



Automatic Speech Recognition

Machine Learning

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Contents

- ☐ Introduction
- ☐ Feature Extraction
- ☐ Acoustic Models
- ☐ Language Models
- ☐ Decoding

Class Objectives

- ☐ Understanding automatic speech recognition
- ☐ Being able to apply HMMs to automatic speech recognition

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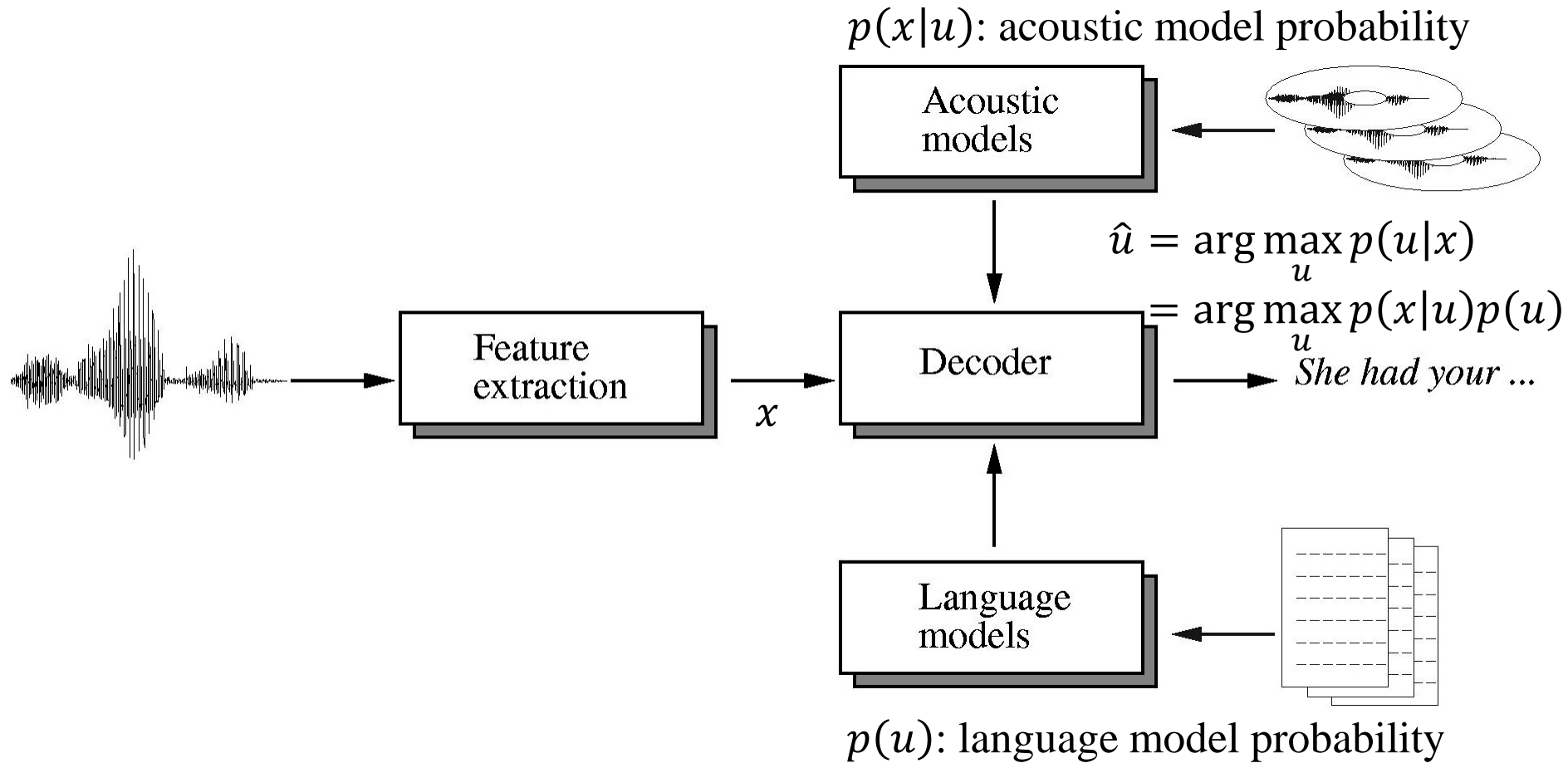
Applications of HMMs

- ☐ Automatic speech recognition
- ☐ Activity recognition
 - e.g., walking, running, ...
- ☐ Part of speech tagging
 - e.g., noun, verb, ...
- ☐ Gene finding
- ☐ Protein sequence alignment

Automatic Speech Recognition

- Find the most probable utterance \hat{u} for a given input speech x (vector sequence).
 - $\hat{u} = \arg \max_u p(u|x)$
$$= \arg \max_u \frac{p(x|u)p(u)}{p(x)}$$
$$= \arg \max_u p(x|u)p(u)$$
 - $p(x|u)$: acoustic model probability
 - $p(u)$: language model probability

Overview of Automatic Speech Recognition

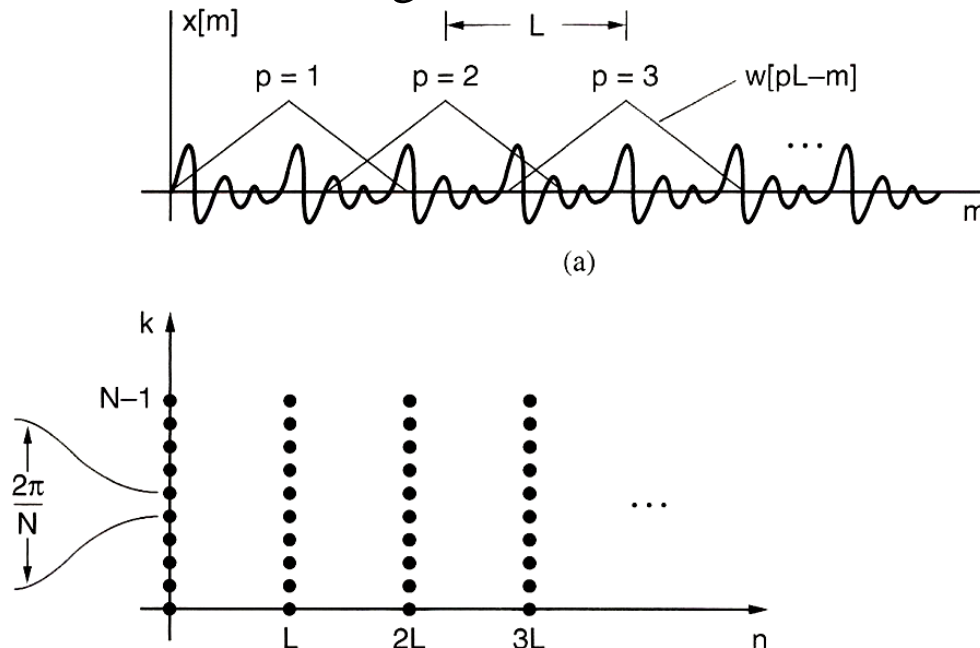


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Spectrograms

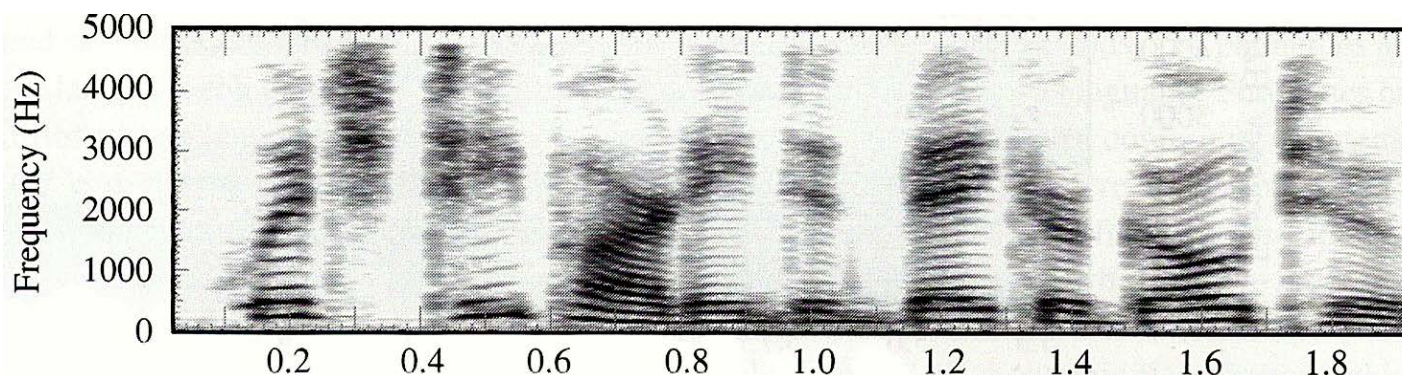
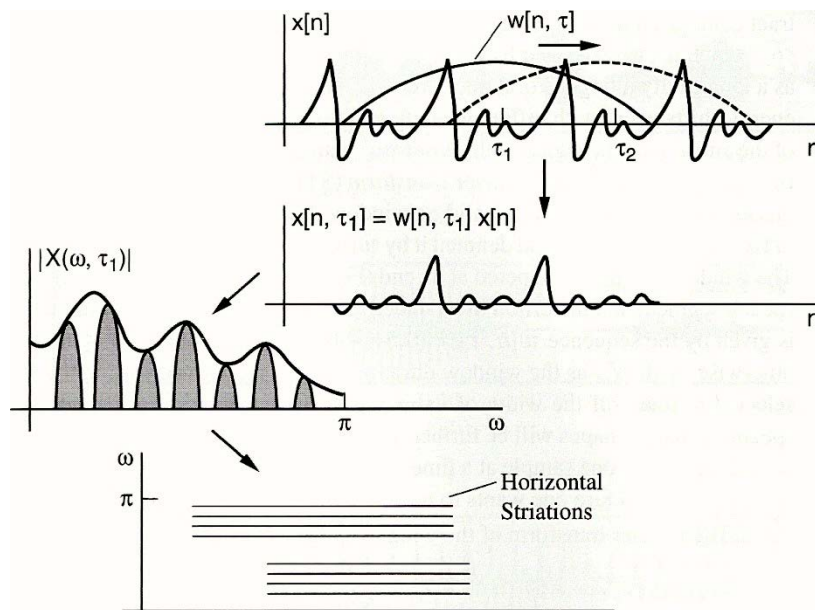
- ❑ A single spectrum of the entire acoustic signal for an utterance is not adequate for representing a time-varying characteristic of the signal. Instead, a sequence of spectra is computed using the signal under a sliding window. That is, a sequence of short time Fourier transforms (STFT) is used to represent the time-varying characteristic of a signal. A *spectrogram* is a graphical display of the magnitude of the time-varying spectral characteristic in two-dimensional time-frequency space. The time variation of a signal is typically decimated by a temporal decimation factor. The multiplying windows is typically tapered at its ends to avoid unnatural discontinuities in the windowed segments.



Narrowband Spectrograms

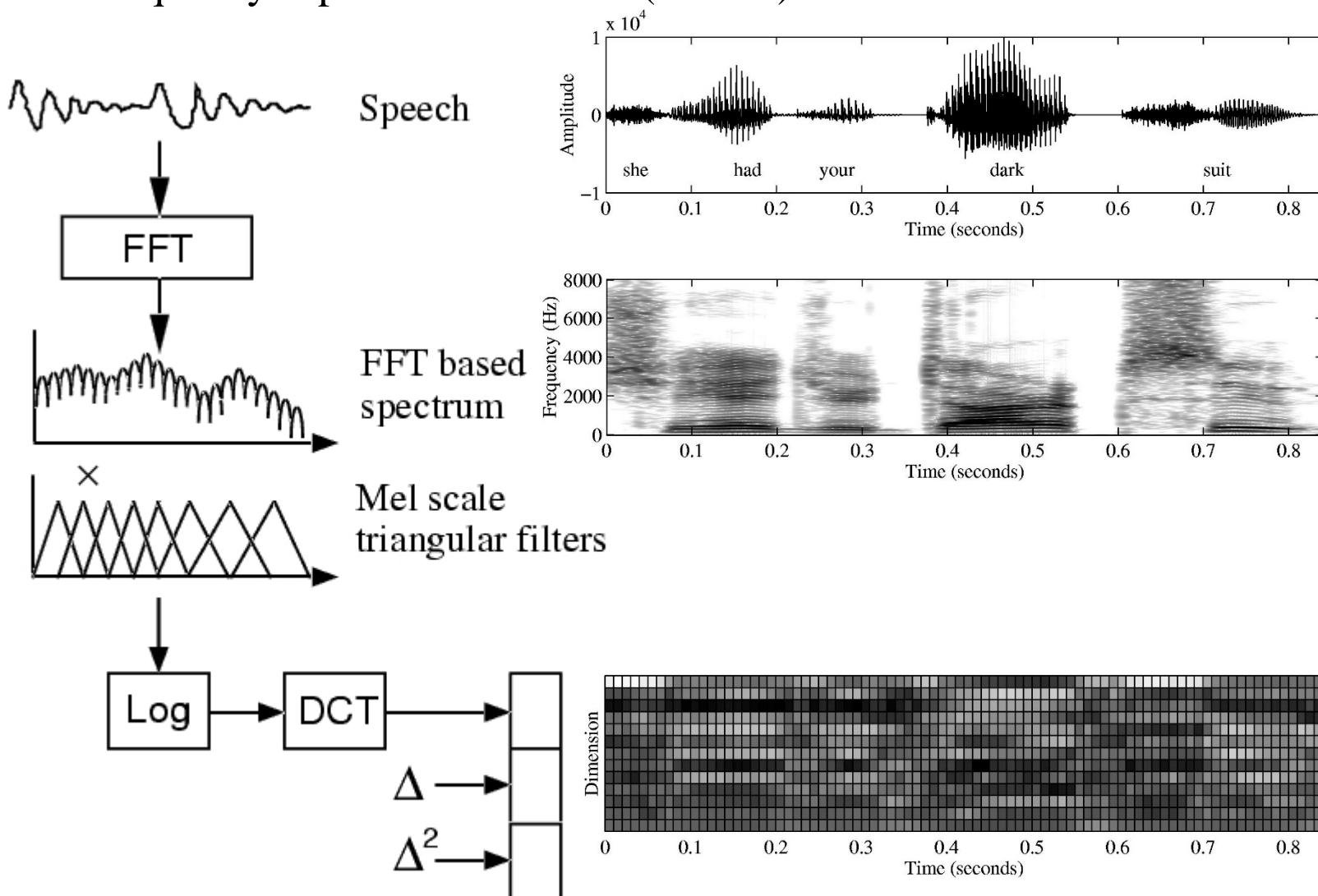
□ Narrowband spectrograms

- The spectra are computed using windowed signals of at least two pitch periods, which give good spectral resolution.



Mel-Frequency Cepstral Coefficients

□ Mel-frequency cepstral coefficients (MFCC)



Time Derivatives

□ Time derivatives of cepstra

■ First order

- $$\frac{\partial x_i}{\partial t} = \frac{\sum_{t=1}^T t(x_i^t - x_i^{-t})}{2 \sum_{t=1}^T t^2}$$

■ Second order

- $$\frac{\partial^2 x_i}{\partial^2 t} = \frac{\sum_{t=1}^T t \left(\frac{\partial x_i^t}{\partial t} - \frac{\partial x_i^{-t}}{\partial t} \right)}{2 \sum_{t=1}^T t^2}$$

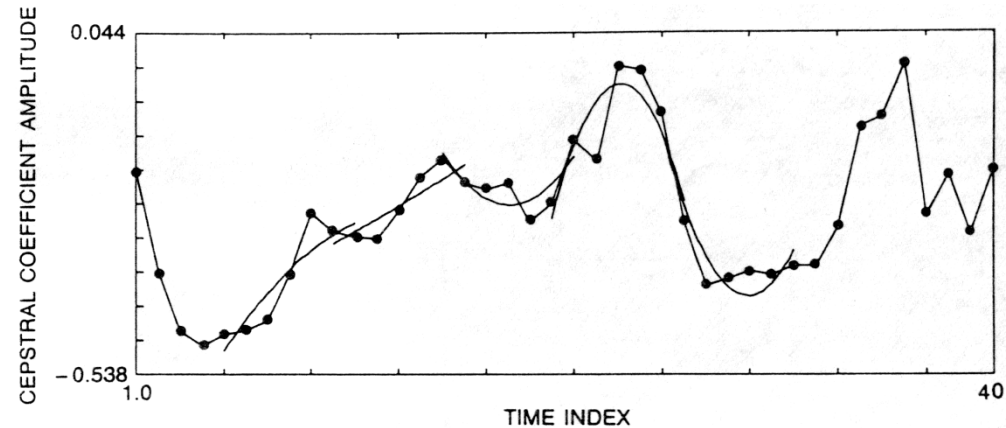


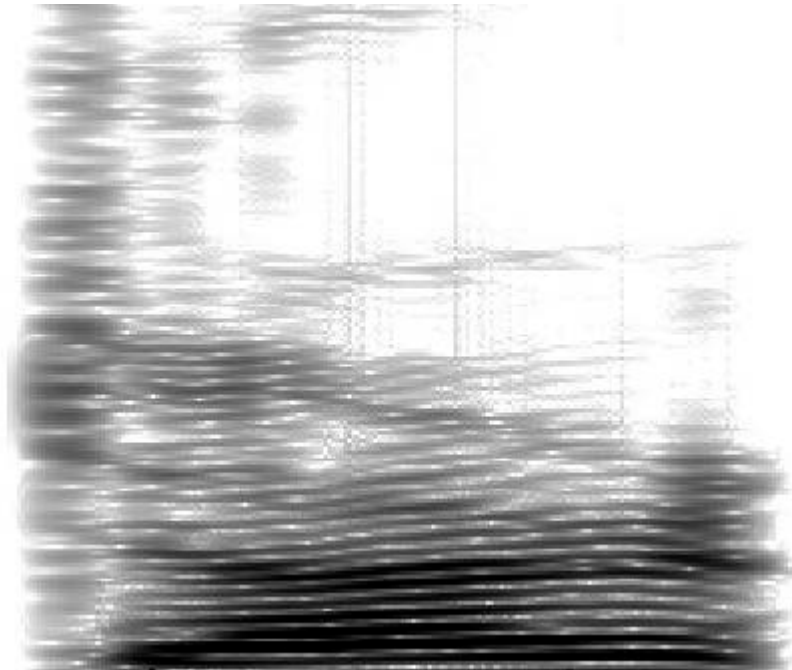
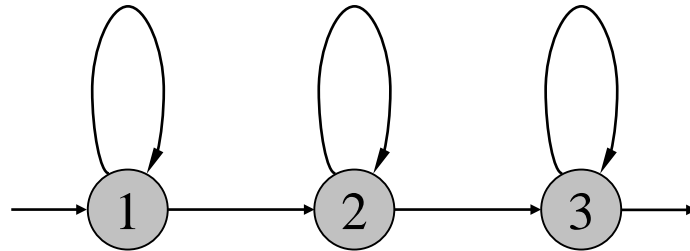
Figure 4.34 A trajectory of the (2nd) cepstral coefficient with 2nd-order polynomial ($h_1 + h_2t + h_3t^2$) fitting on short portions of the trajectory; the width for polynomial fitting is 7 points.

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HMM

□ $p(x|u)$



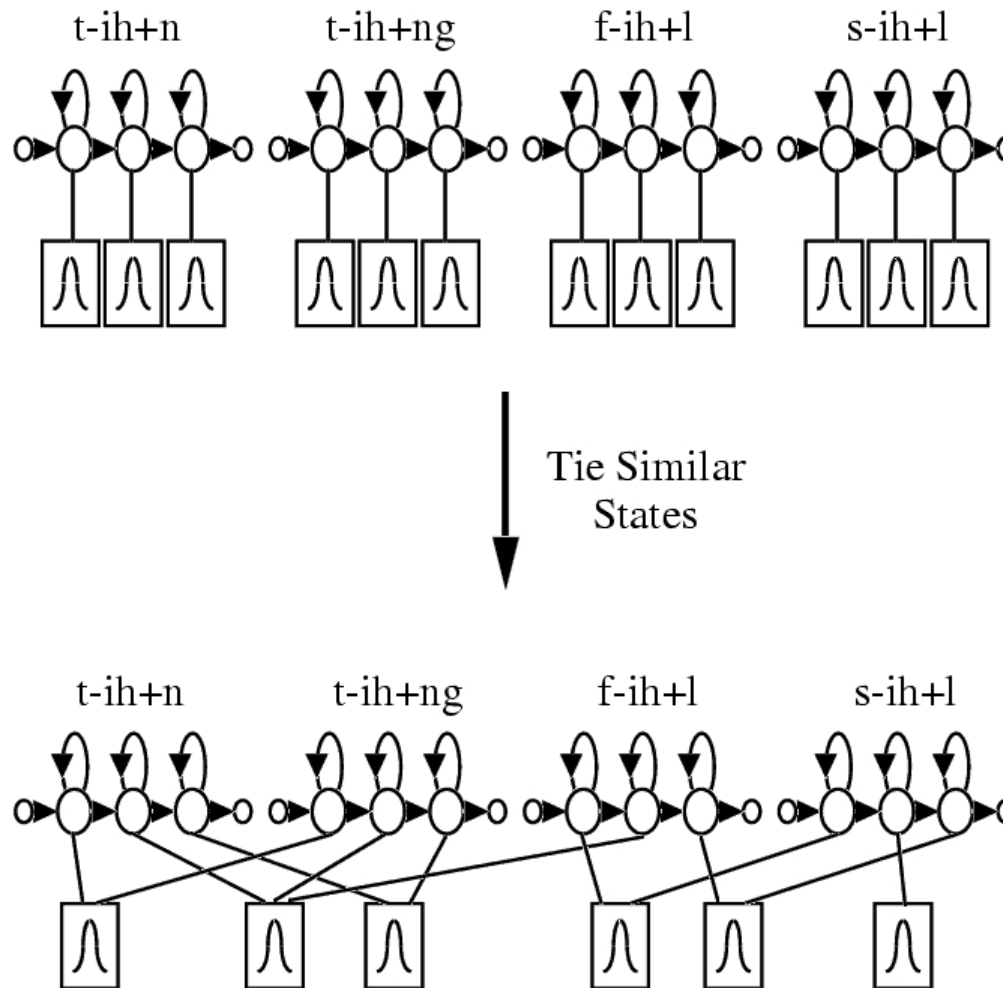
Context-Dependent Phones

- Words
 - She had your dark suit

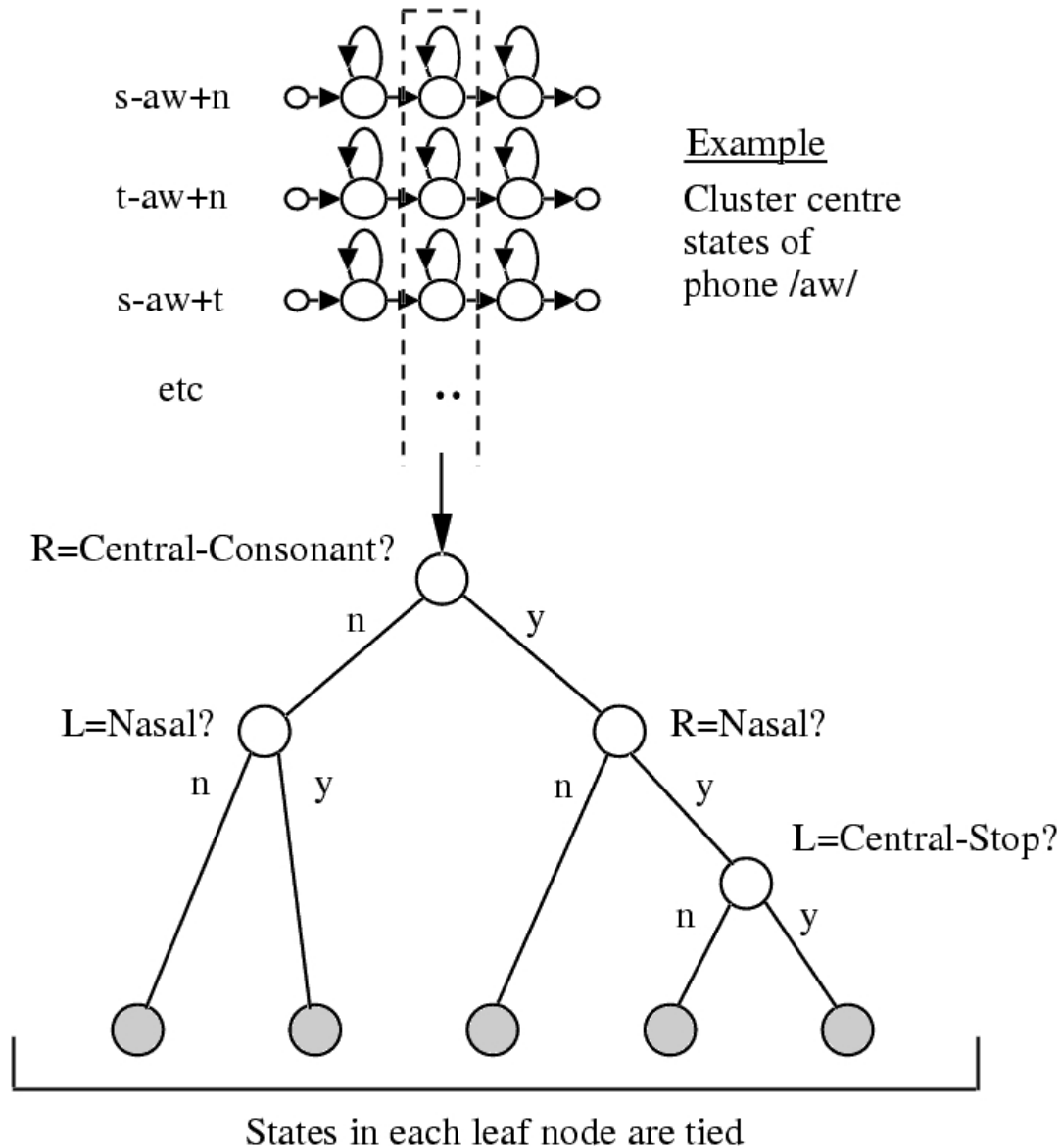
- Monophones
 - sh i y hh ae d y uh r d aa r k s uw t

- Triphones
 - Word internal triphones
sh+i y sh-i y hh+ae hh-ae+d ae-d y+uh y-uh+r uh-r d+aa d-aa+r
aa-r+k r-k s+uw s-uw+t uw-t
 - Cross-word triphones
sil-sh+i y sh-i y+hh i y-hh+ae hh-ae+d ae-d+y d-y+uh y-uh+r uh-r+d
r-d+aa d-aa+r aa-r+k r-k+s k-s+uw s-uw+t uw-t+sil

State Clustering



Decision Tree Based State Clustering



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Language Models

- Probability of an utterance u , where u is a word sequence w^1, w^2, \dots, w^n .
 - $p(u) = p(w^1, w^2, \dots, w^n)$
 $= p(w^1)p(w^2|w^1)p(w^3|w^1, w^2) \dots p(w^n|w^1, w^2, \dots, w^{n-1})$
 $= \prod_i p(w^i | w^1, w^2, \dots, w^{i-1})$
 $\approx \prod_i p(w^i | w^{i-2}, w^{i-1})$; trigram
 $\approx \prod_i p(w^i | w^{i-1})$; bigram
 $\approx \prod_i p(w^i)$; unigram

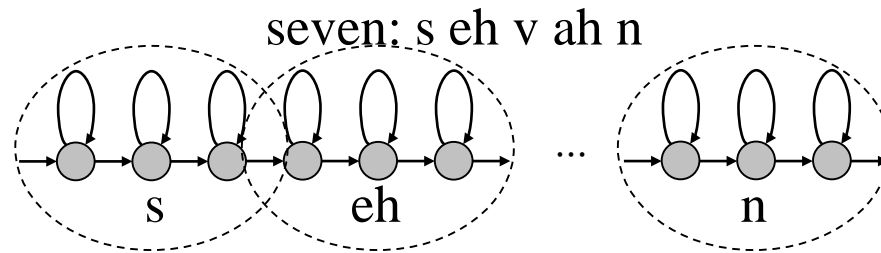
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 - Isolated Word Recognition
 - Continuous Speech Recognition

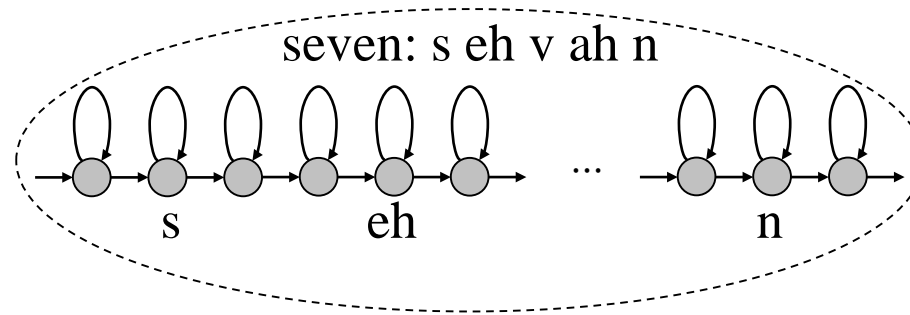
Isolated Word Recognition

- Find the most probable word \hat{w} for a given input speech x (vector sequence).
 - $\hat{w} = \arg \max_w p(w|x)$
$$= \arg \max_w \frac{p(w|x)p(w)}{p(x)}$$
$$= \arg \max_w p(x|w)p(w)$$
 - $p(x|w)$: acoustic model probability
 - $p(w)$: language model probability (e.g., unigram)

Word HMM Construction

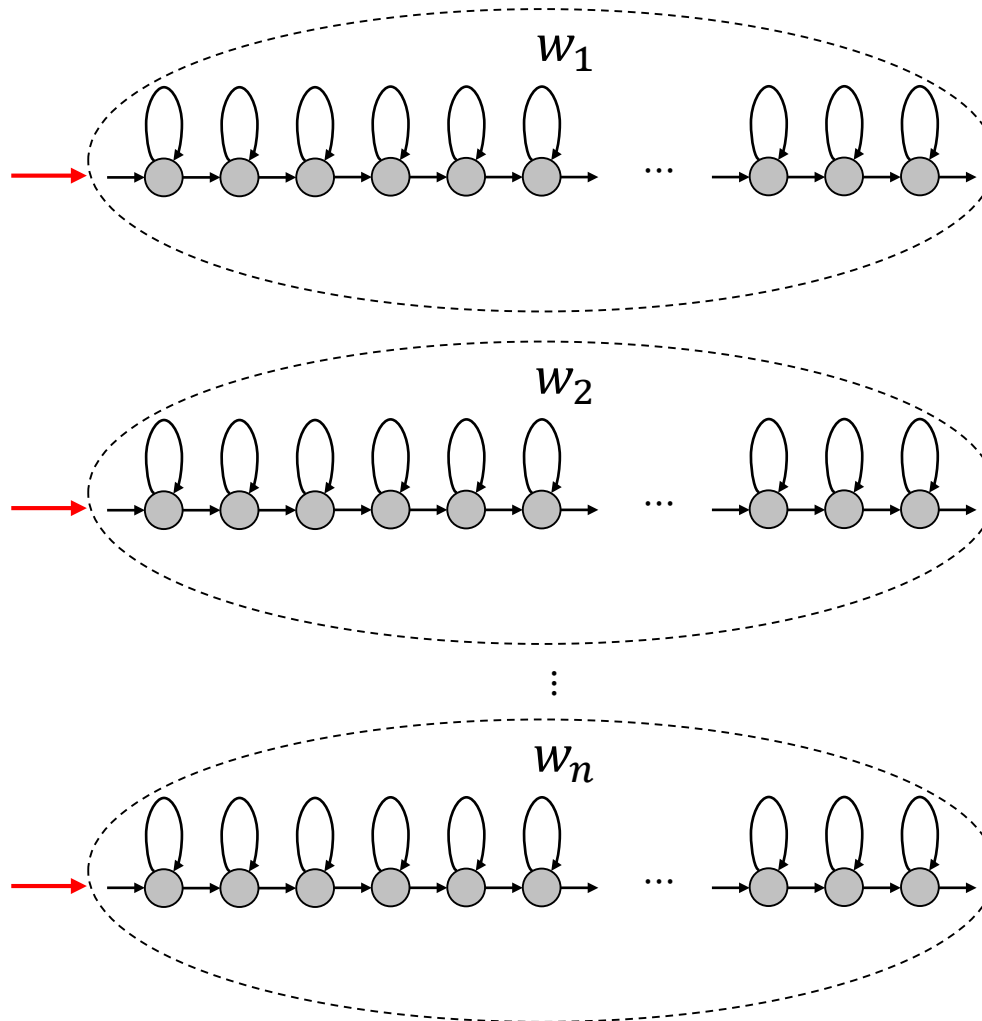


Word HMM Construction



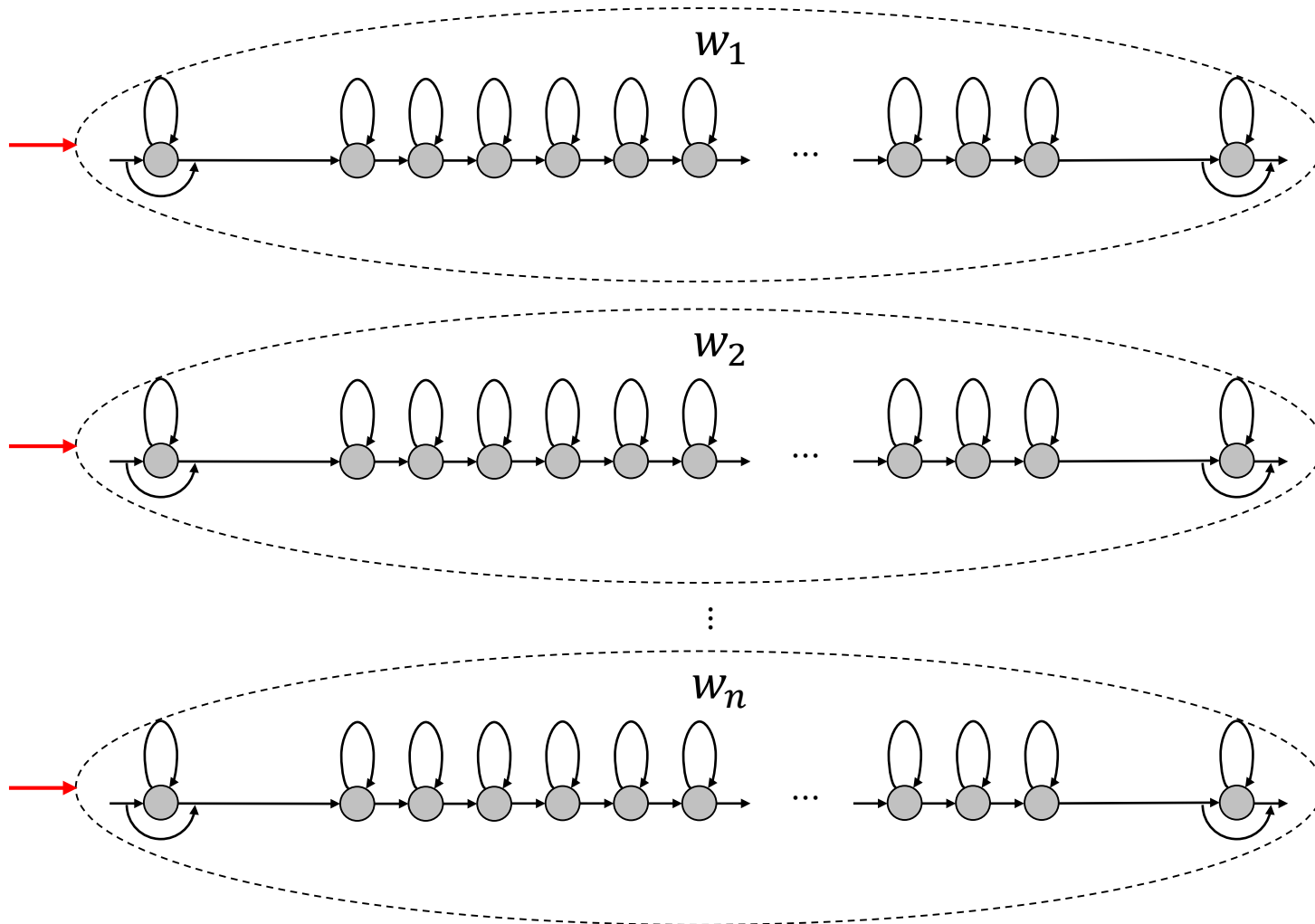
Isolated Word Recognition (Unigram)

$$\begin{aligned}\hat{w} &= \arg \max_w p(w|x) \\ &= \arg \max_w p(x|w) \textcolor{red}{p(w)}\end{aligned}$$



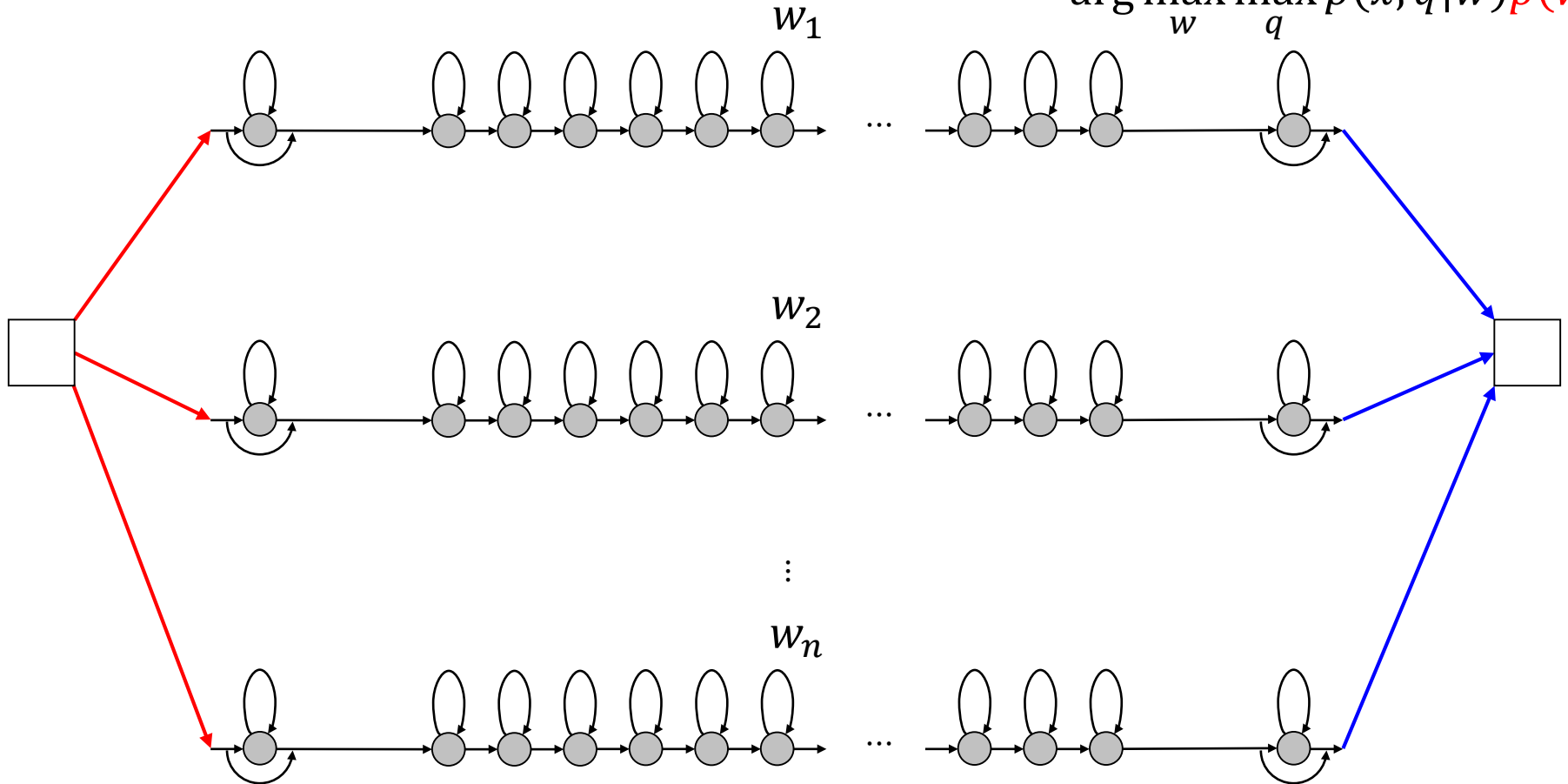
Isolated Word Recognition (Unigram)

$$\begin{aligned}\hat{w} &= \arg \max_w p(w|x) \\ &= \arg \max_w p(x|w) \textcolor{red}{p(w)}\end{aligned}$$



Isolated Word Recognition (Unigram)

$$\begin{aligned}\hat{w} &= \arg \max_w p(w|x) \\ &= \arg \max_w p(x|w) p(w) \\ &\approx \arg \max_w \max_q p(x, q|w) p(w)\end{aligned}$$



Contents

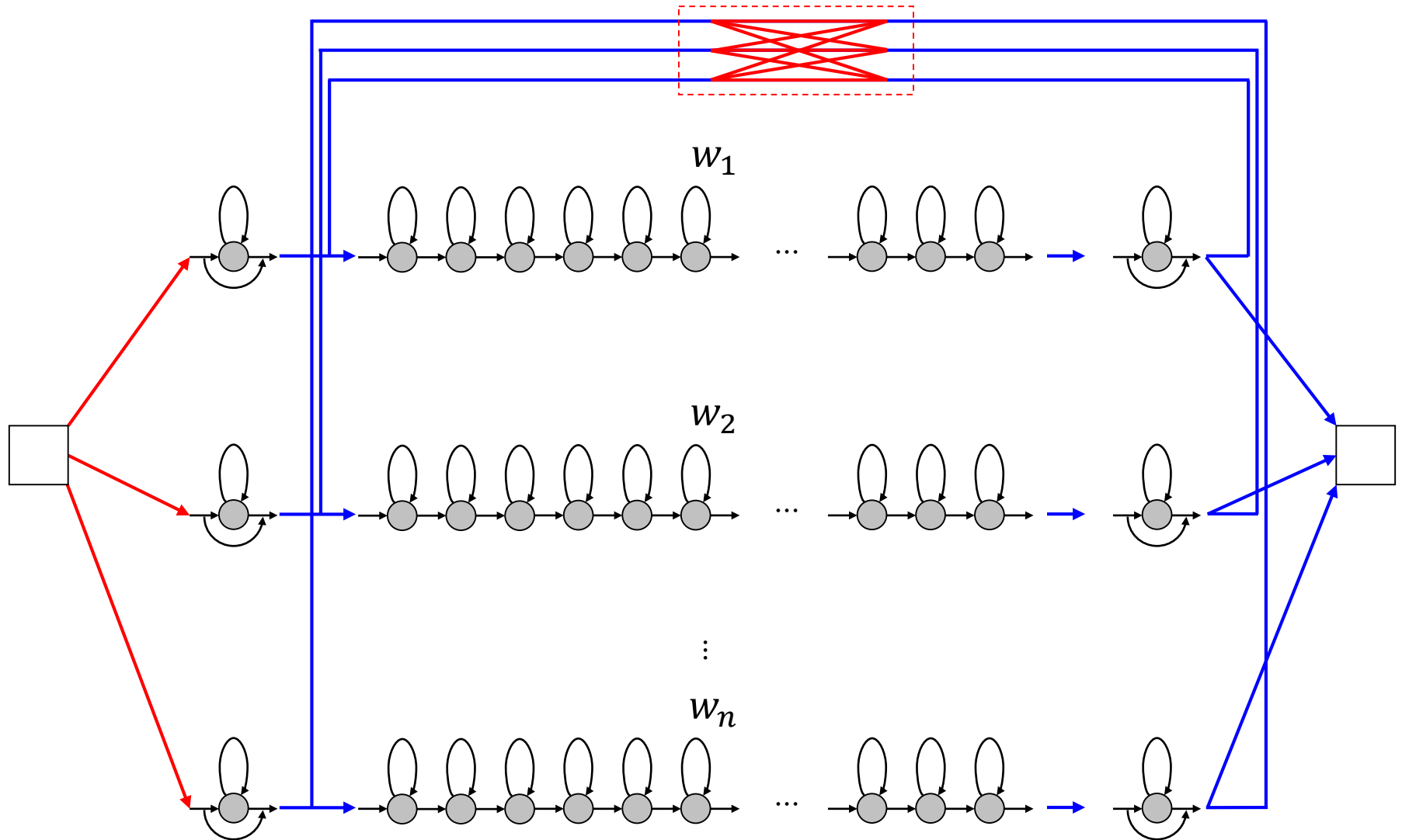
- ☐ Introduction
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Continuous Speech Recognition

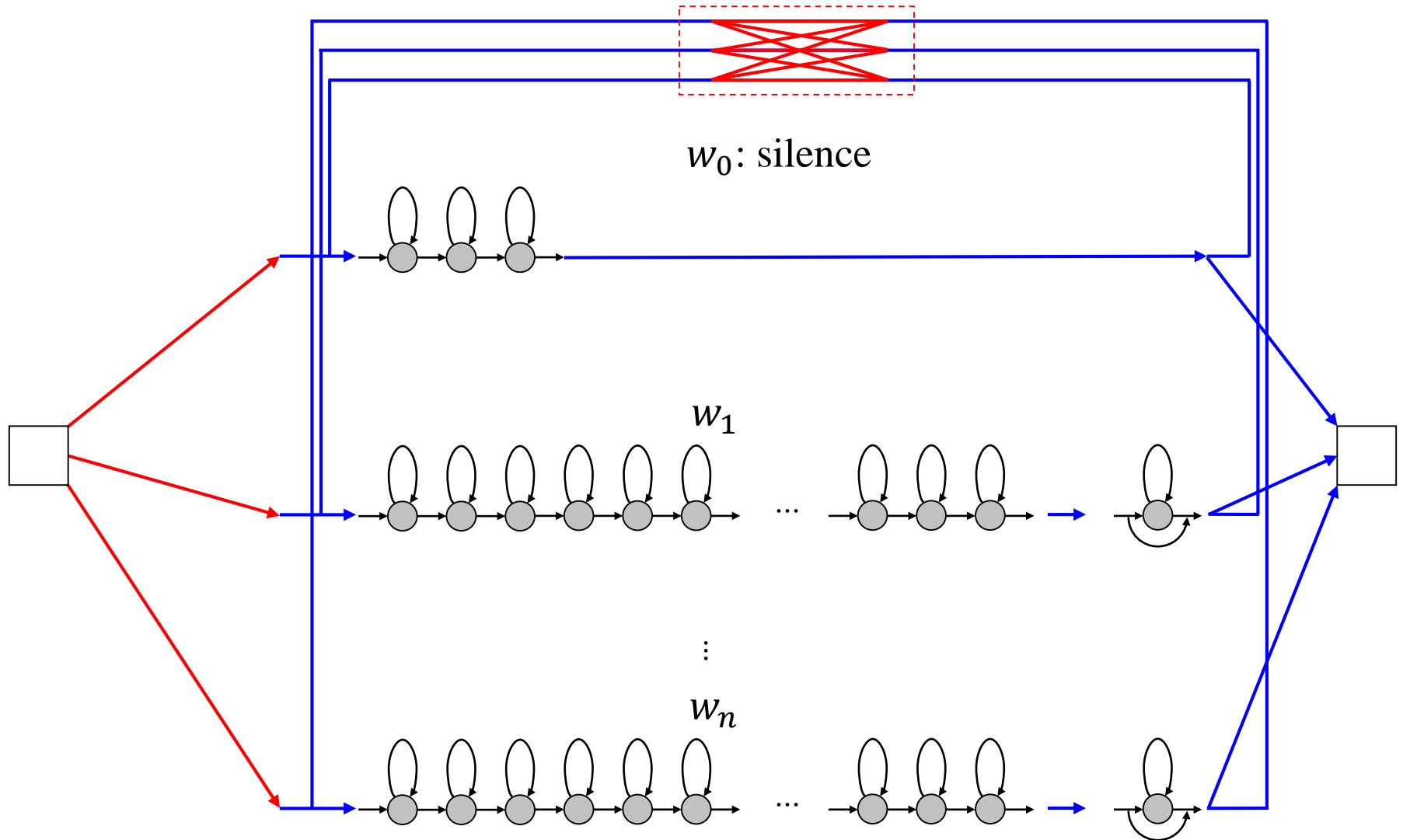
- Find the most probable word sequence \hat{u} for a given input speech x (vector sequence).

- $$\begin{aligned}\hat{u} &= \arg \max_u p(u|x) \\ &= \arg \max_u \frac{p(x|u)p(u)}{p(x)} \\ &= \arg \max_u p(x|u)p(u) \\ &= \arg \max_u \sum_q p(x, q|u) p(u) \quad ; q \text{ state sequence} \\ &\approx \arg \max_u \max_q p(x, q|u) p(u)\end{aligned}$$
- $p(x, q|u)$: acoustic model probability
- $p(u)$: language model probability (e.g., bigram)

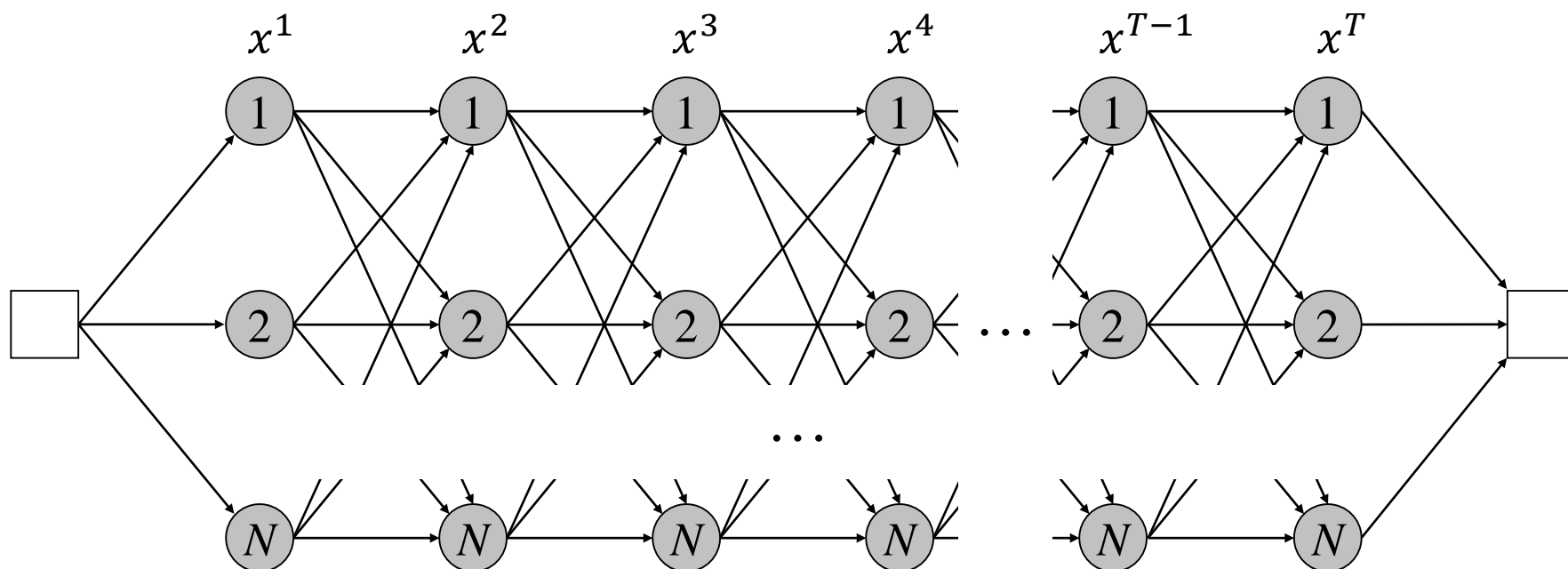
Utterance HMM Construction (Bigram)



Utterance HMM Construction (Bigram)



Continuous Speech Recognition (Bigram)



$$\begin{aligned}
 \hat{u} &= \arg \max_u p(u|x) \\
 &= \arg \max_u \frac{p(x|u)p(u)}{p(x)} \\
 &= \arg \max_u p(x|u)p(u) \\
 &= \arg \max_u \sum_q p(x, q|u) p(u) \\
 &\approx \arg \max_u \max_q p(x, q|u) p(u)
 \end{aligned}$$

Three State HMM

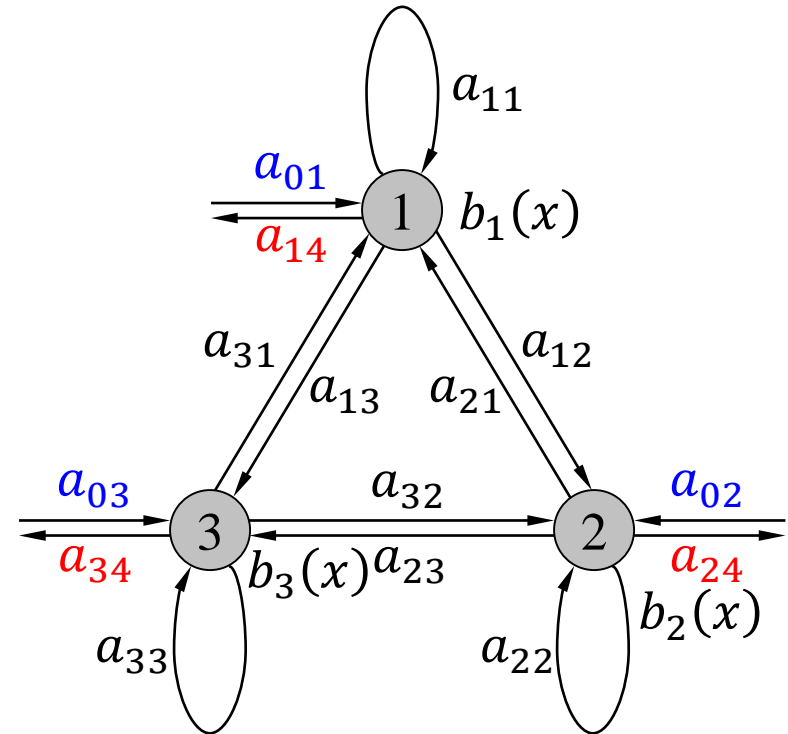
□ HMM $M = (a, b)$

■ Transition probability

- $\pi = [\pi_1 \ \pi_2 \ \pi_3]$
- $a = \begin{bmatrix} a_{00} & a_{01} & a_{02} & a_{03} & a_{04} \\ a_{10} & a_{11} & a_{12} & a_{13} & a_{14} \\ a_{20} & a_{21} & a_{22} & a_{23} & a_{24} \\ a_{30} & a_{31} & a_{32} & a_{33} & a_{34} \\ a_{40} & a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}$

■ Observation probability

- $b = \begin{bmatrix} b_1(1) & b_1(2) & \dots & b_1(N_v) \\ b_2(1) & b_2(2) & \dots & b_2(N_v) \\ b_3(1) & b_3(2) & \dots & b_3(N_v) \end{bmatrix}$



Continuous Observations

❑ Discrete observation probability

$$\blacksquare \quad b = \begin{bmatrix} b_1(1) & b_1(2) & \cdots & b_1(N_v) \\ b_2(1) & b_2(2) & \cdots & b_2(N_v) \\ b_3(1) & b_3(2) & \cdots & b_3(N_v) \end{bmatrix}$$



❑ Continuous observation probability

$$\blacksquare \quad b_s(x) = \mathcal{N}(x|\mu_s, \sigma_s) = \frac{1}{\sqrt{2\pi}\sigma_s} e^{-\frac{1}{2} \frac{(x-\mu_s)^2}{\sigma_s^2}}$$

$$\blacksquare \quad b_s(x) = \mathcal{N}(x|\mu_s, \Sigma_s) = \frac{1}{(2\pi)^{D/2} |\Sigma_s|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_s)^T \Sigma_s^{-1} (x - \mu_s)\right)$$

$$\begin{aligned} \blacksquare \quad b_s(x) &= \sum_{g=1}^G c_{sg} \mathcal{N}(x|\mu_{sg}, \Sigma_{sg}) \\ &= \sum_{g=1}^G c_{sg} \frac{1}{(2\pi)^{D/2} |\Sigma_{sg}|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_{sg})^T \Sigma_{sg}^{-1} (x - \mu_{sg})\right) \\ &\approx \sum_{g=1}^G c_{sg} \frac{1}{(2\pi)^{D/2} \prod_i \sigma_{sgi}^2} \exp\left(-\frac{1}{2} \sum_i \frac{(x_i - \mu_{sgi})^2}{\sigma_{sgi}^2}\right) \end{aligned}$$

Implementation Issues

□ Because of finite precision computation, $\log \alpha$, $\log \beta$, $\log \delta$, and $\log p(x|M)$ are used instead of α , β , δ , and $p(x|M)$, respectively.

■ e.g.,

- e^{-1001}

- $l_1 = \log e^{-1001} = -1001$

- $l_2 = \log e^{-1002} = -1002$

- $l_3 = \log(e^{-1001} + e^{-1002}) = \log(e^{l_1} + e^{l_2})$

- $l_3 = \log(e^{-1001}(e^0 + e^{-1})) = \log e^{-1001} + \log(1 + e^{-1})$

□ $\log \sum_i p_i = \log(p_1 + p_2 + \dots + p_n)$

$$= \log p_1 \left(1 + \frac{p_2}{p_1} + \frac{p_3}{p_1} + \dots + \frac{p_n}{p_1} \right)$$
$$= \log p_1 + \log \left(1 + e^{\log \frac{p_2}{p_1}} + e^{\log \frac{p_3}{p_1}} + \dots + e^{\log \frac{p_n}{p_1}} \right)$$
$$= \log p_1 + \log \left(1 + e^{\log p_2 - \log p_1} + e^{\log p_3 - \log p_1} + \dots + e^{\log p_n - \log p_1} \right)$$
$$= l_1 + \log \left(1 + e^{l_2 - l_1} + e^{l_3 - l_1} + \dots + e^{l_n - l_1} \right) \quad ; \quad l_i \equiv \log p_i$$

Summary

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Input Vector File Format

□ Input vector sequence file

313 39

- 1. 589671e+01	4. 339182e+00	1. 678270e+00	- 4. 386323e- 02	1. 384665e- 01	...
- 1. 573894e+01	2. 713936e+00	2. 918963e+00	1. 807250e+00	- 1. 625646e+00	...
- 1. 589687e+01	1. 784740e+00	- 3. 876205e- 03	1. 939704e+00	1. 013269e+00	...
- 1. 686176e+01	3. 179346e+00	6. 970119e- 01	7. 169858e- 01	- 1. 466554e+00	...
- 1. 602454e+01	4. 159081e+00	2. 404717e+00	1. 300133e+00	- 1. 309275e+00	...
- 1. 794216e+01	- 1. 226994e- 01	- 1. 229748e+00	2. 328833e- 02	3. 530599e+00	...
- 1. 572281e+01	3. 731576e+00	- 4. 482310e- 01	- 1. 252083e- 01	2. 847649e+00	...
- 1. 571102e+01	6. 004687e+00	1. 940033e+00	- 9. 302789e- 01	1. 905544e+00	...
- 1. 866060e+01	- 1. 945088e- 01	- 9. 612672e- 01	- 6. 845327e- 01	- 4. 278716e+00	...
- 1. 790727e+01	- 3. 463200e- 01	- 2. 204390e- 01	- 6. 221546e- 01	- 3. 650035e+00	...
- 1. 687654e+01	1. 089474e+00	- 2. 015056e+00	7. 445039e- 01	2. 003541e+00	...
- 1. 630165e+01	9. 615828e- 01	- 2. 796509e+00	2. 851351e- 02	- 2. 366324e+00	...
- 1. 762898e+01	3. 966002e- 01	- 6. 038963e- 01	5. 937940e- 01	7. 313928e- 02	...
- 1. 687426e+01	1. 015894e+00	- 1. 440334e+00	8. 511196e- 01	- 3. 999560e+00	...
- 1. 656823e+01	2. 526161e+00	- 1. 373639e+00	2. 825755e+00	- 3. 559372e- 01	...
- 1. 605652e+01	2. 725700e+00	1. 645913e+00	4. 513128e+00	1. 367162e+00	...
- 1. 615862e+01	2. 757725e+00	- 1. 037673e- 01	5. 169404e- 01	2. 256959e+00	...
- 1. 697908e+01	2. 430228e+00	1. 174574e+00	- 6. 864926e- 01	- 2. 884347e+00	...
- 1. 562105e+01	4. 122203e+00	6. 119420e- 01	2. 408284e+00	1. 406704e+00	...
- 1. 586861e+01	2. 400448e+00	- 2. 723778e+00	- 3. 281356e+00	1. 186900e+00	...
- 2. 964692e+01	- 4. 892936e+00	5. 048756e+00	- 7. 816375e- 01	9. 942081e+00	...
- 3. 060667e+01	- 5. 355003e+00	5. 724719e+00	7. 978249e- 01	1. 216068e+01	...
- 1. 542544e+01	2. 674652e+00	3. 692956e- 01	- 1. 053609e+00	3. 725806e+00	...
- 1. 660411e+01	5. 190681e+00	3. 267094e- 01	2. 324215e+00	2. 873489e+00	...
- 1. 603844e+01	3. 882752e+00	- 1. 272774e- 01	6. 141130e+00	3. 787947e+00	...
- 1. 589794e+01	1. 520315e+00	- 6. 553339e- 01	2. 869384e+00	- 2. 616245e- 01	...

HMM File Format

□ Single-Gaussian HMM

```
~h "ah"
<BEGINHMM>
<NUMSTATES> 5
<STATE> 2
<MEAN> 39
  1. 898954e+000 - 1. 301708e+001  2. 951807e- 001  - 8. 873045e+000  - 5. 299952e+000  ...
<VARIANCE> 39
  1. 374686e+001  2. 792357e+001  3. 375932e+001  3. 855578e+001  5. 125336e+001  ...
<GCONST> 1. 185189e+002
<STATE> 3
...
<STATE> 4
...
<TRANSP> 5
  0. 000000e+000  1. 000000e+000  0. 000000e+000  0. 000000e+000  0. 000000e+000
  0. 000000e+000  6. 985369e- 001  3. 014631e- 001  0. 000000e+000  0. 000000e+000
  0. 000000e+000  0. 000000e+000  5. 712691e- 001  4. 287309e- 001  0. 000000e+000
  0. 000000e+000  0. 000000e+000  0. 000000e+000  5. 327887e- 001  4. 672113e- 001
  0. 000000e+000  0. 000000e+000  0. 000000e+000  0. 000000e+000  0. 000000e+000
<ENDHMM>
~h "ao"
<BEGINHMM>
...
<ENDHMM>
...
```

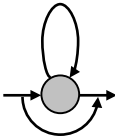
HMM File Format

❑ Two-Gaussian HMM

```
~h "ah"
<BEGINHMM>
<NUMSTATES> 5
<STATE> 2
<NUMMIXES> 2
<MIXTURE> 1 4.817315e-001
<MEAN> 39
  4.137055e+000 -1.180742e+001 1.235130e+000 -6.246143e+000 -5.400127e+000 ...
<VARIANCE> 39
  9.940362e+000 2.234269e+001 3.181495e+001 3.140755e+001 3.038879e+001 ...
<GCONST> 1.134534e+002
<MIXTURE> 2 5.182614e-001
<MEAN> 39
  7.230198e-002 -1.516407e+001 -2.030157e+000 -1.170948e+001 -3.230822e+000 ...
<VARIANCE> 39
  9.100752e+000 2.617574e+001 3.306291e+001 3.100306e+001 7.574311e+001 ...
<GCONST> 1.088633e+002
<STATE> 3
...
<STATE> 4
...
<TRANSP> 5
...
<ENDHMM>
...
```

HMM File Format

❑ Optional silence HMM



```
~h "sp"
<BEGINHMM>
<NUMSTATES> 3
<STATE> 2
<NUMMIXES> 2
<MIXTURE> 1 5.687151e-001
<MEAN> 39
-1.528916e+001 1.884770e+000 -1.786322e-001 9.084788e-001 -2.541062e-001 ...
<VARIANCE> 39
3.127717e+000 3.337751e+000 4.364497e+000 6.843961e+000 9.882758e+000 ...
<GCONST> 6.342905e+001
<MIXTURE> 2 4.312517e-001
<MEAN> 39
-1.353393e+001 5.515828e-001 -1.442452e+000 3.601370e-001 -1.042004e+000 ...
<VARIANCE> 39
9.201511e+000 1.160456e+001 1.037773e+001 9.865545e+000 1.413276e+001 ...
<GCONST> 8.848967e+001
<TRANSP> 3
0.000000e+000 8.050888e-002 9.194912e-001
0.000000e+000 9.276201e-001 7.237989e-002
0.000000e+000 0.000000e+000 0.000000e+000
<ENDHMM>
```

HMM in Header File Format

□ HMM in header file format for C programming

```
#define N_STATE      3
#define N_PDF        10
#define N_DIMENSION  39

typedef struct {
    float weight;
    float mean[N_DIMENSION];
    float var[N_DIMENSION];
} pdfType;

typedef struct {
    pdfType pdf[N_PDF];
} stateType;

typedef struct {
    char *name;
    float tp[N_STATE+2][N_STATE+2];
    stateType state[N_STATE];
} hmmType;
```

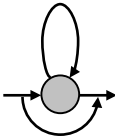

HMM in Header File Format

□ HMM in header file format for C programming

```
hmmType phones[] = {
    { "f", // HMM
      { // transition probability
        { 0.000000e+000, 1.000000e+000, 0.000000e+000, 0.000000e+000, 0.000000e+000 },
        { 0.000000e+000, 8.519424e-001, 1.480576e-001, 0.000000e+000, 0.000000e+000 },
        { 0.000000e+000, 0.000000e+000, 7.039050e-001, 2.960950e-001, 0.000000e+000 },
        { 0.000000e+000, 0.000000e+000, 0.000000e+000, 5.744837e-001, 4.255163e-001 },
        { 0.000000e+000, 0.000000e+000, 0.000000e+000, 0.000000e+000, 0.000000e+000 }
      },
      {
        {{ // state 1
          { // pdf 1
            8.379531e-002,
            { -1.100132e+001, -1.507629e+000, 5.286411e+000, 5.901514e+000, ... },
            { 2.583579e+001, 1.714888e+001, 1.768794e+001, 1.732637e+001, ... }
          },
          { // pdf 2
            ...
          },
          ...
        }},
        {{ // state 2
          ...
        }}
      },
      ...
    }
  },
  { "k", // HMM
    ...
  }
  ...
}
```

HMM in Header File Format

□ HMM in header file format for C programming



```
...
{ "sp", // HMM
  { // transition probability
    { 0.000000e+000, 2.385641e-001, 7.614358e-001 },
    { 0.000000e+000, 9.152609e-001, 8.473914e-002 },
    { 0.000000e+000, 0.000000e+000, 0.000000e+000 }
  },
  {
    {{ // state 1
      { // pdf 1
        1.120568e-001,
        { -1.508647e+001, 1.690120e+000, -3.829488e-001, 6.419236e-001, ... },
        { 3.735557e+000, 4.400073e+000, 6.065806e+000, 7.459801e+000, ... }
      },
      { // pdf 2
        ...
      },
      ...
    }}
  }
},
};
```

Pronunciation Dictionary

❑ Pronunciation dictionary

<s>	si l
ei ght	ey t
fi ve	f ay v
four	f ao r
ni ne	n ay n
oh	ow
one	w ah n
seven	s eh v ah n
six	s ih k s
three	th r iy
two	t uw
zero	z ih r ow
zero	z iy r ow

Language Models

□ Unigram

<s>	0.990000
ei ght	0.000925
fi ve	0.000890
four	0.000886
ni ne	0.000905
oh	0.000968
one	0.000905
seven	0.000869
si x	0.000939
three	0.000883
two	0.000941
zero	0.000889

Language Models

□ Bigram

<s>	ei ght	0. 012084
<s>	fi ve	0. 011881
<s>	four	0. 009139
<s>	ni ne	0. 011474
<s>	oh	0. 012591
<s>	one	0. 010967
<s>	seven	0. 010967
<s>	si x	0. 011779
<s>	three	0. 010865
<s>	two	0. 013201
<s>	zero	0. 010053
ei ght	<s>	0. 012287
ei ght	ei ght	0. 005991
ei ght	fi ve	0. 005788
ei ght	four	0. 006600
ei ght	ni ne	0. 007616
ei ght	oh	0. 006397
ei ght	one	0. 005585
ei ght	seven	0. 005483
ei ght	si x	0. 005991
ei ght	three	0. 005890
ei ght	two	0. 006803
ei ght	zero	0. 006499
fi ve	<s>	0. 013708
fi ve	ei ght	0. 005788
fi ve	fi ve	0. 005686
...		
zero	zero	0. 013911

Label Format

❑ Label format (reference)

#!MLF! #

"tst/f/ak/1237743.1 ab"

one

two

three

seven

seven

four

three

."tst/f/ak/1393387.1 ab"

one

three

ni ne

three

three

ei ght

seven

."tst/f/ak/276317o.1 ab"

two

seven

si x

three

one

seven

oh

Label Format

☐ Label format (recognized)

#!MLF! #

"tst/f/ak/1237743. **rec**"

one

two

three

seven

seven

four

three

·
"tst/f/ak/1393387. **rec**"

one

three

ni ne

three

three

ei ght

seven

·
"tst/f/ak/276317o. **rec**"

two

seven

si x

three

one

seven

oh

Confusion Matrix

❑ Confusion matrix

HResults -p -I reference vocabulary recognized

===== HTK Results Analysis =====

Date: Mon Jan 1 00:00:00 2014

Ref : reference

Rec : recognized

----- Overall Results -----

SENT: %Correct=87.52 [H=1087, S=155, N=1242]

WORD: %Corr=99.82, Acc=97.98 [H=8678, D=4, S=12, I=160, N=8694]

----- Confusion Matrix -----

	z	o	o	t	t	f	f	s	s	e	n	
	e	h	n	w	h	o	i	i	e	i	i	
	r		e	o	r	u	v	x	v	g	n	
	o				e	r	e		e	h	e	
					e				n	t		Del [%c / %e]
zero	815	0	0	0	0	0	0	0	0	0	0	0
oh	0	744	0	1	0	1	0	0	0	0	2	2 [99.5/0.0]
one	0	0	809	0	0	0	0	0	0	0	1	0 [99.9/0.0]
two	0	0	0	803	1	0	0	0	0	0	0	1 [99.9/0.0]
thre	0	0	0	2	812	0	0	0	0	0	0	0 [99.8/0.0]
four	0	0	0	0	0	783	1	0	0	0	0	0 [99.9/0.0]
five	0	0	0	0	0	0	784	0	0	0	0	0
six	0	0	0	0	0	0	0	800	1	0	0	0 [99.9/0.0]
seve	0	0	1	0	0	0	0	0	791	0	0	0 [99.9/0.0]
eigh	0	1	0	0	0	0	0	0	0	824	0	1 [99.9/0.0]
nine	0	0	0	0	0	0	0	0	0	0	713	0
Ins	0	97	5	8	0	0	1	0	0	44	5	

=====