LiveSeg: Unsupervised Multimodal Temporal Segmentation of Long Livestream Videos
Supplementary Materials

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1. More Details of Unsupervised Video Summarization Experiment

We used the same key-fragment-based approach for evaluation [13], where the similarity between a machine-generated and a user-defined ground-truth summary is represented by expressing their overlap using the F-Score. This protocol can be directly applied on the user summaries of the SumMe dataset, while its application on TVSum requires to transform the original frame-level annotations into key-fragment-based summaries.

Finally, for a given video and a machine-generated summary, this protocol matches the latter against all the available user summaries for this video and computes a set of F-Scores. For TVSum the final outcome occurs by averaging the computed F-Scores, while for SumMe this output corresponds to the maximum value among the computed F-Scores [3].

2. More Details about WD, GWD, and CCA

2.0.1 Wasserstein Distance

Wasserstein Distance (WD) is introduced in Optimal Transport (OT), which is a natural type of divergence for registration problems as it accounts for the underlying geometry of the space, and has been used for multimodal data matching and alignment tasks [4, 17]. In Euclidean settings, OT introduces WD $W_{D}(\mu, \nu)$, which measures the minimum effort required to “displace” points across measures $\mu$ and $\nu$, where $\mu$ and $\nu$ are values observed in the empirical distribution. In our setting, we compute the temporal-pairwise Wasserstein Distance on both visual features and language features, considering each feature vector representing each frame or transcript embedding, which are $(\mu, \nu) = (V_{2i}, V_{2(i+1)})$ and $(\mu, \nu) = (L_{2j}, L_{2(j+1)})$ for $i, j \in t - 1$.

For simplicity without loss of generality, assume $\mu \in P(\mathcal{X})$ and $\nu \in P(\mathcal{Y})$ denote the two discrete distributions, formulated as $\mu = \sum_{i=1}^{n} u_i \delta_{x_i}$ and $\nu = \sum_{j=1}^{m} v_j \delta_{y_j}$, with $\delta_{x}$ as the Dirac function centered on x. $\Pi(\mu, \nu)$ denotes all the joint distributions $\gamma(x, y)$, with marginals $\mu(x)$ and $\nu(y)$. The weight vectors $u = \{u_i\}_{i=1}^{n} \in \Delta_n$ and $v = \{v_j\}_{j=1}^{m} \in \Delta_m$ belong to the $n-$ and $m-$dimensional simplex, respectively. The WD between the two discrete distributions $\mu$ and $\nu$ is defined as:

$$ W_{D}(\mu, \nu) = \inf_{\gamma \in \Pi(\mu, \nu)} \mathbb{E}_{(x, y) \sim \gamma}[c(x, y)] $$

$$ = \min_{\Pi(\mu, \nu)} \sum_{i=1}^{n} \sum_{j=1}^{m} T_{ij} \cdot c(x_i, y_j) \tag{1} $$

where $\Pi(u, v) = \{ T \in \mathbb{R}_{+}^{n \times m} \mid T 1_n = u, T^\top 1_m = v \}$, $1_n$ denotes an $n-$dimensional all-one vector, and $c(x_i, y_j)$ is the cost function evaluating the distance between $x_i$ and $y_j$. The temporal-pairwise WD on both visual and language features encodes the temporal difference and consistency within the same domain.

2.0.2 Gromov Wasserstein Distance

Classic OT requires defining a cost function across domains, which can be challenging to implement when the domains are in different dimensions [14]. Gromov Wasserstein Distance (GWD) [12] extends OT by comparing distances between samples rather than directly comparing the samples themselves.

Assume there are metric measure spaces $(\mathcal{X}, d_x, \mu)$ and $(\mathcal{Y}, d_y, \nu)$, where $d_x$ and $d_y$ are distances on $\mathcal{X}$ and $\mathcal{Y}$, respectively. We compute pairwise distance matrices $D_{x}$ and $D_{y}$ as well as the tensor $L = \mathbb{R}_{+}^{n_x \times n_x \times n_y \times n_y}$, where $L_{ijkl} = L(D_{x}^{ik}, D_{y}^{jl})$ measures the distance between pairwise distances in the two domains. Intuitively, $L(d_x(x_1, x_2), d_y(y_1, y_2))$ captures how transporting $x_1$ onto $y_1$ and $x_2$ onto $y_2$ would distort the original distances between $x_1$ and $x_2$ and between $y_1$ and $y_2$. The discrete Gromov-Wasserstein problem is then defined by:

$$ G_{D}(p, q) = \min_{\Gamma \in \Pi(p, q)} \sum_{i,j,k,l} L_{ijkl} \Gamma_{ijkl} \tag{2} $$
where \((p, q) = (V_{2k}, L_{2k})\) is the visual-language feature pairs. For each tuple \((x_i, x_k, y_j, y_l)\), we compute the cost of altering the pairwise distances between \(x_i\) and \(x_k\) when splitting their masses to \(y_j\) and \(y_l\) by weighting them by \(\Gamma_{ij}\) and \(\Gamma_{kl}\), respectively. The computed GWD across domain is to capture the relationship and dependencies between visual and language domains.

### 2.0.3 CCA and DCCA

Canonical Correlation Analysis (CCA) is a method for exploring the relationships between two multivariate sets of variables, which can learn linear transformation of two vectors in order to maximize the correlation between them, which is used in many multimodal problems [1, 7]. In our problem, we apply CCA to capture the cross-domain relationship. For visual features \(V_2\) and language features \(L_2\), where \(l \in \ell\). We assume \((V_{2l}, L_{2l}) \in \mathbb{R}^{n_1} \times \mathbb{R}^{n_2}\) has covariances \((\Sigma_{11}, \Sigma_{22})\) and cross-covariance \(\Sigma_{12}\). CCA finds pairs of linear projections of the two views, \((w_1^l V_{2l}, w_2^l L_{2l})\) that are maximally correlated:

\[
(w_1^l, w_2^l) = \arg \max_{w_1, w_2} \text{corr} \left( w_1^l V_{2l}, w_2^l L_{2l} \right)
\]

\[
= \arg \max_{w_1, w_2} \frac{w_1^l \Sigma_{12} w_2}{\sqrt{w_1^l \Sigma_{11} w_1 w_2^l \Sigma_{22} w_2}} \quad (3)
\]

Since the objective is invariant to scaling of \(\omega_1\) and \(\omega_2\), the projections are constrained to have unit variance:

\[
(w_1^l, w_2^l) = \arg \max_{w_1, w_2} w_1^l \Sigma_{11} w_1 w_2^l \Sigma_{22} w_2 \quad (4)
\]

To obtain \(V_2\) and \(L_2\), Deep CCA (DCCA) is applied in the framework for nonlinear feature transformation. If we assign \(\theta_1\) and \(\theta_2\) to represent the parameters for \(f(V_1)\) and \(g(L_1)\), respectively, where \(V_1\) and \(L_1\) represents the low-level visual and language features, then the transformation aims at:

\[
(\theta_1^*, \theta_2^*) = \arg \max_{\theta_1, \theta_2} \text{corr} \left( f(V_1; \theta_1), g(L_1; \theta_2) \right) \quad (5)
\]

The parameters are trained to optimize this quantity using gradient-based optimization by taking the correlation as the negative loss with backpropagation to update the nonlinear transformation model [1].

### 3. Ablation Experimental Results of Different Parameters

In this section, we provide more experimental results with different parameters, including \(\alpha\), \(\gamma\), \(\beta_0\), \(\nu_0\), \(\kappa_0\), \(l_\epsilon\), init state, and Nmax. The results are shown in Tables 1, 2, 3, and 4, respectively.
Table 5. Comparison of performance with different $\nu_0$.

| $\nu_0$ | Precision | Recall | F1-score |
|---------|-----------|--------|----------|
| 1       | 0.672     | 0.680  | 0.676    |
| 2       | 0.673     | 0.685  | 0.679    |
| 4       | 0.670     | 0.678  | 0.674    |
| 6       | 0.669     | 0.686  | 0.677    |
| 10      | 0.671     | 0.690  | 0.680    |
| 20      | 0.671     | 0.693  | 0.682    |
| 100     | 0.673     | 0.697  | 0.685    |
| 200     | 0.670     | 0.694  | 0.682    |
| 300     | 0.671     | 0.695  | 0.683    |
| 500     | 0.671     | 0.690  | 0.680    |

Table 6. Comparison of performance with different $\kappa_0$.

| $\kappa_0$ | Precision | Recall | F1-score |
|------------|-----------|--------|----------|
| 0.25       | 0.670     | 0.693  | 0.681    |
| 0.5        | 0.673     | 0.697  | 0.685    |
| 0.75       | 0.668     | 0.668  | 0.668    |
| 1          | 0.672     | 0.697  | 0.684    |
| 1.5        | 0.671     | 0.697  | 0.684    |
| 2          | 0.671     | 0.696  | 0.683    |
| 2.5        | 0.668     | 0.687  | 0.677    |

Table 7. Comparison of performance with different $l_s$.

| $l_s$ | Precision | Recall | F1-score |
|------|-----------|--------|----------|
| 0.5  | 0.662     | 0.685  | 0.673    |
| 1    | 0.673     | 0.697  | 0.685    |
| 5    | 0.671     | 0.696  | 0.683    |
| 10   | 0.670     | 0.690  | 0.680    |

Table 8. Comparison of performance with different init state.

| init state | Precision | Recall | F1-score |
|------------|-----------|--------|----------|
| 1          | 0.671     | 0.695  | 0.683    |
| 2          | 0.672     | 0.696  | 0.684    |
| 3          | 0.673     | 0.697  | 0.685    |
| 4          | 0.672     | 0.693  | 0.682    |
| 5          | 0.673     | 0.697  | 0.685    |
| 6          | 0.670     | 0.688  | 0.679    |
| 8          | 0.672     | 0.693  | 0.682    |
| 10         | 0.672     | 0.693  | 0.682    |

Table 9. Comparison of performance with different Nmax.

| Nmax | Precision | Recall | F1-score |
|------|-----------|--------|----------|
| 10   | 0.672     | 0.696  | 0.684    |
| 50   | 0.670     | 0.697  | 0.683    |
| 90   | 0.673     | 0.697  | 0.685    |
| 100  | 0.668     | 0.692  | 0.682    |
| 150  | 0.669     | 0.687  | 0.678    |
| 200  | 0.673     | 0.688  | 0.680    |

4. HSMM

Hidden Markov Model (HMM) is a statistical model which follows the Markov process to identify the hidden states from a set of observations, which has been widely used in sequential data problems [3, 13, 6], but the state duration distributions are restricted to a geometric form and the number of hidden states must be set a priori [16, 10, 9]. To overcome this, Hidden Semi-Markov Model (HSMM) was proposed [16], where there is a distribution placed over the duration of every state, tweaking the idea into a semi-Markov one. However, the number of hidden states in HMM and HSMM is unknown beforehand, and their patterns are subject to a specific distribution defined over a measure space. HMM with Hierarchical Dirichlet Process (HDP) extension can be used for inferring arbitrarily large state complexity from sequential and time-series data [2, 15]. However, the HDP-HMM’s strict Markovian constraints are undesirable in many settings. To overcome the issues, Johnson et al. introduced explicit-duration Hierarchical Dirichlet Process Hidden semi-Markov Model (HDP-HSMM) and provided new methods for sampling inference in the finite Bayesian HSMM [10].

5. The Architecture of DCCA Model

The architecture of the DCCA model and the parameters used in the main paper is shown in Table 10, respectively, where one view contains the visual raw features, and the other view contains the language raw features. The outputs are transformed high-level visual features and language features.

Table 10. DCCA model parameters in the experiments.

| Modality | Model Parameters |
|----------|------------------|
| Visual   | [1024, 512, 256] |
| Language | [1024, 512, 256] |

6. Example of Livestream Video

Fig. 1 shows some examples of the videos collected in our dataset.

![Video Examples](image)

Figure 1. Example of livestream videos.

7. Example of Livestream Transcripts

Some transcript examples are shown in Table 11 which shows the noisy characteristic nature of Livestream video transcripts.
Table 11. Example of livestream transcripts.

| Sentence | Offset | Transcript |
|----------|--------|------------|
| 1        | 79     | Good morning, good morning. My name is Kara Sykes and I am in artist here. |
| 2        | 91     | My light is very bright this morning. |
| 3        | 94     | Sometimes you can turn it down. |
| 12       | 137    | I got more sleep than we have been getting so I was like I’m going Live Today. |
| 20       | 166    | Let’s open up Photoshop Screen, but it’s going to be we’re gonna be working in illustrator. |
| 31       | 204    | Let’s go ahead and create. |
| 32       | 208    | I’ve got a sketch, but I’m actually going to work just without it, but what I want to do here is create some lines. |
| 112      | 568    | Doing letters you never do letters, and I say, I know, but I really wanted to let her his name, so that’s what I’m doing currently. |
| 146      | 698    | Now when I work for the area that I want to create, but let’s just let’s do this OK, I have my do not disturb on because at night we keep it off just so that doesn’t wake up. |
| 160      | 825    | Tell you what these type people who create custom type you are amazing. |

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