An ATM for Meaning? A spaCy-based Approach to the Semantic Tagging of the Parallel Meaning Bank with TAGtical Insertion

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Abstract

Uncovering the meaning behind expressions in discourse can be vital, as this grants a better perception and prevents misunderstanding or ambiguity of a certain phenomenon. As innovation allows the world to better cope with this ever-present challenge, we see more and more NLP solutions arise. In this paper, we present a semantic tagger that is successful and accurate ($F_1 > 0.96$) in tagging sentences with semantic labels, allowing rapid addition of lexical information to these corpora. Our experiments show that our initial model already performs quite well in semantic tagging, and shows a lot of potential for tagging English sentences in general. We used data from the Parallel Meaning Bank to train our semantic tagger.

1 Introduction

What is the meaning behind this publication? What do we want to express with our story? As one can tell, meaning plays an important role in discourse. Semantics - a study of meaning - is an interesting member of both the linguistics domain (often related to lexical semantics) and the logic domain (often related to logical semantics). Current developments in the field of semantics are often related to computational semantics, and the automatic assignment of *meaning labels* or semantic roles is no exception in that regard.

In this paper, we introduce TAGtical Insertion[1]: a `spaCy`-based semantic tagger based on the data and tag set related to the Parallel Meaning Bank. The Parallel Meaning Bank (a *semantically annotated parallel corpus*) contains (tokenized) texts that are enriched with syntactic and lexical information, such as WordNet synsets, VerbNet roles and formal meaning representations (Abzianidze et al., 2017).

1.1 Objectives and research questions

Our objective is quite clear and simple: we want to develop a `spaCy`-based semantic tagger that is capable of successfully and accurately tagging a variety of corpora. At the same time we want to investigate whether or not we can successfully use `spaCy`'s build-in capabilities to fulfill this task, and we are keen on observing how such a model would perform on a tag set that is vastly different from the one that `spaCy` uses by default.

Given our objective and its context, we can formulate the following research questions:

1. How can we implement `spaCy`'s functionality to perform semantic tagging?
2. Is it possible to train and develop a semantic tagging model, using the tag set proposed in Abzianidze and Bos (2017)?
3. How does our semantic tagging model perform in terms of F_1-score, precision, recall and accuracy?

1.2 Document structure

This paper describes the semantic tagging task and our approaches to fulfilling this task, as well as results of our model and the lessons learned. In the following section, we take a look at the related work and give some background information on semantic tagging and the Parallel Meaning Bank. In section 3 - Methods - we discuss how we approach the semantic tagging task and we cover elements such as the data set, our use of `spaCy` and the evaluation of the tagging performances. Section 4 - Baseline System - provides details on the baseline system that we used to compare the performances with, followed by the fifth section - Results

[1] Code can be found at https://www.github.com/leonwetzel/tagtical-insertion

- where we describe the various metrics and the performances of our semantic tagging model. In section 6 - Discussion and Conclusion - we discuss the lessons learned and we look back at the various aspects of our semantic tagging model. A vital part of this section is the error analysis, where we discuss the performance of the tagger and look at the errors made whilst labelling tokens. To conclude this document, we discuss future work in section 7.

2 Previous Work

The task of semantic tagging has always heavily relied upon part-of-speech tagging. When the field was still in its infancy, Bos et al. (2004) laid the groundwork for the approach of formal compositional semantics. They created well-formed semantic representations based on a syntactic parser of Combinatory Categorial Grammar, or CCG. Their reported coverage of 97% for unseen sentences inspired multiple researchers over the years to further innovate in the field of semantic parsing.

A notable example is the work of Mineshima et al. (2015), which presented a system that proved to be a considerable advancement in formal compositional semantics. The authors built a semantic lexicon based on syntactic categories of CCG, similar to Bos et al. (2004). They then utilised lambda-calculus to build the semantic representations from the CCG and create the output formula by applying beta-conversion, similar to some of our exercises in the Computational Semantics course. The following experiment laid its focus on entailment problems to test their system. The authors reported an improvement compared to the state-of-the-art first-order logic system at the time and thus argued that the inclusion of higher-order logic provides more use for computational linguistics than conventionally thought.

Presently, the universal semantic tagset provides the basis for the task of semantic tagging. First introduced by Bjerva et al. (2016), semantic tagging provides more detailed lexical information where more traditional POS-tagsets have lacked. Their system served to disambiguate several linguistic phenomena previously tagged with identical POS-tags. As part of their research, Bjerva et al. (2016) have created a set of semantic tags. Within the tagset, thirteen different classes are defined. Each of these classes contain different types of semantic tags to describe semantic properties of the smallest meaningful units in a sentence. The authors then created a Deep Residual Networks-based semantic tagger to fit the tagset. The results are compared to four baselines divided between the task of semantic tagging as well as POS-tagging. Improvement on every baseline for both tasks is reported, stating the observed adequacy of semantic tagging even in its early days.

The predictions of the model in this paper will be based on version 0.7 of the semantic tagset as created by Abzianidze and Bos (2017). In this version, the authors have eliminated fifteen different tags from the previous iteration of the tagset, created by Bjerva et al. (2016), and replaced them with thirteen new semantic tags. Furthermore, Abzianidze and Bos (2017) have made alterations to several of the thirteen overarching semantic classes, including specifications in the syntactically complex classes of deixis (DXS) and attributes (ATT) to disambiguate these classes.

A rather important feature of the field of semantic tagging, is the lack of a grand vocabulary. Lexical units that are not represented in the data have no precedent and are hard to predict accurately. Recent work into semantic tagging of previously unseen words is performed by Huo and de Melo (2020). Their experiment aims to infer semantic tags based on word representations in the form of vectors. The resulting system is evaluated on both monolingual as well as cross-lingual tasks using gold data from the Parallel Meaning Bank. They report a cosine similarity score of 0.66 for individual semantic tagging, and 0.79 for the tagging of the semantic classes. While their approach features some flaws that hinder the performance[2], their research forms a solid base upon which further research can be based in multiple semantic tasks.

3 Methods

3.1 Semantic tagger

A semantic tagger behaves differently from Part-of-Speech (POS) taggers and Named-Entity Recognizers (NER taggers), acting more as a best-of-both world's approach. What would that mean in our case, where we use functionality from `spaCy` to fulfill the semantic tagging task?

Let's start off with `spaCy`, which is a Python library capable of performing several NLP-related

[2] An example given by the author features their k-nearest neighbor approach. Often the two most similar words are variations of the same lemma. These variations are similar, but often obtain different classifications in semantic tagging

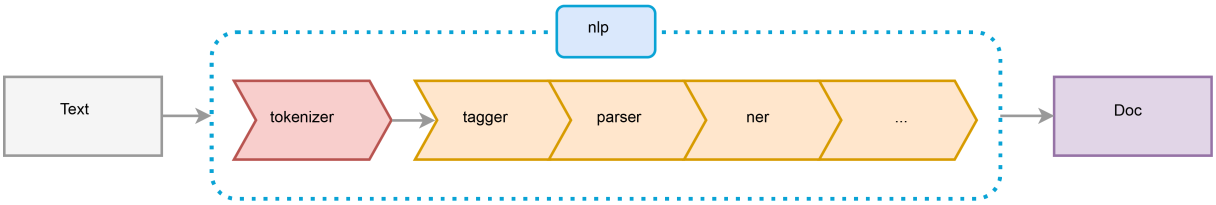

Figure 1: Default processing pipeline in `spaCy` (Honnibal et al., 2010)

tasks such as NER-tagging, POS-tagging, tokenization, text classification and much more (Honnibal et al., 2020). A dedicated semantic tagger is not part of the library, but we can creatively (re-)use the NER-tagger functionality to perform this task.

The way `spaCy` works is quite straightforward. As displayed in figure 1, the processing pipeline takes a string as input - usually a sentence - and performs indicated steps and tasks on this data. For TAGtical Insertion, we created a custom pipeline consisting of only the NER step to execute the semantic tagging.

3.2 Data set

The data used to develop, train and test TAGtical Insertion is based on samples from the PMB, obtained and pre-processed by Abzianidze et al. (2017). The data set we use only consist of so-called Gold data, which contains fully annotated data. This makes it more reliable than Silver or Bronze data, which is only partially or not at all annotated. We only used the data that was given in the English language. The data set contains CCG tags, VerbNet roles, WordNet synsets and semantic tags for each sentence. We only use the sentences, their tokens and their semantic tags. The data contains a training data set, a test set and a validation set. The training set was used to initially train the model; the validation set was used to search for mistakes and solve these mistakes. The final tests were run on the test data set.

3.3 Preparing the data

The .conll files mentioned in the previous subsection cannot be directly used by `spaCy`, as the .conll files contain data in the IOB[3] coding scheme in contrast with `spaCy`'s BILUO[4] format. As supported by Ratinov and Roth (2009), the BILOU format was preferred over IOB in `spaCy` as models had more learning difficulties whilst using the latter format. The essential difference came down to BILOU's marking of boundary tokens, contrary to the IOB scheme where first and final tokens are not explicitly indicated.

We solved the conversion of the IOB format to the BILOU scheme with a custom script, which is part of TAGtical Insertion as well. A major part of the functionality of this script is the localization of beginning and end tokens, as well as the ability to store related information such as tokens, lemmas, semantic tags, POS-tags, WordNet synsets, and VerbNet roles and the (re)construction of the sentence. Apart from the tokens, semantic tags and the generated sentence, we do not need the extra lexical information from the PMB to train our custom model with `spaCy`.

3.4 Training the system

We train the system with the processed training samples from the PMB, as mentioned in subsection 3.2. We create a new `spaCy` processing pipeline for use with the English language and add the entity recognizer step to the pipeline. This configuration allows `spaCy` to only train the tagger, and not any other possible functionalities of the module.

After we created and fitted the pipeline, we can iterate over the training samples. During every iteration, an update is made to the model and for every word a predication - or label - is made. Every prediction will be checked to see if the result is right. If the result is wrong, the weights are adjusted in the hope that the prediction will be more accurate in the future. Finally, the trained model is saved and an initial test will be performed to see if the tagger performs in terms of predicting and tokenization. The latter is an important factor, as we assume that every token in a sentence is tokenized. If the tokenization was not performed correctly, the model cannot predict tags for the entire sentence.

There are possibilities for optimization, regularization and gradient clipping in `spaCy`. We set the (Bernoulli) dropout value to 0.5, and we apply compounding to our minibatches' size ($x_{start} = 4.0$,

[3]Inside-outside-beginning

[4]Beginning, Inside and Last tokens of multi-token chunks, Unit-length chunks and Outside

$x_{stop} = 32.0$, $compound = 1.001$). All these values are the default values for their respective parameters in `spaCy`: given the size of our data set, we do not see optimization opportunities from this perspective.

3.5 Evaluating performances

We can effectively evaluate the performances of our model by using metrics such as precision, recall and subsequently the F_1-score, next to the accuracy. These metrics can be applied to the entire test set, but also label-specifically. This allows us to have a better understanding of how the system performs per label, and it grants us a possible insight in where we may need more data for specific labels and cases.

4 Baseline System

For the baseline system, we opted to predict the semantic tag for empty semantics (NIL) for the last token in every sentence, since the NIL tag is most commonly used to signify punctuation. For every other token, the baseline system has predicted the semantic tag for concepts (CON). The CON tag is chosen simply because it is the most occurring semantic tag in the dataset other than the NIL tag.

The CON label scores an F_1-score of 0.27, while the NIL label scores an F_1-score of 0.90, with every other label scoring 0.00, resulting in a micro-averaged F_1-score of 0.27. We opted to micro-average the harmonic mean because the label predictions are highly imbalanced. As such, a macro-averaged or weighted F_1-score would not be exceedingly informative.

5 Results

The results of the `spaCy`-based semantic tagger can be viewed in Table 1. Out of the 898 sentences in the test set, one single sentence was incorrectly tokenized and one sentence was not tokenised at all. The other 895 sentences have been correctly tokenised by `spaCy`. Of the remaining sentences in the test set, only 180 contained at least one mistakenly labeled token. We report a micro-averaged F_1-score of 0.961 for the `spaCy`-based semantic tagger on the test set.

The system scores an F_1-score of 1.0 for eleven different semantic tags, while only the semantic tag Other Names (NTH) results in an F_1-score of 0.0. Furthermore, forty different semantic tags result in an F_1-score of 0.9 or higher. The full scores and counts for each individual semantic tag can be found in Appendix A. The thirteen different semantic tags that are absent in the dataset are excluded from the table in Appendix A.

6 Discussion and Conclusion

The tagger works very well. Almost all sentences are correctly tokenized and out of the correctly tokenized sentences almost 80% had all tags correctly predicted. The sentences that had some errors when tagging, only had one or two mistakes. It never incorrectly tagged entire sentences. Thus, overall the tagger works very well.

When looking at the different types of mistakes the program made. The sentence that was not tokenized at all is sentence (1). When a symbol occurs that the tokenizer does not recognize, it tends to skip the entire sentence. Looking at sentence (1), this was most likely caused by the 'ã' in 'São-Paulo'.

As for the sentences that had the incorrect number of tokens, these are sentences (2) and (3). Sentence (2) is supposed to have 6 tokens, but the system thinks it should have 5 tokens: the word *value* is skipped. When looking at the data, this sentence has the only occurrence of the word 'value', in the other sets, train.conll and dev.conll the word does not occur. So, something must be going wrong for this specific word. However, when running the code using another computer in a slightly different environment, this error does not occur. So, this error can be considered a anomaly.

For sentence (3) it is a bit clearer what is going wrong. It is supposed to have 6 tokens, where ○C, should be one token. However, the system thinks these need to be two separate tokens. This causes the number of tokens to be incorrectly estimated. For these sentences, the evaluation script has substituted empty labels to make sure the predicted label set and the gold label set have the same amount of tokens.

- (1) We visited a huge amusement-park in São-Paulo

	Results
Total sentences in data	898
Sentences correctly tokenized	895
F_1-score	0.9611
Sentences with 100% correct labels	716

Table 1: Results of `spaCy`-based semantic tagger

Tag	Most mistaken for	Also mistaken for
GPE	PER	CON, GEO, GPO, QUE, ROL
ROL	CON	ENS, PER, UOM
IST	CON	COL, DEG, ENS, EPS, EXS, EXT, INT, ...
AND	DIS	GRP, PRO, SUB
ENS	EXS, NOW	CLO, COL, CON, EFS,EPS,NEC,PST
EXS	CON, ENS	EPS, IST, PRO
PER	GPE	ART, LIT, NOW, NTH, ORG
UOM	QUC	CON
QUC		CON, PRO
CON	ROL	IST, COL, ENS, EXG, GPE, GPO, PER, REL, ...

Table 2: Overview of tags and what they are most commonly mistaken as

- (2) The default value is zero.
- (3) Actinium melts at 1,051 $\circ$ C.

Since there are a lot of tags in the test data, namely 62 different tags, for the discussion we will consider the 10 worst performing tags, based on F_1-score, with at least 30 occurrences in the test data. These 10 tags will be compared with the tags they are most often mistaken for. These tags include starting at the worst performing: GPE, ROL, IST, AND, ENS, EXS, PER, UOM, QUC and CON. This is summarized in Table 2. Listing 1 contains the full evaluation output, including the correct and predicted tags for each sentence that includes at least 1 wrongly identified token.

Below there are five example sentences, that include one of the more common incorrect predictions. To start with sentence (4), here the GPE (geo-political entity) ”Sydney”, gets mistaken for a PER (person). This is not a very weird classification, as the word Sydney can be used as a name. However, the word Sydney did not occur in the training data, so it is unlikely that the model learned that it is a name. It most likely got confused by having the combination of ”city name, country name”.

In sentence (5), the tag ROL (role), gets mistaken for the tag CON (concept). In this case, the program most likely mistook the word fakir for a separate person, who is not Tom. While the actual meaning of the sentence indicates that Tom is a fakir.

In sentence (6), the tag IST (intersective) is mistaken for a concept. In this case, intersective is a type of adjective. The program most likely got confused due to the word ”man” in ”man-made”.

In sentence 7, the tag AND (conjunction and universal quantifier) got mistaken for a DIS (disjunction and existential quantifier). The problem here is that the word ”any” can be considered either a universal quantifier or an existential quantifier depending on the context. Thus, whether the program classifies it as an AND or DIS, depends purely on the examples in the training data set.

Lastly, sentence (8), here the tag ENS (present simple), gets mistaken for a NOW (present tense). Both tags indicate a present verb tense. The main difference is that in the case of ENS, the verb is also indicating the main event. Normally the word ”is” is used as a auxiliary verb, meaning that another verb is the main event verb. Yet, in this case ”is” is the only verb in the sentence, making it the event. In the training data, verbs like ”is” and perhaps also ”have”, may have occurred more as auxiliary verbs, making the program think these are always in the category Tense and Aspect, instead of the Event category.

- (4) Susan and Bob have flown from London to Sydney, Australia.
- (5) Tom is a fakir.
- (6) This is a man-made language.
- (7) You can buy stamps at any post-office.
- (8) He’s a very talented man.

To summarize, during the tokenization part, the types of mistakes the program makes are mostly due to weird characters that the tokenizer cannot handle or words that somehow cannot be dealt with on only some computers. The mistakes that the tagger made, included dubious word meanings, such as whether ”any” should be considered as a universal or existential quantifier, or determining whether a verb is the event of a sentence or just a regular auxiliary verb.

To answer the research questions, first of all "How can we implement `spaCy`'s functionality to perform semantic tagging?". We implemented this by using `spaCy`'s NER-tagger and adjusting it to make it suitable for the semantic tagging task.

The second question, "Is it possible to train and develop a semantic tagging model, using the tag set proposed in Abzianidze and Bos (2017)?" can also be answered positively. We created a model that performs quite well on the tagging task, as it is able to fully correctly tag 79.8% of the test data and having an overall F_1-score of 0.9611. Most of the individual tags rank very highly too; the only tags that perform badly are the tags that occur only very rarely. So yes it is possible to train and develop a semantic tagging model based on the tag set proposed by Abzianidze and Bos (2017).

Then, last but not least, the final research question "How does our semantic tagging model perform in terms of F_1-score, precision, recall and accuracy?", is a bit harder to answer. The way the model was evaluated was by using two arrays. One containing the all correct tags and one containing all predicted tags. Each position in one array corresponds to the same position in the other array. Thus, the comparison is based on the tags themselves, and not on the sentences. Furthermore, as we know the correct answer for each tag, and have every prediction, each will result in either a true positive (TP) or true negative (TN). We will not get any false positives (FP) or true negatives (TP). The recall, precision and F_1 tests are all very similar. See the formulas below:

- $precision = \frac{TP}{TP+FP}$
- $recall = \frac{TP}{TP+FN}$
- $F_1 = \frac{precision*recall}{precision+recall} = \frac{TP}{TP+\frac{FN+FP}{2}}$

Precision works better if you have a low number of false positives, while recall works better if you have a low number of false negatives. F_1 is the harmonic mean of the two. The only difference between these tests is the inclusion of the false positives and true negatives. Since, our result does not give any of these, the score of recall, precision and F_1 will be the exact same. Thus, there are no differences between the precision and the recall. Furthermore, we currently evaluated on the level of single tags. Thus, we compared each tag individually. Instead we could have also tested per sentence. This would probably have resulted in a different score, as then each sentence would have had a specific score and then when these would have been combined this would most likely have resulted in a different score. For example, in a sentence with only 6 tags, making two mistakes would be a bigger influence on the score then just seeing that about 1 in 20 tags is incorrect.

7 Future research

The first part that could be improved upon is the tokenization, currently for each new symbol that may occur it needs to be added to a list of patterns, in order for it to accept a specific symbol. So, work still needs to be done to fully get this to work. When it comes to the tagger part, it is a bit harder. Most tagging mistakes were due to ambiguous sentences or unknown words. When the tagging is only based on previous sentences and their tags, then the only way to improve the tagger is by feeding it more data. But, the problem here is that it is hard to get a lot of Gold data. Furthermore, we will need a lot of data to cover all irregularities of the English language. A possible way to improve upon this is by not only using the tags, but by combining it with for example WordNet synsets. Then, using this information we can remove possible ambiguity when it comes to word meanings. This, would allow us to not make mistakes such as in the case in sentence (7). Adding the VerbNet roles, would enable us to avoid mistakes such as in the case in sentence (8), where the tagger incorrectly tagged an event verb as a regular verb. Using this information in addition to the regular model, could improve the model from a good model, to an exemplary model.

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A F-score per semantic tag

Label	F-score	Counts	Label	F-score	Counts
DEF	1.0	317	EMP	0.936	23
PRX	1.0	30	UOM	0.933	46
YOC	1.0	18	QUV	0.929	29
DST	1.0	15	PER	0.928	266
PFT	1.0	8	EXS	0.924	155
BUT	1.0	6	DEG	0.923	26
TOP	1.0	6	ENS	0.922	204
MOR	1.0	3	CLO	0.917	22
IMP	1.0	2	AND	0.9	43
CTC	1.0	1	IST	0.899	180
PRG	1.0	1	EQU	0.889	5
HAS	0.997	151	COO	0.889	9
PRO	0.996	457	APX	0.875	8
QUE	0.996	112	ROL	0.863	99
DIS	0.995	188	NEC	0.857	4
NOT	0.994	79	GPE	0.822	65
NIL	0.992	879	GPO	0.8	11
REL	0.987	413	DOW	0.8	3
PST	0.978	109	GRP	0.8	7
INT	0.976	21	GEO	0.778	9
EPS	0.975	343	DOM	0.727	7
NOW	0.975	253	EFS	0.667	4
EXG	0.97	98	GRE	0.667	2
FUT	0.97	17	ORD	0.667	2
ALT	0.968	15	REF	0.667	2
COL	0.952	11	SUB	0.667	4
CON	0.95	782	LIT	0.588	10
QUC	0.943	87	ORG	0.467	16
MOY	0.941	8	ART	0.4	4
POS	0.938	15	NTH	0.0	3
EXT	0.936	24	XCL	0.0	1

Table 3: F-scores and count per semantic tag

Listing 1: Full evaluation output

```
We evaluated the model on the file dev.conll
This file consists of 898 sentences.
Out of these 898 sentences, 895 sentences are correctly tokenized

1 sentence(s) are not tokenized at all, and return an empty string,
   these include the following sentence(s):
We visited a huge amusement~park in S o~Paulo .

2 sentence(s) have an incorrect number of tokens. These include the
   following sentence(s):
The default value is zero .
Actinium melts at 1,051  C  .

We evaluated the performance of the tagger on the set of sentences
   that is correctly tokenized.
The F-Score returns the following score:0.9592192401533636
In total 188 sentences with incorrect tags were found. These were
   found in the following sentences:
Sentence: She likes short skirts .
Correct tags: ['PRO', 'ENS', 'IST', 'CON', 'NIL']
Predicted tags: ['PRO', 'ENS', 'CON', 'ENS', 'NIL']

Sentence: You ca n't live on that island .
Correct tags: ['AND', 'POS', 'NOT', 'EXS', 'REL', 'DST', 'CON',
   'NIL']
Predicted tags: ['PRO', 'POS', 'NOT', 'EXS', 'REL', 'DST', 'CON',
   'NIL']

Sentence: How far is it ?
Correct tags: ['QUE', 'DEG', 'NOW', 'PRO', 'QUE']
Predicted tags: ['QUE', 'IST', 'ENS', 'PRO', 'QUE']

Sentence: You stink of cigarettes .
Correct tags: ['PRO', 'ENS', 'REL', 'CON', 'NIL']
Predicted tags: ['PRO', 'ENS', 'REL', 'ROL', 'NIL']

Sentence: Nowadays anybody can get books .
Correct tags: ['NOW', 'AND', 'POS', 'EXS', 'CON', 'NIL']
Predicted tags: ['NOW', 'DIS', 'POS', 'EXS', 'CON', 'NIL']

Sentence: An elephant has a long nose .
Correct tags: ['AND', 'CON', 'EXS', 'DIS', 'DEG', 'CON', 'NIL']
Predicted tags: ['AND', 'CON', 'ENS', 'DIS', 'DEG', 'CON', 'NIL']

Sentence: The bathtub overflowed while she was talking on the phone .
Correct tags: ['DEF', 'CON', 'EPS', 'SUB', 'PRO', 'PST', 'EXG',
   'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['DEF', 'CON', 'EPS', 'CON', 'PRO', 'PST', 'EXG',
   'REL', 'DEF', 'CON', 'NIL']
```

```
Sentence: How deep this lake is !
Correct tags: ['EMP', 'DEG', 'PRX', 'CON', 'NOW', 'EMP']
Predicted tags: ['QUE', 'IST', 'PRX', 'CON', 'ENS', 'EMP']

Sentence: Ted loves his wife Elizabeth .
Correct tags: ['PER', 'ENS', 'HAS', 'ROL', 'PER', 'NIL']
Predicted tags: ['PER', 'ENS', 'HAS', 'ROL', 'LIT', 'NIL']

Sentence: Reinventing~Comics is a book by Scott~McCloud .
Correct tags: ['ART', 'ENS', 'DIS', 'CON', 'REL', 'PER', 'NIL']
Predicted tags: ['CON', 'ENS', 'DIS', 'CON', 'REL', 'GPE', 'NIL']

Sentence: The fire~fighters put out the fire .
Correct tags: ['DEF', 'ROL', 'EPS', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['DEF', 'CON', 'EPS', 'REL', 'DEF', 'CON', 'NIL']

Sentence: That black bird is not a blackbird .
Correct tags: ['DST', 'COL', 'CON', 'EQU', 'NOT', 'DIS', 'CON',
    'NIL']
Predicted tags: ['DST', 'COL', 'CON', 'ENS', 'NOT', 'DIS', 'CON',
    'NIL']

Sentence: Can you whistle ?
Correct tags: ['POS', 'PRO', 'ENS', 'QUE']
Predicted tags: ['POS', 'PRO', 'EXS', 'QUE']

Sentence: What a nuisance that child is !
Correct tags: ['EMP', 'DIS', 'ROL', 'DST', 'CON', 'ENS', 'EMP']
Predicted tags: ['EMP', 'DIS', 'ENS', 'DST', 'CON', 'ENS', 'EMP']

Sentence: He baked muffins .
Correct tags: ['PRO', 'EPS', 'CON', 'NIL']
Predicted tags: ['PRO', 'EPS', 'IST', 'NIL']

Sentence: Ken was fined 7,000 yen for speeding .
Correct tags: ['PER', 'PST', 'EXS', 'QUC', 'UOM', 'REL', 'CON',
    'NIL']
Predicted tags: ['PER', 'PST', 'EXS', 'QUC', 'UOM', 'REL', 'EXG',
    'NIL']

Sentence: If it rains , he wo n't come .
Correct tags: ['IMP', 'NIL', 'ENS', 'NIL', 'PRO', 'FUT', 'NOT',
    'EXS', 'NIL']
Predicted tags: ['IMP', 'PRO', 'ENS', 'NIL', 'PRO', 'FUT', 'NOT',
    'EXS', 'NIL']

Sentence: You must be joking !
Correct tags: ['PRO', 'NEC', 'NOW', 'EXG', 'EMP']
Predicted tags: ['PRO', 'NEC', 'NIL', 'EXG', 'EMP']

Sentence: None of this was your fault .
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Correct tags: ['NOT', 'REL', 'PRX', 'EPS', 'HAS', 'CON', 'NIL']
Predicted tags: ['NOT', 'REL', 'PRX', 'PST', 'HAS', 'CON', 'NIL']

Sentence: With what radioactive substance was Eda~Charlton injected
   in 1945 ?
Correct tags: ['REL', 'QUE', 'IST', 'CON', 'PST', 'PER', 'EXS',
   'REL', 'YOC', 'QUE']
Predicted tags: ['REL', 'QUE', 'ROL', 'CON', 'PST', 'PER', 'EXS',
   'REL', 'YOC', 'QUE']

Sentence: Both Cristina and Luis always dreamt of studying medicine .
Correct tags: ['AND', 'PER', 'GRP', 'PER', 'AND', 'EPS', 'REL',
   'EXG', 'CON', 'NIL']
Predicted tags: ['AND', 'ORG', 'GRP', 'PER', 'AND', 'EPS', 'REL',
   'EXG', 'CON', 'NIL']

Sentence: The official dinner took place at the White~House .
Correct tags: ['DEF', 'IST', 'CON', 'EPS', 'NIL', 'REL', 'DEF',
   'ART', 'NIL']
Predicted tags: ['DEF', 'CON', 'CON', 'EPS', 'NIL', 'REL', 'DEF',
   'ORG', 'NIL']

Sentence: The fly buzzes .
Correct tags: ['DEF', 'CON', 'EXS', 'NIL']
Predicted tags: ['DEF', 'CON', 'ENS', 'NIL']

Sentence: The supermarket hired many part-timers .
Correct tags: ['DEF', 'CON', 'EPS', 'QUV', 'ROL', 'NIL']
Predicted tags: ['DEF', 'CON', 'EPS', 'QUV', 'CON', 'NIL']

Sentence: The room was anything~but tidy .
Correct tags: ['DEF', 'CON', 'PST', 'NOT', 'IST', 'NIL']
Predicted tags: ['DEF', 'CON', 'PST', 'NOT', 'EXS', 'NIL']

Sentence: Uranus is similar to Neptune .
Correct tags: ['NTH', 'NOW', 'IST', 'REL', 'NTH', 'NIL']
Predicted tags: ['GPE', 'NOW', 'IST', 'REL', 'ORG', 'NIL']

Sentence: Tom appears outraged .
Correct tags: ['PER', 'ENS', 'IST', 'NIL']
Predicted tags: ['PER', 'NOW', 'IST', 'NIL']

Sentence: I like the Harry~Potter books .
Correct tags: ['PRO', 'ENS', 'DEF', 'PER', 'CON', 'NIL']
Predicted tags: ['PRO', 'ENS', 'DEF', 'ORG', 'CON', 'NIL']

Sentence: Would you stop babbling ?
Correct tags: ['FUT', 'PRO', 'EXS', 'EXG', 'QUE']
Predicted tags: ['POS', 'PRO', 'EXS', 'EXG', 'QUE']

Sentence: I had my decayed tooth removed .
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Correct tags: ['PRO', 'PST', 'HAS', 'IST', 'CON', 'EXS', 'NIL']
Predicted tags: ['PRO', 'PST', 'HAS', 'EXT', 'CON', 'EPS', 'NIL']

Sentence: Mom spread the table .
Correct tags: ['ROL', 'EPS', 'DEF', 'CON', 'NIL']
Predicted tags: ['PER', 'EPS', 'DEF', 'CON', 'NIL']

Sentence: Camels have either one or two humps .
Correct tags: ['CON', 'ENS', 'NIL', 'QUC', 'DIS', 'QUC', 'CON',
   'NIL']
Predicted tags: ['PER', 'ENS', 'NIL', 'CON', 'DIS', 'QUC', 'CON',
   'NIL']

Sentence: Nebraska is on the plains .
Correct tags: ['GPE', 'ENS', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['PER', 'ENS', 'REL', 'DEF', 'CON', 'NIL']

Sentence: What are brake~pads made of ?
Correct tags: ['QUE', 'NOW', 'CON', 'EXS', 'REL', 'QUE']
Predicted tags: ['QUE', 'ENS', 'CON', 'EPS', 'REL', 'QUE']

Sentence: Open your book on page nine .
Correct tags: ['EXS', 'HAS', 'CON', 'REL', 'CON', 'ORD', 'NIL']
Predicted tags: ['EXS', 'HAS', 'CON', 'REL', 'CON', 'QUC', 'NIL']

Sentence: Everybody calls the small cat Tora .
Correct tags: ['AND', 'ENS', 'DEF', 'DEG', 'CON', 'LIT', 'NIL']
Predicted tags: ['AND', 'ENS', 'DEF', 'DEG', 'CON', 'PER', 'NIL']

Sentence: I was born on 23 March 1969 in Barcelona .
Correct tags: ['PRO', 'PST', 'EXS', 'REL', 'DOM', 'MOY', 'YOC',
   'REL', 'GPE', 'NIL']
Predicted tags: ['PRO', 'PST', 'EXS', 'REL', 'CLO', 'MOY', 'YOC',
   'REL', 'GPE', 'NIL']

Sentence: Dinosaur remains were found in Asia .
Correct tags: ['CON', 'CON', 'PST', 'EXS', 'REL', 'GPE', 'NIL']
Predicted tags: ['PER', 'CON', 'PST', 'EXS', 'REL', 'GPE', 'NIL']

Sentence: She warmed herself by the fire .
Correct tags: ['PRO', 'EXS', 'REF', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['PRO', 'EPS', 'REF', 'REL', 'DEF', 'CON', 'NIL']

Sentence: She 's a real~estate~agent .
Correct tags: ['PRO', 'ENS', 'DIS', 'ROL', 'NIL']
Predicted tags: ['PRO', 'ENS', 'DIS', 'CON', 'NIL']

Sentence: The pasture has an area of 10 acres .
Correct tags: ['DEF', 'CON', 'ENS', 'DIS', 'CON', 'REL', 'QUC',
   'UOM', 'NIL']
Predicted tags: ['DEF', 'CON', 'ENS', 'DIS', 'CON', 'REL', 'QUC',
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   'CON', 'NIL']

Sentence: I met him in January .
Correct tags: ['PRO', 'EPS', 'PRO', 'REL', 'MOY', 'NIL']
Predicted tags: ['PRO', 'EPS', 'PRO', 'REL', 'ORG', 'NIL']

Sentence: Kraft sold Celestial~Seasonings to Lipton in 1986 .
Correct tags: ['ORG', 'EPS', 'ORG', 'REL', 'ORG', 'REL', 'YOC',
   'NIL']
Predicted tags: ['ORG', 'EPS', 'ORG', 'REL', 'PER', 'REL', 'YOC',
   'NIL']

Sentence: We saw nothing strange .
Correct tags: ['PRO', 'EPS', 'NOT', 'IST', 'NIL']
Predicted tags: ['PRO', 'EPS', 'NOT', 'CON', 'NIL']

Sentence: Nancy and Domenic~Ianiero had Canadian citizenship .
Correct tags: ['PER', 'AND', 'PER', 'EPS', 'GPO', 'CON', 'NIL']
Predicted tags: ['PER', 'GRP', 'PER', 'EPS', 'GPO', 'CON', 'NIL']

Sentence: The small skirt is pink .
Correct tags: ['DEF', 'DEG', 'CON', 'NOW', 'COL', 'NIL']
Predicted tags: ['DEF', 'DEG', 'CON', 'NOW', 'IST', 'NIL']

Sentence: What 's your favorite Beatles song ?
Correct tags: ['QUE', 'ENS', 'HAS', 'TOP', 'ORG', 'CON', 'QUE']
Predicted tags: ['QUE', 'ENS', 'HAS', 'TOP', 'PER', 'CON', 'QUE']

Sentence: Tom made a statement .
Correct tags: ['PER', 'EPS', 'DIS', 'CON', 'NIL']
Predicted tags: ['PER', 'EPS', 'DIS', 'ROL', 'NIL']

Sentence: Tom never tells me anything .
Correct tags: ['PER', 'NOT', 'ENS', 'PRO', 'DIS', 'NIL']
Predicted tags: ['PER', 'NOT', 'EPS', 'PRO', 'DIS', 'NIL']

Sentence: Scrooge glanced towards the Phantom .
Correct tags: ['PER', 'EPS', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['PER', 'EPS', 'REL', 'DEF', 'GPE', 'NIL']

Sentence: The fitting room is occupied .
Correct tags: ['DEF', 'CON', 'CON', 'NOW', 'IST', 'NIL']
Predicted tags: ['DEF', 'EXG', 'CON', 'NOW', 'IST', 'NIL']

Sentence: None of his advice was very useful .
Correct tags: ['NOT', 'REL', 'HAS', 'CON', 'PST', 'INT', 'IST',
   'NIL']
Predicted tags: ['NOT', 'REL', 'HAS', 'ROL', 'PST', 'INT', 'IST',
   'NIL']

Sentence: The law was also criticized be the trade~unions .
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Correct tags: ['DEF', 'CON', 'PST', 'ALT', 'EXS', 'REL', 'DEF',
   'CON', 'NIL']
Predicted tags: ['DEF', 'CON', 'PST', 'ALT', 'EXS', 'NIL', 'DEF',
   'CON', 'NIL']

Sentence: Drops dripped .
Correct tags: ['CON', 'EPS', 'NIL']
Predicted tags: ['PER', 'EPS', 'NIL']

Sentence: The diamond shone brightly .
Correct tags: ['DEF', 'CON', 'EPS', 'IST', 'NIL']
Predicted tags: ['DEF', 'CON', 'ALT', 'IST', 'NIL']

Sentence: Where is Prairie~View~A&M~University ?
Correct tags: ['QUE', 'ENS', 'ORG', 'QUE']
Predicted tags: ['QUE', 'ENS', 'PER', 'QUE']

Sentence: My yogurt expires in 2014 !
Correct tags: ['HAS', 'CON', 'EFS', 'REL', 'YOC', 'NIL']
Predicted tags: ['HAS', 'IST', 'CON', 'REL', 'YOC', 'EMP']

Sentence: Tom is an expert watchmaker .
Correct tags: ['PER', 'ENS', 'DIS', 'IST', 'ROL', 'NIL']
Predicted tags: ['PER', 'ENS', 'DIS', 'CON', 'ROL', 'NIL']

Sentence: She scowled at the rude salesman .
Correct tags: ['PRO', 'EPS', 'REL', 'DEF', 'IST', 'ROL', 'NIL']
Predicted tags: ['PRO', 'EPS', 'REL', 'DEF', 'IST', 'CON', 'NIL']

Sentence: They explored Lake~Tanganyika in East~Africa .
Correct tags: ['PRO', 'EPS', 'GEO', 'REL', 'GPE', 'NIL']
Predicted tags: ['PRO', 'EPS', 'GEO', 'REL', 'CON', 'NIL']

Sentence: This bridge looks steady .
Correct tags: ['PRX', 'CON', 'ENS', 'IST', 'NIL']
Predicted tags: ['PRX', 'CON', 'ENS', 'CON', 'NIL']

Sentence: He spent his honeymoon in the Maldives .
Correct tags: ['PRO', 'EPS', 'HAS', 'CON', 'REL', 'DEF', 'GPE',
   'NIL']
Predicted tags: ['PRO', 'EPS', 'HAS', 'CON', 'REL', 'DEF', 'ROL',
   'NIL']

Sentence: A typhoon batters the Philippines .
Correct tags: ['AND', 'CON', 'ENS', 'DEF', 'GPE', 'NIL']
Predicted tags: ['DIS', 'CON', 'ENS', 'DEF', 'GPE', 'NIL']

Sentence: The dictionary contains about half~a~million words .
Correct tags: ['DEF', 'CON', 'ENS', 'APX', 'QUC', 'CON', 'NIL']
Predicted tags: ['DEF', 'CON', 'EFS', 'APX', 'QUC', 'CON', 'NIL']
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Sentence: Get an egg from the refrigerator .
Correct tags: ['EXS', 'DIS', 'CON', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['PRO', 'DIS', 'CON', 'REL', 'DEF', 'CON', 'NIL']

Sentence: Her son is stationed in West~Germany .
Correct tags: ['HAS', 'ROL', 'NOW', 'EXS', 'REL', 'GPE', 'NIL']
Predicted tags: ['HAS', 'ROL', 'NOW', 'EXS', 'REL', 'PER', 'NIL']

Sentence: It 's very sticky .
Correct tags: ['PRO', 'NOW', 'INT', 'DEG', 'NIL']
Predicted tags: ['PRO', 'NOW', 'INT', 'IST', 'NIL']

Sentence: America did away with slavery .
Correct tags: ['GPE', 'EPS', 'REL', 'REL', 'CON', 'NIL']
Predicted tags: ['GPE', 'EPS', 'IST', 'REL', 'CON', 'NIL']

Sentence: Mr. Johnson 's room was a large one .
Correct tags: ['ROL', 'PER', 'HAS', 'CON', 'EPS', 'DIS', 'IST',
   'CON', 'NIL']
Predicted tags: ['ROL', 'PER', 'HAS', 'CON', 'EPS', 'DIS', 'DEG',
   'CON', 'NIL']

Sentence: A man is lumping dough
Correct tags: ['DIS', 'CON', 'NOW', 'EXG', 'CON']
Predicted tags: ['DIS', 'CON', 'NOW', 'EXG', 'IST']

Sentence: I 've always hated Tom .
Correct tags: ['PRO', 'NOW', 'AND', 'EXT', 'PER', 'NIL']
Predicted tags: ['PRO', 'NOW', 'AND', 'EPS', 'PER', 'NIL']

Sentence: Tom has hundreds of books .
Correct tags: ['PER', 'ENS', 'QUV', 'REL', 'CON', 'NIL']
Predicted tags: ['PER', 'ENS', 'CON', 'REL', 'CON', 'NIL']

Sentence: The atomic tests at Bikini~Atoll took place in 1946 .
Correct tags: ['DEF', 'IST', 'CON', 'REL', 'GPE', 'EPS', 'NIL',
   'REL', 'YOC', 'NIL']
Predicted tags: ['DEF', 'CON', 'ENS', 'REL', 'GEO', 'EPS', 'NIL',
   'REL', 'YOC', 'NIL']

Sentence: Tom 's had a lot of girlfriends .
Correct tags: ['PER', 'NOW', 'EXT', 'DIS', 'QUV', 'REL', 'ROL',
   'NIL']
Predicted tags: ['PER', 'NOW', 'EPS', 'DIS', 'QUV', 'REL', 'ROL',
   'NIL']

Sentence: Mr Jenninger will take the witness~stand on 13 May .
Correct tags: ['ROL', 'PER', 'FUT', 'EXS', 'DEF', 'CON', 'REL',
   'DOM', 'MOY', 'NIL']
Predicted tags: ['ROL', 'PER', 'FUT', 'EXS', 'DEF', 'CON', 'REL',
   'QUC', 'MOY', 'NIL']
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Sentence: Two people are kickboxing and spectators are watching
Correct tags: ['QUC', 'CON', 'NOW', 'EXG', 'AND', 'CON', 'NOW',
   'EXG']
Predicted tags: ['QUC', 'CON', 'NOW', 'EXG', 'AND', 'ROL', 'NOW',
   'EXG']

Sentence: Daisuke climbed to the summit .
Correct tags: ['PER', 'EPS', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['PER', 'EPS', 'REL', 'DEF', 'ROL', 'NIL']

Sentence: She borrowed the ruler .
Correct tags: ['PRO', 'EPS', 'DEF', 'CON', 'NIL']
Predicted tags: ['PRO', 'EPS', 'DEF', 'ROL', 'NIL']

Sentence: Tom was staring at Mary .
Correct tags: ['PER', 'PST', 'EXG', 'REL', 'PER', 'NIL']
Predicted tags: ['PER', 'PST', 'EXS', 'REL', 'PER', 'NIL']

Sentence: The parents named the baby Akiyoshi .
Correct tags: ['DEF', 'ROL', 'EPS', 'DEF', 'CON', 'LIT', 'NIL']
Predicted tags: ['DEF', 'ROL', 'EPS', 'DEF', 'CON', 'GPO', 'NIL']

Sentence: This watch was your grandfather 's .
Correct tags: ['PRX', 'CON', 'EPS', 'HAS', 'ROL', 'HAS', 'NIL']
Predicted tags: ['PRX', 'CON', 'PST', 'HAS', 'ROL', 'HAS', 'NIL']

Sentence: Russia rejected both demands .
Correct tags: ['GPE', 'EPS', 'AND', 'CON', 'NIL']
Predicted tags: ['GPE', 'EPS', 'AND', 'ENS', 'NIL']

Sentence: Let 's escape together .
Correct tags: ['FUT', 'PRO', 'EXS', 'GRP', 'NIL']
Predicted tags: ['FUT', 'PRO', 'EXS', 'NIL', 'NIL']

Sentence: Who was Alexander~Hamilton ?
Correct tags: ['QUE', 'ENS', 'PER', 'QUE']
Predicted tags: ['QUE', 'PST', 'PER', 'QUE']

Sentence: The Mongolian army approached the city .
Correct tags: ['DEF', 'GPO', 'CON', 'EPS', 'DEF', 'CON', 'NIL']
Predicted tags: ['DEF', 'GPO', 'ROL', 'EPS', 'DEF', 'CON', 'NIL']

Sentence: The Sioux had signed a treaty with the government in 1868 .
Correct tags: ['DEF', 'CON', 'PST', 'EXT', 'DIS', 'CON', 'REL',
   'DEF', 'CON', 'REL', 'YOC', 'NIL']
Predicted tags: ['DEF', 'ORG', 'PST', 'EXT', 'DIS', 'CON', 'REL',
   'DEF', 'CON', 'REL', 'YOC', 'NIL']

Sentence: He added a little sugar to the coffee .
Correct tags: ['PRO', 'EPS', 'DIS', 'QUV', 'CON', 'REL', 'DEF',
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   'CON', 'NIL']
Predicted tags: ['PRO', 'EPS', 'DIS', 'IST', 'CON', 'REL', 'DEF',
   'CON', 'NIL']

Sentence: She showers every morning .
Correct tags: ['PRO', 'EXS', 'AND', 'CON', 'NIL']
Predicted tags: ['PRO', 'ENS', 'AND', 'CON', 'NIL']

Sentence: The owl hoots .
Correct tags: ['DEF', 'CON', 'ENS', 'NIL']
Predicted tags: ['DEF', 'IST', 'ENS', 'NIL']

Sentence: Mrs. Davis was anything~but a perfect wife .
Correct tags: ['ROL', 'PER', 'EPS', 'NOT', 'DIS', 'IST', 'ROL',
   'NIL']
Predicted tags: ['ROL', 'PER', 'PST', 'NOT', 'DIS', 'IST', 'ROL',
   'NIL']

Sentence: I hate Mondays .
Correct tags: ['PRO', 'EPS', 'DOW', 'NIL']
Predicted tags: ['PRO', 'ENS', 'ROL', 'NIL']

Sentence: Crude~oil has been falling in price .
Correct tags: ['CON', 'NOW', 'PFT', 'EXG', 'REL', 'CON', 'NIL']
Predicted tags: ['PER', 'NOW', 'PFT', 'EXG', 'REL', 'CON', 'NIL']

Sentence: Hundreds~of~thousands of women had been raped .
Correct tags: ['QUV', 'REL', 'CON', 'PST', 'PFT', 'EXS', 'NIL']
Predicted tags: ['PER', 'REL', 'CON', 'PST', 'PFT', 'EXS', 'NIL']

Sentence: Ai sat down beside me .
Correct tags: ['PER', 'EPS', 'REL', 'REL', 'PRO', 'NIL']
Predicted tags: ['NOW', 'EPS', 'REL', 'REL', 'PRO', 'NIL']

Sentence: I saw a bum at the train~station .
Correct tags: ['PRO', 'EPS', 'DIS', 'ROL', 'REL', 'DEF', 'CON',
   'NIL']
Predicted tags: ['PRO', 'EPS', 'DIS', 'CON', 'REL', 'DEF', 'CON',
   'NIL']

Sentence: Chen is not Korean .
Correct tags: ['PER', 'NOW', 'NOT', 'GPO', 'NIL']
Predicted tags: ['GPE', 'ENS', 'NOT', 'CON', 'NIL']

Sentence: Many philosophers come from Greece .
Correct tags: ['QUV', 'ROL', 'ENS', 'REL', 'GPE', 'NIL']
Predicted tags: ['QUV', 'CON', 'ENS', 'REL', 'GPE', 'NIL']

Sentence: Yumi 's boyfriend is a bit antisocial .
Correct tags: ['PER', 'HAS', 'ROL', 'NOW', 'DIS', 'QUV', 'IST',
   'NIL']
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Predicted tags: ['PER', 'HAS', 'ROL', 'ENS', 'DIS', 'QUV', 'CON',
   'NIL']

Sentence: Palestine is called " Filastin " in Arabic .
Correct tags: ['GPE', 'NOW', 'EXS', 'NIL', 'LIT', 'NIL', 'REL',
   'CON', 'NIL']
Predicted tags: ['QUE', 'NOW', 'EXS', 'NIL', 'LIT', 'NIL', 'REL',
   'CON', 'NIL']

Sentence: I am from Portugal .
Correct tags: ['PRO', 'ENS', 'REL', 'GPE', 'NIL']
Predicted tags: ['PRO', 'ENS', 'REL', 'CON', 'NIL']

Sentence: I love hard-boiled eggs .
Correct tags: ['PRO', 'ENS', 'IST', 'CON', 'NIL']
Predicted tags: ['PRO', 'ENS', 'CON', 'CON', 'NIL']

Sentence: Russia is a very big country .
Correct tags: ['GPE', 'ENS', 'DIS', 'INT', 'DEG', 'CON', 'NIL']
Predicted tags: ['GPE', 'ENS', 'DIS', 'INT', 'IST', 'CON', 'NIL']

Sentence: I 'm slightly hungry .
Correct tags: ['PRO', 'NOW', 'INT', 'IST', 'NIL']
Predicted tags: ['PRO', 'NOW', 'IST', 'IST', 'NIL']

Sentence: Tom was expelled from private~school .
Correct tags: ['PER', 'PST', 'EXT', 'REL', 'CON', 'NIL']
Predicted tags: ['PER', 'PST', 'EXS', 'REL', 'CON', 'NIL']

Sentence: The girl started to sob .
Correct tags: ['DEF', 'CON', 'EPS', 'NIL', 'EXS', 'NIL']
Predicted tags: ['DEF', 'CON', 'EPS', 'NIL', 'CON', 'NIL']

Sentence: Soldiers barred the way to the city .
Correct tags: ['ROL', 'EPS', 'DEF', 'CON', 'REL', 'DEF', 'CON',
   'NIL']
Predicted tags: ['CON', 'EPS', 'DEF', 'CON', 'REL', 'DEF', 'CON',
   'NIL']

Sentence: Tom and Mary are always flirting with each~other .
Correct tags: ['PER', 'GRP', 'PER', 'NOW', 'AND', 'EXG', 'REL',
   'REF', 'NIL']
Predicted tags: ['PER', 'GRP', 'PER', 'NOW', 'AND', 'EXG', 'REL',
   'ROL', 'NIL']

Sentence: Bob charged 3 dollars an hour for mowing lawns .
Correct tags: ['PER', 'EPS', 'QUC', 'UOM', 'UOM', 'UOM', 'REL',
   'EXG', 'CON', 'NIL']
Predicted tags: ['PER', 'EPS', 'QUC', 'UOM', 'QUC', 'UOM', 'REL',
   'EXG', 'CON', 'NIL']
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Sentence: I ca n't afford to buy a laptop for my son .
Correct tags: ['PRO', 'POS', 'NOT', 'EXS', 'NIL', 'EXS', 'DIS',
   'CON', 'REL', 'HAS', 'ROL', 'NIL']
Predicted tags: ['PRO', 'POS', 'NOT', 'CON', 'NIL', 'EXS', 'DIS',
   'CON', 'REL', 'HAS', 'ROL', 'NIL']

Sentence: What a beautiful place !
Correct tags: ['EMP', 'DIS', 'IST', 'CON', 'EMP']
Predicted tags: ['EMP', 'DIS', 'IST', 'NIL', 'EMP']

Sentence: The blackbird whistles .
Correct tags: ['DEF', 'CON', 'ENS', 'NIL']
Predicted tags: ['DEF', 'COL', 'CON', 'NIL']

Sentence: The brass~band played three marches .
Correct tags: ['DEF', 'CON', 'EPS', 'QUC', 'CON', 'NIL']
Predicted tags: ['DEF', 'CON', 'EPS', 'QUC', 'UOM', 'NIL']

Sentence: Liu~Bei and Zhuge~Liang are an unbeatable team .
Correct tags: ['PER', 'GRP', 'PER', 'ENS', 'DIS', 'IST', 'CON',
   'NIL']
Predicted tags: ['ORG', 'GRP', 'PER', 'ENS', 'DIS', 'IST', 'CON',
   'NIL']

Sentence: Canada is awesome !
Correct tags: ['GPE', 'NOW', 'IST', 'EMP']
Predicted tags: ['GPE', 'ENS', 'CON', 'EMP']

Sentence: Spartan~Air~Lines acquired United~Airways .
Correct tags: ['ORG', 'EPS', 'ORG', 'NIL']
Predicted tags: ['PER', 'EPS', 'GPE', 'NIL']

Sentence: Dawson teaches at Monash~University .
Correct tags: ['PER', 'ENS', 'REL', 'ORG', 'NIL']
Predicted tags: ['PER', 'ENS', 'REL', 'PER', 'NIL']

Sentence: I speak Uzbek .
Correct tags: ['PRO', 'ENS', 'CON', 'NIL']
Predicted tags: ['PRO', 'ENS', 'REL', 'NIL']

Sentence: Twelve is an even number .
Correct tags: ['QUC', 'EXS', 'DIS', 'IST', 'CON', 'NIL']
Predicted tags: ['QUC', 'ENS', 'DIS', 'COL', 'CON', 'NIL']

Sentence: Who is the leader of Sinn~Fein ?
Correct tags: ['QUE', 'ENS', 'DEF', 'ROL', 'REL', 'ORG', 'QUE']
Predicted tags: ['QUE', 'ENS', 'DEF', 'CON', 'REL', 'PER', 'QUE']

Sentence: I do n't trust politicians .
Correct tags: ['PRO', 'NOW', 'NOT', 'EXS', 'ROL', 'NIL']
Predicted tags: ['PRO', 'NOW', 'NOT', 'EXS', 'CON', 'NIL']
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Sentence: The boy looked like a grownup .
Correct tags: ['DEF', 'CON', 'EPS', 'REL', 'DIS', 'ROL', 'NIL']
Predicted tags: ['DEF', 'CON', 'EPS', 'REL', 'DIS', 'CON', 'NIL']

Sentence: We named the boat the Half~Moon .
Correct tags: ['PRO', 'EPS', 'DEF', 'CON', 'DEF', 'LIT', 'NIL']
Predicted tags: ['PRO', 'EPS', 'DEF', 'CON', 'DEF', 'CON', 'NIL']

Sentence: Elena is the tallest girl in the class .
Correct tags: ['PER', 'ENS', 'DEF', 'TOP', 'CON', 'REL', 'DEF',
   'CON', 'NIL']
Predicted tags: ['GPE', 'ENS', 'DEF', 'TOP', 'CON', 'REL', 'DEF',
   'CON', 'NIL']

Sentence: What is Motley~Crue 's Nikki~Sixx 's real name ?
Correct tags: ['QUE', 'ENS', 'ORG', 'HAS', 'PER', 'HAS', 'IST',
   'CON', 'QUE']
Predicted tags: ['QUE', 'ENS', 'ORG', 'HAS', 'ART', 'HAS', 'IST',
   'CON', 'QUE']

Sentence: Pierce lives on E.~28th~Street .
Correct tags: ['PER', 'ENS', 'REL', 'GEO', 'NIL']
Predicted tags: ['GPE', 'ENS', 'REL', 'PER', 'NIL']

Sentence: She grilled a steak .
Correct tags: ['PRO', 'EPS', 'DIS', 'CON', 'NIL']
Predicted tags: ['PRO', 'EPS', 'DIS', 'ROL', 'NIL']

Sentence: That rope has to be coiled .
Correct tags: ['DST', 'CON', 'NEC', 'NIL', 'NIL', 'EXS', 'NIL']
Predicted tags: ['DST', 'CON', 'NOW', 'NIL', 'NIL', 'EXS', 'NIL']

Sentence: What Liverpool club spawned the Beatles ?
Correct tags: ['QUE', 'GPE', 'CON', 'EPS', 'DEF', 'ORG', 'QUE']
Predicted tags: ['QUE', 'GPO', 'CON', 'EPS', 'DEF', 'ORG', 'QUE']

Sentence: It needs a new battery .
Correct tags: ['PRO', 'ENS', 'DIS', 'IST', 'CON', 'NIL']
Predicted tags: ['PRO', 'ENS', 'DIS', 'IST', 'ROL', 'NIL']

Sentence: As~soon~as he sat down , he picked up the telephone .
Correct tags: ['REL', 'PRO', 'EPS', 'REL', 'NIL', 'PRO', 'EPS',
   'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['BOT', 'PRO', 'EPS', 'REL', 'NIL', 'PRO', 'EPS',
   'REL', 'DEF', 'CON', 'NIL']

Sentence: A dog is sensitive to smell .
Correct tags: ['AND', 'CON', 'NOW', 'IST', 'REL', 'CON', 'NIL']
Predicted tags: ['DIS', 'CON', 'NOW', 'IST', 'REL', 'CON', 'NIL']
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Sentence: Do you want some scrambled~eggs ?
Correct tags: ['NOW', 'PRO', 'ENS', 'DIS', 'CON', 'QUE']
Predicted tags: ['NOW', 'PRO', 'EXS', 'DIS', 'CON', 'QUE']

Sentence: According to a survey , 1~billion people are suffering
   from poverty in the world .
Correct tags: ['IST', 'REL', 'DIS', 'CON', 'NIL', 'QUC', 'CON',
   'NOW', 'EXG', 'REL', 'CON', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['IST', 'REL', 'DIS', 'CON', 'REL', 'QUC', 'CON',
   'NOW', 'EXG', 'REL', 'CON', 'REL', 'DEF', 'CON', 'NIL']

Sentence: The queen stood beside the king .
Correct tags: ['DEF', 'ROL', 'EPS', 'REL', 'DEF', 'ROL', 'NIL']
Predicted tags: ['DEF', 'CON', 'EPS', 'REL', 'DEF', 'CON', 'NIL']

Sentence: Tunisia is located in Africa .
Correct tags: ['GPE', 'NOW', 'IST', 'REL', 'GPE', 'NIL']
Predicted tags: ['PER', 'NOW', 'IST', 'REL', 'GPE', 'NIL']

Sentence: Mary called her stuffed squirrel Tom .
Correct tags: ['PER', 'EPS', 'HAS', 'IST', 'CON', 'LIT', 'NIL']
Predicted tags: ['PER', 'EPS', 'HAS', 'IST', 'CON', 'PER', 'NIL']

Sentence: Tom is timid , is n't he ?
Correct tags: ['PER', 'NOW', 'IST', 'NIL', 'NOW', 'NOT', 'PRO',
   'QUE']
Predicted tags: ['PER', 'NOW', 'CON', 'NIL', 'ENS', 'NOT', 'PRO',
   'QUE']

Sentence: The hamster has stuffed cheeks .
Correct tags: ['DEF', 'CON', 'ENS', 'IST', 'CON', 'NIL']
Predicted tags: ['DEF', 'CON', 'NOW', 'EXT', 'CON', 'NIL']

Sentence: The soldiers resisted the enemy attack .
Correct tags: ['DEF', 'ROL', 'EPS', 'DEF', 'ROL', 'CON', 'NIL']
Predicted tags: ['DEF', 'ROL', 'EPS', 'DEF', 'ROL', 'IST', 'NIL']

Sentence: The bell rang , and the train began to move .
Correct tags: ['DEF', 'CON', 'EPS', 'NIL', 'COO', 'DEF', 'CON',
   'EPS', 'NIL', 'EXS', 'NIL']
Predicted tags: ['DEF', 'CON', 'EPS', 'NIL', 'COO', 'DEF', 'CON',
   'EPS', 'REL', 'CON', 'NIL']

Sentence: Tom received the award posthumously .
Correct tags: ['PER', 'EPS', 'DEF', 'CON', 'IST', 'NIL']
Predicted tags: ['PER', 'EPS', 'DEF', 'CON', 'ENS', 'NIL']

Sentence: He acquired Russian quickly .
Correct tags: ['PRO', 'EPS', 'CON', 'IST', 'NIL']
Predicted tags: ['PRO', 'EPS', 'GPO', 'IST', 'NIL']
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Sentence: The committee consists of twelve members .
Correct tags: ['DEF', 'CON', 'ENS', 'REL', 'QUC', 'ROL', 'NIL']
Predicted tags: ['DEF', 'CON', 'ENS', 'REL', 'QUC', 'UOM', 'NIL']

Sentence: I am lesbian .
Correct tags: ['PRO', 'NOW', 'IST', 'NIL']
Predicted tags: ['PRO', 'NOW', 'ROL', 'NIL']

Sentence: It was the first gold~medal that she had won .
Correct tags: ['PRO', 'EPS', 'DEF', 'ORD', 'CON', 'AND', 'PRO',
    'PST', 'EXT', 'NIL']
Predicted tags: ['PRO', 'EPS', 'DEF', 'ORD', 'CON', 'SUB', 'PRO',
    'PST', 'EXT', 'NIL']

Sentence: Suddenly rain began to fall .
Correct tags: ['IST', 'CON', 'EPS', 'NIL', 'EXS', 'NIL']
Predicted tags: ['CON', 'CON', 'EPS', 'REL', 'IST', 'NIL']

Sentence: Melanie said that she likes swimming .
Correct tags: ['PER', 'EPS', 'SUB', 'PRO', 'ENS', 'CON', 'NIL']
Predicted tags: ['PER', 'EPS', 'SUB', 'PRO', 'ENS', 'EXG', 'NIL']

Sentence: I bought a new pair of glasses .
Correct tags: ['PRO', 'EPS', 'DIS', 'IST', 'NIL', 'AND', 'CON',
    'NIL']
Predicted tags: ['PRO', 'EPS', 'DIS', 'IST', 'CON', 'AND', 'CON',
    'NIL']

Sentence: I was bit by a mosquito .
Correct tags: ['PRO', 'PST', 'EXS', 'REL', 'DIS', 'CON', 'NIL']
Predicted tags: ['PRO', 'PST', 'EXS', 'REL', 'DIS', 'ROL', 'NIL']

Sentence: He 's a traitor .
Correct tags: ['PRO', 'NOW', 'DIS', 'ROL', 'NIL']
Predicted tags: ['PRO', 'ENS', 'DIS', 'CON', 'NIL']

Sentence: I remember meeting him somewhere .
Correct tags: ['PRO', 'ENS', 'EXG', 'PRO', 'DIS', 'NIL']
Predicted tags: ['PRO', 'NEC', 'EXG', 'PRO', 'DIS', 'NIL']

Sentence: How many people survived the Auschwitz concentration~camp ?
Correct tags: ['QUE', 'QUV', 'CON', 'EPS', 'DEF', 'NTH', 'CON',
    'QUE']
Predicted tags: ['QUE', 'QUV', 'CON', 'EPS', 'DEF', 'ORG', 'CON',
    'QUE']

Sentence: Bergen is a Norwegian town .
Correct tags: ['GPE', 'ENS', 'DIS', 'GPO', 'CON', 'NIL']
Predicted tags: ['CON', 'ENS', 'DIS', 'GPO', 'CON', 'NIL']

Sentence: A woman is slicing tofu
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Correct tags: ['DIS', 'CON', 'NOW', 'EXG', 'CON']
Predicted tags: ['DIS', 'CON', 'NOW', 'EXG', 'IST']

Sentence: I am from Rio~de~Janeiro , Brazil .
Correct tags: ['PRO', 'ENS', 'REL', 'GPE', 'REL', 'GPE', 'NIL']
Predicted tags: ['PRO', 'ENS', 'REL', 'PER', 'REL', 'GPE', 'NIL']

Sentence: I need to shit .
Correct tags: ['PRO', 'ENS', 'NIL', 'EXS', 'NIL']
Predicted tags: ['PRO', 'ENS', 'REL', 'CON', 'NIL']

Sentence: Two plus two makes four .
Correct tags: ['QUC', 'CON', 'QUC', 'EXS', 'QUC', 'NIL']
Predicted tags: ['QUC', 'CON', 'QUC', 'ENS', 'QUC', 'NIL']

Sentence: The couple was quarrelling and Chris knocked Beth down .
Correct tags: ['DEF', 'CON', 'PST', 'EXG', 'COO', 'PER', 'EPS',
    'PER', 'REL', 'NIL']
Predicted tags: ['DEF', 'CON', 'PST', 'EXG', 'COO', 'PER', 'EPS',
    'GPE', 'REL', 'NIL']

Sentence: This car is going 60 km an hour .
Correct tags: ['PRX', 'CON', 'NOW', 'EXG', 'QUC', 'UOM', 'UOM',
    'UOM', 'NIL']
Predicted tags: ['PRX', 'CON', 'NOW', 'EXG', 'QUC', 'UOM', 'QUC',
    'UOM', 'NIL']

Sentence: Champagne is imported from France .
Correct tags: ['CON', 'NOW', 'EXS', 'REL', 'GPE', 'NIL']
Predicted tags: ['GPE', 'NOW', 'EXS', 'REL', 'GPE', 'NIL']

Sentence: I worked from six~PM until midnight .
Correct tags: ['PRO', 'EPS', 'REL', 'CLO', 'REL', 'CLO', 'NIL']
Predicted tags: ['PRO', 'EPS', 'REL', 'QUC', 'REL', 'CLO', 'NIL']

Sentence: Mifune has named his dog Maggy~May .
Correct tags: ['PER', 'NOW', 'EXT', 'HAS', 'CON', 'LIT', 'NIL']
Predicted tags: ['PER', 'NOW', 'EXT', 'HAS', 'CON', 'PER', 'NIL']

Sentence: Julio is swinging in the hammock that I hung under the old
    oak~tree .
Correct tags: ['PER', 'NOW', 'EXG', 'REL', 'DEF', 'CON', 'AND',
    'PRO', 'EPS', 'REL', 'DEF', 'DEG', 'CON', 'NIL']
Predicted tags: ['GPE', 'NOW', 'EXG', 'REL', 'DEF', 'CON', 'AND',
    'PRO', 'EPS', 'REL', 'DEF', 'DEG', 'CON', 'NIL']

Sentence: The elephant was killed by the hunter .
Correct tags: ['DEF', 'CON', 'PST', 'EXS', 'REL', 'DEF', 'ROL',
    'NIL']
Predicted tags: ['AND', 'CON', 'PST', 'EXS', 'REL', 'DEF', 'ROL',
    'NIL']
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Sentence: Are they big ?
Correct tags: ['NOW', 'PRO', 'DEG', 'QUE']
Predicted tags: ['NOW', 'PRO', 'IST', 'QUE']

Sentence: Our farm is located in rural Nebraska .
Correct tags: ['HAS', 'CON', 'NOW', 'IST', 'REL', 'IST', 'GPE',
   'NIL']
Predicted tags: ['HAS', 'CON', 'NOW', 'IST', 'REL', 'EXS', 'PER',
   'NIL']

Sentence: Tom~Online earned US$ 42.78~mn in three months .
Correct tags: ['ORG', 'EPS', 'UOM', 'QUC', 'REL', 'QUC', 'UOM',
   'NIL']
Predicted tags: ['PER', 'EPS', 'UOM', 'QUC', 'REL', 'QUC', 'UOM',
   'NIL']

Sentence: The cardinals have elected a new pope .
Correct tags: ['DEF', 'ROL', 'NOW', 'EXT', 'DIS', 'IST', 'ROL',
   'NIL']
Predicted tags: ['DEF', 'CON', 'NOW', 'EXT', 'DIS', 'IST', 'ROL',
   'NIL']

Sentence: Where is the Sea~of~Tranquility ?
Correct tags: ['QUE', 'ENS', 'DEF', 'GEO', 'QUE']
Predicted tags: ['QUE', 'ENS', 'DEF', 'CON', 'QUE']

Sentence: Tom did n't realize he had his sweater on inside~out .
Correct tags: ['PER', 'PST', 'NOT', 'EXS', 'PRO', 'EPS', 'HAS',
   'CON', 'REL', 'IST', 'NIL']
Predicted tags: ['PER', 'PST', 'NOT', 'EXS', 'PRO', 'PST', 'HAS',
   'CON', 'REL', 'IST', 'NIL']

Sentence: I want to marry Martyna .
Correct tags: ['PRO', 'ENS', 'NIL', 'EXS', 'PER', 'NIL']
Predicted tags: ['PRO', 'ENS', 'NIL', 'EXS', 'NTH', 'NIL']

Sentence: I like that tie of yours .
Correct tags: ['PRO', 'ENS', 'DST', 'CON', 'REL', 'PRO', 'NIL']
Predicted tags: ['PRO', 'ENS', 'DST', 'CON', 'REL', 'HAS', 'NIL']

Sentence: Hi .
Correct tags: ['GRE', 'NIL']
Predicted tags: ['CON', 'NIL']

Sentence: How much does a pill of extasy cost in Holland ?
Correct tags: ['QUE', 'QUV', 'NOW', 'DIS', 'CON', 'REL', 'CON',
   'EXS', 'REL', 'GPE', 'QUE']
Predicted tags: ['QUE', 'QUV', 'NOW', 'DIS', 'ROL', 'REL', 'IST',
   'CON', 'REL', 'GPE', 'QUE']
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Sentence: The death~penalty should be abolished .
Correct tags: ['DEF', 'CON', 'NEC', 'FUT', 'EXS', 'NIL']
Predicted tags: ['DEF', 'CON', 'NEC', 'NIL', 'EXS', 'NIL']

Sentence: Only six people came to the party .
Correct tags: ['XCL', 'QUC', 'CON', 'EPS', 'REL', 'DEF', 'CON',
   'NIL']
Predicted tags: ['PER', 'QUC', 'CON', 'EPS', 'REL', 'DEF', 'CON',
   'NIL']

Sentence: The express arrives at 6:30~p.m.
Correct tags: ['DEF', 'CON', 'EFS', 'REL', 'CLO']
Predicted tags: ['DEF', 'CON', 'ENS', 'REL', 'CLO']

Sentence: Negotiations have been adjourned until 18 June .
Correct tags: ['CON', 'NOW', 'PFT', 'EXS', 'REL', 'DOM', 'MOY',
   'NIL']
Predicted tags: ['CON', 'NOW', 'PFT', 'EXS', 'REL', 'CLO', 'MOY',
   'NIL']

Sentence: Latin is a dead~language .
Correct tags: ['CON', 'ENS', 'DIS', 'CON', 'NIL']
Predicted tags: ['PER', 'ENS', 'DIS', 'CON', 'NIL']

Sentence: The animal with big eyes is voraciously eating
Correct tags: ['DEF', 'CON', 'REL', 'DEG', 'CON', 'NOW', 'IST',
   'EXG']
Predicted tags: ['DEF', 'CON', 'REL', 'DEG', 'CON', 'NOW', 'INT',
   'EXG']

Sentence: Many peasants died during the drought .
Correct tags: ['QUV', 'ROL', 'EPS', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['QUV', 'CON', 'EPS', 'REL', 'DEF', 'CON', 'NIL']

Sentence: Improved medical technology has been one of the spin-offs
   of the space~program .
Correct tags: ['IST', 'IST', 'CON', 'NOW', 'EXT', 'QUC', 'REL',
   'DEF', 'CON', 'REL', 'DEF', 'CON', 'NIL']
Predicted tags: ['PER', 'EPS', 'CON', 'NOW', 'EXT', 'QUC', 'REL',
   'DEF', 'CON', 'REL', 'DEF', 'CON', 'NIL']

Sentence: That hat cost around fifty dollars .
Correct tags: ['DST', 'CON', 'EPS', 'APX', 'QUC', 'UOM', 'NIL']
Predicted tags: ['DST', 'CON', 'ENS', 'APX', 'QUC', 'UOM', 'NIL']

Sentence: He was christened John .
Correct tags: ['PRO', 'PST', 'EXS', 'LIT', 'NIL']
Predicted tags: ['PRO', 'PST', 'EXS', 'PER', 'NIL']

Sentence: The problem is being discussed now .
Correct tags: ['DEF', 'CON', 'NOW', 'PRG', 'EXS', 'NOW', 'NIL']
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Predicted tags: ['DEF', 'CON', 'NOW', 'PRG', 'IST', 'NOW', 'NIL']

Sentence: Tom rolled up his sleeves .
Correct tags: ['PER', 'EPS', 'REL', 'HAS', 'CON', 'NIL']
Predicted tags: ['PER', 'EPS', 'REL', 'HAS', 'ROL', 'NIL']

Sentence: The hare was outdistanced by the tortoise .
Correct tags: ['DEF', 'CON', 'PST', 'EXS', 'REL', 'DEF', 'CON',
   'NIL']
Predicted tags: ['DEF', 'CON', 'PST', 'IST', 'REL', 'DEF', 'CON',
   'NIL']

Sentence: Stop kvetching !
Correct tags: ['EXS', 'EXG', 'EMP']
Predicted tags: ['EXS', 'CON', 'EMP']
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