

SelfGraphVQA

Bruno Souza 🏵 🛛 Marius Aasan 🏶 Helio Pedrini 🏵 🛛 Adín Ramírez Rivera 🏶

* University of Oslo (UiO) 😌 University of Campinas (UNICAMP)



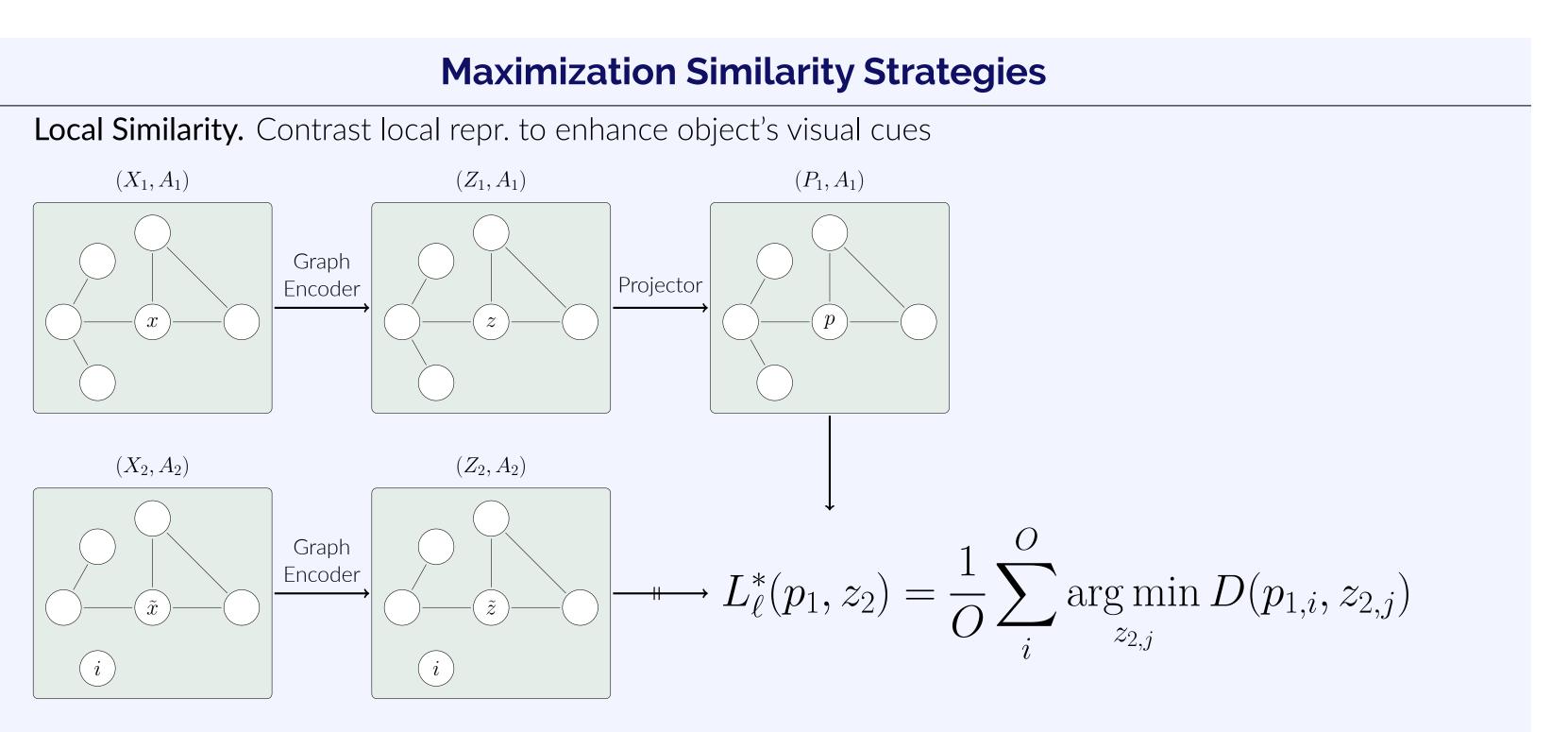
Our Problem

VQA	does not work for non-ideal data!			
Input: Image (Represented as Scene Graph)	Method	Eval. Data	Acc (%)	
pink shake	Human		89.3	
benind on left holding red	GraphVQA	Annotated/SGG	94.8	
red, plastic	LRTA	Annotated/SGG	93.1	
Input: Question What is the red object left of the girl	CRF	Annotated	72.1	
that is holding a hamburger?	LXMERT	Extracted	59.8	

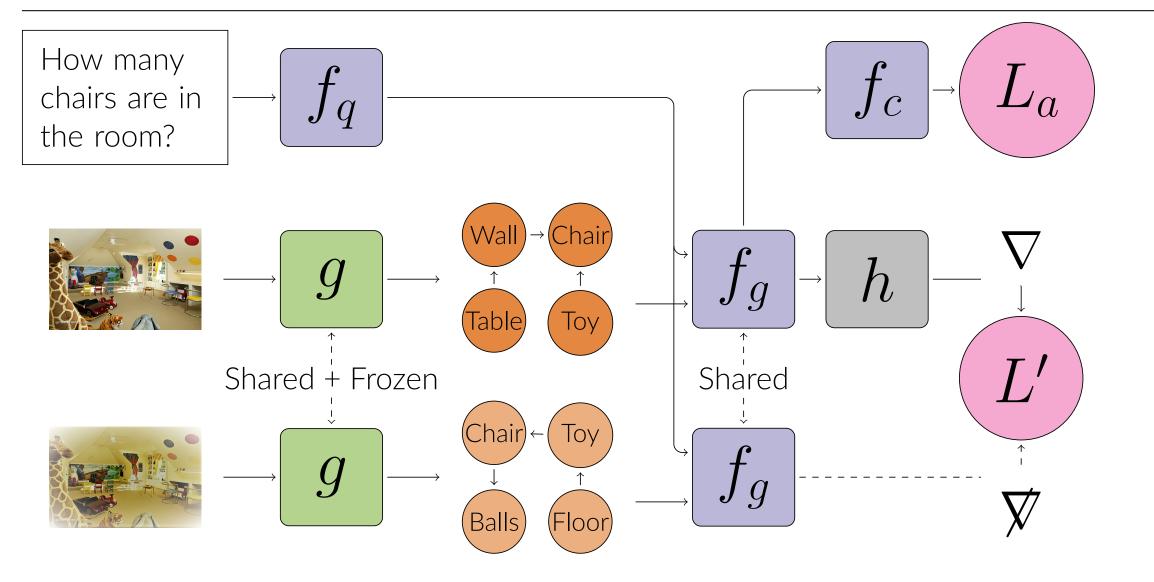
Motivation: Research Questions

• Do scene graph VQA models work with **non-ideal** generated scene graphs? **No.** • Does un-normalized contrastive learning enhance visual information in the VQA task? Yes. (Sometimes)

SelfGraphVQA Architecture



Global Similarity. Contrast global repr. to enhance global visual cues



Three distinct maximization strategies:

1. Local Similarity. A localized node representation (i.e., object-wise):

$$L_{\ell}^{*}(p_{1}, z_{2}) = \frac{1}{O} \sum_{i}^{O} \underset{z_{2,j}}{\operatorname{arg\,min}} D(p_{1,i}, z_{2,j}), \tag{1}$$

where O is the number of object in the scene. Symmetrically, we compute $L_{\ell}^{*}(p_2, z_1),$

$$L_{\ell}(z_1, z_2) = \frac{1}{2} \Big(L_{\ell}^*(p_1, z_2) + L_{\ell}^*(p_2, z_1) \Big).$$
(2)

(3)

(4)

(5)

Method

Baseline

Local

Global

SelfSim

Baseline+BERT

Global+BERT+link

SelfSim+BERT+link

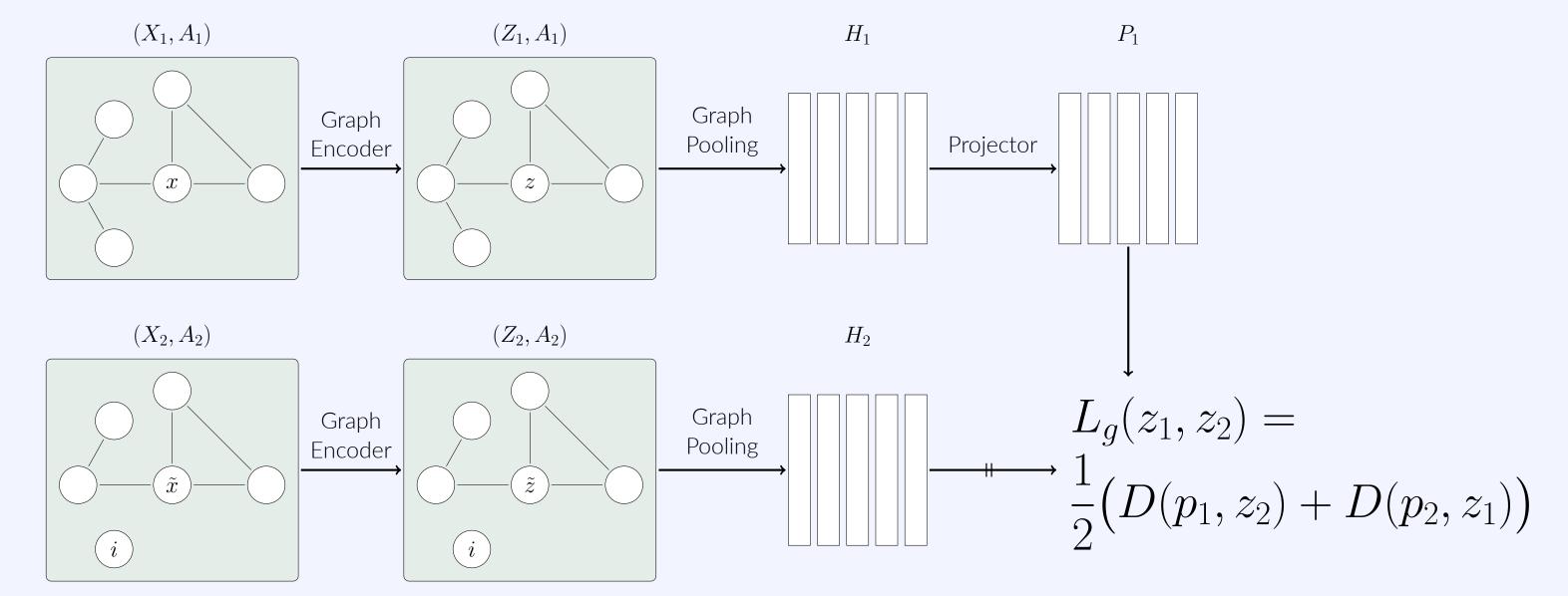
(1) Correct

(2) Correct

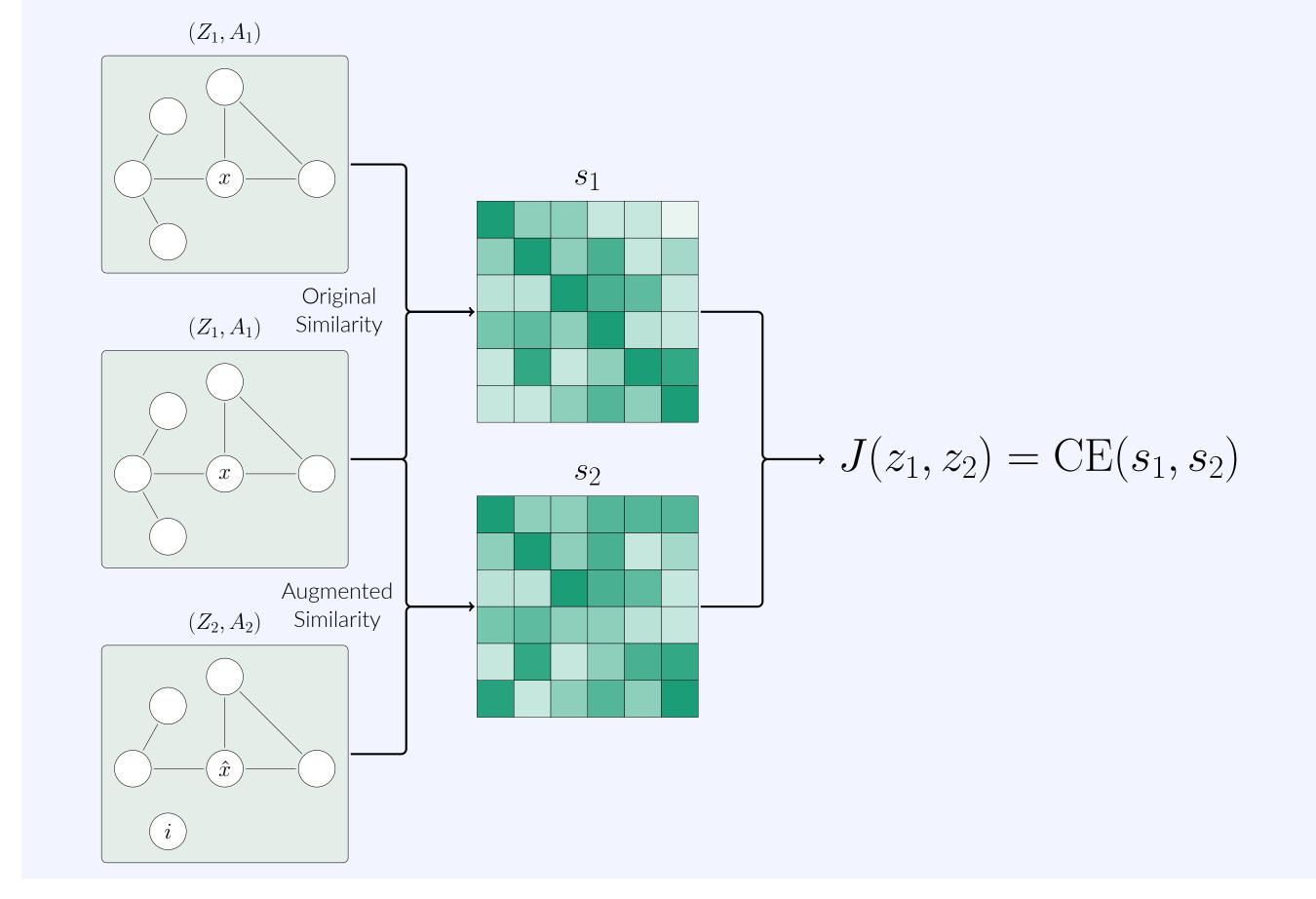
2. Global Similarity. A global pooled graph representation (i.e., scene-wise):

$$L_g(z_1, z_2) = \frac{1}{2} (D(p_1, z_2) + D(p_2, z_1)).$$

3. Regularization for Permutation Equivariance. Align similar nodes and encourage regularization. The anchors' similarity $s_{1,i} = \arg \min_{z_{1,j}} D(z_{1,i}, z_{1,j})$ and similarities



Regularization for Permutation Equivariance (SelfSim). Align similar nodes and regularize



of augmented views $s_{2,ij} = D(z_{2,i}, z_{2,j})$. We compute cross entropy (CE) between anchors and augmentations

$$I(z_1, z_2) = \operatorname{CE}(s_1, s_2),$$

which acts as a regularizer to constrain permutation equivariance for the augmentations in addition to the local loss, yielding

$$L_s(z_1, z_2) = L_\ell(z_1, z_2) + J(z_1, z_2),$$

Ablations

Change in accuracy under potentially disruptive augmentations and perturbations.							
Question Type	Augmentation	Baseline	Global	Local	SelfSim		
Relation	Flip	-1.6	-3.4	-3.2	-3.9		
Attribute	Strong Color Jitter	+1.14	-3.7	-0.8	-1.2		
Global	Gaussian Noise + Crop	-5.6	-7.7	-5.5	-8.1		

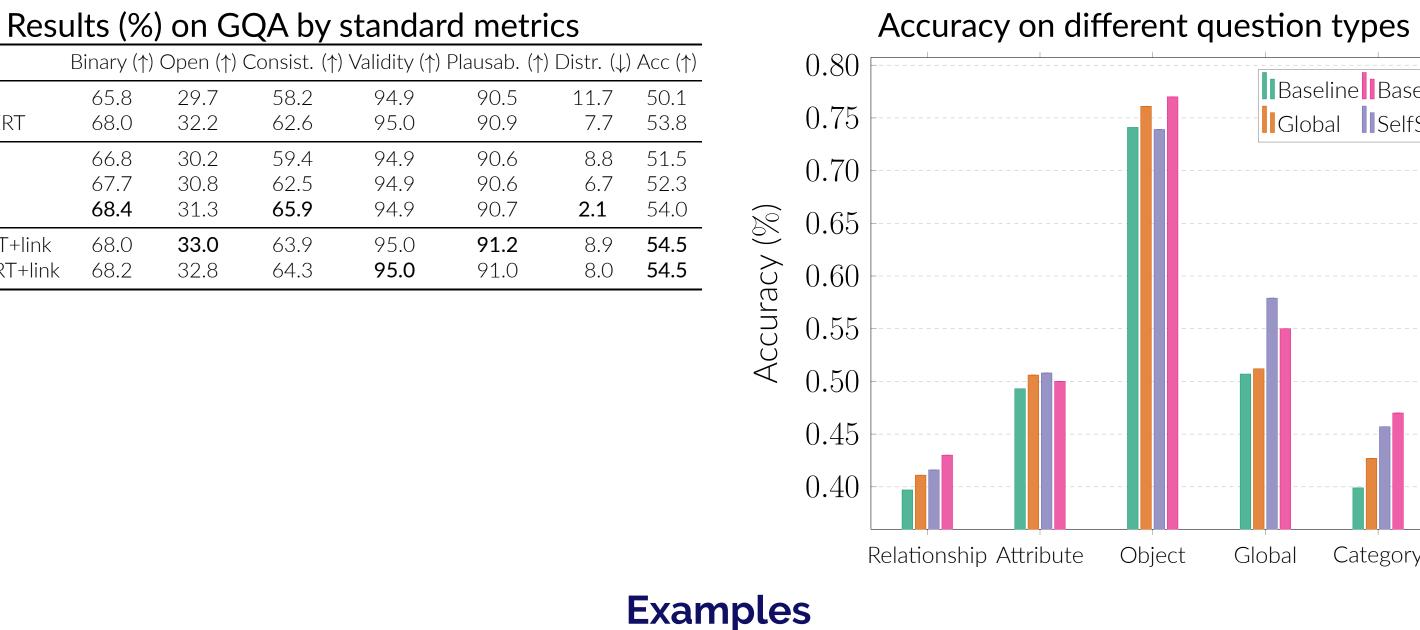
Results (%) of the Aug. Baseline and SelfSim.

Method	Binary	Open	Validity	Plausibility	Acc
Baseline Aug		28.7	94.6	90.1	50.1
SelfSim		31.3	94.9	90.7	54.0

Sensitivity of accuracy (%) for bias question analyzes of SelfGraphVQA and Self-GraphVQABERT.

Setup	Methods			
Scene Graph + Question	Baseline	Local	Global	SelfSim

Results



(3) SG explainable



Global

Baseline Baseline+BERT

Global SelfSim

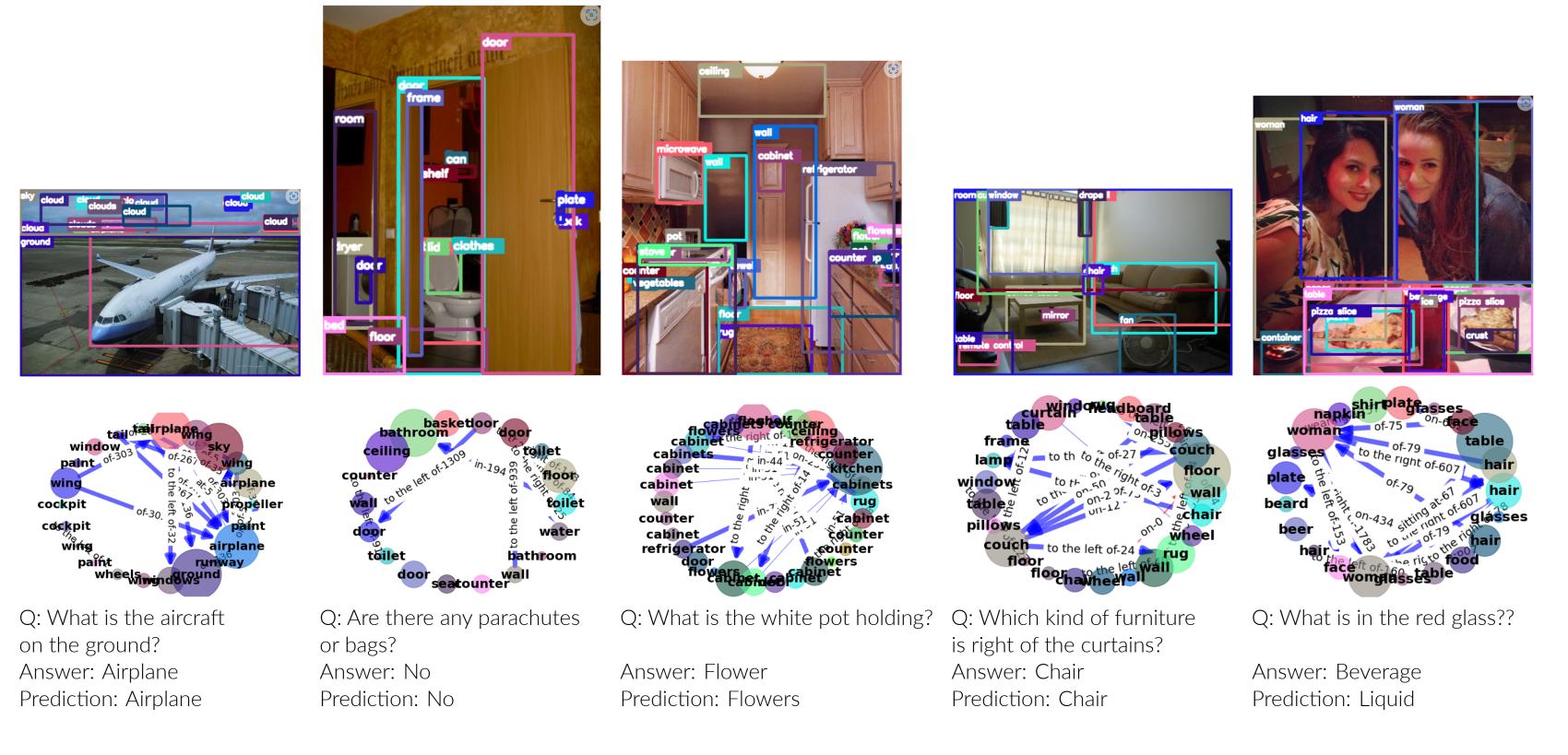
Category

Average

Noise + SG	16.2	16.6	28.6	26.6
Question + Noise	39.9	38.3	37.4	39.8
Noise + Noise	12.7	14.6	18.9	21.0
Question + Scene Graph	BERT Baseline	BERTGlobal+link	BERTSelfSim+link	
Noise + SG	21.0	23.2	24.5	
Question + Noise	42.4	41.8	42.8	
Noise + Noise	19.8	21.7	21.3	

Acknowledgments

This work was partially funded by the FAPESP (São Paulo Research Foundation). The computations were partially performed on resources provided by Sigma2. This work was partially performed at the Artificial Intelligence Lab., Recod.ai. This work was partially funded by the Research Council of Norway, via the Visual Intelligence Centre for Research-based Innovation.



ICCV—Vision-and-Language Algorithm Reasoning Workshop 2023, Paris