

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

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① Motivation

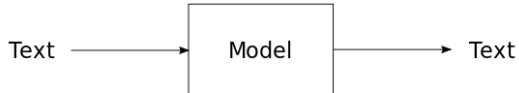
② Methodology

③ Experiments

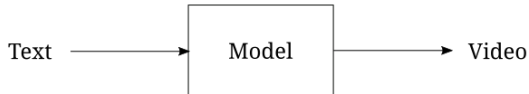
④ Critical Review

Motivation

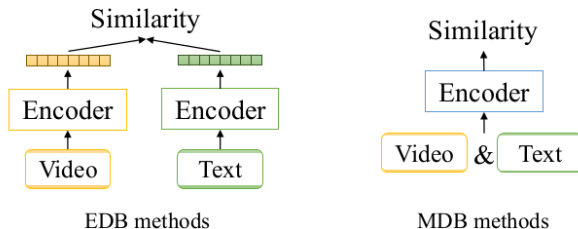
- Unimodal information retrieval task.



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



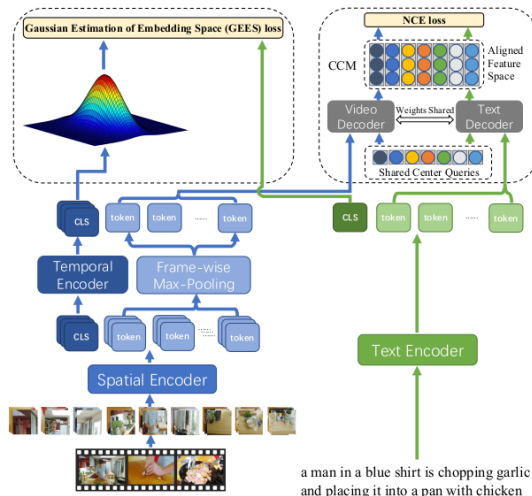
EDB method versus MDB method



(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 the multi-head self-attention mechanism.

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

- Share weights between two decoders.
- Put more importance on features that are close to the query center.

Gaussian estimation of embedding space (GEES)

- Traditional NCE loss: A trade-off between accuracy and computing costs.
- Introduce the multivariate Gaussian distribution assumption.
- Enhance the optimization efficiency of SGD.

Experiments

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

	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.
- Strong points.
 - Algorithm efficiency.
 - Extensive ablation studies and hypothesis tests.
- Weak points.
 - Inaccessibility of source code.
 - Don't report the standard variance and the number of times of running each model.

Appendix: Details of GEES

Vanilla NCE loss:

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

Multivariate Gaussian distribution assumption:

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

Derive the GEES and its upper bound:

$$\begin{aligned} \mathcal{L}_{GEES} &= \frac{1}{N} \sum_{i=1}^N E_{v_i} \left[-\log \left(\frac{\exp(\langle V_{ij}^g, T_i^g \rangle)}{\exp(\langle V_{ij}^g, T_i^g \rangle) + \sum_{(V^{g'}, T^{g'}) \in \Phi_i} \exp(\langle V^{g'}, T^{g'} \rangle)} \right) \right] \\ &\leq -\frac{1}{N} \sum_{i=1}^N \log \frac{\exp(\langle T_i^g, \mu_i \rangle + \frac{1}{2} \langle T_i^g, \sigma_i T_i^g \rangle)}{\sum_{j=1}^N \exp(\langle T_i^g, \mu_i \rangle + \frac{1}{2} \langle T_i^g, \sigma_i T_i^g \rangle)} = \bar{\mathcal{L}}_{GEES} \end{aligned}$$

Appendix: Strategies of training and inference

Training:

$$\mathcal{L}_{CCM} = -\frac{1}{N} \sum_{i=1}^N -\log \left(\frac{\exp(\langle Z_i^v, Z_i^t \rangle)}{\exp(Z_i^v, Z_i^t) + \sum_{(Z^{v'}, Z^{t'}) \in \Psi_i} \exp(\langle Z^{v'}, Z^{t'} \rangle)} \right)$$
$$\mathcal{L}_{total} = \bar{\mathcal{L}}_{GEES} + \alpha \mathcal{L}_{CCM}$$

Inference:

$$S = S_g + \beta S_l$$
$$S_l = \cos(Z^v, Z^t)$$
$$S_g = \cos \left(\frac{1}{M} \sum_{j=1}^M V_{ij}^g, T_i^g \right)$$