Lightweight Attentional Feature Fusion for Video Retrieval by Text

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Abstract

In this paper we revisit feature fusion, an old-fashioned topic, in the new context of video retrieval by text. Different from previous research that considers feature fusion only at one end, let it be video or text, we aim for feature fusion for both ends within a unified framework. We hypothesize that optimizing the convex combination of the features is preferred to modeling their correlations by computationally heavy multi-head self attention. Accordingly, we propose Lightweight Attentional Feature Fusion (LAFF). LAFF performs feature fusion at both early and late stages and at both video and text ends, making it a powerful method for exploiting diverse (off-the-shelf) features. Extensive experiments on four public datasets, i.e. MSR-VTT, MSVD, TGIF, VATEX, and the large-scale TRECVID AVS benchmark evaluations (2016-2020) show the viability of LAFF. Moreover, LAFF is extremely simple to implement, making it appealing for real-world deployment.

1. Introduction

This paper attacks the challenging task of video retrieval by text, i.e. retrieving videos w.r.t. to an ad-hoc textual query from a large collection of unlabeled videos. Both video and text have to be embedded into a cross-modal common space for text-to-video matching. The state-of-the-art addresses the task in multiple aspects, including novel networks for query representation learning [53], multi-modal Transformers for video representation learning [16], hybrid space learning for interpretable cross-modal matching [11], and more recently the CLIP series [14, 30, 39] which perform end-to-end cross-modal similarity learning and obtain the state-of-the-art performance on multiple datasets.

Differently, we look into feature fusion, an important yet largely underexplored topic for text-to-video retrieval.

Feature fusion is not new by itself. In fact, the topic has been extensively studied in varied contexts such as semantic video analysis [42] and multi-view image classification [52]. These earlier efforts focus on combining hand-crafted features, because such kinds of features are known to be domain-specific, suffering from the semantic gap problem [40], and thus insufficient for content representation when used alone. While current deep learning features are already more powerful than their predecessors, no single feature appears to rule all. Dark knowledge about objects and scenes is better carried in pre-trained 2D convolutional neural networks (2D-CNNs) [39], while 3D-CNNs are more suited for representing actions and motions [17]. For text-to-video retrieval, CE [29] and its follow-ups [12,16] show the benefit of combining diverse deep video features, while [23, 26] show the potential of combining distinct text features for better query representation. Even in the era of deep learning, the need for feature fusion remains strong.

Concerning approaches to feature fusion, vector concatenation is commonly used when combining features at an early stage [11, 23]. As for late fusion, multiple features-specific common spaces are learned in parallel, with the resultant similarities combined either by averaging [26] or by Mixture of Experts ensembles [29]. As the number of features grows, vector concatenation suffers naturally from the curse of dimensionality, while constructing common spaces per feature lacks inter-feature interactions. Moreover, the prior works focus either on the video end or on the text end. To the best of our knowledge, no attempt is made to develop a unified learning-based approach that works for both ends.

One might consider feature fusion by Multi-head Self-Attention (MHSA), the cornerstone of Transformers [46]. As Fig. 1a shows, MHSA transforms a specific feature by blending it with information from all other features, with the blending weights produced by a self-attention mechanism termed QKV. Despite its high prevalence in varied contexts, we argue that MHSA might be suboptimal for the current task. Note that the module was initially developed for NLP tasks, for which exploiting element-wise correlations is crucial for resolving semantic ambiguity. However, as video features extracted by distinct 2D-CNNs and 3D-CNNs are meant for describing the video content from different as-
pects, we conjecture that optimizing their combination is a succinct and effective method of modeling their correlations. Following this thought, we propose in this paper a much simplified feature fusion block, termed Lightweight Attention Feature Fusion (LAFF), see Fig. 1c.

LAFF is generic, working for both video and text ends. Video/text features are combined in a convex manner in a specific LAFF block, with the combination weights learned to optimize cross-modal text-to-video matching. Performing fusion at the feature level, LAFF can thus be viewed as an early fusion method. Meanwhile, with the multi-head trick as used in MHSA, multiple LAFFs can be deployed within a single network, with their resultant similarities combined in a late fusion manner. The ability to perform feature fusion at both early and late stages and at both video and text ends makes LAFF a powerful method for exploiting diverse (off-the-shelf) features for text-to-video retrieval. In sum, our main contributions are as follows.

- We are the first to study both video-end and text-end feature fusion for text-to-video retrieval. Given the increasing availability of deep visual / language models for feature extraction, this paper opens up promising avenues for exploiting such dark knowledge for improving text-to-video retrieval.
- We propose LAFF, a lightweight feature fusion block, capable of performing feature fusion at both early and late stages. Compared to MHSA, LAFF is much more compact yet more effective for feature fusion.
- Experiments on five leading benchmarks, i.e. MSR-VTT, MSVD, TGIF, VATEX and TRECVID AVS

2. Related Work

Feature fusion for text-to-video retrieval is less studied, targeted either at the video end or at the text end.

For video-end feature fusion, earlier works often simply use vector concatenation to merge multiple features in advance to cross-modal representation learning [10]. CE [29] is among the first to exploit a learning based method, where seven diverse features are combined by Mixture of Experts (MoE) ensembles. MMT [16] develops multi-modal Transformers to aggregate features from the frame level to the video level, and again uses MoE for combining similarities derived from different feature spaces. Both CE [29] and MMT [16] use a single text feature, leaving text-end feature fusion untouched.

As for text-end feature fusion, W2VV++ [23] takes an early fusion approach, combining the output of three text encoders, i.e. bag-of-words, word2vec and GRU, by vector concatenation. By contrast, SEA [26] opts for late fusion, first building a common space per text feature and then averaging the similarities computed within the individual spaces. Different from the prior art, we consider feature fusion for both ends within a unified framework.

The attentional layer of LAFF is common, as has been used in [2] for aggregating region-level visual features for vision-to-language tasks and in [19] for attention-based multiple instance learning. However, different from [2]
3. Proposed Method

We propose end-to-end feature fusion for both video and text ends. In particular, suppose we have a specific video \( x \) represented by a number of \( k_1 \) video-level features \( \{ f_{v,1}(x), \ldots, f_{v,k_1}(x) \} \), and a specific textual query \( q \) represented by a set of \( k_2 \) sentence-level features \( \{ f_{t,1}(q), \ldots, f_{t,k_2}(q) \} \). We shall construct two feature fusion blocks to encode respectively the video and the query into their \( d \)-dimensional cross-modal embeddings \( e(x) \) and \( e(q) \) so that their semantic similarity \( s(x, q) \) can be effectively measured in terms of the two embeddings, i.e.

\[
\begin{align*}
e(x) & := \text{fusion}_v(\{ f_{v,1}(x), \ldots, f_{v,k_1}(x) \}), \\
e(q) & := \text{fusion}_t(\{ f_{t,1}(q), \ldots, f_{t,k_2}(q) \}), \\
s(x, q) & := \text{similarity}(e(x), e(q)).
\end{align*}
\]

As a consequence, text-to-video retrieval for the given query \( q \) is achieved by sorting all videos in a test collection in light of their \( s(x, q) \) in descending order.

In what follows, we describe the proposed Lightweight Attentional Feature Fusion (LAFF) as a unified implementation of the fusion blocks in Eq. (1), followed by its detailed usage for text-to-video retrieval.

3.1. The LAFF Block

Our design of LAFF is conceptually inspired by attention-based multiple instance learning (MIL) [19], wherein there is a need of aggregating multiple instance-level features into a case-level feature. However, our task differs from MIL in the following two aspects, making the attention-based MIL not directly applicable in the new context. First, instances in a MIL setting are of the same modality, e.g. patches taken from the same image, so the instance-level features are homogeneous and directly comparable. By contrast, the video or text features to be fused are obtained by distinct feature extractors with varied feature dimensions and are thus incompatible. Hence, LAFF shall have a feature transformation layer that rectifies the diverse features to be of the same size. Second, MIL is typically exploited in the context of a classification task, so the case-level feature is used as input to a classification layer. By contrast, our fused feature is meant for cross-modal matching. Hence, a LAFF (in charge of the video feature fusion) shall be used in pair with another LAFF (fully responsible for the text feature fusion).

Without loss of generality, we have a set of \( k \) different features \( \{ f_1, \ldots, f_k \} \), sized as \( d_1, \ldots, d_k \), respectively. We use the following transformation layer to convert the \( i \)-th...
feature to a new $d$-dimensional feature:

$$f'_i = \sigma(Linear_{d_i \times d}(f_i)),$$

where $\sigma$ is a nonlinear activation function, which is $\tanh$ in this work, to increase the learning capacity of the transformer layer. The notation of $\text{Linear}_{d_i \times d}$ indicates a fully connected layer with an input of size $d_i$ and an output of size of $d$. Each input feature has its own $\text{Linear}$. Besides, if $d = d_i$, the $\text{Linear}$ is optional.

Although the transformed features $\{f'_i\}$ are now comparable, they are not equally important for representing the video / text content. We thus consider a weighted fusion, i.e.

$$\bar{f} = \sum_{i} a_i f'_i,$$

with weights $\{a_1, \ldots, a_k\}$ computed by a lightweight attentional layer as follow,

$$\{a_1, \ldots, a_k\} = softmax(\text{Linear}_{d \times 1}(\{f'_1, \ldots, f'_k\})).$$

We can see that the Attention-free feature fusion block, as shown in Fig. 1b, is a special case of LAFF when enforcing the weights in Eq. (3) to be uniform, i.e. $a_i = \frac{1}{k}$. Compared to Attention-free, LAFF has $d$ more parameters to learn, see Tab. 1. Such a small amount of extra parameters turn out to be important for improving the effectiveness of feature fusion, as our ablation study will show shortly.

| Feature fusion block     | #Parameters |
|--------------------------|-------------|
| MHSA (single layer)      | $D \times (d + 4 \times d^2)$ |
| Attention-free           | $D \times d$ |
| LAFF                     | $D \times (d + d)$ |

Table 1. Number of parameters of the feature fusion blocks, with $D$ indicating the overall dimension of the input features and $d$ as the size of the output features.

3.2. Paired LAFFs for Text-to-Video Retrieval

3.2.1 Network Architecture

We now detail the usage of LAFF for text-to-video retrieval. A straightforward solution is to substitute LAFF for the fusion functions in Eq. (1). As such, we have a single configuration of how the video/text features are combined. However, due to the high complexity of the video and text contents, we hypothesize that the single configuration is suboptimal for cross-modal representation and matching. Borrowing the multi-head idea of MHSA, we consider multi-head LAFF. In particular, we deploy $h$ pairs of LAFFs, where each pair of LAFFs jointly determine a latent common space for video-text matching. In particular, a specific pair of LAFFs, denoted as $<\text{LAFF}_{v,i}, \text{LAFF}_{t,i}>$, aggregates the video / text features into a $d$-dimensional cross-modal embedding vector $e_i(x) / e_i(q)$, i.e.

$$\begin{cases}
    e_i(x) = \text{LAFF}_{v,i}(x) \\
    e_i(q) = \text{LAFF}_{t,i}(q) \\
    s_i(x, q) = \text{similarity}(e_i(x), e_i(q))
\end{cases}$$

where similarity is the cosine similarity widely used in the prior art [11, 48, 53].

Accordingly, we compute the final video-text similarity as the mean of the $h$ individual similarities,

$$s(x, q) = \frac{1}{h} \sum_{i=1}^{h} s_i(x, q).$$

The overall architecture is illustrated in Fig. 2. In order to make the amount of trainable parameters invariant with respect to $h$, we set $d = \frac{d_0}{h}$, where $d_0$ is a constant empirically set to 2,048. We use $h = 8$, unless otherwise stated. Hyperparameter $h$ adjustment experiments are provided Tab. 1 in the supplement.

**LAFF for multi-level feature fusion.** So far we presume the features to be fused are already at the video level. In fact, for its high flexibility, LAFF can be extended with ease to a multi-level variant to deal with the situation wherein different frame-level and video-level features co-exist. Fig. 3 shows this variant, which we term LAFF-ml.
3.2.2 Network Training

Following the good practice of the previous work, we adopt as our base loss function the triplet ranking loss with hard-negative mining [13]. For a specific sentence \( q \) in a given training batch, let \( x_+ \) and \( x_- \) be videos relevant and irrelevant w.r.t. \( q \), and \( x^* \) be the hard negative that violates the ranking constraint the most. We have

\[
\begin{align*}
    x^* &= \arg\max_{x_-} (s(x_-, q) - s(x_+, q)) \\
    \text{loss}(q) &= \max(0, \alpha + s(x^*, q) - s(x_+, q)),
\end{align*}
\]

where \( \alpha \) is a positive hyper-parameter controlling the margin of the ranking loss.

As pointed out by SEA [26], when training a cross-modal network that produces multiple similarities, combining losses per similarity gives better results than using a single loss with the combined similarity. Hence, we follow this strategy, computing \( \text{loss}_i(q) \), namely the loss in the \( i \)-th space by substituting \( s_i \) for \( s \) in Eq. (7). The network is trained to minimize a combined loss \( \sum_{i=1}^{h} \text{loss}_i(q) \).

4. Experiments

In order to evaluate the effectiveness of the proposed LAFF block for fusing diverse video and text features for text-to-video retrieval, we conduct a series of experiments. In particular, an ablation study is performed on MSR-VTT, a de facto benchmark, to evaluate LAFF in multiple aspects. We then compare our LAFF-based retrieval model with the state-of-the-art on MSR-VTT and three other popular benchmarks including MSVD, TGIF and VATEX. In order to assess the proposed method for retrieval on a much larger collection, a post-competition evaluation is conducted on the TRECVID AVS benchmark series.

Before we proceed further, we describe common setups: features, implementation details and evaluation criteria.

4.1. Common Setups

Implementation Details. Eight video features and five text features are used, see Tab. 2.

The margin parameter \( \alpha \) in the loss is set to 0.2 according to VSE++ [13]. We perform SGD based training, with a mini-batch size of 128 and RMSProp as the optimizer. The learning rate is initially set to \( 10^{-5} \), decayed by a factor of 0.99 per epoch. Following [20], we half the learning rate if the validation performance does not increase in three consecutive epochs. Early stop occurs when no validation performance does not increase in three consecutive epochs. Following [20], we half the learning rate if the validation performance does not increase in three consecutive epochs.

The dropout rate of the Linear layers is set to 0.2. All experiments are done with PyTorch (1.7.1) [36] on an Nvidia GeForce GTX 2080Ti GPU.

Evaluation Criteria. We report three standard rank-based metrics: Recall at Rank N (R@N, N=1, 5, 10), Mean Average Precision (mAP), and median rank (Med r), and mean Average Precision (mAP) for assessing the overall ranking quality.

4.2. Ablation Study

Our ablation study is conducted on MSR-VTT [51], which has 10k videos in total, each associated with 20 captions. We adopt the official data split: 6,513 videos for training, 497 videos for validation and the remaining 2,990 images for test. In order to distinguish this data split from other customized splits, e.g. JSFusion [55], we term the split MSR-VTT-test3k.

4.2.1 On Combining Diverse Video / Text Features

We investigate how LAFF responds when diverse video/text features are gradually added. For the ease of lateral comparison, we include as baselines the following two models: W2VV++ [23], which simply uses vector concatenation, and SEA [26] which learns cross-modal similarities per text feature.

Given the many video and text features investigated in this work, a complete enumeration of video-text feature combinations is impractical. Therefore, we choose a small subset of features to study, namely a combination of two video and two text features.

Table 2. Video and text features used in our experiments. For visual features originally extracted at frame or segment level, mean pooling is applied to obtain video-level features.

| Feature | Dim. | Short description |
|---------|------|-------------------|
| Video features: |
| rs101 | 2,048 | ResNeXt-101 trained on the full set of ImageNet [33]. |
| re152 | 2,048 | ResNet-152 from the MXNet model zoo. |
| wsl | 2,048 | ResNeXt-101 pre-trained by weakly supervised learning on 940 million public images, followed by fine-tuning on ImageNet1k [31]. |
| clip | 512 | CLIP (ViT-B/32) pre-trained on web images and corpus by contrastive learning [39]. |
| c3d | 2,048 | C3D trained on Kinetics400 [43]. |
| irscn | 2,048 | irCSN-152 which trained by weakly supervised learning on IG-65M [17]. |
| tf | 768 | TimeSformer trained on HowTo100M [5]. |
| x3d | 2,048 | X3D trained on Kinetics400 [15]. |
| Text features: |
| bow | \( m \) | \( m \)-dimensional Bag-of-words feature, with \( m \) being 7,675 (MSR-VTT-test3k), 2,916 (MSVD), 3,980 (TF-IDF), or 10,312 (VATEX). |
| w2v | 500 | Word2Vec trained on Flickr tags [10]. |
| gru | 1,024 | Mean pooling over hidden vectors of GRU trained from scratch [10]. |
| bert | 768 | The base version of BERT, pre-trained on BooksCorpus and English Wikipedia [9]. |
| clip | 512 | The same CLIP as used to extract video features. |

Table 2. Video and text features used in our experiments. For visual features originally extracted at frame or segment level, mean pooling is applied to obtain video-level features.
combinations is impractical. We choose to reduce the computation by only varying the features at one end, with features at the other end fixed. Fig. 4a shows the performance curves of W2VV++, SEA and LAFF with respect to (a) text feature fusion and (b) video feature fusion, respectively. LAFF is both effective and stable for fusing diverse features. Dataset: MSR-VTT-test3k.

4.2.2 Comparing Feature Fusion Blocks

We compare the three feature fusion blocks by replacing LAFF in Fig. 2 with MHSA and Attention-free, respectively. Moreover, we include as a baseline method that uses the simple feature concatenation strategy, as previously adopted in W2VV++ [23]. The performance of text-to-video retrieval with specific feature fusion blocks is reported in Tab. 3.

LAFF performs the best, followed by Attention-free, the concatenation baseline and MHSA. Attention-free, while being extremely simple, is more effective than MHSA for combining the increasing amounts of text features, with its mAP increases from 0.264, 0.321 to 0.326. The superior performance of LAFF against Attention-free (0.358 versus 0.326) justifies the necessity of the attentional layer.

4.2.3 LAFF Weights for Model Interpretability and Feature Selection

Fig. 5 visualizes the LAFF weights of videos and their associated captions selected from the MSR-VTT test set. We observe that 3D-CNN features receive more weight when the video content contains more motions. For each feature, its weight averaged over samples reflects its contribution to the retrieval performance. The weights of text features in descending order are bow (66.4%), clip (11.6%), gru (9.5%), w2v (7.4%), bert (5.0%). For video features, the order is clip (38.0%), x3d (16.8%), ircsn (13.3%), tf (10.9%), rx101 (7.0%), wsl (6.6%), c3d (5.1%), re152 (1.4%). We re-train our model with the top-3 ranked video / text features. Compared to the full setup (mAP of 0.358), the reduced model obtains mAP of 0.353, meaning a relatively small performance loss of 1.4%. Hence, the LAFF weights are helpful for feature selection.

4.2.4 Combined Loss versus Single Loss

As Tab. 4 shows, LAFF trained with the combined loss produces a relative improvement of over 10% in terms of mAP, when compared to its single-loss counterpart.

| Fusion block | R1  | R5  | R10 | Med r | mAP   |
|-------------|-----|-----|-----|-------|-------|
| Text features: \{bow, w2v, gru\} | | | | | |
| Baseline | 14.0 | 35.9 | 47.7 | 12 | 0.249 |
| MHSA | 11.7 | 31.9 | 43.4 | 15 | 0.219 (12.0%↑) |
| Attention-free | 15.4 | 37.8 | 49.7 | 11 | 0.264 (6.0%↑) |
| LAFF | 16.0 | 39.5 | 51.4 | 10 | 0.276 (10.8%↑) |

| Loss | R1  | R5  | R10 | Med r | mAP   |
|-----|-----|-----|-----|-------|-------|
| Text features: \{bow, w2v, clip\} | | | | | |
| Single | 16.0 | 39.5 | 51.4 | 10 | 0.276 (10.4%↑) |
| Combined | 23.7 | 49.1 | 60.6 | 6 | 0.358 (10.5%↑) |

Table 3. Performance of the three feature fusion blocks, i.e. MHSA, Attention-free, and LAFF. The simple feature concatenation previously used in W2VV++ is taken as a baseline. Numbers in parentheses are relative improvements (%) against this baseline. Video features: all features. Dataset: MSR-VTT-test3k.
Table 5. Comparison with the state-of-the-art on four benchmark datasets, i.e. MSR-VTT (with two different data splits: MSR-VTT-test3k and MSR-VTT-test1k), MSVD, TGIF and VATEX. Numbers are cited from the original papers wherever applicable. Our proposed LAFF performs the best on all the four benchmarks. The Med r score is provided in Tab. 2 the supplement.

4.3. Comparison with State-of-the-Art

4.3.1 Experiments on video description datasets

Datasets. Besides MSR-VTT, we include MSVD [7], TGIF [27] and VATEX [47]. For MSVD and TGIF, we follow their official data splits. For VATEX, we follow the data split as used in HGR [8]. As for MSR-VTT, in addition to the official MSR-VTT-test3k split, we also report performance on another popular data split by JSFusion [55], which uses 9,000 videos for training and 1,000 for test. We term this split MSR-VTT-test1k.

Baselines. We compare with the state-of-the-arts that use the same data splits as we have mentioned. In particular, the following eleven published models are included for comparison: W2VV++ [23], Collaborative Experts (CE) [29], Tree-augmented Cross-modal Encoding (TCE) [53], Hierarchical Graph Reasoning (HGR) [8], Sentence Encoder Assembly (SEA) [26], Multi-Modal Transformers (MMT) [16], Dual Encoding (DE) [11], Support-Set Bottlenecks (SSB) [37], Self-Supervised Multi-modal Learning (SSML) [1], CLIP [38] and CLIP with Feature Re-Learning (CLIP-FRL) [6]. Furthermore, we fine-tune the CLIP, termed CLIP-FT. After this, we retrain W2VV++ and SEA with the same features as ours and apply LAFF-ml to substitute for the mean pooling mechanism on the frame-level feature. In addition, we also compare with CLIP2Video [14], a state-of-the-art on Arxiv, which open-sourced pre-trained models.
Specifically, according to the rank by the weight in the ablation study, we use the top four features on text-end (i.e., bow, clip, w2v and gru) and video-end (i.e., clip, x3d, icsn and tf) respectively. Noted that, for the sake of improved performance, we use CLIP-FT which fine-tuned on targeted training datasets to substitute for clip feature, denoted as clip-ft feature. Due to the restriction of CLIP2Video architecture, we can only obtain the global video and text features generated by CLIP2Video, which we use to substitute for text and video-level clip feature for comparison with CLIP2Video.

**Results.** The performance of the different models on the multiple benchmarks is summarized in Tab. 5. The proposed LAFF consistently performs the best on all the test sets. Note that the video/text features used in specific models vary. So for a head-to-head comparison, we re-train W2VV++ and SEA with the same features as ours. Other baselines are not re-run in this setting, because they cannot handle the diverse video and text features without having their architectures re-designed. While both W2VV++ and SEA improve by taking more features into account, the two baselines are not on par with LAFF. LAFF-ml outperforms SEA improve by taking more features into account, the two baselines are not on par with LAFF. LAFF-ml outperforms SEA improve by taking more features into account, the two baselines are not on par with LAFF-ml. LAFF gains a superior performance than CLIP2Video after re-fusing the CLIP2Video features. This indicates that LAFF can indeed obtain better performance by fusing the feature which has excellent performance.

We further compare LAFF and LAFF-ml with W2VV++ and SEA in a cross-dataset setting, wherein a model previously trained on a specific dataset, say MSVD, is now re-evaluated on the test sets of the other three benchmarks, i.e. MSR-VTT, TGIF and VATEX. Tab. 6 shows the averaged cross-dataset performance, measured in terms of mAP. LAFF and LAFF-ml is again consistently better than the two strong baselines, showing its better generalizability.

| Training | Average cross-dataset performance (mAP) |
|----------|----------------------------------------|
|          | MSR-VTT | MSVD | TGIF | VATEX |
| W2VV++   | 0.425   | 0.384| 0.451| 0.451 |
| SEA      | 0.391   | 0.309| 0.397| 0.433 |
| LAFF     | 0.489   | 0.431| 0.496| 0.501 |
| LAFF-ml  | 0.497   | 0.436| 0.504| 0.511 |

Table 6. Cross-dataset performance. All the models are trained given the same video and text features. Performance metric: mAP.

**4.3.2 Experiments on TRECVID AVS 2016-2020**

**Datasets.** The test collection for TRECVID AVS 2016-2018 (i.e. TV16, TV17, TV18) is IACC.3 [35] which contains 4,593 Internet Archive videos (144 GB, 600 hours) with mean duration of almost 7.8 min and 335,944 video segments totally. The test collection for TRECVID AVS 2019–2020 (i.e. TV19, TV20) is V3C1 [4] which contains 7475 videos (1.3 TB, 1000 total hours) with a mean video duration of 8 min and a total of 1,082,659 video segments.

**Performance metric.** We use the official metric, i.e. inferred average precision (infAP) [54].

**Baselines.** Due to the prominent performance of CLIP-FT and CLIP2Video as shown in Sec. 4.3.1, we again compare with the two models. Since the top-3 ranked solutions of the AVS evaluation naturally reflect the state-of-the-art, we include them as well.

Recall that CLIP2Video was trained on the MSR-VTT-test1k split. So for a fair comparison, we train LAFF and CLIP-FT on the same split.

![Table 7. State-of-the-art on TRECVID.](image)

**Results.** As shown in Tab. 7, LAFF performs the best on TV16–TV19. Note that the top performer of TV20 was trained on the joint set of MSR-VTT, TGIF and VATEX. Re-training LAFF on this larger dataset results in infAP of 0.358, marginally better than the top performer.

Furthermore, we conduct a case study on TV20, which shows that LAFF outperforms the CLIP series for action related queries with a large margin, see Tab. 3 of the supplementary materials. We attribute this result to the fact that LAFF integrates 3D-CNN features (icsn, x3d and tf), which were designed to capture action and motion information in the video content.

**5. Conclusions**

For video retrieval by text, we have presented LAFF as a new feature fusion block. Experiments on five benchmark sets support our conclusions as follows. LAFF is more effective than Multi-head Self-Attention, yet with much fewer parameters. Moreover, the attentional weights produced by LAFF can be used to explain the contribution of the individual video features for representing the video content and that of the individual text features for query representation. Consequently, the weights can be used to select fewer features for building a more compact video retrieval model.
With the multi-head multi-level LAFFs, our video retrieval model surpasses the state-of-the-art on four public video description datasets and TRECVID AVS 2016-2020. Given the increasing availability of (deep) video/text features, this research opens up a promising avenue for further research.

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