

Sequence to Sequence – Video to Text

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Abstract

Real-world videos often have complex dynamics; methods for generating open-domain video descriptions should be sensitive to temporal structure and allow both input (sequence of frames) and output (sequence of words) of variable length. To approach this problem we propose a novel end-to-end sequence-to-sequence model to generate captions for videos. For this we exploit recurrent neural networks, specifically LSTMs, which have demonstrated state-of-the-art performance in image caption generation. Our LSTM model is trained on video-sentence pairs and learns to associate a sequence of video frames to a sequence of words in order to generate a description of the event in the video clip. Our model naturally is able to learn the temporal structure of the sequence of frames as well as the sequence model of the generated sentences, i.e. a language model. We evaluate several variants of our model that exploit different visual features on a standard set of YouTube videos and two movie description datasets (M-VAD and MPII-MD).

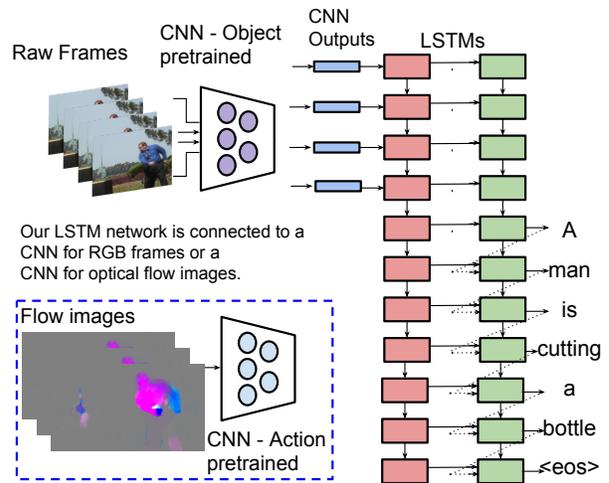


Figure 1. Our S2VT approach performs video description using a sequence to sequence model. It incorporates a stacked LSTM which first reads the sequence of frames and then generates a sequence of words. The input visual sequence to the model is comprised of RGB and/or optical flow CNN outputs.

1. Introduction

Describing visual content with natural language text has recently received increased interest, especially describing images with a single sentence [8, 6, 16, 17, 19, 22, 27, 38]. Video description has so far seen less attention despite its important applications in human-robot interaction, video indexing, and describing movies for the blind. While image description handles a variable length output sequence of words, video description also has to handle a variable length input sequence of frames. Related approaches to video description have resolved variable length input by holistic video representations [27, 26, 11], pooling over frames [37], or sub-sampling on a fixed number of input frames [41]. In

contrast, in this work we propose a sequence to sequence model which is trained end-to-end and is able to learn arbitrary temporal structure in the input sequence. Our model is sequence to sequence in a sense that it reads in frames sequentially and outputs words sequentially.

The problem of generating descriptions in open domain videos is difficult not just due to the diverse set of objects, scenes, actions, and their attributes, but also because it is hard to determine the salient content and describe the event appropriately in context. To learn what is worth describing, our model learns from video clips and paired sentences that describe in natural language the events depicted in video. We use Long Short Term Memory (LSTM) networks [12], a type of recurrent neural networks (RNNs)

which have achieved great success on similar sequence-to-sequence tasks such as speech recognition [10] and machine translation [32]. Due to the inherent sequential nature of videos and language, LSTMs are well-suited for generating descriptions of events in videos.

The main contribution of this work is to propose a novel model, S2VT, which learns to directly map a sequence of frames to a sequence of words. Figure 1 depicts our model. A stacked LSTM first encodes the frames one by one, taking as input the output of a Convolutional Neural Network (CNN) applied to each input frame’s intensity values. Once all frames are read, the model generates a sentence word by word. The encoding and decoding of the frame and word representations are learned jointly from a parallel corpus. To model the temporal aspects of activities typically shown in videos, we also compute the optical flow [3] between pairs of consecutive frames. The flow images are also passed through a CNN and provided as input to the LSTM. Flow CNN models have been shown to be beneficial for activity recognition [29, 8].

To our knowledge, this is the first approach to video description using a general sequence to sequence model. This allows our model to (a) handle variable number of input frames, (b) learn and use the temporal structure of the video and (c) learn a language model to generate natural, grammatical sentences. Our model is learned jointly and end-to-end, incorporating both intensity and optical flow inputs, and does not require an explicit attention model. We demonstrate that S2VT achieves state-of-the-art performance on three diverse datasets, a standard YouTube corpus (MSVD) [4] and the M-VAD [35] and MPII Movie Description [26] datasets. Our implementation (based on the *Caffe* [15] deep learning framework) and pre-trained models will be released open source.

2. Related Work

Early work on video captioning considered tagging videos with metadata [1] and clustering captions and videos [24, 40, 14] for retrieval tasks. Several previous methods for generating sentence descriptions [18, 11, 34] used a two stage pipeline that first identifies the semantic content (subject, verb, object) and then generates a sentence based on a template. This typically involved training object, action, scene classifiers using frame features from HOG, SIFT, ObjectBank, CNN, STIP, and/or dense trajectories to identify candidate objects and actions. They then use a probabilistic graphical model to combine confidences from a language model with the visual confidences in order to estimate the most likely content (subject, verb, object, scene) in the video, which is then used to generate a sentence. While this simplified the problem, by detaching content generation, and surface realization, it is still challenging to select a set of objects and actions to recognize. Moreover, a template-

based approach for generating the sentence is insufficient to model the richness of language used in human descriptions – e.g., which attributes to use and how to combine them effectively to generate a good description. In contrast, our approach avoids the separation of content identification and sentence generation by learning to directly map videos to full human-provided sentences, learning a language model simultaneously conditioned on visual features.

Our models take inspiration from the image caption generation models in [8, 38]. The first step in these approaches is to generate a fixed length vector representation of an image by extracting features from a CNN. The next step learns to decode this vector into a sequence of words composing the description of the image. While any RNN can be used in principle to decode the sequence, the resulting long-term dependencies can lead to inferior performance. To mitigate this issue, LSTM models have been exploited as sequence decoders, as they are more suited to learning long-range dependencies. In addition, since we are using variable-length video as input, we use LSTMs as sequence to sequence transducers, following the language translation models of [32].

In [37], LSTMs were used to generate video descriptions by pooling the representations of individual frames. Their technique extracts CNN features for frames in the video and then mean-pools the results to get a single feature vector representing the entire video. They then use an LSTM as a sequence decoder to generate a description based on this vector. A major shortcoming of this approach is that this representation completely ignores the ordering of the video frames and fails to exploit any temporal information. The approach in [8] also generates video descriptions using an LSTM; however, they employ a version of the two-step approach that uses CRFs to obtain semantic tuples of agent, activity and object and then use an LSTM to translate this tuple of words into a sentence. Moreover, they apply their model to the limited domain of cooking videos while ours is aimed at generating descriptions for videos “in the wild.”

Contemporaneous with our work, the approach in [41] also addresses the limitations of [37] in two ways. First, they employ a 3-D convnet model that incorporates spatio-temporal motion features. To obtain spatio-temporal features, they assume videos are of fixed size $W(\text{width}) \times H(\text{height}) \times T(\text{time})$ and sub-divide the video volume into non-overlapping cuboids each of dimension $(x = 16, y = 12, t = 2)$. They extract dense trajectory features (HoG, HoF, MBH) [39] over each volume and further concatenate these as input to a 3-D convnet. Their 3-D convnet is trained on large activity classification corpora UCF101, HMDB51, and a small portion (50k) of the Sports-1M dataset. Second, they include an attention mechanism that learns to weight the frame features non-uniformly conditioned on the previous word input(s) rather than uniformly weighting features

from all frames as in [37]. The 3-D convnet alone provides limited performance improvement, but in conjunction with the attention model it notably improves performance. We propose a simpler approach to using temporal information by using an LSTM to encode the sequence of video frames into a distributed vector representation that is sufficient to generate a sentential description. Therefore, our direct sequence to sequence model does not require an explicit attention mechanism.

Another recent project [31] uses LSTMs to predict the future frame sequence from an encoding of the previous frames. Their model is more similar to the language translation model in [32], which uses one LSTM to encode the input text into a fixed representation, and another LSTM to decode it into a different language. However our model is different from these previous ones, in that we do not use different LSTMs for encoding and decoding. We employ a single LSTM that learns both encoding and decoding based on the inputs it is provided. This allows the LSTM to share weights between encoding and decoding.

Other related work includes [23, 8], which uses LSTMs for activity classification, predicting an activity class for the representation of each image/flow frame. In contrast, our model generates captions after encoding the complete sequence of optical flow images. Specifically, our final model is an ensemble of the sequence to sequence models trained on raw images and optical flow images.

3. Approach

We propose a sequence to sequence model for video description, where the input is the sequence of video frames (x_1, \dots, x_n) , and the output is the sequence of words (y_1, \dots, y_m) . Naturally, both the input and output are of variable, potentially different, lengths. In our case, there are typically many more frames than words.

In our model, we estimate the conditional probability of an output sequence (y_1, \dots, y_m) given an input sequence (x_1, \dots, x_n) i.e.

$$p(y_1, \dots, y_m | x_1, \dots, x_n) \quad (1)$$

This problem is analogous to machine translation between natural languages, where a sequence of words in the input language is translated to a sequence of words in the output language. Recently, [7, 32] have shown how to effectively attack this sequence to sequence problem with an LSTM Recurrent Neural Network (RNN). We extend this paradigm to inputs comprised of sequences of video frames, significantly simplifying prior RNN-based methods for video description. In the following, we describe our model and architecture in detail, as well as our input and output representation for video and sentences.

3.1. LSTMs for sequence modeling

The main idea to handle variable-length input and output is to first encode the input sequence of frames, one at a time, representing the video using a latent vector representation, and then decode from that representation to a sentence, one word at a time.

In the encoding phase, a portion of the conditional probability (Equation (1)) is computed by generating a fixed length latent hidden representation (h) based on the entire sequence of inputs (x_1, \dots, x_n) . The decoding step then computes the probabilities of the output sequence of words (y_1, \dots, y_m) as

$$p(y_1, \dots, y_m | x_1, \dots, x_n) = \prod_{t=1}^m p(y_t | h, y_1, \dots, y_{t-1})$$

where the distribution of $p(y_t | h, y_1, \dots, y_{t-1})$ is given by a softmax over all of the words in the vocabulary.

This recursive formulation can be effectively modeled by an RNN. In our work, we use a Long Short Term Memory RNN (LSTM), originally proposed in [12], since it is known to learn long range dependencies more effectively than standard RNNs. The core of the LSTM model is a memory cell c which, at each time step, encodes the knowledge of the inputs that have been observed up to that point. The cell is modulated by sigmoidal gates which have range $[0, 1]$ and are applied multiplicatively. If a gate evaluates to one, the LSTM unit accepts the value input via that gate, and if the gate evaluates to zero the value is discarded. The cell has three gates to control the input to the cell, the memory maintained by the cell, and the value output. The input gate (i) controls whether the LSTM considers its current input (x_t), the forget gate (f) allows the LSTM to forget or maintain its previous memory (c_{t-1}), and the output gate (o) decides how much of the memory to transfer to the hidden state (h_t). These gates enable the LSTM to learn complex long-term dependencies. Specifically we use the LSTM unit proposed in [42]:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (2)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \quad (3)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (4)$$

$$g_t = \phi(W_{xg}x_t + W_{hg}h_{t-1} + b_g) \quad (5)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad (6)$$

$$h_t = o_t \odot \phi(c_t) \quad (7)$$

where σ is the sigmoidal non-linearity, ϕ is the hyperbolic tangent non-linearity, \odot represents the element-wise product with the gate value, and the weight matrices denoted by W_{ij} and biases b_j are the trained parameters.

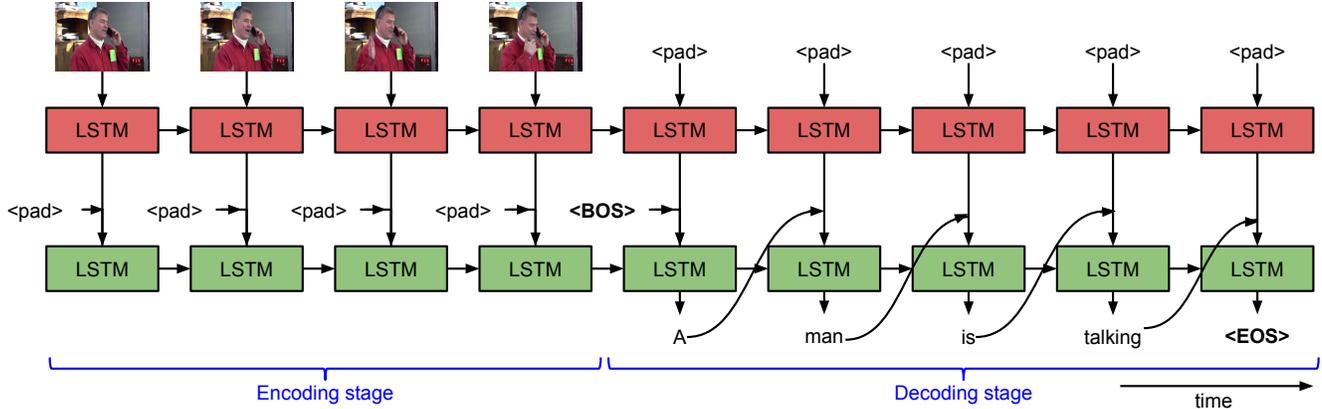


Figure 2. We propose a stack of two LSTMs that learn a representation of a sequence of frames in order to decode it into a sentence that describes the event in the video. The top LSTM layer models visual feature inputs. The second LSTM layer models language given the text input and the hidden representation of the video sequence. We use <BOS> to indicate begin-of-sentence and <EOS> for the end-of-sentence tag. Zeros are used as a <pad> when there is no input at the time step.

3.2. Sequence to sequence video to text

Our approach, S2VT, is depicted in Figure 2. While [7, 32] first encode the input sequence to a fixed length vector using one LSTM and then use another LSTM to map the vector to a sequence of outputs, we rely on a single LSTM for both the encoding and decoding stage. This allows parameter sharing between the encoding and decoding stage.

Our model uses a stack of two LSTMs with 1000 hidden units each. Figure 2 shows the LSTM stack unrolled over time. When two LSTMs are stacked together, as in our case, the hidden representation within the first (top) LSTM (h_t) is provided as the input (x_t) to the second LSTM. The first LSTM layer in our architecture is used to model the visual frame sequence, and the second layer is used to model the output word sequence.

Training and Inference In the first several time steps, the first LSTM layer (Figure 2) receives a sequence of frames and encodes them while the second LSTM layer receives the hidden representation (h_t) and concatenates it with the input padding words (zeros), which it then encodes. There is no loss during this stage when the LSTMs are encoding. After all the frames in the video clip are exhausted, the second LSTM layer is fed the beginning-of-sentence (<BOS>) tag, which prompts it to start decoding its current hidden representation to a sequence of words. While training in the decoding stage, the model maximizes for the log-likelihood of the predicted output sentence given the hidden representation of the visual frame sequence, and the previous words it has seen. For a model with parameters θ and output sequence $Y = (y_1, \dots, y_m)$, this can be formulated as:

$$\theta^* = \underset{\theta}{\operatorname{argmax}} \sum_{(h, Y)} \log p(Y|h; \theta) \quad (8)$$

This log-likelihood is optimized over the entire training dataset using stochastic gradient descent. The loss is computed only when the LSTM is learning to decode. Since this loss is propagated back in time, the LSTM learns to generate an appropriate hidden state representation of the input sequence. The output (z_t) of the second LSTM layer is used to obtain the emitted word (y). We apply a softmax function to get the probability distribution over the words y' in the vocabulary V :

$$p(y|z_t) = \frac{\exp(W_y z_t)}{\sum_{y' \in V} \exp(W_{y'} z_t)} \quad (9)$$

We note that, during the decoding phase, the visual frame representation for the first LSTM layer is simply a vector of zeros that acts as padding input. We require an explicit end-of-sentence tag (<EOS>) to terminate each sentence since this enables the model to define a distribution over sequences of varying lengths. At test time, during each decoding step we choose the word y_t with the maximum probability after the softmax (from Equation 9) until we obtain the <EOS> token.

3.3. Video and text representation

RGB frames. Similar to previous LSTM-based image captioning efforts [8, 38] and video-to-text approaches [37, 41], we apply a convolutional neural network (CNN) to input images and provide the output of the top layer as input to the LSTM unit. In this work, we report results using the output of the fc7 layer (after applying the ReLU non-linearity) on the Caffe Reference Net (a variant of AlexNet) and also the 16-layer VGG model [30]. We use CNNs that are pre-trained on the 1.2M image ILSVRC-2012 object classification subset of the ImageNet dataset [28] and made

available publicly via the Caffe ModelZoo.¹ Each input video frame is scaled to 256x256, and is cropped down to a random 227x227 region. It is then processed by the CNN. We remove the original last fully-connected classification layer and learn a new linear embedding of the features to a 500 dimensional space. The lower dimension features form the input to the LSTM.

Optical Flow. In addition to CNN outputs from raw image (RGB) frames, we also incorporate optical flow measures as input sequences to our architecture. Others [23, 8] have shown that incorporating optical flow information to LSTMs improves activity classification. As many of our descriptions are activity centered, we explore this option for video description as well. We follow the approach in [8, 9] and first extract classical variational optical flow features [3]. We then create flow images (as seen in Figure 1) in a manner similar to [9], by centering x and y flow values around 128 and multiplying by a scalar such that flow values fall between 0 and 255. We also calculate the flow magnitude and add it as a third channel to the flow image. We then use a CNN [9] initialized with weights trained on the UCF101 video dataset to classify optical flow images into 101 activity classes. The fc6 layer activations of the CNN are embedded in a lower 500 dimensional space which is then given as input to the LSTM. The rest of the LSTM architecture remains unchanged for flow inputs.

Text input. The target output sequence of words are represented using one-hot vector encoding (1-of-N coding, where N is the size of the vocabulary). Similar to the treatment of frame features, we learn and embed words to a lower 500 dimensional space which are then given as input to the LSTM stack. When considering the output of the LSTM we apply a softmax over the complete vocabulary as in Equation 9.

4. Experimental Setup

In the following we describe how we evaluate our approach. We first describe the datasets we use, then the evaluation protocol, and then the details of our models.

4.1. Video description datasets

We report results on three video description corpora, namely the Microsoft Video Description corpus (MSVD) [4], the MPII Movie Description Corpus (MPII-MD) [26], and the Montreal Video Annotation Dataset (M-VAD) [35]. They form the three largest parallel corpora with open domain video and natural language description. While MSVD is based on short web videos with short single sentence description, MPII-MD and M-VAD contain Hollywood movie snippets with descriptions sourced from script data and audio description/DVS.

¹<https://github.com/BVLC/caffe/wiki/Model-Zoo>

4.1.1 Microsoft Video Description Corpus (MSVD)

The Microsoft Video description corpus [4], is a collection of about 2,000 YouTube video clips, each 10 seconds to 25 seconds in duration. Amazon Mechanical Turk workers who were employed to collect the videos were instructed to pick small video clips depicting a single activity. The videos were then used to elicit short sentence descriptions from annotators. The original corpus has multi-lingual descriptions, in this work we use only the English descriptions which amount to about 40 sentences for each video. We use the training splits from [37] which consists of 1,200 videos for training, 100 for validation and 670 for test. With regard to text data, the training split has about 48.7k training sentences, 27.7k sentences in test and 4.3k sentences in the validation set. We do minimal pre-processing on the text by converting all text to lower case, tokenizing the sentences and removing punctuation. This yields a vocabulary of 12,594 words for the entire YouTube description dataset. In each video, we sample every tenth frame as done by [37].

4.1.2 MPII Movie Description Dataset (MPII-MD)

MPII-MD [26] contains around 68,000 video clips extracted from 94 Hollywood movies. Each clip is accompanied with a single sentence description which is sourced from movie scripts and audio description (AD) data. The AD or Descriptive Video Service (DVS) track is an additional audio track that is added to the movies to describe explicit visual elements in a movie for the visually impaired. Although the movie snippets are manually aligned to the descriptions, the data is very challenging due to the high diversity of visual and textual content. Typically most snippets only have single reference sentence. We use the training/validation/test split provided by the authors and extract every fifth frame (videos are shorter than MSVD, averaging 94 frames).

4.1.3 Montreal Video Annotation Dataset (M-VAD)

The M-VAD movie description corpus [35] is another recent collection of about 49,000 short video clips from 92 movies. It is similar to MPII-MD, but only contains AD data and only provides automatic alignment. We use the same setup as for MPII-MD.

4.2. Evaluation Metrics

Quantitative evaluation of the models are performed using the METEOR [2] metric which was originally proposed to evaluate machine translation results. The METEOR score is computed based on the alignment between a given hypothesis sentence and a set of candidate reference sentences. METEOR computes the alignment by comparing exact token matches, stemmed tokens, paraphrase matches, as well as semantically similar matches using

WordNet synonyms. This semantic aspect of METEOR distinguishes from others such as BLEU [25], ROUGE-L [20], or CIDEr [36]. The authors of CIDEr [36] evaluated these four measures for image description. They showed that METEOR is always better than BLEU and ROUGE and outperforms CIDEr when the number of references are small (CIDEr is comparable to METEOR when the number of references are large). In the case of MPII-MD and M-VAD we have typically only a single reference. We thus decided to use METEOR in all our evaluations. Our models are evaluated on METEOR version 1.5². We use the code³ released with the Microsoft COCO Evaluation Server [5] to obtain the scores for all our models reported in this paper.

4.3. Experimental details of our models

All our models take as input either the raw RGB frames directly feeding into the CNN (as in the case of our RGB models), or pre-processed optical flow images as described in Section 3.3. In all of our models, we unroll the LSTM to a fixed 80 time steps during training. We found this to be a good trade-off between memory consumption and the ability to provide many frames (videos) to the LSTM. It allowed us to fit multiple videos in a single mini-batch – up to 8 for AlexNet and up to 3 for flow models. We note that 94% of the YouTube training videos satisfied this limit (with frames sampled at the rate of 1 in 10). At test time, we do not constrain the length of the video and our model does not truncate video frames. For videos with fewer than 80 time steps (of words and frames), we pad the remaining inputs with zeros. For longer videos, we truncate the number of frames to ensure that sum of the number of frames and words is within this limit. As described above we use pre-trained AlexNet and VGG model, which we fine-tune. For VGG we fix all layers below fc7 to reduce memory consumption and allow faster training.

We compare our sequence to sequence LSTM architecture with RGB image features extracted from both AlexNet, and the 16-layer VGG network. In order to compare features from the VGG network with previous models, we include the performance of the mean pooled model proposed in [37] using output of the fc7 layer from the 16 layer VGG as a baseline. All our sequence to sequence models are referenced in Table 1 under S2VT. Our first variant, RGB (AlexNet) is the end-to-end model that uses AlexNet on RGB frames. Flow (AlexNet) refers to the model that is obtained by training on optical flow images. RGB (VGG) refers to the model with the 16-layer VGG model on RGB image frames. Our final model is an ensemble of the RGB (VGG) and Flow (AlexNet) where the prediction at each time step is a weighted average of the prediction from the individual models.

²<http://www.cs.cmu.edu/~alavie/METEOR>

³<https://github.com/tylin/coco-caption>

Model	METEOR	
FGM [34]	23.9	(1)
Mean pool		
- AlexNet [37]	26.9	(2)
- VGG	27.7	(3)
- AlexNet COCO pre-trained [37]	29.1	(4)
- GNet [41]	28.7	(5)
Soft-attention		
- GoogleNet [41]	29.0	(6)
- GoogleNet + 3D-CNN [41]	29.6	(7)
S2VT (ours)		
- RGB (AlexNet)	27.9	(8)
- Flow (AlexNet)	24.3	(9)
- RGB (VGG)	29.2	(10)
- RGB (VGG) + Flow (AlexNet)	29.8	(11)

Table 1. MSVD dataset (METEOR in %, higher is better).

4.4. Related approaches

We compare our sequence to sequence models against the factor graph model (FGM) in [34], the mean-pooled models in [37] and the Soft-Attention models proposed in [41].

FGM proposed in [34] uses a two step approach to first obtain confidences on subject, verb, object and scene elements and then combines this with confidences from a language model using a factor graph to infer the most likely (subject, verb, object, scene) tuple in the video. It then generates a sentence based on a template.

Mean Pool model proposed in [37] pools AlexNet fc7 layer features across all frames to create a fixed length vector representation of the video. Following this, it uses an LSTM to decode the vector into a sequence of words. They further propose training their model on the Flickr30k [13] and MSCOCO [21] image-caption datasets and fine-tuning on the YouTube video dataset for a significant improvement in performance. We compare our models against their basic mean pooled model and their best model obtained from fine-tuning on Flickr30k and COCO datasets. We also compare against the GoogleNet [33] variant of the mean-pooled model reported in [41].

Soft-Attention model in [41] is a combination of weighted attention over a fixed set of video frames with input features from GoogleNet and a 3D-convnet trained on HoG, HoF and MBH features from an activity classification model.

5. Discussion

This section discusses the result of our evaluation shown in Tables 1, 2, and 3.

Approach	METEOR
SMT (best variant) [26]	5.6
S2VT: RGB (VGG), ours	6.3

Table 2. MPII Movie Description dataset. METEOR in %, higher is better.

5.1. MSVD dataset

Table 1 shows the results on the MSVD dataset. The upper part shows results of related approaches and the lower part different variants of our S2VT approach.

Our basic S2VT AlexNet model on RGB video frames (line 8 in Table 1) achieves 27.9% METEOR and improves over the basic mean pooled model proposed by [37] (line 2, 26.9%) as well as VGG mean pooled model (line 3, 27.7%). This suggests that our sequence to sequence model even with the less powerful AlexNet features is able to encode video frames well and can exploit the temporal structure.

Our S2VT model which uses flow images (line 9) achieves only 24.3% METEOR but improves the performance of our VGG model from 29.2%(line 10) to 29.8% (line 11), when combined. A reason for the low performance of the flow model could be that optical flow features even for the same activity can vary significantly with context e.g. the flow features for a person eating pizza would be very different from “a cow eating grass” although the action performed in both cases is “eating”. It is also possible that the model only receives very weak signals with regard to the kind of activities depicted in YouTube videos. For example, some commonly used verbs such as “play” can be polysemous and can refer to playing a musical instrument (“A man is playing a guitar”) or playing a sport (“A boy is playing golf”). However, integrating RGB with the Flow model allows the LSTM to relate actions with the objects improving the quality of the descriptions.

Our ensemble using both RGB and Flow achieves a score comparable and slightly better than the best model proposed in [41], Soft-attention with GoogleNet + 3D-CNN (line 7). The edge that our model has is only modest, this is likely due to the much stronger 3D-CNN features (as the difference to GoogleNet alone, line 6, suggest). Thus, the closest comparison between the Soft Attention Model [41] and our S2VT is arguably ours with VGG (line 10) vs. their GoogleNet only model (line 6). Figure 3 shows descriptions generated by our model on some of the videos in the MSVD YouTube video dataset. We note that many of the descriptions generated are relevant. In the next section we evaluate on the much more challenging movie description datasets.

Approach	METEOR
Soft-attention (GNet + 3D-CNN) [41]*	4.1
S2VT: RGB (VGG), ours	
- trained on M-VAD	5.6
- trained on MPII-MD & M-VAD	6.7

Table 3. M-VAD dataset. METEOR in %, higher is better. *We note that we report results using the predictions provided by [41] but using the COCO Evaluation scripts.

5.2. Movie description datasets

For the much larger and more challenging datasets MPII-MD and M-VAD we use our single best model, namely S2VT trained on RGB frames and VGG. On both datasets we clearly outperform the state of the art on this dataset. For MPII-MD, reported in Table 2, we improve over the SMT approach from [26] from 5.6 to 6.3. Note that we compute METEOR on the all variants examined in [26], and only report the best variant with respect to METEOR.

On M-VAD we achieve 5.6% METEOR which significantly outperforms the Soft-attention (GNet + 3D-CNN) [41] which achieves 4.1%.⁴

In addition to training only on the respective training sets, we also joined the training sections of both datasets in order to exploit more data for learning the input encoding of frames. This increases the performance on M-VAD further to 6.7% METEOR. In Figure 4 we present descriptions generated by the combined model on some sample clips from the M-VAD dataset.

Additional examples of video clips and generated sentences for the MPII-MD dataset can be viewed at <https://youtu.be/XTq0huTXj1M> and the M-VAD dataset can be viewed at <https://youtu.be/pER0mjzSYaM>.

6. Conclusion

This paper proposed a novel approach to movie description. In contrast to related work, we construct video descriptions using a sequence to sequence model, where frames are first read sequentially and then words are generated sequentially. This allows us to handle variable-length input and output while simultaneously modeling the temporal structure. Our model achieves state-of-the-art performance on the MSVD dataset, and outperforms related work on two large and very challenging movie description datasets. Despite its conceptual simplicity, our model significantly benefits from additional data, suggesting that it has a high model capacity, and is able to learn complex temporal structure in the input and output sequences on challenging movie description datasets.

⁴[41] report 5.6% for their soft attention model (GNet + 3D-CNN) and their best result is 5.73% METEOR with non-attention (GNet + 3D-CNN) using a different evaluation script.

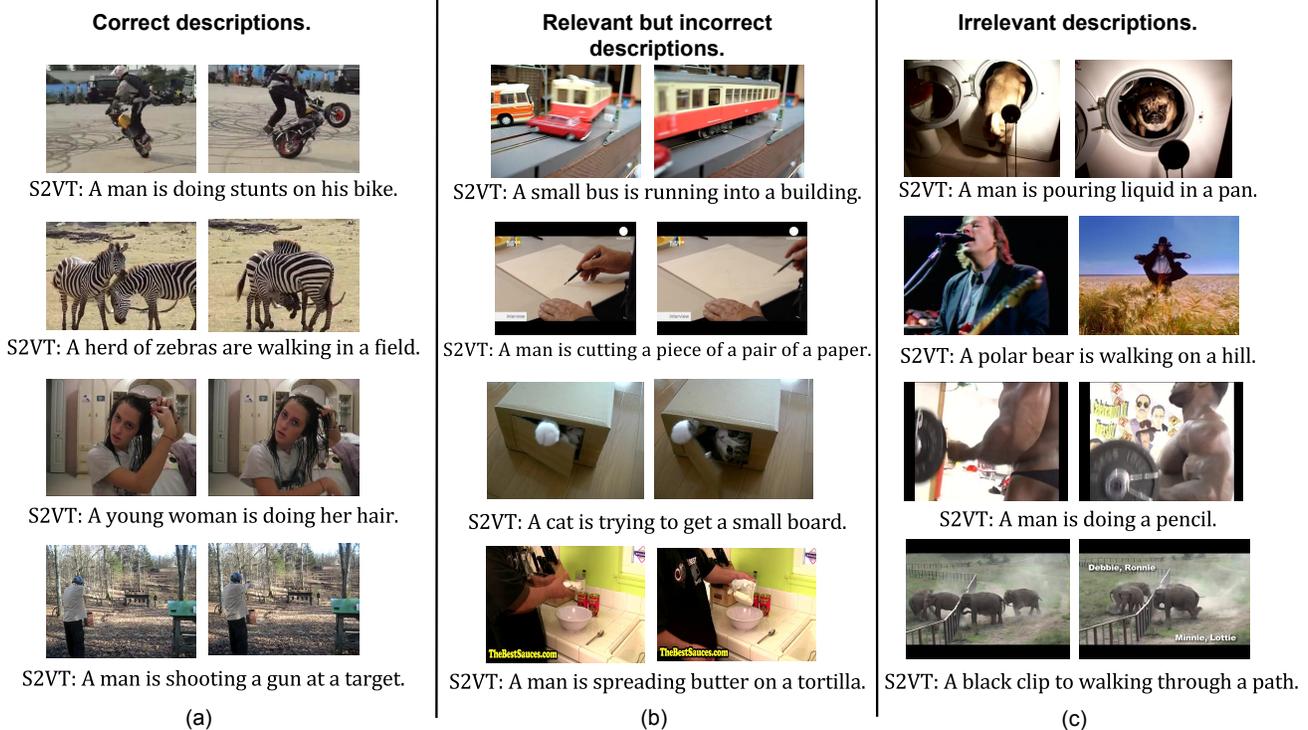


Figure 3. MSVD YouTube video dataset. We present examples where S2VT model (RGB on VGG net) generates correct descriptions involving different objects and actions for several videos (column a). The center column (b) shows examples where the model predicts relevant but incorrect descriptions. The last column (c) shows examples where the model generates descriptions that are irrelevant to the event in the video.

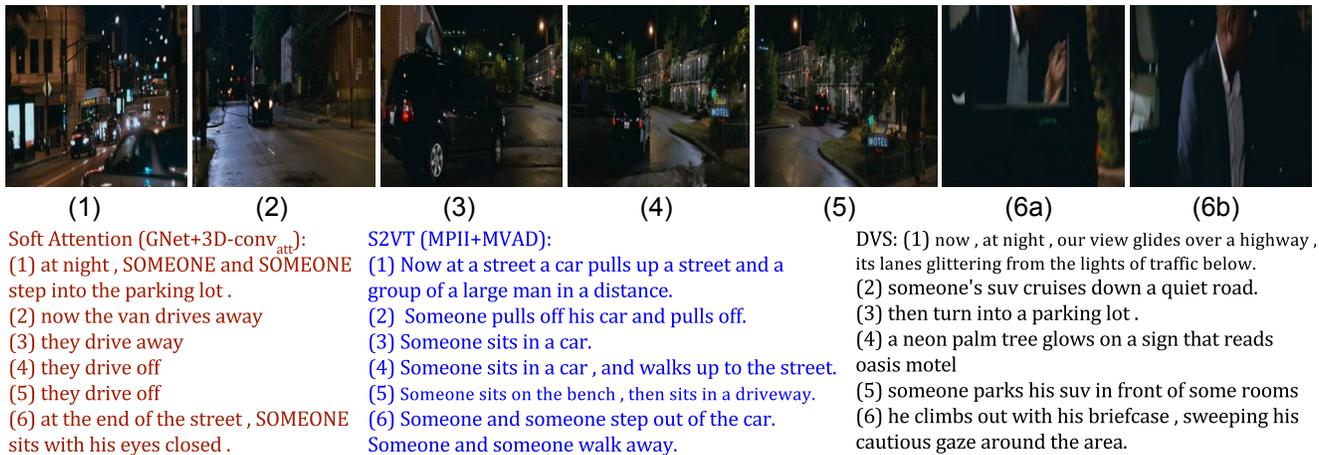


Figure 4. M-VAD Movie corpus: We show a representative frame from 6 contiguous clips from the movie “Big Mommas: Like Father, Like Son”. Soft Attention (GNet + 3D-Conv) are sentences from the model in [41]. S2VT (MPII+MVAD) represents the sentences generated by our model trained on both the MPII and M-VAD datasets. DVS represents the original ground truth sentences in the dataset for each clip.

Acknowledgments

The authors thank Lisa Anne and Matthew Hausknecht for helpful discussions, Damian Mrowca for feedback on early drafts of this work, and Anna Rohrbach for useful comments and help with the DVS corpus. This research was partially supported by ONR ATL Grant N00014-

11-1-010, DARPA’s MSEE and SMISC programs, NSF awards IIS-1427425, IIS-1212798, IIS-1451244 and IIS-1212798, and the Berkeley Vision and Learning Center. Marcus Rohrbach is supported by a fellowship within the FITweltweit-Program of the German Academic Exchange Service (DAAD).

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