Learnability Matters: Active Learning for Video Captioning

Yiqian Zhang[1], **Buyu Liu**[2], **Jun Bao**[2], **Qiang Huang**[3], **Min Zhang**[2], **Jun Yu**[2*]
[1]Hangzhou Dianzi University
[2]Harbin Institute of Technology (Shenzhen)
[3]National University of Singapore
yiqian.zyq@gmail.com, {buyu.liu, baojun}@hit.edu.cn,
huangq@comp.nus.edu.sg, zhangmin2021@hit.edu.cn, zju.yujun@gmail.com

Abstract

This work focuses on the active learning in video captioning. In particular, we propose to address the learnability problem in active learning, which has been brought up by collective outliers in video captioning and neglected in the literature. To start with, we conduct a comprehensive study of collective outliers, exploring their hard-to-learn property and concluding that ground truth inconsistency is one of the main causes. Motivated by this, we design a novel active learning algorithm that takes three complementary aspects, namely learnability, diversity, and uncertainty, into account. Ideally, learnability is reflected by ground truth consistency. Under the active learning scenario where ground truths are not available until human involvement, we measure the consistency on estimated ground truths, where predictions from off-the-shelf models are utilized as approximations to ground truths. These predictions are further used to estimate sample frequency and reliability, evincing the diversity and uncertainty respectively. With the help of our novel caption-wise active learning protocol, our algorithm is capable of leveraging knowledge from humans in a more effective yet intellectual manner. Results on publicly available video captioning datasets with diverse video captioning models demonstrate that our algorithm outperforms SOTA active learning methods by a large margin,*e.g.*we achieve about 103% of full performance on CIDEr with 25% of human annotations on MSR-VTT.

1 Introduction

Video captioning, which aims to understand videos in the form of describing them in natural language Abdar et al. (2023), becomes a heated task Lin et al. (2022) with the emergence of a large amount of data Li et al. (2023a) as well as transformer-based models Liu et al. (2022). Despite the superior performance, existing methods suffer heavily from the need for time-consuming and labor-intensive human annotations Chan et al. (2020) because of their learning-based nature.

Approaches such as active learning Tharwat and Schenck (2023), semi-supervised learning Yang et al. (2023), and domain adaptation Yu et al. (2023) are proposed to address the above-mentioned data issue. This paper takes the active learning approach where we assume there exists a small amount of labelled data together with a large number of unlabelled ones. Our goal is to select the most informative samples from the unlabelled set and have them annotated by humans such that the video captioning model can achieve the best performance with the minimum human effort. Though uncertainty and diversity have been exploited to investigate the properties of unlabelled data, the

[*] Corresponding author

38th Conference on Neural Information Processing Systems (NeurIPS 2024).

https://doi.org/10.52202/079017-1198

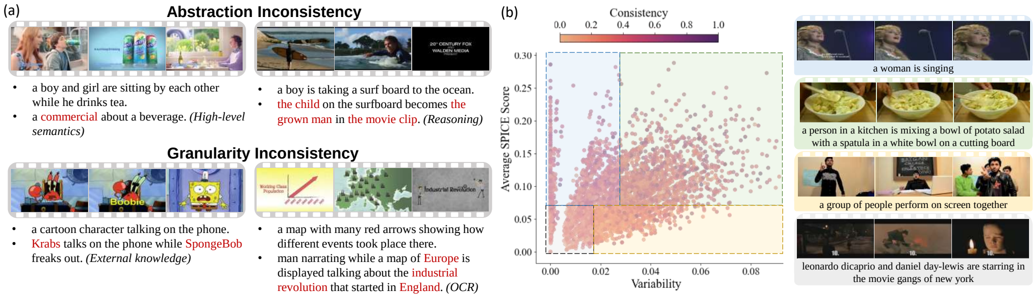


Figure 1: We provide examples of collective outliers as well as their causes in (a). (b) illustrates the Dataset Maps based on the SPICE score for the MSR-VTT training set, with the y-axis representing the average SPICE score over training epochs and the x-axis showing their variability. The consistency score is also measured on ground truth captions. The entire space is divided into four sub-regions based on x,y coordinates, with examples in each region demonstrating different levels of learnability.

potential problem from human annotations is largely neglected in active learning literature as these annotations are not available during the selection process.

In this paper, we first and foremost propose to analyze problems of human annotations in video captioning tasks (see Fig. 1.(b)). With the help of Dataset Maps, we are able to observe the problem, or collective outliers, in human annotations, and conclude its severity by the amount of outliers. Such an amount will further aggravate the learning process due to their hard-to-learn nature, thus worth exploring. We observe that inconsistency in human annotations is one of the main causes of collective outliers, which can be divided into the abstraction and granularity inconsistency (refer to Fig. 1.(a)). The former highlights instances where humans offer different abstractions for videos with complex contents, while the latter reveals that humans may describe the same object at varying semantic levels.

To this end, we incorporate our observations into active learning frameworks. We re-phrase the problem introduced by collective outliers as learnability and aim to address it in our active learning design. Due to the lack of access to human annotations in active learning, directly identifying collective outliers is implausible. Nevertheless, we turn to their main property, or inconsistency, as our breakthrough and propose to estimate the abstraction and granularity inconsistencies in unlabelled data. Concretely, existing image-based large Vision-Language Models (LVLMs) are used to approximate human annotations. Instead of directly using predictions from LVLMs as pseudo ground truths, which would deteriorate the overall performance because of domain gaps, we propose to measure the consistency not only internally among per-frame predictions but externally between predictions from a video captioning model and those per-frame predictions. The internal measurement captures the abstraction consistency and the external one counts on the granularity consistency. Combining both provides us an estimation of sample **learnability**, or how likely this sample belongs to collective outliers. **Diversity** and **uncertainty** are also leveraged in our active learning scheme where we rank samples based on their frequency in the entire dataset and reliability respectively. Our algorithm is able to select reliable, diverse yet learnable samples, and achieves SOTA trade-offs between accuracy and human efforts. Motivated by the causes of collective outliers, we propose a caption-wise active learning protocol such that only a limited number of human-annotated captions are acquired if one video is selected by our active learning algorithm. Our protocol is capable of avoiding inconsistency and providing a more intellectual way to allocate human effort to more diverse videos. In all, our contribution can be summarized as follows:

- To the best of our knowledge, we are the very first in terms of exploring collective outliers on video captioning tasks and providing comprehensive studies on them.
- A novel active learning algorithm that explicitly takes learnability, diversity, and uncertainty into account. Specifically, the learnability is designed to tackle collective outliers, inspired by their abstraction and granularity inconsistency.
- A novel caption-wise active learning protocol that effectively leverages knowledge from humans.
- State-of-the-art performances on video captioning datasets under diverse model backbones.

2 Related Work

Visual Captioning Based on Deep Learning Visual captioning Sharma et al. (2023) is a task that automatically generates textual grammatical and semantically appropriate descriptions for a given visual content. While this task is easy for humans, it is extremely difficult for deep learning models. To perform visual captioning, models are required to have multiple capabilities: including but not limited to detection and recognition capabilities to extract objects in visual content, visual semantic understanding capabilities to determine the attributes and relationships of objects, and enriching language knowledge to describe information with grammatically correct sentences. Visual captioning can be classified into image captioning Ming et al. (2022) and video captioning Abdar et al. (2023). Deep-learning-based image captioning starts with the encoder-decoder framework combining convolutional neural networks and recurrent neural networks Kiros et al. (2014); Vinyals et al. (2015). It is further developed by extracting fine object region features Anderson et al. (2018); Karpathy and Fei-Fei (2015), attribute features Yao et al. (2017), semantic relation features Yao et al. (2018); Yang et al. (2022) and introducing attention mechanisms Xu et al. (2015); Pan et al. (2020); Yu et al. (2020). With breakthroughs in vision-and-language pre-training approaches Radford et al. (2021); Zhang et al. (2021a); Alayrac et al. (2022); Li et al. (2023a), applications in image captioning Li et al. (2020); Mokady et al. (2021); Li et al. (2023c) have emerged in recent years, benefit from the power of LVLMs (*e.g.*rich knowledge and strong recognition ability). The recently proposed BLIP2 Li et al. (2023a) has achieved superior performance on major image-text tasks with a simple pre-training method. Unfortunately, LVLMs focusing on video-text-related tasks have not yet come out. Video captioning still faces many challenges. Video captioning is more difficult than image captioning due to the many frames the video contains, which carry massive amounts of information. This raises the necessity of abstracting semantic information from the temporal dimension and describing content from the spatial dimension with different granularity. Video captioning started with the encoder-decoder framework Venugopalan et al. (2015). Subsequent researchers continued to design new encoders Wang et al. (2019); Pan et al. (2016) and decoders Jin et al. (2020); Guo et al. (2016). Some work is also actively trying to introduce scene graphs Hou et al. (2020); Zhang et al. (2020b), text corpus Shi et al. (2023); Zhang et al. (2021b), and pre-training models Li et al. (2023b); Seo et al. (2022); Tang et al. (2021). Among them, Lin *et al.*proposed the end-to-end video captioning method Lin et al. (2022) for the first time and achieved significant performance improvement. Unlike existing video captioning methods, we focus on underlying data issues. Unlike existing video captioning methods, our work focuses on underlying data issues. We are committed to exploiting knowledge to measure video consistency scores for active learning.

Active Learning Due to the high cost of manually annotating data, active learning Tharwat and Schenck (2023) has attracted widespread attention from academia and industry. Active learning aims to use as few, high-quality samples as possible to achieve the best possible performance of the model. Active learning has many mature works in closed tasks such as image classification Parvaneh et al. (2022), object detection Wu et al. (2022), semantic segmentation Xie et al. (2022), and natural language processing Zhang et al. (2022). Among them, Coreset Sener and Savarese (2018) can minimize the distance between an example in the unlabeled pool to its closest labeled example, and can effectively capture the diversity in the dataset. However, active learning for video captioning remains to be explored. Chan *et al*. Chan et al. (2020) tries to migrate conventional active learning methods to video captioning, and has proposed a new method based on ensemble and clustering. Besides, active learning has been observed to fail on open-ended tasks such as visual question answering due to the presence of collective outliers Karamcheti et al. (2021). There is currently no literature that attempts to address the impact of collective outliers. In this work, we focus on the problem of collective outliers in video captioning. We point out possible causes of collective outliers and attempt to mitigate their impact on active learning methods.

3 Method

As the very first work that explores data learnability in active learning for video captioning, we start our method with a comprehensive analysis of their causes and various forms in Sec. 3.1. According to our analysis, we then propose a novel active learning scheme that in particular considers the

https://doi.org/10.52202/079017-1198

learnability during the unlabelled data selection process in Sec. 3.2, together with novel designs of uncertainty and diversity. Our overall active learning method can be found in Fig. 2.

3.1 Data Learnability in Video Captioning

Motivation The order of training samples is shown to be important in curriculum learning Matiisen et al. (2020). Specifically, it found that feeding models with examples of successively increasing difficulty produces better performances than providing full examples immediately. Though posing a more severe problem in active learning as selecting far more difficult samples at early stages is a waste of human efforts, measuring sample difficulty is largely neglected in the literature as neither ground truth nor the definition itself can be easily obtained. To this end, our goal is to first identify difficult examples in video captioning task, and then perform analysis on them so that our observations can be beneficial for our active learning selection scheme.

Methodology Collective outliers are a group of data objects that fall extremely far from well-defined norms of a data set or given concepts of expected behavior in data-mining Lai et al. (2021), which are much harder to detect as they are more generic yet harder to identify as individuals. Not surprisingly, one important property of collective outliers is learnability, e.g., they are more likely to be hard-to-learn samples compared to normal data Karamcheti et al. (2021). Concretely, we exploit Dataset Maps to diagnose datasets with training dynamics Swayamdipta et al. (2020); Dagan et al. (2013); Sakaguchi et al. (2020). Compared to conventional Dataset Map that exploits two model-specific metrics (*i.e.*average confidence assigned to the correct answer and the variance of these values) to measure the *learnability* of training examples, we propose to utilize SPICE Anderson et al. (2016) to approximate the confidence score on the correct answer. On the one hand, the confidence score is not a reliable criterion as it can be largely affected by random-length text sequences generated by autoregressive models Zhang et al. (2020a). On the other hand, SPICE measures the F1 score between scene graphs generated by predictions and ground truths. It has the useful property of being defined over tuples that are easy to subdivide into meaningful categories, providing a more semantic-centric evaluation in a human-interpretable manner by abstracting away most of the lexical and syntactic idiosyncrasies of natural language compared to CIDEr Vedantam et al. (2015).

Observation We provide an example of Dataset Map of SwinBERT Lin et al. (2022) trained on MSR-VTT Xu et al. (2016) in Fig. 1.(b), where the y-axis and x-axis plots the average SPICE score over training epochs and their variability respectively. Clearly, samples that fall into the upper left area of this figure are easy-to-learn ones whose SPICE scores are consistently high. While the lower left area is occupied with hard-to-learn samples where no observable improvements can be found with longer training time. Unlike conventional close-end tasks where only a small proportion of samples are hard to learn, we observe that a noticeable amount of samples fall into the lower left area.

Analysis Taking a closer look at collective outliers, we observe that the video captioning model struggles when learning from samples with inconsistent human annotations. As shown in Fig. 1.(a), these inconsistencies can be divided into two categories, abstraction and granularity. The inconsistency in abstraction summarizes cases where humans tend to provide not only the description of video contents, but also high-level reasoning behind it. For instance, *a boy is walking to the beach to surf* versus *a movie about a man who likes to surf.* On the other hand, inconsistency in granularity consists of samples with human annotations at different graininess,*e.g.*people might coarsely describe the video as *a cartoon character talking on the phone* while a fine-grained description summarizes the same video with *Krabs talks on the phone while SpongeBob freaks out*. We argue that collective outliers are not impossible to learn. Instead, they can be exploited with more consistent descriptions or learned at a later stage of the training process when general principles from easier examples are already learned by models. Our observations and analysis align well with the philosophy of curriculum learning, encouraging our active learning design in the following paragraphs.

3.2 Our Active Learning Scheme

Denoting the labeled set as $\mathcal{L} = \{V_m, \mathbf{C}_m\}_{m=1}^{M}$, consisting of M video sequences and their human annotated captions $\mathbf{C}_m$, our video captioning model f is initially trained with $\mathcal{L}$. We further denote another set of N unlabelled videos as $\mathcal{U} = \{V_n\}_{n=1}^{N}$. Mathematically, $\mathcal{U} \cap \mathcal{L} = \emptyset$. Our goal of active learning is to select a subsect $S_t \in \mathcal{U}$ at each selecting step $t \in \{1, \ldots, T\}$ such that the overall performance of f can be maximally boosted once annotations on S_t are obtained from humans.

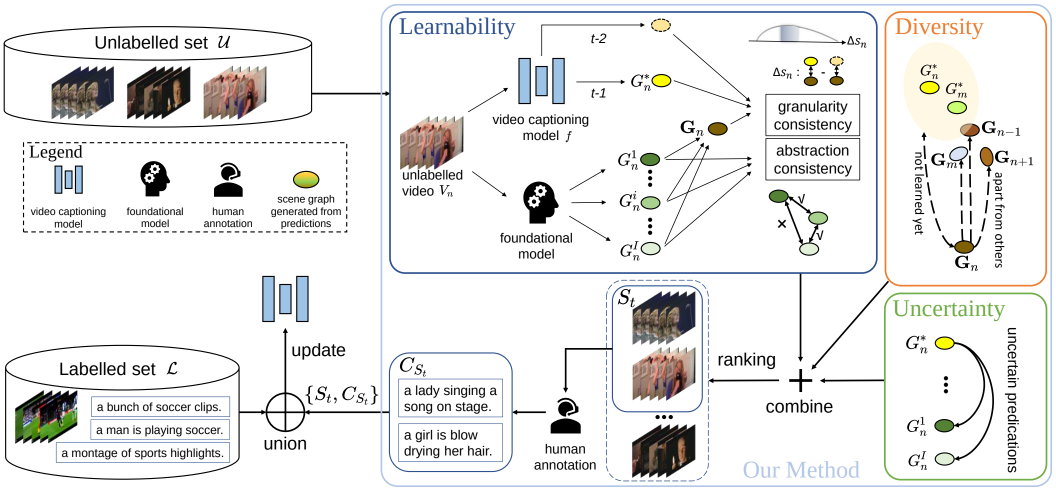


Figure 2: Our method explicitly introduces learnability to reflect the collective outliers in video captioning. Together with uncertainty and diversity, our active learning scheme ranks unlabelled videos and parses them to humans. Our caption-wise protocol further provides an intellectual yet effective way to allocate human efforts, leading to 103% full performances at 25% human annotations.

As stated above, collective outliers can be regarded as a group of hard-to-learn samples in an active learning framework where inconsistencies in human annotations are one of the main causes. Due to the lack of access to these annotations when selecting from $\mathcal{U}$, we propose to mimic them to measure those inconsistencies on the mimicked annotations. In particular, we exploit LVLMs since they provide powerful tools to generate human-like captions at the same granularity. On the one hand, one can approximate the abstraction inconsistency among predictions from LVLMs. On the other hand, by comparing the predictions from f and LVLMs, granularity inconsistency can be further approached. Rather than leveraging foundation models for videos, we utilize the predicted per-frame captions from image-based LVLMs for the following three reasons. Firstly, the image-based LVLMs are more mature and well-exploited compared to the former. Moreover, inconsistency in abstraction occurs more frequently when video samples are complex, e.g., contents vary a lot temporally. Such variety can be better captured by measuring the consistency between frame-wise predictions. Lastly, our design provides a lower bound when measuring the inconsistency in granularity as frame-wise predictions from LVLMs and video captions predicted by f look at videos from different perspectives to the maximum extent, leading to more reliable approximations.

To this end, we uniformly sample $I = 32$ frames from V_n and refer to the i-th frame as V_n^i. Then we apply BLIP2 Li et al. (2023a) on all sampled frames, leading to a set of $\{b_n^i\}_{i=1}^I$. b_n^i is the predicted caption on V_n^i. Meanwhile, we can obtain the video captions on V_n by $f(V_n)$ and further denote the one with the highest confidence as b_n^*. Inspired by SPICE Anderson et al. (2016), we convert captions to scene graphs and measure the consistency over graphs. Specifically, we denote $G_n^i = \{O_n^i, A_n^i, R_n^i\}$ as the scene graph generated from b_n^i, which consists of objects O_n^i, attributes A_n^i, and their relations R_n^i. Then $\mathbf{G}_n = \{G_n^i\}_{i=1}^I$ is the set of all scene graphs generated from $\{b_n^i\}_{i=1}^I$. Similarly, we can obtain scene graph G_n^* from b_n^*. We further denote $\mathbf{O}_n = \bigcup_{i=1}^I O_n^i$, $\mathbf{A}_n = \bigcup_{i=1}^I A_n^i$ and $\mathbf{R}_n = \bigcup_{i=1}^I R_n^i$. In the next few paragraphs, we will introduce our active learning scheme that aims to capture the **learnability**, **diversity** and **uncertainty** in video captioning.

Our scheme is composed of four terms. The first two of them focus on **learnability**, namely abstraction and granularity inconsistencies. The first term L_n^1 focuses on the scene graphs generated by per-frame BLIP2, or $\mathbf{G}_n$, and measures their internal prediction consistency. Our L_n^1 is defined as:

$$L_n^1 = \frac{\sum_{k \in \mathbf{O}_n} H_k(\mathbf{G}_n)}{|\mathbf{O}_n|} + \frac{\sum_{k \in \mathbf{A}_n} H_k(\mathbf{G}_n)}{|\mathbf{A}_n|}, \tag{1}$$

where $H_k(\mathbf{G}_n)$ counts the number of times that an object, an attribute, or a relationship k appears in $\mathbf{G}_n$. $|\mathbf{O}_n|$ and $|\mathbf{A}_n|$ capture the number of unique objects and attributes in $\mathbf{G}_n$, respectively. Intuitively, Eq. 7 prefers $\{b_n^i\}_i$ when they agree with each other. In other words, the higher the L_n^1 is, the more

https://doi.org/10.52202/079017-1198

consistent b_n^i should be w.r.t. predictions from other frames. We purposely neglect relations R_n^i in experiments as the relationship is less reliable in current LVLMs (e.g. BLIP2).

Our second term L_n^2 focuses on granularity inconsistency where human annotations are at different graininess. To this end, we approximate the potential granularity inconsistency between $\mathbf{G}_n$ and G_n^* as predictions from image-based LVLMs and that from video captioning model f tend to capture different aspects of V_n to the maximum extent. In particular, granularity inconsistency can be measured by SPICE between two types of predictions, where a lower SPICE value indicates higher inconsistency. Instead of relying solely on SPICE, which tends to select well-learned samples and undermines the active learning scheme, we focus on the time-variant changes in SPICE for each V_n to simulate the expected changes in granularity consistency. Denoting the absolute distance between the SPICE on an unlabelled sample V_n at time step $t-2$ and $t-1$ as $\bigtriangleup s_n$, we have $L_n^2 = g(\bigtriangleup s_n) \log g(\bigtriangleup s_n)$, where g is a min-max normalization function over all N samples. Our L_n^2 prefers samples with moderate changes, based on our observation that large and small changes are associated with less informative and hard-to-learn examples, respectively.

The third term L_n^3 is designed for **diversity**. Specifically, we prefer unlabelled samples in which contents are beyond the current model f yet of great importance. In practice, we apply the concept of the Term Frequency Inverse Document Frequency (TF-IDF) Robertson (2004) to measure the importance of video content, in which we further incorporate our observation that longer descriptions tend to co-occur more with diverse videos by re-weighting the TF with long captions. Let's denote $\mathbf{G}^*$ as the set that includes predictions of the highest confidence on $\mathcal{L} \cup \mathcal{U}$, or $\mathbf{G}^* = \{G_m^*, G_n^*\}_{n=1,m=1}^{N,M}$. Similarly, the BLIP2 predictions on full dataset is denoted as $\mathbf{G} = \{\mathbf{G}_j\}_{j=1}^{M+N} = \{G_j^i\}_{i=1,j=1}^{I,M+N}$. Mathematically, $L_n^3 = F(\mathbf{O}_n) + F(\mathbf{A}_n)$ where $F(\cdot)$ is defined as:

$$F(x) = \sum_{k \in x} \mathbb{I}[k \notin \mathbf{G}^*] \left(H_k(\mathbf{G}_n) \times \log \frac{N+M}{\sum_j^{N+M} \mathbb{I}[H_k(\mathbf{G}_j) > 0]} \right) \tag{2}$$

where $\mathbb{I}[\cdot]$ is a binary indicator function and equals to 1 iff $\cdot$ is valid. Mathematically, L_n^3 focuses only on contents beyond the current model. Meanwhile, it values distinctive samples with important contents. Overall, a higher L_n^3 indicates greater diversity in V_n.

Uncertainty is captured by our last term L_n^4. Intuitively, inaccurate predictions provide valuable information in active learning. Therefore, we introduce $L_n^4 = |O_n^* \cap \mathbf{O}_n| + |A_n^* \cap \mathbf{A}_n| + |R_n^* \cap \mathbf{R}_n|$. Specifically, L_n^4 counts shared objects, attributes, and relationships between G_n^* and $\mathbf{G}_n$, where $\mathbf{G}_n$ serves as human annotations to measure how well the prediction of highest confidence G_n^* is. A higher L_n^4 reflects more certainty in V_n.

Finally, the overall active learning score on sample $V_n \in \mathcal{U}$ is defined as $L_n = -\lambda_1 L_n^1 + \lambda_2 L_n^2 - \lambda_3 L_n^3 + L_n^4$, where $\lambda_1, \lambda_2, \lambda_3$ are hyper-parameters. At the t-th step of the active learning algorithm, the top unlabelled samples S_t from $\mathcal{U}$ are selected w.r.t. L_n, where the lower L_n signifies greater informativeness. These samples are then fed to human annotators to acquire annotations $\mathbf{C}_{S_t}$. Then we update our labelled and unlabelled set with $\mathcal{L} \leftarrow \mathcal{L} \cup \{S_t, \mathbf{C}_{S_t}\}$ and $\mathcal{U} \leftarrow \mathcal{U} \setminus S_t$. Later on, our video captioning model f is re-trained with the updated $\mathcal{L}$. Our overall active learning algorithm iterates until either the maximum time stamp T or human annotation effort is reached.

3.3 Caption-wise Selection Protocol

Conventional captioning-related active learning algorithms are video-based where all the human annotations from one video sequence are acquired if this video is selected at step t. In practice, there are multiple annotations associated with one video sequence, e.g., we have 20 captions for one video sequence in MSR-VTT dataset Xu et al. (2016). We argue that the current video-based selection protocol is prone to collective outliers, leading to inferior active learning performance. Instead, we propose a caption-wise selection scheme such that not all annotations of one video sequence are acquired if this video has been selected. In practice, we acquire at most 2 [2] captions for each selected video at the t-th step. Such a design reflects two of our observations. Firstly, the fewer annotations are acquired from humans, the less likely they are inconsistent with each other, leading to fewer collective outliers. Moreover, including more videos with fewer annotations rather than fewer videos with more annotations boosts the diversity of S_t. The superiority of our protocol is shown in Sec. 4.

[2] This number is chosen by experiment.

https://doi.org/10.52202/079017-1198

4 Experiment

We validate our ideas with various backbones on two publicly available datasets MSVD Chen and Dolan (2011a) and MSR-VTT Xu et al. (2016), and demonstrate SOTA performances on both.

4.1 Dataset and Experimental Setup

Datasets We conduct our experiments on two datasets, MSVD Chen and Dolan (2011a) and MSR-VTT Xu et al. (2016). Specifically, MSVD consists of 1970 open-domain videos collected from a commercial video search engine, each of which is associated with about 41 human-annotated captions. Similarly, there are 10K open-domain videos in MSR-VTT and each of them has 20 human-labelled annotations. For each dataset, we follow their standard splits and report our active learning performance on their test sets. To mimic the learning process, we initialize $\mathcal{L}$ with 5% of data randomly selected from the training set, including both videos and their annotations. Consequently, $\mathcal{U}$ is composed of videos from the remaining 95% training set. At each selecting step, the annotation budget $\|\mathbf{C}_{S_t}\|$ is set to 5% captions of the full training set. More details can be found in the appendix.

Baselines Active learning for video captioning is under-explored in literature. We follow the existing work Chan et al. (2020) and compare our algorithms with the baselines described below:

- **Random Sampling** serves as a very competitive baseline in open-ended tasks. Basically, it performs random sampling in $\mathcal{U}$ to obtain S_t.
- **Maximum Entropy** Chan et al. (2020) is a conventional uncertainty-based active learning algorithm where samples with the highest entropy will be selected. In video captioning tasks, the entropy of sample V_n is approximated by the averaged entropy over multiple predictions in $f(V_n)$. For each prediction, its entropy is computed over word output distributions at each new word.
- **Minimum Likelihood** Chan et al. (2020) is another uncertainty-based active learning algorithm. Typically, samples with the lowest log-likelihood will be selected. In practice, the averaged log-likelihood over multiple predictions in $f(V_n)$ is used to rank each unlabelled video V_n.
- **Core-Set Selection** Sener and Savarese (2018) is a classical diversity-based active learning algorithm. Specifically, it works on the representation space and aims to select samples that are spread out in the feature space. In practice, features from Liu et al. (2022) are used to select samples that minimize the distance between the unlabelled pool to its closest labeled sample.
- **Clustered-Divergence** Chan et al. (2020) ensembles multiple models and computes the KL-divergence between the conditional distributions of the ensemble members to measure sample uncertainty. Diversity is also implicitly considered as it already ensembles a clustering-based active learning regularization method.

Implementation Details In our experiment, we employ SwinBERT Lin et al. (2022) and CoCap Shen et al. (2023) as our f as they provide good trade-offs between accuracy and efficiency. In contrast, other SOTA video captioning methods or video-based foundation models, such as COSA Chen et al. (2023) and mPLUG-2 Xu et al. (2023), require extensive pre-training or finetuning when adapting to downstream tasks to achieve SOTA video captioning performances. To further speed up the training process, each video is uniformly sampled with 32 frames and these frames are parsed to f. The batch size is set to 4. We refer to the performance of f that trained with the entire training set on the test set as *full performance*. And we are able to achieve comparable performance compared to the official release. As for BLIP2 Li et al. (2023a), we choose an open-sourced version [3]. All experiments are conducted on 4 RTX 3090 GPUs and 4 RTX 4090 GPUs with Pytorch Paszke et al. (2019), Huggingface transformers Wolf et al. (2020). T is set to 4 . For other hyper-parameters, we keep the same configuration as in Das et al. (2022). More details can be found in the appendix.

Evaluation Metrics We provide detailed comparisons using a diverse set of performance metrics, including BLEU4 Papineni et al. (2002), METEOR Banerjee and Lavie (2005), ROUGE-L Lin and Och (2004), CIDEr Vedantam et al. (2015), and SPICE Anderson et al. (2016).

4.2 Main Active Learning Performances

We report the active learning performances of all methods with either SwinBERT or CoCap on MSVD in Fig. 3. To ensure more reliable results, all methods were conducted three times. This figure reports both the average performance and the variance.

[3] Checkout the pre-trained model at `https://huggingface.co/Salesforce/blip2-flan-t5-xl`

https://doi.org/10.52202/079017-1198

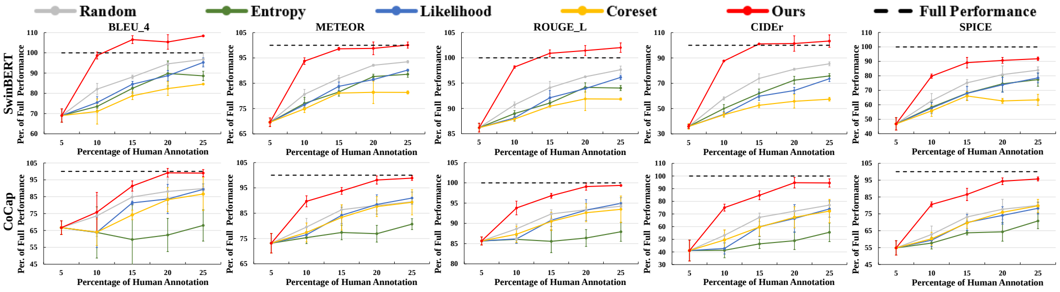


Figure 3: Active learning performances on the MSVD. Ours significantly outperforms other methods.

There are several interesting observations. First and foremost, it is noteworthy that our method consistently outperforms all other baselines across all five evaluation metrics with two backbones, highlighting our superiority. Predictably, random sampling usually ranks as the second-best option, aligning with findings from other open-ended tasks Karamcheti et al. (2021). More importantly, we observe that our method surpasses the full performance of f trained with 100% annotations with SwinBERT out of 4 evaluation metrics, as indicated by the dotted horizontal line, with less than 25% of annotations. For example, we achieve full performance with about 10% and 15% of annotations when measured by BLEU4 and ROUGE-L, respectively. Regarding CIDEr, our method attains 103.65% of the full performance with 25% of annotations. Even with CoCap, we can almost always achieve more than 95% of full performance with 25% annotations. This observation supports our concerns about the negative impacts of collective outliers during the training process. Clearly, our method effectively reduces the impact of collective outliers, leading to significant performance improvements over existing methods and even surpassing full performance. Results on MSR-VTT are reported in the appendix. In summary, our method significantly outperforms the SOTA methods and achieves an averaged 103% full performance with 25% annotations on all metrics.

Cross-dataset Performance To simulate the scenario where people tend to exploit a large unannotated dataset to benefit a small annotated dataset, we use the small annotated dataset MSVD (1,200 videos with 40 captions per video) and treat MSR-VTT as the large unannotated dataset, which includes 6,513 videos paired with 20 captions each. The results using the official SwinBERT implementation are provided in Tab. 1.

Table 1: Starting from fully-annotated MSVD training samples, exploiting data from MSR-VTT with our AL algorithm can further boost the performances on the MSVD test set.

Method	Data Per.	BLEU_4	METEOR	ROUGE_L	CIDEr	SPICE
Starting Point	0	55.71	39.70	75.73	109.39	6.97
Random	20	62.15	42.58	78.66	123.26	7.63
Ours	20	63.70	43.69	79.86	127.41	7.80
Ours	5	63.68	43.34	79.73	126.32	7.57
Ours	+5	63.10	43.64	79.98	130.96	7.89
Ours	+5	63.51	43.80	79.81	129.63	7.93
Ours	+5	64.88	44.25	80.43	129.08	7.77

We report the overall performance on the MSVD test set. "Data Per." is the percentage of human annotations on MSR-VTT. We also report the performance of directly selecting 20% of MSR-VTT (Row 4) and iteratively adding 5% of MSR-VTT four times (Rows 5-8). As shown in the table, our AL algorithm significantly improves the overall performance of MSVD and is a more effective choice compared to random selection. Furthermore, directly selecting 20% of data is slightly less effective than iterative selection, demonstrating the benefits of curriculum learning. Notably, the overall performance peaks at two iterations, or 10% of human annotations on MSR-VTT, according to CIDEr and SPICE. Beyond this point, the performance saturates and slightly declines. This is expected, as 20% of MSR-VTT includes 26K captions and at least 1.3K videos, which is comparable to the original training set of MSVD. Adding more data from a different dataset can degrade performance, as the training may deviate from the original dataset.

4.3 Ablation Study on Learnability, Uncertainty, and Diversity

To demonstrate the effectiveness of individual components of our design, we conduct a thorough ablation study by incrementally integrating various components into our active learning scheme. The steps are as follows: 1) L_n^4 (uncertainty); 2) $+L_n^3$ (diversity); 3) $+L_n^2$ (learnability); 4) $+L_n^1$ (learnability); 5) + Caption-wise Protocol (CP); Specifically, we report the Area-Under-Curve(AUC) score over CIDEr and SPICE curve in Tab. 2. Evidently, incorporating any of these components will enhance overall active learning performance, demonstrating their effectiveness. For example, our designed terms outperform Random Sampling significantly, indicating the effectiveness of our active learning scheme without CP. Notably, we observe a significant performance boost after integrating the CP, which is reasonable as it directly reduces the impact of collective outliers and improves overall diversity.

Table 2: Ablation study on MSVD.

	AUC_{CIDEr}	AUC_{SPICE}
Random	.574	.560
L_n^4	.583	.578
$+L_n^3$	.589	.585
$+L_n^2$	.594	.592
$+L_n^1$	.603	.600
+CP (Ours)	.738	.678

To further demonstrate that learnability, uncertainty, and diversity each reflect distinct aspects of active learning, we report the percentage of overlapped selections in S_1 under active learning schemes focused on individual aspects, as shown in Fig. 4. As expected, our design targeting learnability, uncertainty, and diversity addresses various unlabelled samples, leading to limited overlap in their output S_1. Together with Tab. 2, we conclude that all aspects are complimentary and mutually informative.

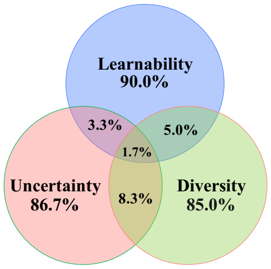
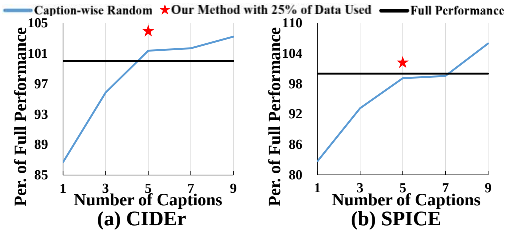


Figure 4: The percentage of overlapped selections in S_1.

4.4 More Analysis

Are we celebrating from more annotations per video? As summarized in Sec. 3.1, ground truth inconsistency is one of the main causes of collective outliers. We further showcase in Fig. 3 that fewer human annotations bring in better performance. Then a natural question to ask is whether we are celebrating from more annotations per video.

To answer this question, we conduct a caption-wise random sampling experiment with SwinBERT on MSR-VTT. Specifically, SwinBERT is trained with all training videos on MSR-VTT where each video is associated with $k \in \{1, 3, 5, 7, 9\}$ captions that are randomly sampled from a full set of 20 human annotations. We visualize the CIDEr and SPICE score on the test set of MSR-VTT in Fig. 5. As shown in the figure, full performance is achieved with approximately 35% of the annotations (equivalent to k=7). Overall performance improves with up to nine annotations. We argue that the performance degradation with the full training set is not due to overfitting, as techniques such as regularization, data augmentation, and early stopping have been applied to mitigate it. Instead, we hypothesize that it is related to collective outliers, where inconsistency increases with the number of annotations. Additionally, we observe that caption-wise random sampling performs worse than ours with the same amount of human annotations, highlighting the effectiveness of the L_n design.



(a) CIDEr

(b) SPICE

Figure 5: The performance of SwinBERT when trained on samples equipped with different numbers k of annotation captions.

Can we truly reduce the impact of collective outliers? Though we leverage the knowledge from LVLMs to approximate human annotations and thus identify collective outliers, it remains unknown how well such approximation or identification is. To address this, we first divide unlabelled samples into different groups w.r.t. their learnabilities, and then we obtain the distribution of S_t according to these groups. Ideally, our method should select fewer samples that belong to collective outliers. Specifically, we divide unlabelled samples into four discretized groups according to their x, y coordinates in Dataset Maps in Fig. 1. (b). Easy samples are those whose $y > 0.07$ and $x < 0.03$.

https://doi.org/10.52202/079017-1198

Moderate ones fall into the region with $y > 0.07$ and $x \geq 0.03$. For these samples whose $y \leq 0.07$ and $x > 0.17$, we call them hard samples. The remaining samples are then collective outliers.

We report the data distribution of S_1 of all methods in Fig. 6. Again, results are obtained on MSR-VTT with SwinBERT as f. First and foremost, we observe that our method is able to select the least collective outliers compared to other baselines, which fulfills our goal as expected. Another interesting observation is that our method prefers to select more easy samples at S_1. It is an effective strategy to select easy and moderate samples for learning in the early stage of model training, which greatly improves the efficiency and effect of training. By avoiding collective outliers and more reliable samples, it's no wonder ours achieves SOTA performance. We refer the readers to the appendix for more analysis.

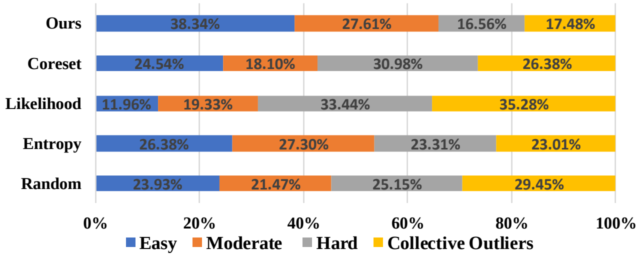


Figure 6: The distribution of samples in S_1 on MSR-VTT.

Can we exploit the knowledge from LVLMs more? Another way to utilize the predictions from LVLMs is to directly apply them as pseudo ground truths to update f in a semi-supervised learning setup. Specifically, this simple approach achieves 0.31 and 0.07 for CIDEr and SPICE on MSR-VTT, which are worse than the starting points. Adding additional control, *e.g.*including only videos when predictions from LVLMs are highly consistent, achieves 0.5185 and 0.0712 for CIDEr and SPICE, which is worse than our algorithm. We refer the readers to the appendix for more details.

Are inconsistencies in ground truths our illusions? To validate our hypothesis that inconsistency in human annotations genuinely exists and is not merely due to subjective judgments, we utilize ChatGPT Radford et al. (2019) as an objective tool. We observe that ChatGPT believes that 49$\%$ of all captions are inconsistent on average. Such inconsistency rate increases when moving from easy to collective outlier sub-regions. More details can be found in the appendix.

Does the reduction of human annotation costs justify the extensive computational cost? Our additional computational costs arise from the active learning algorithm, primarily due to applying BLIP2 to the unlabelled dataset and generating scene graphs from its predictions. This process occurs only once on the unlabelled set. On our hardware, consisting of 4 RTX 4090 graphics cards with a power capacity of 2000 kWh, it takes no more than 9 minutes to run BLIP2 and 5 minutes for scene graph generation on the MSVD training dataset. In contrast, annotating the full dataset in 2010 required hundreds of annotators, around 2 months, and less than 5000 USD in total Chen and Dolan (2011b). Therefore, we argue that active learning is more efficient in terms of both time and cost.

Limitations There are several limitations that we believe are worth further exploration. Firstly, our paper only briefly touches on the relationship between curriculum learning and learnability. Beyond provoking the design of the learnability term, we believe curriculum learning can enhance the interpretability of learnability terms and even active learning. Secondly, we found that current evaluation metrics, such as CIDEr, do not always align with human evaluations. More human analysis is needed for video captioning tasks. Thirdly, we made some preliminary attempts to combine knowledge from LVLMs in a semi-supervised learning manner. Although we did not see a significant improvement, we believe further efforts are warranted. Lastly, our experiments with ChatGPT-4 can be improved with more refined designs. We will include these limitations in our final version.

5 Conclusion

In this work, we propose a novel active learning algorithm for video captioning tasks, which effectively leverages learnability, diversity, and uncertainty. To the best of our knowledge, our algorithm is the very first one that targets collective outliers in video captioning and further proposes to reduce their impacts by measuring sample learnability, as well as introducing a caption-wise protocol. Results on two datasets demonstrate the superiority of our algorithm over SOTA methods, *e.g.*we can achieve 103$\%$ of full performance with 25$\%$ of human annotations on MSR-VTT.

6 Acknowledgement

This work was supported in part by the National Natural Science Foundation of China (No. 62125201, 62020106007).

References

Moloud Abdar, Meenakshi Kollati, Swaraja Kuraparthi, Farhad Pourpanah, Daniel McDuff, Mohammad Ghavamzadeh, Shuicheng Yan, Abduallah Mohamed, Abbas Khosravi, Erik Cambria, and Fatih Porikli. A review of deep learning for video captioning. *CoRR*, abs/2304.11431, 2023.

Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, Roman Ring, Eliza Rutherford, Serkan Cabi, Tengda Han, Zhitao Gong, Sina Samangooei, Marianne Monteiro, Jacob L. Menick, Sebastian Borgeaud, Andy Brock, Aida Nematzadeh, Sahand Sharifzadeh, Mikolaj Binkowski, Ricardo Barreira, Oriol Vinyals, Andrew Zisserman, and Karén Simonyan. Flamingo: a visual language model for few-shot learning. In *NeurIPS*, 2022.

Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. SPICE: semantic propositional image caption evaluation. In *Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part V*, pages 382–398. Springer, 2016.

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 *2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018*, pages 6077–6086. Computer Vision Foundation / IEEE Computer Society, 2018.

Satanjeev Banerjee and Alon Lavie. METEOR: an automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization@ACL 2005, Ann Arbor, Michigan, USA, June 29, 2005*, pages 65–72. Association for Computational Linguistics, 2005.

David M. Chan, Sudheendra Vijayanarasimhan, David A. Ross, and John F. Canny. Active learning for video description with cluster-regularized ensemble ranking. In *Computer Vision - ACCV 2020 - 15th Asian Conference on Computer Vision, Kyoto, Japan, November 30 - December 4, 2020, Revised Selected Papers, Part V*, pages 443–459. Springer, 2020.

David L. Chen and William B. Dolan. Collecting highly parallel data for paraphrase evaluation. In *The 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference, 19-24 June, 2011, Portland, Oregon, USA*, pages 190–200. The Association for Computer Linguistics, 2011a.

David L. Chen and William B. Dolan. Collecting highly parallel data for paraphrase evaluation. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics*, 2011b.

Sihan Chen, Xingjian He, Handong Li, Xiaojie Jin, Jiashi Feng, and Jing Liu. Cosa: Concatenated sample pretrained vision-language foundation model. *arXiv preprint arXiv:2306.09085*, 2023.

Ido Dagan, Dan Roth, Mark Sammons, and Fabio Massimo Zanzotto. *Recognizing Textual Entailment: Models and Applications*. Morgan & Claypool Publishers, 2013.

Gyanendra Das, Xavier Thomas, Anant Raj, and Vikram Gupta. Mavic: Multimodal active learning for video captioning. *CoRR*, abs/2212.11109, 2022.

Zhao Guo, Lianli Gao, Jingkuan Song, Xing Xu, Jie Shao, and Heng Tao Shen. Attention-based LSTM with semantic consistency for videos captioning. In *Proceedings of the 2016 ACM Conference on Multimedia Conference, MM 2016, Amsterdam, The Netherlands, October 15-19, 2016*, pages 357–361. ACM, 2016.

Jingyi Hou, Xinxiao Wu, Xiaoxun Zhang, Yayun Qi, Yunde Jia, and Jiebo Luo. Joint commonsense and relation reasoning for image and video captioning. In *The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020*, pages 10973–10980. AAAI Press, 2020.

Tao Jin, Siyu Huang, Ming Chen, Yingming Li, and Zhongfei Zhang. SBAT: video captioning with sparse boundary-aware transformer. In *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence, IJCAI 2020*, pages 630–636. ijcai.org, 2020.

https://doi.org/10.52202/079017-1198

Siddharth Karamcheti, Ranjay Krishna, Li Fei-Fei, and Christopher D. Manning. Mind your outliers! investigating the negative impact of outliers on active learning for visual question answering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing, ACL/IJCNLP 2021, (Volume 1: Long Papers), Virtual Event, August 1-6, 2021*, pages 7265–7281. Association for Computational Linguistics, 2021.

Andrej Karpathy and Li Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3128–3137. IEEE Computer Society, 2015.

Ryan Kiros, Ruslan Salakhutdinov, and Richard S. Zemel. Multimodal neural language models. In *Proceedings of the 31th International Conference on Machine Learning, ICML 2014, Beijing, China, 21-26 June 2014*, pages 595–603. JMLR.org, 2014.

Dan Klein and Christopher D. Manning. Accurate unlexicalized parsing. In *Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics, 7-12 July 2003, Sapporo Convention Center, Sapporo, Japan*, pages 423–430. ACL, 2003.

Kwei-Herng Lai, Daochen Zha, Junjie Xu, Yue Zhao, Guanchu Wang, and Xia Ben Hu. Revisiting time series outlier detection: Definitions and benchmarks. In *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual*, 2021.

Junnan Li, Dongxu Li, Silvio Savarese, and Steven C. H. Hoi. BLIP-2: bootstrapping language-image pre-training with frozen image encoders and large language models. In *International Conference on Machine Learning, ICML 2023, 23-29 July 2023, Honolulu, Hawaii, USA*, pages 19730–19742. PMLR, 2023a.

Linjie Li, Zhe Gan, Kevin Lin, Chung-Ching Lin, Zicheng Liu, Ce Liu, and Lijuan Wang. LAVENDER: unifying video-language understanding as masked language modeling. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2023, Vancouver, BC, Canada, June 17-24, 2023*, pages 23119–23129. IEEE, 2023b.

Wei Li, Linchao Zhu, Longyin Wen, and Yi Yang. Decap: Decoding CLIP latents for zero-shot captioning via text-only training. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023c.

Xiujun Li, Xi Yin, Chunyuan Li, Pengchuan Zhang, Xiaowei Hu, Lei Zhang, Lijuan Wang, Houdong Hu, Li Dong, Furu Wei, Yejin Choi, and Jianfeng Gao. Oscar: Object-semantics aligned pre-training for vision-language tasks. In *Computer Vision - ECCV 2020 - 16th European Conference, Glasgow, UK, August 23-28, 2020, Proceedings, Part XXX*, pages 121–137. Springer, 2020.

Chin-Yew Lin and Franz Josef Och. Automatic evaluation of machine translation quality using longest common subsequence and skip-bigram statistics. In *Proceedings of the 42nd Annual Meeting of the Association for Computational Linguistics, 21-26 July, 2004, Barcelona, Spain*, pages 605–612. ACL, 2004.

Kevin Lin, Linjie Li, Chung-Ching Lin, Faisal Ahmed, Zhe Gan, Zicheng Liu, Yumao Lu, and Lijuan Wang. Swinbert: End-to-end transformers with sparse attention for video captioning. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pages 17928–17937. IEEE, 2022.

Ze Liu, Jia Ning, Yue Cao, Yixuan Wei, Zheng Zhang, Stephen Lin, and Han Hu. Video swin transformer. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pages 3192–3201. IEEE, 2022.

Tambet Matiisen, Avital Oliver, Taco Cohen, and John Schulman. Teacher-student curriculum learning. *IEEE Trans. Neural Networks Learn. Syst.*, 31(9):3732–3740, 2020.

Yue Ming, Nannan Hu, Chunxiao Fan, Fan Feng, Jiangwan Zhou, and Hui Yu. Visuals to text: A comprehensive review on automatic image captioning. *IEEE CAA J. Autom. Sinica*, 9(8):1339–1365, 2022.

Ron Mokady, Amir Hertz, and Amit H. Bermano. Clipcap: CLIP prefix for image captioning. *CoRR*, abs/2111.09734, 2021.

Pingbo Pan, Zhongwen Xu, Yi Yang, Fei Wu, and Yueting Zhuang. Hierarchical recurrent neural encoder for video representation with application to captioning. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 1029–1038. IEEE Computer Society, 2016.

https://doi.org/10.52202/079017-1198

Yingwei Pan, Ting Yao, Yehao Li, and Tao Mei. X-linear attention networks for image captioning. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 10968–10977. Computer Vision Foundation / IEEE, 2020.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, July 6-12, 2002, Philadelphia, PA, USA*, pages 311–318. ACL, 2002.

Amin Parvaneh, Ehsan Abbasnejad, Damien Teney, Reza Haffari, Anton van den Hengel, and Javen Qinfeng Shi. Active learning by feature mixing. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pages 12227–12236. IEEE, 2022.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Z. Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 8024–8035, 2019.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. 2019.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In *Proceedings of the 38th International Conference on Machine Learning, ICML 2021, 18-24 July 2021, Virtual Event*, pages 8748–8763. PMLR, 2021.

Stephen Robertson. Understanding inverse document frequency: on theoretical arguments for IDF. *J. Documentation*, 60(5):503–520, 2004.

Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. Winogrande: An adversarial winograd schema challenge at scale. In *The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, IAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020*, pages 8732–8740. AAAI Press, 2020.

Sebastian Schuster, Ranjay Krishna, Angel X. Chang, Li Fei-Fei, and Christopher D. Manning. Generating semantically precise scene graphs from textual descriptions for improved image retrieval. In *Proceedings of the Fourth Workshop on Vision and Language, VL@EMNLP 2015, Lisbon, Portugal, September 18, 2015*, pages 70–80. Association for Computational Linguistics, 2015.

Ozan Sener and Silvio Savarese. Active learning for convolutional neural networks: A core-set approach. In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings*. OpenReview.net, 2018.

Paul Hongsuck Seo, Arsha Nagrani, Anurag Arnab, and Cordelia Schmid. End-to-end generative pretraining for multimodal video captioning. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pages 17938–17947. IEEE, 2022.

Dhruv Sharma, Chhavi Dhiman, and Dinesh Kumar. Evolution of visual data captioning methods, datasets, and evaluation metrics: A comprehensive survey. *Expert Syst. Appl.*, 221:119773, 2023.

Yaojie Shen, Xin Gu, Kai Xu, Heng Fan, Longyin Wen, and Libo Zhang. Accurate and fast compressed video captioning. In *IEEE/CVF International Conference on Computer Vision, ICCV 2023, Paris, France, October 1-6, 2023*, pages 15512–15521. IEEE, 2023.

Yaya Shi, Haiyang Xu, Chunfeng Yuan, Bing Li, Weiming Hu, and Zheng-Jun Zha. Learning video-text aligned representations for video captioning. *ACM Trans. Multim. Comput. Commun. Appl.*, 19(2):63:1–63:21, 2023.

Swabha Swayamdipta, Roy Schwartz, Nicholas Lourie, Yizhong Wang, Hannaneh Hajishirzi, Noah A. Smith, and Yejin Choi. Dataset cartography: Mapping and diagnosing datasets with training dynamics. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, EMNLP 2020, Online, November 16-20, 2020*, pages 9275–9293. Association for Computational Linguistics, 2020.

Mingkang Tang, Zhanyu Wang, Zhenhua Liu, Fengyun Rao, Dian Li, and Xiu Li. Clip4caption: CLIP for video caption. In *MM '21: ACM Multimedia Conference, Virtual Event, China, October 20 - 24, 2021*, pages 4858–4862. ACM, 2021.

Alaa Tharwat and Wolfram Schenck. A survey on active learning: State-of-the-art, practical challenges and research directions. *Mathematics*, 11(4820), 2023.

Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 4566–4575. IEEE Computer Society, 2015.

Subhashini Venugopalan, Marcus Rohrbach, Jeffrey Donahue, Raymond J. Mooney, Trevor Darrell, and Kate Saenko. Sequence to sequence - video to text. In *2015 IEEE International Conference on Computer Vision, ICCV 2015, Santiago, Chile, December 7-13, 2015*, pages 4534–4542. IEEE Computer Society, 2015.

Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 3156–3164. IEEE Computer Society, 2015.

Jiangliu Wang, Jianbo Jiao, Linchao Bao, Shengfeng He, Yunhui Liu, and Wei Liu. Self-supervised spatio-temporal representation learning for videos by predicting motion and appearance statistics. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019*, pages 4006–4015. Computer Vision Foundation / IEEE, 2019.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, EMNLP 2020 - Demos, Online, November 16-20, 2020*, pages 38–45. Association for Computational Linguistics, 2020.

Jiaxi Wu, Jiaxin Chen, and Di Huang. Entropy-based active learning for object detection with progressive diversity constraint. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pages 9387–9396. IEEE, 2022.

Binhui Xie, Longhui Yuan, Shuang Li, Chi Harold Liu, and Xinjing Cheng. Towards fewer annotations: Active learning via region impurity and prediction uncertainty for domain adaptive semantic segmentation. In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2022, New Orleans, LA, USA, June 18-24, 2022*, pages 8058–8068. IEEE, 2022.

Haiyang Xu, Qinghao Ye, Ming Yan, Yaya Shi, Jiabo Ye, Yuanhong Xu, Chenliang Li, Bin Bi, Qi Qian, Wei Wang, Guohai Xu, Ji Zhang, Songfang Huang, Fei Huang, and Jingren Zhou. mplug-2: A modularized multi-modal foundation model across text, image and video. *ArXiv*, abs/2302.00402, 2023.

Jun Xu, Tao Mei, Ting Yao, and Yong Rui. MSR-VTT: A large video description dataset for bridging video and language. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 5288–5296. IEEE Computer Society, 2016.

Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron C. Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Bengio. Show, attend and tell: Neural image caption generation with visual attention. In *Proceedings of the 32nd International Conference on Machine Learning, ICML 2015, Lille, France, 6-11 July 2015*, pages 2048–2057. JMLR.org, 2015.

Xu Yang, Hanwang Zhang, and Jianfei Cai. Auto-encoding and distilling scene graphs for image captioning. *IEEE Trans. Pattern Anal. Mach. Intell.*, 44(5):2313–2327, 2022.

Xiangli Yang, Zixing Song, Irwin King, and Zenglin Xu. A survey on deep semi-supervised learning. *IEEE Trans. Knowl. Data Eng.*, 35(9):8934–8954, 2023.

Ting Yao, Yingwei Pan, Yehao Li, Zhaofan Qiu, and Tao Mei. Boosting image captioning with attributes. In *IEEE International Conference on Computer Vision, ICCV 2017, Venice, Italy, October 22-29, 2017*, pages 4904–4912. IEEE Computer Society, 2017.

Ting Yao, Yingwei Pan, Yehao Li, and Tao Mei. Exploring visual relationship for image captioning. In *Computer Vision - ECCV 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part XIV*, pages 711–727. Springer, 2018.

Jun Yu, Jing Li, Zhou Yu, and Qingming Huang. Multimodal transformer with multi-view visual representation for image captioning. *IEEE Trans. Circuits Syst. Video Technol.*, 30(12):4467–4480, 2020.

Zhiqi Yu, Jingjing Li, Zhekai Du, Lei Zhu, and Heng Tao Shen. A comprehensive survey on source-free domain adaptation. *CoRR*, abs/2302.11803, 2023.

Beichen Zhang, Liang Li, Li Su, Shuhui Wang, Jincan Deng, Zheng-Jun Zha, and Qingming Huang. Structural semantic adversarial active learning for image captioning. In *MM '20: The 28th ACM International Conference on Multimedia, Virtual Event / Seattle, WA, USA, October 12-16, 2020*, pages 1112–1121. ACM, 2020a.

Pengchuan Zhang, Xiujun Li, Xiaowei Hu, Jianwei Yang, Lei Zhang, Lijuan Wang, Yejin Choi, and Jianfeng Gao. Vinvl: Revisiting visual representations in vision-language models. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2021, virtual, June 19-25, 2021*, pages 5579–5588. Computer Vision Foundation / IEEE, 2021a.

Wenqiao Zhang, Xin Eric Wang, Siliang Tang, Haizhou Shi, Haochen Shi, Jun Xiao, Yueting Zhuang, and William Yang Wang. Relational graph learning for grounded video description generation. In *MM '20: The 28th ACM International Conference on Multimedia, Virtual Event / Seattle, WA, USA, October 12-16, 2020*, pages 3807–3828. ACM, 2020b.

Ziqi Zhang, Zhongang Qi, Chunfeng Yuan, Ying Shan, Bing Li, Ying Deng, and Weiming Hu. Open-book video captioning with retrieve-copy-generate network. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2021, virtual, June 19-25, 2021*, pages 9837–9846. Computer Vision Foundation / IEEE, 2021b.

Zhisong Zhang, Emma Strubell, and Eduard H. Hovy. A survey of active learning for natural language processing. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, EMNLP 2022, Abu Dhabi, United Arab Emirates, December 7-11, 2022*, pages 6166–6190. Association for Computational Linguistics, 2022.

https://doi.org/10.52202/079017-1198

A Appendix

In our appendix, we first share our quantitative results on the MSR-VTT Xu et al. (2016) dataset in Sec. A.1, followed by more details about our implementation in Sec. A.2. We further include our comprehensive analysis of the property of Dataset Maps, knowledge from LVLMs, and results with ChatGPT in Sec. A.3, Sec. A.4, and Sec. A.5, respectively. Our code and model will be made available.

A.1 Results on MSR-VTT

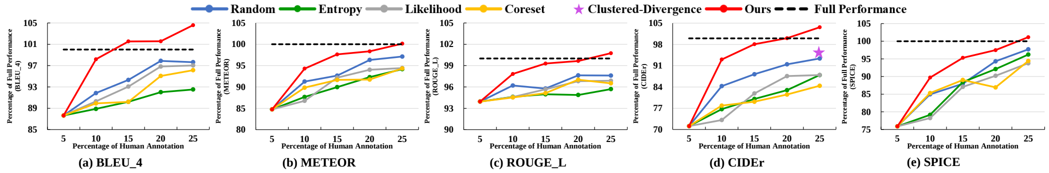
We report the overall performances on MSVD in Fig 7 where methods are visualized with different colors. As can be found in this figure, results on MSR-VTT share similar trends with those on MSVD. First and foremost, our proposed method consistently surpasses all baselines under all evaluation metrics. Among them, random sampling remains the safest choice as it almost always is the second-best. Both observations verify our motivation for tackling collective outliers in open-ended tasks. Remarkably, our proposed active learning method quickly achieves full performance using only a few annotations. For example, our method achieves more than 90% of the full performance under four evaluation metrics including BLEU4, METEOR, ROUGE, and CIDEr, with only 10% annotations. Moreover, it achieves 107% of the full performance under CIDEr, when only 25% of the full annotations are exploited. We would like to note that our hyper-parameters in L_n are learned on MSR-VTT only and directly applied to MSVD, which further showcases the robustness and generalizability of our proposed method.

A.2 Implementation Details

A.2.1 More Details of Baselines

As described in our main paper, we include two uncertainty-based active learning baselines as suggested in Chan et al. (2020), or Maximum Entropy and Minimum Likelihood, for video captioning tasks. More details of them are provided in the following.

Given a video input V_n, the output of the video captioning model f, or $f(V_n)$, comprises a set of K generated captions $\mathbf{Y}_n$ with length W. We denote the k-th caption in $\mathbf{Y}_n$ as $y_{n,k}$ and the w-th word in $y_{n,k}$ as $y_{n,k}^w$. Therefore, $\mathbf{Y}_n = \{y_{n,k}^w\}_{k=1,w=1}^{K,W}$. During inference, these W words are obtained in a sequential manner, where the prediction of the w-th word relies on its $w-1$ predecessors. Mathematically, we can obtain the conditional probability of the w-th word in the k-th caption $P(y_{n,k}^w | y_{n,k}^{w-1}, \cdots, y_{n,k}^1, V_n; f)$, representing the likelihood of generating the w-th word given the previous words as well as the input video. Before introducing the two baselines, let's further denote the joint distribution of the W-th word in the k-th caption by $P(y_{n,k}^W) = \prod_{w=1}^{W} P(y_{n,k}^w | y_{n,k}^{w-1}, \cdots, y_{ni}^1, V_n; f)$.



(a) BLEU_4 (b) METEOR (c) ROUGE_L (d) CIDEr (e) SPICE

Figure 7: Active learning performances on MSR-VTT with Swinbert. The y-axis shows the percentage of the full performance under various evaluation metrics, which is obtained by training f with 100% training data. Our proposed algorithm outperforms all other methods by a large margin. Similar to what we observed on MSVD, our algorithm surpasses the full performance with only 25% of annotations. Numbers of Clustered-Divergence Chan et al. (2020) come from the original paper [6]. In particular, it is able to achieve 95% of the full performance with 25% of the annotations with Transformer mode Chan et al. (2020).

Maximum Entropy To approximate the expected entropy of V_n in video captioning tasks, the averaged entropy over $\mathbf{Y}_n$ is utilized. For each prediction $y_{n,k} \in \mathbf{Y}_n$, its entropy is computed over word output distributions at each new word. Mathematically, the acquisition function of Maximum Entropy Chan et al. (2020) is defined as:

$$L_n = \frac{1}{|\mathbf{Y_n}|} \sum_{k=1}^{K} \sum_{w=1}^{W} -P(y_{n,k}^w) \ln P(y_{n,k}^w), \tag{3}$$

At each time step t, Maximum Entropy selects the unlabelled videos with high L_n, reflecting the intuition that samples with high uncertainty are more likely to be informative.

Minimum Likelihood In contrast, Minimum Likelihood directly focuses on the averaged probabilities rather than entropy. Specifically, we follow the literature Chan et al. (2020) and define the acquisition function of Minimum Likelihood as:

$$L_n = \frac{1}{|\mathbf{Y_n}|} \sum_{k=1}^{K} \sum_{w=1}^{W} \ln P(y_{n,k}^w | y_{n,k}^{w-1}, \cdots, y_{n,k}^1, V_n; f), \tag{4}$$

Similarly, Minimum Likelihood favors unlabelled samples with low L_n, which is well-aligned with the assumption that uncertain samples are more valuable.

A.2.2 More Details of Our Method

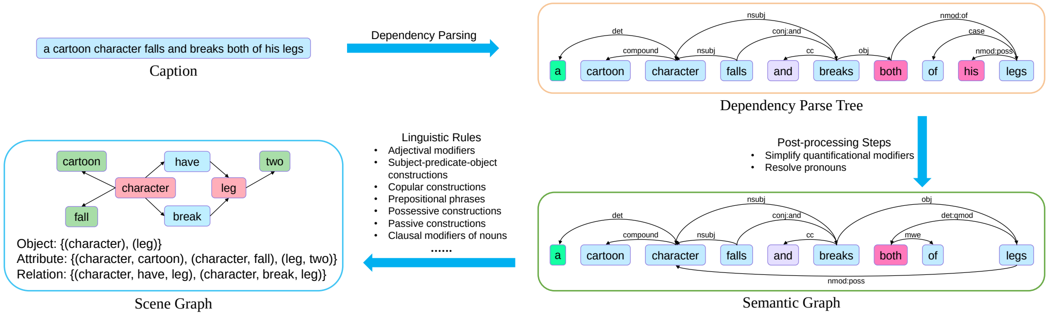


Figure 8: Pipeline of the scene graph parser.

Scene Graph Parser Scene graphs are of great importance to our method as our learnability, uncertainty, and diversity are all measured upon them. Therefore, we describe the scene graph parser in length here. Specifically, We reused the pipeline of SPICE Anderson et al. (2016) to generate scene graphs from caption predictions, in which a Stanford Scene Graph Parser Schuster et al. (2015) is adopted. In particular, given a caption b_n^i or b_n^*, a Probabilistic Context-Free Grammar (PCFG) dependency parser Klein and Manning (2003) aims to firstly translate it into dependency parse trees. Then a semantic graph can be obtained by simplifying quantificational modifiers and resolving pronouns. After parsing the semantic graph through some simple linguistic rules, a scene graph G_n^i or G_n^*, which consists of objects, their attributes, and relationships, can be obtained. We provide an example of one caption and its scene graph in Fig.8.

Selection Protocols As formulated in the main paper, our acquisition function for the unlabelled sample V_n is:

$$L_n = -\lambda_1 L_n^1 + \lambda_2 L_n^2 - \lambda_3 L_n^3 + L_n^4, \tag{5}$$

where $\lambda_1, \lambda_2, \lambda_3$ are hyper-parameters. Let's further denote the annotation budget, or the amount of annotations to be obtained, at the t-th step of the active learning algorithm as $\mathbf{A}_t$. In our case, $\mathbf{A}_t = \|\mathbf{C}_{S_t}\|$.

Video-wise Selection Under conventional video-wise selection protocol, once $V_n \in \mathcal{U}$ is selected by active learning algorithms, all annotations in V_n will be acquired. Assuming that each V_n is associated with D captions, the video-wise selection protocol then selects the top $\|S_t\| = \frac{\mathbf{A}_t}{D}$ videos from $\mathcal{U}$ and get all their captions. In practice, D equals to 20 and 40 in MSR-VTT Xu et al. (2016)

https://doi.org/10.52202/079017-1198

and MSVD Chen and Dolan (2011a). As a reference, we denote the annotations for the m-th labelled video V_m as $\mathbf{C}_m$. Denoting the d-th caption as C_m^d, our $\mathbf{C}_m$ can be represented as $\mathbf{C}_m = \{C_m^d\}_{d=1}^D$.

Caption-wise Selection Rather than assuming that all D captions will be acquired once V_n is chosen by active learning algorithms, our caption-wise selection scheme allows more flexibility w.r.t. Eq. 5. Specifically, at each selection step, the video that has been least annotated with lower Eq. 5 will be chosen to get captions. Mathematically, we make the following revision:

$$\hat{L}_n = L_n + \frac{|\mathbf{C}_n|}{q}, \tag{6}$$

where $\mathbf{C}_n$ denotes the number of annotations that already obtained on V_n. And q is a dataset-specific hyper-parameter served as a re-ranking factor. Eq. 6 reflects our intuition that videos that have not been annotated are more informative due to both diversity and inconsistent annotations from collective outliers. Consequently, we will rank all V_n according to $\hat{L}_n$ as long as $|\mathbf{C}_n| \neq D$ with our caption-wise selection scheme.

After ranking all V_n that has not been fully annotated, we then start to acquire human annotations w.r.t. $\mathbf{A}_t$. Instead of equally allocating human efforts to top-ranking videos, which neglects the learnability property, we further introduce an intellectual design where more budgets are provided to topper-ranking videos. Compared to their peers, these topper-ranking ones are less likely to be collective outliers. Therefore it is safer and more effective to spend more effort on them. Specifically, we propose a stage-wise acquisition scheme by dividing the ranked videos into R consecutive and exclusive regions according to their L_n. If the ranked V_n belongs to the r-th region, where $r \in \{1, \ldots, R\}$, then we allocate $A_{t,r}$ annotations to it. Let's denote annotations V_n get at time step t as $\mathbf{C}_n^t$. In this case, $A_{t,r} = |\mathbf{C}_n^t|$. As a reference, we have $\mathbf{A}_t = \sum_n |\mathbf{C}_n^t|$ and $\mathbf{C}_n = \bigcup_t \mathbf{C}_n^t$. Our full caption-wise algorithm is summarized in Alg. 1.

Hyper-parameter Setting We set the number of sampled frames I, the total active learning step T, and the per-step annotation budget $\mathbf{A}_t$ to 32, 4, and 5% of full annotations in each dataset. The hyper-parameters $\lambda_1, \lambda_2, \lambda_3$ in Eq. 5 are 3, 1, and 2, respectively. And they are chosen based on experiments on the validation set via grid search. Our re-ranking factor q in Eq. 6 is set to 10 on MSR-VTT. Meanwhile, R is set to 3, dividing the ranked videos into 3 regions according to $\hat{L}_n$. Specifically, both the first and last regions consist of 2000 videos. $A_{t,r}$ equals to 2, 1, and 0 with $r = \{1, 2, 3\}$. On the MSVD dataset, q and R are set to 20 and 5. These 5 regions in MSVD consist of 250, 250, 250, 188, and 262 unlabelled videos, respectively. With increasing r, we have $A_{t,r}$ set to 4, 3, 2, 1, 0.

We would like to note that hyper-parameters related to the Caption-wise Selection Protocol are not optimal due to the lack of tuning. We might expect performance boosts with a more careful search.

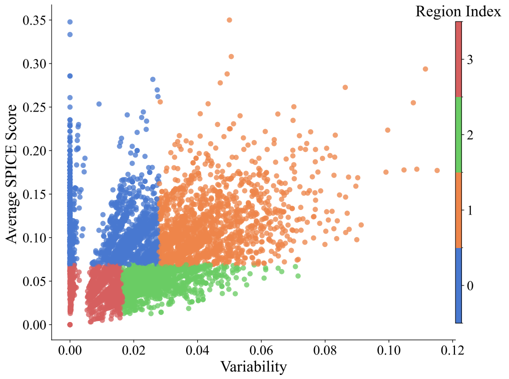


Figure 9: We divide the data in Dataset Maps on MSR-VTT into four regions according to their learnability. Specifically, we have EASY, MODERATE, HARD, and COLLECTIVE OUTLIER colored in blue, orange, green, and red, respectively.

A.3 Analysis on Dataset Maps

To the best of our knowledge, we are the very first to address the collective outliers in video captioning tasks. As described in our paper, we adapt Dataset Maps Swayamdipta et al. (2020) to perform analysis on collective outliers. We provide Dataset Maps on the training set of MSR-VTT in Fig. 9. In particular, y and x axis are the averaged SPICE score over all training epochs and their variance. Intuitively, the average SPICE score reflects sample difficulty, while the variance represents its

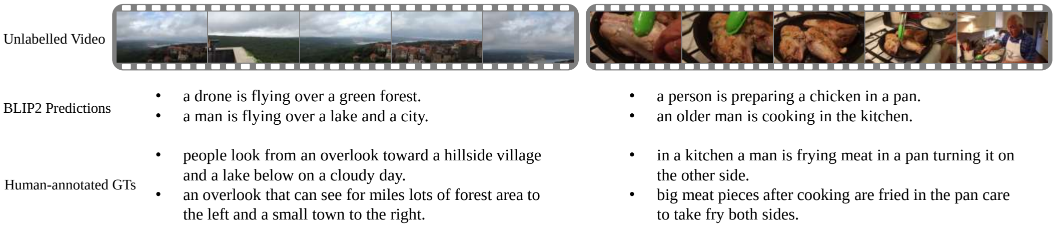
```
Algorithm 1: Our Caption-wise Algorithm
Input: The labeled set $\mathcal{L} = \{V_m, \mathbf{C}_m\}_{m=1}^{M}$, the unlabelled set $\mathcal{U} = \{V_n\}_{n=1}^{N}$, a video
       captioning model $f$, a foundational model $f'$, the number of sampled frames $I$, the total
       active learning step $T$, number of stages $R$ and stage-wise budget $A_{t,r}$
Output: Updated video captioning model $f$
Initialize $f$ by training it on $\mathcal{L}$;
Generate frame-wise captions $\{b_j^i\}_{i=1,j=1}^{I,M+N}$ with the foundational model $f'$;
Parse $\{b_j^i\}_{i,j}$ into scene graphs $\mathbf{G} = \{G_j^i\}_{i,j}$;
for $t$ = 1 to $T$ do
    Generate predicted captions $b_j^*$ with $f$ for each video on $\mathcal{U} \cup \mathcal{L}$;
    Parse $\{b_j^*\}_j$ into a scene graph $\mathbf{G}^*$;
    Compute $\hat{L}_n$ based on Eq. 6 $\forall V_n \in \mathcal{U}$;
    Ranking videos in $\mathcal{U}$;
    for $V_n \in \mathcal{U}$ do
        for $r$ = 1 to $R$ do
            if $V_n$ belongs to the $r$-th region then
                Acquire $A_{t,r}$ annotations $\mathbf{C}_n^t$ for $V_n$
            end
        end
        if $|\boldsymbol{C}_n^t| \neq 0$ then
            $S_t \leftarrow S_t \cup V_n$;
            $\mathbf{C}_{S_t} \leftarrow \mathbf{C}_{S_t} \cup \mathbf{C}_n^t$
        end
        if $\sum_t |\boldsymbol{C}_n^t| == D$ then
            $\mathcal{U} \leftarrow \mathcal{U} \setminus V_n$;
        end
    end
    $\mathcal{L} \leftarrow \mathcal{L} \cup \{S_t, \mathbf{C}_{S_t}\}$;
    Update the video captioning model $f$ with $\mathcal{L}$;
end
```

Table 3: Results of SwinBERT on MSR-VTT test set. Specifically, SwinBert is trained with 25% of training data in MSR-VTT. Among them, $Ours$ and $Random$ are active learning methods where data is chosen based on various acquisition functions. The remaining four are decided by Dataset Maps.

	BLEU_4	METEOR	ROUGE_L	CIDEr	SPICE
Ours	43.86	29.93	62.57	55.74	7.39
Random	40.95	29.02	60.63	50.20	7.14
Easy	40.23	27.93	59.50	45.76	6.53
Moderate	39.76	27.93	59.71	46.07	6.74
Hard	32.29	25.49	55.66	31.75	5.84
Collective Outliers	28.92	25.87	54.39	29.43	5.71

ambiguity. Combining both would provide us with a way to capture data learnability. Dataset Maps, to this end, provide an interpretable way to identify collective outliers w.r.t. data learnability.

To verify our assumption that Dataset Maps helps in terms of figuring out collective outliers, we propose to divide samples according to their learnability. Specifically, samples are firstly divided into two halves based on the average SPICE score. Then the two halves are equally divided into four regions (*i.e.*Easy, Moderate, Hard, and Collective Outliers) based on variance. Each region exclusively contains 25% of the samples from the full training set to avoid the interference of data size on the results. We then train f with data from each region and show the overall performance on



- a drone is flying over a green forest.
- a man is flying over a lake and a city.

- people look from an overlook toward a hillside village and a lake below on a cloudy day.
- an overlook that can see for miles lots of forest area to the left and a small town to the right.

- a person is preparing a chicken in a pan.
- an older man is cooking in the kitchen.

- in a kitchen a man is frying meat in a pan turning it on the other side.
- big meat pieces after cooking are fried in the pan care to take fry both sides.

Figure 10: Qualitative comparisons between BLIP2 predictions and human-annotated ground truths.

Table 4: Results of SwinBERT trained with different mixed MVR-VTT datasets combined with 5% ground truths (*i.e.*initial seed set) and BLIP2 captions filtered by threshold th.

th	4	8	12	16	20	24	28
Number of BLIP2 captions	92765	58050	28880	12561	4509	1406	391
CIDEr	31.92	32.82	32.88	33.39	34.96	39.32	39.90
SPICE	7.09	6.99	6.92	6.65	6.56	6.24	5.70

the test set in Tab. 3. In short, We can draw the following two conclusions: (1) There exist obvious gaps between regions of various averaged SPICE scores (e.g. Easy v.s. Collective Outliers, Moderate v.s. Hard), indicating that simple samples bring in more performance boosts. (2) When the difficulty of samples is close, samples of higher variances lead to better performance (*e.g.*. Moderate v.s. Easy, Hard v.s. Collective Outliers). In our active learning scenario, this observation can be interpreted as simple and learnable samples with certain uncertainty (*e.g.*samples in the Moderate region) are of greater informativeness.

We further conduct another baseline where f is trained with 25% randomly sampled data from the full training set. Compared to results from data with various learnability, we observe that this new baseline gives better performance. We argue that such inferiority comes from a lack of data diversity and uncertainty. As a reference, we also report the performance of our active learning method with 25% training data, which clearly gives the best performance with the same amount of data.

A.4 Efforts to Combine Knowledge from LVLMs

Given the observation that LVLM predictions provide satisfactory approximations to human-annotated ground truths, one might wonder whether they can be directly used to either replace the human annotations or enrich them.

Motivated by this idea, we conduct a simple semi-supervised learning experiment where the initial setup is the same w.r.t. our active learning scheme, e.g., 5% and 95% split for labelled and unlabelled sets. For each video in the unlabelled set, we obtain its pseudo ground truth from BLIP2 by randomly selecting 16 captions from 32 frame-wise predictions. We then update our f with these pseudo ground truths and report its performance on the MSR-VTT test set in Fig. 10. Apparently, there exist clear differences in language style between captions generated by BLIP2 and human-annotated ground truths. Specifically, this simple semi-supervised learning method achieves 0.31 and 0.07 for CIDEr and SPICE, which are worse than the starting points. Such performance drop might be caused by domain gaps between video and image captioning tasks, as well as the lack of ability to capture temporal information.

Can the gap between human-annotated video captions and predictions from image-based foundational models become smaller if the V_n is so simple that video caption degenerates to image caption? Since there is no way to recover the temporal information from frame-wise image caption, we propose to address this factor from another perspective. Specifically, we believe that the impact of temporal information can be minimized if videos are highly coherent among frames. Such coherency can be further approximated by frame-wise consistency. To this end, we propose to include videos whose frame-wise BLIP2 captions are of high abstraction consistency. Mathematically, let's denote $P(b_n^i)$

https://doi.org/10.52202/079017-1198

as follows:

$$P(b_n^i) = \frac{\sum_{k \in O_n^i} H_k(\mathbf{G}_n)}{|O_n^i|} + \frac{\sum_{k \in A_n^i} H_k(\mathbf{G}_n)}{|A_n^i|}, \tag{7}$$

Then the abstraction consistency of each BLIP2 caption in unlabelled videos is defined as follows:

$$\hat{P}(b_n^i) = P(b_n^i) + \frac{\sum_{k \in R_n^i} H_k(\mathbf{G}_n)}{|R_n^i|}. \tag{8}$$

As long as its score $\hat{P}(b_n^i)$ is not lower than a threshold th, a BLIP2 caption will be counted as a pseudo ground truth. Later on, these pseudo ground truths will be used to re-train f, which is initialized with 5% of training data only. We report the performance of f in Tab. 4 with $th \in \{4, 8, 12, 16, 20, 24, 28\}$. Noticeably, CIDEr score increases with the increasing th. This observation validates our hypothesis that videos of highly consistent content generally have a smaller domain gap in terms of video and image captioning, thanks to the neglectable impact of temporal information. In contrast, including more captions generated by BLIP2 brings higher SPICE. This is mainly because of the semantic-centric property of SPICE. In short, captions that are semantically similar but grammatically different will be regarded as correct ones in SPICE.

Since semi-supervised learning is beyond the scope of our paper, we do not include more experiments in this section. Though not observing performance improvements by introducing BLIP2 predictions as pseudo ground truths, we still believe that domain adaption methods with much more delicate designs would help. We look forward to seeing more work in this direction.

A.5 Results with ChatGPT

To validate our hypothesis that inconsistency in human annotations genuinely exists and is not merely due to subjective judgments, we utilize ChatGPT as an objective tool.

Specifically, we randomly sample 500 videos from each sub-region from MSR-VTT, and then randomly select 2 ground truth captions for each sample. We then ask ChatGPT whether it believes these 2 captions describe the same content. ChatGPT will respond with one of three answers: yes, no, or $undecided$. There are two main observations. First of all, we notice that ChatGPT can provide reasonable answers to our provided examples. Here we provide one pair of examples for each answer from ChatGPT:

- *Yes*: "two teams play soccer on a field" & "a man gives commentary for a soccer game"
- *No*: "there is a man talking in front of his computer" & "there are some tips to use your computer"
- *Undecided*: "a video showcasing a modded jeep" & "a person gets his lifted jeep stuck in the dirt"

Noticeably, based on the feedback of ChatGPT, there are 49.5% and 22.5% of inconsistent data and hard-to-decide among all 2000 samples respectively, indicating the severity of inconsistency in human-annotated ground truths. Moreover, when comparing the percentage of data among sub-regions, we observe a clear trend of consistency increases when moving from collective outliers to easy. For instance, 22.4% and 33% of captions from easy and collective outliers are believed to be consistent. This observation aligns well with our arguments and supports our hypothesis as well as motivation.

https://doi.org/10.52202/079017-1198

NeurIPS Paper Checklist

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: The abstract and introduction accurately introduce the proposed active learning method.

   Guidelines:

   - The answer NA means that the abstract and introduction do not include the claims made in the paper.
   - The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
   - The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
   - It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [No]

   Justification: The limitations of this article may come from the capabilities of LVLMs. Experiments have proven that the capabilities of LVLMs can initially meet the needs.

   Guidelines:

   - The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
   - The authors are encouraged to create a separate "Limitations" section in their paper.
   - The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
   - The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
   - The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
   - The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
   - If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
   - While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. **Theory Assumptions and Proofs**

   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

https://doi.org/10.52202/079017-1198

Answer: [No]

Justification: This paper does not contain theorems that require rigorous proof.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. **Experimental Result Reproducibility**

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: This paper provides sufficient experimental details and the code will be published upon acceptance.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general. releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
  (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
  (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
  (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
  (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. **Open access to data and code**

https://doi.org/10.52202/079017-1198

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: The code will be published after this paper is accepted.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (`https://nips.cc/public/guides/CodeSubmissionPolicy`) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. **Experimental Setting/Details**

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: The paper provides detailed experimental details in the appendix.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. **Experiment Statistical Significance**

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: Experiments were run in triplicate and averages and variances are reported.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)

https://doi.org/10.52202/079017-1198

- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. **Experiments Compute Resources**

   Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

   Answer: [Yes]

   Justification: This paper describes the computing resources used to run the experiments.

   Guidelines:

   - The answer NA means that the paper does not include experiments.
   - The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
   - The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
   - The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. **Code Of Ethics**

   Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

   Answer: [Yes]

   Justification: The research conducted conformed in all respects to the NeurIPS Code of Ethics.

   Guidelines:

   - The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
   - If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
   - The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. **Broader Impacts**

    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [NA]

    Justification: no societal impact of the work performed.

    Guidelines:

    - The answer NA means that there is no societal impact of the work performed.
    - If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
    - Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

https://doi.org/10.52202/079017-1198

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. **Safeguards**

    Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

    Answer: [NA]

    Justification: the paper poses no such risks

    Guidelines:

    - The answer NA means that the paper poses no such risks.
    - Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
    - Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
    - We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. **Licenses for existing assets**

    Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

    Answer: [Yes] the paper does not use existing assets.

    Justification: the paper state which version of the asset is used. The authors cite the original paper that produced the code package or dataset.

    Guidelines:

    - The answer NA means that the paper does not use existing assets.
    - The authors should cite the original paper that produced the code package or dataset.
    - The authors should state which version of the asset is used and, if possible, include a URL.
    - The name of the license (e.g., CC-BY 4.0) should be included for each asset.
    - For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
    - If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, `paperswithcode.com/datasets` has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
    - For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.

https://doi.org/10.52202/079017-1198

- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New Assets**

    Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

    Answer: [NA]

    Justification: the paper does not release new assets.

    Guidelines:

    - The answer NA means that the paper does not release new assets.
    - Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
    - The paper should discuss whether and how consent was obtained from people whose asset is used.
    - At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and Research with Human Subjects**

    Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

    Answer: [NA]

    Justification: the paper does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
    - According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

    Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

    Answer: [NA]

    Justification: the paper does not involve crowdsourcing nor research with human subjects.

    Guidelines:

    - The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
    - Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
    - We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
    - For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

https://doi.org/10.52202/079017-1198