Abstract

Multimedia summarization with multimodal output (MSMO) is a recently explored application in language grounding. It plays an essential role in real-world applications, i.e., automatically generating cover images and titles for news articles or providing introductions to online videos. However, existing methods extract features from the whole video and article and use fusion methods to select the representative one, thus usually ignoring the critical structure and varying semantics. In this work, we propose a Semantics-Consistent Cross-domain Summarization (SCCS) model based on optimal transport alignment with visual and textual segmentation. In specific, our method first decomposes both video and article into segments in order to capture the structural semantics, respectively. Then SCCS follows a cross-domain alignment objective with optimal transport distance, which leverages multimodal interaction to match and select the visual and textual summary. We evaluated our method on three recent multimodal datasets and demonstrated the effectiveness of our method in producing high-quality multi-modal summaries.

1 Introduction

New multimedia content in the form of short videos and corresponding text articles has become a significant trend in influential digital media, including CNN, BBC, Daily Mail, social media, etc. This popular media type has shown to be successful in drawing users’ attention and delivering essential information in an efficient manner.

Multimedia summarization with multimodal output (MSMO) has recently drawn increasing attention. Different from traditional video or textual summarization (Gygli et al., 2014; Jadon and Jasim, 2020), where the generated summary is either a keyframe or textual description, MSMO aims at producing both visual and textual summaries simultaneously, making this task more complicated.

Figure 1: We proposed a segment-level cross-domain alignment model to preserve the structural semantics consistency within two domains for MSMO. We solve an optimal transport problem to optimize the cross-domain distance, which in turn finds the optimal match.

Previous works addressed the MSMO task by processing the whole video and article together and used fusion or attention methods to generate scores for summary selection, which overlooked the structure and semantics of different domains (Duan et al., 2022; Haopeng et al., 2022; Sah et al., 2017; Zhu et al., 2018; Mingzhe et al., 2020; Fu et al., 2021, 2020). However, we believe the structure of semantics is a crucial characteristic that can not be ignored for multimodal summarization tasks. Based on this hypothesis, we proposed Semantics-Consistent Cross-domain Summarization (SCCS) model, which explores segment-level cross-domain representations through Optimal Transport (OT) based multimodal alignment to generate both visual and textual summaries.

The comparison of our approach and previous works is illustrated in Figure 1. We regard the video and article as being composed of several topics related to the main idea, while each topic specifically corresponds to one sub-idea. Thus, treating the whole video or article uniformly and learning a general representation will ignore these structural semantics and leads to biased summarization. To address this problem, instead of learning averaged
representations for the whole video & article, we focus on exploiting the original underlying structure. Our model first decomposes the video & article into segments to discover the content structure, then explores the cross-domain semantics relationship at the segment level. We believe this is a promising approach to exploit the consistency lie in the structural semantics between different domains. Since MSMO generates both visual & textual summaries, We believe the optimal summary comes from the video and text pair that are both 1) semantically consistent and 2) best matched globally in a cross-domain fashion. In addition, our framework is more computationally efficient as it conducts cross-domain alignment on segment-level rather than taking the whole videos/articles as inputs.

Our contributions can be summarized as follow:
• We propose SCCS (Semantics-Consistent Cross-domain Summarization), a segment-level alignment model for MSMO tasks.
• Our method preserves the structural semantics and explores the cross-domain relationship through optimal transport to match and select the visual and textual summary.
• Our method serves as a hierarchical MSMO framework that provides better interpretability via Optimal Transport alignment.
• We provide both qualitative and quantitative results on three public datasets. Our method outperforms baselines and provides good interpretation of learned representations.

2 Related Work

Optimal Transport Optimal Transport (OT) studies the geometry of probability spaces (Villani, 2003), a formalism for finding and quantifying mass movement from one probability distribution to another. OT defines the Wasserstein metric between probability distributions, revealing a canonical geometric structure with rich properties to be exploited. The earliest contribution to OT originated from Monge in the eighteenth century. Kantorovich rediscovered it under a different formalism, namely the Linear Programming formulation of OT. With the development of scalable solvers, OT is widely applied to many real-world problems (Flamary et al., 2021; Chen et al., 2020a; Yuan et al., 2020; Klicpera et al., 2021; Alqahtani et al., 2021; Lee et al., 2019; Chen et al., 2019; Qiu et al., 2022; Duan et al., 2022; Han et al., 2022; Zhu et al., 2022).

Multimodal Alignment Aligning representations from different modalities is an important technique in multimodal learning. With the recent advancement, exploring the explicit relationship across vision and language has drawn significant attention (Wang et al., 2020). Torabi et al. (2016); Yu et al. (2017) adopted attention mechanisms, Dong et al. (2021) composed pairwise joint representation, Chen et al. (2020b); Wray et al. (2019); Zhang et al. (2018) learned fine-grained or hierarchical alignment, Lee et al. (2018); Wu et al. (2019) decomposed the inputs into sub-tokens, Velickovic et al. (2018); Yao et al. (2018) adopted graph attention for reasoning, and Yang et al. (2021) applied contrastive learning algorithms.

Multimodal Summarization Multimodal summarization explored multiple modalities, i.e., audio signals, video captions, Automatic Speech Recognition (ASR) transcripts, video titles, etc, for summary generation. Otani et al. (2016); Yuan et al. (2019); Wei et al. (2018); Fu et al. (2020) learned the relevance or mapping in the latent space between different modalities. In addition to only generating visual summaries, Li et al. (2017); Atri
et al. (2021); Zhu et al. (2018) generated textual summaries by taking audio, transcripts, or documents as input along with videos or images, using seq2seq model (Sutskever et al., 2014) or attention mechanism (Bahdanau et al., 2015). Recent trending on the MSMO task have also drawn much attention (Zhu et al., 2018; Mingzhe et al., 2020; Fu et al., 2021, 2020; Zhang et al., 2022).

3 Methods

Our SCCS is a segment-level cross-domain semantics alignment model for the MSMO task, where MSMO aims at generating both visual and language summaries. We follow the problem setting in Mingzhe et al. (2020), for a multimedia source with documents/articles and videos, the document $X_D = \{x_1, x_2, ..., x_d\}$ has $d$ words, and the ground truth textual summary $Y_D = \{y_1, y_2, ..., y_g\}$ has $g$ words. The corresponding video $X_V$, the video segmentation encoder separates the video sequence into segments $[X_{v1}, X_{v2}, ..., X_{vn}]$, where $n$ is the number of segments.

As shown in Figure 3(b), the video segmentation encoder contains a VTS module and a Bi-LSTM. Video $X_V$ is first split into shots $[S_{v1}, S_{v2}, ..., S_{vn}]$ (Castellano, 2021), then the VTS module takes a clip of the video with $2\omega_b$ shots as input and outputs a boundary representation $b_i$. The boundary representation captures both differences and relations between the shots before and after. VTS consists of two branches, VTS$^d$ and VTS$^r$, as shown in

3.1 Video Temporal Segmentation

Video temporal segmentation aims at splitting the original video into small segments, which the summarization tasks build upon. VTS is formulated as a binary classification problem on the segment boundaries, similar to Rao et al. (2020). For a video $X_V$, the video segmentation encoder separates the video sequence into segments $[X_{v1}, X_{v2}, ..., X_{vn}]$, where $n$ is the number of segments.
Equation 1.

\[ b_i = \text{VTS} \left( \left[ S_{s_1-\omega_1}, \ldots, S_{s_{n_1}+\omega_1} \right] \right) = \left[ \text{VTS}_d \left( \left[ S_{s_1-\omega_1}, \ldots, S_{s_{n_1}+\omega_1} \right] \right), \text{VTS}_r \left( \left[ S_{s_1-\omega_1}, \ldots, S_{s_{n_1}+\omega_1} \right] \right) \right] \]  

(1)

VTS_d is modeled by two temporal convolution layers, each of which embeds the \( w_i \) shots before and after the boundary, respectively, following an inner product operation to calculate the differences. VTS_r contains a temporal convolution layer followed a max pooling, aiming at capturing the relations of the shots. It predicts a sequence binary labels \([p_{t1}, p_{t2}, \ldots, p_{tm}]\) based on the sequence of representatives \([b_1, b_2, \ldots, b_n]\). A Bi-LSTM (Graves and Schmidhuber, 2005) is used with stride \( \omega \) to predict a sequence of coarse score \([s_1, s_2, \ldots, s_n]\), as shown in Equation 2,

\[ [s_1, s_2, \ldots, s_n] = \text{Bi-LSTM} ([b_1, b_2, \ldots, b_n]) \]  

(2)

where \( s_i \in [0, 1] \) is the probability of a shot boundary to be a scene boundary. The coarse prediction \( \hat{p}_{ti} \in \{0, 1\} \) indicates whether the \( i \)-th shot boundary is a scene boundary by binarizing \( s_i \) with a threshold \( \tau \), \( \hat{p}_{ti} = \begin{cases} 1 & \text{if } s_i > \tau \\ 0 & \text{otherwise} \end{cases} \). The results with \( \hat{p}_{v1} = 1 \) result in the learned video segments \([X_{v1}, X_{v2}, \ldots, X_{vn}]\)

3.2 Textual Segmentation

The textual segmentation module takes the whole document or articles as input and splits the original input into segments based on concept understanding. We used a hierarchical BERT as the textual segmentation module (Lukasik et al., 2020). As shown in Figure 3(c), the textual segmentation module contains two-level transformer encoders, where the first-level encoder is for sentence-level encoding, and the second-level encoder is for the article-level encoding. The hierarchical BERT starts by encoding each sentence with BERT\text{LARGE} independently, then the tensors produced for each sentence are fed into another transformer encoder to capture the representation of the sequence of sentences. All the sequences start with a [CLS] token to encode each sentence with BERT at the first level. If the segmentation decision is made at the sentence level, we use the [CLS] token as input of the second-level encoder. The [CLS] token representations from sentences are passed into the article encoder, which can reflect the different sentences through cross-attention.

3.3 Visual Summarization

The visual summarization module generates visual keyframes from each segment as its corresponding summary. We use a encoder-decoder architecture with attention as the visual summarization module (Ji et al., 2020), taking each video segment as input and outputting a sequence of keyframes. The encoder is a Bi-LSTM (Graves and Schmidhuber, 2005) to model the temporal relationship of video frames, where the input is \( X = [x_1, x_2, \ldots, x_m] \) and the encoding representation is \( E = [e_1, e_2, \ldots e_m] \). The decoder is a LSTM (Hochreiter and Schmidhuber, 1997) to generate output sequences \( D = [d_1, d_2, \ldots, d_m] \).

To exploit the temporal ordering across the entire video, we introduce attention mechanism: \( E_t = \sum_{i=1}^{m} \alpha_t^i e_i \), s.t. \( \sum_{i=1}^{n} \alpha_t^i = 1 \), and

\[ p (d_i \mid \{d_i \mid i < t\}, E_t) = \psi (s_{t-1}, d_{t-1}, E_t) \]  

(3)

where \( s_t \) is the hidden state, \( E_t \) is the attention vector at time \( t \), \( \alpha_t^i \) is the attention weight between the inputs and the encoder vector, \( \psi \) is the decoder function. To obtain \( \alpha_t^i \), the relevance score \( e_t^i \) is computed by \( e_t^i = \text{score}(s_{t-1}, e_i) \), where the score function decides the relationship between the \( i \)-th visual features \( e_i \) and the output scores at time \( t \):

\[ \beta_t^i = e_t^T W_d s_{t-1}, \quad \alpha_t^i = \exp (\beta_t^i) / \sum_{j=1}^{m} \exp (\beta_j^t) \]

3.4 Textual Summarization

Language summarization can produce a concise and fluent summary which should preserve the critical information and overall meaning. Our textual summarization module takes Bidirectional and Auto-Regressive Transformers (BART) (Lewis et al., 2020) as the summarization model to generate abstractive textual summary candidates. BART is a denoising autoencoder that maps a corrupted document to the original document it was derived from. As in Figure 3(a), BART uses the standard sequence-to-sequence Transformer architecture, where both the encoder and the decoder include 12 layers. In addition to the stacking of encoders and decoders, cross attention between encoder and decoder is also applied. BART is trained by corrupting documents and then optimizing a reconstruction loss, where the pretraining task involves randomly shuffling the order of the original sentences and a novel in-filling scheme, where spans of text are replaced with a single mask token. BART works well for comprehension tasks,
including achieving new state-of-the-art results on summarization tasks (Lewis et al., 2020).

### 3.5 Cross-Domain Alignment via Optimal Transport

Cross-domain alignment module learns the alignment between keyframes and textual summaries to generate the final multimodal summaries. Our alignment module is based on OT, which has been explored in several cross-domain tasks (Chen et al., 2020a; Yuan et al., 2020; Lu et al., 2021). OT is the problem of transporting mass between two discrete distributions supported on latent feature space \( X \).

Let \( \mu = \{x_i, \mu_i\}_{i=1}^n \) and \( v = \{y_j, v_j\}_{j=1}^m \) be the discrete distributions of interest, where \( x_i, y_j \in X \) denotes the spatial locations and \( \mu_i, v_j \) respectively, denoting the non-negative masses. Without loss of generality, we assume \( \sum_i \mu_i = \sum_j v_j = 1 \). \( \pi \in \mathbb{R}^{n \times m} \) is a valid transport plan if its row and column marginals match \( \mu \) and \( v \), respectively, which is \( \sum_i \pi_{ij} = v_j \) and \( \sum_j \pi_{ij} = \mu_i \).

Intuitively, \( \pi \) transports \( \pi_{ij} \) units of mass at location \( x_i \) to new location \( y_j \). Such transport plans are not unique, and one often seeks a solution \( \pi^* \in \Pi(\mu, v) \) that is most preferable in other ways, where \( \Pi(\mu, v) \) denotes the set of all viable transport plans. OT finds a solution that is most cost effective w.r.t. cost function \( C(x, y) \):

\[
D(\mu, v) = \sum_{ij} \pi_{ij} C(x_i, y_j) = \inf_{\pi \in \Pi(\mu, v)} \sum_{ij} \pi_{ij} C(x_i, y_j)
\]

where \( D(\mu, v) \) is known as OT distance. \( D(\mu, v) \) minimizes the transport cost from \( \mu \) to \( v \) w.r.t. \( C(x, y) \). When \( C(x, y) \) defines a distance metric on \( X \), and \( D(\mu, v) \) induces a distance metric on the space of probability distributions supported on \( X \), it becomes the Wasserstein Distance (WD).

The Cross-domain alignment module is shown in Figure 3(d), which is inspired by OT (Yuan et al., 2020). The image features \( V = \{v_k\}_{k=1}^K \) are extracted from pre-trained ResNet-101 (He et al., 2016) concatenated to faster R-CNN (Ren et al., 2015) as Yuan et al. (2020). For text features, every word is embedded as a feature vector and processed by a Bi-GRU to account for context (Yuan et al., 2020). The extracted image and text embeddings are \( V = \{v_k\}_{k=1}^K \), \( E = \{e_i\}_{i=1}^M \), respectively.

We take image and text sequence embeddings as two discrete distributions supported on the same feature representation space. Solving an OT transport plan between the two naturally constitutes a matching scheme to relate cross-domain entities (Yuan et al., 2020). To compute the OT distance, we compute a pairwise similarity between \( V \) and \( E \) using cosine distance:

\[
C_{km} = C(v_k, e_m) = 1 - \frac{e^T_k v_k}{\|e_k\| \|v_m\|}
\]

Then the OT can be formulated as:

\[
L_{OT}(V, E) = \min_{\pi} \sum_{k=1}^K \sum_{m=1}^M C_{km} \pi_{km} + \lambda H(T)
\]

where \( \sum_m T_{km} = \mu_k, \sum_k T_{km} = v_m, \forall k \in [1, K], m \in [1, M], T \in [0, 1]^{K \times M} \) is the transport matrix, \( d_k \) and \( d_m \) are the weight of \( v_k \) and \( e_m \) in a given image and text sequence, respectively. We assume the weight for different features to be uniform, i.e., \( \mu_k = \frac{1}{K}, v_m = \frac{1}{M} \). The objective of optimal transport involves solving linear programming and may cause potential computational burdens since it has \( O(n^3) \) efficiency. To solve this issue, we add an entropic regularization term equation (5) and the objective of our optimal transport distance becomes:

\[
L_{OT}(V, E) = \min_{\pi} \sum_{k=1}^K \sum_{m=1}^M C_{km} \pi_{km} + \lambda \sum_{k=1}^K T_{km} C_{km} + \lambda H(T)
\]

where \( H(T) = \sum_{i,j} T_{i,j} \log T_{i,j} \) is the entropy, and \( \lambda \) is the hyperparameter that balances the effect of the entropy term. Thus, we are able to apply the celebrated Sinkhorn algorithm (Cuturi, 2013) to efficiently solve the above equation in \( O(n \log n) \), where the algorithm is shown in Algorithm 1. The optimal transport distance computed via the Sinkhorn algorithm is differentiable and it can be implemented by Flamary et al. (2021). After training the alignment module, the WD between each keyframe-sentence pair of all the visual & textual summary candidates could be computed, where the best match is selected as the final multimodal summaries.

#### Algorithm 1 Compute Alignment Distance

1: **Input:** \( V = \{v_i\}_{i=1}^K, E = \{e_i\}_{i=1}^M \)
2: \( C = C(V, E), \sigma \leftarrow \frac{1}{M} 1_m, T^{(1)} \leftarrow 11^T \)
3: \( G_{ij} \leftarrow \exp \left( -\frac{d_{ij}}{\tau} \right) \)
4: for \( t = 1, 2, 3, ..., N \) do
5: \( Q \leftarrow G \odot T^{(t)} \)
6: for \( l = 1, 2, 3, ..., L \) do
7: \( \delta \leftarrow \frac{1}{nq} \sigma, \sigma \leftarrow \frac{1}{MQ+1} \)
8: end for
9: \( T^{(t+1)} \leftarrow \text{diag}(\delta)Q \text{diag}(\sigma) \)
10: end for
11: \( \text{Dis} = <C^T, T> \)
4 Datasets and Baselines

4.1 Datasets

We evaluated our models on three datasets: VMSMO dataset, Daily Mail dataset, and CNN dataset from Mingzhe et al. (2020); Fu et al. (2021, 2020). The VMSMO dataset contains 184,920 samples, including articles and corresponding videos. Each sample is assigned with a textual summary and a video with a cover picture. We adopted the available data samples from Mingzhe et al. (2020). The Daily Mail dataset contains 1,970 samples, and the CNN dataset contains 203 samples, which include video titles, images, and captions, similar to Hermann et al. (2015). For data splitting, we take the same experimental setup as Mingzhe et al. (2020) for the VMSMO dataset. For the Daily Mail dataset and CNN dataset, we split the data by 70%, 10%, 20% for train, validation, and test sets, respectively, same as Fu et al. (2021, 2020).

4.2 Baselines

We select state-of-the-art MSMO baselines and representative pure video summarization & pure textual summarization baselines for comparison. For VMSMO dataset, we compare our method with (i) multimodal summarization baselines (MSMO, MOF, and DIMS (Zhu et al., 2018, 2020; Mingzhe et al., 2020)), (ii) video summarization baselines (Synergistic and PSAC (Guo et al., 2019; Li et al., 2019)), and (iii) textual summarization baselines (Lead, TextRank, PG, Unified, and GPG (Nallapati et al., 2017; Mihalcea and Tarau, 2004; See et al., 2017; Hsu et al., 2018; Shen et al., 2019)). For Daily Mail and CNN datasets, we compare our method with (i) multimodal baselines (VisTaNet, MM-ATG, Img+Trans, TFN, HNNattTI, and M^2SM (Truong and Lauw, 2019; Zhu et al., 2018; Hori et al., 2019; Zadeh et al., 2017; Chen and Zhuge, 2018; Fu et al., 2021, 2020)), (ii) video summarization baselines (VSUMM, and DR-DSN (De Avila et al., 2011; Zhou et al., 2018a)), and (iii) textual summarization baselines (Lead3, NNSE, and M^2SM (Cheng and Lapata, 2016; Fu et al., 2021, 2020)).

5 Experiments

5.1 Experimental Setting and Implementation

For the VTS module, we used the same model setting as Rao et al. (2020); Castellano (2021) and same data splitting setting as Mingzhe et al. (2020); Fu et al. (2021, 2020) in the training process.

The visual summarization model is pre-trained on the TVSum (Song et al., 2015) and SumMe (Gygli et al., 2014) datasets. TVSum dataset contains 50 edited videos downloaded from YouTube in 10 categories, and SumMe dataset consists of 25 raw videos recording various events. Frame-level importance scores for each video are provided for both datasets and used as ground-truth labels. The input visual features are extracted from pre-trained GoogLeNet on ImageNet, where the output of the pool5 layer is used as visual features.

For the textual segmentation module, due to the quadratic computational cost of transformers, we reduce the BERT’s inputs to 64 word-pieces per sentence and 128 sentences per document as Lukasik et al. (2020). We use 12 layers for both the sentence and the article encoders, for a total of 24 layers. In order to use the BERT\_BASE checkpoint, we use 12 attention heads and 768-dimensional word-piece embeddings. The hierarchical BERT model is pre-trained on the Wiki727K dataset (Koshorek et al., 2018), which contains 727 thousand articles from a snapshot of the English Wikipedia. We used the same data splitting method as Koshorek et al. (2018).

For textual summarization, we adopted the pre-trained BART model (bart-large-cnn) from Lewis et al. (2020), which contains 1024 hidden layers and 406M parameters and has been fine-tuned using CNN and Daily Mail datasets.

In cross-domain alignment module, the feature extraction and alignment module is pretrained by MS COCO dataset (Lin et al., 2014) on the image-text matching task. We added the OT loss as a regularization term to the original matching loss to align the image and text more explicitly.

5.2 Evaluation Metrics

The quality of generated textual summary is evaluated by standard full-length Rouge F1 (Lin, 2004) following previous works (See et al., 2017; Chen et al., 2018; Mingzhe et al., 2020). ROUGE-1 (R-1), ROUGE-2 (R-2), and ROUGE-L (R-L) refer to overlap of unigram, bigrams, and the longest common subsequence between the decoded summary and the reference, respectively (Lin, 2004).

For VMSMO dataset, the quality of chosen cover frame is evaluated by mean average precision
Table 1: Comparison with multimodal baselines on the VMSMO dataset.

| Category                        | Methods  | Textual | Video  |
|---------------------------------|----------|---------|--------|
|                                 |          | R-1     | R-2    | R-L    | MAP  | R_{10}@1 | R_{10}@2 | R_{10}@5 |
| Video summarization baselines   | Synergistic | –       | –      | –      | 0.558| 0.444    | 0.557    | 0.759    |
|                                 | PSAC     | –       | –      | –      | 0.524| 0.363    | 0.481    | 0.730    |
| Textual summarization baselines | Lead     | 16.2    | 5.3    | 13.9   | –    | –        | –        | –        |
|                                 | TextRank | 13.7    | 4.0    | 12.5   | –    | –        | –        | –        |
|                                 | PG       | 19.4    | 6.8    | 17.4   | –    | –        | –        | –        |
|                                 | Unified  | 23.0    | 6.0    | 20.9   | –    | –        | –        | –        |
|                                 | GPG      | 20.1    | 4.5    | 17.3   | –    | –        | –        | –        |
| Multimodal baselines            | MSMO     | 20.1    | 4.6    | 17.3   | 0.554| 0.361    | 0.551    | 0.820    |
|                                 | MOF      | 21.3    | 5.7    | 17.9   | 0.615| 0.455    | 0.615    | 0.817    |
|                                 | DIMS     | 25.1    | 9.6    | 23.2   | 0.654| 0.524    | 0.634    | 0.824    |
| Ours                            | Ours-textual | 26.2    | 9.6    | 24.1   | –    | –        | –        | –        |
|                                 | Ours-video | –      | –      | –      | 0.678| 0.561    | 0.642    | 0.863    |
|                                 | Ours     | 27.1    | 9.8    | 25.4   | 0.693| 0.582    | 0.688    | 0.895    |

(MAP) and recall at position \(R_n@k\) \((Zhou et al., 2018b; Tao et al., 2019)\), where \(R_n@k\) measures if the positive sample is ranked in the top \(k\) positions of \(n\) candidates. For Daily Mail dataset and CNN dataset, we calculate the cosine image similarity (Cos) between image references and the extracted frames from videos \((Fu et al., 2021, 2020)\).

### 5.3 Results and Discussion

The comparison results on the VMSMO dataset of multimodal, video, and textual summarization are shown in Table 1. Synergistic \((Guo et al., 2019)\) and PSAC \((Li et al., 2019)\) are pure video summarization approaches, which did not perform as good as multimodal methods, like MOF \((Zhu et al., 2020)\) or DIMS \((Mingzhe et al., 2020)\), which means taking additional modality into consideration actually helps to improve the quality of the generated video summaries. Our method shows the ability to preserve the structural semantics and is able to learn the alignment between keyframes and textual deceptions, which shows better performance than the previous ones. If comparing the quality of generated textual summaries, our method still outperforms the previous ones. For Daily Mail dataset and CNN dataset, we calculate the cosine image similarity (Cos) between image references and the extracted frames from videos \((Fu et al., 2021, 2020)\).

### 5.4 Ablation Study

To evaluate each component’s performance, we performed ablation experiments on different modalities and different datasets. For the VMSMO dataset, we compare the performance of using only visual information, only textual information, and multimodal information. The comparison result is shown in Table 1. We also carried out experiments on different modalities using Daily Mail dataset to show the performance of unimodal and multimodal components, and the results are shown in Table 2. For the ablation results, when only textual data is available, we adopt BERT \((Devlin et al., 2019)\), TFN \((Zadeh et al., 2017)\), HN-NattTI \((Chen and Zhuge, 2018)\) and M^2SM \((Fu et al., 2021)\) on the quality of generated textual summaries. While on the Daily Mail dataset, our approach showed better performance on both textual summaries and visual summaries. We also compare with the traditional pure video summarization baselines \((De Avila et al., 2011; Zhu et al., 2018a; Fu et al., 2021)\) and pure textual summarization baselines \((Nallapati et al., 2017; Cheng and Lapata, 2016)\) on the Daily Mail dataset, and the results are shown in Table 2. We can find that our approach performed competitive results compared with NN-SE \((Cheng and Lapata, 2016)\) and M^2SM \((Fu et al., 2021)\) for the quality of generated textual summary. For visual summarization comparison, we can find that the quality of generated visual summary by our approach still outperforms the other visual summarization baselines.
Table 2: Comparisons of multimodal baselines on the Daily Mail and CNN datasets.

| Category                        | Methods       | CNN dataset | Daily Mail dataset |
|---------------------------------|---------------|-------------|--------------------|
|                                 |               | R-1  R-2 R-L| R-1   R-2 R-L      | Cos(%) |
| Video summarization baselines   | VSUMM         | –  –  –    | –  –  –           | 68.74  |
|                                 | DR-DSN        | –  –  –    | –  –  –           | 68.69  |
| Textual summarization baselines | Lead3         | –  –  –    | 41.07  17.87 30.90| –      |
|                                 | NN-SE         | –  –  –    | 41.22  18.15 31.22| –      |
| Multimodal baselines            | VistaNet      | 9.31 3.24 6.33 | 18.62 6.77 13.65 | –      |
|                                 | MM-ATG        | 26.83 8.11 18.34 | 35.38 14.79 25.41 | 69.17  |
|                                 | Img+Trans     | 27.04 8.29 18.54 | 39.28 16.64 28.53 | –      |
|                                 | TFN           | 27.68 8.69 18.71 | 39.37 16.38 28.09 | –      |
|                                 | HNNattTI      | 27.61 8.74 18.64 | 39.58 16.71 29.04 | 68.76  |
|                                 | M^2SM         | 27.81 8.87 18.73 | 41.73 18.59 31.68 | 69.22  |
| Ours                            | Ours-textual  | –  –  –    | 40.28  17.93 31.89| –      |
|                                 | Ours-video    | –  –  –    | 41.22  18.15 31.22| –      |
|                                 | Ours-Multimodal| 28.02 8.94 18.89 | 44.52 19.87 35.79 | 73.19  |

In an unsupervised manner, where we use K-Means clustering to cluster frames using image histogram and then select the best frame from clusters based on the variance of laplacian as the visual summary.

From Table 1 and Table 2, we can find that multimodal methods outperform unimodal approaches, showing the effectiveness of exploring the relationship and taking advantage of the cross-domain alignments of generating high-quality summaries.

5.5 Interpretation

To show a deeper understanding of the multimodal alignment between the visual domain and language domain, we compute and visualize the transport plan to provide an interpretation of the latent representations, which is shown in Figure 4. When we are regarding the extracted embedding from both text and image spaces as the distribution over their corresponding spaces, we expect the optimal transport coupling to reveal the underlying similarity and structure. Also, the coupling seeks sparsity, which further helps to explain the correspondence between the text and image data.

Figure 4 shows comparison results of matched image-text pairs and non-matched ones. The top two pairs are shown as matched pairs, where there is overlapping between the image and the corresponding sentence. The bottom two pairs are shown as non-matched ones, where the overlapping of meaning between the image and text is relatively small. The correlation between the image domain and the language domain can be easily interpreted by the learned transport plan matrix. In specific, the optimal transport coupling shows the pattern of sequentially structured knowledge. However, for non-matched image-sentences pairs, the estimated couplings are relatively dense and barely contain any informative structure. As shown in Figure 4, we can find that the transport plan learned in the cross-domain alignment module demonstrates a way to align the features from different modalities to represent the key components. The visualization of the transport plan contributes to the interpretability of the proposed model, which brings a clear understanding of the alignment module.

6 Conclusion

In this work, we proposed SCCS, a segment-level Semantics-Consistent Cross-domain Summarization model for the MSMO task. Our model decomposed the video & article into segments based on the content to preserve the structural semantics, and explored the cross-domain semantics relationship via optimal transport alignment at the segment level. The experimental results on three MSMO datasets show that SCCS outperforms previous summarization methods. We further provide interpretation by the OT coupling. Our approach provides a new direction for the MSMO task, which can be extended to many real-world applications.
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