CRET: Cross-Modal Retrieval Transformer for Efficient Text-Video Retrieval

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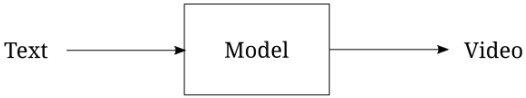
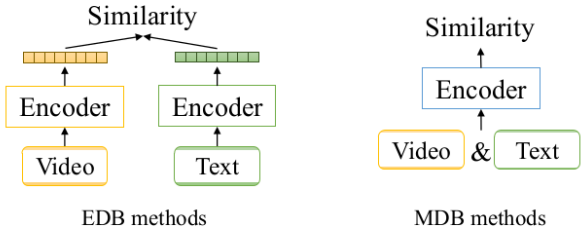
Motivation

- Unimodal information retrieval task.

- Multimodal information retrieval task, e.g. text-to-video retrieval.



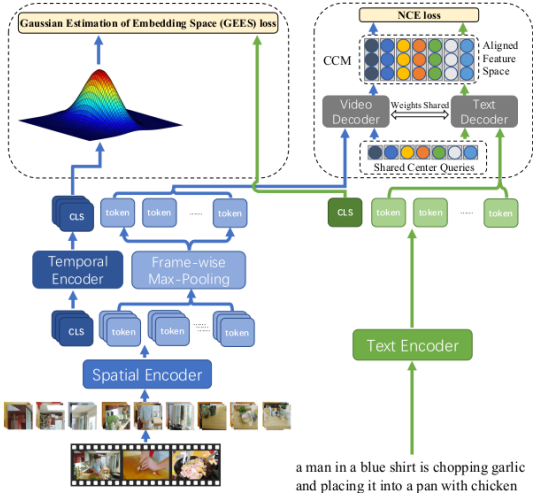
EDB method versus MDB method



(a) EDB and MDB methods mainly differ at whether explicit embeddings of text/video are generated.

- EDB method: Inferior performance due to the lack of feature alignment.
- MDB method: Low efficiency due to the exhaustive scan over the entire database.

Overview of the CRET model



Two main contributions: CCM & GEES

Cross-modal correspondence modeling (CCM)

- Utilize transformer decoders to align the features from text and video modalities.
- Use queries as common centers of features from both modalities.
- Parameters are shared between decoders of two modalities.

Gaussian estimation of embedding space (GEES)

$$\mathbf{Z}_{c,j} = \text{softmax}\left(\frac{(Q_c W_j^Q)(EW_j^K)^T}{\sqrt{d_k}}\right)(EW_j^V)$$

1. Calculate the distance between token features and the query center. Regard the distance as the weight of corresponding features.
2. Concatenate and project the aligned features.
3. Calculate the similarity score of features from text and video modalities.

Experiments

- **Datasets**: MSRVTT, LSMDC, MSVD, DiDeMo.
- **Metrics**: R@K, MdR.
- **Results**:
  - MSRVTT

	Weight Initialization		E2E	Type	R@1↑	R@5↑	R@10↑	MdR↓
	Visual	Textual						
MIL-NCE [36]	K+H	G+H	✓	EDB	9.9	24.0	32.4	29.5
JSFusion [54]	I	N.A.	✓	MDB	10.2	31.2	43.2	13.0
HT [38]	I	G	✓	EDB	12.4	36.0	52.0	10.0
HT [38]	I+H	G+H	✓	EDB	14.9	40.2	52.8	9.0
ActBERT [59]	I+H	B+H		MDB	16.3	42.8	56.9	10.0
HiT(appearance-only) [30]	I+H	B+H	✓	EDB	18.2	41.9	55.5	5.0
TACo(R-152) [53]	I+H	B+H	✓	MDB	18.9	46.2	58.8	7.0
UniVL(FT-Joint) [33]	K+H	B+H		EDB	20.6	49.1	62.9	6.0
UniVL(FT-Align) [33]	K+H	B+H		MDB	21.2	49.6	63.1	6.0
ClipBERT [28]	I+C+V	C+V	✓	MDB	22.0	46.8	59.9	6.0
Ours	I	B	✓	EDB	**23.9**	**50.8**	**63.4**	**5.0**

Experiments

- **Results**:
  - LSMDC

	E2E	Type	R@1↑	R@5↑	R@10↑	MdR↓
CT-SAN [55]	✓	MDB	5.1	16.3	25.2	46.0
HT [38]	✓	EDB	5.8	18.8	28.4	45.0
HT* [38]	✓	EDB	7.1	19.6	27.9	40.0
NoiseE* [1]		EDB	6.4	19.8	28.4	39.0
JSFusion [54]	✓	MDB	9.1	21.2	**34.1**	36.0
Ours	✓	EDB	**10.0**	**24.9**	33.4	**34.0**

  - MSVD

	E2E	Type	R@1↑	R@5↑	R@10↑	MdR↓
HT [38]	✓	EDB	13.0	37.4	52.4	10.0
HT* [38]	✓	EDB	15.5	40.9	55.7	8.0
NoiseE* [1]		EDB	20.3	49.0	63.3	6.0
CLIP4Clip† [34]		EDB	46.2	76.1	84.6	2.0
Ours	✓	EDB	**49.0**	**87.0**	**95.0**	**2.0**

Experiments

- **Results**:
  - DiDeMo

	E2E	Type	R@1↑	R@5↑	R@10↑	MdR↓
S2VT [49]	✓	EDB	11.9	33.6	-	13.0
FSE [57]	✓	EDB	13.9	36.0	-	11.0
ClipBERT‡ [28]	✓	MDB	20.4	48.0	60.8	6.0
Ours	✓	EDB	**21.2**	**50.3**	**63.5**	**6.0**

- **Ablation studies**.
- **Validation of Gaussian assumption**.

Critical review

- Readability and structure.
  - Illustrate CRET method clearly.
  - Satisfy requirements of the scientific paper.
- Reproducibility: Source code, the availability of data sets, experimental settings.
- Importance.
  - Theoretical contributions.
  - Practical applications.
- Summary of strong and weak points.

Appendix: Details of GEES

Vanilla NCE loss:

$$\mathcal{L}_{NCE} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{M}\sum_{j=1}^{M} -\log\left(\frac{\exp\left(< V_{ij}^{g}, T_{i}^{g} >\right)}{\exp\left(< V_{ij}^{g}, T_{i}^{g} >\right) + \sum_{(V^{g'}, T^{g'})\in\Phi_i}\exp\left(< V^{g'}, T^{g'} >\right)}\right)$$

Multivariate Gaussian distribution assumption:

$$v_i \sim \mathcal{N}\left(\mu_i, \sigma_i\right)$$

Derive the GEES and its upper bound:

$$\mathcal{L}_{GEES} = \frac{1}{N}\sum_{i=1}^{N} E_{v_i}\left[-\log\left(\frac{\exp\left(< V_{ij}^{g}, T_{i}^{g} >\right)}{\exp\left(< V_{ij}^{g}, T_{i}^{g} >\right) + \sum_{(V^{g'}, T^{g'})\in\Phi_i}\exp\left(< V^{g'}, T^{g'} >\right)}\right)\right]$$

$$\leq -\frac{1}{N}\sum_{i=1}^{N}\log\frac{\exp\left(< T_{i}^{g}, \mu_i > + \frac{1}{2} < T_{i}^{g}, \sigma_i T_{i}^{g} >\right)}{\sum_{j=1}^{N}\exp\left(< T_{i}^{g}, \mu_i > + \frac{1}{2} < T_{i}^{g}, \sigma_i T_{i}^{g} >\right)} = \bar{\mathcal{L}}_{GEES}$$

Strategies of training and inference

Training:

$$\mathcal{L}_{CCM} = -\frac{1}{N}\sum_{i=1}^{N} -\log\left(\frac{\exp\left(< Z_i^v, Z_i^t >\right)}{\exp\left(Z_i^v, Z_i^t\right) + \sum_{(Z^{v'}, Z^{t'})\in\Psi_i}\exp\left(< Z^{v'}, Z^{t'} >\right)}\right)$$

$$\mathcal{L}_{total} = \bar{\mathcal{L}}_{GEES} + \alpha\mathcal{L}_{CCM}$$

Inference:

$$S = S_g + \beta S_l$$

$$S_l = \cos\left(Z^v, Z^t\right)$$

$$S_g = \cos\left(\frac{1}{M}\sum_{j=1}^{M} V_{ij}^g, T_i^g\right)$$