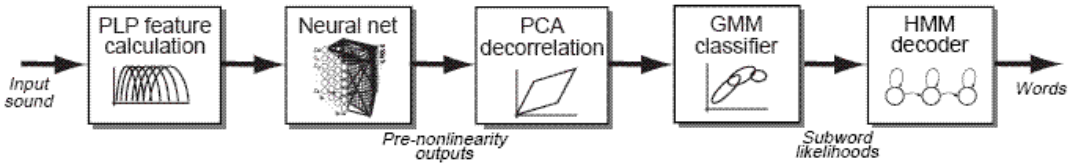
Neural Network-based ASR



- Artificial neural network models were first explored for ASR in 1990s
- Over the last decade ANNs have replaced GMMs as the dominant acoustic model for ASR
- ANN outputs can replace GMMs altogether (*Hybrid*), or be used as inputs to HMM-GMMs (*Tandem*)



- Connectionist Temporal Classification (CTC) and Seq2Seq models replace HMMs (next lecture!)

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References

- Readings:
  - Jurafsky and Martin, “Speech and Language Processing”, Chp. 26

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