Natural Language Processing

Speech Inference

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Grading

- Class is now big enough for big-class policies
- Late days: 7 total, use whenever
- Grading: Projects out of 10
  - 6 Points: Successfully implemented what we asked
  - 2 Point: Submitted a reasonable write-up
  - 1 Point: Write-up is written clearly
  - 1 Point: Substantially exceeded minimum metrics
  - Extra Credit: Did non-trivial extension to project
- Letter Grades:
  - 10=A, 9=A-, 8=B+, 7=B, 6=B-, 5=C+, lower handled case-by-case
  - Cutoffs at 9.5, 8.5, etc., A+ by discretion

State Model

FSA for Lexicon + Bigram LM

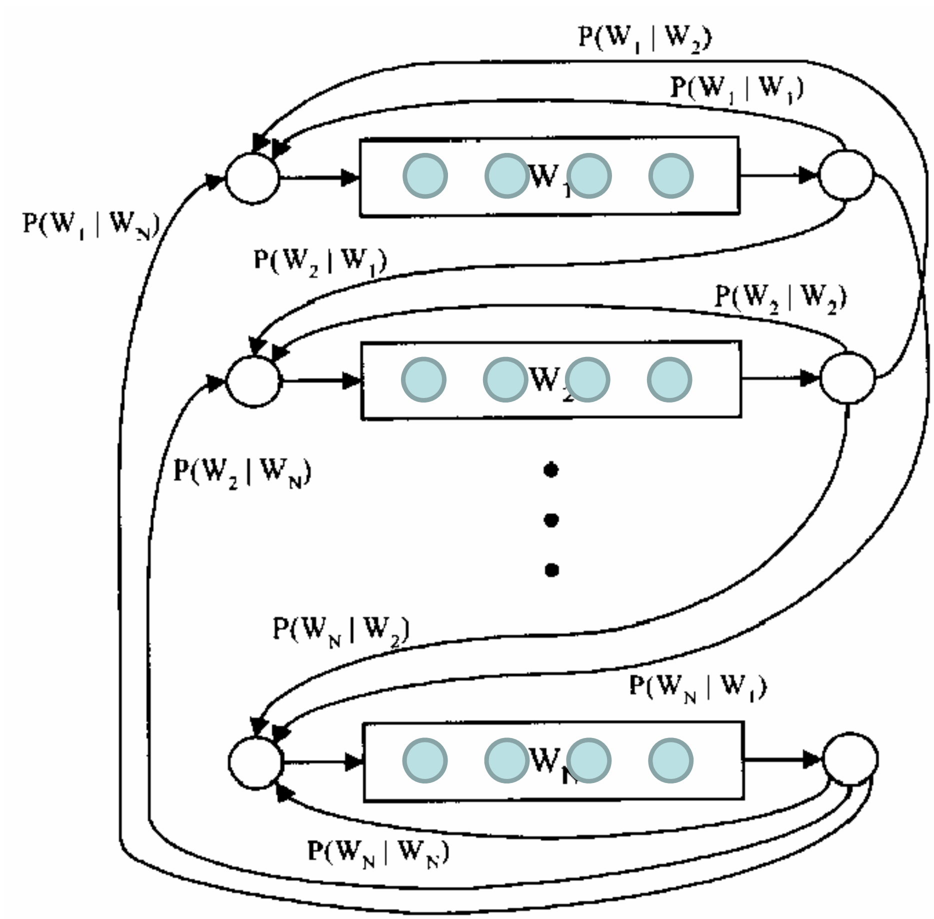


Figure from Huang et al page 618

State Space

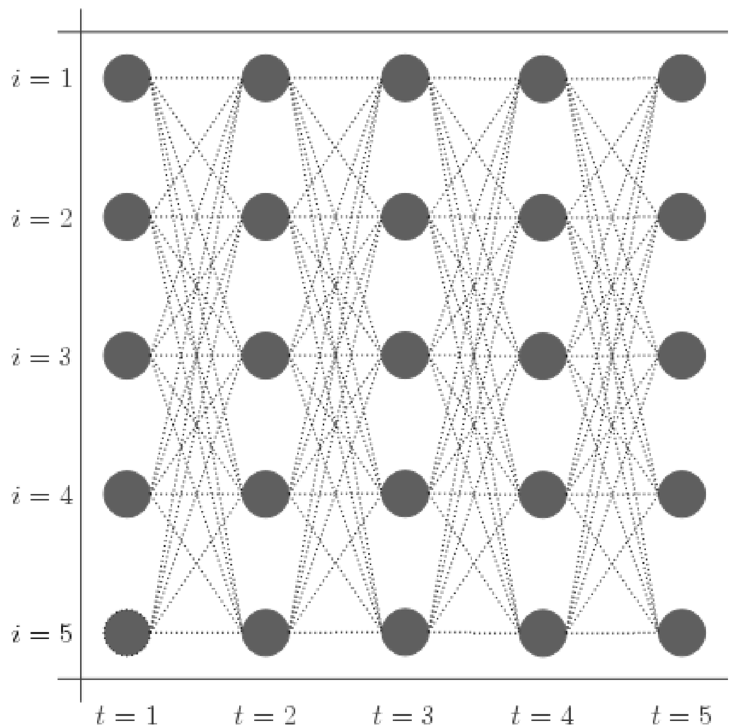
- Full state space

(LM context, lexicon index, subphone)

- Details:
  - LM context is the past n-1 words
  - Lexicon index is a phone position within a word (or a trie of the lexicon)
  - Subphone is begin, middle, or end
  - E.g. (after the, lec[t-mid]ure)
- Acoustic model depends on clustered phone context
  - But this doesn’t grow the state space

Decoding

State Trellis



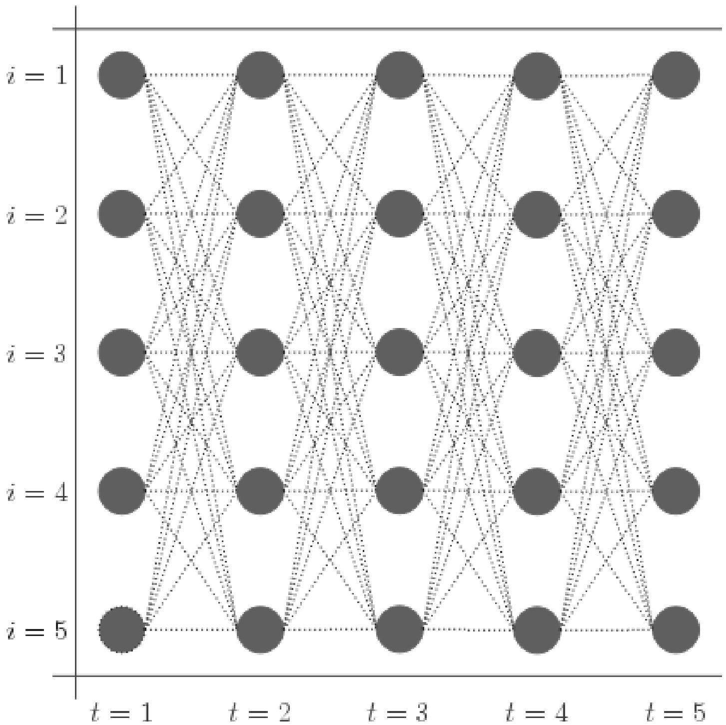
$$\phi_t(s_{t-1}, s_t) = P(x_t|s_t)P(s_t|s_{t-1})$$

$$P(x, s) = \prod_i P(x_i|s_i)P(s_i|s_{i-1})$$

$$= \prod_i \phi_t(s_{i-1}, s_i)$$

Figure: Enrique Benimeli

Naïve Viterbi



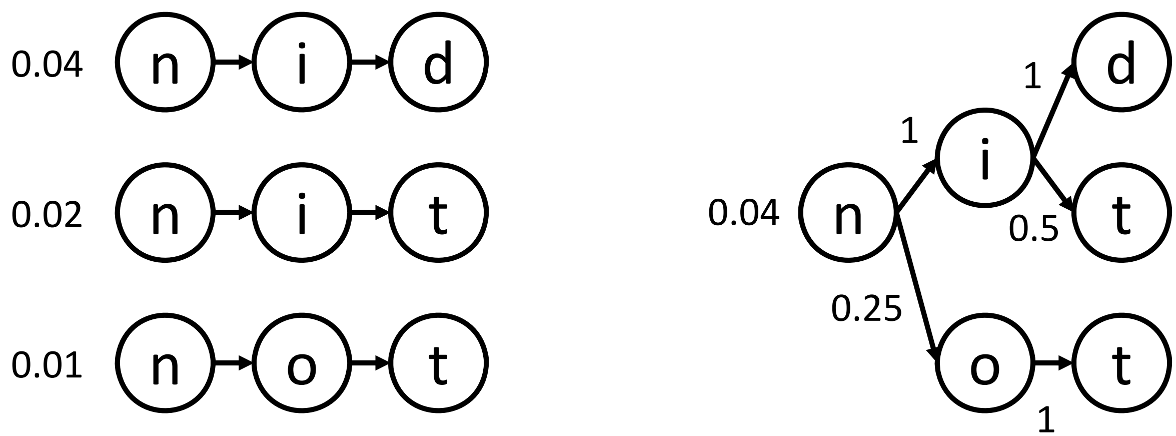
$$v_t(s_t) = \max_{s_{t-1}} v_{t-1}(s_{t-1})\phi_t(s_{t-1}, s_t)$$

Beam Search

- At each time step
  - Start: Beam (collection) v_t of hypotheses s at time t
  - For each s in v_t
    - Compute all extensions s’ at time t+1
    - Score s’ from s
    - Put s’ in v_{t+1} replacing existing s’ if better
  - Advance to t+1
- Beams are priority queues of fixed size* k (e.g. 30) and retain only the top k hypotheses

Prefix Trie Encodings

- Problem: many partial-word states are indistinguishable
- Solution: encode word production as a prefix trie (with pushed weights)

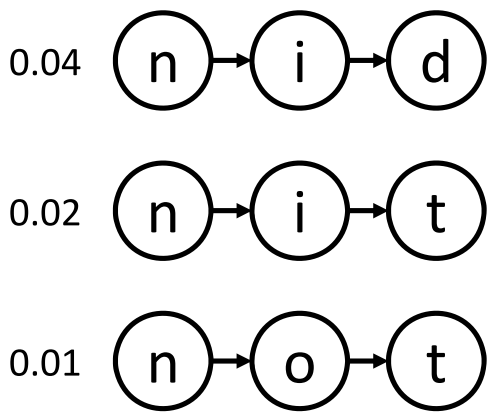


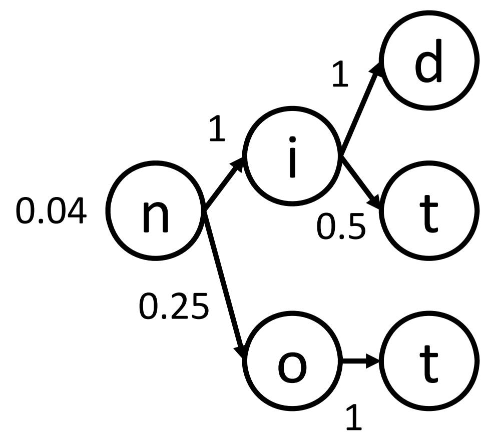
- A specific instance of minimizing weighted FSAs [Mohri, 94]

Example: Aubert, 02

LM Score Integration

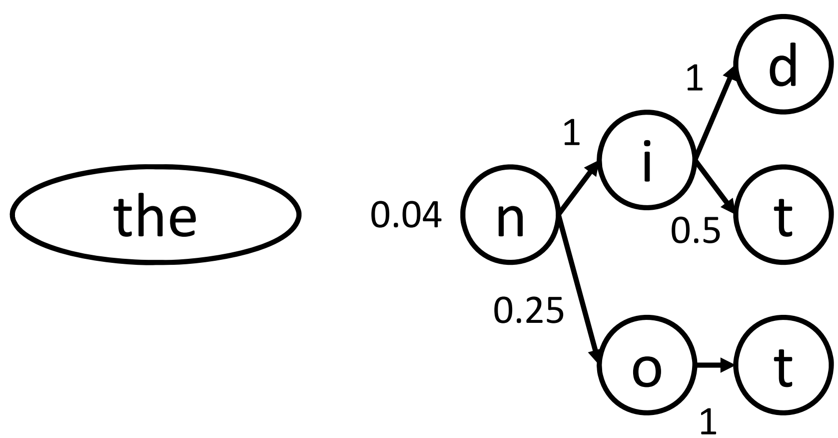
- Imagine you have a unigram language model
- When does a hypothesis get “charged” for cost of a word?
  - In naïve lexicon FSA, can charge when word is begun
  - In naïve prefix trie, don’t know word until the end
  - … but you can charge partially as you complete it





LM Factoring

- Problem: Higher-order n-grams explode the state space
- (One) Solution:
  - Factor state space into (lexicon index, lm history)
  - Score unigram prefix costs while inside a word
  - Subtract unigram cost and add trigram cost once word is complete



  - Note that you might have two hypotheses on the beam that differ only in LM context, but are doing the same within-word work

LM Reweighting

- Noisy channel suggests

$$P(x|w)P(w)$$

- In practice, want to boost LM

$$P(x|w)P(w)^{\alpha}$$

- Also, good to have a “word bonus” to offset LM costs

$$P(x|w)P(w)^{\alpha}|w|^{\beta}$$

- The needs for these tweaks are both consequences of broken independence assumptions in the model, so won’t easily get fixed within the probabilistic framework

Other Good Ideas

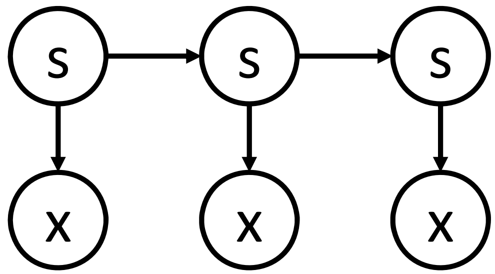
- When computing emission scores, P(x|s) depends on only a projection π(s), so use caching

- Beam search is still dynamic programming, so make sure you check for hypotheses that reach the same HMM state (so you can delete the suboptimal one).

- Beams require priority queues, and beam search implementations can get object-heavy. Remember to intern / canonicalize objects when appropriate.

Training

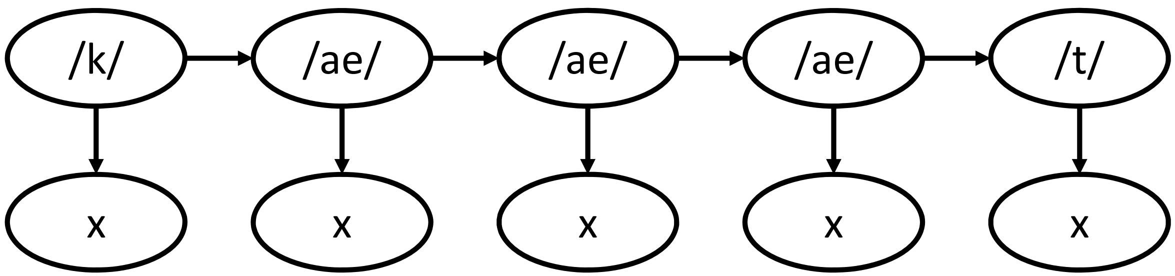
What Needs to be Learned?



- Emissions: P(x | phone class)
  - X is MFCC-valued
- Transitions: P(state | prev state)
  - If between words, this is P(word | history)
  - If inside words, this is P(advance | phone class)
  - (Really a hierarchical model)

Estimation from Aligned Data

- What if each time step was labeled with its (context-dependent sub) phone?



- Can estimate P(x|/ae/) as empirical mean and (co-)variance of x's with label /ae/

- Problem: Don't know alignment at the frame and phone level

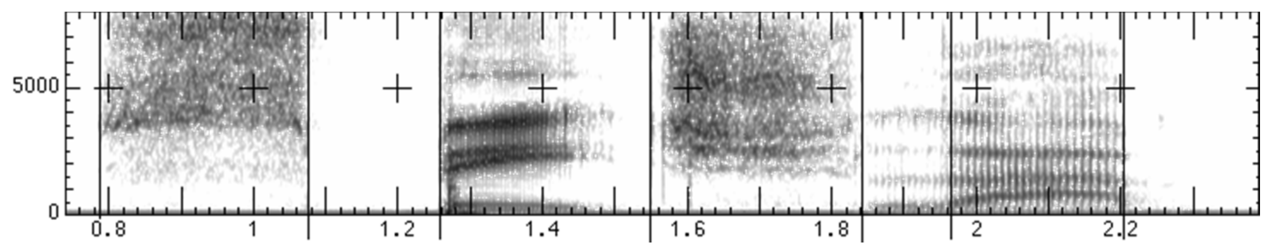
Forced Alignment

- What if the acoustic model P(x|phone) was known?
  - … and also the correct sequences of words / phones

- Can predict the best alignment of frames to phones

“speech lab”

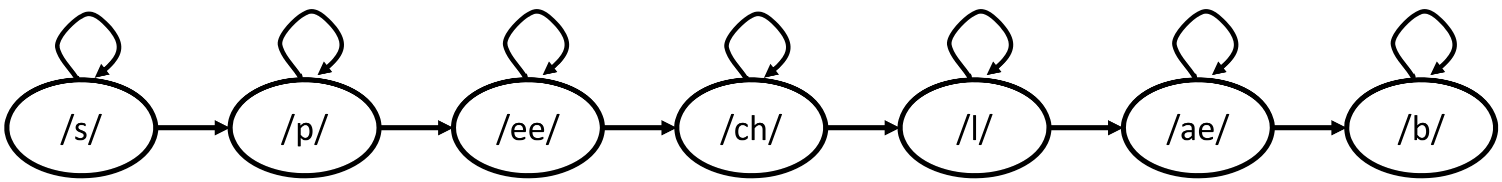
ssssssssppppeeeeeeeetshshshshllllaeaeaebbbbb



- Called “forced alignment”

Forced Alignment

- Create a new state space that forces the hidden variables to transition through phones in the (known) order



- Still have uncertainty about durations

- In this HMM, all the parameters are known
  - Transitions determined by known utterance
  - Emissions assumed to be known
  - Minor detail: self-loop probabilities

- Just run Viterbi (or approximations) to get the best alignment

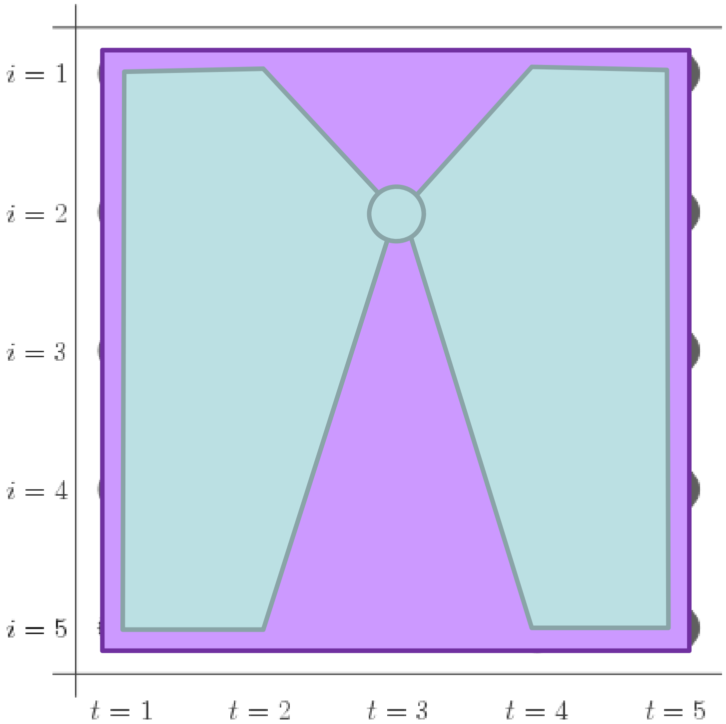
EM for Alignment

- Input: acoustic sequences with word-level transcriptions
- We don’t know either the emission model or the frame alignments
- Expectation Maximization (Hard EM for now)
  - Alternating optimization
  - Impute completions for unlabeled variables (here, the states at each time step)
  - Re-estimate model parameters (here, Gaussian means, variances, mixture ids)
  - Repeat
  - One of the earliest uses of EM!

Soft EM

- Hard EM uses the best single completion
  - Here, single best alignment
  - Not always representative
  - Certainly bad when your parameters are initialized and the alignments are all tied
  - Uses the count of various configurations (e.g. how many tokens of /ae/ have self-loops)
- What we'd really like is to know the fraction of paths that include a given completion
  - E.g. 0.32 of the paths align this frame to /p/, 0.21 align it to /ee/, etc.
  - Formally want to know the expected count of configurations
  - Key quantity: $P(s_t \mid x)$

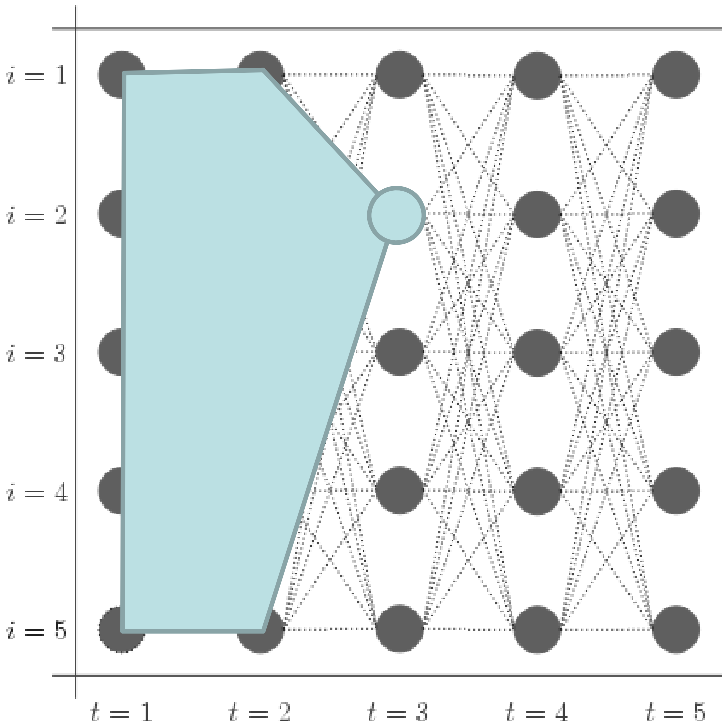
Computing Marginals



$$P(s_t|x) = \frac{P(s_t, x)}{P(x)}$$

$$= \frac{\text{sum of all paths through s at t}}{\text{sum of all paths}}$$

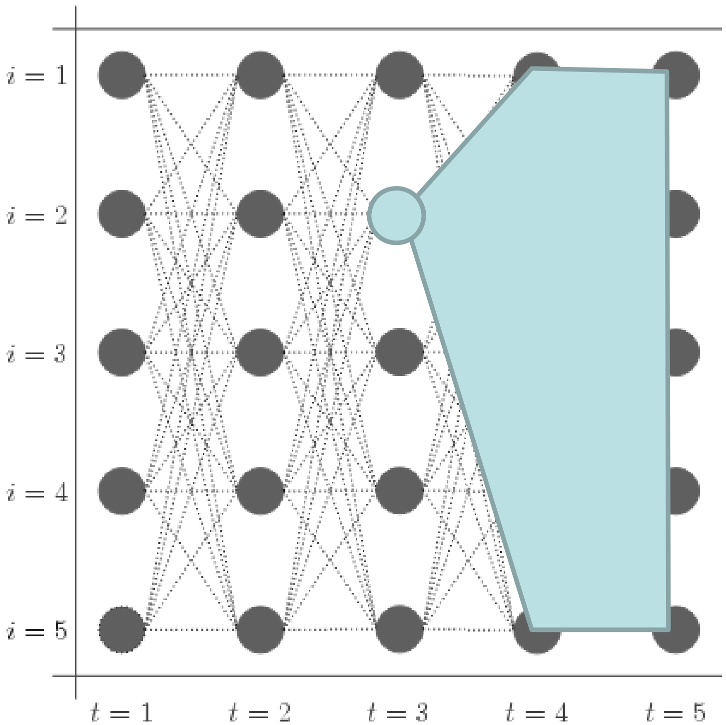
Forward Scores



$$v_t(s_t) = \max_{s_{t-1}} v_{t-1}(s_{t-1})\phi_t(s_{t-1}, s_t)$$

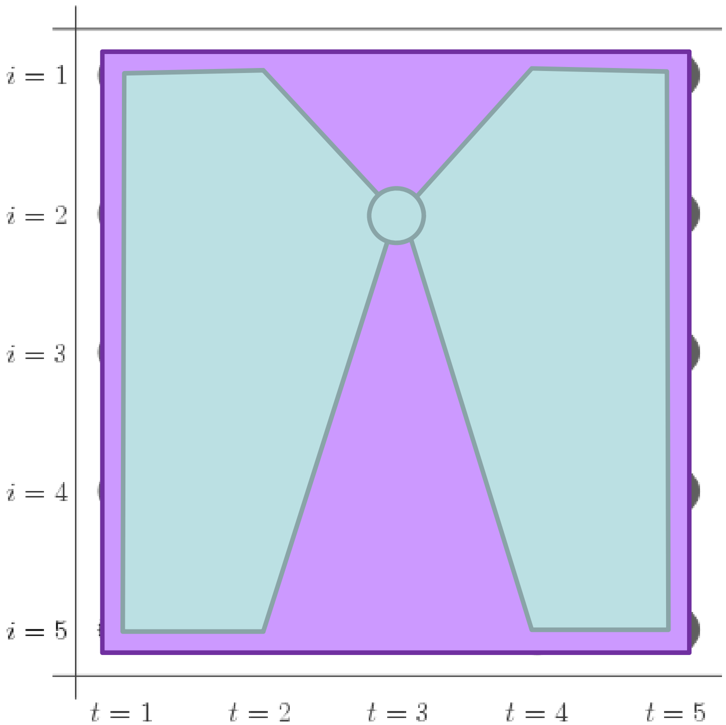
$$\alpha_t(s_t) = \sum_{s_{t-1}} \alpha_{t-1}(s_{t-1})\phi_t(s_{t-1}, s_t)$$

Backward Scores



$$\beta_t(s_t) = \sum_{s_{t+1}} \beta_{t+1}(s_{t+1})\phi_t(s_t, s_{t+1})$$

Total Scores



$$P(s_t, x) = \alpha_t(s_t)\beta_t(s_t)$$

$$P(x) = \sum_{s_t} \alpha_t(s_t)\beta_t(s_t)$$
$$= \alpha_T(\text{stop})$$
$$= \beta_0(\text{start})$$

Fractional Counts

- Computing fractional (expected) counts
  - Compute forward / backward probabilities
  - For each position, compute marginal posteriors
  - Accumulate expectations
  - Re-estimate parameters (e.g. means, variances, self-loop probabilities) from ratios of these expected counts

Staged Training and State Tying

- Creating CD phones:
  - Start with monophone, do EM training
  - Clone Gaussians into triphones
  - Build decision tree and cluster Gaussians
  - Clone and train mixtures (GMMs)
- General idea:
  - Introduce complexity gradually
  - Interleave constraint with flexibility