



AURORA: An Information Extraction System of Domain-specific Business Documents with Limited Data

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ABSTRACT

Information extraction is a well-known topic that plays a critical role in many NLP applications as its outputs can be considered as an entrance step for digital transformation. However, there still exist gaps when applying research results to actual business cases. This paper introduces AURORA, an information extraction for domain-specific business documents. The intuition of AURORA is to use transfer learning for extraction. To do that, it utilizes the power of transformers for dealing with the limitation of training data in business cases and stacks additional layers for domain adaptation. We demonstrate AURORA in the context of actual scenarios where users are invited to experience two functions: fine-grained and whole paragraph extraction of Japanese business documents. A video of the system is available at <http://y2u.be/xHQpYE41Tqw>.

CCS CONCEPTS

• Information systems → Information extraction; • Computing methodologies → Information extraction.

KEYWORDS

Information extraction, Business document analysis, Transformers

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1 INTRODUCTION

Information extraction (IE) is an important research topic of natural language processing (NLP), in which IE provides a way for converting unstructured to structured data. The conversion can be considered as a crucial step for digital transformation [6]. With

the rapid growth of unstructured data, IE has received attention from the research community [1, 2, 10, 14]. From the business side, IE provides an effective method for document analysis and many systems have developed for real business cases [7, 9, 10, 14]. The outputs of IE systems can be used many NLP applications [5, 11].

Named entity recognition (NER) is an important sub-task of IE, in which it focuses on extracting specific predefined entities, such as organization names, personal names, addresses, etc with many studies [4, 7, 8]. There are two common approaches for NER: dictionary-based [13] and machine learning-based methods [7, 8]. While NER has successfully achieved promising results on relatively-easy tasks, e.g. extracting persons or organizations, it is not always straightforward for applying common NER techniques to actual business cases, which require to distill a large number of specific information.

In the context of business document assessment, we introduce an actual scenario of IE, which challenges common NER algorithms. From the business side, users usually face the problem of understanding business documents. For example, given a bidding document, they want to know who is the payee, who is the payer, or the deadline for applying qualification. As a result, building an IE system is a potential solution. However, creating this system, in fact, is a non-trivial task due to two challenges. The first challenge is the limited number of training samples. In business cases, because IE only focuses on narrow and specific domains, so providing a large number of training data is expensive and requires a lot of effort. For example, we usually receive a small number of documents, e.g. 100 for training IE models. It is different from CoNLL, which provides around 15,000 training examples for recognizing four entity types. The second challenge comes from the nature of IE for business documents, in which the identification of entity types cannot be merely the categories [11]. As mentioned, two types of organizations, such as payee and payer in bidding documents should be identical.

This paper introduces AURORA, a prototype of our product based on transformers for transfer learning. The system bridges the gaps of IE between academia and industry by addressing the two challenges above. The goal of AURORA is to extract structured information from domain-specific business documents. The intuition behind the system is to utilize the power of transformers trained on a huge amount of general data and fine-tune the transformers into downstream tasks by using transfer learning. This simulates real cases in which we only receive a small number of training data for information extraction. AURORA has three crucial characteristics:

- It provides two main functions of extraction on two levels: fine-grained and whole paragraph extraction. The first

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function is to extract very detailed information, e.g. payee and payer of bidding documents. The second function is to retain all information in paragraphs. We believe these two functions provide flexible solutions for users.

- It uses a small number of samples for training IE models. Precisely, we used 78 public bidding documents for training the fine-grained IE model and 45 public benefit pension plan documents for training the whole paragraph IE model. By using transfer learning based on transformers, AURORA can adapt to new domains with limited training data.
- It can extract a large number of entity types. For example, the fine-grained IE model can clip 24 information types (tags), which facilitate the analysis of users.

2 SYSTEM OVERVIEW

Figure 1 shows the architecture of the system. AURORA receives an input document that includes tags and segments (note that tags and segments were already annotated in the labeling process). A tag-segment pair is separated by a special token ([SEP], please refer to the original paper of BERT for more detailed information [3]). Each tag-segment pair is fed into the transformer layer to transform raw texts into hidden representation, which is the input of transfer learning. The information extraction layer detects the start and end positions of each segment as extracted information.

2.1 Transformers

A Transformer is a transduction model which relies on self-attention for computing the representation of its inputs and outputs, without using sequence-aligned RNNs or convolution [12]. The Transformer includes the architecture of encoder-decoder which uses stacked self-attention and point-wise, and fully connected layers. The attention is to map a query and a set of key-value pairs to an output. Then, the output is computed as a weighted sum of the values, where the weight corresponding to each value is computed by a compatibility function of the query with the correlated key.

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \quad (1)$$

where dimension d_k of keys, and dimension d_v of values. Moreover, Transformer performs the attention function in parallel, resulting d_v -dimensional output values using “multi-head attention” as following: $MultiHead(Q, K, V) = Concat(head_1, ..., head_h)W^O$ where $head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$.

It is possible to take any transformer to implement the system, however we selected BERT [12] as an example. The reason is that BERT pioneered a new way of training language models and obtained state-of-the-art results on many NLP tasks. More importantly, in actual cases, we usually receive a small number of training data which challenges the training process of IE models. To address this obstacle, AURORA employs BERT to utilize its power for dealing with the limitation of training data. The transformer layer outputs the hidden representation of input for the transfer learning layer.

2.2 Transfer learning

BERT provides an appropriate solution for input representation due to contextual embeddings learned from a large amount of data.

However, it needs to be adapted to downstream tasks. To do that, we employed transfer learning to fine-tuning BERT for our IE problem. The transfer learning was done by stacking a CNN layer on BERT due to the efficiency of CNN for capturing local context between tags and extracted information. We also tested with LSTM and BiLSTM but the model BERT+CNN outputs the best results.

The CNN layer includes two operations: convolution and pooling. The convolution transforms input vectors from BERT by using transformation functions to create feature maps. The pooling operates on the feature maps for removing unnecessary information. In practice, we used multiple kernel sizes ($N = 3$) to enrich representation and max pooling for avoiding over-fitting.

2.3 Information extraction

Once input data has transformed, the system extracts information. To do that, we formulated the extraction as a Question Answering (QA) task based on the suggestion from BERT. An input question (tag) and a passage as a single packed sequence were fed into the system. The prediction outputs the result of the dot product between token T_i and start (S)/end (E) vectors as the probability of word i being the start/end of the answer span (see Eq. 2). The final score of a potential answer spanned from position i to position j defined as $\max_{i,j}(ST_i + ET_j)$ with $j \geq i$.

$$P_{start_i} = \frac{e^{S.T_i}}{\sum e^{S.T_j}}; \quad P_{end_i} = \frac{e^{E.T_i}}{\sum e^{E.T_j}} \quad (2)$$

The extraction uses the positions *start* and *end* to extract values (information) corresponding to input tags.

2.4 Implementation

For implementation, we used a multilingual BERT-base model trained for 102 languages (including Japanese) on a huge amount of texts from Wikipedia [3]. The BERT model has 12 layers, a hidden layer of 430 with 768 neurons, 12 heads, and 110M parameters.

For training the system, data was internally annotated by our QAs (quality assurance), who have at least the N3 certificate (Japanese-Language Proficiency Test - JLPT, with N1 is the highest level). Given a tag, the QAs assigned the starting position and ending position of a corresponding segment in the document. The starting and ending positions are an indicator showing that which segments belong to which tags. The training process was done in two steps: pre-training and fine-tuning. For the first step, the pre-trained weights of BERT were reused, while the weights of the rest layers were generated with a truncated normal distribution. For the second step, these weights were fine-tuned on new domains. Precisely, AURORA used 78 bidding documents and 300 sale documents for training two fine-grained IE models and 45 pension documents for training a paragraph IE model. The system was fine-tuned in 20 epochs by using cross-entropy loss with a single GPU. The number of kernel sizes is 3 and the convolutional output size is 768.

2.5 Experimental results

We internally tested the accuracy of AURORA on two functions: fine-grained extraction and whole paragraph extraction. For the first function, AURORA was tested on two datasets: bidding and sale documents. The bidding documents are public data of competitive bids

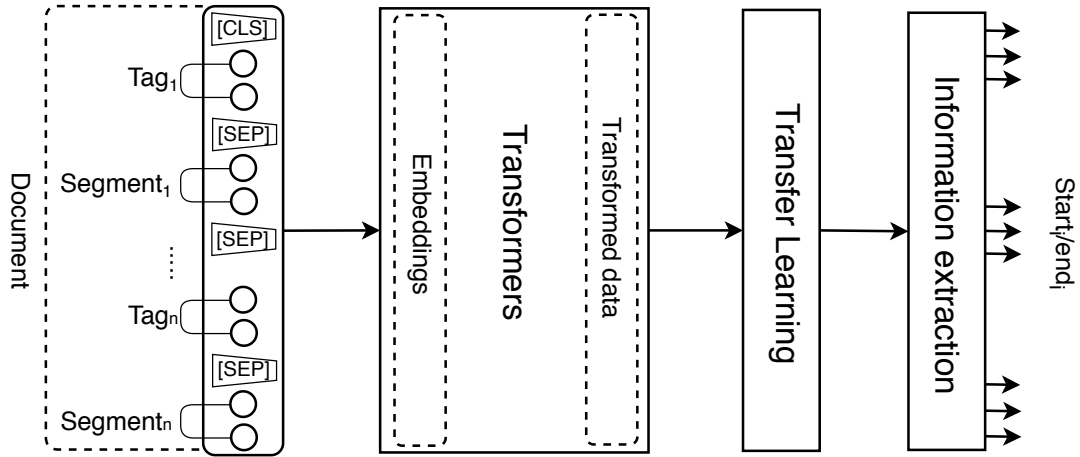


Figure 1: The system architecture of AURORA.

for development projects in Japan with 24 tags. The sale documents are public documents for selling hardware devices in Japanese with eight tags. For training, we used 78 bidding documents and 300 sale documents. For testing, AURORA was tested on 22 bidding documents and 165 sale documents. Table 1 shows the comparison.

Table 1: Comparison of methods according the average of F1-score. Bold is the best and *italic* is the second best. [†] shows that our model is significantly better with p -value ≤ 0.05 .

Method	Bidding docs	Sale docs
BERT (QA)	<i>0.8607</i>	<i>0.8456</i>
BERT+CRF	0.1773 [†]	0.1254 [†]
BERT+LSTM+CRF	0.3817 [†]	0.5572 [†]
<i>n</i> -grams+MLP+Regex	0.8523	0.7177 [†]
CNN+BiLSTM+CRF	0.6766 [†]	0.7513 [†]
AURORA	0.9062	0.8614

The evaluation used the average F-score over all tags (by fields) for comparison. As observed, AURORA achieves promising results compared to BERT, its extensions, and two methods based on n -grams features ($n = 4$) and CNN. BERT+CRF and BERT+LST+CRF output poor results because they were formulated as a NER task, not a QA task. The n -grams+MLP obtains the second-best results, showing that the n -grams features can be used for such IE task.

For the whole paragraph extraction, AURORA was tested on 27 documents with five tags. As showed in Table 2, AURORA achieves the best results in terms of F-scores computed by char. The MLP method obtains very promising results by using n -grams features. Interestingly, the HAN (hierarchical attention network) model gives poor results due to the long-term dependency of tags and extracted information on this dataset.

3 DEMONSTRATION SCENARIO

The audience has the opportunity to experience Aurora on the web interface to extract information from business documents with two functions: fine-grained extraction and whole paragraph extraction. Figure 2 presents the interface.

Table 2: Comparison on the average of F1-score.

Method	Pension documents
BERT (QA)	<i>0.9251</i>
<i>n</i> -grams+MLP+Regex	0.9567
HAN	0.6436 [†]
AURORA	0.9738

Users can upload an input document into the system. After uploading, the left side shows the original document and the right side contains extracted information. The interface shows some tags such as prefecture, the title of bidding, name of institution, address of demand, public announcement date, the deadline for delivery of the specification of a bidding document.

3.1 Testing datasets

We released two small testing datasets for the user’s experience of AURORA. The first dataset includes five bidding samples collected from Japan Oil, Gas and Metals National Corporation (JOGMEC).¹ This dataset is used for testing the fine-grained extraction model trained on 78 bidding documents stated in Section 2.4. The second dataset contains five benefit pension plan documents. These samples are used for testing the whole paragraph extraction model trained on 45 pension plan documents stated in Section 2.4. All the samples can be download in the **Help** menu in Figure 2.

To provide a better assessment of AURORA, we introduce a larger dataset named CinBidding² for evaluating the quality of the fine-grained IE model. This is because in actual cases the extraction of fine-grained information receives higher demand than the extraction of whole paragraphs. The dataset includes 124 documents with correct answers, in which 82 documents are for training, 22 for development, and 20 for testing. The agreement computed by Cohen Kappa³ among annotators is 0.8275. Also, note that we did not re-train the fine-grained IE model on this dataset; therefore, we leave the comparison on this dataset as a future task.

¹<http://www.jogmec.go.jp/news/bid/search.php>

²<https://github.com/DungLe13/bidding-dataset>

³<http://graphpad.com/quickcalcs/kappa1.cfm>



Figure 2: The web interface of Aurora.

3.2 User interaction

AURORA⁴ offers two main scenarios for user experience on the interface of the system. After logging the system with the user as **cinnamon** and the password as **cinnamon**, users can use these functions. Firstly, we encourage users to read the guideline of the system in the **Help** menu. This guideline explains the system, main functions, data, and how to use the system for IE. Users should download samples for testing the system. Once the samples are ready, users can select one of two functions: fine-grained extraction and whole paragraph extraction. For testing the fine-grained IE, users are encouraged to use both samples and the CinBidding dataset. It provides a better way to observe extracted information from the system and correct answers created by humans. After uploading testing samples and clicking on the process button, AURORA processes the user's requests. Finally, the extracted information is showed on the right side of the interface denoted in Figure 2.

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⁴<https://aurora-demo.cinnamon.is/login>