LEARNING CONTEXT-ADAPTED VIDEO-TEXT RETRIEVAL BY ATTENDING TO USER COMMENTS

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ABSTRACT

Learning strong representations for multi-modal retrieval is an important problem for many applications, such as recommendation and search. Current benchmarks and even datasets are often manually constructed and consist of mostly clean samples where all modalities are well-correlated with the content. Thus, current video-text retrieval literature largely focuses on video titles or audio transcripts, while ignoring user comments, since users often tend to discuss topics only vaguely related to the video. In this paper we present a novel method that learns meaningful representations from videos, titles and comments, which are abundant on the internet. Due to the nature of user comments, we introduce an attention-based mechanism that allows the model to disregard text with irrelevant content. In our experiments, we demonstrate that, by using comments, our method is able to learn better, more contextualised, representations, while also achieving competitive results on standard video-text retrieval benchmarks.

1 INTRODUCTION

Training large scale multi-modal models from paired visual/text data from the web has seen great success in video understanding and retrieval. However, typically only the caption or "alt text" is used during training, ignoring potentially relevant text present on the web page, such as user comments, tags, descriptions and other metadata.

The challenge in using this extra context is that it may often be not directly relevant to the video (a comment "cool video!"), or it may be relevant but non-distinctive (a tag "cat" could apply to many videos). Similarly, other modalities can also exhibit this behavior. For example, current work that learns from audio-visual correspondence (Asano et al., 2020; Alwassel et al., 2020a; Morgado et al., 2020) need clean datasets such as VGGSound (Chen et al., 2020a) to learn meaningful correspondence between videos and sound, whereas online videos tend to have for example background music that replaces the actual sounds happening in the video.

In this paper, we propose a method that can take advantage of this auxiliary context while simultaneously filtering it for meaningful information. Most current models enforce a strict correlation between the different input modalities under the assumption that all are informative of the content. The main intuition of our work is that when training a model on partially unrelated data, we need to introduce a mechanism that allows the model to discount auxiliary data when it is not helpful for the task.

To this end, we build a model with a hierarchical attention structure. Current representation learning models that are based on transformer architectures already exploit the idea of an attention mechanism to model the correlation between different *parts* of an input signal. For example in text understanding, the attention mechanism is applied per word, allowing the model to understand the structure of natural language. Even though in principle one could use the same scheme to model the importance of different text inputs on a per-word basis, we find that this makes it difficult to learn the individual importance of inputs. Moreover, due to the computational complexity of current transformers (squared with sequence length) this approach would only work for a small number of short comments. We thus add a second layer of attention per processed input that allows the model to assess the amount of information at a higher level of features. We find that this mechanism aligns well with the intuition that some inputs are very relevant to the problem and others can be disregarded.

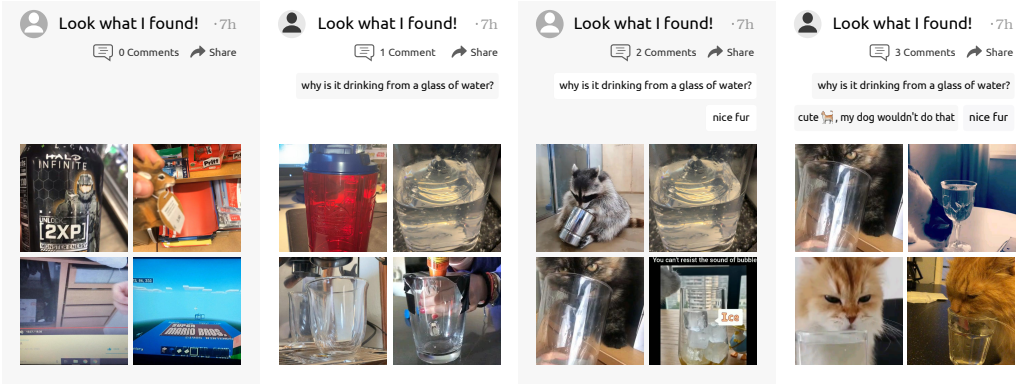


Figure 1: **Video Retrieval from Title and comments.** We show the top 4 videos retrieved for the ambiguous title "Look what I found!", and from left to right we progressively add more comments which our model uses to refine the results.

In our experiments we show that we can indeed learn meaningful information from user comments that translates to good zero-shot retrieval performance on common benchmarks. Additionally, we can show that the model can correctly identify whether auxiliary information is informative of the content of a video or not.

The ability to incorporate auxiliary contextual information also opens up possibilities for useful applications. In the video retrieval setting our method can be used to iteratively refine a text descriptor with new inputs as shown in Fig. 1, allowing incremental searching. In the zero-shot video classification setting (*i.e.*, "retrieving" the correct class description prompt) the prediction for an ambiguous video can be steered towards the correct class using surrounding text from a webpage or user hints (Fig. 4).

2 Related Work

In this work, we focus on multi-modal learning with a particular focus on learning video-text encoders for retrieval by proposing a novel, multi-modal adaptation module.

Video-text pretraining. Originating from the NLP domain, where the transformer architectures has been a key ingredient and subject to optimization in a multitude of ways (Vaswani et al., 2017; Devlin et al., 2019; Radford et al., 2019; Raffel et al., 2019; Lewis et al., 2020b; Clark et al., 2020; Lewis et al., 2020a), it has recently found applications in the vision-language domain. For example, recent works have leveraged transformers to learn generalizeable image (Desai & Johnson, 2020; Sariyildiz et al., 2020; Chen et al., 2020b) or multi-modal image-text (Li et al., 2019; Lu et al., 2019; Tan & Bansal, 2019; Su et al., 2019; Li et al., 2020; Chen et al., 2019) and video-multilingual text (Huang et al., 2021) representations. A few works (Sun et al., 2019b;a; Zhu & Yang, 2020; Luo et al., 2020) combine visual and text modalities as inputs to a BERT model to simultaneously learn semantic video and text representations. For representation learning, the availability of large-scale datasets such as HowTo100M (Miech et al., 2019a) has enabled more effective pretraining of video-text representations for multiple downstream tasks. More recently, Patrick et al. (2020b) show that adding a generative objective to contrastive pretraining can yield gains in video-text downstream tasks. Based on the CLIP model (Radford et al., 2021), which works well even without finetuning for some retrieval tasks (Luo et al., 2021), Bain et al. (2021) train video-text CLIP-initialized models by gradually scaling up video training from image training and a custom dataset. While we also start with a CLIP initialization as in Luo et al. (2021), the focus of our paper lies in developing a novel method for leveraging user comments, a modality that has previously been overlooked in the text-video retrieval literature, as a valuable source of information. As is standard, the pretrained representations are subsequently evaluated on smaller datasets such as MSVD (Venugopalan et al., 2015) and MSR-VTT (Xu et al., 2016a).

Multi-modal domain adaptation. While residual adapters for domain adaptation have been explored for uni-modal models such as CNNs, e.g. in Rebuffi et al. (2017), there are no works that translate

this concept to the multi-modal domain, where cross-modal learning dominates (Alwassel et al., 2020b; Asano et al., 2020; Morgado et al., 2020).

Multi-modal pretraining. There is little prior work using user comments as additional context in multimodal settings. The use of user comments and reactions to refine predictions has been discussed by Halevy et al. (2020) for minimising harms on facebook.com. Overall, we are the first to demonstrate that user comments can be used as a complementary modality when learning video-text representations.

3 METHODS

In this section we will first recap the mechanism behind current contrastive, multi-modal representation learning methods that rely on clean data. We will then introduce our Context Adapter Module that allows learning from the auxiliary modality through an attention mechanism. Finally, we will describe how we can extend an existing backbone for images to videos, to be able to leverage large, pretrained models.

3.1 BACKGROUND

In multi-modal representation learning we are given a dataset $\mathcal{X}$ of N samples $x_i \in \mathcal{X}, i \in \{1, \dots N\}$ that individually consists of different signals. Most previous work focuses on two modalities and we will—for now—also adhere to this standard to simplify the notation. This means that each input sample $x_i = (v_i, t_i)$ is a pair of—in our case—a visual input $v_i \in \mathcal{V}$ and its associated text, often the title, $t_i \in \mathcal{T}, 1 \leq i \leq N$.

The goal is now to learn mappings $f_v : \mathcal{V} \mapsto \mathcal{Y}, f_v(v_i) = \phi_{v,i}$ and $f_t : \mathcal{T} \mapsto \mathcal{Y}, f_t(t_i) = \phi_{t,i}$ from each of the modalities to a d-dimensional, joint embedding space $\mathcal{Y} = \mathbb{R}^d$. Recent methods, such as Radford et al. (2021), learn the mapping (in their case from images and their captions) to the embedding space with a double contrastive loss over a mini-batch $\mathcal{B} \subset \mathcal{X}$ using an affinity matrix A computed between all pairs of samples in the batch:

$$A_{ij} = \left\langle \frac{\phi_{v,i}}{\sqrt{\tau}\|\phi_{v,i}\|}, \frac{\phi_{t,j}}{\sqrt{\tau}\|\phi_{t,j}\|} \right\rangle \tag{1}$$

An entry A_{ij} measures the similarity between the embeddings $\phi_v(v_i)$ and $\phi_t(t_i)$ via cosine similarity that is scaled by a temperature parameter τ. The idea is now to maximize the similarity between the embeddings from the *same* sample, *i.e.* the diagonal of A and minimize all non-diagonal entries. This can be achieved efficiently using a double-contrastive formulation that operates across columns and rows of A,

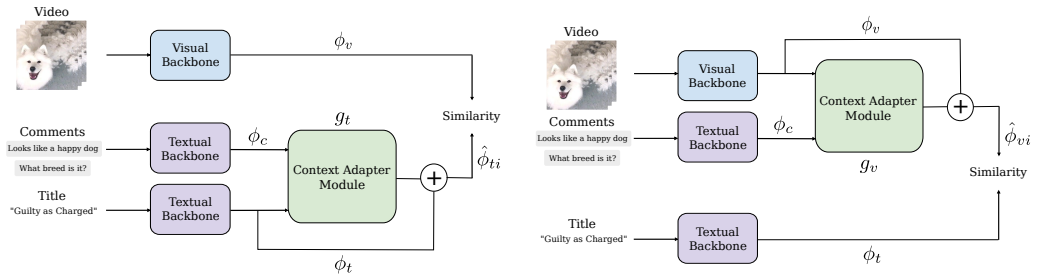
$$\mathcal{L}(A) = \frac{1}{2} \sum_{i=1}^{|\mathcal{B}|} \frac{A_{ii}}{\log \sum_{j=1}^{|\mathcal{B}|} \exp A_{ij}} + \frac{A_{ii}}{\log \sum_{j=1}^{|\mathcal{B}|} \exp A_{ji}}. \tag{2}$$

This formulation has the neat effect that it accomplishes maximizing the diagonal entries and minimizing all other entries of A in one self-balancing formulation. However, it makes the critical assumption that both modalities are equally informative of each other. In the case of sometimes irrelevant data, or when one modality has much less information content than the other (*e.g.* "*nice video!*"), this assumption does not hold and training with this objective will result in a very volatile learning objective and thus a sub-optimal joint embedding.

In the next section we will introduce our Context Adapter Module that is able to deal with this type of inputs by allowing it to discount information when it is not relevant for the context.

3.2 CONTEXT ADAPTER MODULE

In order to capture and filter the relevant information from the comments, we propose a transformer-based Context Adapter Module (CAM) which operates in a residual fashion, additively adapting either the visual or text branch of CLIP with contextual information obtained from the comments (see Fig. 2). Formally, we are now adding another modality—the comments—to the input which



(a) Adapting the text branch.

(b) Adapting the visual branch.

Figure 2: **Method Overview.** We introduce a context adapter module that uses inputs of the auxiliary modality to adapt the embedding of another branch. With this module the model is able to accept or discount information.

extends it to $x_i = (v_i, t_i, c_{i,1}, \ldots, c_{i,M})$ with $c_{i,k} \in \mathcal{T}$. To reduce clutter in the notation, we have defined a fixed number of comments M for each sample. Since both, title and comments, share the same underlying modality, namely text, we can leverage the same encoder to transform comments to embeddings $f_t(c_{ik}) = \phi_{c,ik}$.

As we expect the comments to be sometimes unrelated, our Context Adapter Module needs a mechanism to discount off-topic comments and update the primary modality $\phi_v(v_i)$ or $\phi_t(t_i)$, steering it in the most informative direction.

We introduce this mechanism as a function of both the primary modality and the comment embeddings $\phi_{c,ik}$, as we want to compare the informativeness of all these inputs at a high level. To this end, we design adapter modules g_v and g_t that extract information from the comments in the form of a residual:

$$\hat{\phi}_{oi} = \phi_{oi} + g_o(\phi_{oi},\, \phi_{c,i,1},\, \ldots,\, \phi_{c,i,M})\,,\; o \in \{v, t\} \tag{3}$$

With the adapted embeddings $\hat{\phi}_{vi}$ and $\hat{\phi}_{ti}$ we recompute the affinity matrix (now $\hat{A}$) (Eq. 1) and use it for the loss $\mathcal{L}(\hat{A})$. This design has several advantages. On one hand, extracting "only" a residual from the auxiliary inputs c_{ik} means that the model is easily able to ignore them by predicting $g(\cdot) = 0$. On the other hand, this effectively allows us to skip the adapter module when we benchmark the model on a dataset that does not have comments, while still learning the joint embedding from richer data.

In practice, we implement g as a small transformer architecture. Rather than operating on tokenised words, this transformer operates on embeddings (ϕ_{vi} and ϕ_{ti}) themselves, taking as input the encoded feature from the branch to be adapted, along with comment features $\phi_{c,ik}$. By treating embeddings as tokens in their own right, we allow the embeddings to attend to each other and learn what combinations of the inputs should be used to update the original feature through the residual connection.

Additionally, to avoid bleeding information between the two modalities through the Context Adapter Module, during training, we only adapt either the video embedding with g_v or the text embedding with g_t. If we would use both adapters simultaneously, there is a trivial solution that minimizes the loss $\mathcal{L}$: when the adapters learn to remove the original embedding through the residual, *e.g.* $g_o(\phi_{oi},\, \{\phi_{c,i,k},\}) = -\phi_{oi} + \phi_{c,i,1}$ both adapted embeddings become the same $\hat{\phi}_{vi} = \hat{\phi}_{ti}$ which trivially maximizes their similarity, thus preventing the model to learn a meaningful modality alignment. To prevent the model from learning a transformation of the embedding space through the residual, we train only one adapter at a time. We also consider the case where $g_v = g_t$ and choose a random modality to adapt for each minibatch, leading to an adapter that is agnostic to the source of the primary embedding.

3.3 From Images to Videos

To leverage the capacity of large pre-trained computer vision models, we adopt the architecture by Radford et al. (2021) as our backbone models f_v and f_t. While this transformer was trained on a huge volume of image-text data, it cannot be applied directly to videos since it is built for images and has no temporal extent. To take advantage of the temporal information present in video

Table 1: **Comments as a modality.** Treating comments as an auxiliary modality to a video improves Text-to-Video retrieval for both RedditVC and KineticsComments test sets. As a baseline, we use the CLIP model on just the first frame. We then train just our CAM on top of CLIP, adapting the visual embedding with information from the comments, which improves retrieval metrics. Training our full model, which includes temporal attention, on RedditVC again validates that the inclusion of comments helps, with a further jump in Kinetics performance when using the Kinetics training set.

				Reddit Eval.		**Kinetics Eval.**	
Method	#Frames	Train w/ Comm.	Test w/ Comm.	R@5	R@10	R@5	R@10
CLIP	1	no	no	19.1	23.9	36.6	47.0
CLIP + Our CAM	1	yes	yes	30.3	37.9	42.4	53.3
Ours (RedditVC)	8	yes	no	21.8	27.5	43.4	55.6
Ours (RedditVC)	8	yes	yes	31.7	39.6	46.3	58.6
Ours (RedditVC+KineticsCmts)	8	yes	no	19.8	24.8	50.3	63.7
Ours (RedditVC+KineticsCmts)	8	yes	yes	31.2	38.8	52.9	67.4

data, we use the Divided Space-Time attention mechanism recently introduced in the TimeSformer architecture (Bertasius et al., 2021). We modify the image transformer architecture by adding patchwise self-attention across 8 frames in time to each of the 12 residual attention blocks, followed in each case by a zero-initialised linear layer. We also add a learned temporal position embedding which is summed to the input and again zero-initialised. The initialisation is transparent, such that when loading pretrained weights trained from images, at initialization time, the modifications do not affect the inference of the model. During training, the model can then gradually activate the additional temporal components to learn from the temporal information of a video. Full details on the architecture are provided in the appendix.

4 EXPERIMENTS

4.1 IMPLEMENTATION DETAILS

We use CLIP (Radford et al., 2021) as the initialisation for the backbone. Our concrete implementation of the CAM g is a 2-layer transformer, consisting of two residual multihead self-attention blocks. The input consists of $M + 1$ input embeddings (for the M comments and title/video embedding ϕ_{oi}) having 512 dimensions each. Each block performs 8-head self-attention on the inputs, followed by two linear layers with output size 2048 and 512 respectively. LayerNorm normalisation is used, along with GELU activation following the first linear layer. From the $M + 1$ outputs of the transformer, we take only the output at index 1 (the index of the text/video embedding), and pass it through a final 512×512 linear layer. We use learning rate 0.001 for training the CAM, and 1×10^{-6} when training the entire model, using the Adam Kingma & Ba (2015) optimizer.

All implementation and architecture details can be found in the appendix.

4.2 PRE-TRAINING DATASETS

RedditVC. We collect a dataset "RedditVC" of videos along with their titles and comment threads from social news site reddit.com, using their provided API. The videos are collected and used in a manner compatible with national regulations on usage of data for research. Unlike most curated video datasets, this data is more representative of the types of videos shared "in the wild", containing a large proportion of videogames, screenshots and memes.

Using a classifier trained on a small amount of labelled data, we estimate that videogame footage makes up 25% of examples, other screenshots, memes and comics make up 24%, live action footage is 49% and artistic styled content (such as drawn animation) is 2%. The average video length is 33s.

From 1 million raw videos collected, we perform deduplication and filtering, ending up with a training set of 461k videos, and validation and test sets of 66k videos each. For the video evaluation results in Table 1, we use a subset of the test set, consisting of 5000 videos with at least three comments each.

Table 2: **Ablation Study.** Comparing Text-to-Video and Video-to-Text retrieval results between different baselines and our method.

	Finetune Backbone	Train. CAM	Eval. CAM	Text → Video R@1	Text → Video R@10	Video → Text R@1	Video → Text R@10
(a)	✗	-	-	1.70	7.30	1.57	6.86
(b)	✓	-	-	2.25	9.85	2.22	9.28
(c)	✓	$\text{rand}(\phi_t, \phi_{ck})$	-	2.06	9.40	2.04	8.83
(d)	✓	$\text{rand}(\phi_t, \phi_{ck})$	$\text{avg}(\phi_t, \phi_{ck})$	1.64	7.99	1.96	9.49
(e)	✓	$\text{avg}(\phi_t, \phi_{ck})$	-	1.67	7.79	1.97	9.01
(f)	✓	$\text{avg}(\phi_t, \phi_{ck})$	$\text{avg}(\phi_t, \phi_{ck})$	2.49	11.75	2.63	12.06
(g)	✓	g_t	-	2.28	9.70	2.14	9.22
(h)	✗	g_t	g_t	1.98	9.93	1.70	8.87
(i)	✓	g_t	g_t	2.06	10.49	1.96	9.98
(j)	✓	g_v	-	2.22	9.67	2.11	9.11
(k)	✗	g_v	g_v	2.71	12.22	2.86	12.44
(l)	✓	g_v	g_v	2.86	13.07	2.93	13.07

In addition to comments, for one experiment in Table 4 we also obtain textual labels of objects in the video thumbnails, using the Google Vision API. We obtain labels for 10,212 different classes, from "Abacus" to "Zwiebelkuchen". This serves as a useful comparison, giving textual metadata that can be expected to be more directly related to the visual video contents than user comments, and can be seen as a proxy for user-generated "hashtags". It also illustrates how, by using text as an intermediary, we can integrate predictions from any black-box classifier in the same framework.

KineticsComments. As an additional video dataset with comments, we construct a dataset based on Kinetics-700 (Kay et al., 2017; Carreira et al., 2019), for which we download the videos along with associated YouTube metadata including title, description and comments. We translate non-English titles and descriptions into English using a commercial translation API. We use the title as the primary text modality, and for auxiliary context we use comments and (when training) sentences from the description. This leaves us with 484,914 videos for training, each being around 10s. We also construct a test set, consisting of videos from the Kinetics test set for which we have at least 3 comments, giving a set of 2700 videos which we use to evaluate our method in Table 1.

4.3 Evaluating the Context Adapter Module

We evaluate our Context Adapter Module on the above described datasets with comments in Table 1. We find that on both datasets adding comments boosts the retrieval performance significantly, confirming the value of the modality. Further, moving from images to videos also improves the performance. Since KineticsComments (human actions) is quite different to RedditVC (broad range of videos, games, etc.) combining both datasets bridges the domain gap and improves the evaluation performance on KineticsComments.

Baseline Comparisons. Since the main purpose of the Context Adapter Module is to extract meaningful information from sometimes unrelated auxiliary data, we perform most of the experiments in this section with an image/text backbone using a single video frame instead of a video/text backbone to reduce the computational burden of the evaluation.

In Table 2 we evaluate the efficacy of the proposed Context Adapter Module against various baselines in various settings on our RedditVC dataset. The most basic baseline is achieved by not using any form of context adaption, which degenerates the model to the one proposed by Radford et al. (2021).

Across all experimental settings, we find that finetuning the backbone architecture helps to improve the performance, while using the proposed CAM with frozen backbones (rows h,k) even outperforms the naive baseline of row (a). We also compare to two baselines. The first baseline is randomly replacing the title features with comments during training (Table 2(c-d)), however, this does not yield any improvement over no adaptation. In the second baseline we average the title features ϕ_t and the

Table 3: **Adapting different heads.** Text-to-video R@10 results on RedditVC-5. We either adapt the text or image features.

train CAM	test ϕ_v	test ϕ_t
g_v	11.48	2.98
g_t	0.50	9.48
g_v & g_t	10.08	9.16

Table 4: **Influence of Auxiliary Data.** Text-to-video retrieval results on RedditVC-5. We vary the auxiliary text source during training and testing. Using images labels from a classifier during training works well but does not generalize.

	R@10		
Aux. Train Data	**Im. Labels**	**Comments**	**Rand. Words**
Image labels	22.20	6.91	3.06
Comments	10.45	9.48	6.67

comment features ϕ_c which can be seen as a very simple adapter module (Table 2(e-f)). This yields a small benefit when both training and evaluation use averaging, but falls behind utilizing proposed CAM on the visual modality (Table 2(l)). Surprisingly, we find that training with comments performs best when they are added to the image branch (rows j-l), as opposed to the text-branch (rows g-i). We hypothesize that this is because the comments can better adapt the semantically richer feature of the visual modality as opposed to the text, which can often be as short as a single word.

Adapting Different Modalities. Since both the visual embedding ϕ_v and the text embedding ϕ_t, come from the same embedding space and should be similar for the same sample, we perform an experiment where we swap the embeddings during evaluation time. In Table 3 we find that there are still differences between ϕ_v and ϕ_t and swapping results in decreased performance. When we train both adapters we can achieve good performance in both cases.

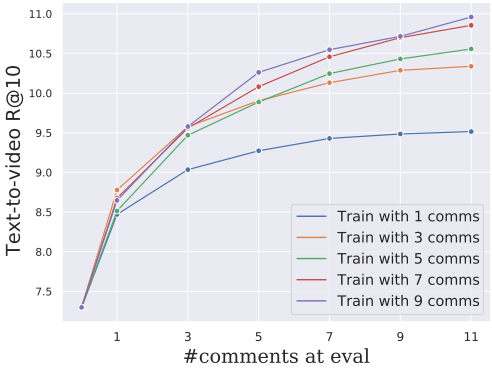


Figure 3: **Varying Number of Comments.** The model can effectively benefit from additional auxiliary information and models trained with more comments become better at extracting information even when fewer are available during testing.

Table 5: **MSVD** (Chen & Dolan, 2011) Zero-shot text-to-video retrieval. CLIP is an important baseline since we use it as our backbone initialisation. Even though comments are not available for this benchmark the model trained with comments has learned better representations.

Method	R@1	@5	@10	Rk
CLIP-Straight (Portillo-Quintero et al., 2021)	37.0	64.1	73.8	3
CLIP4Clip (Luo et al., 2021)	38.5	66.9	76.8	**2**
Ours (no comments)	39.5	68.4	78.3	**2**
Ours (no TimeSformer)	37.7	66.0	76.5	3
Ours	39.5	68.6	78.4	**2**
Ours (with Kinetics)	**40.9**	**69.5**	**78.7**	**2**

Auxiliary Information. Additionally, Table 4 shows how varying the source of the text at train and test time impacts the retrieval results. Whilst the performance of the model trained with image labels degrades when given comments at evaluation time, a model trained with comments still benefits from image labels at test time. As expected, the performance of both models is negatively impacted when tested with uncorrelated random words as additional text. However, the model trained with image labels does noticeably worse in this setting. This suggests that it has become overly reliant on image labels and easily fooled by irrelevant information, which overrides the title feature.

Varying the number of comments. In Fig. 3 we vary the number of comments during training and evaluation time. Training on more comments results in better retrieval results when evaluated on the same number of comments. However, while there is little difference for models trained with only a few comments, we found that increasing the number of comments at train time leads to models that are more robust to different number of comments at test time, indicating that training with more

comments learns an overall better context adapter module that is then able to work efficiently in various settings.

4.4 COMPARISON TO THE STATE OF THE ART

In order to compare to other methods, we use the text-to-video retrieval benchmarks MSR-VTT (Xu et al., 2016a) and MSVD (Venugopalan et al., 2015). While these benchmarks do not directly take into account the novel ability of our method to consider contextual information, they give a measure of the transferability of the learned text and video features. For evaluation, we skip the CAM and use ϕ_{vi} and ϕ_{ti} directly since these benchmarks do not involve comments. Fine-tuning a learned representation only yields an indirect measure of the original model's quality. Since we are interested in the immediate quality of the learned representations, we focus this evaluation on zero-shot performance on the datasets, without fine-tuning. Nonetheless, fine-tuning results can be found in the appendix.

Datasets. For MSVD (Table 5), we use the test split consisting of 670 videos and approximately 40 captions each.

For MSR-VTT (Table 6), we use the 1k-A or "jsfusion" evaluation split of the data, consisting of 1000 (video,text) pairs and 20 captions per video.

Moreover, we show the zero-shot performance of our method on 2 additional datasets. In Table 7 we report the Text-to-Video retrieval results on the ActivityNet (Fabian Caba Heilbron & Niebles, 2015) dataset. We evaluate on the "val 1" split, as in SSB (Patrick et al., 2020b) who we compare to. In Table 8, we show our Text-to-Video retrieval performance on the LSMDC Rohrbach et al. (2017) dataset, where we use the test set comprising of 1000 videos.

Finally, we report the Video-to-Text retrieval results for MSVD and MSR-VTT, which follow similar patterns, in the Appendix.

Results. Across all benchmarks we improve over all other methods in zero-shot retrieval performance. On MSR-VTT our performance is even slightly better than CLIP4Clip (Luo et al., 2021), that uses the same backbone initialization as us but additionally trains on HowTo100M which is more than 100 times larger than our dataset.

It is interesting to note, that we are the only method that evaluates the performance on such a wide spectrum of datasets which shows good generalization performance.

Using comments, videos and more data. In Tables 6, 9 and 10 we also show the performance of our model in different variants.

Across all three benchmarks, our model trained with comments is consistently better than the variant trained without comments. This means that even though the evaluation is performed without comments (none of these datasets provides user comments), the additional context during training has improved the underlying video-text representations.

Similarly, using video instead of a single image improves the results as well. The main difference here, however, is that the video is also available during evaluation. Thus, the observation is that video provides more or a better context for retrieval than single images.

Finally, we find that adding Kinetics to the training set has only a small effect on the quality of the learned representation and can—depending on the domain gap between Kinetics and the benchmark dataset—even affect the results slightly negatively.

Thus, while achieving state-of-the-art performance, we can also show that comments provide a strong signal to improve multi-modal representation learning, even when comments are not available during test time.

Table 6: Text-to-video retrieval on MSR-VTT. **Vis. Enc. Init.:** Datasets used for pretraining visual encoders for tasks *other than visual-text retrieval*, eg object classification. **pre-training:** Visual-text pretraining data. † Object, Motion, Face, Scene, Speech, OCR and Sound classification features. **#samp. PT:** size of the pre-training dataset in millions of samples.

Method	Vis Enc. Init.	pre-training	#samp. PT	R@1	R@5	R@10	Rk
HT MIL-NCE (Miech et al., 2019b)	-	HowTo100M	100M	7.5	21.2	29.6	38
SupportSet (Patrick et al., 2020b)	IG65M, ImageNet	HowTo100M	100M	8.7	23.0	31.1	31
FiT (Bain et al., 2021)	ImageNet	CC3M, WebVid-2M	5.5M	18.7	39.5	51.6	10
CLIP4Clip	-	CLIP, HowTo100M	500M	32.0	**57.0**	66.9	4
VideoCLIP (Xu et al., 2021)	-	HowTo100M	100M	10.4	22.2	30.0	-
Ours - (no comments)	-	CLIP, RedditVC	401M	31.5	54.3	64.5	4
Ours - (no TimeSformer)	-	CLIP, RedditVC	401M	31.9	53.5	65.3	5
Ours	-	CLIP, RedditVC	401M	**32.2**	54.9	65.4	4
Ours - (with K700)	-	CLIP, RedditVC, K700	402M	30.8	56.1	**67.1**	4

Table 7: **ActivityNet** (Fabian Caba Heilbron & Niebles, 2015) Text-to-Video retrieval.

Method	R@1	R@5	R@10	MedR
SSB (Patrick et al., 2020b)	0.0	0.2	0.3	2238
Ours	8.4	22.7	33.0	26

Table 8: **LSMDC** (Rohrbach et al., 2017) Text-to-Video retrieval.

Method	R@1	R@5	R@10	MedR
JSFusion (Yu et al., 2018)	9.1	21.2	34.1	36.0
CE (Liu et al., 2019)	11.2	26.9	34.8	25.3
MMT (Patrick et al., 2020a)	12.9	29.2	38.8	19.3
FiT (Bain et al., 2021)	15.0	30.8	39.8	20.0
Ours	24.0	48.0	60.1	6

4.5 Limitations

We find that the context adapter can be led to override the information in a title if we adversarially craft comments that all point to different content. Qualitative examples of this can be seen in Fig. 4. The model without comments, correctly associates the image with a cookie (jar), however when adding a comment about a "dog" the model prefers the dog label over the cookie label. More examples can be found in the appendix.

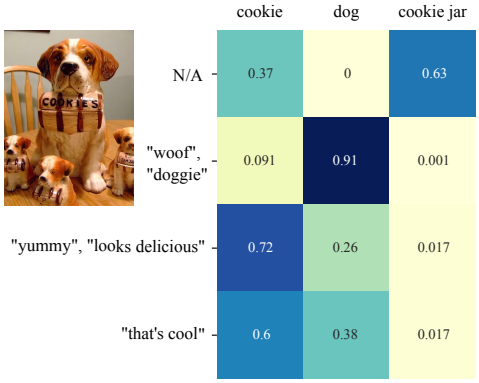


Figure 4: **Failure Case.** A heatmap showing the similarities between the image adapted with different comments (rows), and captions (columns). The adapter can steer away the embedding from the right association "cookie jar" depending on the comment input.

5 Conclusion

We have presented the Context Adapter Module, which is able to extract information from auxiliary input sources for learning a joint, multimodal embedding. In our experiments, we are able to show that the model improves the representation quality of video-text embedding learning when adapting the representation with user comments. Moreover, it is able to identify whether an auxiliary input is relevant to the content in the other modalities or not. This mechanism could, for example, be used to filter datasets for meaningful auxiliary content. The model can be initialized from existing, large-scale image-text backbones and the context adapter learns from a comparatively small number of examples (<500k). The module itself is modality-agnostic and can potentially be used in a large variety of multi-modality representation learning tasks such as audio-visual learning, or to combine the outputs of unreliable expert models.

REPRODUCIBILITY AND BROADER IMPACT

Online data collected from user-generated content are subject to all sorts of biases and potentially problematic content. We have carefully selected the discussion topics from which we source the data, to include topics with a lower chance of problematic topics such as pets, art, jokes and games. On top of that we filter text content with Detoxify (Hanu & Unitary team, 2020) for harmful content. The use of a content filtering text model such as Detoxify can introduce its own biases. Although we have used the 'unbiased' version of Detoxify to minimise these, there might still be particular words that are associated with offensive or hateful language that will likely be strongly correlated with high toxicity scores, regardless of the intent of the author. This could lead to overfiltering non-toxic text that contains particular identity terms, which might result in discrimination against already vulnerable groups. Moreover, the user-base of Reddit is predominantly young, male and western (Barthel et al., 2016) and thus inherently there will be certain biases present regardless of how thoroughly the dataset is filtered. The use of a primarily English language data source and pretrained model means learned concepts will be far from globally representative. The social biases discussed in Section 7.1 of Radford et al. (2021) all still apply. Additionally, as the data is downloaded from a public website, content creators and users could not be asked for consent to be included in the dataset.

The presented context adapter mechanism has a wide applicability across different multi-modal tasks where one input source is expected to sometimes be uninformative. However, as detailed in the previous section, when trained on online data, the model has no mechanism to distinguish between true and false statements and will simply learn from correlations. It has been repeatedly shown that algorithms trained on online user content are often unfit for any kind of production system and pose risks (Bender et al., 2021). Our work and analysis is for research purposes only and we strongly advise against using models trained on the RedditVC dataset in non-research applications.

Given the above discussion on impact and biases, we refrain for now from publicly releasing the RedditVC dataset or models trained on it, as their intent is for research proposes only and not fit for real-world applications. However, we are planning to release the comments collected for the KineticsComments dataset as the content of the videos is much more constrained, which results in easier filtering of the data.

For further reproducibility of the general approach we will release the code. Additionally, models trained on datasets other than RedditVC will be released as well.

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A APPENDIX

A.1 QUALITATIVE EXAMPLES

Figure 5: Examples of retrieved video thumbnails when adapting the text branch.

In Fig. 5 we adapt the text branch, similar to Fig. 1 of the main paper. The example in the second row of Fig. 5 shows how our Context Adapter Module can leverage the comments to learn that the

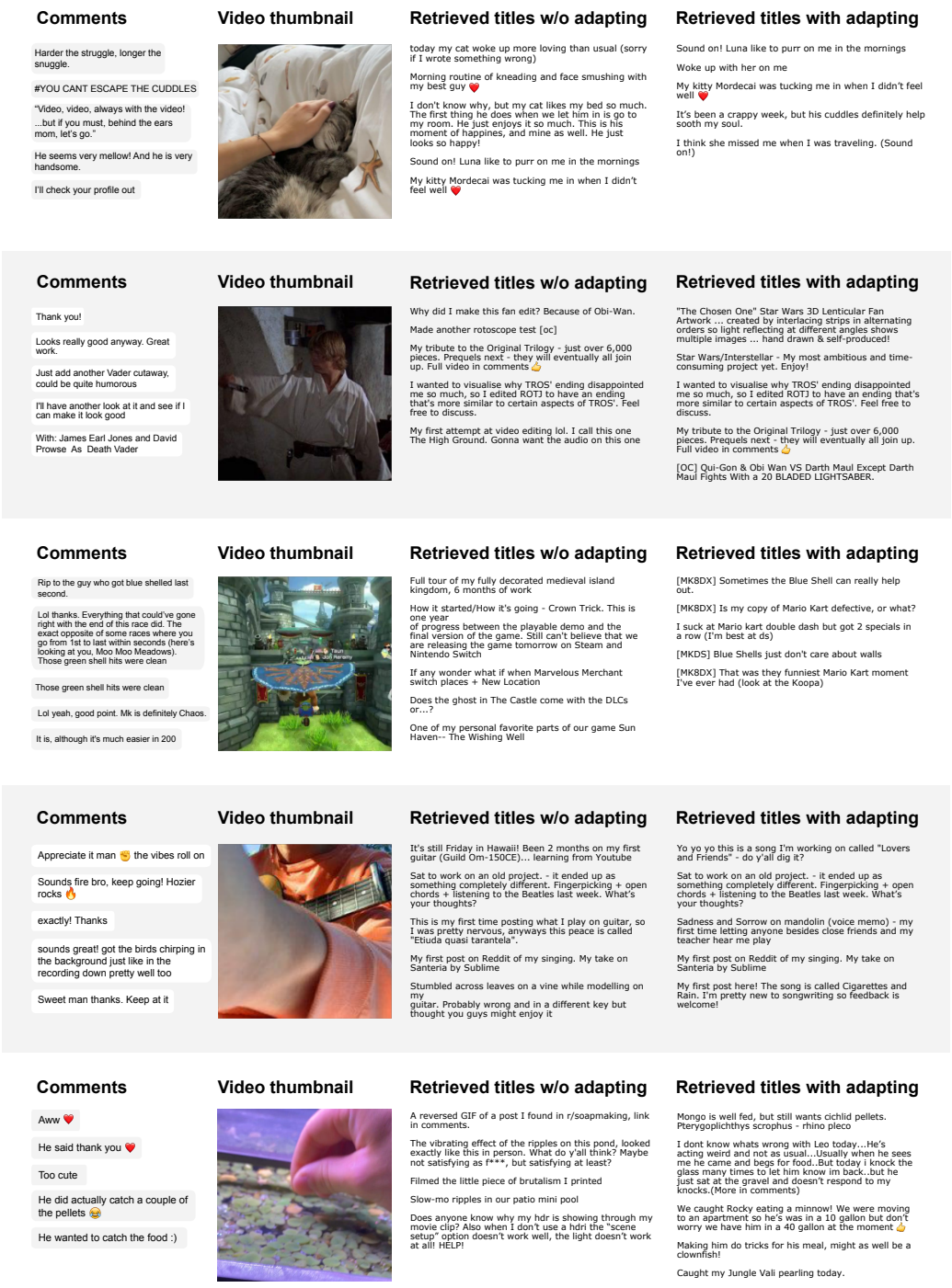

Figure 6: Examples of retrieved titles when adapting the visual branch.

content is indeed about parrots, as opposed to dogs. The fourth row shows that without comments, the title alone can be extremely ambiguous while comments can again guide the model to retrieve relevant videos of drumming.

We provide examples where the video branch has been adapted in Fig. 6. In most cases, the retrieved titles are broadly related to the video thumbnails. However, when provided with the comments, the

retrieved titles become more specific to the videos. For example, in the example from the second row of a screenshot from Mario Kart, the retrieved titles are generally about games e.g. The Castle or Sun Haven, whereas when adapting the video with the comments, the model retrieves titles specifically about Mario Kart. Similarly, in the example from the last row, the model seems to get confused about the content of the video when deprived of the comments, which provide the necessary context about feeding a fish.

Finally, in Fig. 7, we show the saliency of comments with regards to a given video and title. For this, we use the approach of masking out each comment in turn, allowing us to visualise the effect of each individual comment on the network output. We compare the output descriptor when including all comments to the descriptors with a comment masked, using the inner product as a score of similarity, and present the comments sorted from lowest to high, the expectation being that an uninformative comment will not cause a large shift in the descriptor (so will still have high similarity when excluded) whereas a salient comment will cause a larger shift (and so a lower similarity when excluded). We show results for adapting both the text branch (left) and visual branch (right), and observe that, as expected, uninformative comments such as "That was great!" and "Possibly?!?!?!?! Lol" cause little change to the descriptor, whereas comments related to objects in the video cause a larger shift. This demonstrates that the method is able to pick out and filter the relevant information.

A.2 Training Details

The majority of experiments were conducted on a rented 4xA100-40GB GPU server costing approximately 170USD per day, over the course of three months. Image models (using batch size 128) and video models without comments (using batch size 50) could train on a single 40GB GPU. For TimeSformer models the visual branch was processed on a separate GPU (when training with CAM and batch size 50) or pair of GPUs (for finetuning on video benchmarks with batch size 128). Pretraining the adapter on images takes approximately one hour per epoch. Training the full video model with CAM takes approximately 6 hours per epoch. For the video experiments, we first train the CAM for 5 epochs with the backbone frozen, and then train the rest of the network for one epoch, with the backbone modified to have temporal attention as described in Section 3.3. We use the CAM with 5 comments, and adapt the visual branch of the model.

We use both photometric and temporal data augmentation. For photometric augmentation we employ random crops ($0.5 - 1.0$ scale), random horizontal flipping, and colour jitter (brightness, contrast, saturation, hue). For temporal augmentation, we first temporally subsample the input frames (which are often 30fps) according to a random stride selected uniformly from $(4, 8, 16, 32)$ and then choose a random 8-frame segment uniformly. We normalise inputs using the same preprocessing as Clip (ImageNet mean and standard deviation, 224×224 input size).

At evaluation time we use a temporal stride of 16 and split the video into 8-frame chunks, taking the average of the descriptors of the chunks.

We randomly mask out comments with probability 0.5. We randomly skip adding the residual from the adapter with probability 0.5, which ensures that unadapted descriptors are also used in the loss and so the backbone network can still be used without the adapter.

All retrieval experiments are GPU accelerated using the FAISS[1] library.

A.3 Video-to-Text Retrieval

We report our zero-shot Video-to-Text Retrieval evaluation results on MSVD and MSR-VTT in Table 9 and Table 10.

[1] https://github.com/facebookresearch/faiss

Figure 7: **Visualising comment saliency.** We show the title and thumbnail for three videos, and show the ranked saliency of comments when adapting using the Text branch (left) and Image branch (right). Comments mentioning topics relevant to the title or image are ranked highly, while irrelevant comments are lower.

Table 9: **MSVD** Chen & Dolan (2011) Video-to-Text retrieval.

Method	R@1	R@5	R@10	MedR
SSB (Patrick et al., 2020b)	21.4	46.2	57.7	6.0
CLIP (Portillo-Quintero et al., 2021)	59.9	85.2	90.7	1
Ours (no comments)	62.5	87.0	92.8	1
Ours (no TimeSformer)	59.1	85.1	91.0	1
Ours	61.6	87.9	93.4	1
Ours (with Kinetics)	61.3	87.0	92.4	1

Table 10: **MSRVTT** (Xu et al., 2016a) Video-to-Text retrieval.

Method	R@1	R@5	R@10	MedR
SSB (Patrick et al., 2020b)	12.7	27.5	36.2	24.0
CLIP (Portillo-Quintero et al., 2021)	27.2	51.7	62.6	5
Ours (no comments)	33.0	57.9	66.9	4
Ours (no TimeSformer)	31.8	56.9	66.7	4
Ours	33.2	58.5	68.1	3
Ours (with Kinetics)	33.0	58.3	68.2	4

A.4 DATASET DETAILS

We report additional details on the benchmark datasets used in the paper.

ActivityNet ActivityNet Fabian Caba Heilbron & Niebles (2015) is a video dataset with 200 classes, 100 videos per class and 1.5 activity instances per video. The dataset contains 648h of video. There are 10,024 training videos (15,410 instances) and 4,926 validation videos (7,654 instances). The dataset itself has no license and is provided as an annotated list of youtube links. The copyright of the individual videos remains with their creators.

MSR-VTT MSR-VTT Xu et al. (2016b) is a video dataset with 10 categories, and 10,00 clips from 7180 videos. For training we use the 6.5k video training set with 20 captions each. It is annotated with 200,000 sentences of video descriptions created by crowd workers. The dataset itself has no license and the copyright of the individual videos remains with their creators.

MSVD MSVD Chen & Dolan (2011) consists of 1200/20/670 videos for training/validation/testing. The dataset itself has no license and the copyright of the individual videos remains with their creators.

LSMDC Large Scale Movie Description Challenge (LSMDC) Rohrbach et al. (2017) consists of 118K video clips from 202 movies. We evaluate on a test set of 1,000 videos from movies disjoint from the train and val sets, as done in (Bain et al., 2021). The dataset itself has no license and the copyright of the individual videos remains with their creators and the dataset is solely to be used for research purposes.

A.5 DATASET CURATION

Table 11: **Prevalence of toxic text in the dataset.** We report the proportion of posts, titles, and comments that are flagged as having potentially offensive content by the open-source library Detoxify. We use a threshold of 0.9.

Detoxify label	% titles	% comments
toxicity	2.32	5.62
severe toxicity	0.00	0.00
obscenity	1.23	3.73
identity attack	0.00	0.00
insult	0.82	1.95
threat	0.05	0.07
sexually explicit	0.09	0.22

Table 12: **Bootstrapping confidence interval estimates**. Showing mean and 95% confidence intervals obtained by bootstrapping with 80% of the test sets. Recall in units of percentage points. Using models trained on RedditVC and finetuned on the respective benchmark training sets.

Method	R@1	R@5	R@10	MedR
MSR-VTT	42.6±1.5	70.0±0.9	81.6±0.7	2.0±0.0
MSVD	48.5±1.1	79.2±0.7	87.5±0.6	2.0±0.0

We use the GPU implementation of the FAISS similarity search toolkit (Johnson et al., 2017) to efficiently deduplicate the dataset by indexing the video thumbnail embeddings obtained from a ResNet18. These indices are then used to discard video entries with a high similarity to other posts.

A.6 CONFIDENCE INTERVALS

We report the mean retrieval results in Table 13 and the confidence intervals of the best two image models from the ablation study (Table 1, main paper), namely the models adapting the visual branch, with and without finetuning the backbone. These are computed across five independent training runs with different random seeds. Since training the video model takes a considerable amount of time, we estimate the variance of our method through bootstrapping the validation dataset. We generate 5 validation datasets with 80% of the full size by sampling with replacement and use the quantitative results to estimate the standard deviation, reported in Table 12.

Table 13: Mean recall performance and 95th percentile confidence intervals across five experiments trained with different random seeds for the best two models from Table 1 in the main paper.

Finetune Backbone	**Train. CAM**	**Eval. CAM**	**Text → Video**		**Video → Text**	
			R@1	**R@10**	**R@1**	**R@10**
✗	g_v	g_v	2.65±0.09	12.03±0.14	2.79±0.16	12.33±0.10
✓	g_v	g_v	2.95±0.10	13.08±0.12	2.91±0.12	12.94±0.13