Global2Local: A Joint-Hierarchical Attention for Video Captioning

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Abstract

Recently, automatic video captioning has attracted increasing attention, where the core challenge lies in capturing the key semantic items, like objects and actions as well as their spatial-temporal correlations from the redundant frames and semantic content. To this end, existing works select either the key video clips in a global level (across multi frames), or key regions within each frame, which, however, neglect the hierarchical order, i.e., key frames first and key regions latter. In this paper, we propose a novel joint-hierarchical attention model for video captioning, which embeds the key clips, the key frames and the key regions jointly into the captioning model in a hierarchical manner. Such a joint-hierarchical attention model first conducts a global selection to identify key frames, followed by a Gumbel sampling operation to identify further key regions based on the key frames, achieving an accurate global-to-local feature representation to guide the captioning. Extensive quantitative evaluations on two public benchmark datasets MSVD and MSR-VTT demonstrates the superiority of the proposed method over the state-of-the-art methods.

Introduction

Automatically describing videos, a.k.a. video captioning, has recently received increasing attention in artificial intelligence with broad applications, such as intelligent video surveillance, navigation aids, human-robot interaction, etc. Video captioning involves both video content understanding and description generation, regarded as a typical cross-domain task between computer vision and natural language processing. Different from image captioning (Xu et al. 2015; Chen et al. 2018a; Anderson et al. 2018), video captioning is more challenging due to the consideration both the static semantic content and the temporal correlation among frames (Chen et al. 2018b). Recent advances in video captioning mostly follow an encoder-decoder architecture like CNN-RNN model and put forward different solutions to capture the key frames and key regions. To this end, existing works can be briefly divided into global (frame-based) and local (region-based) attention-driven schemes. For example, (Yao et al. 2015; Wang et al. 2018b) used temporal attention mechanisms to identify and weight the importance of frames/clips globally on the temporal dimension.

Frames and clips were combined together to enhance the representation ability of the global attention component (Pei et al. 2019; Aafaq et al. 2019). For local attention, Yang et al. (Yang, Han, and Wang 2017) proposed to apply spatial attention on frames’ feature maps with guidance from a dual memory recurrent model to reduce spatial information loss. (Li et al. 2017) applied spatial attention for each frame in the encoding stage and generated captions with the weighted frame features. In (Chen and Jiang 2019), spatial attention was adopted over video frames with the guidance of motion.

However, all the above methods focus on capturing either the global video sequence or the key spatial regions in the local frames, respectively, without considering the joint modeling of these two perspectives. Although some recent attempts have been made to explore several alternative solutions via the straightforwardly jointly modeling (Wu et al. 2018; Zhang and Peng 2019; Aafaq et al. 2019), the hierarchical interaction between the global video sequence and the local spatial region are still out of consideration. In contrast, as revealed in the human vision system (Buschman and Miller 2007; Cromwell et al. 2008), the temporal attention processes first via the sensory gating mechanism to understand the video globally, followed by the spatial attention to allocate volitionally to find the local elements in each frame. This inspires us to develop a more systematic method for the
Figure 2: The architecture of our G2L model. Temporal aligned video clips and frames are processed with 3d and 2d CNNS, respectively. An object detector is applied to extract local features from sparsely sampled frames. At each word generating step, we use temporal attention on concatenated frames’ and clips’ features to jointly get a temporal weight sequence, which can guide Gumbel TopK Sampler selecting the most crucial frames. Then, a spatial attention is applied on the local features of these frames to obtain local embeddings.

joint global and local attention to guide video captioning.

Furthermore, the structure of the video is hierarchical. A video consists of successive frames globally, and each specific frame is composed of objects. This sequence-frame-objects hierarchy gives a certain level of video semantics, e.g., capturing the semantic information of actions should be at the sequence level, while the attributes of an object should be at the objects level. We should take this hierarchical feature into account when building video captioning models as well as other video-related spatial-temporal models. Hierarchical models also have the benefit of reducing the computational and storage cost, without the need to use all object-level information like (Li et al. 2017; Zhang and Peng 2019).

Driven by the above insights, we propose to model the joint global and local attention in a hierarchical manner for video captioning, which, however, involves two challenging issues. On the one hand, video sequence contains not only actions in each clip but also objects in the corresponding frames, which are jointly captured to characterize the clip-frame context. On the other hand, key local regions in the individual frames are identified via a progressive but differentiable selection and localization with the guidance of the semantic context.

In this paper, we propose a novel joint-hierarchical attention for video captioning, where the key frames are first selected in a global level, and the key regions are then selected in a local level based on the key frames. We term this method as G2L, which is illustrated in Fig. 2. G2L contains three modules, i.e., the joint clip-frame attention for keyframe selection, the hierarchical frame-region attention for the key region selection and the hierarchical embedding for caption generation. In joint clip-frame attention, the features of frames and clips are respectively attended with the hidden feature of the word context to represent the entire video sequence jointly. Another temporal attention is used to weight the aligned global representations, as well as selecting keyframes with Gumbel top-k sampler. In hierarchical frame-region attention, the region selection module selects selected representations, which is subsequently sent to a parameter-shared spatial attention module to find the key local regions. At last, we concatenate the hierarchical global and local representations as the visual embedding for caption generation.

The main contributions of this paper are summarized as follows: (1) A novel end-to-end trainable model is proposed to select the key video frames and key spatial regions hierarchically. Joint clip-frame and hierarchical frame-region attentions are designed to capture the key video frames as well as key local regions, respectively. (2) A differentiable top-k probability sampler is proposed to make above two selection proceed orderly. We have conducted the evaluation on two public benchmark datasets i.e., MSVD and MSR-VTT, which demonstrates that the proposed method surpasses the
state-of-the-art methods.

**Related Work**

Early works on video captioning mainly adopted template-based methods (Guadarrama et al. 2013; Rohrbach et al. 2013), which pre-defined the sentence templates and predicted the semantic concepts or words from the video content to match these templates. Template-based methods heavily rely on the template definition, which limits the nature and diversity of the description. However, such video captioning mainly resorted to the powerful deep visual representation like (Szegedy, Ioffe, and Vanhoucke 2017; Hara, Kataoka, and Satoh 2018) and the deep sequence-to-sequence models like (Cho et al. 2014), which is regarded as a cross-modal “translating” process via an encoder-decoder architecture. For example, (Venugopalan et al. 2014) proposed to extract the CNN feature of the individual frame and compute the average value of these features to represent video, followed by an LSTM module to generate descriptions. As another classical benchmark model, S2VT (Venugopalan et al. 2015) adopted a shared encoder-decoder based on LSTMs to embed CNN features and then generated the captions.

Current advances in video captioning mainly focus on exploring the attention mechanism (Yao et al. 2015; Wang et al. 2018a; Wu et al. 2018). These methods typically work on the temporal domain, which weights the input features at each step to the word sequence generation. For example, (Yao et al. 2015) combined the 2d-CNN with the 3d-CNN to extract the descriptor as the motion representation. (Wang et al. 2018b) proposed a multi-model memory network to guide the visual attention for the long-term visual-textual dependency. (Fei et al. 2019) used a memory structure to explore the full-spectrum correspondence between a word and various similar visual contexts in the training set. (Aaafq et al. 2019) used 3d-CNN to extract the high-level semantic concepts and employed the Short Fourier Transform to enrich the visual representation.

To explicitly model the spatial cues, some works explored the local attention modules for video captioning. Inspired by (Xu et al. 2015), spatial attention (Yang, Han, and Wang 2017; Li et al. 2017) was applied on the feature maps of the individual frame with the guidance from the dual memory recurrent model and the recurrent states of RNNs, respectively. Chen et al. (Chen and Jiang 2019) used spatial attention on video frames according to the guidance of motion. In (Wu et al. 2018), the spatial-temporal representation was extracted at the trajectory level using an attention mechanism. Subsequently, the work in (Zhang and Peng 2019) further proposed a video captioning approach based on the object-aware aggregation with the bidirectional temporal graph, which aggregates several local objects from the global frame sequence.

**Approach**

The framework of the proposed G2L approach is illustrated in Fig.2, which consists of three main components: the joint clip-frame attention for keyframe selection, the hierarchical frame-region attention for the key region selection and the hierarchical embedding for caption generation.

**Joint Clip-frame Attention**

We adopt global features with temporal attention to keyframes selection. Such global features are extracted from different time intervals to extract 2d (frames) and 3d (clips) features as $X_{2d} = \{f_1, f_2, ..., f_L\}$ and $X_{3d} = \{v_1, v_2, ..., v_L\}$, whose vector dimensions are $d_{2d}$ and $d_{3d}$, respectively. Then, the obtained visual features are projected into the hidden spaces via the nonlinear transformations with the activation functions $\sigma$:

$$f'_t = \sigma(W_f f_t + b_f), \quad v'_i = \sigma(W_v v_i + b_v) \quad (1)$$

where $W_f \in \mathbb{R}^{d_{2d} \times d_{2d}}$, $W_v \in \mathbb{R}^{d_{2d} \times d_{3d}}$ and bias $b_v$ are learnable parameters.

In the attention module, we compute the attention weight for the global features based on the decoder’s output $h_{t-1}$ before the time step $t$. The attention weight is computed as follows:

$$a^*_{i,t} = \exp \left\{ F_{att}^*(h_{t-1}, V_i) \right\} / \sum_{i=1}^{L} \exp \left\{ F_{att}^*(h_{t-1}, V_i) \right\} . \quad (2)$$

$F_{att}^*$ is the attention operation, defined as:

$$F_{att}^*(h_{t-1}, V_i) = w^T \tanh \{ (W_{ha} h_{t-1}) \odot (W_{va} V_i) + b_v \} . \quad (3)$$

where $w \in \mathbb{R}^{d_a}$, $W_{ha} \in \mathbb{R}^{d_{2d} \times d_a}$, $W_{va} \in \mathbb{R}^{d_{2d} \times d_a}$ and $b_v \in \mathbb{R}^{d_a}$ are the parameters of the feature transformation, which are used to embed $h_{t-1}$ and $V_i$ to the same dimension $d_a$. Notably, unlike the previous methods with the similar structures as (Yao et al. 2015), which uses $W_{ha} h_{t-1} + W_{va} V_i$ to calculate the cross-modal relationship, we use a bilinear product attention to replace it, where the $\odot$ denotes the Hadamard element-wise product.

To select the most crucial frames with the joint global features, 2d and 3d features are aligned on the temporal dimension as $[f'_i, v'_i]$. Then an attention module $F_{att}^{2d+3d}$ is applied to obtain the weight sequence $\{a^*_{1,t}, a^*_{2,t}, ..., a^*_{L,t}\}$ for each period.

Beyond getting the weight sequence for the keyframe selection, we also get the global visual representation of the
t-th step $x_{t,G}$ at the same time. Concretely, another two temporal attention mechanisms are applied to get weighted $x_{t,G}$, which is calculated by:

$$x_{t,G} = \sum_{i=1}^{T} [a_{i,t}^2 f_{i,t}^2, a_{i,t}^3 v_{i,t}^3, \varphi(a_{i,t}^l [f_{i,t}^l, v_{i,t}^l])],$$

(4)

where $a_{i,t}^2$ and $a_{i,t}^3$ come from $F_{att}^{2d}$ and $F_{att}^{3d}$ respectively. In order to avoid feature duplication, we use a non-linear mapping $\varphi(x) = \sigma(W_{al}x + b_{al})$ that is the same as the transform in Eq.1 to obtain a compact representation, where $W_{al} \in \mathbb{R}^{(d_{al} + d_{obj}) \times d_{al}}$ and $b \in \mathbb{R}^{d_{al}}$.

In the next step, temporally aligned attention weights $\{ a_{i,t}^l \}$ are transformed into another sparse time sequence to guide a Gumbel top-k sampler to select the crucial frames (see next section).

**Hierarchical Frame-region Attention**

In the keyframe selection stage, we choose the largest ones from the discrete probability distribution. The conventional approach to use argmax will face a problem that the gradient is not conductive. We modify Gumbel-Softmax (Jang, Gu, and Poole 2016) to approximate such an one-hot distribution, and propose Gumbel top-k sampler, which screens out the $K$ largest approximations in turn and adapts to the inputting discrete probability values.

As shown in Fig [4], given a discrete probability distribution $\pi^0, \pi^1, \pi^2, \pi^3$ from the attention calculation, we generate the top-1 max sample vectors as:

$$\pi^k_i = \frac{\exp((\log(\lambda \pi^0_i) + g^k_i)/\tau)}{\sum_{j=1}^{n} \exp((\log(\lambda \pi^0_j) + g^k_j)/\tau)}, i = 1, 2, ..., n.$$  

(5)

where $\lambda$ is the scaling ratio, $\tau$ is softmax temperature and $g^0_i ... g^m_i$ are i.i.d samples drawn from Gumbel(0, 1)$^k$. To get another top values, we use the previous top approximations to suppress the original distributions:

$$\pi^k_i = \frac{\exp((\log(\lambda \pi^0_i) - \sum_{m=1}^{k-1} \lambda g^m_i) + g^k_i)/\tau)}{\sum_{j=1}^{n} \exp((\log(\lambda \pi^0_j) - \sum_{m=1}^{k-1} \lambda g^m_j) + g^k_j)/\tau)}.$$  

(6)

Then, the $k$ approximate one-hot distributions are obtained, where the largest value approaches to 1 and the others approach to 0. Each value of a distribution is multiplied to the local frame at the corresponding position as to complete frame selection.

Next, we use the global attention weights $\{ a_{i,t}^l \}$ to guide the sampler to select the most important frames. According to (Feichtenhofer et al. 2019), spatial semantic information can be captured at low frame rates for videos, therefore we select the middle of multiple frames for object-level feature extraction to reduce redundancy, which called sparse sampling as shown in Fig.2. In our implementation, we select one from every 3 frames to get the frames. Following (Anderson et al. 2018), the obtained region features are $X_{obj} = \{ r_1, r_2, ..., r_{L/3} \}$, where $r_j \in \mathbb{R}^{d_{obj} \times d_{obj}}$ and $N_o$ denotes number of region proposals for each frame. We then project the features into the hidden spaces:

$$r^*_{i,j} = \sigma(W_r r_{i,j} + b_r), \quad j = 1, 2, ..., N_o,$$  

(7)

where $W_r \in \mathbb{R}^{d_{obj} \times d_{obj}}$ and $b_r \in \mathbb{R}^{d_{obj}}$ are learnable parameters.

Simultaneously, the global attention weights $\{ a_{i,t}^l \}$ are transform to align $X_{obj}$, where

$$a^l_j = (a_{j3-2,t}^l + a_{j3-1,t}^l + a_{j3,t}^l)/3.$$  

(8)

Finally, the Gumbel top-k sampler is used to several frames with high weights whose features set can be abbreviated as $J$. We apply a shared local spatial attention $F_{att}^{l}$ to calculate each region’s weight $a_{j,t}^l$ in $j$-th selected frames. Therefore, the selected key regions’ embeddings $x_{t,L}$ can be given by:

$$x_{t,L} = \sum_{j} \sum_{i} a_{j,i,t}^l r^*_{j,i}.$$  

(9)

**Caption Generation**

At each time step $t$, the attention modules are controlled by the last time step output $h_{t-1} \in \mathbb{R}^{d_h}$ to weight the input visual features. A recurrent neural network is utilized as the backbone of the decoder to generate the description word-by-word. As shown in Fig[3], we use GRU as the decoder in our implementation. The hidden feature at time step $t$ can be computed as follows:

$$h_t = \text{GRU}(x_t, e_t, h_{t-1}),$$  

(10)

where $x_t$ is the weighted visual features we selected, $e_t$ is the word embedding of the $t$-th input that is given by $e_t = W_e \Pi_t$, where $W_e \in \mathbb{R}^{d_{emb} \times |\Omega|}$ is a word embedding matrix for a vocabulary $\Omega$, $d_{emb}$ is the word embedding dimension and $\Pi_t$ is the one-hot encoding of the input word at the time step $t$. 

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**Figure 4:** An example for Gumbel top-k sampler, which uses the previously sampled values to suppress the current sample step, using Gumbel-Softmax with low temperature to obtain approximate one-hot distributions.
| Model           | B@4 | M   | R   | C   |
|-----------------|-----|-----|-----|-----|
| Global\textsubscript{base} | 40.1| 27.7| 59.4| 45.2|
| + Alignment     | 41.7| 27.9| 60.4| 46.8|
| + Local\textsubscript{1f}   | 41.9| 27.9| 60.6| 48.4|
| + Local\textsubscript{2f}   | 42.2| **28.6**| **61.1**| **50.3**|
| + Local\textsubscript{3f}   | 42.3| 28.1| 60.9| 50.0|
| + Local\textsubscript{2f} (w/o Gumbel) | 41.1| 27.3| 59.7| 47.1|

Table 1: Settings and results of ablation studies on MSR-VTT. All the results are reported as percentage (%). Global\textsubscript{base} model only use 2d, and 3d features without temporal alignment; Local\textsubscript{k} means the Gumbel sampler samples k key frames to calculate local attention.

| Model           | B@4 | M   | R   | C   |
|-----------------|-----|-----|-----|-----|
| S2VT            | 31.4| 25.5| 55.9| 35.2|
| SA-LSTM         | 36.3| 25.5| 58.3| 39.9|
| PickNet         | 38.9| 27.2| 59.5| 42.7|
| M\textsuperscript{3}-JC | 38.1| 26.6| -   | -   |
| RecNet          | 39.1| 26.6| 59.3| 42.7|
| GRU-EVE         | 38.3| 28.4| 60.7| 48.1|
| MGSA            | **42.4**| 27.6| -   | 47.5|
| MARN            | 40.4| 28.1| 60.7| 47.1|
| OA-BTG          | 41.4| 28.2| -   | 46.9|
| Ours            | 42.2| **28.6**| **61.1**| **50.3**|

Table 2: Comparison with different video captioning models on the MSR-VTT dataset. All the results are reported as percentage (%)

We concatenate the global embeddings \(x_{t,G}\) given by Eq.5 and local embeddings \(x_{t,L}\) given by Eq.10 as visual input for each generation step of the GRU:

\[
x_t = [x_{t,G}, x_{t,L}].
\]

As in the standard captioning models, the output \(h_t\) of each step will be mapped to the vocabulary dimension for conditional distribution over possible output words. Using the notation \(y_{1:T}\) to refer to a sequence of words. The conditional distribution at time step \(t\) is given by:

\[
p(y_t|y_{1:t-1}) = \text{softmax}(W_pb_t + b),
\]

where \(W_p \in \mathbb{R}^{I \times d_k}\) and \(b_p \in \mathbb{R}^{I}\) are learned parameters. Given a target ground truth sequence \(y^*_{1:T}\) and a captioning model with to-be-learn parameters \(\theta\), we minimize the cross-entropy loss to optimize the entire model:

\[
\text{Loss}(\theta) = -\sum_{t=1}^{T} \log(p(y_t^*|y_{1:t-1}^*)).
\]

**Experiment**

**Datasets and Evaluation Metrics**

We conduct the evaluation of the proposed G2L method on MSVD (Chen and Dolan 2011) and MSR-VTT (Xu et al. 2016) datasets. MSVD is composed of 1,970 open domain video clips from YouTube. Each clip describes a single activity with 41 ground truth captions on average. We adopt the commonly-used data split: 1,200 clips for training, 100 clips for validating and 670 clips for testing.

MSR-VTT is a widely-used benchmark dataset for video captioning, which is more challenging than MSVD. It contains 10,000 video clips from 20 general action categories. Each video clip is attached with 20 human-annotated natural captions. We follow its standard data split: 6513 clips for training, 497 clips for test and the left 2990 clips for the test.

In order to evaluate the proposed G2L method, we conduct the performance comparisons on the four standard metrics, including BLEU (Papineni et al. 2002), METEOR (Denkowski and Lavie 2014), CIDEr (Vedantam, Lawrence Zitnick, and Parikh 2015) and ROUGE (Lin 2004). These metrics reflect the accuracy of the generated captions by estimating the similarity of the human-annotated captions and the generated captions.

**Experimental Setting**

We construct the vocabulary based on the training set by filtering out the words that occur fewer than two times. We change all characters to lowercase, which results in vocabularies with 13491 words and 3468 words for MSR-VTT and MSVD, respectively. For the 2d visual features, we employ the Inception-V4 model (Szegedy, Ioffe, and Vanhoucke 2017) that is pre-trained on ImageNet with time stride 5. For the 3d features, we opt for the 3d-ResNxt-101 model (Hara, Kataoka, and Satoh 2018) pre-trained on Kinetics dataset with temporal resolution 8 and frame stride 5. Furthermore, according to (Anderson et al. 2018), the local region features are extracted from a pre-trained Faster-RCNN model on Visual Genome. Local time stride is set to 15, and the number of region proposals \(N_r\) is setting to 16. For the encoder, we first extract 2d, 3d and local region features and then transform them into 1024-dim vectors. The dimension of the word embedding is set to 300. For the GRU decoder, the number of hidden units is set to 768 with two hidden layers. The dimension of the temporal aligned embedding is 512 and the dimensions of the attention modules are all 384. The scaling ratio \(\lambda\) and softmax temperature \(\tau\) in Gumbel top-k sampler are set to 10 and 1e-4, respectively. To avoid overfitting, we use Adam optimizer with fixed weight decay 2e-5 (Loshchilov and Hutter 2019). We perform training for 30 epochs with the learning rate upgrading linearly from 1e-7 to 1e-4 for the first 3 epochs and then drop to 1e-6 for the last 7 epochs. In the testing stage, beam search with size 5 is used for the final caption generation.

**Ablation Study and Model Analysis**

In this part, we first conduct quantitative comparisons to evaluate the effects of different components. Then, we analyze the abilities of the attention models on capturing the key visual information. In order to ensure the generalization, we chose a larger dataset, i.e., MSR-VTT for the ablation study and model analysis.

**Effect of temporal alignment.** In Table I we compare the performances of the basic Global decoder and the one
Figure 5: Captions generated by the Global (with only Global branch, G) and Global2Local (G2L), as well as the corresponding ground truth (GT). Each line shows different gains with our model: (a) increasing the richness of caption components; (b) correcting the sentence with wrong predicted words; (c) generating accurate descriptions due to the discriminative features, even with a few samples (Squidward and the show with these two people have only 29 and 18 samples in training dataset).

Figure 6: Experiments on the abilities of capturing key information for different attention modules. In test stage, we set the smaller attention weights to 0 in a certain proportion (x axis) and renormalize the remaining values, obtaining the ratio of performance to the original (y axis).

with the temporal alignment. The results manifest that temporal alignment boosts all metrics. Even though this method uses the same features as the basic model, adding only an attention and an embedding operation. This proves that two independent temporal attention (on the 2d and 3d features) can not fully capture the useful full-spectrum context information. Temporal alignment is an effective promotional method to enhance the temporal correlation between the 2d and 3d features.

Effect of local key regions information. As shown in Table 1, we use a different number of local frames with the maximum weights to test its impact on captioning performance. When the local frame is 1, it means that the model only captures the key regions from one keyframe from Gumbel sampler. However, some relationships or actions require the local information from multiple keyframes to be recognized. Conversely, suppose too many frames are selected, such as using 3 keyframes. In that case, the weighted key regions’ features will not be discriminative enough due to the inter-polluted after the addition operation leading to performance degradation.

Furthermore, we also use SPICE (Anderson et al. 2016) metric to evaluate the feature effects on different visual semantic types. The results in Fig 7 shows that when 2d and 3d features are combined with the temporal alignment, the quality of the generated captions significantly improve. After adding the local features, the indicators on the objects and relationships improve accordingly, which reflects that the model can learn accurate representations with local key information.

Effect of Gumbel top-k sampler. In Table 1, we compare the performances of using Gumbel TopK Sampler and the argmax sampling method. The table shows that the BELU-4, METEOR and ROUGE have decreased with local regions
Table 3: Comparison with different video captioning models on the MSVD dataset. All the results are reported as percentage (%).

| Model       | B@4 | M   | R   | C   |
|-------------|-----|-----|-----|-----|
| S2VT        | 39.6| 31.2| 67.5| 66.7|
| SA-LSTM     | 45.3| 31.9| 64.2| 76.2|
| MAM-RNN     | 41.3| 32.2| 68.8| 53.9|
| DMRM        | 51.1| 33.6| -   | 74.8|
| TSA-ED      | 51.7| 34.0| -   | 74.9|
| PickNet     | 52.3| 33.3| 69.6| 76.5|
| M^2-IC      | 52.8| 33.3| -   | -   |
| RecNet      | 52.3| 34.1| 69.8| 80.3|
| GRU-EVE     | 47.9| 35.0| 71.5| 78.1|
| MGSA        | 53.4| 35.0| -   | 86.7|
| MARN        | 48.6| 35.1| 71.9| 92.2|
| OA-BTG      | 56.9| 36.2| -   | 90.6|
| Ours        | 53.6| 35.6| 73.5| 97.1|

without Gumbel sampler, reflecting the importance of the joint optimization between the global and local branches.

Besides, we have also observed that another reason for this performance degradation is due to the model overfitting. Using argmax or softmax with temperature \( \tau \) only output the local frame with the maximum probability. In contrast, the proposed Gumbel softmax conducts sampling based on the probabilities in training stage, which can be regarded as data augmentation, improving the generalization ability of the model.

**Key information selection ability.** As shown in Fig. 6 for the different attention modules, we mask the sorted attention weights in a certain proportion in test stage. With the gradual increase of the mask ratio, the performance of our model is still stable, which indicates that the key features with larger attention weights effectively guide the caption generation. When the mask ratio reaches 1.0, the performance drop sharply without the key visual information. This reveals that the proposed joint-hierarchical attention model has a powerful ability on the key information selection.

In addition, this experiment can also reflect the influence of different types of features on the quality of the generated sentences. When mask ratio for 3d attention increases from 0 to 1, the overall metrics drop the most, which indicates that the global 3d features with temporal information play a crucial role in the process of generating captions.

**Qualitative Analysis**

To gain more insight in the proposed G2L, we present several examples to qualitatively compare the alternatives of G2L with different modules in Fig. 5. Each line in Fig. 5 shows a different advantage of the G2L model: (a) increasing the richness of captions components; (b) correcting the sentence containing the wrongly predicted words; (c) generating the accurate descriptions. These benefits show the powerful ability of the proposed G2L in capturing key information. For example, in videos at line (c), our method can easily recognize the main characters due to the selected discriminative key regions.

**Comparison with Other Methods**

We compare our model with existing methods for video captioning on both MSR-VTT and MSVD datasets. We compare two groups of baselines with our model: the fundamental methods and the newly published state-of-the-art methods. Specifically, the fundamental methods include S2VT (Venugopalan et al. 2015) and SA-LSTM(2d) (Wang et al. 2018a). For state-of-the-art methods, we compare the proposed G2L with MAM-RNN (Li et al. 2017), DMRM (Yang, Han, and Wang 2017), TSA-ED (Wu et al. 2018), PickNet (Chen et al. 2018b), M^2-IC (Wang et al. 2018b), RecNet (Wang et al. 2018a), GRU-EVE (Aafaq et al. 2019), MGSA (I+C) (Chen and Jiang 2019), MARN (Pei et al. 2019) and OA-BTG (Zhang and Peng 2019).

As shown in Table 2 the proposed G2L provides significant gains on the captioning performance in three metrics, especially, it gets the improvement of 4.6% in CIDEr. Similarly, in Table 3 the proposed G2L also achieves the competitive performance with 6.4% increase on CIDEr. These results show that our proposed joint-hierarchical attention can well model the global and local visual information and generate descriptions with high quality.

**Conclusion**

In this paper, we explore to capture both key video frames at a global level and key spatial regions at a local level for video captioning. To this end, we propose a novel joint-hierarchical attention model (termed G2L) to selects the key video frames jointly and key spatial regions hierarchically. Such a joint global-local attention module first perform a global selection to identify keyframes, followed by a Gumbel sampling operation to identify key objects further, achieving an accurate global-to-local content description to guide the captioning. Extensive experiments have evaluated the effectiveness of joint-hierarchical attention and the superiority of the proposed G2L compared to the state-of-the-art methods.
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