Modelling speech with HMMs

Steve Renals

Automatic Speech Recognition
ASR Lecture 7
9 February 2008

Overview

Phone models

- Modelling phones with HMMs
- The need to model phonetic context
- Triphone models
- Smoothing—interpolation and backing-off
- Parameter sharing—tied mixtures, generalised triphones, state clustering
- Choosing which states to share—phonetic decision trees

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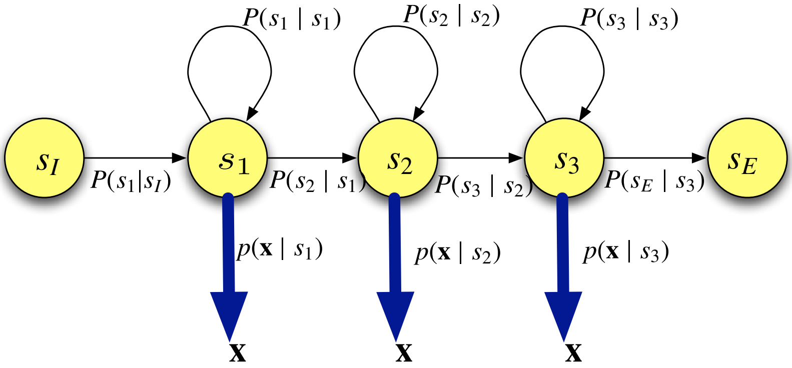
Recap: Continuous Density HMM



Probabilistic finite state automaton

Paramaters $\boldsymbol{\lambda}$:

- Transition probabilities: $a_{kj} = P(s_j \mid s_k)$
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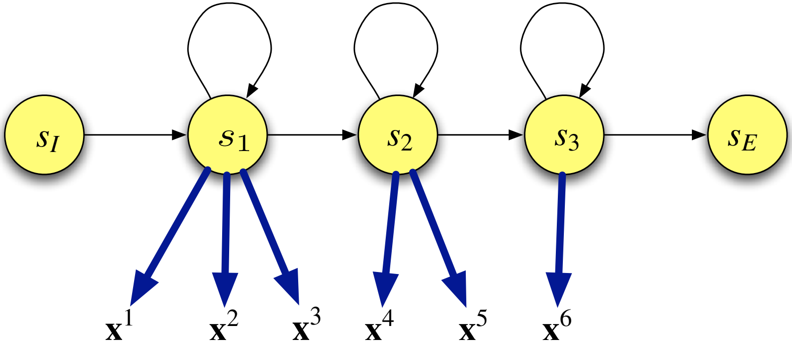

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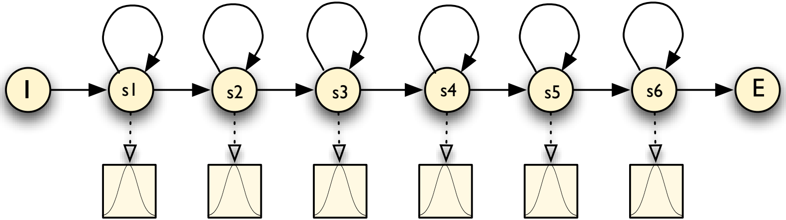
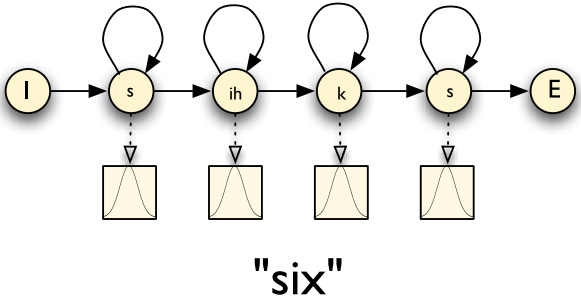
Whole word models

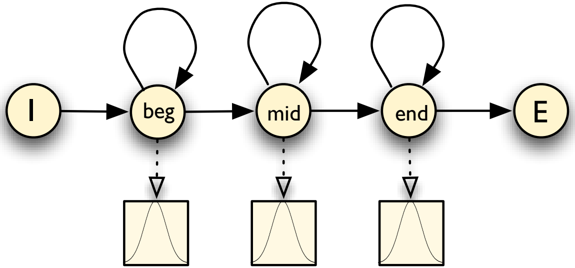


"six"

One state per phone models



Three-state phone models



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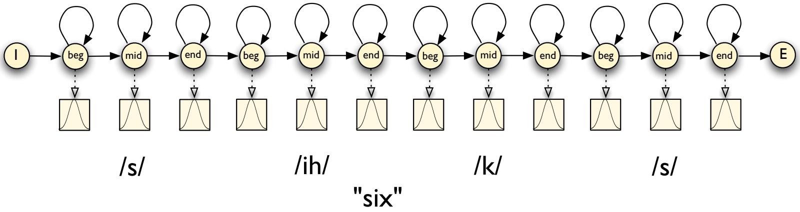
Word model made of phone models



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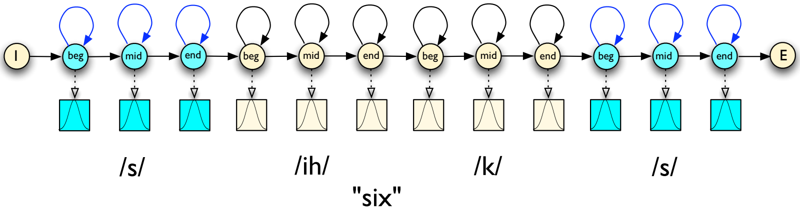
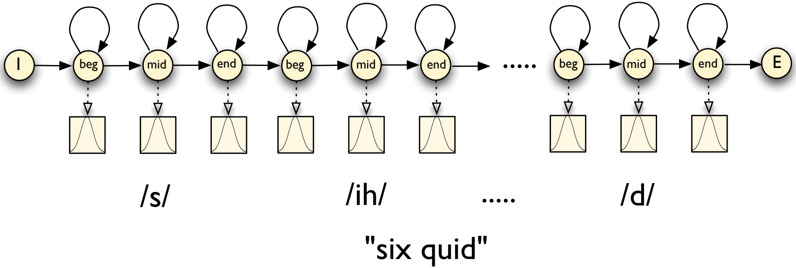
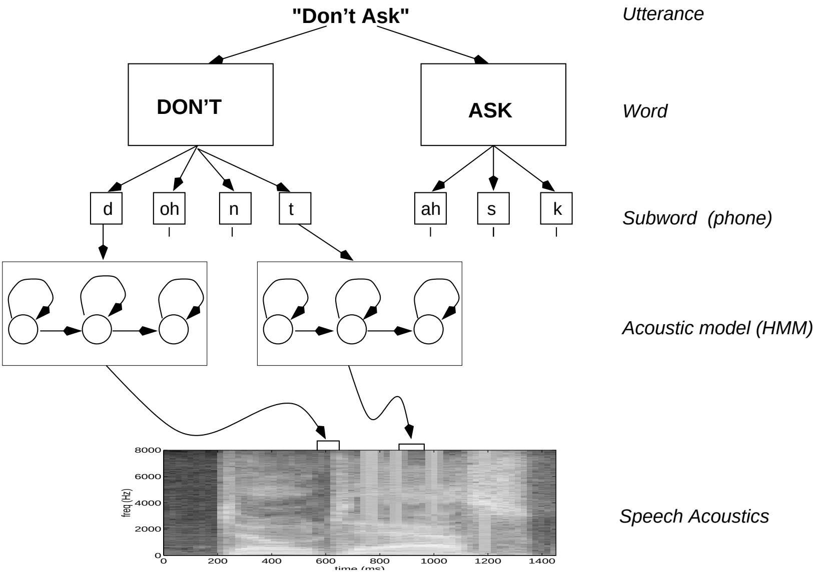


Word sequence models



Hierarchical Modelling in Speech Recognition



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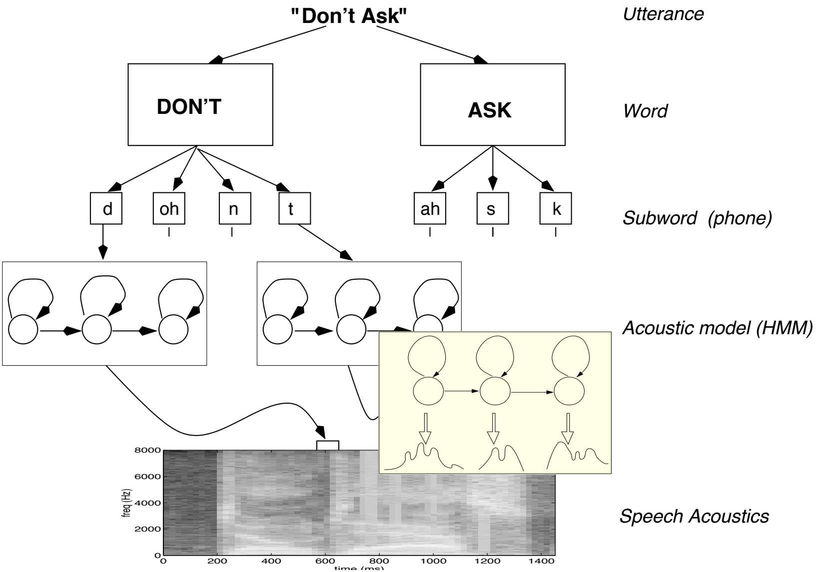
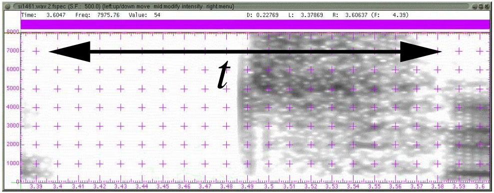


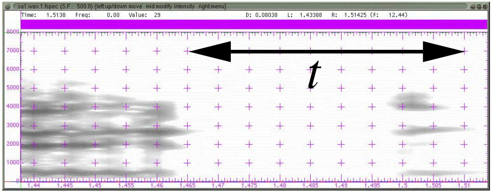
Phonetic Context

- Context The acoustic phonetic context of a speech unit has an effect on its acoustic realization
- Coarticulation the place of articulation for one speech sound depends on a neighbouring speech sound.
- Consider /n/ in ten and tenth
  - dental in ten
  - alveolar in tenth

Phonetic Context Example



"tube"



"suit"

Modelling Context

- Subword units Individual phone units need to deal with a lot of variability
  - Use longer units that incorporate context, eg: diphones, demisyllables, syllables
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- Pronunciations
  - "did you" `d ih jh y ah`
  - "around this" `ix r aw n ih s`

Context-dependent phone models

- Triphones Each phone has a unique model for each left and right context. Represent a phone `x` with left context `l` and right context `r` as `l-x+r`

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  Note that triphone context extends across words (eg unit `n-t+ah`)
- Word-internal triphones Only take account of context within words, so "don't ask" is represented by:
  `sil d+oh d-oh+n oh-n+t n-t ah+s ah-s+k s-k sil`
  Word internal triphones result in far fewer models, and enable the subword sequence for a word to be known independent of the neighbouring words.
  But: context is not well-modelled at word boundaries.

Divide and conquer

- Context-dependent models are more specific than context-independent models
- Increase the detail of modelling by extending the state space — but by defining multiple context dependent models, rather than more complex context independent models
- Divide and conquer: as more context-dependent models are defined, each one becomes responsible for a smaller region of the acoustic-phonetic space
- Let the data tell us how many contexts to model

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    - 50 000 three-state HMMs, with 10 component Gaussian mixtures per state: 1.5M Gaussians
    - 39-dimension feature vectors (12 MFCCs + energy), deltas and accelerations
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  - Total about 118 million parameters!
- We would need a very large amount of training data to train such a system
  - to enable robust estimation of all parameters
  - to ensure that all possible triphones are observed (more than once) in the training data

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The number of possible triphone types is much greater than the number of observed triphone tokens.

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- All approaches are data driven

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- Ensures that each model is well trained
- But training data is sparse (especially when cross-word triphones are used) so relatively few specific triphone models

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- Estimate the interpolation parameters α using deleted interpolation
- This enables more triphone models to be estimated, but adds robustness by sharing training data from other contexts (through the biphone and monophone models)

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3. Sharing models: merge those context-dependent models that are the most similar (generalised triphones)

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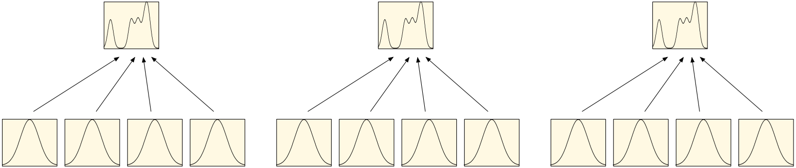
Tied Mixture Model



Gaussian mixture model

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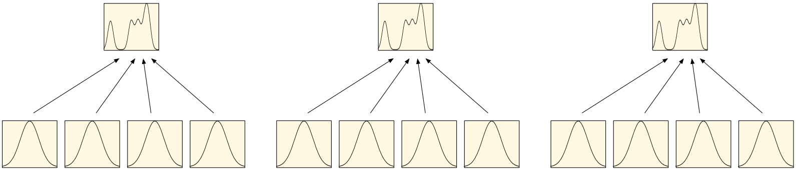

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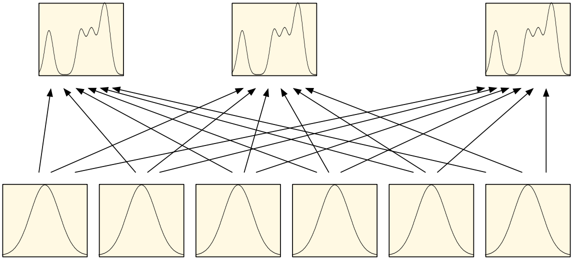

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- But we can do better (state clustering)!
- Tied mixtures are still used when time and memory efficiency is important (eg embedded systems)

Interim Summary

Modelling phones with HMMs

- Hierarchical modelling with HMMs
- Acoustic context and coarticulation
- Divide and conquer approaches to modelling context: context-dependent phone models
- Modelling detail with limited training data: smoothing and parameter sharing
- Next lecture: state clustering, phonetic decision trees

Context-Dependent Models (part 2)

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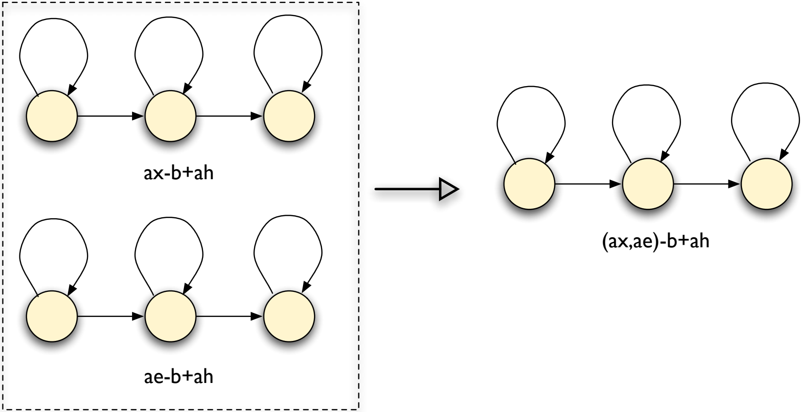
- The resultant merged models are referred to as generalized triphones

Example: Generalized Triphones



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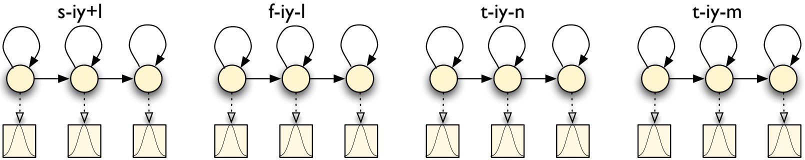
- More flexible than clustering whole models: left and right contexts may be clustered separately

Generalized triphones



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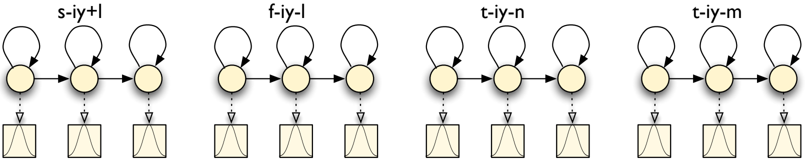

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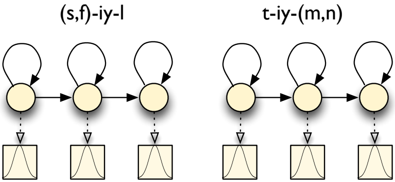

Generalized triphones (model sharing)

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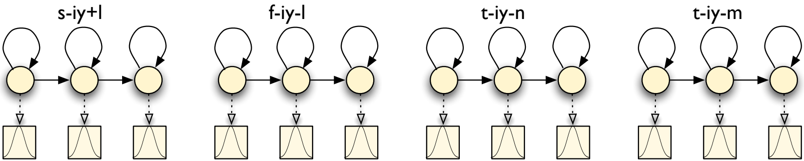

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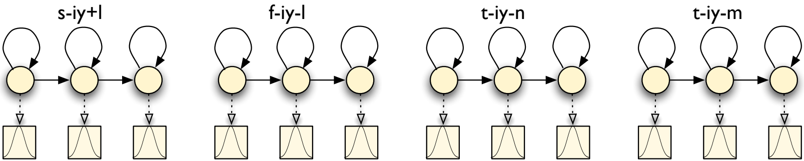

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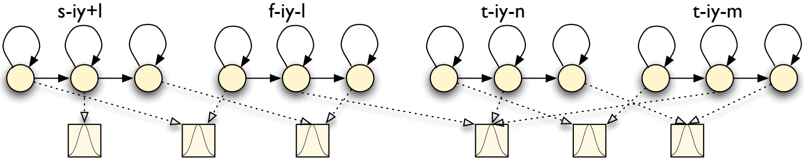

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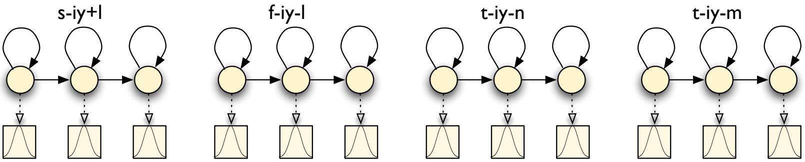

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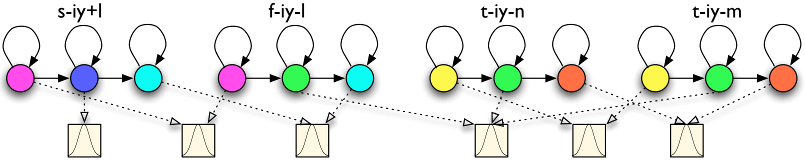

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- Phonetic decision trees

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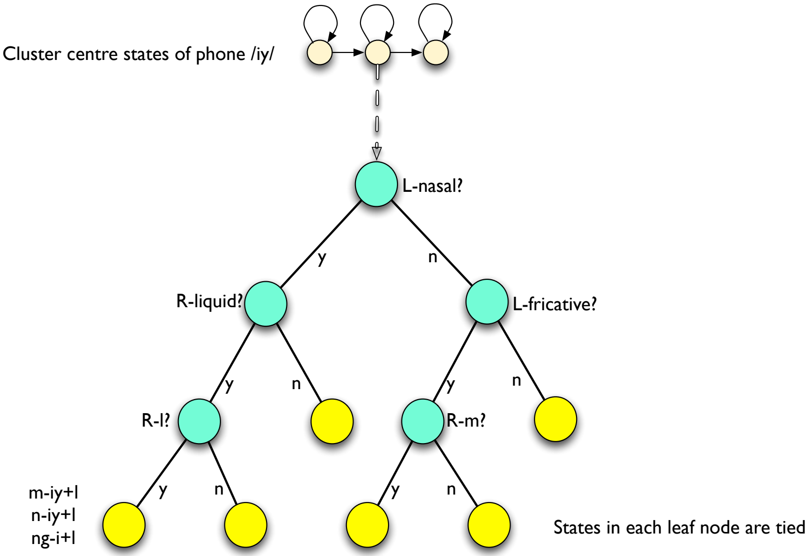
- Stop splitting if either: (a) the likelihood does not increase by more than a predefined threshold; or (b) the amount of data associated with a split node would below a threshold

Phonetic Decision Tree



Phonetic questions

- Ask questions of the form: does phone at offset s have feature f?
- Offsets are +/–1 for triphone context
- Example general questions:
  - Stop: `b d g p t k`
  - Nasal: `m n ng`
  - Fricative: `ch dh f jh s sh th v z zh`
  - Liquid: `l r w y`
  - Vowel: `aa ae ah ao aw ax axr ay eh er ...`
- Example consonant questions: Un/voiced, front/central/back, fortis (`ch f k p s sh t th`), lenis (`b d dh g jh v z zh`), voiced stop, ...
- Example vowel questions: front, central, back, long, short, diphthong, rounded, ...

Most useful phonetic questions

- All states of all models:
  `+Vowel -Vowel +Unrounded -UnFortisLenis +UnFortisLenis +r`
- Entry state of all models:
  `-UnFortisLenis -Vowel -Nasal -CentralFront -Unrounded -Fortis`
- Exit state of all consonants:
  `+Vowel +Unrounded +High +ee +Rounded +Syllabic`

(for Wall St Journal read speech—Young, Odell and Woodland 1994)

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$$L(\mathbf{S}) = \sum_{i=1}^{K} \log P(\mathbf{X}_i | \boldsymbol{\mu}_S, \boldsymbol{\Sigma}_S)$$

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- State occupation count: sum of state occupation probabilities for a state over time

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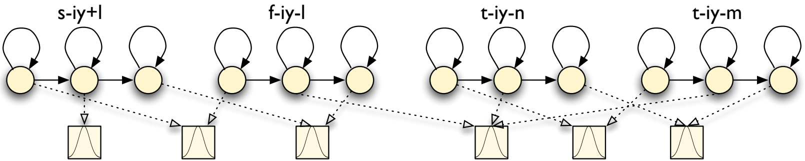
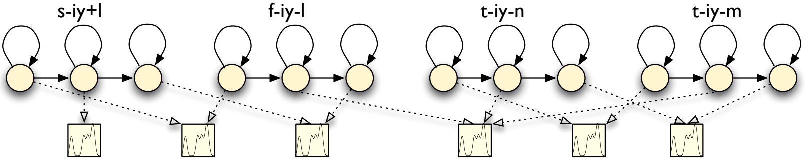
- The above methods for state clustering assume that the state outputs are Gaussians—this makes the computations much simpler
- BUT: Gaussian mixtures offer much better acoustic models than Gaussians
- Solution:
  - Perform state clustering using Gaussian distributions
  - Split the Gaussian distributions in the clustered states, by cloning and perturbing the means by a small fraction of the standard deviation, and retrain.
  - Repeat by splitting the dominant (highest state occupation count) mixture components in each state

"Mixing up"



State-clustered triphones (Gaussians)



State-clustered triphones (GMMs)

Summary: Context-dependent acoustic modelling

- Share parameters through state clustering
- Cluster states using phonetic decision trees for each state of parent phone
- Use Gaussian distributions when state clustering
- Then split Gaussians and retrain to obtain a GMM state clustered system

References: context-dependent acoustic modelling

- c1980: First proposed by Bahl et al (IBM)
- Schwartz et al (1985): first paper using triphone models
- Lee (1990): generalized triphones
- Bellegarda (1990), Huang (1992): tied mixture modelling
- Bahl et al (1991): phonetic decision trees first proposed
- Young and Woodland (1994): state clustering
- Young et al (1994): decision tree-based state clustering