

Deep Multimodal Neural Architecture Search

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Yu, Zhou, et al. "Deep Multimodal Neural Architecture Search."

Proceedings of the 28th ACM International Conference on Multimedia. 2020.

- Task

Visual Question Answering task: {images, questions, answers}

Image-Text matching task: {images, captions}

Visual Grounding task: {images, query}

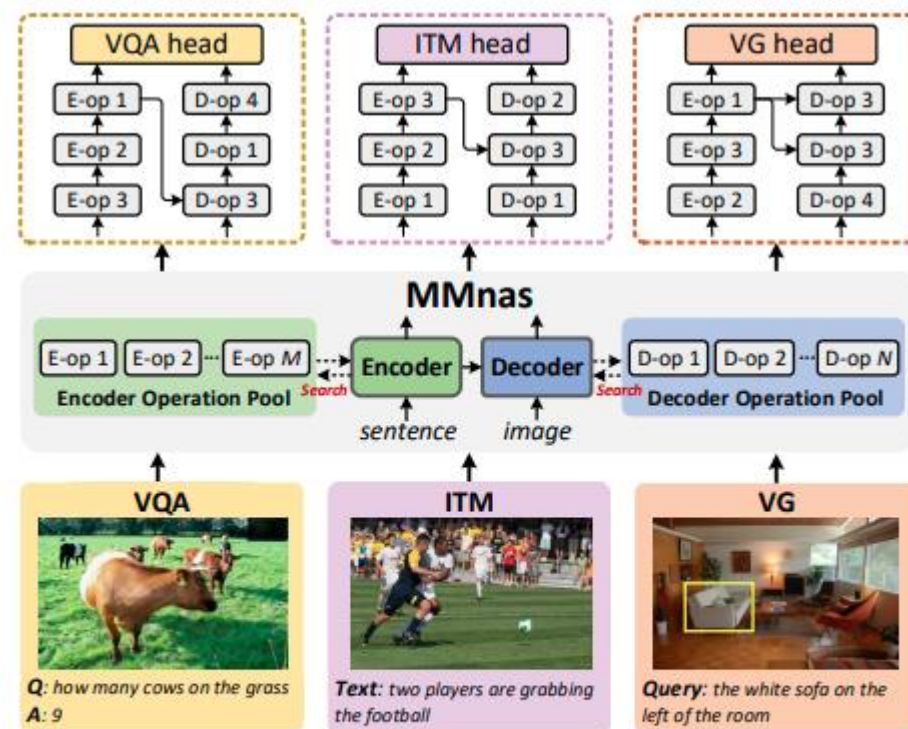


Figure 1: Schematic of the proposed generalized MMnas framework, which searches for the optimal architectures for the VQA, image-text matching, and visual grounding tasks.

Deep Multimodal Neural Architecture Search

- MMnas Framework

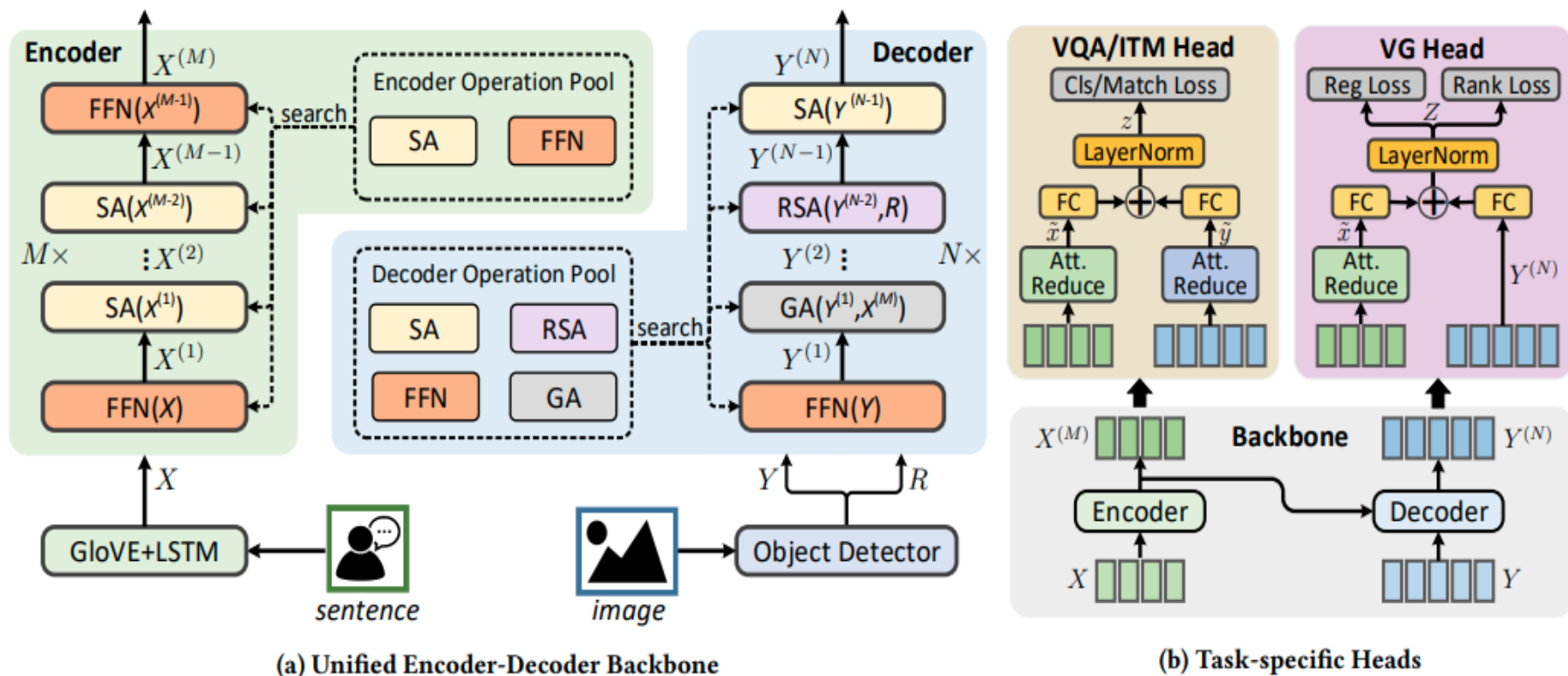


Figure 2: The flowchart of the MMnas framework, which consists of (a) unified encoder-decoder backbone and (b) task-specific heads on top the backbone for visual question answer (VQA), image-text matching (ITM), and visual grounding (VG).

Deep Multimodal Neural Architecture Search

- Experiment Settings

- Dataset

VQA-v2: Visual Question Answering {images, questions, answers}

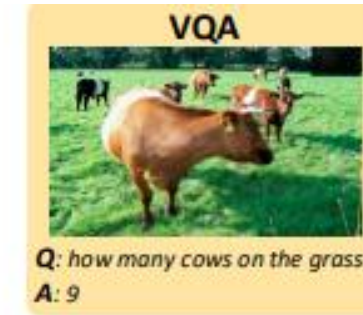
200,000 images, 1,106,000 questions

Flickr 30K: image with caption from Flickr website {images, captions}

31,000 images

RefCOCO, RefCOCO+ and RefCOCOg: {images, query}

66,600 images and queries



Deep Multimodal Neural Architecture Search

- Experiment Settings
 - MMnas search space module

MHA: Multi-head Attention

Self-attention operation $Z = \text{SA}(X) = \text{MHA}(X, X, X, \mathbf{0})$ (4)

Guided-attention operation $Z = \text{GA}(X, Y) = \text{MHA}(X, Y, Y, \mathbf{0})$ (5)

Feed-forward network operation $Z = \text{FFN}(X) = \text{FC}_d \circ \text{Drop}_{0.1} \circ \text{ReLU} \circ \text{FC}_{4d}(X)$ (6)

Relation self-attention operation $\text{MLP}(R) = \text{ReLU} \circ \text{FC}_1 \circ \text{ReLU} \circ \text{FC}_{d_h}(R)$
 $Z = \text{RSA}(X, R) = \text{MHA}(X, X, X, \log(\text{MLP}(R) + \epsilon))$ (7)

Deep Multimodal Neural Architecture Search

- MMnas Search Algorithm

$$(\theta^*, W^*) = \operatorname{argmin}_{\theta, W} \mathbb{E}_{a \sim \mathcal{A}(\theta)} [\mathcal{L}(\mathcal{N}(a, W))] \quad (16)$$

θ : Architecture weights

W : Model weights

Algorithm 1: Search Algorithm for MMnasNet.

Input: A supernet parameterized by the architecture weights θ and the model weights W . Training set $\mathcal{D}_a$ and $\mathcal{D}_m$ are used to optimize θ and W , respectively. T_w and T_j denote the number of epochs for the warming-up and iterative optimization stages, respectively. u is a factor to balance the update frequencies of θ and W .

Output: The searched optimal architecture a^*

Random initialize θ and W ;

The warming-up stage;

for $t = 1$ **to** T_w **do**

 Random sample an architecture $a \sim \mathcal{A}$;

 Random sample a mini-batch $d_m \subseteq \mathcal{D}_m$;

 Update W by descending $\nabla_W \mathcal{L}_{\text{train}}(\mathcal{N}(a, W))$ on d_m ;

end

The iterative optimization stage;

for $t = 1$ **to** T_j **do**

for $i = 1$ **to** u **do**

 Random sample a mini-batch $d_m \subseteq \mathcal{D}_m$;

 Sample an architecture $a \sim \mathcal{A}(\theta)$ with respect to θ ;

 Update W by descending $\nabla_W \mathcal{L}_{\text{train}}(\mathcal{N}(a, W))$ on d_m ;

end

 Random sample a mini-batch $d_a \subseteq \mathcal{D}_a$;

 Sample an architecture $a \sim \mathcal{A}(\theta)$ with respect to θ ;

 Update θ by descending $\nabla_\theta \mathcal{L}_{\text{train}}(\mathcal{N}(a, W))$ on d_a ;

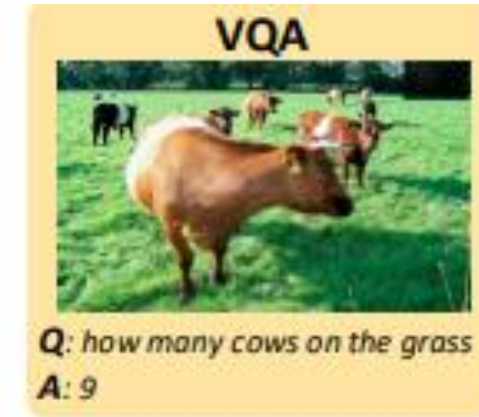
end

Return a^* by picking the operation with the largest value in θ^* for each block.

Deep Multimodal Neural Architecture Search

- Experiment Results : *Visual Question Answering Task*

Method	All	Yes/No	Num	Other
Bottom-Up	65.32	81.82	44.21	56.05
MFH+CoAtt	68.76	84.27	49.56	59.89
BAN-8	69.52	85.31	50.93	60.26
BAN-8 (+G+C)	70.04	85.42	54.04	60.52
DFAF-8	70.22	86.09	53.32	60.49
MCAN-6	70.63	86.82	53.26	60.72
MMnasNet (paper)	71.24	87.27	55.68	61.05
MMnasNet (me)	67.53	84.93	51.74	58.47



Number

Deep Multimodal Neural Architecture Search

- Experiment Results : *Visual Grounding Task*

Method	Object Detector			Validation Acc
	Dataset	Model	Backbone	
Spe.+Lis.+Rein.+MMI	COCO	SSD	VGG-16	69.50
MAttNet	COCO	MRCN	ResNet-101	76.7
DDPN	Genome	FRCN	ResNet-101	76.8
MMnasNet (paper)	COCO	MRCN	ResNet-101	81.5
MMnasNet (me)	COCO	MRCN	ResNet-101	81.2