Query-controllable Video Summarization

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ABSTRACT
When video collections become huge, how to explore both within and across videos efficiently is challenging. Video summarization is one of the ways to tackle this issue. Traditional summarization approaches limit the effectiveness of video exploration because they only generate one fixed video summary for a given input video independent of the information need of the user. In this work, we introduce a method which takes a text-based query as input and generates a video summary corresponding to it. We do so by modeling video summarization as a supervised learning problem and propose an end-to-end deep learning-based method for query-controllable video summarization to generate a query-dependent video summary. Our proposed method consists of a video summary controller, video summary generator, and video summary output module. To foster the research of query-controllable video summarization and conduct our experiments, we introduce a dataset that contains frame-based relevance score labels. Based on our experimental result, it shows that the text-based query helps control the video summary. It also shows the text-based query improves our model performance. https://github.com/JhhuangKay/Query-controllable-Video-Summation.

CCS CONCEPTS
• Computing methodologies → Artificial intelligence; Video summarization.

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1 INTRODUCTION
Video data is now ubiquitous in our daily life. Most of the raw videos are too long and are containing redundant content. As a consequence, the amount of video data people have to watch is overwhelming. This raises new challenges in efficiently exploring both within and across videos. Video summarization helps people explore a video efficiently by capturing the essence of the video. Learning what is essential depends on the information need of the user. Yet, traditional video summarization methods, such as [3, 4, 7, 17, 20, 27, 36, 40], generate one fixed video summary for a given input video. Hence, they either create a video capturing all possible information needs and therefore yield limited reduction in time, or they lose essential information for specific needs. Having a fixed summary limits the effectiveness of video exploration.

To make the video exploration more effective and efficient, we will need a new specialized method that, steered by the information need of the user, is capable of generating various video summaries for a given video. We call this query-controllable video summarization. There are two main features of query-controllable video summarization which complicate this task when compared to the well-studied domain of conventional video summarization. One example is that query-controllable video summarization has a text-based query input and a video input, where the conventional video summarization only has a video input. So, in query-controllable video summarization, we need to model the implicit relations or interactions between the input query and video. Evaluating the generated video summaries is another challenge. Previously, researchers usually conduct human expert evaluation based on predefined rules or showing human experts two different video summaries and asking them to select the better one [20, 25, 28]. Human expert-based evaluation methods for this task are problematic, as these methods are expensive and time-consuming because they rely on the judgments of humans for each evaluation [7]. In this paper, we prefer to conduct automatic evaluation which is more efficient.

There are different solutions to model the video summarization problem, both supervised [6–8, 21, 32, 41–43, 45, 47] and unsupervised [3, 4, 17, 20, 22, 23, 26, 27, 29–31, 46]. For the automatic
videos. Our experimental result shows that the text-based input query improves the performance of our summarization methods and different datasets. We first discuss the two main types of deep model, +

In this section, we discuss related work in terms of different methods and different datasets. We first discuss the two main types of approaches for query-controllable video summarization. [3, 4, 17, 20, 22, 25–27, 29–31, 36, 37, 46], usually exploit hand-crafted heuristics to satisfy some properties, such as interestingness, representativeness, and diversity. In [4], the authors propose a method, based on color feature extraction from video frames and k-means clustering. The authors of [3] observe that the key visual concepts usually appear repeatedly across videos with the same topic. So, they propose to create a summarized video by finding shots that co-occur most frequently across videos. They develop a Maximal Biclique Finding (MBF) algorithm to find sparsely co-occurring patterns. In [17], the authors introduce a space-time video summarization method to extract the visually informative space-time portions of input videos and analyze the distribution of the spatial and temporal information in a video, simultaneously. The authors of [20] present a video summarization method for egocentric camera data. They develop region cues, e.g., the nearness to hands, gaze, and frequency of occurrence, in egocentric video and learn a model to predict the relative importance of a new region based on these cues. The authors of [25] present a video summarization method to discover the story of a given egocentric video. Their proposed method is capable of selecting a short chain of sub shots of video which depicting the essential events. In [26], based on the modeling of the viewer's attention, the authors propose a generic framework of video summarization. The framework, without the fully semantic content understanding of a given video, eliminates the needs of complicated heuristic rules in video summarization task and takes advantage of computational attention models. In [27], the authors introduce a unified method for video summarization based on the analysis of structures and highlights of the video. Their approach emphasizes the content balance and perceptual quality of a video summary at the same time. They also incorporate a normalized cut algorithm to partition a video into clusters and a motion attention model based on human perception to compute the perceptual quality of clusters and shots. The authors of [29] develop a new method to extract a video summary that captures important particularities arising in a given video and generalities identified from a set of given videos simultaneously. The authors of [46] introduce a method to learn a dictionary from the given video using group sparse coding. A video summary is then generated by combining segments that cannot be reconstructed sparsely using the dictionary. In [31], the authors propose a new formulation to perform video summarization from unpaired data. Their model aims to learn mapping, from a set of raw videos to a set of video summaries, such that the distribution of the generated video summary is similar to the distribution of the set of video summaries with the help of an adversarial objective. Also, they enforce a diversity constraint on the mapping to ensure the generated video summaries are diverse enough visually. In [47], the authors introduce an end-to-end reinforcement learning-based framework to train their video summarization model. The framework incorporates a new reward function to jointly account for diversity and representativeness of generated video summaries. The design of the reward function makes it not rely on user interactions or labels at all. The authors of [37] propose a more optimization-based method with a specific objective for query-adaptive video

To build a query-controllable system for videos, using multiple information sources requires dedicated datasets and evaluation methods. We undertake such a study in this work. Starting from an existing dataset [37], we establish a new video dataset on which to build our models. With such a dataset in place, it is the right time to research how to exploit deep learning-based models with textual query inputs which are to steer the output.

As mentioned above, our proposed model takes a text-based query and video as input, so how to effectively fuse the multi-modal features with minimum loss of information is one of the technical problems. It has been shown that, in similar multi-modal contexts, the performance of models can decrease if feature fusion methods are improper; how to solve this issue, in general, remains an open question [2, 5]. So, we not only conduct experiments to see how the input query affects our model performance, but also conduct experiments to see how the commonly used feature fusion methods affect our model performance. To foster the research community of video summarization, we intend to publish the dataset and code.

We demonstrate experimental results of the proposed end-to-end deep model and show that our proposed method is capable of creating query-dependent and controllable video summaries for given videos. Our experimental result shows that the text-based input query helps control the video summary. It also shows that the text-based input query improves the performance of our summarization model, +5.83% in the sense of accuracy.

Contributions.

- We propose a new end-to-end deep learning based model for a text-visual embedding space for query-controllable video summarization.
- We conduct detailed experiments to show that the text-based query not only helps control the video summary but also improves the performance of the proposed end-to-end model.
- We introduce a query-video pair based dataset, based on the dataset proposed in [37], for a query-controllable video summarization task. The dataset contains 190 videos and corresponding frame-based relevance score annotations.

2 RELATED WORK

In this section, we discuss related work in terms of different methods and different datasets. We first discuss the two main types of evaluation, in this paper, we model video summarization as a supervised learning problem. Then, we propose an end-to-end deep learning based model, illustrated in Figure 1, to generate video summaries depending on the text-based input queries. To the best of our knowledge, we are the first proposing an end-to-end deep model for query-controllable video summarization. Note that a non-end-to-end method for query-controllable video summarization needs many preprocessing steps, and in practice, it will reduce the efficiency of video exploration. The model consists of a video summary controller, a video summary generator, and a video summary output module. The controller uses text, such as words, phrases, or sentences, to describe the desired video summary. Then, the generator creates a video summary based on the implicit relationship between the text-based description and the input video. The video summary output module then outputs a video summary based on a relevance score prediction vector.

To generate a video summary, the controller takes a textual query as input. The controller uses a language model to generate a summary relevance score prediction vector. The video summary generator then outputs a video summary based on a relevance score prediction vector.
summarization. Since the method is not end-to-end, it will need many preprocessing steps before generating a video summary. So, in practice, it is inconvenient and not efficient for video exploration. This motivates us to propose an end-to-end deep learning based method. Although many existing works model video summarization task as an unsupervised problem and propose their methods to tackle it, in general, the performance of the unsupervised approach is worse than the supervised one.

2.2 Supervised Video Summarization

The other type of approach for video summarization task is supervised, [6–8, 21, 32, 33, 41–45, 47]. The learning of these methods is supervised by human expert labeled data, i.e., ground truth video summaries. The authors of [6] treat video summarization as a supervised subset selection task. They propose a probabilistic model for selecting a diverse sequential subset, called the sequential determinantal point process (SeqDPP). Note that the standard DPP treats video frames as randomly permutable elements. The SeqDPP heeds the inherent sequential structures in video data, so it not only overcomes the deficiency of the standard DPP, but also retains the power of modeling diverse subsets, which is essential for video summarization. The authors of [7] introduce a novel video summarization method and focus on user videos containing a set of interesting events. The method starts by segmenting a given video based on a superframe segmentation, tailored to raw videos. Then, according to the estimation score of visual interestingness per superframe, by using a set of low-level, mid-level, and high-level features, the method picks an optimal subset of superframes to generate a video summary. In [8], the authors propose a new model to learn the importance score of global characteristics of a video summary. The models, jointly optimized for multiple objectives, is capable of generating high-quality video summaries. In [21], the authors introduce a new probabilistic model, built upon SeqDPP, to tackle video summarization problem. The period of a video segment, where the local diversity is imposed, can be dynamically controlled by the model. To get a well-trained summarization model, the authors develop a reinforcement learning algorithm to train the proposed model. The authors of [32] formulate video summarization as a sequence labeling problem. They propose a convolutional sequence models to tackle the video summarization task. First, they establish a novel connection between video summarization and semantic segmentation. Second, the adapted popular semantic segmentation networks are used to generate video summaries. In [33], the authors propose an improved sequential determinantal point process (SeqDPP) model. In terms of modeling, a new probabilistic distribution is designed to make, when it is integrated into SeqDPP, the resulting model accepts the input of a user, about the intended length of the video summary. In terms of learning, a large-margin algorithm is proposed to address the problem of exposure bias in SeqDPP. In [41], the authors propose a subset selection method that leverages supervision in the form of human-created video summaries to perform keyframe-based video summarization. The main idea of this method is nonparametrically transferring structures of summaries from annotated videos to unseen testing videos. Also, the authors generalize the proposed method to sub-shot-based video summarization. The authors of [42] cast a video summarization task as a structured prediction problem on sequential data. Then, they propose a new supervised learning technique, incorporating Long Short-Term Memory (LSTM), to model the variable-range dependencies entailed in the task. Also, they exploit domain adaptation techniques, based on the auxiliary annotated video datasets, to improve the quality of the video summary. In [43], the authors propose a sequence-to-sequence learning model to tackle the video summarization problem. To complement the discriminative losses with another loss, such as measuring whether the generated video summary preserves the same information as the original video, they propose to augment standard sequence learning models with a retrospective encoder that embeds the predicted video summary into an abstract semantic space. Then, the embedding is compared to the original video’s embedding in the same space. The authors of [45] introduce a novel dilated temporal relational generative adversarial network (DTR-GAN) to tackle the frame-based video summarization. DTR-GAN exploits an adversarial manner with a three-player loss to learn a dilated temporal relational generator and discriminator. The authors introduce a new dilated temporal relational unit to enhance the capturing of temporal representation, and then the generator creates keyframes based on the unit. The Supervised methods are capable of learning useful cues, which are hard to capture with hand-crafted heuristics, from ground truth video summaries. So, they usually outperform the unsupervised models. That is the reason why we prefer to model video summarization as a supervised learning problem in this paper.

2.3 Video Summarization Dataset Comparison

In this section, we briefly introduce a commonly used video summarization dataset, [7, 36], and do some comparison with the dataset used in this paper. To tackle the video summarization task, the authors of [36] propose a dataset, named TVSum. It contains 50 videos, with 10 categories, and the corresponding shot-level importance scores obtained via crowdsourcing. The 10 categories are selected from the TRECVID Multimedia Event Detection (MED) task [35], and the 50 videos, five per category, are collected from YouTube by using the names of categories as search queries. From the search results, videos are chosen based on the following criteria: (i) the selected video should contain more than a single shot; (ii) the title of video is descriptive of the visual topic in the video; (iii) under the Creative Commons license; (iv) the duration of video is around 2 and 10 minutes. The authors exploit Amazon Mechanical Turk (AMT) to collect 1,000 responses, 20 per video, and these responses are treated as gold standard labels [7, 10–13, 15, 18, 24, 30, 38, 39]. A participant from AMT is asked to (i) read the title of video first, simulating a typical scenario of online video browsing; (ii) watch the whole video in a single take; (iii) provide an importance score to each of uniform length shots for the whole video, denoting from 1 (not important) to 5 (very important). The audio is muted to ensure the important scores are only based on visual stimuli. According to the authors’ experience, a two-second shot length is appropriate for capturing local context with good visual coherence. In [7], the authors introduce another video summarization benchmark, called SumMe, consisting of 25 videos, covering holidays, events and sports. The length of video ranges from 1 to 6 minutes and each video is summarized by 15 to 18 different people. The authors asked 19 males and 22 females to participate in making the dataset. Given a video, participants are asked to produce a video summary containing most of the important content in the video. They are allowed to watch, cut, and edit a video by using a simple
Table 1: Summary of commonly used video summarization datasets. Based on this table, we find that the proposed dataset is much larger than the other datasets, and it contains two types of input modalities including video and text. The other two video summarization dataset only contains video data, and the dataset size is not large. So, the proposed dataset is unique. Relevance scores in this work and important scores from TVSum are different, referring to “Crowd-sourced Annotation” subsection.

| Name of Dataset       | Annotation Type                  | Content            | Number of Videos | Input Modality |
|-----------------------|----------------------------------|--------------------|------------------|----------------|
| SumMe [7]             | Interval-based shot and frame-level scores | User videos        | 25               | Video          |
| TVSum [36]            | Frame-based important scores     | YouTube videos     | 50               | Video          |
| Ours based on [37]    | Frame-based relevance scores     | YouTube videos     | 190              | Video, Text    |

interface. The length of a video summary is required to range from 5% to 15% of the original video length. That is to ensure the input video is indeed summarized rather than being shortened slightly. The videos are shown randomly and the audio is muted to ensure the generated video summaries are only based on visual stimuli. Regarding the evaluation of video summarization approaches, previously, researchers conduct the human expert evaluation in one of the following ways: i) based on a set of predefined criteria, such as the degree of redundancy, counting the inclusion of predefined important content, summary duration, and so on [28]. ii) showing human experts two different video summaries and asking them to select the better one [20, 25]. The authors of [7] claim that the above human expert evaluation methods are problematic, as these methods are expensive and time-consuming because they rely on judges of human for each evaluation. For example, in [25], the evaluation of the method requires one full week of human labor. Both of the human expert evaluation methods help to tell which video summary is better than another but fail to show what a good video summary should look like. So, the authors of [7] do not exploit the above approaches. Instead, they let a set of participants create their video summaries and collect multiple video summaries for each video. The reason is that there is no true answer for correct video summarization, but rather multiple possible ways. With these human expert video summaries, they can compare any summarization method which creates an automatic video summary in a repeatable and efficient way. In [4, 18], such automatic versus human comparison has already been used successfully for keyframes. Also, the authors of [18] show that comparing automatic keyframe-based summaries to human keyframe-based selections yields ratings that are comparable to letting humans directly judge the automatic video summaries. Both TVSum and SumMe datasets allow the automatic evaluation of video summarization approaches. In this paper, we also establish a dataset, based on [37], with automatic evaluation for our query-controllable video summarization task. The proposed dataset contains 190 videos with frame-level relevance score annotations. For convenience, we summarize the above existing datasets and comparison with our dataset in Table 1.

3 DATASET INTRODUCTION AND ANALYSIS

In this section, we start to describe and analyze our proposed dataset for query-controllable video summarization in terms of types of videos, video labels, and some statistics of the dataset. Note that although the dataset from [37] partially matches our research purpose and is publicly available, we discover that the specification, such as annotations and amount of videos, of the published dataset are different from the one mentioned in [37]. Also, some parts of the published dataset are not available anymore. We base our evaluation on the dataset published in [37]. So, we will first describe the process they have used to create the dataset and from there indicate what changes needed to make it suitable for our purpose.

3.1 Setup

Since our dataset is based on [37], the rules from [37] for the dataset collection are similar. The proposed dataset consists of 190 videos and each video is retrieved based on a given text-based query. Then, according to [37], the authors use Amazon Mechanical Turk (AMT) to annotate the video frames with the labels of text-based query relevance scores. The labels in this dataset are used similarly in the MediaEval diverse social images challenge [16]. The purpose of human expert annotated labels in the proposed dataset is to automatically evaluate the methods for generating relevant and diverse video summaries. In the proposed dataset based on [37], the representative samples of queries and videos are collected based on the following procedure: The seed queries, with 22 different categories, are selected from the top YouTube queries between 2008 and 2016. Typically, since these queries are generic concepts and short, the YouTube auto-complete function is exploited to obtain more realistic and longer queries, e.g., “ariana grande focus instrumental” and “ark survival evolved dragon”. For each query, the top video result
In this subsection, we analyze the frame-based relevance score annotations obtained through the above procedure. Also, we explain how we merge these relevance score annotations for each video into one set of ground truth labels.

**Label distributions of relevance scores.** The distribution of relevance score annotations is “Very Good”: 18.65%, “Good”: 55.33%, “Not good”: 13.03% and “Bad”: 12.99%.

**Ground truth.** As mentioned in the “Video Summarization Dataset Comparison” subsection, human-based evaluation is problematic and time-consuming [7]. So, in this work, based on [37], the following approach are used for evaluation. For evaluation of the testing videos, one way is to ask human experts to watch the full video, instead of just video summaries, and access the relevance of every single part of the video. Then, their responses are considered as gold standard annotations [7, 18, 30]. The advantage of this approach is that once the annotations are obtained, experiments can be carried out indefinitely. This is desirable, especially for a computer vision system involving multiple iterations and testing. Note that, in the proposed dataset, we create a single ground truth relevance score label for each query-video pair by merging the corresponding relevance score annotations from AMT workers. Then, we base on the majority vote rule, [1, 14], to evaluate the model performance for a relevance score prediction, i.e., a predicted relevance score is correct if the majority of human annotators provided that exact score. Note that we map annotations, “Very Good” to 3, “Good” to 2, “Not Good” to 1, and “Bad” to 0. Note that, referring to 1, the relevance score in this work and the importance score from TVSum [36] are different. The relevance score in this work is to capture the relation between a given text-based query and a video frame. The important score is to capture the importance between a video frame and a final video summary of the video [36].

### 4 METHOD

#### Overview

In this section, we start to describe the proposed query-controllable video summarization method. The proposed method is composed of a video summary controller, video summary generator, and video summary output module. The summary controller takes a text-based query as input and outputs the vector representation of the query. The summary generator takes the embedded query and a video as inputs and outputs the frame-based relevance score prediction. Finally, the video summary output module will use the score prediction to generate a video summary. Figure 1 explains the above procedure.

#### 4.1 Video Summary Controller

Text-based queries are meant to represent the expected video summary content while subtly alludes its semantic relationship. Therefore, we use the following way to encode input queries and add their contribution to our proposed method. In our paper, we exploit the vector representation of the text-based input query to control the generated video summary. The main idea of our video summary controller is to generate a vector representation of an input query, based on a dictionary. In the beginning, we form a dictionary based on a bag of words which are collected from all the unique words of the training queries. Then, we encode an input query by exploiting the dictionary. After the encoding, we have a vector representation of the input query to represent the expected video summary content. To make the procedure clearer, we make a flowchart to explain the above, referring to Figure 3.

#### 4.2 Video Summary Generator

The main idea of the video summary generator is to take a vector representation of an input text-based query and a video to generate a frame-based relevance score vector. The summary generator is composed of a convolutional neural network (CNN) structure and a multi-modality features fusion module. Note that the CNN structure will be trained on our training set. Before an input video goes to the CNN structure, it is sampled at 1 fps. Then, in our case, we use ResNet-34, [9], to extract the 199 frame-based features for each input video. Note that the feature used is the visual layer one layer below the classification layer. After the features are extracted, we exploit a feature fusion module to fuse the frames-based features and the input text-based query feature. The fused feature vector will be sent to a fully connected layer for the frame-based relevance score prediction. The feature fusion module will be depicted in the following subsection. Please refer to Figure 4 for the flowchart of the above procedure. Note that we take “Cross-Entropy Loss”
as our loss function, referring to Equation 1, and Adam [19] as our optimizer. For the optimizer parameters, coefficients used for computing moving averages of gradient and its square are $\beta_1 = 0.9$ and $\beta_1 = 0.999$, respectively. The term added to the denominator to improve numerical stability is $\epsilon = 1e-8$, and the learning rate $\alpha = 1e-4$.

$$\text{Loss}(x, \text{class}) = -x[\text{class}] + \ln \sum_j \exp(x[j]),$$

where “class” denotes the ground truth class, and “x” indicates the prediction.

**Multi-modality Features Fusion Module.** One of the technical problems of our proposed method is fusing the query and frame-based features with minimum loss of information. It has been shown that, in similar multi-modal contexts, the performance of models can decrease if models are poorly designed; how to solve this issue, in general, remains an open question [2, 5]. In this work, we exploit 3 difference commonly used approaches, summation, concatenation, and element-wise multiplication, to fuse query and frame-based features.

### 4.3 Video Summary Output Module

After we get the frame-based relevance score prediction vector from the video summary generator, we pass this vector to our video summary output module. The main idea of this module is to output a video summary based on the relevance score prediction vector. In our case, we map labels, “Very Good” to 3, “Good” to 2, “Not Good” to 1, and “Bad” to 0. If a predicted relevance score is greater than or equal to 2, then we consider the corresponding frame is relevant. If a predicted relevance score is less than 2, then we consider the corresponding frame is irrelevant. Finally, we collect $k$ relevant frames in time order as our video summary. Note that $k$ is a user-defined parameter for the length of a video summary.

## 5 EXPERIMENTS AND ANALYSIS

In this section, we will evaluate our proposed end-to-end method for the query-controllable video summarization task based on the setup of the proposed dataset. We will also analyze the effectiveness of the query and methods of multi-modal features fusion.

### 5.1 Dataset preparation

To validate our proposed query-controllable video summarization method, we base on the following dataset setup to conduct our experiments. We separate the whole dataset into 60%/20%/20%, i.e., 114/38/38, for training/validation/testing, respectively. One video has one corresponding query. The maximum number of words of the query is 8. Regarding the frame size input of CNN is 128 with 3 channels, i.e., red, green, and blue. Note that we normalize each image channel by $\text{mean} = (0.4280, 0.4106, 0.3589)$ and $\text{std} = (0.2737, 0.2631, 0.2601)$. The maximum number of frames of video is 199. Similar to the video preprocessing method in [34], we make all the videos have the same number of frames, i.e., 199. We show the original number of frames of each video in Figure 2.

### 5.2 Effectiveness Analysis of Query

In this experiment, we want to know whether the text-based query will help generate a better video summary or not. So, we conduct the experiment based on two types of models, query-driven, and non-query-driven. According to Figure 5, we discover that the query-driven model, with the testing accuracy 0.6191, is better than the non-query-driven one, with the testing accuracy 0.5608. Also, based on the validation accuracy versus the number of epochs, we can see that the textual query is capable of guiding the query-driven model to perform better the non-query-driven one. However, when...
we compare the worst model, fusing features by summation, in Figure 6 to the non-query-driven model, we discover that the non-query-driven model performs better. This motivates us to conduct the other experiment about the comparison of multi-modal feature fusion methods, referring to the next subsection.

5.3 Effectiveness Analysis of Different Fusion Methods

In general, multi-modal features fusion is still an open question [2, 5]. So, we base on the commonly used methods, summation, concatenation, and the element-wise multiplication, to conduct our experiment. According to Figure 6, we can see that the model with element-wise multiplication fusion method has the best performance. If we compare the performance of the other 2 feature fusion methods to the non-query-driven model, we discover that the model with the concatenation fusion method is still better than the non-query-driven model. However, the model with the summation fusion method is worse than the non-query-driven model.

Interaction between query and video. Based on the result of Figure 5 and Figure 6, it implies that using a proper multi-modal feature fusion method is important. The reason is that the fused feature embeds the implicit interaction between video, i.e., frames, and query. If we use an improper fusion method, such as summation, the query will confuse the network in some sense. This situation also happens in [1].

5.4 Qualitative Results and Analysis

In this subsection, we show some qualitative results, illustrated in Figure 7. Note that because of the limited space, we are only able to show some frames to represent the original video and the corresponding generated video summary in time order. In Figure 7-(a), the input is a video with the query “civil war spiderman”. Based on our “Video Summary Output Module” subsection, we use “green” to indicate the relevant frame and “black” to indicate irrelevant frames. The second row in (a) represents the video frames with ground truth labels. The third row in (a) represents the video frames with predicted labels. The correct number of relevance score prediction is 94 out of 199. Note that the number of frames of the original input video is 75, so we only show the video summary frames selected from 0 to 74 in order. In Figure 7-(b), the input is another video with the query “3d movies”. We also use the same color to indicate the relevant and irrelevant frames. The second row of (b) indicates the video frames with ground truth labels. The third row in (b) represents the video frames with predicted labels. The correct number of relevance score prediction is 120 out of 199. Similar to (a), since the number of frames of the original input video is 198, so we only show the video summary frames selected from 0 to 197 in order. Based on Figure 7, it shows that our proposed method is capable of generating video summaries with content relevant to the input query.

6 CONCLUSION AND FUTURE WORK

To sum up, we treat a query-controllable video summarization task as a supervised learning problem in this work. To tackle this problem, we propose an end-to-end deep learning based approach to generate a query-dependent video summary. The proposed method contains a video summary controller, video summary generator, and video summary output module. To foster the query-controllable video summarization research and conduct our experiments, we propose a new dataset. Each video in the proposed dataset is annotated by frame-based relevance score labels. Our experimental results show that the text-based query not only helps control video summary, but also improves the model performance with +5.83% in the sense of accuracy. Based on our experiment, we know that the multi-modal feature fusion method is crucial, so developing a new fusion approach will be interesting future work.
Figure 7: In this figure, based on a similar qualitative result visualization method from [32], we show two generated video summaries with the corresponding queries. In (a), “75” color-coded by red indicates the original total number of frames of the input video. In the first row, we show some frames from the original video, with “75” frames, to represent the input video. The second row represents the original input video. The third row represents the prediction. In the fourth row, we show \( k \), e.g., \( k = 7 \), frames to represent our generated video summary. The numbers at the bottom indicate the frame index in the original video. Note that the video frame index is starting from 0. In (b), we show the second generated video summary result and the corresponding notations are similar to (a).
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REFERENCES

[1] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. 2015. Vqa: Visual question answering. In Proceedings of the IEEE international conference on computer vision. 2425–2433.

[2] Hedi Ben-Younes, Rêmi Cadene, Matthieu Cord, and Nicolas Thome. 2017. Mutan: Multimodal tucker fusion for visual question answering. In Proceedings of the IEEE international conference on computer vision. 2612–2620.

[3] Wen-Sheng Chu, Yale Song, and Alejandro Jaimes. 2015. Video co-summarization: Video summarization by visual co-occurrence. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 3584–3592.

[4] Sandra Eliza Fontes De Avila, Ana Paula Brandão Lopes, Antonio da Luz Jr, and Arnaldo de Albuquerque Araújo. 2011. VSUMM: A mechanism designed to produce static video summaries and a novel evaluation method. Pattern Recognition Letters 32, 1 (2011), 56–68.

[5] Akira Fukui, Dong Huk Park, Daylen Yang, Anna Rohrbach, Trevor Darrell, and Marcus Rohrbach. 2016. Multimodal compact bilinear pooling for visual question answering and visual grounding. arXiv preprint arXiv:1606.01847 (2016).

[6] Boqing Gong, Wei-Lun Chao, Kristen Grauman, and Fei Sha. 2014. Diverse sequential subset selection for supervised video summarization. In Advances in Neural Information Processing Systems. 2069–2077.

[7] Michael Gugli, Helmut Grabner, Hayko Riemschneider, and Luc Van Gool. 2014. Creating summaries from user videos. In European conference on computer vision. Springer, 505–520.

[8] Michael Gugli, Helmut Grabner, and Luc Van Gool. 2015. Video summarization by learning submodular mixtures of objectives. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 5090–5098.

[9] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. 770–778.

[10] Tao Hu, Pascal Mettes, Jia-Hong Huang, and Cees GM Snoek. 2019. SILCO: Show a few Images, Localize the Common Object. In Proceedings of the IEEE International Conference on Computer Vision. 5067–5076.

[11] Jia-Hong Huang. 2017. Robustness Analysis of Visual Question Answering Models by Basic Questions. King Abdullah University of Science and Technology Ph.D thesis (2017).

[12] Jia-Hong Huang, Modar Alldayf, and Bernard Ghanem. 2017. Vqa: Visual question answering by basic questions. CVPR VQA Challenge Workshop (2017).

[13] Jia-Hong Huang, Modar Alldayf, Bernard Ghanem, and Marcel Worrell. 2019. Assessing the Robustness of Visual Question Answering. arXiv preprint arXiv:1912.01452 (2019).

[14] Jia-Hong Huang, Cuong Duc Dao, Modar Alldayf, and Bernard Ghanem. 2019. A novel framework for robustness analysis of visual qa models. In Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 33. 8449–8456.

[15] Jia-Hong Huang, Cuong Duc Dao, Modar Alldayf, C Huck Yang, and Bernard Ghanem. 2018. Robustness analysis of visual qa models by basic questions. CVPR VQA Challenge and Visual Dialog Workshop (2018).

[16] Bogdan Ionescu, Alexandru Lucian Cînicea, Bogdan Boteanu, Adrian Popescu, Mihai Lupu, and Henning Müller. 2014. Retrieving Diverse Social Images at MediaEval 2014: Challenge, Dataset and Evaluation. MediaEval 2014: Challenge, Dataset and Evaluation. MediaEval 1263 (2014).

[17] Hong-Wen Kang, Yusuyuki Matsuhashi, Xiaoao Tang, and Xue-Quan Chen. 2006. Space-time video montage. In 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’06). Vol. 2. IEEE, 1331–1338.

[18] Aditya Khosla, Raffay Hamid, Chih-Jen Lin, and Neel Sundaresan. 2013. Large-scale video summarization using web-image priors. In Proceedings of the IEEE conference on computer vision and pattern recognition. 2698–2705.

[19] Yong Jae Lee, Joydeep Ghosh, and Kristen Grauman. 2012. Discovering important key frame sequences of variable length. In European conference on computer vision. Springer, 403–417.

[20] Yi-Chieh Liu, Yiming-Hsien Chu, Ming-Hung Chen, Chao-Han Huck Yang, Jesper Tegner, and Yi-Chang James Tsai. 2019. Interpretable Self-Attention Temporal Reasoning for Driving Behavior Understanding. arXiv preprint arXiv:1911.02172 (2019).

[21] Yi-Chieh Liu, Hao-Hsiang Yang, C-H Huck Yang, Jia-Hong Huang, Meng Tian, Hiromasa Morikawa, Yi-Chang James Tsai, and Jesper Tegner. 2018. Synthesizing New Retinal Symptom Images by Multiple Generative Models. In Asian Conference on Computer Vision. Springer, 235–250.

[22] Zheng Lu and Kristen Grauman. 2013. Story-driven summarization for egocentric video. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2714–2721.

[23] Yu-Fei Ma, Lie Lu, Hong-Jiang Zhang, and Mingjing Li. 2002. A user attention model for video summarization. In Proceedings of the tenth ACM international conference on Multimedia. ACM, 533–542.

[24] Chong-Wah Ngo, Ye Fei Ma, and Hong-Jiang Zhang. 2003. Automatic video summarization by graph modeling. In Proceedings Ninth IEEE International Conference on Computer Vision. IEEE, 104–109.

[25] Paul Oser, Alan F Smeaton, and George Awdar. 2008. The TRECVID 2008 BBC rushes summarization evaluation. In Proceedings of the 2nd ACM TRECVID Video Summarization Workshop. ACM, 1–20.

[26] Rameswar Panda and Amit K Roy-Chowdhury. 2017. Collaborative summarization of topic-related videos. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 7083–7092.

[27] Danila Potapov, Matthias Douze, Zaid Harchaoui, and Cordelia Schmid. 2014. Category-specific video summarization. In European conference on computer vision. Springer, 540–555.

[28] Mirganka Rokcan and Yang Wang. 2019. Video Summarization by Learning from Unpaired Data. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 7902–7911.

[29] Mirganka Rokcan, Liuwei Wang, and Yang Wang. 2018. Video summarization using fully convolutional sequence networks. In Proceedings of the European Conference on Computer Vision (ECCV). 347–363.

[30] Ansean Sharghi, Ali Borji, Chengtao Li, Tianbao Yang, and Boqing Gong. 2018. Improving sequential deterministic point processes for supervised video summarization. In Proceedings of the European Conference on Computer Vision and Pattern Recognition. 585–594.

[31] Alan F Smeaton, Paul Over, and Wessel Kraaij. 2006. Evaluation campaigns and TRECVID. In Proceedings of the 8th ACM international workshop on Multimedia information retrieval. ACM, 321–330.

[32] Yule Song, Jia-Hong Huang, and Alejandro Jaimes. 2015. TsVsumm: Summarizing web videos using titles. In Proceedings of the IEEE conference on computer vision and pattern recognition. 5179–5187.

[33] Arun Balaje Vatansevan, Michael Gugli, Anna Volokitin, and Luc Van Gool. 2017. Query-adaptive video summarization via quality-aware relevance estimation. In Proceedings of the 25th ACM international conference on Multimedia. ACM, 582–590.

[34] C-H Huck Yang, Jia-Hong Huang, Fangyu Liu, Fang-Yi Chiu, Mengyu Gao, Weifeng Lyu, Jesper Tegner, et al. 2018. A novel hybrid machine learning model for auto-classification of retinal diseases. Joint ICM and IJCAI Workshop on Computational Biology (2018).

[35] C-H Huck Yang, Fangyu Liu, Jia-Hong Huang, Meng Tian, MD H-Hung Liu, Yi Chieh Liu, Hiromasa Morikawa, Hao-Hsiang Yang, and Jesper Tegner. 2018. Auto-classification of retinal diseases in the limit of sparse data using a two-streams machine learning model. In Asian Conference on Computer Vision. Springer, 323–338.

[36] Chao-Han Huck Yang, Yi-Chieh Liu, Pin-Yu Chen, Xiaoli Ma, and Yi-Chang James Tsai. 2019. When causal intervention meets adversarial examples and image masking for deep neural networks. In 2019 IEEE International Conference on Image Processing (ICIP). IEEE, 3811–3815.

[37] Ke Zhang, Wei-Lun Chao, Fei Sha, and Kristen Grauman. 2016. Summary transfer: Exemplar-based subset selection for video summarization. In Proceedings of the IEEE conference on computer vision and pattern recognition. 1059–1067.

[38] Ke Zhang, Wei-Lun Chao, Fei Sha, and Kristen Grauman. 2016. Video summarization with long short-term memory. In European conference on computer vision. Springer, 766–782.

[39] Ke Zhang, Kristen Grauman, and Fei Sha. 2018. Retrospective encoders for video summarization. In Proceedings of the European Conference on Computer Vision (ECCV). 383–399.

[40] Yujia Zhang, Michael Kampffmeyer, Xiaodan Liang, Min Tan, and Eric P Xing. 2018. Query-conditioned self-player adversarial network for video summarization. arXiv preprint arXiv:1807.06677 (2018).

[41] Yujia Zhang, Michael Kampffmeyer, Xiaodan Liang, Min Tan, and Dtran. 2019. Dtran: Dilated temporal relational adversarial network for video summarization. Proceedings of the ACM Turing Celebration Conference-China. ACM, 49.

[42] Bin Zhao and Eric P Xing. 2014. Quasi real-time summarization for consumer videos. In Proceedings of the IEEE conference on computer vision and pattern recognition. 2513–2520.
[47] Kaiyang Zhou, Yu Qiao, and Tao Xiang. 2018. Deep reinforcement learning for unsupervised video summarization with diversity-representativeness reward. In Thirty-Second AAAI Conference on Artificial Intelligence.