KSU Systems at the NTCIR-15 Data Search Task

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ABSTRACT

Our methods

- 1. Category search
 - Narrows down the documents by category
- 2. Metadata augmentation by table headers
- 3. Reranking using BERT

Result

The combination of <u>category search and BM25</u> resulted in 0.426 for Japanese subtask and 0.240 for English subtask, both at nDCG@10, where each showed the highest score among all the official runs.

Aim

Narrows down the documents by category, to properly capture the scope of the query.

Goal

Ad-hoc retrieval of governmental statistical data

and the length of metadata is short

The main body basically composed of numbers,

When indexing

Data Search task

Adopts the **categories** used in **Yahoo! Chiebukuro or Yahoo! Answers**

Building a classifier

1. Collection of datasets

Scrape all QA data and the **categories set on** each page from Yahoo! Chiebukuro and Yahoo! Answers. Table 1 shows the average and standard deviation for each category and total

Category Search

2. Training the classifier

Select the **best combination** of part-of-speech, vectors, and training methods via 10-fold crossvalidation.

Part-of-speech: Noun, verb, all part-of-speech **Vectors :** fastText, GloVe, TF



Assigns each document a category by a prebuilt text classifier

When searching

The result is **ranked only on the set of** documents belonging to the category estimated from the given query

QA number.

Tab. 1. Distribution of collected data

	Average	Stddev	QA datas	Category
English	158	99.26	3,541	23
Japanese	149.4	6.28	1,494	10

Training: MLP, SVM, Logistic Regression Accuracy :

- Japanese \rightarrow 69% (N+V, fastText, SVM)
- English \rightarrow 58% (all POS, fastText, SVM)

Augmentation by Table Header

Aim

Compensates for the short document length of the metadata

Preliminary Analysis

After examining the metadata, we found that their **document length was short**. A typical metadata has an average length of **300-400 words**. Tab. 2. Statistics on metadata in the data collection

Sub Task	documen	number of document <u>s</u>		
	average	stddev		
English	101.93	81.19	46,615	
Japanese	11.83	3.02	1,338,402	

In order to deal with various formats of statistical data, the table data is **first converted into** images, and contour extraction is performed to recognize the cell regions. Then, the header is **recognized** for each cell using the classifier. Finally, the text is extracted from the cells recognized as header by **OCR**.

2. Simple heuristics to avoid misidentification of OCR

Gets the text from **the rough area** where the header is likely to present.

Input: statistical data *sd* Output: column headers hdr_col prev = 0hdr col = []*max_col = sd.column*.length for $i = 1, \dots, max_col$ do *curr* = *sd.column*[*i*].*unempty_cells*.length if curr > prev then

hdr_col.append(sd.column[i].unempty_cells) end if prev = curr

Two approaches for header extraction:

1. Extraction through images with OCR

2-1. English subtask

Limits to **PDF** files and obtains **the entire string** from each file.

2-2. Japanese subtask

Extracts headers based on **changes in the** number of non-empty cells as shown in Fig.2.

Reranking by BERT

reported to have high performance in various fields.

• Applying reranking using BERT to the top set of documents obtained by normal search with BM25 could be more accurate than normal search.

Score calculation

Inference by BERT is performed for each sentence of the candidate document, and the **sentence level score is**

end for return h*dr_col*

the following equation:

prev: number of non-empty cells in the previous column hdr_col : column header **max_col** : number of columns of the statistical data **curr**: number of non-empty cells

Fig. 2. Extraction focused on changes in the number of non-empty cells

combined with the normal document score according to

Aim

Understands how much contribution can be **expected** from the pretrained language model.

BERT and reranking

BERT is a pre-trained language model that has been

$S_f = a \cdot S_{doc} + (1-a) \cdot \sum_{i=1}^{i=1} w_i \cdot S_i$

 S_f : final doc score S_i : top i-th sentence score by BERT S_{doc} : doc score before reranking a, w_i : parameters

Result for Japanese subtask

Tab. 3. Evaluation result for Japanese subtask

Text classifier for Table Table ranking nDCG RUN Category

Result and Discussion

Result for English subtask

Tab. 4. Evaluation result for English subtask

RUN	Category search	Table header	ranking	Te c	ext classific ategory se	Table header	nDCG @10	
				POS	Vector	training		
KSU-E-2	\checkmark	\checkmark	BM25	ALL	TF	MLP	OCR+CRF	0.240
KSU-E-4		✓	Bert rerankin g				OCR+CRF	0.051
KSU-E-6	\checkmark		BM25	ALL	TF	MLP		0.240
KSU-E-8			Bert rerankin g					0.038
KSU-E- EX-4	\checkmark	\checkmark	BM25	ALL	Fasttest	SVM	ALL	0.042
KSU-E- EX-5	\checkmark		BM25	ALL	Fasttest	SVM		0.181
KSU-E- EX-9	\checkmark	\checkmark	BM25	ALL	Fasttest	LR	ALL	0.043
KSU-E- EX-10	\checkmark		BM25	ALL	Fasttest	LR		0.216

Discussion for Japanese subtask

• There were **some tables** where header extraction **did** not work properly. The semantic content of the header may need to be considered in extracting

	search	header	category search		header	@10			
				POS	Vector	training	extraction		
KSU-J-1	\checkmark	\checkmark	BM25	ALL	TF	MLP	OCR+CRF	0.391	К
KSU-J-3		\checkmark	Bert reranking				OCR+CRF	0.110	K
KSU-J-5	\checkmark		BM25	ALL	TF	MLP		0.413	
KSU-J-7			Bert reranking					0.110	К к
KSU-J- EX-1	\checkmark	\checkmark	BM25	N+V	Fasttest	SVM	ROW+COL	0.426	
KSU-J- EX-2	\checkmark	\checkmark	BM25	N+V	Fasttest	SVM	ROW	0.276	[
KSU-J- EX-3	\checkmark		BM25	N+V	Fasttest	SVM		0.353	I
KSU-J- EX-6	\checkmark	✓	BM25	N+V	Fasttest	LR	ROW+COL	0.426	
KSU-J- EX-7	\checkmark	\checkmark	BM25	N+V	Fasttest	LR	ROW	0.276	ķ
KSU-J- EX-8	\checkmark	~	BM25	N+V	Fasttest	LR		0.342	

headers.



Fig. 3. Example of a table where header extraction failed

Discussion for English subtask

- The maximum number of documents per category in the collected dataset was 260 and the minimum was 20, indicating a large variation in the dataset. Therefore, the classification accuracy varies greatly depending on the category.
- All strings were extracted as table headers. The • extracted data contained a lot of numbers and some text consisting of ordinary words. **Excluding the** numbers might have led to better results.

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