Japanese Named Entity Recognition from Automatic Speech Recognition Using Pre-trained Models

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Abstract

This paper details our study on Japanese Named Entity Recognition (NER) from Automatic Speech Recognition (ASR), which frequently contain speech recognition errors and unknown named entities due to abbreviations and aliases. One possible solution to this problem is to use a pre-trained model trained on a large quantity of text to acquire various contextual information. In this study, we performed NER on the dialogue logs of a task-oriented dialogue system on road traffic information in Fukui, Japan, using pre-trained BERT-based models and T5. The results confirmed that these pre-trained models exhibited significantly higher accuracies on unseen entities than methods based on dictionary matching.

1 Introduction

This study focused on named entity recognition (NER) in the context of a task-oriented dialogue system that provides information in response to the user's requests pertaining to road traffic. In our system, NER is accomplished by linking the automatic speech recognition (ASR) text with a dictionary created for each task (see Fig. 1). One way to achieve more accurate recognition is to extract the named entities before the linking.

Although we enforce the inputs to include location names by system-driven conversation, speech recognition errors and unknown named entities by abbreviations and aliases may occur. For example, "いちごっぱ" (*ichi-go-ppa*, 158) is a colloquial expression for "国道158号" (*kokudou-hyaku-goju-hachi-gou*, Japan National Route 158). Therefore, in this setting, NER using conventional methods is difficult, especially for rule-based methods.

To improve text processing functionality, this study forcused on NER on ASR texts. [1] We focused on context-based NER in the ASR texts because named entities may be unknown surfaces as a result of speech recognition errors or abbreviations. Based on the assumption that contextual information can be used effectively by pre-trained models trained on a large number of sentences, we used BERT-based models (Devlin et al., 2019; Clark et al., 2020), large-scale pre-trained models, for NER. We also investigated the performance of T5 (Raffel et al., 2020), a pre-trained encoder-decoder model.

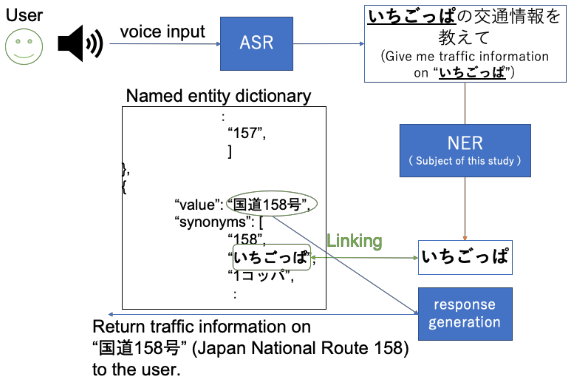

Figure 1: Flowchart of our envisioned spoken dialogue system. This study forcuses on the NER component. The goal is to extract named entities even from noisy text due to speech recognition errors or abbreviations.

2 Our Method

In this study, we used road traffic data for NER evaluation of ASR text containing speech recognition errors and obtained named entities related to roads and addresses. We assumed that the output labels (roads and addresses) could be specified as a precondition.

2.1 NER using BERT based models

Devlin et al. (2019) demonstrated that a fine-tuned BERT model performs competitively with state-

[1] Note that, although Omachi et al. (2021) postulated that an end-to-end (E2E) approach for processing speech recognition results might be preferable, we used existing ASR to enable the flexible exchange of modules and resources, making it necessary process ASR texts.

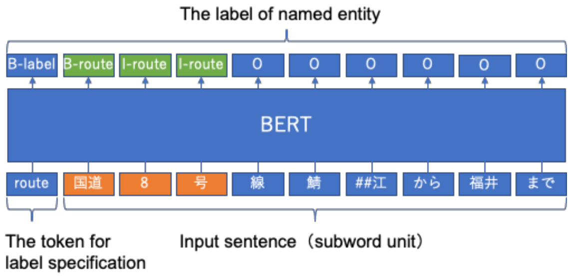

Figure 2: NER using BERT-based models

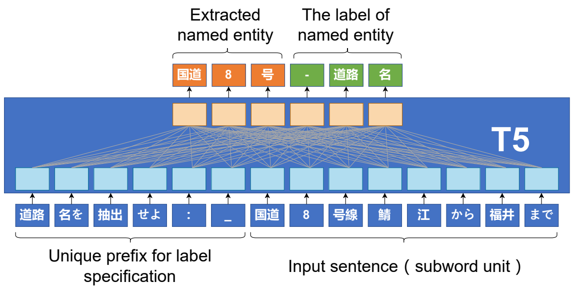

Figure 3: NER using T5

of-the-art on the CoNLL-2003 NER task (Tjong Kim Sang and De Meulder, 2003). Following their approach, we considered NER as a sequence labeling task. The text was tokenized, split into subwords, and labeled based on the BIO model, in which "B" was assigned to the beginning, "I" was assigned to the interior and the end of the named entities, and "O" was assigned to any other tokens. A schematic view is presented in Figure 2. Labels for road information were considered as "`{B, I}-route`", and labels for address information as "`{B, I}-address`". To specify a label, we prefixed the statement with a "route" or "address" token and gave "B-label".

2.2 NER using T5

We performed NER with a Seq2Seq pre-trained model because Constantin et al. (2019) reported that Seq2Seq models achieves excellent sequence labeling of noisy texts. Also,Phan et al. (2021) performed performed NER using domain-adapted T5 on medical literature. Following their approach, we considered NER as a question-and-answer task. A text with a special label at the beginning was the input sequence, and named entities corresponding to this special label were output. The system was set up such that each extracted named entity was added to the end with a label followed by a dash. A schematic view is presented in Figure 3. Labels for road information were considered as "道路名"

	text
match	鯖江から敦賀市へ向かう高速道路 (Highway from Sabae to Tsuruga City)
fallback	えーとサザエさん、サザエ市春江町 (Well, Sazae-san, Sazae City, Harue-cho)

Table 1: Example of match and fallback data (the underlined parts are named entities):サザエ (*sazae*, turban shell) is a recognition error of 鯖江 (*sabae*), which is the name of a city in Fukui.

(road name), and the labels for address information as "住所名" (address name). To specify the label, the special tokens "道路名を抽出せよ:" (extract road names) or "住所名を抽出せよ:" (extract address names) were added at the beginning of the sentence.

3 Experiments

3.1 Data

In this study, we conducted NER using a system-driven dialogue log containing road traffic information in Fukui, Japan [2]. The dialogue logs were obtained from the turns where the user seemed to have uttered the names of roads or addresses based on the conversation before and after. A dictionary of the named entities to be extracted was provided. In this dictionary, aliases, abbreviations, and speech recognition errors were registered (the dictionary is shown in Fig. 1). The target texts for which NER succeeded and failed were *match* and *fallback*, respectively; an example is presented in Table 1.

The match data were labeled by dictionary matching, with incorrect labels manually removed. For the data in fallback, we manually annotated named entities related to the road and the address. This annotation was performed considering speech recognition errors and any named entities existing in Fukui even though not in the dictionary. Notably, because fallback data were annotated based on whether the named entities exist in Fukui, a difference existed in the criteria of labeled words between match and fallback data. The number of data instances is shown in Table 3 in Appendix A.

Acheaving accurate NER with match and small fallback train data is practical, since the former requires only a reasonable sized dictionary but the latter needs human annotation. For data collection,

[2]We will perform NER on other dialogue log data as well in the future.

we considered match data as inexpensive to obtain because they could be extracted by dictionary matching, and fallback data as expensive because they could not (Subsection 3.4).

3.2 Setting

We compared four NER systems, viz., a string matching model based on a dictionary, two pre-trained BERT-based models, and T5. For the BERT-based models, we used the BERT published by Tohoku University [3] and ELECTRA published by Megagon Labs [4]. We fine-tuned both models through token classification. For BERT, we set the batch size to 8, the number of epochs to 3, and the maximum sequence length to 258. For ELECTRA, we set the learning rate to 0.00005, the batch size to 8, the number of epochs to 20, and the maximum sequence length to 128. The T5 model was fine-tuned from the model published by Megagon Labs [5]. We set the learning rate of T5 to 0.0005, the batch size to 8, the number of epochs to 20, and the maximum sequence length to 128. The script of transformers, published by Huggingface [6], was used for fine-tuning all models. Note that the pre-training datasets for T5 and ELECTRA were approximately the same size, and that for BERT was much smaller.

3.3 Evaluation

We evaluated performance by calculating precision, recall, and F1 scores, considering a perfect match as a true positive. Because of the difference between the labeling criteria of the match and fallback data (Subsection 3.1), we evaluated each test set separately. Evaluation of match data serves as a measure of whether named entities flagged by dictionary matching can be extracted, whereas evaluation of fallback data measures whether it is possible to extract named entities that are not included in the dictionary.

In this study, we assumed that entity linking was performed in the downstream task. If the extracted named entities are shorter than the original entities, linking may become problematic. In contrast, when the extracted named entities are longer than the original entities, the problem in linking is considered minor. Therefore, under the lenient evaluation setting, we considered the cases in which the named entities were covered as true positives, but we still considered the cases in which the partial matches were not covered as false positives. For example, if the named entity “**8号線**” (Route 8) is in the reference, the extraction of “**国道8号線**” (Japan National Route 8) is acceptable, but the extraction of only “**8号**” (Route 8) is not acceptable.

3.4 Experimental results and discussion

Experimental results for the match and fallback test sets are presented in Table 2, when both datasets are used as training data and when only the match dataset is used. Examples of NER results for BERT and T5 are presented in Appendix B.

String Matching For the match data, the recall was 100 because the data was created using dictionary matching. Precision was not 100 because we manually removed mislabeled data (Subsection 3.1) when creating the match data. Conversely, for the fallback data all the evaluation scores were less than 50.0, and so the unseen named entities were not sufficiently extracted.

BERT For the match test data, the F1 and c_F1 scores of BERT were comparable or superior to that of string matching, which was a desirable result for NER for subsequent tasks. For the fallback test data, the score was 20.2 points higher when training using only the match data and 43.3 points higher when training using all data compared with string matching. In particular, the improvement in the recall was remarkable, which indicated that BERT could extract unique named entities that could not be extracted by string matching. Adding the fallback data to the match data for training considerably increased the score. This increase is attributed to words not included in the match data (dictionary) being considered during training.

ELECTRA The score of ELECTRA is lower than that of BERT except for match test data when the model was trained using match data. This result shows that the amount of data used for pre-training has a small impact on the results of NER.

T5 The trend observed for T5 is the same as that for BERT. For the match test data, the performance was comparable to BERT. For the fallback test data,

[3] https://huggingface.co/cl-tohoku/bert-base-japanese-v2

[4] https://huggingface.co/megagonlabs/transformers-ud-japanese-electra-base-discriminator

[5] https://huggingface.co/megagonlabs/t5-base-japanese-web

[6] https://github.com/huggingface/transformers

method	data	P	R	F1	c_P	c_R	c_F1	P	R	F1	c_P	c_R	c_F1
String	M	96.3	**100**	**98.1**	96.3	**100**	98.1	—	—	—	—	—	—
Match	F	50.0	23.3	31.7	50.0	23.3	31.7	—	—	—	—	—	—
		trained by all data						trained by match data					
BERT	M	97.3	97.3	97.3	**99.2**	99.2	**99.2**	97.3	97.3	97.3	98.8	98.8	98.8
	F	67.9	83.7	75.0	67.9	83.7	75.0	**58.8**	46.5	**51.9**	**58.8**	46.5	**51.9**
ELECTRA	M	96.9	98.1	97.5	98.1	99.2	98.6	**97.7**	**98.1**	**97.9**	**99.2**	**99.6**	**99.4**
	F	66.0	72.1	68.9	66.0	72.1	68.9	54.5	41.9	47.4	57.6	44.2	50.0
T5	M	**98.0**	97.7	97.9	**99.2**	98.8	99.0	97.3	97.7	97.5	98.5	98.8	98.6
	F	**74.0**	**86.0**	**79.6**	**74.0**	**86.0**	**79.6**	41.3	**60.5**	49.1	42.3	**62.8**	50.9

Table 2: Experimental results for string matching, BERT, ELECTRA, and T5. M and F denote match and fallback data, respectively. "c_" means results of re-scoring named entities as true positives when they are predicted to be longer than the reference.

the precision was lower than that of BERT when training with only the match data. However, adding the fallback data to the match data for training improves the precision, and the F1 score is +4.6 points compared with BERT, which indicates that the extraction is consistent with the intention.

Comparison to human performance To evaluate the upper limit of the fallback test data, we calculated the human recognition score by asking another person, not the annotator. The precision, recall, and F1 were 80.0, 97.6, and 87.9, respectively. These results and Table 2 suggest that there is still room for improvement based on the performance of the pre-trained models. For example, pre-trained models failed to extract named entities containing speech recognition errors compared to the human, and further improvement could be achieved by considering such erroneous ASR inputs.

4 Related Work

NER from ASR. Wang et al. (2021) performed NER from speech recognition using the matching approach. Specifically, they used the embeddings of the top N prediction candidates of ASR. In this study, we experimented with using only the top predicted ASR candidate, and performed string matching with rule-based NER for simplicity.

NER from speech recognition results with neural models for English has been studied previously. Raghuvanshi et al. (2019) extracted personal names from text containing speech recognition errors using additional information not contained in the text, and reported that the recall was thereby improved. Yadav et al. (2020) studied the E2E approach and were able to extract named entities robustly and efficiently. We used neural models to perform NER from Japanese ASR texts under the assumption that the ASR architecture cannot be changed.

Japanese NER. Rule-based matching methods (Sekine et al., 1998) and machine learning-based methods (Utsuro and Sassano, 2000; Sassano and Utsuro, 2000) have been proposed for Japanese NER. However, these studies focused on manually written texts, whereas ASR texts often contain speech recognition errors.

NER in Japanese speech recognition has been performed using support vector machines (SVMs). Sudoh et al. (2006b,a) reported that when training SVMs on ASR text, precision can be improved by incorporating a confidence feature that indicates whether a word is correctly recognized. In contrast, we aimed to extract named entities from the text containing speech recognition errors, focusing on recall to lead to subsequent linking tasks and using a pre-trained model for this purpose.

5 Conclusion

We performed Japanese NER on speech recognition results by using pre-trained BERT-based models and T5. The results of the experiment showed that data generated by dictionary matching was generally well extracted by the pre-trained models. Furthermore, by adding manually annotated data to the training data, we confirmed that it is possible to extract named entities not included in the dictionary. In the future, we will consider more context-sensitive methods, including fine-tuning methods, to robustly extract named entities from noisy text containing unknown named entities, such as adding data that masks named entities to the training data.

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		train	dev	test
match	utterance	1,757	220	220
	address	1,220	144	147
	route	802	104	110
fallback	utterance	949	118	122
	address	197	30	26
	route	92	8	17

Table 3: Number of data instances used in the experiment (number of utterances and number of named entities with each label)

model	text	translation
BERT (address)	吉田郡 **永平寺町**	(Yoshida-gun Eiheiji-cho)
T5 (address)	田尻町から**福井市**までの**福井市**内まで	(From Tajiri-cho to Fukui City to Fukui City)
BERT/T5 (route)	**イチゴったー**	(Ichigotta)

Table 4: Example of NER failure in match data. Bold and underlined texts denote the reference and hypothesis.

model	text	translation
BERT (route)	**青年の道**	(Youth Road)
T5 (address)	低い	(low)
BERT (address)	あの高みの方のエルパ行きのバスは取った後	(After taking the bus to Elpa at that height)
T5 (address)	あの高みの方のエルパ行きのバスは取った後	(After taking the bus to Elpa at that height)

Table 5: Example of NER failure in fallback data. Bold and underlined texts denote the reference and hypothesis.

A Dataset

Table 3 lists the statitics for match and fallback datasets.

B Example

Examples of successful extractions with T5 and failures with BERT, successful extractions with BERT and failures with T5, and failures with both are presented in Tables 4 and 5.

Because the test data of "match" are based on a dictionary match, the reference does not include "吉田郡" (*Yoshida-gun*) and "田尻町" (*Tajiri-cho*), but it must be noted that these are actually place names that exist in Fukui, and are therefore actual examples that should be extracted. "イチゴったー" (*Ichigotta*) is thought to be a misrecognition of "いちごっぱ" (*ichi-go-ppa*, 158), which is sometimes uttered for "158号線" (Route 158). Such examples are difficult to extract using both BERT and T5.

Although "青年の道" (Youth Road) displayed in the fallback is not included in the training data, it is a road name that actually exists in Fukui. T5 was able to extract it because it predicted the road name from the word "道" (road) at the end. Only T5 can predict the road name from such a context, probably because of its different model structure and NER method. The identification of these factors is a subject for future research. Both BERT and T5 extracted "高みの（方の）" (height) as a named entity representing an address, which reveals that these models contextually tried to extract named entities from expressions that represent directions ("方").