NLP Programming Tutorial 5 - Part of Speech Tagging with Hidden Markov Models

Graham Neubig
Nara Institute of Science and Technology (NAIST)

Part of Speech (POS) Tagging

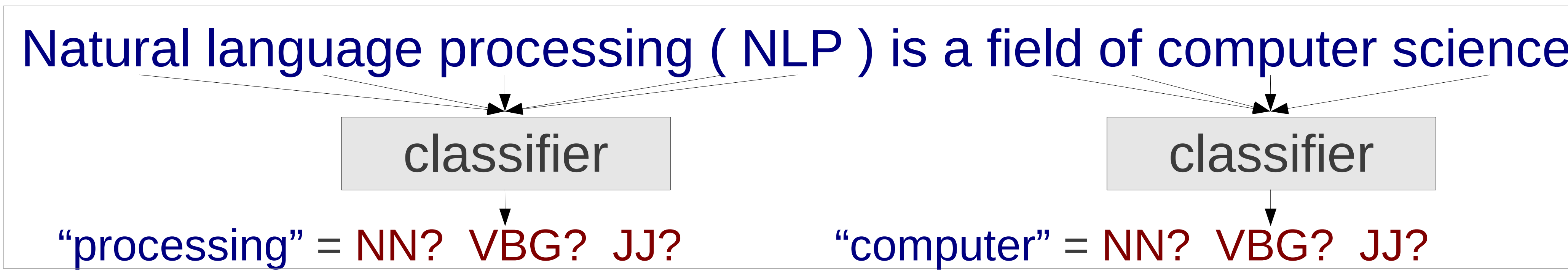
- Given a sentence X, predict its part of speech sequence Y

Natural	language	processing	(	NLP	)	is	a	field	of	computer	science
JJ	NN	NN	-LRB-	NN	-RRB-	VBZ	DT	NN	IN	NN	NN

- A type of “structured” prediction, from two weeks ago
- How can we do this? Any ideas?

Many Answers!

- Pointwise prediction: predict each word individually with a classifier (e.g. perceptron, tool: KyTea)



- Generative sequence models: todays topic! (e.g. Hidden Markov Model, tool: ChaSen)
- Discriminative sequence models: predict whole sequence with a classifier (e.g. CRF, structured perceptron, tool: MeCab, Stanford Tagger)

Probabilistic Model for Tagging

- “Find the most probable tag sequence, given the sentence”

Natural language processing (NLP) is a field of computer science

JJ NN NN LRB NN RRB VBZ DT NN IN NN NN

$$\underset{Y}{\operatorname{argmax}}\, P(Y|X)$$

- Any ideas?

Generative Sequence Model

- First decompose probability using Bayes' law

$$\underset{Y}{\text{argmax}}\, P(Y|X) = \underset{Y}{\text{argmax}} \frac{P(X|Y)\,P(Y)}{P(X)}$$
$$= \underset{Y}{\text{argmax}}\, P(X|Y)\,P(Y)$$

Model of word/POS interactions
"natural" is probably a JJ

Model of POS/POS interactions
NN comes after DET

- Also sometimes called the "noisy-channel model"

Hidden Markov Models

Hidden Markov Models (HMMs) for POS Tagging

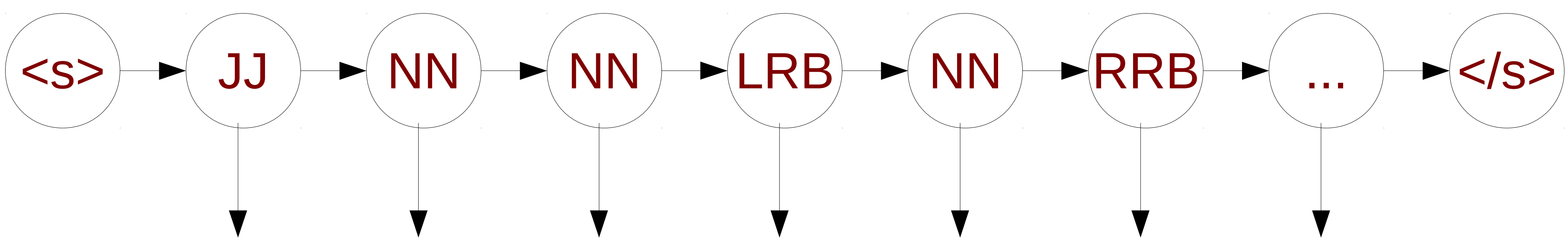
- POS→POS **transition** probabilities
  - Like a bigram model!

$$P(Y) \approx \prod_{i=1}^{I+1} P_T(y_i|y_{i-1})$$

- POS→Word **emission** probabilities

$$P(X|Y) \approx \prod_{1}^{I} P_E(x_i|y_i)$$

$P_T(\text{JJ}|\text{<s>}) * P_T(\text{NN}|\text{JJ}) * P_T(\text{NN}|\text{NN})$ …



natural language processing (nlp) ...

$P_E(\text{natural}|\text{JJ}) * P_E(\text{language}|\text{NN}) * P_E(\text{processing}|\text{NN})$ …

Learning Markov Models (with tags)

- Count the number of occurrences in the corpus and

natural language processing (nlp) is …

c(JJ→natural)++ c(NN→language)++ …

<s> → JJ → NN NN LRB NN RRB VB … </s>

c(<s> JJ)++ c(JJ NN)++ …

- Divide by context to get probability

P_T(LRB|NN) = c(NN LRB)/c(NN) = 1/3

P_E(language|NN) = c(NN → language)/c(NN) = 1/3

Training Algorithm

```
# Input data format is “natural_JJ language_NN …”
make a map emit, transition, context
for each line in file
    previous = “<s>”                              # Make the sentence start
    context[previous]++
    split line into wordtags with “ “
    for each wordtag in wordtags
        split wordtag into word, tag with “_”
        transition[previous+“ “+tag]++ # Count the transition
        context[tag]++                            # Count the context
        emit[tag+“ “+word]++                      # Count the emission
        previous = tag
    transition[previous+” </s>”]++
# Print the transition probabilities
for each key, value in transition
    split key into previous, word with “ “
    print “T”, key, value/context[previous]
# Do the same thing for emission probabilities with “E”
```

Note: Smoothing

- In bigram model, we smoothed probabilities

$$P_{LM}(w_i|w_{i-1}) = \lambda\ P_{ML}(w_i|w_{i-1}) + (1-\lambda)\ P_{LM}(w_i)$$

- HMM transition prob.: there are not many tags, so smoothing is not necessary

$$P_T(y_i|y_{i-1}) = P_{ML}(y_i|y_{i-1})$$

- HMM emission prob.: smooth for unknown words

$$P_E(x_i|y_i) = \lambda\ P_{ML}(x_i|y_i) + (1-\lambda)\ 1/N$$

Finding POS Tags

Problem!

- There are many, many combinations of POS tags!
- How many?

Problem!

- There are many, many combinations of POS tags!
- How many?
- Answer:
  - T = POS tags, N = words: $O(T^N)$
- How do we find our answer in this situation?

This Man Has an Answer!

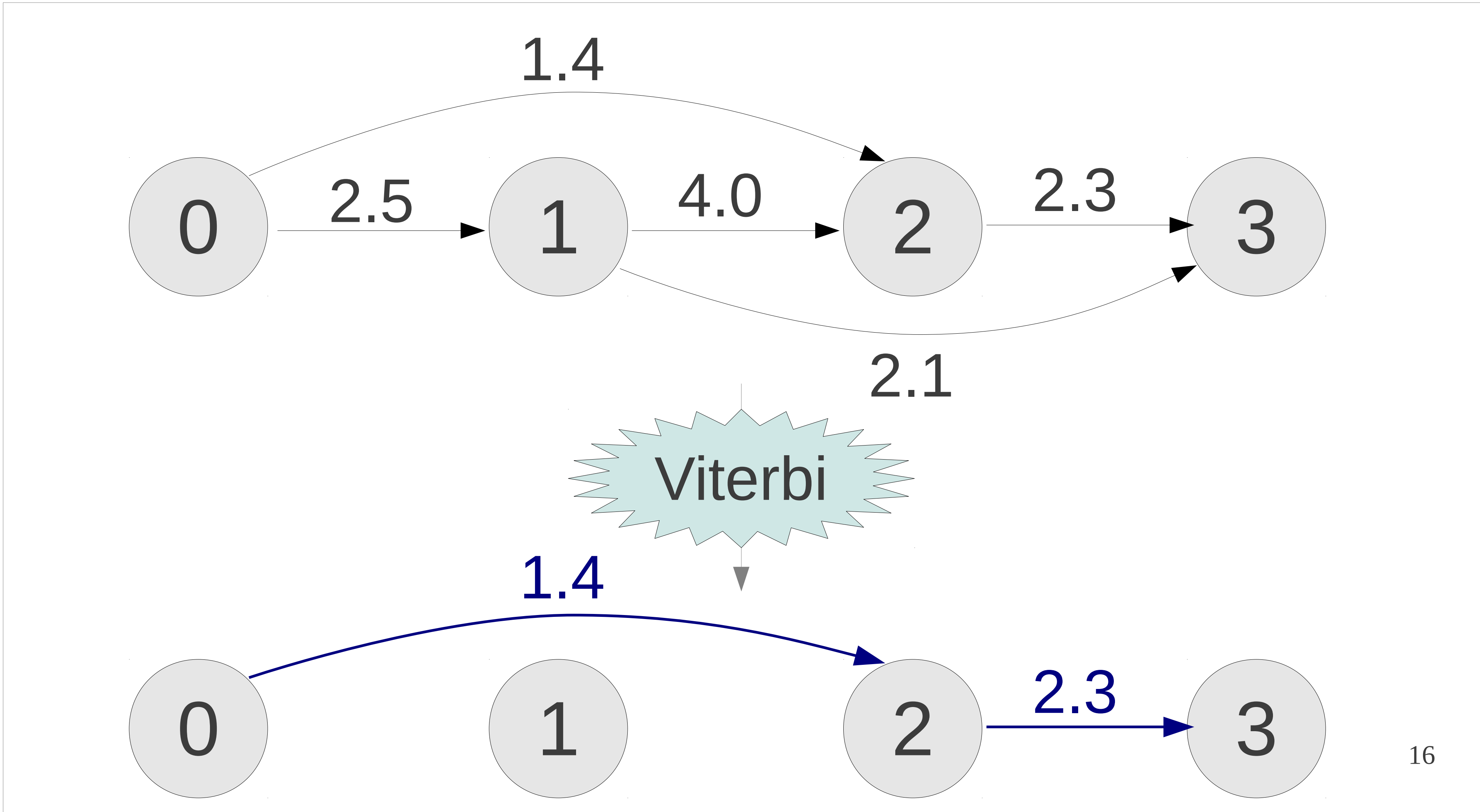
Andrew Viterbi

(Professor UCLA → Founder of Qualcomm)

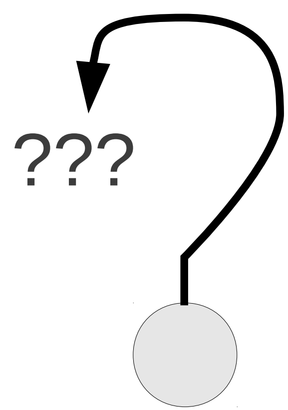
Viterbi Algorithm

The Viterbi Algorithm

- Efficient way to find the shortest path through a graph



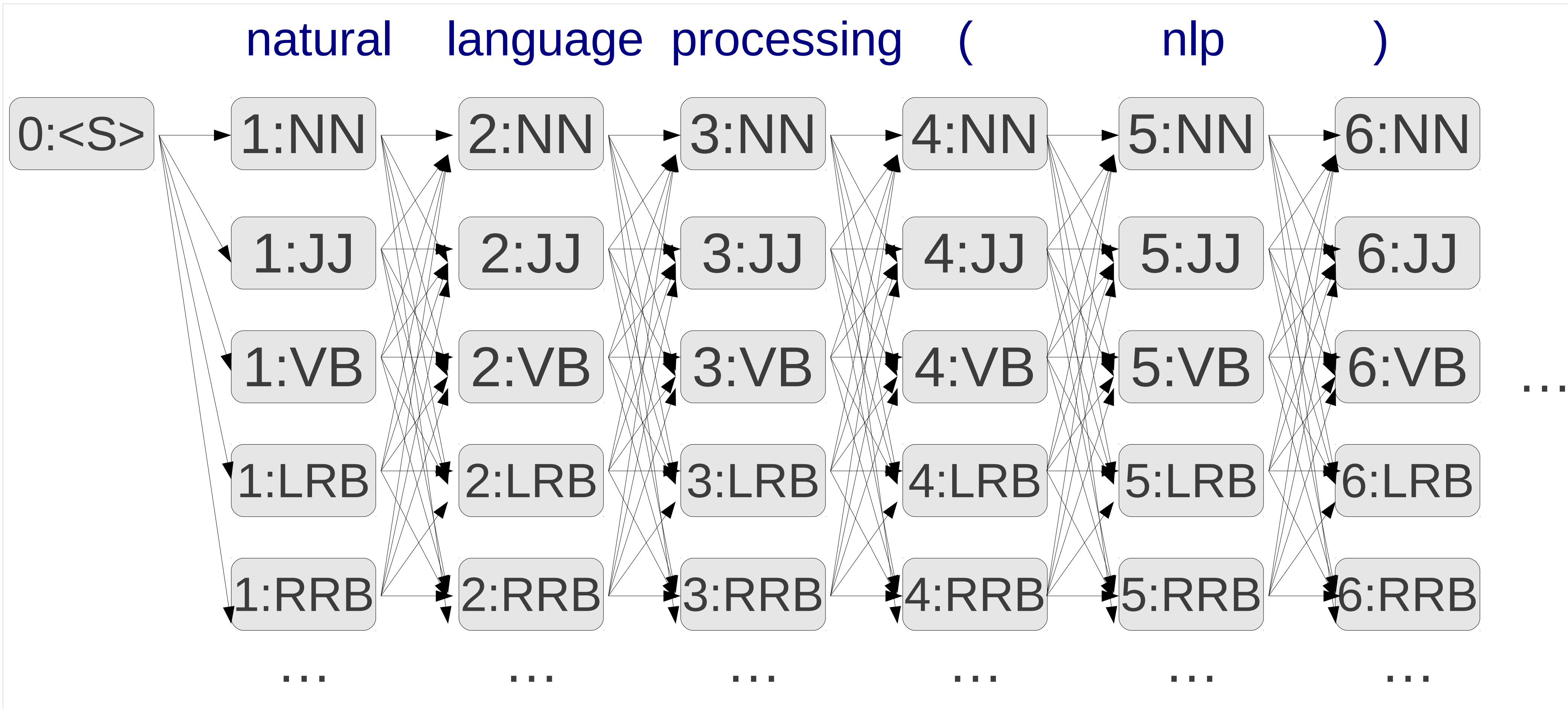
Graph?! What?!



(Let Me Explain!)

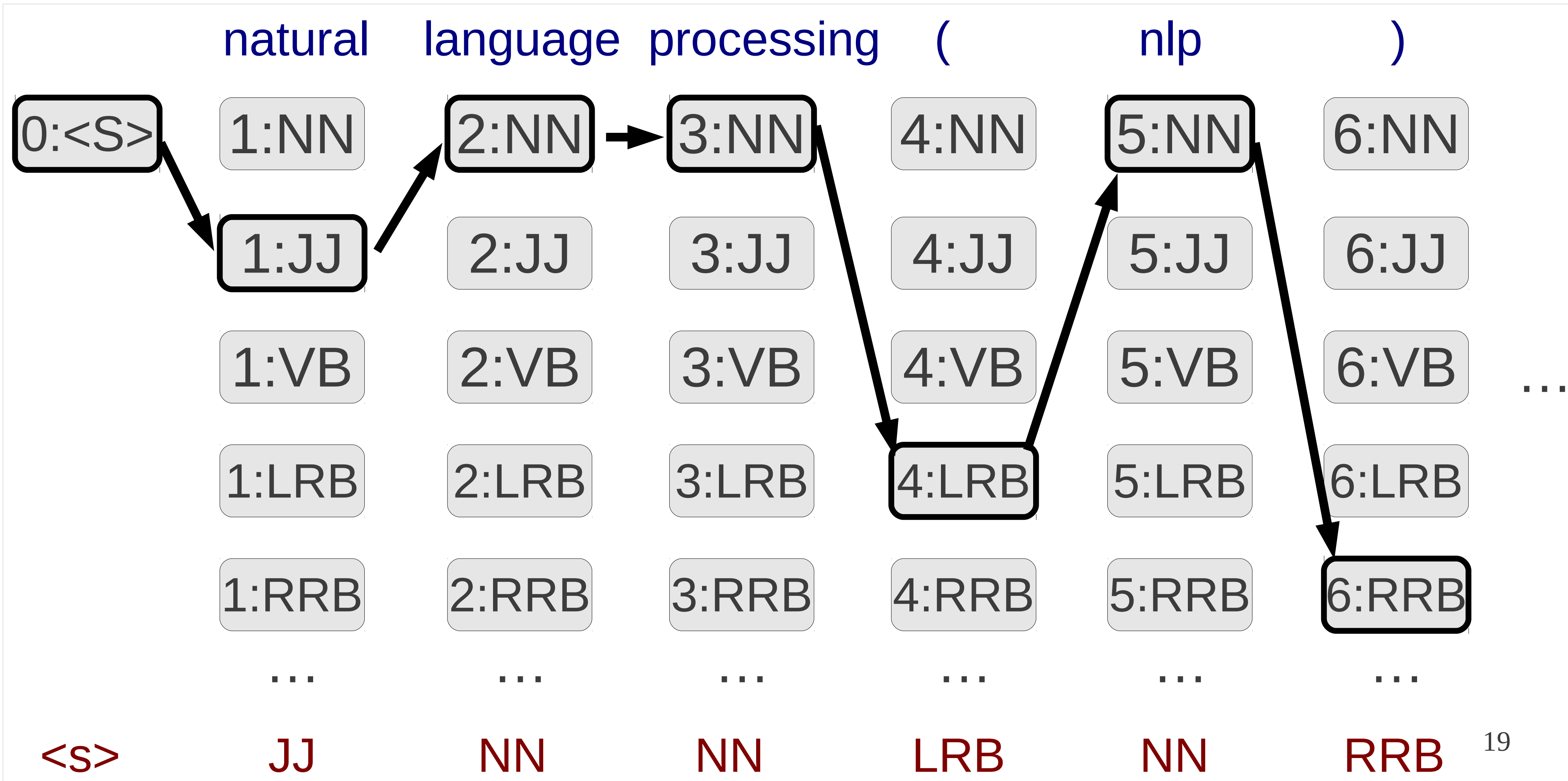
Graphs for POS Tagging

- What does our graph look like? Answer:



Graphs for POS Tagging

- The best path is our POS sequence

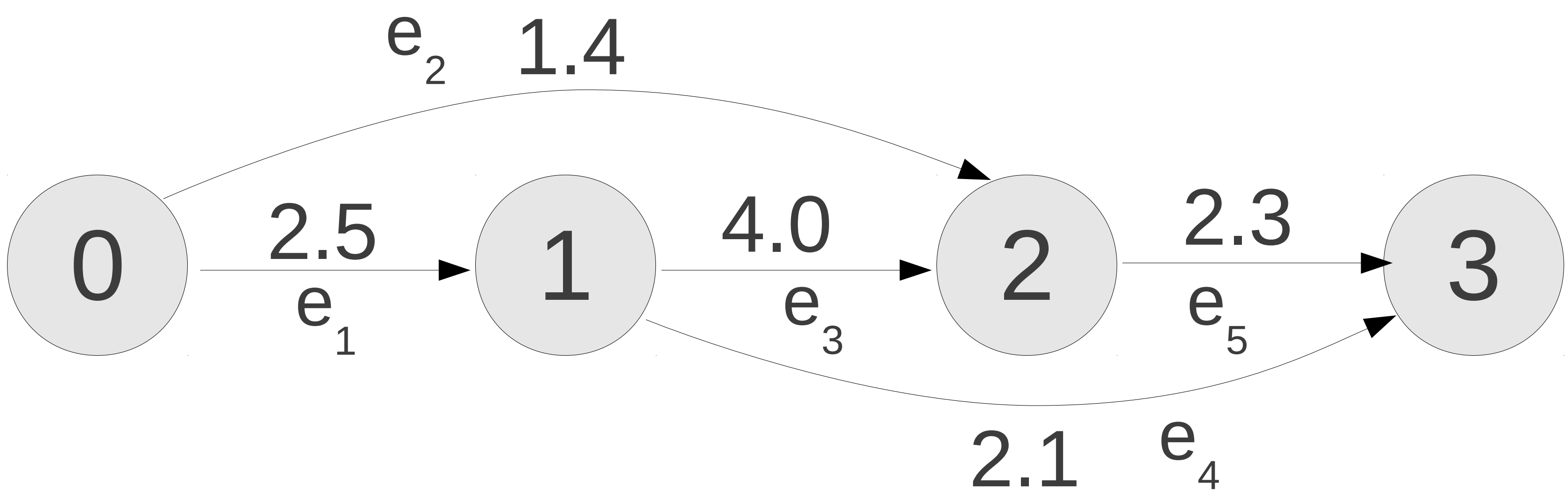


Ok Viterbi, Tell Me More!

- The Viterbi Algorithm has two steps
  - In forward order, find the score of the best path to each node
  - In backward order, create the best path

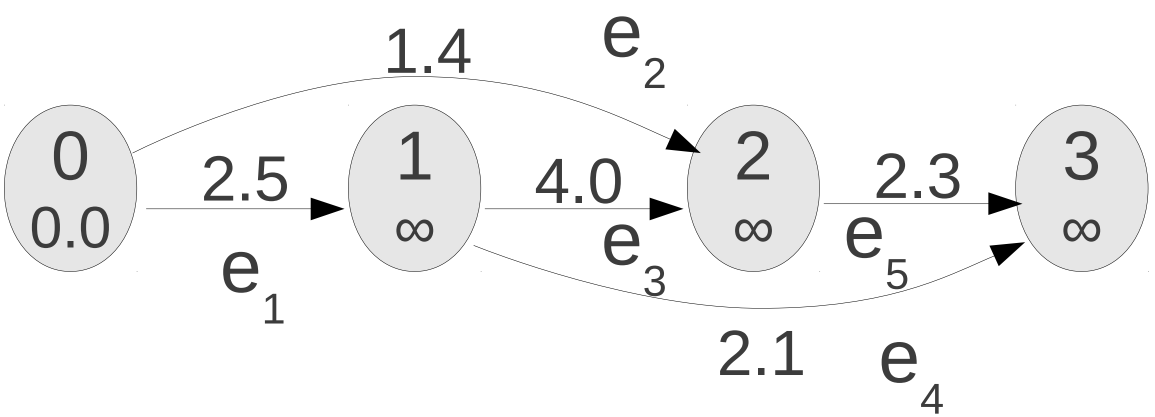
Forward Step

Forward Step



best_score[0] = 0
for each *node* in the *graph* (ascending order)
    best_score[*node*] = ∞
    for each incoming *edge* of *node*
        score = *best_score*[*edge.prev_node*] + *edge.score*
        if *score* < *best_score*[*node*]
            best_score[*node*] = *score*
            best_edge[*node*] = *edge*

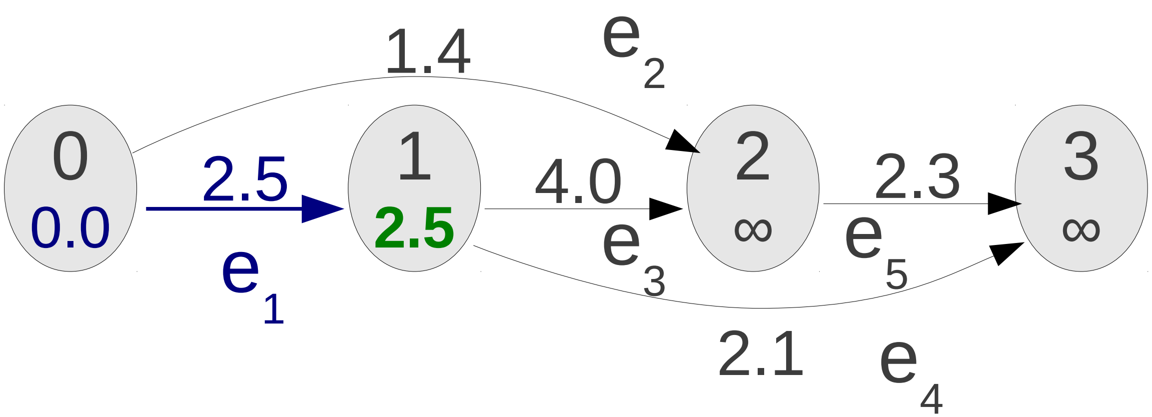
Example:



Initialize:

best_score[0] = 0

Example:



Initialize:

best_score[0] = 0

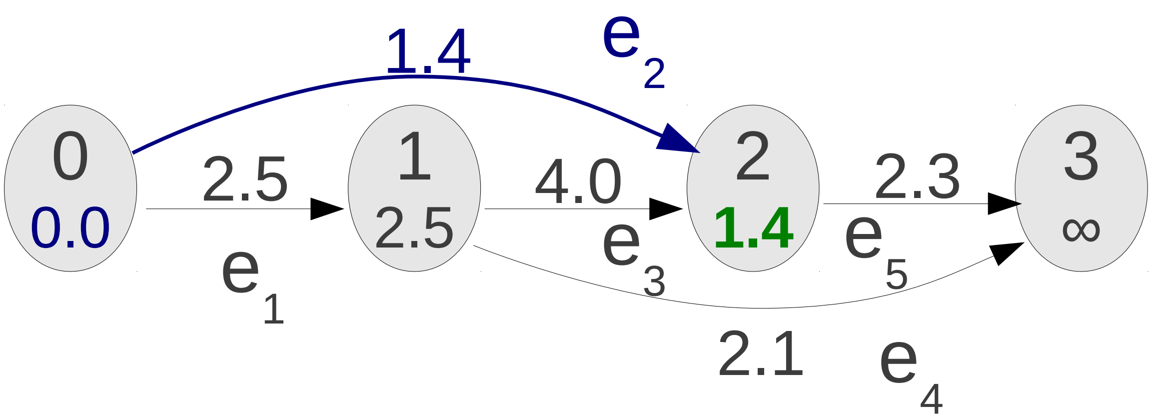
Check e_1:

score = 0 + 2.5 = 2.5 (< ∞)

best_score[1] = 2.5

best_edge[1] = e_1

Example:



Initialize:

best_score[0] = 0

Check e_1:

score = 0 + 2.5 = 2.5 (< ∞)

best_score[1] = 2.5

best_edge[1] = e_1

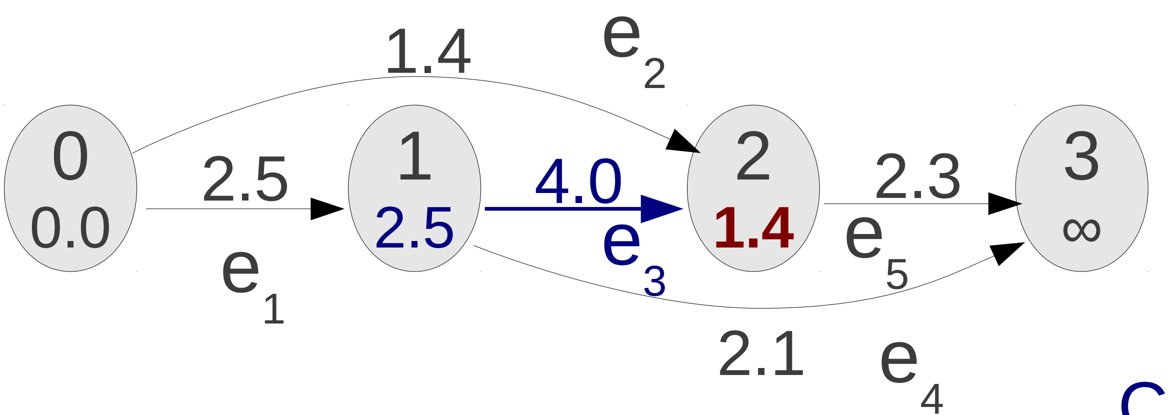
Check e_2:

score = 0 + 1.4 = 1.4 (< ∞)

best_score[2] = 1.4

best_edge[2] = e_2

Example:



Initialize:

best_score[0] = 0

Check e_1:

score = 0 + 2.5 = 2.5 (< ∞)

best_score[1] = 2.5

best_edge[1] = e_1

Check e_2:

score = 0 + 1.4 = 1.4 (< ∞)

best_score[2] = 1.4

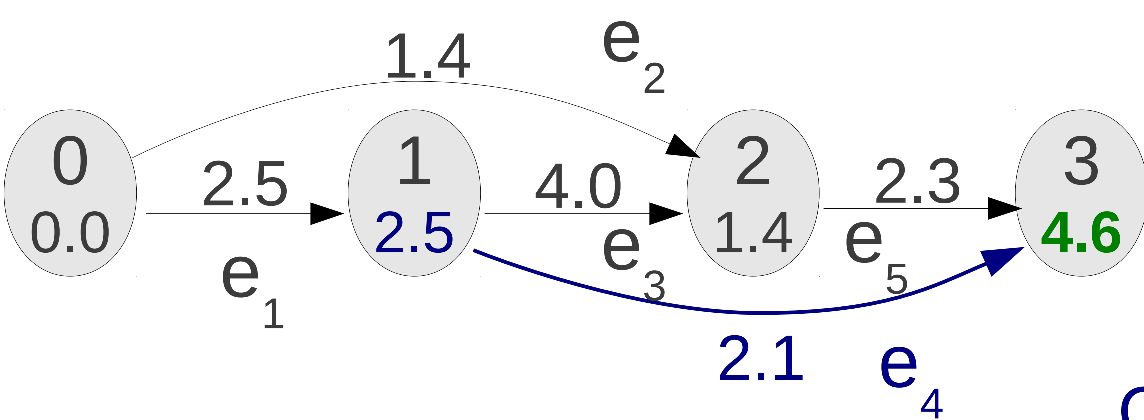
best_edge[2] = e_2

Check e_3:

score = 2.5 + 4.0 = 6.5 (> 1.4)

No change!

Example:



Initialize:

best_score[0] = 0

Check e_1:

score = 0 + 2.5 = 2.5 (< ∞)

best_score[1] = 2.5

best_edge[1] = e_1

Check e_2:

score = 0 + 1.4 = 1.4 (< ∞)

best_score[2] = 1.4

best_edge[2] = e_2

Check e_3:

score = 2.5 + 4.0 = 6.5 (> 1.4)

No change!

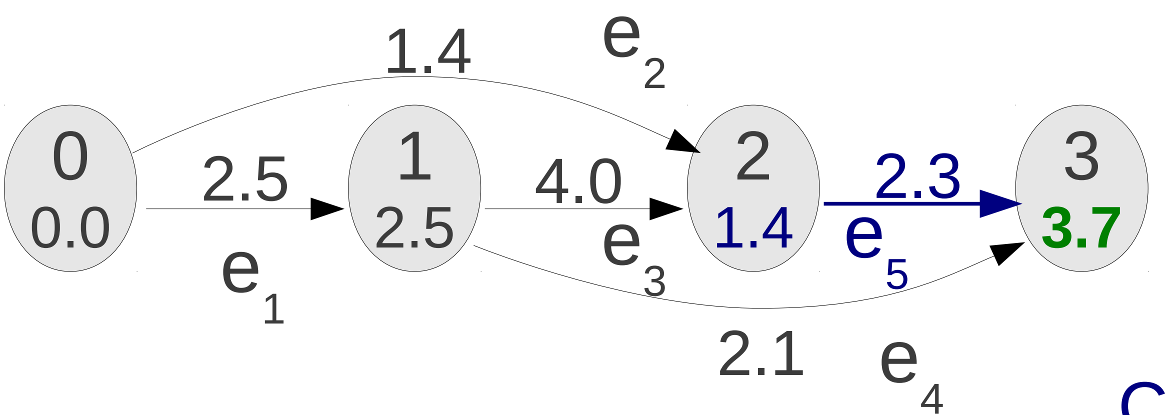
Check e_4:

score = 2.5 + 2.1 = 4.6 (< ∞)

best_score[3] = 4.6

best_edge[3] = e_4

Example:



Initialize:

best_score[0] = 0

Check e_1:

score = 0 + 2.5 = 2.5 (< ∞)

best_score[1] = 2.5

best_edge[1] = e_1

Check e_2:

score = 0 + 1.4 = 1.4 (< ∞)

best_score[2] = 1.4

best_edge[2] = e_2

Check e_3:

score = 2.5 + 4.0 = 6.5 (> 1.4)

No change!

Check e_4:

score = 2.5 + 2.1 = 4.6 (< ∞)

~~best_score[3] = 4.6~~

~~best_edge[3] = e_4~~

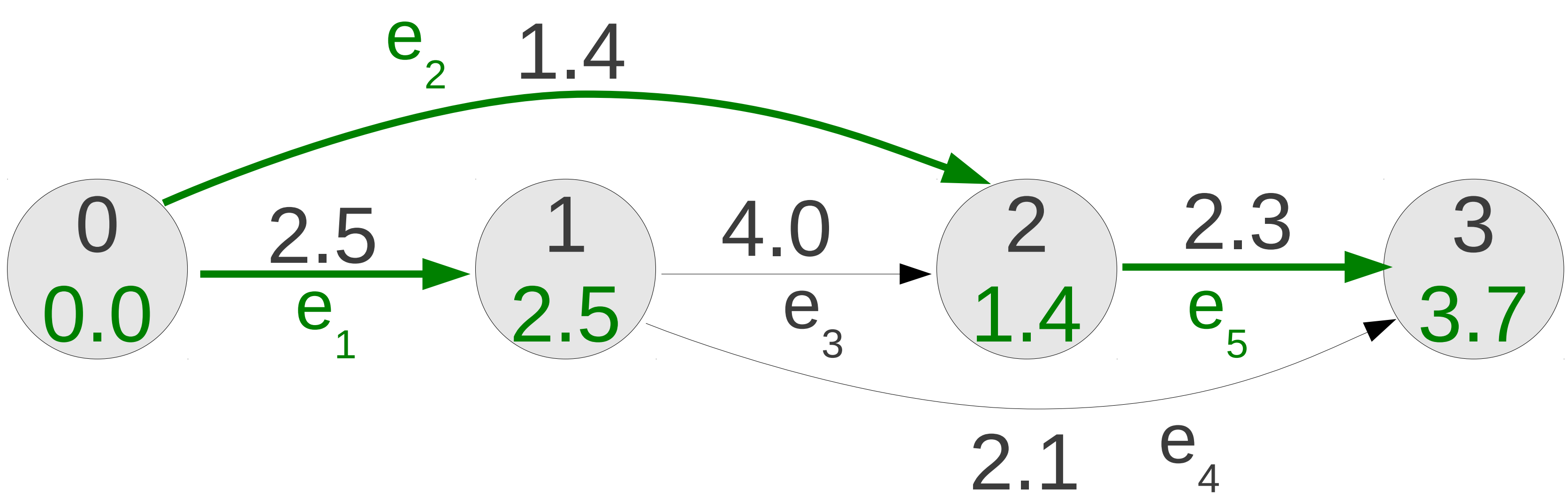
Check e_5:

score = 1.4 + 2.3 = 3.7 (< 4.6)

best_score[3] = 3.7

best_edge[3] = e_5

Result of Forward Step

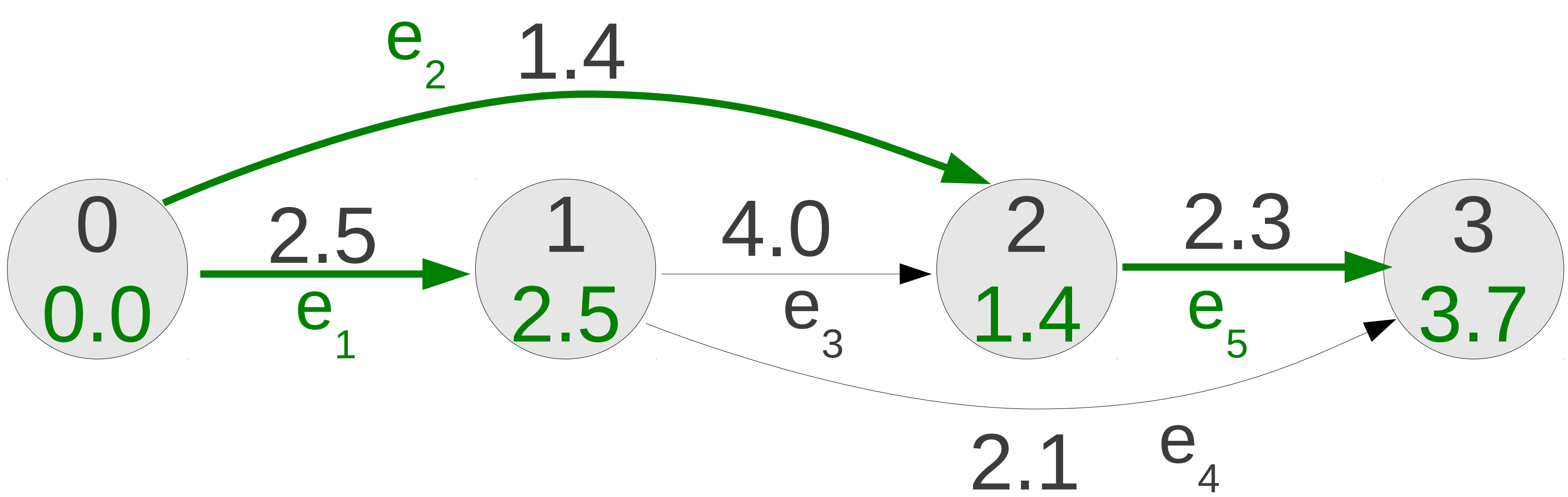


best_score = (0.0, 2.5, 1.4, 3.7)

best_edge = (NULL, e_1, e_2, e_5)

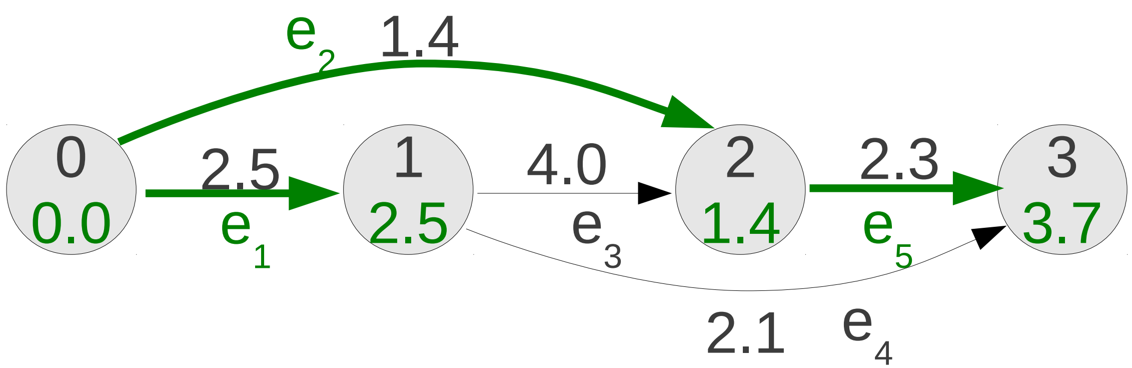
Backward Step

Backward Step



best_path = [ ]
next_edge = *best_edge*[*best_edge*.length – 1]
while *next_edge* != NULL
    add *next_edge* to *best_path*
    next_edge = *best_edge*[*next_edge.prev_node*]
reverse best_path

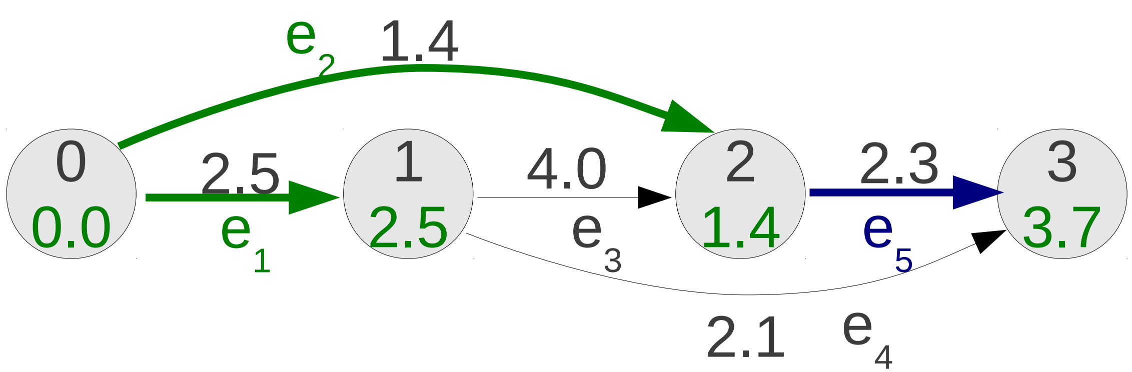
Example of Backward Step



Initialize:

best_path = []
next_edge = best_edge[3] = e_5

Example of Backward Step



Initialize:

best_path = []

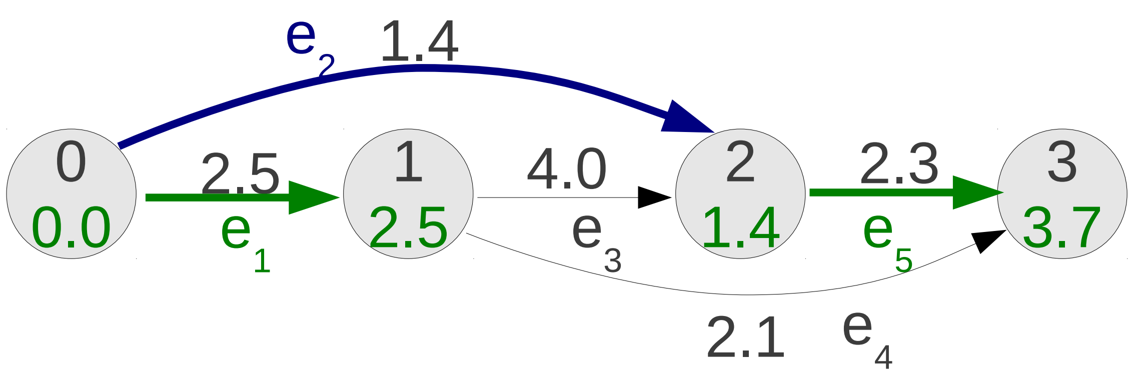
next_edge = best_edge[3] = e_5

Process e_5:

best_path = [e_5]

next_edge = best_edge[2] = e_2

Example of Backward Step



Initialize:

best_path = []

next_edge = best_edge[3] = e_5

Process e_5:

best_path = [e_5]

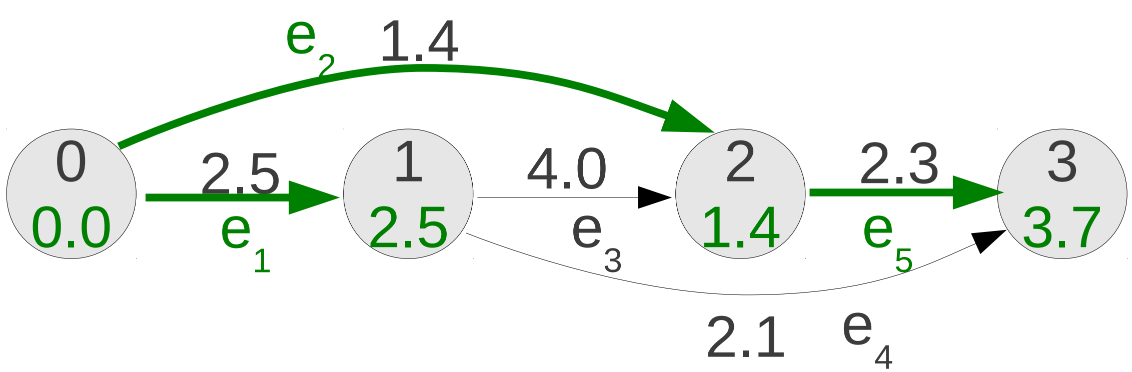
next_edge = best_edge[2] = e_2

Process e_2:

best_path = [e_5, e_2]

next_edge = best_edge[0] = NULL

Example of Backward Step



Initialize:

best_path = []
next_edge = best_edge[3] = e_5

Process e_5:

best_path = [e_5]
next_edge = best_edge[2] = e_2

Process e_5:

best_path = [e_5, e_2]
next_edge = best_edge[0] = NULL

Reverse:

best_path = [e_2, e_5]

Tools Required: Reverse

- We must reverse the order of the edges

```
my_list = [ 1, 2, 3, 4, 5 ]
my_list.reverse()

print my_list
```

```
$ ./my-program.py
[5, 4, 3, 2, 1]
```

Forward and Backward Step for POS Tagging

Forward Step: Part 1

- First, calculate transition from <S> and emission of the first word for every POS

natural

0:<S>

1:NN best_score[“1 NN”] = -log P_T(NN|<S>) + -log P_E(natural | NN)

1:JJ best_score[“1 JJ”] = -log P_T(JJ|<S>) + -log P_E(natural | JJ)

1:VB best_score[“1 VB”] = -log P_T(VB|<S>) + -log P_E(natural | VB)

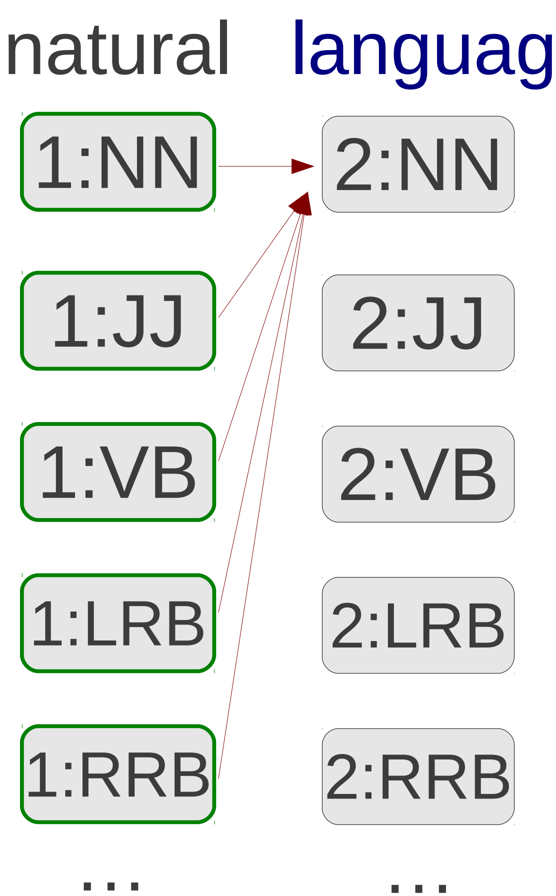
1:LRB best_score[“1 LRB”] = -log P_T(LRB|<S>) + -log P_E(natural | LRB)

1:RRB best_score[“1 RRB”] = -log P_T(RRB|<S>) + -log P_E(natural | RRB)

…

Forward Step: Middle Parts

- For middle words, calculate the minimum score for all possible previous POS tags

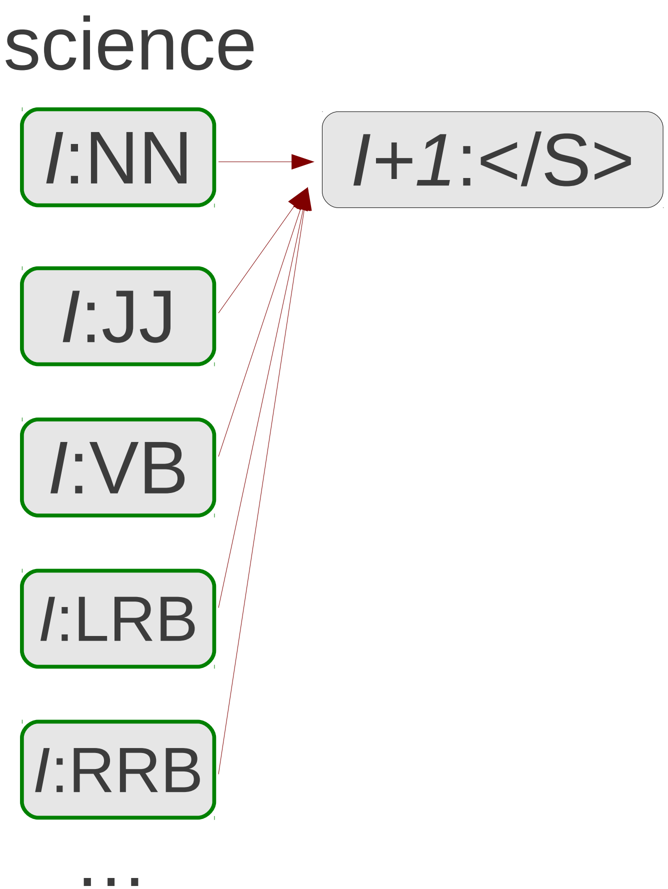


best_score["2 NN"] = min(
best_score["1 NN"] + -log P_T(NN|NN) + -log P_E(language | NN),
best_score["1 JJ"] + -log P_T(NN|JJ) + -log P_E(language | NN),
best_score["1 VB"] + -log P_T(NN|VB) + -log P_E(language | NN),
best_score["1 LRB"] + -log P_T(NN|LRB) + -log P_E(language | NN),
best_score["1 RRB"] + -log P_T(NN|RRB) + -log P_E(language | NN),
...
)

best_score["2 JJ"] = min(
best_score["1 NN"] + -log P_T(JJ|NN) + -log P_E(language | JJ),
best_score["1 JJ"] + -log P_T(JJ|JJ) + -log P_E(language | JJ),
best_score["1 VB"] + -log P_T(JJ|VB) + -log P_E(language | JJ),
...

Forward Step: Final Part

- Finish up the sentence with the sentence final symbol



best_score["*I+1* </S>"] = min(
  best_score["*I* NN"] + -log P_T(</S>|NN),
  best_score["*I* JJ"] + -log P_T(</S>|JJ),
  best_score["*I* VB"] + -log P_T(</S>|VB),
  best_score["*I* LRB"] + -log P_T(</S>|LRB),
  best_score["*I* NN"] + -log P_T(</S>|RRB),
  ...
)

Implementation: Model Loading

```
make a map for transition, emission, possible_tags

for each line in model_file
    split line into type, context, word, prob
    possible_tags[context] = 1  # We use this to
                                # enumerate all tags
    if type = "T"
        transition["context word"] = prob
    else
        emission["context word"] = prob
```

Implementation: Forward Step

split *line* **into** *words*
I = length*(words)*
make maps *best_score, best_edge*
best_score[0, “<s>”] = 0   # Start with <s>
best_edge[0, “<s>”] = None
for *i* **in** 0 … *I*-1:
    for each *prev* **in** keys of *possible_tags*
        for each *next* **in** keys of *possible_tags*
            if best_score[“*i prev*”] **and** transition[“prev next”] **exist**
                score = best_score[“i prev”] +
                                -log P_T(next|prev) + -log P_E(word[i]|next)
                if *best_score*[“*i+1 next*”] **is** new **or** > *score*
                    best_score[“*i+1 next*”] = score
                    best_edge[“*i+1 next*”] = “*i prev*”
Finally, do the same for </s>

Implementation: Backward Step

tags = [ ]
next_edge = *best_edge*[*“I </s>”*]
while *next_edge* != “0 <s>”
    # Add the substring for this edge to the words
    split *next_edge* **into** *position*, *tag*
    append *tag* **to** *tags*
    next_edge = *best_edge*[*next_edge*]
tags.reverse()
join *tags* into a string and **print**

Exercise

Exercise

- Write train-hmm and test-hmm
- Test the program
  - Input: `test/05-{train,test}-input.txt`
  - Answer: `test/05-{train,test}-answer.txt`
- Train an HMM model on `data/wiki-en-train.norm_pos` and run the program on `data/wiki-en-test.norm`
- Measure the accuracy of your tagging with `script/gradepos.pl data/wiki-en-test.pos my_answer.pos`
- Report the accuracy
- Challenge: think of a way to improve accuracy

Thank You!