Align before Fuse: Vision and Language Representation Learning with Momentum Distillation

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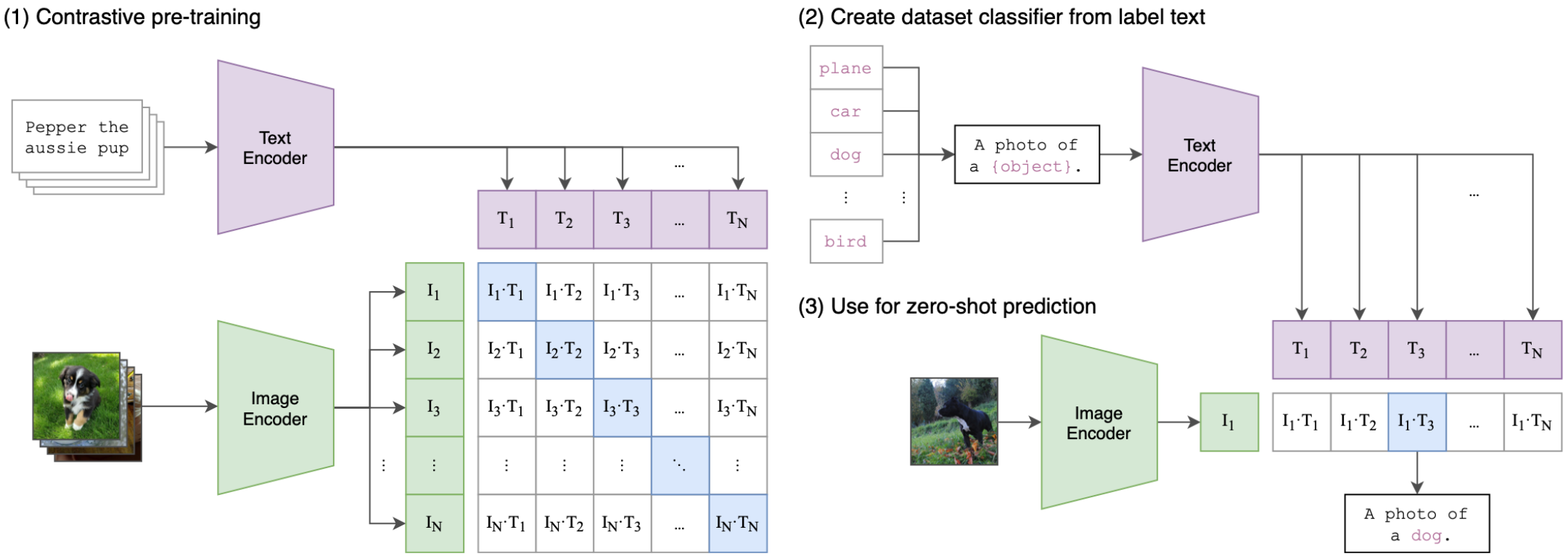
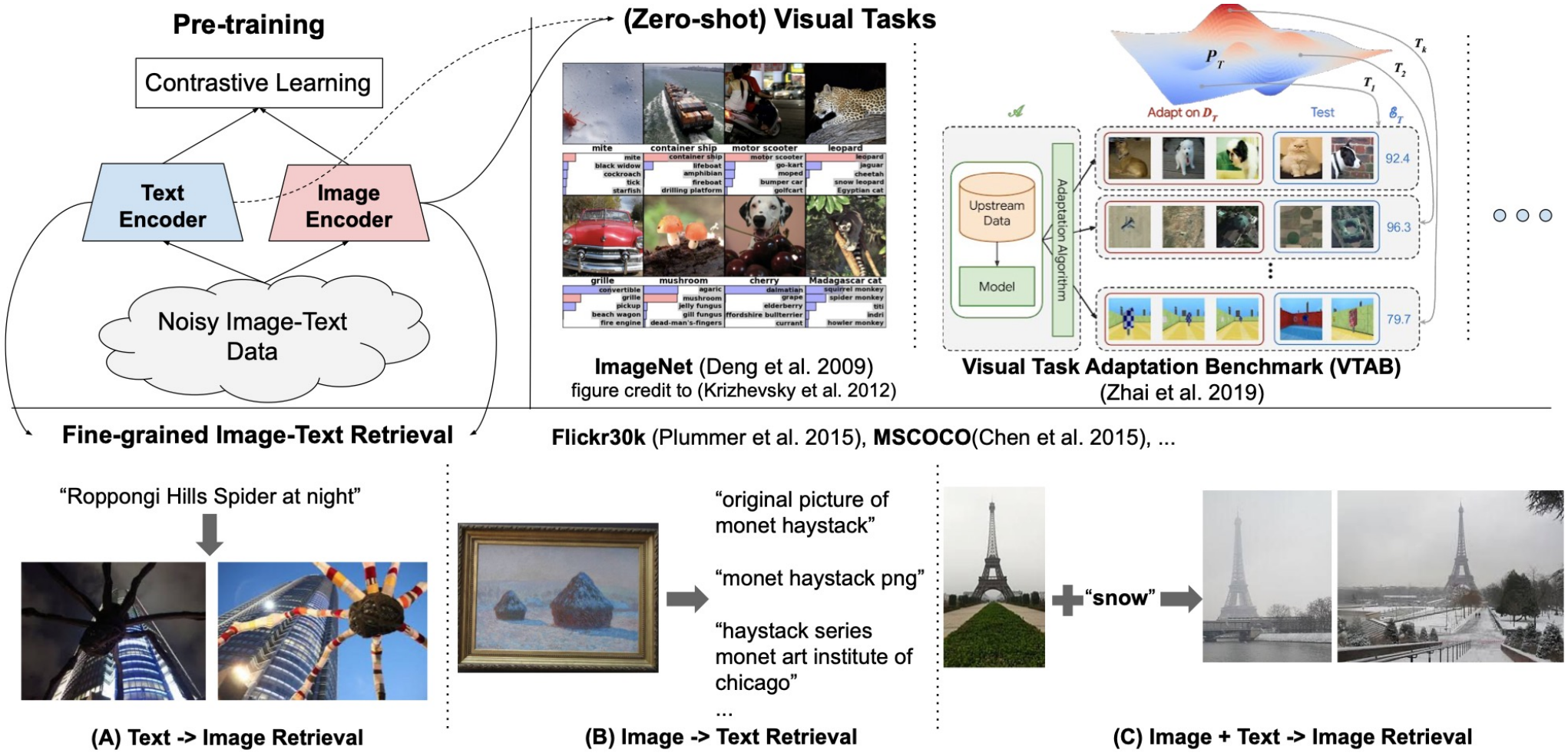
Motivations



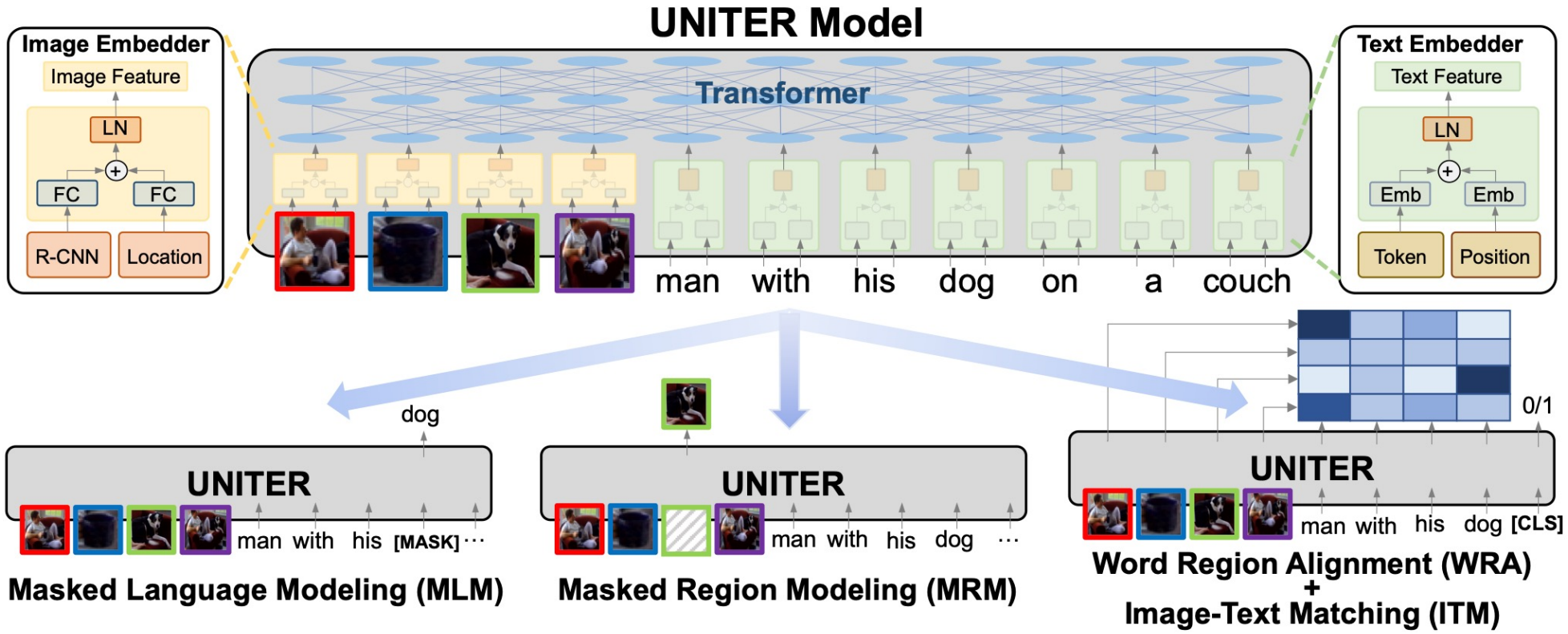
Radford, A., J. W. Kim, C. Hallacy, et al. Learning transferable visual models from natural language supervision. arXiv preprint arXiv:2103.00020, 2021.

Motivations



Jia, C., Y. Yang, Y. Xia, et al. Scaling up visual and vision-language representation learning with noisy text supervision. arXiv preprint arXiv:2102.05918, 2021.

Motivations



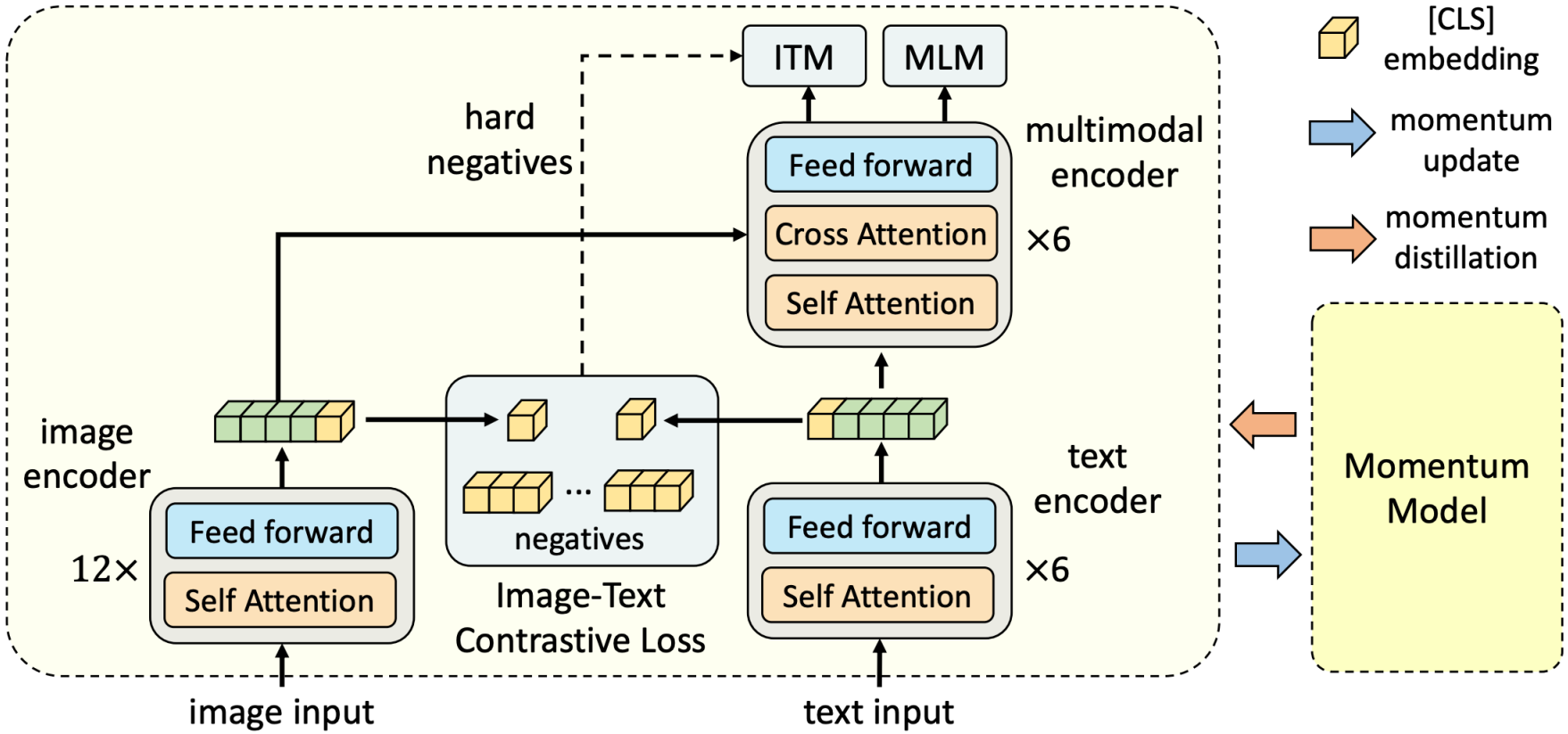
Chen, Y., L. Li, L. Yu, et al. UNITER: universal image-text representation learning. In ECCV, 2020.

Motivations

Li, J., Li, D., Xiong, C., & Hoi, S. (2022, June). Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *International Conference on Machine Learning* (pp. 12888-12900). PMLR.

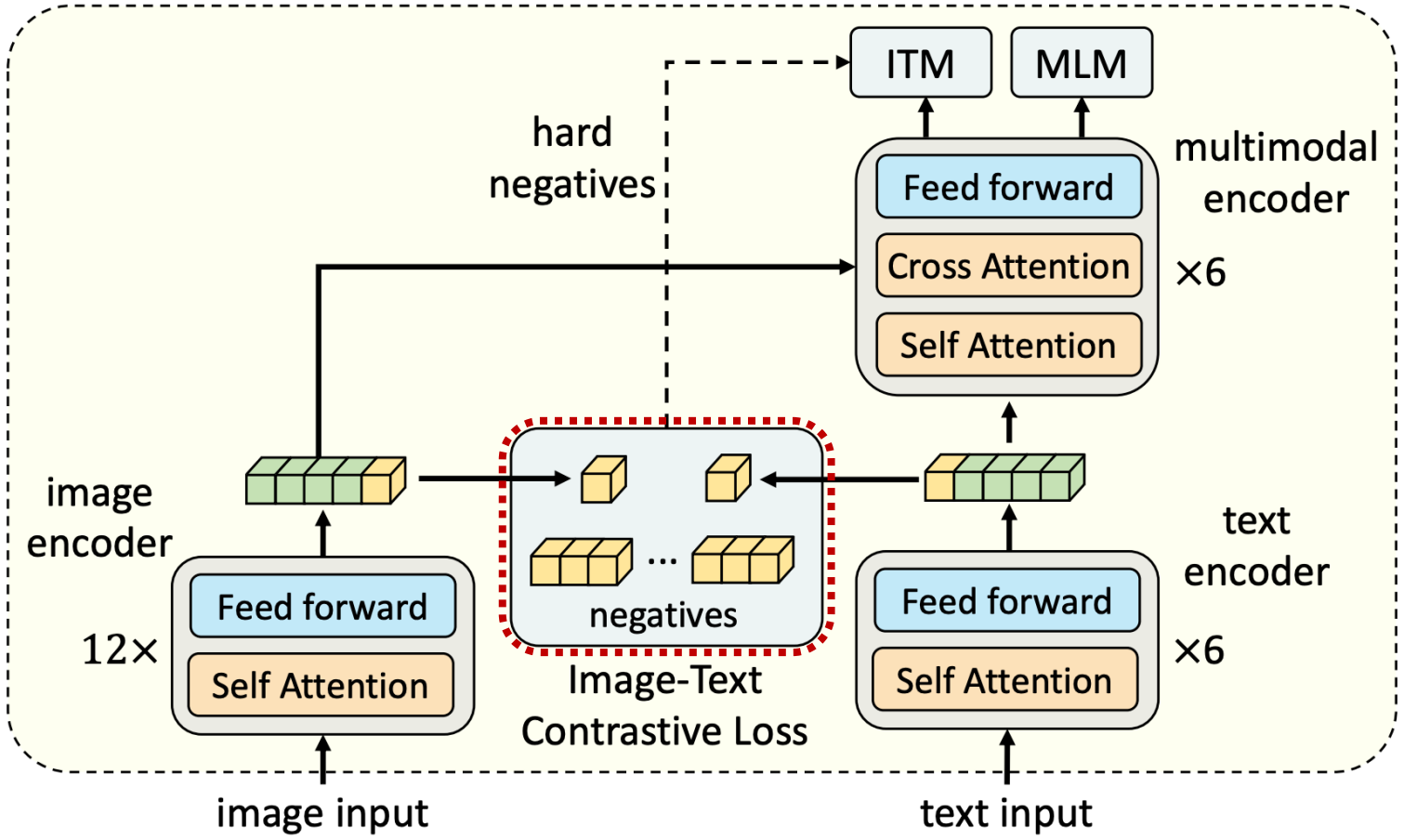
Methods

- Image-text Contrastive(ITC)
- Masked language model(MLM)
- Image-Text matching(ITM)



ALBEF

Methods



ALBEF

- Use [CLS] embedding as unimodal representation
- Encourage an image-text pair to have similar feature
- Align the unimodal features
- Learn better unimodal encoders

Methods

$$s = g_v(v_{\text{cls}})^\top g_w(w_{\text{cls}})$$

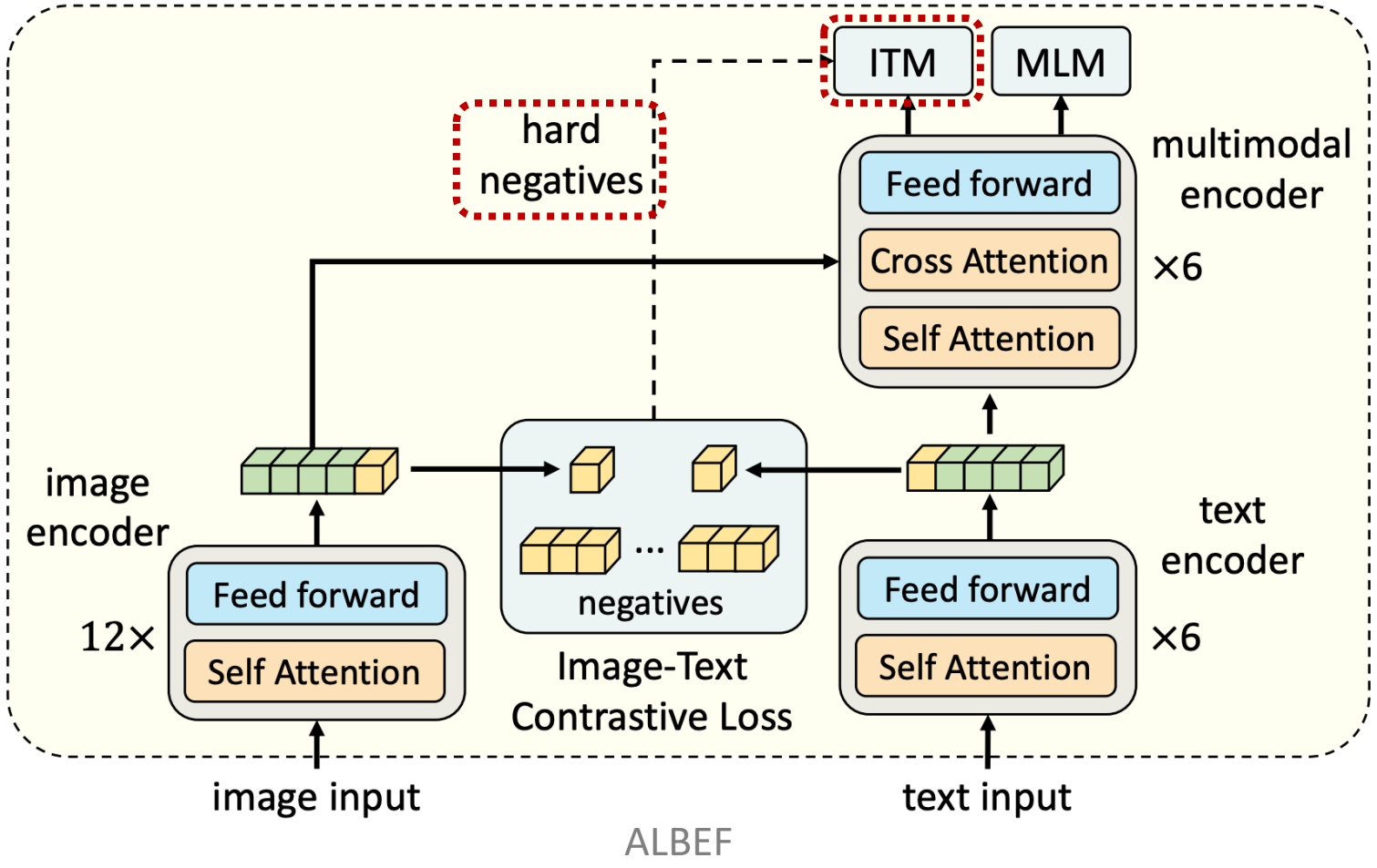
$$s(I,T) = g_v(v_{\text{cls}})^\top g'_w(w'_{\text{cls}}),\ s(I,T) = g_w(w_{\text{cls}})^\top g'_v(v'_{\text{cls}})$$

$$p_m^{i2t}(I) = \frac{\exp(s(I,T_m)/\tau)}{\sum_{m=1}^{M}\exp(s(I,T_m)/\tau)},\ p_m^{t2i}(I) = \frac{\exp(s(T,I_m)/\tau)}{\sum_{m=1}^{M}\exp(s(T,I_m)/\tau)}$$

$$\mathcal{L}_{\text{itc}} = \frac{1}{2}\mathbb{E}_{(I,T)\,D}[H(p^{i2t}(I), y^{i2t}(I)) + H(p^{t2i}(T), y^{t2i}(T))]$$

- M: most recent M image-text representations from the momentum unimodal encoders. $M = 65536$
- H: cross-entropy

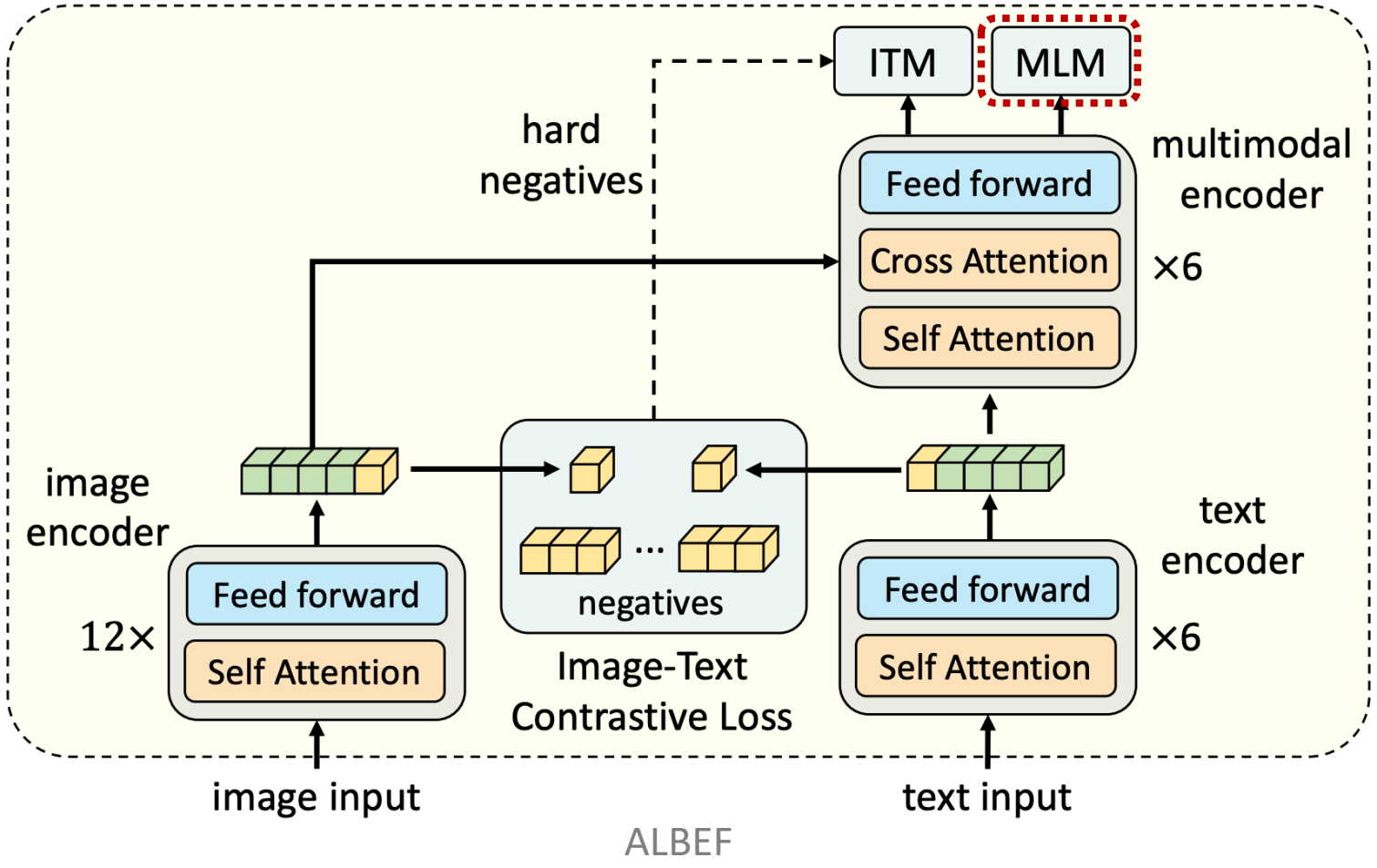
Methods



ALBEF

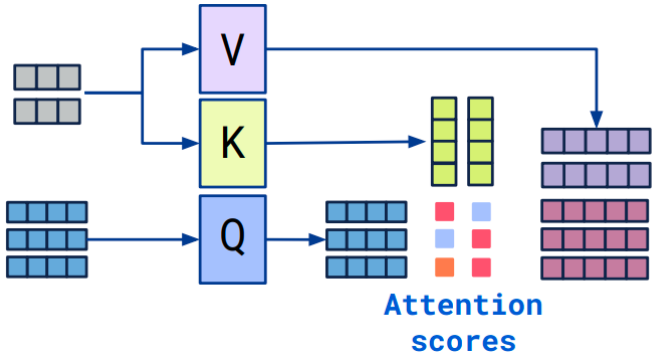
- Binary classification of positive and negatives
- Contrastive hard negative mining
- Mine more informative negatives with zero computation

Methods

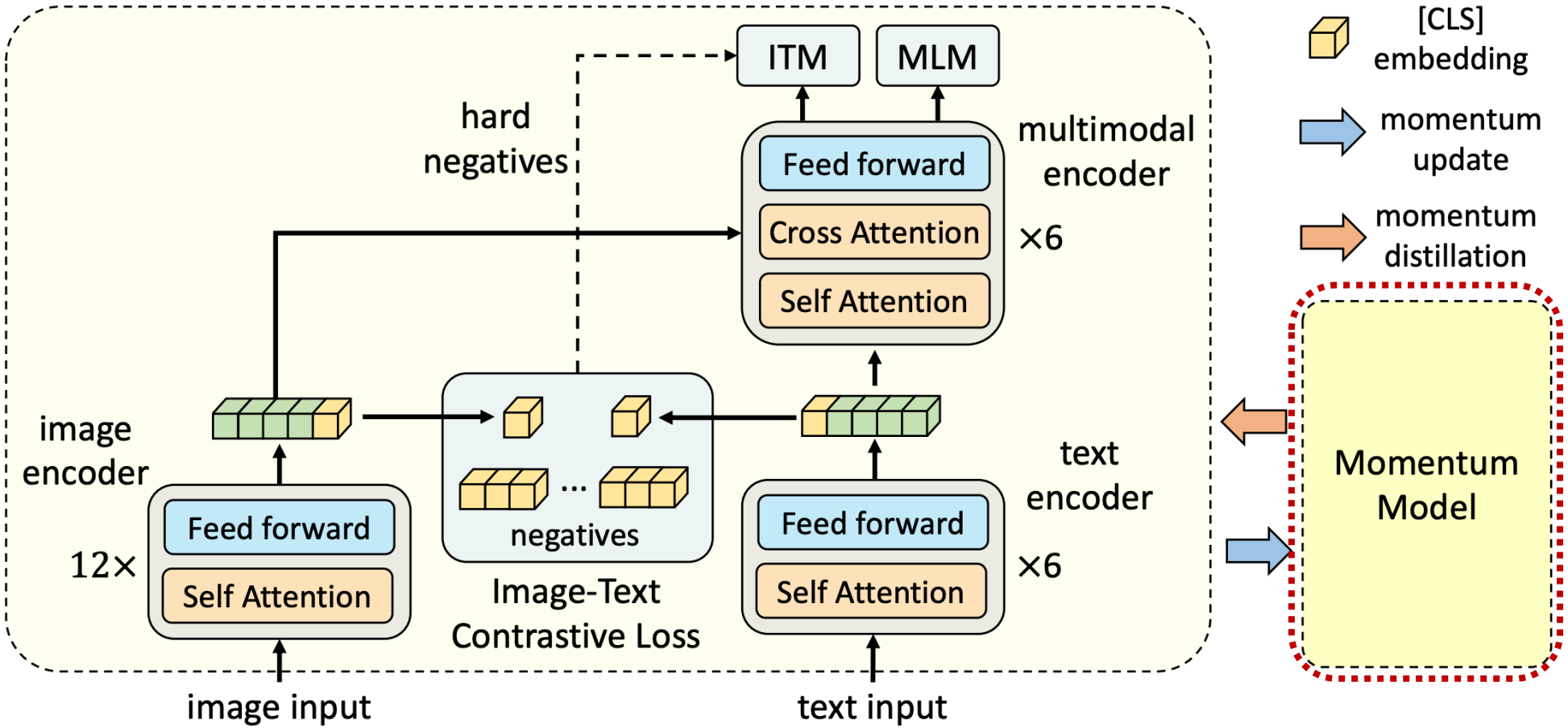


ALBEF

- Predict word based on image and contextual text



Methods



- Momentum model: a continuously-evolving teacher whose parameters are exponential moving-average of the base model's
- Generate pseudo-labels for ITC and MLM

Methods

** Contrastive Learning with Momentum**

$$s'(I,T) = g'_v(v'_{\text{cls}})^\top g'_w(w'_{\text{cls}}),\ s'(I,T) = g'_w(w'_{\text{cls}})^\top g'_v(v'_{\text{cls}})$$

$$q_m^{i2t}(I) = \frac{\exp(s'(I,T_m)/\tau)}{\sum_{m=1}^{M}\exp(s'(I,T_m)/\tau)},\ q_m^{t2i}(I) = \frac{\exp(s'(T,I_m)/\tau)}{\sum_{m=1}^{M}\exp(s'(T,I_m)/\tau)}$$

$$\mathcal{L}_{itc}^{\text{mod}} = (1-\alpha)\mathcal{L}_{\text{itc}} + \frac{\alpha}{2}\mathbb{E}_{(I,T)\sim D}[\text{KL}(p^{\text{i2t}}(I), q^{\text{i2t}}(I))\text{KL}(p^{\text{t2i}}(T), q^{\text{t2i}}(T))]$$

** MLM with Momentum**

$$\mathcal{L}_{\text{mlm}}^{\text{mod}} = (1-\alpha)\mathcal{L}_{\text{mlm}} + \alpha\mathbb{E}_{(I,\hat{T})\sim D}\text{KL}(p^{\text{msk}}(I,\hat{T}), q^{\text{msk}}(I,\hat{T}))$$

Pseudo-targets for MLM

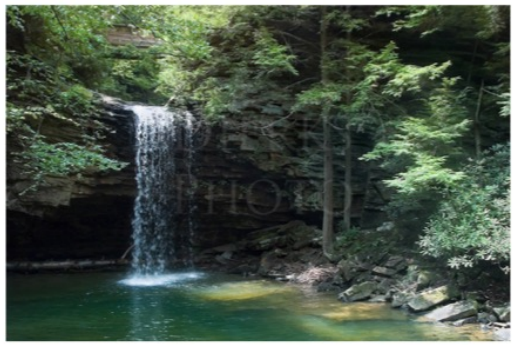
"polar bear in the [MASK]"

GT: wild

Top-5 pseudo-targets:

1. zoo
2. pool
3. water
4. pond
5. wild

"a [MASK] waterfall in the deep woods"



GT: remote

Top-5 pseudo-targets:

1. small
2. beautiful
3. little
4. secret
5. secluded

"a man [MASK] along a road in front of nature in summer"

GT: standing

Top-5 pseudo-targets:

1. walks
2. walking
3. runs
4. running
5. goes

Pseudo-targets for ITC

GT: breakdown of the car on the road
Top-5 pseudo-targets:

1. young woman get out of the car near the road
2. a woman inspects her damaged car under a tree
3. a woman looking into a car after locking her keys inside
4. young woman with a broken car calling for help
5. breakdown of the car on the road

GT: the harbor a small village
Top-5 pseudo-targets:

1. the harbour with boats and houses
2. replica of the sailing ship in the harbour
3. ships in the harbor of the town
4. the harbor a small village
5. boats lined up alongside the geographical feature category in the village

Datasets and Implement Details

** Pre-training Datasets**

- Datasets Used:
  1. Conceptual Captions [4]
  2. SBU Captions [5]
  3. COCO [41]
  4. Visual Genome [42]
  5. Conceptual 12M dataset [43] (to demonstrate scalability with larger web data)

- Statistics:
  - Unique Images: 4.0M
  - Image-Text Pairs: 5.1M
  - Total Images after including Conceptual 12M dataset: 14.1M

Implementation Details

- Model Architecture:
  1. BERTbase: 123.7M parameters
  2. ViT-B/16: 85.8M parameters

Downstream task: image-text retrieval

- Finetune the pre-trained model using the ITC and ITM loss
- Two-step inference:
    1. Compute the feature similarity score Site for all image-text pairs (fast).
    2. For each query, select the top-k candidates and compute their image-text matching score s (slow)
    3. A small k can produce a high recall.

Method	# Pre-train Images	Flickr30K (1K test set)						MSCOCO (5K test set)					
		TR			IR			TR			IR		
		R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
UNITER	4M	87.3	98.0	99.2	75.6	94.1	96.8	65.7	88.6	93.8	52.9	79.9	88.0
VILLA	4M	87.9	97.5	98.8	76.3	94.2	96.8	-	-	-	-	-	-
OSCAR	4M	-	-	-	-	-	-	70.0	91.1	95.5	54.0	80.8	88.5
ALIGN	1.2B	95.3	99.8	100.0	84.9	97.4	98.6	77.0	93.5	96.9	59.9	83.3	89.8
ALBEF	4M	94.3	99.4	99.8	82.8	96.7	98.4	73.1	91.4	96.0	56.8	81.5	89.2
ALBEF	14M	**95.9**	**99.8**	**100.0**	**85.6**	**97.5**	**98.9**	**77.6**	**94.3**	**97.2**	**60.7**	**84.3**	**90.5**

Table 2: Fine-tuned image-text retrieval results on Flickr30K and COCO datasets.

Downstream task: zero-shot image-text retrieval

ALBEF outperforms CLIP and ALIGN which are trained on orders of magnitude larger datasets

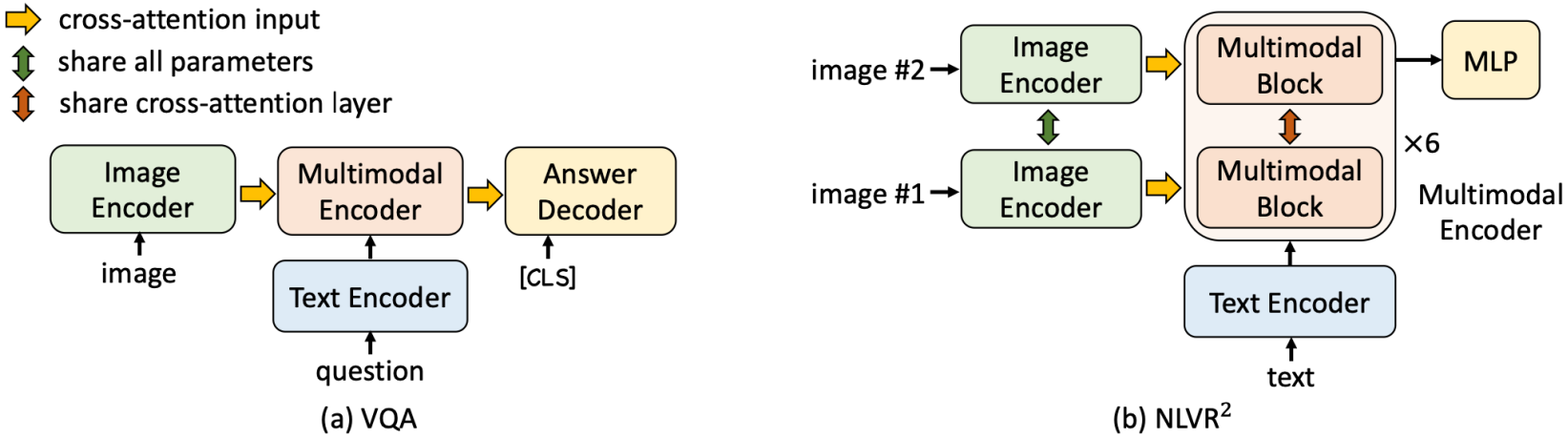
Method	# Pre-train Images	Flickr30K (1K test set)					
		TR			IR		
		R@1	R@5	R@10	R@1	R@5	R@10
UNITER [2]	4M	83.6	95.7	97.7	68.7	89.2	93.9
CLIP [6]	400M	88.0	98.7	99.4	68.7	90.6	95.2
ALIGN [7]	1.2B	88.6	98.7	99.7	75.7	93.8	96.8
ALBEF	4M	90.5	98.8	99.7	76.8	93.7	96.7
ALBEF	14M	**94.1**	**99.5**	**99.7**	**82.8**	**96.3**	**98.1**

Table 3: Zero-shot image-text retrieval results on Flickr30K.

Downstream task: Vision Language tasks

Method	VQA		NLVR^2		SNLI-VE	
	test-dev	test-std	dev	test-P	val	test
VisualBERT [13]	70.80	71.00	67.40	67.00	-	-
VL-BERT [10]	71.16	-	-	-	-	-
LXMERT [1]	72.42	72.54	74.90	74.50	-	-
12-in-1 [12]	73.15	-	-	78.87	-	76.95
UNITER [2]	72.70	72.91	77.18	77.85	78.59	78.28
VL-BART/T5 [54]	-	71.3	-	73.6	-	-
ViLT [21]	70.94	-	75.24	76.21	-	-
OSCAR [3]	73.16	73.44	78.07	78.36	-	-
VILLA [8]	73.59	73.67	78.39	79.30	79.47	79.03
ALBEF (4M)	74.54	74.70	80.24	80.50	80.14	80.30
ALBEF (14M)	**75.84**	**76.04**	**82.55**	**83.14**	**80.80**	**80.91**

Table 4: Comparison with state-of-the-art methods on downstream vision-language tasks.



Downstream task: Vision Grounding

Method	Val	TestA	TestB
ARN [57]	32.78	34.35	32.13
CCL [58]	34.29	36.91	33.56
$\text{ALBEF}_{\text{itc}}$	51.58	60.09	40.19
$\text{ALBEF}_{\text{itm}}$	**58.46**	**65.89**	**46.25**

Table 5: Weakly-supervised visual grounding on RefCOCO+ [56] dataset.

Figure 4: Grad-CAM visualization on the cross-attention maps in the 3rd layer of the multimodal encoder.

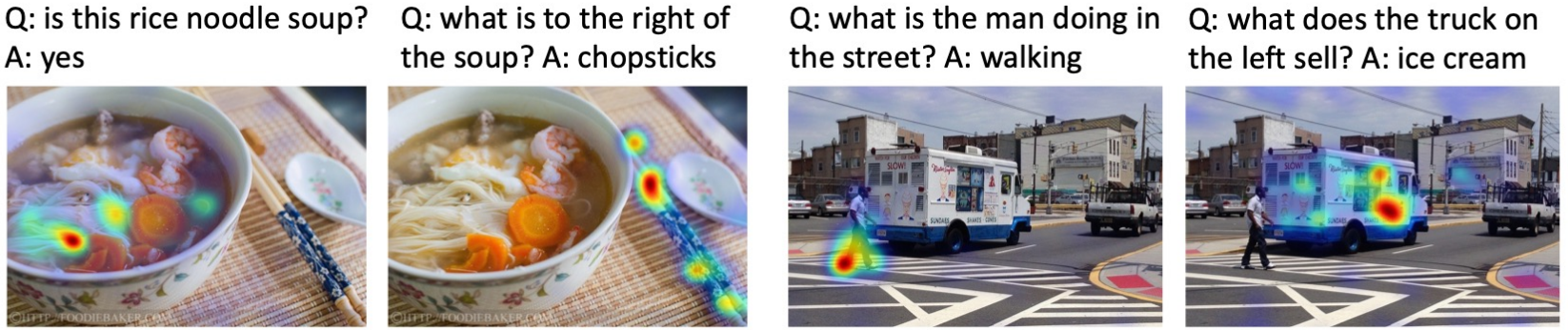


Figure 5: Grad-CAM visualizations on the cross-attention maps of the multimodal encoder for the VQA model.

Figure 6: Grad-CAM visualizations on the cross-attention maps corresponding to individual words.

QUIZ 1

In ALBEF, why does it make sense to align before merging?

Answer: In traditional methods, these two steps are often intertwined, which can lead to competition between alignment and fusion. To solve this problem, ALBEF proposes a new strategy, which is to align first before merging. In this way, models can be aligned in low-dimensional space and then fused, thus avoiding the competition between alignment and fusion.

QUIZ 2

Question: Key ideas of ALBEF (List at list 3Points to earn credits)