GEB+: A benchmark for generic event boundary captioning, grounding and text-based retrieval

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\textbf{Abstract.} Cognitive science has shown that humans perceive videos in terms of events separated by state changes of dominant subjects. State changes trigger new events and are one of the most useful among the large amount of redundant information perceived. However, previous research focuses on the overall understanding of segments without evaluating the fine-grained status changes inside. In this paper, we introduce a new dataset called Kinetic-GEBC (Generic Event Boundary Captioning). The dataset consists of over 170k boundaries associated with captions describing status changes in the generic events in 12K videos. Upon this new dataset, we propose three tasks supporting the development of a more fine-grained, robust, and human-like understanding of videos through status changes. We evaluate many representative baselines in our dataset, where we also design a new TPD (Temporal-based Pairwise Difference) Modeling method for current state-of-the-art backbones and achieve significant performance improvements. Besides, the results show there are still formidable challenges for current methods in the utilization of different granularities, representation of visual difference, and the accurate localization of status changes. Further analysis shows that our dataset can drive developing more powerful methods to understand status changes and thus improve video level comprehension.

\textbf{Keywords:} Video Captioning, Generic Event Understanding, Status Changes, Difference Modelling

1 Introduction

According to cognitive science \cite{25}, humans perceive videos in terms of different events, which are separated by the status changes of dominant subjects in the video. For example, in Fig. \textbf{1}, humans perceive the process of “javelin sport” by the action events such as “walking”, “running” and “throwing”. These events are triggered by the athlete’s status changes, like the instantaneous change from “walking” to “running”. The moment that instantly triggers status changes of persons, objects, or scenes often conveys useful and interesting information
among a large amount of repeated, static, or regular events. Therefore, developing the understanding of the salient, instantaneous status changes is another step towards a more fine-grained and robust video understanding. Previous works, like Dense Video Captioning [14,40,34,16,12] and Video Grounding [26,9,5,10,21,37,38] attempt to develop the understanding of event in video or video segments. However, these works only focus on developing an overall understanding of events rather than delving into the fine-grained status changes in the video. Other researches focusing on image level changes [23,13] employ the visual difference modeling to capture the status changes in image pairs. However, since the image contains only static information, the state changes exhibited by the two images involve only a few simple patterns, e.g., appear, move. These tasks are hard to evaluate the ability on understanding generic status change.

More recently, Shou et al. [29] proposes Kinetic-GEBD dataset with annotated boundary timestamps for detection in Kinetic-400 videos [6], where a boundary is defined as the splitter between two status of the subject. Though the videos in Kinetic-400 [6] are categorized, the events selected inside are generic and mostly independent from the whole video’s category. However, in addition to letting the model predict where is the boundary, it is more important to explain why this is the boundary. The machine needs an in-depth understanding of the status changes which can associate the visual information of boundaries with natural human languages.

Motivated by this idea, we build a new dataset called **Kinetic-GEBC (Generic Event Boundary Captioning)** which includes the video boundaries indicating status changes happening in generic events. For every boundary, our Kinetic-GEBC provides the temporal location and a natural language description, which consists of the dominant *Subject, Status Before* and *Status After*
Table 1. Comparison with most relevant Video Captioning datasets. Our Kinetic-GEBC has comparable scale and is the only one targeting the generic boundaries, while conventional datasets focus on entire videos or video segments.

| Dataset         | Videos | Domain          | Captions | Target          | Type               | Annotation Modality               |
|-----------------|--------|-----------------|----------|-----------------|--------------------|-----------------------------------|
| MSR-VTT         | 7,180  | 20 categories   | 200K     | video generic event | caption            |                                   |
| VATEX           | 41,250 | in-the-wild     | 825K     | video action     | caption            |                                   |
| Charades        | 67,000 | household       | 20K      | segment          | time range + caption|                                   |
| MSVD            | 2,089  | in-the-wild     | 85K      | segment          | time range + caption|                                   |
| YouCook2        | 2,000  | kitchen         | 15K      | segment          | time range + caption|                                   |
| ActivityNet Captions | 20,000 | in-the-wild     | 100K     | segment          | time range + caption|                                   |
| Kinetics-GEBC   | 12,434 | in-the-wild     | 177K     | boundary         | generic event      | timestamp/range + caption         |

In total, our dataset includes 176,681 boundaries in 12,434 videos selected from all categories in Kinetic-400 [6]. The detailed definition of our boundary is described in Section 3.1. For future applications like AI assistant robots, with the comprehension developed from the video status changes and natural language descriptions, they could understand the real time, instantaneous occurrences without hints so as to assist the users.

In order to comprehensively evaluate the machine’s understanding of our boundaries, we further propose three downstream tasks shown in Fig. 1: (1) Boundary Captioning. Provided with the timestamp of a boundary, the machine is required to generate sentences describing the status change at the boundary. (2) Boundary Grounding. Provided with a description of a boundary, the machine is required to locate that boundary in the video. (3) Boundary Caption-Video Retrieval. Provided with the description of a boundary, the machine is required to retrieve the video containing that boundary from video corpus.

In the experiment, we compare several state-of-the-art methods [15,20,41,39,3] along with many variants on our datasets to analyze the limitation of current methods and show the challenges of the proposed tasks. Due to the need of visual difference for understanding the status changes, we further propose a Temporal-based Pairwise Difference (TPD) Modeling method representing a fine-grained visual difference before and after the boundary. This method brings a significant performance improvement. However, on the other hand, the results show that there are still formidable challenges for current SOTA methods in developing the comprehension of status changes: (1) The requirement of multi-granularity visual information. (2) The exclusion of disturbance by adaptively paying attention to different granularities of visual features. (3) The fine-grained but also wide-viewing representation of visual differences. (4) The accuracy localization of boundaries.

2 Related Work

Video Captioning is a conventional task with many benchmarks established [36,7,35,14,40] which aim to caption trimmed videos with natural language descriptions. More recently, several works [14,41,34,16,12], e.g., Dense Video Captioning [14], focus on captioning the self-proposed event segments in videos. All tasks above are evaluating the overall understanding of an event, whether the event is presented in the form of a trimmed video or a video segment. In contrast, our Boundary Captioning task is to develop the comprehension of instantaneous status changes happening at boundaries, i.e., describing the important moment that caused a
dramatic change in the state of persons, objects or scenes. As a result, there is a more urgent need for models to understand the changes in various granularity of visual concepts, e.g., action, attributes, scene status, etc. In Table 1, we compare most relevant video captioning datasets with our dataset.

**Image Change Captioning** is a task evaluating the ability on capturing and describing the difference between two images. There are many existing benchmarks targeting at this task. Early works [30,19] focus on changes in aerial imagery for monitoring disaster. Some other datasets [11,3] are about captioning the changes in street scenes, e.g., Spot-the-diff [13]. Recently, [23] proposes a more challenging change caption dataset, CLEVR-change, which utilizes the CLEVR engine to construct complicated synthetic scenes to evaluate models on finds more subtle change. One crucial limitation of previous works is that images can only present static information, thus status changes presented by two images only can involve a limited number of patterns, e.g., ”appear”, ”disappear”, ”add” and ”move”. Towards a generic understanding of change, we extend the setting from images to videos which supports a open set of change pattern, including human action change, scene state change, etc.

**Video Retrieval and Grounding** are both language-to-vision tasks. Given a text description of a video or event, Video Retrieval requires models to select the target video from the corpus [35,24], and Video Grounding requires models to locate the target event segment (i.e. start and end boundaries) from an untrimmed video [5,10,21,37,38]. These tasks are based on the event level understanding to find the best matching video or time span. Compared with previous works, our Boundary Caption-Video Retrieval and Boundary Grounding tasks require finding the matching moment that the instantaneous changes in the status of things.

**Generic Understanding** is a popular topic aiming to drive models from understanding predefined classes to open world vocabulary. Many pioneer works [4] propose open-set recognition tasks, which extend image classification tasks to generic understanding versions. Some works [14,40] introduce datasets for the generic event understanding requiring models to describe videos with natural language. More recently, a new dataset called Kinetic-GEBD [29] (Generic Event Boundary Detection) is proposed, which focuses on detecting the status changes between generic events. Our work is an extension to Kinetic-GEBD. We also study the boundary between events. However, we believe a sophisticated model should not only needs to know where the boundary is, but more importantly, explain why it is a boundary. Thus, this paper constructs a dataset with a large scale of boundary captions and introduces new boundary language-related tasks.

### 3 Benchmark Construction: Kinetic-GEBC

To build the Kinetic-GEBC dataset, we select 12,434 videos from the Kinetic-400 dataset and annotate 177,681 boundaries following a designed guideline and format. In total, our selected videos cover all the 400 categories of the Kinetic-400. It is split into 70% train, 15% val and 15% test non-overlapping sets. Several samples are shown in Fig. 2.
Boundary Collection

When annotating Kinetic-GEBC, one simple way would be directly captioning the boundaries in Kinetic-GEBD [29]. However, different people may have different opinions about where the event boundaries are, and sometimes the captioning annotators do not get why a certain event boundary was marked as in Kinetic-GEBD [29]. We find it more efficient to re-do the event boundaries annotation together with captioning annotation, to achieve the consistency.

Format and Guideline. Following GEBD [29], a boundary is defined as the splitter between two status of the subject in the video. Generally, we categorized our boundaries into five types: Change of Action, Change of Subject, Change of Object, Change of Color and Multiple Changes. When annotating, we accept both single timestamps and time ranges as in [29], and each video is allocated to at least five annotators. Each annotator could independently decide whether to accept or reject the video following the rejection criteria. The statistical results of annotation numbers and formats is shown in Table 3 and Table 4. Following [29], we set a minimum threshold for both temporal and spatial details’ level to ensure the consistency among different annotators. Further details are shown in Supp.

Table 2. Annotation number per video

| #Annotations | 1   | 2   | 3   | 4   | 5   |
|--------------|-----|-----|-----|-----|-----|
| #Videos      | 605 | 536 | 582 | 928 | 978 |
| Per. (%)     | 4.87| 4.31| 4.68| 7.46| 78.68|

Table 3. Timestamp v.s. Time Range

| Boundary | Num. | Time Range |
|----------|------|------------|
| Num.     | 172103| 4578      |
| Per. (%) | 97.41| 2.59      |

Caption Collection

In our Kinetic-GEBC, each annotator is supposed to add a natural language description for each boundary he or she annotated in Section 3.1. To clearly
and comprehensively represent humans’ understanding of the status changes, we randomly sampled 300 videos for pilot annotation, where we proposed and evaluated formats and guidelines for captioning.

**Format.** Our finalized format of the caption consists of three compulsory items: (1) Dominant Subject that performs the status changes. (2) Status Before the boundary of the subject. (3) Status After the boundary of the subject. In the pilot stage, we evaluate and compare different versions of annotation schemes, with the result shown in Fig. 3:

**One-Sentence format:** In the first scheme of format shown in Fig. 3, we only use a single sentence to describe the status change happening at the boundary. In order to obtain an open-vocab description close to daily language, we do not restrict or request anything to the expression and annotators have full autonomy in narrating. However, though this format could generate fluent and natural descriptions, we notice that there are significant problems in the annotations: (1) Ambiguity of subject: In the one-sentence caption with no further requests, annotators tend to describe the subject shortly, which could lead to ambiguity. For example, in scenes full of people, the short descriptions like “a man” could indicate multiple subjects, though the word itself is natural in daily language. (2) Dual changes: Without restriction, annotators could wrongly combine two state changes of different subjects together to describe a boundary, like “The man stops playing and an auditor starts clapping”. We found that the one-sentence format could easily lead to such mistakes. (3) Low efficiency: Sometimes the annotation could be slow, in that annotators need to spend some time on finding proper conjunctions to construct the sentences. Besides, our raters find it time-consuming to understand every description, since the sentence patterns vary a lot in different annotations.

**Two-Items format:** To address the problems in the one-sentence format, we separate the sentence into a “Subject” item and its “Change” item, like the example shown in Fig. 3. For the Subject item, annotators are required to fill in a noun phrase. We notice that this separation makes it easier for annotators to check the singularity and specification of their descriptions in “Subject”. And from Fig. 3 we see that the efficiency of both annotation and evaluation are improved. However, this scheme still have some shortcomings: (1) Incomplete status: In the pilot stage, we found annotators sometimes forget to describe the status before the boundary. For example, when describing an athlete’s changing from walking to running, an annotator only filled “starts to run on the track” in
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**Fig. 4.** Top. Distribution of boundary types in Train/Val/Test split. Bottom Left. Annotation numbers versus the numbers of boundary in the annotation. Bottom Right. Boundary numbers versus the duration of the interval before the boundary.

“Change” and forgot to mention the “walking” status before the boundary. (2) **Low efficiency:** Even though the separation of “Subject” and “Change” improves the efficiency, the “Change” item is still too long and could be overwhelming for auditors to evaluate. To solve the problems in Two-Items format, we further separate “Change” into Status Before and Status After to ensure the completeness of the status’ description. In the pilot stage, we find that this fully separated format is the most efficient and robust scheme for annotation as shown in Fig. 3.

**Guideline.** In our Kinetic-GEBC, the caption is defined as the reason why the annotator separates the preceding and succeeding segment of the boundary. Following the three-items format of annotation, we brought up some specific guidance for annotating the items. Specifically, when annotating the “Subject” item, annotators are required to provide distinguishable attributes of the dominant subject. However, in complex cases where the subject is difficult to describe without ambiguity (e.g. many people dressing similarly in the scene), the annotator could just describe some attributes to avoid verbose descriptions.

When annotating “Status Before” and “Status After”, annotators are required to limit their attention to the time range between the proceeding boundary and succeeding boundary, thus to ensure all the status changes in the same video are at the same temporal level. To further improve the consistency of expressions, we employ the symbol `/1` and `/0` to represent the appearance and disappearance of a subject in the scene, as shown in Example 2 of Fig. 2. Finally, we embrace all the tenses only if the annotators feel natural. In this way, we ensure the specification of descriptions while keeping their naturalness.

### 3.3 Statistics

**Splitting.** When splitting our Kinetic-GEBC into train, validation and test sets, the boundary type is the most important characteristic of consistency, since it determines which granularities the model should depend on to understand the
state change. We allocate videos containing different types of boundaries by proportion to ensure the distribution is the same in all splits. The final distribution is shown in Fig. 4, where we see the distribution is consistent in three splits. More details of splitting criteria is discussed in Supp.

**Boundary number.** To quantify the density of annotated boundaries, we make a statistics of the boundary number in each piece of annotation. Notably, due to the variant understanding of annotator, annotations of the same video could have different numbers of boundaries. The bottom left side of Fig. 4 shows the counts of annotations versus their boundary numbers, from which we could see that most of annotations have 1 to 4 boundaries.

**Boundary interval.** Furthermore, to investigate the duration of events located between two boundaries, we conduct the statistics on the length of intervals. For the first boundary in the video, we take the distance to the start of the video as its interval duration. The result is shown in the bottom right side of Fig. 4 which is similar to the statistic of boundary numbers.

**Part of speech comparison in caption.** For the captions in our dataset, we first analyze and compare the part of speech distributions in the subject and two status parts. In Fig. 5(a), the comparison result indicates that the status parts contain more verbs and focus more on actions than the subject part. On the other hand, the subject part includes more nouns and adjectives than the two status parts, suggesting it focuses more on appearance information.

**Frequent subjects and actions in caption.** To further analyze the different aspects of information in the three parts. In Fig. 5(b)(c), we extract the first noun in every Subject as well as the first verb in all Status Before and Status After, and then illustrate the 20 most frequent words. Same with Kinetic-400, we see that both the nouns and verbs in our datasets are mainly correlated with the appearance and motions of humans. This conforms to the scenarios of practical application, since humans are also the dominant subject in most of the scenes.

### 3.4 Adjustment for downstream tasks

Before applying Kinetic-GEBC, we post-process the annotations for the three downstream tasks. First, for the boundary annotated in time range, we convert them into timestamps by taking the middle point of the ranges. Secondly, nearly
all of the videos are annotated by more than one annotator. To exclude that
duplication, we compute the consistency F1 score following [29] and only select
the annotation with highest score in each video for downstream tasks. Finally,
this selection includes 40k boundaries from all videos.

Furthermore, we need to remark the ground truths for Boundary Grounding
and Boundary Caption-Video Retrieval. Specifically, if two different boundaries
are too similar in semantics for even humans, they are defined as a repetition
pair. When querying with the caption of one boundary in the pair, the timestamp
of another boundary is also a correct answer. To mark these repetition pairs,
we compared the captions of different boundaries. For Boundary Capiton-Video
Retrieval, we randomly sampled 300 boundary captions from different videos and
found no repetition pairs. However, for Boundary Grounding, we find plenty of
repetition pairs from the same videos. We employed Sentence-BERT to compute
the similarity score between the captions of every two boundaries from the same
videos. For the pairs scoring higher than a maximum threshold, we mark both
the timestamps as a correct answer towards each others’ captions. The details
of threshold selection are described in Supp.

4 Experiments

Kinetic-GEBC dataset enables us to benchmark how well current mainstream
methods could comprehend the instantaneous status changes in videos. For each
task, we implement and compare among SOTA models with our modifications.
Furthermore, we explore the input granularities and the modeling of visual dif-
ference in Section 4.2 which could be a stepping stone for further improvements.

4.1 Methods

Granularities of Input Features. We extract multiple granularities of features and utilize different combinations of them in experiments. Given each
boundary, we sampled multiple frames before and after the timestamp and one frame at the timestamp for further extraction.

Our features include: (1) ResNet: Firstly, we extract a 1024 dimensional ResNet-roi feature using ResNet [11] followed by Region of Interest (RoI) pooling. Then we extract another ResNet-conv feature to fit [23]: We sample one frame before and another frame after the boundary, then extract the Conv features from the two frames. (2) TSN: For frames before and after the timestamp, we extract a 2048 dimensional TSN feature for the before and after snippets using pre-trained TSN [33] network. (3) Faster R-CNN: For every sampled frame, we employ Faster R-CNN [28] to extract the 1024 dimensional R-CNN feature by selecting 20 objects with highest confidence. (4) C3D: Similar to the TSN feature, we extract 4096 dimensional C3D features with pre-trained C3D [31] network for the before and after snippets to fit [39].

These features are categorized into two granularities: **Instant-granularity** features extracted from the instantaneous appearance in a single frame, such as the R-CNN and ResNet features, are to provide fine-grained visual information of instants. **Event-granularity** features, like the TSN and C3D feature, could provide an overall representation of appearance and motion information in event snippets. We assume that developing a fine-grained understanding of status changes requires both the granularities.

**Backbones.** In experiments, we implement the following backbones, while the adoption and modification varies with tasks: (1) CNN+LSTM: A rudimentary backbone that simply uses a vanilla LSTM which takes the CNNs extracted features as input. The output of LSTM is mapped to caption tokens in Boundary Captioning, or is max-pooled to be the matching score in other two tasks. (2) Dual Dynamic Attention Model (DUDA): The baseline method in [23] which consists of a CNN-based Change Detector and a LSTM-based Dynamic Speaker. Besides, it utilizes a simple visual difference modeling by subtraction. (3) ActionBERT-revised: A one-stream BERT architecture using early fusion from [41]. We modify the structure by applying difference modeling after the embedding and employing different feature combinations. (4) UniVL-revised: A two-stream BERT architecture from [20], which includes a caption encoder, a context encoder and a cross-encoder for late fusion. We apply difference modeling to the context encoder and employ different feature combinations. (5) FROZEN-revised: A two-stream BERT architecture from [3], which includes a caption encoder and a context encoder with no fusion. The revision is the same as ActBERT-revised. (6) TVQA: The baseline method in [15], where we remove all the “answer” substreams and process each visual granularity with one stream. (7) 2D-TAN: The baseline method in [39]. Since all our candidates are processed as single timestamps, we only keep the diagonal elements in the 2D map and mask all other elements.

**Visual Difference Modeling.** Developing a fine-grained understanding of status changes at the boundary requires visual difference information. Current modeling methods are mostly designed for image pair differences [23], where the difference is obtained by simply subtracting the “before” image from the “after”
Table 4. Performance of Different Methods in Boundary Captioning. For UniVL-revised and ActBERT-revised, we apply the TPD Modeling and take the “ResNet-roi+TSN” combination as input feature.

| Method                        | CIDEr | SPICE | ROUGE-L |
|-------------------------------|-------|-------|---------|
|                              | Avg.  | Sub. Bef. | Aft. | Avg.  | Sub. Bef. | Aft. | Avg.  | Sub. Bef. | Aft. | Avg.  | Sub. Bef. | Aft. |
| CNN+LSTM                      | 49.73 | 80.11 | 34.39 | 34.69 | 13.62 | 18.84 | 9.92 | 12.10 | 26.46 | 39.77 | 20.77 | 18.83 |
| Robust Change Captioning      | 58.56 | 104.41 | 47.12 | 16.34 | 21.72 | 14.63 | 12.68 | 27.57 | 42.76 | 21.76 | 18.18 |
| UniVL-revised (two-stream)    | 65.74 | 91.51 | 56.58 | 49.13 | 18.06 | 21.08 | 17.06 | 26.12 | 40.67 | 19.42 | 18.28 |
| ActBERT-revised (one-stream)  | 74.71 | 85.33 | 75.98 | 62.82 | 19.52 | 20.10 | 19.51 | 28.15 | 39.16 | 23.70 | 21.60 |

Table 5. Ablation study results of the Boundary Captioning utilizing ActBERT-revised, as well as the performance comparison of visual difference modeling methods.

| Input Granularity | CIDEr | SPICE | ROUGE-L |
|-------------------|-------|-------|---------|
|                   | Avg.  | Sub. Bef. | Aft. | Avg.  | Sub. Bef. | Aft. | Avg.  | Sub. Bef. | Aft. | Avg.  | Sub. Bef. | Aft. |
| ResNet-roi        | 51.93 | 67.79 | 46.59 | 41.42 | 14.30 | 16.01 | 13.34 | 24.29 | 35.42 | 19.04 | 18.13 |
| ResNet-conv       | 66.18 | 96.86 | 54.77 | 46.91 | 17.07 | 20.58 | 15.82 | 26.30 | 40.38 | 19.17 | 18.82 |
| TSN               | 70.80 | 92.54 | 65.64 | 54.21 | 19.00 | 20.97 | 18.98 | 26.89 | 40.53 | 20.82 | 19.32 |
| ResNet-roi + ResNet-conv | 56.64 | 83.82 | 45.64 | 40.45 | 15.68 | 19.17 | 13.77 | 14.11 | 25.46 | 38.64 | 19.26 | 18.47 |
| ResNet-conv + TSN  | 69.58 | 83.56 | 68.88 | 56.3 | 18.95 | 20.15 | 19.51 | 27.14 | 38.52 | 22.36 | 20.53 |
| ResNet-roi + TSN   | 74.71 | 85.33 | 75.98 | 62.82 | 19.52 | 20.10 | 19.51 | 28.15 | 39.16 | 23.70 | 21.60 |
| ResNet-roi + ResNet-conv + TSN | 65.83 | 80.89 | 63.22 | 53.38 | 18.69 | 19.37 | 19.25 | 28.43 | 37.82 | 22.11 | 20.59 |
| ResNet-roi + TSN (w/o Diff.) | 67.38 | 85.59 | 63.06 | 53.49 | 18.47 | 19.84 | 18.09 | 16.87 | 24.23 | 31.65 | 21.14 | 19.99 |
| ResNet-roi + TSN (simple)  | 67.75 | 85.31 | 64.28 | 53.65 | 18.96 | 20.35 | 19.13 | 26.78 | 39.14 | 21.20 | 20.00 |
| ResNet-roi + TSN       | 74.71 | 85.33 | 75.98 | 62.82 | 19.52 | 20.10 | 19.51 | 28.15 | 39.16 | 23.70 | 21.60 |

image. A simple inference of this method to video tasks would be pooling the sampled frames and then subtracting. However, this modeling method could only provide an event-granularity representation of the visual difference between the before and after snippets, and will lose the instant-granularity visual differences after pooling.

To address this problem, we design a new method of Temporal-based Pairwise Difference (TPD) Modeling for BERT models. As shown in Fig. 6, our method consists of two parts. Using the feature embeddings of the frames sampled in Section 4.1, we compute the pairwise subtraction between the embedding of frames in ”before” and ”after” as Part a, this part of difference provides a fine-grained and wide-viewing visual comparison between the status before and after. To represent the visual difference between the boundary and other sampled timestamps, we further compute Part b and Part c, which includes the pairwise subtraction between the frame embeddings at the boundary and that before or after the boundary. Finally, we concatenate all these differences together as the output of TPD Modeling.

The advantage of our TPD Modeling is that, compared with previous methods designed for image tasks, it provides multiple granularities of information and ensure the fine-grained representation of visual differences. In the ablation study of Boundary Captioning, we design an experiment to explore the difference modeling methods and verify our perceptions.

4.2 Boundary Captioning

For Boundary Captioning, we first implement and compare the performance of CNN+LSTM, DUDA, UniVL-revised and ActBERT-revised. To further explore how different input granularities support the understanding, we design a series
of ablation studies using ActBERT-revised for all combinations of input features. In these two experiments, we apply our TPD Modeling as shown in Fig. 6.

To find the best schemes to represent visual difference, we further compare the performances of three schemes on ActBERT-revised: (1) Embedding with no difference modeling. (2) Max-pooling the frames before and after the boundary and simply subtracting one from another, which is inferred from the current method in [23]. (3) Using TPD Modeling to represent the visual differences.

Implementation Details. For CNN+LSTM and DUDA, we utilize the ResNet-conv feature as did in [23]. For UniVL-revised and ActBERT-revised, we utilize the ResNet-roi feature and TSN feature described in Section 4.1, where the sampling range is from the preceding boundary to the succeeding boundary. In evaluation, we separate the prediction into Subject, Status Before and Status After, and then compute the similarity score of each item with the ground truth. After that, we employ CIDEr [32], SPICE [2] and ROUGE-L [17] as evaluation metrics, which are widely utilized in image and video captioning benchmarks. Further details are discussed in Supp.

Result. From Table 4 and Table 5, we see that the ActBERT-revised backbone with "ResNet-roi+TSN" features performs the best, and our TPD Modeling method brings significant improvements. However, the results in Table 4 are still far from satisfactory, thus we further analyze the challenges of our task and derive some conclusions through the result in Table 4:

Accurate captioning of the status changes requires both the instant and event granularities. Firstly, the event-granularity features perform as the base of the understanding. In Table 5, the "ResNet-roi+TSN" combination outperforms all the groups employing only the instant-granularity features (e.g. only using the combinations of ResNet features). Secondly, proper usage of the instant-granularity features could help to enrich the understanding, which could be seen in Table 5, where the "ResNet-roi+TSN" combination outperforms the single "TSN" feature.

Our task requires adaptive usage of different granularities. Machines need to know when to look at which granularity. Simply assembling different features together could sometimes disturb the attention thus rendering the performance worse. In Table 5, when only utilizing the TSN feature, the performance is better than employing either the "ResNet-roi+TSN" or the "ResNet-roi+ResNet-conv+TSN" combination, and the combination of "ResNet-roi+TSN" also outperforms "ResNet-roi+ResNet-conv+TSN". This disturbance also appears in specific items, when only using the ResNet-conv or the TSN feature, the scores in "Subject" are higher than assembling them with other features.

Understanding the status changes requires effective modeling of visual differences. In the comparison of difference modeling schemes in Table 5, the plain embedding without difference modeling performs the worst, while the utilization of simple-subtraction difference modeling brings little improvement to the performance. However, the group with our TPD Modeling method significantly outperforms others. This gap in performance conforms to our perspective that
Table 6. Performance comparison among different methods in Boundary Grounding. For UniVL-revised and ActBERT-revised, we apply TPD Modeling and take the “ResNet-roi+TSN” combination as input feature.

| Method              | Threshold (s) | 0.1 | 0.2 | 0.5 | 1   | 1.5 | 2   | 2.5 | 3   | Avg. |
|---------------------|---------------|-----|-----|-----|-----|-----|-----|-----|-----|------|
| Random Guess        |               | 2.14 | 4.56 | 11.46 | 22.81 | 31.63 | 40.41 | 48.06 | 54.37 | 26.93 |
| TVQA                |               | 2.60 | 5.30 | 12.90 | 23.73 | 32.94 | 41.33 | 48.56 | 55.17 | 27.82 |
| 2D-TAN              |               | 2.91 | 6.32 | 15.04 | 26.95 | 36.94 | 45.34 | 51.87 | 58.22 | 30.45 |
| ActBERT-revised     |               | 3.12 | 6.14 | 14.79 | 26.78 | 36.61 | 45.45 | 52.99 | 59.41 | 30.66 |
| FROZEN-revised      |               | 4.28 | 8.54 | 18.33 | 31.04 | 40.48 | 47.86 | 54.81 | 61.45 | 33.35 |
| FROZEN-revised-GEJB |               | 4.28 | 8.48 | 18.49 | 29.91 | 39.54 | 48.37 | 55.29 | 61.55 | 33.23 |

learning a fine-grained understanding of status changes requires not only an overall but also a fine-grained representation of visual differences.

4.3 Boundary Grounding

In Boundary Grounding, we implement and compare the performance of four backbones: TVQA, 2D-TAN, FROZEN-revised and ActBERT-revised. Given a video and the caption query, the model is to compute the matching scores of each candidate sampled from the video, and then the post-processing is employed to finalize the prediction.

**Implementation Details.** In the training period, we use the ground truth processed in Section 3.4. In testing, we employ two strategies to sample the candidate timestamps: (1) By default, we sample a candidate for every 3 frames, since most of the videos in our datasets are in 30fps, the most common interval between two candidates is 0.1s. (2) If attached with GEBD, the boundary candidates are generated using the baseline in [29].

When implementing 2D-TAN, we utilize the C3D feature as in the original work. For TVQA, we utilize the R-CNN and ResNet-roi features as context. Besides, we build the triplets consisting of one positive and two negative pairs, and then compute the cross-entropy loss for each triplet in training. In ActBERT-revised and FROZEN-revised, in the training period, we apply the contrastive loss in FROZEN [3] as objective. Moreover, we implemented a batch-randomed sequential sampler in training to ensure that most boundaries in the same videos are also in the same batches. This strategy encourages the model to learn the visual differences within a video.

After the models generate the matching scores of all candidate timestamps, we apply the Laplace-of-Gaussian filter in [29] to derive local maximas of the scores. Then we select the top-k maximas as final prediction, where k is subject to the statistical number of ground truth timestamps marked in Section 3.4. To evaluate the accuracy of the prediction, we compute F1 scores based on the absolute distance between ground truth timestamps and predicted timestamps, with the threshold varying from 0.1s to 3s. Further details are discussed in Supp.

**Result.** We see that FROZEN-revised performs the best in the comparison of SOTA methods in Table 6. However, all the SOTA methods struggle when the threshold is less than 1s, indicating that improving the temporal resolution of understanding is still a main challenge of our task. Future improvements still
Table 7. Performance comparison of different methods in Boundary Caption-Video Retrieval. For FROZEN-revised, we add another group without difference modeling

| Method                                      | mAP  | R@1  | R@5  | R@10 | R@50 |
|---------------------------------------------|------|------|------|------|------|
| Random                                      | 2.39 | 0.05 | 0.23 | 0.44 | 2.52 |
| CNN+LSTM                                    | 9.25 | 4.08 | 12.49| 19.53| 42.26|
| ActBERT-revised (one-stream)                | 19.14| 9.52 | 28.89| 40.14| 64.50|
| FROZEN-revised (two-stream)                 | 23.39| 12.80| 34.81| 45.66| 68.10|
| FROZEN-revised (two-stream) w/o diff        | 22.44| 12.12| 33.42| 43.89| 65.61|

need to focus on how to delve deeper into the temporal details and prevent the models from taking a glance and learning a rough impression of status changes.

4.4 Boundary Caption-Video Retrieval

We implement and compare the performance of the CNN+LSTM, FROZEN-revised and ActionBERT-revised backbones. Same as in Boundary Grounding, the backbones is to compute the matching score between the query and context.

Implementation Details. Similar to Boundary Grounding, in this task we also let the models compute the matching score. However, in order to find the target video from the corpus, each query is to be tried to match with every boundary candidate from all videos. Considering the corpus size, we only apply the baseline in [29] to generate the boundary candidates. When implementing CNN+LSTM, we take the R-CNN and ResNet-roi features as visual contexts. In the FROZEN-revised and ActBERT-revised, we utilize the same configuration with Boundary Grounding. To evaluate the retrieval accuracy, for each query, we sort all the videos by the highest scores of the boundary candidates inside them, then we compute the mAP and recall and average the metrics for all queries.

Result. In Table 7, the accuracy of FROZEN-revised with difference modeling is higher than that without difference modeling. However, the performance gap is significantly smaller than in Boundary Captioning, suggesting that the video-level retrieval task relies less on the fine-grained visual differences. This result is natural since the overall video-level understanding is already enough to distinguish the target among different videos. Due to space limitations in the main body, we show the qualitative results in Supp.

5 Conclusion

In this paper, we have introduced our new dataset Kinetic-GEBC and the methods of benchmark construction. For the new dataset, we proposed three tasks that aim to develop a more fine-grained, robust and human-like understanding of videos based on status changes. After that, we further explore the challenges with designed experiments, where we design a new Temporal-based Pairwise Difference (TPD) modeling method to represent visual differences and obtain significant improvement in performance.

Concluding the results from the experiments, we summarize the challenges of our benchmarks as three parts: (1) How to adaptively utilize multiple granularities of features and exclude the disturbance. (2) How to effectively represent
the visual differences around the boundary. (3) How to improve the temporal resolution of understanding.

We believe our work could be a stepping stone for future works to develop more powerful methods to understand status changes and thus improve video-level comprehension. In the future, we plan to combine with the methods in [29] to form an end-to-end baseline and improve the detection accuracy with the captions in our dataset.

Supp: Overview

In the supplementary material, we provide a video illustrating the basic information of our dataset (Sec. 6 and the video under supplementary folder), more details of annotations (Sec. 7) and more implementation details of the baselines (Sec. 8).

6 Supp: List of Contents in the Attached Supplementary Video

In our submitted supplementary video, we illustrate four parts of our work: (1) Annotation Interface. The interface we designed for our annotators. (2) Examples for Boundary Types. Several samples of boundaries from our Kinetic-GEBC dataset that due to different types of status changes. (3) Annotation Formats and Examples. Visualized comparison among different format schemes of caption annotating, as well as the finalized raw annotation towards a sample video. (4) Visualization of Predictions. Examples of predictions generated by the best-performing method in Boundary Captioning, Boundary Grounding and Boundary Caption-Video Retrieval.

7 Supp: More Details of Annotations

7.1 Boundary Definition

Specifying the level of details. A great number of our video sources from Kinetic-400 contain more than one actor or object with different levels of status changes, and different annotators could have high-variance opinions on the boundary positions. According to [29], to reduce the variance among annotators, the highest priority is to specify the level of the spatial and temporal details we take into consideration. For the level of spatial details, we only focus on the events that are performed by dominant subjects. For the level of temporal details, we only consider the “one-level-deeper” granularity as in [29]. By specifying this, we ensure that most of the boundaries are in the same granularity, rendering it possible for annotators to basically reach an agreement on the boundary location without predefined classes.
Embracing the Ambiguity. Knowing the specified level of details, however, different annotators could still have some disagreements on the dominant subjects and the “one-step-deeper” granularity events. Following [29], we embrace this varsity when annotating. For each video, we take all the annotations as correct. Then we supervise the consistency among different annotations towards the same video by calculating the F1 score in Section 7.2.

7.2 Quality Assurance

Criteria for Rejecting a Video. To ensure the quality of videos, we designed a rejection criteria for annotators to filter the video sources. Each video is simultaneously allocated to at least 5 annotators, and each annotator could independently decide whether to annotate or reject the video. Following [29], the criteria is designed based on the understandability and the boundary number of the video. Specifically, a video is expected to be rejected in four cases: (1) Not understandable due to blurry or overspeeding. (2) Contains no boundary or too many boundaries. (3) Includes shot changes like zooming, panning or cutting. (4) Violating content. The statistics on the number of annotations in all selected videos is shown in Table 8. We could see that a majority of videos are accepted by at least 5 annotators, indicating the consistency of annotators’ opinions on our annotated videos.

| Table 8. Annotation number per video | Table 9. Timestamp v.s. Time Range |
|--------------------------------------|-----------------------------------|
| #Annotations | 1 | 2 | 3 | 4 | 5 | Boundary Timestamp | Time Range |
| #Videos     | 605 | 536 | 582 | 928 | 9783 | Num. | 172103 | 4578 |
| Per. (%)    | 4.87 | 4.31 | 4.68 | 7.46 | 78.68 | Per. (%) | 97.41 | 2.59 |

Evaluation of Annotators’ Consistency. Following [29], we compute F1 score to evaluate the consistency of the annotations towards the same videos. When computing, we take the timestamps of each annotation as the “prediction” and all other annotations in the same video as the “ground truth”. Then for each threshold varying from 0.2s to 1s, we compute the precision and recall for the ”prediction” to obtain its F1 score. Finally, we average the F1 scores under all thresholds as the final result of the evaluation. The distribution of the average F1 score is shown in Fig. 7 where over 92% percent of annotations are scored higher than 0.4, suggesting the high consistency of annotators’ opinions on the boundary position.

7.3 Statistics based on the Video Categories in Kinetic-400

Since we take the “one-step-deeper” events in videos as [29], the video-level categories in Kinetic-400 could not determine the pattern of events. However, the category provides a higher-level background for our events, thus we conduct further statistics towards it.
Fig. 7. Distribution of consistency F1 scores in all annotations. We first compute the F1 scores with different thresholds from 0.2s to 1s, and then average the scores in all thresholds as the final score.

Fig. 8. Left. Average number of boundaries in videos in each Kinetic-400 category. Right. Average duration of boundary intervals in videos in each Kinetic-400 category.

Boundary Number and Interval Duration. Firstly we investigate the distribution of boundary numbers in each category of videos. Given a Kinetic-400 category, we compute the average number of boundaries per video in the category. From the result in Fig. 8 we see that the boundary numbers slightly vary with the category and most categories have 2 to 3 boundaries per video. We also illustrate the interval durations versus categories in the right of Fig. 8. In most categories of videos, we could see the average duration of boundary intervals is around 2s.

Distributions in Splits. Furthermore, we conduct statistics on the video numbers of each category in our train/val/test splits. The percentage distribution is shown in Fig. 9 where the categories are sorted by their video numbers in the entire dataset. We see that the categories’ distribution in the three splits are consistent with the distribution in the entire dataset.
Fig. 9. Percentage distributions of the videos in each Kinetic-400 category in the entire dataset and the train/val/test splits. The categories are sorted by their video numbers in the entire dataset.

7.4 Details of the Adjustment for Downstream Tasks

In the raw annotation of Kinetic-GEBC, each video is allocated to more than 5 annotators. Due to the variance of annotators’ opinions, the boundary locations in different annotations towards the same video are not the same. When preparing the data for downstream tasks, we utilize the simplest filtering strategy that only keeps the annotation with highest F1 score (computed in Section 7.2) for each video. Finally, we collected 40,000 from the total 176,681 boundaries in 12,434 videos.

In addition, the videos in our Kinetic-GEBC could sometimes contain repeated events or actions, which could disturb the Boundary Grounding task. We found that the difference among some repetition boundaries within a video is too subtle even for humans to distinguish. Therefore, we need to find these repetition pairs of boundaries and mark them as “equal” boundaries to each other for the Boundary Grounding task. Specifically, when queried by a boundary caption, the machine is supposed to answer the locations of that boundary as well as all the “equal” boundaries. An example is shown in Fig. 12, where the man changes his status from sitting to standing twice in the video, thus these two status changes are marked as a repetition pair.

To find and mark these repetition pairs, we employ Sentence-BERT [27] to compute the similarity score between the annotated captions of every two different boundaries inside a video. Firstly, we take the 40,000 filtered annotations with the highest F1 score. Then for each video, we combine every two of its boundaries to form all the possible pairs. After that, we separate each pair of captions into subject, status before and status after items, and then compute the similarity score for each item using Sentence-BERT. The range of similarity scores is from 0 to 1. In order to distinguish these repetition pairs, we need to set a maximum threshold for similarity scores. First we find that the item pairs scoring less than 0.9 usually have significant differences that are easy for humans to recognize. Hence, we collect the pairs of all the three items that score higher than 0.9, and then we annotate manually to classify if each pair is a repetition pair. After that, we simulate the decision accuracy of different candidate thresholds varying from 0.9 to 1.0 and finally choose 0.93 as the threshold, where the corresponding accuracy is 95.5% (i.e. the 2-sigma probability in normal distribution). Finally, we found and marked 4,426 repetition pairs consisting of 4,295 boundaries.
7.5 More Examples of Kinetic-GEBC

Here we illustrate more examples from our Kinetic-GEBC in Fig.10. The Example 1 to 4 are all based on Change of Action. The Example 5 is based on Change of Subject, since the man was at first appearing in the scene and then disappears after the boundary. In Example 6, the color of the stage suddenly changes from blue to pink, causing the boundary based on Change of Color. In Example 7, the woman was first interacting with the trophy and then retreats her hands to stop interacting after the boundary. This boundary is thus due to the Change of Object being interacted with. Finally in Example 8, the boundary is based on Multiple types of status changes. The man in the scene changes his action and simultaneously stops interacting with the iron ball at the boundary.

8 Supp: Implementation Details

8.1 Schemes for frame sampling

In all our experiment groups, if not specified, we employ the two following schemes for frame sampling:

**Scheme 1.** In most cases, when using the ground truth boundaries, we set two sampling ranges before and after each boundary timestamp. For the range before the boundary, we set the preceding boundary as the start and the current boundary as the end. Similarly, the range after is between the current boundary and the succeeding boundary. Notably, the predecessor of the first boundary in videos is set to 0, and the successor of the last boundary in videos is set to the end of videos. Finally, we sample 10 frames in each range and 1 frame at the timestamp of the current boundary. This scheme is also employed when using the proposal timestamps generated by GEBD baseline [29].

**Scheme 2.** Sometimes there is no predefined boundary or proposal like in the testing period of Boundary Grounding, and thus the locations of the preceding and succeeding timestamps are unknown. Therefore, we replace the predecessor and successor with the timestamps 1s before and after the current timestamp. Then we sample 10 frames in each range and 1 frame at the candidate timestamp for further extraction.

8.2 Further Details in Training

For each backbone utilized in our experiments, we trained for 50 epochs. For all the BERT based models, we used AdamW optimizer with a linearly decreasing learning rate starting from $5 \cdot 10^{-5}$. Notably, in Boundary Grounding we modify the original contrastive loss in FROZEN [3] by adding an additional intra loss. Given a batch of embeddings, the intra loss is computed in the same way yet only among the caption and context embeddings from the same videos. Besides, as mentioned in previous sections, we design a batch-random sequential sampler for Boundary Grounding. It ensures more boundaries in the same video to be collected in the same batch, since the boundaries are sequentially sorted by their videos in
the dataset. This intra loss and new sampler encourage the model to learn the differences among the boundaries in the same videos, which conforms to the goal of Video Grounding that is selecting the best match among all timestamps in a video.

8.3 Post-processing and Evaluation

In Boundary Captioning, we separate and evaluate the Subject, Status Before and Status After items of the generated captions. We found that the conventional BLEU [22] metric is not suitable for our task and its scores are often inconsistent with humans' impression, since it only considers the simple repetition of word grams. Samples of predicted captions in a video are illustrated in Fig. 11. We see that the first two generated captions are relatively great, while the caption generated from the last boundary is not satisfying. For Boundary Grounding, we conduct a post-processing after the models generating the matching scores of all candidates. First we apply the LoG filter [18] to find the local maximas following [29]. Then we select the top-\(K\) maximas as final prediction following the statistics of the ground truth timestamp numbers for all queries. After that, we evaluate the finalized prediction by calculating the F1 score under different thresholds, where the computation is the same as in Section 7.2. Samples of predictions are shown in Fig. 12. Notably, the boundaries at 00:00.93 and 00:06.11 are a pair of repetition boundaries, thus we mark both of their timestamps as the ground truths for their caption queries. For Boundary Caption-Video Retrieval, several samples of predicted ranking are illustrated in Fig. 13. For the first three samples in the figure, the prediction result is relatively satisfying and the ground truth video is within the top-5 of the ranking. However, given the caption of the last sample in the figure, the machine could not clearly recognize the target video from the corpus, and the ground truth video is ranked to \#42.
Example 1
Subject: man in white t-shirt and black shorts
Status Before: taking the steps backward
Status After: take the steps towards the left
Change of Action

Example 2
Subject: man in red t-shirt and red shorts
Status Before: sitting down holding the barbell
Status After: stand up holding the barbell
Change of Action

Example 3
Subject: man in black vest
Status Before: lifting the barbell from the weight rack
Status After: lower the barbell downwards
Change of Action

Example 4
Subject: human hand with toothbrush
Status Before: taking the brush towards the shoe
Status After: scrub the shoe with the help of the toothbrush
Change of Action

Example 5
Subject: man in orange jacket
Status Before: / 
Status After: / 
Change of Subject

Example 6
Subject: man in black shirt and woman in stripe one piece
Status Before: dancing on the floor in the blue color lights
Status After: dance in the pink color light
Change of Color

Example 7
Subject: woman in orange hoodie and pants with a blue cap
Status Before: standing on the left and handing over a trophy to a man
Status After: retreat the hands from the trophy
Change of Object

Example 8
Subject: man in black shorts and black tank top
Status Before: running back and turned back
Status After: throw the iron ball and stand straight
Multiple (Change of Action + Object)

Fig. 10. More samples from Kinetic-GEBC dataset
Input Caption:
Output Caption:
Ground Truth:

Input Video:

Input Caption:
Output Caption:
Ground Truth:

Fig. 11. Samples of Prediction in Boundary Captioning

Input Video:

Input Caption:
Output Caption:
Ground Truth:

Input Video:

Input Caption:
Output Caption:
Ground Truth:

Input Video:

Input Caption:
Output Caption:
Ground Truth:

Input Video:

Input Caption:
Output Caption:
Ground Truth:

Input Video:

Input Caption:
Output Caption:
Ground Truth:

Input Video:

Input Caption:
Output Caption:
Ground Truth:

Fig. 12. Samples of Prediction in Boundary Grounding

Input Video:

Input Caption:
Output Ranking of Videos by Boundaries:
Ground Truth:

Input Video:

Input Caption:
Output Ranking of Videos by Boundaries:
Ground Truth:

Input Video:

Input Caption:
Output Ranking of Videos by Boundaries:
Ground Truth:

Input Video:

Input Caption:
Output Ranking of Videos by Boundaries:
Ground Truth:

Fig. 13. Samples of Prediction in Boundary Caption-Video Retrieval
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