Multi-View Features and Hybrid Reward Strategies 
for Vatex Video Captioning Challenge 2019

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Abstract

This document describes our solution for the VATEX Captioning Challenge 2019, which requires generating descriptions for the videos in both English and Chinese languages. We identified three crucial factors that improve the performance, namely: multi-view features, hybrid reward, and diverse ensemble. Our method achieves the 2nd and the 3rd places on the Chinese and English video captioning tracks, respectively.

1. Introduction

Video captioning aims at describing the video content with natural language. The fundamental challenge of this task is to accurately recognize the activities in a video clip, and depict them with high-quality, diverse captions. To promote the progress in video captioning, the VATEX Captioning Challenge is held. The training and test sets of this challenge are from the recently proposed largest multilingual dataset, i.e. VATEX [10]. VATEX contains videos covering 600 human activities, with each video paired with 10 English and 10 Chinese diverse captions.

The biggest challenge of this dataset is the large variety of video content, which is often very challenging to recognize. An example is shown in Figure 1, where we show a video, the corresponding English caption generated by our baseline model and the ground-truth captions. Our baseline video captioning model mistakes the activity, “jet skiing”, in the video as “surfing” and the man “falls off” is ignored because this action too fast to be noticed.

Another challenge in this task is the vast diversity of the captions. Still, we take Figure 1 for example. The ground-truth captions for this specific video differ a lot either in the caption content or in the caption length.

In this work, we propose multi-view features and hybrid reward methods to address the above two challenges respectively. Multi-view features extracted by different backbone models are aim to provide more comprehensive and discriminative video representation. The hybrid reward method directly optimizes a linear combination of CIDEr, METEOR, ROUGE and BLEU scores during the reinforcement learning stage, which we found performs significantly better than solely optimizing one of them. Furthermore, by using a diverse ensemble of models, trained with different architectures and different video features as inputs, we can achieve CIDEr scores of 56.8 and 70.0 on the test-Chinese and test-English splits of the VATEX dataset respectively.

2. Methods

Multi-View Video Features To better extract the semantic features of the video, we refer to a variety of video feature extraction methods to extract more semantic features. We hope to enhance the model’s understanding of the different semantic information of the video by combining multiple features. Multiple video feature extraction networks: the method provided by the author [2]: the nonlocal extraction method [4, 7, 8]: the TSM model proposed in ICCV2019 [5]. To better extract the video features, we also use the strategy of randomly cropping video frames and randomly selecting partial videos.
Figure 1. Example of captions from our baseline model and the ground-truth captions.

Model Architectures Our whole model is consisted of two different caption models: Top-Down [1] and Transformer [9]. The Top-down is a state-of-the-art model in image captioning and VQA field. It utilizes a two-layer LSTM and attention mechanism to explore the relationship between visual features and caption vectors. Its multi-modality processing faculty can extend to video caption task due to the essence of sequence generation within visual information.

The Transformer is another standard encoder-decoder framework, largely different from the lstm-based framework, and has advanced the state-of-the-art on various natural language processing tasks. It is a stack of multi-head attention substantially, using the self-attention mechanism to compute hidden representations of two arbitrary positional inputs. Disintegrate a whole video into a serial of clip features, video captioning task can be adjusted to fit the transformer framework. Inspired by this insight, we transfer transformer architecture into video captioning tasks.

Hybrid Reward For Reinforcement Learning Reinforcement Learning can further promote the performance of the model and it has been proved that the optimization for the CIDEr criterion can advance other criterions indirectly [6]. CIDEr, METEOR, ROUGE and BLEU [3] are the criterions for the caption quality requested by the official VATEX website. The partial optimization for some criterions can result in better performance on the corresponding criterions. In this task, we find that using a hybrid reward, i.e. a linear combination of different metric scores, can result in a better overall result.

Diverse Ensemble of Models We adopt the common practice of ensemble methods, e.g. Average Ensemble and Weighted Ensemble. The experimental results demonstrate that Weighted Ensemble method has little improvement over Average Ensemble so we solely choose the former strategy. Our single models mainly belong to two different architectures, i.e. LSTM-based and Transformer-based, and each type of model is reserved by four strategies for ensemble: the models with different initialized seeds; the models trained with different settings, i.e. the learning rate, scheduled sampling probability; the models with different visual features as inputs. Fourth, we choose the models trained by diverse combined optimization strategies with the reinforce learning. Finally, we integrate all those models by average method.

3. Experiments

3.1. Data pre-processing

We train the models on the VATEX dataset following the official splits[4] and preprocess similar procedures on all captions: Both the English and the Chinese captions are truncated to a maximum of 30 words and transform all sentences to lowercase for the English caption. The word occurring less than 5 times in training captions is filtered and replaced by a special token UNK. We use the segmented Chinese words rather than raw Chinese characters. Both the English model and Chinese model use the beam search strategy during the testing stage. The vocabulary sizes of Chinese and English captions are 7105 and 11719 respectively.

3.2. Implementation Details

Top-Down Model We conduct our experiments based on the pytorch framework. We used a similar training strategy for training the English model and the Chinese model. We use Adam optimizer to train the model with a batch size of 64. For the Top-Down model, we use the strategy of warm up for the first. Each epoch learning rate increases by 1e-4 until it grows to 3e-4. Then, we started to reduce the learning rate at the 6th epoch and the learning rate dropped by half after every 6 epochs. Our training is divided into two phases, the first phase is cross entropy training and the second phase is reinforcement learning training. The training
Table 1. The ensemble results of our ultimate models on Vatex test set and **Top-Down+Transformer** is our final submission on the leaderboard.

| Language | Method                  | CIDEr | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE-L |
|----------|-------------------------|-------|--------|--------|--------|--------|--------|---------|
| Chinese  | VATEX-team [10]          | 35.1  | 74.5   | 53.7   | 36.6   | 24.8   | 29.4   | 51.6    |
|          | Top-Down                | 54.7  | 81.5   | 63.3   | 45.6   | 31.7   | 31.9   | 56.0    |
|          | Top-Down+Transformer    | **56.8** | **82.0** | **63.9** | **46.1** | **32.2** | **32.1** | **56.2** |
| English  | VATEX-team [10]          | 45.1  | 71.3   | 53.3   | 39.6   | 28.5   | 21.6   | 47.0    |
|          | Top-Down                | 67.1  | 80.1   | 64.6   | 50.4   | 37.8   | 24.2   | 51.8    |
|          | Top-Down+Transformer    | **70.0** | **80.8** | **65.4** | **51.1** | **38.4** | **24.5** | **52.1** |

of our model experienced a total of 60 epochs, of which the first stage is 30 epochs and the second stage is 30 epochs. The rnn size of the model is set to 2048, and the input size of the LSTM model is set to 512. Label smoothing is used and set to 0.1.

**Transformer Model** The setting in the Transformer model is similar to the Top-Down model. The latent dimensionalities in the self-attention and the feed-forward network are 1024 and 4096. The number of heads \( h \) is 16 and the latent dimensionality for each head \( d_h = d/h = 64 \). The number of attention blocks \( L \) in the encoder and decoder is 1. All models are first trained for 15 epochs using the cross-entropy loss under the learning rate of 5e-4 but with the warm up strategy in the first 20000 iterations, and then are further trained for additional 10 epochs using the self-critical loss under the learning rate of 1e-5.

### 4. Results

In the testing phase, we ensemble a variety of models trained by different hyper-parameters. Since we used all the data sets including the validation set in some models, we only listed the results of the test set. Due to the limitation of the submissions number, we directly submitted predictions of the ensemble models. We show the results of VATEX Chinese in the official test set in Table 1. The final result combines the prediction results of 8 Top-Down models and 5 Transformer models. At the same time, we show the results of VATEX English in the official test set subsequently. The final result combines 12 Top-Down models and 15 Transformer models.

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