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| |  |  |  |  |
| Ground Truth | woman hold knife knife cut meat meat placed on chopping board chopping board on table | hand hold towel water wet towel tower scrub baby baby hold toy duck basin filled with water toy duck float on water | left hand hold handcuffs right hand hold woman handcuffs handcuff woman | syringe inserted into slice of bread wheat next to slice of bread |
| ClipCap | man hold knife knife cut meat meat placed on chopping board chopping board on table | right hand hold toothbrush toothbrush inside mouth | crowd sit on chair crowd look at man | left hand press bread right hand hold knife knife cut bread |
| Git | man hold hammer hammer beat nail nail nailed to wooden board | boy hold toy duck toy duck in bathtub | crowd sit on chair crowd look at man | electric drill drill bread |
| Ours | man hold knife knife cut meat meat placed on chopping board chopping board on table | boy sit in bathtub boy hold toy toy immersed in water water in bathtub | man hold handcuffs handcuffs handcuff woman | syringe pierce bread bread placed on chopping board |

Figure 7: Comparisons of triplets generation across diverse OVRE methods. The illustration highlights accurately described triplets in green, triplets with semantic correlation in blue, and irrelevant triplets in red.

algorithm to obtain 5 tracklet features per video. These features replace patch features as input to the model. Specifically, we utilize RegionCLIP (?) pre-trained from LVIS to crop bounding boxes and seqNMS (?) for object tracking. (II) Frame features: We directly utilize features extracted from individual frames using CLIP, concatenating them to form a representation of frame-level features. As depicted in Table 4, both frame features and region features exhibit poor performance. Notably, frame features capture the overall visual content of an image but overlook finer details such as objects and relationships. Surprisingly, region features fare even worse compared to frame features. We hypothesize that this is attributed to the limited generalization capability of existing object detectors. The diverse range of object categories complicates their accurate detection within our Moments-OVRE context.

Conclusion

In this paper, we introduce a new task named OVRE, where the model is required to generate all relationship triplets associated with the video actions. Concurrently, we present the corresponding Moments-OVRE dataset, which encompasses a diverse set of videos along with annotated relationships. We conduct extensive experiments on Moments-OVRE and demonstrated the superiority of our proposed approach over other baseline methods. We hope that our task and dataset will inspire more intricate and generalizable research in the realm of video understanding.

Limitations: (I) This version of Moment-OVRE has currently omitted BBox annotation due to the high cost of an-

notation. We are committed to progressively enhancing this dataset and intend to introduce BBox annotations in upcoming versions of Moments-OVRE. (II) For extracting action-centric relations, leveraging commonsense among action categories and relations (?) or implicit knowledge-driven representation learning methods (??) have shown promise. We will consider these knowledge-driven methods in future work.

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