Children riding bikes and skateboards

A crowd attending a community fair

Improving Cross-modal Retrieval with Set of Diverse Embeddings

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POSTECH

Cross-modal Retrieval

Text-to-image

Children riding bikes and skateboards

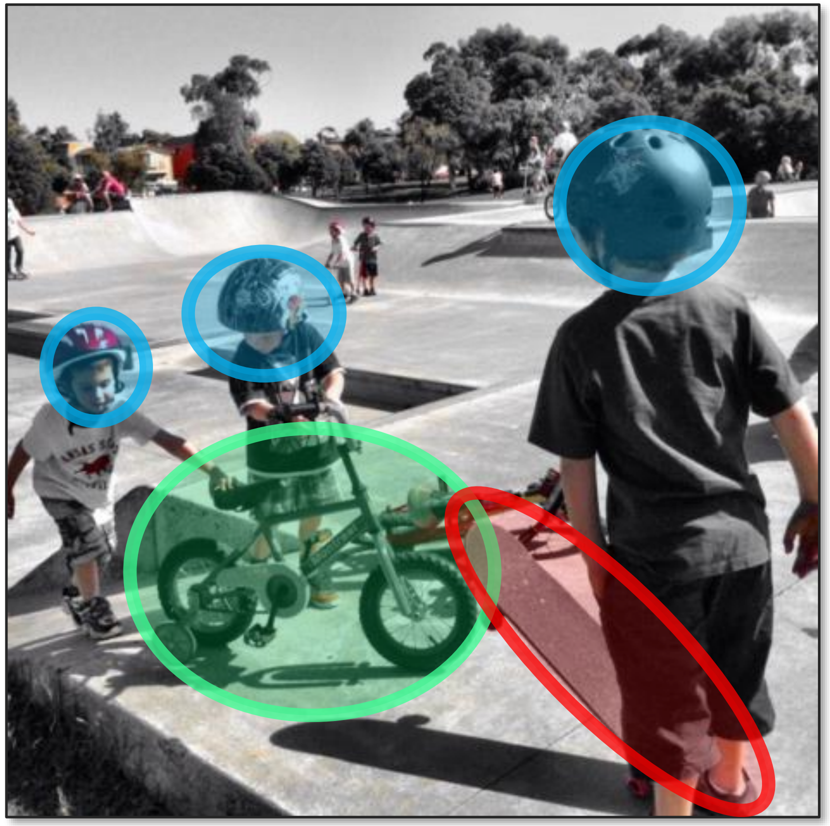
Image-to-text

Boys wearing helmets carry a bike up a ramp at a skate park.

Small children stand near bicycles at a skate park.

A group of young children riding bikes and skateboards.

Semantic Ambiguity



"Boys wearing helmets carry a bicycle up a ramp at a skate park."

"Small children stand near bicycles at a skate park."

"A group of young children riding bikes and skateboards."

An image or a sentence often illustrates multiple entities and their relations.

Semantic Ambiguity

"Boys wearing helmets carry a bicycle up a ramp at a skate park."

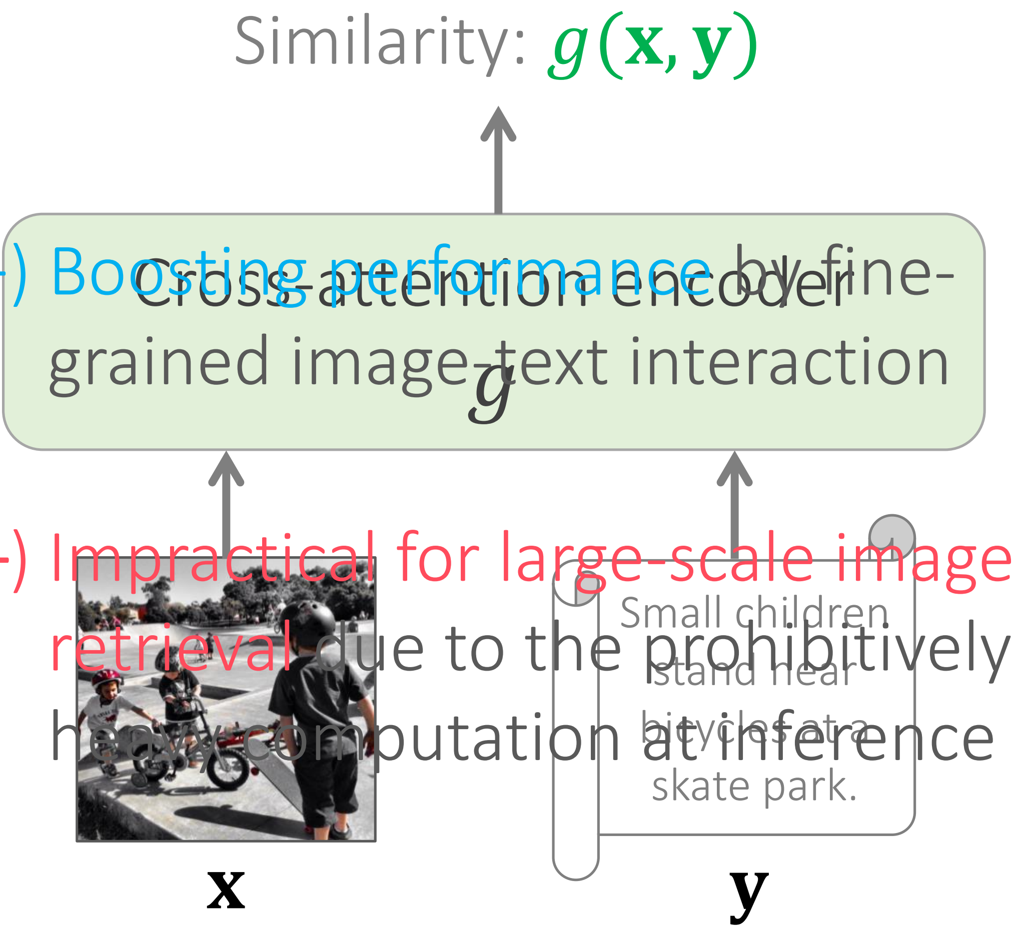
"Small children stand near bicycles at a skate park."

"A group of young children riding bikes and skateboards."

It is impractical to manually annotate such entities and their correspondences.

Embedding Network Architectures

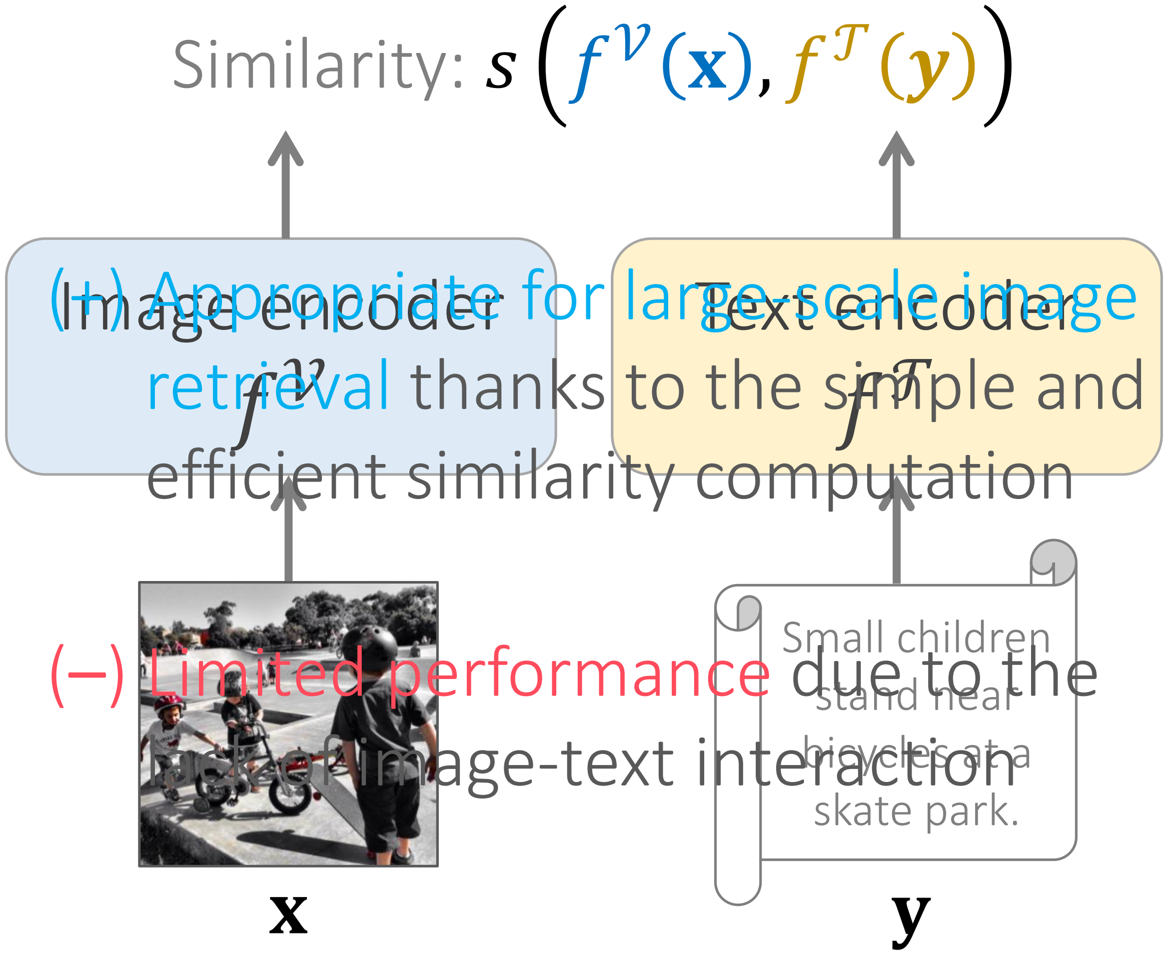
Single Cross-attention Encoder



(+) Boosting performance by fine-grained image-text interaction

(–) Impractical for large-scale image retrieval due to the prohibitively heavy computation at inference

Image Encoder + Text Encoder



(+) Appropriate for large-scale image retrieval thanks to the simple and efficient similarity computation

(–) Limited performance due to the lack of image-text interaction

Embedding Network Architectures

Single Cross-attention Encoder

Similarity: $g(\mathbf{x}, \mathbf{y})$

(+) Boosting performance by fine-grained image-text interaction

(–) Impractical for large-scale image retrieval due to the prohibitively heavy computation at inference

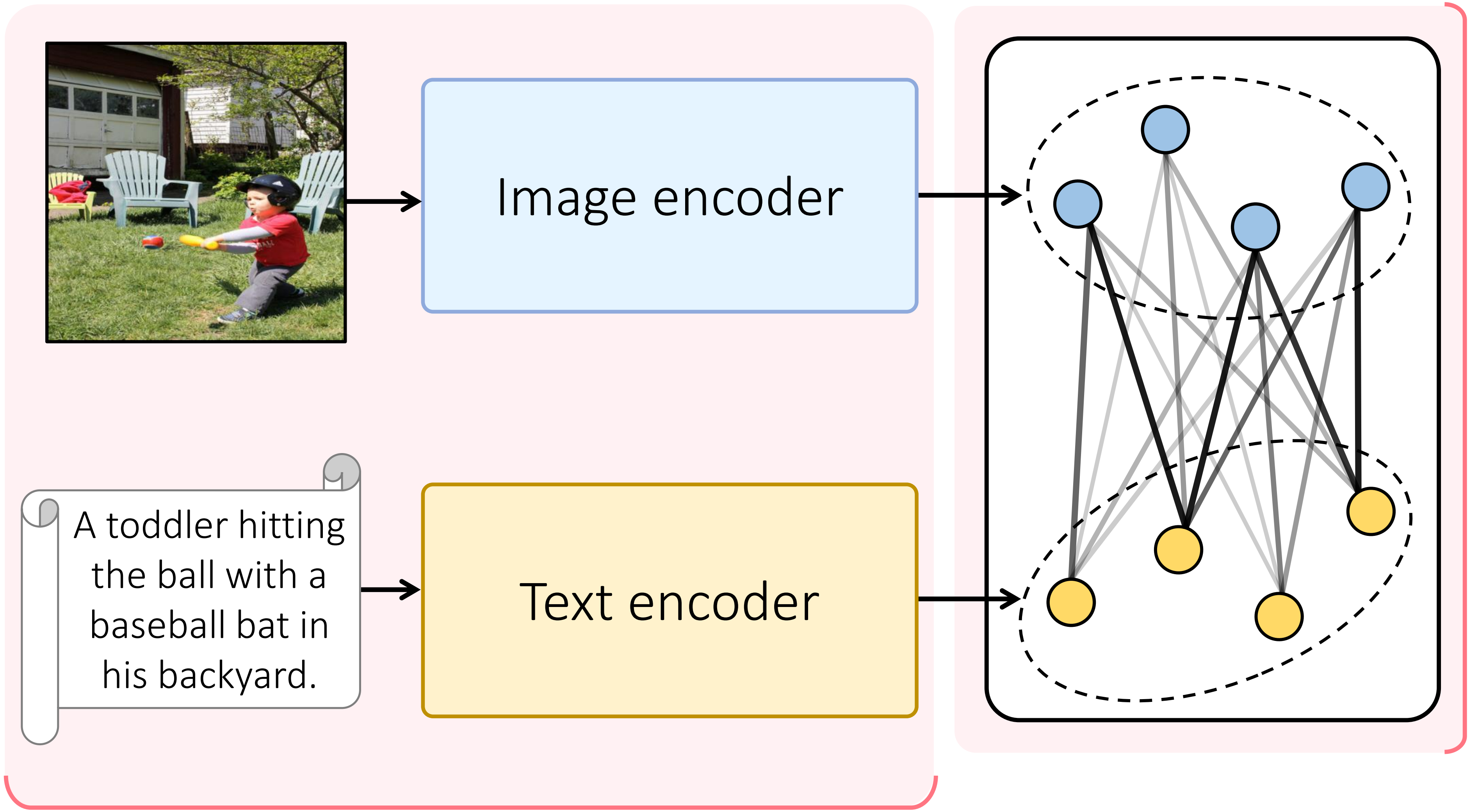
Image Encoder + Text Encoder

Similarity: $s\left(f^{\mathcal{V}}(\mathbf{x}), f^{\mathcal{T}}(\mathbf{y})\right)$

(+) Appropriate for large-scale image retrieval thanks to the simple and efficient similarity computation

(–) Limited performance due to the lack of image-text interaction

Our Approach



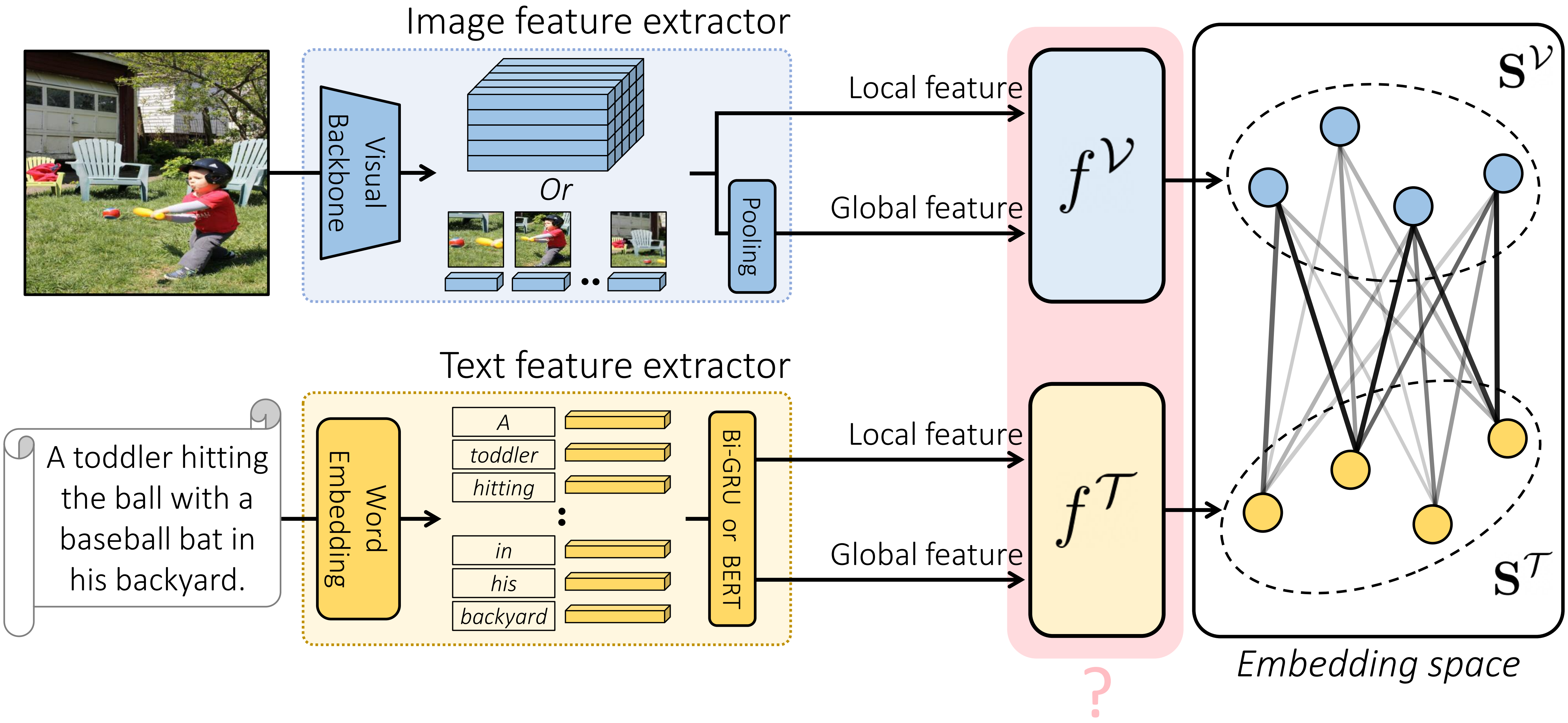
② *Embedding set representation* + *set similarity metric* for resolving the ambiguity issue

① *Separate encoders* for efficient retrieval

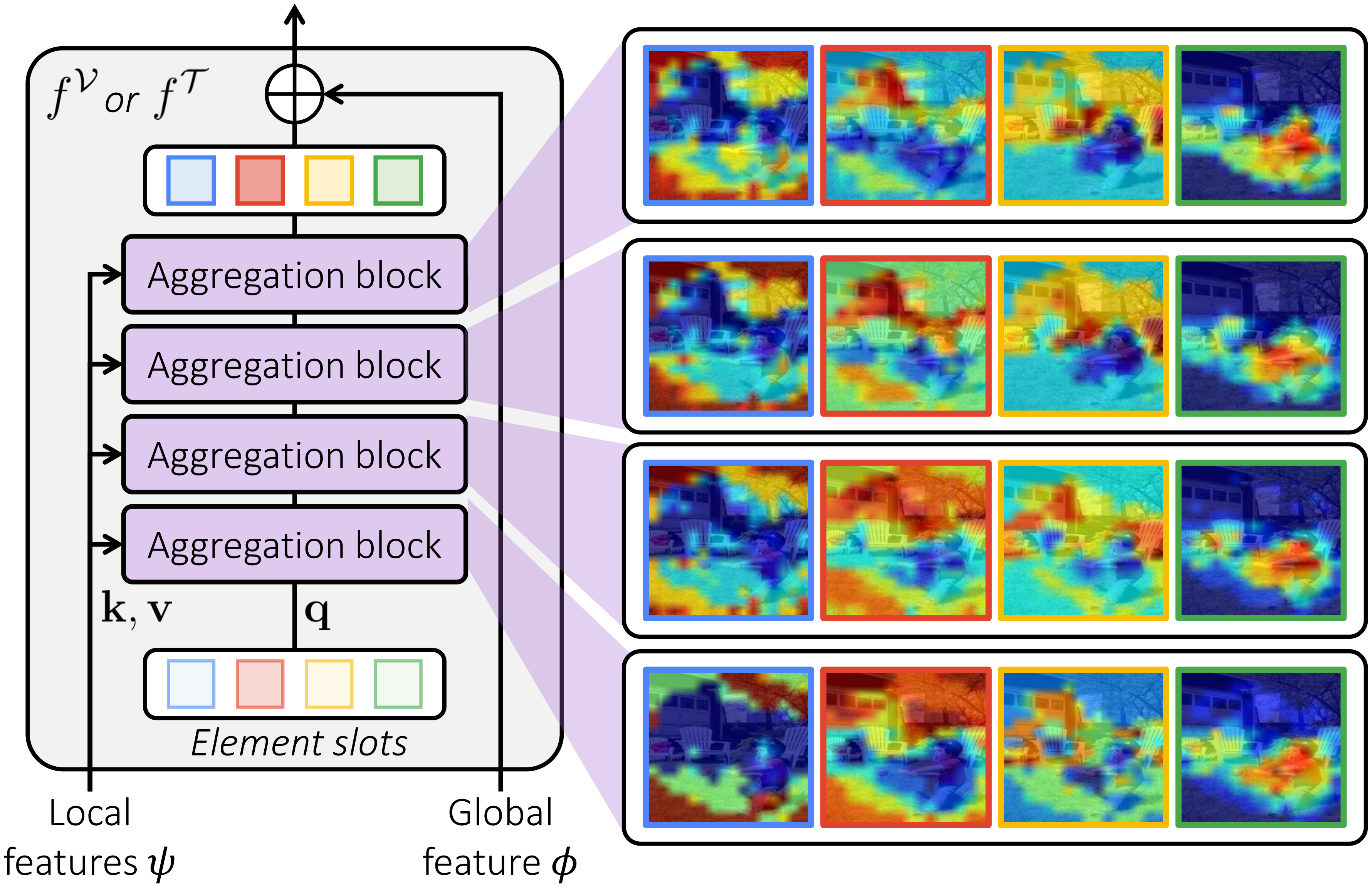
Contribution

- A new set-based embedding architecture
  - Set-prediction modules based on slot attention
- A new set similarity metric
  - Smooth-Chamfer similarity
- Outstanding performance
  - State of the art in most settings on four public benchmarks
  - Leading to substantially less latency than cross-attention models

Proposed Architecture



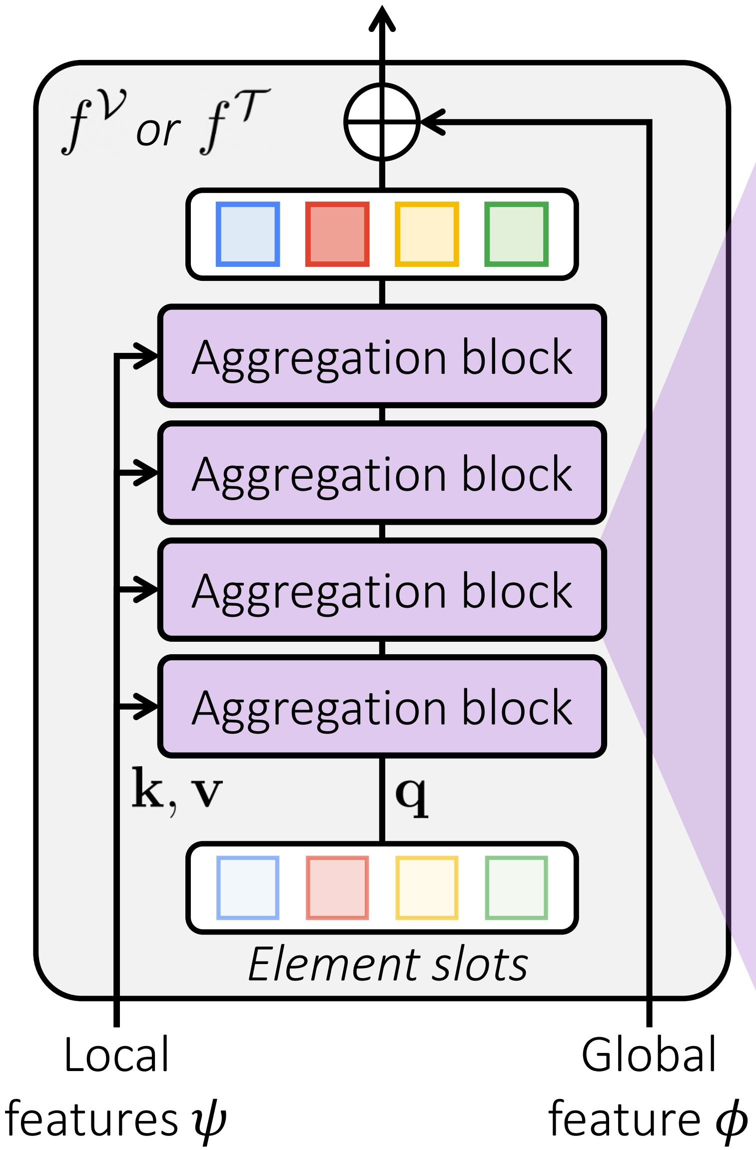
Proposed Architecture: Set Prediction Modules



The element slots[1] compete with each other to aggregate input features and thus reveal diverse contexts.

[1] Locatello *et al.*, Object-centric Learning with Slot Attention, NeurIPS 2020.

Proposed Architecture: Set Prediction Modules



Local features ψ → (Key, Value) pairs: $\mathbf{k}, \mathbf{v} \in \mathbb{R}^{N \times D_h}$

Element slots $\mathbf{E}^{t-1}$ → Queries: $\mathbf{q} \in \mathbb{R}^{K \times D_h}$

Computing an attention map

$$A_{n,k} = \frac{\exp M_{n,k}}{\sum_{i=1}^{K} \exp M_{n,i}}, \quad \text{where} \quad M = \frac{\mathbf{k}\mathbf{q}^{\top}}{\sqrt{D_h}}$$

Normalization over the slots[1]

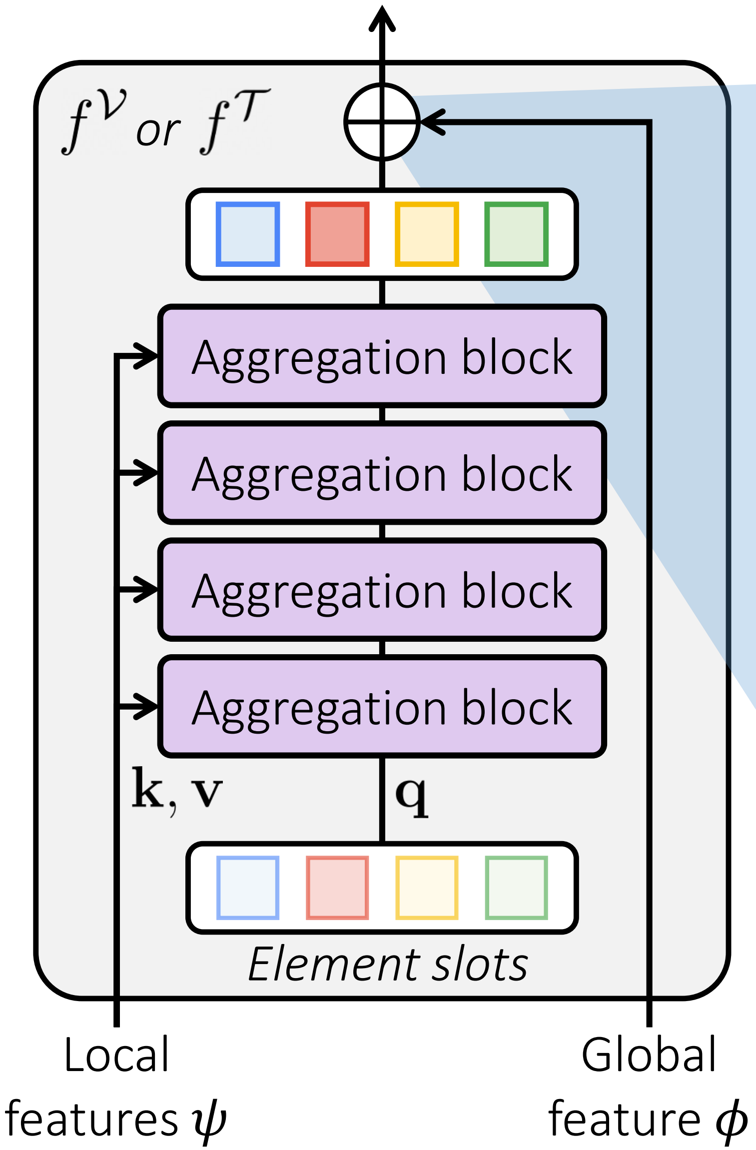
Updating the element slots

$$\mathbf{E}^{t} = \mathrm{MLP}(\bar{\mathbf{E}}^{t}) + \bar{\mathbf{E}}^{t}, \quad \text{where}$$

$$\bar{\mathbf{E}}^{t} = \hat{A}^{\top}\mathbf{v}\, W_o + \mathbf{E}^{t-1} \quad \text{and} \quad \hat{A}_{n,k} = \frac{A_{n,k}}{\sum_{i=1}^{N} A_{n,k}}$$

[1] Locatello *et al.*, Object-centric Learning with Slot Attention, NeurIPS 2020.

Proposed Architecture: Set Prediction Modules



Adding the global feature to each element

$$\mathbf{S} = \mathrm{LN}(\mathbf{E}) + \underbrace{[\mathrm{LN}(\phi), \cdots, \mathrm{LN}(\phi)]}_{K \text{ repetitions}} \in \mathbb{R}^{K \times D}$$

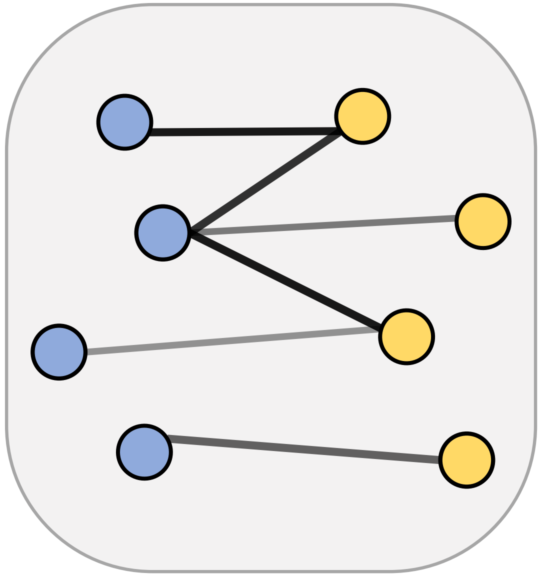
- Embedding the global context in every element of the set
- Particularly useful when treating samples with little ambiguity

Set Similarity Metric: Smooth-Chamfer Similarity

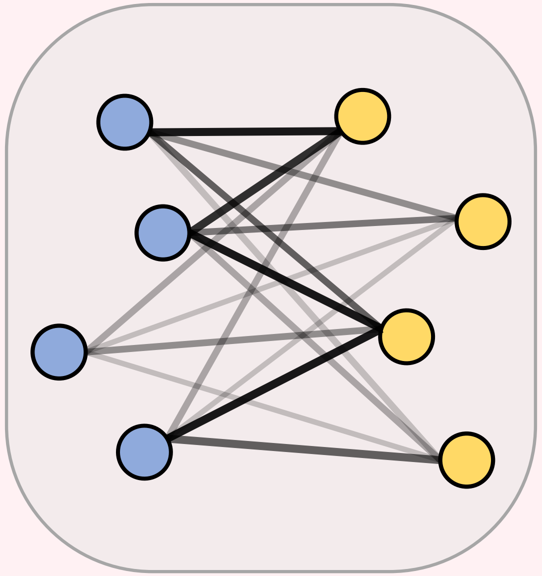
$$s(\mathbf{S}^{\mathcal{V}}, \mathbf{S}^{\mathcal{T}}) = \frac{1}{2\alpha|\mathbf{S}^{\mathcal{V}}|} \underbrace{\sum_{\mathbf{e}\in\mathbf{S}^{\mathcal{V}}} \mathop{\mathrm{LSE}}_{\mathbf{e}'\in\mathbf{S}^{\mathcal{T}}} \left(\alpha \cos(\mathbf{e}, \mathbf{e}')\right)}_{\log\left(\sum_{y\in\mathbf{S}_2} \exp[\alpha\cos(x,y)]\right)} + \frac{1}{2\alpha|\mathbf{S}^{\mathcal{T}}|} \underbrace{\sum_{\mathbf{e}'\in\mathbf{S}^{\mathcal{T}}} \mathop{\mathrm{LSE}}_{\mathbf{e}\in\mathbf{S}^{\mathcal{V}}} \left(\alpha \cos(\mathbf{e}, \mathbf{e}')\right)}_{\log\left(\sum_{x\in\mathbf{S}_1} \exp[\alpha\cos(x,y)]\right)}$$

Set Similarity Metric: Smooth-Chamfer Similarity

$$s(\mathbf{S}^{\mathcal{V}}, \mathbf{S}^{\mathcal{T}}) = \frac{1}{2\alpha|\mathbf{S}^{\mathcal{V}}|} \sum_{\mathbf{e}\in\mathbf{S}^{\mathcal{V}}} \mathop{\mathrm{LSE}}_{\mathbf{e}'\in\mathbf{S}^{\mathcal{T}}} (\alpha \cos(\mathbf{e}, \mathbf{e}')) + \frac{1}{2\alpha|\mathbf{S}^{\mathcal{T}}|} \sum_{\mathbf{e}'\in\mathbf{S}^{\mathcal{T}}} \mathop{\mathrm{LSE}}_{\mathbf{e}\in\mathbf{S}^{\mathcal{V}}} (\alpha \cos(\mathbf{e}, \mathbf{e}'))$$



Chamfer similarity (MAX instead of LSE)



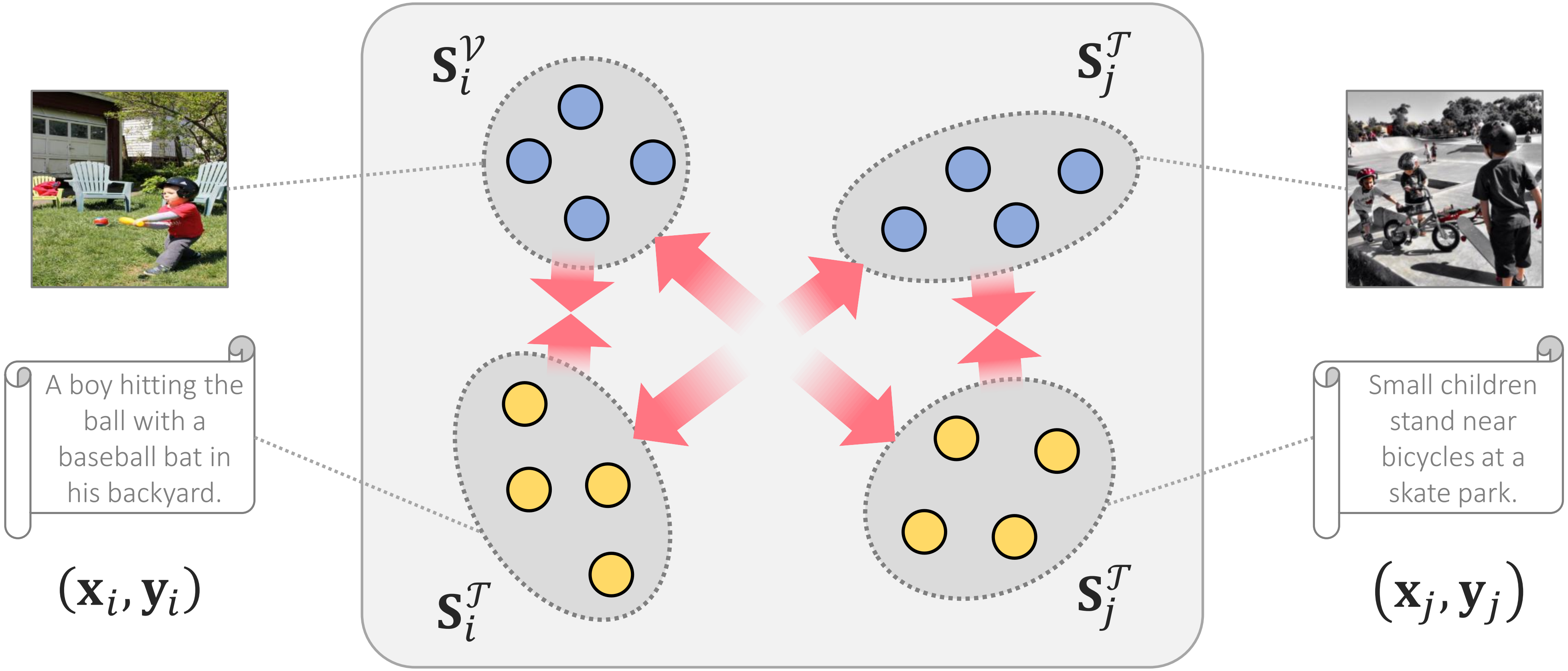
Smooth-Chamfer similarity

- Establishing *soft correspondences between elements*
- Improving retrieval performance

Training Objective

$$\mathcal{L}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) = \mathcal{L}_{\text{tri}}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) + \mathcal{L}_{\text{mmd}}\left(\{\mathbf{s}_i^{\mathcal{V}}\}_{i=1}^{N}, \{\mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) + \mathcal{R}_{\text{div}}$$

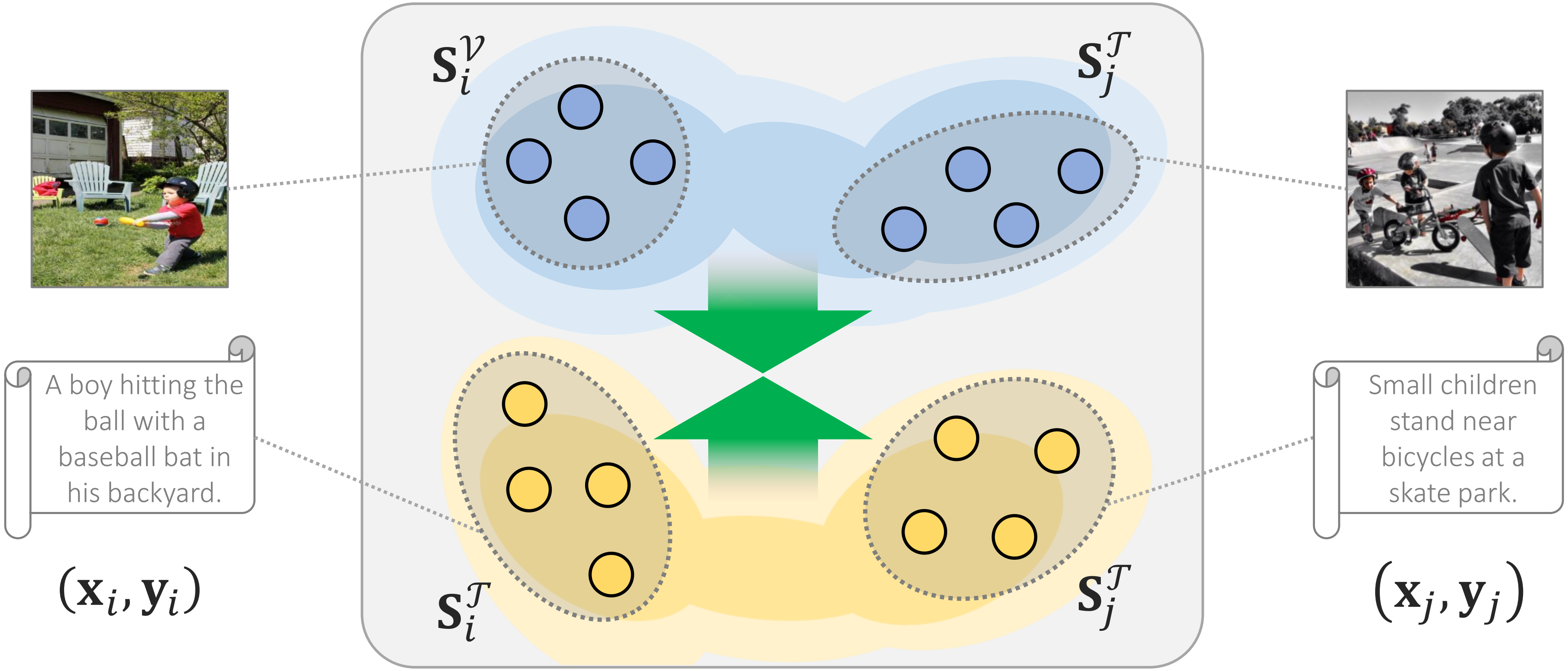
Metric learning



Training Objective

$$\mathcal{L}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) = \mathcal{L}_{\text{tri}}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) + \boxed{\mathcal{L}_{\text{mmd}}\left(\{\mathbf{s}_i^{\mathcal{V}}\}_{i=1}^{N}, \{\mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right)} + \mathcal{R}_{\text{div}}$$

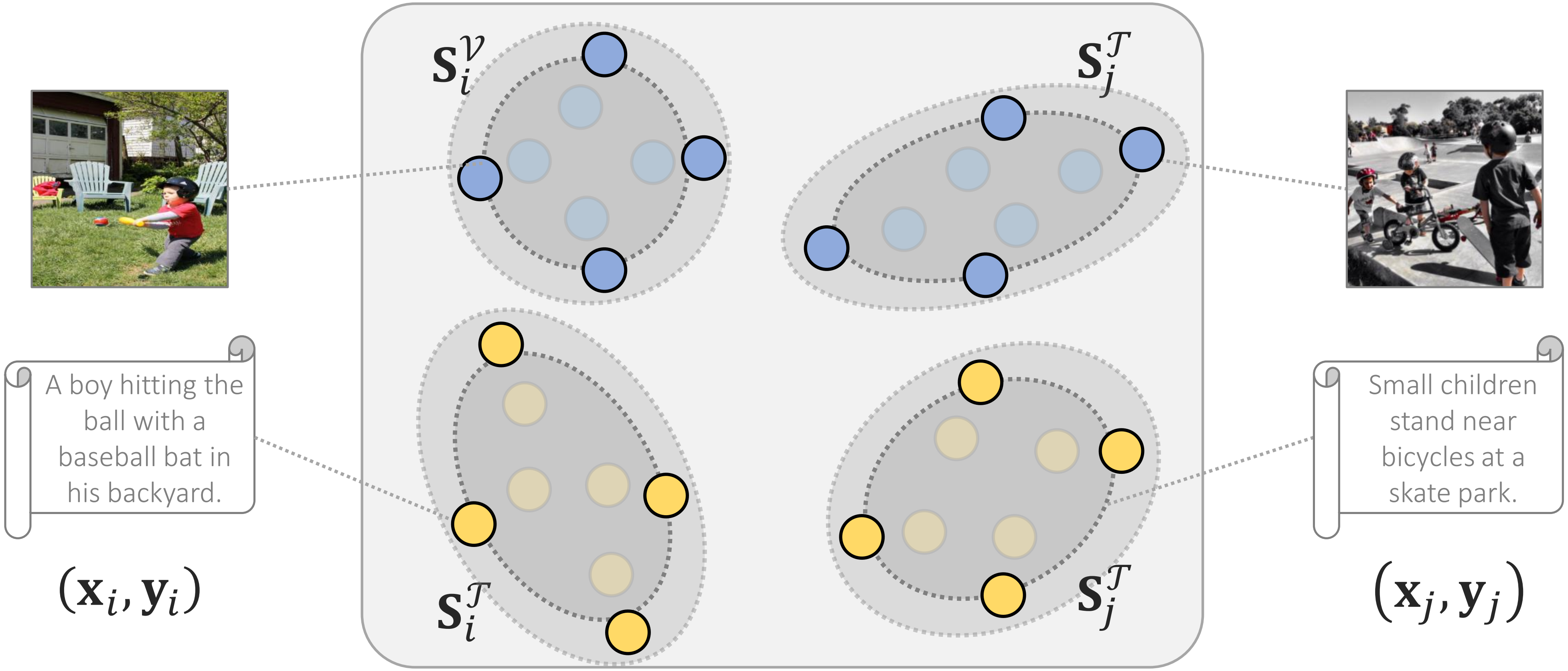
Closing the modality gap



Training Objective

$$\mathcal{L}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) = \mathcal{L}_{\text{tri}}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) + \mathcal{L}_{\text{mmd}}\left(\{\mathbf{s}_i^{\mathcal{V}}\}_{i=1}^{N}, \{\mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) + \boxed{\mathcal{R}_{\text{div}}}$$

Enhancing within-set diversity



Training Objective

$$\mathcal{L}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) = \mathcal{L}_{\mathrm{tri}}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) + \mathcal{L}_{\mathrm{mmd}}\left(\{\mathbf{s}_i^{\mathcal{V}}\}_{i=1}^{N}, \{\mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) + \mathcal{R}_{\mathrm{div}}$$

Triplet rank loss with hard negative mining

$$\mathcal{L}_{\mathrm{tri}}\left(\{\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) = \sum_{i=1}^{N} \max_j \left[\delta + s(\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_j^{\mathcal{T}}) - s(\mathbf{s}_i^{\mathcal{V}}, \mathbf{s}_i^{\mathcal{T}})\right]_+ + \sum_{i=1}^{N} \max_j \left[\delta + s(\mathbf{s}_i^{\mathcal{T}}, \mathbf{s}_j^{\mathcal{V}}) - s(\mathbf{s}_i^{\mathcal{T}}, \mathbf{s}_j^{\mathcal{V}})\right]_+$$

Maximum mean discrepancy[2] loss

$$\mathcal{L}_{\mathrm{mmd}}\left(\{\mathbf{s}_i^{\mathcal{V}}\}_{i=1}^{N}, \{\mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right) = \mathrm{MMD}\left(\{\mathbf{s}_i^{\mathcal{V}}\}_{i=1}^{N}, \{\mathbf{s}_i^{\mathcal{T}}\}_{i=1}^{N}\right)$$

Diversity regularizer

$$\mathcal{R}_{\mathrm{div}} = \sum_{e, e' \in \mathbf{E}} \exp(-2\|e - e'\|_2^2)$$

[2] Gretton *et al.*, A Kernel Two-sample Test, JMLR 2012.

Experiments

- Datasets
  - COCO[3], Flickr30K[4], ECCV Caption[5], CrissCrossed Caption (CxC)[6]
- Evaluation metrics
  - Recall@k: Percentage of the queries that have matching samples among top-k retrieval results
  - RSUM: Sum of Recall@k at $k \in \{1,5,10\}$ in both image-to-text and text-to-image settings
- 4 agg. blocks and 4 element slots for each set-prediction module

[3] Lin *et al.*, Microsoft COCO: Common Objects in Context, ECCV 2014.
[4] Plummer *et al.*, Flickr30k Entities: Collecting Region-to-phrase Correspondences for Richer Image-to-sentence Models, ICCV 2015.
[5] Chun *et al.*, ECCV Caption, Correcting False Negatives by Collecting Machine-and-human-verified Image-Caption Associations for MS-COCO, ECCV 2022.
[6] Parekh *et al.*, Crisscrossed Captions: Extended Intra-modal and Inter-modal Semantic Similarity Judgments for MS-COCO, EACL 2020.

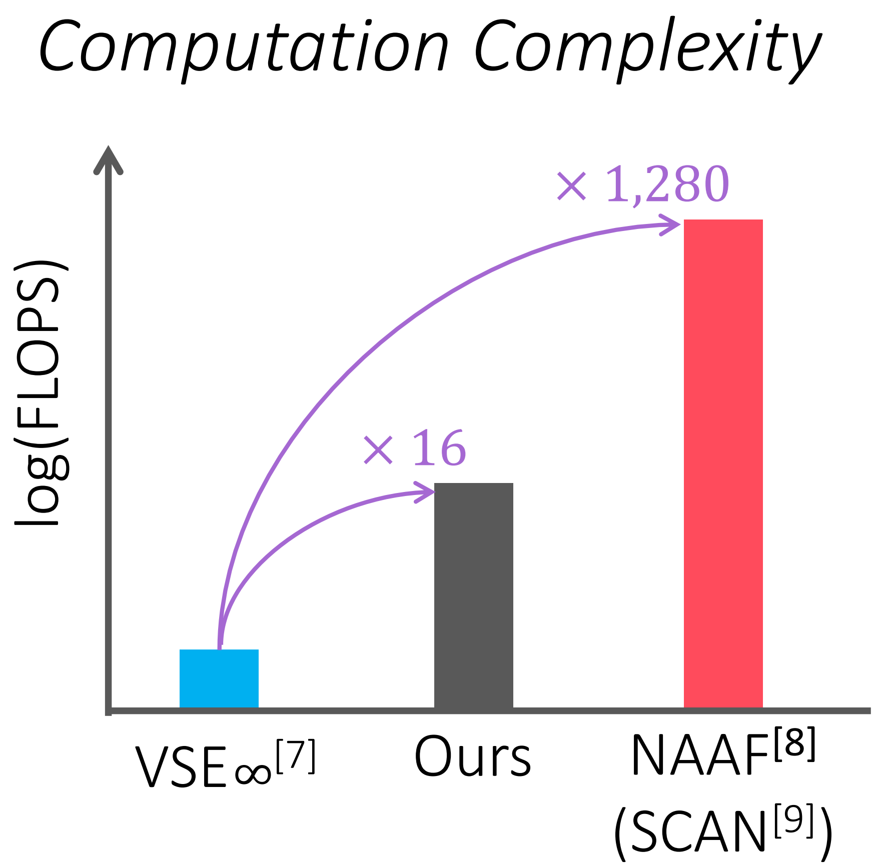
Experiments: Performance on COCO

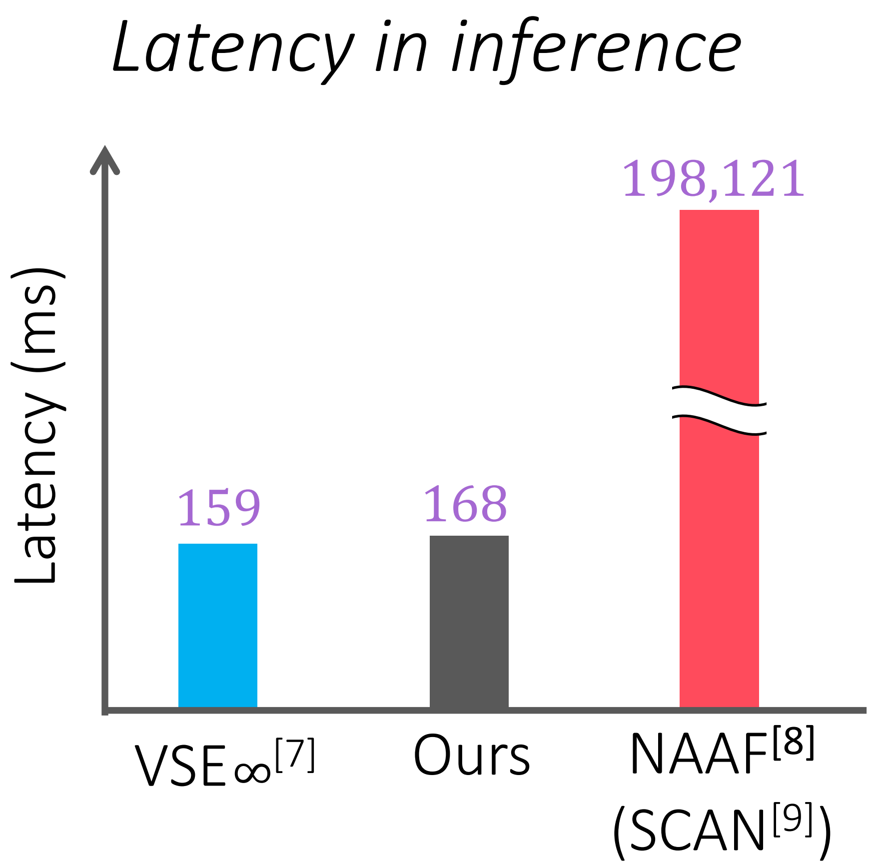
Method	CA	1K Test Images: Image-to-Text R@1	R@5	R@10	Text-to-Image R@1	R@5	R@10	RSUM	5K Test Images: Image-to-Text R@1	R@5	R@10	Text-to-Image R@1	R@5	R@10	RSUM
ResNet-152 + Bi-GRU															
VSE++	✗	64.6	90.0	95.7	52.0	84.3	92.0	478.6	41.3	71.1	81.2	30.3	59.4	72.4	355.7
PVSE	✗	69.2	91.6	96.6	55.2	86.5	93.7	492.8	45.2	74.3	84.5	32.4	63.0	75.0	374.4
PCME	✗	68.8	-	-	54.6	-	-	-	44.2	-	-	31.9	-	-	-
Ours	✗	70.3	91.5	96.3	56.0	85.8	93.3	**493.2**	47.2	74.8	84.1	33.8	63.1	74.7	**377.7**
Faster R-CNN + Bi-GRU															
SCAN†	✓	72.7	94.8	98.4	58.8	88.4	94.8	507.9	50.4	82.2	90.0	38.6	69.3	80.4	410.9
VSRN†	✗	76.2	94.8	98.2	62.8	89.7	95.1	516.8	53.0	81.1	89.4	40.5	70.6	81.1	415.7
CAAN	✓	75.5	95.4	98.5	61.3	89.7	95.2	515.6	52.5	83.3	90.9	41.2	70.3	82.9	421.1
IMRAM†	✓	76.7	95.6	98.5	61.7	89.1	95.0	516.6	53.7	83.2	91.0	39.7	69.1	79.8	416.5
SGRAF†	✓	79.6	96.2	98.5	63.2	90.7	96.1	524.3	57.8	-	91.6	41.9	-	81.3	-
VSE$_\infty$	✗	78.5	96.0	98.7	61.7	90.3	95.6	520.8	56.6	83.6	91.4	39.3	69.9	81.1	421.9
NAAF†	✓	80.5	96.5	98.8	64.1	90.7	96.5	527.2	58.9	85.2	92.0	42.5	70.9	81.4	430.9
Ours	✗	79.8	96.2	98.6	63.6	90.7	95.7	524.6	58.8	84.9	91.5	41.1	72.0	82.4	430.7
Ours†	✗	80.6	96.3	98.8	64.7	91.4	96.2	**528.0**	60.4	86.2	92.4	42.6	73.1	83.1	**437.8**
ResNeXt-101 + BERT															
VSE$_\infty$	✗	84.5	98.1	99.4	72.0	93.9	97.5	545.4	66.4	89.3	94.6	51.6	79.3	87.6	468.9
VSE$_\infty$†	✗	85.6	98.0	99.4	73.1	94.3	97.7	548.1	68.1	90.2	95.2	52.7	80.2	88.3	474.8
Ours	✗	86.3	97.8	99.4	72.4	94.0	97.6	547.5	69.1	90.7	95.6	52.1	79.6	87.8	474.9
Ours†	✗	86.6	98.2	99.4	73.4	94.5	97.8	**549.9**	71.0	91.8	96.3	53.4	80.9	88.6	**482.0**

Experiments: Performance on Flickr30K

Method	CA	Image-to-text			Text-to-image			RSUM
		R@1	R@5	R@10	R@1	R@5	R@10	
ResNet-152 + Bi-GRU								
VSE++	✗	52.9	80.5	87.2	39.6	70.1	79.5	409.8
PVSE*	✗	59.1	84.5	91.0	43.4	73.1	81.5	432.6
PCME*	✗	58.5	81.4	89.3	44.3	72.7	81.9	428.1
Ours	✗	61.8	85.5	91.1	46.1	74.8	83.3	**442.6**
Faster R-CNN + Bi-GRU								
SCAN†	✓	67.4	90.3	95.8	48.6	77.7	85.2	465.0
VSRN†	✗	71.3	90.6	96.0	54.7	81.8	88.2	482.6
CAAN	✓	70.1	91.6	97.2	52.8	79.0	87.9	478.6
IMRAM†	✓	74.1	93.0	96.6	53.9	79.4	87.2	484.2
SGRAF†	✓	77.8	94.1	97.4	58.5	83.0	88.8	499.6
VSE_∞	✗	76.5	94.2	97.7	56.4	83.4	89.9	498.1
NAAF†	✓	81.9	96.1	98.3	61.0	85.3	90.6	**513.2**
Ours	✗	77.8	94.0	97.5	57.5	84.0	90.0	500.8
Ours†	✗	80.9	94.7	97.6	59.4	85.6	91.1	509.3
ResNeXt-101 + BERT								
VSE_∞	✗	88.4	98.3	99.5	74.2	93.7	96.8	550.9
VSE_∞†	✗	88.7	98.9	99.8	76.1	94.5	97.1	555.1
Ours	✗	88.8	98.5	99.6	74.3	94.0	96.7	551.9
Ours†	✗	90.6	99.0	99.6	75.9	94.7	97.3	**557.1**

Experiments: Performance on Flickr30K





[7] Jiacheng *et al.*, Learning the Best Pooling Strategy for Visual Semantic Embedding, CVPR 2021.
[8] Zhang *et al.*, Negative-aware Attention Framework for Image-text Matching., CVPR 2022.
[9] Lee *et al.*, Stacked Cross Attention for Image-text Matching, ECCV 2018.

Experiments : Performance on ECCV Caption and CxC

	Image-to-text				Text-to-image			
	ECCV Caption			CxC	ECCV Caption			CxC
	mAP@R	R-P	R@1	R@1	mAP@R	R-P	R@1	R@1
VSRN	30.8	42.9	73.8	55.1	**53.8**	**60.8**	89.2	42.6
VSE_∞	34.8	45.4	81.1	67.9	50.0	57.5	**91.8**	53.7
Ours	**36.0**	**46.4**	**84.7**	**72.3**	51.0	58.5	91.6	**55.5**

VSRN[10] is one of the machine annotators used to construct the ECCV Caption dataset.

[10] Li *et al.*, Visual Semantic Reasoning for Image-text Matching, ICCV 2019.

Experiments: Ablation Study on Flickr30K

Similarity	Arch.	RSUM
MIL [11]	Ours	491.7
MP [12]	Ours	490.5
Ours (Chamfer)	Ours	499.6
Ours (S-Chamfer)	PIE-Net	483.3
Ours (S-Chamfer)	Ours	**500.8**

Impact of set-similarity metric

Smooth-Chamfer similarity is best suited to our framework.

Setting	log(Var.)	RSUM
PIE-Net [11,12]	-7.35	483.3
Ours \w MP	-5.27	490.5
Transformer [13]	-2.27	496.1
Ours	-2.13	**500.8**

Impact of set-embedding architecture

Our architecture results in most diverse embeddings and best performance.

Circular variance $\mathrm{Var} = 1 - \left\| \sum_{\mathbf{e} \in \mathbf{S}} \frac{\mathbf{e}}{|\mathbf{S}|} \right\|_2$

[11] Song and Soleymani, Polysemous Visual Semantic Embedding for Cross-modal Retrieval, CVPR 2019.
[12] Chun *et al.*, Probabilistic Embeddings for Cross-modal Retrieval, CVPR 2021.
[13] Dosovitskiy *et al.*, An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale, ICLR 2021.

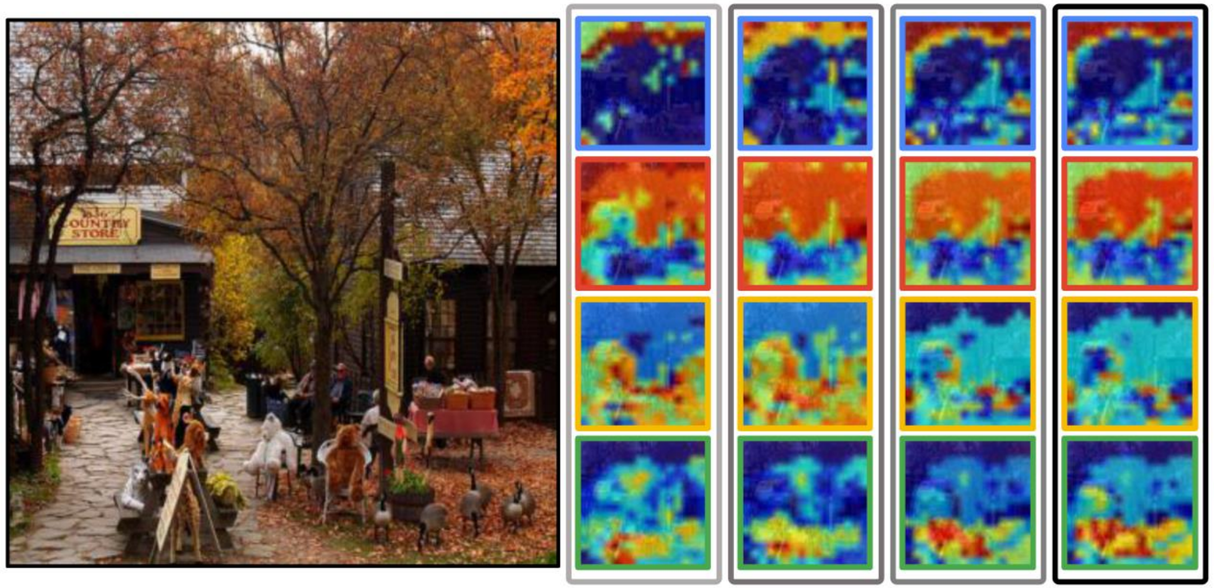
Experiments: Ablation Study on Flickr30K

Evaluation $\mathbf{S}^{\mathcal{V}}(1)$	$\mathbf{S}^{\mathcal{V}}(2)$	$\mathbf{S}^{\mathcal{V}}(3)$	$\mathbf{S}^{\mathcal{V}}(4)$	RSUM
✓	✓	✓	✓	**500.8**
✓				491.1
	✓			309.6
		✓		484.9
			✓	486.0

Evaluation $\mathbf{S}^{\mathcal{T}}(1)$	$\mathbf{S}^{\mathcal{T}}(2)$	$\mathbf{S}^{\mathcal{T}}(3)$	$\mathbf{S}^{\mathcal{T}}(4)$	RSUM
✓	✓	✓	✓	**500.8**
✓				481.9
	✓			483.0
		✓		481.7
			✓	497.2

Contribution of each embedding element

Experiments: Qualitative Examples

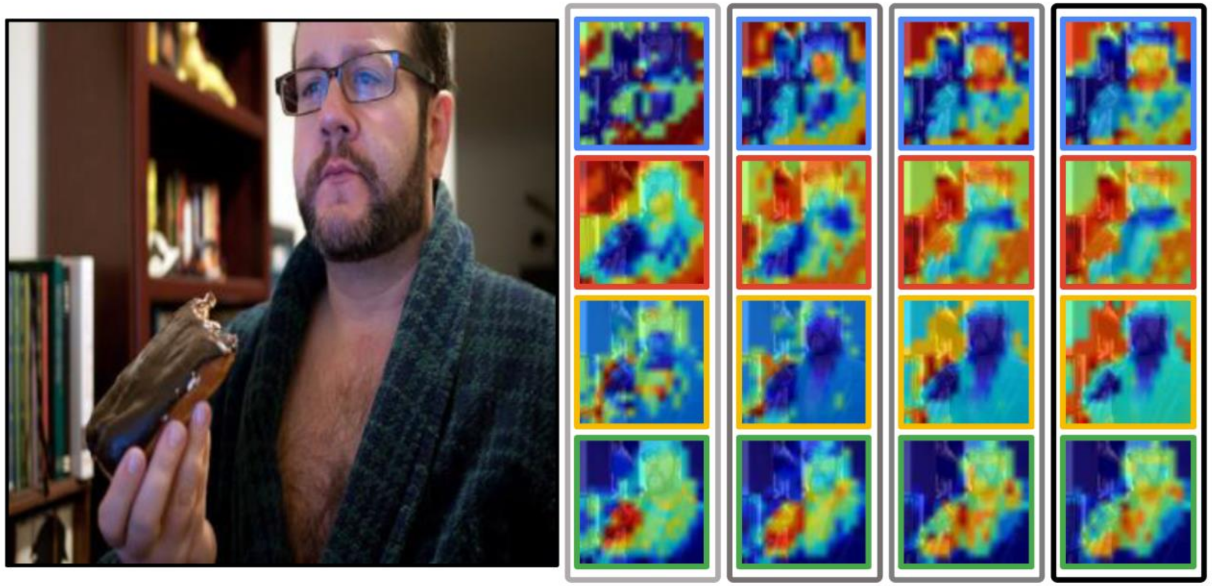


R1: Picture of an outdoor place that is very beautiful.

R1: An old coutnry store has a display of stuffed animals outside.

R1: A park is full of patrons on a fall day.

R1: A country store with several teddy bears and geese there.



R1: Here is a soul in the image alone.

R1: A man in a robe eating a chocolate donut.

R1: A hairy man eating a chocolate doughnut in his house.

R1: A man is holding a chocolate dessert in his hand as he stares ahead.

Conclusion

- Contributions
  - A new set-based embedding architecture
  - A new set similarity metric
  - Outstanding performance on four public benchmarks

- Next on agenda
  - Adopting CLIP-pretrained weights[14]
  - Adopting an advanced slot attention mechanism (*e.g.*, [15])
  - Learning vision-language models with the proposed method

[14] Radford *et al.*, Learning Transferable Visual Models From Natural Language Supervision, ICML 2021.
[15] Kim *et al.*, Shatter and Gather: Learning Referring Image Segmentation with Text Supervision, ICCV 2023.

References

[1] Locatello *et al*., Object-centric Learning with Slot Attention, NeurIPS 2020.

[2] Gretton *et al.*, A Kernel Two-sample Test, JMLR 2012.

[3] Lin *et al.*, Microsoft COCO: Common Objects in Context, ECCV 2014.

[4] Plummer *et al.*, Flickr30k Entities: Collecting Region-to-phrase Correspondences for Richer Image-to-sentence Models, ICCV 2015.

[5] Chun *et al.*, ECCV Caption, Correcting False Negatives by Collecting Machine-and-human-verified Image-Caption Associations for MS-COCO, ECCV 2022.

[6] Parekh *et al.*, Crisscrossed Captions, EACL 2020.

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