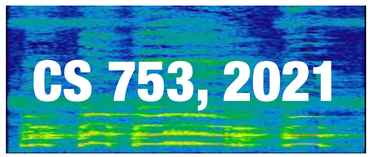
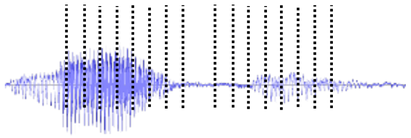
Tied-State HMMs for Acoustic Modeling

Lecture 2a

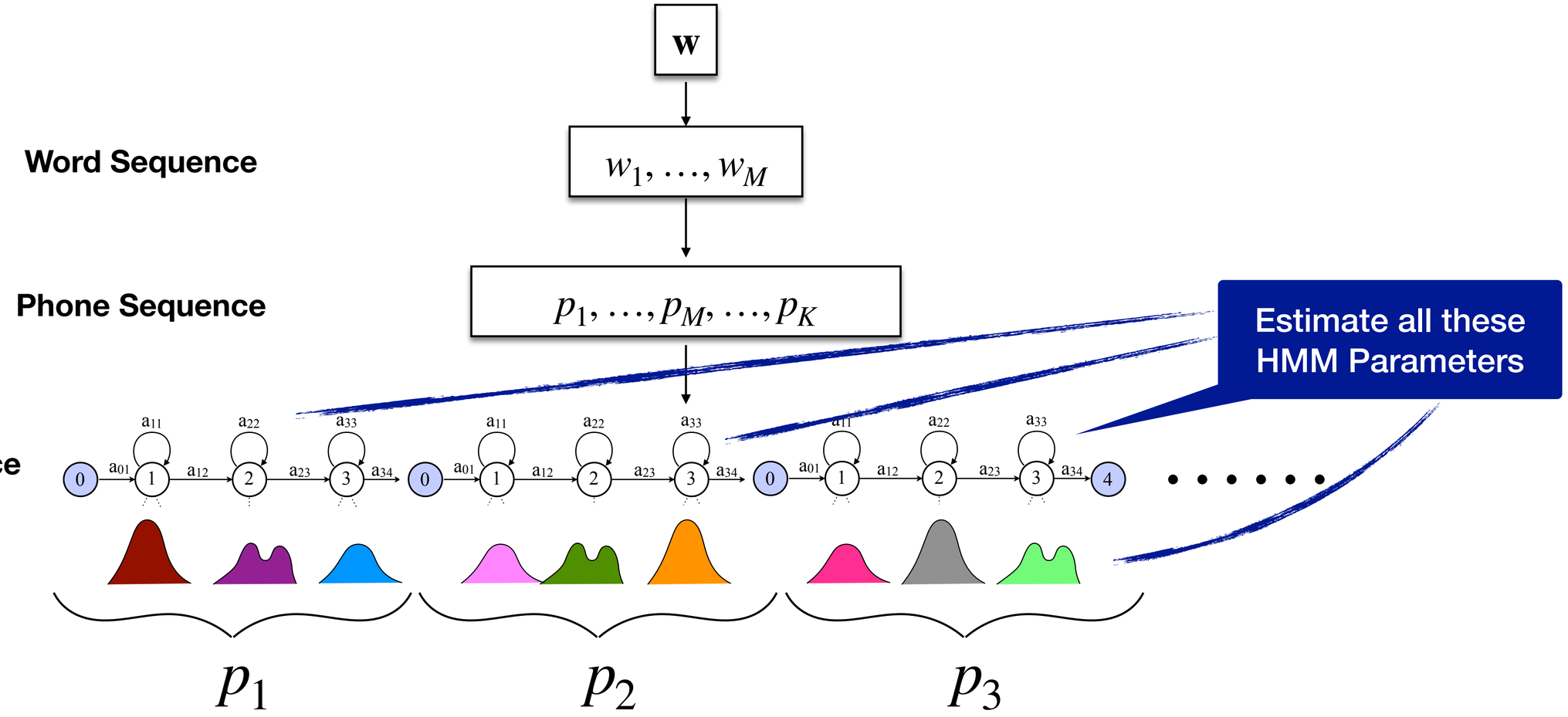


Instructor: Preethi Jyothi, IITB

Recap: HMM-based Acoustic Models

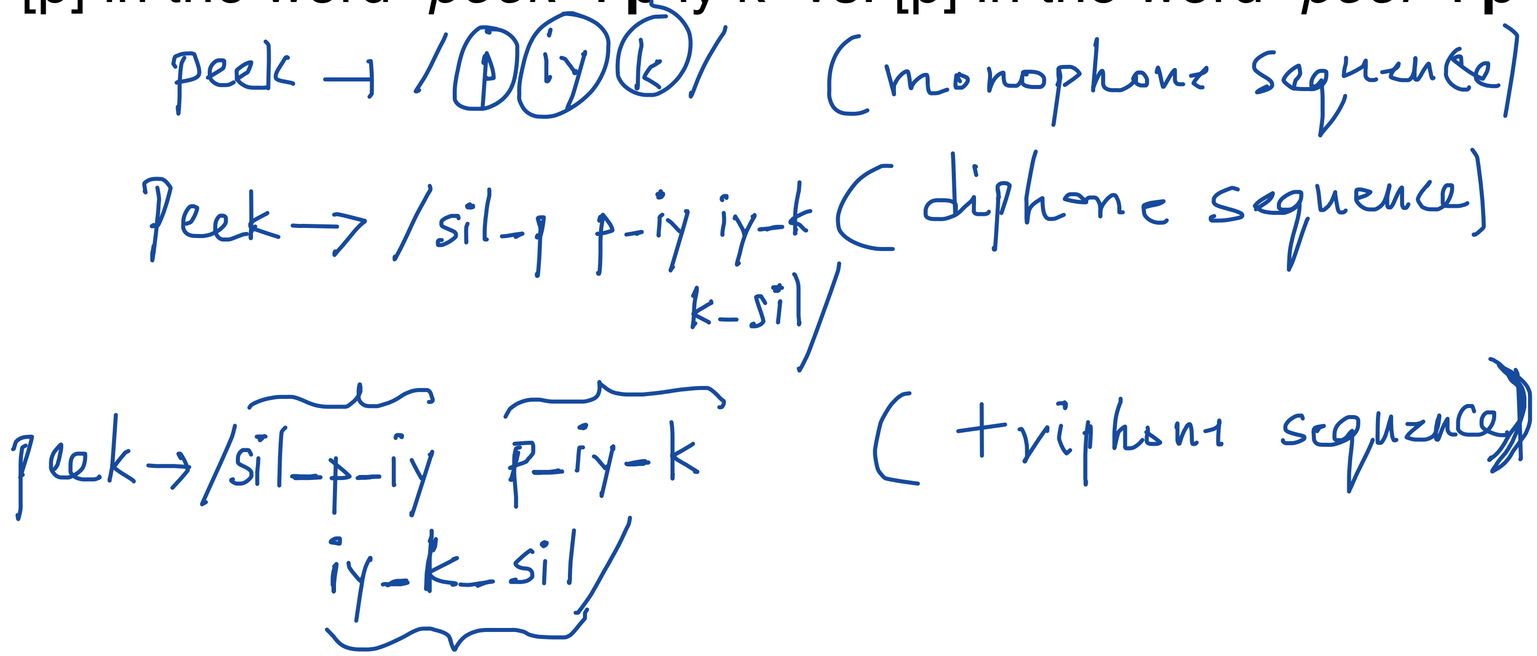


$\mathbf{O} = O_1, \ldots, O_T$ and $\mathbf{w} = w_1, \ldots, w_M$



Triphone HMM Models

- Each phone is modelled in the context of its left and right neighbour phones
  - Pronunciation of a phone is influenced by the preceding and succeeding phones.
    E.g. The phone [p] in the word "*peek*" : **p** iy k" vs. [p] in the word "*pool*" : **p** uw l



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- If each triphone HMM has 3 states and each state generates m-component GMMs ($m \approx 64$), for d-dimensional acoustic feature vectors ($d \approx 40$) with Σ having d^2 parameters
  - Hundreds of millions of parameters!
- Insufficient data to learn all triphone models reliably. What do we do? Share parameters across triphone models!

Parameter Sharing

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- Sharing of parameters (also referred to as “parameter tying”) can be done at any level:
  - Parameters in HMMs corresponding to two triphones are said to be tied if they are identical

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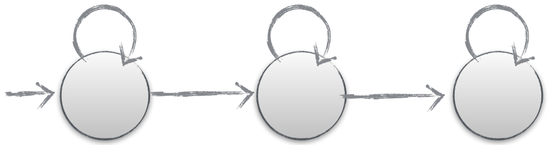

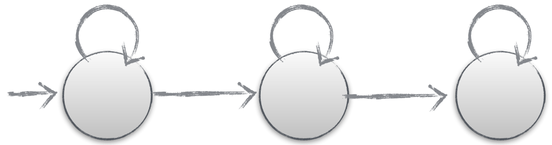

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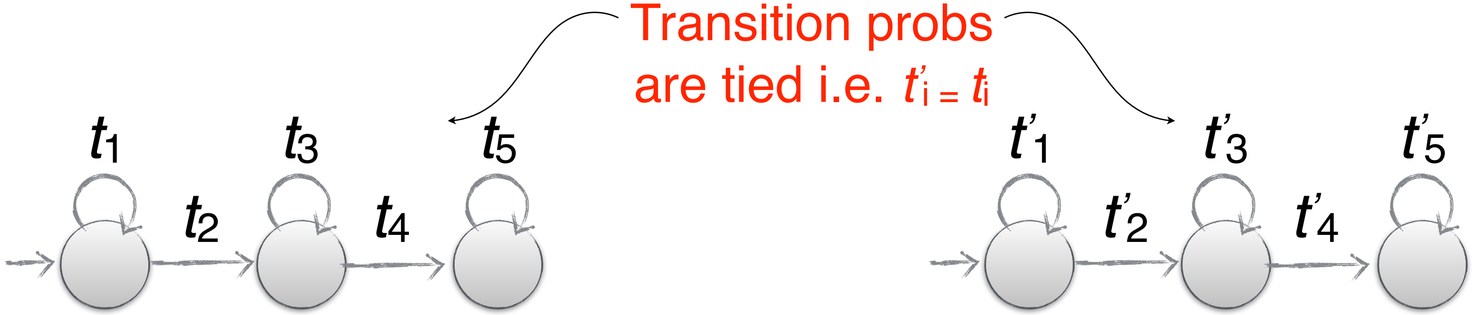

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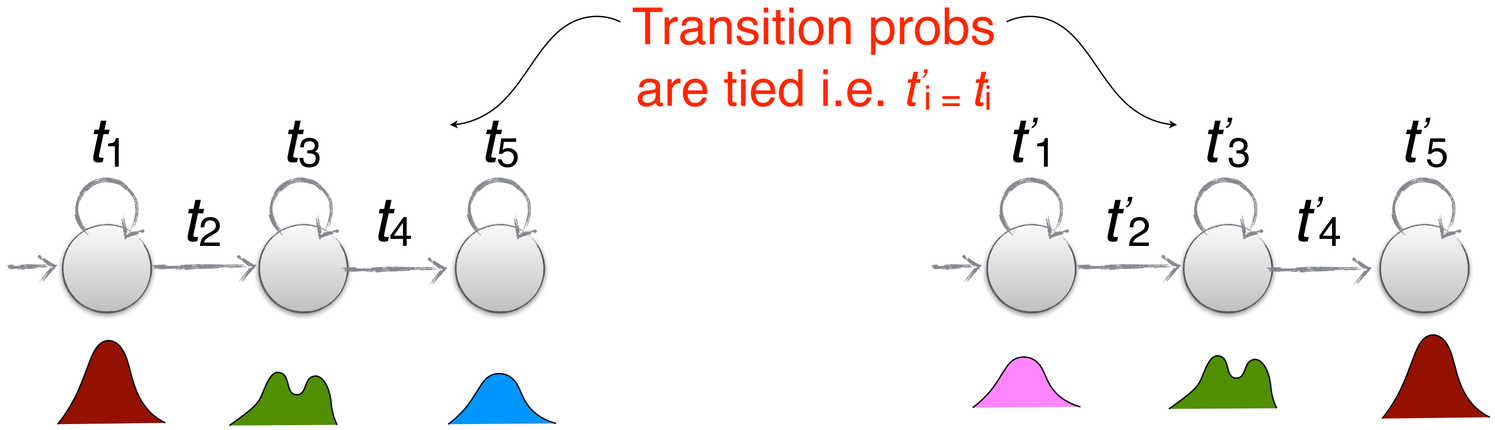

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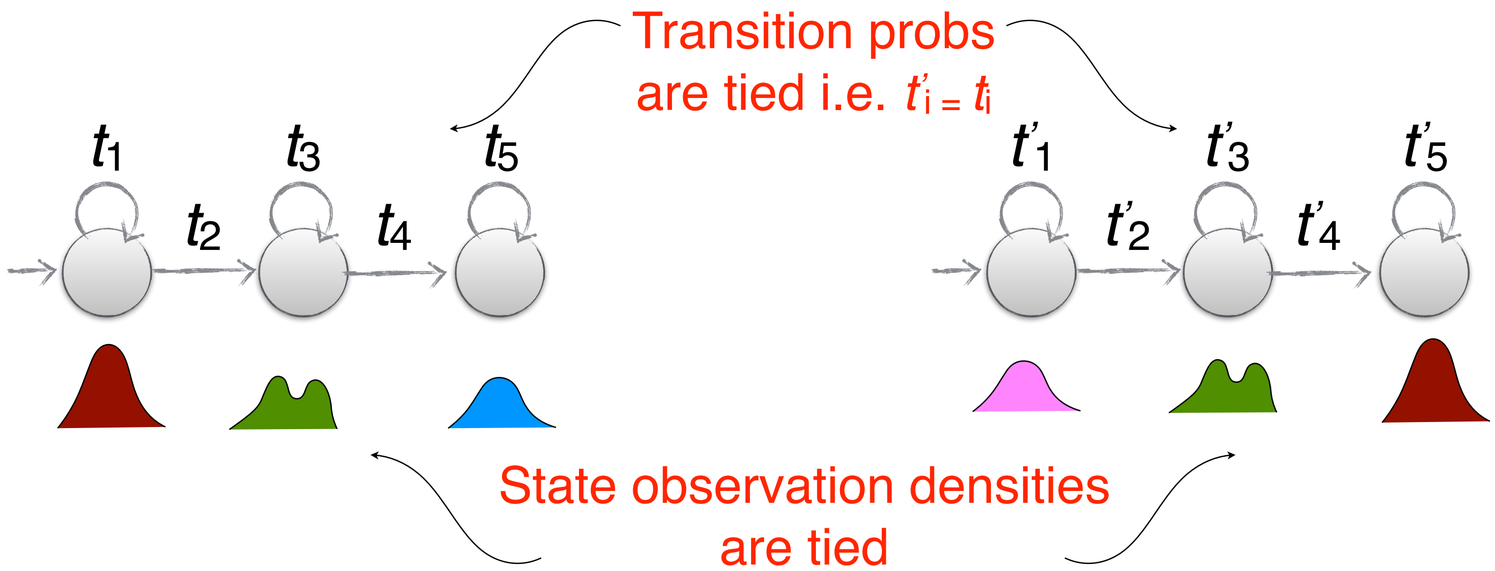

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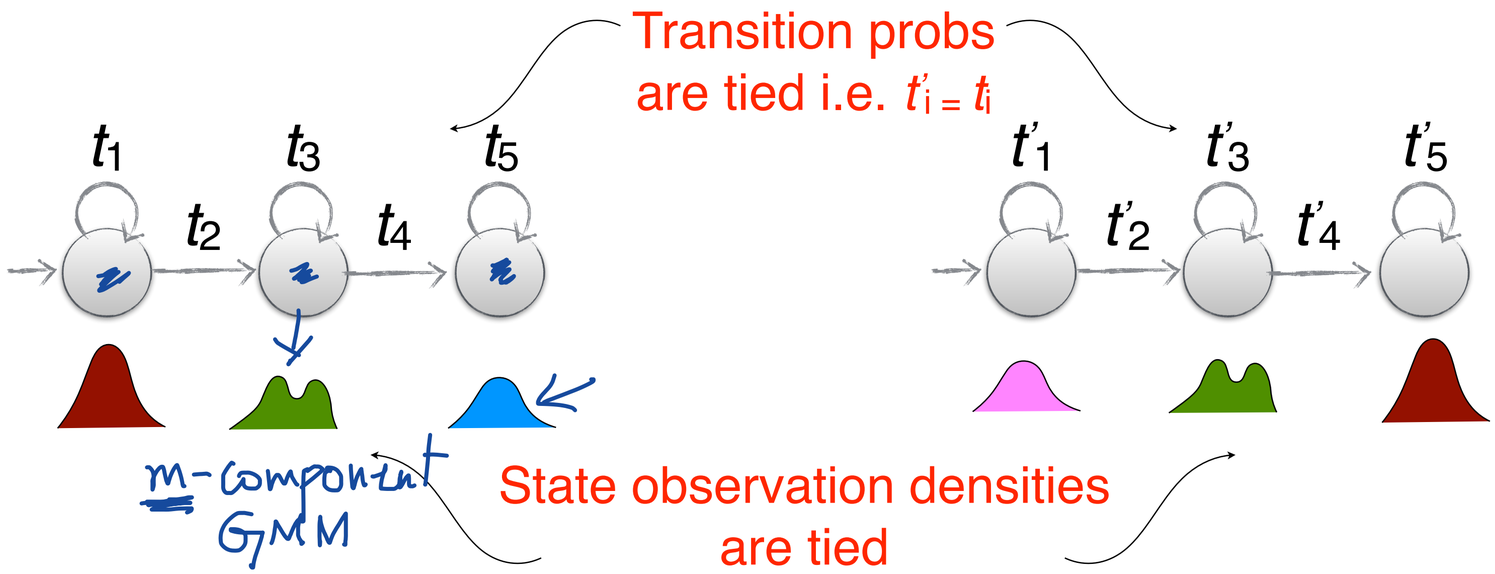

- More parameter tying: Tying variances of all Gaussians within a state, tying variances of all Gaussians in all states, tying individual Gaussians, etc.

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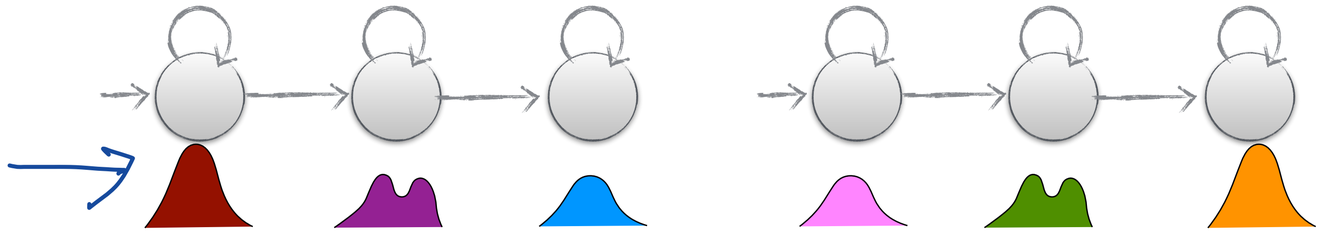
- All states share the same Gaussians (i.e. same means and covariances)
- Mixture weights are specific to each state



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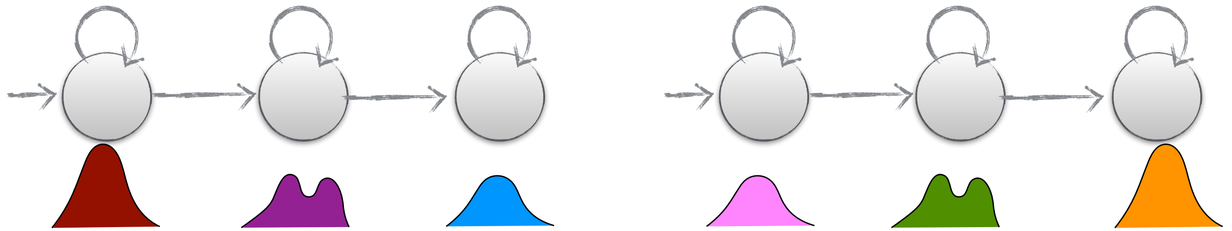

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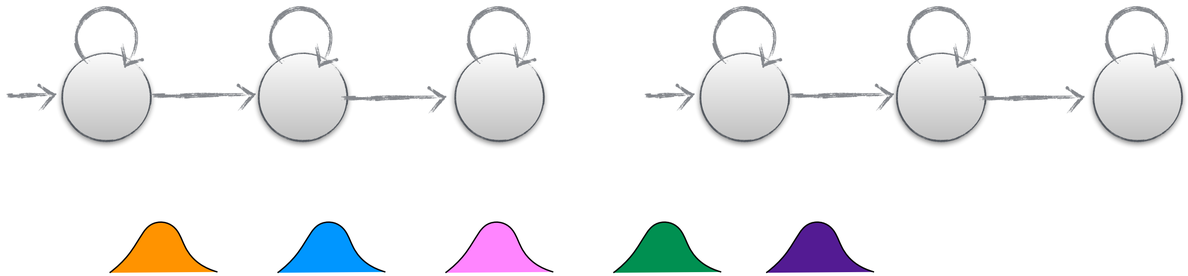

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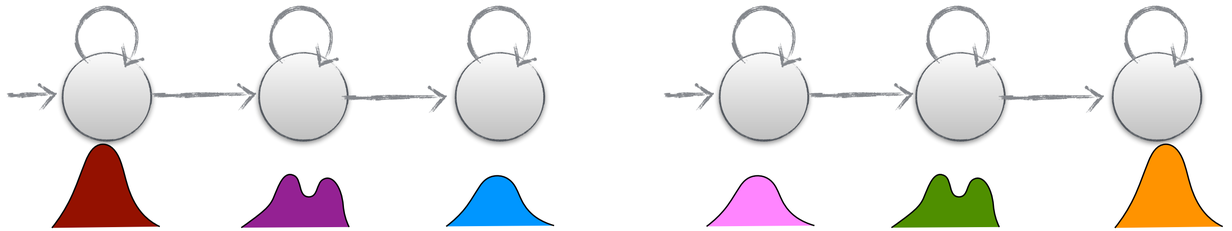

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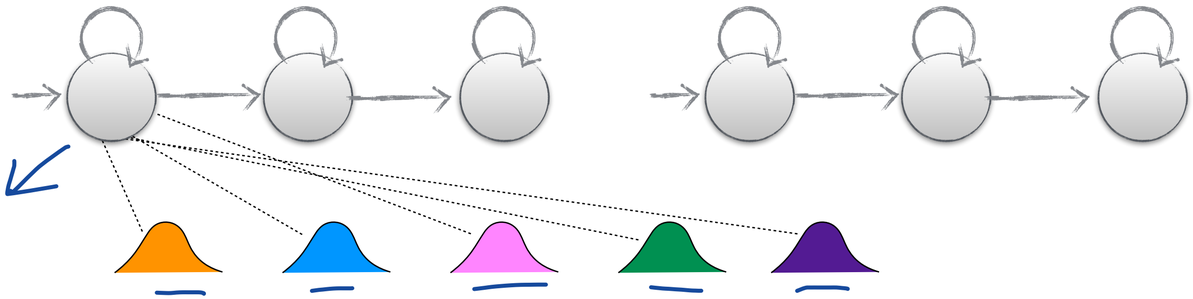

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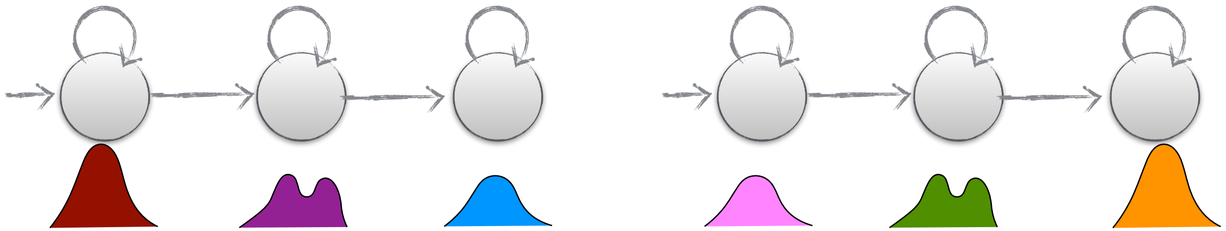

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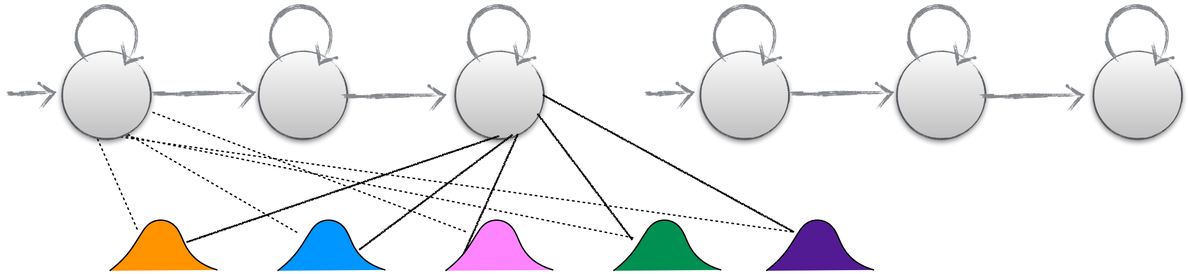

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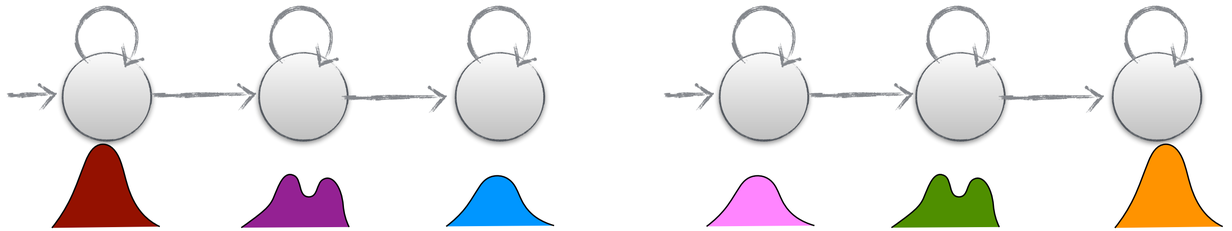

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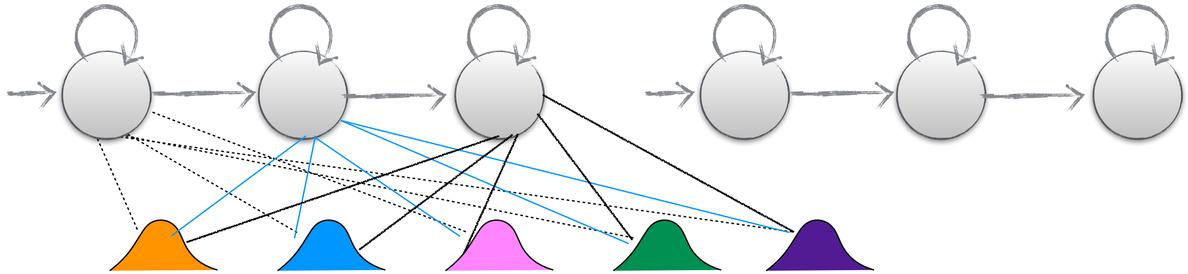

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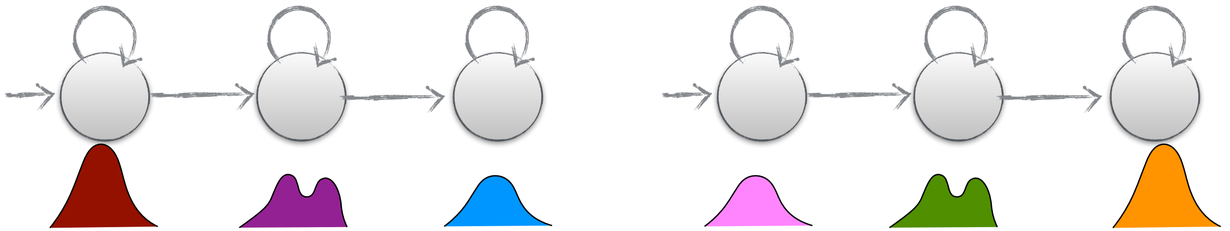

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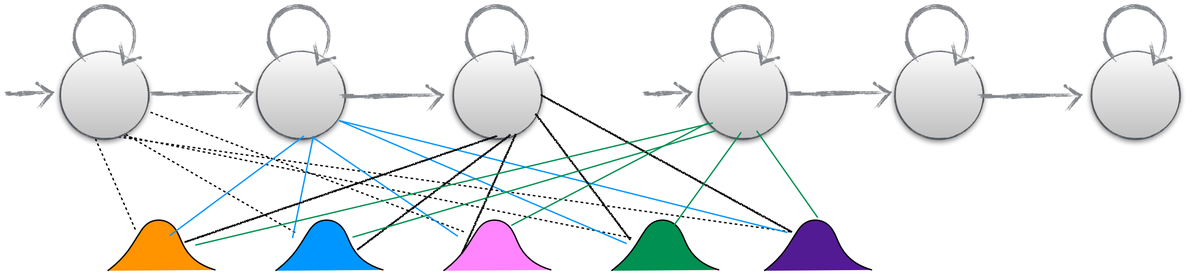

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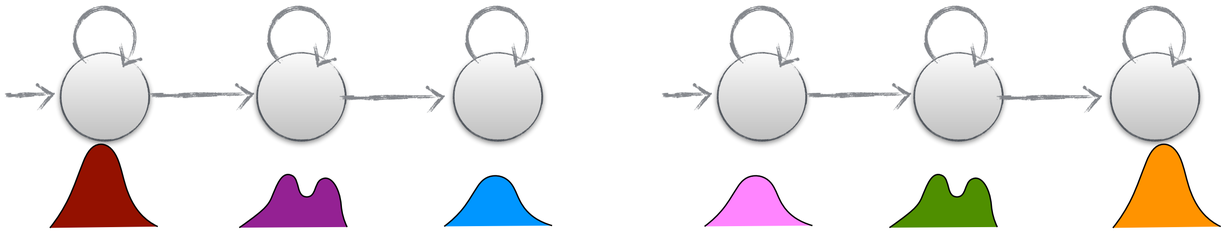

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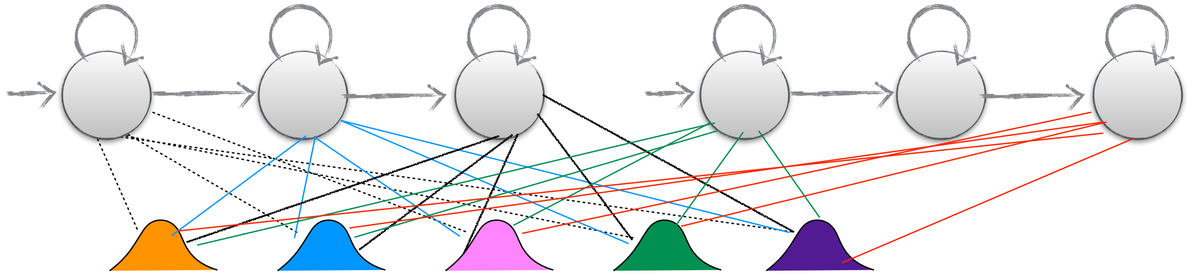

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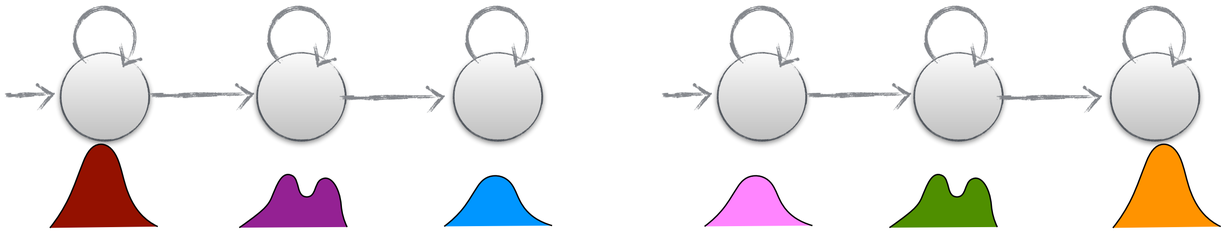

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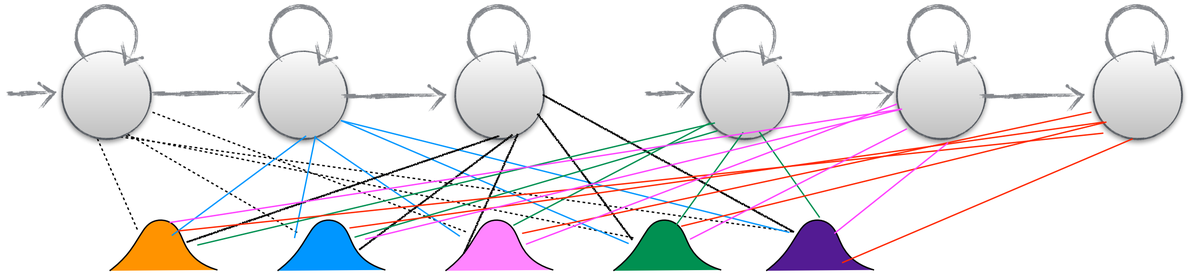

Triphone HMMs (Tied Mixture Models)

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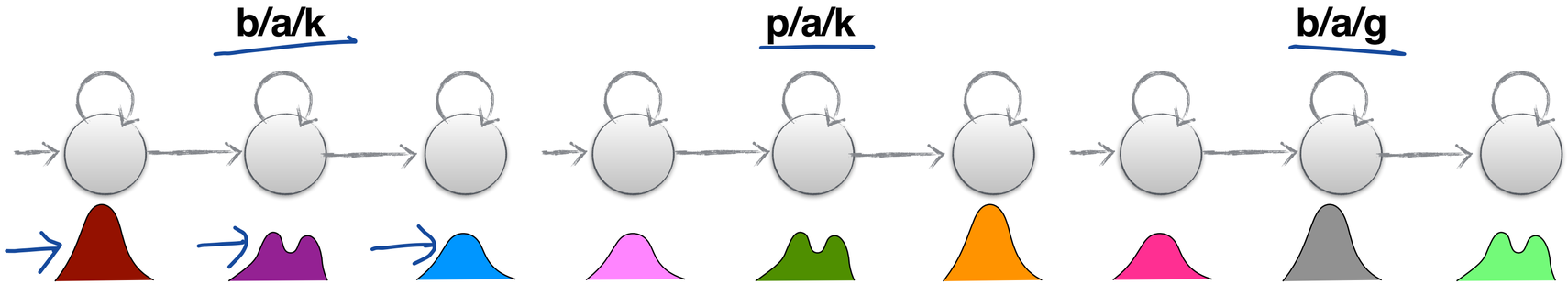

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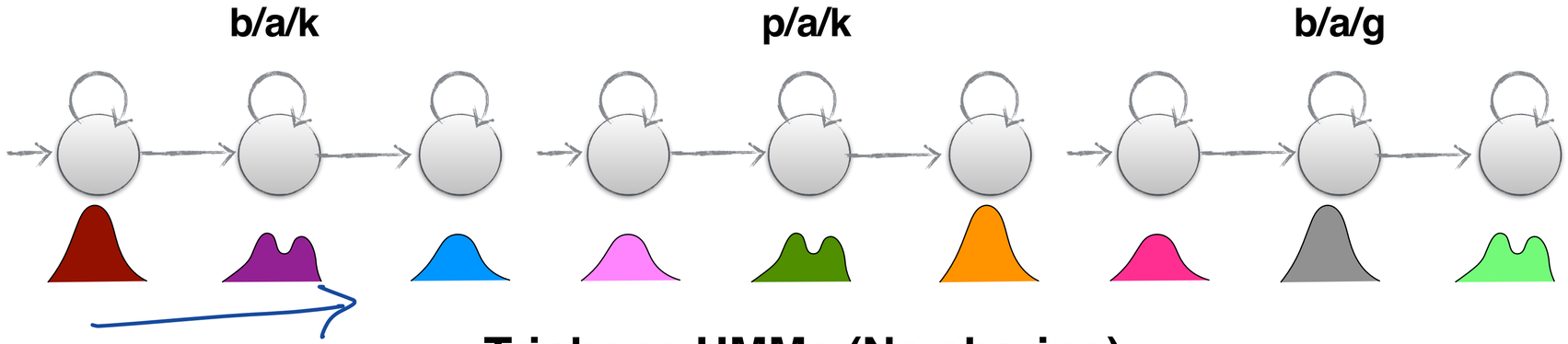

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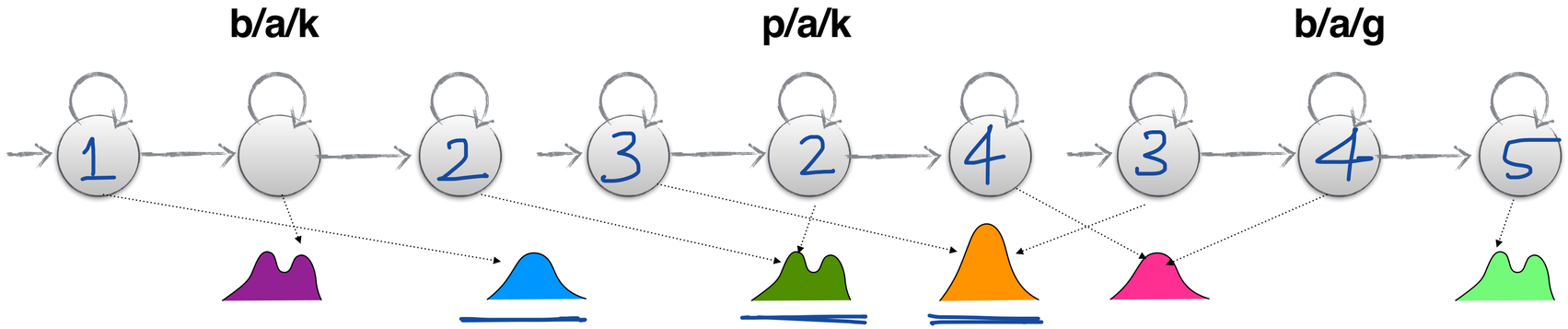


Triphone HMMs (State Tying)

Tied state HMMs: Step 1

Create and train 3-state monophone HMMs with single Gaussian observation probability densities

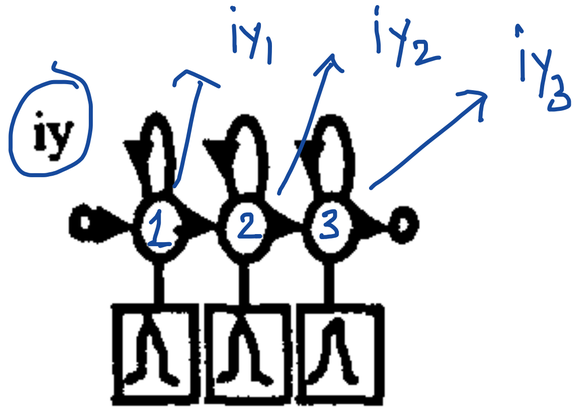
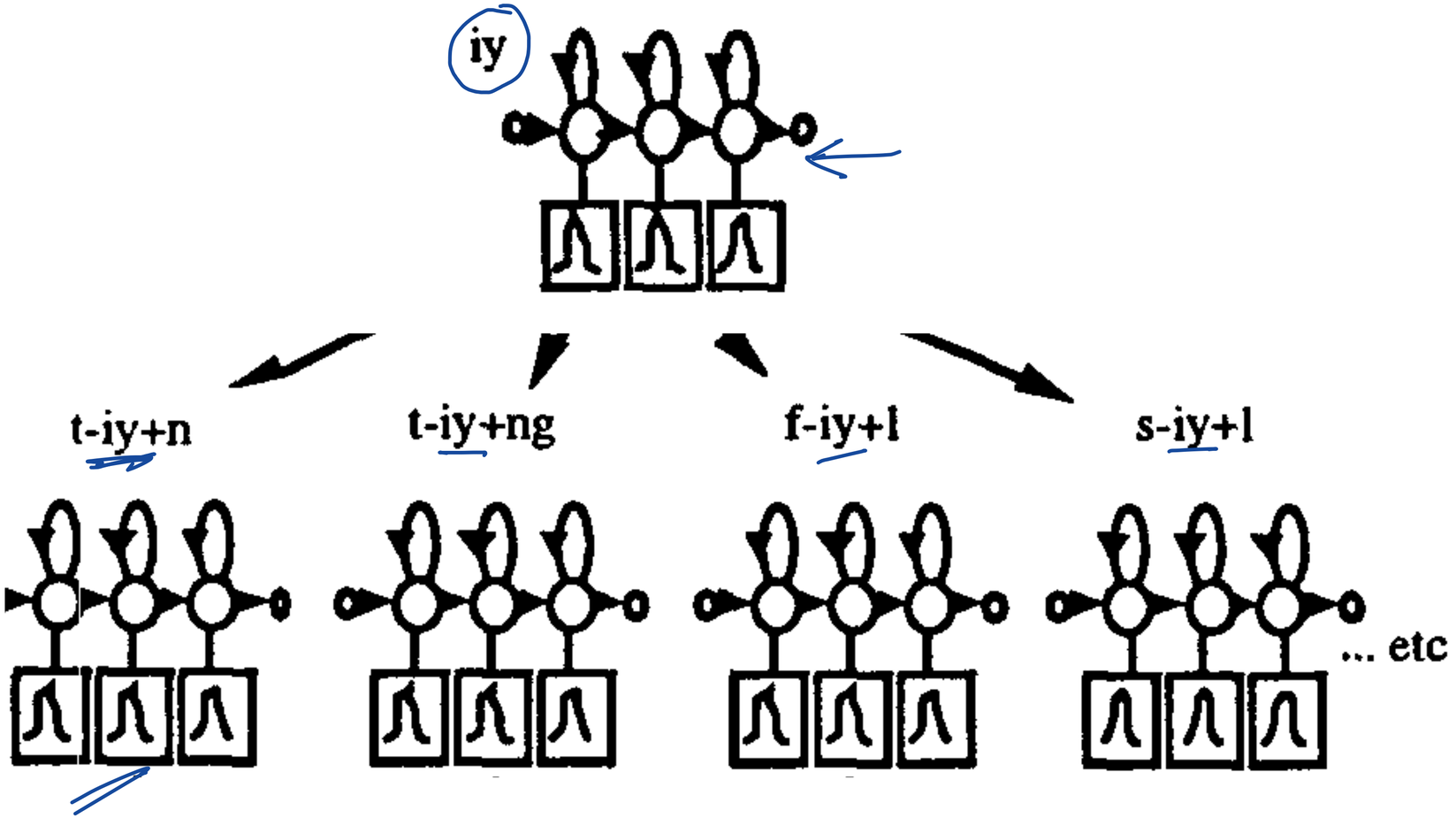


Image from: Young et al., “Tree-based state tying for high accuracy acoustic modeling”, ACL-HLT, 1994

Tied state HMMs: Step 2

Clone these monophone distributions to initialise a set of untied triphone models



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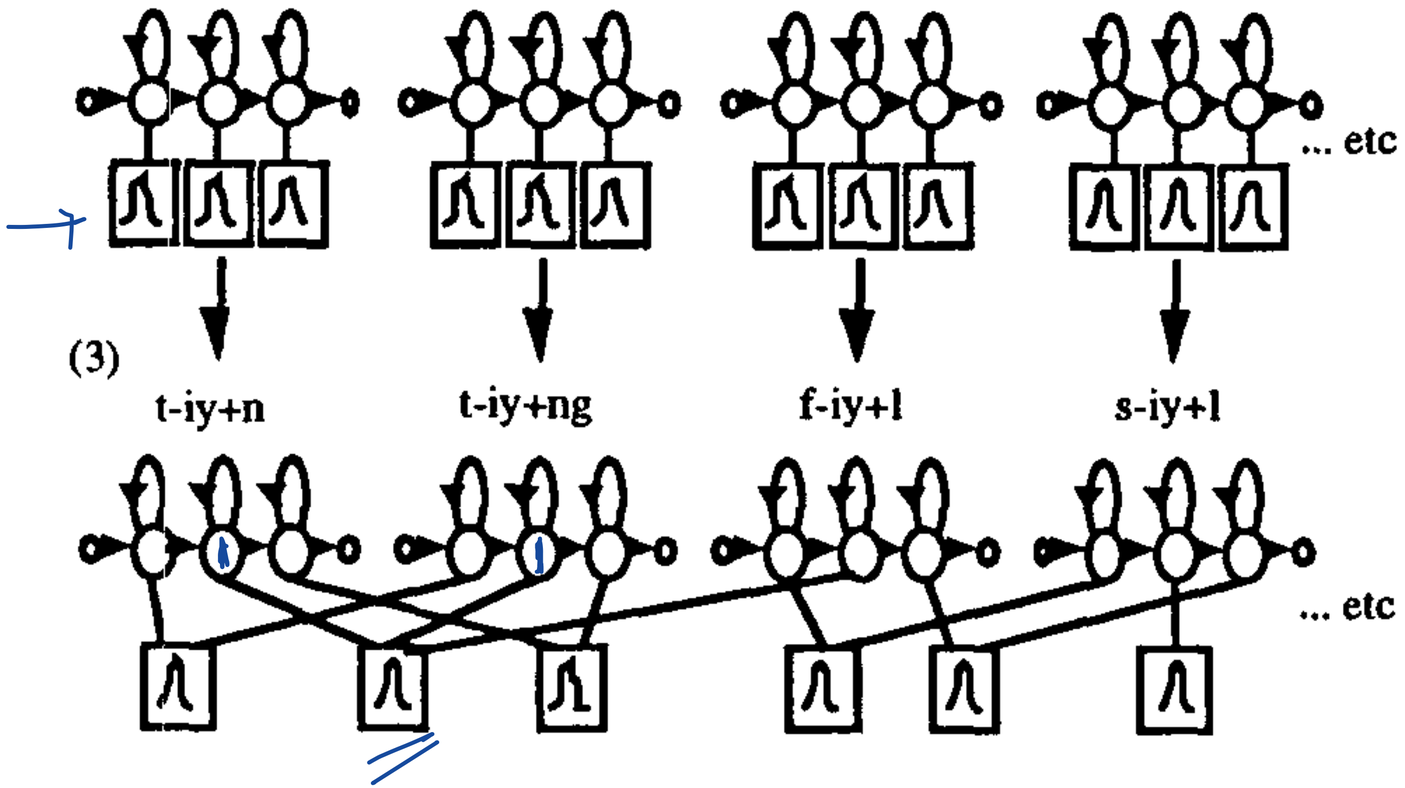
Tied state HMMs: Step 3



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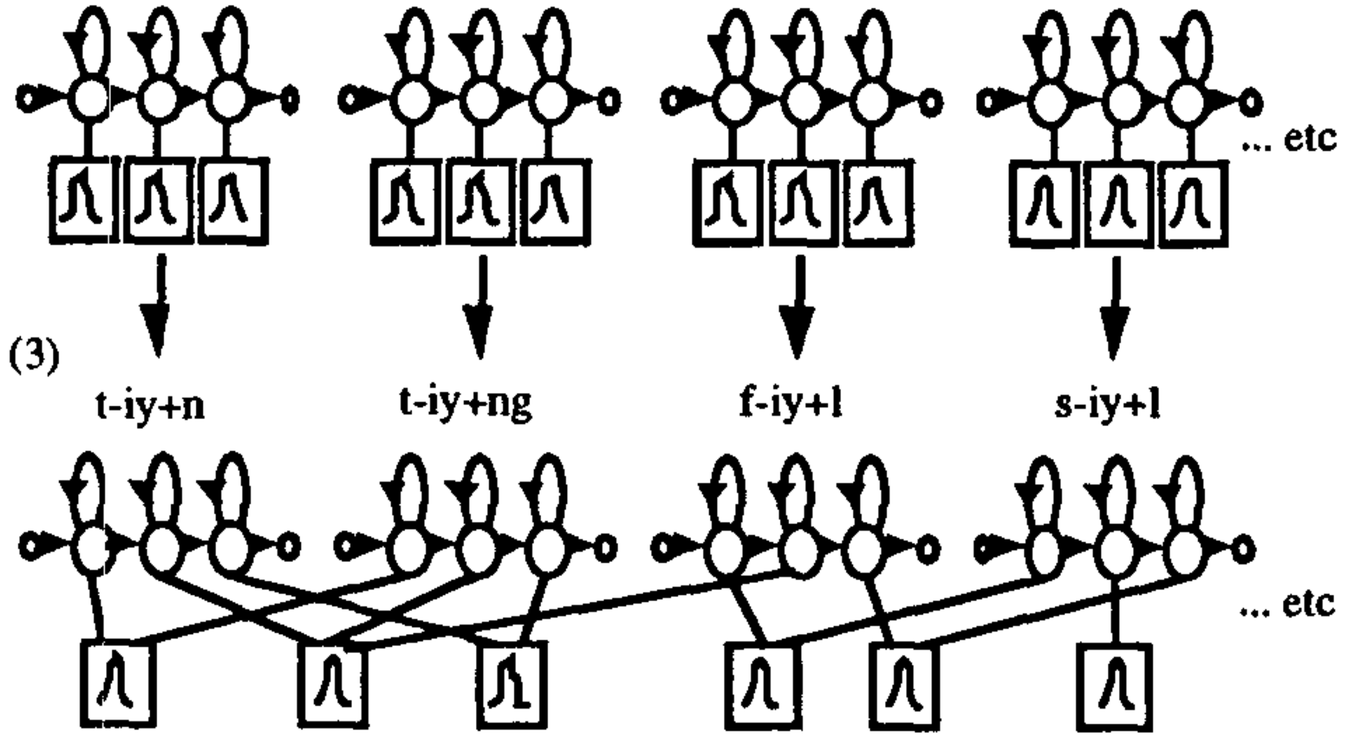

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Popular option: Use ***decision trees*** to determine which states should be tied together!

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Decision Trees

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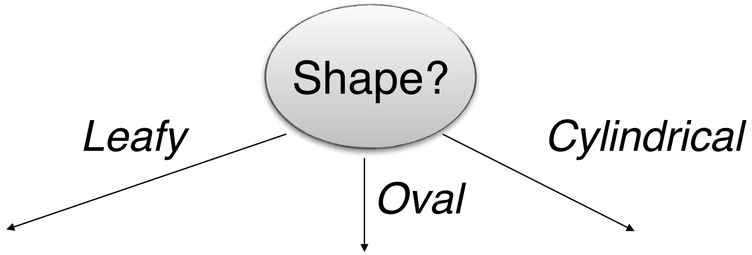
Classification using a decision tree:

Begins at the root node: What property is satisfied?



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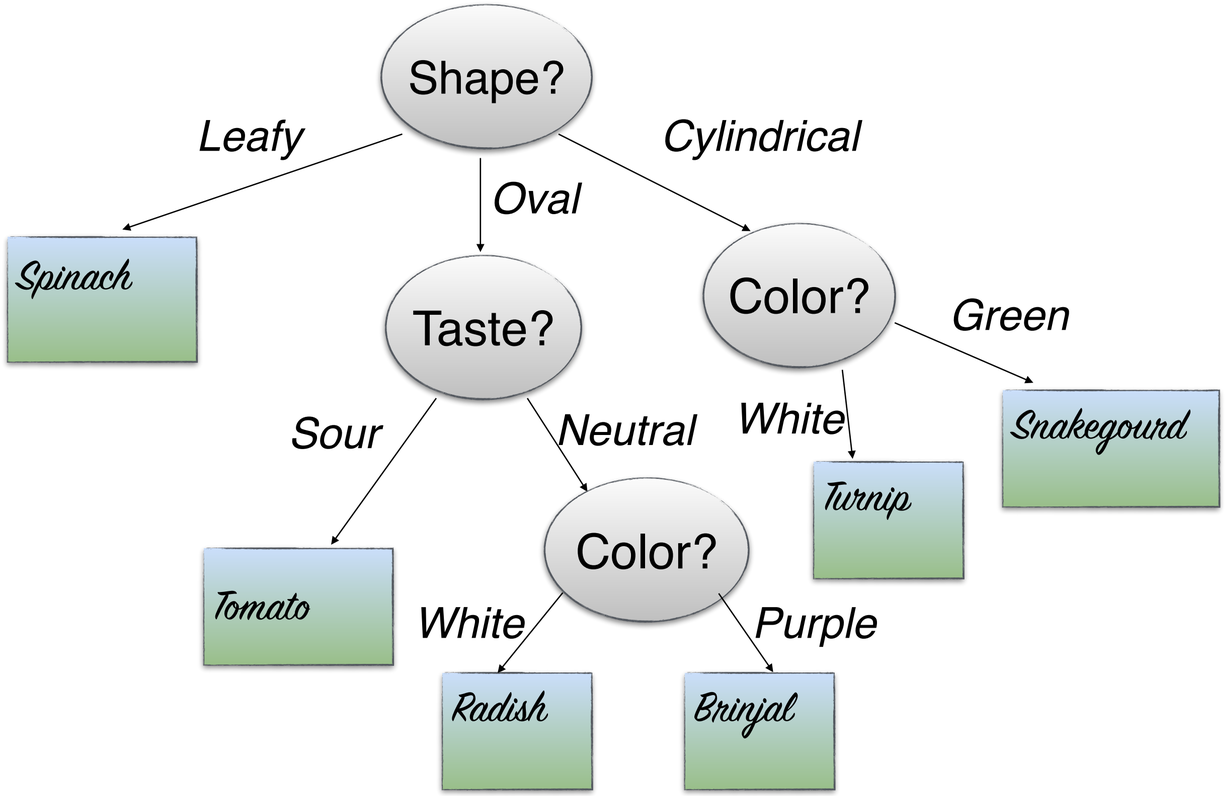
Depending on answer, traverse to different branches



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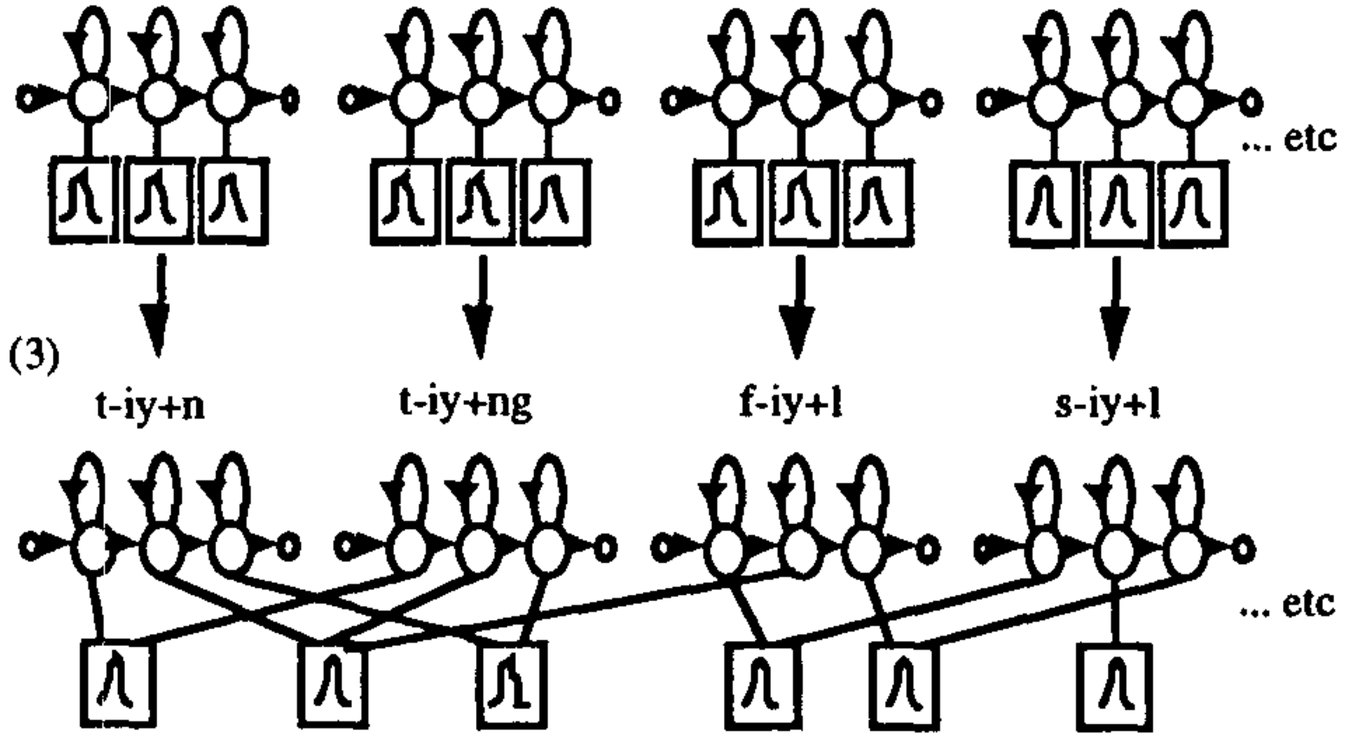
  3. When is a node a leaf?
     Set threshold in reduction in impurity

Tied state HMMs: Step 3



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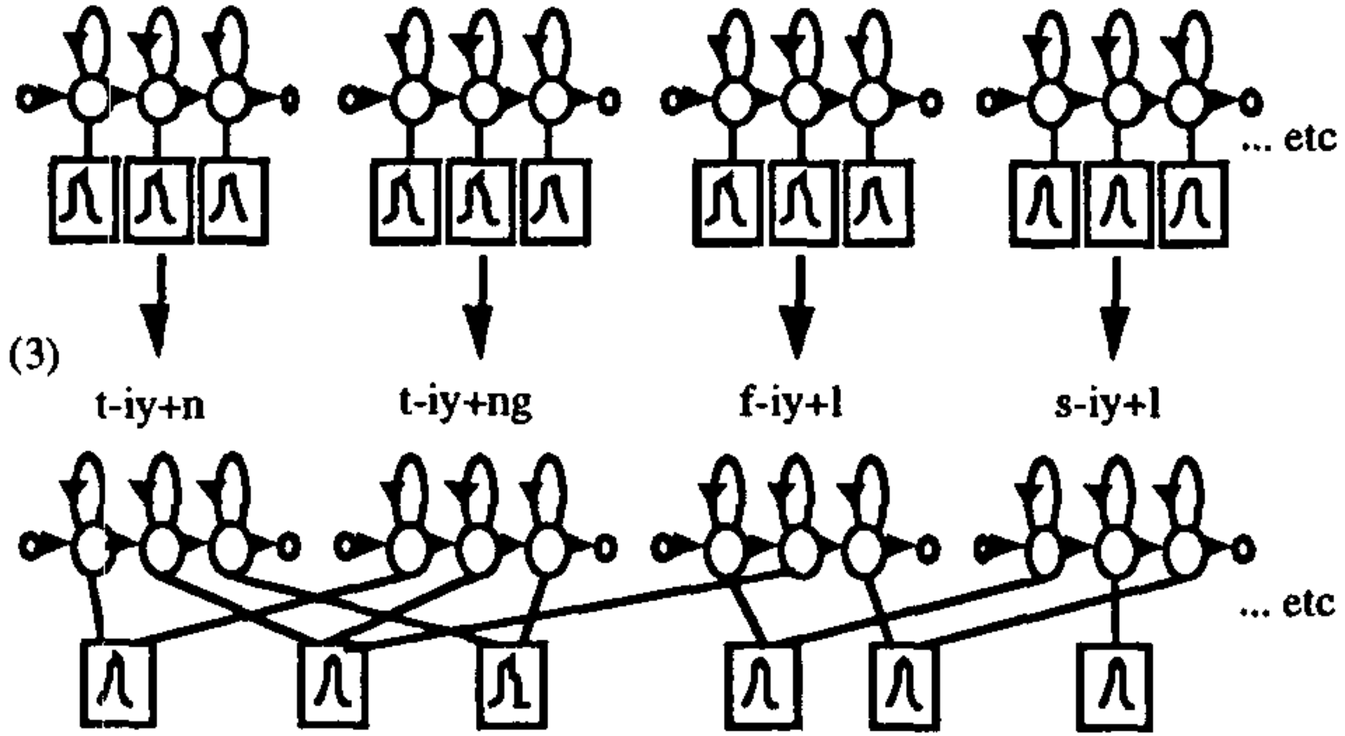

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Example: Phonetic Decision Tree (DT)

One tree is constructed for each state of each monophone to cluster all the corresponding triphone states

OW1 OW2 OW3

Head node
aa2/ow2/f2, aa2/ow2/s2,
aa2/ow2/d2, h2/ow2/p2,
aa2/ow2/n2, aa2/ow2/g2,
…

DT for center state of [ow]

Uses all training data tagged with *-*ow*$_2$+*

$O_1, \ldots, O_T$

$P_1, \ldots, P_K$

$O_1, \ldots, O_T$

$P'_1, \ldots, P'_T$

$P'_1 = P_1$

$P'_T = P_K$

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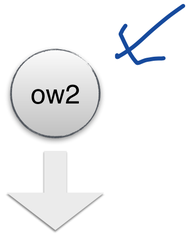

Head node
aa_2/ow_2/f_2, aa_2/ow_2/s_2,
aa_2/ow_2/d_2, h_2/ow_2/p_2,
aa_2/ow_2/n_2, aa_2/ow_2/g_2,
…

DT for center state of [ow]

Uses all training data tagged with *-ow_2+*

How do we determine this training data? Coming up in two slides.

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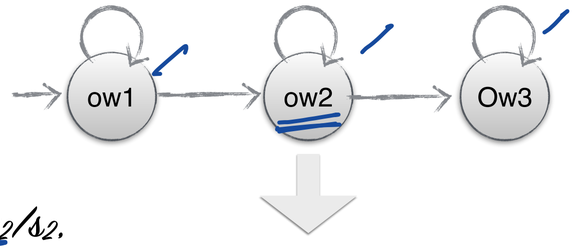

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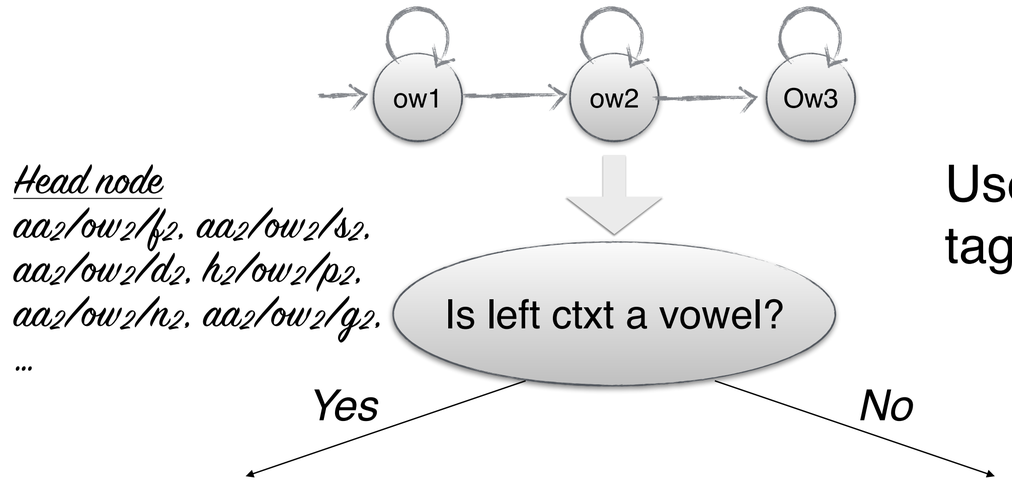

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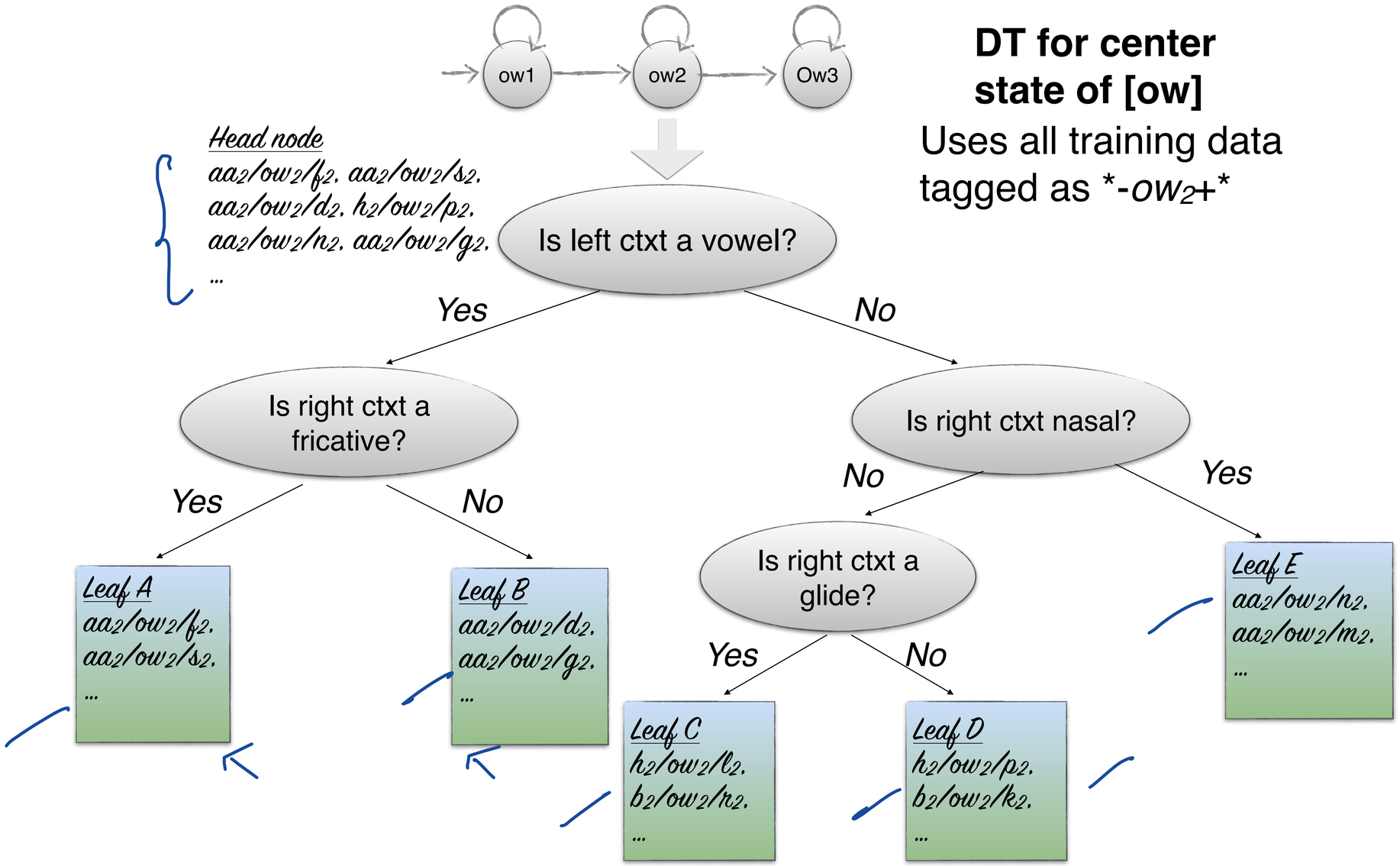

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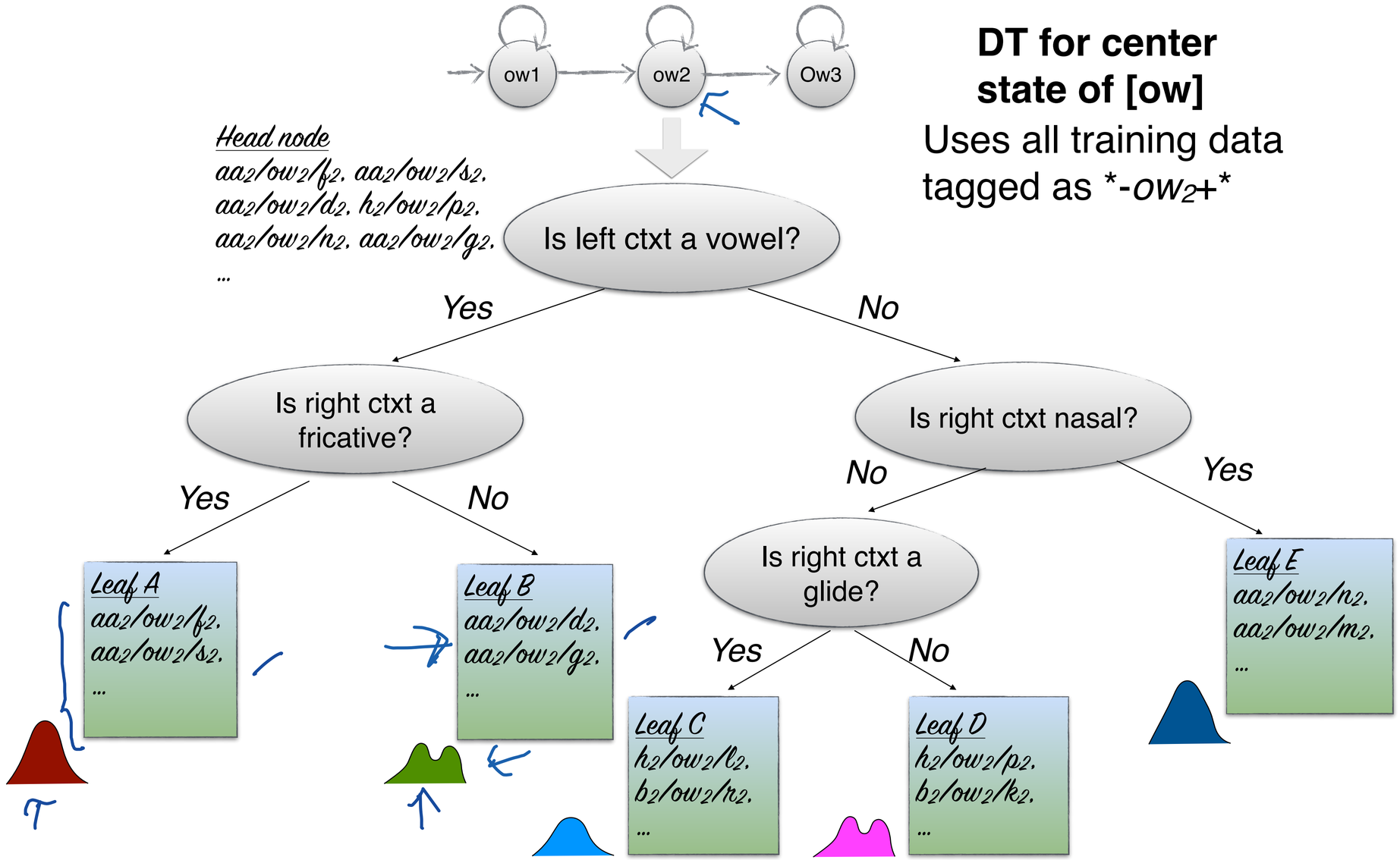

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How do we build these phone DTs?

1. What questions are used?

   Linguistically-inspired binary questions: “Does the left or right phone come from a broad class of phones such as vowels, stops, etc.?” “Is the left or right phone [k] or [m]?”

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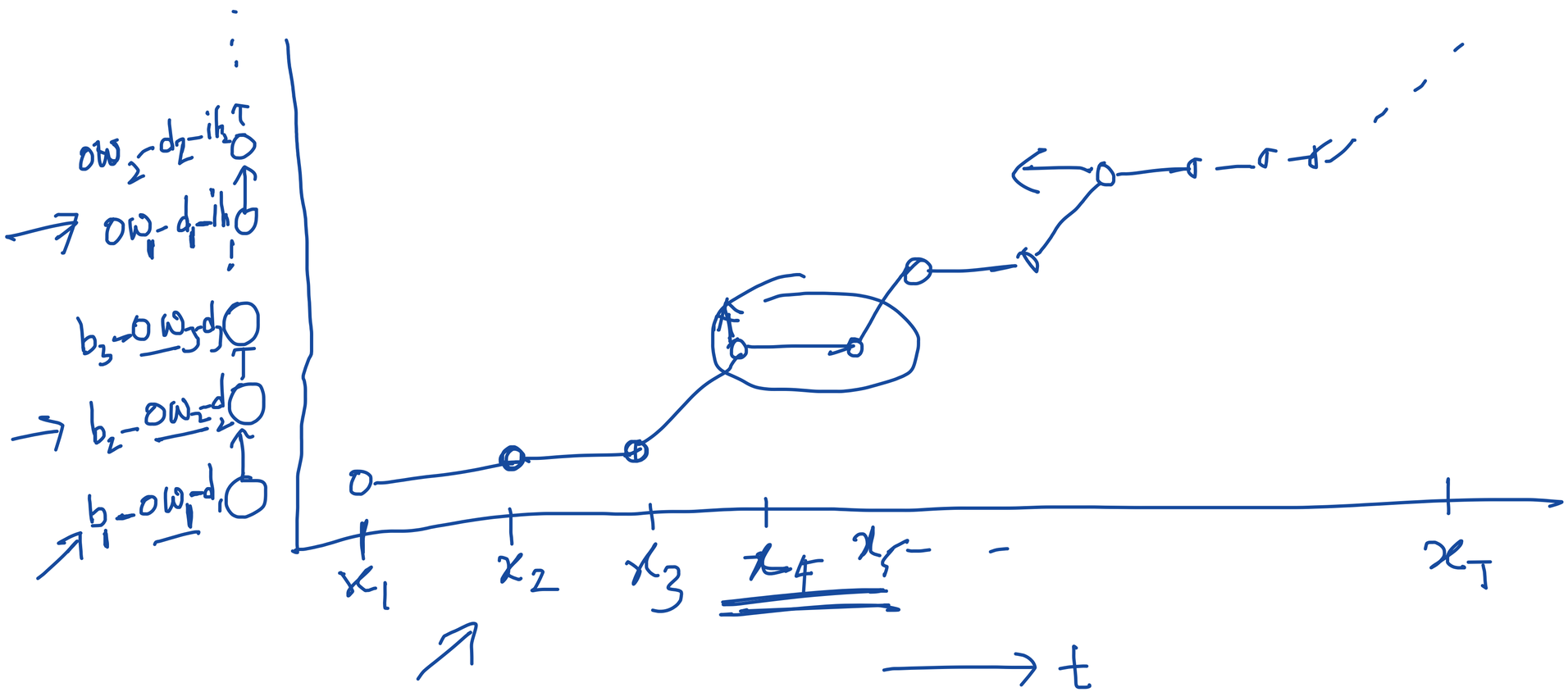
2. What is the training data for each phone state, p_j? (root node of DT)

   All speech frames that align with the j^{th} state of every triphone HMM that has p as the middle phone

Training data for DT nodes

Training data for DT nodes

- Align training instance $x = (x_1, \ldots, x_T)$ where $x_i \in \mathbb{R}^d$ with a set of triphone HMMs
- Use Viterbi algorithm to find the best HMM triphone state sequence corresponding to each x



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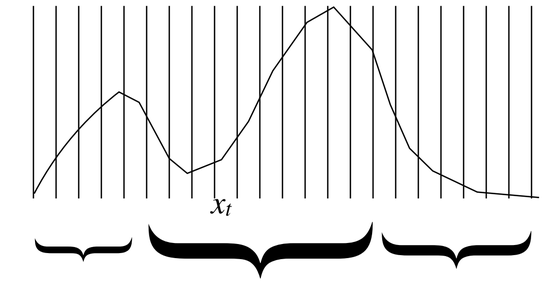

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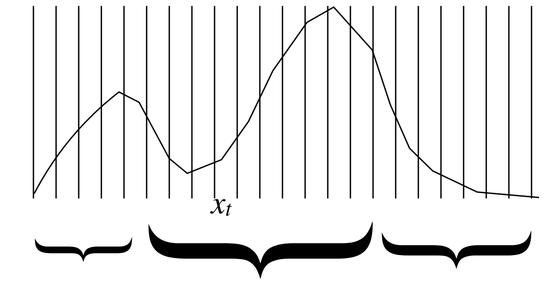

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- Training data corresponding to state j in phone p: Gather all x_t's that are tagged with ID *-p_j+*

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   Linguistically-inspired binary questions: “Does the left or right phone come from a broad class of phones such as vowels, stops, etc.?” “Is the left or right phone [k] or [m]?”

2. What is the training data for each phone state, p_j? (root node of DT)

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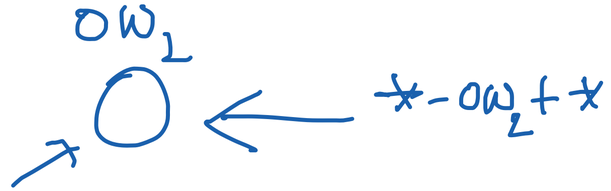
3. What criterion is used at each node to find the best question to split the data on?

   Find the question which partitions the states in the parent node so as to give the maximum increase in log likelihood

Likelihood of a cluster of states



- If a cluster of HMM states, $S = \{s_1, s_2, \ldots, s_M\}$ consists of M states and a total of K acoustic observation vectors are associated with S, $\{x_1, x_2 \ldots, x_K\}$, then the log likelihood associated with S is:

$$\mathcal{L}(S) = \sum_{i=1}^{K} \sum_{s \in S} \log \Pr(x_i; \mu_S, \Sigma_S) \gamma_s(x_i)$$

state occupancy probability

- For a question q that splits S into S_{yes} and S_{no}, compute the following quantity:

$$\Delta_q = \mathcal{L}(S^q_{\text{yes}}) + \mathcal{L}(S^q_{\text{no}}) - \mathcal{L}(S)$$

$$q^* = \arg\max_q \Delta_q$$

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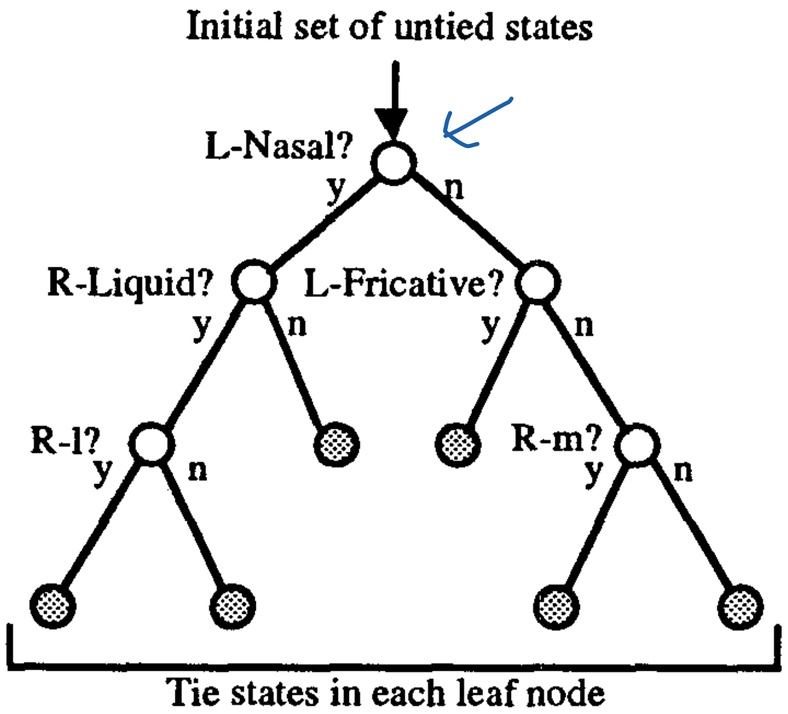
- Terminate when: Final Δ_q is below a threshold or data associated with a split falls below a threshold

Likelihood criterion



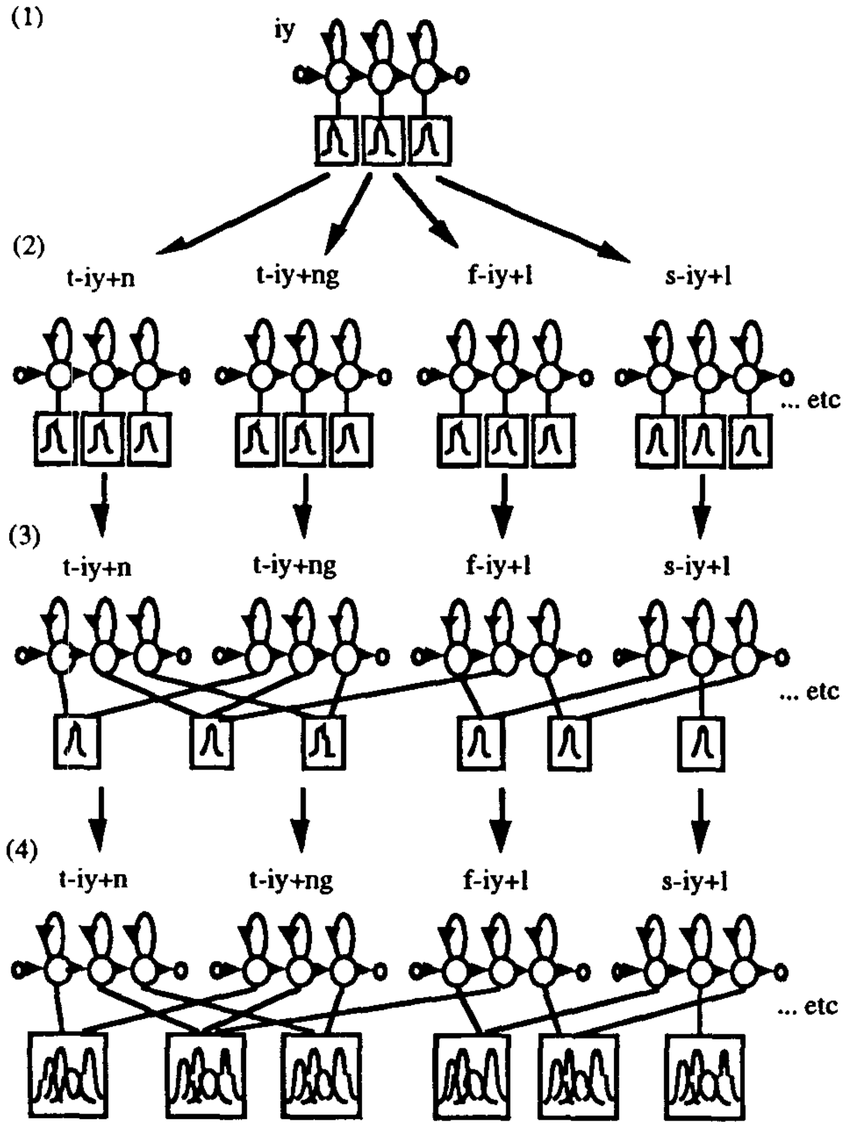
Given a phonetic question, let the initial set of untied states S be split into two partitions S_{yes} and S_{no}

Each partition is clustered to form a single Gaussian output distribution with mean $\mu_{S_{yes}}$ and covariance $\Sigma_{S_{yes}}$

Use the likelihood of the parent state and the subsequent split states to determine which question a node should be split on

Image from: Young et al., “Tree-based state tying for high accuracy acoustic modeling”, ACL-HLT, 1994

Tied state HMMs



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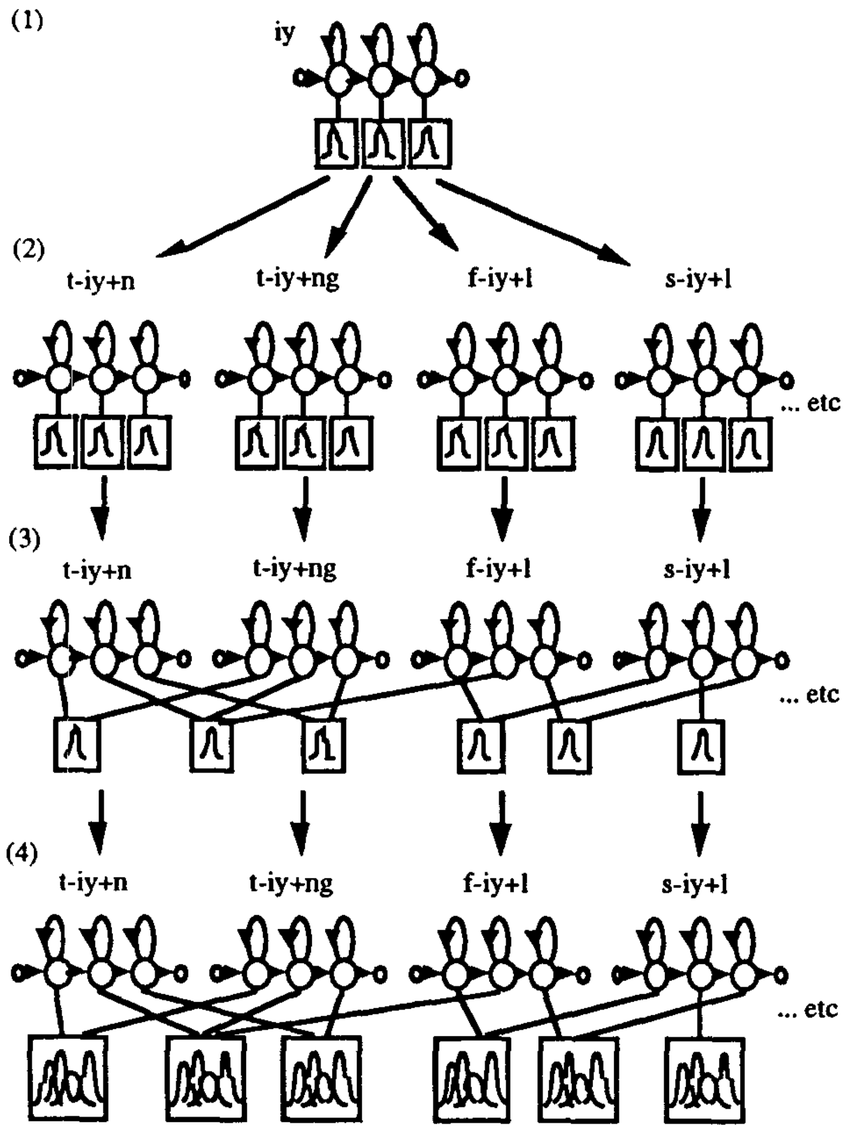

Four main steps in building a tied state HMM system:

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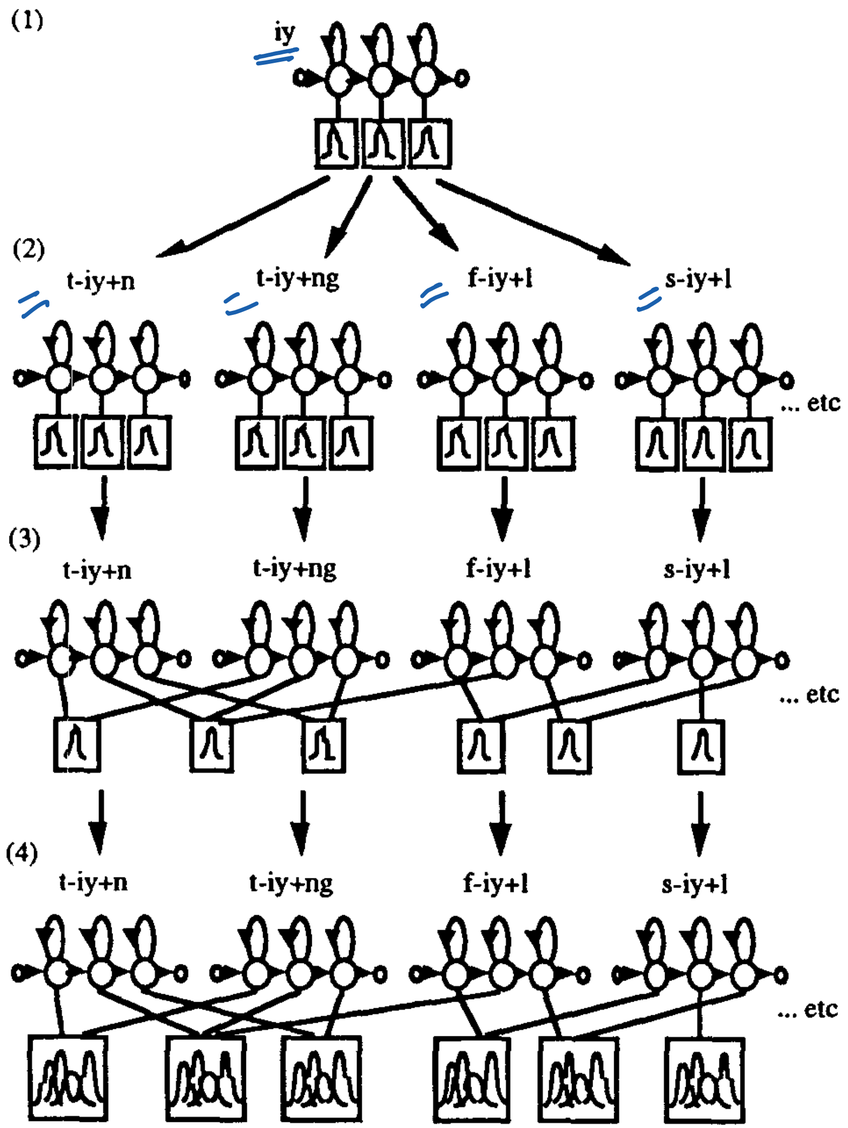

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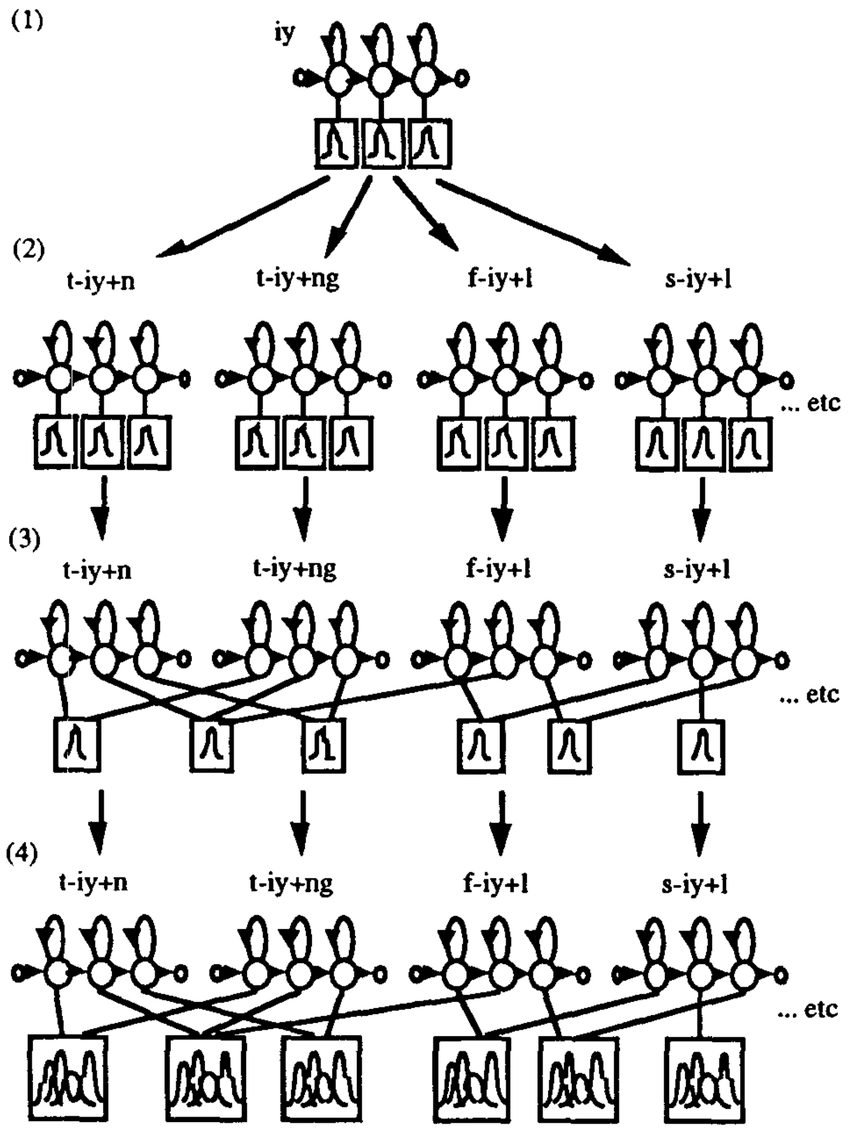

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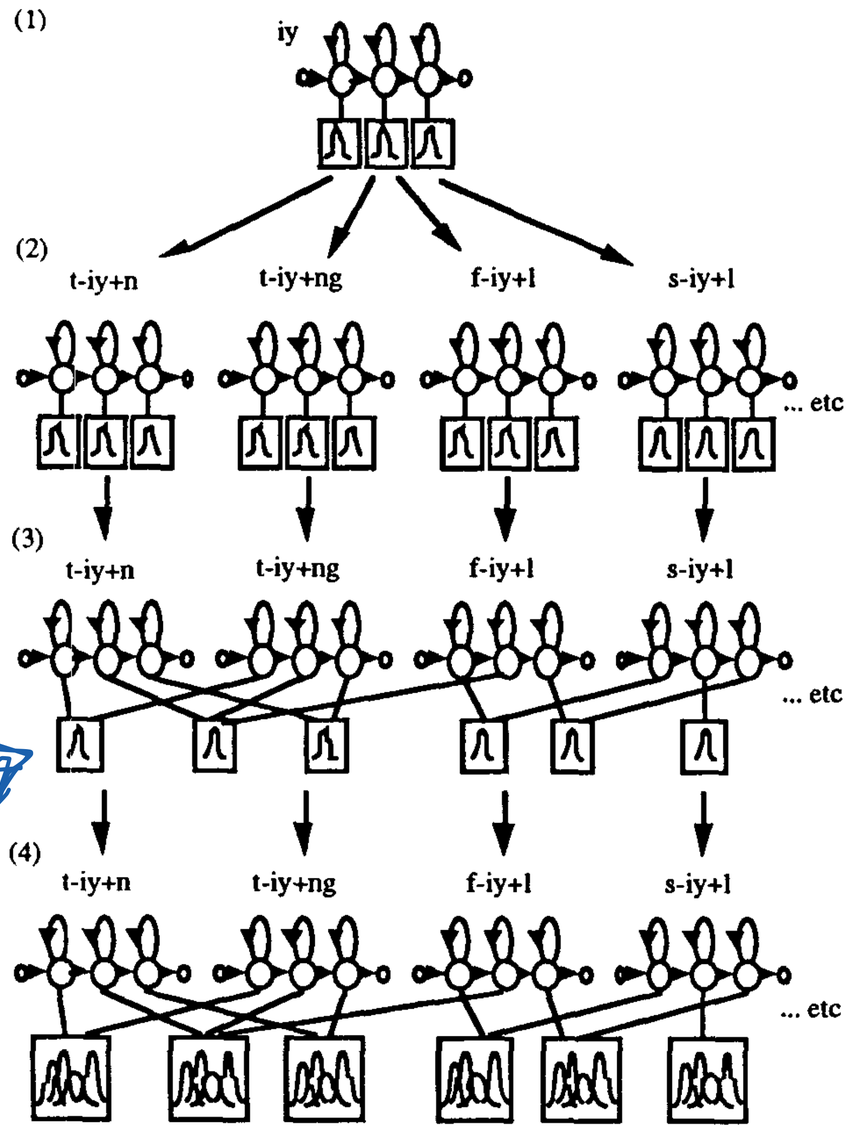

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4. Number of mixture components in each tied state is increased and models re-estimated using BW

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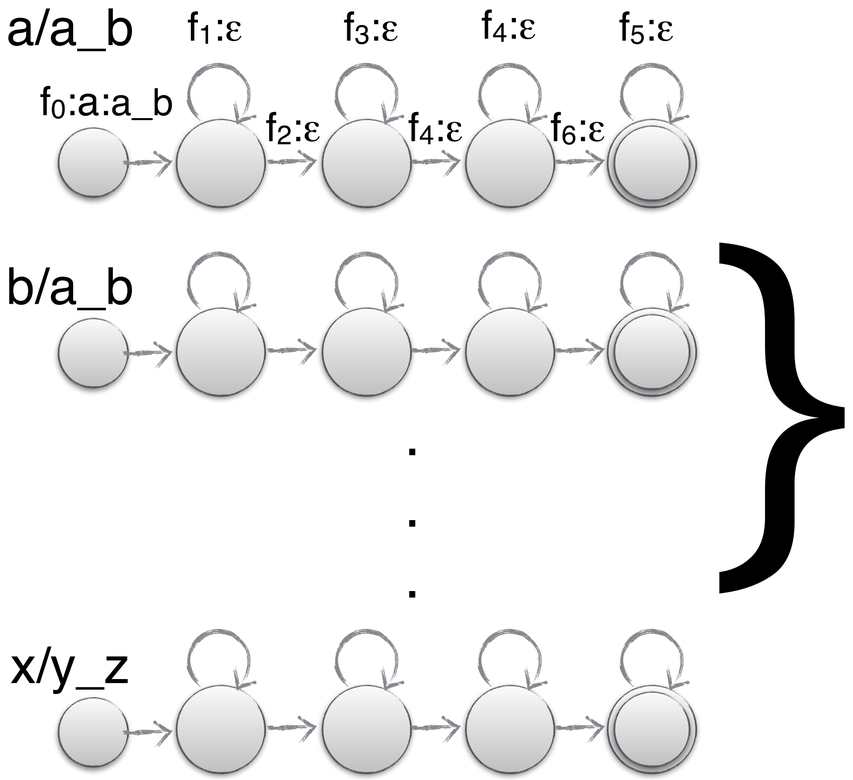
That's a wrap on HMM-based acoustic models

H



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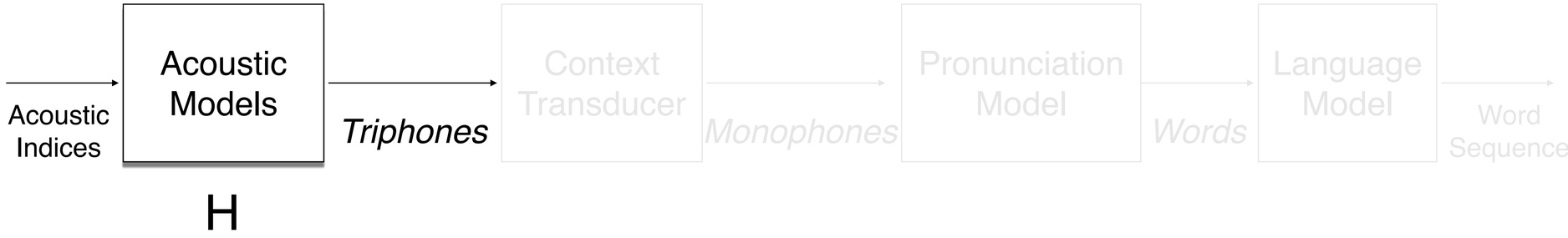

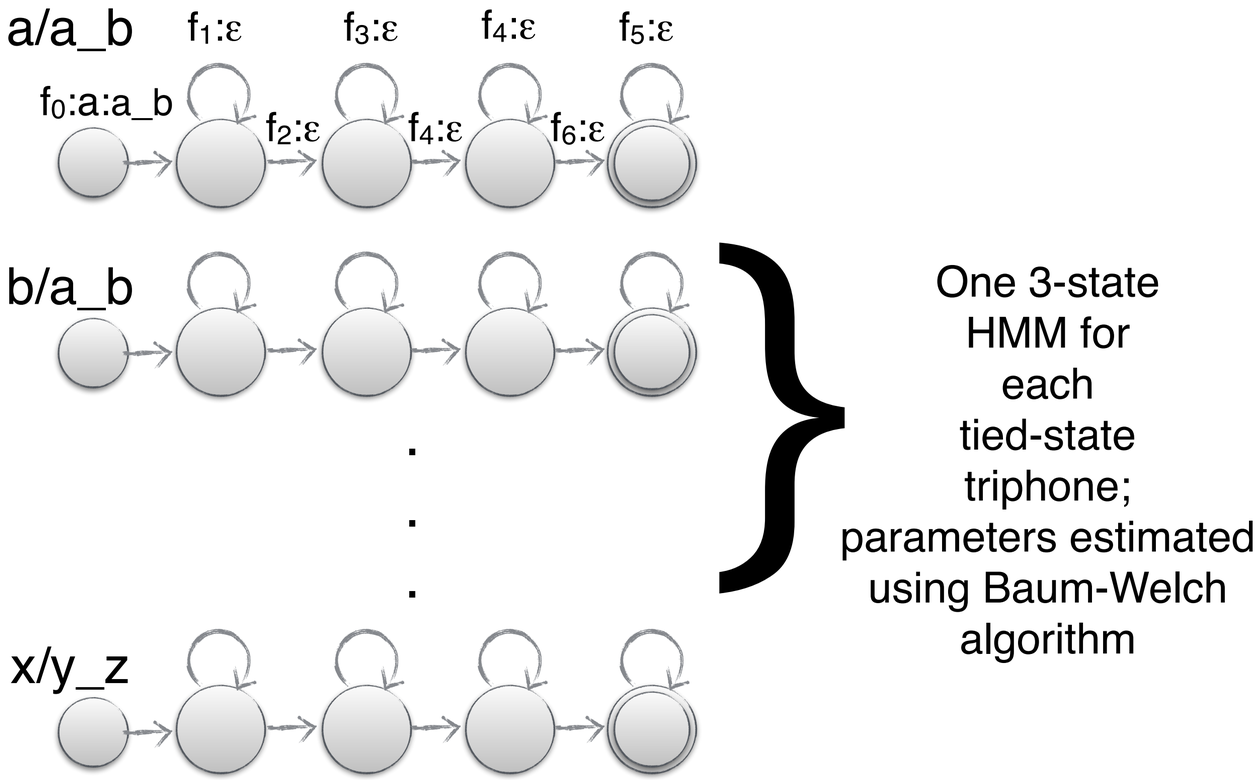

One 3-state HMM for each tied-state triphone; parameters estimated using Baum-Welch algorithm

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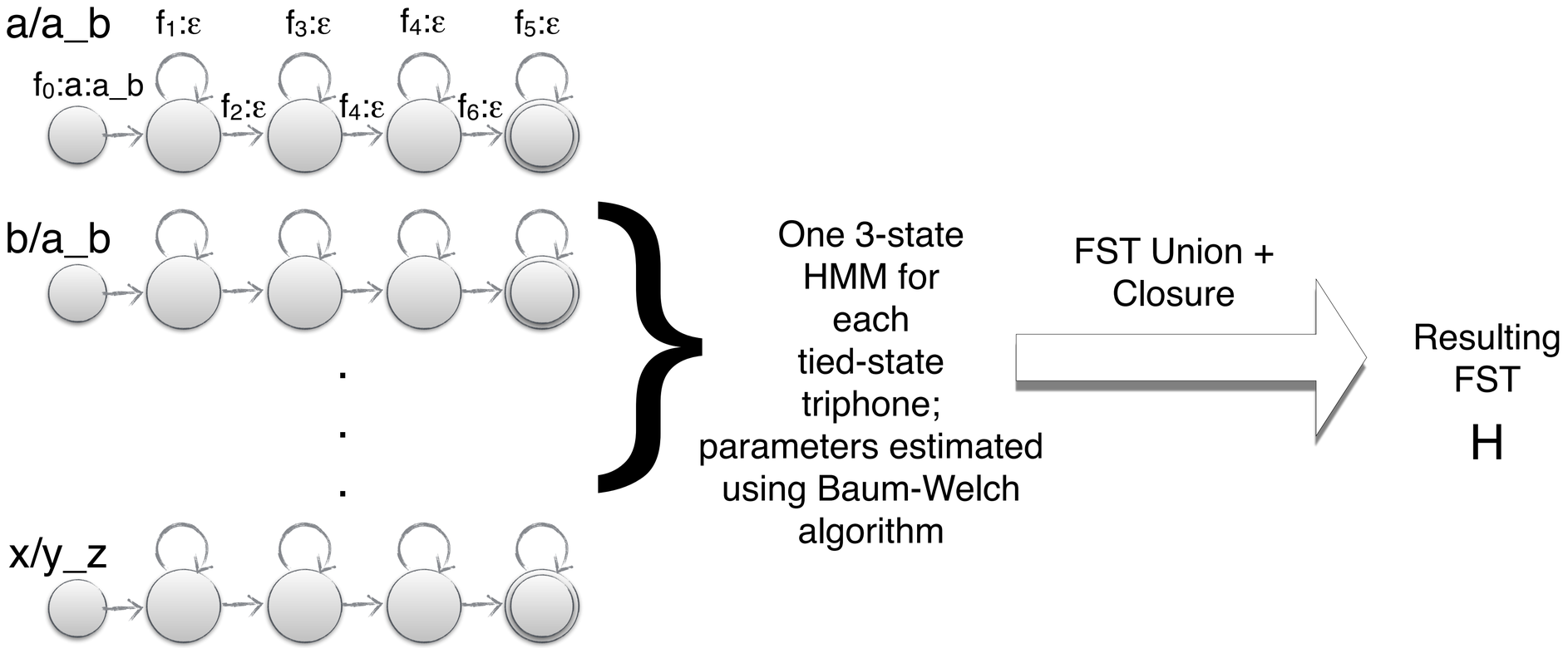

DNN-based acoustic models?

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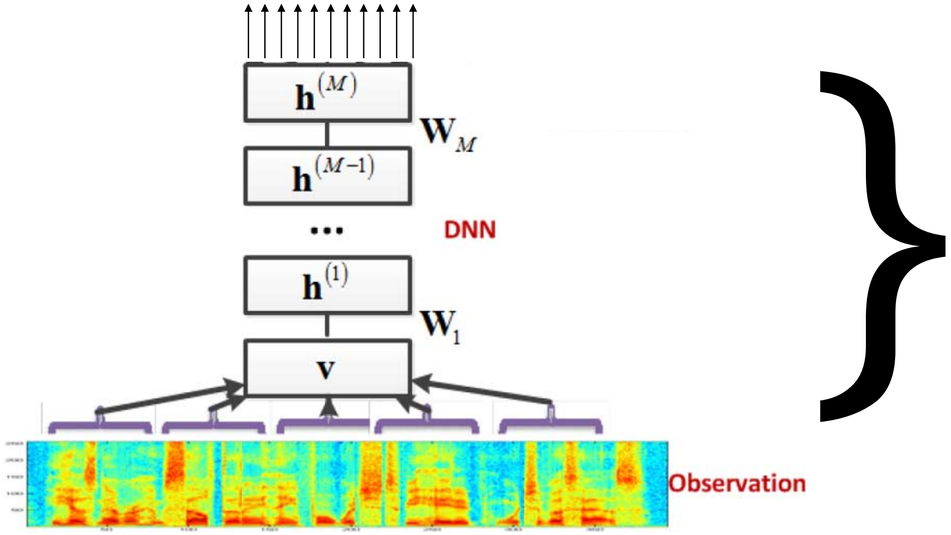
Phone posteriors



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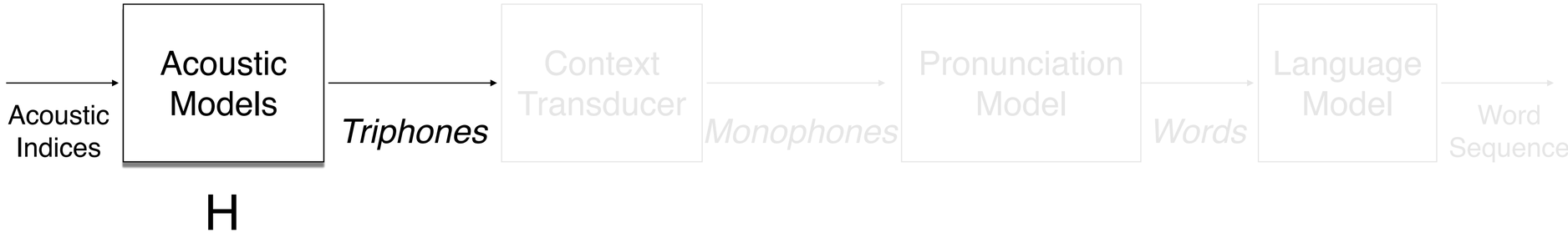

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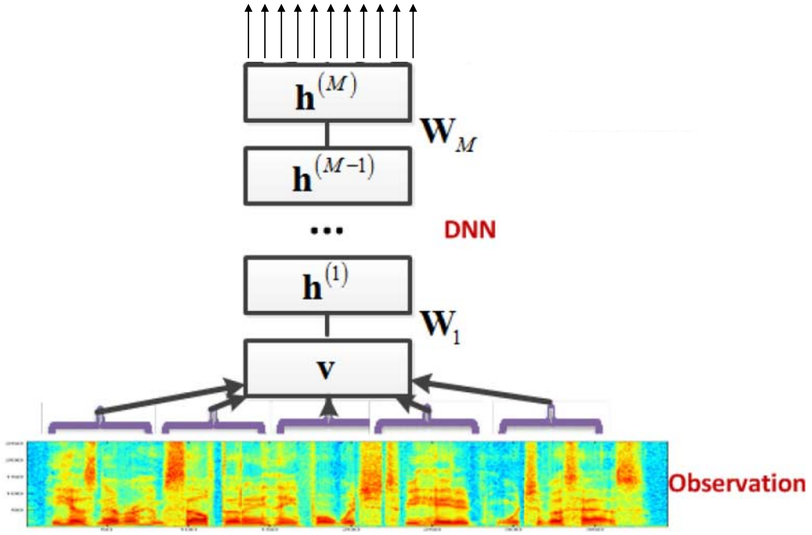

Can we use deep neural networks instead of HMMs to learn mappings between acoustics and phones?

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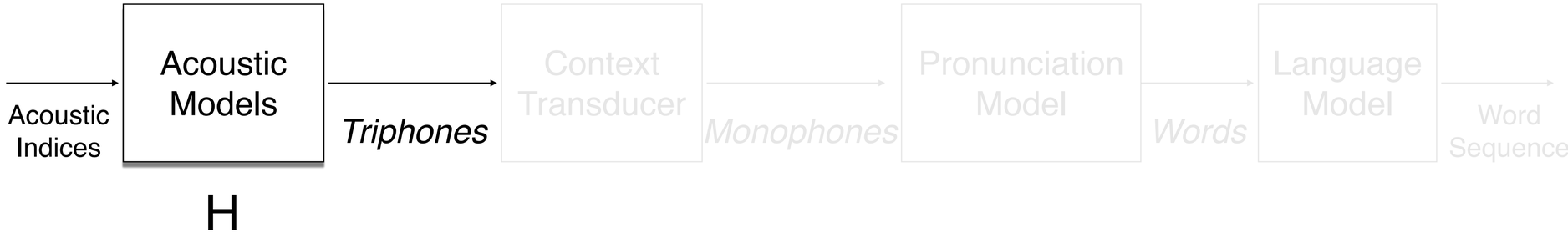

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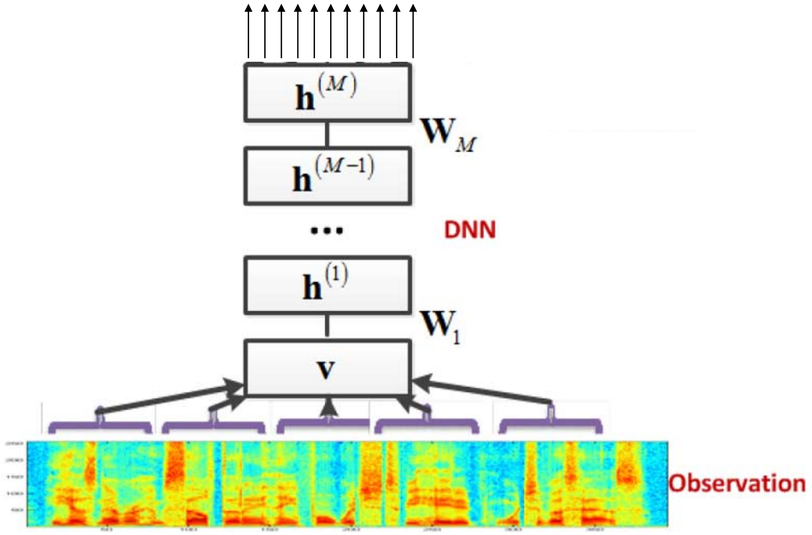

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Resulting FST

H