Textually Customized Video Summaries

Jinsoo Choi  Tae-Hyun Oh  In So Kweon
KAIST, Republic of Korea
jschoi@rcv.kaist.ac.kr, thoh.kaist.ac.kr@gmail.com, iskweon@kaist.ac.kr

Figure 1: Our algorithm generates video summaries customized by simple user text descriptions. Basically, given a preferred summary description, our method extracts and temporally aligns the semantically relevant parts in a video.

Abstract

The best summary of a long video differs among different people due to its highly subjective nature. Even for the same person, the best summary may change with time or mood. In this paper, we introduce the task of generating customized video summaries through simple text. First, we train a deep architecture to effectively learn semantic embeddings of video frames by leveraging the abundance of image-caption data via a progressive and residual manner. Given a user-specific text description, our algorithm is able to select semantically relevant video segments and produce a temporally aligned video summary. In order to evaluate our textually customized video summaries, we conduct experimental comparison with baseline methods that utilize ground-truth information. Despite the challenging baselines, our method still manages to show comparable or even exceeding performance. We also show that our method is able to generate semantically diverse video summaries by only utilizing the learned visual embeddings.

1. Introduction

It is a great irony that as more memory storage becomes available, the task of summarizing and its importance become more prevalent. Today, we are able to collect hours worth of videos without worrying about the lack of memory, which has enabled people to store more memories and experiences. Also, we are exposed to visual media being uploaded on the web nonstop. These phenomena has led to the desire of automatically extracting only meaningful parts from this ever-growing media [2, 14, 28]. As an effect, video summarization has gathered much attention from not only academia, but also from corporations. In the computer vision community, there have been numerous approaches to summarizing videos, many of which define what aspects are important in a video in an attempt to automatically extract keyframes or subshots that do so. Some recent works attempt to learn what aspects are important from example video summaries.

In this paper, we do not attempt to define nor learn what aspects are important in a video. Instead, we learn the semantical relationship between video frames and text, and allow the user to simply define what is desired as a summary in natural language. Our method is able to instill the semantics expressed in the natural language description into video summaries. Video summarization is a highly subjective task [10, 46] which cannot be left up to a single algorithm’s decision. Our method can generate customized video summaries reflecting the semantics expressed via text which will differ dramatically among different people and even change for the same person with time or emotions.

As an overview of our approach, we first jointly learn semantic embeddings of video frames and its sentence descriptions. We leverage the already existing abundant image-caption data to effectively learn from a relatively smaller video-caption dataset via a progressive and resid-
ual training method. As a result, we are able to jointly learn semantically rich video frame and sentence representations in a common embedding space. Based on the learned embeddings, our algorithm extracts the semantically relevant video frames given the user-specific summary description. The actual video summary is then produced by combining the video segments containing the relevant frames and preserving the temporal order by making use of the hidden Markov model (HMM) and a decoding method based on the Forward-backward algorithm. We evaluate our method components in comparison to challenging baselines both quantitatively and qualitatively.

Our main contributions are as follows: (1) We introduce a textually customized video summarization method. Our task differs from that of previous video summarization methods in that our task involves summarizing videos in terms of user-specific texts. Consequently, the evaluation must be done based on the user-specific texts. To evaluate this aspect, we develop comparison baselines which directly uses the ground truth text annotations. In such challenging comparisons, our method still manages to produce comparable or exceeding performances. (2) We learn a pairwise ranking model with a progressive and residual training method in order to learn valuable information from abundant image-caption data and effectively learn from relatively smaller video-caption data which proves to learn more rich representations compared to fine-tuning results. (3) We utilize the HMM and a marginal posterior decoding method based on the Forward-backward algorithm to produce quality summaries which are temporally aligned. (4) We show the effectiveness of our approach with fair metrics and define a fair evaluation metric as well. The qualities of our learned representations and video summaries are also visually analyzed.

2. Related Work

Extracting the best summary from a video has been studied in several view points. Video summarization methods have been characterized by how to define summarization criteria for “better” or “representative” summaries. Early works have mainly developed model-based approaches which exploit low-level visual features such as motion [40, 43], background stitching [1] and spatio-temporal features [16] to find interesting keyframes or subshots. Based on an interestingness metric, model-based approaches compose summaries with an emphasis on simplicity or diversity of subshots depending on the model representations such as graph [26], curve simplification [4] and compact core-set representation [28]. A thorough review of early research can be found in Truong et al. [38].

Summaries generated by low-level features or model constraints rarely retain high level context information. More recent works focus on retaining semantic information for better human correspondence. Lee et al. [17] incorporate important objects, and Liu et al. [20] use object tracks to select summary keyframes or subshots. Furthermore, Lu et al. [21] develop a model considering the relationship of influential objects contributing to event progression. While these methods deal with higher level context information, they only consider a single crafted criterion to produce video summaries.

In order to make up for the shortfall of hand crafted summarization criteria, recent works introduce various data driven approaches. These approaches build a computational model that learns human summary preferences from data. Supervised methods use summary annotations obtained from human workers in the form of ground truth summaries [7, 8], highlight annotations [45] or GIF-formatted summaries [9]. In particular, Gygli et al. [9] and Yao et al. [45] learn a scoring function for frames or subshots, while Gong et al. [7] and Gygli et al. [8] directly learn an objective function that scores a set of subshots. On the other hand, Khosla et al. [12] and Yang et al. [44] leverage unsupervised learning techniques to mine representativeness from web data, instead of supervised data. However, these learning-based models most likely learn common sense summarization through reference summaries, leading to a general algorithm that neglects subjective summary preferences.

As mentioned, video summarization is a highly subjective task. We discuss two types of the video summary approaches that attempts to reflect subjective characteristics either implicitly or explicitly, i.e. data driven or user interaction-based. For a data driven approach, Sharghi et al. [31] propose a noun-based video summarization where the summaries are learned via reference summaries specific to a predefined set of noun classes. Users have control over which nouns (up to 3 noun classes) to include in the summary, but not over specific summary composition which is learned via reference summaries. Also, this approach is not applicable to novel nouns other than the predefined set of nouns. The data driven approaches [3, 14] do not require any user interaction, while its purpose is to co-summarize a collection of videos (or images) provided. Given a collection of videos with a similar theme, the method observes an underlining co-occurrence of events among videos which is used to generate a coherent summary per video. If a user provides a personal collection of videos, these approaches are most likely to reflect implicit user preferences. In turn, these approaches are not applicable to video summarization from a single video.

As user interaction-based approaches, Goldman et al. [6] propose to render action summary layouts via a series of user annotations, and Han et al. [10] propose to propagate subshots out of user specified keyframes. These methods require the user to traverse through the video frames in order to reflect personal summary preferences. By contrast,
our approach allows a user to describe one’s personally preferred summary via text. Thus, the user does not need to iteratively interact with video frames, leading to high efficiency in terms of time and human effort for customized video summarization. Our textually customized video summarization approach is motivated by recent developments on joint embedding of image and text [5, 13, 22, 27, 33, 36]. Textural descriptions itself is fully semantic and contextual, which our algorithm aims to naturally reflect in our video summary results.

3. Customizing Video Summaries via Text

We introduce a method which takes a simple text description as input and generates the corresponding video summary as output. Firstly, our goal is to find a set of frames semantically relevant to the input text. In order to do this, we learn a semantic embedding function that jointly maps frames and sentences to a common embedding space (Sec. 3.1). Once the set of semantically relevant frames are selected, the video summary is generated by combining the subshots containing the selected frames. By making use of the hidden Markov model, temporal alignment is induced on the summary via a marginal posterior decoding method based on the Forward-backward algorithm (Sec. 3.2).

3.1. Progressive-residual embedding

Given a text description, we aim to extract semantically relevant frames from a whole video. Common practice would be to train or fine-tune a deep model with a video-caption dataset. However, we instead leverage an image-caption dataset (source domain) to transfer useful knowledge not found in video-caption datasets (target domain) in a progressive and residual manner. As opposed to recent video-caption datasets, large image-caption datasets such as MS COCO [19] contain multiple detailed sentence descriptions per image. This enables training with diverse textual descriptions, leading to not only a model learning rich semantical relations between image and language, but also a model robust to subjective textual descriptions. Since a video frame is essentially an image, we can leverage insight from the image-caption domain.

Our deep semantic embedding model is a pairwise ranking model [30, 42] (i.e. triplet network) which learns similarity between frame (image) and text modalities. Our model is trained on triplet data \( t^{(i)} = (y^{(i)}, x_+^{(i)}, x_-^{(i)}) \) where \( y^{(i)} \) is the anchor sentence, and \( (x_+^{(i)}, x_-^{(i)}) \) are the positive and negative frames respectively. The hinge loss for a triplet \( (y^{(i)}, x_+^{(i)}, x_-^{(i)}) \) is defined as:

\[
l(y^{(i)}, x_+^{(i)}, x_-^{(i)}) = 
\max\left\{ 0, m - s(f(x_+^{(i)}), g(y^{(i)})) + s(f(x_-^{(i)}), g(y^{(i)})) \right\},
\]

where \( m \) is a margin parameter that regularizes the margin between positive and negative pairs. The functions \( f(\cdot) \) and \( g(\cdot) \) denote embedding functions for frames and sentences respectively. The compatibility scoring function \( s(\cdot, \cdot) \) is the cosine similarity scoring function.

Our model is progressively trained, which the image and sentence features trained with an image-caption dataset are transferred into our model. An overview of our progressively trained model is shown in Fig. 2. Basically, we train a two-column progressive network where the first column is a deep multimodal architecture such as the \( m \)-CNN [23] or order embedding network [41] trained in the image-caption domain. The second column consists of fully connected layers which take the frame and sentence features as input (video-caption domain). Here, the feature outputs from the first column is transferred via lateral connections so that the second column is able to access rich knowledge already learned from the first column.

What is different from our progressive model to the original progressive neural network [29] is that our model only transfers the output feature from the first column rather than all of its layer activations. Also, the transferred features are “frozen” which cannot be transformed by the second column. These differences in fact give rise to residual task learning, meaning that the second column is explicitly let to fit a residual mapping across columns. The residual task learning we mention here is slightly different from that of the deep residual network of He et al. [11] in that our task involves learning the (scaled) residual mapping across columns, whereas deep residual networks involve residual learning adopted to every few stacked layers. In this way, the first column most likely learns most of the rich semantic representations and the second column learns the “residual” knowledge such as frame-caption semantics specific to the target domain. Formally, the embedding feature learned by

\[
\text{Figure 2: Overview of our progressively trained model.}
\]
our method can be defined as:
\[ v_t = \mathcal{F}(h_t, \{W\}) + \alpha v_s, \]
where \( v_t \) and \( v_s \) denote the embedding features from the second and first columns (i.e. target and source domain columns) respectively. The function \( \mathcal{F}(h_t, \{W\}) \) represents the residual mapping to be learned with frame/sentence feature input \( h_t \) and weights \( W \). The value \( \alpha \) is a learned scalar, initialized by a random small value.

Since the second column is explicitly designed to learn the residual information, a relatively smaller network such as the fully connected layer is sufficient enough. This is shown in Sec. 4.1 where our method generally performs better than the baselines. Also, since the second column consists of fully connected layers, it does not introduce any noticeable additional parameters nor computational complexity during training compared to simple fine-tuning if not less. Another advantage of our progressive model is that since most of the semantic representation is learned from the first column which is transferred to the second column, we are able to learn even with a relatively small video-caption data and still learn rich representations.

### 3.2. Video summary construction

An intuitive way to construct video summaries based on a text description is to assign a relevant subshot to each sentence in the text description, while also preserving the temporal order of subshot events. Thus, our goal is to select the best possible matching subshot for each sentence so that the subsequent subshots are temporally aligned. In other words, we would like to select just enough most relevant frames for each sentence, and only consider those frames to construct a temporally aligned sequence of subshots containing the selected frames. We can achieve all this by the hidden Markov model (HMM).

We simply model the summary transition behavior in the following HMM structure.

- The observation space \( \mathcal{Y} = \{y_1, y_2, \ldots, y_N\} \) is the set of text description sentences.
- The state space \( \mathcal{Z} = \{z_1, z_2, \ldots, z_T\} \) is all the sampled frames of an input video.
- Sequence of observations \( \mathcal{O} = [o_1, o_2, \ldots, o_T] \) is essentially the description sentence sequence in order, where \( T = N \) and \( o_i = i \), thus \( \mathcal{O} = [1, 2, \ldots, N] \).
- State transition probability matrix

\[
A = \begin{bmatrix}
0 & 1 & 0 & \cdots & 0 \\
0 & 0 & 1 & \cdots & 0 \\
0 & 0 & 0 & \cdots & 1 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & 1
\end{bmatrix}
\]

is a \( F \)-by-\( F \) matrix of which entries \( A_{i,j} \) stores the transition probability from the state \( z_i \) to the state \( z_j \). This transition matrix has non-zero entries for \( A_{i,j} \), row-wise normalized. Due to this matrix, transition can only occur forward in time, enforcing the result sequence of frames to be temporally aligned.

- Observation probability (or emission) matrix

\[
B = \begin{bmatrix}
B_1 & B_2 & \cdots & B_N
\end{bmatrix}
\]

is a \( F \)-by-\( N \) matrix where \( B_{ij} \) stores the probability of observing \( y_j \) from the state \( z_i \), i.e., \( p(y_j|z_i) \). Here, only the top-\( k \) compatibility scores among \( F \) frames between a sentence is assigned at the corresponding positions while other entries are kept as zeros. Thus, the column vectors \( B_j \) of the emission matrix have non-zero score entries only at top-\( k \) scoring frame positions for each observation \( o_j \). The value \( k \) (iteratively found) is the minimal number of top scoring frames per sentence required to produce a temporally aligned sequence prediction. The emission matrix is row-wise normalized.

- Sequence of states \( Q = [q_1, \ldots, q_T] \) is a hidden variable which is regarded as generating the observation sequence, where \( q_i \in \mathcal{Z} \). This is what we ultimately want to find from a given observation.

Given a specified HMM model, the most common method for decoding the most likely sequence of states from the given observation is through the Viterbi algorithm. The Viterbi algorithm finds the maximum a posteriori (MAP) state sequence such that

\[
Q^* = \arg \max_Q p(Q|O) = \arg \max_Q p(Q,O). \tag{5}
\]

However, we empirically found that finding the sequence of most probable states from the marginal posterior gives better results than the Viterbi-based MAP solution for our task. We pose the problem as

\[
q_t^* = \arg \max_{q_t} p(q_t|O) = \arg \max_{q_t} p(q_t,O). \tag{6}
\]

Here, the marginal probability \( p(q_t,O) \) is computed by marginalizing the joint distribution \( p(Q,O) \) over all possible permutations of \( \{q_t \in [1, \ldots, T]\} \). However, the brute-force marginalization will take \( O(F^N N) \) complexity which is intractable.

In order to efficiently compute \( p(q_t,O) \), we use a simple trick to decompose \( p(q_t,O) \). Let us denote \( O_{t:j} = [o_i, o_{i+1}, \ldots, o_j] \), where \( j > i \). Then,

\[
p(q_t,O) = p(O_{1:t}, O_{t+1:T}|q_t)p(q_t) = p(O_{1:t}|q_t)p(O_{t+1:T}|q_t)p(q_t)
\]

(by independence of \( o_i \)’s)

\[
= p(O_{1:t}, q_t)p(O_{t+1:T}|q_t). \tag{7}
\]

This decomposition can be seen as just another representation, but interestingly the terms \( p(O_{1:t}, q_t) \) and \( p(O_{t+1:T}|q_t) \) can be efficiently computed by the conventional Forward and Backward algorithms [25] respectively.
This only takes $O(F^2N)$ for computing $p(q_t, O)$, and further reduces to $O(kFN)$ in our case due to the sparsity of the emission matrix $\mathbf{B}$. Now we efficiently obtain the most likely states $q_t$ for $t \in \{1, \cdots, N\}$ by Eq. (6), which corresponds to the resulting video summary.

A probable rational behind the better performance of this marginal posterior method is that the marginalization in the Markov process has a smoothing effect over neighboring information [24, 25, 34], while the Viterbi algorithm maxes out a specific value from neighbors during decoding.

4. Experiments

We analyze our method and its components using two datasets: the Egocentric daily life dataset [17] and the TV episodes dataset [46]. The egocentric dataset consists of 4 extremely diverse videos captured from head-mounted cameras, lasting for 3-5 hours each — a total of over 17 hours of video. The videos contain scenarios such as eating, working, driving, shopping, cooking, etc. in various locations and viewpoints. The TV episodes dataset consists of 4 television episodes of 40 minutes each. These videos contain even more diverse scenarios and dramatic situations which shift frequently within the relatively short 40-minute duration. All training and values presented are results of leave-one-out cross-validation for each video in the datasets.

We divide our experiment into 3 parts in order to evaluate our method component qualities, which are discussed separately in Sec. 4.1, 4.2 and 4.3.

- **Evaluating embedding quality**: We evaluate the embedding quality by considering the task as a retrieval problem, measuring the recall-at-K and median rank.

- **Evaluating summary quality**: To evaluate overall video summary quality, we measure the mean Average Precision (mAP) and a distance metric from the ground truth, in comparison to some challenging baselines.

- **Generating summaries without text**: Here we show our method’s capability to generate semantically diverse video summaries without the use of text inputs — a traditional video summary — by only utilizing our learned visual embeddings.

4.1. Evaluating embedding quality

To assess the embedding quality of video frames and sentences, we regard quality assessment as a retrieval task, as done in [23, 41]. Unlike image-caption datasets which involve multiple (usually 5) elaborate sentences directly describing what is seen in the image, the aforementioned datasets involve single sentence descriptions for a collection of frames in simple terms. Sentences in the egocentric dataset describe video segments in terms of what the first-person is doing, instead of what is seen. For example, a video segment showing the inside of a room is labeled with a single sentence “I looked around the room,” rather than describing what is actually seen in the room. For the case of TV episodes dataset, the majority of video segments involves characters speaking to each other about a specific topic, which is vaguely captioned. For instance, a scene is described as “Rigsby recognizes Hanson, and discusses his past marriage” which involves specific prior knowledge and more importantly, does not sufficiently describe the visual scene. In this sense, retrieval using these datasets is a highly challenging task.

The retrieval results on egocentric and TV episodes datasets are shown in Table 1. We adopt a standard metric for retrieval assessment, recall-at-K (R@K) where K values are selected depending on the scale of test frames and sentences, shown at the top-left entry of each subtable, and on which would sufficiently express retrieval quality. The scale of test frames and sentences shown are averaged over all videos in the dataset. The median rank (Med. r) is reported in top-percentile manner in order to take test data scale into account.

**Baseline methods** We compare our model with a number of state-of-the-art models with varied training or fine-tuning schemes: (1) a pairwise ranking model (triplet network) with VGG-19 [32] image features and skip-thought [15] sentence vectors as inputs, (2) an $m$-CNN model [23] trained from scratch, (3) $m$-CNN model fine-tuned (whole model), (4) $m$-CNN model fine-tuned (last output layer only), (5) an order-embedding model [41] trained from scratch, (6) order-embedding fine-tuned (whole model), (7) order-embedding fine-tuned (last output layer only). Our progressive-residual embeddings are trained by having either $m$-CNN or order-embedding models as the first column, and a pairwise ranking model as the second column with VGG-19 and skip-thought feature inputs. Our embeddings are learned by training the first column with an image-caption dataset MS COCO [19], and training the second column with the egocentric or TV episodes datasets where frames are sampled every second. The fine-tuned baselines are pre-trained with the MS COCO dataset and fine-tuned with the egocentric or TV episodes datasets as well. All of the embeddings are set to 1024-dimensional vectors. Fig. 3 illustrates the embeddings from baselines and our method.

Our learned embeddings (*i.e.* ProgRes $m$CNN, ProgRes order) show better performances for the majority of R@K metrics compared to other fine-tuned baselines, and consistently show better results for median rank. We also provide performances of the baselines trained with C3D [37] clip features which directly trains with video clip segment and sentence pairs (shown in Table 2). Notice that the networks trained with frame/sentence pairs show better performances, especially for text-to-visual retrieval, which is actually the main concern for our method.
Figure 3: Embeddings from baselines and our model. Embeddings from (a) a pairwise ranking model (triplet network) trained on the target task with VGG-19 skip-thought features; (b) an embedding model (either m-CNN or order-embedding) trained from scratch; (c) fine-tuned model (whole); (d) fine-tuned model (last layer only); and (e) our model.

| #sen: 1516, #frm: 15267 | Egocentric dataset | #sen: 225, #frm: 2584 | TV episodes dataset |
|--------------------------|---------------------|--------------------------|---------------------|
|                          | Frame-to-Text       |                          | Text-to-Frame       |
|                          | R@1 | R@8 | R@64 | R@512 | Med. r (%) | R@1 | R@10 | R@100 | R@1000 | Med. r (%) |
| VGG-skip. triplet        | 0.50 | 4.46 | 22.91 | 74.67 | 15.88 | 0.59 | 3.69 | 17.49 | 57.84 | 6.57 |
| m-CNN scratch           | 0.26 | 3.58 | 18.51 | 61.46 | 26.53 | 0.47 | 3.42 | 15.30 | 47.87 | 10.05 |
| m-CNN whole             | 0.32 | 2.89 | 16.90 | 61.76 | 26.25 | 0.59 | 3.19 | 14.89 | 47.83 | 9.23  |
| m-CNN last              | 0.47 | 4.18 | 17.66 | 65.84 | 22.42 | 0.62 | 2.96 | 15.36 | 54.77 | 6.05  |
| ProgRes mCNN            | 0.67 | 4.79 | 22.76 | 75.36 | 15.88 | 0.75 | 4.26 | 19.08 | 59.61 | 6.05  |
| order-emb. scratch      | 0.12 | 1.04 | 13.65 | 61.59 | 26.14 | 0.59 | 3.59 | 16.92 | 52.12 | 7.49  |
| order-emb. whole        | 0.15 | 1.31 | 13.42 | 58.17 | 28.06 | 0.80 | 3.86 | 16.98 | 52.75 | 7.49  |
| order-emb. last         | 0.34 | 3.87 | 16.82 | 62.08 | 25.48 | 0.58 | 3.05 | 15.60 | 53.11 | 6.99  |
| ProgRes order           | 0.62 | 5.13 | 23.96 | 74.11 | 17.03 | 0.73 | 4.20 | 19.42 | 60.02 | 5.38  |
| VGG-skip. triplet       | 0.94 | 5.22 | 37.03 | -     | 41.67 | 0.64 | 4.53 | 27.67 | 90.74 | 10.38 |
| m-CNN scratch           | 0.61 | 4.35 | 34.97 | -     | 43.33 | 0.76 | 4.49 | 22.93 | 84.91 | 13.34 |
| m-CNN whole             | 0.39 | 4.74 | 33.23 | -     | 45.71 | 0.36 | 3.50 | 24.23 | 86.14 | 12.41 |
| m-CNN last              | 0.85 | 5.34 | 35.51 | -     | 43.72 | 0.41 | 4.71 | 26.66 | 88.28 | 10.74 |
| ProgRes mCNN            | 1.22 | 5.90 | 38.58 | -     | 40.24 | 0.85 | 5.97 | 30.08 | 91.50 | 8.74  |
| order-emb. scratch      | 0.51 | 5.17 | 36.71 | -     | 42.31 | 0.85 | 5.84 | 27.32 | 87.88 | 10.91 |
| order-emb. whole        | 0.76 | 5.42 | 36.52 | -     | 42.19 | 0.99 | 5.60 | 28.26 | 87.63 | 10.30 |
| order-emb. last         | 1.16 | 5.94 | 35.46 | -     | 44.02 | 1.42 | 4.89 | 24.89 | 86.11 | 11.87 |
| ProgRes order           | 0.97 | 6.34 | 38.42 | -     | 40.49 | 1.22 | 5.62 | 28.71 | 87.61 | 9.21  |

Table 1: Ranking results on egocentric and TV episodes datasets. The best and runner-up results are shown in red and blue respectively. For R@K, a higher value is better, while a lower value is better for Med. r (%).

4.2. Evaluating summary quality

From each dataset, 3 reference summary texts (written by different individuals) for each of the 4 videos are given. These texts are each composed of 24 sentences to which 5-second video subshots are each assigned, resulting in 2-minute ground truth video summaries. In consensus to the dataset, we also uniformly sample frames every 5 seconds and apply our proposed summary construction algorithm (Sec. 3.2). Evaluation is simply done by measuring how similar the predicted video summaries are with the ground truth summaries. We use the popular performance metric, mean Average Precision (mAP) [35]. In addition to this popular metric we propose another metric that reveals another aspect of video summary quality. This metric measures the average of the normalized temporal distance between ground truth reference summary segments and its closest segment from the predicted summary. We call this metric as the mean Average Distance (mAD). While mAP measures the degree of overlap between the predicted summary and reference, mAD reflects how temporally close the predicted summary segments are to the reference summary segments. This allows for a more semantic evaluation since temporally close segments in a video most likely have similar semantics. Note that reference summary texts are different from ground truth text annotations, where annotations are used for training, while testing is done solely on reference texts.

1The TV episodes dataset reference texts involves 12 sentences and 10-second subshots, to which we adjust our samples accordingly.
Since this work addresses the task of generating a video summary customized by a reference text, we need to develop comparison baselines that also produce a customized video summary given a reference text for fair evaluation. The baselines we develop take a reference text as input and matches its constituent sentences directly with the ground truth sentence annotations of the video. In this way, the baselines combine the video segments corresponding to the matched text annotations to generate textually customized video summaries. The following is the detailed explanation of the baselines:

1. **Greedy Text-embedding Selection**: The ground truth sentences as well as the reference text are regarded as skip-thought embeddings. Subshots are greedily selected by matching the reference summary text embeddings with the ground truth.

2. **Embedding-based Ordered Subshot**: Subshots are selected by matching the reference summary text skip-thought embeddings with the ground truth, but by preserving the temporal order via a dynamic programming approach.

Despite our efforts to devise baselines for fair comparisons, the baselines in fact have more advantage over our method since they directly use the ground truth text annotations. However, in this challenging comparison, our method still manages to show comparable and even exceeding results. Our method aims for personally customized video summarization, and thus we exclude reference summaries from our evaluation that entirely reuse sentences from the ground truth sentence annotations. The summarization quality results on the egocentric and TV episodes datasets are shown...
in Table 3. Our methods both based on ProgRes \textit{mCNN} and ProgRes \textit{order} embeddings manage to produce better results in terms of all metrics on the egocentric dataset. On the TV episodes dataset, the greedy baseline performs best followed by our methods in terms of mAP. On the other hand, our methods show better performance than the baselines in terms of mAD. We point out that the reference summary texts of the TV episodes dataset closely resembles the ground truth text annotations if not identical. This may have caused high confidence matches leading to high mAP for the baselines since they are text-based, whereas our method is based on semantics.

It is worth noting that our method is able to produce video summaries that are \textit{semantically} relevant to the provided reference text descriptions. Because of this, our method performs better than the baselines in all aspects on the egocentric dataset which contains diverse semantical reference texts. Furthermore, our method consistently performs the best in terms of mAD on the TV episodes dataset despite its near identical reference texts to the ground truth text annotations. An overview of the predicted summaries for baselines and our method is shown in Fig. 4.

4.3. Generating summaries without text

In this section, we demonstrate how our learned video frame embeddings can produce semantically diverse summaries when applied with a typical keyframe selection algorithm. Without the user-specified text, our model enables the generation of semantically diversified summaries only via the visual embeddings learned. The video summary is generated by combining the subshots that contain the keyframes chosen by the Video-MMR [18] algorithm. Basically, a keyframe that is similar to the frames not yet selected while different from already selected keyframes is chosen at each iteration.

We compare Video-MMR applied to our ProgRes \textit{mCNN} and ProgRes \textit{order} visual embeddings to Video-MMR applied to VGG-19 features. We also compare with the uni-

|          | mAP | mAD |
|----------|-----|-----|
| Base Uniform | 18.75 | 0.99 |
| Base VMMR (VGG) | 28.12 | 1.31 |
| Our VMMR (ProgRes \textit{mCNN}) | 31.25 | 1.45 |
| Our VMMR (ProgRes \textit{order}) | 30.21 | 1.45 |

Table 4: Video summarization (without text) quality results on egocentric dataset. The best and runner-up results are shown in red and blue respectively.

form sampling method which performs surprisingly well quantitatively. Previous works on video summarization such as [8] have shown that uniform sampling actually returns near state-of-the-art quantitative results, but show poor qualitative performance. In this sense, we present uniform sampling quantitative results for relative reference. The results are shown in Table 4. Our method performs the best in terms of mAP while comparable in terms of mAD. For a visual quality assessment, we provide Barnes-Hut t-SNE visualization [39] of VGG-19 and our semantic embeddings of a test-split video frames in Fig. 5. Notice how the clusters in VGG-19 plot are relatively close together due to the visually oriented embeddings, whereas the supposedly same clusters in our ProgRes \textit{order} plot are further away due to difference in semantics.

5. Conclusion

Language is an inherent ability of humans, making it one of the most natural means of communication and interaction. In this era of unlimited media and elaborate means, we present customized video summarization via language. We leverage the abundance of images and its captions to effectively learn joint embeddings of video frames and text. Our algorithm is able to generate temporally aligned video summaries instilled with the semantics written by individuals. For a task as subjective as video summarization, our work presents a means of customization with an ability inherent to humans.
References

[1] A. Aner-Wolf and J. R. Kender. Video summaries and cross-referencing through mosaic-based representation. *Computer Vision and Image Understanding*, 95(2):201–237, 2004.

[2] J. Choi, T.-H. Oh, and I. S. Kweon. Video-story composition via plot analysis. In *IEEE CVPR*, 2016.

[3] W.-S. Chu, Y. Song, and A. Jaimes. Video co-summarization: Video summarization by visual co-occurrence. In *IEEE CVPR*, pages 3584–3592, 2015.

[4] D. DeMenthon, V. Kobla, and D. Doermann. Video summarization by curve simplification. In *Proceedings of the ACM international conference on Multimedia*, pages 211–218, 1998.

[5] A. Frome, G. S. Corrado, J. Shlens, S. Bengio, J. Dean, T. Mikolov, et al. Deive: A deep visual-semantic embedding model. In *NIPS*, pages 2121–2129, 2013.

[6] D. B. Goldman, B. Curless, D. Salesin, and S. M. Seitz. Schematic storyboarding for video visualization and editing. In *ACM Transactions on Graphics (TOG)*, volume 25, pages 862–871. ACM, 2006.

[7] B. Gong, W.-L. Chao, K. Grauman, and F. Sha. Diverse sequential subset selection for supervised video summarization. In *NIPS*, pages 2069–2077, 2014.

[8] M. Gygli, H. Grabner, and L. Van Gool. Video summarization by learning submodular mixtures of objectives. In *IEEE CVPR*, pages 3090–3098, 2015.

[9] M. Gygli, Y. Song, and L. Cao. Video2gif: Automatic generation of animated gifs from video. In *IEEE CVPR*, 2016.

[10] B. Han, J. Hamm, and J. Sim. Personalized video summarization with human in the loop. In *WACV*, pages 51–57, 2011.

[11] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In *IEEE CVPR*, 2016.

[12] A. Khosla, R. Hamid, C.-J. Lin, and N. Sundaresan. Large-scale video summarization using web-image priors. In *IEEE CVPR*, pages 2698–2705, 2013.

[13] G. Kim, S. Moon, and L. Sigal. Ranking and retrieval of image sequences from multiple paragraph queries. In *IEEE CVPR*, pages 1993–2001, 2015.

[14] G. Kim, L. Sigal, and E. P. Xing. Joint summarization of large-scale collections of web images and videos for story-line reconstruction. In *IEEE CVPR*, pages 4225–4232, 2014.

[15] R. Kiros, Y. Zhu, R. R. Salakhutdinov, R. Zemel, R. Urtasun, A. Torralba, and S. Fidler. Skip-thought vectors. In *NIPS*, 2015.

[16] R. Lagnanière, R. Bacco, A. Hocevar, P. Lambert, G. Païs, and B. E. Ionescu. Video summarization from spatio-temporal features. In *Proceedings of the 2nd ACM TRECVID Video Summarization Workshop*, pages 144–148. ACM, 2008.

[17] Y. J. Lee, J. Ghosh, and K. Grauman. Discovering important people and objects for egocentric video summarization. In *IEEE CVPR*, pages 1346–1353, 2012.

[18] Y. Li and B. Meriaudeau. Multi-video summarization based on av-mmr. In *CBMI*, 2010.

[19] T. Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, and C. L. Zitnick. Microsoft coco: Common objects in context. In *ECCV*, 2014.

[20] D. Liu, G. Hua, and T. Chen. A hierarchical visual model for video object summarization. *IEEE TPAMI*, 32(12):2178–2190, 2010.

[21] Z. Lu and K. Grauman. Story-driven summarization for egocentric video. In *IEEE CVPR*, pages 2714–2721, 2013.

[22] L. Ma, Z. Lu, L. Shang, and H. Li. Multimodal convolutional neural networks for matching image and sentence. In *IEEE ICCV*, pages 2623–2631, 2015.

[23] L. Ma, Z. Lu, L. Shang, and H. Li. Multimodal convolutional neural networks for matching image and sentence. In *IEEE ICCV*, 2015.

[24] J. Marroquin, S. Mitter, and T. Poggio. Probabilistic solution of ill-posed problems in computational vision. *Journal of the american statistical association*, 82(397):76–89, 1987.

[25] K. P. Murphy. *Machine Learning: A Probabilistic Perspective*. MIT Press, 2012.

[26] C.-W. Ngo, Y.-F. Ma, and H.-J. Zhang. Automatic video summarization by graph modeling. In *IEEE ICCV*, pages 104–109. IEEE, 2003.

[27] Y. Pan, T. Mei, T. Yao, H. Li, and Y. Rui. Jointly modeling embedding and translation to bridge video and language. In *IEEE CVPR*, 2016.

[28] G. Rosman, M. Volkov, D. Feldman, J. W. Fisher III, and D. Rus. Coresets for k-segmentation of streaming data. In *NIPS*, pages 559–567, 2014.

[29] A. A. Rusu, N. C. Rabinowitz, G. Desjardins, H. Soyer, J. Kirkpatrick, K. Kavukcuoglu, and R. Hadsell. Progressive neural networks. In *arXiv preprint arXiv:1606.04671*, 2016.

[30] F. Schroff, D. Kalenichenko, and J. Philbin. Facenet: A unified embedding for face recognition and clustering. In *IEEE CVPR*, 2015.

[31] A. Sharghi, B. Gong, and M. Shah. Query-focused extractive video summarization. In *ECCV*, 2016.

[32] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. In *ICLR*, 2015.

[33] H. O. Song, Y. Xiang, S. Jegelka, and S. Savarese. Deep metric learning via lifted structured feature embedding. In *IEEE CVPR*, 2016.

[34] R. L. Stratonovich. Conditional markov processes. *Theory of Probability & Its Applications*, 5(2):156–178, 1960.

[35] M. Sun, A. Farhadi, and M. Seitz. Ranking domain-specific highlights by analyzing edited videos. In *ECCV*, 2014.

[36] M. Tapaswi, M. Bauml, and R. Stiefelhagen. Book2movie: Aligning video scenes with book chapters. In *IEEE CVPR*, pages 1827–1835, 2015.

[37] B. L. F. R. T. L. . P. M. Tran, D. Learning spatiotemporal features with 3d convolutional networks. In *IEEE CVPR*, 2016.

[38] B. T. Truong and S. Venkatesh. Video abstraction: A systematic review and classification. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, 3(1):3, 2007.
[39] L. Van Der Maaten. Accelerating t-sne using tree-based algorithms. In JMLR, 2014. 8
[40] N. Vasconcelos and A. Lippman. A spatiotemporal motion model for video summarization. In IEEE CVPR, pages 361–366, 1998. 2
[41] I. Vendrov, R. Kiros, S. Fidler, and R. Urtasun. Order-embeddings of images and language. In arXiv preprint arXiv:1511.06361, 2015. 3, 5
[42] K. Q. Weinberger, J. Blitzer, and L. K. Saul. Distance metric learning for large margin nearest neighbor classification. In NIPS, 2005. 3
[43] W. Wolf. Key frame selection by motion analysis. In IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), volume 2, pages 1228–1231, 1996. 2
[44] H. Yang, B. Wang, S. Lin, D. Wipf, M. Guo, and B. Guo. Unsupervised extraction of video highlights via robust recurrent auto-encoders. In IEEE ICCV, pages 4633–4641, 2015. 2
[45] T. Yao, T. Mei, and Y. Rui. Highlight detection with pairwise deep ranking for first-person video summarization. In IEEE CVPR, 2016. 2
[46] S. Yeung, A. Fathi, and L. Fei-Fei. Videoset: Video summary evaluation through text. arXiv preprint arXiv:1406.5824, 2014. 1, 5