SEJONG UNIVERSITY

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PAPER REVIEW

T2VLAD: GLOBAL-LOCAL SEQUENCE ALIGNMENT FOR TEXT-VIDEO RETRIEVAL

CONTENT

I. OVERVIEW

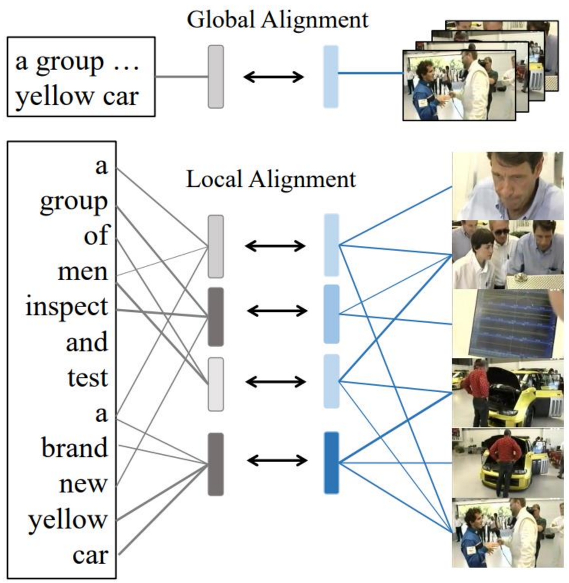
- X. Wang, L. Zhu, and Y. Yang, "T2VLAD: global-local sequence alignment for text-video retrieval,", In *Proc. IEEE/CVF CVPR*, Jun. 2021, pp. 5079-5088.
- **"T2VLAD"** – **Text-to-Video VLAD**

VLAD: Vector of Locally Aggregated Descriptors (slide 6)

- **T2VLAD –** text-video retrieval model, which aligns text and video features in a global and local perspective:

- Local alignment: the fine-grained comparisons by computing the similarities between the local text-video features in sematic topics.

- Global alignment: encoding text and video content and comparing their similarities in the global perspective



X. Wang, L. Zhu, and Y. Yang, "T2LVAD: global-local sequence alignment for text-video retrieval,". In *Proc. IEEE/CVF CVPR*, Jun. 2021, pp. 5079-5088.

II. PROBLEM STATEMENT

- Most existing methods: encode the descriptions and video content to global representations and compare their similarities from a **global perspective;**
- Some other works: leveraged complex cross-modal matching operations to exploit the **local details** and align multiple semantic cues.
- **HGR** [1] *(CVPR 2020)* proposed a hierarchical graph reasoning model to capture both **global events and local actions** through local graph matching

=> require a **high computational cost** due to the expensive pairwise matching operation.

Global perspective

Local perspective

Global + Local perspective

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III. RELATED MODELS (PAPERS)

Text representation: BERT (NAACL-HLT 2019)

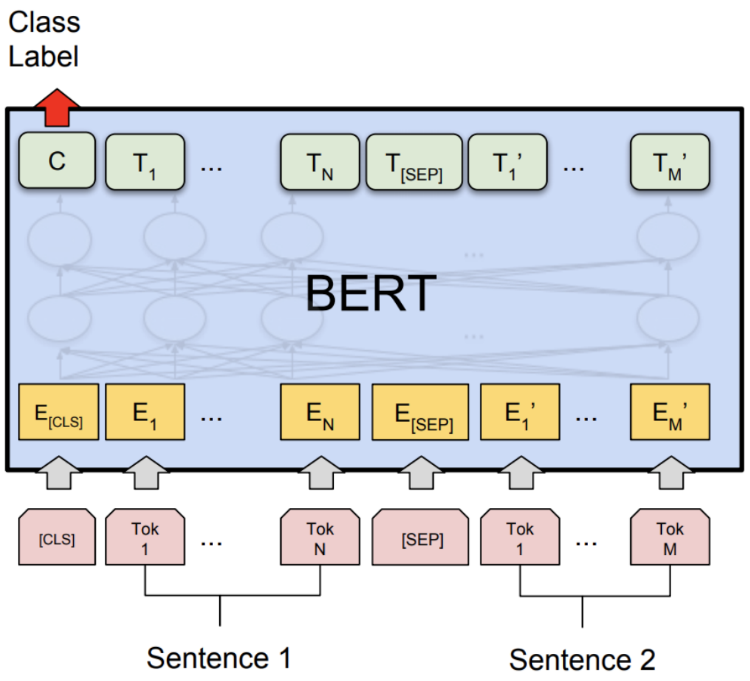
Video embedding in MME (2018)

Sematic topic alignment: NetVLAD (CVPR 2016)

1. BERT

- Bidirectional Encoder Representations from Transformers (BERT) [2] *(NAACL-HLT 2019)*
- BERT - *transformer-based* machine learning technique learns contextual relations between words (or sub-words) in a text.
- State of the art language model results in a wide variety of Natural Language Processing (NLP) tasks (question answering, text classification, ...)

=> Text representations



Example of BERT in language pair classification

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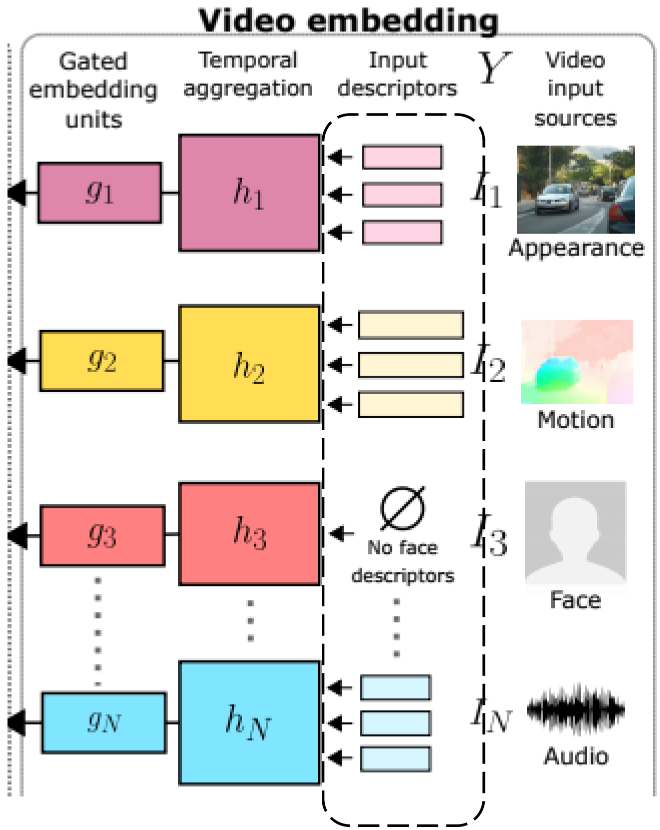
2. MEE

- MEE [3] Mixture-of-Embedding-Experts: computes similarities between text and a varying number of video modalities
- "Expert" video feature extractor - an effective representation from different modalities inherent in video data (appearance, motion, audio,...)
- Video embedding in MME: take advantage of the rich and varied additional information present in videos: motion dynamics, speech and other background sounds.

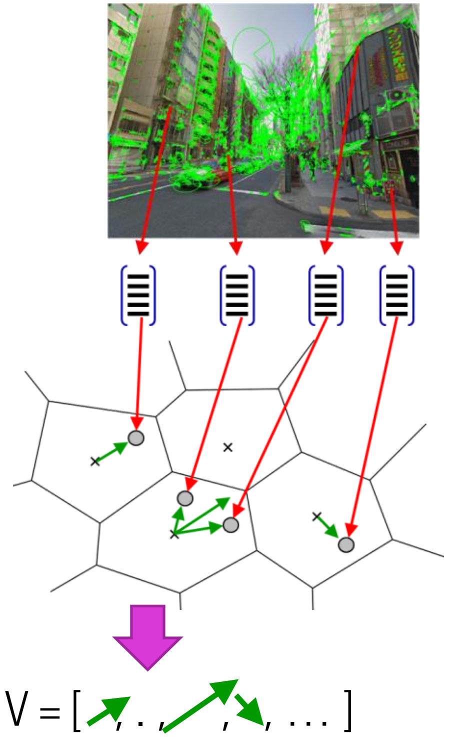
=> Use Video embedding in MME for Video representations



Expert Encoding

3. NETVLAD

- Vector of Locally Aggregated Descriptors (VLAD) [2] *(CVPR 2010)* is an image representation model that commonly used in image retrieval
  - Accumulate the residual of each descriptor with respect to its assigned cluster (K-mean clustering)
  - Store the sum of the differences of the descriptors assigned to the cluster and the centroid of the cluster
  - VLAD is pooling method, not a CNN architecture -> not trainable
- **NetVLAD** [3] *(CVPR 2016)* – a powerful image representation trainable end-to-end on the image retrieval - mimic VLAD in a CNN framework and design a trainable generalized VLAD layer.



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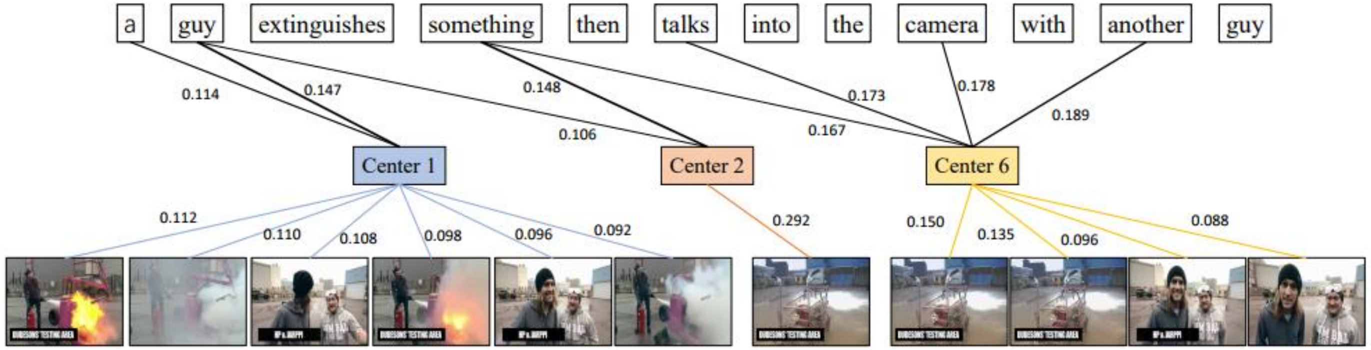
3. NETVLAD (CONT.)

=> **Sematic topic alignment** by NetVLAD: for **both text and video modalities** (can be readily utilized as latent semantic topics on cross-modal)

- NetVLAD operations can obtain an aggregated feature for each topic, where the **topic centers** are **shared** between the two modalities.

(a) Mobile phone query (b) Retrieved image of same place

Example of NetVLAD
(in image retrieval task)



Example of shared topic center

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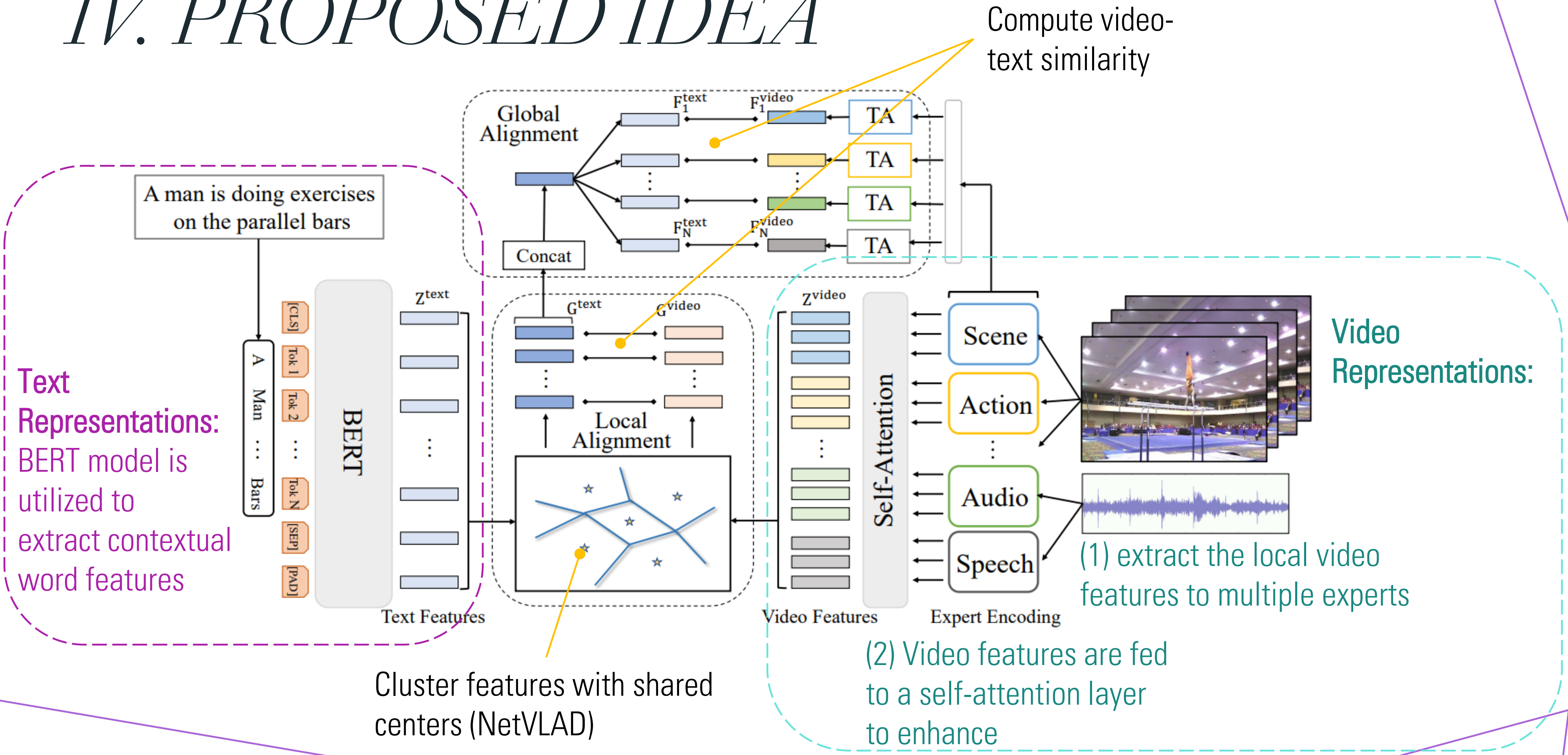
IV. PROPOSED IDEA



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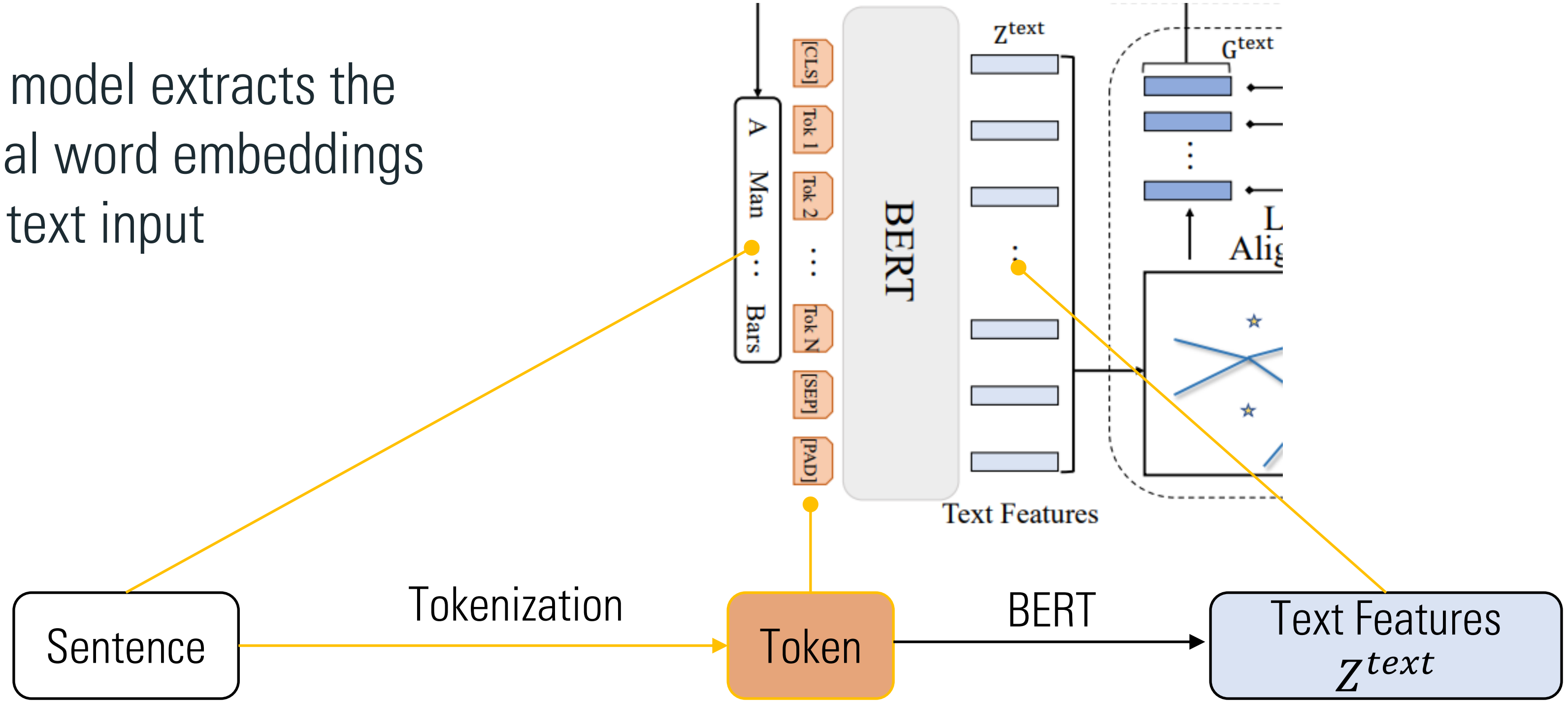
1. TEXT REPRESENTATION

- BERT [2] model extracts the contextual word embeddings for each text input



[CLS]: class token, marked for begin a sequence
[SPS]: separator token, added among 2 sentences in a sequence

$Z^{text} = \{z_1^{text}, z_2^{text}, \ldots, z_B^{text}\}$
Where B is the sequence length

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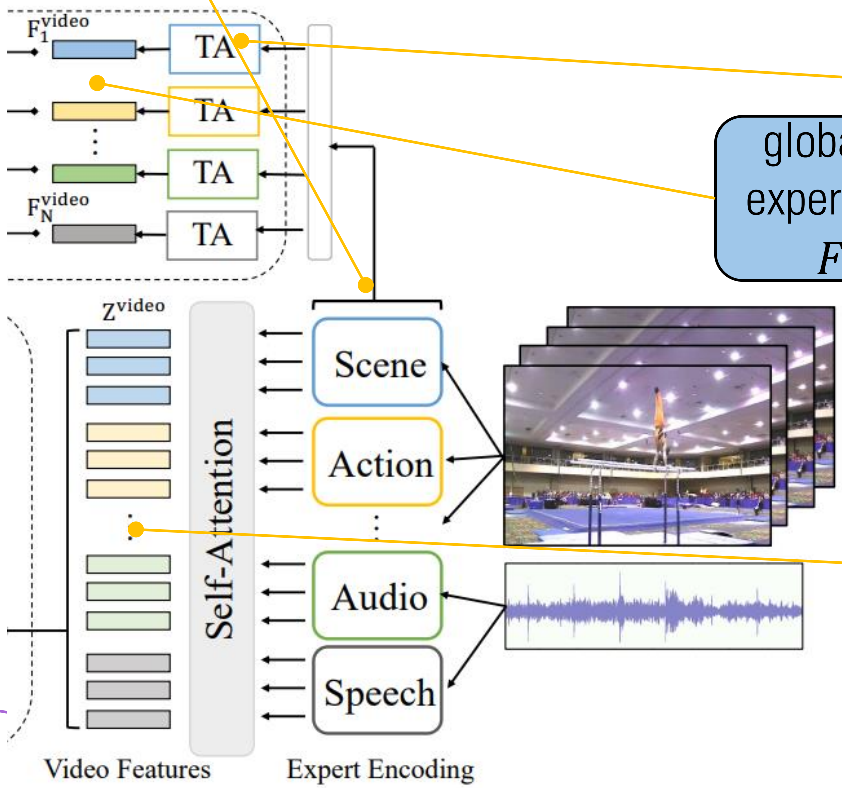
2. VIDEO REPRESENTATION

x_t is the t-th segment from a video

Segment-level video representation $E^n(x_t)$

Encode by expert E^n

Raw video



- Global expert features for global alignment:

global video expert feature F_i^{text}

Self-gating

Temporal-aggregated feature

Max-pooling

Segment-level video representation $E^n(x_t)$

- Fuse multi expert features for local alignment:

Video local features Z^{video}

Self-attention layer

Segment-level video representation $E^n(x_t)$

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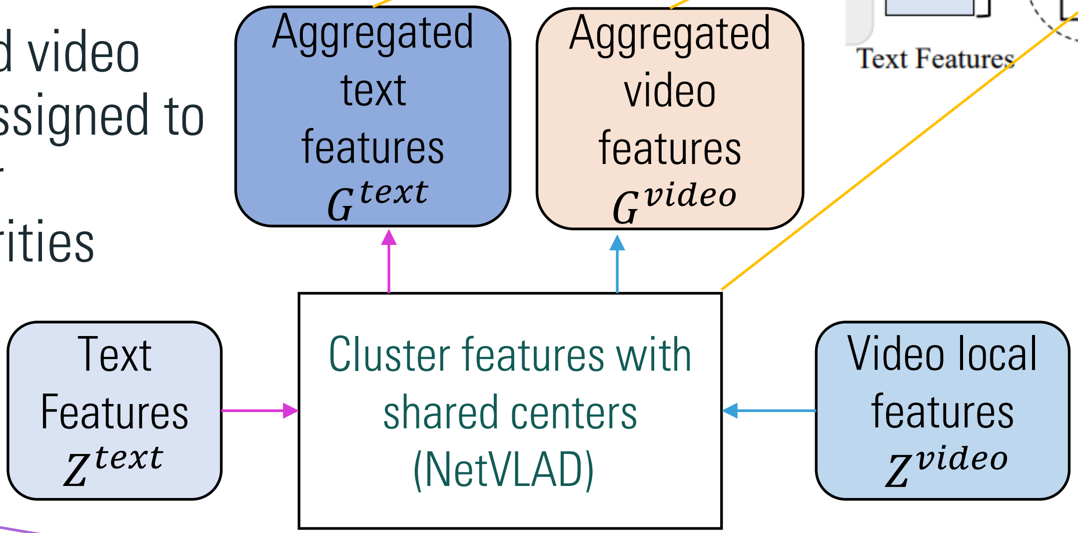
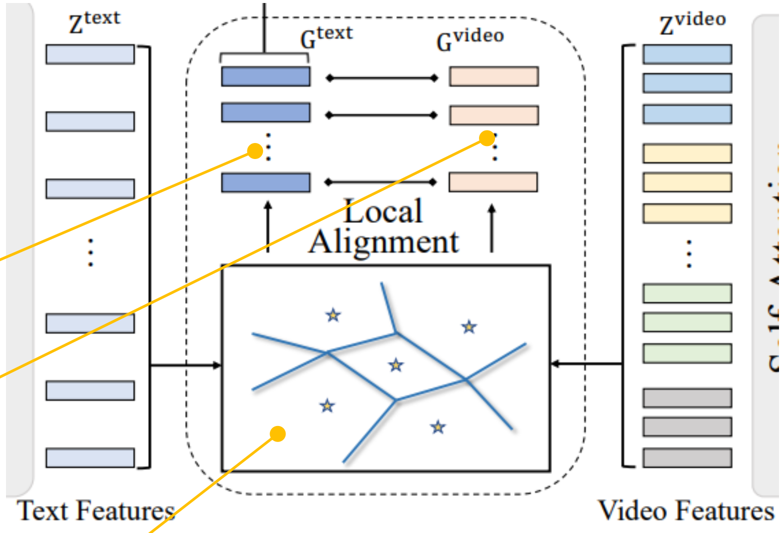
3. LOCAL ALIGNMENT

- Use NetVLAD operations for both text and video modalities, to obtain an **aggregated feature** for each topic, where the topic centers are **shared** between the two modalities.
- The text features and video features are softly assigned to topics based on their corresponded similarities





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3. LOCAL ALIGNMENT (CONT.)

The aggregated features g_j^{video}, g_j^{text} are calculated by using the shared cluster centers c_j [3]

$$g_j^{video} = normalize(\sum_{i=1}^{M} \frac{\exp(z_i^{video} c_j^T + b_j)}{\sum_{k=1}^{K+1} \exp(z_i^{video} c_k^T + b_k)} (z_i^{video} - c_j'))$$

$$g_j^{text} = normalize(\sum_{i=1}^{B} \frac{\exp(z_i^{text} c_j^T + b_j)}{\sum_{k=1}^{K+1} \exp(z_i^{text} c_k^T + b_k)} (z_i^{text} - c_j'))$$

Where:

M: the number of features from all experts (video)

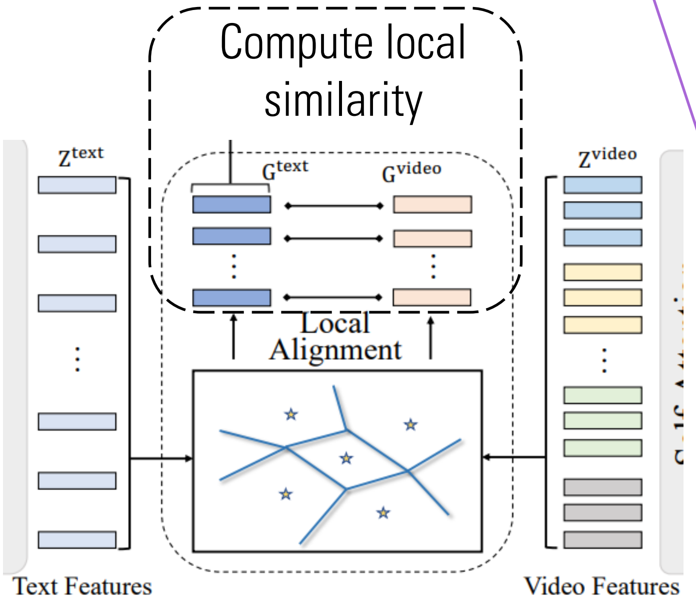
B: sequence length of text feature

$c_1, c_2, \dots c_{K+1}$ shared cluster center of 1 to K+1

b_j is a learnable bias term

z_i^{video}, z_i^{text} are local video feature / local word embedding

c_j' trainable weights



Local similarity = cosine distance between video feature $G^{video} = \{g_1^{video}, \dots, g_K^{video}\}$ and text feature $G^{text} = \{g_1^{text}, \dots, g_K^{text}\}$

$$s_{local} = dist(G^{video}, G^{text})$$

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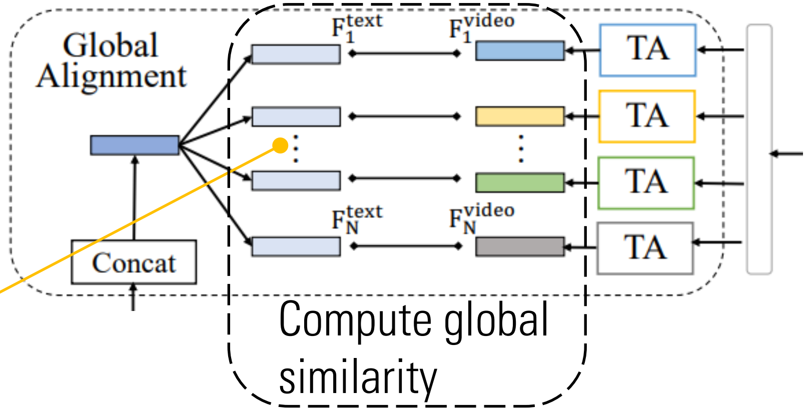
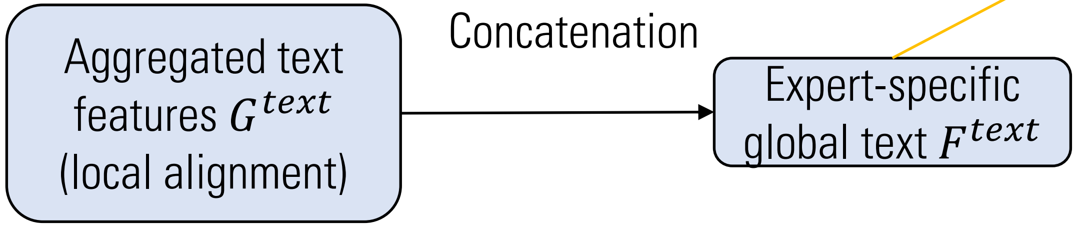
4. GLOBAL ALIGNMENT

- 2 reasons of using global alignment:
  - More comprehensive and complementary to local features
  - Lacking auxiliary supervision of local alignment with trainable centers





Global similarity: weighted sum of cosine distances between each global video expert feature F_i^{text} and corresponding text feature F_i^{video}

$$s_{global} = \sum_{i=1}^{N} w_i * dist(F_i^{text}, F_i^{video})$$

(w_i is the weight for the i-th expert, generated from G^{text} by a linear projection with a soft-max normalization)

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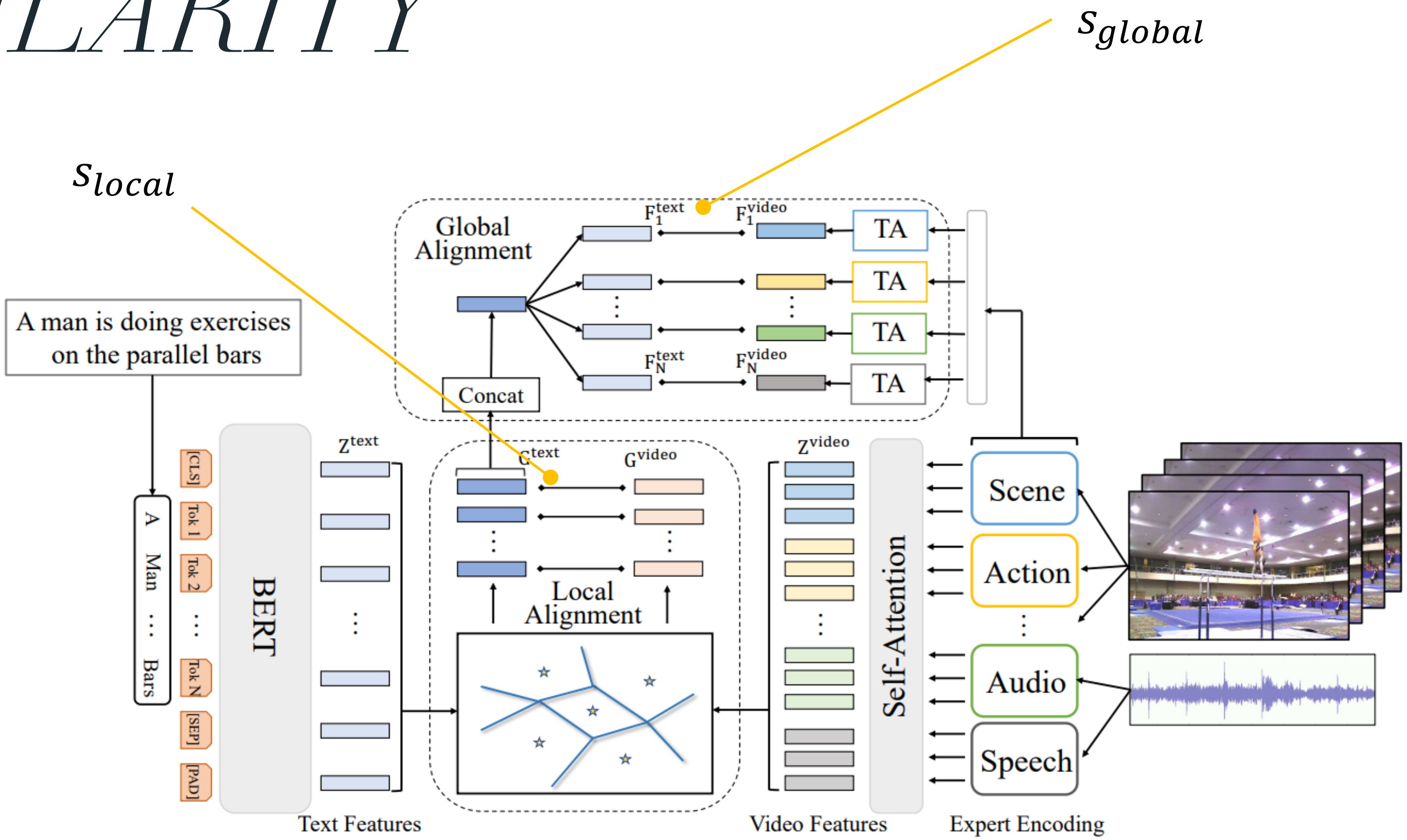
SIMILARITY



Text-video similarity s:

$$s = \frac{1}{2}(s_{global} + s_{local})$$

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V. RESULT

- T2VLAD outperforms **MMT** (Multi-modal Transformer for Video Retrieval) [5] *(ECCV 2020)* and other proposed methods with MRS-VTT dataset

Method	Split	Text → Video				Video → Text			
		R@1↑	R@5↑	R@10↑	MdR↓	R@1↑	R@5↑	R@10↑	MdR↓
JSFusion [37]	1k-A	10.2	31.2	43.2	13	-	-	-	-
HT [25]	1k-A	14.9	40.2	52.8	9	-	-	-	-
CE [22]	1k-A	20.9	48.8	62.4	6	20.6	50.3	64.0	5.3
MMT [9]	1k-A	24.6	54.0	67.1	4	24.4	56.0	67.8	4
MMT + HT pretrain [9]	1k-A	26.6	57.1	69.6	4	27.0	57.5	69.7	3.7
Our T2VLAD	1k-A	**29.5**	**59.0**	**70.1**	**4**	**31.8**	**60.0**	**71.1**	**3**
MEE [24]	1k-B	13.6	37.9	51.0	10	-	-	-	-
JPose [31]	1k-B	14.3	38.1	53.0	9	16.4	41.3	54.4	8.7
MEE-COCO [24]	1k-B	14.2	39.2	53.8	9	-	-	-	-
CE [22]	1k-B	18.2	46.0	60.7	7	18.0	46.0	60.3	6.5
MMT [9]	1k-B	20.3	49.1	63.9	6	21.1	49.4	63.2	6
Our T2VLAD	1k-B	**26.1**	**54.7**	**68.1**	**4**	**26.7**	**56.1**	**70.4**	**4**

- T2VLAD outperforms MMT and other proposed methods with ActivityNet dataset

Method	Text → Video				Video → Text			
	R@1 ↑	R@5 ↑	R@50 ↑	MdR ↓	R@1 ↑	R@5 ↑	R@50 ↑	MdR ↓
FSE [39]	18.2	44.8	89.1	7	16.7	43.1	88.4	7
CE [22]	18.2	47.7	91.4	6	17.7	46.6	90.9	6
HSE [39]	20.5	49.3	-	-	18.7	48.1	-	-
MMT [9]	22.7	54.2	93.2	5	22.9	54.8	93.1	4.3
Ours	**23.7**	**55.5**	**93.5**	**4**	**24.1**	**56.6**	**94.1**	**4**

Table 2. The comparisons with the state-of-the-art methods on the ActivityNet Captions dataset.

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V. RESULT (CONT.)

- Comparison with papers of CVPR/CVPRW 2021

(Text -> Video Retrieval with **ActivityNet** dataset)

Method	Model	R@1	R@5	R@50	MdR
M. Dzabraev, el al. "MDMMT: Multidomain Multimodal Transformer for Video Retrieval," *IEEE/CVF CVPRW, Jun. 2021*, pp. 3354-3363.	MDMMT	17.7	41.6	-	8.3
L. Jie, et al, "Less is more: ClipBERT for video-and-language learning via sparse sampling," In *Proc. IEEE/CVF CVPR*, Jun. 2021, pp. 7331-7341.	ClipBERT	21.3	49.0	-	6.0
X. Wang, el al. "T2VLAD: global-local sequence alignment for text-video retrieval," In *Proc. IEEE/CVF CVPR*, Jun. 2021, pp. 5079-5088.	T2VLAD	**23.7**	**55.5**	93.5	**4.0**

X. Wang, L. Zhu, and Y. Yang, "T2LVAD: global-local sequence alignment for text-video retrieval,". In *Proc. IEEE/CVF CVPR*, Jun. 2021, pp. 5079-5088.

VI. ABLATION STUDY

- The effectiveness of the the global-local alignment
  - Global-local alignment proves local alignment (**global feature is complementary to the local information**)

Method	Text → Video				Video → Text			
	R@1↑	R@5↑	R@10↑	MdR↓	R@1↑	R@5↑	R@10↑	MdR↓
Ours w/o Global Alignment	24.3	51.5	63.4	5	26.6	52.9	62.6	5
Ours w/o Local Alignment	22.2	49.9	64.6	6	24.0	51.7	65.6	5
Full model	**29.5**	**59.0**	**70.1**	**4**	**31.8**	**60.0**	**71.1**	**3**

Table 4. The ablation studies on the MSRVTT [35] dataset to investigate the effectiveness of global-local alignment.

- The effectiveness of collaborative VLAD
  - **The sharing centers (shared VLAD) outperform separated VLAD**

Method	Text → Video				Video → Text			
	R@1↑	R@5↑	R@10↑	MdR↓	R@1↑	R@5↑	R@10↑	MdR↓
Ours w/ only text VLAD	27.4	57.3	68.2	4	27.5	57.4	69.7	4
Ours w/ two separate VLAD	28.6	58.1	70.4	4	30.4	60.7	72.1	3
Ours w/ two shared VLAD	**29.5**	**59.0**	70.1	**4**	**31.8**	60.0	71.1	**3**

Table 5. The ablation studies on the MSRVTT [35] dataset to investigate the effectiveness of the VLAD encoding.

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VII. CONCLUSION

- Contributions:
    - Propose **automatically learn** text-and-video semantic topics
    - Re-emphasize the importance of **local semantic alignment between texts and videos** for better cross-modal retrieval
    - T2VLAD – exploit **shared centers** (NetVLAD) to reduce the sematic gap between texts and videos
    - T2VLAD outperforms recently proposed method
- Local semantic alignment between texts and videos is critical for high-performance
- Future work: obtain better global video features with end-to-end optimization.

X. Wang, L. Zhu, and Y. Yang, "T2LVAD: global-local sequence alignment for text-video retrieval,". In *Proc. IEEE/CVF CVPR*, Jun. 2021, pp. 5079-5088.

REFERENCES

[1] S. Chen, Y. Zhao, Q. Jin, and Q. Wu. “Fine-grained video-text retrieval with hierarchical graph reasoning.” In CVPR, 2020.

[2] J. Devlin, M.W. Chang, K. Lee, and K. Toutanova,“BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding.” In *NAACL-HLT*, 2019.

[3] A. Miech, I. Laptev, and J. Sivic. “Learning a text-video embedding from incomplete and heterogeneous data.” arXiv preprint arXiv:1804.02516, 2018

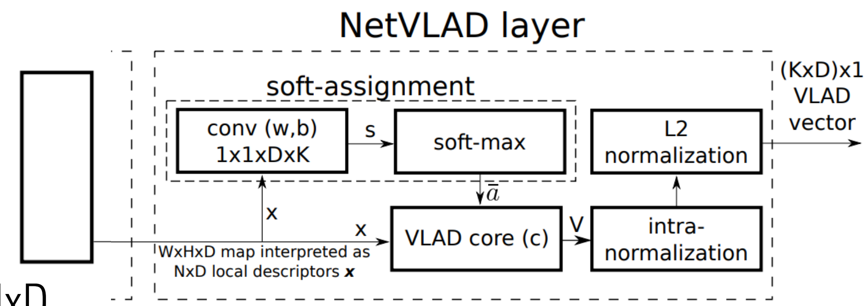
[4] H. Jegou, M. Douze, C, and P. Perez. “Aggregating local descriptors into a compact image representation.” In CVPR, 2010.

[5] R. Arandjelovic, P. Gronat, A. Torii, T. Pajdla, and J. Sivic. “NetVLAD: Cnn architecture for weakly supervised place recognition.” In CVPR, 2016.

[6] V. Gabeur, C. Sun, K. Alahari, and C. Schmid, “Multi-modal Transformer for Video Retrieval,” In *ECCV, 2020.*

APPENDIX

- Calculation in NetVLAD [3]:



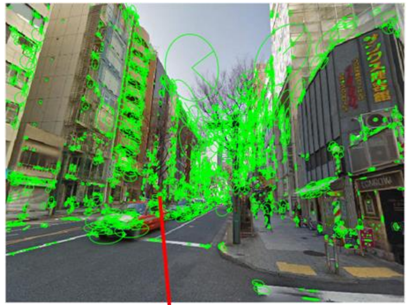
WxHxD
feature map
of last conv.
layer

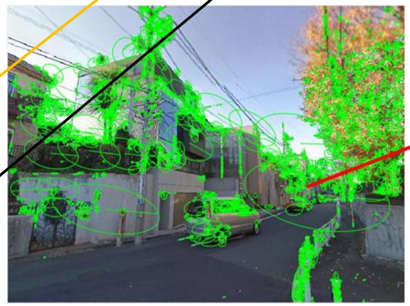
Convolution with filters
w_k and biases b_k

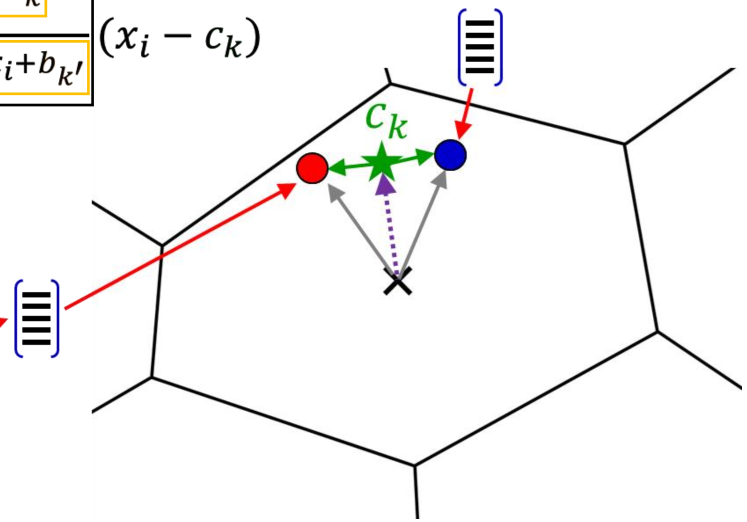
Soft-max -> $\bar{a}$

Decouple assignment (w_k b_k) from anchor point c_k

$$V(:,k) = \sum_{i=1}^{N} \frac{\boxed{e^{w_k^T x_i + b_k}}}{\sum_{k'} \boxed{e^{w_{k'}^T x_i + b_{k'}}}} (x_i - c_k)$$







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https://www.di.ens.fr/willow/research/netvlad/

THANK YOU!