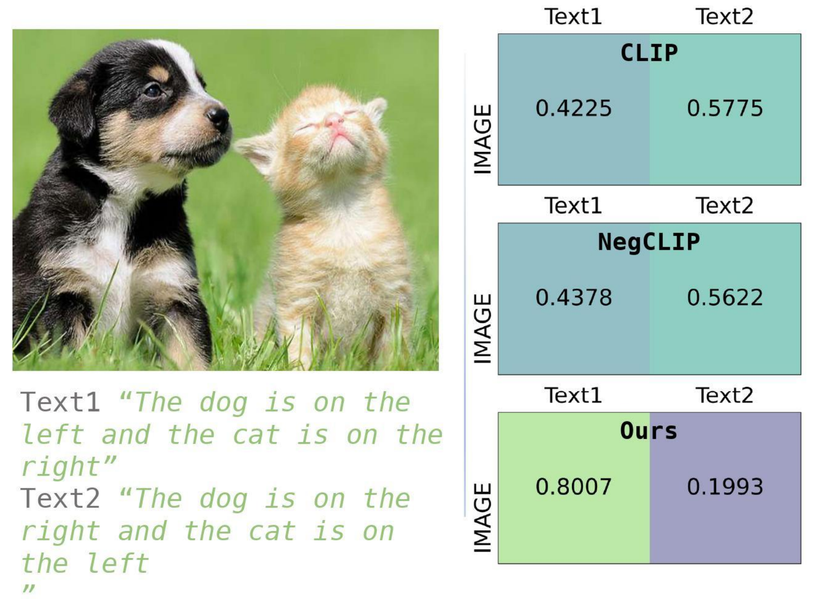
Contrasting Intra-modal and Ranking Cross-Modal Hard Negatives to Enhance Visio-Linguistic Fine-Grained Understanding

Le Zhang, Rabiul Awal, Aishwarya Agrawal

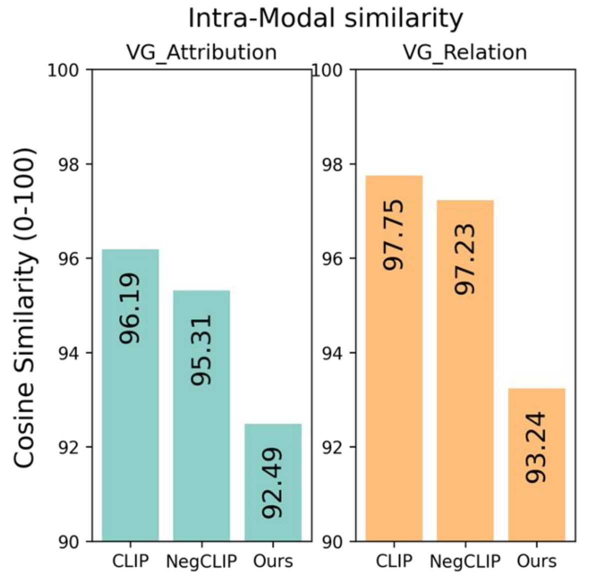
Mila - Quebec AI Institute, Université de Montréal

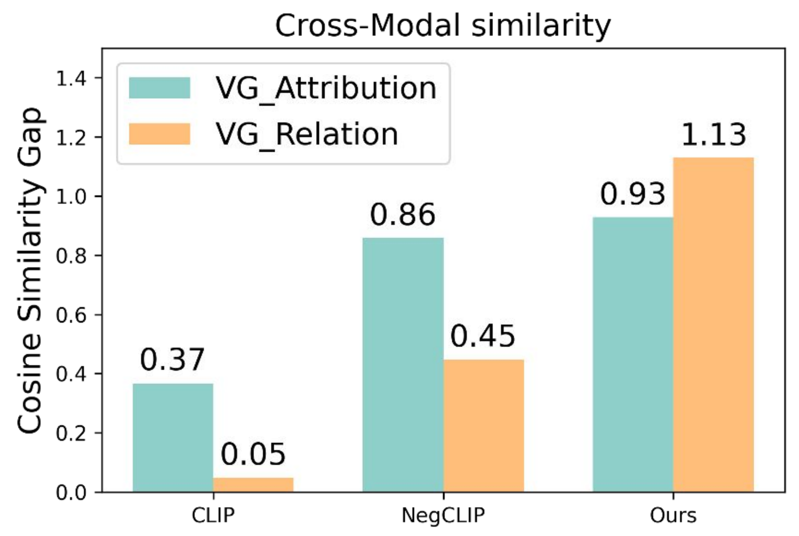
JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

- **Task: fine-grained understanding (relation, attribution, object existence)**



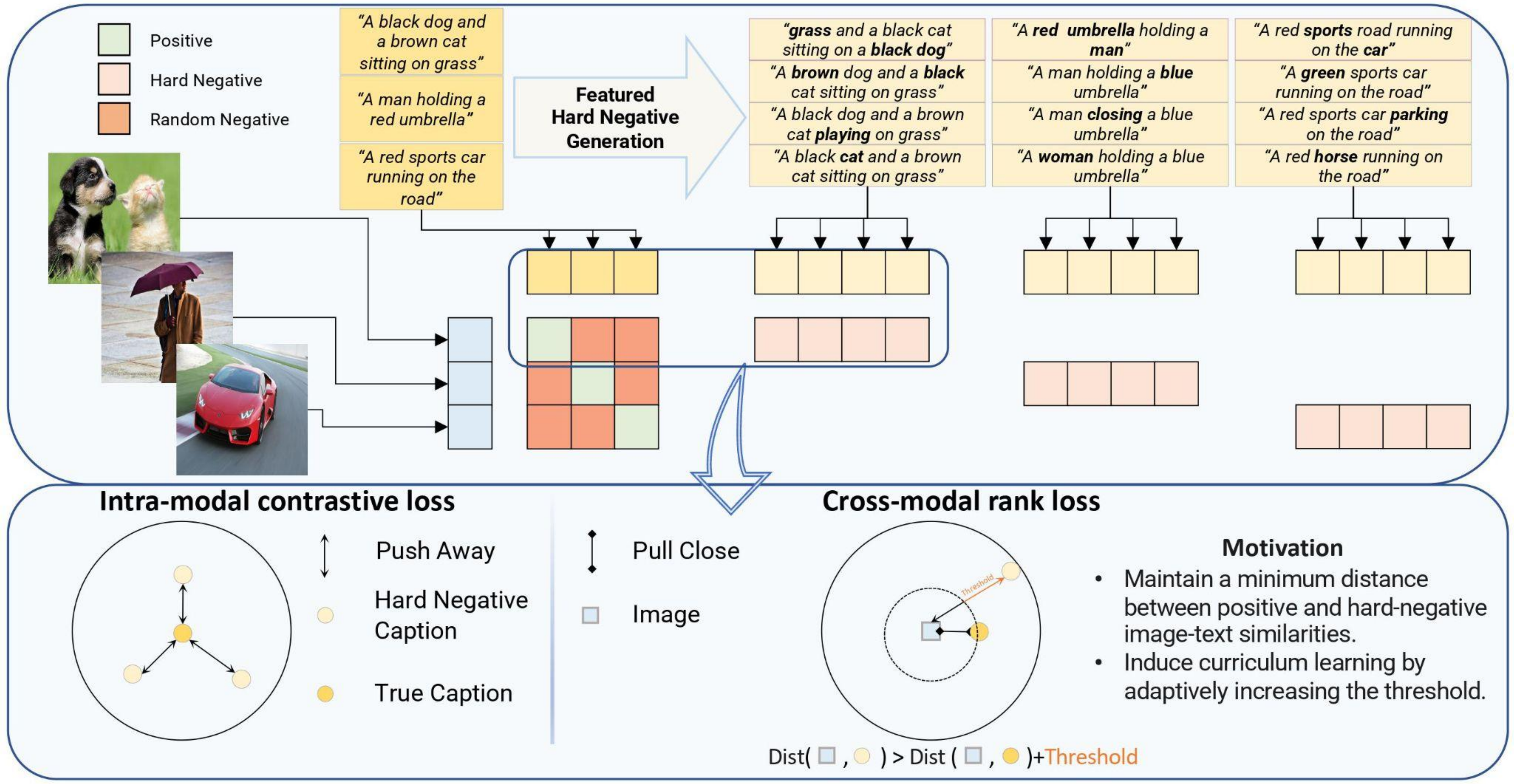
- **Limitation of current models**
  - High intra-modal similarity between positive and hard negative captions
  - Small gap between true and hard negative image-text cross-modal similarity





- **Examples**

Method



$$\mathcal{L}_{itc(hn)} = \sum_{(I,T)\in\mathcal{B}} -\left(\log \frac{\exp^{S(I,T)}}{\sum_{T_i\in\mathcal{B}} \exp^{S(I,T_i)} + \sum_{T_k\in\mathcal{T}_{hn}} \exp^{S(I,T_k)}} + \log \frac{\exp^{S(I,T)}}{\sum_{I_j\in\mathcal{B}} \exp^{S(I_j,T)}} \right)$$

- **Intra-Modal Contrastive (IMC) loss**

$$\mathcal{L}_{imc} = \sum_{(I,T)\in\mathcal{B}} -\log \frac{\exp^{S(I,T)}}{\sum_{T_k\in\mathcal{T}_{hn}} \exp^{S(T,T_k)}}$$

- **Cross-Modal Rank (CMR) loss with adaptive threshold**

$$\mathcal{L}_{cmr} = \sum_{(I,T)\in\mathcal{B}} \sum_{T_k\in\mathcal{T}_{hn}} max(0, S(I,T_k) - S(I,T) + Th_k^t)$$

$$Th_k^t = \frac{1}{|\mathcal{B}|} \sum_{(I,T)\in\mathcal{B}} (S^{t-1}(I,T) - S^{t-1}(I,T_k))$$

$$\mathcal{L} = \mathcal{L}_{itc(hn)} + \alpha \cdot \mathcal{L}_{imc} + \beta \cdot \mathcal{L}_{cmr}$$

Experiments

Model	ARO		VALSE							
	Relation	Attribution	Existence	Plurality	Counting	Relations	Actions	Coreference	Foil-it	Avg
Random	50									
BLIP	59.0	88.0	86.3	73.2	68.1	71.5	69.1	51.0	93.8	69.96
LXMERT†	-	-	78.6	64.4	58.0	60.2	50.3	45.5	87.1	59.6
CLIP	59.3	62.9	68.7	57.1	61.0	65.4	74.8	52.5	89.8	65.3
NegCLIP	80.2	70.5	76.8	71.7	**65.0**	72.9	83.2	**56.2**	91.9	71.6
CLIP *Ours*	**83.0**	**76.4**	**78.6**	**77.7**	64.4	**74.4**	**84.9**	54.7	**93.7**	**72.5**
XVLM-coco	73.4	86.8	83.0	**75.6**	67.5	69.8	71.2	48.0	**94.8**	69.5
XVLM *Ours*	**73.9**	**89.3**	**83.3**	73.8	**69.8**	**70.0**	**71.5**	**48.4**	93.3	**70.8**

Table 2: **Results (%) of ARO and VALSE**, the best scores for each section emphasized in boldface. † represents scores extracted from papers.

Model	VL-CheckList									
	Attribute					Object		Relation		Avg
	Action	Color	Material	Size	State	Location	Size	Action	Spatial	
Random Chance	50									
BLIP†	79.5	83.2	84.7	59.8	68.8	83.0	81.3	81.5	59.5	75.7
CLIP-SVLC†	69.4	77.5	77.4	73.4	62.3	-	-	74.7	63.2	-
CLIP	70.5	69.4	69.5	60.7	67	80.2	79.7	72.2	53.8	69.2
NegCLIP	72.1	**75.7**	78.1	61.3	67.3	84.4	83.8	**80.7**	57.1	73.4
CLIP *Ours*	**75.6**	72.7	**79.7**	**65.3**	**69.8**	**84.8**	**84.5**	78.5	**65.0**	**75.1**
XVLM-coco	80.4	**81.1**	**83.1**	60.3	**70.8**	86.3	85.3	79.0	61.8	76.5
XVLM *Ours*	**80.5**	76.0	80.6	**67.2**	69.8	**87.3**	**86.6**	**80.8**	**78.6**	**78.6**

Table 3: **Results (%) of VL-CheckList.** † represents scores are extracted from papers.

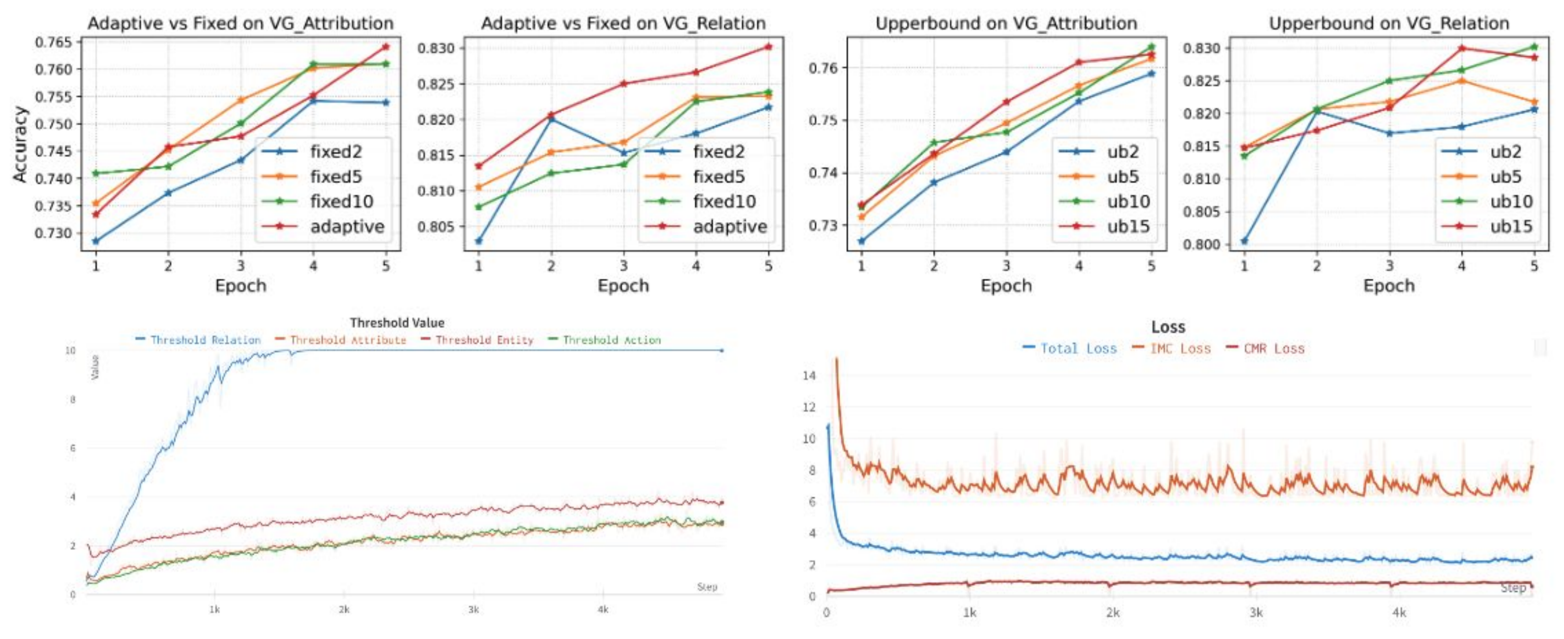


Figure 4: **Ablation study and analysis on threshold** (Top Left) Adaptive threshold vs Fixed threshold; (Top Right) Performance with different upper bound values.; (Bottom Left) Curves showing how the thresholds evolve over time ; (Bottom Right) Proposed loss curves change over time

Conclusion

- **Hard-negatives can largely improve fine-grained understanding of VLMs**
- **Teaching models to contrast intra-modal hard negatives improve cross-modal fine-grained understanding**
- **Cross-modal rank encourage model to better distinguish between positive and hard negative image-text pairs, adaptive threshold entails curriculum learning**