## A License

The YouTube-News-Timeline dataset is under the CC BY 4.0 International license. Please refer to https://creativecommons.org/licenses/by/4.0/legalcode for license details.

## B Data Format Example

A data format example is shown below.

## Listing 1: A data example

```
{"https:// apnews.com/article/japan-accidents - tsunamis - earthquakes - 42
    C4947609becd7f141e9524a8c98937": # The URL link of the webpage
    \hookrightarrowhere we crawl the timeline.
    [
        [
            "OhEbGK4PnZg"
            "cl19tfn33hI",
            "ROl6z0HaUAM",
            "5QhCsR-t-qM",
            "ev3FBIoHMX8'
        ],
        [
            "psAuFr8Xeqs",
            "BsRd7WQuBHc",
            "Dp_8rLL1Y18",
            "h1m7GFPAq3o"
        ] ,
        [
            "f4TaKPKe1gg",
            "DL1sKd-QC2o"
        ],
        [
            "ocluW1Vhvcg",
            "vusthiUFx_0",
            "vGHzuZQLYtg",
            "7XpLbhQxpLw",
            "UsPFUzXisq4"
        ],
        [
            "hA3fNKOrxcs"
        ]
    ] # The URL links of the retrieved YouTube news videos. Each list
            \hookrightarrowin the nested list corresponds to one node on the timeline.
            These nodes are ordered in the nested list.
```


## C More Dataset Characteristics

We include more details on the dataset's characteristics here. As demonstrated in Figure 8 the reference timelines are curated from a diverse set of more than 1,000 publishers. The primary topics, each recurring more than 30 times, are depicted in In Figure 9 . The topic annotations are given by an in-house proprietary entity linking algorithm. Moreover, the distribution of the event date, corresponding to each node on timelines, is shown in Figure 10

## D More Experimental Studies

To assess the impact of video duration on our model's performance, in Figure 11, we present a correlation between the video length and the corresponding video-level Euclidean distance, based


Figure 8: Pei chart of the news publishers.


Figure 9: Distribution of the covered main topics.
on our Tri-Transformer model over the test set. The video-level Euclidean distance is not sensitive to video length. It can be observed that the variance becomes large for longer videos as the longer videos are less in both the training and test sets.


Figure 10: Distribution of the event date.


Figure 11: Number of videos and average video-level Euclidean distances in relation to video duration.

## E Examples of Predicted Timelines

we present two examples of timelines predicted by our Tri-Transformer model in Table 4 and 5 The videos that have been assigned to incorrect nodes are highlighted for clarity.

## F Societal Impacts

We expect that the proposed benchmark dataset and methods will facilitate future advancements in video timeline modeling. On the positive side, it offers a helpful tool for understanding and navigating large volumes of news video data, enabling more efficient news consumption and ensuring a more comprehensive understanding of events.

One the negative side, the crawled timelines might not always reflect absolute precision. They might be mistakenly used as evidence in some situations. This highlights the importance of using and interpreting these timelines carefully. In addition, while we have taken steps to diversify our data sources, news content can inherently carry biases based on various factors. We acknowledge this challenge and emphasize the future need for more diverse data sourcing to capture a broad spectrum of perspectives and reduce inherent biases. Also, there could be potential misuse if the technology were applied unethically. Specifically, the construction of timelines could be manipulated to present


Table 4: A timeline of "Major milestones in Chinese space exploration".


Table 5: A timeline of "50 Years of Title IX: The Defining Moments of Women's Sports".
events in a way that supports a particular opinion, thereby distorting the truth. To alleviate this potential concern, regular validation and fact-checking mechanisms can help ensure the constructed timelines align with factual occurrences.

## G Discussions on Future Directions

Here, we highlight several promising directions, including more principle exploration for problems and methodologies, for future research in this field.

On one hand, more effective and principle methodologies are highly desired. First, as demonstrated in the experiments, we can develop more effective strategies to leverage textual information during training. Second, while our current method, as an exploratory work, treats the problem as a multi-class
classification problem, it would be more principle to consider the problem as a ranking problem and use differentiable ranking models. Third, our algorithms assign a set of videos simultaneously, which may result in different assignments for the same video if we add or delete a video in the set. It remains challenging to model video interactions while keeping the prediction of videos less dependent. This aspect presents a potential avenue for enhancement.

In addition, future research can also be made from a problem-oriented perspective. Given that our defined problem and evaluation standard concentrate solely on assigning input video sets to ordered nodes, one possible extension is to integrate the event summarization step with our defined problem to construct a timeline with both associated videos and event information. The event information can be in the form of text, key frames, etc. Although our YouTube-News-Timeline dataset can be used to evaluate the generated event text descriptions, the evaluation protocol and algorithms need to be dedicatedly redesigned. In addition, extending the single linear timeline to more complex relationship modeling, such as multiple timelines [Yu et al., 2021] and graphs, can be a promising future direction to enhance the understanding of news stories

