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

Sequence tagging
assigns the set of tags for the input sequence
rather than a single tag at a time

HMM p-o-s Tagger

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

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

HMM p-o-s Tagger

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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...

and Markov assumptions

Independence Assumptions (factor 1)

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

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

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

Independence Assumptions (factor 2)

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

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Independence Assumptions (factor 2)

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

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

Assuming bigram model:

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

$$\prod_{i=1,n} \underbrace{P(t_i|t_{i-1})}_{\text{transition probabilities}} * \underbrace{P(w_i|t_i)}_{\text{lexical generation probabilities}}$$

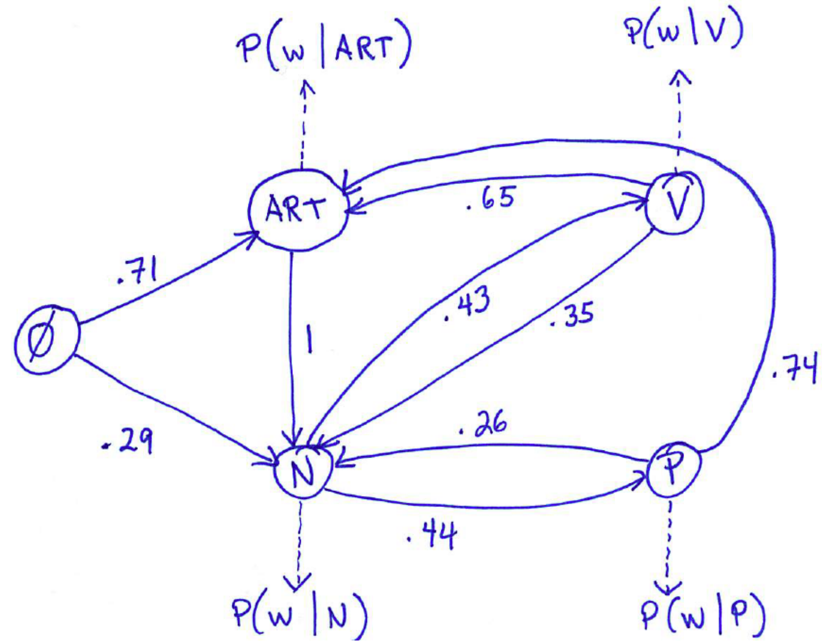
Still have a problem

How to <u>efficiently</u> find the sequence of tags that maximizes the product?????

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.



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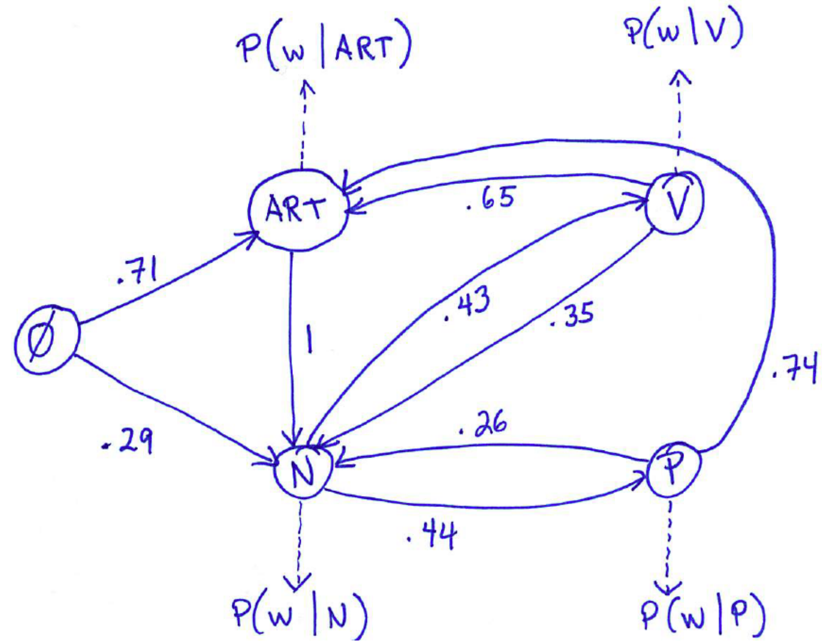
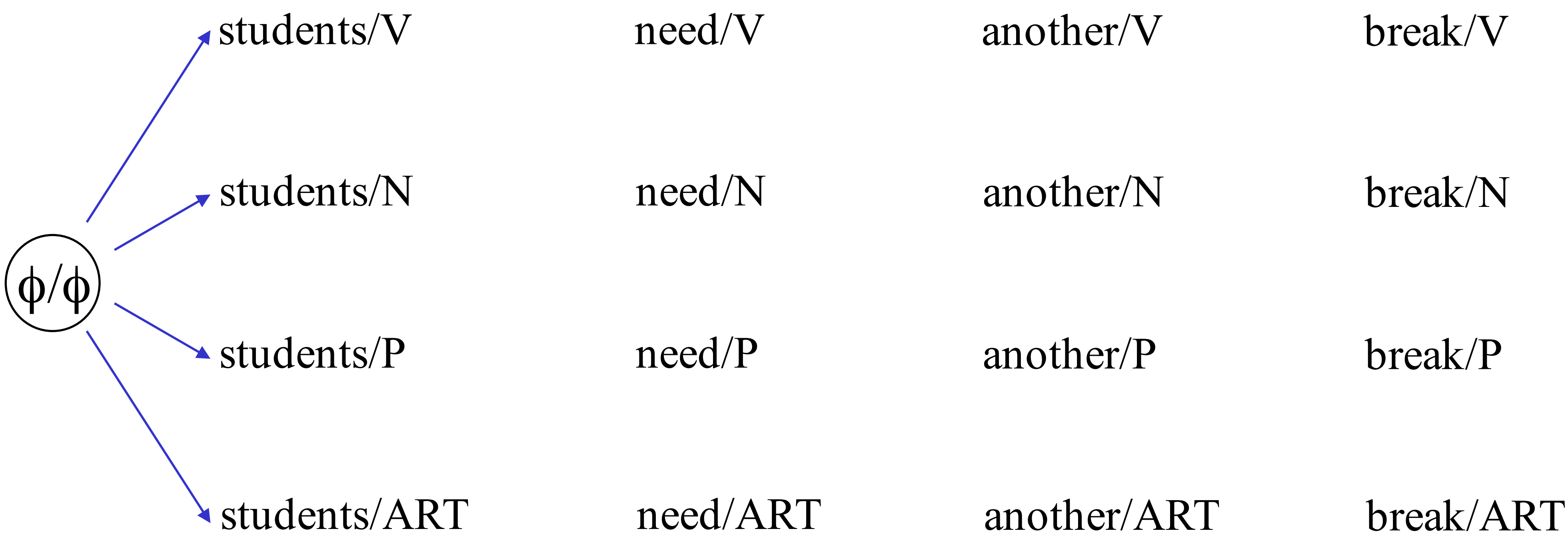
$$\prod_{i=1,n} P(t_i|t_{i-1}) * P(w_i|t_i)$$



Viterbi Algorithm



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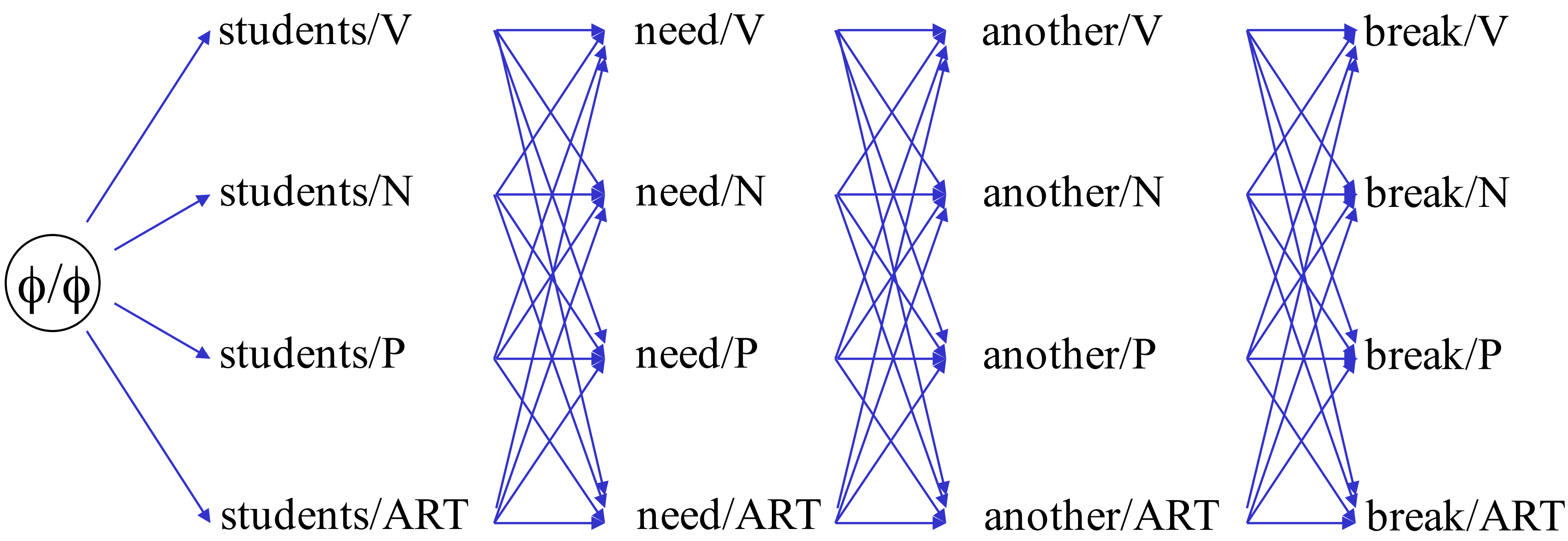

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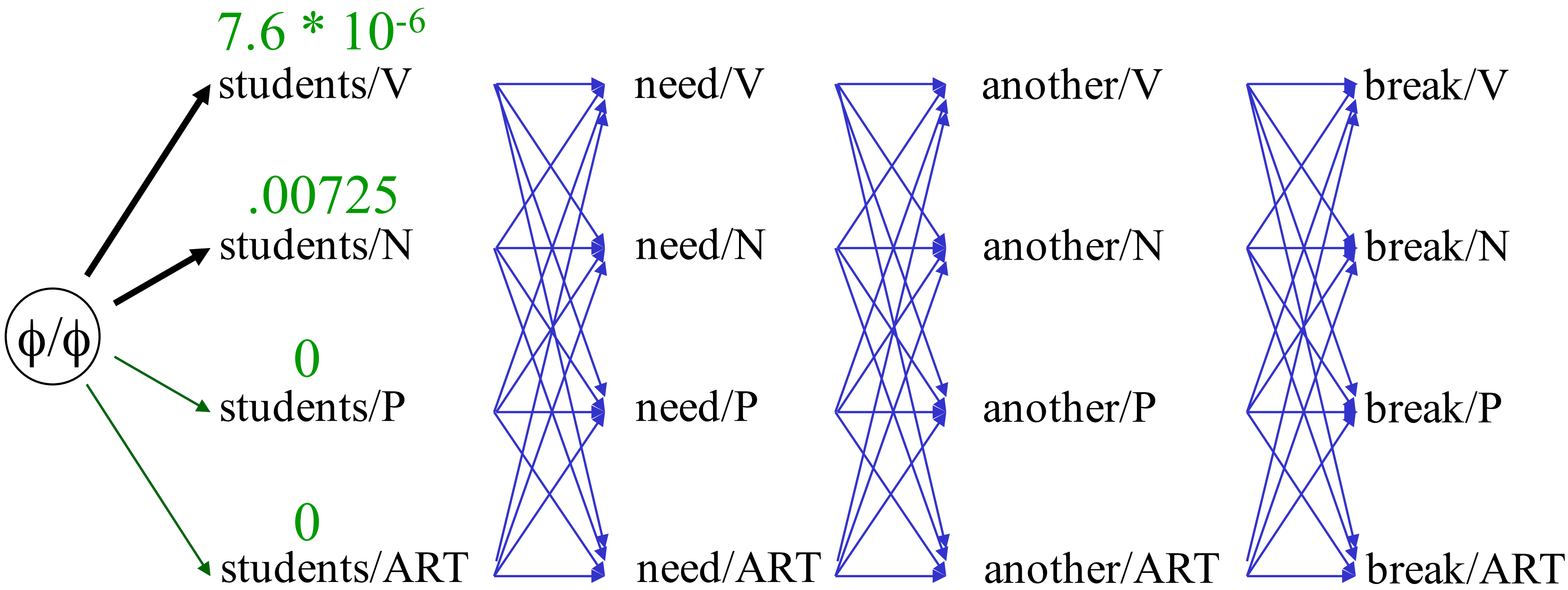

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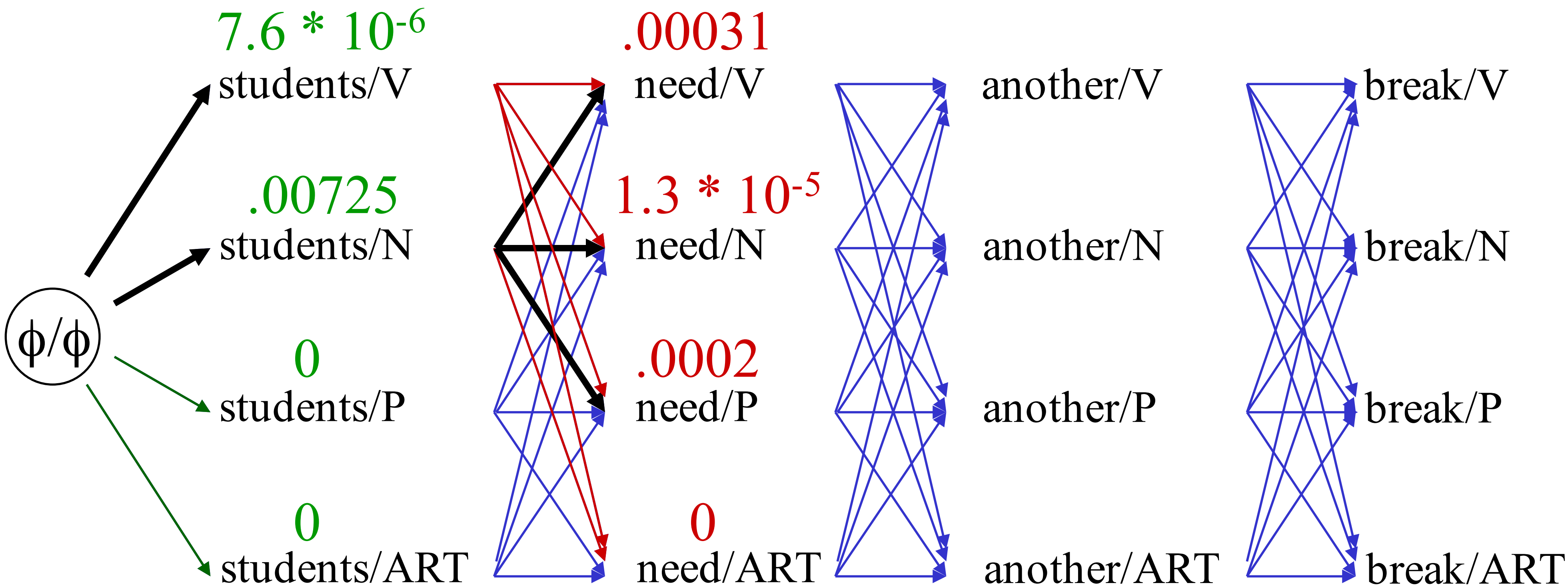

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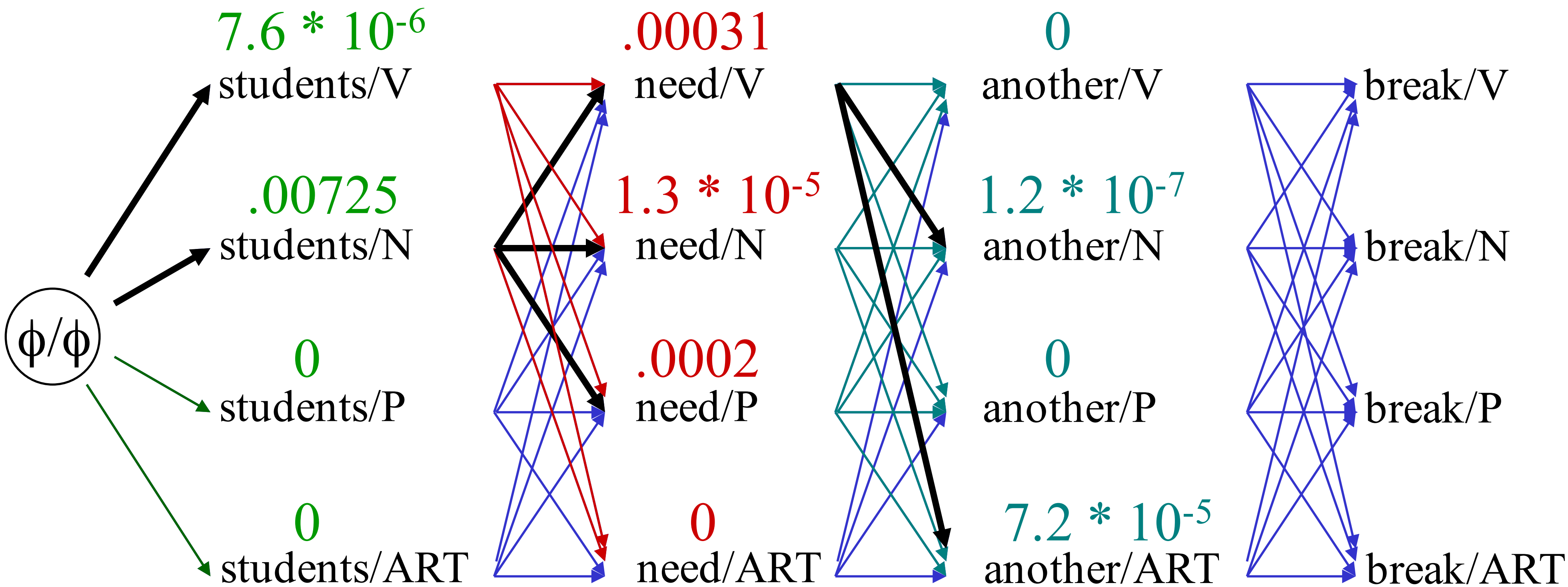

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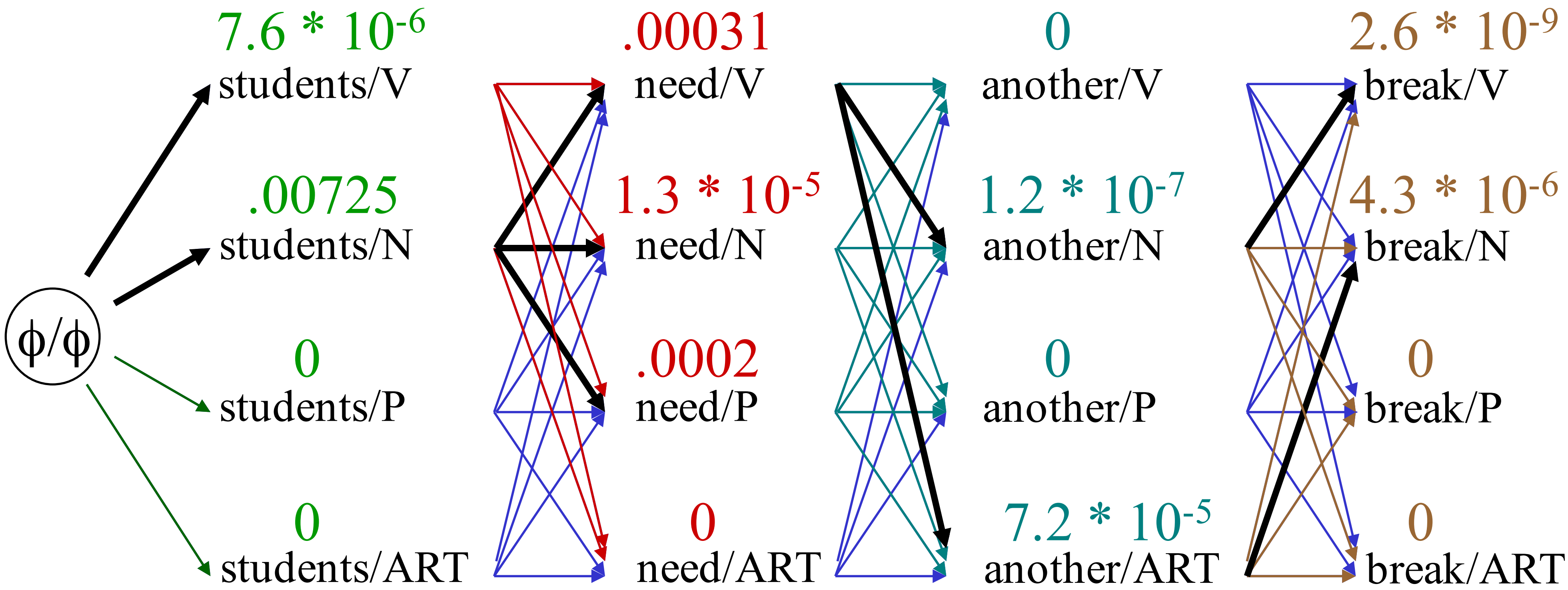

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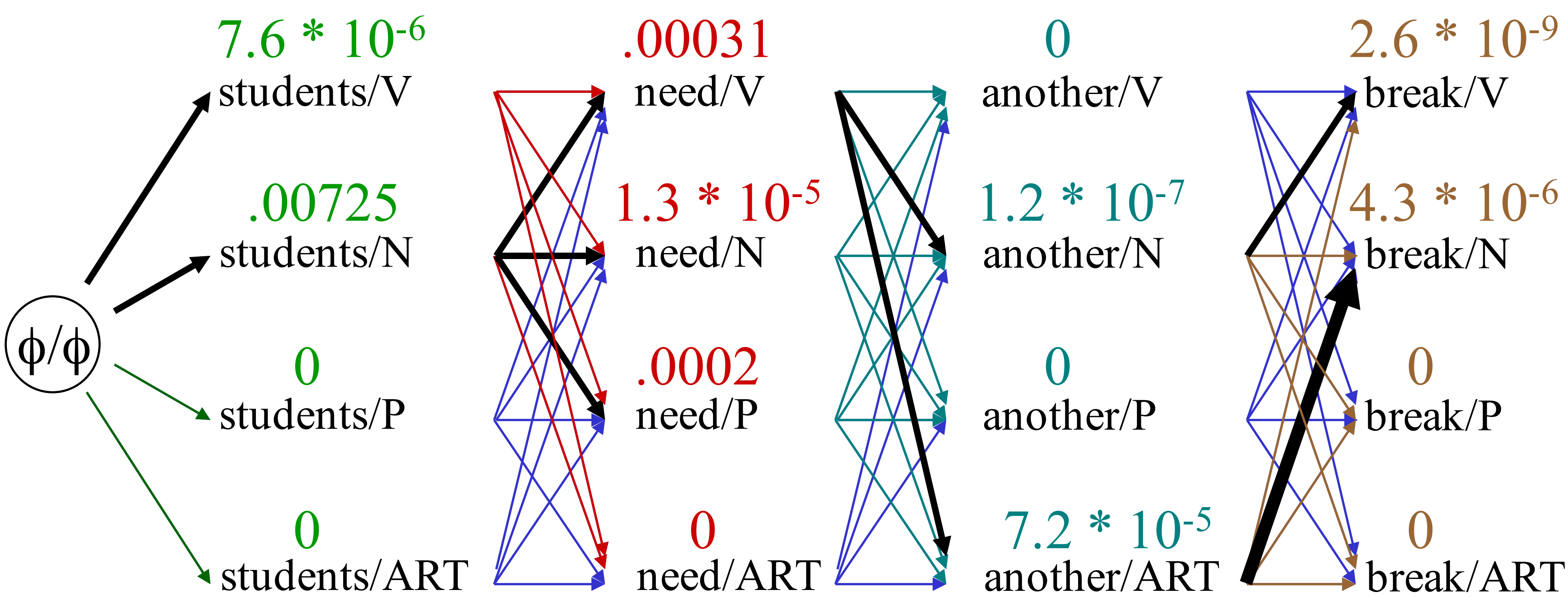

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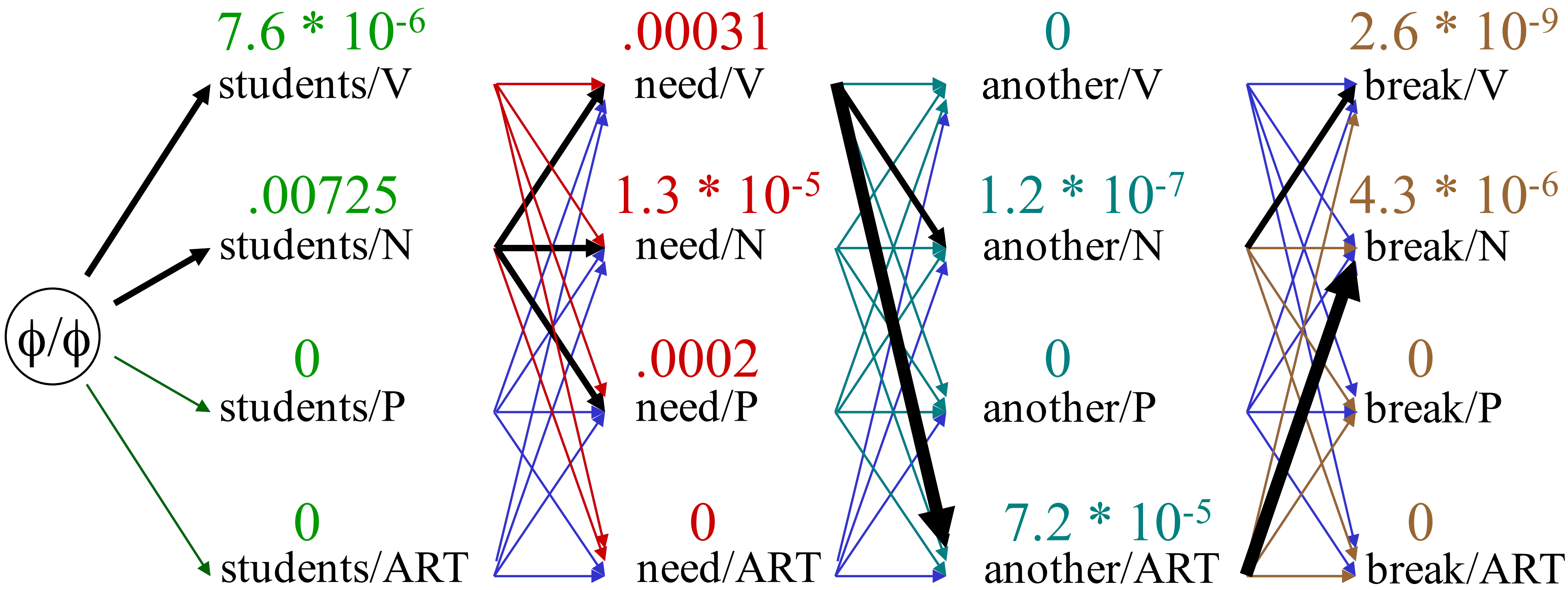

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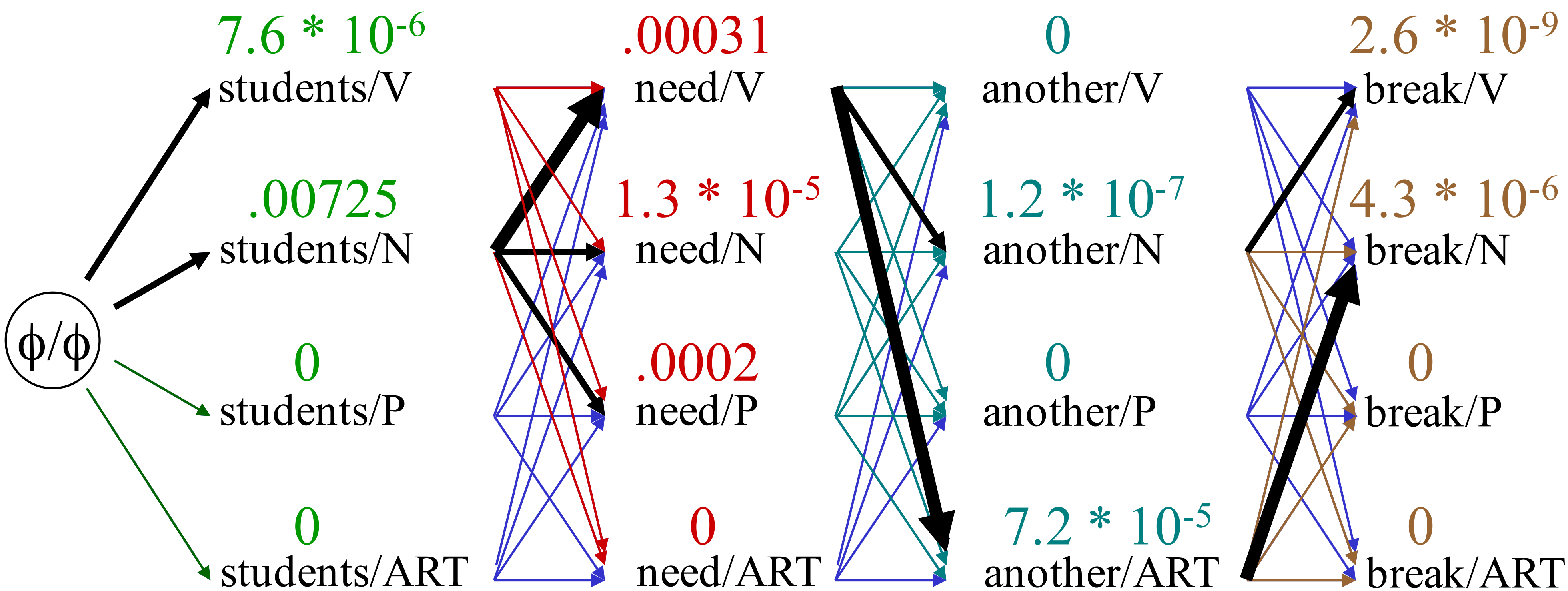

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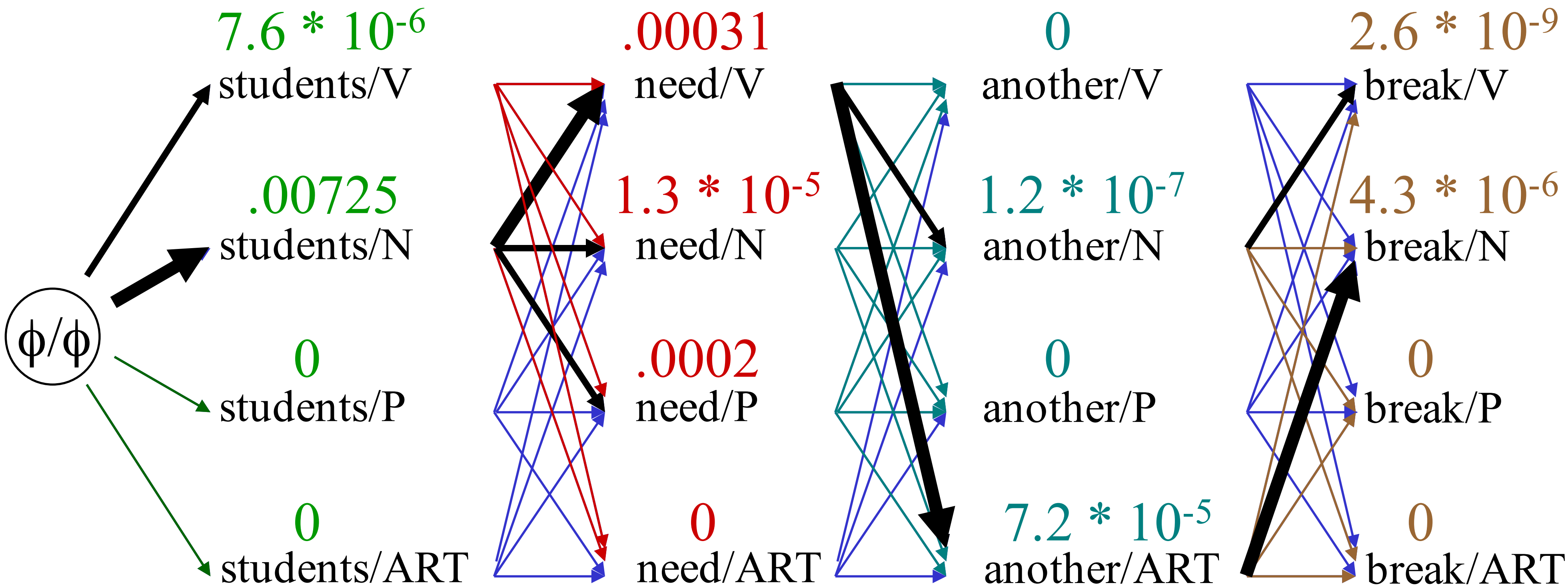

Viterbi Algorithm

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)