Named Entity-Factored Transformer for Proper Noun Translation

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Background

✓ Proper noun translation for Machine Translation(MT)

- MT: useful in practical applications
- Social implementation: importance of proper noun translation

Watashi wa Akage no Anne no musical wo miniikitai
(I want to watch a musical of Anne Green Gables)

↓

MT result：I want to see Anne's musical with red hair

Examples of proper noun (bleu)
mistaken translation (red)

Background

Problem: Proper noun translation for Machine Translation(MT)

Proper nouns are often processed as out-of-vocabulary (OOV) words in MT systems

Two major approach:

(1) Handcraft bilingual corpus or dictionary ⇒ High developing cost

(2) Subword ⇒ Doesn’t always work well for proper noun translation

Motivation

✓ Work well for proper noun translation by effectively **using training corpus**

Proposed method based on subword approach

✓ Use **Named Entity (NE) features** for an enhance of NMT

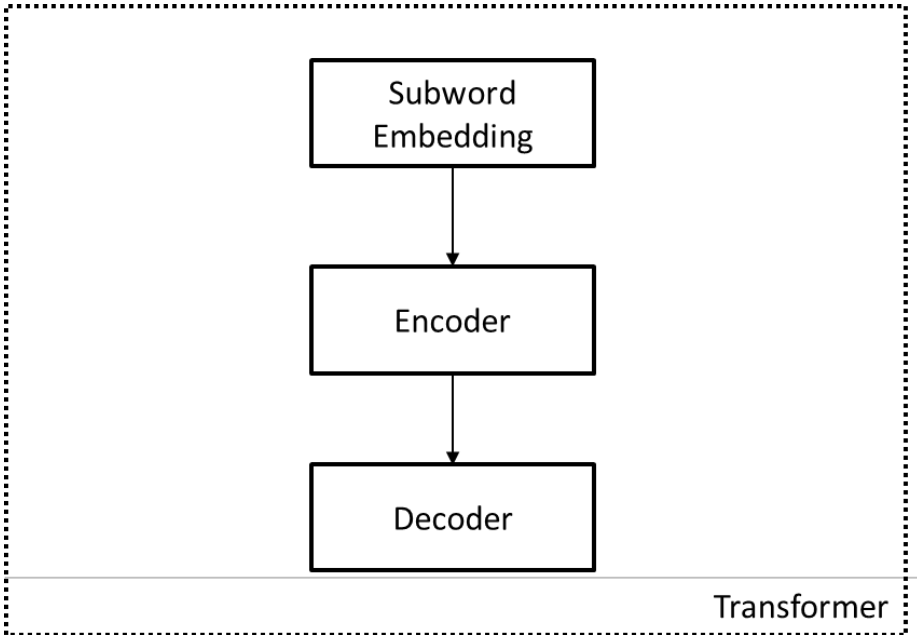
✓ Also use distributions for an unclear NE of proper noun

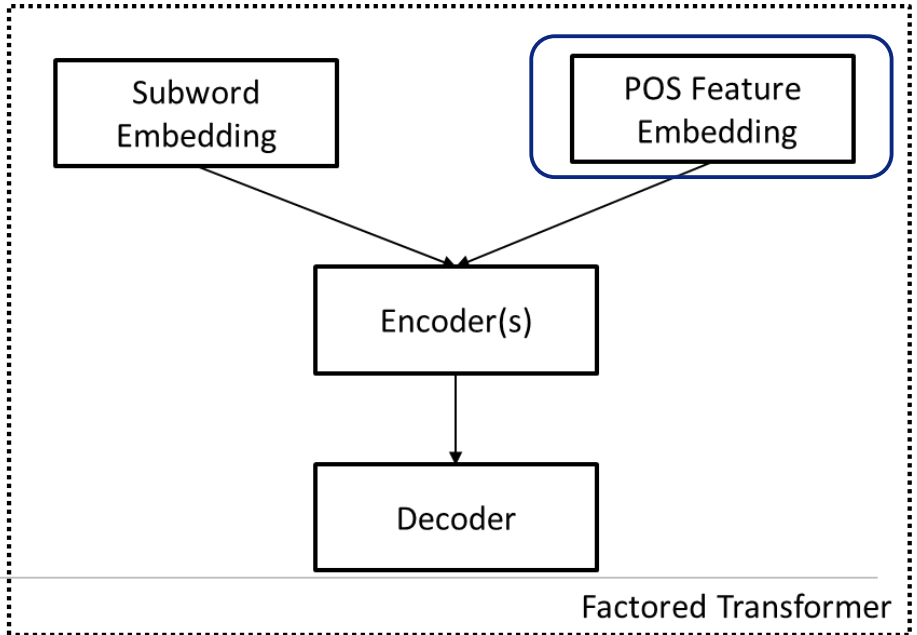
Akage no Anne: Person, Work of Art, or Movie Title as NE

Conventional Method

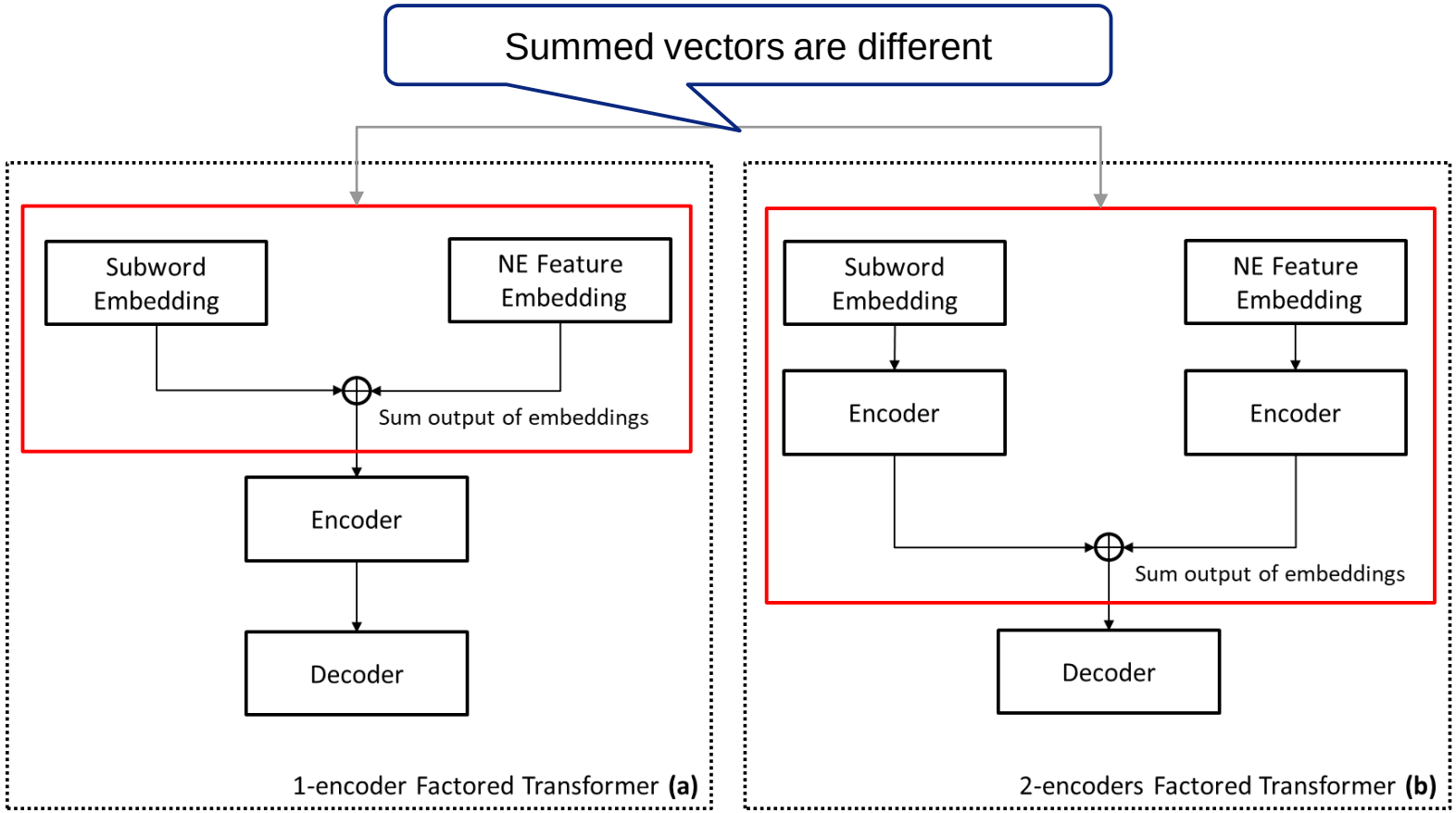
Factored Transformer:

- ✓ García-Martínez et al use morphological and grammatical features of a word
- ✓ Jordi et al use grammatical features in low-resource NMT





Concatenation structures in Factored Transformer



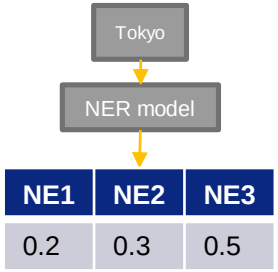
NE features

- one-hot vector of NE

Input

Embedding

Encoder



one-hot(BERT-NER(Tokyo)) × E

one-hot

NE1	NE2	NE3
0	0	1

×

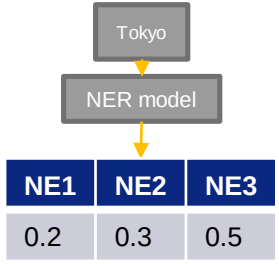
	v1	…	v512
NE1	0.98	…	0.53
NE2	0.22	…	0.33
NE3	0.33	…	0.55

=

v1	…	v512
0.33	…	0.55

x1 = 0*0.98+0*0.22+1*0.33 = 0.33

- Probability Distribution of NE



BERT-NER(Tokyo) × E

Probability

NE1	NE2	NE3
0.2	0.3	0.5

×

	v1	…	v512
NE1	0.98	…	0.53
NE2	0.22	…	0.33
NE3	0.33	…	0.55

=

v1	…	v512
0.47	…	0.48

x1 = 0.2*0.98+0.3*0.22+0.5*0.33 = 0.47

Experiments ~Corpus~

- JParaCrawl: the training of the NMT models (Morishita et al., 2020)
  In Japanese-English chose 160,000 sentence pairs that contain proper nouns
  Sentence pair scores higher than 0.786, and shorter than 250 subwords

- Our field experiments with taxis in Japan:
  For Japanese-English task, we used an evaluation dataset of 271 sentences containing a single proper noun.

- WMT2020: For English-Japanese task

	Corpus	direction	# of sentence	# of subwords	# of uniq subwords
Training	JParaCrawl	JA-EN	159,888	5,318,140	10,073
Test	Field experiments	JA-EN	271	4,258	646
Training	JParaCrawl	EN-JA	10,116,570	332,520,888	47,087
Test	WMT2020	EN-JA	1,000	32,696	5,171

Compared Methods

- **Transformer: baseline**
- Proposed method with combination
  1-encoder / 2-encoder
  NE one-hot vector / NE probability distribution vector

Baseline		
Transformer	**PRPacc1**	**BLEU1**
Proposed method	1-encoder	
	2-encoders	
Factored-Transformer with NE one-hot vector	**PRPacc2**	**BLEU2**
	PRPacc3	**BLEU3**
Factored-Transformer + NE probability Distribution vector	**PRPacc4**	**BLEU4**
	PRPacc5	**BLEU5**

Compared Methods

- **Proposed method with combination**
  1-encoder / 2-encoder
  NE one-hot vector / NE probability distribution vector

- NER model
  Japanese: BERT-NER(Devlin et al., 2018)
  English: Stanza

Baseline		
Transformer	**PRPacc1**	**BLEU1**
Proposed method	1-encoder	
	2-encoders	
Factored-Transformer with NE one-hot vector	**PRPacc2**	**BLEU2**
	PRPacc3	**BLEU3**
Factored-Transformer + NE probability Distribution vector	**PRPacc4**	**BLEU4**
	PRPacc5	**BLEU5**

Compared Methods

- **Proposed method with combination**
  1-encoder / 2-encoder
  NE one-hot vector / **NE probability distribution vector**

- NER model
  Japanese: BERT-NER(Devlin et al., 2018)
  English: Stanza*

*http://nlp.stanford.edu/software/stanza/1.2.2/en/ner/ontonotes.pt

Baseline		
Transformer	**PRPacc1**	**BLEU1**
Proposed method	1-encoder	
	2-encoders	
Factored-Transformer with NE one-hot vector	**PRPacc2**	**BLEU2**
	PRPacc3	**BLEU3**
Factored-Transformer + NE probability Distribution vector	**PRPacc4**	**BLEU4**
	PRPacc5	**BLEU5**

Evaluation Metrix

- proper noun translation accuracy (PRPacc):
- BLEU (Papineni et al., 2002)

Baseline		
Transformer	PRPacc1	BLEU1
Proposed method	1-encoder	
	2-encoders	
Factored-Transformer with NE one-hot vector	PRPacc2	BLEU2
	PRPacc3	BLEU3
Factored-Transformer + NE probability Distribution vector	PRPacc4	BLEU4
	PRPacc5	BLEU5

Experiments Results: PRPacc and BLEU

■ Japanese-English

Baseline		
Transformer	56.1	11.37
Proposed method	1-encoder	
	2-encoders	
Factored-Transformer with NE one-hot vector	43.2	10.1
	63.4	13.8
Factored-Transformer + NE probability Distribution vector	53.5	10.9
	65.7	13.8

Training set: 160k sentences of JParaCrawl
Test set: 271 sentences of Gifu field experiments
NER model: BERT-NER

■ English-Japanese

Baseline		
Transformer	46.5	17.54
Proposed method	1-encoder	
	2-encoders	
Factored-Transformer with NE one-hot vector	50.1	18.8
	47.5	17.8
Factored-Transformer + NE probability Distribution vector	49.5	18.4
	46.7	17.6

Training set: 10m sentences of JParaCrawl
Test set: 1,000 sentences of WMT 2020 News
NER model: Stanza in Stanford NLP toolkit

Conclusion

The NE feature vectors are injected into Factored Transformer model as factors.

- Japanese-to-English experiments: small bilingual training corpus
  - 2-encoders and NE probability distribution vector is best
  - 9.6 points in proper noun accuracy and 2.5 points in the BLEU

- English-to-Japanese experiments:
  - 1-encoder and NE one-hot vector is best
  - 3.6 points in proper noun accuracy and 1.3 points in the BLEU

- In English-to-Japanese the improvement in PRPacc and BLEU was smaller:
  - One of reasons is the difference in the training data sizes and NER
  - Another is the difference in the degrees of difficulty in these domains

Appendix

Approaches for proper noun translation

✓ Subword-based approach: Sennrich et al 2016
Subwords decompose a word into shorter units but does not always work on a proper noun translation.

✓ Class-based approach: Okuma et al 2008, Li et al 2016
Hand-crafted bilingual lexicon as external knowledge uses a bilingual proper noun dictionary.

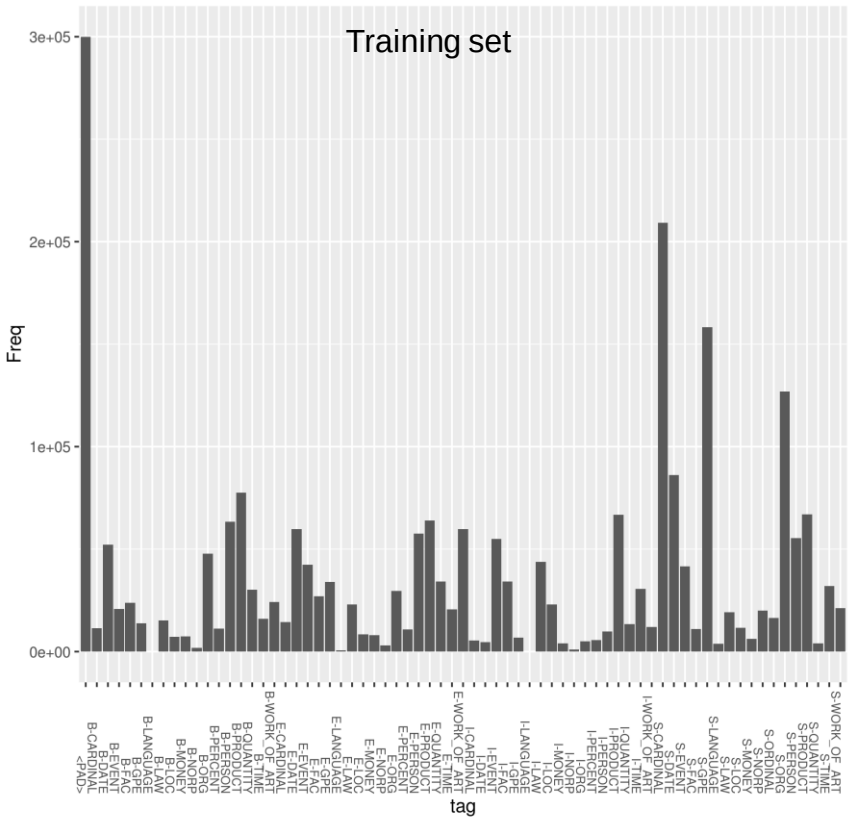
✓ LCD(lexically constrained decoder) and LeCA(Lexical-Constraint-Aware NMT) approach:
Hokamp et al 2017, Chen et al 2020, Chousa et al 2021
Select target language sentence constrained by a bilingual dictionary
Extends the beam search algorithm to find the hypothesis that contains all of the proper nouns

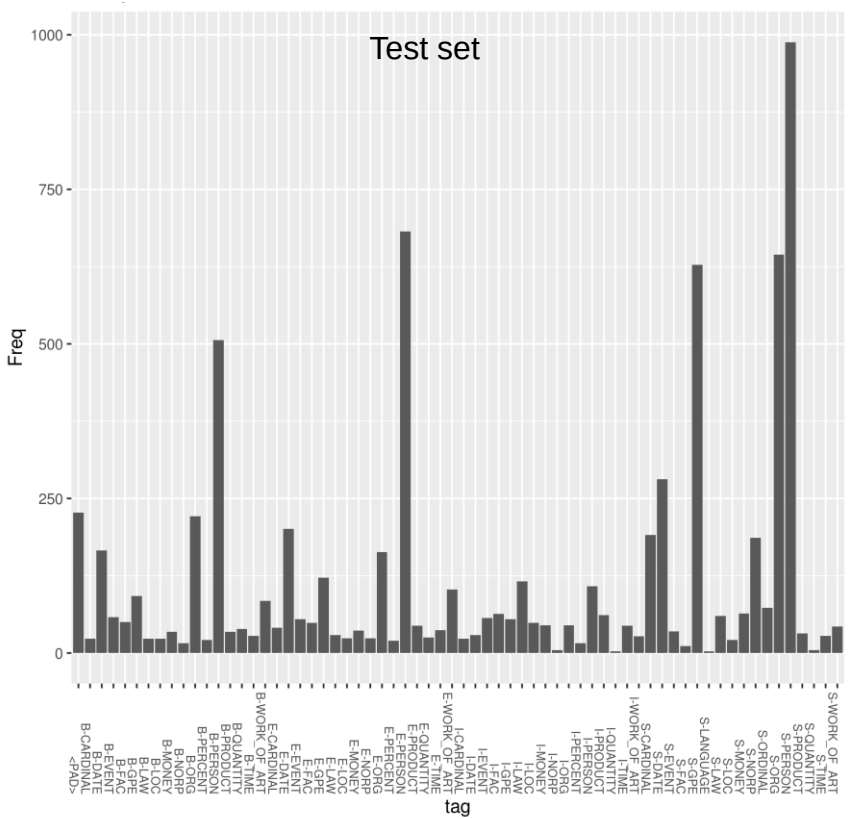
	Subword-based	Class-based	LCD	LeCA	Proposed method
Source side proper noun	✓	✓ + NE	✓	✓	✓
Target side proper noun	Nan	✓	✓	✓	Nan
Real-time processing	✓	✓	Not enough	✓	✓

Appendix

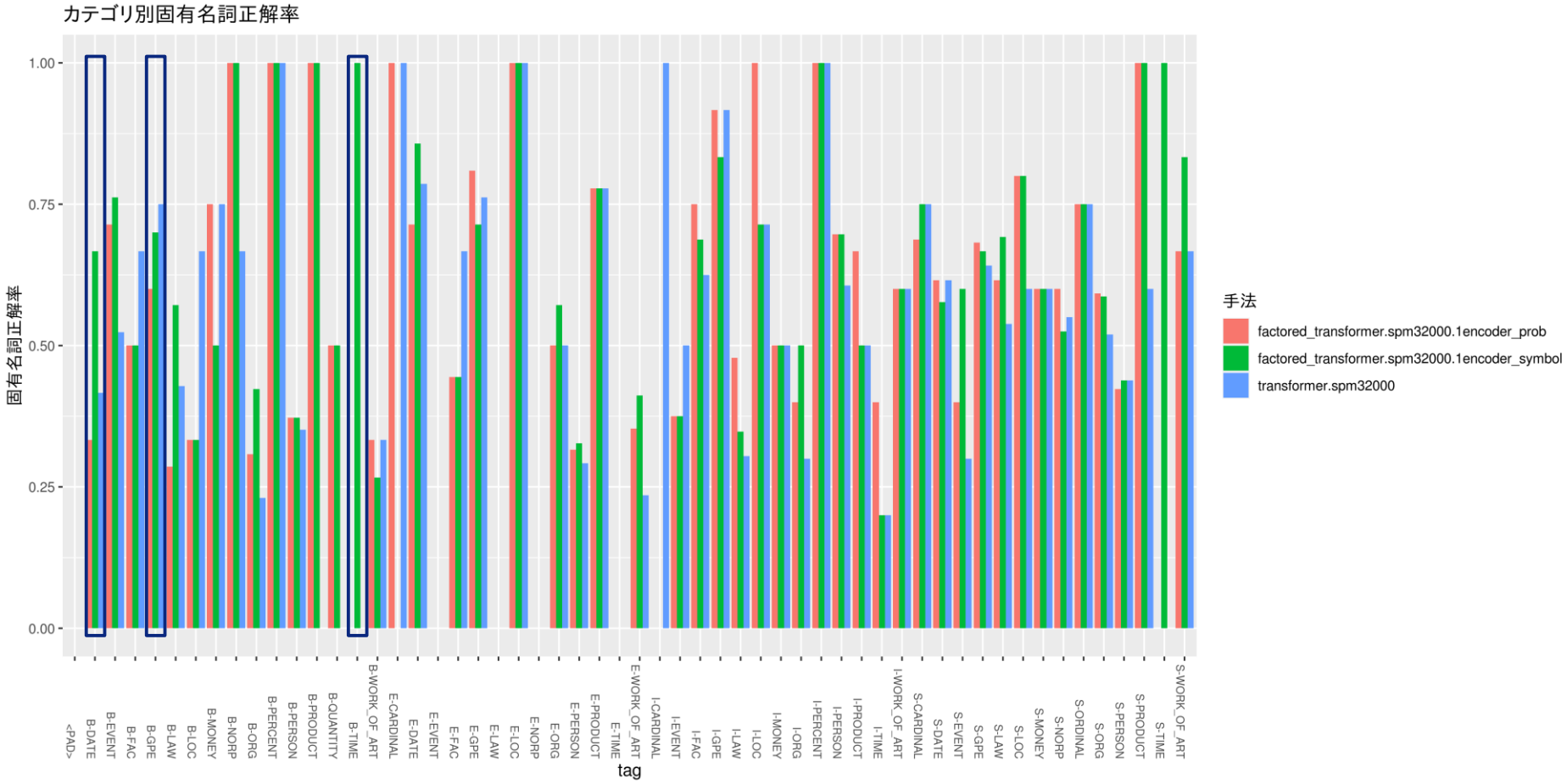
(1) Input sentence: 飛騨牛を使った料理です。		
baseline	-	it is a cooking cuisine using hida flavored cuisine .
1-encoder	symbols	i tried to use the hida dish of the cuisine .
1-encoder	Probability Distributions	i used cuisine as a dish of hidafuruga .
2-encoder	symbols	it's a dish that was used with **hida beefs** .
2-encoder	Probability Distributions	it is a dish used with **hida beef** .
(2) Input sentence: 戦国武将の豊臣秀吉が三日で作ったと言われています。		
baseline	-	the minister of battlefield was created by the third day in yoshino , Japan
1-encoder	symbols	thirdly , the minister of foreign affairs said that japan had been pursuing three days .
1-encoder	Probability Distributions	the minister's commendation was created in toyotomi , where he said , "it was created in 3 days"
2-encoder	symbols	**toyotomi hideyoshi**'s president of the battleship is said to be made in three days .
2-encoder	Probability Distributions	the minister of battlefield headquartered in mie , japan , said it was created on third day .
(3) Input sentence: このお城は豊臣秀吉が作りました。		
baseline	-	this castle was created by an excellent Japanese castle .
1-encoder	symbols	this castle was created by yoshino **hideyoshino hideyoshinori** .
1-encoder	Probability Distributions	this castle was created by minister **toyotomi hideyoshi** .
2-encoder	symbols	the castle of this castle was created by **toyotomi hideyoshi** .
2-encoder	Probability Distributions	this castle was created by **toyotomi hideyoshi** .
(4) Input sentence: 岐阜は初めてですか？		
baseline	-	what is **gifu** ?
1-encoder	symbols	what is the first battery ?
1-encoder	Probability Distributions	what is the first time ?
2-encoder	symbols	is **gifu** is the first time ?
2-encoder	Probability Distributions	**gifu** is the first time ?
(5) Input sentence: 島根県ですここかここから六時間ほどかかります。		
baseline	-	It takes about 6 hours from shimane here .
1-encoder	symbols	you can take about 6 hours from shimane island .
1-encoder	Probability Distributions	it takes about 6 hours to get here from **shimane prefecture** here .
2-encoder	symbols	it takes about six hours from here to the island .
2-encoder	Probability Distributions	it takes about six hours from here to **shimane prefecture** .

Appendix ~ 2. number of NE category in corpus ~





Appendix ~ 2. proper noun acracy each category ~



Appendix ~2. Token's difference of between subword and NE inputs~

NE token

Subword token

	買い物	も	最近	は	名古屋	へ	出かける	方	が	多い	です	。
_	0	0	0	0	0	0	0	0	0	0	0	0
買い物	3	0	0	0	0	0	0	0	0	1	0	0
も	3	4	3	3	3	3	3	3	3	3	3	3
最近	3	4	6	4	4	4	4	4	4	4	4	4
は	3	4	6	7	6	6	6	6	6	6	6	6
名古屋	3	4	6	7	10	7	7	7	7	7	7	7
へ	3	4	6	7	10	11	10	10	10	10	10	10
出	3	4	6	7	10	11	12	11	11	11	11	11
かけ	3	4	6	7	10	11	14	12	12	12	12	12
る	3	4	6	7	10	11	15	14	14	14	14	14
方	3	4	6	7	10	11	15	16	15	15	15	15
が多い	4	4	6	7	10	11	15	16	17	18	16	16
です	4	4	6	7	10	11	15	16	17	18	20	18
。	4	4	6	7	10	11	15	16	17	18	20	21

・How to synchronize two tokens of NE and subword whose sometimes has multiple POS

⇒ In this research, after Japanese tagger, divide token as subword