SPEECH MODELS AND AUTOMATIC SPEECH RECOGNITION (ASR) SYSTEMS

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Outline (1/2)

- Quick intro to speech recognition systems
- Mel Frequency Cepstral Coefficients (MFCC)
  - What are they for?
- Computing MFCC
  - The 6 basic steps for their computation
  - The Mel scale for human perceived frequency
  - The 6 steps in greater detail
- Additional features
  - Energy
  - Delta coefficients
  - Delta-Delta coefficients

Outline (2/2)

- Automatic Speech Recognition (ASR) sytems
  - The noisy channel model
  - The ASR system
    - Language, pronunciation and acoustic models
    - Viterbi decoding – decoding example
    - General ASR architecture
    - HMM training
  - Performance & open issues

Speech recognition: a quick intro

- Raw audio samples are not suitable for statistical modeling
  - We represent them using feature vectors
- Speech recognition
  - Input: sampled & digitized speech data
  - Desired output: sequence of words that were spoken
  - It is a pattern matching problem
    - Combines *acoustic* and *language* models
    - Most modern systems use HMM
    - A speech signal is modeled as a sequence of piecewise stationary signals
- HMM
  - Training: forward-backward algorithm with labeled speech data
  - Gaussian Mixture models (GMM) used to model emissions

SPEECH FEATURES

MFCC – what are they for?

- First step in any speech recognition system
  - MFCC are audio features: should be good to identify the linguistic content (neglecting background noise, emotion, etc.)
- Sounds generated by humans
  - Are filtered by the shape of the vocal tract, including tongue, teeth, etc.
  - This shape determines which sound comes out
  - If we determine this shape accurately, this should give a good representation of the phoneme that is being produced
- Shape of the vocal tract
  - Manifests itself in the envelope of the *short-term power spectrum*
  - The job of MFCCs is to accurately represent this envelope [1]

[1] S. Davis, P. Mermelstein, "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sequences," *IEEE Transactions on Acoustic, Speech and Signal Processing*, Vol. 28, No. 4, 1980.

Computing MFCC – what is it?

- A highly engineered preprocessing of the audio waveform
- Designed
  - to discard the large amount of information in waveforms that has been found to be irrelevant for discrimination
  - to express the remaining information in a form that facilitates discrimination, e.g., with GMM-HMMs or Neural Networks
- GMM advantages
  - given enough components, (i) they can model PDFs *to any degree level of accuracy* & (ii) they are fairly *easy to train through EM*

MFCC computation involves 6 steps

1. Segment the signal into short frames
2. For each frame: calculate its power spectrum
3. Apply a Mel filterbank to the power spectrum
   - sum the energy within each filter
4. Take the logarithm of all filterbank energies
5. Take the DCT of the log filterbank energies
6. Keep DCT coefficients 2-13, discard the others

Step 1 - framing

- An audio signal is constantly changing (*non-stationary*)
- Dealing with non-stationary data is difficult
- To simplify things
  - We assume that on short time scales the signal does not change much
  - “Doe not change” means it is statistically stationary
- This is why we frame the signal into 20-40ms time windows
  - Standard value is 25ms
  - **Shorter:** not enough samples to get a reliable spectral estimate
  - **Longer:** the signal (statistics) changes too much within each frame

Step 2 – power spectrum

- Compute the power spectrum of a frame
  - This is motivated by the human *cochlea* (organ in the ear)
  - It vibrates at different spots depending on the frequency of the incoming sound waves
  - Depending on the location of the cochlea that vibrates, different nerves fires informing the brain that certain frequencies are present
  - This is then translated by the brain into words, sentences, etc.

- The periodogram estimate of the power spectrum
  - Does a similar job
  - Informing us on which frequencies are present in the current frame

Step 3 – filterbank

- The periodogram estimate of the power spectrum
  - Still contains a lot of information that is not required by Autonomous Speech Recognition (ASR) systems
  - In fact, the cochlea cannot discern the difference between two closely spaced frequencies
  - This effect becomes more apparent as frequencies increase
- Hence
  - We take clumps of periodogram **bins** and sum them up to get an *idea of how much energy there exists in each region*
  - This is performed using a Mel filterbank
    - **First Mel filter is very narrow:** to get an idea of how much energy there is around 0 Hertz
    - **Filters get wider as frequencies get higher:** we become less concerned about variations (Mel scale tells us how to space filterbanks)

Step 4 – logarithm

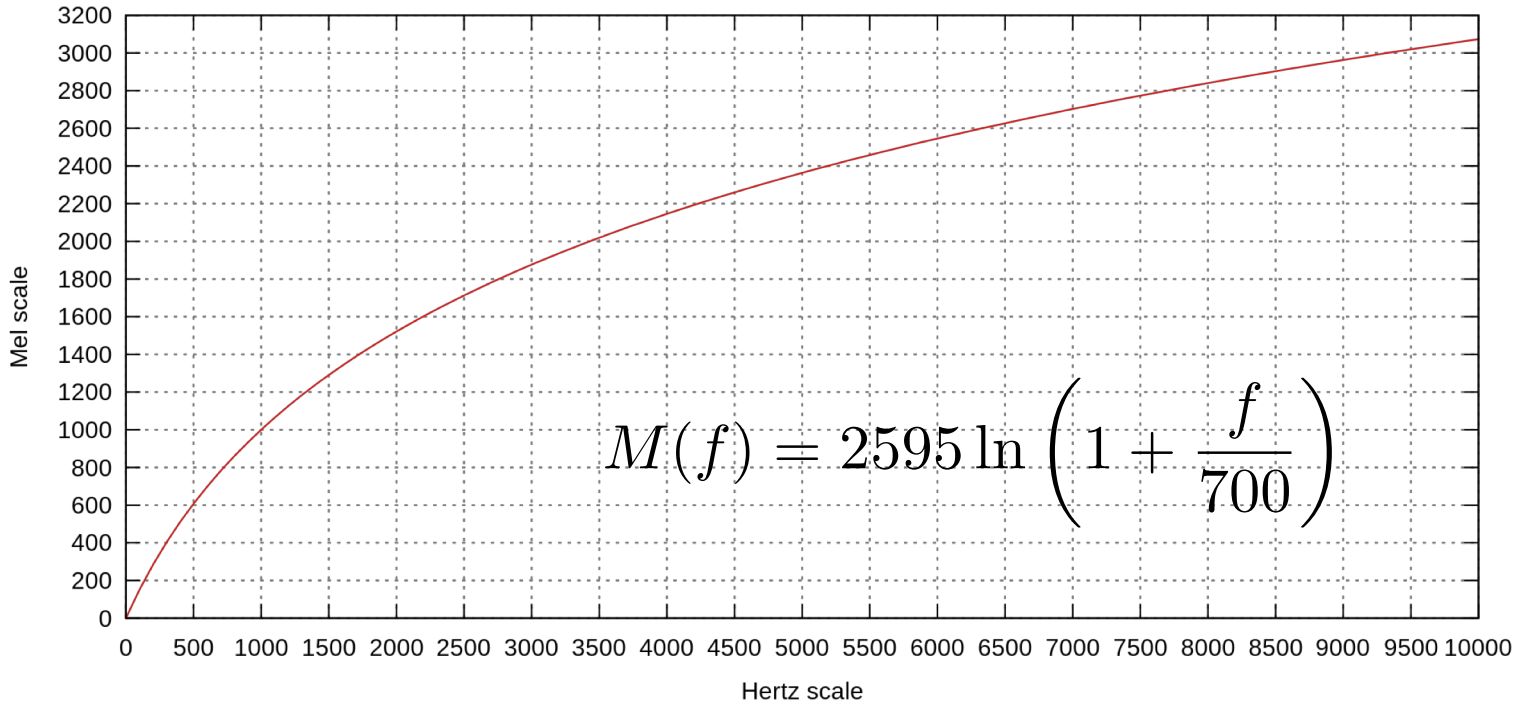
- Once we have the filterbank energies
  - We take their logarithm
  - This is also motivated by human hearing: we do not hear loudness on a linear scale
  - Generally, to double the perceived volume of a sound we need to put 8 times as much energy into it
  - This means that large variations in energy *may not sound that different* if the sound is loud
- Hence
  - This compression operation (logarithm) makes our features match more closely what humans actually hear

Steps 5 and 6 – DCT

- Discrete Cosine Transform (DCT)
  - There are two main reasons for applying it
  - First: filterbanks are quite overlapping (meaning that filterbank energies are quite correlated with each other)
    - DCT decorrelates filterbank energies
    - This means that diagonal covariance matrices can be used to model the features with GMM and/or GMM/HMM systems (very desirable)
    - Also (energy compaction property of DCT) we obtain a compact representation in the first DCT coefficients
  - Second: discard some information for improved performance
    - Only 12 of the 26 DCT coefficients are kept (energy compaction of DCT)
    - Higher DCT coefficients represent fast changes in the filterbank energies
    - These fast changes degrade ASR performance
    - A (small) improvement is achieved by dropping them

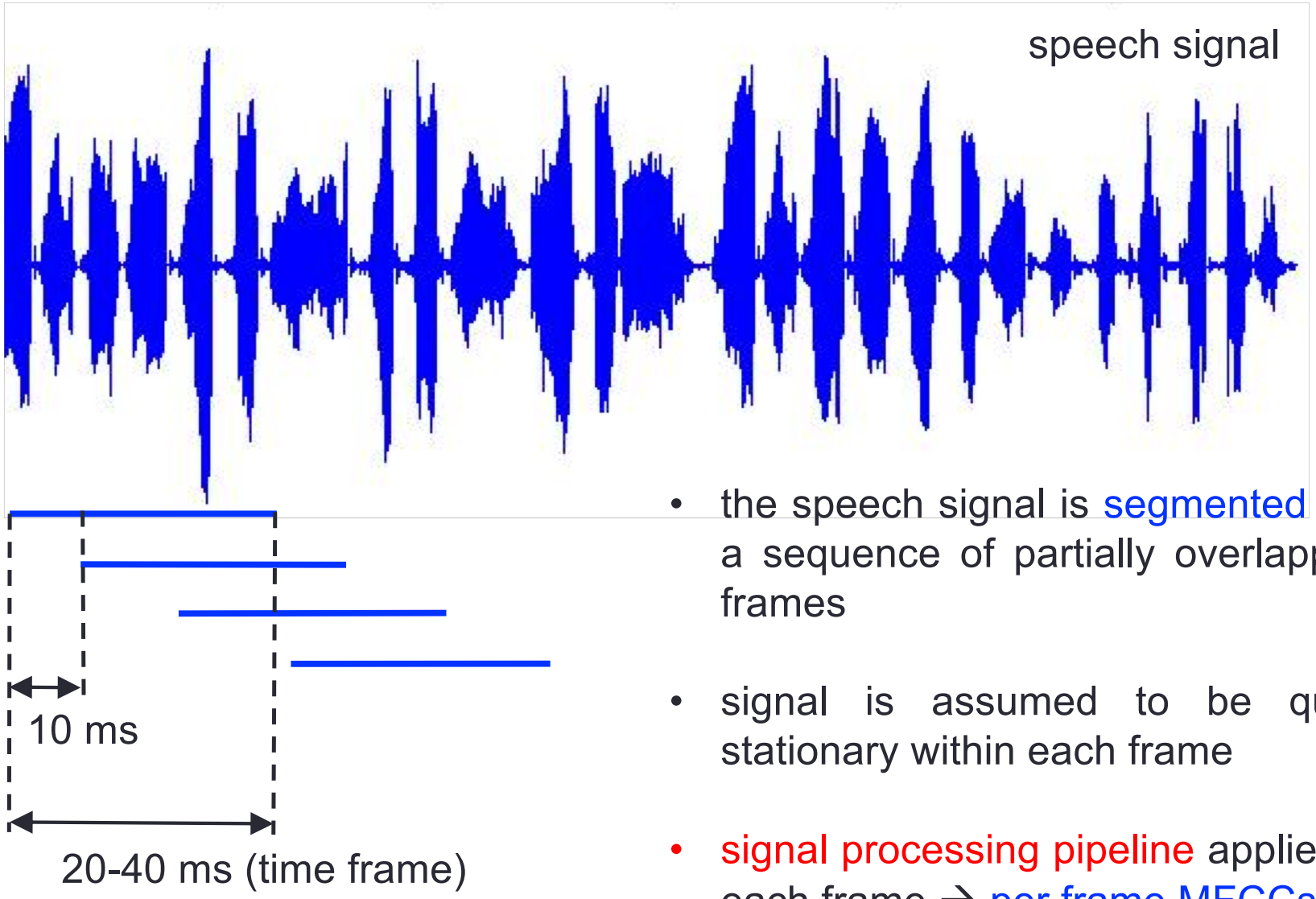
The Mel scale - M(f)

- Relates the *human perceived frequency* (or pitch) of a pure tone to its *actual measured (perceived) frequency*
- Humans are much better at discerning small changes in pitch at low frequencies that they are at high frequencies
- Incorporating it makes ASR match more closely what humans hear



STEPS 1-6 IN MORE DETAIL

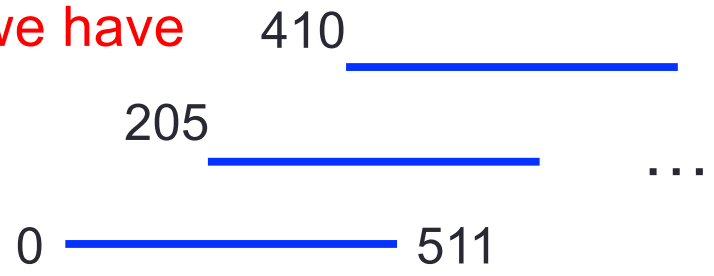
Step 1 – framing (1/2)



- the speech signal is segmented into a sequence of partially overlapping frames
- signal is assumed to be quasi stationary within each frame
- signal processing pipeline applied to each frame → per frame MFCCs

Step 1 – framing (2/2)

- Frame the audio signal into [20,40] ms frames (standard value is 25 ms)
- Example: 20.480 kHz signal, with 25 ms we have
  - sampling rate: 20,480 samples/second
  - 0.025 * 20,480 = 512 samples/frame



- Frame step is usually 10 ms (205 samples)
  - This allows for some overlap between subsequent frames
  - First frame (of 512 samples) starts at sample 0
  - Second frame (still of 512 samples) start at sample 205, etc.
  - Keep framing until the end of the speech signal
  - If the signal does not divide into an even number of frames, pad it with zeros so it does
- Notation
  - s(n) is the “raw” audio signal (i.e., time domain signal)
  - $s_i(n)$ is frame i with n ranging from 0 to 511 in our example

Step 2 – power spectrum (1/4)

- For each frame $s_i(n)$, $n = 0, 1, \ldots, N-1$ $(N = 512)$
  - Calculate the complex DFT (Discrete Fourier Transform)

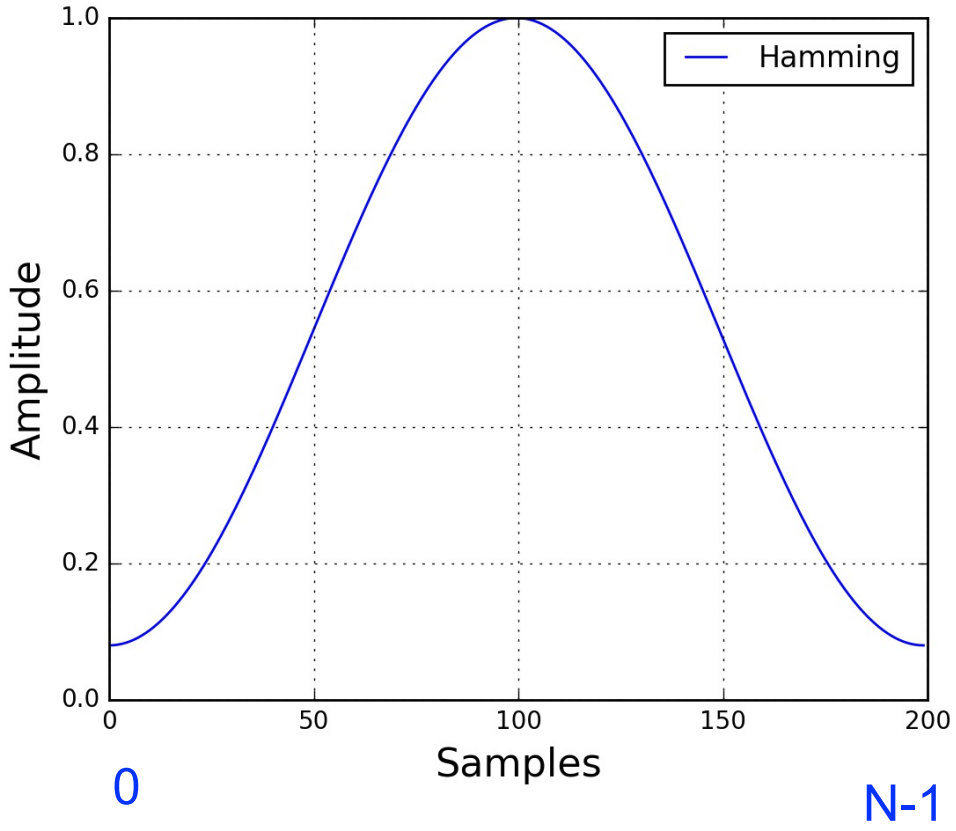
$$S_i(k) = \sum_{n=0}^{N-1} s_i(n) w(n) e^{-j2\pi kn/N}, \; k = 0, 1, \ldots, N-1$$

  - DFT
    - Converts a time sequence of N equally spaced samples into an N-long complex sequence, which is a complex-valued function of frequency
    - The DFT (with w(n)=1) completely describes the discrete Fourier transform of an N-periodic time sequence
    - When applying DFT, we are implicitly applying it to an infinitely repeating (periodic) signal. However, if this is not the case, e.g., first and last samples of $s_i(n)$ do not match, this is *interpreted as a discontinuity* in the signal and *generates a lot of high frequency response in the transformed signal*, that we do not want → use of "windowing" w(n)

Step 2 – power spectrum (2/4)

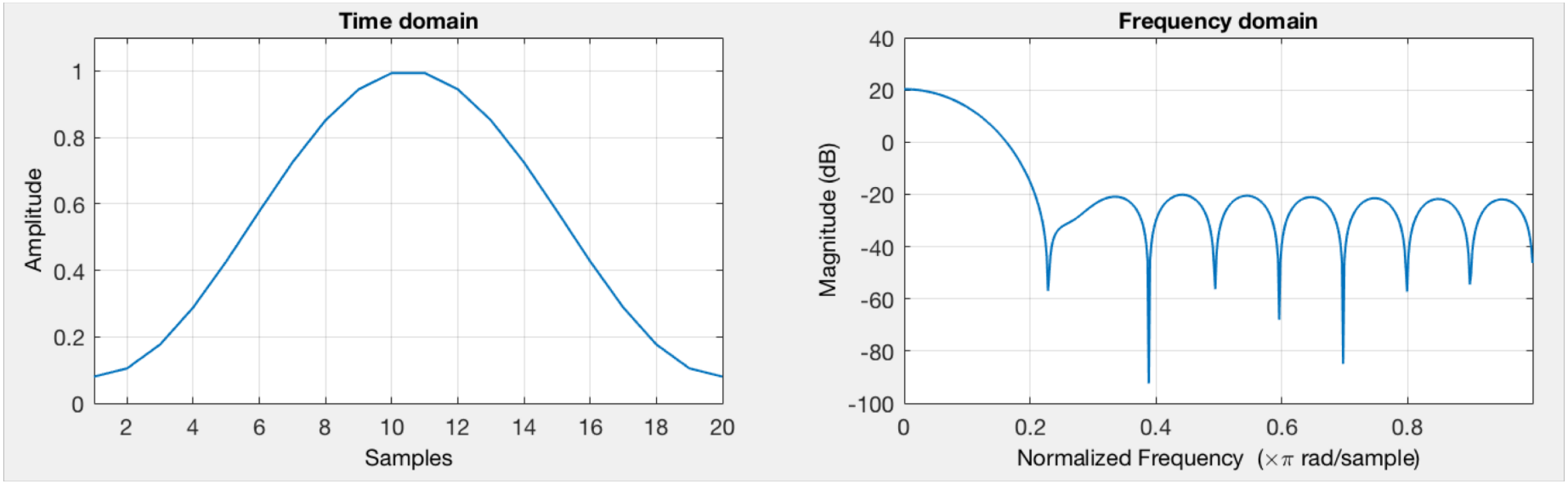
- Often used: Hamming window - w(n)

$$w(n) = 0.54 - 0.46 \cos\left(\frac{2\pi n}{N-1}\right), \; n = 0, \ldots, N-1$$



Step 2 – power spectrum (3/4)

- Hamming window – transformation (with N=20)



- The center of the main lobe of a smoothing window occurs at each frequency component of the input signal (of course, freq. plot is symmetric around zero)
- Center lobe width (across negative & positive freqs.) is $4\Omega_N=4(2\pi/N)$
- Ideally, only the main lobe should be emphasized while the side lobes should be zeroed (this prevents energy leakage across subsequent frequencies)

Step 2 – power spectrum (4/4)

- Note
  - Among the N=512 (in our example) complex DFT values
  - Only the first 1+N/2 values are significant, the remaining ones are complex conjugates of the first 1+N/2 values (this is how DFT works)
  - Hence, the first 1+N/2=257 elements *are kept*, while the remaining ones (N/2-1 values) *are discarded*
- Compute the periodogram estimate of the power spectrum:

$$P_i(k) = \frac{|S_i(k)|^2}{N}, \; k = 0, \ldots, N/2$$

Remember that: k=0 is the DC component (frequency f=0). Then, with DFT the step size is F_s/N (F_s is the *sampling frequency*). Hence, k=1 corresponds to frequency $f_1=F_s/N$ and element k=N/2 corresponds to frequency $f_{N/2}=F_s/2$ (this is the Nyquist critical frequency, i.e., the highest signal frequency that can be represented by sampling at frequency F_s)

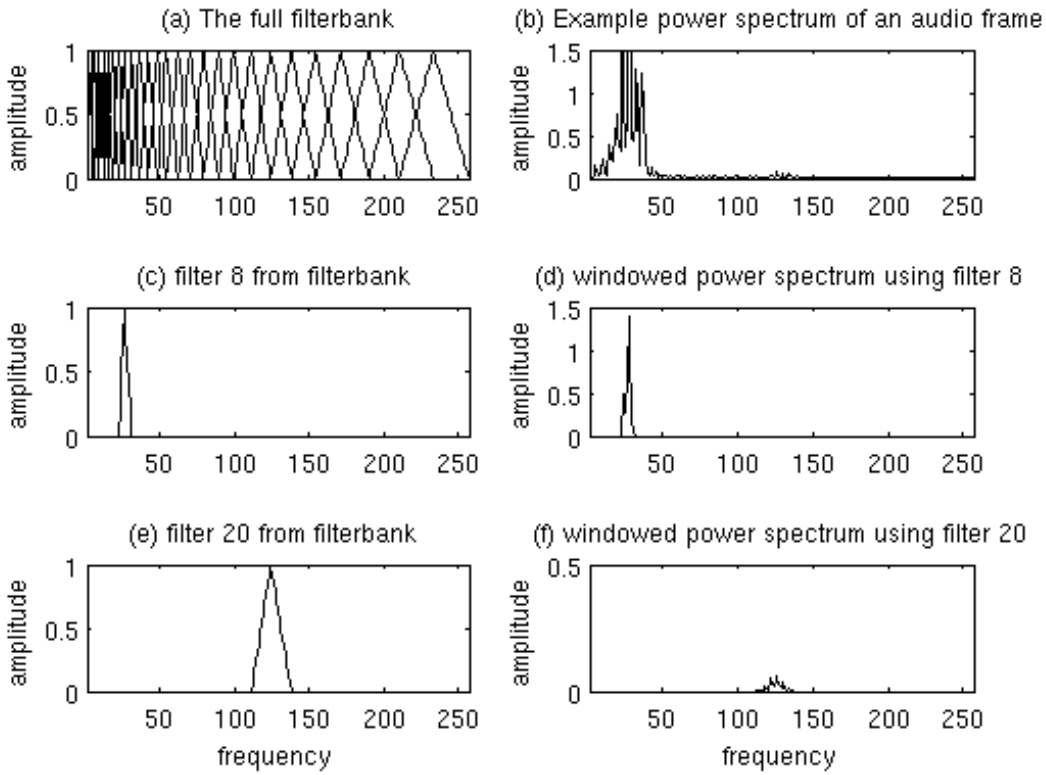
Step 3 – filterbanks (1/3)

- Compute Mel-spaced filterbanks (through Mel's equation)
  - They amounts to 20-40 triangular filters
  - Each filter (in our case) has 257 values (1+N/2, to match the output of step 2) and it is multiplied by the entire power spectrum from step 2

full filterbank (left)
full power spectrum (right)

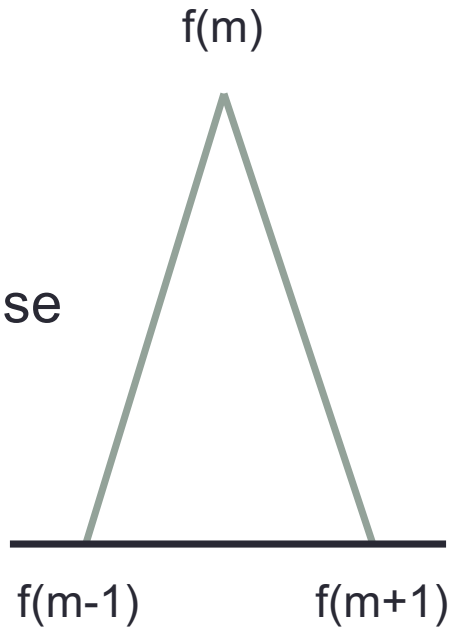
filter 8 from filterbank (left)
output when this filter is applied (right)

filter 20 from filterbank (left)
output when this filter is applied (right)



Step 3 – filterbanks (2/3)

- Obtain N_{fb} Mel-spaced triangular filters
  - Pick the number of filters (usually N_{fb}=26)
  - Set the maximum frequency as $f_{max}=F_s/2$
  - Set the minimum frequency as, e.g., f_{min}=300 Hz (user defined)
  - Compute N_{fb} center frequencies f(1), f(2), …, f(N_{fb})
    - Linearly spaced in Mel's domain
    - Non-linearly spaced in frequency domain [Hz]
- Each filter m
  - Is centered at frequency f(m)
  - Is equal to 1 for f(m) and decreasing linearly otherwise
  - Is zero at f(m-1), f(m+1) and outside [f(m-1), f(m+1)]
  - N_{fb} filters require N_{fb}+2 thresholds

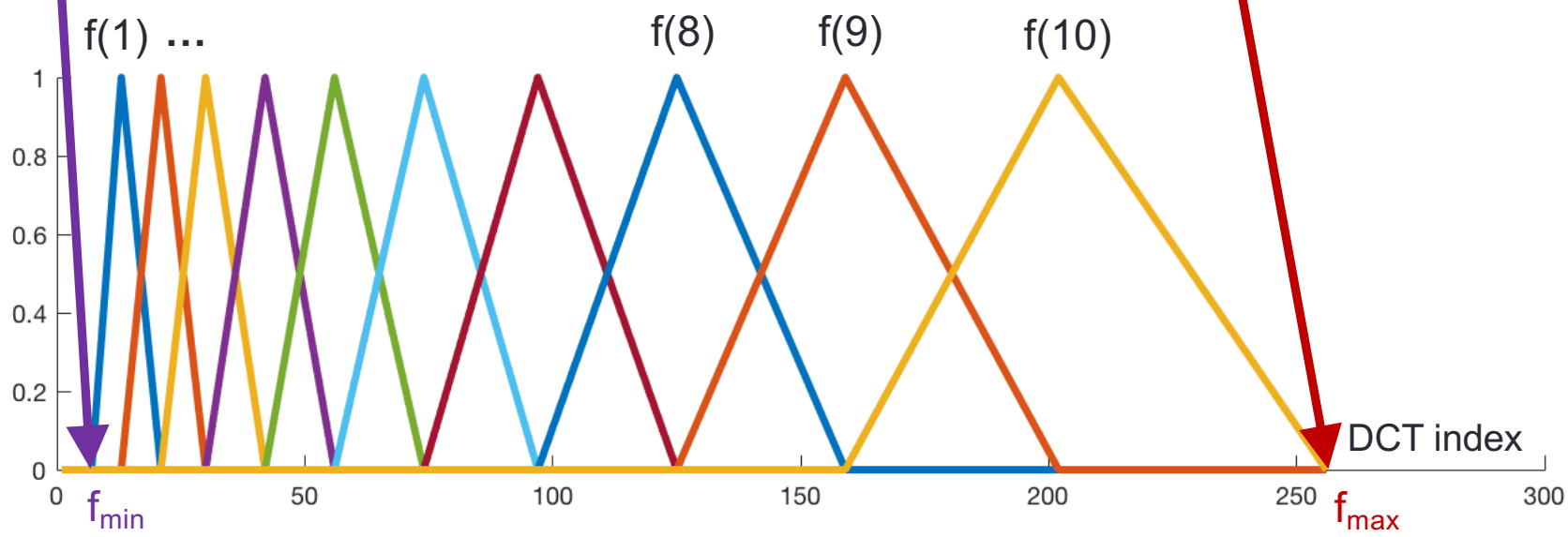


Step 3 – filterbanks (3/3)

- Example
  - F_s= 20.480 kHz, N=512, N_{fb}=10, $f_{max}=F_s/2$=10,240 Hz, f_{min}=300 Hz
- Frequencies [Hz]

  300=f_{min} 543=f(1) 845=f(2) 1,220=f(3) 1,687=f(4) 2,267=f(5) 2,988=f(6)
  3,883=f(7) 4,997=f(8) 6,381=f(9) 8,102=f(10) 10,240=f_{max}
- Corresponding DFT indices

  [7 13 21 30 42 56 74 97 125 159 202 256]



S

```
FminMel=1125*log(1+(Fmin/700)); % min Mel's frequency
FmaxMel=1125*log(1+(Fmax/700)); % Max Mel's frequency

Nthresh=Nfb+2;      % number of required threshold values
step=(FmaxMel-FminMel)/(Nthresh-1); % step size (linearly partition Mel's space)
```

- Example
  - F_s= 20.480 kHz, N=512, N_{fb}
- Frequencies [Hz]

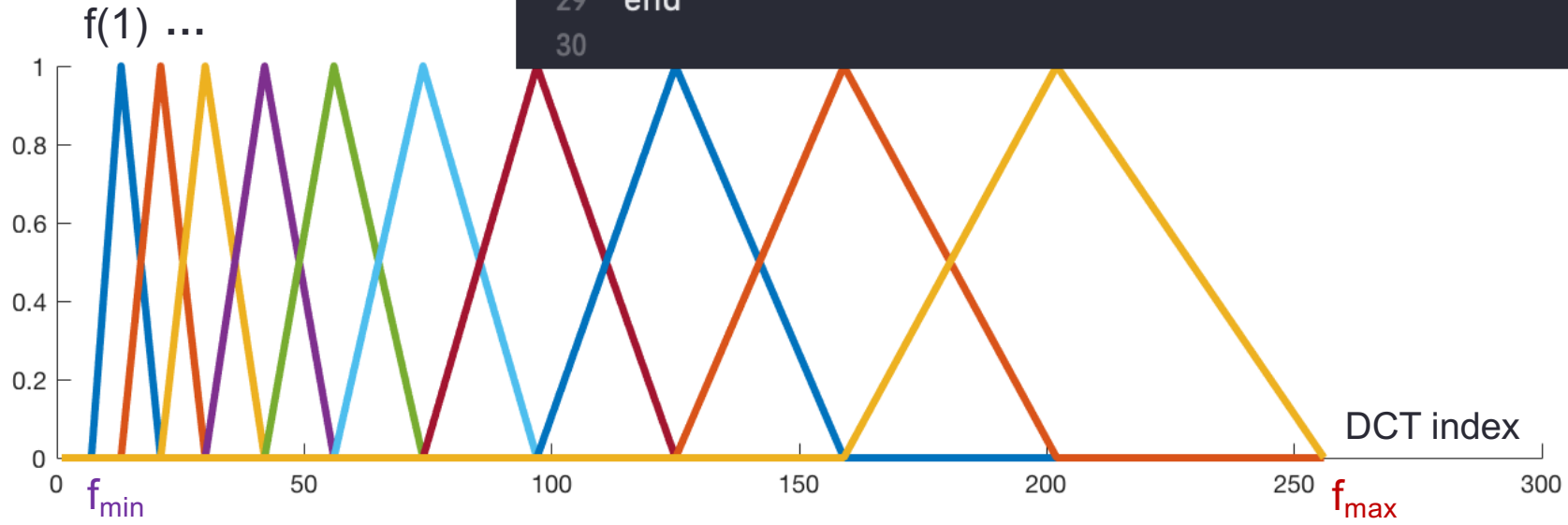
  300=f_{min} 543=f(1) 845=f(
  3,883=f(7) 4,997=f(8) 6,3
- Corresponding DFT indices

  [7 13 21 30 42 56

```
% for each threshold do
for i = 0:(Nthresh-1)
    % Mel frequencies, evenly distributed
    melvec(i+1) = FminMel+i*step;

    % Hz frequencies, obtained inverting Mel relation
    freqvec(i+1) = 700*(exp(melvec(i+1)/1125)-1);

    % DFT indices, obtained from Hz frequencies
    f(i+1) = floor((nDFT+1)*freqvec(i+1)/Fs);
end
```



Step 4 – logarithms

- We now have N_{fb} Mel-spaced triangular filters
- For each filter m=1,2,…, N_{fb}
  1. Multiply filter m by the full power spectrum from step 2 (the resulting energy trace will be mostly 0 (besides around f(m), the filter acts as a mask, centered at f(m))
  2. Add up the non-zero coefficients in this trace → obtain E_m
  3. Take the logarithm: $\log(E_m)$

- This gives us N_{fb} real values:
- $\log(E_1)$, $\log(E_2)$, …, $\log(E_M)$, with $M= N_{fb}$
  - One for each Mel's frequency band
  - They tell how much energy there is within each band

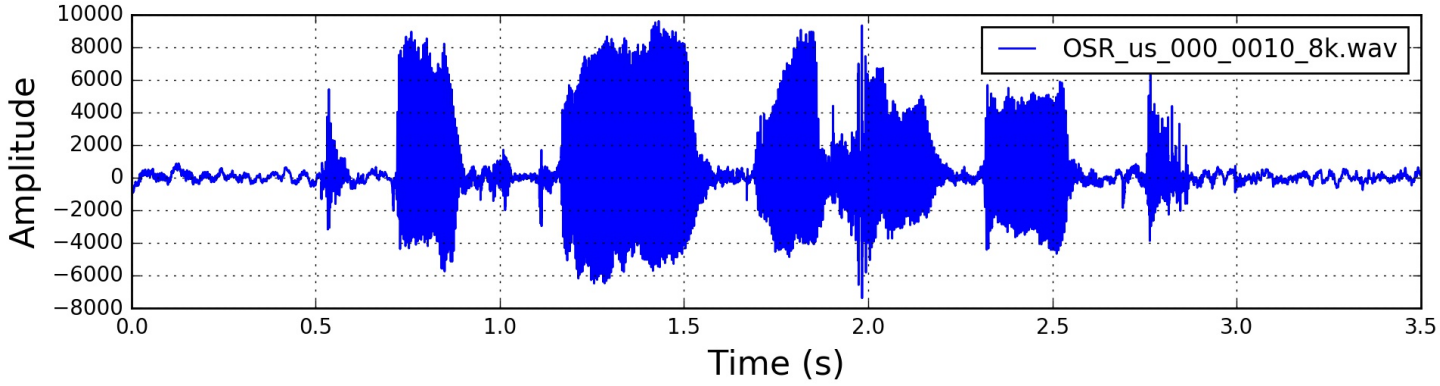
Steps 5 and 6

- Step 5 – for each frame
  - Take the DCT (Discrete Cosine Transform) of the vector containing the logarithms of the energy within each band
  - The result of the DCT is a vector of N_{fb} cepstral coefficients
- Step 6 – for each frame
  - For ASR, the cepstral coefficients no. 2,3, …,13 are kept
  - The remaining ones are discarded
  - Note that: the first DCT coefficient is the sum of all the log-energies computed at the previous step (by the very def. of DCT) – thus, it is an overall measure of signal loudness and is not very informative - it is often discarded for *speech recognition* or *speaker id applications* where the system has to be robust to loudness variations
- Final result of this processing is
  - 12 cepstral coefficients for each frame. For frame i:

$$\boldsymbol{c}(i) = [c_1(i), c_2(i), \ldots, c_{12}(i)]^T$$

Some visual insight (1/2)

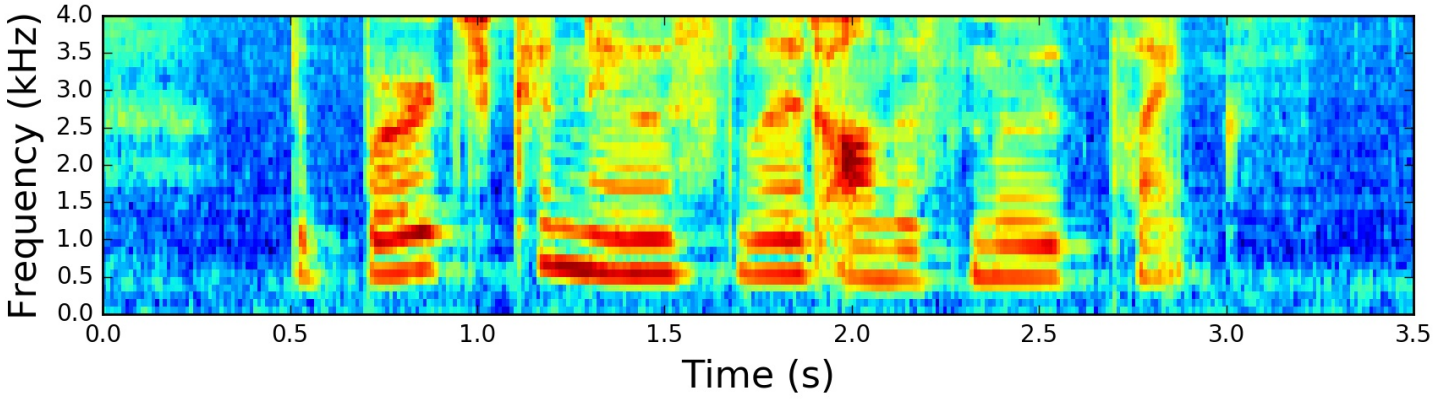
F_s = 8 kHz time signal



Signal in the Time Domain

After applying the filterbank to the power spectrum (periodogram):

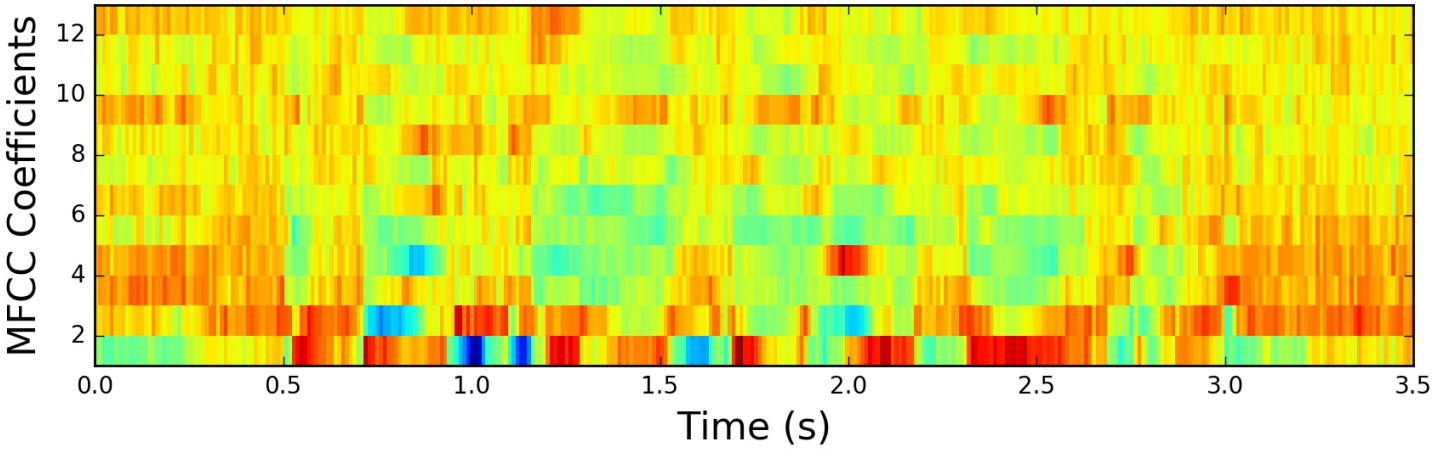
- colors represent log-energies



Spectrogram of the Signal

Some visual insight (2/2)

Mel's Frequency Cepstral Coefficients (MFCCs):



MFCCs

ADDITIONAL FEATURES

Additional features

- Up to now, we got 12 MFCC coefficients, for each frame i:

$$\boldsymbol{c}(i) = [c_1(i), c_2(i), \ldots, c_{12}(i)]^T$$

- Additional features are usually tracked:
  1. Energy (1 additional coefficient)
  2. Δ coefficients (12 additional coefficients)
  3. Δ–Δ coefficients (12 additional coefficients)

- Adding these leads to much better ASR performance

Energy

- Let the raw signal (time domain) be represented by $s(n)$
- Where n is the discrete sampling time
- The energy of the generic frame i:

$$E(s_i) = \sum_{n=n_1(i)}^{n_2(i)} s(n)^2$$

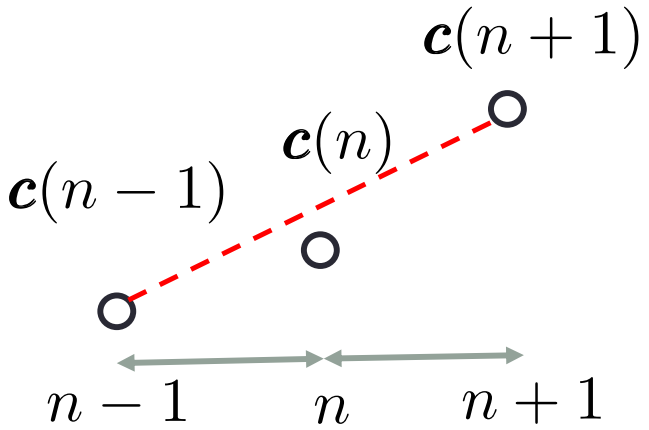
- $n_1(i)$ and $n_2(i)$ are first and last audio sample in frame i
- Sometimes, logarithms are used to limit dynamics

$$\log_{10} E(s_i)$$

Delta coefficients (1/2)

- MFCC feature vector
  - Only describes the power spectrum of a single frame
  - However, speech also has information in the dynamics, i.e.,
  - trajectories of MFCC coefficients over time
- Delta MFCC coefficients
  - Represent local derivatives of MFCC coefficients ("velocity" of s(n))
  - Append those coefficients to the MFCC feature vector
  - A delta is computed for each element of the MFCC feature vector
    - 12 MFCC elements → 12 Δ coefficients
    - At sampling time n we have:

$$\boldsymbol{\Delta}(n) = \frac{\boldsymbol{c}(n+1) - \boldsymbol{c}(n-1)}{2}$$



Delta coefficients (2/2)

- Common regression formula (e.g., used by HTK)

$$\boldsymbol{\Delta}(n) = \frac{\sum_{m=1}^{M} m(\boldsymbol{c}(n+m) - \boldsymbol{c}(n-m))}{2\sum_{m=1}^{M} m^2}, \text{ usually } M = 2$$

Delta-Delta coefficients

- Trajectory in the Delta coefficients ("acceleration" of s(n))
- So the new estimation formula is:

$$\mathbf{\Delta}^2(n) = \frac{\mathbf{\Delta}(n+1) - \mathbf{\Delta}(n-1)}{2}$$

- In practice, the following is implemented:

$$\mathbf{\Delta}^2(n) = \frac{\sum_{m=1}^{M} m(\mathbf{\Delta}(n+m) - \mathbf{\Delta}(n-m))}{2\sum_{m=1}^{M} m^2}, \text{ usually } M = 2$$

Full feature vector

- For each frame:
  - 12 MFCC coefficients
  - 12 Delta coefficients
  - 12 Delta-Delta coefficients
  - 1 signal energy coefficient
  - 1 Delta energy coefficient
  - 1 Delta-Delta energy coefficient

- Total: 39 coefficients
  - Used in most speech recognition applications

$$\begin{bmatrix} c_1 \\ \vdots \\ c_{12} \\ \hline \Delta_1 \\ \vdots \\ \Delta_{12} \\ \hline \Delta_1^2 \\ \vdots \\ \Delta_{12}^2 \\ \hline E(s) \\ E(\boldsymbol{\Delta}) \\ E(\boldsymbol{\Delta}^2) \end{bmatrix}$$

Implementations

- HTK Speech recognition toolkit

http://htk.eng.cam.ac.uk/

- Phyton library to extract MFCCs

https://github.com/jameslyons/python_speech_features

AUTOMATIC SPEECH RECOGNITION SYSTEMS

Automatic Speech Recognition Systems (ASRS): some history

- Initial work at Carnergie Mellon & IBM in the 1970's
  - Discrete density HMM (to model observations)
- Subsequent work @ Bell Labs
  - Continuous density HMM (GMM)
- Initially
  - Speaker *dependent* large vocabularies
  - Speaker *independent* small vocabularies
- In the mid-1990's
  - Large speaker independent vocabularies
  - DARPA funded several research programs (since 1971), e.g., the "1,000 words vocabulary challenge"
  - Worthy of note: the HTK Software Toolkit (Cambridge University)

The statistical HMM approach

- Main tool is the HMM
  - Learning is based on *forward-backward algo*
  - Also called the "Baum-Welch algorithm"
  - Named after Leonard Esau-Baum, a mathematician that developed HMM algorithms at the Institute for Defense Analyses (IDA), Priceton University, in the late 1960's

Leonard E. Baum
(August 23, 1931 – August 14, 2017)

1980 – 1990: HMM become ubiquitous

HMMs become extensively used

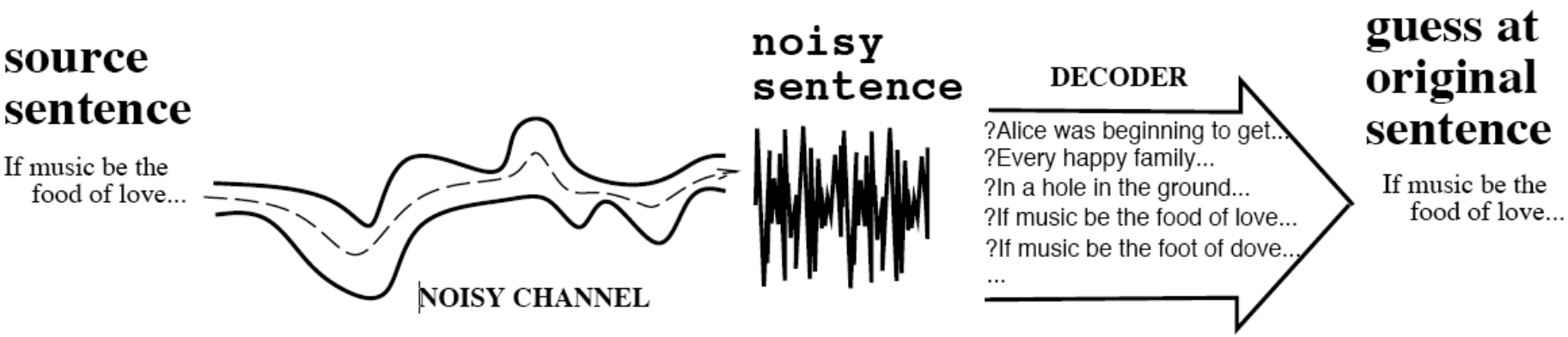
- Lawrence R. Rabiner
  - writes a wonderful tutorial
  - pushes on ASR research using HMMs

R. V. Cox, C. A. Kamm, L. R. Rabiner, J. Schroeter, and J. G. Wilpon, Speech and Language Processing for Next-Millennium Communications Services, Proceedings of the IEEE, Vol. 88, No. 8, August 2000.

L. R. Rabiner, A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition, Proceeding of the IEEE, Vol. 77, No. 2, February 1989.

Lawrence R. Rabiner
(born 28 September 1943)

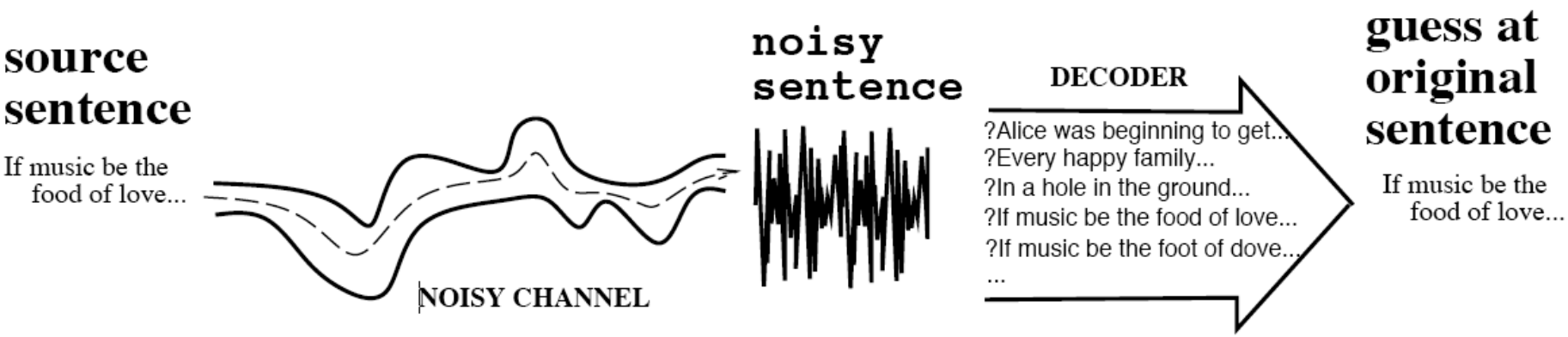
The noisy channel model



- Idea: treat the acoustic waveform as a "noisy" version of the string of words that was spoken, i.e., a string that has been passed through a *noisy communication channel*
- Goal: is to build a model of the noisy channel so that we can figure out how it modifies the true sentence and, in turn, retrieve it
- Insight: if we know how the channel distorts the source, we could find the true source sentence by:

(i) taking every possible sentence in the language

The noisy channel model



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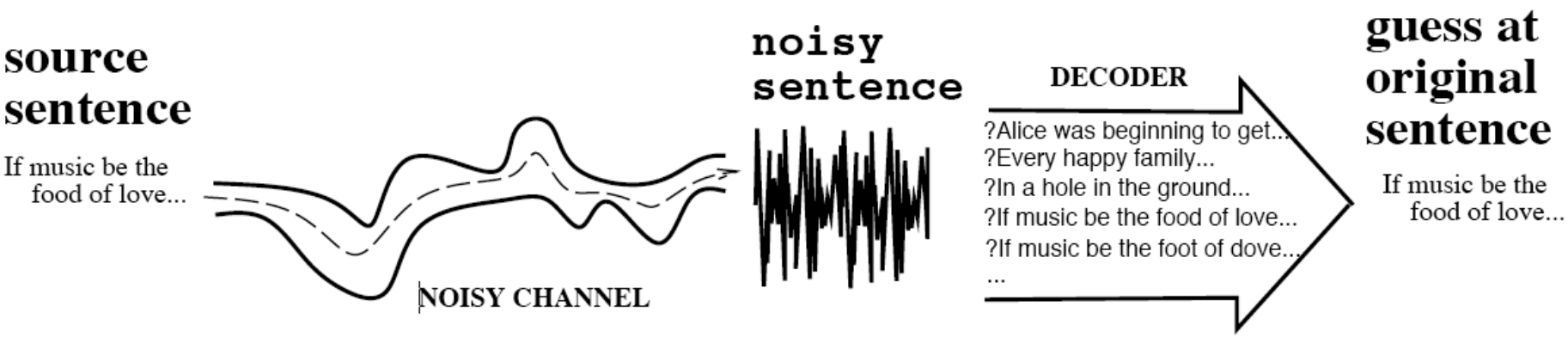
- Goal: is to build a model of the noisy channel so that we can figure out how it modifies the true sentence and, in turn, retrieve it
- Insight: if we know how the channel distorts the source, we could find the true source sentence by:

(ii) running each sentence through our noisy channel model

The noisy channel model

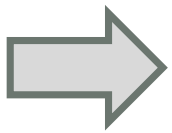


- Idea: treat the acoustic waveform as a "noisy" version of the string of words that was spoken, i.e., a string that has been passed through a *noisy communication channel*
- Goal: is to build a model of the noisy channel so that we can figure out how it modifies the true sentence and, in turn, retrieve it
- Insight: if we know how the channel distorts the source, we could find the true source sentence by:

(iii) seeing whether it matches the output: we then select the best matching source sentence as our desired source sentence

Decoding

- We need a complete metric for a “best match”
- Problem: speech is very variable
  - No acoustic model will provide an exact match for a given sentence
- Solution: use probabilistic models
  - Speech recognition as a special case of Bayesian inference
- Goal: to combine various probabilistic models to get a complete estimate for the probability of a noisy acoustic observation-sequence *given a candidate source sentence*. We can then search through the space of all sentences, and choose the one with the highest probability



DECONDING and SEARCH

ARS: the challenge

- 1) Record a speech waveform representing a sentence

- 2) Feature extraction: *input speech waveform* is converted into a number of *feature vectors* (e.g., 25ms each, spaced 10 ms apart)

$$\boldsymbol{Y}_{1:T} = \{\boldsymbol{y}_1, \boldsymbol{y}_2, \ldots, \boldsymbol{y}_T\}$$

What is the most likely sentence out of all sentences in the language $\mathcal{L}$ given some acoustic input $\boldsymbol{Y}_{1:T}$?

ARS (1/3)

- 3) Decoder: attempts to find the sequence of words

$$\boldsymbol{w}_{1:L} = \{w_1, w_2, \ldots, w_L\}$$

which is most likely to have generated $\boldsymbol{Y}_{1:T}$
(subscripts dropped for the sake of notation's compactness)

$$\tilde{\boldsymbol{w}} = \underset{\boldsymbol{w} \in \mathcal{L}}{\operatorname{argmax}}\, P(\boldsymbol{w}|\boldsymbol{Y})$$

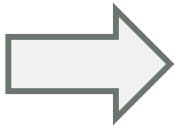
ARS (2/3)

$$\tilde{\boldsymbol{w}} = \underset{\boldsymbol{w} \in \mathcal{L}}{\operatorname{argmax}} P(\boldsymbol{w}|\boldsymbol{Y})$$

- This equation returns the optimal sentence estimate
- But it is very difficult to use, we need to make it operational:

$$\tilde{\boldsymbol{w}} = \underset{\boldsymbol{w} \in \mathcal{L}}{\operatorname{argmax}} P(\boldsymbol{w}|\boldsymbol{Y}) = \underset{\boldsymbol{w} \in \mathcal{L}}{\operatorname{argmax}} \frac{P(\boldsymbol{Y}|\boldsymbol{w})P(\boldsymbol{w})}{P(\boldsymbol{Y})}$$

- P(**w**): prob. of the word string, estimated by an N-gram language model
- P(**Y**|**w**): can be easily estimated as well (HMM)
- P(**Y**): very difficult to estimate, but we do not need it. As it is a constant term that appears for each **w**.



The search for a maximizer does not depend on it!

ARS (3/3)

$$\tilde{\boldsymbol{w}} = \underset{\boldsymbol{w} \in \mathcal{L}}{\operatorname{argmax}} \overbrace{P(\boldsymbol{Y}|\boldsymbol{w})}^{\text{likelihood}} \overbrace{P(\boldsymbol{w})}^{\text{prior}}$$

- The prior P(w) is computed through the language model
- The likelihood P(**Y**|**w**) is computed by the acoustic model (HMM)

MODELING LANGUAGE AND LEXICON (PRONUNCIATION)

Language modeling

- Language Models (LMs)
  - capture regularities in spoken language
- Context-free grammars
  - Contain grammatical constraints that are hand-crafted
  - Are suitable for small to medium size dictionaries
- Large Vocabulary Continuous Speech Recognition (LVCSR)
  - Are all based on data driven approaches
  - Dependencies among words are automatically discovered

- N-gram model
  - The most popular approach

N-gram model (1/3)

$$P(\boldsymbol{w}_{1:L}) = \prod_{\ell=1}^{L} P(w_\ell | w_{\ell-1}, w_{\ell-2}, \ldots, w_{\ell-N+1})$$

- Probability of word sequence $\boldsymbol{w}_{1:L}$
  - Markovian assumption
    - occurrence of each word depends on previous N-1 words
  - Word history (memory) reduced to previous N-1 words
  - Usually N=3 (tradeoff between complexity & performance)

N-gram model (2/3)

- Obtaining the model
  - Very large text corpus
  - To compute *N-gram transition probabilities* (usually N=3, “trigrams”)
  - Most steps are standards: automatic counting of words occurrences
  - Important choices
    - Choice of the vocabulary: minimizing *out-of-vocabulary* occurrences
    - Definition & treatment of words (e.g., compound words, acronyms)
  - Normalization
    - Reduce lexical variability (increases the coverage of fixed size vocabulary)
    - E.g., numerical expression are expanded to approximate spoken form
    - 150$ -> *one hundred fifty dollars*
    - 2018 -> *twenty eighteen* or *two thousand and eighteen*
    - hundred <nb> -> replaced by *hundred and <nb>* 50% of the time
    - Semi-automatic processing to correct common text problems (misspelling)

N-gram model (3/3)

- Estimation of probabilities
  - Uses the Maximum Likelihood (ML) criterion
  - Estimated from the frequencies of text sequences of length N in the training corpus (texts or speech transcriptions)

$$P(w_i|w_{i-1}, w_{i-2}) \approx \frac{C(w_i, w_{i-1}, w_{i-2})}{C(w_{i-1}, w_{i-2})}$$

  - C: counts how many times the tri(bi)grams appear in the training data
- Many additional implementation details are needed
  - Back-off: estimate probabilities for rare N-grams (not present in the training). Probs. of N-grams estimated from probs. on (N-1)-grams
  - Model interpolation: often needed; to merge language models obtained from heterogeneous (in size, context, format) training corpora

Pronunciation modeling

- Pronunciation dictionary
  - Links acoustic level representation and lexical items output by the speech decoder
  - Associated with each lexical entry (“word”)
    - One or more pronunciations
    - Described using elementary units (“phones” or “phonemes”)
    - For example work “bat” has three phones \b\ \ae\ \t\
    - Standard phones
      - 45 for English
      - 50 for Italian and German
      - 35 for French and Mandarin
      - 25 for Spanish
- For any given word w
  - The corresponding acoustic model is synthetized by concatenating phone models, as defined by a pronunciation dictionary

Open source pronunciation dictionary

- The MCU pronunciation dictionary
  - http://www.speech.cs.cmu.edu/cgi-bin/cmudict

Input: “POLLY WANTS A CRACKER”
(Kurt Cobain, 1991)

Output: P AA L IY . W AA N T S . AH . K R AE K ER
(input sentence broken down into phones)

English phones

- The 45 phones for English
  - Illustrative word examples are shown for each phone
  - Portion corresponding to the phone sound is underlined

Phone	*Example*	*Phone*	*Example*
Vowels		Fricatives	
i	b<u>ee</u>t	s	<u>s</u>ue
I	b<u>i</u>t	z	<u>z</u>oo
e	b<u>ai</u>t	ʃ	<u>sh</u>oe
ɛ	b<u>E</u>t	ʒ	mea<u>s</u>ure
æ	b<u>a</u>t	f	<u>f</u>an
ʌ	b<u>u</u>t	v	<u>v</u>an
ɑ	b<u>o</u>tt	θ	<u>th</u>in
o	b<u>oa</u>t	Plosives	
u	b<u>oo</u>t	b	<u>b</u>et
U	b<u>oo</u>k	d	<u>d</u>ebt
ɝ	b<u>ir</u>d	g	<u>g</u>et
Diphthongs		p	<u>p</u>et
ɑʲ	b<u>i</u>te	t	<u>t</u>at
ɔʲ	b<u>oy</u>	k	<u>c</u>at
ɑʷ	b<u>ou</u>t	Affricates	
Reduced Vowels		ʧ	<u>ch</u>eap
ə	<u>x</u>bout	ʤ	<u>j</u>eep
ɨ	dat<u>e</u>d	Nasals	
ɚ	butt<u>er</u>	m	<u>m</u>et
Semivowels		n	<u>n</u>et
l	<u>l</u>ed	ŋ	thi<u>ng</u>
r	<u>r</u>ed	Syllabics	
w	<u>w</u>ed	m̩	bott <u>om</u>
y	<u>y</u>et	n̩	butt<u>on</u>
h	<u>h</u>at	l̩	bott<u>le</u>

Pronunciation (lexicon)

COUPON	kupɑn (0.63) kyupɑn (0.37)
ORGANIZATION	ɔrgənIzeʃən (0.93) ɔrgənɑʲzeʃən (0.07)
HUNDRED	hʌndʒᵘd (0.44) hʌndrəd (0.34)
	hʌnʒᵘd (0.18) hʌnrəd (0.04)
MODERATE	mɑdəᵘIt (0.82) mɑdəᵘet (0.18)
TO	tə (0.66) tu (0.34)
I_DON'T_KNOW	ɑʲdonno (0.57) ɑʲdontno (0.05)
	ɑʲdʌno (0.28) ɑʲdno (0.10)
DON'T_KNOW	donno (0.73) dontno (0.18)
	dʌno (0.09)
DID_YOU	dIdyu (0.65)
	dIʤə (0.30) dIdyə (0.05)
GOING_TO	goɬŋtə (0.13) goɬŋtu (0.09)
	gʌnə (0.70) gcnə (0.08)

Some examples of lexical entries and their pronunciations along with estimated probabilities. For compound words, the original concatenated pronunciation is given in the 1st line, the reduced forms are given in the second line

THE ACOUSTIC MODEL

The HMM acoustic model (1/3)

- Each word w
  - Is decomposed into a sequence of K_w basic sounds called *phones*
  - This sequence is called pronunciation: $\boldsymbol{q}_{1:K_w}^{(w)} = q_1\, q_2\, \ldots\, q_{K_w}$
- To allow for the possibility of multiple pronunciations

$$P(\boldsymbol{Y}|\boldsymbol{w}) = \sum_{\boldsymbol{Q}} P(\boldsymbol{Y}|\boldsymbol{Q})P(\boldsymbol{Q}|\boldsymbol{w})$$

$$\text{where: } \boldsymbol{w} = \boldsymbol{w}_{1:L}$$

$$\boldsymbol{w}_{1:L} = \{w_1, w_2, \ldots, w_L\}$$

- where **Q** is a particular sequence of pronunciations
- formed by concatenating the constituent base phones

$$\boldsymbol{Q} = \{\boldsymbol{q}^{(w_1)}, \boldsymbol{q}^{(w_2)}, \ldots, \boldsymbol{q}^{(w_L)}\}$$

The HMM acoustic model (1/3)

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$$P(\boldsymbol{Y}|\boldsymbol{w}) = \sum_{\boldsymbol{Q}} P(\boldsymbol{Y}|\boldsymbol{Q})P(\boldsymbol{Q}|\boldsymbol{w}) \quad \text{where: } \boldsymbol{w} = \boldsymbol{w}_{1:L}$$

- For P(**Q** | **w**) we have:

$$P(\boldsymbol{Q}|\boldsymbol{w}) = \prod_{\ell=1}^{L} P(\boldsymbol{q}^{w_\ell}|w_\ell)$$

The HMM acoustic model (2/3)

- Given the composite HMM **Q**
  - formed by concatenating the constituent base phones

$$\boldsymbol{Q} = \{\boldsymbol{q}^{(w_1)}, \boldsymbol{q}^{(w_2)}, \ldots, \boldsymbol{q}^{(w_L)}\}$$

  - then, the acoustic likelihood is given by:

$$P(\boldsymbol{Y}|\boldsymbol{Q}) = \sum_{\boldsymbol{\theta}} P(\boldsymbol{\theta}, \boldsymbol{Y}|\boldsymbol{Q})$$

  - where θ is a sequence of HMM (hidden) states (represent sub-phones)

$$P(\boldsymbol{\theta}, \boldsymbol{Y}|\boldsymbol{Q}) = a_{\theta_0,\theta_1} \prod_{t=1}^{T} b_{\theta_t}(\boldsymbol{y}_t) a_{\theta_t\theta_{t+1}}$$

  - θ_0 and θ_{T+1} are the non-emitting entry and exit states

The HMM acoustic model (2/3)

- Given the composite HMM **Q**
  - formed by concatenating the constituent base phones

$$\boldsymbol{Q} = \{\boldsymbol{q}^{(w_1)}, \boldsymbol{q}^{(w_2)}, \ldots, \boldsymbol{q}^{(w_L)}\}$$

$T \rightarrow$ number of phones in current sentence, $t \in \{1, \ldots, T\}$

$\theta_t \rightarrow$ hidden HMM states

$\boldsymbol{y}_t \rightarrow$ speech observation associated with phone t

$b_{\theta_t}(\boldsymbol{y}_t) \rightarrow$ emission probability, to generate $\boldsymbol{y}_t$ if HMM state is θ_t

$$P(\boldsymbol{\theta}, \boldsymbol{Y}|\boldsymbol{Q}) = a_{\theta_0,\theta_1} \prod_{t=1}^{T} b_{\theta_t}(\boldsymbol{y}_t) a_{\theta_t\theta_{t+1}}$$

- θ_0 and θ_{T+1} are the non-emitting entry and exit states

The HMM acoustic model (3/3)

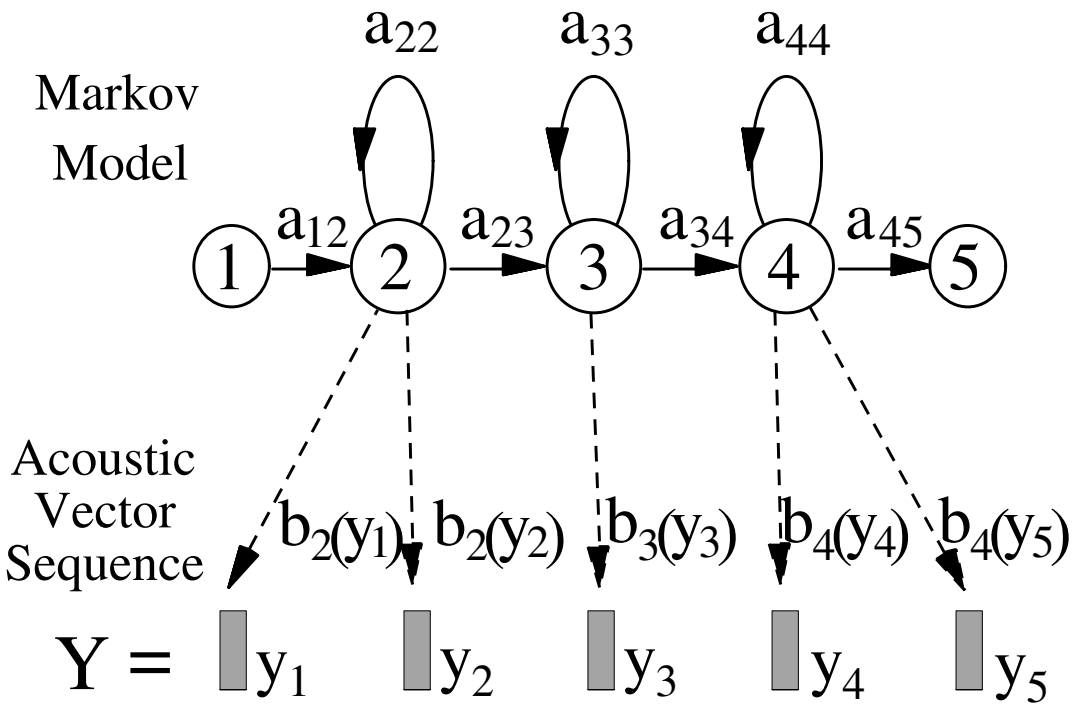
- The previous equations formally define the max. problem
- Amounts to finding the seq. of words (phones & sub-phones)
  - That maximizes the overall probability of the observations **Y**

- Question: how do we implement this search efficiently?
  - Defining an HMM of concatenated phones
  - Applying Viterbi decoding
  - Viterbi returns the most likely path (across phones) given **Y**

- In the next slides we see this through an example
  - Digit recognition

HMM-based phone model

- For each phone a continuous density HMM is trained
  - Three sub-phones (HMM states) for each phone model
  - $b_j(\mathbf{y}_j)$: are the emission PDFs (Gaussian mixture model)



We need to train:

- Matrix **A**
- Emission PDFs (b_i)

Components of the HMM acoustic model

$$\boldsymbol{\theta} = \{\theta_1, \theta_2, \ldots, \theta_N\}$$

A set of HMM states corresponding to **sub-phones**

$$\boldsymbol{A} = [a_{ij}]$$

Transition probability matrix from previous state i to current state j. θ and ***A*** implement a **pronunciation lexicon**, a state graph structure for each word that the system is capable of recognizing

$$\boldsymbol{B} = [b_i(\boldsymbol{y}_n)] = [p(\boldsymbol{y}_n|\theta_n = i)]$$

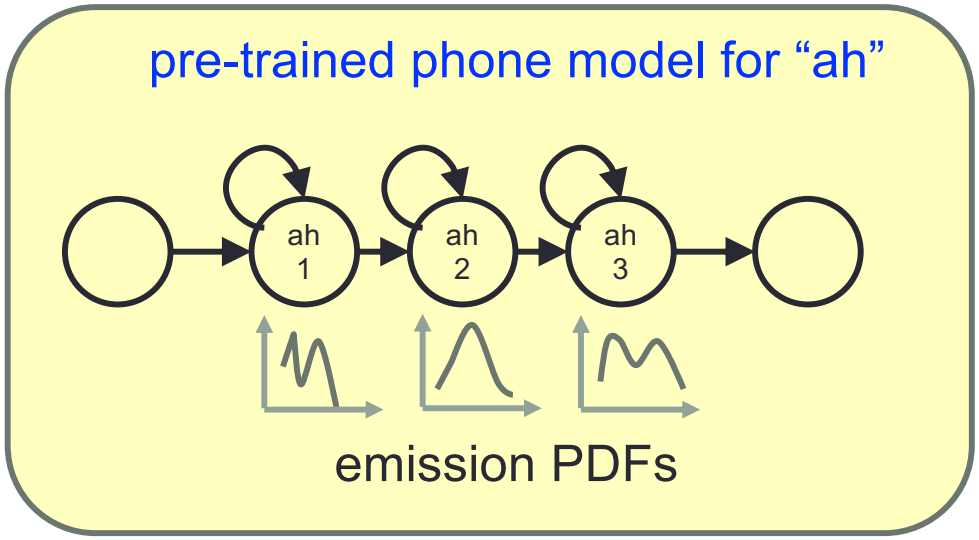
A set of **observation likelihoods B:** also called **emission probabilities**, each expressing the probability of a cepstral feature vector (observation $\mathbf{y}_n$) being generated given that sub-phone state (HMM state) is i

Example: digit recognition problem (1/5)

- 11 words: digits 0 to 9 plus “oh”
- Assume we have a pre-trained HMM for each phone
- Pronunciation dictionary (lexicon): maps words onto phones

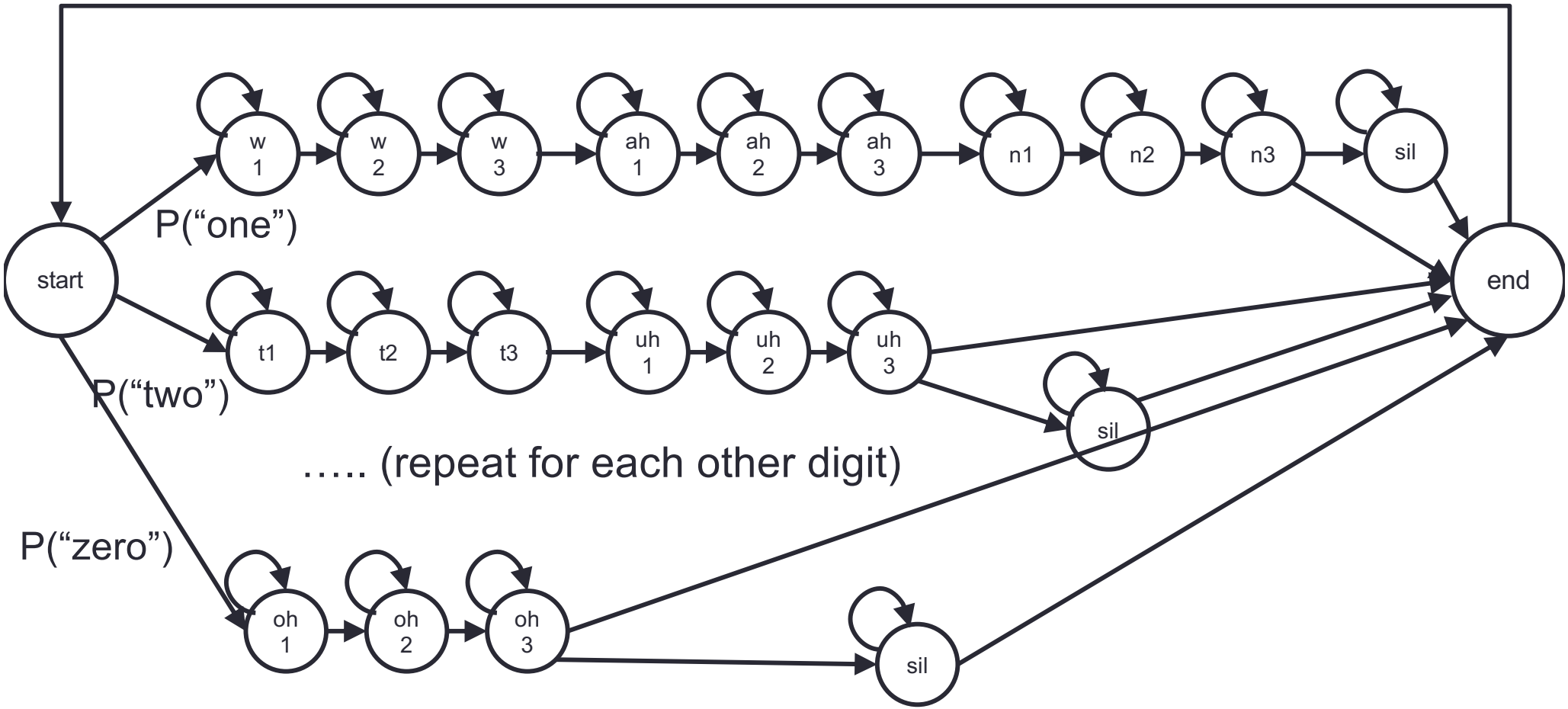
Lexicon (11 words, 0-9 + “oh”)

one	w ah n
two	t uw
three	th r iy
four	f ao r
five	f ay v
six	s ih k s
seven	s eh v ax n
eight	ey t
nine	n ay n
zero	z iy r ow
oh	ow



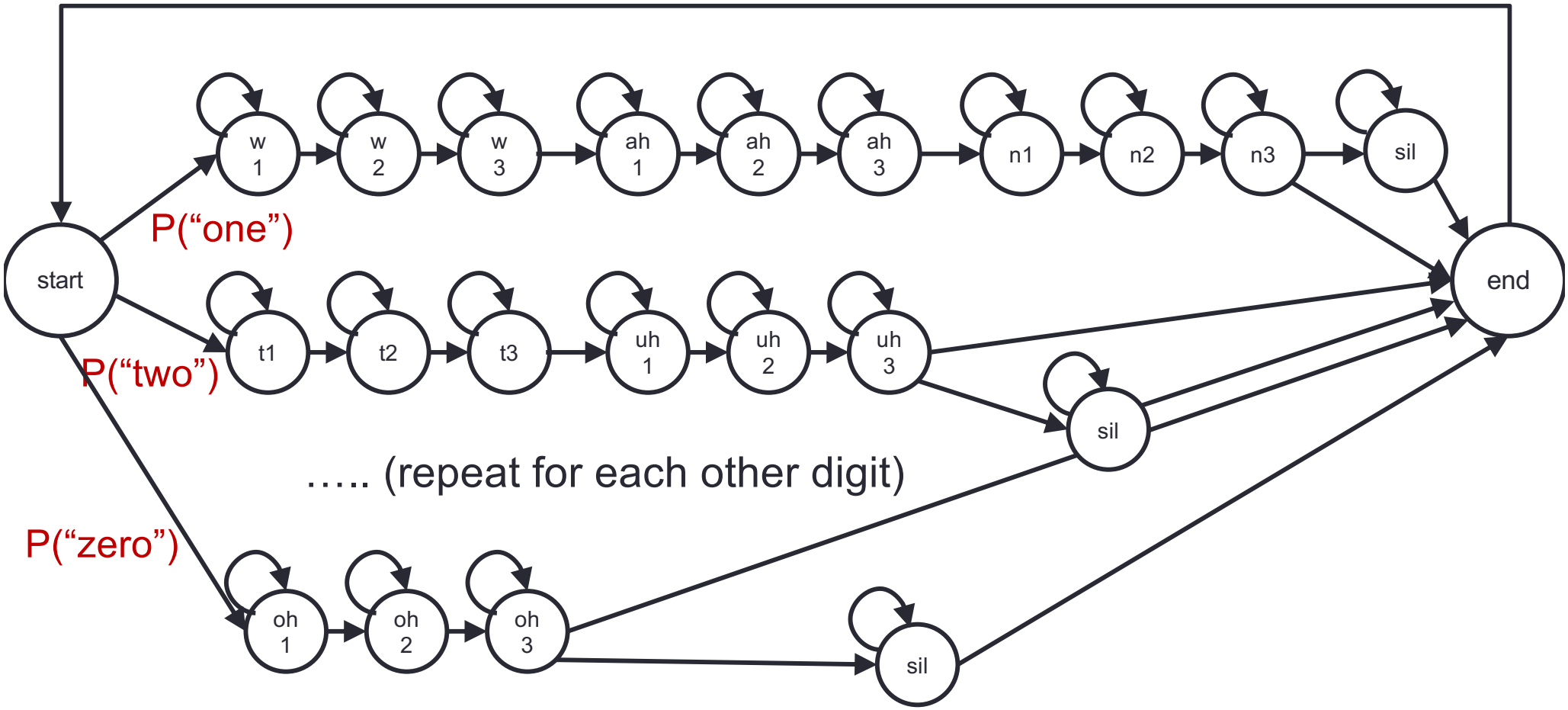
Matrix **A** (transitions) and matrix **B** (emissions) are pre-trained from labeled data using Baum-Welch algo

Digit recognition problem (2/5)



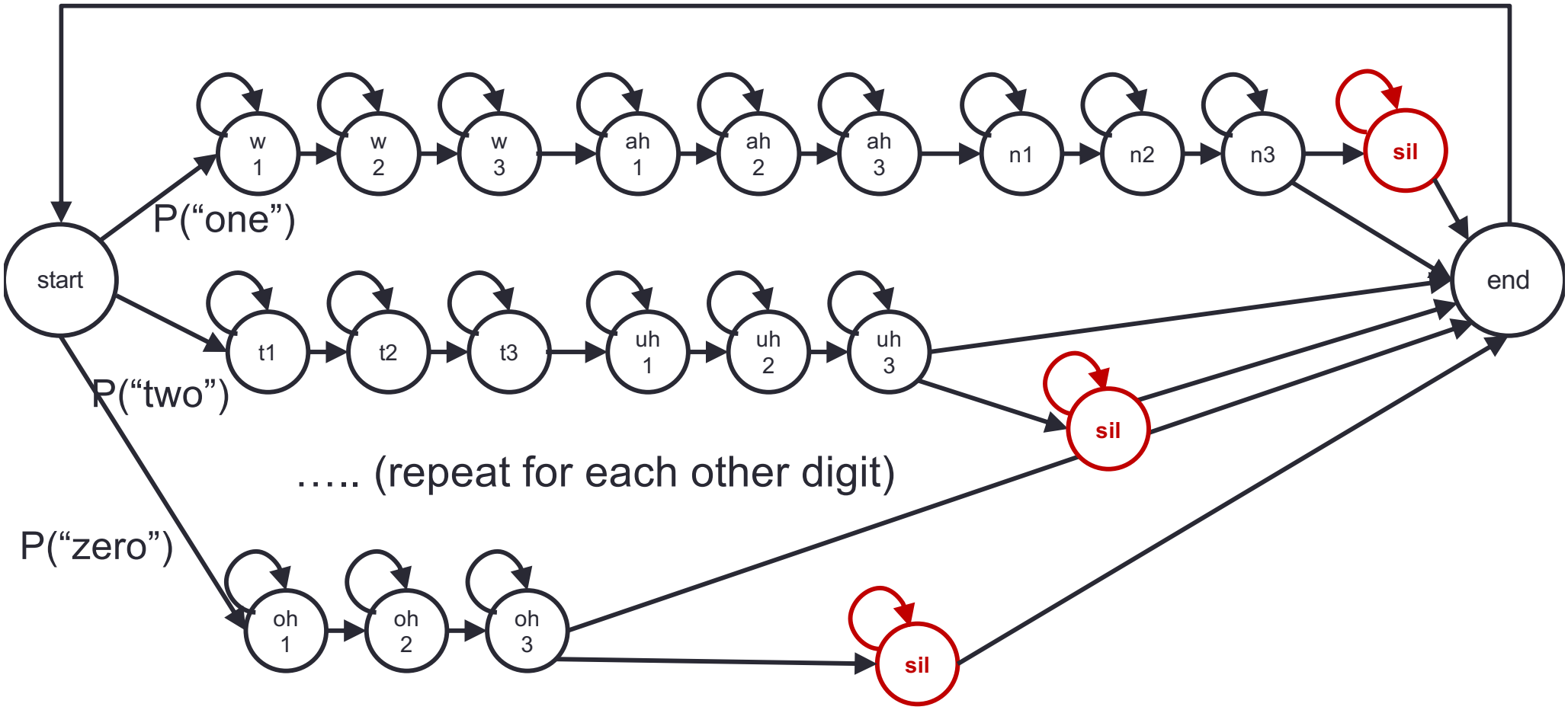
An HMM for the digit recognition task. A lexicon specifies the phone sequence (e.g., "w" "ah" "n"), each phone is composed of three subphones, each with GMM emission. Combining these and adding an optional silence at the end of each word, results in a single HMM for the whole task. The transition from the End state to the Start state to allow digit sequences of any length.

Digit recognition problem (3/5)



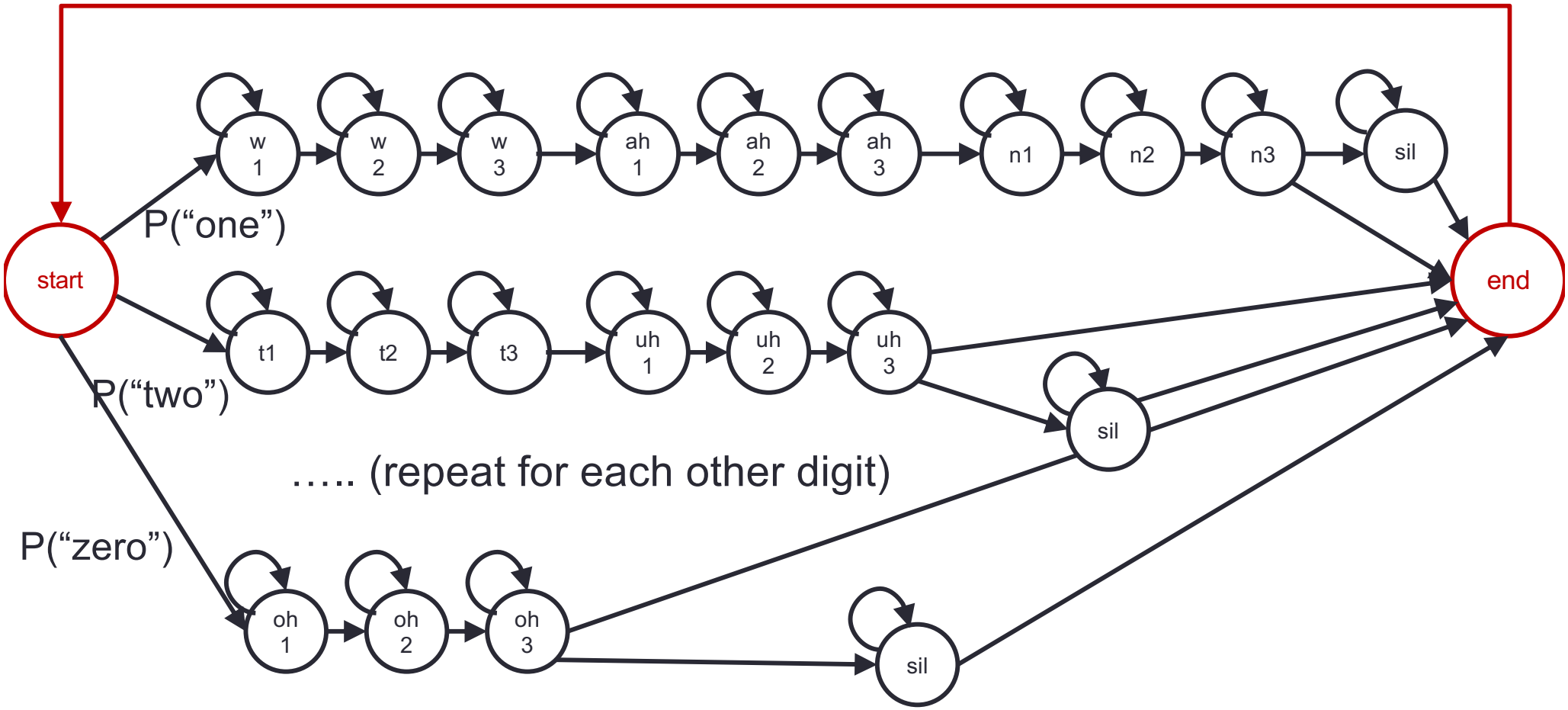
Trained **A** matrix and **B** matrices (GMMs) are used to model each phone, whereas connection among words are modeled using a language model (prior) → probabilities that the next digit is a "one", "two", etc. (these are conditional probabilities). This means that the transition matrices are concatenated and extended using the language model

Digit recognition problem (4/5)



The model is pre-trained → optimal decoding is achieved applying the Viterbi decoder on the trellis that is implied by this diagram, moving from the first to the last audio frame. Note that word segmentation / silence detection is automatic (it is part of the decoding as silence states "sil" are accounted for)

Digit recognition problem (5/5)

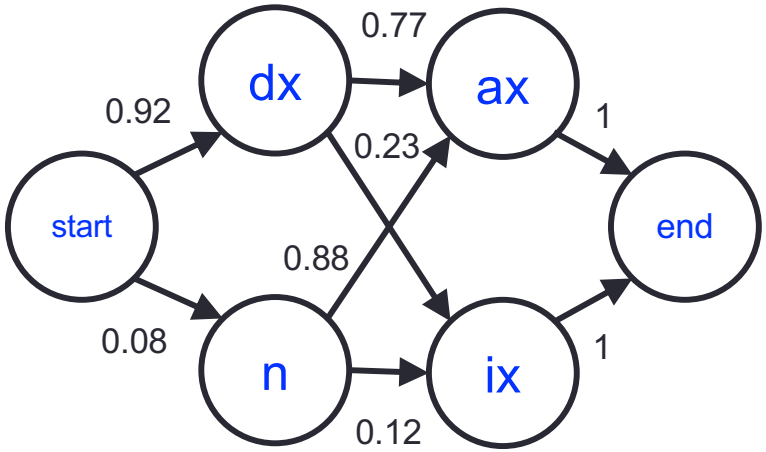


Finally, since we connect END to START

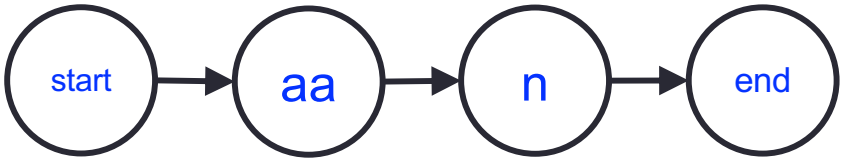
- we can decode sequences of digits of arbitrary length

Accounting for pronunciation

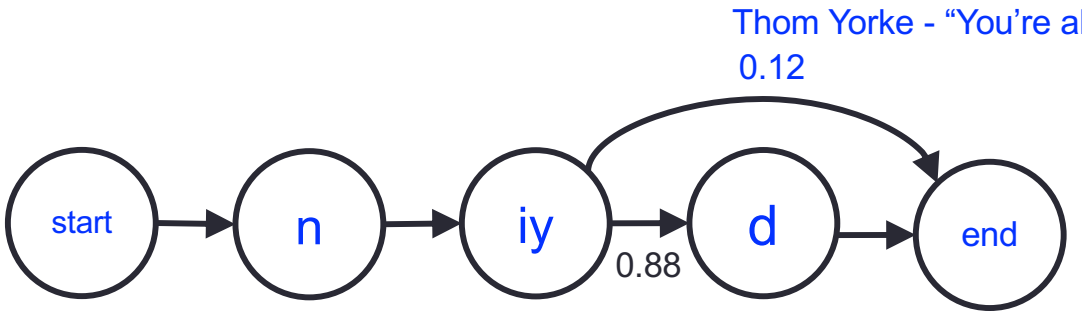
- The simplest way of representing words is concatenating phones
- But, word models can be complicated without changing the approach
- When a word can be pronounced in several manners, the model can be extended, through a slightly more complex Markov chain, e.g.:



Word model for "the"



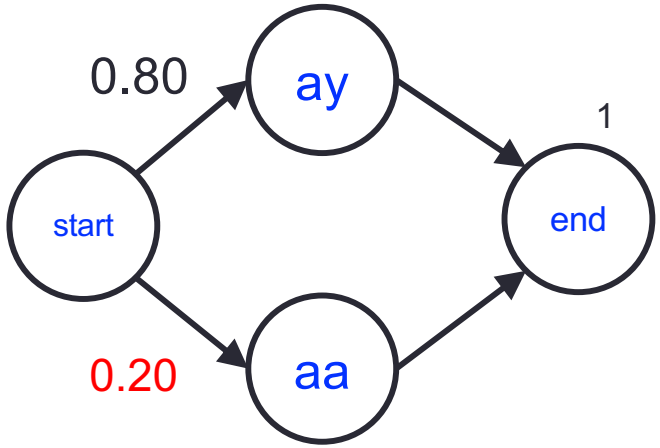
Word model for "on"



Word model for "need"

Accounting for pronunciation

- The simplest way of representing words is concatenating phones
- But, word models can be complicated without changing the approach
- When a word can be pronounced in several manners, the model can be extended, through a slightly more complex Markov chain, e.g.:



Word model for "I"

Breed – Nirvana
I don't care X5
Care if it's old
I don't mind X4
Mind, don't have a mind
….

Decoding general sentences

- It is conceptually equivalent to the digit recognition problem
- Differences are:
  - Many more words
    - a more complex language model
    - each word encodes multiple pronunciations
    - more conditional probabilities for words
      (prob. of word that follow given previous word)
  - This leads to a much larger HMM decoding diagram
    - the trellis to be used for decoding is much larger too

DECODING EXAMPLE

Viterbi trellis example

- Example: consider the word "five"
  - 3 phones: "f" "ay" "v"
  - We exemplify Viterbi decoding over a sequence of 5 feature vectors

$$\boldsymbol{Y}_{1:5} = \{\boldsymbol{y}_1, \boldsymbol{y}_2, \boldsymbol{y}_3, \boldsymbol{y}_4, \boldsymbol{y}_5\}$$

- For simplicity:
  - a single state is considered for each phone (instead of 3 sub-phones)
  - $\mathbf{y}_n$ represents the feature vector at time n (one per audio frame)
  - Given an observation $\mathbf{y}_n$, the probability that it is measured (observed), given that the HMM is in the hidden (phone) state i is:

$$b_i(\boldsymbol{y}_n) = p(\boldsymbol{y}_n | \theta_n = i)$$

  - These posterior PDFs are trained through EM (see later)

Viterbi trellis example

Key variables

$\nu_{n-1}(j)$ Viterbi path probability for state j from previous time step n-1

(remember: implementations use logarithms)

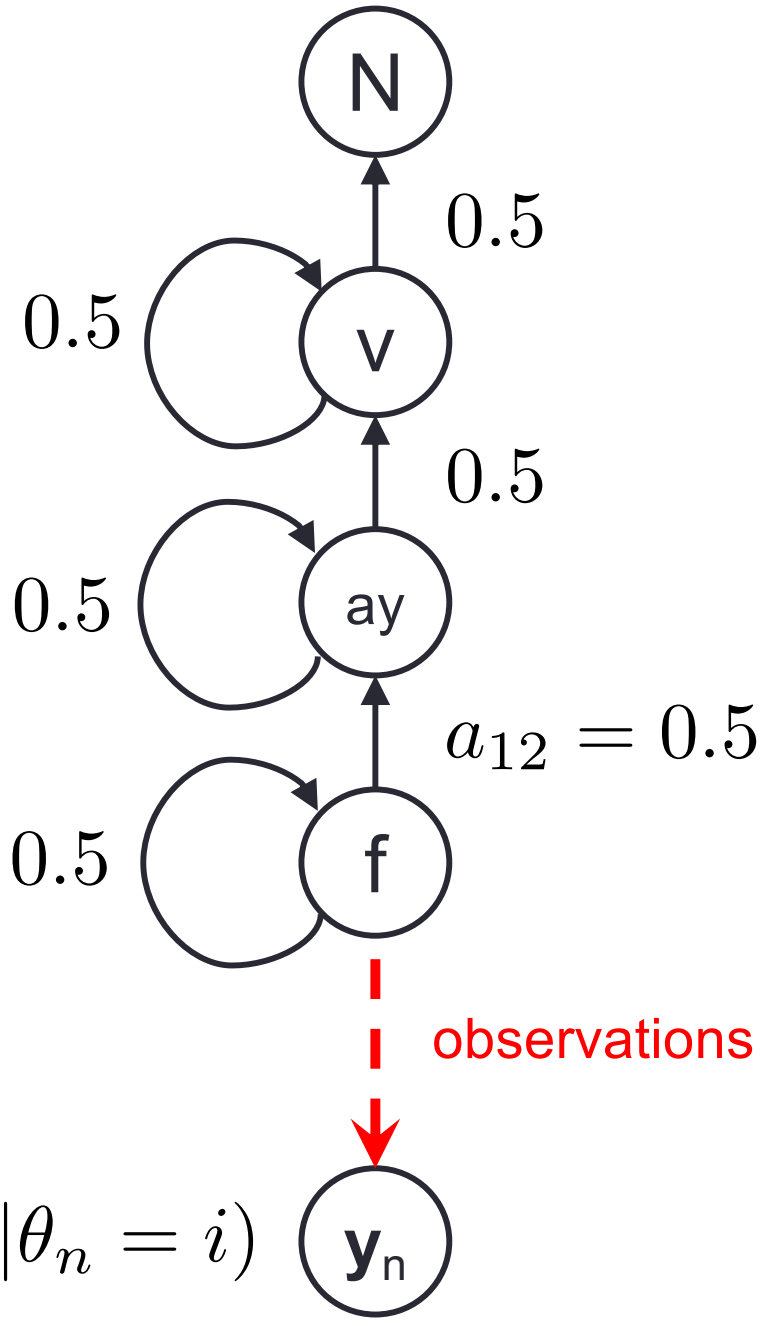
$$\nu_n(j) = \max_{i=1,\ldots,K} \left[\nu_{n-1}(i) a_{ij} b_j(\boldsymbol{y}_n)\right]$$

$\boldsymbol{A} = [a_{ij}]$ Transition probability matrix from previous state i to current state j

$b_i(\boldsymbol{y}_n) = p(\boldsymbol{y}_n|\theta_n = i)$ Emission probabilities ($\mathbf{y}_n$ is feature vector at time n, j is hidden sub-phone state)

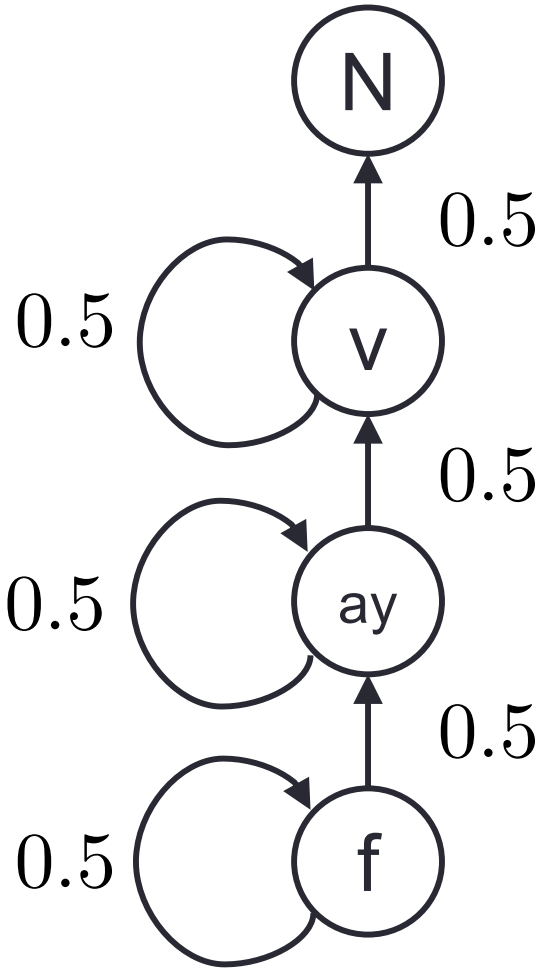
Viterbi trellis example

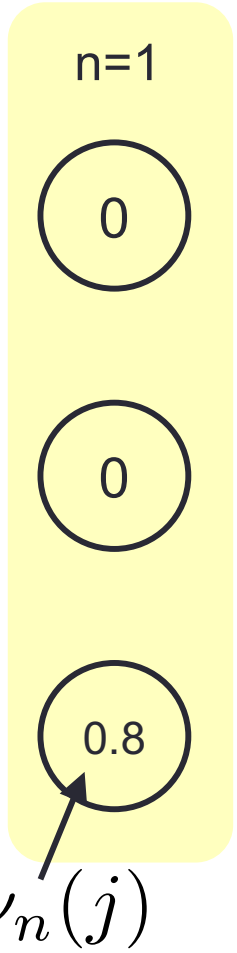
- The trained HMM
  - State 1 = “f”
  - State 2 = “ay”
  - State 3 = “v”
- State N = next word
  - Proceed to decode next word



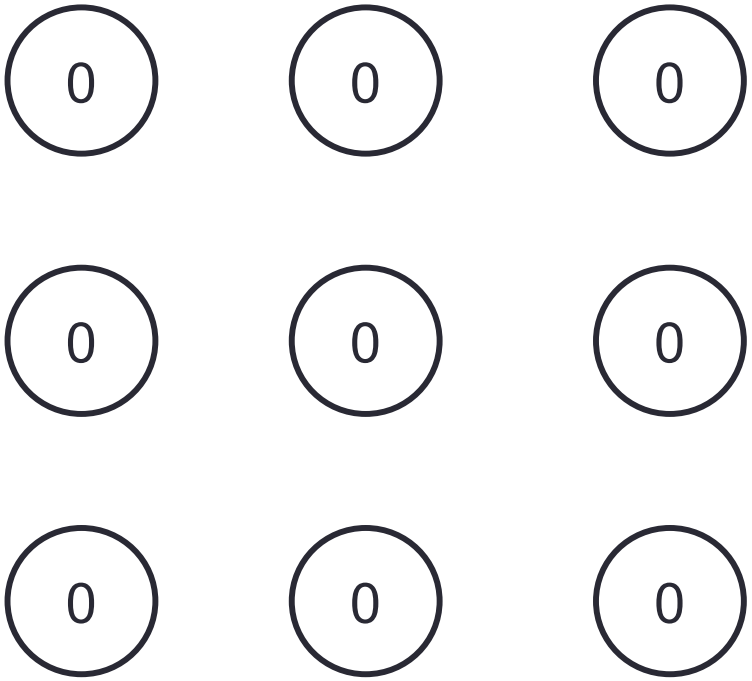
$$b_i(\boldsymbol{y}_n) = p(\boldsymbol{y}_n | \theta_n = i)$$

Viterbi trellis decoding





$$\boldsymbol{\pi} = [\pi_{\mathrm{f}}\ \pi_{\mathrm{ay}}\ \pi_{\mathrm{v}}]^T = [1\ 0\ 0]^T$$

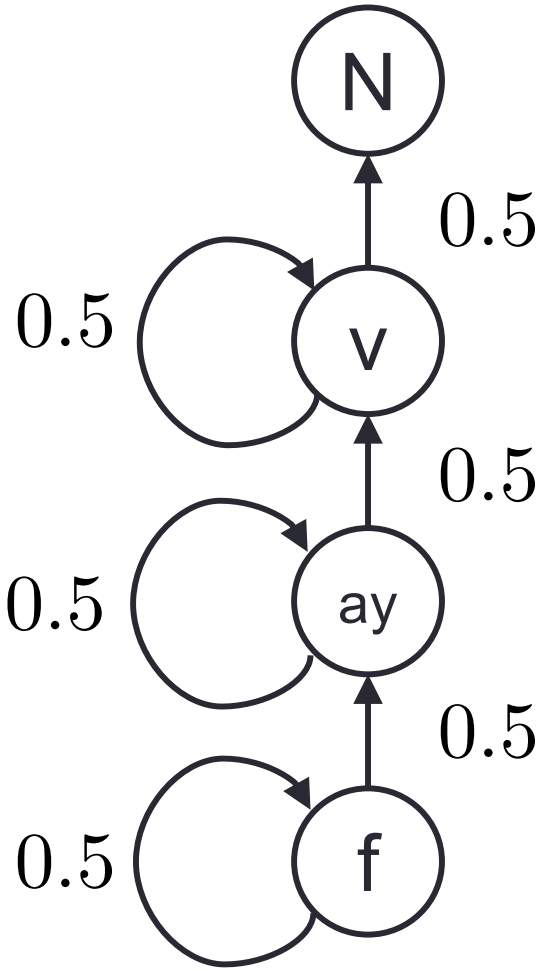


Time n=1, posterior vector $b_j(\mathbf{y}_1)$

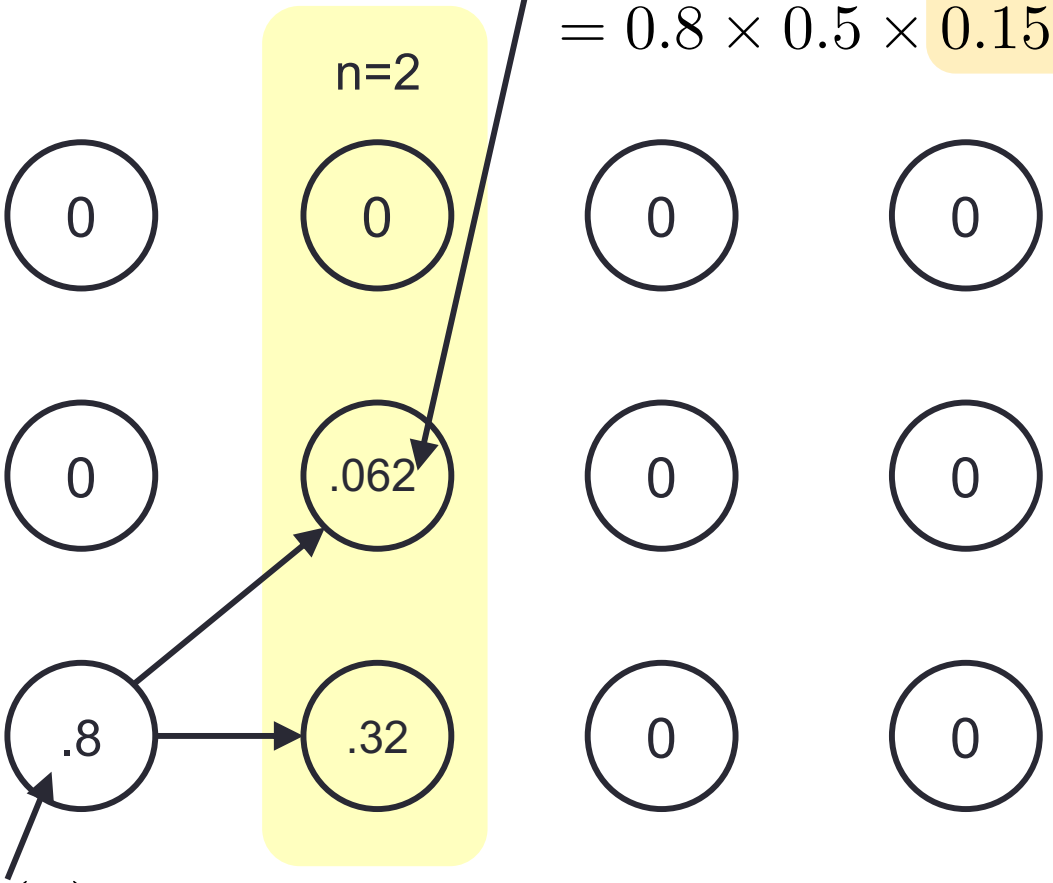
$$\boldsymbol{b} = [0.8\ \ 0.155\ \ 0.045]^T$$

Prob. feature vector is $\mathbf{y}_1$ given that state is 1 (means "f")

Viterbi trellis decoding



$$\nu_2(2) = 0.8 \times a_{12} \times 0.155 =$$
$$= 0.8 \times 0.5 \times 0.155 = 0.062$$

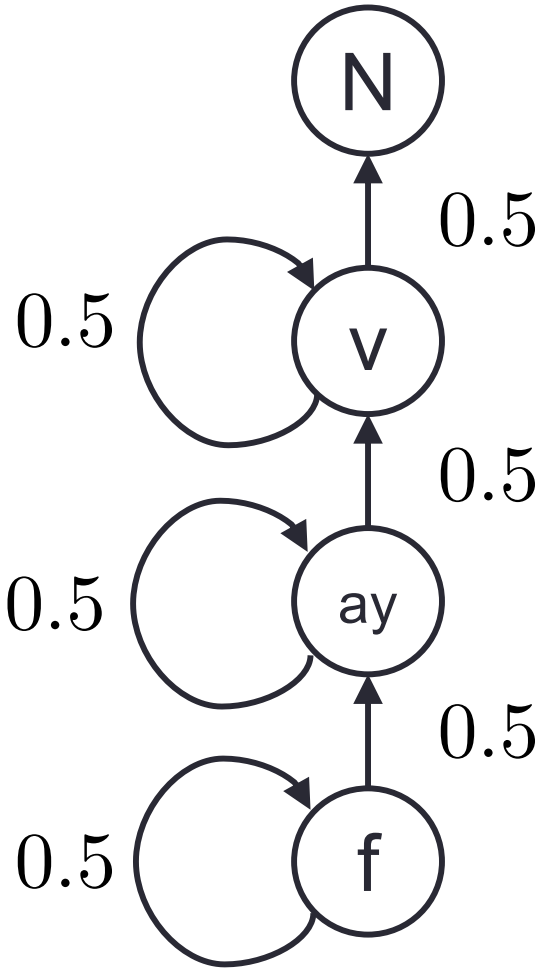


$\nu_n(j)$

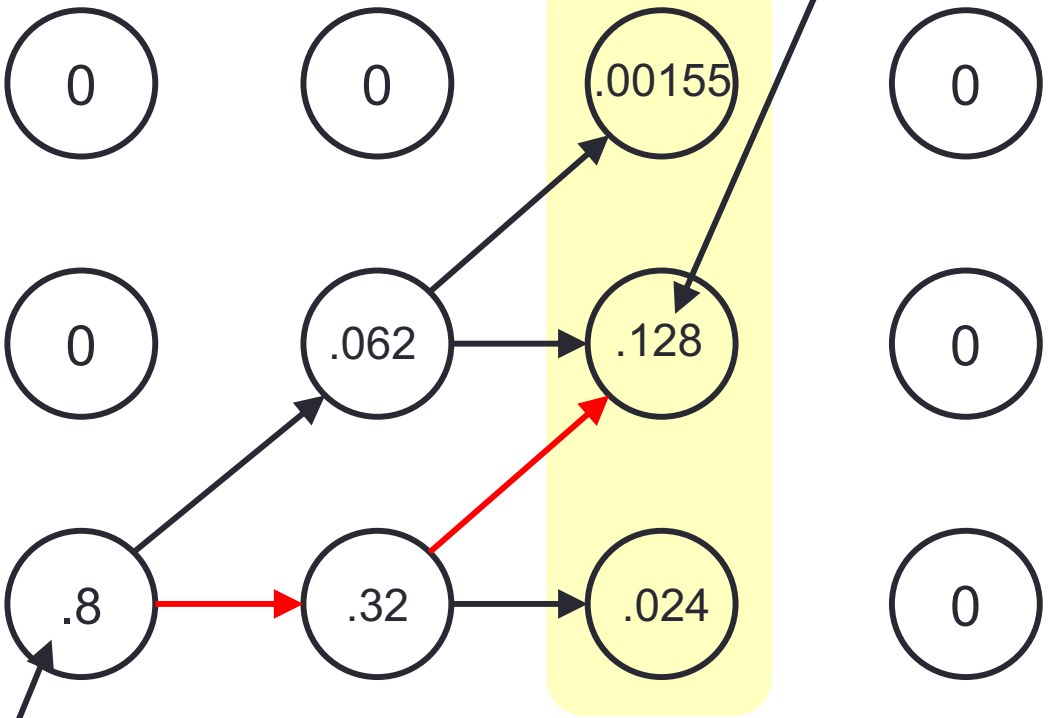
Time n=2, posterior vector $b_j(\mathbf{y}_2)$

$$\boldsymbol{b} = [0.8 \;\; 0.155 \;\; 0.045]^T$$

Viterbi trellis decoding



$$\nu_3(2) = \max[0.062 \times 0.5 \times 0.8, 0.32 \times 0.5 \times 0.8] =$$
$$= \max[0.0248, 0.128] = 0.128$$

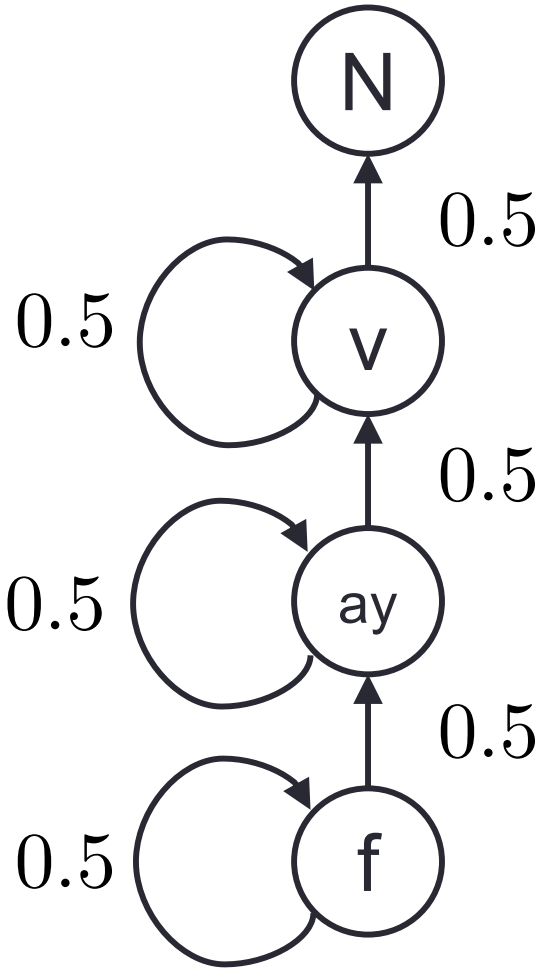


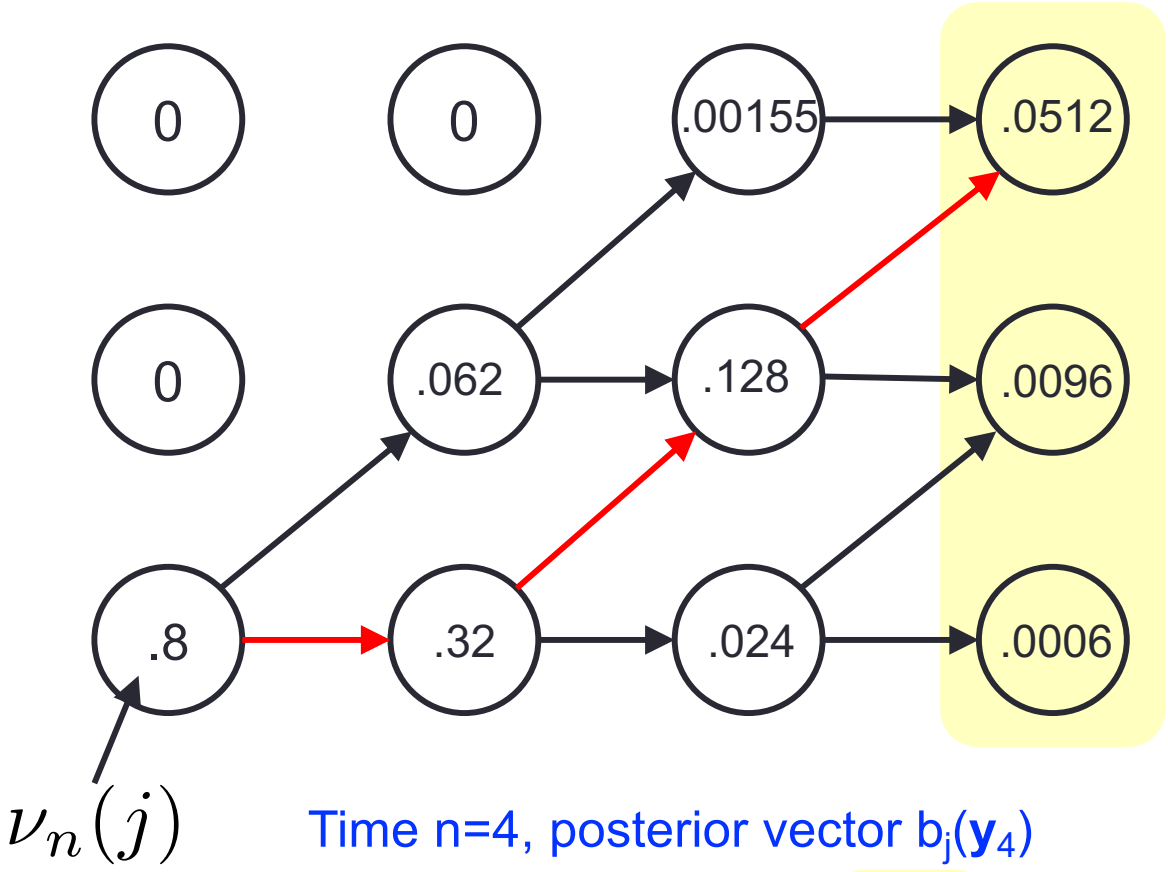
$\nu_n(j)$

Time n=3, posterior vector $b_j(\mathbf{y}_3)$

$$\boldsymbol{b} = [0.15 \;\; 0.8 \;\; 0.05]^T$$

Viterbi trellis decoding





Time n=4, posterior vector $b_j(\mathbf{y}_4)$

$$\boldsymbol{b} = [0.05 \;\; 0.15 \;\; 0.8]^T$$

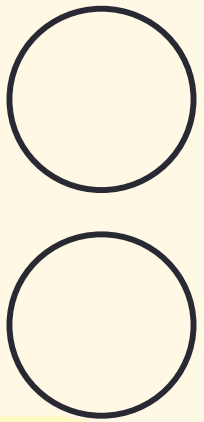
Finally, assume next words can be “one” or “two”
We concatenate to next possible words:

P(“one”|”five”)=P_{51}=0.6, P(“two”| “five”)=P_{52}=0.4

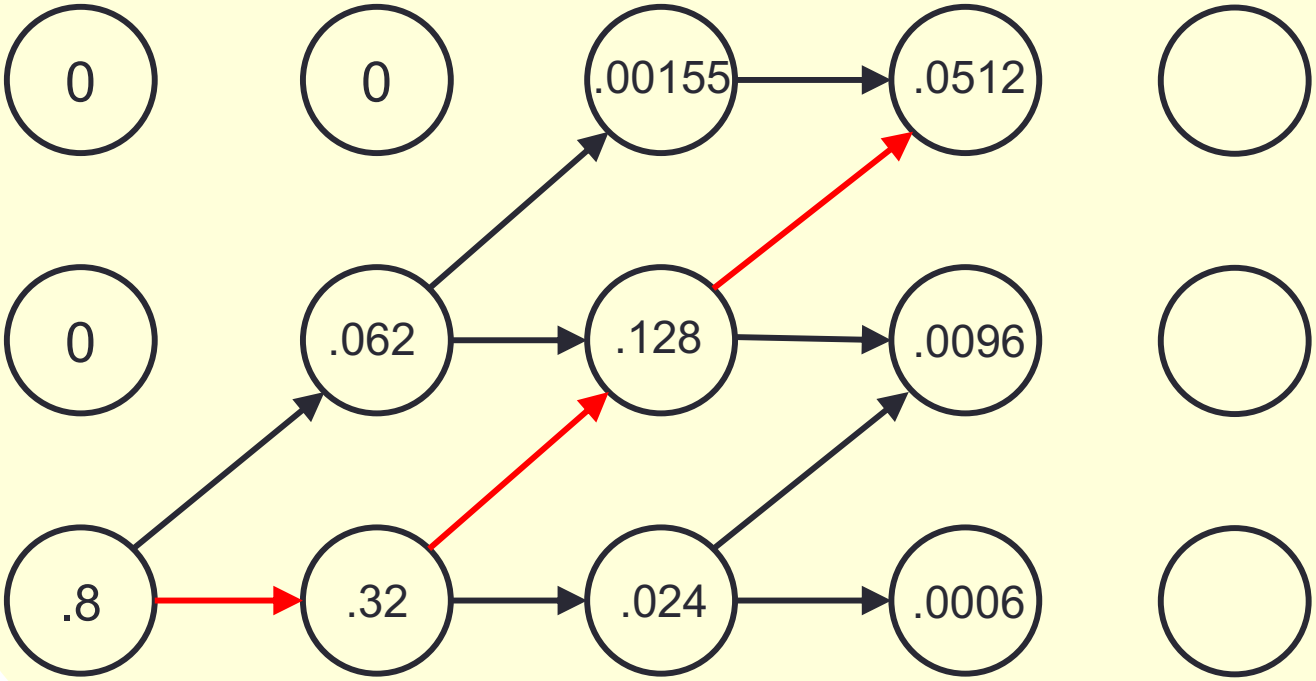
$$\boldsymbol{b} = [0.01 \;\; 0.05 \;\; 0.15 \;\; 0.2 \;\; 0.1 \;\; 0.6 \;\; 0.09]^T$$

“f” “ay” “v” “w” “ah” “t” “uw”

Trellis for one = “w” “ah” “n”



Trellis for word five



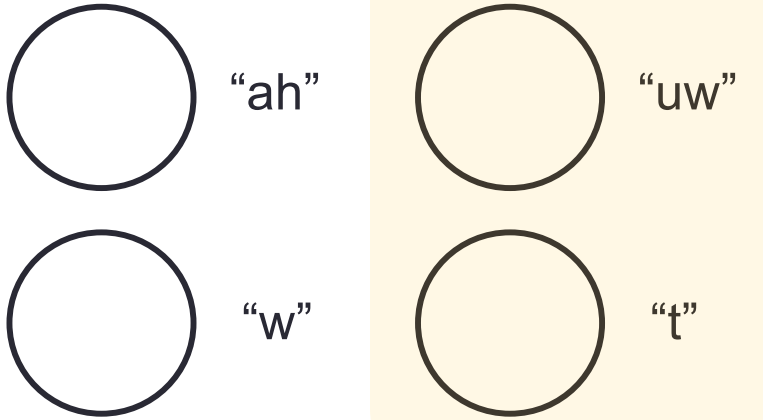
Finally, assume next words can be “one” or “two”
We concatenate to next possible words:

P(“one”|”five”)=P_{51}=0.6, P(“two”| “five”)=P_{52}=0.4

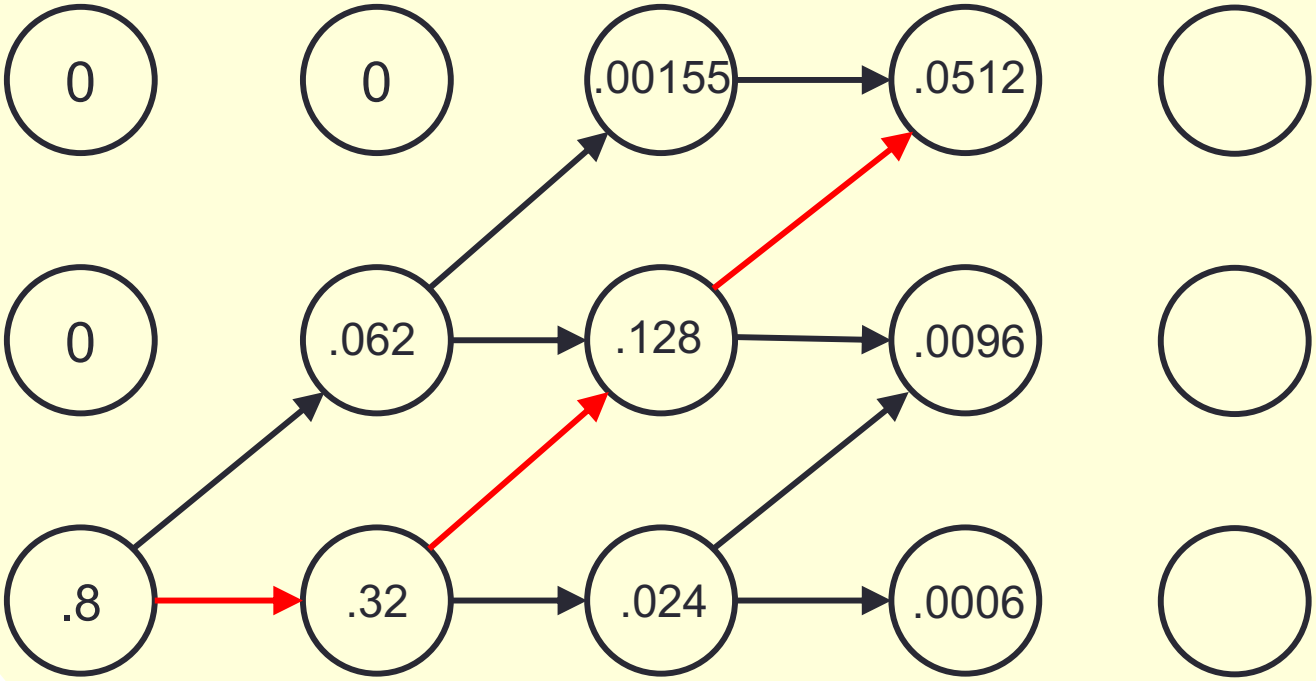
$$\boldsymbol{b} = [0.01 \;\; 0.05 \;\; 0.15 \;\; 0.2 \;\; 0.1 \;\; 0.6 \;\; 0.09]^T$$

“f” “ay” “v” “w” “ah” “t” “uw”

Trellis for two = “t” “uw”



Trellis for word five



Finally, assume next words can be “one” or “two”

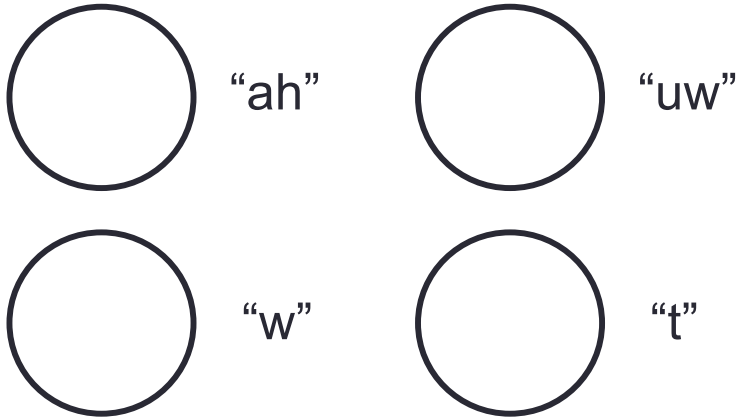
We concatenate to next possible words:

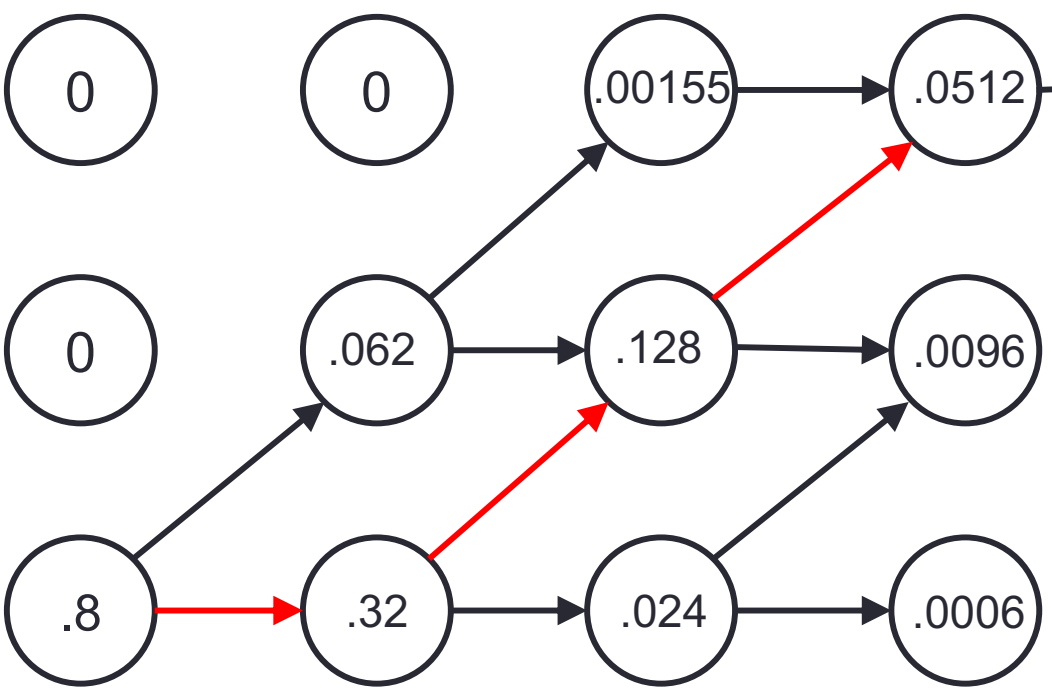
Trellis for two = “t” “uw”

P(“one”|”five”)=P_{51}=0.6, P(“two”| “five”)=P_{52}=0.4

$$\boldsymbol{b} = [0.01 \;\; 0.05 \;\; \underbrace{0.15}_{b_3} \;\; 0.2 \;\; 0.1 \;\; 0.6 \;\; 0.09]^T$$

“f” “ay” “v” “w” “ah” “t” “uw”





$$0.0512 \times a_{33} \times b_3 =$$

$$0.0512 \times 0.5 \times 0.15 = 0.00384$$

remain in word five (a_{33}) and emit $\mathbf{y}_5$ (b_3)

Finally, assume next words can be “one” or “two”

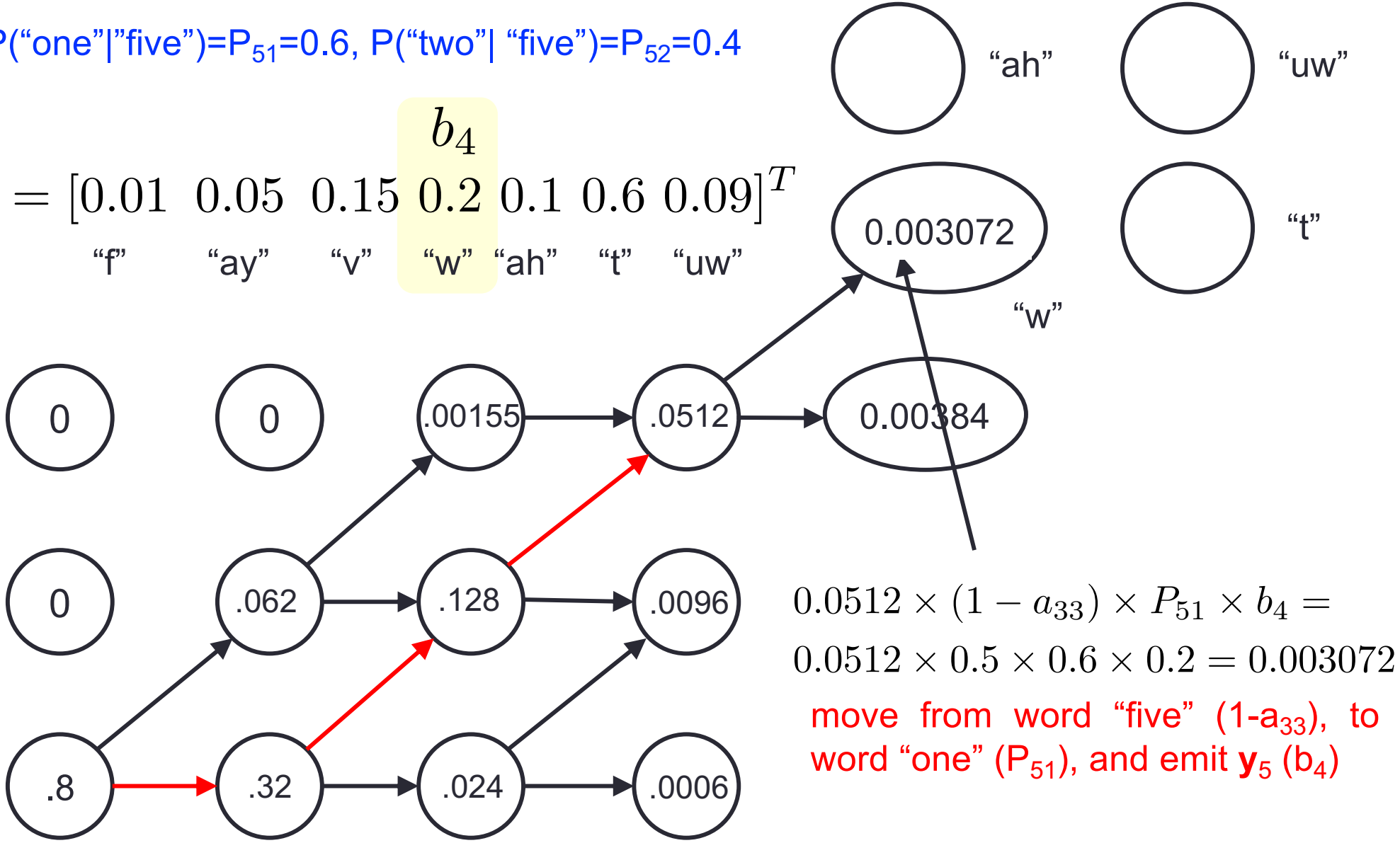
We concatenate to next possible words:

Trellis for two = “t” “uw”

P(“one”|”five”)=P_{51}=0.6, P(“two”| “five”)=P_{52}=0.4

$$\boldsymbol{b} = [0.01 \;\; 0.05 \;\; 0.15 \;\; \underbrace{0.2}_{b_4} \;\; 0.1 \;\; 0.6 \;\; 0.09]^T$$

“f” “ay” “v” “w” “ah” “t” “uw”



$$0.0512 \times (1 - a_{33}) \times P_{51} \times b_4 =$$

$$0.0512 \times 0.5 \times 0.6 \times 0.2 = 0.003072$$

move from word “five” (1-a_{33}), to word “one” (P_{51}), and emit $\mathbf{y}_5$ (b_4)

Finally, assume next words can be “one” or “two”

We concatenate to next possible words:

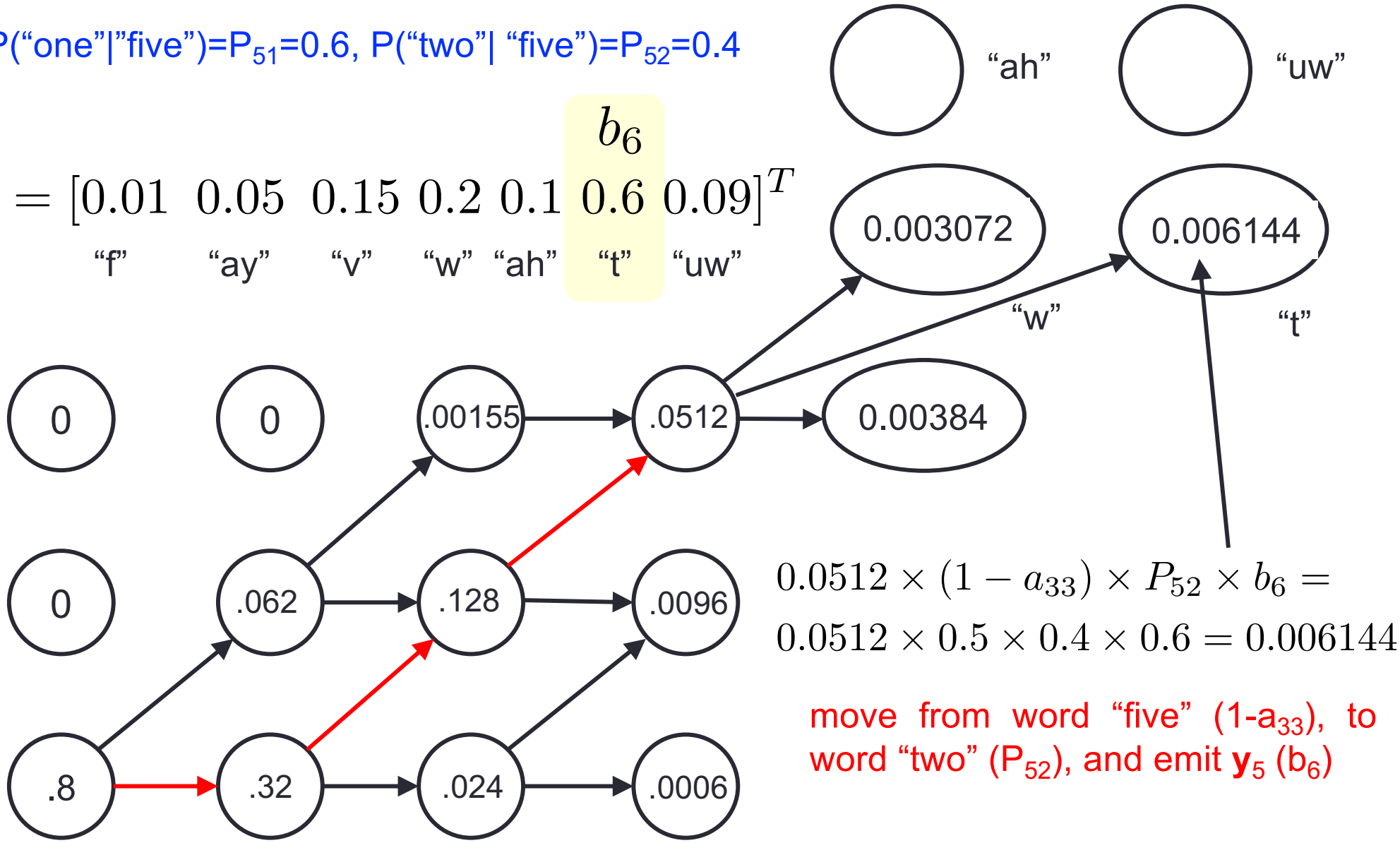
P(“one”|”five”)=P_{51}=0.6, P(“two”| “five”)=P_{52}=0.4

$$\boldsymbol{b} = [0.01 \;\; 0.05 \;\; 0.15 \;\; 0.2 \;\; 0.1 \;\; 0.6 \;\; 0.09]^T$$

b_6

“f” “ay” “v” “w” “ah” “t” “uw”

Trellis for two = “t” “uw”



$$0.0512 \times (1 - a_{33}) \times P_{52} \times b_6 =$$
$$0.0512 \times 0.5 \times 0.4 \times 0.6 = 0.006144$$

move from word “five” (1-a_{33}), to word “two” (P_{52}), and emit $\mathbf{y}_5$ (b_6)

Finally, assume next words can be “one” or “two”

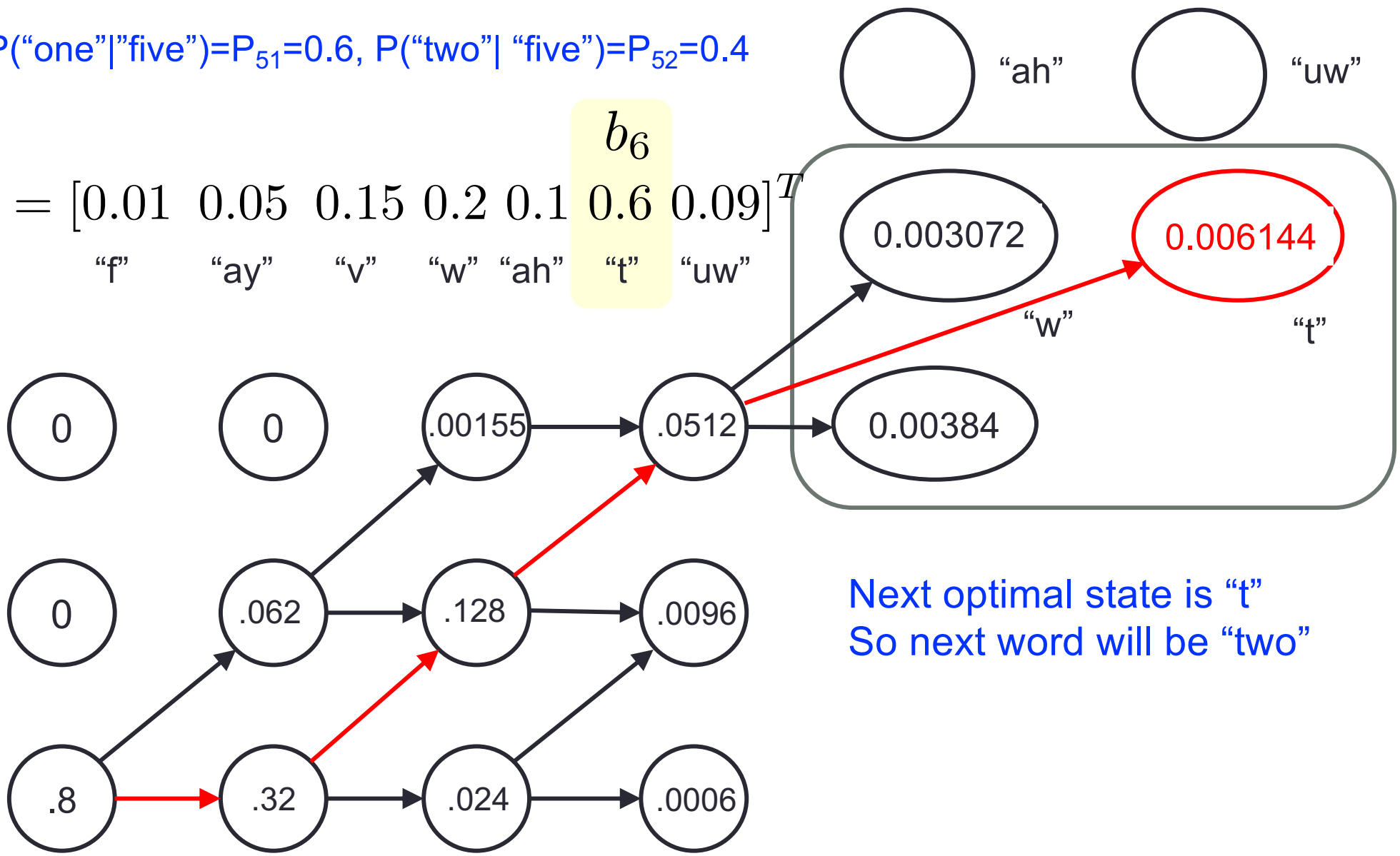
We concatenate to next possible words:

Trellis for two = “t” “uw”

P(“one”|”five”)=P_{51}=0.6, P(“two”| “five”)=P_{52}=0.4

$$\boldsymbol{b} = [0.01 \;\; 0.05 \;\; 0.15 \;\; 0.2 \;\; 0.1 \;\; \underbrace{0.6}_{b_6} \;\; 0.09]^T$$

“f” “ay” “v” “w” “ah” “t” “uw”



Next optimal state is “t”

So next word will be “two”

Finally, assume next words can be “one” or “two”
We concatenate to next possible words:

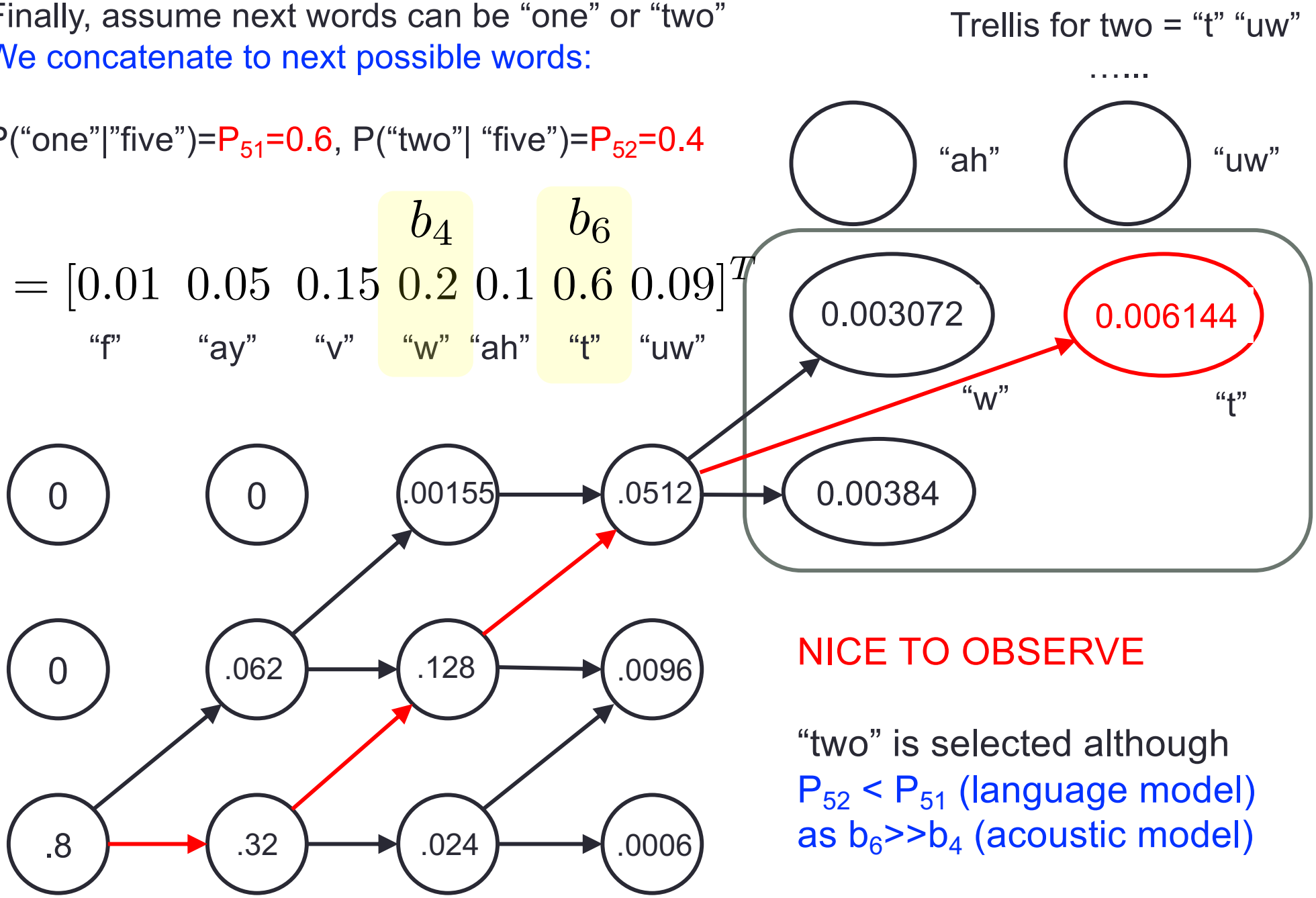
P(“one”|”five”)=P_{51}=0.6, P(“two”| “five”)=P_{52}=0.4

$$\boldsymbol{b} = [0.01 \;\; 0.05 \;\; 0.15 \;\; 0.2 \;\; 0.1 \;\; 0.6 \;\; 0.09]^T$$

“f” “ay” “v” “w” “ah” “t” “uw”

(b_4 = 0.2, b_6 = 0.6)

Trellis for two = “t” “uw”



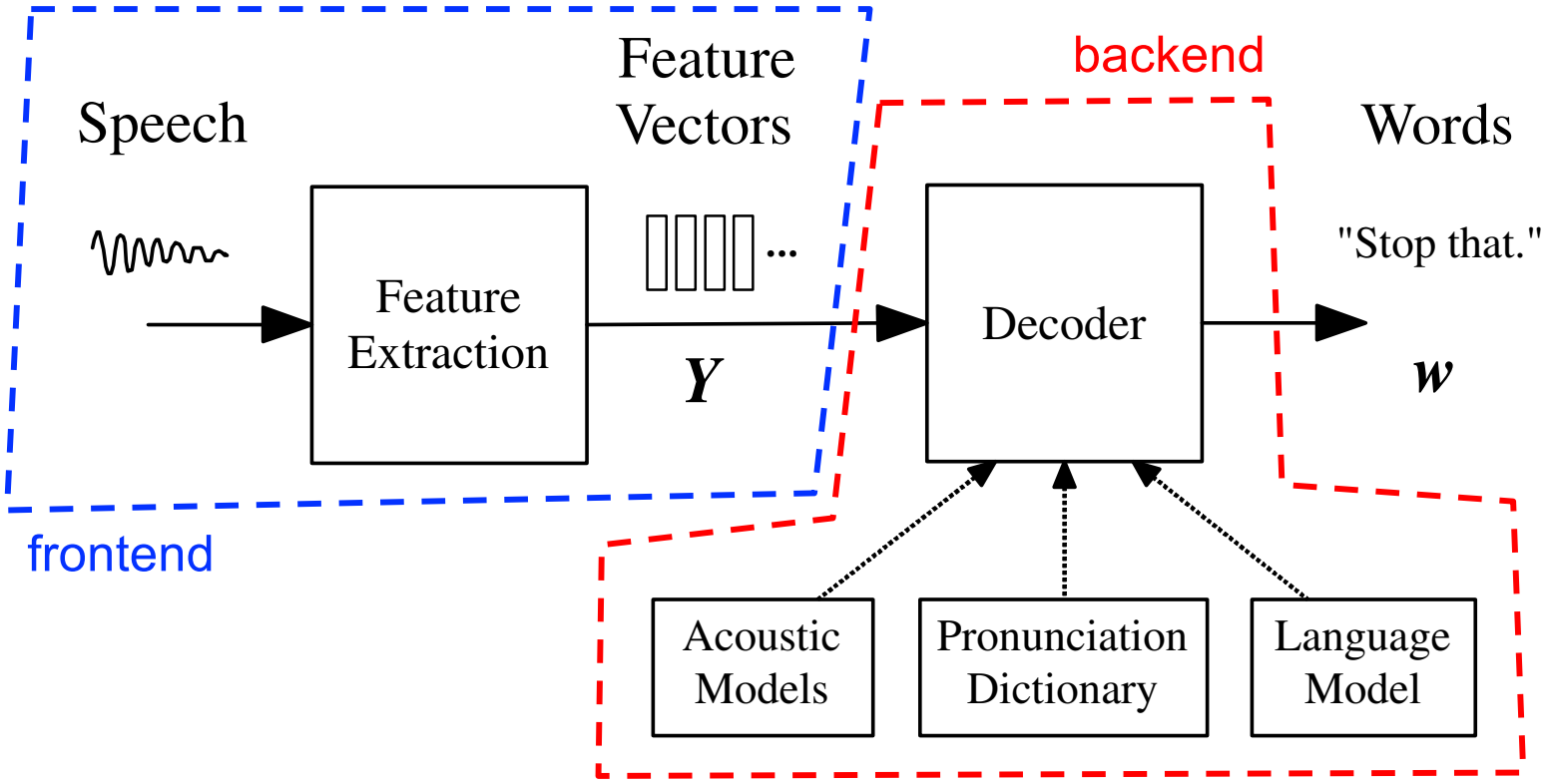
NICE TO OBSERVE

“two” is selected although
$P_{52} < P_{51}$ (language model)
as $b_6 >> b_4$ (acoustic model)

In a real HMM speech decoder

- Words structures can be more complex
  - to account for different pronunciations
- Phones
  - are expanded into sub-phones
- Language model
  - accounts for N-1 previous words in the Viterbi trellis (N-gram)
- Programming
  - Logarithms and other tricks for numerical stability, etc.
  - Not all possible words that follow are fully explored, low probability paths are pruned: “beam search”, i.e., prune paths to next word with prob. smaller than a threshold wrt best following path (“word”). With beam search 90-95% of the states are not considered
- Conceptually
  - nothing changes, the Viterbi algorithm will find the most probable path

ASR architecture



- Feature extraction: aka frontend processing (transforms waveform into features)
- Acoustic model (HMM): probability of observation *given* a word sequence
- Pronunciation dictionary (lexicon): mapping each word into a phone sequence
- Language Model: computes the prior probability of any word sequence

ON HMM MODEL TRAINING

HMM training - ingredients

$$\boldsymbol{\theta} = \{\theta_1, \theta_2, \ldots, \theta_N\}$$

A set of **states** corresponding to **sub-phones**

$$\boldsymbol{A} = [a_{ij}]$$

Transition probability matrix from previous state i to current state j. θ and ***A*** implement a **pronunciation lexicon**, a state graph structure for each word that the system is capable of recognizing.

$$\boldsymbol{B} = [b_i(\boldsymbol{y}_n)] = [p(\boldsymbol{y}_n|\theta_n = i)]$$

A set of **observation likelihoods B:** also called **emission probabilities**, each expressing the probability of a cepstral feature vector (observation $\mathbf{y}_n$) being generated given that subphone (HMM) state is i

HMM training: considerations

- It is expensive to use humans to hand-label phonetic boundaries (sub-phones)
  - it can take up to 400 times real time (i.e., 400 labeling hours to label just 1 hour of speech)
  - humans do not do phonetic labeling very well for units smaller than the phone
  - humans are bad at consistently finding the boundaries of sub-phones
- We then use embedded training
  - We provide the system with sentences
  - Words within each sentence were labeled
  - Sub-phone boundaries are automatically found by the training algorithm

Training: full picture

Transcribed sentence:
LUCY IN THE SKY WITH DIAMONDS

PRONUNCIATION DICIONARY

L UW S IY IH N DH AH S K AY W IH DH
D AY M AH N D Z

word1 word2 . . . wordN

words in the sentence: HMM for each from phone model, concatenated into a raw HMM

FEATURE EXTRACTION

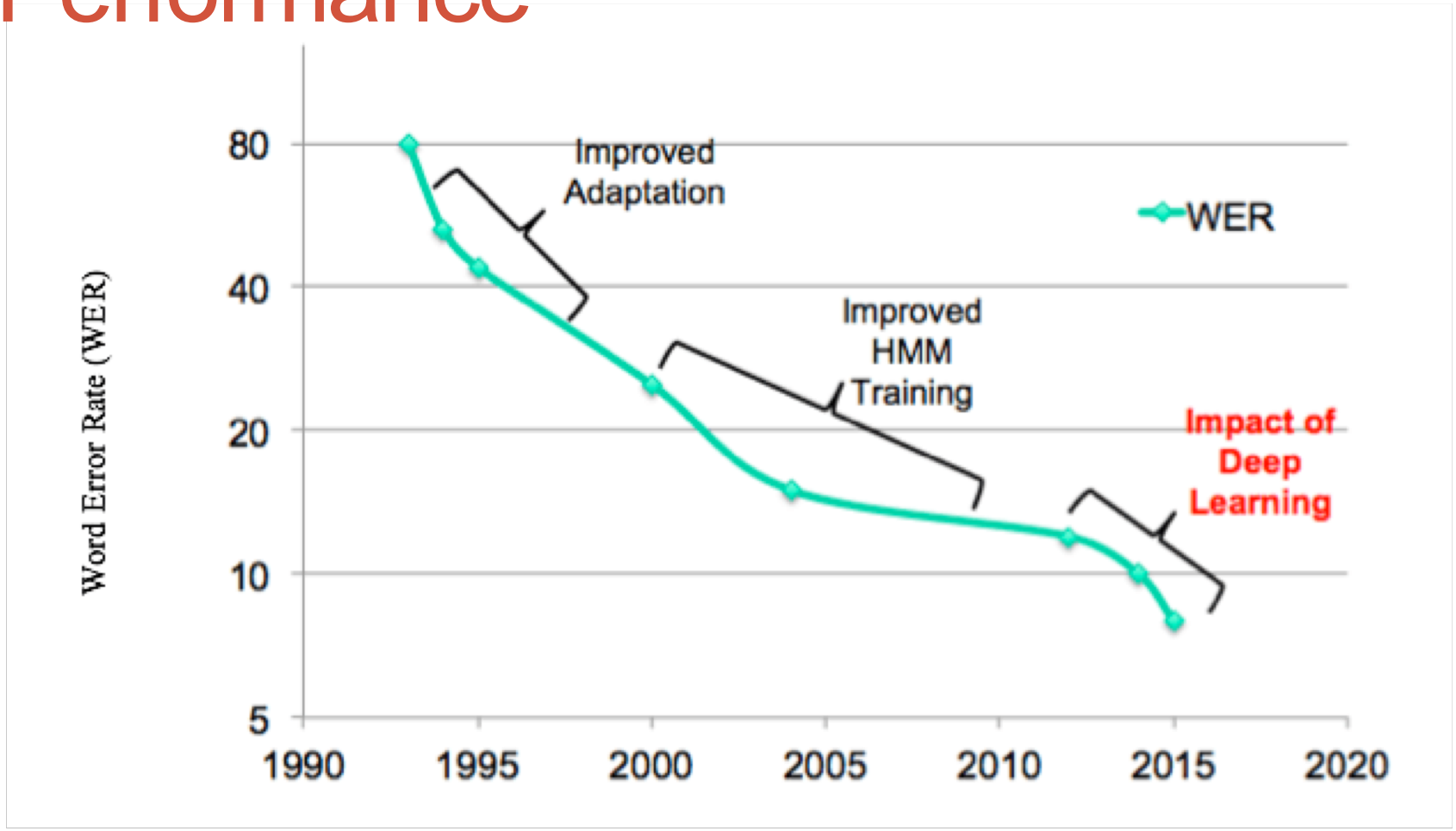
Baum-Welch training

Training: some further discussion

- Beauty of Baum-Welch training
  - We do not need phonetically transcribed data
  - We do not even need to know *where each word stars and ends*
  - The Baum-Welch algorithm *will sum over all possible segmentations of words and phones*
  - Matrices **A** and **B** will be obtained to maximize the likelihood of observing the provided (input) feature vectors
- HMM Initialization for training: FLAT START
  - Set to zero all transition probabilities that we want to be structurally zero (phones that are not in the sentence and/or that are not consecutive given the input word sequence)
  - If a state i has probs. a_{ij} and K possible following states → $a_{ij}=1/K$
  - Mean vector and covariance matrix of state i are taken equal to mean and covariance matrix of the entire sentence

PERFORMANCE AND FINAL CONSIDERATIONS

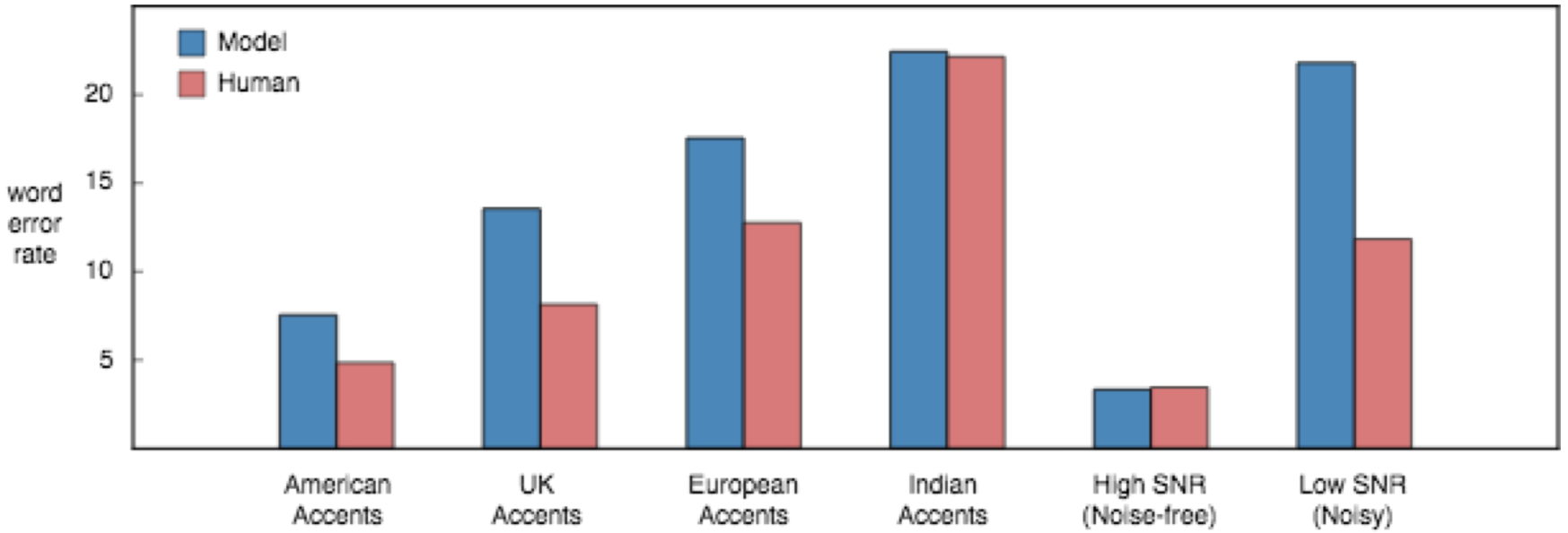
Performance



ASR word error rate (WER) over the last two decades on a public benchmark test for English conversational speech. Improved adaptation and training of HMM resulted in significant progress until 2005. The performance reached a plateau between 2005 and 2012. The introduction of deep learning around 2012 is leading to a future generation of speech recognition systems

Open issues

- Background noise
  - SNR can be as low as -5dB in a moving car
  - People do not have much problem but ASR systems struggle
- Accents
  - Non-US accents are more difficult to comprehend



Open issues

- Semantic errors
  - WER alone might not be the right metric
  - Example1: “let’s meet up today” → “let’s meet Tuesday”
  - Example2: “uh” (often translated into) → “uh huh”
    - “uh” is a filler (no meaning)
    - “uh huh” is a backchannel acknowledgement
- Multiple users single channel
  - Source separation (diarisation) in arbitrary conditions
- Domain variations ASR should be robust to
  - Reverberation from varying the acoustic environment
  - Artefacts from the hardware
  - The codec used for the audio and compression artefacts
  - The sample rate
  - The age of the speaker

Next few years?

- Broadening the capabilities to:
  - new domains, accents and low SNR speech
- Incorporating more *context information*
  - Context example: people talking about being hungry
  - Spoken: I think I'm gonna have lunch early today
  - Translation: I think I'm gonna have lounge early today
- Diarisation
  - partitioning an audio stream according to the speaker's identity
- Semantic error rates and innovative evaluation methods
- Super low-latency and efficient inference

References

- [Jurafsky2008]:
  - Chapter 2 “Speech”
    - Section 2.9 “Automatic Speech Recognition”

- A place to look at:
  - https://research.google.com/pubs/SpeechProcessing.html

[Jurafsky2008] Daniel Jurafsky, James H. Martin, “Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition,” Prentice Hall Series in Artifical Intelligence, 2008.

APPENDIX A

Matlab code to compute filterbanks

Filterbanks Matlab code (1/2)

```
Fs=20480;               % sampling rate
nDFT=512;               % number of DFT samples
Fnyq=Fs/2;              % Nyquist frequency

Nfb=10;                 % number of filterbanks to generate
Fmin=300;               % min frequency of filterbanks [Hz]
Fmax=Fnyq;              % max frequency of filterbanks [Hz]

FminMel=1125*log(1+(Fmin/700));   % min Mel's frequency
FmaxMel=1125*log(1+(Fmax/700)); % Max Mel's frequency

Nthresh=Nfb+2;          % number of required frequency thresholds

step=(FmaxMel-FminMel)/(Nthresh-1); % step size (linearly partition Mel's space)

% allocate memory for frequency thresholds
melvec=zeros(1,Nthresh);
freqvec=zeros(1,Nthresh);
f=zeros(1,Nthresh);

% for each frequency threshold do
for i = 0:(Nthresh-1)
    melvec(i+1) = FminMel+i*step;                % assign Mel thresholds (linearly)
    freqvec(i+1) = 700*(exp(melvec(i+1)/1125)-1); % compute corresponding frequencies (Mel's transformation)
    f(i+1) = floor((nDFT+1)*freqvec(i+1)/Fs);    % express frequency thresholds in terms of DFT indeces
end
```

Filterbanks Matlab code (2/2)

```
H=zeros(Nfb,Nthresh); % filterbank matrix, here we store the N_fb filters

% for each filter m do (m is the filterbank index)
for m = 2:(Nfb+1)
    for k=1:f(Nthresh)
        if      ((k>=f(m-1)) && (k<=f(m))) H(m-1,k) = (k-f(m-1))/(f(m)-f(m-1)); % increase
        elseif  ((k>=f(m)) && (k<=f(m+1))) H(m-1,k) = (f(m+1)-k)/(f(m+1)-f(m)); % decrease
        else    H(m-1,k) = 0;
        end
    end
end

clf
figure(1);
hold on
for m = 1:Nfb
 % read Filterbank matrix by row, each row contains a filter
 plot(H(m,:),'LineWidth',3)
end
```

SPEECH MODELS AND AUTOMATIC SPEECH RECOGNITION (ASR) SYSTEMS

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