ADL Project: Cinnamon - Information Extraction

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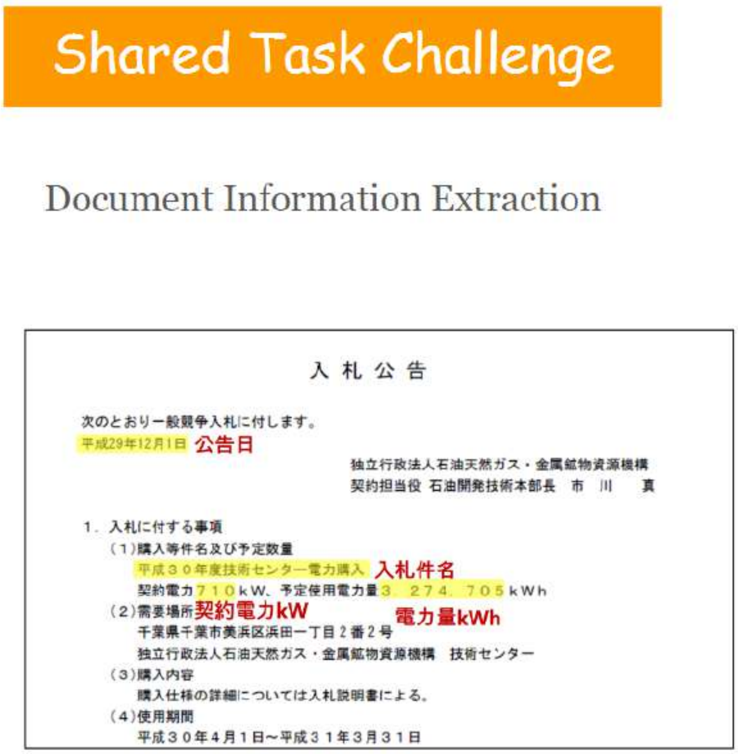

No	Japanese Tag	English Tag	Type
1	調達年度	Year of procurement	year
2	都道府県	Prefecture	text
3	入札件名	Title of bidding	text
4	施設名	Name of institution	text
5	需要場所	Address for demand	address
6	調達開始日	Start date of procurement	date
7	調達終了日	End date of procurement	date
8	契約電力(kW)	Contracted electric energy (kW)	number
9	電力量(kW)	Amount of electric energey	number
10	予備電力区分	Classification of reserved electric energey	number
11	予備契約電力(kW)	Contracted reserved electric energey	number
12	公告日	Public announcement date	date
13	仕様書交付期限	Deadline for delivery the specification	date
14	質問表締切日時	Deadline for questionnarie	date
15	資格申請締切日時	Deadline for applying qualification	date
16	入札書締切日時	Deadline for bidding	date
17	開札日時	Oening application date	date
18	質問箇所 所属/担当者	PIC of inquirt of question	name
19	質問箇所 TEL/FAX	TEL&FAX of inquiry of question	tel/fax
20	資格申請送付先	Address for submitting application of qualification	address
21	資格申請送付先 部署／担当者	Department & PIC for submitting application of qualification	name
22	入札書送付先	Address of submitting for of bid	address
23	入札書送付先 部署／担当者名	Deparment & PIC for submitting of bid	name
24	開札場所	Place of opening bid	address

Figure 1. Cinnamon Information Extraction Task, 2020.

Abstract

This work is carried out on the data-set provided by Cinnamon Company. The challenge of shared tasks is mainly focused on information extraction, which is similar to the NER(Named Entity Recognition) task in NLP. The purpose of the task is to extract the important information from the official documents. Source code is avalible at https://github.com/wubinary/Information_Extraction

Keywords: datasets, neural networks, natural language, named entity recognition, text tagging

Reference Format:
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https://www.csie.ntu.edu.tw/~miulab/s108-adl/doc/Project.pdf

1 Introduction

The Named Entity Recognition aims to locate and classify named entity in the text into predefined categories, such as personnel name, locations, organizations, etc. Generally, four types of algorithms would be used in NER tasks as follows: rule-base, unsupervised, feature-based and deep learning methods. Among unsupervised classification algorithms, the well-known classic algorithm is clustering, which recognizes named entities based on statistics and text similarity.Today, researchers usually choose deep learning methods to complete NER tasks. Compared with traditional machine learning HMM, CRF and other feature-based methods, deep learning methods can achieve better performance. In our work, we use the BERT pre-trained model as the model backbone. Through the application of transfer learning, although there is not much training data, we still can get a good performance.

2 Approach

2.1 Pre-processing

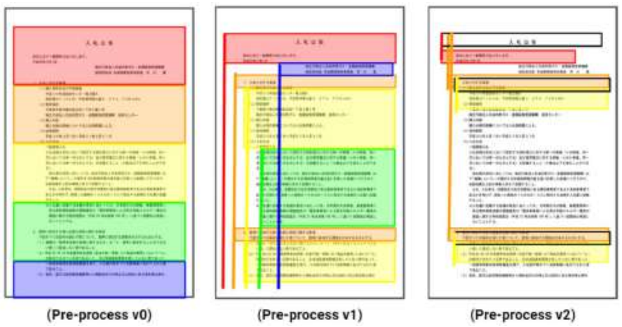


Figure 2. Three type of pre-processing

We have try three different type of preprocessing, Pre-process v0 v3 , and in the experiments the v0 is the poorest, v1 and v2 are much more better than v0, and v2 is a little bit performance better than v1. For v0 and v1, the model acts like human reading a paragraph, but for v2 it doesn' t act like human we give it pairs to let it learn pattern of pairs.

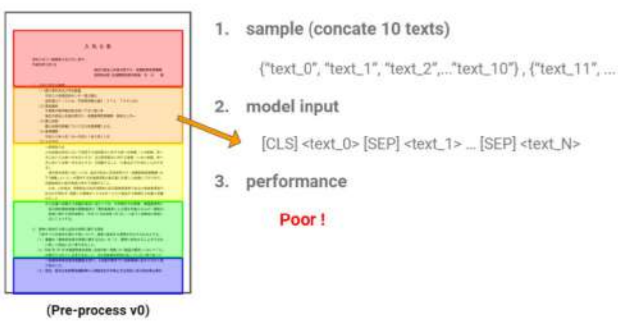
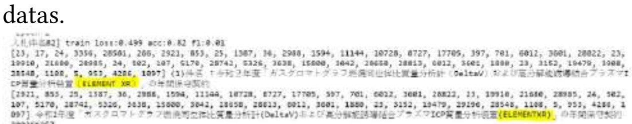


Figure 3. For V0 we apply the simplest way to preprocess the document, we read the xlsx file and fifo text with 10 rows concatenate together, and each sub paragraph then become one training sample to our dl model.

2.1.1 data cleaning.

Like the example below some values can' t work well by finding the substrings in text, so we need to apply maximum length sequence (MLS) to find the most possible place of index, which is probably not exact matching, but it is the best way to label this kind of unclean datas.



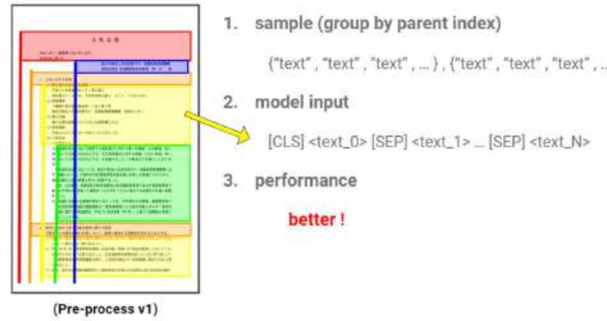


Figure 4. For V1 we group the text by it' s parent index, we think that text have same parent index should have information share with each other so every sample can get furthermore informations, and it indeed perform better than V0.

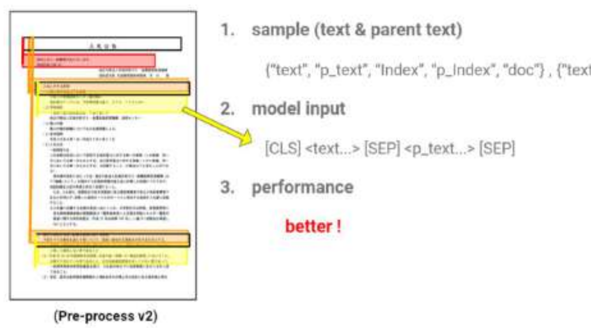


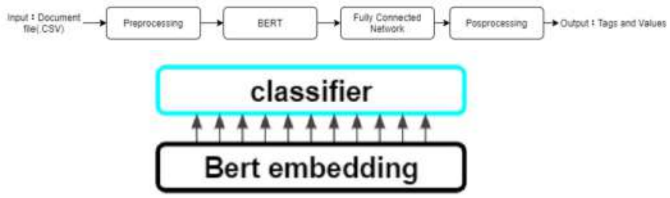
Figure 5. For V2 we don' t let model read paragraphs. Alternatively, we pairs datas text with parent index' s text. And for this kind of pre-processing, our model performed the best, finally we choose this as our preprocessin approach.

2.2 Model Architecture

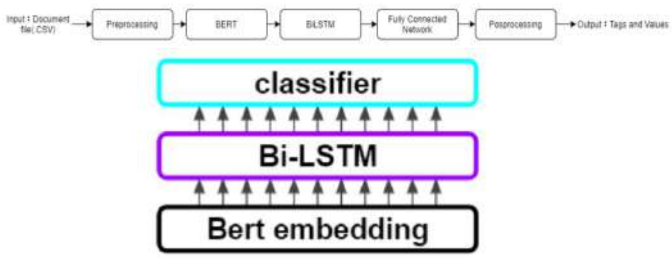
2.2.1 BERT.

pretrained: 'cl-tohoku/bert-base-japanese-whole-word-masking' tokenizer: BertJapaneseTokenizer, BertTokenizer There are plentiful pretrained model can choose, we choose cl-tohoku because it was used by most people, and for tokenizer there are two choices, for BertJapaneseTokenizer it tokenized the sentences into words, and for BertTokenizer it tokenized sentences into chars, and for our experiences BertJapaneseTokenizer is better, so we choose it as our tokenizer.

2.2.2 Baseline Model.



2.2.3 BiLSTM Model.



Our model is quite easy because the cinnamon information extraction dataset is only 80 docs, it may be overfitting if we apply too complicated models. And for this kind of dataset, we should pay more attention on data preprocessing and postprocessing it will make more improve for performance.

2.3 Post-processing

We find that the char is sometimes full char, so we will make checks if of our prediction texts matches the size of char in text.

3 Experiments ANALYSIS

3.1 Training

- Batch size : 32
- Learning rate : 2e-5 (with decline)
- Critirion: BCE Loss (pos weight=[40])
- Optimizer : AdamW

3.2 Ablation test

- Pre-processing 1 :

	Epoch	F1(ours)	dev Score	F1 EM
naive baseline	60	0.72	0.92147	0.93612
Bi-LSTM	90	0.74	0.92168	0.93322

- Pre-processing 2 :

	Epoch	F1(ours)	dev Score	F1 EM
naive baseline	60	0.77	0.94640	0.95169
Bi-LSTM	90	0.74	0.95234	0.95518

f1 (ours) : The metric defined by ourselves.
f1 em: The score of kaggle submission.

3.3 Statistics

The statistical analysis in this part is to collect the parent texts corresponding to the value of the same tag. We want

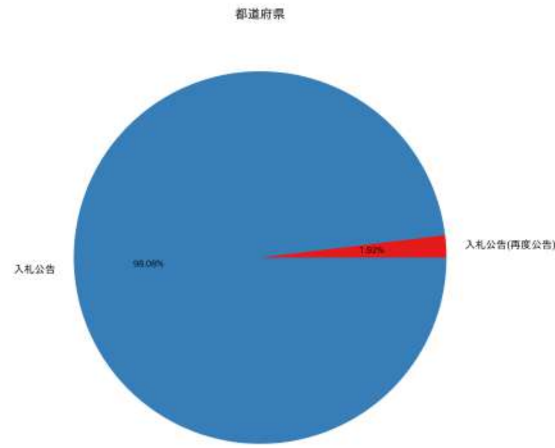


Figure 6

to know the relationship between parent text and the tag-value pairs. After statistics, we found that some tags almost only appear under a specific parent text. Like, the tag - 都道府🄵 only appears in the paragraph where 入札公告 is the parent index text. It can be speculated that the occurrence of this phenomenon is related to the file format. Some tags will only appear in certain paragraphs of the document. By the way, if it is a date and time tag (such as 調達年度), we guess that the document format has no restrictions, so this tag may appear in any paragraph of the file. This leads to various possible parent texts for this kind of tag.

3.4 t-SNE

調達年度	都道府県	入札件名	施設名	需要場所(住所)	調達開始日	調達終了日	公告日	仕様書交付期限	質問票締切日時	資格申請締切日時	入札書締切日時	開札日時	質問箇所所属/担当者	質問箇所TEL/FAX	資格申請送付先	資格申請送付先部署/担当者名	入札書送付先	入札書送付先部署/担当者名	開札場所
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19

Figure 7. Numbering and Tags pair in Figure 8

The figure 8 shows the visual distribution of each sentence embedded in the Cinnamon Dataset (including the training/dev dataset) corresponding to the ground truth tag-value pair. After t-SNE processing, the distribution is simplified to a two-dimensional data distribution. (For example, it is to perform t-SNE analysis after sentence embedding of the values in the ground truth "tag: 公告日 value: 平成 29 年 9

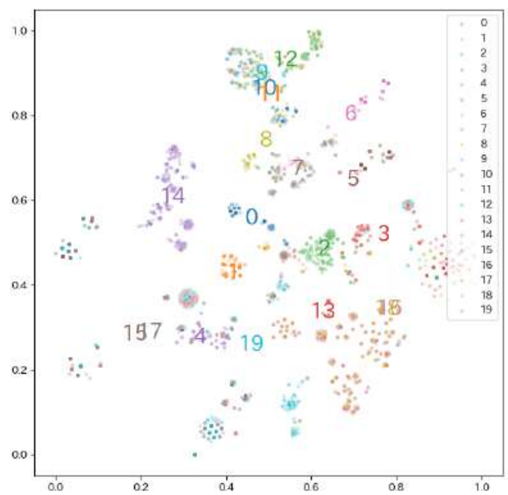


Figure 8. t-SNE analysis about ground truth tag-value pair

月 22 日".) The sentence embedding method we adopt is to convert the value into word embedding through the BERT pre-training model (Japanese). After embedding all the tokens in this sentence, the average value of the word embedding of the tokens are as the representative of this sentence embedding. As shown in the figure above, it can be found that the distribution of sentence embedded values of some tags is more concentrated than the distribution of sentence embedded values of other tags, such as type 14(tag: 質問F所 TEL/FAX). However, for some tags, the sentence embedding distribution of their corresponding values is very similar, such as type 9, type 10, type 11, type12(tag: 質問票締切日時⊠資格申請締切日時⊠入札書締切日時⊠開札日時). After careful observation, we found that this is because the target tags they are looking for correspond to the same text - date and time. If you want to distinguish each other, you need to use keywords before and after the date paragraph to help classification. This thing can be discussed later.

3.5 BERT model attention hidden layers

This analysis is to analyze the BERT model. We know that the BERT model is a deep neural network and can be divided into 12 layers. The embedding performance of these 12 layers should be as deep as possible. Since we have 20 kinds of tags, we divided the ground truth value into 20 groups according to their respective tags. We want to observe the performance of inter-similarity between different groups and intra-similarity inside the same groups on the 12 different layers of the bert model. For similarity calculation we use the cosine similarity. Sentence embedding selection is the same as previous in section 5-1.

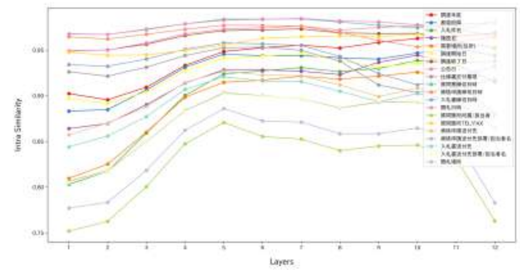


Figure 9. Intra-Similarity about different tag clusters(for BERT 12 different hidden layers)

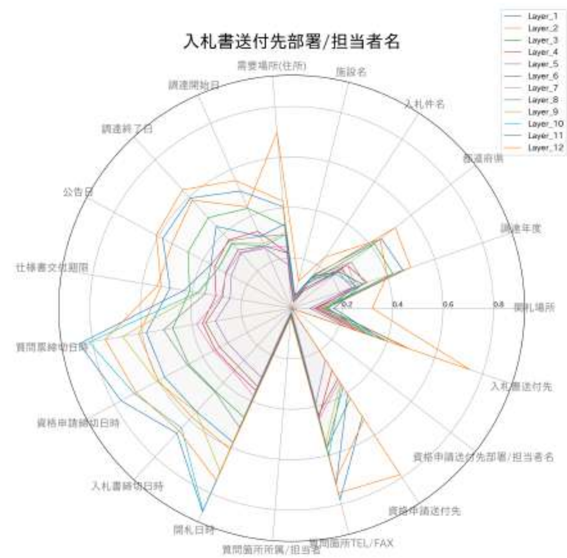


Figure 10. Inter-Similarity about the cluster of the tag:「資格申請送付先部署/担当者名」with other clusters(for BERT 12 different hidden layers)

Usually the intra-similarity of the cluster is high and the inter-similarity is low, which means that the classification effect is better. It is reasonable to say that as the number of layers increases, cluster classification should be better. However, as shown in Figure 5-1, it can be found that although for the inter-similarity between different layers, for most tags, the similarity value also increases as the model layer increases. Nevertheless, for the intra-similarity corresponding to some tags, the intra-similarity value decreases with the increase of the BERT model of layers. We suspect that this phenomenon may be similar to the situation when we do t-SNE analysis previous. Due to the values of certain tags, their corresponding values are very similar sentences, such as date and time. Therefore, if we want to classify the tags correctly, we should find some keywords through the context to make a correct judgment. In addition, when considering the clustering performance of clustering, not only the performance of intra-similarity but also the performance of inter-similarity must be considered. This means that the model is indeed learning in the right direction. For the above problem, if the decoder is properly selected and attached to the fine-tuned bert model, we think this should be an effective solution.

4 CONCLUSION

In whis work, we use bert pre-trained model to extract the sentence feature and use bi-LSTM to decode which label the sentence token should be. By analyzing the given training dataset and the model we use, we know there is still room for improvement in our work. Through pre-processing and post-processing, the final mean f-score in the test dataset can reach 0.95. For us, if we want to improve the performance of our work, we think that perhaps a more complex model as Fuzzy-LSTM-CRF, may be used to complete this work.

5 Work Distribution

- Dataset: B.-R. Wu
- Analysis: H.-W. Hsu
- Training: B.-R. Wu , H.-W. Hsu

B.-R. Wu and H.-W. Hsu works same effort.

References

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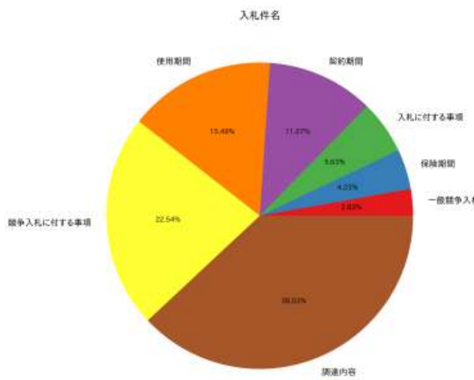
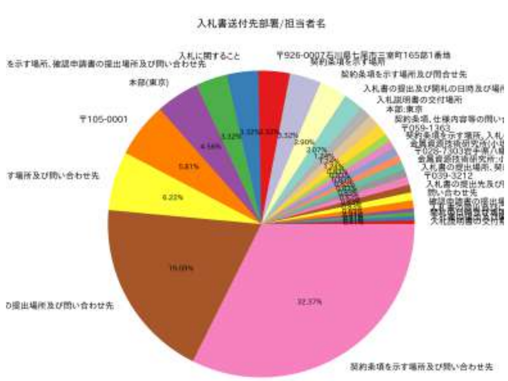
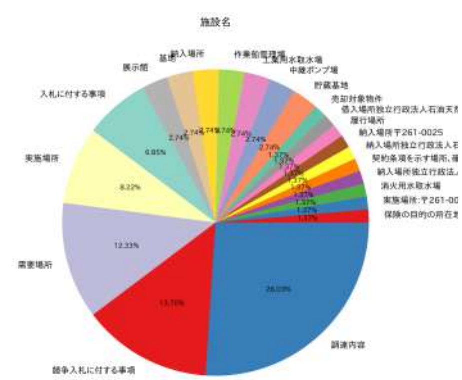
A Figure - PIE:

These Figures are the supplement of the part 3.3: Statistics. More figures in here: https://drive.google.com/drive/folders/1zgNNdWEWeuZjqgyaJCj1jOXwX7u-UAbE?usp=sharing







B Figure - Cluter Similarity:

These Figures are the supplement of the part 3.5: BERT attention hidden layers. More figures in here: https://drive.google.com/drive/folders/1mJXbl-Cob842ht8PeImmSQo0PkK-AW2l?usp=sharing