# The Rule of Three: Abstractive Text Summarization in Three Bullet Points

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## Abstract

Neural network-based approaches have become widespread for abstractive text summarization. Though previously proposed models for abstractive text summarization addressed the problem of repetition of the same contents in the summary, they did not explicitly consider its information structure. One of the reasons these previous models failed to account for information structure in the generated summary is that standard datasets include summaries of variable lengths, resulting in problems in analyzing information flow, specifically, the manner in which the first sentence is related to the following sentences. Therefore, we use a dataset containing summaries with only three bullet points, and propose a neural network-based abstractive summarization model that considers the information structures of the generated summaries. Our experimental results show that the information structure of a summary can be controlled, thus improving the performance of the overall summarization.

## 1 Introduction

Summarization can be achieved using two approaches, namely the extractive and abstractive approaches. The extractive approach involves selecting some part of a document (i.e., sentence, phrase, or word) to construct a summary; in contrast, the abstractive approach involves generating a document summary with words that are not necessarily present in the document itself.

Thus, the extractive approach (Nallapati et al., 2017; Li et al., 2013) is considered to yield a more grammatical summary than the abstractive approach, because the former involves directly extracting output expressions from the source text. However, as is obvious, because words that are not present in the source text cannot be selected in the case of the extractive approach, abstractive approaches are becoming increasingly popular for automatic summarization tasks.

In previous work, Rush et al. (2015) proposed an abstractive sentence summarization method that involves generating novel words in a summary based on the sequence-to-sequence model proposed by Sutskever et al. (2014). Furthermore, recently, improvements to the abstractive text summarization method were proposed by (Nallapati et al., 2016; See et al., 2017). Although their proposed model generates fluent summaries owing to the use of a large-scale dataset, it cannot produce a structured summarization, because it is trained using the CNN / Daily Mail datasets, which are not annotated with any structural information.

Therefore, in this work, we focus on generating a structured summary for a document, in particular, a summary in three sentences. Because the CNN / Daily Mail datasets include summaries with a varying number of sentences, they cannot be annotated with information structures directly. Considering this, we employ a Japanese summarization dataset from Livedoor News, whose size is the same as the CNN / Daily Mail datasets. Because Livedoor News broadcasts news with a summary in three sentences, it is easy to analyze summaries using this dataset.

To produce a summary in three bullet points, we first annotate the dataset with an information struc-

ture. Then, we train a binary classifier using the information structure of summaries to build two summarization sub-models on our dataset. Finally, the obtained summarization model selects the summary structure based on the input, and generates the summary according to the desired structure.

The contributions of our work are as follows:

- We annotated and analyzed the structure of summaries in a Japanese news summarization dataset, whose summaries are in the form of three sentences.[1]

- Our proposed model generates a summary in three bullet points.

## 2 Related Works

### 2.1 Dataset

In the case of abstractive sentence summarization, Rush et al. (2015) proposed a new summarization method to generate an abstractive summary using a sequence-to-sequence model; in particular, they achieved state-of-the-art performance on the DUC-2004 and Gigaword corpora.

In contrast, for abstractive text summarization using the CNN / Daily Mail datasets, the objective is to output a summary of an article consisting of multi-sentences. Nallapati et al. (2016) proposed an improved summarization model for this task, which is essentially an attention encoder-decoder model, including a trick to use a large vocabulary (Jean et al., 2015), switching pointer-generator mechanism, and hierarchical networks. They proposed a new dataset for multi-sentence summarization and established a benchmark using this dataset.

However, these works did not address the problem of information structure in a generated summary. Therefore, in our work, we attempt to consider the information structure of a summary to further improve the summarization model.

### 2.2 Model

Currently, the model proposed by See et al. (2017) is the state-of-the-art summarization model on the

CNN / Daily Mail datasets. In particular, their baseline model is based on the one proposed by (Nallapati et al., 2016), which is further improved by including a hybrid pointer-generator network and coverage mechanism. Because our model is based on their model, we describe their model in greater detail in this subsection.

**Attention encoder decoder.** Let the input sequences be tokens of the article $w_i$ and the output sequences be tokens of the summary $y_i$. A bidirectional long short-term memory (LSTM) network is used as the encoder, whereas a unidirectional LSTM is used as the decoder. A sequence of encoder hidden states $h_i$ are produced by the encoder. At each step $t$, the decoder receives the word embedding of the previous word [2], and has decoder state $s_t$. The attention distribution $a^t$ is calculated as in (Bahdanau et al., 2014):

$$
\begin{aligned}
e_i^t &= v^T \tanh(W_h h_i + W_s s^t + b_a) \quad (1) \\
a^t &= \text{softmax}(e^t) \quad (2)
\end{aligned}
$$

where $v, W_h, W_s$, and $b_a$ are learnable parameters. The attention distribution indicates the importance of the encoder hidden states as a probability distribution at time step $t$. Furthermore, the context vector $h_t^*$ is computed as follows:

$$
h_t^* = \sum_i a_i^t h_i \quad (3)
$$

The context vector is concatenated with the decoder state $s_t$ and input through two linear layers to produce the vocabulary distribution $P_{vocab}$:

$$
P_{vocab} = \text{softmax}(V'(V([s_t, h_t^*] + b) + b')) \quad (4)
$$

where $V, V', b$ and $b'$ are learnable parameters. While training, the loss at timestep $t$ is the negative log likelihood of the target word $w_t^*$ for that timestep, which is used to calculate the overall loss for the entire sequense:

$$
\begin{aligned}
\text{loss}_t &= -\log P_{vocab}(w_t^*) \quad (5) \\
\text{loss} &= \frac{1}{T}\sum_{t=0}^{T} \text{loss}_t \quad (6)
\end{aligned}
$$

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[1] https://github.com/KodairaTomonori/ThreeLineSummaryDataset/

[2] During training, this is the previous word of the reference; however, during testing, this is the previous word output by the decoder.

**Hybrid pointer-generator network.** See et al. (2017) also proposed a hybrid pointer-generator network, which combines the attention and vocabulary distributions. In particular, their pointer-generator network is a hybrid between a sequence-to-sequence attention model (Section 2.2) and pointer network (Vinyals et al., 2015). Thus, this network considers the source as well as target word distributions, and thereby addresses the problem of unknown word generation. In the pointer-generator model, the generation probability $p_{gen} \in [0, 1]$ at time step $t$ is calculated from the context vector $h_t^*$, decoder state $s_t$, and decoder input $x_t$:

$$p_{gen} = \sigma(w_{h^*}^T h_t^* + w_s^T s_t + w_x^T x_t + b_g) \quad (7)$$

where vectors $w_{h^*}, w_s, w_x$, and scalar $b_g$ are learnable parameters, and $\sigma$ represents the sigmoid function. $p_{gen}$ is used as a soft switch to select a word from the vocabulary distribution $P_{vocab}$ or a word from the attention distribution $a^t$. For each document, the authors developed an extended vocabulary, which is the union of the vocabulary and all words in the source document. The probability of the extended vocabulary is calculated as follows:

$$P(w) = p_{gen} P_{vocab}(w) + (1 - p_{gen}) \sum_{i:w_i=w} a_i^t \quad (8)$$

If $w$ is an out-of-vocabulary (OOV) word, $P_{vocab}(w)$ is 0; in addition, if $w$ does not exist in the source words, $\sum_{i:w_i=w} a_i^t$ is 0.

**Coverage mechanism.** Aside from the above-mentioned changes, See et al. (2017) improved the coverage model (Tu et al., 2016) to address the repetition problem. In their model, a coverage vector $c^t$, which is the sum of attention distributions at all previous decoder timesteps, is saved:

$$c^t = \sum_{t'=0}^{t-1} a^{t'} \quad (9)$$

where $c^t$ is a distribution over the source document words that indicates the magnitude of attention each word in the source document receives until timestep $t$. The coverage vector is applied to the attention mechanism as follows:

$$e_i^t = v^T \tanh(W_h h_i + W_s s_t + w_c c_i^t + b_a) \quad (10)$$

where vector $w_c$ is a learnable parameter. This prevents the attention mechanism from repeatedly visiting the same location in the document, and thus avoids generating repetitive text. In addition, they constructed a new loss function to incorporate the coverage loss to penalize repeated attention to the same location.

$$\text{loss}_t = -\log P(w_t^*) + \lambda \sum_i \min(a_i^t, c_i^t) \quad (11)$$

## 3 Annotation of the Summary Structure

### 3.1 Dataset

We crawled pairs of Japanese articles and summaries from Livedoor News [3] in a manner similar to the previous work (Tanaka et al., 2016). These summaries are written by human editors. In particular, these summaries consist of exactly three sentences, which we will discuss in detail later. We crawled data from January 2014 to December 2016, which included 214,120 pairs of articles and summaries. We divided these pairs into 211,744 training pairs, 1,200 development pairs, and 1,200 test pairs. The development and test pairs were extracted from the data of January 2016 to December 2016, which included 100 pairs of articles and summaries per month.

Each article was tagged with a category selected from the nine primary categories [4] as well as a subcategory selected from the several available subcategories. Furthermore, the articles also included some special tags (such as keywords, key phrases, or more specific category information). In the crawled data, each news item includes a title and article, as well as a shorter title and abstractive summary.

However, in our experiments, we only use the article and summary from the dataset. Other useful information will be exploited in future work.

### 3.2 Annotation

The summaries of the Livedoor News dataset consist of three sentences, which enables us to analyze the structure of the output. We annotated summaries with the structure of sentences for the development and test data. Summaries are typically single sentences whose lengths are less than 36 characters

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[3]http://news.livedoor.com/

[4]National, World, IT Business, Entertainment, Sports, Movies, Foods, Lifestyle (Women), and Latest.
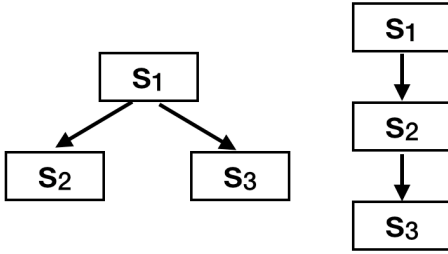
Figure 1: Parallel and sequence summary structures.

| | dev | test | total |
|---|---|---|---|
| parallel | 843 | 755 | 1,598 |
| parallel w/ enumeration | 72 | 65 | 137 |
| sequence | 268 | 275 | 543 |
| sequence w/ segmented sents. | 12 | 5 | 17 |

Table 1: Results of annotation of the summaries.

(counted as full-width). The average length of the summaries in the test set is 32.5. We did not perform any pre-processing for annotation, and did not refer to the original article to assign labels.

After a preliminary investigation, we divide the summaries into four types: *parallel*, *parallel with enumeration*, *sequence*, and *sequence with segmented sentences*. Enumeration in a summary is when recommended items are introduced, whereas segmented sentences in a summary are those that were originally part of a longer sentence in the article.

However, almost all summaries are divided into the following two types: *parallel* and *sequence*. Figure 1 illustrates the difference between these types. In both these summary types, the first sentence describes the primary incident, and the second sentence contains additional information about the primary incident. Then, in the case of the parallel type, the third sentence explains the first sentence; however, its content is different from that of the second sentence. In contrast, in the case of the sequence type, the third sentence includes detailed information about the second sentence. Thus, the parallel types have no particular order in terms of the second and third sentences, whereas the sequence types have these two sequences in order.

In addition, the subject is often omitted in Japanese, thus the third sentence's zero-subject is almost the same as the second sentence's subject. When we annotate such a sentence, the summary is marked as an instance that requires zero anaphora resolution to generate an appropriate output.

### 3.3 Analysis

Table 1 lists the results of annotation of the summaries of the Livedoor News dataset. Approxi-

mately 80% of the summaries are tagged as *parallel*, while the remainder are tagged as *sequence*. In a *sequence* summary, the second and third sentences simply indicate examples related to the first sentence, but not in the form of a sentence.

In addition, annotation revealed that the first sentence is similar to the title, and almost all the second sentences include additional information such as an example of the first sentence. Therefore, the first and second sentences can be successfully generated by existing models.

However, the third sentence plays various roles in this dataset. In particular, in a *sequence* summary, the third sentence is based on the second sentence, whereas in a *parallel* summary, the third sentence is based on the first sentence. Thus, our proposed model uses this characteristic to generate the third sentence in a summary.

## 4   Structure-aware Summarization Model

We generate a summary considering its structure. First, we predict the structure of the summary to be generated, and then generate the summary according to the predicted structure.

**Summary structure classification.**   First, we need to train structure-specific summarization models for the parallel and sequence types. However, because the training dataset is not annotated with summary types, we build a binary classifier for summary types using summary information to label the summaries.

Using the binary classifier, the summaries are assigned to either *parallel* or *sequence* types (Figure 2). Let the input sequences be tokens of a summary $x_i$ and the output label be $l$. We use a bidirectional LSTM as an encoder. A sequence of encoder hidden states $h_i$ is produced by the encoder. Furthermore, the final hidden states of the forward and backward encoders are concatenated. Finally, a linear transfor-
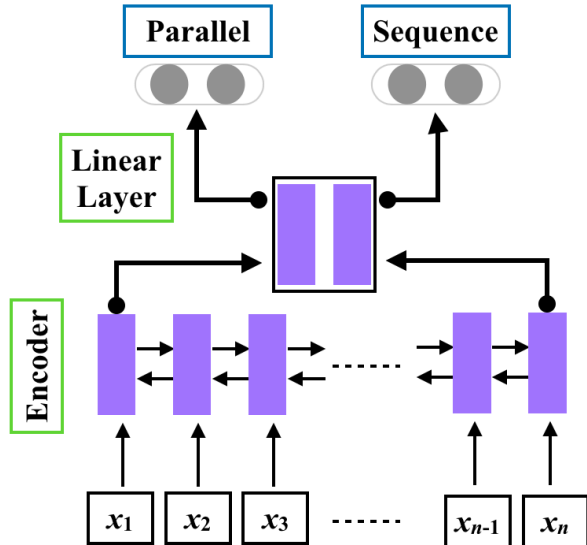
Figure 2: Summary structure classification.

mation is applied to the vector $h$ for each type:

$$h = [h_n^{forward}, h_1^{backward}] \quad (12)$$
$$y_{parallel} = \text{softmax}(W_p h + b_p) \quad (13)$$
$$y_{sequence} = \text{softmax}(W_s h + b_s) \quad (14)$$

where $W_p$, $W_s$, $b_p$ and $b_s$ are learnable parameters.

**Structure-specific sub-models.** Second, we construct the structure-specific summarization models using the automatically annotated dataset.

In Section 2.2, we describe the base summarization model (See et al., 2017). In particular, we pre-train the structure-specific summarization models using all training data as in (See et al., 2017) regardless of the summary structures, and then perform fine-tuning for each type using the automatically annotated dataset.

**Structure-aware summarization.** Finally, we build another binary classifier for summary types; however, in this case, we use only articles, because summaries are not available in the test data. Then, we generate a summary based on the type predicted by the second summary-type classifier using the structure-specific summarization models.

To decide which model should be used to generate a summary, we construct another summary structure classification model in a manner similar to the one specified above. In this case, because summaries

| | precision | recall | F1 |
|---|---|---|---|
| parallel | 0.897 | 0.325 | 0.477 |
| sequence | 0.833 | 0.156 | 0.263 |

Table 2: Classification results based on summaries.

| | precision | recall | F1 |
|---|---|---|---|
| parallel | 0.71 | 0.53 | 0.61 |
| sequence | 0.25 | 0.42 | 0.31 |

Table 3: Classification results based on articles.

cannot be used as input during testing, articles are used for training; based on the classification results of this model, our proposed summarization model selects a structure-specific summarization model to output the final summary.

## 5 Experiments

### 5.1 Experiment 1: Classification

**Setup.** The articles and summaries were segmented using MeCab v0.996 [5] (ipadic v2.7.0). The hidden states are represented as 256-dimensional matrices, while the word embeddings are 256-dimensional vectors. The size of the vocabulary is 2,350, which includes words that appear more than once. The model is trained using Adagrad (Duchi et al., 2011) with a learning rate of 0.01.

The annotated portion of the development data is divided into 1,080 and 120 training and test pairs, respectively. Because the summary structure is biased, as indicated by the results in Table 1, we optimize our model by under-sampling to achieve high precision. In particular, we sample data for each label until its precision exceeds 0.8.

**Results using summary as input.** Table 2 lists the test results and number of classified summaries for training data. We obtained 53,809 and 7,813 instances for automatically labeled parallel and sequence summaries, respectively.

**Results using article as input.** Table 3 lists the results of classification of the summary structures using articles as input. The accuracy of the binary classification is 0.50. Because the number of instances

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[5]https://github.com/taku910/mecab

| | Coverage | | | Parallel_model | | | Sequence_model | | | Proposed | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| All | 47.22 | 21.65 | 32.96 | 47.41 | 21.75 | 33.36 | **47.88** | **21.92** | 33.40 | 47.69 | 21.75 | **33.41** |
| Parallel | 47.02 | 21.83 | 32.92 | 47.16 | 21.94 | 33.21 | 47.43 | 21.97 | 33.20 | **47.83** | **22.00** | **33.63** |
| Sequence | 47.80 | 21.20 | 33.05 | 48.14 | 21.34 | **33.85** | **49.11** | **21.86** | 33.80 | 47.34 | 21.09 | 32.80 |

Table 4: Evaluation results for three bullets summarization. 'Coverage' is baseline model which is proposed by See et al. (2017). 'Parallel_model' and 'Sequence_model' are sub-models of the proposed method.

| | | 1st | | | 2nd | | | 3rd | | |
|---|---|---|---|---|---|---|---|---|---|---|
| pair | # of pairs | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| 123 | 528 (44.0%) | 55.07 | 34.56 | 40.22 | 36.93 | 17.31 | 25.21 | **32.64** | **13.19** | **22.62** |
| 132 | 381 (31.8%) | 52.38 | 31.94 | 37.72 | 33.59 | 14.14 | 23.15 | **30.83** | **11.00** | **20.93** |
| 213 | 100 (8.3%) | 38.03 | 18.30 | 26.50 | **31.32** | **10.34** | **21.25** | 34.73 | 15.47 | 24.64 |
| 231 | 66 (5.5%) | 41.46 | 21.95 | 28.09 | 37.22 | 17.95 | 27.23 | **26.96** | **6.02** | **18.08** |
| 312 | 64 (5.3%) | **28.37** | **7.78** | **19.26** | 34.19 | 13.56 | 23.36 | 34.68 | 13.60 | 22.76 |
| 321 | 61 (5.1%) | **27.10** | **6.74** | **18.15** | 33.36 | 14.36 | 23.53 | 32.16 | 10.67 | 21.85 |

Table 5: Evaluation of pairwise alignment. Leftmost column indicates alignment between each sentence of the system summary and the oracle summary. The columns of '1st', '2nd' and '3rd' list the score of each sentence in the system summary. The **bolded** scores show the lowest scores.

of sequence data is less than parallel data, its recall is lower than that of the parallel data.

## 5.2 Experiment 2: Summarization

**Setup.** In our experiment, we use two models: the baseline (See et al., 2017) and proposed models. Similar to (See et al., 2017), the hidden states of these two models are represented by 256-dimensional matrices, while the word embeddings are represented by 128-dimensional vectors. The vocabulary size is 50,000 words in the case of both the source and target documents.

Furthermore, we also followed See et al. (2017) to perform several data cleanup operations: the articles were truncated to 400 words from the beginning of the article for the training and test sets, while the summaries shorter than 70 words were excluded. The models were trained using Adagrad (Duchi et al., 2011) with a learning rate of 0.15, and gradient clipping with a maximum gradient norm of 2.

**Evaluation metric.** We use the $F_1$ scores for ROUGE-1, ROUGE-2 and ROUGE-L (Lin, 2004) to evaluate the output; this evaluation is applied to all test cases, *parallel* summaries, and *sequence* summaries, respectively.

Furthermore, we align each sentence in the sys-

tem summary with a sentence of an oracle summary to evaluate consistency. The alignment is selected to maximize the average score of ROUGE-L under the condition that there is no duplicate.

**Result.** Tables 4 and 6 list the evaluation results for all, parallel, and sequence test data. As can be seen from Tables 4 and 6a, the proposed models outperform the baseline model (Coverage). It is clear from Table 6b, in a manner similar to the results in Table 6a, the sequence model outperforms the others on average. However, as is evident from Table 6c, each model behaves differently. We explore the reason for this in the next section.

## 6 Discussion

### 6.1 Model Comparison

For the 'All' values in Table 4 and 'Ave' values in Table 6a, the scores of the sequence model are the highest. It can be said that the sequence model considers previous sentences more than the parallel model while generating the third sentence in a summary. The parallel model fails to incorporate the information of the second sentence while generating the third sentence (Table 6c).

Table 7 shows an example of summarization. The

|  | Coverage | | | Parallel_model | | | Sequence_model | | | Proposed | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| 1st | 48.23 | 28.42 | 35.29 | 48.86 | 28.80 | 35.53 | 49.20 | 28.84 | 35.38 | **49.48** | **29.15** | **35.82** |
| 2nd | 34.37 | 14.50 | 23.38 | 34.30 | 14.18 | 23.28 | **35.09** | **15.41** | **24.15** | 34.69 | 15.24 | 23.78 |
| 3rd | 31.91 | 12.36 | 22.00 | **32.28** | **12.80** | **22.51** | 32.01 | 12.18 | 21.97 | 31.67 | 11.46 | 21.80 |
| Ave | 38.17 | 18.43 | 26.89 | 38.48 | 18.59 | 27.11 | **38.77** | **18.81** | **27.17** | 38.61 | 18.62 | 27.13 |

(a) Evaluation results in all test data.

|  | Coverage | | | Parallel_model | | | Sequence_model | | | Proposed | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| 1st | 48.38 | 28.97 | 35.68 | 48.75 | 29.30 | 35.68 | 49.35 | **29.38** | 35.68 | **49.63** | 29.18 | **35.95** |
| 2nd | 34.48 | 14.93 | 23.40 | 33.62 | 13.89 | 22.81 | 34.32 | 14.97 | 23.64 | **34.51** | **15.13** | **23.74** |
| 3rd | 31.62 | 12.53 | 21.82 | **32.45** | **13.29** | **22.67** | 31.58 | 12.50 | 21.80 | 32.12 | 11.80 | 22.16 |
| Ave | 38.16 | 18.81 | 26.97 | 38.27 | 18.82 | 27.05 | 38.42 | **18.95** | 27.04 | **38.75** | 18.70 | **27.28** |

(b) Evaluation results in *parallel* test data.

|  | Coverage | | | Parallel_model | | | Sequence_model | | | Proposed | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
|  | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L | R-1 | R-2 | R-L |
| 1st | 47.83 | 26.92 | 34.25 | **49.18** | 27.45 | 35.14 | 48.81 | 27.38 | 34.54 | 49.09 | **29.08** | **35.47** |
| 2nd | 34.05 | 13.34 | 23.32 | 36.14 | 14.96 | 24.55 | **37.18** | **16.58** | **25.53** | 35.17 | 15.52 | 23.90 |
| 3rd | 32.68 | **11.93** | **22.47** | 31.82 | 11.48 | 22.08 | **33.17** | 11.34 | 22.42 | 30.46 | 10.55 | 20.84 |
| ave | 38.19 | 17.40 | 26.68 | 39.05 | 17.96 | 27.26 | **39.72** | **18.43** | **27.50** | 38.24 | 18.38 | 26.74 |

(c) Evaluation results in *sequence* test data.

Table 6: Evaluation results per sentence breakdown. The scores in the row of '1st' are computed between the first sentence of the system summary and the sentence of the oracle summary. The rows of '2nd' and '3rd' are worked out in the same process. The row of 'ave' is the average scores of '1st', '2nd' and '3rd'.

example was annotated as a parallel type. The first sentence in the reference mentions the result of a game. However, it is difficult for all models to generate this information because it is not described in the article. Among all the models, only the sequence model produces a sentence similar to the reference. This can be attributed to its ability to generate the second sentence based on previous information more effectively than the others models.

## 6.2 Pairwise Evaluation

To analyze the system summary in greater detail, we evaluate the performance of our proposed method for each pair combination. Table 5 lists the results of our pairwise evaluation.

The pairs of '123' occurred most frequently. It is considered that the summaries in the case of sequence or parallel types are suitably generated. These scores for the pairs of '123' are higher than the others. The pairs of '132' account for the second

largest proportion of pair combinations; their scores are almost as high as those of the pairs of '123'. This is because the second and third sentences in a parallel type summary are in no particular order.

In contrast, the score of the sentences in the reverse order is low (e.g., the scores shown in bold in the row of '213' and the second column). Thus, based on the above discussion, it is suggested that the first sentence should be correctly generated in order to evaluate the summary structure appropriately.

## 6.3 Evaluation Methods

In this work, we evaluated the generated summaries using two methods of evaluation. We applied the ordinary evaluation, which is discussed in Section 5.2, as well as the evaluation of each pair based on the ROUGE-L score, which is discussed in Section 6.2.

The ordinary evaluation indicates summary informativeness. In contrast, the evaluation of each pair

shows how the proposed model generated summary sentences. It should be noted that the generated summary does not consist of the same order of sentence compared with the oracle summary. By performing pairwise evaluation using ROUGE-L, we were able to evaluate the order of the summary appropriately for the dataset.

## 7   Conclusion

In this study, we constructed a dataset focused on summaries with three sentences. We annotated and analyzed the structure of the summaries in the considered dataset. In particular, we proposed a structure-aware summarization model combining the summary structure classification model and summary-specific summarization sub-models. Through our experiment, we demonstrated that our proposed model improves summarization performance over the baseline model.

In future work, we will use category and subcategory tags to analyze the characteristics for each category so that we can build specific models to improve the summarization system.

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## Appendix A. Example of Generated Summary

*Source*

Cologne's local paper Express praised that Yuya Osako demonstrated its power in the game against Wolfsburg the other day. It is reported that he demonstrated his power as a Japan representative FW who showed up trying to toss the Wolfsburg defense team.

In the last season, due to insufficient scoring ability, he received fierce criticism from passionate Cologne fans so that Cologne coach Stöger dare to avoid appointment in a home game.

Nonetheless head coach Stöger and manager Joerg Schmadtke is constantly defending Osako as "a wonderful football player."

On the other hand, CF Modeste is showing off his team's top scorers, "I knew that his main job was CF," said Stöger, "but I really wanted to appoint him," resulting in various positions by trial and error.

But this season's Cologne has adopted the 4-4-2 system from the opening, "I am clear now. He will play as CF," he asserted. Osako got two goals in the first round of Pokal, and also scored in the test match during international matches.

And the first opportunity of this season, due to Rudnevs' injury, Osako showed off a success that the Express paper praised as "Osako showed ball-keeping ability, speed, breadth of vision, and scoring ability through the game." In Cologne's FW team, he was even appreciated as the only player who achieves all the performance.

As for the score, this day he did not score at all because Casteels played a blinder, but he wants to maintain the good performance at CF as his professional career so as to secure a fixed position.

*Reference*

Cologne to which Yuya Osako belongs drew 0-0 in Wolfsburg on the 10th
A local newspaper praised that Osako tossed at the Wolfsburg defense team
In Cologne's FW team, he was described as having all the performance

*Coverage*: ROUGE-L=47.02

Cologne's local paper Express reported that Yuya Osako demonstrated his power
It defends Osako as "a wonderful football player" in the 2015 Wolfsburg game
"I understood that I am clear now," he said

*Parallel_model*: ROUGE-L=47.16

Cologne's local paper Express recieved a fierece criticism from the team top scorers fan
"I knew that CF was his main job," said head coach Stöger with a blinder
Last season, Yuya Osako said "I am clear now, he will play as CF"

*Sequence_model*: ROUGE-1=47.43

Cologne's local paper Express reported that Yuya Osako demonstrated his power in the Wolfsburg game
Japan representative FW who tried to toss at the Wolfsburg defense team, is praised as he demonstrated his performance
"I understood that I am clear now," as he defended

Table 7: Example of generated three bullet points summarization in *parallel* structure. Retrieved from `http://news.livedoor.com/article/detail/12016209/` on the 11th January, 2018.