Object-Oriented Video Captioning with Temporal Graph and Prior Knowledge Building

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Abstract. Traditional video captioning requests a holistic description of the video, yet the detailed descriptions of the specific objects may not be available. Besides, most methods adopt frame-level inter-object features and ambiguous descriptions during training, which is difficult for learning the vision-language relationships. Without associating the transition trajectories, these image-based methods cannot understand the activities with visual features. We propose a novel task, named object-oriented video captioning, which focuses on understanding the videos in object-level. We re-annotate the object-sentence pairs for more effective cross-modal learning. Thereafter, we design the video-based object-oriented video captioning (OVC)-Net to reliably analyze the activities along time with only visual features and capture the vision-language connections under small datasets stably. To demonstrate the effectiveness, we evaluate the method on the new dataset and compare it with the state-of-the-arts for video captioning. From the experimental results, the OVC-Net exhibits the ability of precisely describing the concurrent objects and their activities in details.

Keywords: Video understanding, video captioning, object-level analysis, temporal graph

1 Introduction

With the rapid growth of videos on the Internet, it becomes more important to automatically understand the videos. Video captioning calls for a systematic description of the videos, which is an intriguing challenge to learn the connections between vision and natural language [39,35,21,41,17,19,33]. With the methods of image captioning gradually getting matured [37,11,20], more and more attention shift to video captioning [13,15,31,28,34,10]. Video captioning has significance to human-robot interaction and visually impaired people [19,33].

Previously, video captioning requests a holistic description of the entire video with fewer detailed information associated with objects. Actually, while human watching video, instead of focusing on the entire video, we pay attention on specific objects and the associated attributes/actions based on different interests.
Fig. 1. In natural videos, there are multiple concurrent objects and activities. We propose the object-oriented video captioning aimed at understanding the videos in object-level, which can describe concurrent objects and activities with more details.

Therefore, comparing to giving a coarse description of the video, it seems to be more meaningful to allow detailed descriptions on object-level.

So far, most works of video captioning are frame-level based approaches [39, 35, 21, 14, 11, 17, 19, 38, 13, 31, 38, 32, 7] under the encoder-decoder structure and use video-sentence pairs for training. Each video has multiple sentences for different objects. However, with the frame-level features, which are inter-tangled among all the objects and the ambiguous descriptions, it is difficult for the captioning system to find the relationships between objects and sentences. Therefore, when multiple objects exist, most previous methods can neither accurately learn the connections between the vision and text, nor can they generate precise descriptions for different objects with detailed information.

In previous works, the features of a single frame are independently extracted without definite temporal associations of objects among consecutive frames. Therefore, besides the visual features, most works adopt the models for action recognition [29, 10, 9] to extract the spatio-temporal 3D convolutional (C3D) features as temporal cues [13, 33, 32, 16, 36]. Nonetheless, most datasets for action recognition only consist of actions of human. However, in the datasets for video captioning, the main objects sometimes are not human, e.g., animal, vehicle etc. More critically, there is only a single object which has activities in the videos for action recognition. While in videos for video captioning, most videos have multiple concurrent objects, and all the objects have individual or interactive activities. Hence, using the pretrained models for action recognition to extract temporal information on the videos for video captioning brings two problems: one is it cannot capture effective features under the situation of multi-objects; the other is that it cannot capture the action information of the objects which are not human. Besides, the C3D features and the visual features are usually independent, which means that these two kinds of features fed into a recurrent neural network (RNN) at the same time step always represent the information of different frames, resulting in confusion in the training of neural networks.
To overcome these limitations, we propose a novel task, named object-oriented video captioning transforming the video-level captioning to object-level. We further design the video-based object-oriented video captioning (OVC)-Net instead of the image-based methods. The main contributions of our work are three-fold:

Object-oriented video captioning. We shift the holistic video captioning to object-level. Instead of a rough and holistic description of the entire video, we aim at understanding the video in object-level. This strategy is closer to human thinking while watching videos. Understanding the activities in object-level leads to detailed understanding of the videos, deserving more of our attentions.

Object-oriented video captioning network. We design the object-oriented video captioning network (OVC)-Net to replace previous image-based methods. We build the object-oriented temporal graph to achieve the aim of reasoning activities along time without any supplementary cues from other tasks. Our OVC-Net can analyze the activities along time with only visual features, allowing the proposed method turn into real video understanding.

Object-oriented video captioning dataset. All available datasets for classical video captioning just have the video-sentence pairs. With the uncertain one-to-many video-sentence pairs, it is difficult to learn the vision-language connections. We re-annotate a portion of videos from the ActivityNet dataset with object-sentence pairs. With this kind of data, we can learn the functional the vision-language functional and translational relationships more effectively.

We conduct experiments on the new dataset and compare with the state-of-the-arts for video captioning. The experimental results demonstrate that our proposed approach can achieve the state-of-the-art performance in terms of BLEU@4, METEOR, CIDEr and ROUGE-L metrics [22,30,18,2]. More importantly, our proposed method can understand most concurrent activities with more details rather than giving a holistic description.

The paper is organized as follows. Section 2 overviews recent related works. Section 3 describes our OVC-Net in details. In Section 4, we first introduce the re-annotated dataset. Then, report the experimental results and give the ablation study. Finally, Section 5 presents the conclusions and future works.

2 Related Works

Video captioning, which bridges two modalities: vision and language, poses a great challenge for artificial intelligence. Recently, a large number of methods have been proposed for video captioning, where the encoder-decoder architectures have been widely adopted [19,33,37,13,15,31,33,32,1,18,25,27,12]. The encoder learns a high-level representation of the video, then the decoder generates the descriptions word-by-word for the high-level representation. The encoder is commonly a pretrained convolutional neural network (CNN), e.g., VGG19 [20], Inception v4 [28] and DenseNet [14]. The decoder usually adopts a recurrent neural network (RNN), e.g., long short time memory (LSTM) [12] and gated recurrent network (GRU) [5]. With the development of attention mechanism, Xu et al. and Liu et al. adopt a spatial attention to automatically exploit impact of
different regions in each frame [19,37]. A lot of works focus on exploiting the
temporal information to select the key frames for the current word generation
[38,40,27]. Considering most works relying on the forward flow from videos to
sentences, Wang et al. refer to the idea of dual learning and propose RecNet [33]
to exploit the backward flow (sentence-to-video). On top of captioning system,
RecNet stacks another module to reconstruct the visual features.

So far, most methods executed as image-based methods which utilize the
frame-level features via pretrained models for image classification [39,35,21,11,17,19,33,13,31,38,32,10,10,6]. The holistic features for different frames are in-
dependently extracted without temporal associations of objects. To explore the
moving trajectories, some works introduce tracking operations into video cap-
tioning. Zhang et al. build the object-aware aggregation with a bidirectional
temporal graph (OA-BTG) [42] to track salient objects in the video. Nonethe-
less, they merge all objects by adding their visual features without associating
the trajectories. The mixed features act as a complement for the frame-level
features, resulting in less perfect performance.

In addition, natural videos usually contain numerous concurrent events, it is
difficult to reveal much information with only one sentence. To capture multiple
activities, Li et al. [16] propose dense video captioning which bridges two separate
tasks: temporal action location and video captioning. It requires to locate a set
of clips where events happen and describe the predicted clips. Despite it can
describe multiple events, it still cannot analyze specific object instances. For
available short clips, dense video captioning still performs the same as previous
video captioning.

Overall, previous video captioning fails to provide sufficient information for
object-level analyses. Moreover, although significant improvements have been
achieved, most methods are image-based which cannot reason the step-by-step
object-level activities along time.

In this paper, we propose a novel task for object-oriented video captioning,
which shifts the video-level based captioning to object-level based video cap-
tioning. To learn the activities better, we further change the activity exploration
methods from a holistic-oriented image-based to an object-oriented video-based
approach and achieve the purpose of understanding activities along time. In a
word, our work aims to achieve real video understanding.

3 Architecture

As illustrated in Fig. 2, our OVC-Net is also based on the classical encoder-
decoder structure and consists of three modules: (1) **Object-oriented temporal graph:** For each input video, we first get a set of object trajectories and
extract the global features and local features respectively for each object at every
frame where the object occurs. Then, for each object, we construct a temporal
graph to represent the activity. (2) **Prior knowledge module:** We design the
prior knowledge network to further capture more discriminative features among
different classes of objects. The local features of objects are fed into this module
Fig. 2. Overview of the proposed OVC-Net. Our OVC-Net consists of three modules: first build the object-oriented temporal graph, then the prior knowledge module gets the final high-level representations, finally the high-level representation, which are used by the captioning module to generate the descriptions word-by-word to generate the prior scores which are fed into the subsequent captioning module together with other features. (3) Captioning module: Based on the object-oriented temporal graph from module (1) and the prior scores from module (2), we generate the final descriptions word-by-word for the objects. In the following subsections, we will address the three modules in turn.

3.1 Object-Oriented Temporal Graph

In this subsection, we present how to build the object-oriented temporal graph. With the advances of object-level visual analyses, many excellent works have emerged, such as Faster R-CNN, YOLO, Mask R-CNN for object detection and Tracktor, TrackletNet Tracker(TNT) for multi-object tracking [23,24,34,11,3]. Recently, Yang et al. propose MaskTrackRCNN, built upon Mask R-CNN, to perform object detection, instance segmentation and object tracking at the same time. MaskTrackRCNN is trained on natural videos from YouTube which are similar to our training data, while most other tracking methods are mainly trained on scenes for video surveillance or autonomous driving. Therefore, adopting the MaskTrackRCNN as a combined detector-tracker in our work has two salient advantages: (1) MaskTrackRCNN can solve the above mentioned three tasks at the same time, we do not need to do each task separately; (2) MaskTrackRCNN is trained on videos which have more similar scenes to our scenarios. This module consists of three steps: first, the detection and tracking results are obtained by the MaskTrackRCNN. Second, with the detection and tracking results, the local features and global features of corresponding objects at different frames are extracted. Third, the temporal graph for each corresponding object in the video is built. In the following, we will introduce the three steps successively.
First, given a $T$-frame video $V = v^1, ..., v^T$, the MaskTrackRCNN is adopted to get the trajectories for all objects as

$$O = F_{\text{MTRCNN}}(V),$$

where $F_{\text{MTRCNN}}$ is the MaskTrackRCNN model. $O = o_1, ..., o_n$ is a set of detected objects of the video. For each object $o$, we record the time $v_o$ when it occurs and the spatial corresponding detected locations where it exist $b_o$. $v_o = \{v^{t_1}, ..., v^{t_m}\}$ denotes a set of frames where the object $o$ occurs, $m$ is the total number of the frames where the object $o$ exists. $b_o = \{b_{o1}^t, ..., b_{om}^t\}$, where $b_{ot} = [x_{ot}, y_{ot}, w_{ot}, h_{ot}]$ denotes the spatial location of $o$ at $t$.

Second, for each object trajectory, we extract its local and global features as

$$\phi_{lo}^t = [\Theta(o^t), c_{ot}^t],$$

where $\Theta$ is a pretrained neural network for extracting the semantic visual features. We feed each cropped object into $\Theta$ to get its local features. The features from the top layers of a neural network contain more semantic information, yet fewer detailed appearance information, such as color and texture. However, the color information is important for distinguishing different individuals, therefore, we further combine the color histograms into the local features. Finally, the local feature $\phi_{lo}^t$ of $o$ at $t$ consists of two components: visual features of objects from the neural network $\Theta(o^t)$ and the color histogram vectors $c_{ot}^t$ as show in Eq. (3).

To incorporate the interactions of a tracked object with other objects and the stuff, we again adopt $\Theta$ to extract the visual features of the frames where the object occurs as the global features $\phi_{go}^t$ in Eq. (4). Our method is quite different from other works which directly adopt frame-level features. In previous works, the activities are mainly learned based on the frame-level features which are inter-objects features of all objects and background. However, in our work, with the foreground objects and background being separated, the activities are learned by analyzing the local features of the objects along time. The global features serve as a supplement of the interactions and background. Some works, e.g., the Fine-grained Spatial Temporal Attention Model (FSTA) [19], also use the results from Mask R-CNN [11] to separate the objects and background, but the background is completely ignored in their efforts. In fact, background makes up the majority...
of our visual surroundings, e.g., road, sky, grass, beach, building, etc., and helps to infer the positions and orientations of the objects, object-object interactions and object-background interactions. Therefore, background is crucial for scene understanding. Besides, some works adopt the C3D features as a supplement for learning activities [13,38,32,16,36]. However, the global features and the C3D features, which are fed into an RNN at the same time step, usually represent the information for different periods of the video. For this reason, the model cannot discover the relationships between local features and global features. In our work, we extract the features for the frame where the object exists as global features, which are also paired with local features among detected objects, so the network can learn the inherent relationships between local and global features more effectively. To better exploit the connections between objects and the background, we combine the spatial locations of the objects $b_o^t$ with the combined local and global features $\phi_o^t = [\phi_{lo}^t, \phi_{go}^t]$. As shown in Fig. 3, our paired local and global information is more straightforward for learning the interactions between different objects or between objects and background.

Based on the results obtained in the previous step, we build a temporal graph $G_o$ for each object. Each node represents the attributes of the object at a time instance. The attributes consist of the combined feature $\phi_o^t$ and the spatial location $b_o^t$. Since our graph is built along time, the edge represents the temporal relationships between different frames rather than different objects. Thus, the edges in our graph only exist between adjacent frames when the same object occurs. FSTA [19] and OA-BTG [42] use the detector to get effective features for objects as well, yet without combining the spatial information. Actually, the temporal evolution of spatial locations associated with the object helps a lot in understanding the activities, e.g., jump, walk, squat. So we further combine the spatial transformation, which helps for learning activities under limited data.

With the object-oriented temporal graph, we directly utilize the graph-sentence pairs for training. It is more effective and specific for learning the activities with visual features along time. This object-oriented temporal graph achieves the ob-
jective of reasoning activities without extra temporal cues from other tasks. In Fig. 4, we show an example of our graph-sentence pairs. Actually, we have the graph-sentence pair for each object in the video. Thus, we have more graph-sentence pairs in more complex videos to process all concurrent activities.

3.2 Prior Knowledge Module

The goal of caption generation is to generate informative descriptions for different objects and identities. Actually, the objects which may have activities in most videos can be roughly grouped into three super-classes: human, animal and vehicle. Different from other object-level captioning approaches, the detailed information, such as gender, is very important in object-level descriptions. Nonetheless, this kind of detailed information cannot be obtained with the detector or tracker. To learn more effective and discriminative features for different super-classes, we design the Prior Knowledge Module (see Fig. 2).

\[
\gamma_o = F_p \left( W_p \sum_{t_1}^{t_m} \phi_{t_1}^o / m + b_p \right). \tag{5}
\]

As shown in Eq. (5), \(F_p\) is the prior class network which consists of fully connected layers, and \(\gamma_o\) is the obtained prior scores. \(W_p\) and \(b_p\) separately denote the parameters and bias which need to be learned. Each dimension of \(\gamma_o\) represents the probability of \(o\) associated with each predefined class. The categorical cross-entropy is adopted as the loss function. Finally, the prior scores are concatenated with the local features as the input for the captioning module. Thus, for \(o\), the final input of the captioning module at \(t\) is \(\tilde{\phi}_t^o = [\phi_t^o, b_t^o, \gamma_o]\).

With the prior knowledge, the network can learn more discriminative features for different classes, and the following captioning module can thus learn better the connections between vision and natural language.

3.3 Captioning Module

With the results from previous step, we can train a model with the obtained graph-sentence pairs shown in Fig. 4. Given an object-oriented temporal graph \(G\), the captioning module is required to understand the activities and automatically generate a sentence \(S = \{s_1, s_2, \ldots, s_K\}\) word-by-word in Eq. (6), where \(\theta\) represents the parameters to be learned, and \(K\) is the length of the sentence. \(s_1, s_2, \ldots, s_{k-1}\) denote the generated partial words. During training, the parameters \(\theta^*\) are learned by maximizing the formulation in Eq. (7).

\[
P(S|G) = \prod_{k=1}^{K} P(s_k|s_1, s_2, \ldots, s_{k-1}, G; \theta). \tag{6}
\]

\[
\theta^* = \arg\max_{\theta} \sum_{(G,S)} \log p(S|G; \theta). \tag{7}
\]
The RNN has the capability to decode video contents to sentences, so most works adopt LSTMs or GRUs as the decoder. In our scheme, we choose the GRU for GRU because it is easier to converge under fewer training data. Actually, a GRU is a variant of an LSTM. Instead of using three gates (input gate, forget gate, output gate) as in an LSTM, a GRU only has two gates: update gate and reset gate. Different from an LSTM using the memory cells to transfer the information, a GRU directly use the hidden states. The reset gate decides how much past information to forget. The update gate controls what information to throw away and what information to carry over. In brief, the GRU can be updated by Eq. (8). $\phi_k$ and $h_{k-1}$ are the input and the previous hidden state. In addition we also adopt the temporal attention mechanism to help decide which frames are the key frames for the current word generation.

$$h_k = \text{GRU} \left( \phi_k, h_{k-1} \right).$$  \hspace{1cm} (8)

Given a target ground truth sequence $S_* = \{S^*_1, S^*_2, \ldots, S^*_K\}$, we train the model by minimizing the cross-entropy loss in Eq. (9). The prior knowledge module and the captioning module are trained jointly. The total loss is calculated by Eq. (10), where the hyper-parameter $\lambda$ is used to balance the prior knowledge module and the captioning module.

$$L_{cap}(\theta) = -\sum_{k=1}^{K} \log \left( p_\theta \left( s^*_k | s^*_1, s^*_2, \ldots, s^*_{k-1} \right) \right).$$  \hspace{1cm} (9)

$$L = L_{cap} + \lambda L_{prior}.$$  \hspace{1cm} (10)

4 Experiments

In this section, we first introduce the dataset of object-oriented captioning, following by the implementation details. Next, our experimental results are reported accompanied by the comparisons with other methods. Finally, present the ablation studies which discuss the impact of each component in our OVC-Net.

4.1 Object-Oriented Video Captioning Dataset

The most widely used datasets for video captioning are the MSR-Video to Text (MSR-VTT) dataset [36] and the Microsoft Video Description (MSVD) dataset [3]. The MSR-VTT dataset contains 10K short video clips and 200K video-sentence pairs, and the MSVD dataset provides 1970 YouTube clips. The ActivityNet Captions dataset [16], which contains 20k videos from 200 activity classes (e.g. drinking, dancing, playing games), is the most popular benchmark for dense video captioning. We summarize all the datasets in Table 1 in terms of type of data, length of sentences, verbs per sentence, adjectives per sentence, etc. From Table 1, we can see the type of data in all of these datasets are clip-sentence pairs. Each video clip has multiple sentences for different objects.
Table 1. Comparisons of the standard datasets for video description. We group all objects which may have activities into three super object-classes: human, animal and vehicle. Except only FSN, which requests to describe human activities, other datasets need to describe all the three object-classes.

| Dataset          | Task                  | Data Type | Length of Video (sec) | Object Classes | Length of Sentence | Verbs per Sentence | Verbs Ratio (%) | Adjectives per Sentence | Adjectives Ratio (%) |
|------------------|-----------------------|-----------|------------------------|----------------|--------------------|---------------------|-------------------|------------------------|----------------------|
| MSR-VTT          | video captioning      | clip-sen  | 20                     | 3              | 9.28               | 1.37                | 14.80            | 0.66                   | 24.83                |
| MSVD             | video captioning      | clip-sen  | 10                     | 3              | 8.67               | 1.33                | 19.60            | 0.25                   | 17.48                |
| ActivityNet      | dense video captioning| clip-sen  | 180                    | 3              | 13.48              | 1.41                | 10.40            | 0.67                   | 21.16                |
| FSN              | fine-grained video    | clip-sen  | 5                      | 1              | 9.39               | 1.67                | 18.30            | -                      | -                    |
|                  | captioning             |           |                        |                |                    |                     |                  |                        |                      |
| Ours             | object-oriented video | object-sen| 73                     | 3              | 16.56              | 2.02                | 21               | 1.97                   | 11.81                |

Table 2. Constituents of most words in our re-annotated data (the words in boldface type are more common in our data)

| Words                          | Object          | Activity       | Color            | Interaction     | Stuff           |
|--------------------------------|-----------------|----------------|------------------|-----------------|-----------------|
| boy, girl, man, woman, hopscotch| dog, car, truck| stand, play,  | white, red,     | following,      | sidewalk, lawn  |
|                                | bike, motor,   | look, jump,   | green, grey,     | towards, back   | concrete ground |
|                                | bottle, curb,  | run, lean,    | yellow, blue,    | to, right, left | playground,     |
|                                | mat, glasses,  | adjust, bend, | orange, pink,    | in front of,    | cement, park    |
|                                | shorts, pants, | blow, celebrate| purple, beige,   | looking, holding| wall, soil,     |
|                                | sweater, tee,  | draw, hold,   | plaid, floral,   |                 | beach, ...      |
|                                | shirt, dress,  | hug, keep,    |                  |                 |                 |
|                                | skirt, vest,   | lie, lean,    |                  |                 |                 |
|                                | coat, bag, ... | wave, listen, |                  |                 |                 |
|                                |                 | sit, park,    |                  |                 |                 |
|                                |                 | pass, pat,    |                  |                 |                 |
|                                |                 | pick, pull,   |                  |                 |                 |
|                                |                 | push, reach,  |                  |                 |                 |
|                                |                 | squat, speak, |                  |                 |                 |
|                                |                 | ...           |                  |                 |                 |

However, object-level information is not available, for example, which sentence describes which object. Using this kind of data for training cannot effectively learn the functional mappings and the vision-language connections due to the one-to-many nature.

To better learn functional mappings across vision and language, we re-annotate a portion of videos from the ActivityNet dataset with explicit object-sentence pairs to construct the new dataset. We choose all videos from the class of playing games in the ActivityNet Captions dataset. The videos of this class have more diverse activities and scenes than that of other classes. Also each video contains more diverse individuals and interacting activities. Totally, we re-annotate 75 videos with 534 object-sentence pairs. Each video is of length between 10 seconds to 234 seconds. On average, each video contains about 5 objects which have activities, and the average length of each object trajectory is about 248 frames. Most importantly, we have the identities of the objects in our object-oriented video captioning dataset, and there is one sentence associated with each object motion trajectory in our re-annotation. As shown in Table 1, our data are object-sentence pairs type which is different from all the other datasets. According to the detailed statistics of our captioning annotations, our sentences contain more words in each sentence including verbs and adjectives. More specifically, in MSR-VTT, MSVD and ActivityNet Captions, one description only has less than 1.4 verbs on average. Fine-grained Sports Narrative (FSN) Dataset is a dataset for fine-grained video captioning of Sports Narrative [40], which has more verbs to describe fine-grained actions. Even compared with FSN, our sentences provide richer information. Similarly, we analyze the adjectives in the annotated
Fig. 5. Examples of our re-annotated data. We annotate salient objects which may have activities in the video. Obviously, our data has quite diverse sentences especially in more complex scenarios.

sentences. Each sentence in our dataset has about 2 adjectives, however, the sentences from all the other datasets only have less than 0.67 adjectives. The wide difference shows our data are more informative to distinguish different objects and the corresponding activities. The ratios of adjectives and verbs is not significantly higher than that of the other datasets, the reason is because we have much fewer videos than the others, and therefore we can adequately describe the objects using these adjectives. Although our videos are fewer that other datasets, we believe that good performance using limited training data is more credible to prove the generalization capabilities and effectiveness of the method. In our experiments, we utilize 55 videos for training and 20 videos for testing.

Table 2 further shows the constituents of words in our data. Our sentences contain more detailed information for distinguishing different individuals, for example, color of the clothes (common color, plaid, floral), type of clothes (shirt, sweater, pants, shorts). Fig. 5 shows two examples of our re-annotated data. Our re-annotated dataset will be publicly released upon acceptance.

4.2 Implementation Details

Object trajectory processing. For each trajectory, we sample 40 equally-spaced frames. We adopt VGG19 pretrained on ImageNet as the backbone to extract the semantic visual features from the last pooling layer. While building the object-oriented temporal graph, we feed the cropped objects into the backbone to get their corresponding object-level local features. Meanwhile, we feed the frames where the object exists into the backbone to get the global features. Finally, for each channel of RBG, we extract 16-dimensional color histograms, resulting in the final 4144-dim local features and 4096-dim global features.
Table 3. Prior knowledge definitions. All the objects which have activities are grouped into three super-classes: human, vehicle and animal. For human class, we further split it into two sub-classes: male and female

| Prior Class         | Words            |
|---------------------|------------------|
| 1 Human-Male        | woman, girl,...  |
| 2 Human-Female      | man, boy,...     |
| 3 Vehicle           | car, truck, motor, bicycle,... |
| 4 Animal            | dog, cat,...     |

Table 4. Performance comparisons with state-of-the-arts for video captioning. TG represents the object-oriented temporal graph. P represents the Prior Knowledge Module

| Model       | B@1 | B@2 | B@3 | B@4 | M  | R  | C  |
|-------------|-----|-----|-----|-----|----|----|----|
| MP-LSTM     | 43.2| 29.2| 21.7| 16.2| 18.2| 40.3| 38.8|
| SA-LSTM     | 43.7| 29.8| 22.0| 16.3| 18.3| 39.7| 37.3|
| S2VT        | 40.2| 26.8| 19.6| 14.1| 16.6| 37.9| 31.7|
| RecNet      | 43.5| 29.6| 21.7| 16.0| 17.7| 40.8| 42.1|
| Ours (TG)   | 47.0| 33.4| 25.7| 20.2| 20.0| 45.1| 50.4|
| Ours (TG+P) | 45.0| 32.4| 25.0| 19.3| 19.7| 45.0| 50.4|

Sentence processing. For the sentences, we remove the punctuations, split them with blank space and convert all words into lower-case. We set the maximum length of each sentence to be 25. The sentences longer than 25 are truncated. We randomly initialize all the word embedding with a fixed-size of 512.

Training details. The prior knowledge module consists of three fully-connected layers. Table 3 shows our pre-defined super-classes. In the captioning module, the GRU is initialized to have 2 layers with 1024-dimensional hidden units. We empirically set the hyper-parameter $\lambda$ in Eq. (10) to 0.1. We adopt the adaptive moment estimation (Adam) for optimization. The initialized learning rate is 0.0001. We train the model with a mini-batch of 50 object-sentence pairs.

4.3 Experimental Results

Comparisons with State-of-the-arts. We adopt the metrics, BLEU (B) \[22\], METEOR (M) \[2\], ROUGE-L (R) \[18\], CIDEr-D (C) \[30\] which are widely used in text generation tasks, to quantitatively evaluate our proposed approach. The higher scores represent better performance of the methods. We compare the performance of our method with four methods for classical video captioning, MP-LSTM \[32\], SA-LSTM \[38\], S2VT \[33\] and RecNet \[31\]. MP-LSTM is a baseline method relying on the mean pooling to process the frame features. SA-LSTM utilizes temporal attention to decide the key frames. RecNet achieves the state-of-the-art for video captioning. As shown in Table 4, our proposed object-oriented approach, with temporal graph and prior knowledge module, can achieve the highest BLEU@4 score of 20.2. The MP-LSTM and SA-LSTM perform better.
Table 5. Ablation study of the proposed OVC-Net. Note that \( G, L, C, B \) and \( P \) represent global information, local information, color information and spatial locations, respectively. \( G, L, C, B \) and \( P \) makes up our object-oriented temporal graph.

| Ours | B@1 | B@2 | B@3 | B@4 | M  | R  | C  |
|------|------|------|------|------|----|----|----|
| ✓ ✓ ✓ ✓ ✓ | 47.0 | 33.4 | 25.7 | 20.2 | 20.0 | 45.1 | 50.4 |
| ✓ ✓ ✓ ✓ | 45.1 | 32.4 | 25.0 | 19.3 | 19.7 | 45.0 | 50.2 |
| ✓ ✓ ✓ ✓ | 45.8 | 31.4 | 24.7 | 18.7 | 19.5 | 44.3 | 50.9 |
| ✓ ✓ ✓ ✓ | 46.7 | 32.6 | 24.1 | 18.1 | 19.3 | 44.5 | 52.1 |
| ✓ ✓ ✓ | 42.8 | 29.7 | 22.1 | 16.6 | 18.0 | 42.3 | 45.5 |
| ✓ ✓ | 41.3 | 28.4 | 21.3 | 16.1 | 16.9 | 39.3 | 38.5 |

than S2VT and RecNet, for they have fewer parameters and can be trained well under small data. With the object-oriented temporal graph, the OVC-Net can better analyze the connections between the vision and language, yet not relying on training on large amount of data. Therefore, the proposed method has ability to understand the activities and attributes under limited data. From the visualization examples in Fig. 6, it can be seen that the proposed OVC-Net can generate more accurate descriptions for the activities, like ‘draw’, ‘throw a stone’. Meanwhile, it can describe the interactions between objects and background, and the attributes of objects in details more accurately.

Ablation Study. To verify the importance of each component of our method, we perform detailed ablation studies as shown in Table 5. From the experiments, we find that the BLEU@4 performance with only global features is only 16.1, which is worse than all the others. However, the performance with only local features are 16.6 which proves the explicit features of objects are benefit for learning the relationships across vision and language. After adding the color information, the performance has further improvement to 18.7 as shown in Table 5. With the color information, the model can generate more accurate descriptions of the attributes. Then, we further combine spatial locations of the objects to help learn activities based on the moving trajectories. It verifies that the temporal evolution of spatial locations works great in understanding activities along time. The four components mentioned above make up our object-oriented temporal graph. The last row of Table 5 shows the results of our full model which combines the object-oriented temporal graph and the prior knowledge module. Comparing the performance with and without prior knowledge module, the performance has a significant improvement in terms of BLEU score as well. The experimental results fully prove the OVC-Net can learn the more discriminative features for different prior class and generate more accurate descriptions with details.

We further show some visualization results for ablation study. From Fig. 7, after adding the spatial locations, the model can learn more detailed spatial information of the objects, and generate in front of, on the right. In the second example, the model can further reason the boy then back to the camera from
Fig. 6. Visualization examples of comparisons with SA-LSTM and RecNet. GT is the ground-truth sentence for the trajectory.

Fig. 7. Visualization examples for ablation study. G, L, B represents the global features, the local features and the spatial location separately. Ours is our full framework.

the spatial location evolution. In addition, after combining the prior knowledge module, the detailed attributes of the objects becomes more accurate as well.

Overall, the experimental results indicate that our method can understand the actions more precisely even without temporal cues from action recognition. It demonstrates that our object-oriented temporal graph can represent the activity of the object effectively. Meanwhile, the color information and prior knowledge module significantly improve detailed attributes. Furthermore, the sentence-object pairs help the model bridge the combinations between vision and language. All in all, our method can describe concurrent objects and their corresponding attributes in more details.

5 Conclusions

In the paper, we propose a novel task of object-oriented video captioning which transforms the task of video-level video captioning to the task of object-level
analyses. Unlike most previous image-based methods, we designed the video-based framework for more realistic video understanding to analyze the concurrent activities in details. The proposed method can understand the activities along time based on visual features only. To the best of our knowledge, this is the first work which proposes to shift the video captioning from generating a holistic description to detailed descriptions for each object. The re-annotated dataset is the first dataset which provides explicit object-sentence pairs. With this kind of data, further works can learn the connections between vision and language better. Experimental results demonstrate that our method achieves better performance than the state-of-the-arts. The results also indicate that the proposed method can effectively understand the activities and provide more detailed information of the whole scene and existed objects.

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