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, 22, 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-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-V AD [32] focus on movie domain. In order to collect comprehensive and representative GIF videos, we first extract the objects, actions, and SVO (subject-verb-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 (∼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 high-frequency 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.

[1] https://pypi.org/project/profanity-filter/
2.5. Data Statistics

Table 1 shows the comparison of video-sentence datasets. 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 vision-language pre-training in video domain.

3. Vision-language Pre-training

Inspired by the recent successes of Transformer self-attention networks [22, 29] for vision-language tasks, we present a base model with Transformer-based encoder-decoder 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).
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 Auto-captions 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 each video in MSR-VTT, we take all the frames as inputs (maximum frame number: 50).

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$_{RL}$ training consistently exhibits better performances than fine-tuning it on task-specific data. 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 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 by submitting the results to online testing server [3]. 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$_{RL}$) which is further optimized with CIDEr reward.

Table 2. Performance comparisons on MSR-VTT with official split, where B@4, M, R, C and S are short for BLEU@4, METEOR, 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 | C | 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) [26] | 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 |

Table 3. Performance comparisons on online testing server.

| Model | B@4 | M | R | C | 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 |
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.

References

[1] Nayyer Aafaq, Naveed Akhtar, Wei Liu, Syed Zuqarnain Gilani, and Ajmal Mian. Spatio-temporal dynamics and semantic attribute enriched visual encoding for video captioning. In CVPR, 2019.

[2] Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. Bottom-up and top-down attention for image captioning and visual question answering. In CVPR, 2018.

[3] Lisa Anne Hendricks, Oliver Wang, Eli Shechtman, Josef Sivic, Trevor Darrell, and Bryan Russell. Localizing moments in video with natural language. In ICCV, 2017.

[4] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In ICCV, 2015.

[5] David I. Chen and William B Dolan. Collecting highly parallel data for paraphrase evaluation. In ACL, 2011.

[6] Jingwen Chen, Yingwei Pan, Yehao Li, Ting Yao, Hongyang Chao, and Tao Mei. Temporal deformable convolutional encoder-decoder networks for video captioning. In AAAI, 2019.

[7] Shaoxiang Chen and Yu-Gang Jiang. Motion guided spatial attention for video captioning. In AAAI, 2019.

[8] Yangyu Chen, Shuhuai Wang, Weigang Zhang, and Qiuming Huang. Less is more: Picking informative frames for video captioning. In ECCV, 2018.

[9] Pradipto Das, Chenliang Xu, Richard F Doell, and Jason J Corso. A thousand frames in just a few words: Lingual description of videos through latent topics and sparse object stitching. In CVPR, 2013.

[10] Jingyi Hou, Xinxiao Wu, Wentian Zhao, Jiebo Luo, and Yunde Jia. Joint syntax representation learning and visual cue translation for video captioning. In ICCV, 2019.

[11] Jie Lei, Licheng Yu, Mohit Bansal, and Tamara Berg. Tvqa: Localized, compositional video question answering. In EMNLP, 2018.

[12] Yehao Li, Yingwei Pan, Ting Yao, Hongyang Chao, Yong Rui, and Tao Mei. Learning click-based deep structure-preserving embeddings with visual attention. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 2019.

[13] Yuncheng Li, Yale Song, Liangliang Cao, Joel Tetreault, Larry Goldberg, Alejandro Jaimes, and Jiebo Luo. Tgif: A new dataset and benchmark on animated gif description. In CVPR, 2016.

[14] Yehao Li, Ting Yao, Yingwei Pan, Hongyang Chao, and Tao Mei. Jointly localizing and describing events for dense video captioning. In CVPR, 2018.

[15] Yehao Li, Ting Yao, Yingwei Pan, Hongyang Chao, and Tao Mei. Pointing novel objects in image captioning. In CVPR, 2019.

[16] Sheng Liu, Zhou Ren, and Junsong Yuan. Sibnet: Sibling convolutional encoder for video captioning. In ACM MM, 2018.

[17] Edward Loper and Steven Bird. Nltk: The natural language toolkit. In Proceedings of the ACL-02 Workshop on Effective Tools and Methodologies for Teaching Natural Language Processing and Computational Linguistics, 2002.

[18] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In NeurIPS, 2019.

[19] Yingwei Pan, Tao Mei, Ting Yao, Houqiang Li, and Yong Rui. Jointly modeling embedding and translation to bridge video and language. In CVPR, 2016.

[20] Yingwei Pan, Zhaofan Qiu, Ting Yao, Houqiang Li, and Tao Mei. To create what you tell: Generating videos from captions. In MM, 2017.

[21] Yingwei Pan, Ting Yao, Houqiang Li, and Tao Mei. Video captioning with transferred semantic attributes. In CVPR, 2017.

[22] Yingwei Pan, Ting Yao, Yehao Li, and Tao Mei. X-linear attention networks for image captioning. In CVPR, 2020.

[23] Yingwei Pan, Ting Yao, Tao Mei, Houqiang Li, Chong-Wah Ngo, and Yong Rui. Click-through-based cross-view learning for image search. In SIGIR, 2014.

[24] Wenjie Pei, Jiuyuan Zhang, Xiangrong Wang, Lei Ke, Xiaoyong Shen, and Yu-Wing Tai. Memory-attended recurrent network for video captioning. In CVPR, 2019.

[25] Michaela Regneri, Marcus Rohrbach, Dominikus Wetzel, Stefan Thater, Bernt Schiele, and Manfred Pinkal. Grounding action descriptions in videos. Transactions of the Association for Computational Linguistics, 1:25–36, 2013.

[26] Anna Rohrbach, Marcus Rohrbach, Wei Qiu, Annemarie Friedrich, Manfred Pinkal, and Bernt Schiele. Coherent multi-sentence video description with variable level of detail. In German conference on pattern recognition, pages 184–195, 2014.

[27] Anna Rohrbach, Marcus Rohrbach, Niket Tandon, and Bernt Schiele. A dataset for movie description. In CVPR, 2015.
[28] Marcus Rohrbach, Wei Qiu, Ivan Titov, Stefan Thater, Manfred Pinkal, and Bernt Schiele. Translating video content to natural language descriptions. In ICCV, 2013.

[29] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In ACL, 2018.

[30] Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. Vi-bert: Pre-training of generic visual-linguistic representations. arXiv preprint arXiv:1908.08530, 2019.

[31] Hao Tan and Mohit Bansal. Lxmert: Learning cross-modality encoder representations from transformers. In EMNLP-IJCNLP, 2019.

[32] Atousa Torabi, Christopher Pal, Hugo Larochelle, and Aaron Courville. Using descriptive video services to create a large data source for video annotation research. arXiv preprint arXiv:1503.01070, 2015.

[33] Subhashini Venugopalan, Marcus Rohrbach, Jeffrey Donahue, Raymond Mooney, Trevor Darrell, and Kate Saenko. Sequence to sequence - video to text. In ICCV, 2015.

[34] Subhashini Venugopalan, Huijuan Xu, Jeff Donahue, Marcus Rohrbach, Raymond Mooney, and Kate Saenko. Translating videos to natural language using deep recurrent neural networks. In NAACL HLT, 2015.

[35] Jing Wang, Yingwei Pan, Ting Yao, Jinhui Tang, and Tao Mei. Convolutional auto-encoding of sentence topics for image paragraph generation. In IJCAI, 2019.

[36] Xin Wang, Wenhu Chen, Jiawei Wu, Yuan-Fang Wang, and William Yang Wang. Video captioning via hierarchical reinforcement learning. In CVPR, 2018.

[37] Angim Wu and Yahong Han. Multi-modal circulant fusion for video-to-language and backward. In IJCAI, 2018.

[38] Jun Xu, Tao Mei, Ting Yao, and Yong Rui. Msr-vtt: A large video description dataset for bridging video and language. In CVPR, 2016.

[39] Jun Xu, Ting Yao, Yongdong Zhang, and Tao Mei. Learning multimodal attention lstm networks for video captioning. In ACM MM, 2017.

[40] Li Yao, Atousa Torabi, Kyunghyun Cho, Nicolas Ballas, Christopher Pal, Hugo Larochelle, and Aaron Courville. Describing videos by exploiting temporal structure. In ICCV, 2015.

[41] Ting Yao, Tao Mei, and Chong-Wah Ngo. Learning query and image similarities with ranking canonical correlation analysis. In ICCV, 2015.

[42] Ting Yao, Yingwei Pan, Yehao Li, and Tao Mei. Incorporating copying mechanism in image captioning for learning novel objects. In CVPR, 2017.

[43] Ting Yao, Yingwei Pan, Yehao Li, and Tao Mei. Exploring visual relationship for image captioning. In ECCV, 2018.

[44] Ting Yao, Yingwei Pan, Yehao Li, and Tao Mei. Hierarchy parsing for image captioning. In ICCV, 2019.

[45] Ting Yao, Yingwei Pan, Yehao Li, Zhaofan Qiu, and Tao Mei. Boosting image captioning with attributes. In ICCV, 2017.

[46] Luowei Zhou, Hamid Palangi, Lei Zhang, Houdong Hu, Jason J Corso, and Jianfeng Gao. Unified vision-language pre-training for image captioning and vqa. In AAAI, 2020.