Memory-augmented Attention Modelling for Videos

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Abstract

We present a method to improve video description generation by modeling higher-order interactions between video frames and described concepts. By storing past visual attention in the video associated to previously generated words, the system is able to decide what to look at and describe in light of what it has already looked at and described. This enables not only more effective local attention, but tractable consideration of the video sequence while generating each word. Evaluation on the challenging and popular MSVD and Charades datasets demonstrates that the proposed architecture outperforms previous video description approaches without requiring external temporal video features.

1. Introduction

Deep neural architectures have led to remarkable progress in computer vision and natural language processing problems. Image captioning is one such problem, where the combination of convolutional structures (Krizhevsky et al., 2012; LeCun et al., 1998), and sequential recurrent structures (Sutskever et al., 2014) leads to remarkable improvements over previous work (Fang et al., 2015; Devlin et al., 2015). One of the emerging modelling paradigms, shared by models for image captioning as well as related vision-language problems, is the notion of an attention mechanism that guides the model to attend to certain parts of the image while generating (Xu et al., 2015a).

The attention models used for problems such as image captioning typically depend on the single image under consideration and the partial output generated so far, jointly capturing one region of an image and the words being generated. However, such models cannot directly capture the temporal reasoning necessary to effectively produce words that refer to actions and events taking place over multiple frames in a video. For example, in a video depicting "someone waving a hand", the "waving" action can start from any frame and can continue on for a variable number of following frames. At the same time, videos contain many frames that do not provide additional information over the smaller set of frames necessary to generate a summarizing description. Given these challenges, it is not surprising that even with recent advancements in image captioning (Fang et al., 2015; Xu et al., 2015a; Johnson et al., 2016; Vinyals et al., 2015), video captioning has remained challenging.

Motivated by these observations, we introduce a memory-based attention mechanism for video captioning and description. Our model utilizes memories of past attention in the video when reasoning about where to attend in a current time step. This allows the model to not only effectively leverage local attention, but also to consider the entire video as it generates each word. This mechanism effectively binds information from both vision and language sources into a coherent structure.

Our work shares the same goals as recent work on attention mechanisms for sequence-to-sequence architectures, such as Rocktäschel et al. (2016) and Yang et al. (2016). Rocktäschel et al. (2016) consider the domain of entailment relations, where the goal is to determine entailment given two input sentences. They propose a soft attention model that is not only focused on the current state, but the previous as well. In our model, all previous attentions are explicitly stored into memory, and the system learns to memorize the encoded version of the input videos conditioned on previously seen words. Yang et al. (2016) and our work both try to solve the problem of locality of attention in vision-to-language, but while Yang et al. (2016) introduce a memory architecture optimized for single image caption generation, we introduce a memory architecture that operates on a streaming video’s temporal sequence.

The contributions of this work include:

- A deep learning architecture that represents video with an explicit model of the video’s temporal structure.
- A method to jointly model the video description and temporal video sequence, connecting the visual video space and the language description space.
- A memory-based attention mechanism that learns hi-
erarchical attention relationships in a simple and effective sequence-to-sequence memory structure.

- Extensive comparison of this work and previous work on the video captioning problem on the MSVD (Chen & Dolan, 2011) and the Charades (Sigurdsson et al., 2016) datasets.

We focus on the video captioning problem, however, the proposed model is general enough to be applicable in other sequence problems where attention models are used (e.g., machine translation or recognizing entailment relations).

2. Related Work

One of the primary challenges in learning a mapping from a visual space (i.e., video or image) to a language space is learning a representation that not only effectively represents each of these modalities, but is also able to translate a representation from one space to the other. Rohrbach et al. (2013) developed a model that generates a semantic representation of visual content that can be used as the source language for the language generation module. Venugopalan et al. (2015b) proposed a deep method to translate a video into a sentence where an entire video is represented with a single vector based on the mean pool of frame features. However, it was recognized that representing a video by an average of its frames loses the temporal structure of the video. To address this problem, recent work (Yao et al., 2015; Pan et al., 2016a; Venugopalan et al., 2015a; Shin et al., 2016; Pan et al., 2016b; Xu et al., 2015b; Ballas et al., 2016; Yu et al., 2016) proposed methods to model the temporal structure of videos as well as language.

The majority of these methods are inspired by sequence-to-sequence (Sutskever et al., 2014) and attention (Bahdanau et al., 2015) models. Sequence learning was proposed to map the input sequence of a source language to a target language (Sutskever et al., 2014). Applying this method with an additional attention mechanism to the problem of translating a video to a description showed promising initial results, however, revealed additional challenges. First, modelling the video content with a fixed-length vector in order to map it to a language space is a more complex problem than mapping from a language to a language, given the complexity of visual content and the difference between the two modalities. Since not all frames in a video are equally salient for a short description, and an event can happen in multiple frames, it is important for a model to identify which frames are most salient. Further, the models need additional work to be able to focus on points of interest within the video frames to select what to talk about. Even a variable-length vector to represent a video using attention (Yao et al., 2015) can have some problems.

More specifically, current attention methods are local (Yang et al., 2016), since the attention mechanism works in a sequential structure, and lack the ability to capture global structure. Moreover, combining a video and a description as a sequence-to-sequence problem motivates using some variant of a recurrent neural network (RNN) (Hochreiter & Schmidhuber, 1997): Given the limited capacity of a recurrent network to model very long sequences, memory networks (Weston et al., 2014; Sukhbaatar et al., 2015) have been introduced to help the RNN memorize sequences. However, one problem these memory networks suffer from is difficulty in training the model. The model proposed by Weston et al. (2014) requires supervision at each layer, which makes training with backpropagation a challenging task. Sukhbaatar et al. (2015) proposed a memory network that can be trained end-to-end, and the current work follows this research line to tackle the challenging problem of modeling vision and language memories for video description generation.

3. Learning to Attend and Memorize

A main challenge in video description is to find a mapping that can capture the connection between the video frames and the video description. Sequence-to-sequence models, which work well at connecting input and output sequences in machine translation (Sutskever et al., 2014), do not perform as well for this task, as there is not the same direct alignment between a full video sequence and its summarizing description.

Our goal in the video description problem is to create an architecture that learns which moments to focus on in a video sequence in order to generate a summarizing natural language description. The modelling challenges we set forth for the video description problem are: (1) Processing the temporal structure of the video; (2) Learning to attend to important parts of the video; and (3) Generating a description where each word is relevant to the video. At a high-level, this can be understood as having three primary parts: When moments in the video are particularly salient; what concepts to focus on; and how to talk about them. We directly address these issues in an end-to-end network with three primary corresponding components (Figure 1): A Temporal Model (TEM), A Hierarchical Attention/Memory Model (HAM), and a Decoder. In summary:

- **When**: Frames within the video sequence - The Temporal Model (TEM).
- **What**: Language-grounded concepts depicted in the video - The Hierarchical Attention/Memory mechanism (HAM).
- **How**: Words that fluently describe the what and when
- The Decoder.

The Temporal Model is in place to capture the temporal structure of the video: It functions as a when component. The Hierarchical Attention/Memory is a main contribution of this work, functioning as a what component to remember relationships between words and video frames, and storing longer term memories. The Decoder generates language, and functions as the how component to create the final description.

To train the system end to end, we formulate the problem as sequence learning to maximize the probability of generating a correct description given a video:

$$\Theta^* = \arg \max_{\Theta} \sum_{S,f_1,\ldots,f_N} \log p(S|f_1,\ldots,f_N; \Theta)$$  \hspace{1cm} (1)

where $S$ is the description, $f_1, f_2, \ldots, f_N$ are the input video frames, and $\Theta$ is the model parameter vector. In the next sections, we will describe each component of the model, then explain the details of training and inference.

Notational note: Numbered equations use bold face to denote multi-dimensional learnable parameters, e.g., $W^j_p$. To distinguish the two different sets of time steps, one for video frames and one for words in the description, we use the notation $t$ for video and $t'$ for language. Throughout, the terms description and caption are used interchangeably.

### 3.1. Temporal Model (TEM)

The first module we introduce encodes the temporal structure of the input video. A clear framework to use for this is a Recurrent Neural Network (RNN), which has been shown to be effectual in modelling the temporal structure of sequential data such as video (Ballas et al., 2016; Sharma et al., 2015; Venugopalan et al., 2015a) and speech (Graves & Jaitly, 2014). In order to apply this in video sequences to generate a description, we seek to capture the fact that frame-to-frame temporal variation tends to be local (Brox & Malik, 2011) and critical in modeling motion (Ballas et al., 2016). Visual features extracted from the last fully connected layers of Convolutional Neural Networks (CNNs) have been shown to produce state-of-the-art results in image classification and recognition (Simonyan & Zisserman, 2014; He et al., 2016), and thus seem a good choice for modeling visual frames. However, these features tend to discard low level information useful in modeling the motion in the video (Ballas et al., 2016).

To address these challenges, we implement an RNN we call the Temporal Model (TEM). At each time step of the TEM, a video frame encoding from a CNN serves as input. Rather than extracting video frame features from a fully connected layer of the pretrained CNN, we extract intermediate convolutional maps.

In detail, for a given video $X$ with $N$ frames $X = [X^1, X^2, \ldots, X^N]$, $N$ convolutional maps of size $R^{L \times D}$ are extracted, where $L$ is the number of locations in the input frame and $D$ is the number of dimensions (See TEM in Figure 1). To enable the network to store the most important $L$ locations of each frame, we use a soft location attention mechanism, $f_{Latt}$ (Bahdanau et al., 2015; Xu et al., 2015a; Sharma et al., 2015). We first use a softmax to compute $L$ probabilities that specify the importance of different parts in the frame, and this creates an input map for $f_{Latt}$.

Formally, given a video frame at time $t$, $X^t \in R^{L \times D}$, the
\( f_{\text{Latt}} \) mechanism is defined as follows:

\[
\rho_j^t = \frac{\exp(W_p^j h_{v}^{t-1})}{\sum_{k=1}^{L} \exp(W_p^k h_{v}^{t-1})} \tag{2}
\]

\[
f_{\text{Latt}}(X^t, h_{v}^{t-1}; W_p) = \sum_{j=1}^{L} (\rho_j^t)^T X_j^t \tag{3}
\]

where \( h_{v}^{t-1} \in R^K \) is the hidden state of the TEM at time \( t-1 \) with \( K \) dimensions, and \( W_p \in R^{K \times K} \). For each video frame time step, TEM learns a vector representation by applying location attention on the frame convolution map, conditioned on all previously seen frames:

\[
F^t = f_{\text{Latt}}(X^t, h_{v}^{t-1}; W_p) \tag{4}
\]

\[
h^t_v = f_v(F^t, h_{v}^{t-1}; \Theta_v) \tag{5}
\]

where \( f_v \) can be an RNN/LSTM/GRU cell and \( \Theta_v \) is the parameters of the \( f_v \). Due to the fact that vanilla RNNs have gradient vanishing and exploding problems (Pascu et al., 2013), we use gradient clipping, and an LSTM with the following flow to handle potential vanishing gradients:

\[
i^t = \sigma(F^t W_{xi} + (h_{v}^{t-1})^T W_{hi})
\]

\[
f^t = \sigma(F^t W_{xf} + (h_{v}^{t-1})^T W_{hf})
\]

\[
o^t = \sigma(F^t W_{xo} + (h_{v}^{t-1})^T W_{ho})
\]

\[
g^t = \tanh(F^t W_{xg} + (h_{v}^{t-1})^T W_{hg})
\]

\[
c^t = f^t \odot c_{v}^{t-1} + i^t \odot g^t
\]

\[
h^t_v = o_t \odot \tanh(c^t)
\]

where \( W_{hi}, W_{xf}, W_{xo}, W_{xg} \in R^{K \times K} \), and we define \( \Theta_v = \{W_{hi}, W_{xf}, W_{xo}, W_{xg}\} \).

### 3.2. Hierarchical Attention/Memory (HAM)

A main contribution of this work is a global view for the video description task: A memory-based attention mechanism that learns hierarchical attention relationships in an efficient sequence-to-sequence memory structure. We refer to this as the Hierarchical Attention/Memory mechanism (HAM), and it aggregates information from previously generated words and all input frames.

The HAM component is a hierarchical memorized attention between an input video and a description. More specifically, it learns a hierarchical attention structure for where to attend in a video given all previously generated words (from the Decoder), and previous states (from the TEM). This functions as a memory structure, remembering encoded versions of the video with corresponding language, and in turn, enabling the Decoder to access the full encoded video and previously generated words as it generates new words.

- Given:
  \[ N = \text{Number of frames in a given video} \]
  \[ T = \text{Number of words in description} \]
  \[ H_v = \text{Input video states, } [h_v^1, ..., h_v^N] \]
  \[ H_{v}^{t-1} = \text{Decoder state } h_{t} \text{ at time } t-1, \text{ repeated } N \text{ times} \]
  \[ H_{m}^{t-1} = \text{Memory state } h_{m} \text{ at time } t-1, \text{ repeated } N \text{ times} \]
  \[ W_v, W_g \in R^{K \times K} \]
  \[ W_m \in R^{M \times K} \]
  \[ u \in R^K \]
  \[ \alpha = \text{Probability over all } N \text{ frames} \]
  \[ \Theta_a = \{W_v, W_g, W_m, u\} \]

- Attention update \([\hat{F}(\Theta_a)]\):
  \[
  Q_A = \text{tanh}(H_v W_v + H_{v}^{t-1} W_g + H_{m}^{t-1} W_m) \tag{6}
  \]
  \[
  \alpha_t = \text{softmax}(Q_A u) \tag{7}
  \]
  \[
  \hat{F} = H_v^T \alpha_t \tag{8}
  \]

- Memory update:
  \[
  h_{m}^{t} = f_m(h_{m}^{t-1}, \hat{F}; \Theta_m) \tag{9}
  \]

This component addresses several key issues in generating a coherent video description. In video description, a single word or phrase often describes action spanning multiple frames within the input video. By employing the HAM, the model can effectively capture the relationship between a relatively short bit of language and an action that occurs over multiple frames. This also functions to directly address the problem of identifying which parts of the video are most relevant for description.

The proposed Hierarchical Attention/Memory mechanism is formalized with an Attention update and a Memory update, detailed in Figure 2. Figure 1 illustrates where the HAM sits within the full model, with the Attention module shown in 1a and the Memory module shown in 1b.

As formalized in Figure 2, the Attention update \( \hat{F}(\Theta_a) \) computes the set of probabilities in a given time step for attention within the input video states, the memory state, and the decoder state. The Memory update stores what has been attended to and described. This serves as the memorization component, combining the previous memory with the current hierarchical attention \( \hat{F} \). We use an LSTM \( f_m \) with the equations described above to enable the network to learn multi-layer attention over the input video and its corresponding language. The output of this function is then...
used as input to the Decoder.

3.3. Decoder

In order to generate a new word conditioned on all previous words and HAM states, a recurrent structure is modelled as follows:

\[
\hat{s}_t = \text{softmax}(h_y^T \Theta_g) \quad (10)
\]

\[
h_y^t = f_g(s_t, h_y^t-1, \Theta_g) \quad (11)
\]

where \( h_y^t \in \mathbb{R}^K \), \( s_t \) is a word vector at time \( t \), \( W_e \in \mathbb{R}^{K \times C} \), and \( C \) is the vocabulary size. In addition, \( \hat{s}_t \) assigns a probability to each word in the language. \( f_g \) is an LSTM where \( s_t \) and \( h_y^t \) are inputs and \( h_y^t \) is the recurrent state.

3.4. Training and Optimization

The goal in our network is to predict the next word given all previously seen words and an input video. In order to optimize our network parameters \( \Theta = \{ W_g, \Theta_h, \Theta_e, \Theta_m, \Theta_g, W_e \} \), we minimize a negative log likelihood loss function:

\[
L(S, X; \Theta) = -\sum_{t=1}^{T} \sum_{i}^{V} s_t^i \log(\hat{s}_t^i) + \lambda \| \Theta \|^2 \quad (12)
\]

where \( |V| \) is the dictionary size. We fully train our network in an end-to-end fashion using first-order stochastic gradient-based optimization method with an adaptive learning rate. More specifically, in order to optimize our network parameters, we use Adam (Kingma & Ba, 2015) with learning rate \( 2 \times 10^{-5} \) and set \( \beta_1, \beta_2 \) to 0.8 and 0.999, respectively. During training, we use a batch size of 16.

4. Experiments

Dataset We evaluate the model on the Charades (Sigurdsson et al., 2016) dataset and the Microsoft Video Description Corpus (MSVD) (Chen & Dolan, 2011). Charades contains 9,848 videos (in total) and provides 27,847 videos. We follow the same train/test splits as Sigurdsson et al. (2016), with 7569 train, 1,863 test, and 400 validation. A main difference between this dataset and others is that it uses a “Hollywood in Homes” approach to data collection, where “actors” are crowdsourced to act out different actions. This yields a diverse set of videos, with each containing a specific action.

MSVD is a set of YouTube videos annotated by workers on Mechanical Turk, who were asked to pick a video clips representing an activity. In this dataset, each clip is annotated by multiple workers with a single sentence. The dataset contains 1,970 videos and about 80,000 descriptions, where 1,200 of the videos are training data, 670 test, and the rest (100 videos) for validation. In order for the results to be comparable to other approaches, we follow the exact training/validation/test splits provided by Venugopal et al. (2015b).

Evaluation metrics We report results on the video description generation task. In order to evaluate descriptions generated by our model, we use model-free automatic evaluation metrics. We adopt METEOR, BLEU-N, and CIDER metrics available from the Microsoft COCO Caption Evaluation code to score the system.

Video and Caption preprocessing We preprocess the captions for both datasets using the Natural Language Toolkit (NLTK) and clip each description up to 30 words, since the majority have less. We extract sample frames from each video and pass each frame through VGGNet (Simonyan & Zisserman, 2014) without fine-tuning. For the experiments in this paper, we use the feature maps from conv5_3 layer after applying ReLU. The feature map in this layer is \( 14 \times 14 \times 512 \). Our TEM component operates on the flattened \( 196 \times 512 \) of this feature cubes. For the ablation studies, features from the fully connected layer with 4096 dimensions are used as well.

Hyper-parameter optimization We use random search (Bergstra & Bengio, 2012) on the validation set to select hyper-parameters on both datasets. The word-embedding size, hidden layer size (for both the TEM and the Decoder), and memory size of the best model on Charades are: 237, 1316, and 437, respectively. These values are 402, 1479, and 797 for the model on the MSVD dataset. A stack of two LSTMs are used in the Decoder and TEM. The number of frame samples is a hyperparameter which is selected among 4, 8, 16, 40 on the validation set. ATT + NO TEM and NO HAM + TEM get the best results on the validation set with 40 frames, and we use this as the number of frames for all models in the ablation study.

4.1. Video Caption Generation

We first present an ablation analysis to elucidate the contribution of the different components of our proposed model. Then, we compare the overall performance of our model to other recent models.

\[ \text{https://github.com/tylin/coco-caption} \]

\[ \text{http://www.nltn.org/} \]
Ablation Analysis

Ablation results are shown in Table 1, evaluating on the MSVD test set. The first (ATT + NO TEM) corresponds to a simpler version of our model in which we remove the TEM component and instead pass each frame of the video through a CNN, extracting features from the last fully-connected hidden layer. In addition, we replace our HAM with a simpler version where the model only memorizes the current step instead of all previous steps. In the next ablation (NO HAM + TEM), we remove the HAM component from our model and keep the rest of the model as-is. In the next variation (HAM + NO TEM), we remove the TEM and calculate features for each frame, similar to ATT + NO TEM. Finally, the last row in the table is our proposed model (HAM + TEM) with all its components.

The HAM plays a significant role in the proposed model, and removing it causes a large drop in performance, as measured by both BLEU and METEOR. On the other hand, removing the TEM by itself does not drop performance as much as dropping the HAM. Putting the two together, they complement one another to result in overall better performance for METEOR. However, further development on the TEM component in future work is warranted. In the NO HAM + TEM condition, an entire video must be represented with a fixed-length vector, which may contribute to the lower performance (Bahdanau et al., 2015). This is in contrast to the other models, which apply single layer attention or HAM to search relevant parts of the video aligned with the description.

Performance Comparison

To extensively evaluate the proposed model, we compare with state-of-the-art models and baselines for the video caption generation task on the MSVD dataset. In this experiment, we use 8 frames per video as the inputs to the TEM module. As shown in Table 2, our proposed model achieves state-of-the-art scores in BLEU-4, and outperforms almost all systems on METEOR. The closest-scoring comparison system, from Pan et al. (2016a), shows a trade-off between METEOR and BLEU: BLEU prefers descriptions with short-distance fluency and high lexical overlap with the observed descriptions, while METEOR permits less direct overlap and longer descriptions. A detailed study of the generated descriptions between the two systems would be needed to better understand these differences.

The improvement over previous work is particularly noteworthy because we do not use external features for the video, such as Optical Flow (Brox et al., 2004) (denoted Flow), 3-Dimensional Convolutional Network features (Tran et al., 2015) (denoted C3D), or fine-tuned CNN features (denoted FT), which further enhances aspects such as action recognition by leveraging an external dataset such as UCF-101. The only system using external features that outperforms the model proposed here is from Yu et al. (2016), who uses a slightly different version of the same dataset along with C3D features for a large improvement in results (compare Table 2 rows 4 and 11); future work may explore the utility of external visual features for this work. Here, we demonstrate that the proposed architecture maps visual space to language space with improved performance over previous work, before addition of further resources.

We additionally report results on the Charades dataset (Sigurdsson et al., 2016), which is challenging to train on because there are only a few (∼2) captions per video. In this experiment, we use 16 frames per video as the input to the TEM module. As shown in Table 3, our method achieves a 10% relative improvement over the Venugopalan et al. (2015a) model reported by Sigurdsson et al. (2016). It is worth noting that humans reach a METEOR score of 24 and a BLEU-4 score of 20, illustrating the low upper bound in this task.\(^6\)

Results Discussion

We show some example descriptions generated by our system in Figure 3. The model generates mostly correct descriptions, with naturalistic variation from the ground truth. Errors illustrate a preference to describe items that have a higher likelihood of being mentioned, even if they appear in less of the frames. For example, in the “a dog is on a trampoline” video, our model focuses on the man, who appears in only a few frames, and generates the incorrect description “a man is washing a bath”. The errors, alongside the ablation study shown in Table 1, suggest that the TEM module in particular may be further improved by focusing on how frames in the video sequence are captured and passed to the HAM module.

5. Conclusion

We introduce a general framework for an memory-based sequence learning model, trained end-to-end. We apply this framework to the task of describing an input video with a natural language description. Our model utilizes a deep learning architecture that represents video with an explicit

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\(^6\)Yu et al. (2016) uses the MSVD dataset reported in (Guadarrama et al., 2013), which has different preprocessing.

\(^7\)For comparison, the upper bound BLEU score in machine translation for English to French is above 30.
model of the video’s temporal structure, and jointly models the video description and the temporal video sequence. This effectively connects the visual video space and the language description space.

A memory-based attention mechanism helps guide where to attend and what to reason about as the description is generated. This allows the model to not only reason efficiently about local attention, but also to consider the full sequence of video frames during the generation of each word. Our experiments confirm that the memory components in our architecture, most notably from the HAM module, play a significant role in improving the performance of the entire network.

Future work should aim to refine the temporal video frame model, TEM, and explore how to improve performance on capturing the ideal frames for each description.

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| Method                      | METEOR | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | CIDEr |
|-----------------------------|--------|--------|--------|--------|--------|-------|
| ATT + NO TEM                | 31.20  | 77.90  | 65.10  | 55.30  | 44.90  | **63.90** |
| NO HAM + TEM                | 30.50  | 78.10  | 65.20  | 55.10  | 44.60  | 60.50  |
| HAM + NO TEM                | 31.00  | 78.70  | **66.90** | **57.40** | **47.00** | 62.10  |
| HAM + TEM                   | **31.70** | **79.00** | 66.20  | 56.00  | 45.60  | 62.20  |

*Table 1. Ablation of proposed model with and without the HAM component on the MSVD test set.*

| Method                      | METEOR | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | CIDEr |
|-----------------------------|--------|--------|--------|--------|--------|-------|
| Venugopalan et al. (2015b)  | 27.7   | –      | –      | –      | –      | –     |
| Venugopalan et al. (2015a)  | 29.2   | –      | –      | –      | –      | –     |
| Pan et al. (2016b)          | 29.5   | 74.9   | 60.9   | 50.6   | 40.2   | –     |
| Yu et al. (2016)            | 31.10  | 77.30  | 64.50  | 54.60  | 44.30  | –     |
| Pan et al. (2016a)          | **33.10** | 79.20  | 66.30  | 55.10  | 43.80  | –     |
| Our Model                   | 31.80  | **79.40** | **67.10** | **56.80** | **46.10** | **62.70** |
| Yao et al. (2015) + C3D      | 29.60  | –      | –      | –      | –      | 41.92 | 51.67  |
| Venugopalan et al. (2015a) + Flow | 29.8   | –      | –      | –      | –      | –     |
| Ballas et al. (2015) + FT    | 30.75  | –      | –      | –      | –      | 49.0  | 59.37  |
| Pan et al. (2016b) + C3D     | 31.0   | 78.80  | 66.0   | 55.4   | 45.3   | –     |
| Yu et al. (2016) + C3D       | 32.60  | 81.50  | 70.40  | 60.4   | 49.90  | –     |

*Table 2. Video captioning evaluation on MSVD (670 videos).*

| Method                      | M     | B@1  | B@2  | B@3  | B@4  | C     |
|-----------------------------|-------|------|------|------|------|-------|
| Human (Sigurdsson et al., 2016) | 24    | 62   | 43   | 29   | 20   | 53    |
| Sigurdsson et al. (2016)     | 16    | 49   | 30   | 18   | 11   | 14    |
| Our Model                    | **17.6** | **50** | **31.1** | **18.8** | **11.5** | **16.7** |

*Table 3. Video captioning evaluation on Charades (1863 videos). M=METEOR, B=BLEU, C=CIDEr. Sigurdsson et al. (2016) results use the Venugopalan et al. (2015a) model.*
| Example Video Frame Sequence | Proposed Model | Ground Truth |
|-----------------------------|----------------|--------------|
|                             | A group of people are dancing | A group of young children performing together |
|                             | A person is cutting the vegetable | A woman is cutting garlic |
|                             | A man is playing a guitar | A man is playing the guitar |
|                             | A woman is pouring eggs into a bowl | A woman is pouring ingredients into a bowl |
|                             | A man is playing a flute | A man is playing a large flute |
|                             | A woman is applying a makeup | A woman is putting on makeup |

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