- **Today**
  - Part-of-speech tagging
    - HMM's for p-o-s tagging

HMM p-o-s Tagger

Given $W = w_1, \ldots, w_n$, find $T = t_1, \ldots, t_n$ that maximizes

$$P(t_1, \ldots, t_n | w_1, \ldots, w_n)$$

Restate using Bayes' rule:

$$(P(t_1, \ldots, t_n) * P(w_1, \ldots, w_n | t_1, \ldots, t_n))/P(w_1, \ldots, w_n)$$

Ignore denominator...
Make independence assumptions...

$P(t_1, \ldots, t_n)$: approximate using **n-gram model**

bigram $\prod_{i=1,n} P(t_i \,|\, t_{i-1})$

trigram $\prod_{i=1,n} P(t_i \,|\, t_{i-2} t_{i-1})$

$P(w_1, \ldots, w_n \,|\, t_1, \ldots, t_n)$: approximate by assuming that a word appears in a category independent of its neighbors

$$\prod_{i=1,n} P(w_i \,|\, t_i)$$

Assuming bigram model:

$$P(t_1, \ldots, t_n) * P(w_1, \ldots, w_n | t_1, \ldots, t_n) \approx$$

$$\prod_{i=1,n} P(t_i | t_{i-1}) * P(w_i | t_i)$$

transition probabilities

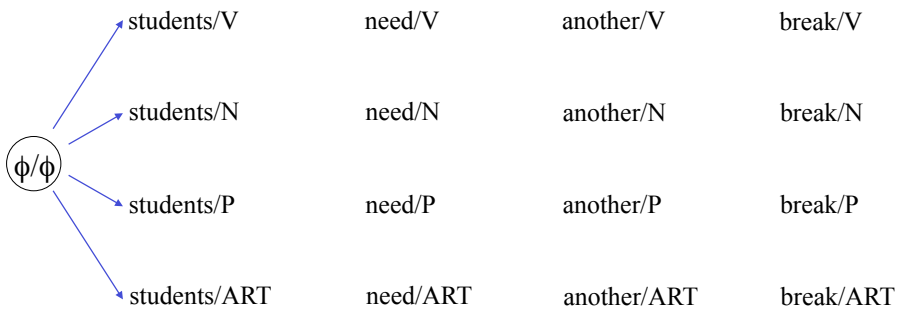
lexical generation probabilities

Hidden Markov Models

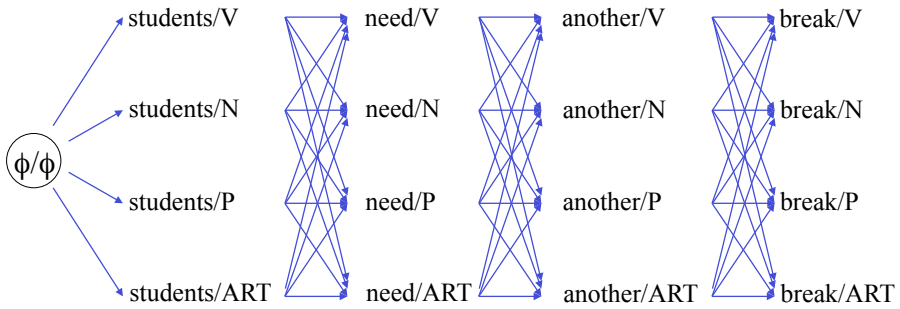
Equation can be modeled by an HMM.

- **states**: represent a possible lexical category
- **transition probabilities**: bigram probabilities
- **observation probabilities, lexical generation probabilities**: indicate, for each word, how likely that word is to be selected if we randomly select the category associated with the node.

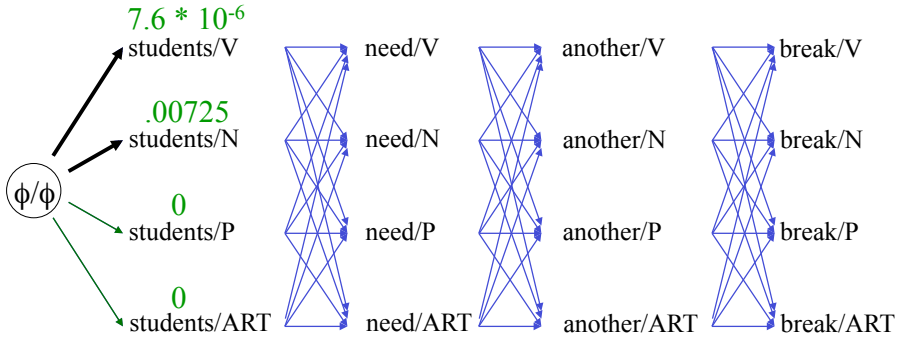
Viterbi Algorithm



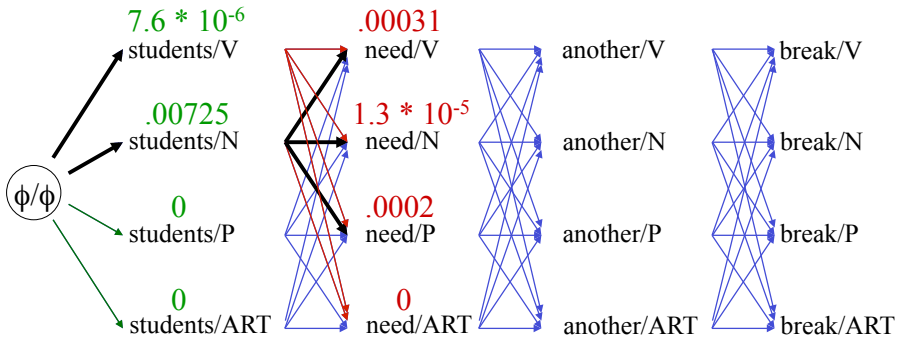
Viterbi Algorithm



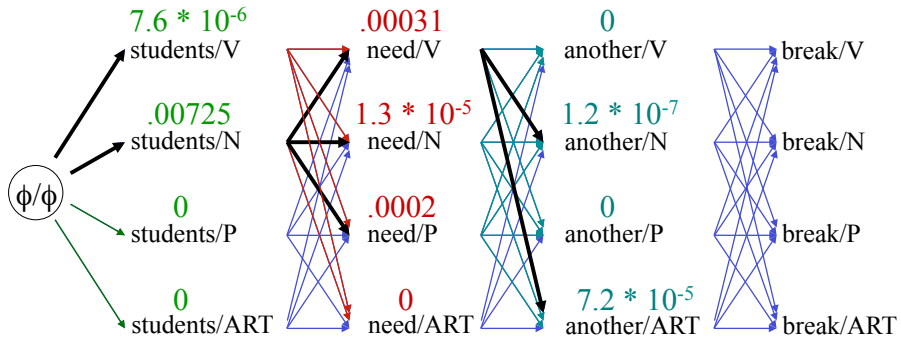
Viterbi Algorithm



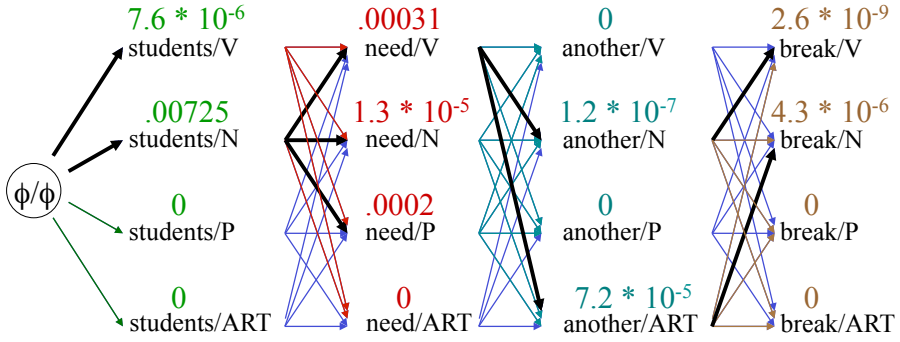
Viterbi Algorithm



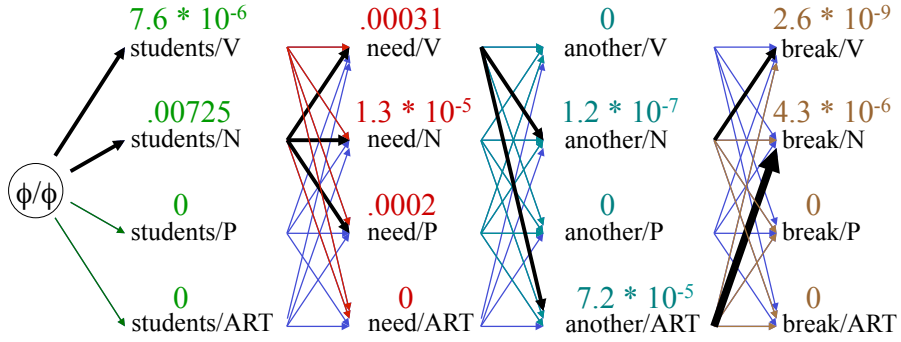
Viterbi Algorithm



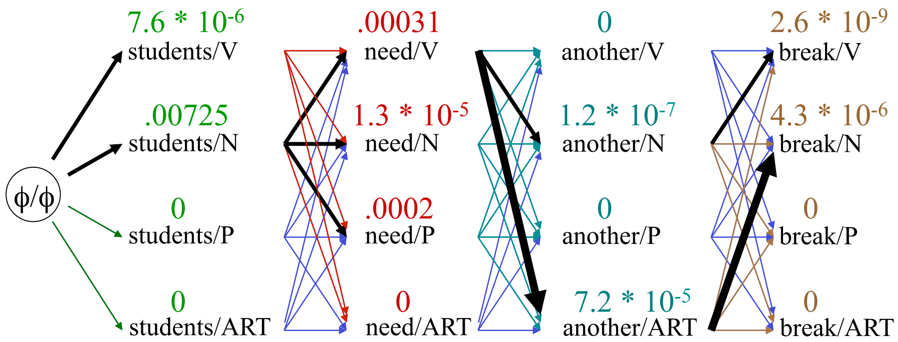
Viterbi Algorithm



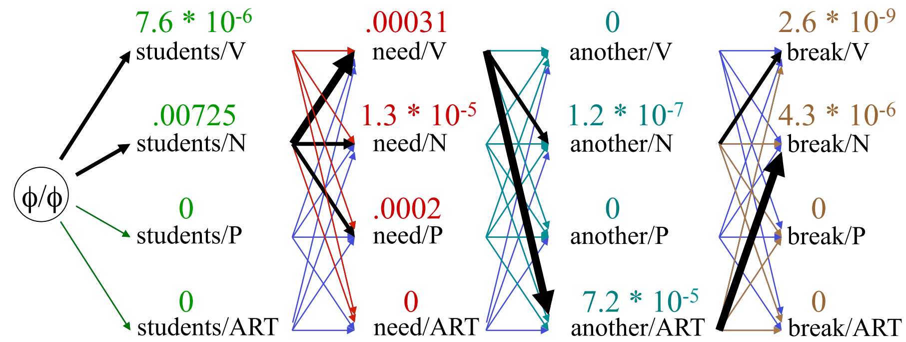
Viterbi Algorithm



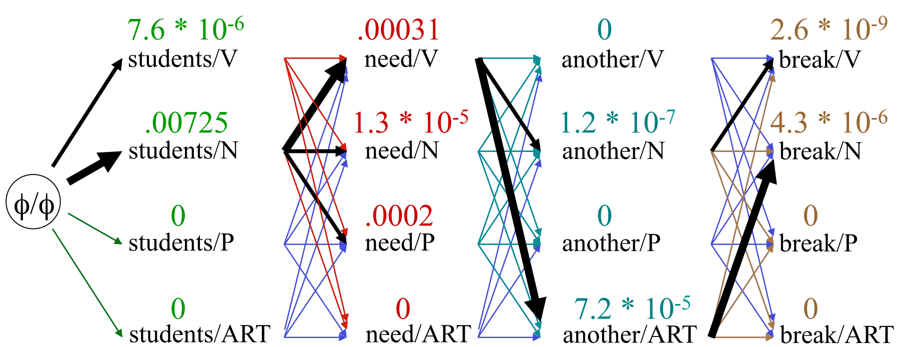
Viterbi Algorithm



Viterbi Algorithm



Viterbi Algorithm



Viterbi Algorithm

c: number of lexical categories

$P(w_t|t_i)$: lexical generation probabilities

$P(t_i|t_j)$: bigram probabilities

Find most likely sequence of lexical categories $T_1, \ldots, T_n$ for word sequence.

Initialization

For i = 1 to c do
  SCORE(i,1) = $P(t_i|\phi) * P(w_1|t_i)$
  BPTR(i,1) = 0

Iteration

For t = 2 to n

For i = 1 to c

SCORE(i,t) =

$MAX_{j=1..c}(SCORE(j, t-1) * P(t_i|t_j)) * P(w_t|t_i)$

BPTR(i,t) = index of j that gave max

Identify Sequence

T(n) = i that maximizes SCORE(i,n)

For i = n-1 to 1 do

T(i) = BPTR(T(i+1), i+1)

Results

- Effective if probability estmates are computed from a large corpus
- Effective if corpus is of the same style as the input to be classified
- Consistently achieve accuracies of 97% or better using trigram model
- Cuts error rate in half vs. naive algorithm (90% accuracy rate)
- Can be smoothed using backoff or interpolation or discounting...

Extensions

- Can train HMM tagger on unlabeled data using the EM algorithm, starting with a dictionary that lists which tags can be assigned to which words.
- EM then learns the word likelihood function for each tag, and the tag transition probabilities.
- Merialdo (1994) showed, however, that a tagger trained on even a small amount hand-tagged data works better than one trained via EM.