Annotation Cleaning for the MSR-Video to Text Dataset

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Abstract—The video captioning task is to describe the video contents with natural language by the machine. Many methods have been proposed for solving this task. A large dataset called MSR Video to Text (MSR-VTT) is often used as the benchmark dataset for testing the performance of the methods. However, we found that the human annotations, i.e., the descriptions of video contents in the dataset are quite noisy, e.g., there are many duplicate captions and many captions contain grammatical problems. These problems may pose difficulties to video captioning models for learning. We cleaned the MSR-VTT annotations by removing these problems, then tested several typical video captioning models on the cleaned dataset. Experimental results showed that data cleaning boosted the performances of the models measured by popular quantitative metrics. We recruited subjects to evaluate the results of a model trained on the original and cleaned datasets. The human behavior experiment demonstrated that trained on the cleaned dataset, the model generated captions that were more coherent and more relevant to contents of the video clips. The cleaned dataset is publicly available.

Index Terms—MSR-VTT dataset, data cleaning, data analysis, video captioning.

1 INTRODUCTION

The goal of the video captioning task is to summarize the content of a video clip by a single sentence, which is an extension of image captioning task [1], [2], [3], [4]. To accomplish this task, one must use both computer vision (CV) techniques and natural language processing (NLP) techniques. A benchmark dataset, called MSR-Video to Text 1.0 (MSR-VTT v1) [5], was released in 2016. It contains 10,000 video clips and each clip is described by 20 captions, which are supposed to be different, given by human annotators. The dataset has become popular in the field of video captioning. Until February 8th, 2021, that work [5] has been cited by 501 times according to Google scholar.

However, with a quick look, one can find many duplicate annotations, spelling mistakes and syntax errors in the annotations (Figs. 1, 2). It is unknown how many mistakes there are exactly in the dataset and whether/how these mistakes would influence the performance of the video captioning models.

We quantitatively analyzed the annotations in the MSR-VTT dataset, and identified four main types of problems. First, thousands of annotations have duplicates for some of the video clips in the dataset. Second, thousands of special characters, such as ‘+’, ‘-’, ‘/’, ‘:’, exist in the annotations. Third, thousands of spelling mistakes exist in the annotations. Fourth, hundreds of sentences are redundant or incomplete. We developed some techniques to clean the annotations by solving these problems. Our experiments demonstrated that existing models, trained on the cleaned training set, had better performances compared to the results obtained by the models trained on the original training set. A human evaluation study also showed that a state-of-the-art model trained on the cleaned training set generated better captions than trained on the original training set in terms of semantic relevance and sentence coherence.

The cleaned dataset is available to the public.

1. A man is throwing a football at a target. × 2
2. A man throws an American football at an aiming board. × 3
3. Kids throws football at target. × 4
4. Man throwing football to target in slow motion. × 2
5. People are playing sports. × 2
6. Someone is throwing a football at a target. × 2

Figure 1. An example video clip (No. 4290, starting from 0) with duplicate annotations. ×t denotes repeating t times.
2 RELATED WORK

2.1 Datasets

Two datasets MSVD (also called YouTube2Text) and MSR-VTT, unlimited to a specific domain, are widely used in recent video captioning researches as benchmarks. MSVD was published in 2013 [6]. It contains 1970 video clips and roughly 80,000 captions. Each video clip pairs with 40 captions. MSR-VTT v1 was published in 2016 [3]. It contains 10,000 video clips and 200,000 captions. Each video clip pairs with 20 captions. The MSR-VTT v2 dataset was proposed in the second Video Captioning Competition using the MSR-VTT v1 dataset as the training and validation sets and additional 3000 video clips as the test set. However, the annotations of the test set are not open to the public.

2.2 Models

Many models have been proposed for video captioning [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19]. With semantic concepts detected from the video, the probability distribution of each tag is integrated into the parameters of a recurrent unit in SCN [7]. Video captioning is improved by sharing knowledge with two related tasks on the encoder and the decoder of a sequence-to-sequence model [8]. Reinforced learning is enhanced for video captioning with the mixed-loss function and the CIDEr-entailment reward in CIDEnt-RL [9]. Multiple modalities are fused by hierarchical attention, which helps to improve the model performance, in HATT [10]. The video feature produced by Efficient Convolutional Network is fed into a video captioning model, which boosts the quality of the generated caption, in the model named ECO [11]. In the GRU-EVE, the Short Fourier Transform is applied to video features and high level semantics is derived from the object detector in order to generate captions rich in semantics [12]. A memory structure is used to capture the comprehensive visual information across the whole training set for a word in the MARN [13]. The encoder employs a sibling (dual-branch) architecture to encode video clips in the SibNet [14]. HACA fuses both global and local temporal dynamics existing in a video clip and generates an accurate description with knowledge from different modalities [15]. Different expert modules are trained to provide knowledge for describing out-of-domain video clips in the TAMoE [16]. The model called SAM-SS is trained under the self-teaching manner to reduce the gap between the training and the test phase with meaningful semantic features [17]. Different types of representations are encoded and fused by the cross-gating block and captions are generated with Part-of-Speech information in the POS_RL [18]. In the VNS-GRU, “absolute equalitarianism” in the training process is alleviated by professional learning while a comprehensive selection method is used to choose the best checkpoint for the final test [19].

3 ANALYSIS AND CLEANING OF THE MSR-VTT DATASET

Since MSR-VTT v2 uses MSR-VTT v1 for training and validation, and the annotations of the test set of MSR-VTT v2 are not open to the public, we performed analysis on MSR-VTT v1.

The MSR-VTT v1 dataset contains 10,000 video clips. Its training set has 6,513 video clips, the validation set has 497 video clips and the test set has 2,990 video clips. All clips are categorized into 20 classes with diverse contents and scenarios. A total of 0.2 million human annotations were collected to describe those video clips. The training/validation/test sets have 130,260/9,940/59,800 annotations, respectively. The vocabulary sizes of the training/validation/test set are 23,666/5,993/16,001, respectively.

3.1 Special Characters

There are 60 different characters in the dataset, including 0-9, a-z and 24 special characters in Table 1 (space is neglected). Generally speaking, those special characters are not used to train a model. We are intended to remove
special characters while preserve information integrity in annotations.

We processed those special characters as follow:

1) Some special characters were removed from the sentences, include “#”, “$”, “%”, “&”, “(”, “)”, “,”, “!”, “:”, “;”, “>”, “[”, “]”, “{”, “}”, “(”, “)”, “,”, “|”, “´e” were removed only when they were not in pairs.
2) The contents between bracket pairs “{” and “}” were removed.
3) Special characters “,”, “,”, “,”, “@”, “,”, “,”, “,”, “/” were replaced with spaces.
4) Characters from another language were replaced by the most similar English characters. For example, “ê” was replaced by “e” in “error” and “н” by “b” in “beautiful”.
5) “&” between two different words was substituted by “and”.

In total, 7,247 sentences, which account for 3.6% of all sentences, were modified.

### 3.2 Spelling Mistakes

Many spelling mistakes were found in the annotations during manual check. Tokenization is a process of demarcating a string of an input sentence into a list of words. After tokenization on each of the sentences, we used a popular spelling check software Hunspell to check spelling errors.

Before we used Hunspell to do spelling checks, we added 784 new words to its vocabulary. We chose these words manually by four criteria:

1) word abbreviations that are popular, eg. F1, WWF, RPG;
2) specific terms that are widely used, eg. Minecraft, Spongebob, Legos;
3) new words that are popular on the Internet, eg. gameplay, spiderman, talkshow;
4) names of persons, eg. Mariah, Fallon, Avril.

After that, we found spelling mistakes in 19,038 annotations out of 200,000 annotations. 21,826 words might have spelling mistakes suggested by Hunspell. We corrected those candidates in the following steps:

1) Substituted British English spellings with the corresponding American English spellings. For instance, colour → color, travelling → traveling, programme → program, practising → practicing, theatre → theater. There were 61 such pairs.
2) Split unusual words that were created by concatenating two different words, e.g. rockclimbing → rock climbing, blowdrying → blow drying, sword-fighting → sword fighting, screencaster → screen caster, rollercoaster → roller coaster. In total, 34 distinct words were found.
3) Corrected words that truly contain spelling mistakes, e.g., discussing → discussing, explaining → explaining, conversation → conversation, video → video, different → different.

In total 32,056 words were substituted, split or corrected in these three steps.

### 3.3 Duplicate Annotations

We found duplicate sentences for many video clips (Fig. 1). For each video clip, duplicates were removed. The similarity between two sentences was defined as follow

\[
s_{a,b} = 0.5(\mu(a,b)/\bar{\mu}(a) + \mu(a,b)/\bar{\mu}(b)),
\]

where \(i(x)\) denotes the word count in the sentence \(x = \{x_1, x_2, \ldots\}\) and \(\mu(a,b)\) denotes the word count of the longest common subsequence in \(a\) and \(b\). \(\bar{\mu}(a, b)\) is defined as follows,

\[
\mu(a,b) = \max_i (i(c)) \quad \text{s.t.} \quad c \in a, c \in b,
\]

where \(x_1 \in x_2\) stands for that \(x_1\) is a subsequence of \(x_2\). Word \(w_1\) and word \(w_2\) were regarded as the same if the Levenshtein distance between them was less than or equal to \(\bar{\varepsilon}\). Two sentences were regarded as duplicated if \(s_{a,b} > \bar{s}\), where \(\bar{s}\) is the similarity threshold. With proper values of \(\varepsilon\) and \(\bar{\varepsilon}\), we could find duplicated sentences that had little difference. For example, considering the second pair of sentences in Table 2 the character “m” is missing in the word “woan” and the second sentence just has one more word “young” than the first sentence. These two sentences are almost the same in terms of meaning.

After duplicate removal, 183,856 video annotations remained in the dataset with 119,625 in the training set, 9,126 in the validation set and 55,105 in the test set. Each clip has 9 annotations at least, 20 at most and 18.4 on average.

### 3.4 Successive Sentences without Punctuations

In the task of video captioning, we expect each annotation contains one sentence. For many annotations in the dataset, each of them consists of multiple sentences. In Fig. 3 the first
1. A woman in a dress talks about data scientist she tells how they are problem solvers and well educated she starts asking how you can stand out among other data scientist.

2. A video game is displayed on the screen and in this game a man riding a motorcycle hits a car then we see a webpage with cars with a man speaking as a voice over.

Figure 3. Redundancy samples in the MSR-VTT dataset. Caption 1 can be divided into three sentences. And Caption 2 can be divided into two or three sentences.

Annotation can be split into three complete sentences: "A woman in a dress talks about data scientist." "She tells how they are problem solvers and well educated." "She starts asking how you can stand out among other data scientist." It causes two potential problems. First, the models trained on such annotations may output grammatically problematic sentences because these annotations are syntactically incorrect. Second, such annotations in the test set are no longer reliable ground truth so that the metrics, computed with them, are not reliable, neither.

To solve these two problems, one needs to manually separate the annotations into several complete sentences and merge them into a single sentence. But there are too many annotations in the training and validation sets. We only did this for the test set. For the training and validation sets, we truncated the sentences longer than $l_a + 2\sigma$, where $l_a$ and $\sigma$ denote the average sentence length and its standard deviation, respectively.

4 Experiments

We conducted experiments on the original and cleaned MSR-VTT datasets with several existing video captioning models, SCN [7], ECO [11], SAM-SS [17] and VNS-GRU [19]. They were trained for 30, 30, 50, 80 epochs, respectively. They were evaluated on the validation set at the end of each epoch. The first two models used the early stopping strategy with cross-entropy loss as the indicator. The last two models used the Comprehensive Selection Method to select a checkpoint for testing [19]. For the sake of fair comparison, the experiment settings were the same as the original papers. The two hyperparameters $\bar{e}$ and $\bar{s}$ (see section 3.3) were set to 0 and 0.85 in our experiments, unless otherwise stated.

4.1 Evaluation Metrics

We adopted BLEU, CIDEr, METEOR and ROUGE-L as objective metrics for evaluating the results of the models. BLEU is a quick and easy-to-calculate metric, originally used for evaluating the performance of machine translation models [21]. CIDEr is a metric that captures human consensus [22]. METEOR is a metric that involves precision, recall and order correlation, based on unigram matches [23]. ROUGE-L is a metric that determines the quality of a summary by finding the longest common subsequence [24]. Besides these individual metrics, we used a score to combine all of these metrics [17]:

$$O_i = \left( \frac{B_4}{B_b} + \frac{C_i}{C_b} + \frac{M_i}{M_b} + \frac{R_i}{R_b} \right) / 4,$$

(4)

where the subscript $i$ denotes the model $i$ and the subscript $b$ denotes the best score of the metric $b$ over a group of models for comparison. B4, C, M, R and O denote BLEU-4, CIDEr, METEOR, ROUGE-L and the overall score, respectively.

4.2 Influence of Edit Distance Threshold and Similarity Threshold on Duplicates Removal

In the step of removing duplicated annotations, there are two hyperparameters: the edit distance threshold $\bar{e}$ and similarity threshold $\bar{s}$. We investigated the sensitivity of the hyperparameters on the output of this step. As shown in Table 3, the threshold of edit distance $\bar{e}$ was inversely proportional to the remained sentence count. The performance of the model VNS-GRU was the best when $\bar{e} = 0$. As shown in Table 4, the threshold of similarity was proportionate to the remained sentence count. The performance of the model VNS-GRU was the best when $\bar{s} = 0.85$.

Table 3 shows that with the method described in the Section 3.3 we can find similar sentences, in terms of semantics, with one or two words different.
4.3 Comparison between the Original/Cleaned MSR-VTT Datasets

In Table 5, a model name without any superscript indicates that the model was trained on the original training set and the metrics were calculated on the original test set. A model name with a superscript indicates that the model was trained on the cleaned training set and the metrics were calculated on the original test set. A model name with a superscript indicates that the model was trained on the original training set and tested on the cleaned test set. For instance, VNS-GRU\textsuperscript{a} was trained on the cleaned training set and the metrics were calculated on the original test set. In Table 5, a model name without any superscript indicates that the model was trained on the original training set, even though the metrics were calculated on the original test set. A model name with a superscript indicates that the model was trained on the cleaned training set and tested on the cleaned test set. For instance, VNS-GRU\textsuperscript{a} was trained on the cleaned training set and the metrics were calculated on the original test set. A model name with a superscript indicates that the model was trained on the cleaned training set and tested on the cleaned test set. For instance, VNS-GRU\textsuperscript{a} was trained on the cleaned training set and the metrics were calculated on the original test set.

As shown in Tables 6 and 7, Step I brought improvements in all the metrics since it reduced the number of irregular words and phrases, which contain special characters. After Step II, the four metrics remained similar to those after Step I when measured on the original test set (Table 6), but the metrics were improved when measured on the cleaned test set (Table 7). After Step III, all metrics except METEOR increased in the both cases. The METEOR value slightly decreased when measured on the cleaned test set (Table 7). After the last step, almost all metrics were further improved, except BLEU-4. If we focus on the performance of the model measured on the cleaned test set (Table 7), we found that the overall score was improved after each step. These results suggest that all steps are necessary for cleaning the annotations.

5 Human Evaluation

It is well-known that the metrics including BLEU-4, CIDEr, METEOR, ROUGE-L do not fully reflect the quality of the video captioning results. We then conducted a human evaluation study. We recruited 17 people (11 male and 6 female, names]
The first three models are from ACM Multimedia MSR-VTT Challenge 2016 [25]. VideoLAB was used as the baseline (0% change).

Figure 4. The performance of typical models on the MSR-VTT dataset during 2016 and 2020. The models include VideoLAB, Aalto, v2t_navigator, MTVC [8], CIDEnt-RL [9], SibNet [14], HACA [15], TAMoE [16], SAM-SS [17] and POS_RL [18] and VNS-GRU [19]. The first three models are from ACM Multimedia MSR-VTT Challenge 2016 [25]. VideoLAB was used as the baseline (0% change).

Caption A: a group of people are singing and playing instruments
Caption B: a man is singing

Question. In terms of relevance and coherence, which caption is better?
A. Caption A
B. Caption B
C. Indistinguishable

Figure 5. An example question in the human evaluation experiment. Captions A and B were generated by VNS-GRU or VNS-GRU*.

ages between 20 and 35) with normal or corrected-to-normal vision to do this experiment. The subjects were mainly from Tsinghua University, Beijing, China. All subjects had at least college level English. This study was approved by the Department of Psychology Ethics Committee, Tsinghua University, Beijing, China.

The subjects watched video clips from the MSR-VTT dataset and compared the results of VNS-GRU trained on the original and cleaned annotations of the dataset (Figure 5). The subjects were instructed to compare the results based on two criteria:

1) relevance, the match between the contents of the video clip and the caption;

2) coherence, the language fluency and grammatical correctness in the caption.

For each video clip, there were three options: (A) Caption A is better; (B) Caption B is better; and (C) Indistinguishable. The two captions were generated by VNS-GRU or VNS-GRU*, which were trained on the original and cleaned annotations of the dataset, respectively. The subjects needed to choose one and only one of three options. A total of 30 video clips were randomly sampled from the test set and presented to all subjects in a fixed order. Every subject completed the experiment within half an hour.

We recorded the number of votes for VNS-GRU, VNS-GRU* and Indistinguishable for every subject and calculated the average over all subjects (Figure 6). On average, for 11.8 video clips the subjects voted for “VNS-GRU is better” and for 10.1 video clips the subjects voted for “VNS-GRU is better”. The one-sided student t-test indicated that VNS-GRU* performed better than VNS-GRU (p = 0.02, n = 17). On average, for 8.1 videos the subjects could not distinguish the quality of the results.

These results suggested that annotation cleaning could boost the quality of the generated captions by video captioning models from subjective evaluation of humans.

6 Conclusion

The MSR-VTT dataset is a widely used dataset in the video captioning area. We found many problems in its annotations, and many of them are obvious mistakes. We inspected the influence of these problems on the results of video
captioning models. In four steps, we removed or corrected these problems, and compared the results of several popular video captioning models. The models trained on the cleaned dataset generated better captions than the models trained on the original dataset measured by both objective metrics and subjective evaluations. In particular, trained on the cleaned dataset, our previous model VNS-GRU achieved the new state-of-the-art results on this dataset. We recommend to use this cleaned dataset for developing video captioning models.

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