Abstract

With the tremendously increasing number of videos, there is a great demand for techniques that help people quickly navigate to the video segments they are interested in. However, current works on video understanding mainly focus on video content summarization, while little effort has been made to explore the structure of a video. Inspired by textual outline generation, we introduce a novel video understanding task, namely video outline generation (VOG). This task is defined to contain two sub-tasks: (1) first segmenting the video according to the content structure and then (2) generating a heading for each segment. To learn and evaluate VOG, we annotate a 10k+ dataset, called DuVOG. Specifically, we use OCR tools to recognize subtitles of videos. Then annotators are asked to divide subtitles into chapters and title each chapter. In videos, highlighted text tends to be the headline since it is more likely to attract attention. Therefore we propose a VisualSubtitle feature Enhanced video outline generation model (VSENet) which takes as input the textual subtitles together with their visual font sizes and positions. We consider the VOG task as a sequence tagging problem that extracts spans where the headings are located and then rewrites them to form the final outlines. Furthermore, based on the similarity between video outlines and textual outlines, we use a large number of articles with chapter headings to pretrain our model. Experiments on DuVOG show that our model largely outperforms other baseline methods, achieving 77.1 of F1-score for the video segmentation level and 85.0 of ROUGE-L for the headline generation level.

1 Introduction

Over the past few years, the number of videos has been growing at an incredible rate due to the progress of portable video filming devices and the prevalence of video-sharing platforms. To help people understand videos, numerous video summarization technologies have sprung up. For example, some works (Li, Ma, and Han 2015; Song et al. 2015) compress the video content to a shot clip, and others (Shetty and Laaksonen 2016; Venugopalan et al. 2016) generate natural language descriptions according to the video. However, existing works focus on summarizing a video into a short synopsis, but little effort is made to analyze and explore the video content structure. Recently, many companies, such as Google and Baidu, have launched a new video feature to reveal video structures. As shown in Figure 1, they present some time stamps on the progress bar, along with the corresponding descriptions. These time stamps and descriptions function like book chapters and chapter titles. We call this new video feature video outline. With the help of video outlines, it is more convenient for the audience to glance at the current video content and jump to wherever they are interested, thus improving the viewing experience and increasing viewer engagement. Video outlines also facilitate platforms to understand which parts of the video are popular and raise the video quality of those parts.

However, most of the current video outlines are provided...
by authors artificially, which seriously hinders the promotion of this new feature. Inspired by text outline generation (Zhang et al. 2019a) which identifies the potential sections and generates their corresponding headings, we define a novel task named video outline generation (VOG) and develop an automated solution for it. VOG needs to segment the video content and then generate a heading for each segment. Intuitively, this task can be regarded as a compound of video summarization (Ma et al. 2002) and video caption generation (Tang et al. 2002). However, since subtitles in video usually contain information more relevant to the structure of the video content and that image key frame extraction is time-consuming, we mainly choose to use the subtitles as the basis for VOG.

In order to develop and evaluate the VOG solutions, we annotate a new benchmark dataset called DuVOG. Concretely, we collect 10k+ Chinese videos on generic topics from Baidu haokan videos and adopt a public OCR tool, PaddleOCR[^2] to recognize subtitles. For each video, its subtitles are concatenated with the time points where they appear to form a complete text description for subsequent annotation. We ask the annotators to understand the video content thoroughly first and then segment the video subtitles by marking the time points that denote segment boundaries. Next, the annotators are instructed to write a concise heading for each segment.

As Figure 2 shows, to attract attention, headlines implied in video subtitles usually have distinct visual features, manifesting as their outstanding visual font size and placement. This kind of visual features may benefit the detection of important segments. To this end, we propose VSENet[^1] which adopts the visual subtitle feature to enhance the model capability of video outline generation. Our VSENet leverages the textual subtitles as well as their visual information (i.e., the visual font sizes and positions of subtitles) as input. We formulate this VOG task as a sequence tagging problem and apply a two-stage framework to learn video segmentation and outline rewriting. In the segmentation stage, we encode the text utilizing BERT (Devlin et al. 2018) and inject visual subtitle features to extract spans where the headings are located. In the rewriting stage, we remove the redundant characters in the extracted spans using a Seq2Edit model LaserTagger (Malmi et al. 2019). In addition, based on the similarity with the text outlines, we crawl a large scale articles with chapter headings and pretrain our model to detect the headings.

To summarize, our contributions are as follows:

- We propose a visual subtitle feature enhanced model (VSENet) which adopts the textual subtitles and visual subtitle features for video outline generation.
- We investigate an article heading detection pretraining task to improve the competence of structure understanding for our model.

![Figure 2: Pictures (a) - (d) show the frames where “✓” denotes the subtitle whether contains the headline. The red box denotes the highlighted parts.](https://haokan.baidu.com)

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[^1]: https://github.com/PaddlePaddle/PaddleOCR
[^2]: https://github.com/PaddlePaddle/PaddleOCR
[^3]: This model has been used in an industrial system and more descriptions will be presented in the final version.

2 Related Work

To the best of our knowledge, video outline generation is a novel task. Therefore, in this section, we briefly introduce three related tasks: 1) video summarization (Ma et al. 2002); 2) video caption generation (Tang et al. 2002); 3) textual outline generation (Zhang et al. 2019a). The former two tasks are classic video understanding tasks, while the latter one is to learn the textual structure.

**Video Summarization** Video summarization aims to generate a short synopsis that summarizes the video content by selecting its most informative and important shots. Existing methods could be cast into three categories: unsupervised methods, weakly supervised methods, and supervised methods. For the first category, some works (Zhou, Qiao, and Xiang 2018; Zhang et al. 2019b; Yaliniz and Ikizler-Cinbis 2021) attempted to reconstruct and discriminate the original video by the techniques of GAN and VAE. For the second category, representative methods (Song et al. 2015; Panda et al. 2017) leverage some auxiliary information, including web-image priors, video titles, and video categories. Although unsupervised and weakly supervised methods have achieved remarkable progress, they can not learn well from human annotated summaries. For supervised learning, some deep learning methods (Rochan, Ye, and Wang 2018; Hussein et al. 2019; Zhu et al. 2020; Narasimhan, Rohrbach, and Darrell 2021) take this a big step forward. They usually form this task as a key frame extraction problem and employ technologies like CNN, RNN, LSTM and Transformer.

**Video Caption Generation** Video caption generation aims to describe the video content using natural language sentences automatically. Early works (Lee et al. 2008; Lee et al. 2010; Lee et al. 2010a) formulate this task as a sequence labeling problem and employ technologies like CNN, RNN, LSTM and Transformer.
3 VOG Dataset Construction

In order to study and evaluate the VOG task, we build a new benchmark dataset named DuVOG. We collect 10k+ raw videos with more than 500 pageviews from BAIDU haokan videos. Most of these videos belong to the knowledge explanation/evaluation type, as their content has a clear structure. The topics of video content are about diverse domains, including education, science, etc.

For the aim of the VOG task, we first extract images for each video at two frames per second and adopt PaddleOCR, an open source OCR tool, to recognize all text in the frames. Then we remove the duplicate recognized sentences and stitch them with their time points together to compose the final context for follow-up annotation. It is worth noting that although we have proofread the recognition result of each frame against its adjacent frames, some errors such as missing characters, duplicate characters and spelling errors will inevitably occur during the OCR recognition process.

The following sections present the details about the annotation target, criteria and procedure. Finally, we describe the characteristics of this dataset.

Annotation Procedure In order to ensure the annotation quality, we recommend that the annotators first understand the video content thoroughly, and then divide it into segments. For each segment, annotators need to mark the segmentation points and their outlines reference. Meanwhile, they are required to write the final outlines according to the reference. We recruited four general annotators and two high-rank reviewers in all. The high-rank reviewers are required to proofread the annotation results of the general annotators. They all undergo professional labeling training and assessment. The annotation accuracy rates of these high-rank reviewers and general annotators are 95%+ and 85%+, respectively. The whole annotation process lasted for one month and we checked the annotation results once per week. Furthermore, to make the annotation results more in line with our expectations, when it comes to some complex or uncertain samples, we collect them and discuss regularly to improve the annotation criterion.

Textual Outline Generation The goal of textual outline generation is to produce a structure output with short descriptions (i.e., headlines). Zhang et al. (2019a) proposed a hierarchical LSTM model with an attention mechanism to improve the consistency and eliminate duplication between section headings. With a similar modeling method, another work (Barrow et al. 2020) adopted the segment pooling LSTM model to split a document and label segments.
Table 1: Statistics of the DuVOG dataset. “s” stands for time in seconds.

|               | Train  | Dev   | Test  |
|---------------|--------|-------|-------|
| Size          | 10,585 | 158   | 160   |
| Median video time (s) | 130.0  | 94.5  | 84.5  |
| Median text length | 654.0  | 421.0 | 384.0 |
| # Avg. outlines | 6.2    | 5.6   | 5.7   |
| Avg. outline length | 6.9    | 5.9   | 5.4   |
| Rewriting ratio | 21.2%  | 30.8% | 28.0% |
| Remove ratio   | 99.6%  | 99.6% | 99.2% |

In the following parts, we describe these two stages in detail.

### 4.3 Span Extraction

The goal of this stage is to detect and extract the important spans where the headings are located. We consider this period as a sequence tagging task where the input is the sequence of subtitle characters and the output is the sequence of BIO (Beginning, Inside, Outside) tags.

**Input** We remove the timestamp characters from the subtitles for the purpose of preserving the complete contextual semantics of the sentence. Each subtitle is then combined with a comma. As Figure 4 shows, “[32]” is removed while these two adjacent subtitles are combined with a comma.

**Output** According to the start/end index of outline reference in the dataset, we automatically generate the continuous token tags from \{B,I,O\} which used in the named entity recognition (NER) task (Zeng et al. 2014). The tag of token in outline reference is set to “B” and others are formed as “O”. In Figure 4, it can be seen that the target we focus on in this period is the underlined span, regardless of highlighted characters.

**Subtitles:** ...不要着急, [32], 时期的乳液也有很大的妙用, ...

**Tags:** ...OOOOOBBIIIIIIIIIIIIIIIIIIIO...

Figure 4: An example of conversion from a subtitle to the input data, along with its corresponding tags.

**Model Description** Depending on when each subtitle appears, we extract its corresponding frame. As shown in the top left subfigure of Figure 5, we earn the position of the subtitle box, as well as its size. Based on the size of the video image and the information of the text box, we can calculate the relative position of the text box and the area of its individual character.

Formally, we first obtain the height \(D_h\) and width \(D_w\) of the original video image. Then, according to the timestamps of subtitles, we extract their corresponding frames and recognize the subtitle boxes \(B = \{b_1, b_2, \ldots, b_m\}\) where a box \(b_i\) is comprised of tokens \(\{x_p, x_{p+1}, \ldots, x_{p+1}\}\). We consider the box as a whole, then the relative position (i.e., \(v_k^{TM}\) and \(v_k^{LM}\)) and font size \(v_k^{SZ}\) of each token in the box is:

\[
v_k^{TM} = \frac{d_i^{TM}}{D_h}, \quad v_k^{LM} = \frac{d_i^{LM}}{D_w},
\]

\[
v_k^{SZ} = \frac{d_i^b \cdot d_i^w}{D_h \cdot D_w \cdot l},
\]
where $d^T_i$, $d^L_i$, $d^b_i$ and $d^w_i$ denote the top margin, left margin, height and width of box $b_i; k \in [p, p + l]$.

Following most NLP approaches (Xu et al. 2019), we adopt the pretrained language model BERT as our text encoder and truncate the part that exceeds the length. Note, we have also attempted XLNet (Yang et al. 2019) with no input length limit as the text encoder (see details in Section 4). Then we combine the textual embedding with the visual representation by a gate mechanism. To learn the dependency between labels, we add the conditional random fields (CRF) layer (Lafferty, McCallum, and Pereira 2001) following Huang, Xu, and Yu (2015). We obtain the prediction $\hat{Y}$ as follows:

$$H^0 = \text{BERTEncdoer}(X),$$

$$H^v = [V^T, V^L, V^S],$$

$$H^p = \sigma(WH^v + b) \odot H^i,$$

$$\hat{Y} = \text{CRFLayer}(H^p),$$

where $W$ and $b$ are learnable parameters. $\sigma$ is a nonlinear activation function, which is a ReLU function in our implementation. ‘$\odot$’ represents element-wise multiplication.

**Heading Detection Pretraining** Due to the limited amount of data for the VOG task, we use articles with outlines to additionally pretrain the base model BERT based to improve its ability for chapter segmentation.

Specifically, we collect articles from Baidu BAIJIAHAO (https://baijiahao.baidu.com) and obtain the headlines from the HTML tag information. Next, we discard the articles with less than 3 headings to ensure the structure completeness. For the rest approximately 3.3 million articles, we concatenate each main context and headings with commas to form a long sequence. We mapped the formulated text sequences to labels for follow-up self-supervised learning, depending on whether the character belonged to a headline. As Figure 6 shows, if the character is part of a heading, its corresponding tag will be set to “B/I”, otherwise “O”, like the tags in the VOG task.

Similar to our span extraction period, it aims to detect heading segments in context. Considering that the model can learn from a large scalar training data and the CRF layer may cause additional overhead, we formulate this task as a token classification task with three labels {B, I, O}. Formally, given a text sequence $X = \{x_1, x_2, \ldots, x_n\}$, we obtain the prediction $\hat{Y} = \{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n\}$ as followed:

$$H^i = \text{BERTEncdoer}(X),$$

$$P = \text{Softmax}(H^i),$$

$$\hat{Y} = \text{argmax}(P).$$

### 4.4 Outline Rewriting

The extracted spans are available as a summary in many cases. To generate a concise outline, we feed the extracted spans to a rewriting model to delete the redundant characters. Motivated by the similar purpose of grammatical error correction (Dahlmeier and Ng 2012), we apply a simple yet effective Seq2Edit model, LaserTagger (Malmi et al. 2019), to rewrite the extracted spans. Since character deletion accounts for the majority of rewriting, we only retain the “Keep” and “Delete” operations as the prediction tags. Notably, there are two decoding methods in LaserTagger, and we leverage the autoregressive Transformer decoder.

Overall, we extract segments with headlines and view timestamps they appeared as segmentation points of the video structure. Then the extracted spans are rewritten to obtain final outlines.

### 5 Experiment

#### 5.1 Experimental Settings

To evaluate the performance of our model, we conduct experiments on our DuVOG benchmark dataset. We implement our model based on huggingface’s pytorch implementation of transformers and google’s tensorflow implementation of lasertagger. The pre-trained bert-base-chinese is employed to initialize the BERT model. For the extraction stage, we set the training batch size to 32 and the AdamW optimizer (Loshchilov and Hutter 2017) is applied. The initial learning rate of model parameters is set to 3e-5, except for that of the CRF layer which is set to 1e-2. We set the training epoch of this stage to 20 empirically. Concerning the heading detection pretraining, the training batch size is 1280 and the training steps are 50k including 2k warmup steps. The learning rate of AdamW algorithm is set as 5e-5.

For the rewriting stage, we set the training batch size and the optimizer the same as that in extraction stage. The training epoch is set to 10 empirically. The experiment is conducted on a Tesla A100 GPU card with a memory size of 40G.

#### 5.2 Evaluation Metrics

To measure the quality of generated video outlines, we introduce the segmentation level metric and headline generation level metric. In terms of segmentation, we first count the segmentation points and then calculate their precision, recall and F1 score. As regards to headline generation level, we adopt the automatic metric ROUGE-L for evaluation.

Similar to the grammatical error correction task (Zhang et al. 2022), precision is more important than recall for rewriting. Thus we adopt ROUGE-L$_{F0.5}$ as the main metric for generation evaluation. Notably, the outline will be meaningless once its corresponding segmentation point is wrong. Therefore we only calculate prediction results of headings with correct segmentation points. Finally, we conclude the model overall performance by multiplying the F1 score at segmentation level and ROUGE-L$_{F0.5}$ at headline generation level. In addition, we perform human evaluation to ensure the prediction quality.

#### 5.3 Baseline Methods

We compare four different methods: 1) JointBC: This approach considers the non-continuous token tags of {B, I, O} as its prediction labels. Likewise, it adopts the BERT encoder to encode sentences and add the CRF layer to output

- https://github.com/google-research/lasertagger
- https://github.com/huggingface/transformers
Figure 5: Our framework overview. In the top left part, the red area represents the text box while the top margin, left margin of the box are in blue.

Figure 6: An example of the conversion from article to training samples. Sentences surrounding by the blue box in article (left) represent the headlines, corresponding to the underlined text in the training sample (right).

2) BC-base: This method applies BERT as the text encoder and combines the CRF layer additionally. 3) BC-PT: This model enhances its structural understanding by heading detection pretraining based on BC-base. 4) VSE-Bert: This model utilizes BERT as the text encoder and a fully connected network as the final layer to predict results. 5) VSENet: This is our proposed model. As illustrated in Table 2, the heading detection pretraining (PT) is adopted to enhance the model performance of BC-PT, VSEBert and VSENet. For the latter two methods, the visual subtitle feature (VSE) is also used to improve the structure understanding capability. As mentioned in Section 4.3, we have also tried XLNet (Yang et al. 2019) as the text encoder. However, compared with above the baseline methods, its training speed is 8× slower. Meanwhile, we have attempted to use DSNet (Zhu et al. 2020) to extract key frames in videos. But it also costs much time to extract visual features.

To show the difference between joint and pipeline approaches, we compare JointBC and BC-base. For the aim of verifying the effectiveness of PT, we compare BC-base and BC-PT. We made a comparison between VSEBert and VSENet to reveal the necessity of the CRF layer.

In addition, we use different settings in the rewriting stage: 1) w/o rewriting: It means that the extraction results are directly used to be the final outlines; 2) w/ BC: It forms the B/I/O as its tags, where “B/I” corresponds to the redundant span and “O” corresponds to the in-hold character. Meanwhile, it adopts a BERT-Encoder combined with the CRF layer as the base model; 3) w/ LT: This is our approach to rewrite the span by using LaserTagger.

| Baselines | CRF | VSE | PT |
|-----------|-----|-----|----|
| JointBC   | ✓   | ✓   | ✓  |
| BC-base   | ✓   | ✓   | ✓  |
| BC-PT     | ✓   | ✓   | ✓  |
| VSEBert   | ✓   | ✓   |   |
| VSENet    | ✓   | ✓   | ✓  |

Table 2: Baseline methods, VSE/PT denotes the visual subtitle feature enhancement/heading detection pretraining.

5.4 Results Analysis

Main Result The overall performance of all baselines is shown in Table 3. As can be seen, our model obviously surpasses other methods in the overall score metric. JointBC is even inferior to the simple model BC-base by 3 points. The main resistance we deduced is that the segmentation requires global attention for a long sequence, while generation focuses on local attention for a short span. We thus mainly concentrate on the two stage pipeline method. At the segmentation level, by comparing the results of BC-base and BC-PT, we observe that our proposed heading detec-
tion pretraining has a promising advantage, achieving 1.4 points improvement. With the help of visual caption feature enhancement, VSENet scores approximately 2 points higher than BC-PT, which verified its effectiveness. Meanwhile, the increase over VSEBert demonstrates that the CRF layer is an essential part of our VSENet for the continuous span target.

Generally speaking, the rewriting module raises the ROUGE-L\textsubscript{F0.5} metric result. The human evaluation has also found that compressive rewriting improves audience experience. Moreover, the LaserTagger shows a marginally increasing compared with BC\textsubscript{r}. We believe the autoregressive generation could benefit the final rewriting result. By comparison, it is not difficult to find that the enhancement of the extraction stage would also help the results of the generation phase to some extent.

### Ablation Study
To investigate the effectiveness of each component in our VSENet, we conduct several ablation experiments with the following settings: 1) w/o VSE: removing the visual subtitle feature; 2) w/o PT: removing the heading detection pretraining; 3) w/ cat: concatenating the textual embedding and visual subtitle feature. As illustrated in Table 4, we can observe that by removing the visual subtitle enhance feature, the precision drops significantly although the recall rises at the segmentation level. The reason is that adding visual features would take an opposite effect since some videos do not have highlight parts. In addition, heading detection pretraining plays an important role in our model due to its enhancement of structure understanding. Another fusion method is still weaker than the gate mechanism although it achieves competitive performance.

### Quality Evaluation
We perform human evaluation to ensure that our increase in overall scores is also followed by an increase in machine understanding of video content structure. We show the original videos, their subtitles, the ground truth in test set, as well as outlines generated by BC-Base and our VSENet side by side to a human evaluator. Two scores from 0 to 3 are then assigned to each video outline, one for segmentation (how accurate the segmentation boundary position) and one for generation (how quality of the headline is). Each summary is rated by 4 different human evaluators and the results are averaged across all examples and evaluators. The result in Table 5 demonstrates that VSENet has a better understanding of the video content architecture which is consistent with the higher overall score.

### 6 Conclusion
In this paper, we introduce a novel and practical video understanding task named video outline generation (VOG). For evaluating the VOG task, we annotate a 10k+ Chinese video dataset called DuVOG. What’s more, we propose a visual subtitle feature enhanced model (VSENet) which adopts

| Competition | Pre. | Rec.  | F1  | ROUGE-L\textsubscript{P} | ROUGE-L\textsubscript{R} | ROUGE-L\textsubscript{F0.5} | Score |
|-------------|------|-------|-----|----------------|----------------|----------------|-------|
| JointBC     | 73.6 | 69.7  | 71.6| 81.2           | 93.8           | 81.6           | 58.4  |
| BC-base     |      |       |     |                |                |                |       |
| w/o rewriting | 79.0 | 68.9  | 73.6| 83.5           | 94.0           | 83.6           | 61.5  |
| w/ BC\textsubscript{r} | 83.8 | 93.8  |     | 83.9           | 83.9           | 61.8           |       |
| w/ LT       | 84.1 | 93.0  |     | 84.1           | 84.1           | 61.9           |       |
| BC-PT       |      |       |     |                |                |                |       |
| w/o rewriting | 76.1 | 73.9  | 75.0| 83.0           | 93.4           | 83.2           | 62.4  |
| w/ BC\textsubscript{r} | 83.4 | 93.4  |     | 83.5           | 83.5           | 62.6           |       |
| w/ LT       | 83.7 | 92.3  |     | 83.8           | 83.8           | 62.8           |       |
| VSEBert     |      |       |     |                |                |                |       |
| w/o rewriting | 77.9 | 70.8  | 74.3| 80.5           | 92.7           | 80.7           | 59.9  |
| w/ BC\textsubscript{r} | 80.8 | 92.6  |     | 80.9           | 80.9           | 60.1           |       |
| w/ LT       | 81.1 | 91.6  |     | 81.1           | 81.1           | 60.3           |       |
| VSENet      |      |       |     |                |                |                |       |
| w/o rewriting | 83.1 | 71.9  | 77.1| 84.0           | 94.7           | 84.6           | 65.2  |
| w/ BC\textsubscript{r} | 84.3 | 94.6  |     | 84.9           | 84.9           | 65.5           |       |
| w/ LT       | 84.7 | 93.5  |     | 85.0           | 85.0           | 65.6           |       |

Table 3: Performance on the DuVOG dataset. Best results are in **bold**. The results of model in segmentation period are the same because the rewriting module only works in the generation period. Besides, there is no need to add additional rewriting periods to JointBC, since the non-contiguous tags can implement the removing operation.

| Competition | Pre. | Rec.  | F1  | Score |
|-------------|------|-------|-----|-------|
| VSENet      | 83.1 | 71.9  | 77.1| 65.6  |
| w/o VSE    | 76.1 | 73.9  | 75.0| 62.8  |
| w/o PT     | 81.4 | 66.7  | 73.3| 63.3  |
| w/ cat     | 81.6 | 72.7  | 76.9| 65.1  |

Table 4: Ablation experiment results. VSE/PT denotes the visual subtitle feature enhanced method/heading detection pretraining method.

| Competition | Segmentation | Generation |
|-------------|--------------|------------|
| BC-base     | 1.54         | 1.43       |
| VSENet      | 1.68         | 1.61       |

Table 5: The result of human evaluation.
the textual subtitles and visual subtitle features simultaneously to segment the video content and generate a headline for each segment. To enhance structure understanding, we pretrain our base model BERT with a large scalar articles with headings. Experimental results reveal the effect of our VSENet. Since this task is first introduced, there are many potential treasures to investigate, such as the extraction and fusion method of multi-modality information in videos.

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A Appendix

A.1 Dataset Details

Figure 7 shows the video time distribution of our DuVOG dataset, as well as the text length distribution. Most video lasts between 40 seconds and 150 seconds, while the text length is distributed centrally in the range of 0-800. It can be seen that our DuVOG dataset is dominated by short-time and medium-time videos.

A.2 Supplementary Experiment

We also conduct the sentence-level experiment, namely sentence extraction and rewriting. Specifically, similar to the span extraction and rewriting, we extract sentences which contain headlines and rewrite them to formulate the final outlines. For sentence extraction, we generate the tag for each subtitle sentence. The tag is only labeled on the comma which replaces the original time point. Considering the headline would cross different subtitles, we adopt the tags from {B,I,O}. We leverage the BERT as our base model and integrate the CRF layer to predict the result. For rewriting, we feed the extracted sentences to LaserTagger model, to predict the final outlines. The settings, evaluation metrics and training hyperparameters are the same as that mentioned before.

Experiment Result Table 6 shows the comparison between the result of span-level based method BC and sentence-level based method Sent-BC. It can observed that Sent-BC has a better segmentation performance but is weak in terms of generation. We believe that for segmentation, the sentences contain more global structural information, while for generation, it is more difficult to retain an important part from a complete sentence than from a span. Overall, a sentence-level based approach would be weaker.

|       | Segmentation | Generation | Overall |
|-------|--------------|------------|---------|
|       | Pre. | Rec. | F1   | ROUGE-L F0.5 | Score |
| BC    | 79.0 | 68.9 | 73.6 | 84.1 | 61.9 |
| Sent-BC | 82.9 | 67.2 | 74.2 | 81.8 | 60.7 |

Table 6: Performance of sentence-level