Hierarchical Memory Decoding for Video Captioning

Aming Wu, Yahong Han
College of Intelligence and Computing, Tianjin University, Tianjin, China
{tjwam, yahong}@tju.edu.cn

Abstract

Recent advances of video captioning often employ a recurrent neural network (RNN) as the decoder. However, RNN is prone to diluting long-term information. Recent works have demonstrated memory network (MemNet) has the advantage of storing long-term information. However, as the decoder, it has not been well exploited for video captioning. The reason partially comes from the difficulty of sequence decoding with MemNet. Instead of the common practice, i.e., sequence decoding with RNN, in this paper, we devise a novel memory decoder for video captioning. Concretely, after obtaining representation of each frame through a pre-trained network, we first fuse the visual and lexical information. Then, at each time step, we construct a multi-layer MemNet-based decoder, i.e., in each layer, we employ a memory set to store previous information and an attention mechanism to select the information related to the current input. Thus, this decoder avoids the dilution of long-term information. And the multi-layer architecture is helpful for capturing dependencies between frames and word sequences. Experimental results show that even without the encoding network, our decoder still could obtain competitive performance and outperform the performance of RNN decoder. Furthermore, compared with one-layer RNN decoder, our decoder has fewer parameters.

1 Introduction

For video captioning, the state of the art methods often follow the encoder-decoder or sequence-to-sequence framework [Sutskever et al., 2014]. Particularly, in the encoder, they first employ an RNN unit to obtain the representation of the whole video clip. And based on the video representation, in the decoder, they often use a RNN, e.g., LSTM [Hochreiter and Schmidhuber, ] and GRU [Chung et al., 2014], to generate captions. Although LSTM decoder has memory unit to memorize information and obtains good performance of the task [Jia et al., 2015; Vinyals et al., 2015], as is shown in Weston et al. [Weston et al., 2014], memorized information in the LSTM cell is limited to several time steps, because the long-term information is gradually diluted at each time step.

Recent methods [Gehring et al., 2017; Kaiser et al., 2017] explored the utilization of CNN for sequence modeling. As is constrained by the convolutional kernel, the one-layer structure could not model sequences. The CNN model often employs a hierarchical structure, i.e., stacking multiple convolution layers, to model sequences. Although the hierarchical CNN structure has been demonstrated to be effective in tasks like machine translation [Gehring et al., 2017], the performance is constrained by the size of the convolutional kernel and cannot fully capture the information of each layer. Thus, for image captioning, sequence modeling with CNN does not obtain comparable performance [Aneja et al., 2018].

Recent efforts have demonstrated that MemNet [Weston et al., 2014; Sukhbaatar et al., 2015] is effective in many tasks, e.g., video question answering [Tapaswi et al., 2016] and natural language processing [Sukhbaatar et al., 2015]. As MemNet has a mechanism of storing long-term information, it has the ability to capture important elements from the input sequence and alleviate the loss of memory information. Based on the ability, we explore to employ the MemNet-based method to construct the decoder.

In this paper, we devise a hierarchical memory decoder for video captioning. The framework is shown in Fig. 1. Particularly, after obtaining the representation of each frame, we first fuse the visual and lexical features. Here, we devise a new multi-modal fusion method, i.e., cross-convolution multi-modal fusion (CCMF). Then, at each time step, we construct a MemNet-based decoder. Meanwhile, to fully capture the sequential information, we stack five memory layers as the decoder. And in each layer, we employ the soft-attention mechanism [Yao et al., 2015] to obtain elements which are related to the current input. Finally, in order to reduce the risk of vanishing gradients, we use a multi-layer cross-entropy loss to train this decoder.

In experiments, we evaluate our method on two benchmark datasets of MSVD [Chen and Dolan, 2011] and MSRVTT [Xu et al., 2016]. To the best of our knowledge, ours is the first memory sequence decoder for video captioning. And compared with several baseline methods which use a single kind of visual feature as input, our method could obtain competitive performance and outperforms the performance of RNN decoder.
2 Related Work

The goal of video captioning is to generate a sentence to describe the video content. The state of the art methods often follow encoder-decoder framework [Venugopalan et al., 2015]. Thus, most methods improve the encoder or the decoder to improve the performance.

Particularly, for the encoder, Pan et al. [Pan et al., 2016a] proposed a hierarchical recurrent neural encoder to fully capture the sequential information of the input video. And Baraldi et al. [Baraldi et al., 2017] proposed a hierarchical boundary-aware encoder for video captioning. This encoder could fully capture the discriminative feature among video frames. Besides, Wang et al. [Wang et al., 2018b] designed a memory network-based framework to leverage much more video content. The work [Chen et al., 2018] designed a method to pick informative frames to generate caption. In short, the role of the encoder is to fully leverage video content to improve the quality of the generated caption.

Compared with encoder, the work about the improvement of decoder is relatively less. The commonly used decoder is still LSTM-based framework [Hochreiter and Schmidhuber, 1997]. The work [Yao et al., 2015] proposed an attention mechanism to help the decoder capture the video content which is related to the generated word. Song et al. [Song et al., 2017] proposed a hierarchical LSTM as the decoder. However, as using multiple LSTM units in the decoder, this method increased the number of parameters and computational costs. Recently, Mehri et al. [Mehri and Sigal, 2018] proposed a middle-out decoding method to improve the LSTM. Though this method improves the decoding efficiency, it still could not solve the problem of long-term information dilution. In this paper, we propose a MemNet-based hierarchical decoder. As the MemNet has the advantage of storing long-term information, our decoder avoids losing long-term information. Moreover, employing the hierarchical structure and multi-layer loss could not only promote the decoder to model sequences and reduce the risk of vanishing gradients but also help the decoder gradually learn to generate accurate captions. Experimental results on two benchmark datasets demonstrate the effectiveness of our decoder.

3 Hierarchical Memory Decoder

In this section, we delve into the main contribution of this paper, i.e., a hierarchical memory decoder with a new multi-modal fusion method.

Feature Extraction. Given a video including $m$ frames, we first employ a pre-trained deep convolutional neural network [Szegedy et al., 2015; He et al., 2016] to extract feature for each of the $m$ frames, which results in a vector $X_i \in \mathbb{R}^q$ for the $i$-th frame. In order to reduce parameters and computational cost, we employ a filter $W_c \in \mathbb{R}^{1 \times q \times n}$ ($n \leq q$) to obtain lower dimensional representation $Z_i \in \mathbb{R}^n$ of $X_i$. Meanwhile, we use $V \in \mathbb{R}^n$ to indicate the mean of these lower dimensional representations.

3.1 Cross-Convolution Multi-modal Fusion

As shown in Fig. 1(a), the input of our hierarchical memory decoder includes the visual and lexical information. Thus, we should first fuse these two multi-modal information. The
common used multi-modal fusion methods mainly include element-wise addition, element-wise product, concatenation, bilinear pooling [Fukui et al., 2016] and circulant fusion [Wu and Han, 2018]. And recent work [Fukui et al., 2016] has shown that bilinear pooling is an effective fusion method. This inspires us that exploiting complex interactions among the feature dimensions is helpful for capturing the common semantics of multi-modal features.

To better exploit complex interaction and reduce the number of parameters, we design a CCMF method (Fig. 2). Given two feature vectors in different modalities, e.g., the visual feature \( V \in \mathbb{R}^n \) and the lexical feature \( C \in \mathbb{R}^n \). We respectively take the visual feature and the lexical feature as the 1-dimensional convolution kernel to make 1-dimensional convolution operation. The details are shown as follows:

\[
\begin{align*}
 kernel1 &= VW_1^T \\
 kernel2 &= CW_2^T \\
 A &= kernel2 \odot V \\
 B &= kernel1 \odot C \\
 M &= ReLU(A) + ReLU(B)
\end{align*}
\]

where \( W_1^T \) and \( W_2^T \) are the transpose of \( W_1 \in \mathbb{R}^{n \times n} \) and \( W_2 \in \mathbb{R}^{n \times n} \). \( M \) is the final fusion result. Here, for the convenience of calculation, we set the dimensions of the visual feature and lexical feature the same. The goal of convolution operation is to make the multi-modal elements fully interact.

### 3.2 Hierarchical Memory Decoder Architecture

In this paper, we stack five identical memory layers to form the memory sequence decoder. In the following, we denote the predicted word sequence by \( \hat{Y} = \{\hat{Y}_1, \ldots, \hat{Y}_T\} \). We denote the target word sequence by \( Y = \{Y_1, \ldots, Y_T\} \), where \( T \) denotes sequence length. ‘\( \odot \)’ is an element-wise product operation. \( Z = \{Z_1, Z_2, \ldots, Z_m\} \). \( \sigma(\cdot) \) is a sigmoid function. In this paper, we use gated activation unit [Oord et al., 2016]. \( \text{attention}(Q, S) \) represents the attention operation based on the query vector \( Q \) and the feature set \( S \).

**First Memory Layer.** At each time step \( t \), we take the fusion result \( M_t \) as the input of the first layer. The operations of this layer are shown as follows:

\[
\begin{align*}
 S_{t-1}^1 &= [M_1, M_2, \ldots, M_{t-1}] \\
 A_t^1 &= \text{attention}(M_t, S_{t-1}^1) \\
 h_t^1 &= \tanh(w_f^1 \odot M_t + b_f^1) \odot \sigma(w_g^1 \odot A_t^1 + b_g^1)
\end{align*}
\]

where \( M_t \) represents the fusion result. \( S_{t-1}^1 \) is the set of fusion result from the time step 1 to \( t - 1 \). \( w_f^1 \) and \( w_g^1 \) denote convolutional filters on the first layer, which are used to adjust the number of channels of \( M_t \) and \( A_t^1 \). \( b_f^1 \) and \( b_g^1 \) denote bias on the first layer.

**Second Memory Layer.** For the second layer, we first use the output \( h_t^1 \) of the first layer to compute visual attention \( \varphi_t^1(Z) \). Then we take the concatenation of \( \varphi_t^1(Z) \) and \( h_t^1 \) as the input. The operations of this layer are shown as follows:

\[
\begin{align*}
 I_t^2 &= w_2 \odot |h_t^1, \varphi_t^1(Z)| + b_2 \\
 S_{t-1}^2 &= [I_t^2, I_{t-1}^2, \ldots, I_{t-2}^2] \\
 A_t^2 &= \text{attention}(I_t^2, S_{t-1}^2) \\
 h_t^2 &= \tanh(w_f^2 \odot I_t^2 + b_f^2) \odot \sigma(w_g^2 \odot A_t^2 + b_g^2)
\end{align*}
\]

where \( w_2 \) is a learnable filter to convert the channel of concatenated representation. \( |a, b| \) represents the concatenation of \( a \) and \( b \). \( w_f^2 \) and \( w_g^2 \) denote convolutional filters on the second layer, which are used to adjust the number of channels of \( I_t^2 \) and \( A_t^2 \). \( b_f^2 \) and \( b_g^2 \) denote bias on the second layer.

Then, the operations of the next two layers are as:

\[
\begin{align*}
 S_{t-1}^3 &= [h_{t-1}^1, h_{t-1}^2, \ldots, h_{t-1}^2] \\
 A_t^3 &= \text{attention}(h_t^3, S_{t-1}^3) \\
 h_t^3 &= \tanh(w_f^3 \odot h_t^3 + b_f^3) \odot \sigma(w_g^3 \odot A_t^3 + b_g^3)
\end{align*}
\]

where \( h_t^3 \) represents the output of \( t \)-th layer at the time step \( t \). \( S_{t-1}^{l-1} \) is the set of the output of \((l-1)\)-th layer from the time step 1 to \( t - 1 \). \( w_f^3 \) and \( w_g^3 \) denote convolutional filters on the \( l \)-th layer, which are used to adjust the number of channels of \( h_{t-1}^l \) and \( A_t^l \). \( b_f^3 \) and \( b_g^3 \) denote bias on the \( l \)-th layer.

**Output Layer.** For the output layer, we first use the output \( h_t^4 \) of the fourth layer to compute visual attention \( \varphi_t^4(Z) \). Then we take the sum of \( h_t^4 \) and \( \varphi_t^4(Z) \) as the input. The operations of this layer are shown as follows:

\[
\begin{align*}
 I_t^5 &= h_t^4 + \varphi_t^4(Z) \\
 S_{t-1}^5 &= [I_t^5, I_{t-1}^5, \ldots, I_{t-2}^5] \\
 A_t^5 &= \text{attention}(I_t^5, S_{t-1}^5) \\
 h_t^5 &= \tanh(w_f^5 \odot I_t^5 + b_f^5) \odot \sigma(w_g^5 \odot A_t^5 + b_g^5)
\end{align*}
\]

where \( w_f^5 \) and \( w_g^5 \) denote convolutional filters on the 5th layer, which are used to adjust the number of channels of \( I_t^5 \) and \( A_t^5 \). \( b_f^5 \) and \( b_g^5 \) denote bias.

Finally, the \( t \)-th generated word \( \hat{Y}_t \) is computed as follows:

\[
\hat{Y}_t \sim \text{softmax}(w_p(h_t^5 + \varphi_t^4(Z)) + b_p)
\]
shown in Fig. 1(b)). And for these two types of attention, we all use soft attention mechanism [Yao et al., 2015]. Concretely, for memory attention, at step $t$, based on the set $S^l_{t-1}$, we first compute the dynamic attention weight $\alpha^t_i$:

$$e^t_i = w^T \tanh(W_a h^l_{t-1} + U_a S^l_{t-1}[i] + b_a)$$

$$\alpha^t_i = \exp(e^t_i) / \sum_{j=1}^{t-1} \exp(e^t_j)$$ (7)

where $w$, $W_a$, $U_a$, and $b_a$ are learnable parameters. $w^T$ is the transpose of $w$. $h^l_{t-1}$ represents the output of $(l - 1)$-th layer.

Finally, we take the dynamically weighted sum of the set $S^l_{t-1}$ as the attention result of the $l$-th layer.

$$\phi^l_i(S) = \sum_{i=1}^{t-1} \alpha^t_i S^l_{t-1}[i]$$ (8)

And the process of visual attention is same as that of memory attention. Here we replace the set $S^l_{t-1}$ with $Z = (Z_1, Z_2, ..., Z_m)$.

**Training Loss.** In order to reduce the risk of vanishing or exploding gradients, inspired by the work [Zhang et al., 2016], we enforce intermediate supervision for some hidden layers. In this paper, we empirically enforce supervision for the first, third, and fifth memory layer. For each layer $j \in \{1, 3, 5\}$, we employ a cross-entropy loss.

$$L^j_{XE} = -\sum_{t=1}^{T} \log(p(Y_t|Y_{t-1}, Z))$$ (9)

where $Y_t$ is the ground-truth word at time $t$, $p(Y_t|Y_{t-1}, Z)$ is the output probability of word $Y_t$ given the previous word $Y_{t-1}$ and encoding output $Z$. By summing the loss of each layer, we obtain the training loss of memory decoder:

$$L_{XE} = \lambda_1 L^1_{XE} + \lambda_3 L^3_{XE} + \lambda_5 L^5_{XE}$$ (10)

where $\lambda_1$, $\lambda_3$, and $\lambda_5$ are hyper-parameters. Here we keep the sum of $\lambda_1$, $\lambda_3$, and $\lambda_5$ is 1. Besides, as the fifth layer is the output layer, we should keep $\lambda_5$ is larger than $\lambda_1$ and $\lambda_3$.

4 Experiments

In the following, we first compare our method with some baseline methods. Then we make some ablation analysis about our method. All results are evaluated by metrics of BLEU [Papineni et al., 2002], METEOR [Denkowski and Lavie, 2014], and CIDEr [Vedantam et al., 2015].

4.1 Dataset and Implementation Details

**Datasets.** MSVD [Chen and Dolan, 2011] contains 1,970 video clips with multiple descriptions for each video clip. Following the work [Venugopalan et al., 2014], we use 1,200 video clips for training, 100 video clips for validation, and 670 video clips for testing. MSVRVT [Xu et al., 2016] is the largest dataset for video captioning. The dataset contains 10,000 video clips. Following the work [Xu et al., 2016], we use 6,513 videos for training, 497 videos for validation, and 2,990 videos for testing.

**Video Processing.** For the MSVD dataset, we select 40 equally-spaced frames from each video and feed them into GoogLeNet [Szegedy et al., 2015] and ResNet-152 [He et al., 2016] to extract a 1,024 and 2,048-dimensional frame-representation. For the MSVRVT dataset, we select 20 equally-spaced frames from each video and feed them into GoogLeNet and ResNet-152 to extract 1,024 and 2,048-dimensional representation, respectively.

**Parameters Setting.** In the experiment, we set the channel $r$ of $Z_l$ to 512. For each memory layer, we set $w \in \mathbb{R}^{100 \times 1}$, $W_a \in \mathbb{R}^{100 \times 512}$, $U_a \in \mathbb{R}^{100 \times 512}$, $b_a \in \mathbb{R}^{100}$ (Eq. (7)), and $w^f_l \in \mathbb{R}^{1 \times 512 \times 512}$, $w^g_l \in \mathbb{R}^{1 \times 512 \times 512}$, $b^f_l \in \mathbb{R}^{512}$, $b^g_l \in \mathbb{R}^{512}$, $l \in \{1, \ldots, 5\}$, (Eq. (4)). The parameter settings of visual attention are same as those of the memory layers.

**Training Details.** The vocabulary size is 12,596 for MSVD and 23,308 for MSVRVT, respectively. During training, all parameters are randomly initialized. We use Adam optimizer with an initial learning rate of $1 \times 10^{-3}$ and a momentum parameter of 0.9. We empirically set $\lambda_1$, $\lambda_3$, and $\lambda_5$ to 0.2, 0.2, and 0.6, respectively. Note that we do not conduct beam search in testing.

4.2 Experiment Results

As our method is only a decoder with attention mechanism, here for fair comparison, we compare some baseline methods, e.g., the work [Yao et al., 2015] and the work [Song et al., 2017]. And these methods include different types of the decoder and rarely encode the video content.

**MSVD Dataset.** On MSVD dataset, we compare our method with some baseline methods. The results are shown in Table 1. Particularly, compared with the work [Yao et al., 2015] which only includes LSTM decoder and visual attention, our method outperforms its performance obviously. This shows that our decoder is very effective. Although the methods [Ballas et al., 2015; Pan et al., 2016b; Yu et al., 2016] use different types of RNN as the decoder, the performance of our method also outperforms them. Moreover, the work [Song et al., 2017] stacks multiple LSTM layers as the decoder. However, its performance is also weaker than us on the metric of ‘METEOR’. Besides, stacking multiple LSTM layers often leads to the increase of training time and computational cost. These all demonstrate our decoder could obtain comparable performance as RNN decoder. Meanwhile, the amount of parameter in our decoder is 4.13 M, which is fewer than that of one-layer LSTM whose amount of parameter is 4.28 M. This shows our hierarchical memory decoder is effective. Besides, the Middle-out [Mehri and Sigal, 2018] is a newly proposed decoder. Compared with Middle-out decoder, our method still outperforms it. And we do not use encoding network. This further shows the effectiveness of our decoder.

**MSVRVT Dataset.** On MSVRVT dataset, we compare our method with some state of the art methods. Compared with the work [Song et al., 2017], our method also outperforms its performance on the metric of ‘METEOR’. Compared with the work [Venugopalan et al., 2014] which uses the GoogLeNet
Table 1: Comparison with other models. Here 'G' denotes GoogLeNet. 'R' denotes ResNet. 'Memory' represents our memory sequence decoder. 'self' denotes self-attention. All values are measured by percentage (%).

| Method                                      | BLEU@4 | METEOR | CIDEr |
|----------------------------------------------|--------|--------|-------|
| S2VT [Venugopalan et al., 2015]              | -      | 29.20  | -     |
| VGG-LSTM-E [Pan et al., 2016b]               | 40.20  | 29.50  | -     |
| C3D-LSTM-E [Pan et al., 2016b]               | 41.70  | 29.90  | 62.10 |
| VGG+2p-RNN [Yu et al., 2016]                 | 44.30  | 31.10  | 53.60 |
| C3D+2p-RNN [Yu et al., 2016]                 | 47.40  | 30.50  | 63.60 |
| Tempor-attention [Yao et al., 2015]          | 41.92  | 29.60  | 51.67 |
| G+Bi-GRU-RCN1 [Ballas et al., 2015]          | 48.42  | 31.70  | 65.38 |
| G+Bi-GRU-RCN2 [Ballas et al., 2015]          | 43.26  | 31.60  | 68.01 |
| G+LSTM [Song et al., 2017]                   | 48.50  | 31.90  | -     |
| C3D+bLSTM [Song et al., 2017]                | 47.50  | 30.50  | -     |
| MAMRN1 [Li et al., 2017]                     | 41.40  | 32.20  | 53.90 |
| R+PickNet [Chen et al., 2018]                | 46.10  | 33.10  | 76.00 |
| MCF [Wu and Han, 2018]                       | 46.46  | 33.72  | 75.46 |
| RecNet [Wang et al., 2018a]                  | 51.10  | 34.10  | 80.30 |
| Middle-out [Mehri and Sigal, 2018]           | 40.80  | 30.90  | 68.60 |
| Middle-out-selt [Mehri and Sigal, 2018]      | 47.00  | 34.10  | 79.90 |
| G+Memory                                     | 45.74  | 33.01  | 73.11 |
| R+Memory                                     | 49.28  | 34.67  | 81.49 |

Table 2: Comparison with other models on MSRVTT. Note that we use the dataset of MSRVTT 2016. Here 'G' and 'R' denote GoogLeNet and ResNet features. 'Memory' represents our hierarchical memory decoder. All values are measured by percentage (%).

| Method                                      | BLEU@4 | METEOR | CIDEr |
|----------------------------------------------|--------|--------|-------|
| MA-LSTM [Xu et al., 2017]                    | 36.5   | 26.5   | 41.0  |
| G+LSTM [Venugopalan et al., 2014]            | 34.6   | 24.6   | -     |
| C3D+SA [Yao et al., 2015]                    | 36.1   | 25.7   | 35.2  |
| R+S2VT [Sutskever et al., 2014]              | 31.4   | 25.7   | 35.2  |
| R+BLSTM [Song et al., 2017]                  | 38.3   | 26.3   | -     |
| R+Consensus [Phan et al., 2017]               | 37.5   | 26.6   | 41.5  |
| M3-VC [Wang et al., 2018b]                   | 38.1   | 26.6   | -     |
| G+Memory                                     | 35.7   | 26.9   | 41.7  |
| R+Memory                                     | 37.5   | 26.9   | 41.7  |

Table 3: Comparison of different fusion methods. All values are measured by percentage(%).

| Method                                      | BLEU@4 | METEOR | CIDEr |
|----------------------------------------------|--------|--------|-------|
| Bilinear Pooling                             | 45.51  | 32.20  | 70.15 |
| Circulant Fusion                             | 44.32  | 32.84  | 72.16 |
| CCMF                                         | 45.74  | 33.01  | 73.11 |

4.3 Ablation Analysis

In the following, we make some ablation analysis about our method on the MSVD dataset. We use GoogLeNet feature.

**Fusion Method.** In order to make the decoder fully leverage the video features, at each time step, the input of the decoder includes the lexical feature and the mean representation of video features (Fig. 1(a)). This requires us to use a proper method to fuse the visual and lexical feature. To demonstrate CCMF is effective for our decoder, compare our method with two effective fusion method, i.e., bilinear pooling [Fukui et al., 2016] and circulant fusion [Wu and Han, 2018]. We can see from Table 3 that for our decoder, our fusion method outperforms the compared methods. This shows our fusion method is effective for our decoder.

**Attention Mechanism.** Dot-product attention [Vaswani et al., 2017] and soft attention [Yao et al., 2015] are the two commonly used attention mechanisms. In order to demonstrate the soft attention used in our decoder is effective, here we replace the soft attention with the dot-product attention.
and keep other components of the decoder invariant. The results are shown in Table 4. We can see that in our decoder, the performance of soft attention outperforms dot-product attention. This shows that for our decoder, the soft attention mechanism is effective.

Table 4: Comparison of different attention mechanism. ‘Dot-Attention’ denotes the dot product attention. All values are measured by percentage (%).

| Method          | BLEU@4 | METEOR | CIDEr |
|-----------------|--------|--------|-------|
| Dot-Attention    | 45.95  | 32.24  | 68.62 |
| Soft-Attention   | 45.74  | 33.01  | 73.11 |

In Fig. 3, we show some examples of dot-product attention and soft attention. We can see that the results generated by the soft attention are better than those of dot-product attention. Taking the fifth and seventh results as examples, our method successfully recognizes the ‘tiger’ and ‘panda’. This further shows that the soft attention mechanism is effective.

Performance of Each Memory Layer. In the following, we analyze the performance of different memory layer. Here, we choose the first, the third, and the output layer (Eq. (10)). The results are shown in Table 5. We can see that the results from the first memory layer to the output memory layer continuously improve. This shows that stacking multiple memory layers is helpful for capturing the sequence information and improving performance. In order to further show stacking multiple layers is helpful, we show some examples in Fig. 4. We can see that from the first layer to the output layer, the accuracy of the generated caption is increasingly getting better. Besides, from the bottom of each example, we can see that as the layer getting deeper, the attention weight of each memory layer changes towards the more important word. Taking the first and the second result as example, when generating the last word ‘exercise’ and ‘pot’, the main attention of output layer is ‘girl’, ‘doing’, and ‘pouring’, ‘sauce’, which are important for the generating of the last word. These all show that the hierarchical memory decoder could capture the relevance corresponding to a generated word. The relevance is helpful for capturing much more important memory and generating accuracy captions.

Table 5: Comparison of different memory layer. All values are measured by percentage (%).

| Method          | BLEU@4 | METEOR | CIDEr |
|-----------------|--------|--------|-------|
| First-Layer     | 39.21  | 28.75  | 44.80 |
| Third-Layer     | 45.22  | 32.64  | 70.18 |
| Output-Layer    | 45.74  | 33.01  | 73.11 |

5 Conclusion

In this paper, we propose a new hierarchical memory decoder for video captioning. We first design a new multi-modal fusion mechanism, i.e., CCMF, to fuse visual and lexical information. Then, at each time step, taking the fusion result as the input, we construct a memory network-based decoder to generate captions. Experimental results on two benchmark datasets demonstrate the effectiveness of our method.
References

[Anjeja et al., 2018] Iyoti Anjeja, Aditya Deshpande, and Alexander G Schwing. Convolutional image captioning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5561–5570, 2018.

[Ballas et al., 2015] Nicolas Ballas, Li Yao, Chris Pal, and Aaron Courville. Delving deeper into convolutional networks for learning video representations. arXiv preprint arXiv:1511.06432, 2015.

[Baraldi et al., 2017] Lorenzo Baraldi, Costantino Grana, and Rita Cucchiara. Hierarchical boundary-aware neural encoder for video captioning. In Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on, pages 3185–3194. IEEE, 2017.

[Chen and Dolan, 2011] David L. Chen and William B. Dolan. Collecting highly parallel data for paraphrase evaluation. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, pages 190–200. Association for Computational Linguistics, 2011.

[Chen et al., 2018] Yanyun Chen, Shuhui Wang, Weiqiang Zhang, and Qingming Huang. Less is more: Picking informative frames for video captioning. arXiv preprint arXiv:1803.01437, 2018.

[Chung et al., 2014] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555, 2014.

[Denkowski and Lavie, 2014] Michael Denkowski and Alon Lavie. Meteor universal: Language-specific evaluation for any target language. In Proceedings of the ninth workshop on statistical machine translation, pages 376–380, 2014.

[Fukui et al., 2016] Akira Fukui, Dong Huk Park, Daylen Yang, Anna Rohrbach, Trevor Darrell, and Marcus Rohrbach. Multimodal compact bilinear pooling for visual question answering and visual grounding. arXiv preprint arXiv:1606.01847, 2016.

[Gehring et al., 2017] Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, and Yann N Dauphin. Convolutional sequence to sequence learning. arXiv preprint arXiv:1705.03122, 2017.

[Hajishirzi et al., 2016] Caiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

[Hochreiter and Schmidhuber, 1997] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation.

[Jia et al., 2015] Xin Jia, Effrosini Gavrva, Basura Fernando, and Tinne Tuytelaars. Guiding long-short term memory for image caption generation. arXiv preprint arXiv:1509.04994, 2015.

[Kaiser et al., 2017] Lukasz Kaiser, Aidan N Gomez, and Francois Chollet. Depth-wise separable convolutions for neural machine translation. arXiv preprint arXiv:1706.03059, 2017.

[Li et al., 2017] Xuelong Li, Bin Zhao, and Xiaoqiang Lu. Mam-rnn: multi-level attention for image captioning. In Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, 2017.

[Mehr and Sigal, 2018] Shihib Mehr and Leonid Sigal. Middle-out decoding. In Advances in Neural Information Processing Systems, pages 5532–5534, 2018.

[Oord et al., 2016] Aaron van den Oord, Nal Kalchbrenner, and Koray Kavukcuoglu. Pixel recurrent neural networks. arXiv preprint arXiv:1601.06759, 2016.

[Pan et al., 2016a] Pingbo Pan, Zhongwen Xu, Yi Yang, Fei Wu, and Yutong Zhuang. Hierarchical recurrent neural encoder for video representation with application to captioning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1029–1038, 2016.

[Pan et al., 2016b] Yingwei Pan, Tao Mei, Ting Yao, Houqing Li, and Yong Rui. Jointly modeling embedding and translation to bridge video and language. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4594–4602, 2016.

[Papineni et al., 2002] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: A method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting on association for computational linguistics, pages 311–318. Association for Computational Linguistics, 2002.

[Phan et al., 2017] Sang Phan, Gustav Eje Henter, Yusuke Miyao, and Shin’ichi Satoh. Consensus-based sequence training for video captioning. arXiv preprint arXiv:1712.09532, 2017.

[Song et al., 2017] Jingkuan Song, Zhao Guo, Lianli Gao, Wu Liu, Dongxiang Zhang, and Heng Tao Shen. Hierarchical lstm with adjusted temporal attention for video captioning. arXiv preprint arXiv:1706.01231, 2017.

[Sukhbaatar et al., 2015] Sainbayar Sukhbaatar, Jason Weston, Rob Fergus, et al. End-to-end memory networks. In Advances in neural information processing systems, pages 2440–2448, 2015.

[Sutskever et al., 2014] Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. Sequence to sequence learning with neural networks. In Advances in neural information processing systems, pages 3104–3112, 2014.

[Szegedy et al., 2015] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1–9, 2015.

[Tapaswi et al., 2016] Makarand Tapaswi, Yukun Zhu, Rainer Stiefelhagen, Antonio Torralba, Raquel Urtasun, and Sanja Fidler. Movieqa: Understanding stories in movies through question-answering. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4631–4640, 2016.

[Vaswani et al., 2017] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Advances in Neural Information Processing Systems, pages 5998–6008, 2017.

[Venugopalan et al., 2014] Subhashini Venugopalan, Hujun Xu, Jeff Donahue, Marcus Rohrbach, Raymond Mooney, and Kate Saenko. Translating videos to natural language using deep recurrent neural networks. arXiv preprint arXiv:1412.4729, 2014.

[Venugopalan et al., 2015] Subhashini Venugopalan, Marcus Rohrbach, Jeffrey Donahue, Raymond Mooney, Trevor Darrell, and Kate Saenko. Sequence to sequence video to text. In Proceedings of the IEEE international conference on computer vision, pages 4534–4542, 2015.

[Vinyals et al., 2015] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3156–3164, 2015.

[Wang et al., 2018a] Bairui Wang, Lin Ma, Wei Zhang, and Wei Liu. Reconstruction network for video captioning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7622–7631, 2018.

[Wang et al., 2018b] Junbo Wang, Wei Wang, Yan Huang, Liang Wang, and Tieniu Tan. M3: Multimodal memory modelling for video captioning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7512–7520, 2018.

[Winston et al., 2014] Jason Weston, Sumit Chopra, and Antoine Bordes. Memory networks. arXiv preprint arXiv:1410.3916, 2014.

[Wu and Han, 2018] Aiming Wu and Yahong Han. Multi-modal circular fusion for video-to-language and backward. In IJCAI, pages 1029–1035, 2018.

[Xu et al., 2016] Jun Xu, Tao Mei, Ting Yao, and Yong Rui. Ms-vtt: A large video description dataset for bridging video and language. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 5288–5296, 2016.

[Xu et al., 2017] Jun Xu, Ting Yao, Yangdong Zhang, and Tao Mei. Learning multimodal attention lstm networks for video captioning. In Proceedings of the 2017 ACM on Multimedia Conference, pages 537–543. ACM, 2017.

[Yan et al., 2015] Li Yao, Arousa Torabi, Kyunghyun Cho, Nicolas Ballas, Christopher Pal, Hugo Larochelle, and Aaron Courville. Describing videos by exploiting temporal structure. In Proceedings of the IEEE international conference on computer vision, pages 4507–4515, 2015.

[Yu et al., 2016] Haonan Yu, Jiang Wang, Zhiheng Huang, Yi Yang, and Wei Xu. Video paragraph captioning using hierarchical recurrent neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4584–4593, 2016.

[Zhang et al., 2016] Yuting Zhang, Kibok Lee, and Honglak Lee. Augmenting supervised visual neural networks with unsupervised objectives for large-scale image classification. In International Conference on Machine Learning, pages 612–621, 2016.