Auto-captions on GIF: A Large-scale Video-sentence Dataset for Vision-language Pre-training

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Abstract

In this work, we present Auto-captions on GIF, which is a new large-scale pre-training dataset for generic video understanding. All video-sentence pairs are created by automatically extracting and filtering video caption annotations from billions of web pages. Auto-captions on GIF dataset can be utilized to pre-train the generic feature representation or encoder-decoder structure for video captioning, and other downstream tasks (e.g., sentence localization in videos, video question answering, etc.) as well. We present a detailed analysis of Auto-captions on GIF dataset in comparison to existing video-sentence datasets. We also provide an evaluation of a Transformer-based encoder-decoder structure for vision-language pre-training, which is further adapted to video captioning downstream task and yields the compelling generalizability on MSR-VTT. The dataset is available at http://www.auto-video-captions. top/2020/dataset.

1. Introduction

Vision-language pre-training has been an emerging and fast-developing research topic in image domain [18, 30, 31, 46], which transfers multi-modal knowledge from rich-resource pre-training task to limited-resource downstream tasks (e.g., visual question answering [2, 4], cross-modal retrieval [12, 23, 41], image captioning [15, 42, 43, 44, 45], and image paragraph generation [35]). Nevertheless, the pre-training of generic feature or structure for video understanding is seldom explored and remains challenging. This is in part due to the simplicity of current video-sentence benchmarks, which mostly focus on specific fine-grained domains with limited videos (e.g., cooking scenario [9, 25, 28] and movie domain [27, 32]). Furthermore, the human annotations (e.g., video-sentence pairs) are resourcefully expensive and thus cannot be scaled up.

In this paper, we present the Auto-captions on GIF dataset, which is a new large-scale video-sentence bench-

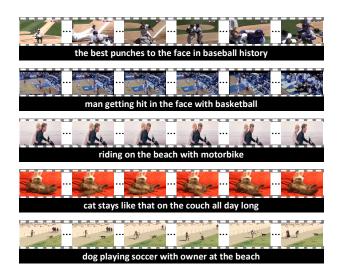


Figure 1. Examples of the GIF videos and the automatically extracted descriptions in our Auto-captions on GIF dataset. We give five samples, with each containing six frames to represent the GIF video and the corresponding sentence.

mark for vision-language pre-training, to pursue the generic video understanding. This is achieved by automatically extracting, filtering, and refining raw descriptions from the Alt-text HTML attribute of web GIF videos in billions of web pages. In particular, an automatic pipeline is devised to extract, filter, and refine the raw video-sentence pairs, leading to the current version of Auto-captions on GIF with 164,378 video-sentence pairs.

With such large-scale programmatically created video-sentence data, we can pre-learn the generic representation or encoder-decoder structure via vision-language pre-training. The pre-trained generic representation or structure can better reflect the cross-modal interaction in a free way and thus benefit a series of downstream video-language tasks, such as video captioning [14, 21, 33], sentence localization in videos [3], sentence-to-video generation [20], and video question answering [11]. Technically, we devise a pre-trainable Transformer-based Encoder-Decoder struc-

ture (TransED) for vision-language pre-training in video domain. Most specifically, the encoder-decoder structure is first pre-trained on Auto-captions on GIF dataset with four common proxy tasks (masked sequence generation, masked frame-feature regression, video-sentence matching, and masked language modeling). After that, the learnt encoder-decoder structure is further fine-tuned over MSR-VTT for the downstream task of video captioning.

In summary, we make the following contributions in this work: (I). We build to-date the first automatically generated video-sentence dataset with diverse video content. (II). We design a Transformer-based encoder-decoder structure for vision-language pre-training in video domain. (III). We demonstrate the effectiveness of exploiting vision-language pre-training over our Auto-captions on GIF dataset, that facilitates video captioning downstream task.

2. Auto-captions on GIF Dataset

The Auto-captions on GIF dataset is characterized by the unique properties including the large-scale video-sentence pairs and the automatic collection process, as well as the comprehensive and diverse video content. In this section, we introduce the automatic pipeline for constructing this dataset in detail, followed by the summarization of our Auto-captions on GIF in comparison to existing video-sentence datasets.

2.1. Collection of Comprehensive GIF Videos

Most of existing video-sentence datasets mainly focus on specific fine-grained domains. This adversely hinders the generalization of pre-learnt representation or structure on downstream tasks. For instance, YouCook [9] and TACoS [25, 28] are constructed in cooking scenario. MPII-MD [27] and M-VAD [32] focus on movie domain. In order to collect comprehensive and representative GIF videos, we first extract the objects, actions, and SVO (subjectverb-object) triplets from all the sentences in several existing image/video benchmarks (e.g., MSCOCO, MSR-VTT, MSVD, and Conceptual Captions). All the massive extracted items ($\sim 1,200,000$) are taken as the search queries, and we crawl the GIF videos on web pages via several commercial GIF video search engines for each query. We remove the invalid GIF videos. Ultimately, we collect an original set of comprehensive and representative GIF videos from billions of web pages.

2.2. Filtering of Sentences

Next, for each crawled GIF video, we harvest the corresponding raw sentence from the Alt-text HTML attribute. All the raw sentences are filtered as following:

• We discard the sentences that score too high/low on the polarity annotations via NLTK [17], or trigger the pornography/profanity detectors ¹.

- The sentences with a high rate of token repetition are filtered out.
- By parsing sentences via NLTK [17], we discard the ones with no determiner, no noun, or no preposition.
- The sentences containing questions, and specific names of movie, TV show, or music video, are discarded.
- We discard the sentences with the pre-defined highfrequency but less informative phrases (e.g., "proverb of the day" and "this week in rock").
- The pre-defined boiler-plate prefix/suffix (e.g., "click on this" and "back to the top of the page link") in sentences are cropped.

2.3. Filtering of Video-sentence Pairs

The previous filtering of sentences stage only examines and filters the raw sentences, leaving the inherent relations between GIF videos and sentences unexploited. Next we additionally filter the video-sentence pairs depending on the semantic relevance in between. In particular, with the assumption that each crawled GIF video is semantically correlated to the search query, we discard the sentence that has no overlap with the search query of the corresponding GIF video. As such, this filtering stage discards the semantically mismatched video-sentence pairs.

2.4. Selection of Human-like Sentences

To further screen out the sentences which are similar to human-written descriptions, we train two binary classifiers to recognize whether each sentence is manually written, depending on the whole sentence or the parsed SVO triplet, respectively. Specifically, we take all the human-written sentences in existing image/video captioning benchmarks (e.g., MSCOCO, MSR-VTT, MSVD, and Conceptual Captions) as positive samples, and all the discarded raw sentences in the filtering of sentences stage as negative samples. Finally, only the sentences that simultaneously pass the two classifiers will be taken as the human-like ones for constructing the final dataset.

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profanity-filter/;https://pypi.org/project/
better-profanity/;https://github.com/
areebbeigh/profanityfilter;https://pypi.org/
project/profanity-filter/;https://github.
com/areebbeigh/profanityfilter

Table 1. Comparison of video-sentence datasets.

Dataset	Context	Sentence Source	#Video	#Sentence	#Word	Vocabulary
YouCook [9]	cooking	labeled	-	2,668	42,457	2,711
TACos [25, 28]	cooking	AMT workers	7,206	18,227	-	-
TACos M-L [26]	cooking	AMT workers	14,105	52,593	-	-
M-VAD [32]	movie	DVS	48,986	55,905	519,933	18,269
MPII-MD [27]	movie	DVS+Script	68,337	68,375	653,467	24,549
MSVD [5]	multi-category	AMT workers	1,970	70,028	607,339	13,010
TGIF [13]	multi-category	Crowd workers	102,068	125,781	1,418,775	11,806
MSR-VTT [38]	20 categories	AMT workers	10,000	200,000	1,856,523	29,316
Auto-captions on GIF	multi-category	Automatic crawling from web	163,183	164,378	1,619,648	31,662

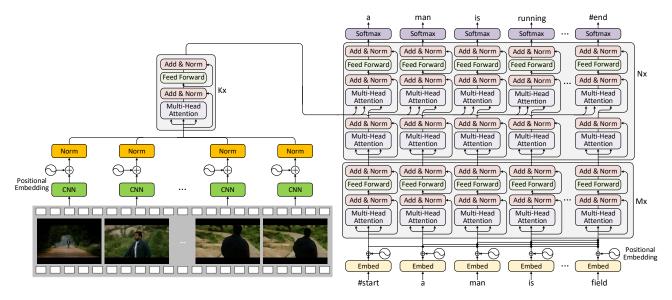


Figure 2. A Transformer-based Encoder-Decoder structure (TransED) for vision-language pre-training, which can be further adapted to the downstream task of video captioning.

2.5. Data Statistics

Table 1 details the statistics and comparison among different video-sentence dataset. Note that we are continuing to crawl more GIF videos from new web pages, and thus more data will be released in the future. In current version, our Auto-captions on GIF contains 163,183 GIF videos and 164,378 sentences, and is the largest video-sentence dataset in terms of video number (163,183) and word vocabulary (31,662). Moreover, different from the most existing datasets which focus on specific fine-grained domains and require human annotations, our Auto-captions on GIF is derived from billions of web pages with massive video categories. As such, the resources can significantly benefit the generalization capability of pre-trained representation or encoder-decoder structure on downstream tasks. To sum up, Auto-captions on GIF represents the most comprehensive, diverse, and complex video-sentence dataset for video understanding, and thus can naturally facilitate the visionlanguage pre-training in video domain.

3. Vision-language Pre-training

Inspired by the recent successes of Transformer selfattention networks [22, 29] for vision-language tasks, we present a base model with Transformer-based encoderdecoder structure to access the impact of Auto-captions on GIF dataset for vision-language pre-training.

Encoder-Decoder Structure. Figure 2 details the architecture of the Transformer-based Encoder-Decoder structure (TransED). Technically, for video encoder, we utilize K=6 stacked multi-head self-attention layers to model the self-attention among input frames. The language decoder consists of M=3 multi-head self-attention layers and N=6 multi-head cross-attention layers (each cross-attention layer is composed of a self-attention sub-layer and a cross-attention sub-layer). More specifically, the stacked multi-head self-attention layers are firstly leveraged to capture the word dependency. Furthermore, the multi-head cross-attention layers are utilized to exploit the co-attention between visual content (frame features from video encoder) and textual tokens (input words).

Table 2. Performance comparisons on MSR-VTT with official split, where B@4, M, R, C and S are short for BLEU@4, ME-TEOR, ROUGE-L, CIDEr-D and SPICE scores. All values are reported as percentage (%). The short name in the brackets indicates the frame/clip features, where G, C, R, I and A denotes GoogleNet, C3D, ResNet, Inception-Resnet-V2 and Audio feature.

Model	B@4	M	R	С	S
MP-LSTM (R) [34]	34.1	25.4	-	35.8	-
TA (R) [40]	33.2	24.9	-	34.5	-
S2VT (R) [33]	34.4	25.8	-	36.7	-
LSTM-E (R) [19]	34.5	25.7	-	36.1	-
MA-LSTM (G+C+A) [39]	36.5	26.5	59.8	41.0	-
MCNN+MCF (R) [37]	38.1	27.2	-	42.1	-
PickNet (R) [8]	39.4	27.3	59.7	42.3	-
SibNet (G) [16]	40.9	27.5	60.2	47.5	-
HRL (R) [36]	41.3	28.7	61.7	48.0	-
TDConvED (R) [6]	39.5	27.5	59.3	42.8	-
GRU-EVE (I+C) [1]	36.1	27.7	59.9	45.2	-
MARN (R+C) [24]	40.4	28.1	60.7	47.1	-
MGSA (I+C) [7]	42.4	27.6	-	47.5	-
POS+VCT (R) [10]	41.4	28.9	62.0	48.1	-
TransED (R)	38.3	26.8	59.2	44.3	5.8
TransED+Pre-training (R)	39.0	27.3	59.7	45.2	5.9
TransED $_{RL}$ (R)	40.2	28.3	61.0	53.6	6.8
TransED _{RL} +Pre-training (R)	41.0	28.5	61.4	54.4	6.9

Proxy Tasks for Vision-language Pre-training. In order to endow the base structure with the capabilities of multi-modal reasoning between vision and language, we pre-train TransED with four vision-language proxy tasks on Auto-captions on GIF dataset: (1) masked language modeling [30, 31]; (2) masked frame-feature regression as in [31]; (3) video-sentence matching (in analogy to image-sentence matching [18]); (4) sequence to sequence generation [46].

4. Experiments

In this section, we fully verify the merit of using Autocaptions on GIF for vision-language pre-training and then fine-tuning the pre-trained TransED on MSR-VTT for video captioning downstream task.

4.1. Datasets and Implementation Details

Pre-training Data of Auto-captions on GIF. The Auto-captions on GIF contains 163,183 GIF videos and 164,378 sentences, and we utilize the whole dataset for pre-training the base encoder-decoder structure (TransED). For each GIF video, we take all the frames as inputs (maximum frame number: 50).

Fine-tuning Data of MSR-VTT. MSR-VTT is a widely adopted video-sentence dataset for video captioning task, which consists of 10,000 video clips from 20 well-defined categories. There are 6,513 training videos, 497 validation videos, and 2,990 testing videos in the official split. For the downstream task of video captioning, we fine-tune the pretrained TransED on the training data of MSR-VTT in the

Table 3. Performance comparisons on online testing server.

Model	B@4	M	R	С	S			
Fine-tune with 6.5k videos (train split), online evaluation								
TransED (R)	16.4	15.5	39.1	17.0	4.4			
TransED+Pre-training (R)	17.1	15.8	39.5	18.0	4.6			
$TransED_{RL}$ (R)	16.6	15.8	40.0	20.4	4.8			
TransED _{RL} +Pre-training (R)	18.1	16.4	40.9	22.3	5.1			
Fine-tune with 9.5k videos (train+test splits), online evaluation								
TransED (R)	17.4	16.2	39.6	19.6	4.8			
TransED+Pre-training (R)	18.8	16.3	40.6	19.7	4.8			
$TransED_{RL}$ (R)	17.9	16.3	40.5	22.5	5.1			
TransED _{RL} +Pre-training (R)	19.5	16.8	41.3	23.9	5.4			

official split. In addition, we also evaluate the pre-trained TransED on the online testing set by submitting the results to online testing server 2 . For each video in MSR-VTT, we sample the frames at 3 fps and the maximum number of frames is also set as 50. During the fine-tuning stage on MSR-VTT, we optimize TransED with cross-entropy loss. Note that we involve a variant of TransED (named TransED $_{BL}$) which is further optimized with CIDEr reward.

4.2. Performance Comparison

Offline Evaluation on Official Split. Table 2 shows the performance comparisons on MSR-VTT with official split. It is worth noting that the reported performances of different state-of-the-art task-specific models are often based on different frame/clip representations. For fair comparisons, we evaluate our base models (TransED, TransED $_{RL}$) on the most commonly adopted frame representation (i.e., the output from ResNet). Moreover, we involve two different experimental settings for each base model: TransED/TransED $_{RL}$ denotes the base model which is only trained with task-specific data, without pre-training on our Auto-captions on GIF dataset; TransED/TransED $_{RL}$ +Pre-training represents that the base model is pre-trained over Auto-captions on GIF and further fine-tuned on task-specific data.

Overall, under the same task-specific setting without vision-language pre-training, TransED and TransED $_{RL}$ obtain comparable results with other state-of-the-art task-specific models. Furthermore, by pre-training TransED/TransED $_{RL}$ on Auto-captions on GIF and then fine-tuning it on MSR-VTT, the TransED/TransED $_{RL}$ +Pre-training consistently exhibits better performances than TransED/TransED $_{RL}$ across all the evaluation metrics. This confirms the merit of exploiting vision-language pre-training over our Auto-captions on GIF, that facilitates the downstream task of video captioning on MSR-VTT.

Online Evaluation on Online Testing Server. In addition, we evaluate the base models on the online testing set. Table 3 details the performances over online test-

²http://www.auto-video-captions.top/2020/ leaderboard

ing videos. Note that here we adopt two different sets (6.5k training videos, and 9.5k training plus testing videos in official split) for fine-tuning TransED/TransED $_{RL}$ on MSR-VTT. Similar to the observations in offline evaluation, TransED/TransED $_{RL}$ +Pre-training performs better than TransED/TransED $_{RL}$ by additionally pre-training the based model on Auto-captions on GIF.

5. Conclusions

We introduced a new video-sentence dataset, Auto-captions on GIF, which is automatically created from billions of web pages. This dataset contains to-date the largest amount of videos with the most comprehensive and representative video content, and thus supports vision-language pre-training in video domain. We experimentally evaluated the base models with Transformer-based encoder-decoder structure for vision-language pre-training over our Auto-captions on GIF dataset. The results demonstrate the compelling generalizability of pre-trained encoder-decoder structure by fine-tuning it to video captioning downstream task on MSR-VTT.

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