NLP Programming Tutorial 6 - Kana-Kanji Conversion

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Formal Model for Kana-Kanji Conversion (KKC)

- In Japanese input, users type in phonetic Hiragana, but proper Japanese is written in logographic Kanji
- **Kana-Kanji Conversion**: Given an unsegmented Hiragana string X, predict its Kanji string Y

かなかんじへんかんはにほんごにゅうりょくのいちぶ

↓

かな漢字変換は日本語入力の一部

- Also a type of structured prediction, like HMMs or word segmentation

There are Many Choices!

かなかんじへんかんはにほんごにゅうりょくのいちぶ

かな漢字変換は日本語入力の一部　good!

仮名漢字変換は日本語入力の一部　good?

かな漢字変換は二本後入力の一部　bad

家中ん事変感歯に☒御乳力の胃治舞 ?!?!

...

- How does the computer tell between good and bad?

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

Remember (from the HMM): Generative Sequence Model

- Decompose probability using Bayes' law

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

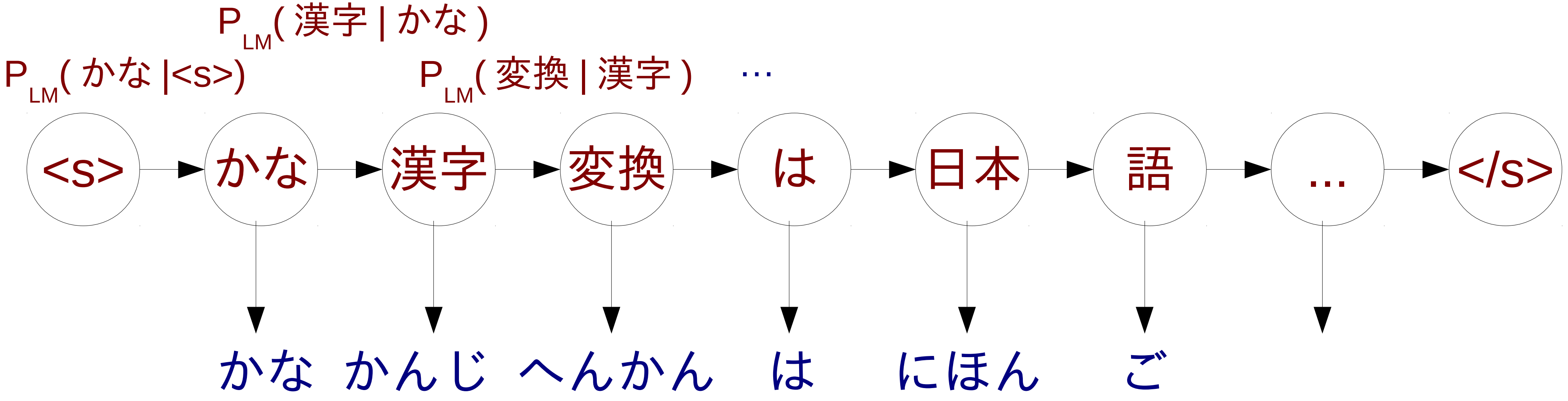
$$= \underset{Y}{\operatorname{argmax}}\, P(X|Y)\,P(Y)$$

Model of Kana/Kanji interactions
“ かんじ” is probably “ 感じ”

Model of Kanji-Kanji interactions
“ 漢字” comes after “ かな”

Sequence Model for Kana-Kanji Conversion

- Kanji→Kanji **language model** probabilities
  - Bigram model $$P(Y) \approx \prod_{i=1}^{I+1} P_{LM}(y_i|y_{i-1})$$
- Kanji→Kana **translation model** probabilities $$P(X|Y) \approx \prod_{1}^{I} P_{TM}(x_i|y_i)$$



P_{LM}(漢字 | かな)

P_{LM}(かな |<s>) P_{LM}(変換 | 漢字) …

<s> かな 漢字 変換 は 日本 語 … </s>

かな かんじ へんかん は にほん ご

P_{TM}(かな | かな) $*$ P_{TM}(かんじ | 漢字) $*$ P_{TM}(へんかん | 変換) …

Generative Sequence Model

Emission/Translation Probability

Wait! I heard this last week!!!

Transition/Language Model Probability

Structured Prediction

Differences between POS and Kana-Kanji Conversion

- 1. Sparsity of $P(y_i|y_{i-1})$:
    - **HMM:** POS→POS is not sparse → no smoothing
    - **KKC:** Word→Word is sparse → need smoothing
- 2. Emission possibilities
    - **HMM:** Considers all word-POS combinations
    - **KKC:** Considers only previously seen combinations
- 3. Word segmentation:
    - **HMM:** 1 word, 1 POS tag
    - **KKC:** Multiple Hiragana, multiple Kanji

1. Handling Sparsity

- Simple! Just use a smoothed bi-gram model

Bigram: $$P(y_i|y_{i-1}) = \lambda_2 P_{ML}(y_i|y_{i-1}) + (1-\lambda_2) P(y_i)$$

Unigram: $$P(y_i) = \lambda_1 P_{ML}(y_i) + (1-\lambda_1) \frac{1}{N}$$

- Re-use your code from Tutorial 2

2. Translation possibilities

- For translation probabilities, use maximum likelihood

$$P_{TM}(x_i|y_i)=c(y_i \rightarrow x_i)/c(y_i)$$

  - Re-use your code from Tutorial 5
- Implication: We only need to consider some words

c(感じ → かんじ) = 5
c(漢字 → かんじ) = 3
c(幹事 → かんじ) = 2

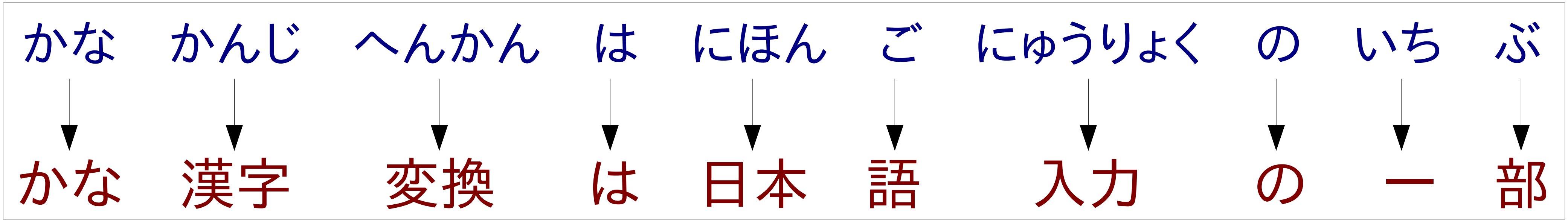
c(トマト → かんじ) = 0
c(奈良 → かんじ) = 0
c(監事 → かんじ) = 0
…

X

→ Efficient search is possible

3. Words and Kana-Kanji Conversion

- Easier to think of Kana-Kanji conversion using words



かな	かんじ	へんかん	は	にほん	ご	にゅうりょく	の	いち	ぶ
かな	漢字	変換	は	日本	語	入力	の	一	部

- We need to do two things:
  - Separate Hiragana into words
  - Convert Hiragana words into Kanji
- We will do these at the same time with the Viterbi algorithm

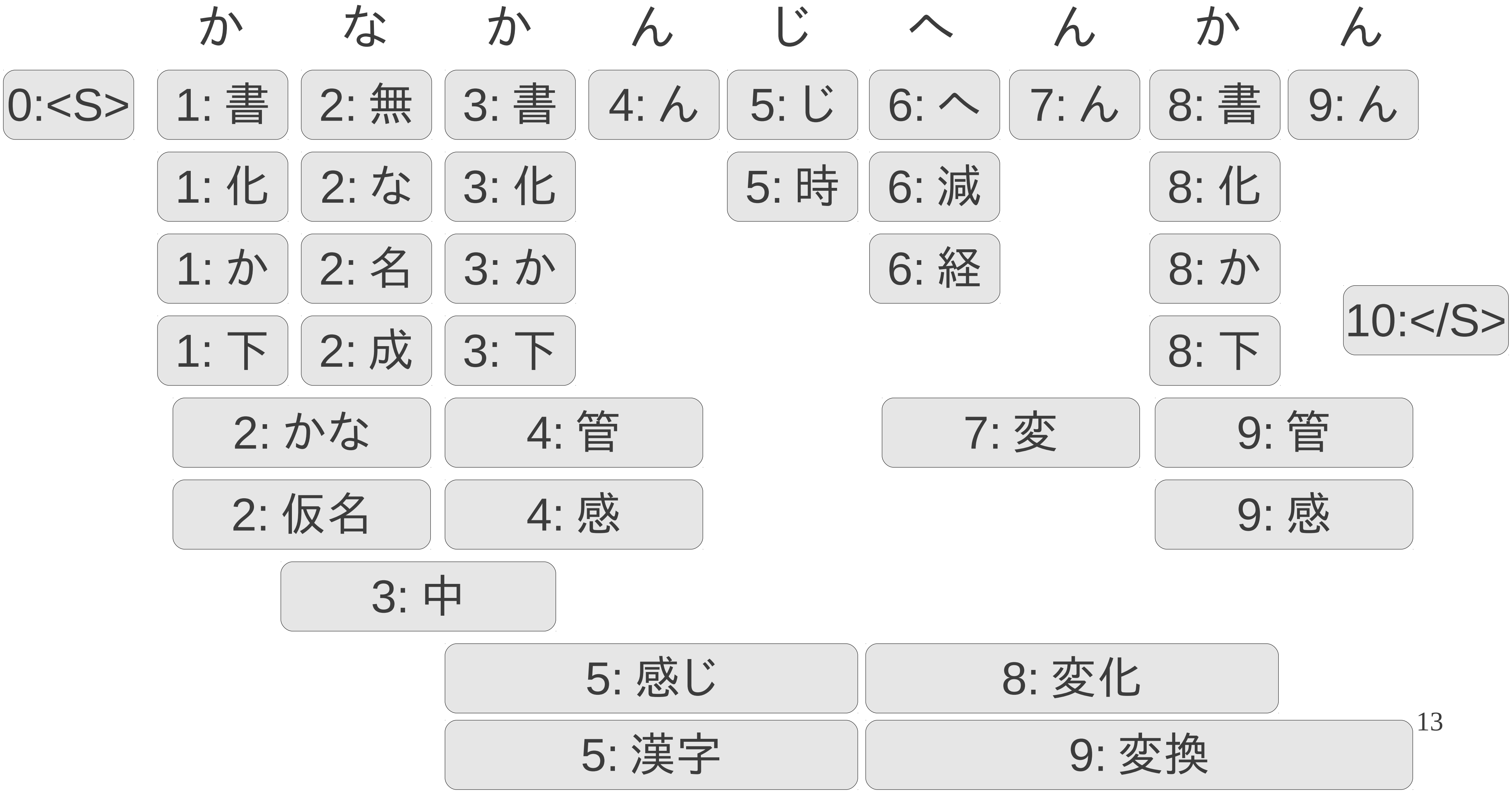
Search for Kana-Kanji Conversion

Search for Kana-Kanji Conversion

- Use the Viterbi Algorithm
- What does our graph look like?

Search for Kana-Kanji Conversion

- Use the Viterbi Algorithm



か な か ん じ へ ん か ん

0:<S>

1: 書 2: 無 3: 書 4: ん 5: じ 6: へ 7: ん 8: 書 9: ん

1: 化 2: な 3: 化 5: 時 6: 減 8: 化

1: か 2: 名 3: か 6: 経 8: か

1: 下 2: 成 3: 下 8: 下

10:</S>

2: かな 4: 管 7: 変 9: 管

2: 仮名 4: 感 9: 感

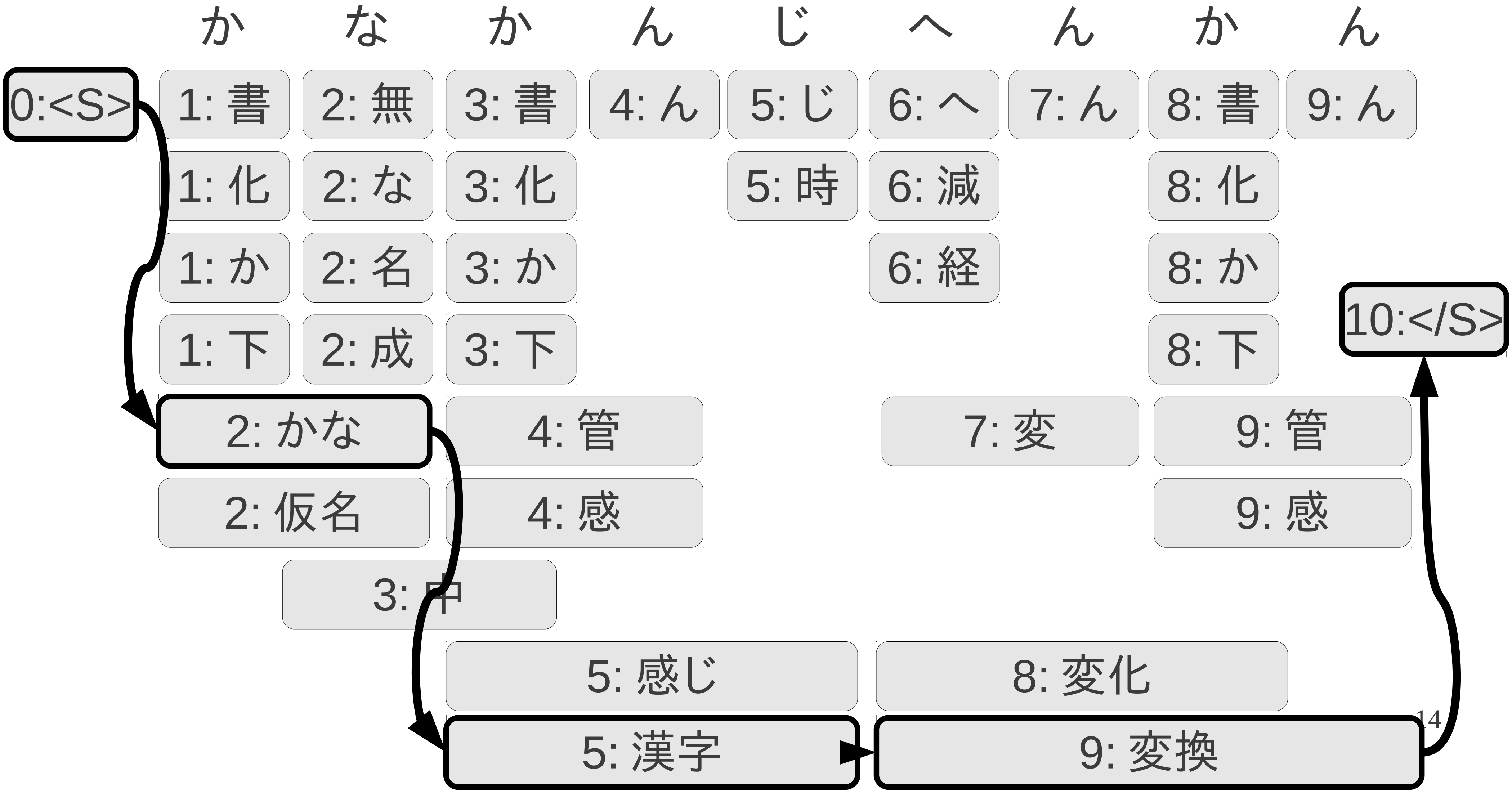
3: 中

5: 感じ 8: 変化

5: 漢字 9: 変換

Search for Kana-Kanji Conversion

- Use the Viterbi Algorithm



か な か ん じ へ ん か ん

0:<S>
1: 書 2: 無 3: 書 4: ん 5: じ 6: へ 7: ん 8: 書 9: ん
1: 化 2: な 3: 化 5: 時 6: 減 8: 化
1: か 2: 名 3: か 6: 経 8: か
1: 下 2: 成 3: 下 8: 下
10:</S>
2: かな 4: 管 7: 変 9: 管
2: 仮名 4: 感 9: 感
3: 中
5: 感じ 8: 変化
5: 漢字 9: 変換

Steps for Viterbi Algorithm

- First, start at 0:<S>

か　な　か　ん　じ　へ　ん　か　ん

0:<S>　S["0:<S>"] = 0

Search for Kana-Kanji Conversion

- Expand 0 → 1, with all previous states ending at 0

か な か ん じ へ ん か ん

0:<S>

1: 書 $S[\text{“1: 書”}] = -\log (P_{TM}(\text{か} \mid \text{書}) * P_{LM}(\text{書} \mid \text{<S>})) + S[\text{“0:<S>”}]$

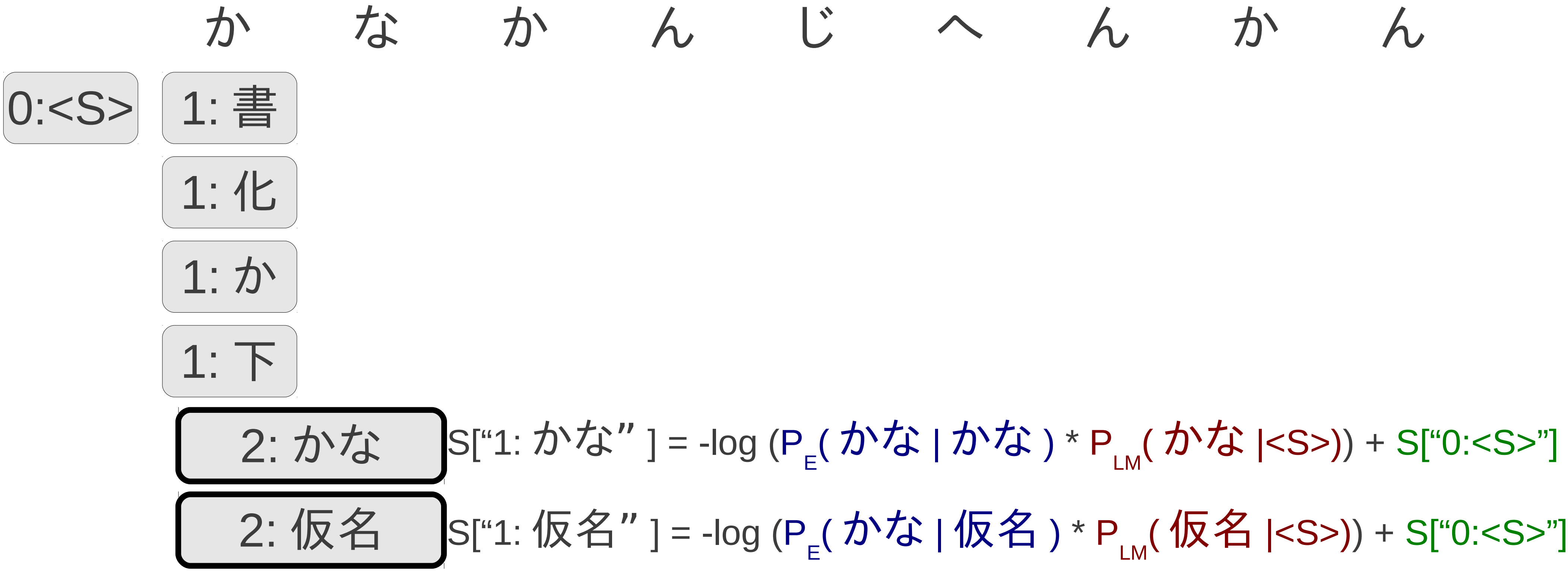
1: 化 $S[\text{“1: 化”}] = -\log (P_{TM}(\text{か} \mid \text{化}) * P_{LM}(\text{化} \mid \text{<S>})) + S[\text{“0:<S>”}]$

1: か $S[\text{“1: か”}] = -\log (P_{TM}(\text{か} \mid \text{か}) * P_{LM}(\text{か} \mid \text{<S>})) + S[\text{“0:<S>”}]$

1: 下 $S[\text{“1: 下”}] = -\log (P_{TM}(\text{か} \mid \text{下}) * P_{LM}(\text{下} \mid \text{<S>})) + S[\text{“0:<S>”}]$

Search for Kana-Kanji Conversion

- Expand 0 → 2, with all previous states ending at 0



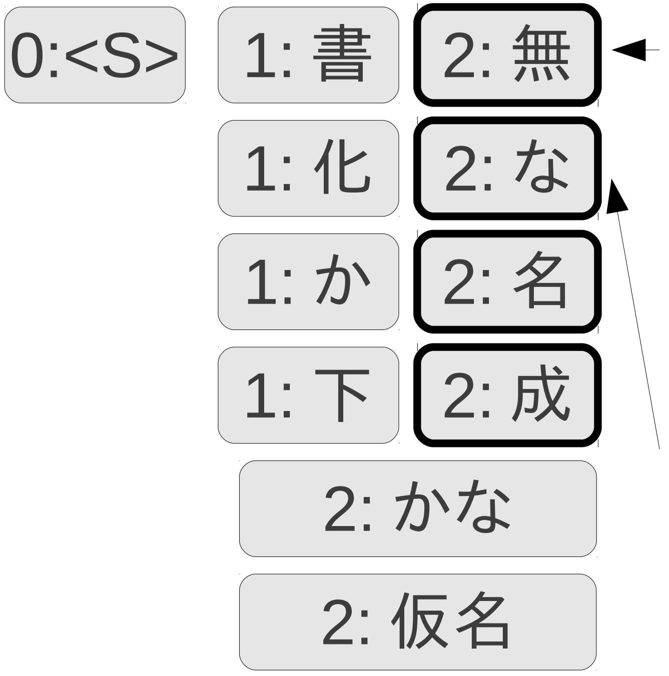
S[“1: かな”] = -log (P_E(かな | かな) * P_{LM}(かな |<S>)) + S[“0:<S>”]

S[“1: 仮名”] = -log (P_E(かな | 仮名) * P_{LM}(仮名 |<S>)) + S[“0:<S>”]

Search for Kana-Kanji Conversion

- Expand 1 → 2, with all previous states ending at 1

か　な　か　ん　じ　へ　ん　か　ん



0:<S>

1: 書
1: 化
1: か
1: 下

2: 無
2: な
2: 名
2: 成
2: かな
2: 仮名

S[“2: 無”] = min(
-log (P_E(な | 無) * P_{LM}(無 | 書)) + S[“1: 書”],
-log (P_E(な | 無) * P_{LM}(無 | 化)) + S[“1: 化”],
-log (P_E(な | 無) * P_{LM}(無 | か)) + S[“1: か”],
-log (P_E(な | 無) * P_{LM}(無 | 下)) + S[“1: 下”])

S[“2: な”] = min(
-log (P_E(な | な) * P_{LM}(な | 書)) + S[“1: 書”],
-log (P_E(な | な) * P_{LM}(な | 化)) + S[“1: 化”],
-log (P_E(な | な) * P_{LM}(な | か)) + S[“1: か”],
-log (P_E(な | な) * P_{LM}(な | 下)) + S[“1: 下”])

■ ■ ■

Algorithm

Overall Algorithm

```
load lm                     # Same as tutorials 2
load tm                     # Similar to tutorial 5
                            # Structure is tm[pron][word] = prob
for each line in file
    do forward step
    do backward step        # Same as tutorial 5
    print results           # Same as tutorial 5
```

Implementation: Forward Step

```
edge[0][“<s>”] = NULL, score[0][“<s>”] = 0
for end in 1 .. len(line)                          # For each ending point
    create map my_edges
    for begin in 0 .. end – 1                      # For each beginning point
        pron = substring of line from begin to end # Find the hiragana
        my_tm = tm_probs[pron]                     # Find words/TM probs for pron
        if there are no candidates and len(pron) == 1
            my_tm = (pron, 0)                      # Map hiragana as-is
        for curr_word, tm_prob in my_tm            # For possible current words
            for prev_word, prev_score in score[begin] # For all previous words/probs
                # Find the current score
                curr_score = prev_score + -log(tm_prob * $P_{LM}$(curr_word | prev_word))
                if curr_score is better than score[end][curr_word]
                  score[end][curr_word] = curr_score
                  edge[end][curr_word] = (begin, prev_word)
```

Exercise

Exercise

- Write kkc.py and re-use train-bigram.py, train-hmm.py
- Test the program
  - `train-bigram.py test/06-word.txt > lm.txt`
  - `train-hmm.py test/06-pronword.txt > tm.txt`
  - `kkc.py lm.txt tm.txt test/06-pron.txt > output.txt`
  - Answer: `test/06-pronword.txt`

Exercise

- Run the program
  - `train-bigram.py data/wiki-ja-train.word > lm.txt`
  - `train-hmm.py data/wiki-ja-train.pronword > tm.txt`
  - `kkc.py lm.txt tm.txt data/wiki-ja-test.pron > output.txt`
- Measure the accuracy of your tagging with `06-kkc/gradekkc.pl data/wiki-ja-test.word output.txt`
- Report the accuracy (F-meas)
- Challenge:
  - Find a larger corpus or dictionary, run KyTea to get the pronunciations, and train a better model

Thank You!