THE UNIVERSITY OF BRITISH COLUMBIA

Topics in AI (CPSC 532S):
Multimodal Learning with Vision, Language and Sound

Lecture 23: Large Scale Visio-Lingual Models (cont.)

Today is our **last lecture** …

… I hope you enjoyed the class!

(Please do fill out evaluation reports on **Canvas**)

Logistics

— **Assignment 3** & **4** grades (blank output)

— **Assignment 3** grade fixes (out of 100, not 135 — fixed)

— Be careful of looking at Average Grade on Canvas

— **Assignment 5** is due **today** (can hand in by Friday)

— **Research Paper Presentations** (all are in)

— **Reading Reviews** (some 3 & 4 outstanding)

Logistics

My todo's

— List of paper presentations

— Grades for **Paper Readings** and **Presentations**

— Grades for **Assignment 5**

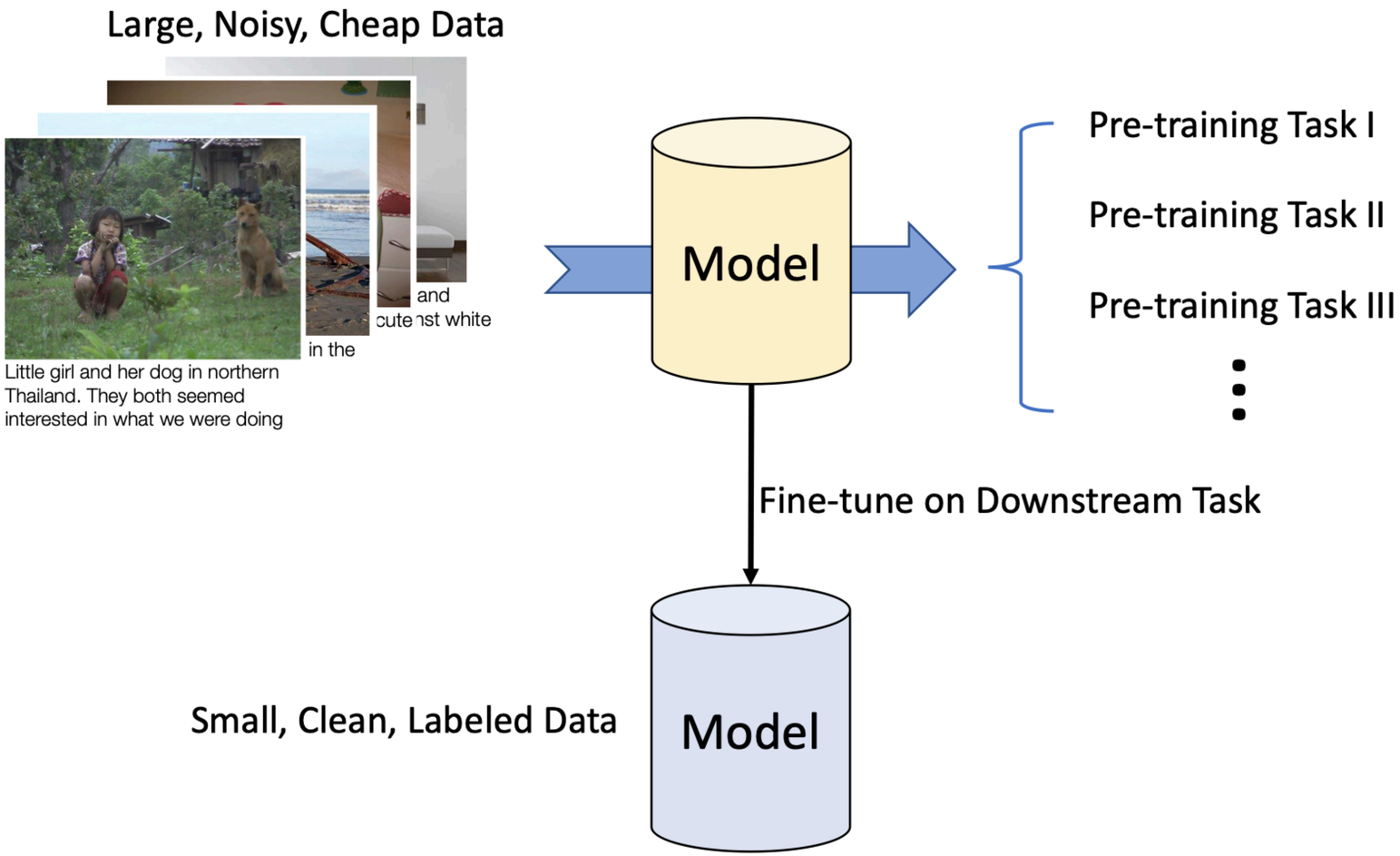
Your todo's

— Hand in **Assignment 5**

— Hand in **Paper Readings 3** & **4** (if you have not done this yet)

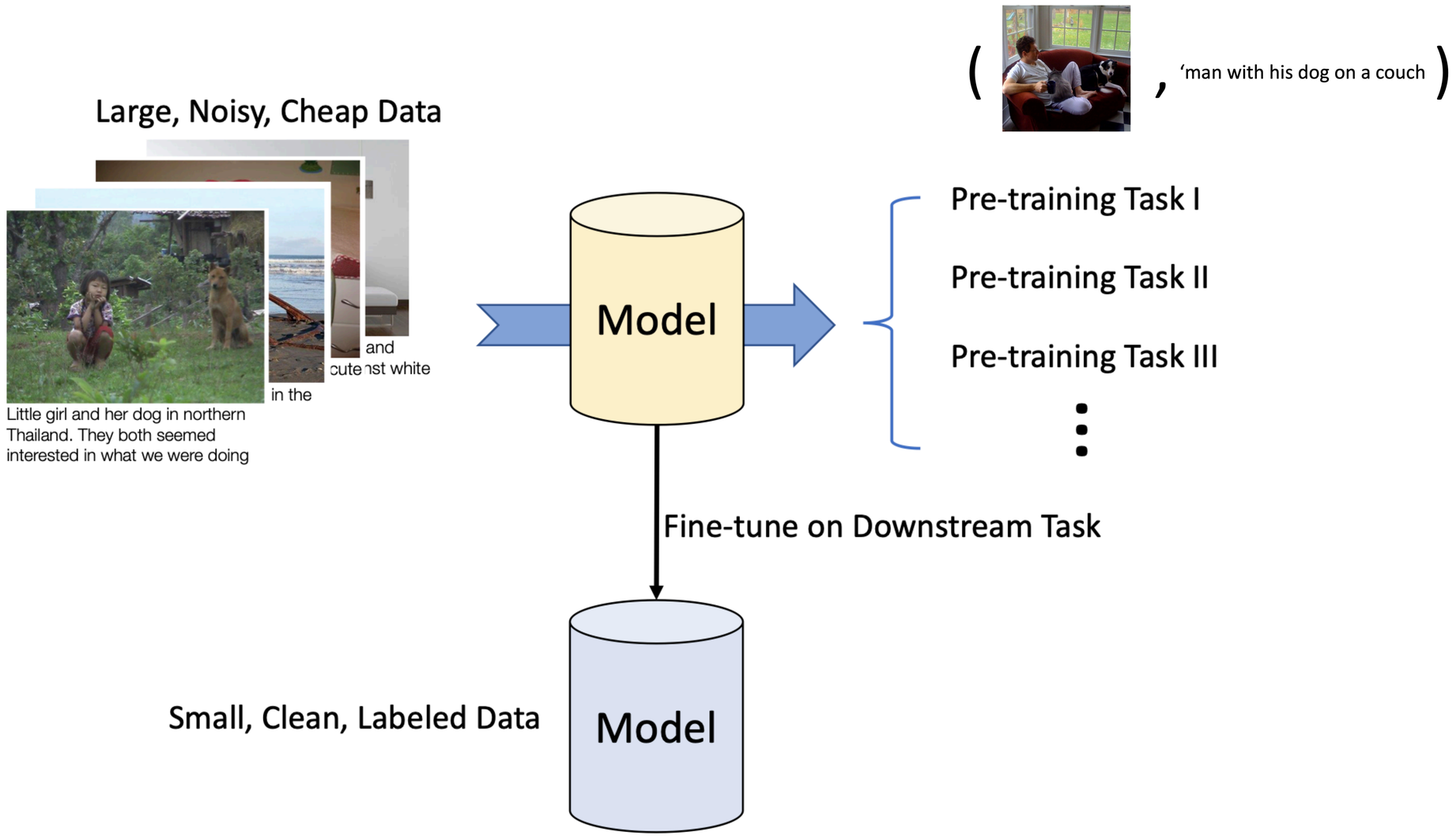
— Final Project Presentations on Tuesday next week 12-3pm

Pre-training and **Foundational Models**



Slide from **Zhe Gan**

Pre-training and **Foundational Models**



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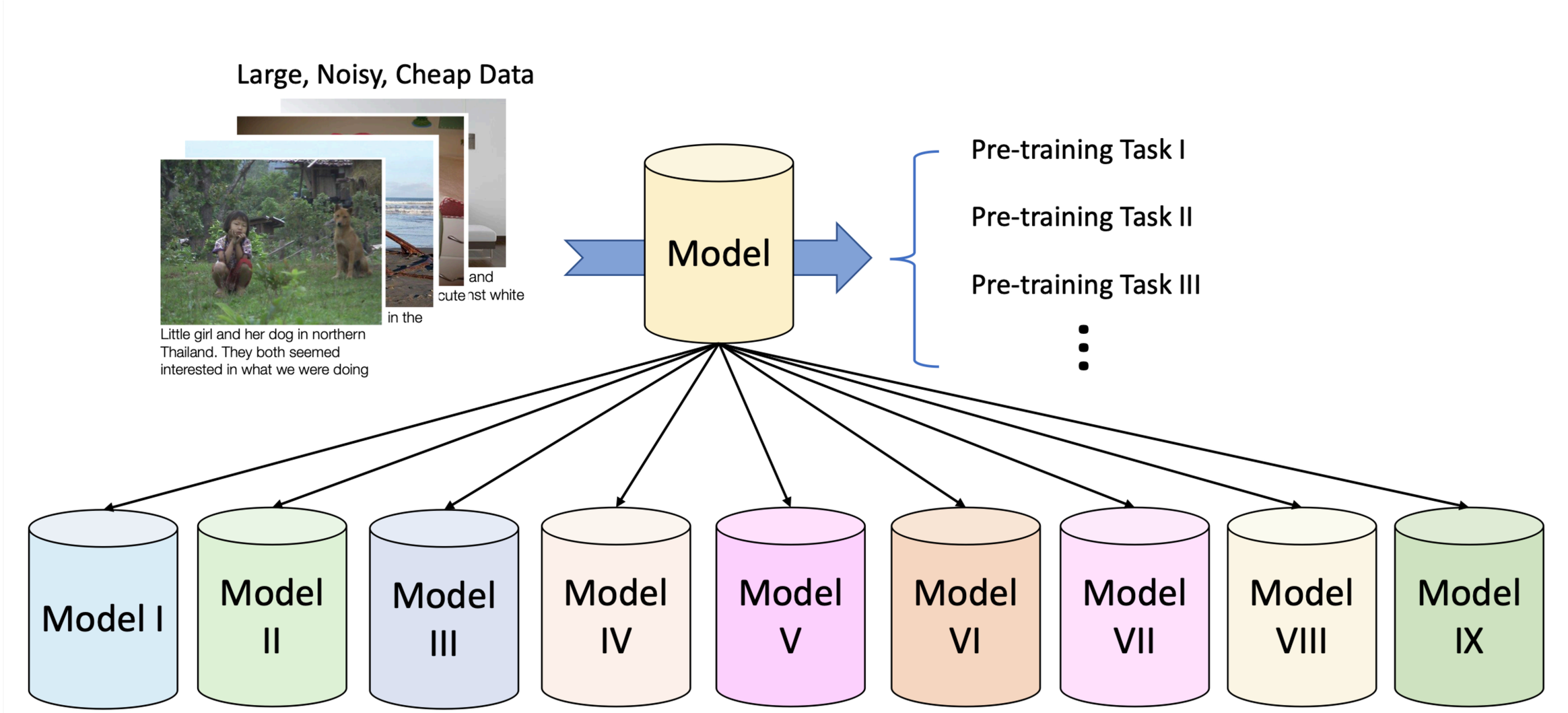
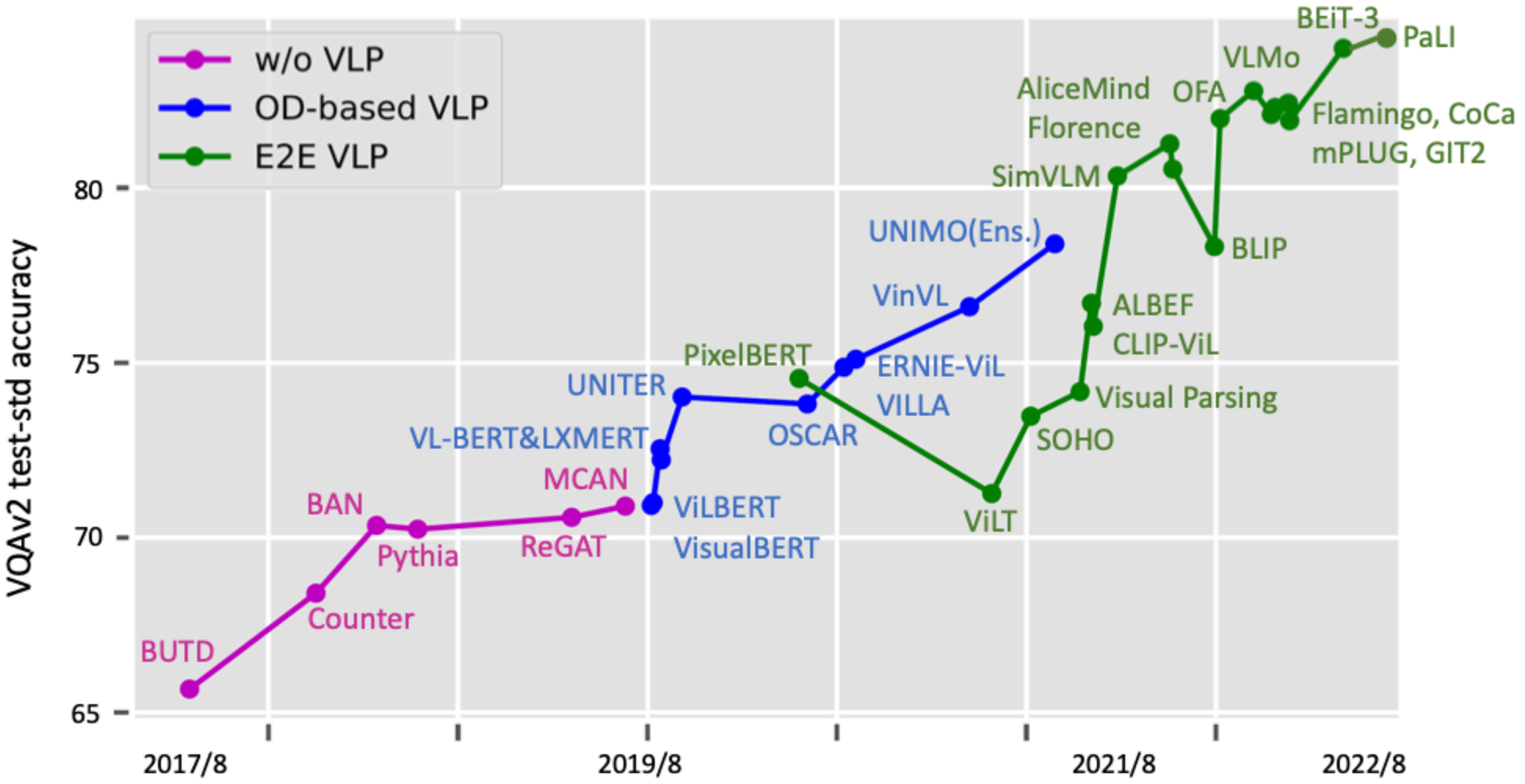
Pre-training and **Foundational Models**



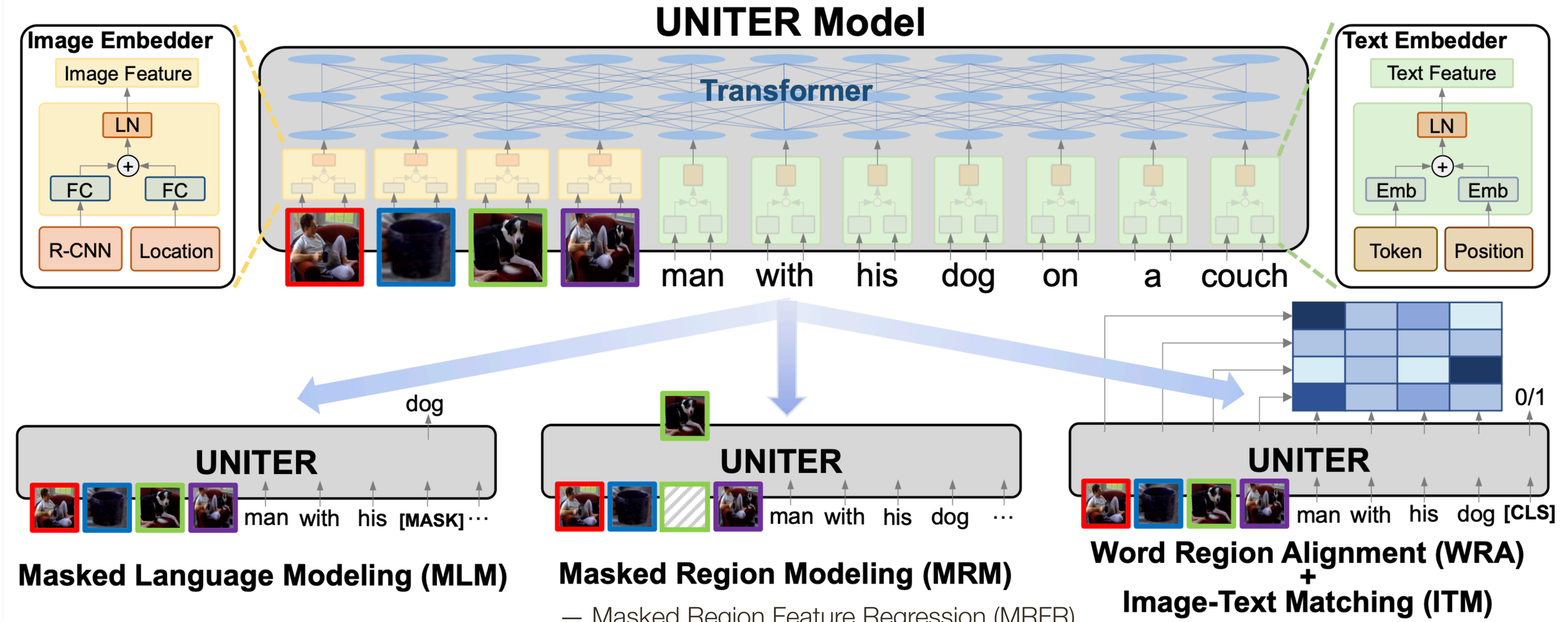
Slide from **Zhe Gan**

Recent History of **Visio-Lingual Models**



Slide from **Zhe Gan**

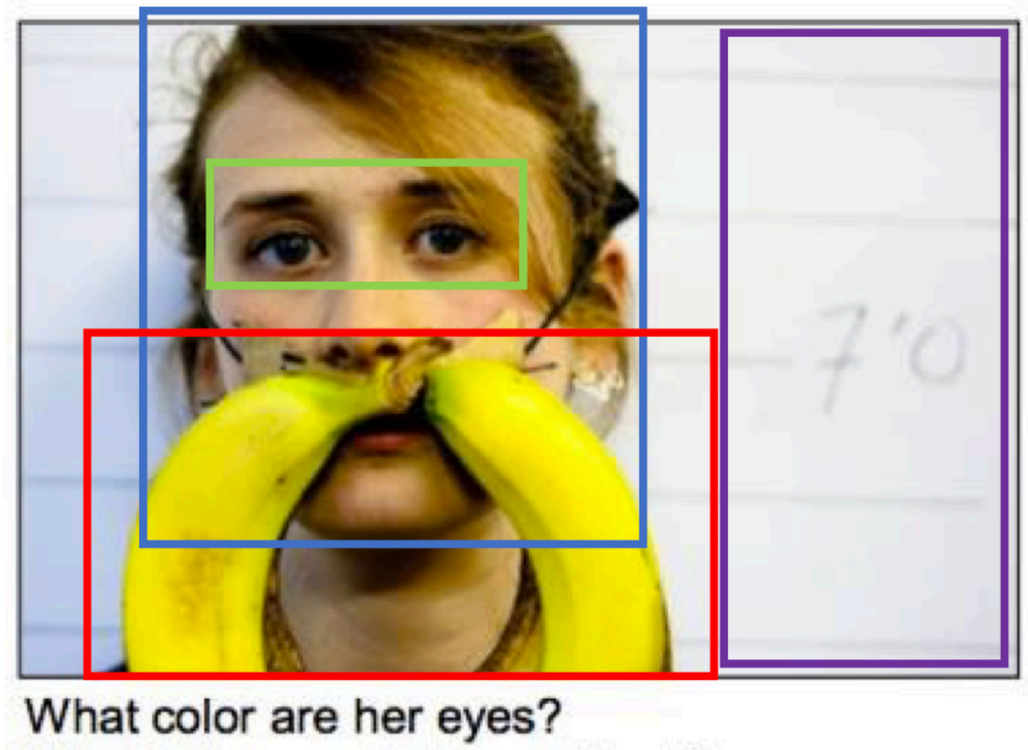
UNITER: UNiversal Image-TExt Representation Learning

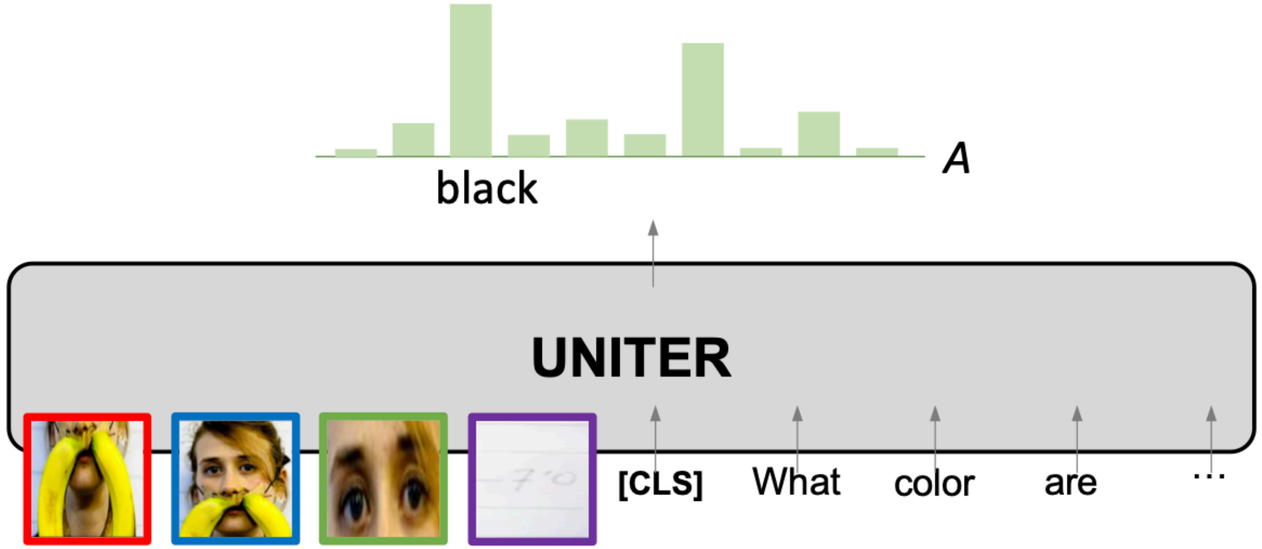


Slide from **Zhe Gan**

[Chen et al. ECCV 2020]

Downstream Task 1: **Visual Question Answering**





Slide from **Zhe Gan**

[Antol et al., ICCV 2015]

Downstream Task 2: **Visual Entailment**

+

- *Two woman are holding packages.*
- *The sisters are hugging goodbye while holding to go packages after just eating lunch.*
- *The men are fighting outside a deli.*

=

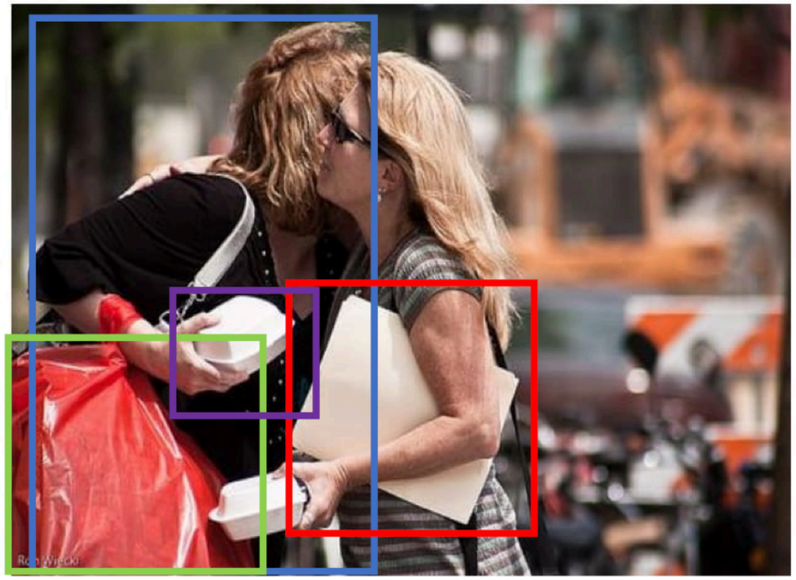
- *Entailment*
- *Neutral*
- *Contradiction*

Premise *Hypothesis* *Answer*

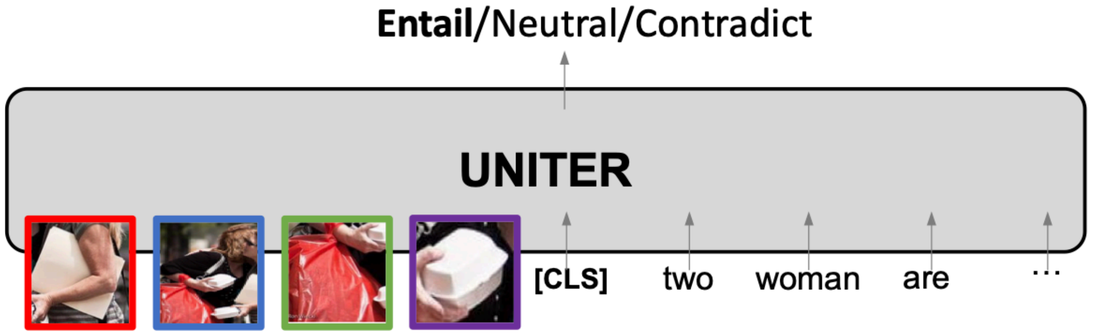
Slide from **Zhe Gan**

[Xie et al., 2019]

Downstream Task 2: **Visual Entailment**

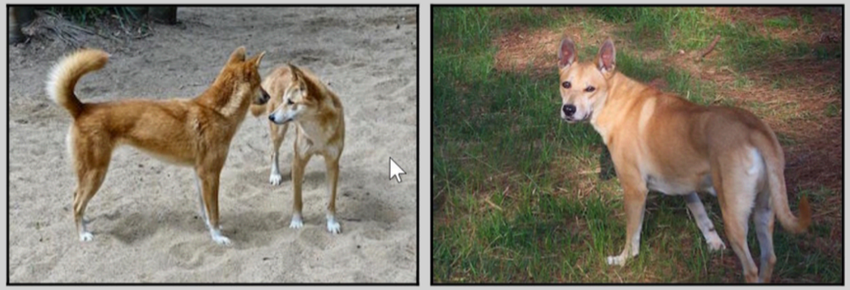


Two woman are holding packages.



Slide from **Zhe Gan**

Downstream Task 3: Natural Language for **Visual Reasoning**



The left image contains twice the number of dogs as the right image, and at least two dogs in total are standing.

true

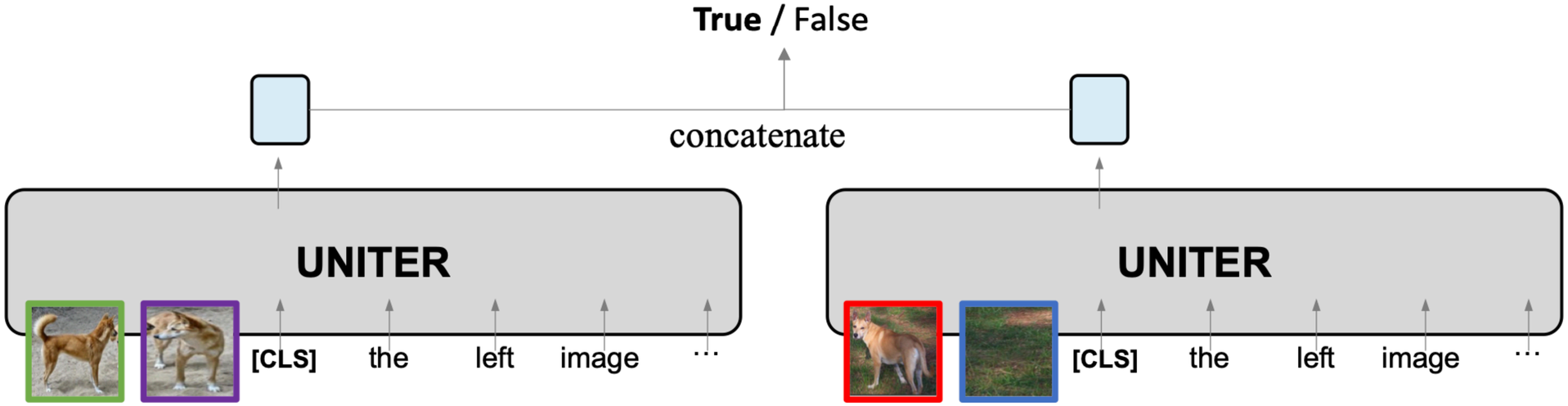
One image shows exactly two brown acorns in back-to-back caps on green foliage.

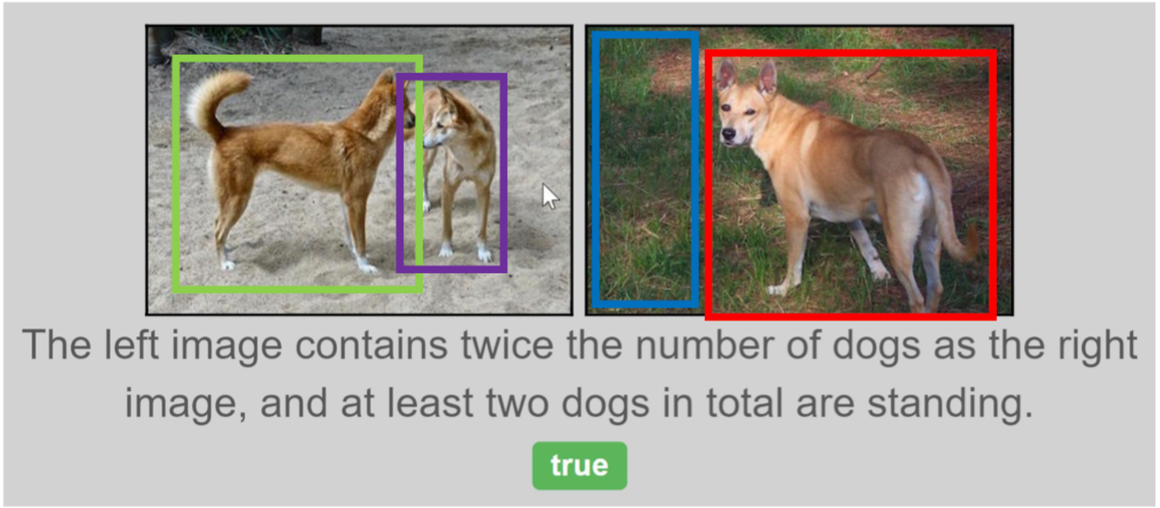
false

Slide from **Zhe Gan**

[Suhr et al., ACL 2019]

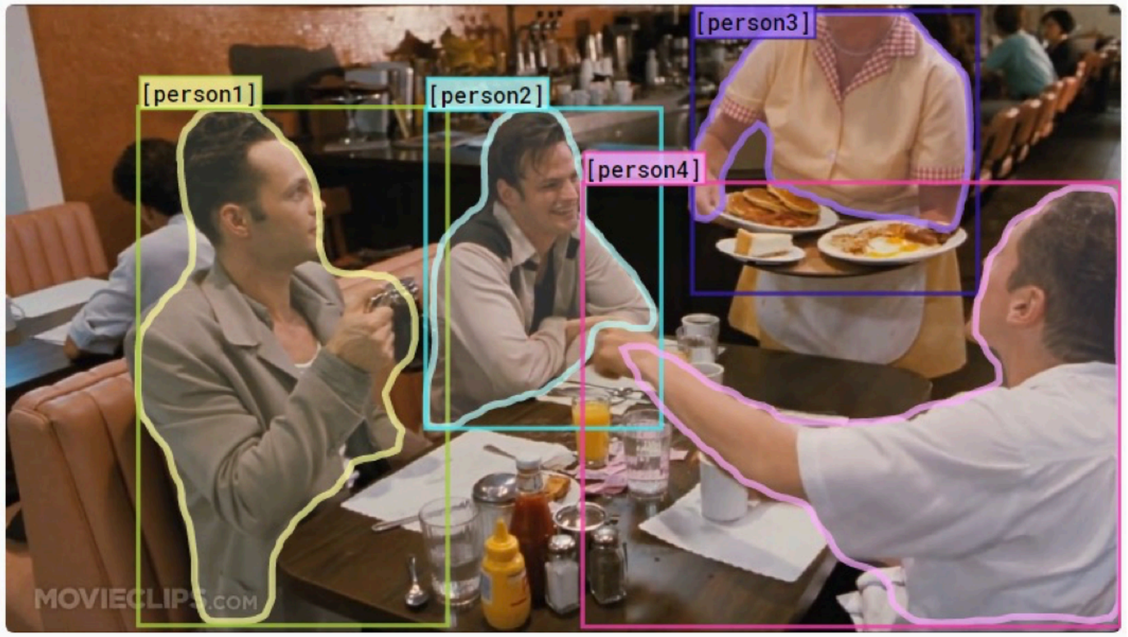
Downstream Task 3: Natural Language for **Visual Reasoning**





Slide from **Zhe Gan**

Downstream Task 4: **Visual Commonsense Reasoning**



Why is [person4] pointing at [person1]?

a) He is telling [person3] that [person1] ordered the pancakes.
b) He just told a joke.
c) He is feeling accusatory towards [person1].
d) He is giving [person1] directions.

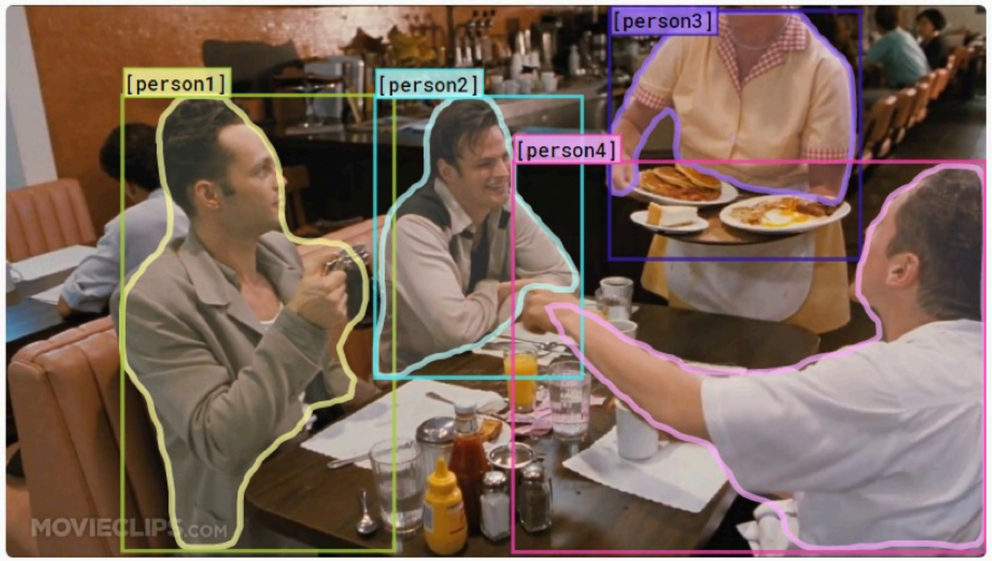
I choose (a) because:

a) [person1] has the pancakes in front of him.
b) [person4] is taking everyone's order and asked for clarification.
c) [person3] is looking at the pancakes and both she and [person2] are smiling slightly.
d) [person3] is delivering food to the table, and she might not know whose order is whose.

[Zellers et al., CVPR 2019]

Slide from **Zhe Gan**

Downstream Task 4: **Visual Commonsense Reasoning**



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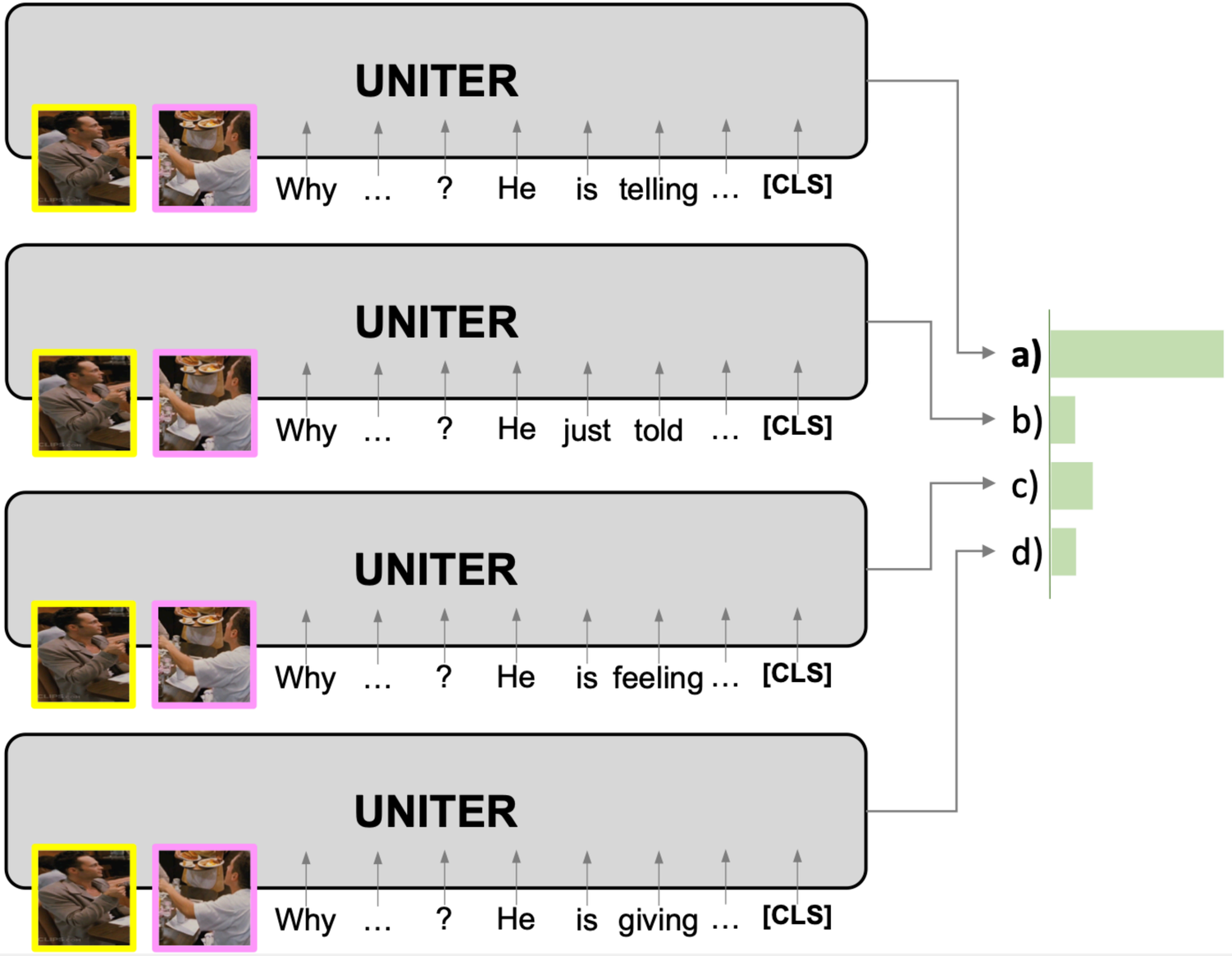


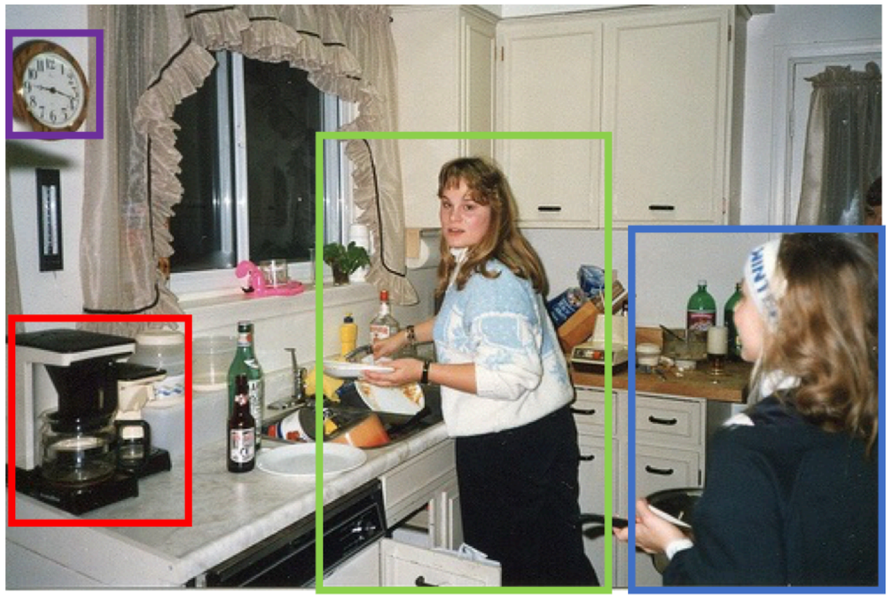
Slide from **Zhe Gan**

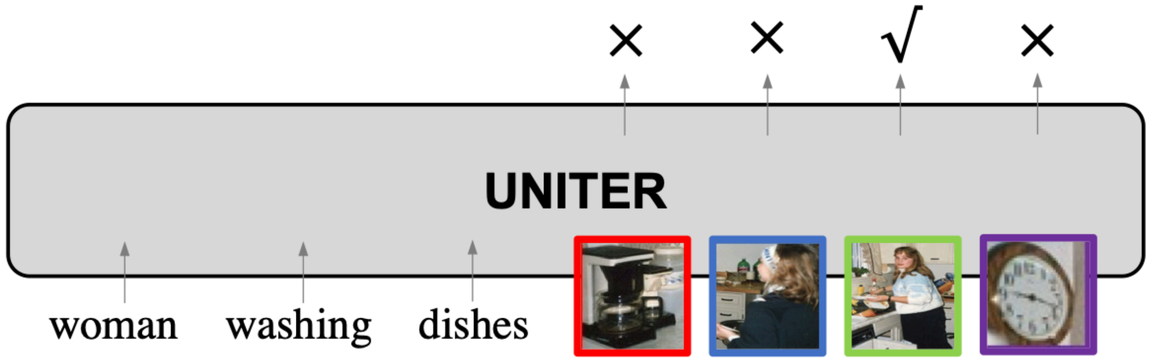
Downstream Task 5: **Referring Expression Comprehension (Grounding)**

woman washing dishes

Slide from **Zhe Gan**

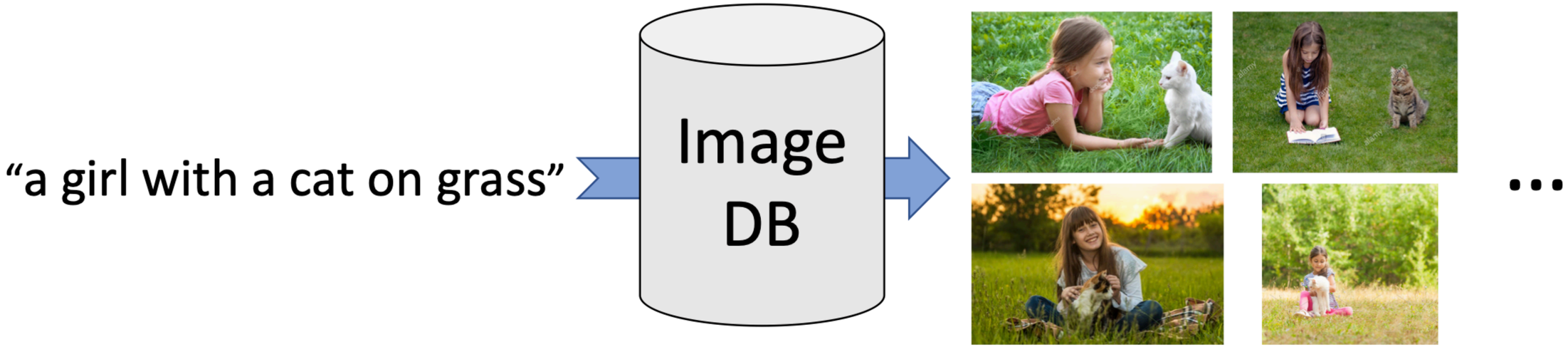
Downstream Task 5: **Referring Expression Comprehension (Grounding)**





Slide from **Zhe Gan**

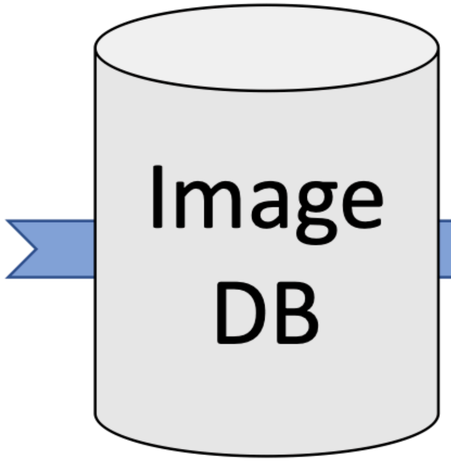
Downstream Task 6: **Image-Text Retrieval**



Slide from **Zhe Gan**

Downstream Task 6: **Image-Text Retrieval**

"a girl with a cat on grass"



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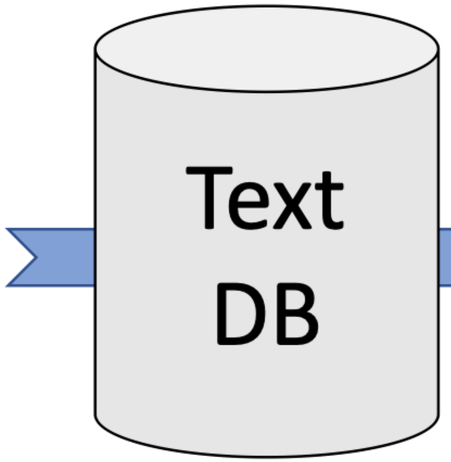

"four people with ski poles in their hands in the snow"
"four skiers hold on to their poles in a snowy forest"
"a group of young men riding skis"
"skiers pose for a picture while outside in the woods"
"a group of people cross country skiing in the woods"

⋮

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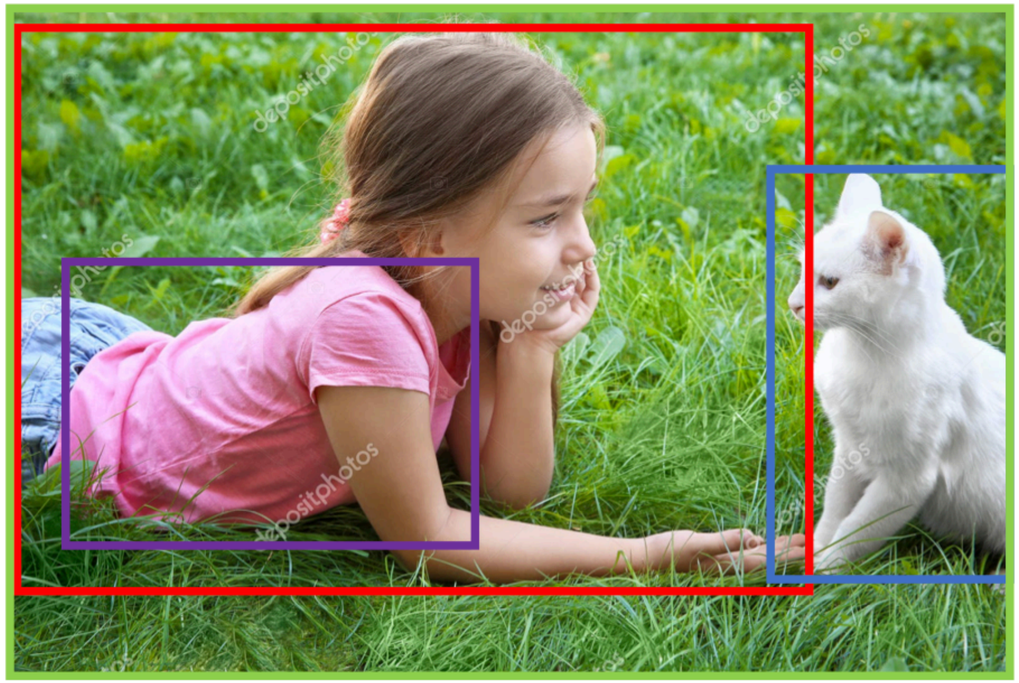
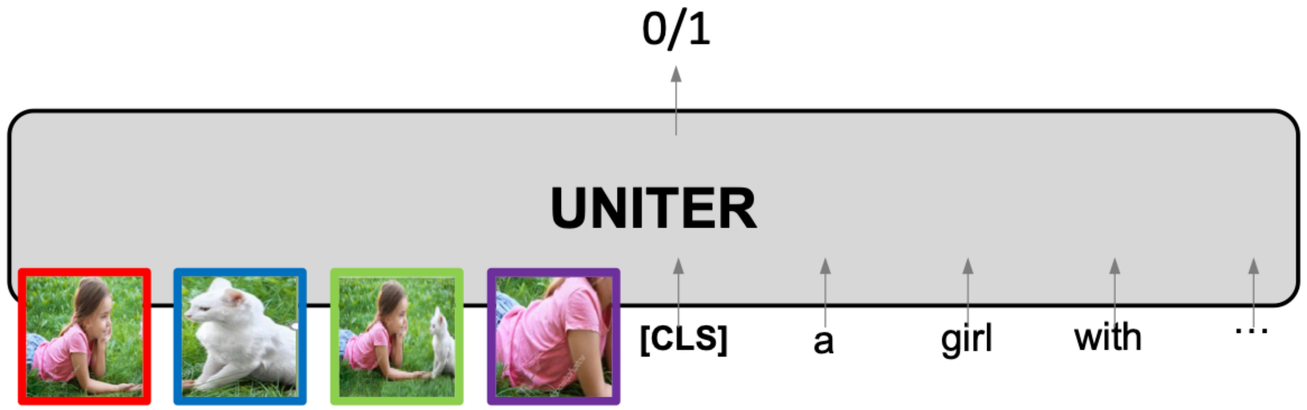
Downstream Task 6: **Image-Text Retrieval**





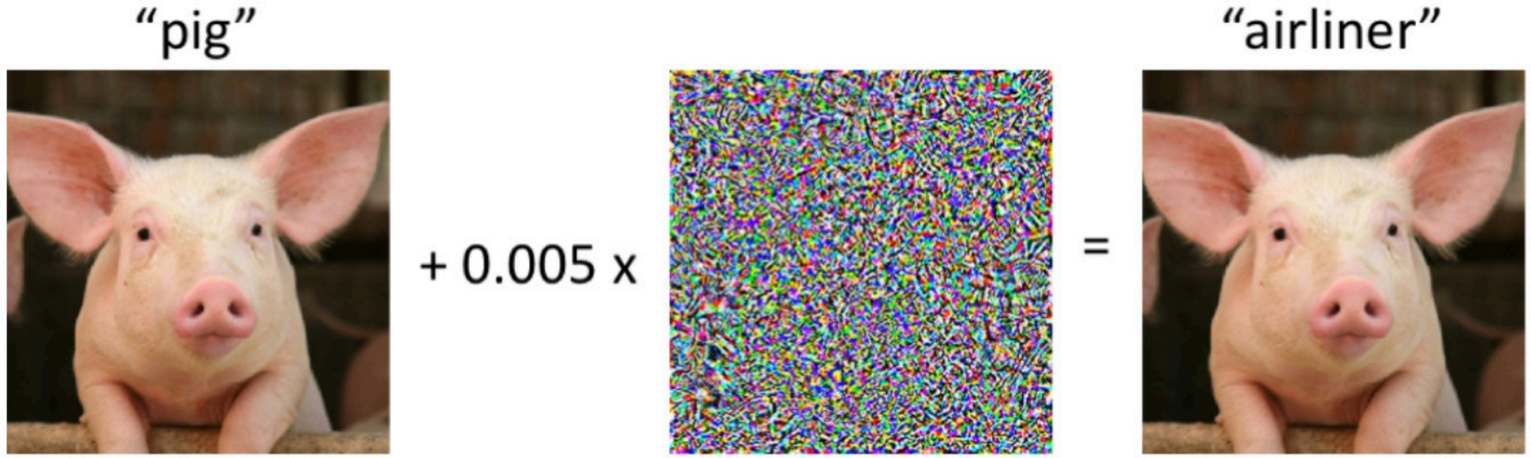
Slide from **Zhe Gan**

VILLA: Vision-and-Language Large-scale Adversarial Training

Preliminary: Adversarial Attacks

- Neural Networks are prone to label-preserving adversarial examples

Computer Vision:



Natural Language Processing:

Original: What is the oncorhynchus also called? **A:** chum salmon	**Original:** How long is the Rhine? **A:** 1,230 km
Changed: What's the oncorhynchus also called? **A:** keta	**Changed:** How long is the Rhine?? **A:** more than 1,050,000

(b) Example for (*WP is→WP's*) (c) Example for (*?→??*)

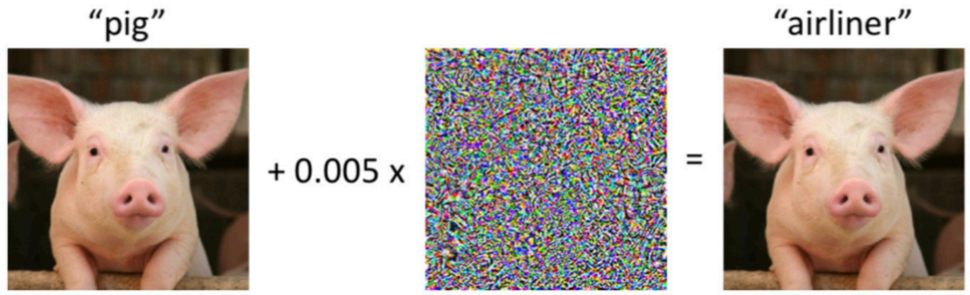
[1] Explaining and harnessing adversarial examples. *arXiv:1412.6572*
[2] Semantically equivalent adversarial rules for debugging nlp models. *ACL (2018)*

Slide from **Zhe Gan**

Preliminary: Adversarial Training

- A min-max game to harness adversarial examples

$$\min_{\theta} \mathop{\mathbb{E}}_{(x,y)\sim\widehat{\mathcal{D}}} \left[\max_{\delta \in S} \mathcal{L}(x+\delta, y; \theta) \right]$$



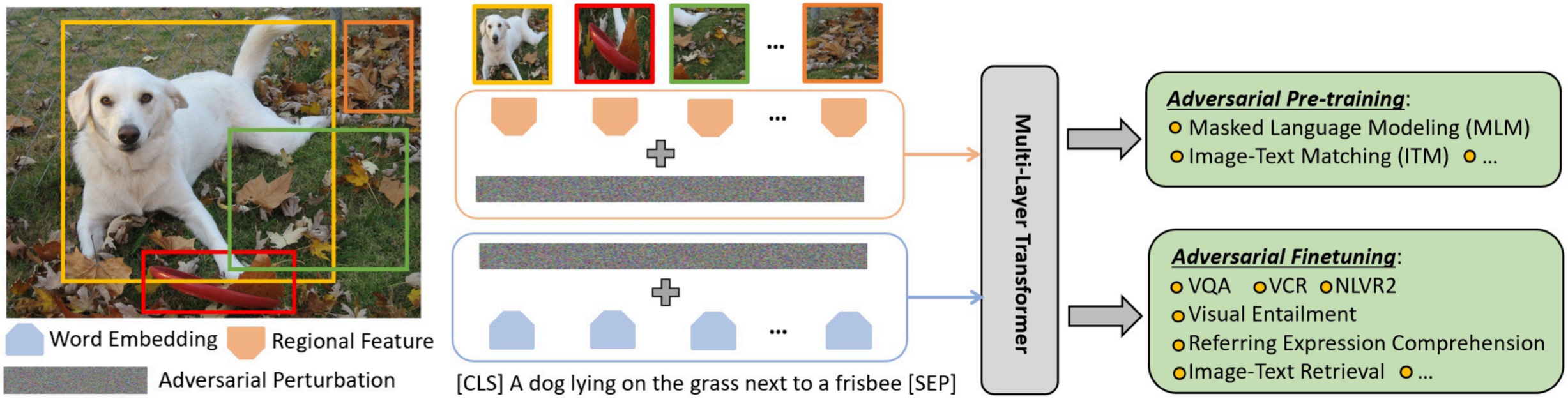
- Use adversarial examples as additional training samples
  - On one hand, we try to find perturbations that maximize the empirical risk
  - On the other hand, the model tries to make correct predictions on adversarial examples
- *What doesn't kill you makes you stronger!*

Explaining and harnessing adversarial examples. *arXiv:1412.6572*

Slide from **Zhe Gan**

VILLA: Vision-and-Language Large-scale Adversarial Training

- Ingredient #1: Adversarial pre-training + finetuning
- Ingredient #2: Perturbations in the embedding space
- Ingredient #3: Enhanced adversarial training algorithm



Slide from **Zhe Gan**

VILLA: Vision-and-Language Large-scale Adversarial Training

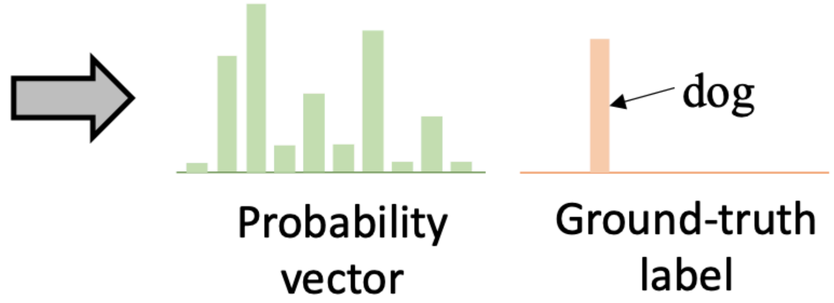
- **Training objective:**

$$\min_{\boldsymbol{\theta}} \mathbb{E}_{(\boldsymbol{x}_{img}, \boldsymbol{x}_{txt}, \boldsymbol{y}) \sim \mathcal{D}} \Big[\mathcal{L}_{std}(\boldsymbol{\theta}) + \mathcal{R}_{at}(\boldsymbol{\theta}) + \alpha \cdot \mathcal{R}_{kl}(\boldsymbol{\theta}) \Big]$$

- **Cross-entropy loss on clean data:**

$$\mathcal{L}_{std}(\boldsymbol{\theta}) = L(f_{\boldsymbol{\theta}}(\boldsymbol{x}_{img}, \boldsymbol{x}_{txt}), \boldsymbol{y})$$

, A [MASK] lying on the grass next to a frisbee



Slide from **Zhe Gan**

VILLA: Vision-and-Language Large-scale Adversarial Training

- **Training objective:**

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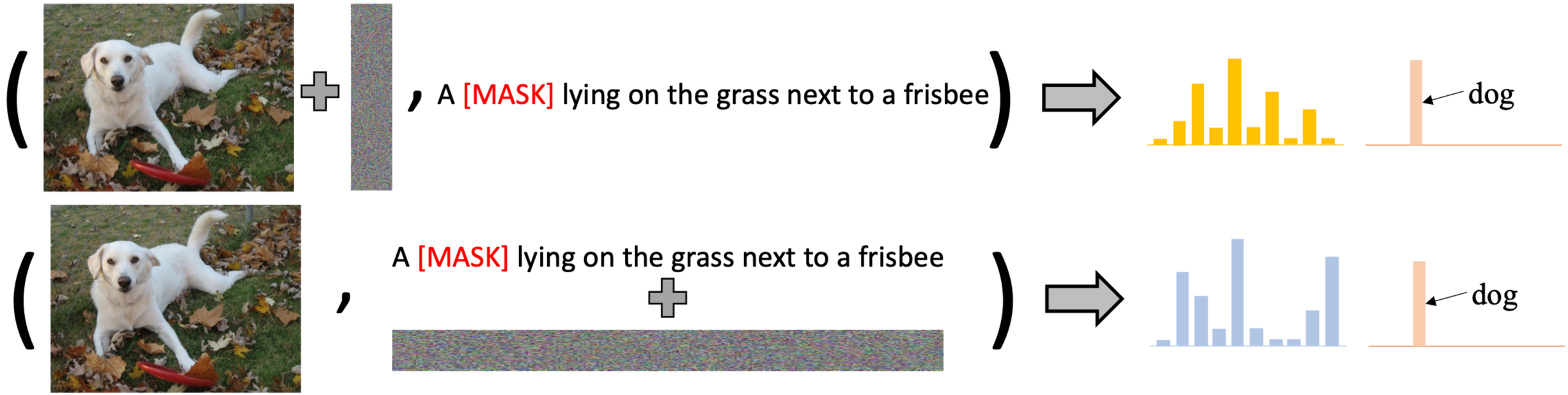
- **Cross-entropy loss on adversarial embeddings:**

$$\mathcal{R}_{at}(\boldsymbol{\theta}) = \max_{||\boldsymbol{\delta}_{img}|| \leq \epsilon} L(f_{\boldsymbol{\theta}}(\boldsymbol{x}_{img} + \boldsymbol{\delta}_{img}, \boldsymbol{x}_{txt}), \boldsymbol{y}) + \max_{||\boldsymbol{\delta}_{txt}|| \leq \epsilon} L(f_{\boldsymbol{\theta}}(\boldsymbol{x}_{img}, \boldsymbol{x}_{txt} + \boldsymbol{\delta}_{txt}), \boldsymbol{y})$$



Slide from **Zhe Gan**

VILLA: Vision-and-Language Large-scale Adversarial Training

- Training objective:

$$\min_{\boldsymbol{\theta}} \mathbb{E}_{(\boldsymbol{x}_{img}, \boldsymbol{x}_{txt}, \boldsymbol{y})\sim\mathcal{D}} \Big[\mathcal{L}_{std}(\boldsymbol{\theta}) + \mathcal{R}_{at}(\boldsymbol{\theta}) + \alpha \cdot \mathcal{R}_{kl}(\boldsymbol{\theta}) \Big]$$

- KL-divergence loss for fine-grained adversarial regularization

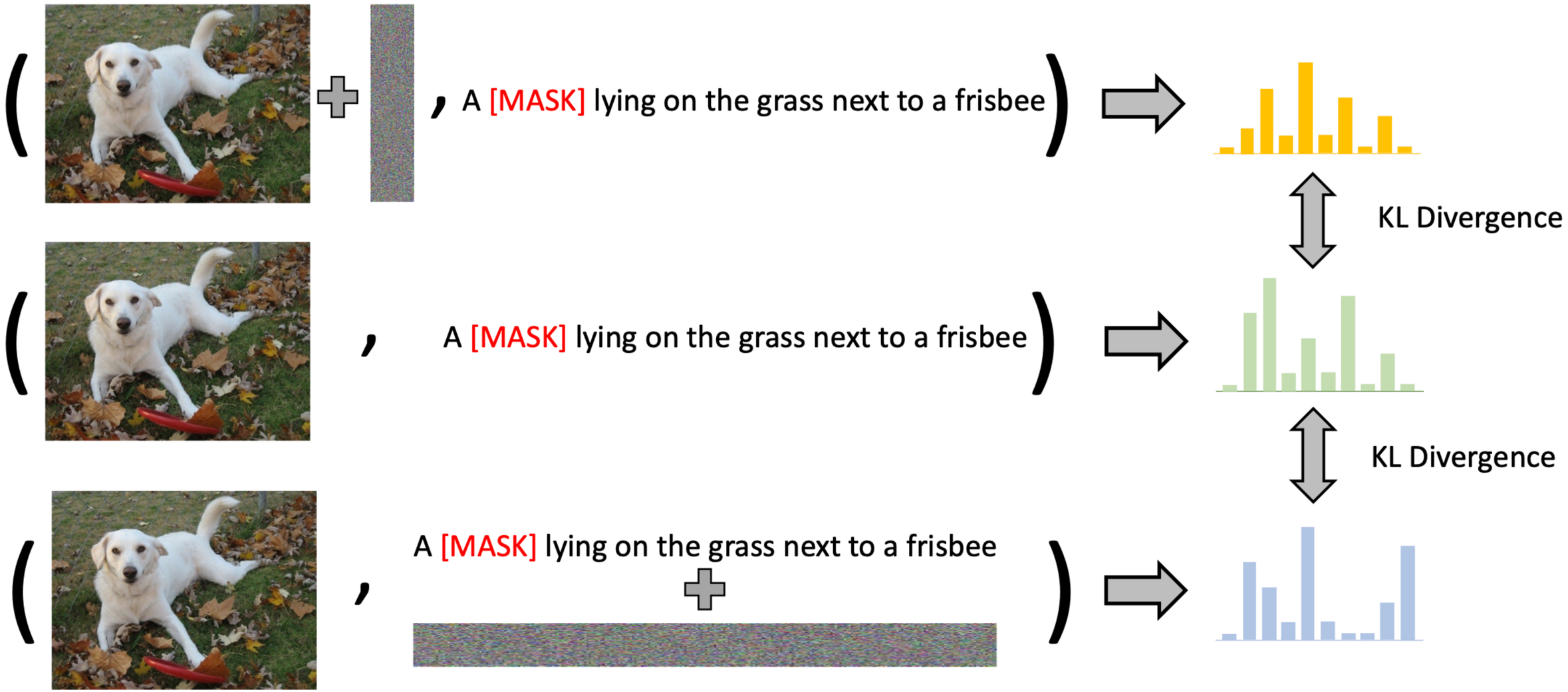
$$\begin{aligned} \mathcal{R}_{kl}(\boldsymbol{\theta}) = & \max_{||\boldsymbol{\delta}_{img}||\leq\epsilon} L_{kl}(f_{\boldsymbol{\theta}}(\boldsymbol{x}_{img} + \boldsymbol{\delta}_{img}, \boldsymbol{x}_{txt}), f_{\boldsymbol{\theta}}(\boldsymbol{x}_{img}, \boldsymbol{x}_{txt})) \\ & + \max_{||\boldsymbol{\delta}_{txt}||\leq\epsilon} L_{kl}(f_{\boldsymbol{\theta}}(\boldsymbol{x}_{img}, \boldsymbol{x}_{txt} + \boldsymbol{\delta}_{txt}), f_{\boldsymbol{\theta}}(\boldsymbol{x}_{img}, \boldsymbol{x}_{txt})) \,, \end{aligned}$$

where $L_{kl}(p, q) = \mathrm{KL}(p||q) + \mathrm{KL}(q||p)$.

- Not only label-preserving, but the confidence level of the prediction between clean data and adversarial examples should also be close

Slide from **Zhe Gan**

VILLA: Vision-and-Language Large-scale Adversarial Training



Slide from **Zhe Gan**

VILLA: Vision-and-Language Large-scale Adversarial Training

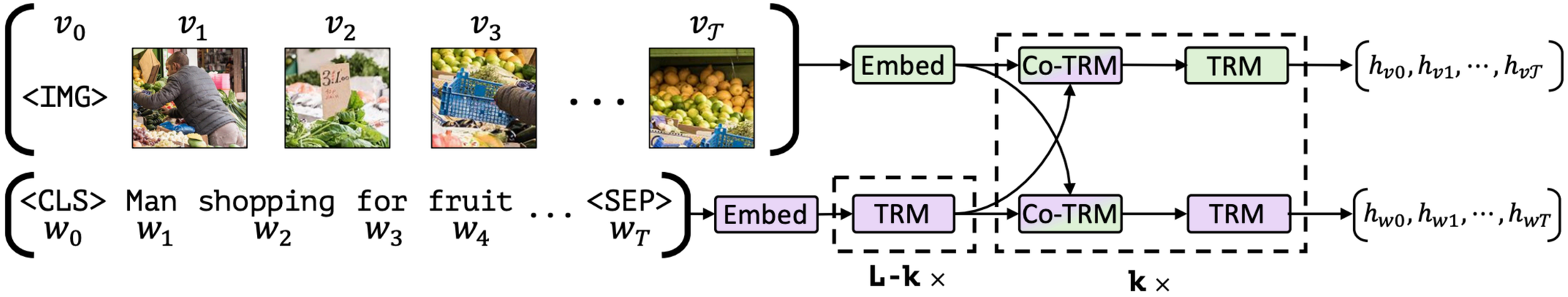
- **Established new state of the art on all the tasks considered**
- **Gain: +0.85 on VQA, +2.9 on VCR, +1.49 on NLVR2, +0.64 on SNLI-VE**

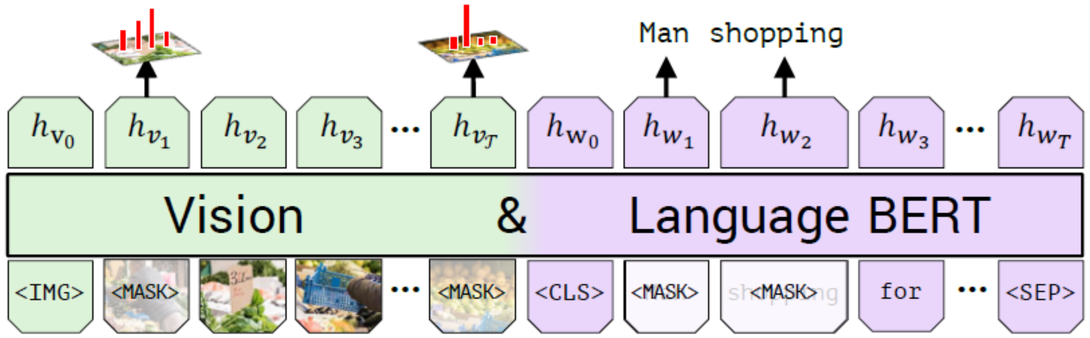
Method	VQA		VCR			NLVR^2		SNLI-VE	
	test-dev	test-std	Q→A	QA→R	Q→AR	dev	test-P	val	test
ViLBERT	70.55	70.92	72.42 (73.3)	74.47 (74.6)	54.04 (54.8)	-	-	-	-
VisualBERT	70.80	71.00	70.8 (71.6)	73.2 (73.2)	52.2 (52.4)	67.4	67.0	-	-
LXMERT	72.42	72.54	-	-	-	74.90	74.50	-	-
Unicoder-VL	-	-	72.6 (73.4)	74.5 (74.4)	54.4 (54.9)	-	-	-	-
12-in-1	73.15	-	-	-	-	-	78.87	-	76.95
VL-BERT$_{\text{BASE}}$	71.16	-	73.8 (-)	74.4 (-)	55.2 (-)	-	-	-	-
Oscar$_{\text{BASE}}$	73.16	73.44	-	-	-	78.07	78.36	-	-
UNITER$_{\text{BASE}}$	72.70	72.91	74.56 (75.0)	77.03 (77.2)	57.76 (58.2)	77.18	77.85	78.59	78.28
VILLA$_{\text{BASE}}$	**73.59**	**73.67**	**75.54 (76.4)**	**78.78 (79.1)**	**59.75 (60.6)**	**78.39**	**79.30**	**79.47**	**79.03**
VL-BERT$_{\text{LARGE}}$	71.79	72.22	75.5 (75.8)	77.9 (78.4)	58.9 (59.7)	-	-	-	-
Oscar$_{\text{LARGE}}$	73.61	73.82	-	-	-	79.12	80.37	-	-
UNITER$_{\text{LARGE}}$	73.82	74.02	77.22 (77.3)	80.49 (80.8)	62.59 (62.8)	79.12	79.98	79.39	79.38
VILLA$_{\text{LARGE}}$	**74.69**	**74.87**	**78.45 (78.9)**	**82.57 (82.8)**	**65.18 (65.7)**	**79.76**	**81.47**	**80.18**	**80.02**

(a) Results on VQA, VCR, NLVR^2, and SNLI-VE.

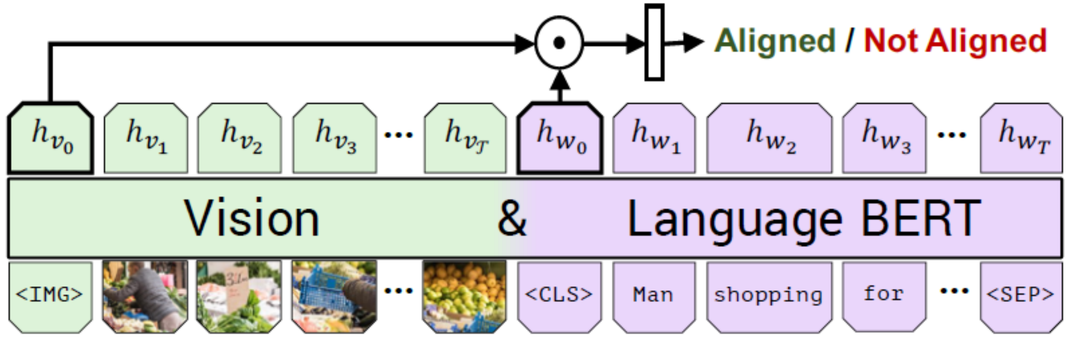
Slide from **Zhe Gan**

Visual BERT (VilBERT)





(a) Masked multi-modal learning



(b) Multi-modal alignment prediction

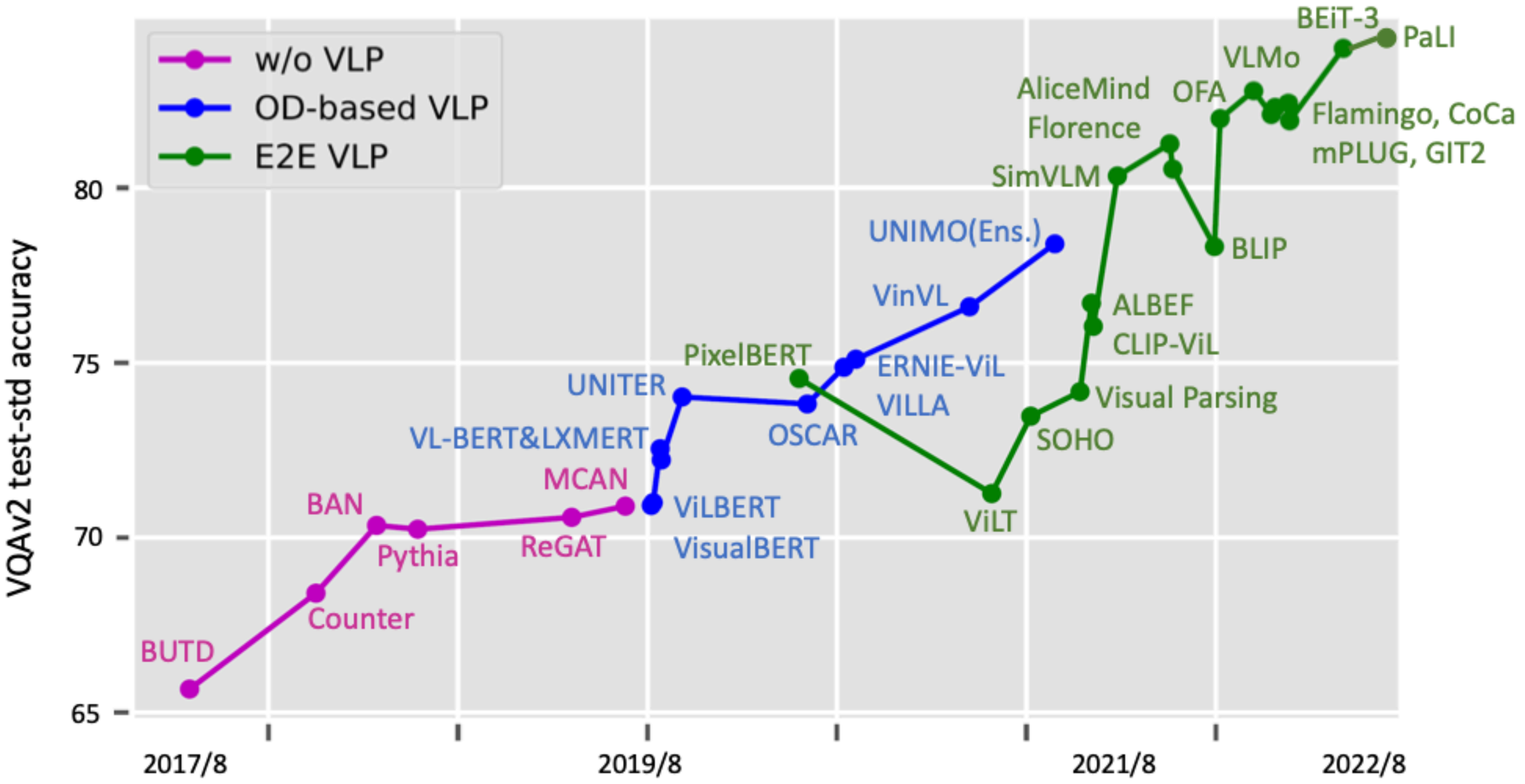
[Lu et al., 2019]

12-in-1: Multi-task Vision and Language Representation

			Vocab-based VQA (G1)			Image Retrieval (G2)		Referring Expression (G3)					Verification (G4)			
			VQAv2	GQA	VG QA	COCO	Flickr30k	COCO	COCO+	COCOg	V7W	GW	$NLVR^2$	SNLI-VE	# params (# models)	All Tasks Average
		Clean	test-dev	test-dev	val	test(R1)	test(R1)	test	test	test	test	test	testP	test		
1	Single-Task (ST)		71.82	58.19	34.38	65.28	61.14	78.63	71.11	72.24	80.51	62.81	74.25	76.72	3B (12)	67.25
2	Single-Task (ST)	✓	71.24	59.09	34.10	64.80	61.46	78.17	69.47	72.21	80.51	62.53	74.25	76.53	3B (12)	67.03
3	Group-Tasks (GT)	✓	72.03	59.60	36.18	65.06	66.00	80.23	72.79	75.30	81.54	64.78	74.62	76.52	1B (4)	68.72
4	All-Tasks (AT)	✓	72.57	60.12	36.36	63.70	63.52	80.58	73.25	75.96	82.75	65.04	78.44	76.78	**270M (1)**	69.08
5	$\text{All-Tasks}_{\text{w/o G4}}$	✓	72.68	62.09	36.74	64.88	64.62	80.76	73.60	75.80	83.03	65.41	-	-	266M (1)	-
6	GT $\xrightarrow{\text{finetune}}$ ST	✓	72.61	59.96	35.81	66.26	66.98	79.94	72.12	75.18	81.57	64.56	74.47	76.34	3B (12)	68.81
7	AT $\xrightarrow{\text{finetune}}$ ST	✓	72.92	60.48	36.56	65.46	65.14	80.86	73.45	76.00	83.01	65.15	**78.87**	76.73	3B (12)	69.55
8	AT $\xrightarrow{\text{finetune}}$ ST		**73.15**	**60.65**	**36.64**	**68.00**	**67.90**	**81.20**	**74.22**	**76.35**	**83.35**	**65.69**	**78.87**	**76.95**	3B (12)	**70.24**

[Lu et al., 2020]

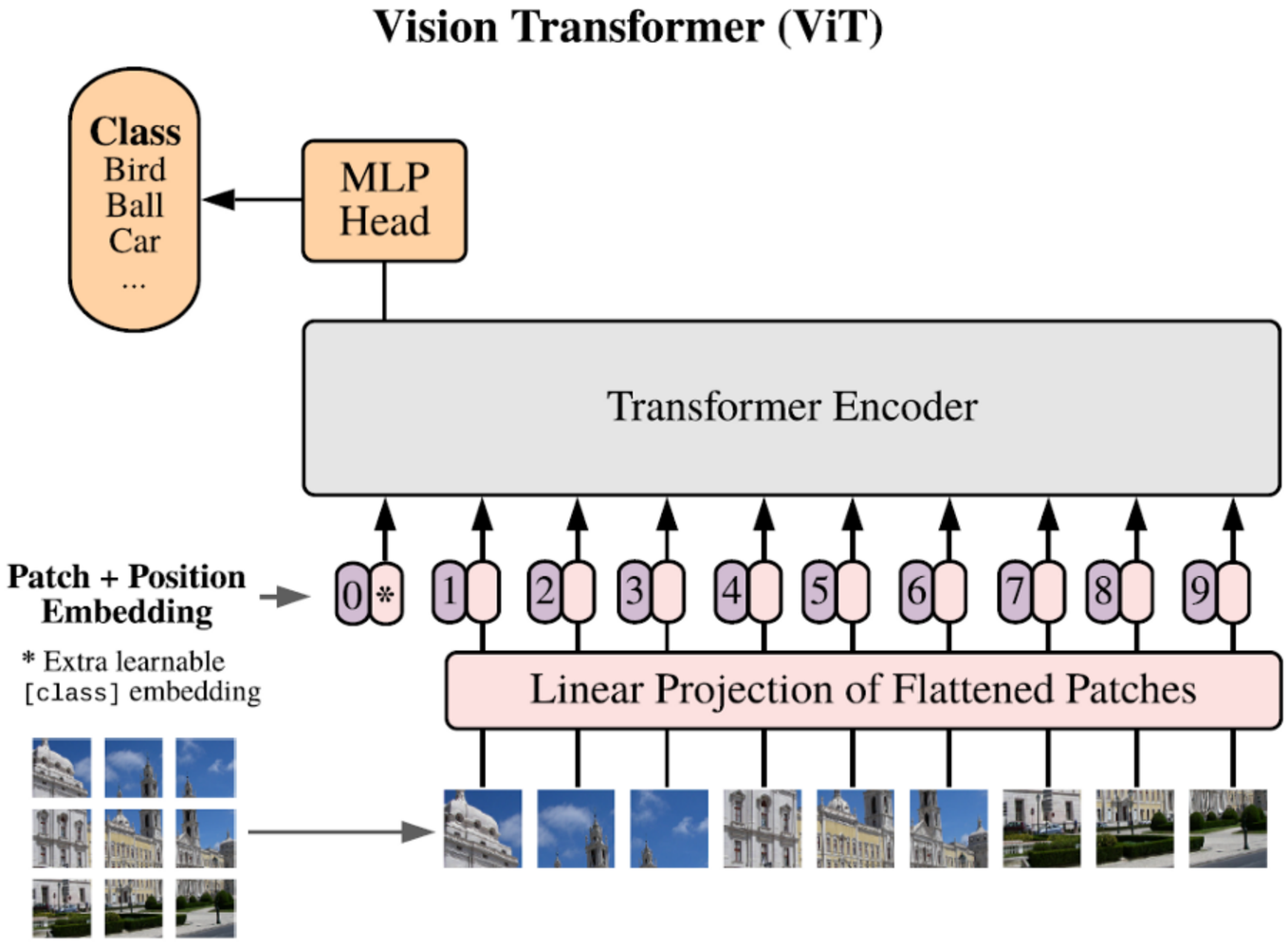
Recent History of **Visio-Lingual Models**

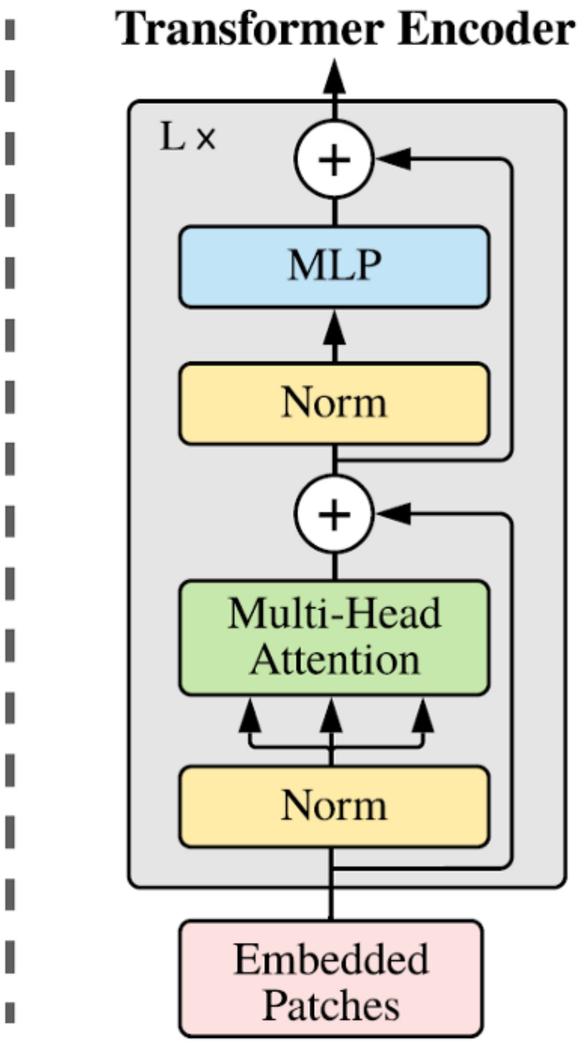


Slide from **Zhe Gan**

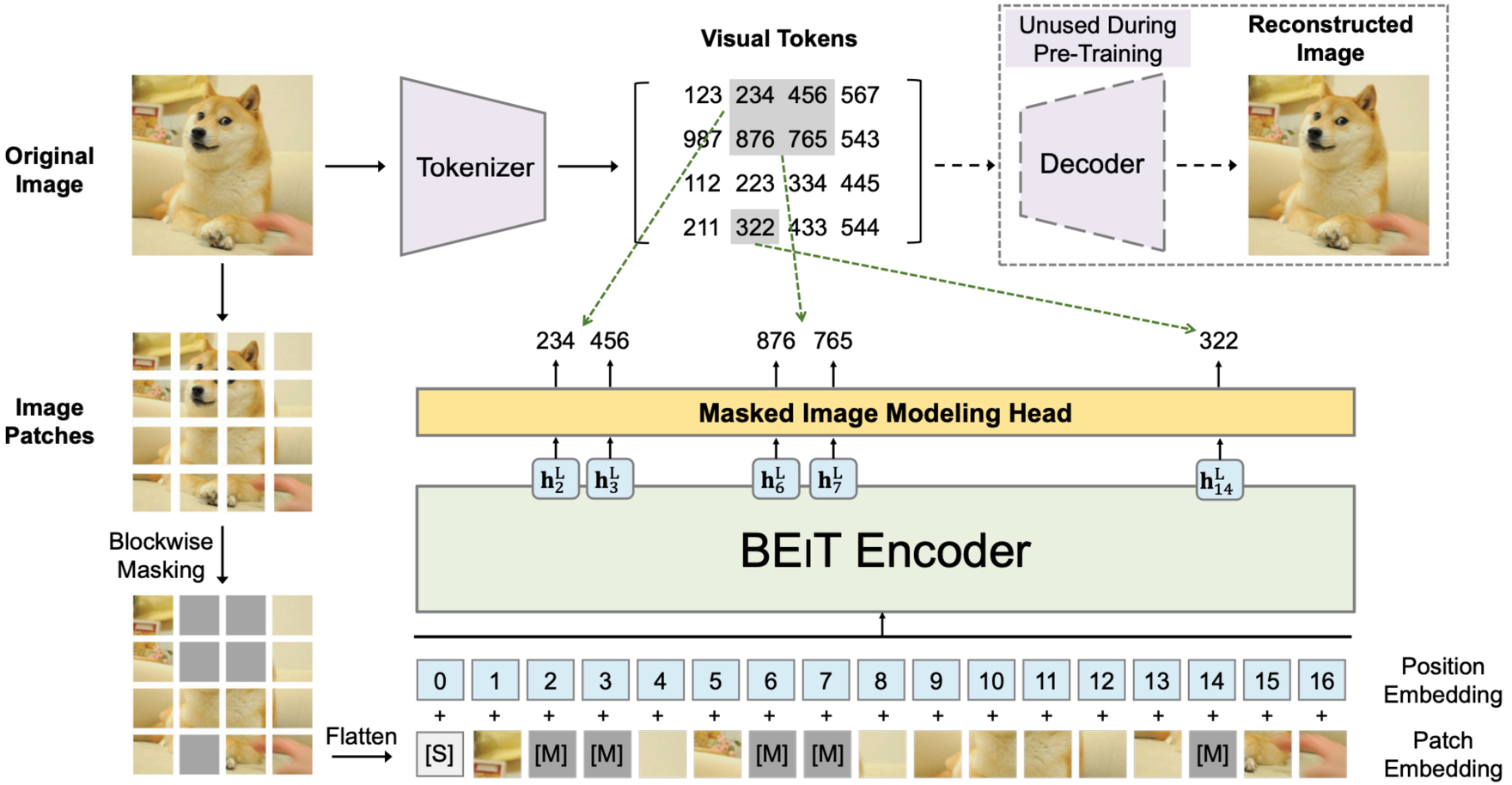
Vision Transformer

[Dosovitskiy et al., 2020]



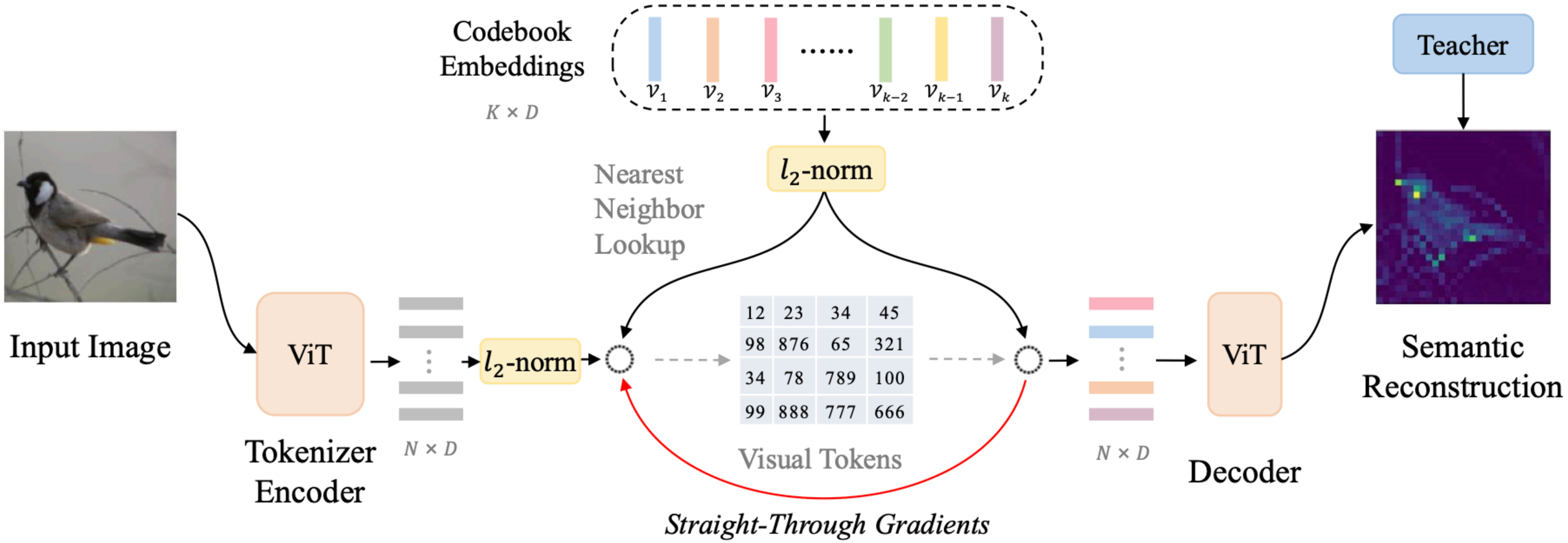


BEiT: BERT Pre-Training of Image Transformers



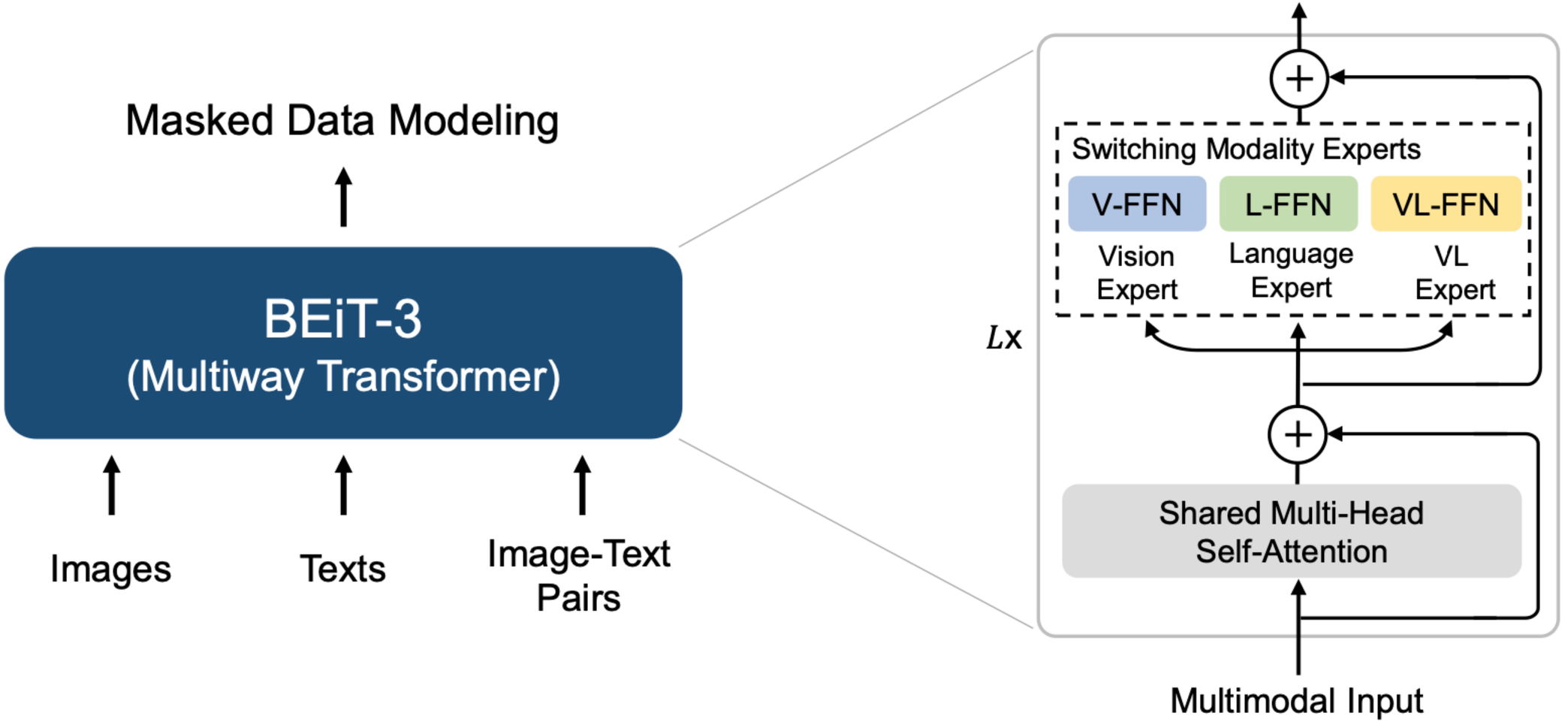
[Bao et al., 2022]

BEiT-v2



[Peng et al., 2022]

BEiT-v3: Image as a Foreign Language



[Wang et al., 2022]

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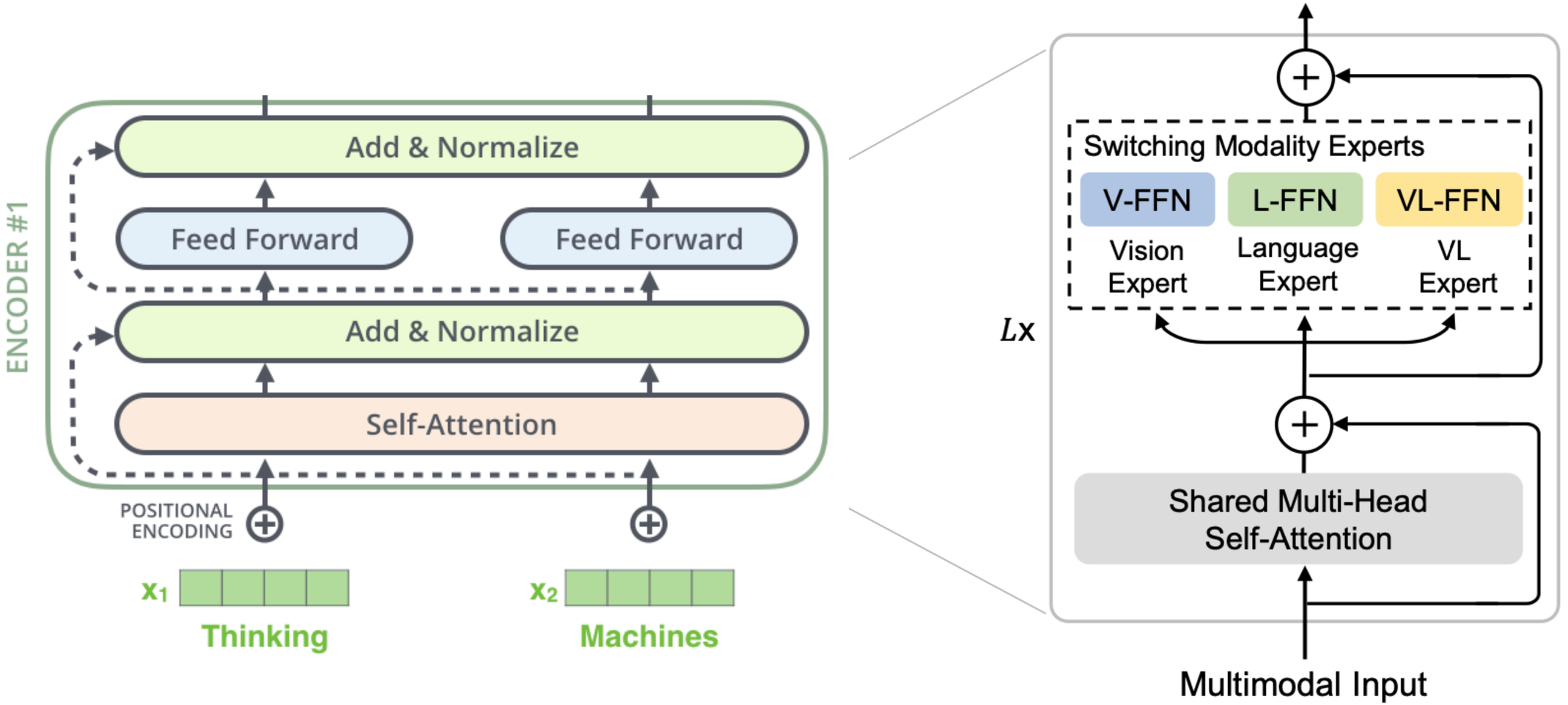

[Wang et al., 2022]

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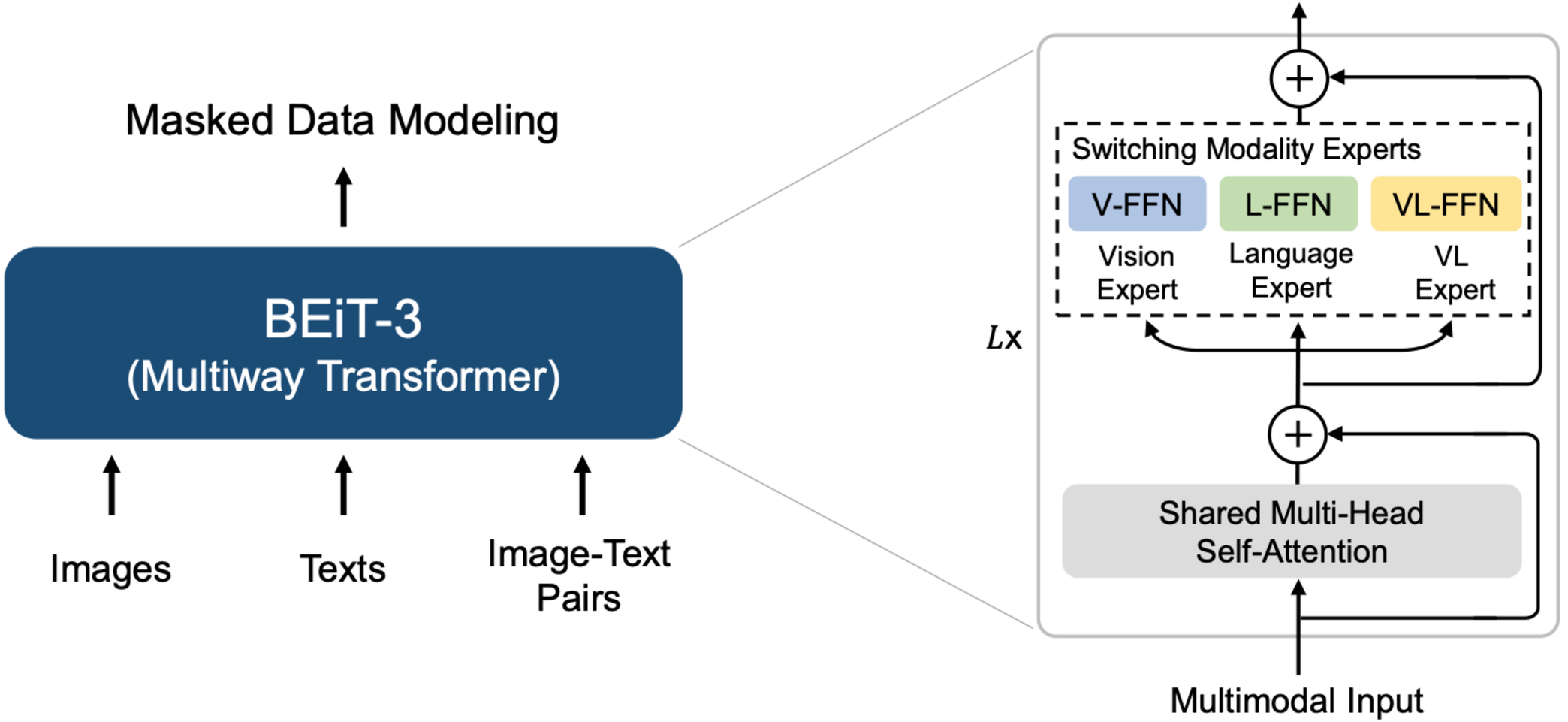

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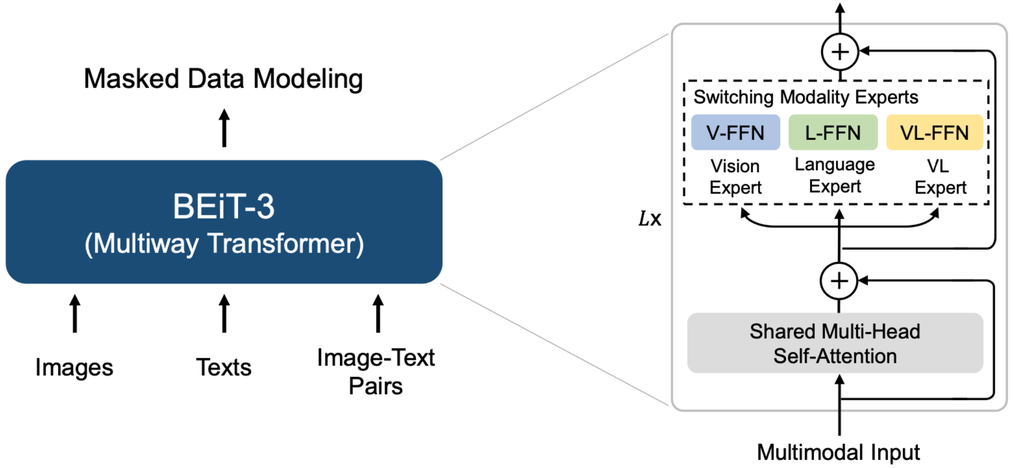

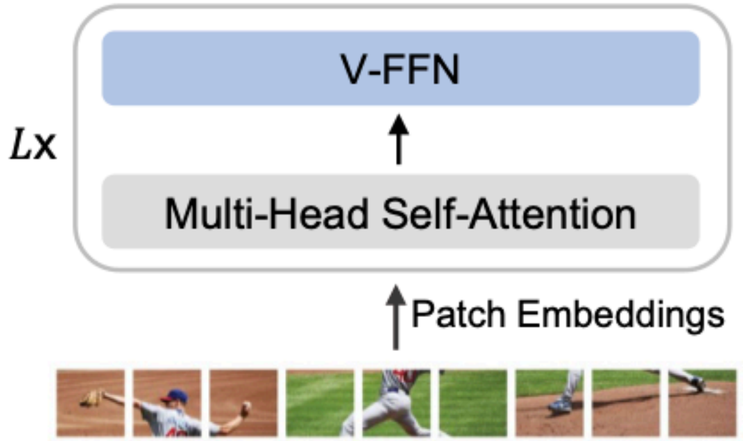

(a) Vision Encoder

Masked Image Modeling
Image Classification (IN1K)
Semantic Segmentation (ADE20K)
Object Detection (COCO)

[Wang et al., 2022]

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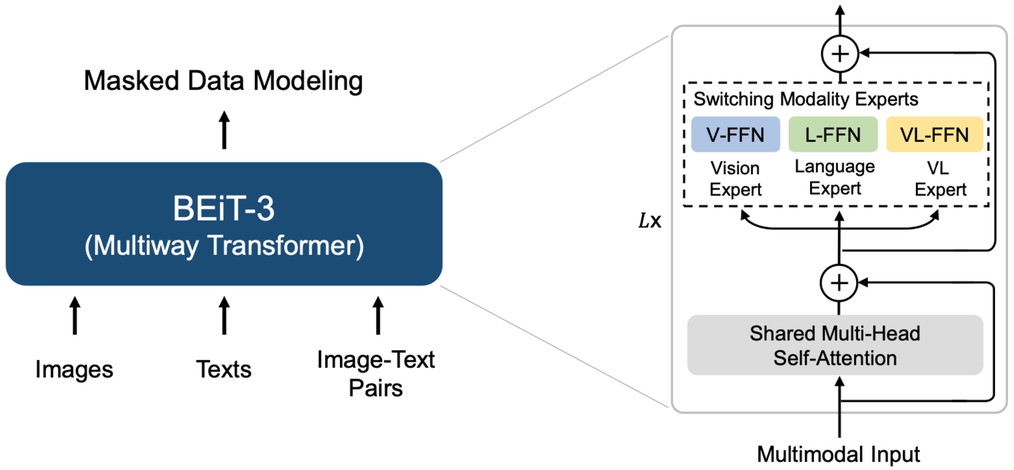

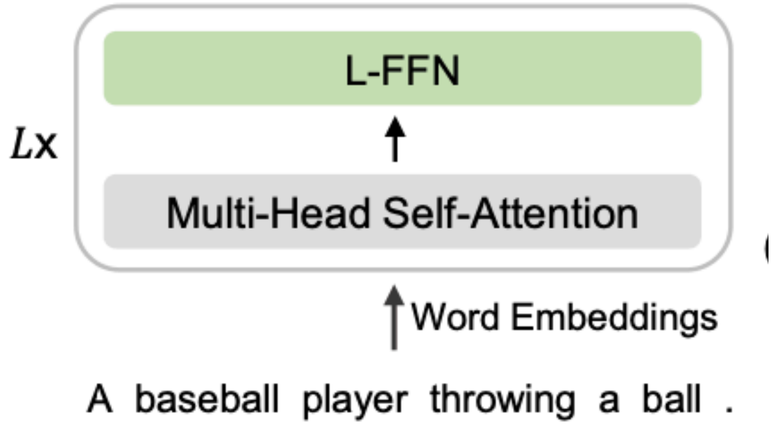

(b) Language Encoder

Masked Language Modeling

[Wang et al., 2022]

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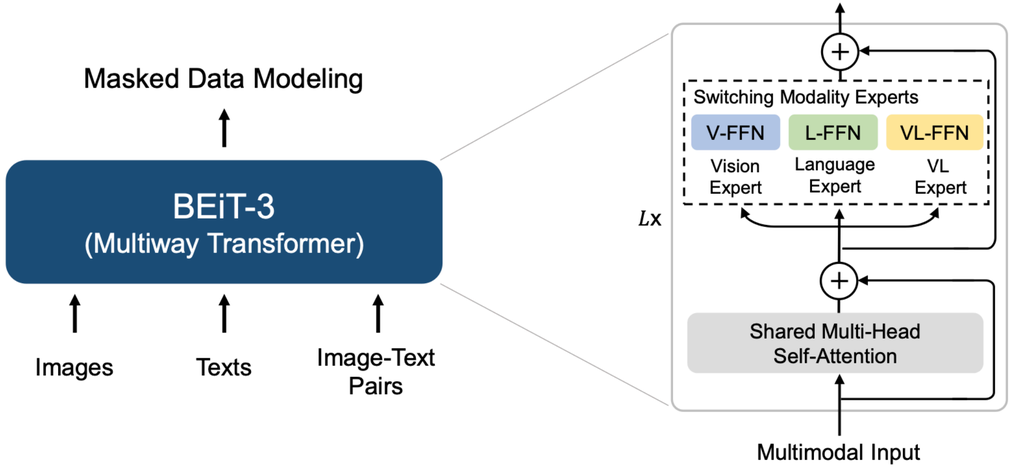
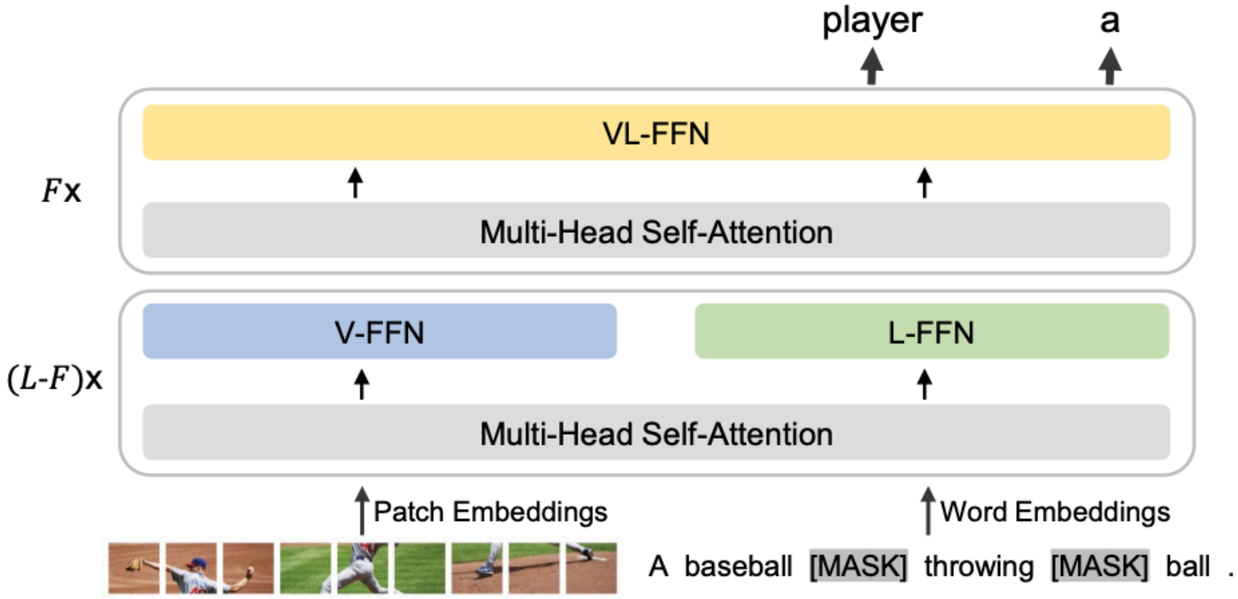




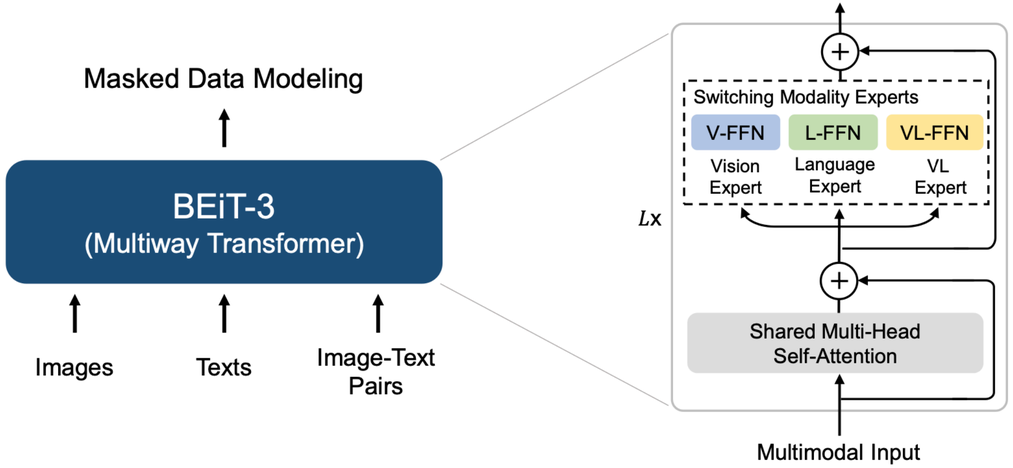
(c) Fusion Encoder

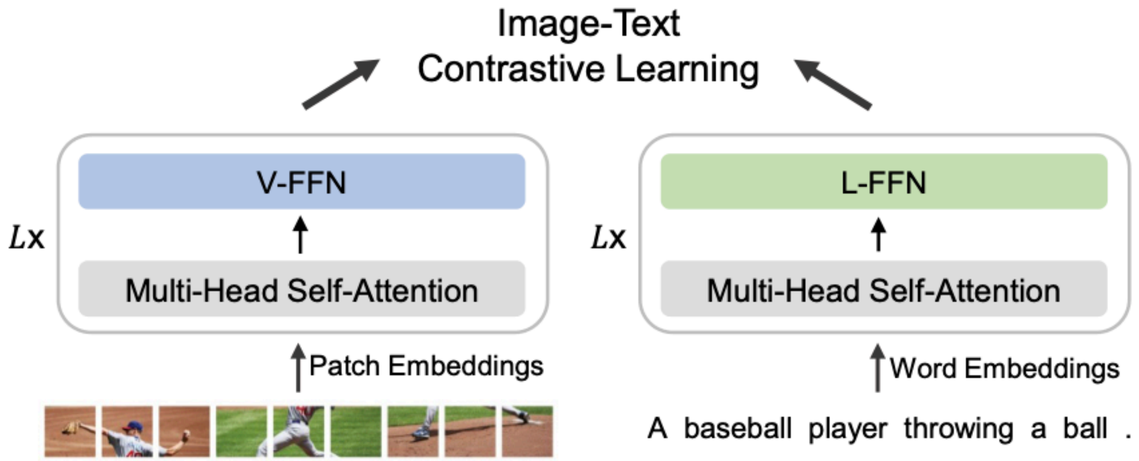
Masked Vision-Language Modeling

Vision-Language Tasks (VQA, NLVR2)

[Wang et al., 2022]

BEiT-v3: Image as a Foreign Language



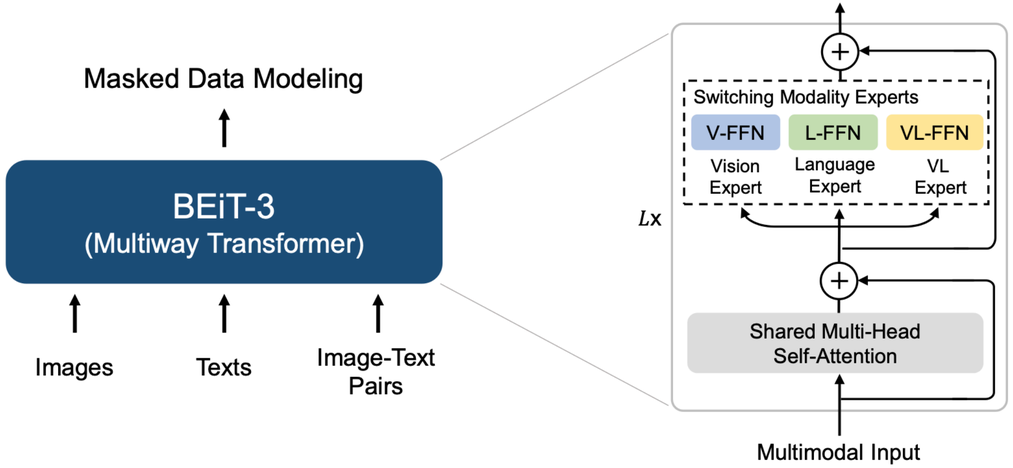


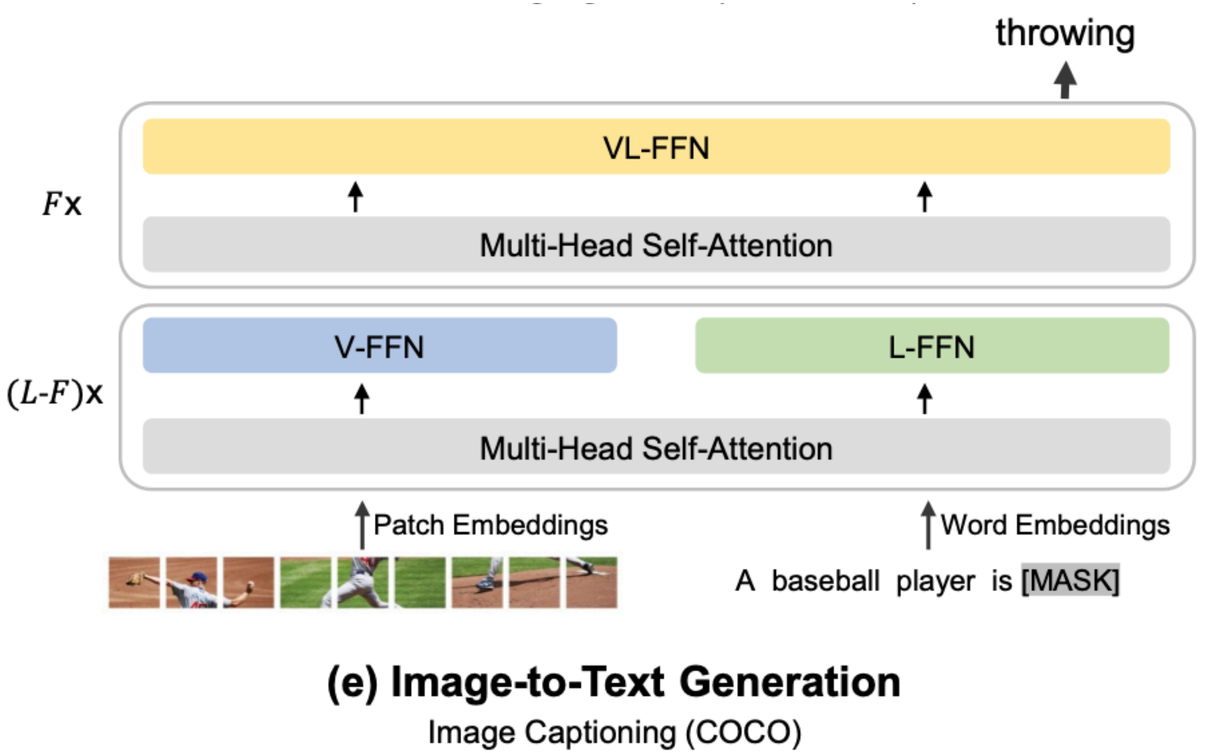
(d) Dual Encoder

Image-Text Retrieval (Flickr30k, COCO)

[Wang et al., 2022]

BEiT-v3: Image as a Foreign Language





(e) Image-to-Text Generation

Image Captioning (COCO)

[Wang et al., 2022]

BEiT-v3: Image as a Foreign Language

Model	MSCOCO (5K test set)						Flickr30K (1K test set)					
	Image → Text			Text → Image			Image → Text			Text → Image		
	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
Fusion-encoder models												
UNITER [CLY+20]	65.7	88.6	93.8	52.9	79.9	88.0	87.3	98.0	99.2	75.6	94.1	96.8
VILLA [GCL+20]	-	-	-	-	-	-	87.9	97.5	98.8	76.3	94.2	96.8
Oscar [LYL+20]	73.5	92.2	96.0	57.5	82.8	89.8	-	-	-	-	-	-
VinVL [ZLH+21]	75.4	92.9	96.2	58.8	83.5	90.3	-	-	-	-	-	-
Dual encoder + Fusion encoder reranking												
ALBEF [LSG+21]	77.6	94.3	97.2	60.7	84.3	90.5	95.9	99.8	**100.0**	85.6	97.5	98.9
BLIP [LLXH22]	82.4	95.4	97.9	65.1	86.3	91.8	97.4	99.8	99.9	87.6	97.7	99.0
Dual-encoder models												
ALIGN [JYX+21]	77.0	93.5	96.9	59.9	83.3	89.8	95.3	99.8	**100.0**	84.9	97.4	98.6
FILIP [YHH+21]	78.9	94.4	97.4	61.2	84.3	90.6	96.6	**100.0**	**100.0**	87.1	97.7	99.1
Florence [YCC+21]	81.8	95.2	-	63.2	85.7	-	97.2	99.9	-	87.9	98.1	-
BEIT-3	**84.8**	**96.5**	**98.3**	**67.2**	**87.7**	**92.8**	**98.0**	**100.0**	**100.0**	**90.3**	**98.7**	**99.5**

[Wang et al., 2022]

BEiT-v3: Image as a Foreign Language

Model	Extra OD Data	Maximum Image Size	COCO test-dev AP^{box}	COCO test-dev AP^{mask}
ViT-Adapter [CDW+22]	-	1600	60.1	52.1
DyHead [DCX+21]	ImageNet-Pseudo Labels	2000	60.6	-
Soft Teacher [XZH+21]	Object365	-	61.3	53.0
GLIP [LZZ+21]	FourODs	-	61.5	-
GLIPv2 [ZZH+22]	FourODs	-	62.4	-
Florence [YCC+21]	FLOD-9M	2500	62.4	-
SwinV2-G [LHL+21]	Object365	1536	63.1	54.4
Mask DINO [LZX+22]	Object365	1280	-	54.7
DINO [ZLL+22]	Object365	2000	63.3	-
BEIT-3	Object365	1280	**63.7**	**54.8**

[Wang et al., 2022]

THE UNIVERSITY OF BRITISH COLUMBIA

Topics in AI (CPSC 532S):
Multimodal Learning with Vision, Language and Sound

Lecture 23: Meta-learning

Few-shot Learning

Given abundant training examples for the base classes, few-shot learning algorithms aim to learn to recognize novel classes with a limited amount of labeled examples

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Task: classify test (a.k.a. query) set images with "novel labels" (labels not present in base data but available in support set)

Given: limited novel-labelled Support Set with K images from each of N novel classes

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Given: limited novel-labelled Support Set with K images from each of N novel classes

At test time: n-way k-shot tasks

2-way 4-shot

Few-shot Learning

Transfer learning baselines

1. Pre-training: supervised learning of model on base data
2. Fine-tuning: supervised learning of (parts of or whole) model on labelled support data
3. Testing on test / query dataset

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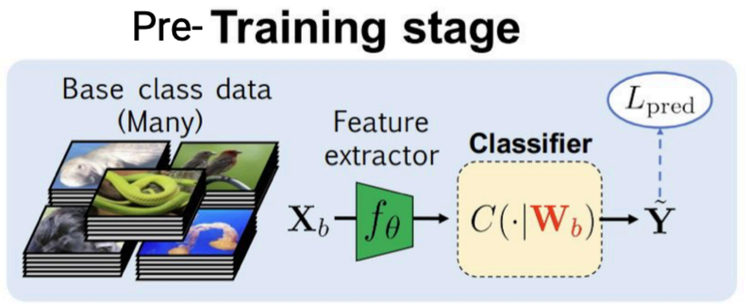

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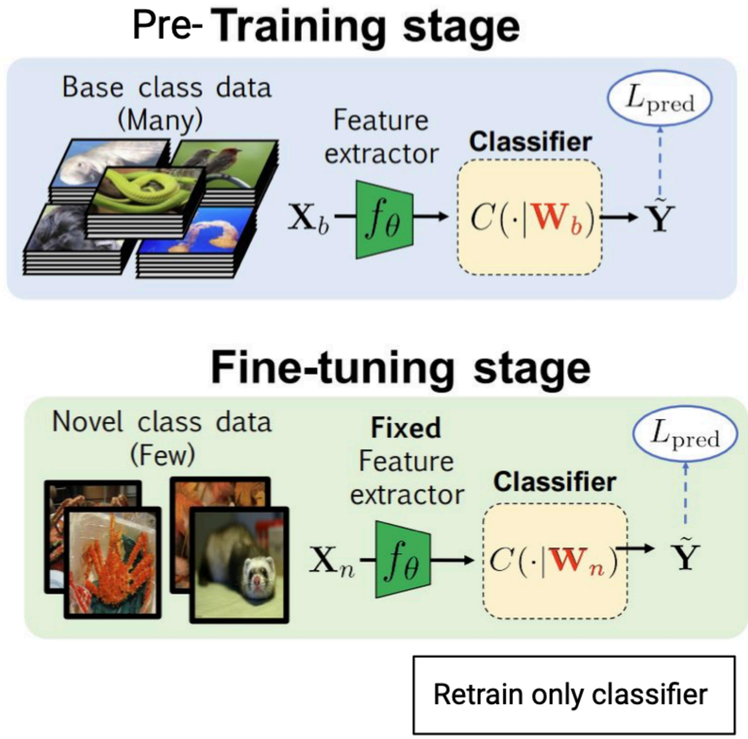

Retrain only classifier

Few-shot Learning

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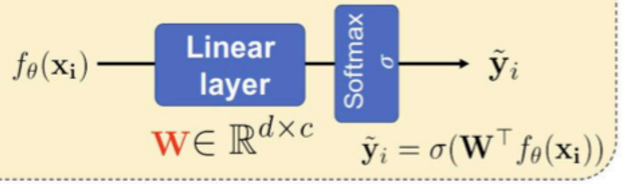
Choice of Classifier

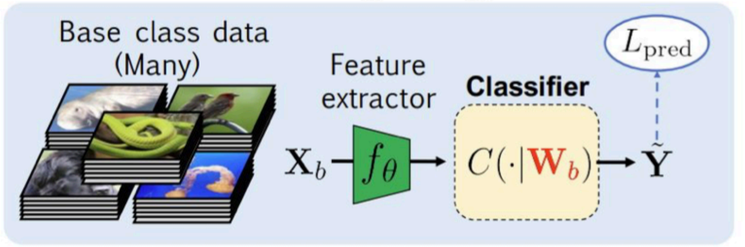
Baseline



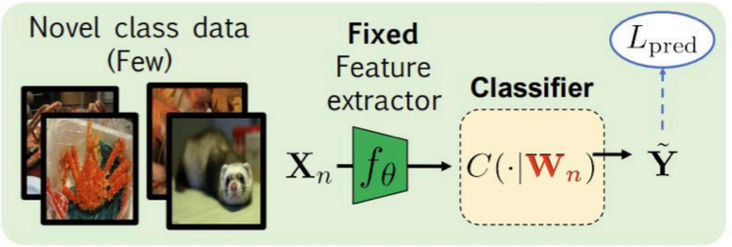
(Standard procedure)

Commonly seen last layer (*a.k.a.* logits) in a deep neural network classifying image into one of classes by min loss = f(predicted label probability vector, true one-hot encoded label).

Pre-**Training stage**



Fine-tuning stage



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Few-shot Learning

Transfer learning baselines

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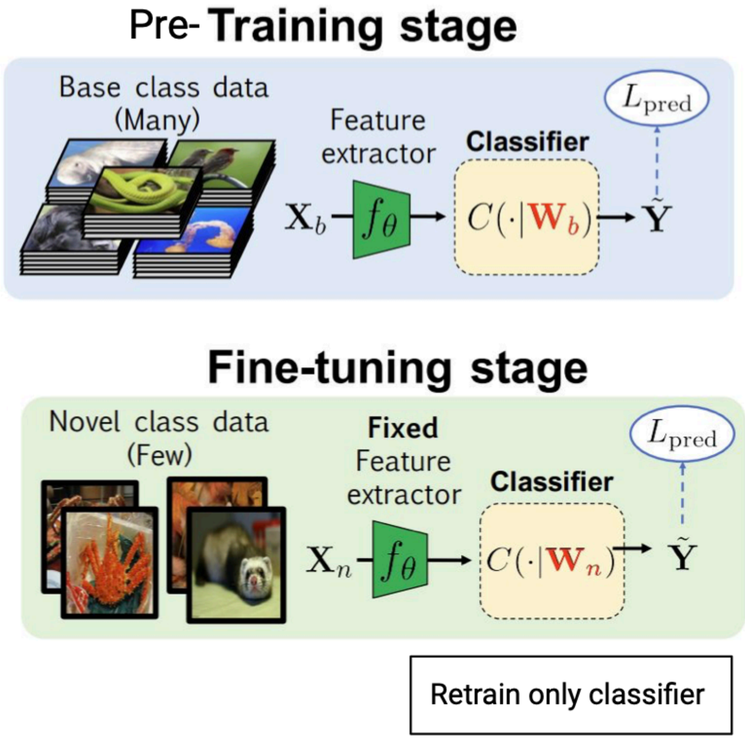
Expected to not perform well on test / query dataset without large support set (in fine-tuning stage)



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Meta-learning

"Learning to learn": a paradigm specifically for the k-shot n-way task that uses base data to "learn to learn", *i.e.* learn a *meta-learner*, and applies the meta-learner on the testing phase (support + query) data.

Few-shot Learning

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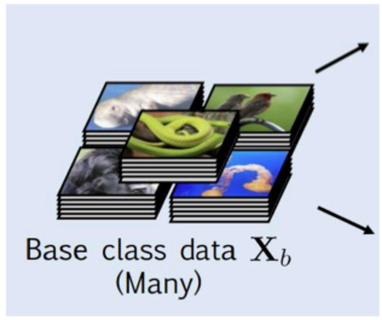
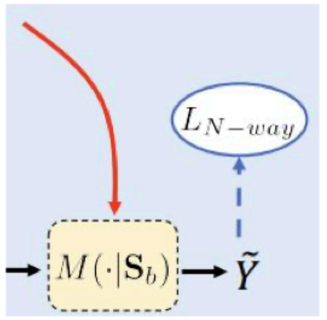
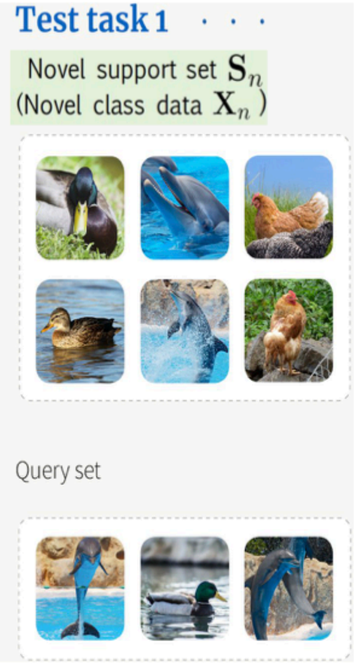
Randomly sample N classes and rearrange base class data into meta-training tasks that simulate test (usually same k, N).







Meta-Learning

Training

Train dataset #1: “cat-bird”

cats




birds




Train dataset #2: “flower-bike”

flowers




bikes



Testing

Test dataset: “dog-otter”

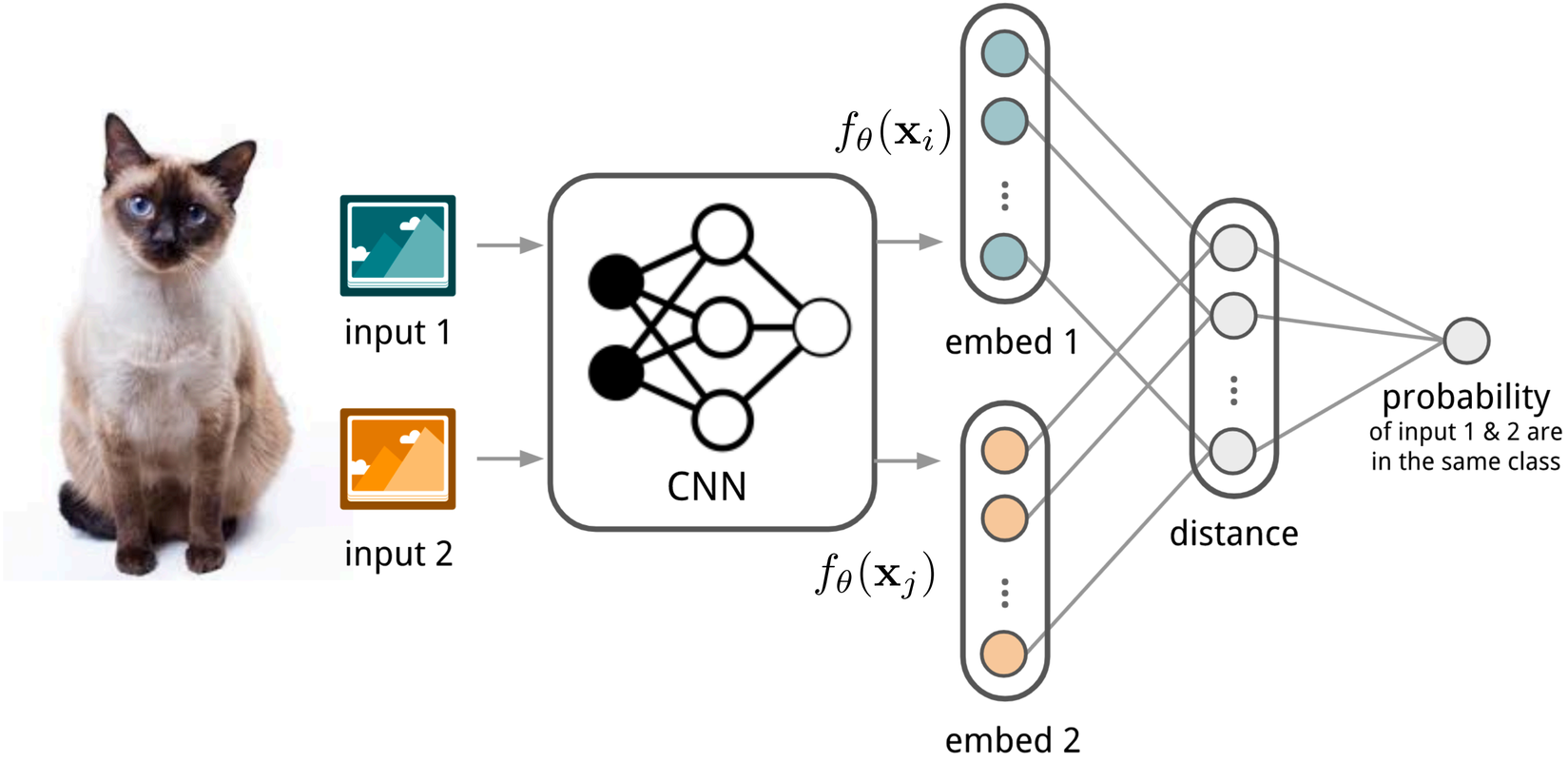
dogs




otters




Metric-Based Meta-Learning — Siamese Neural Nets



https://lilianweng.github.io/posts/2018-11-30-meta-learning/

[Koch et al. 2015]

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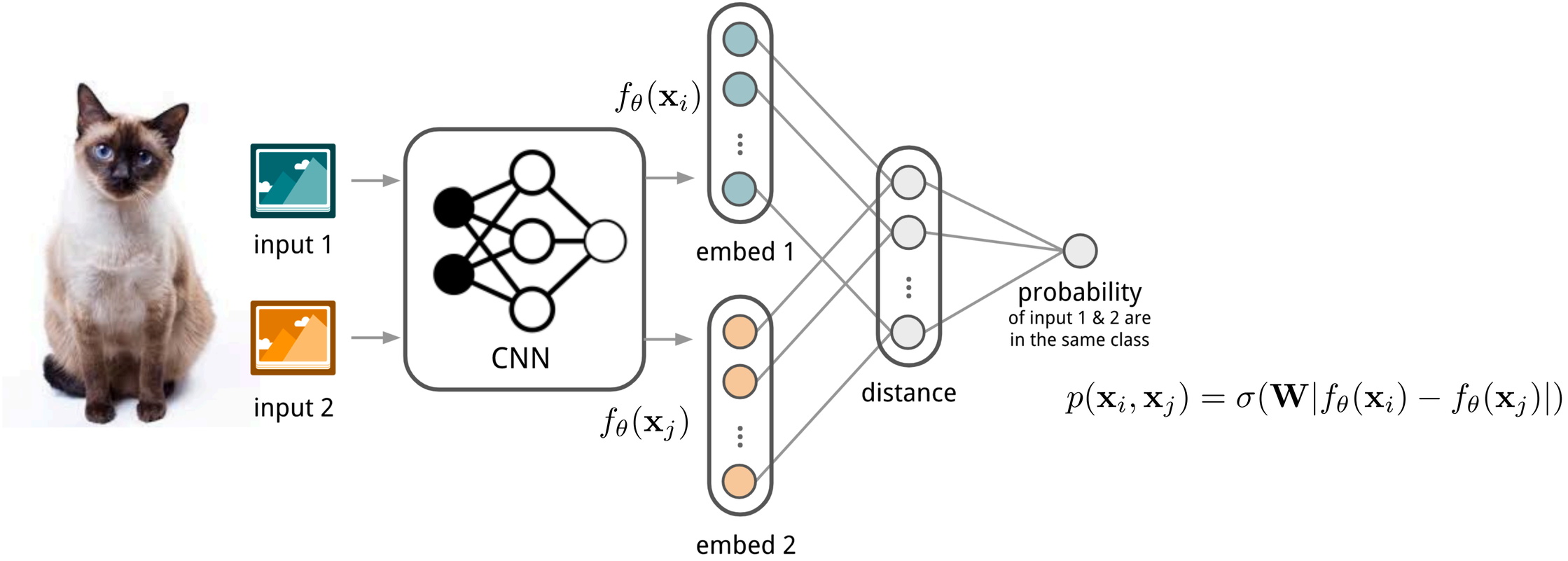


Training Objective: do two images belong to same class

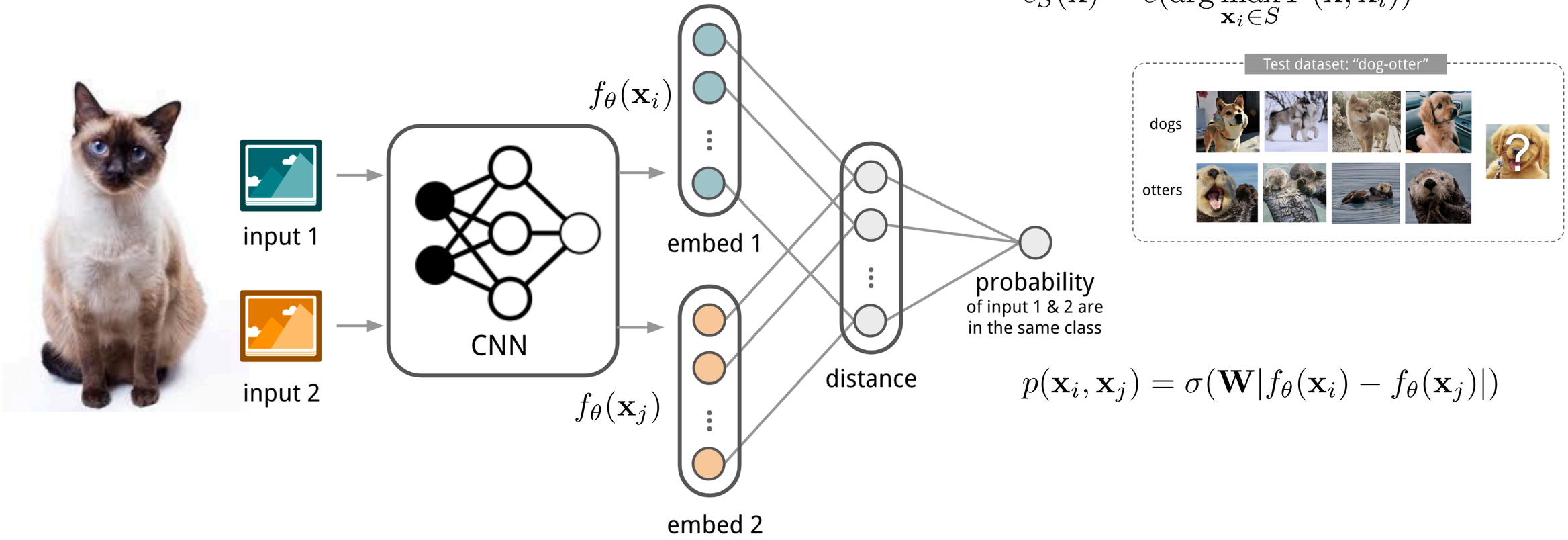
https://lilianweng.github.io/posts/2018-11-30-meta-learning/

[Koch et al. 2015]

Siamese Neural Nets

Inference: output the label of the most similar support image (i.e., nearest neighbor)

$$\hat{c}_S(\mathbf{x}) = c(\arg\max_{\mathbf{x}_i \in S} P(\mathbf{x}, \mathbf{x}_i))$$



$$p(\mathbf{x}_i, \mathbf{x}_j) = \sigma(\mathbf{W}|f_\theta(\mathbf{x}_i) - f_\theta(\mathbf{x}_j)|)$$

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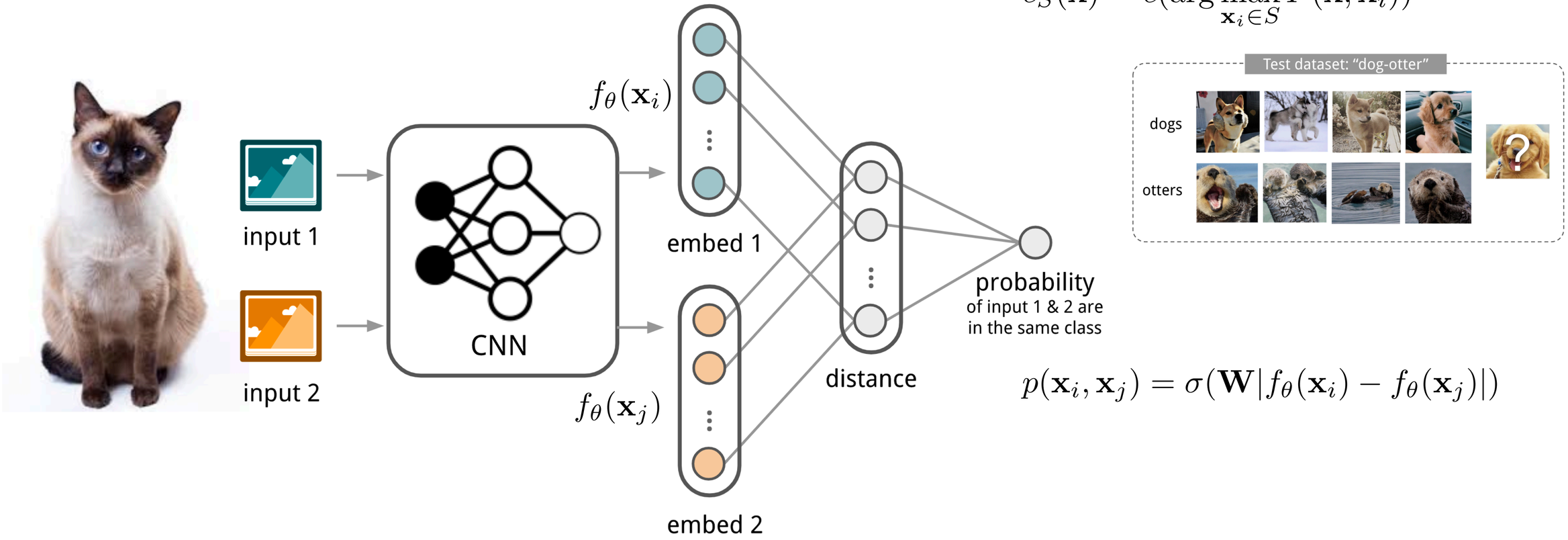

$$p(\mathbf{x}_i, \mathbf{x}_j) = \sigma(\mathbf{W}|f_\theta(\mathbf{x}_i) - f_\theta(\mathbf{x}_j)|)$$

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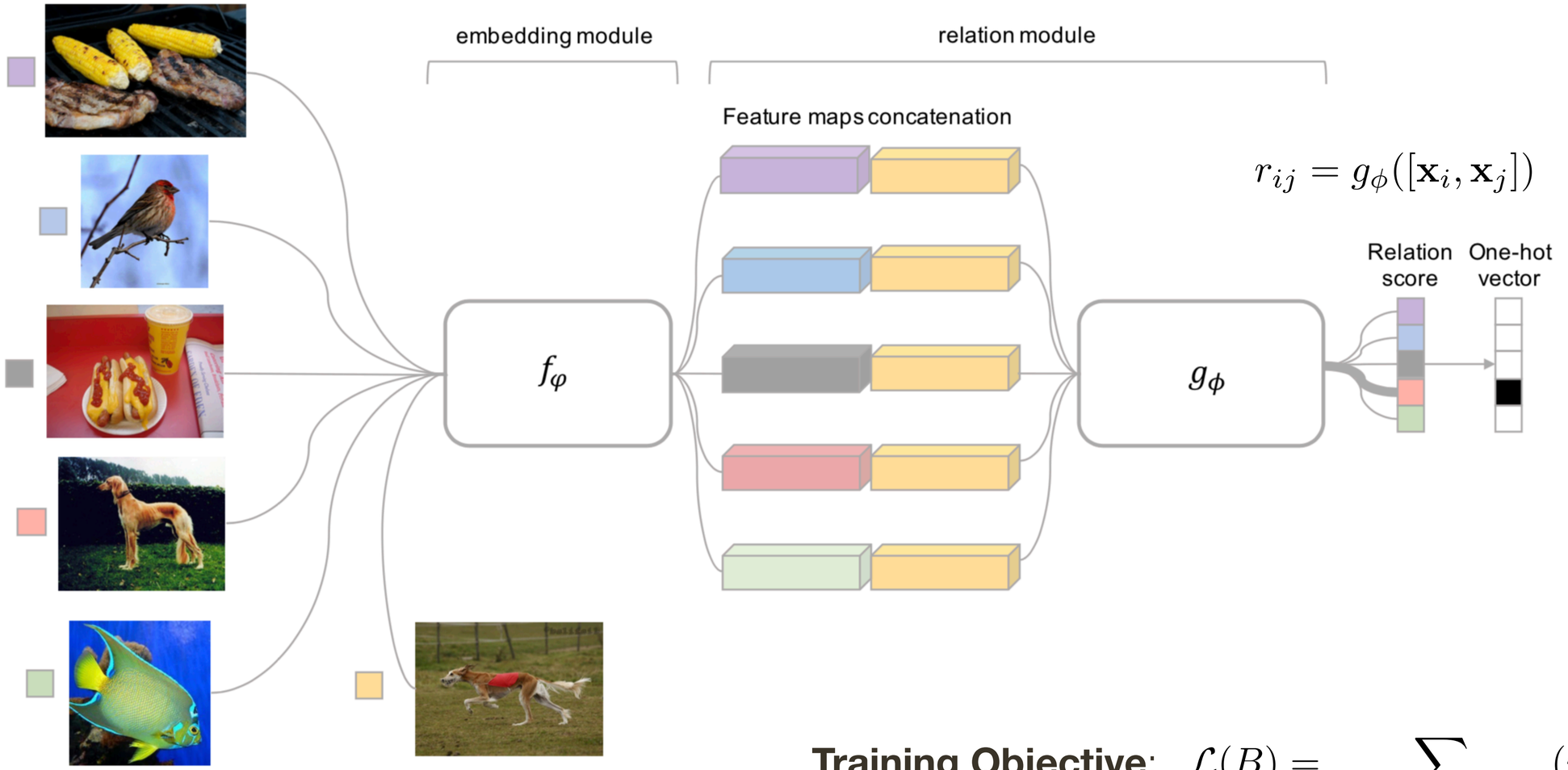
$$\mathcal{L}(B) = \sum_{(\mathbf{x}_i, \mathbf{x}_j, y_i, y_j) \in B} \mathbf{1}_{y_i = y_j} \log p(\mathbf{x}_i, \mathbf{x}_j) + (1 - \mathbf{1}_{y_i = y_j}) \log(1 - p(\mathbf{x}_i, \mathbf{x}_j))$$

https://lilianweng.github.io/posts/2018-11-30-meta-learning/

[Koch et al. 2015]

Metric-Based Meta-Learning — Relation Networks



$$r_{ij} = g_\phi([\mathbf{x}_i, \mathbf{x}_j])$$

Training Objective: $\mathcal{L}(B) = \sum_{(\mathbf{x}_i, \mathbf{x}_j, y_i, y_j) \in B} (r_{ij} - \mathbf{1}_{y_i = y_j})^2$

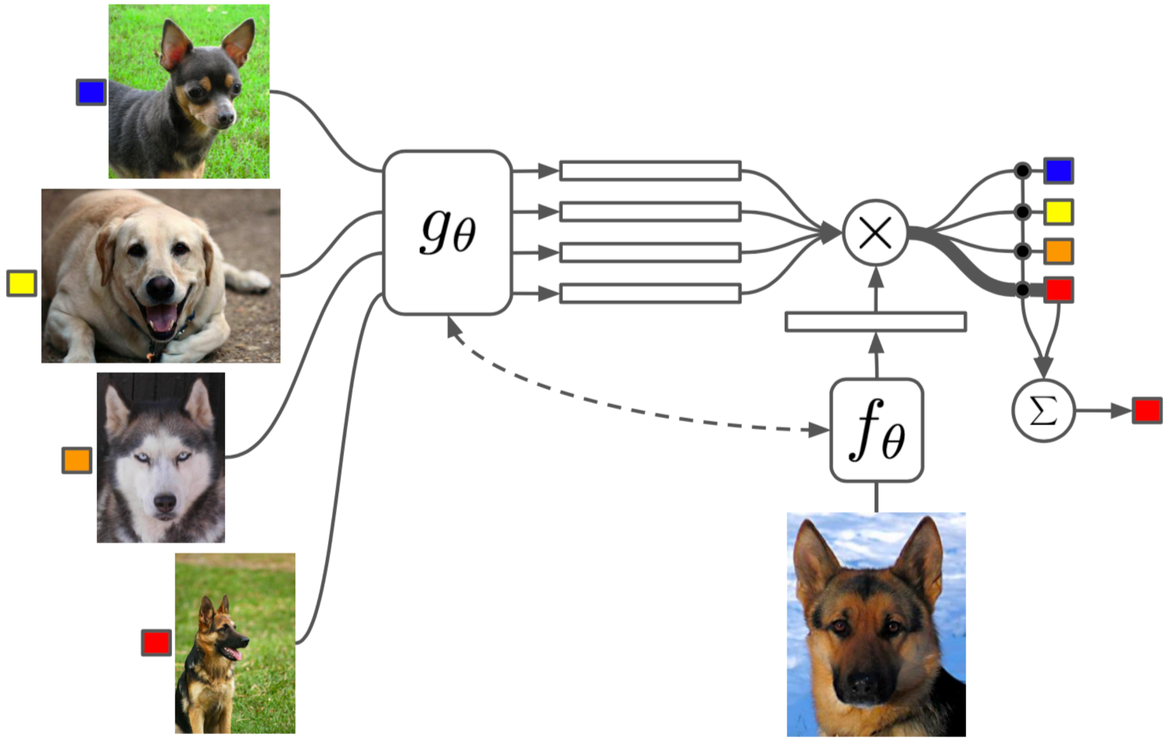
https://lilianweng.github.io/posts/2018-11-30-meta-learning/

[Sung et al. 2018]

Metric-Based Meta-Learning — Marching Networks

Inference: output the label distribution is simply sum of labels from support set, weighted by similarity/relevance

$$c_S(\mathbf{x}) = P(y|\mathbf{x}, S) = \sum_{i=1}^{k} a(\mathbf{x}, \mathbf{x}_i) y_i, \text{ where } S = \{(\mathbf{x}_i, y_i)\}_{i=1}^{k}$$



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[Vinyals et al.. 2016]

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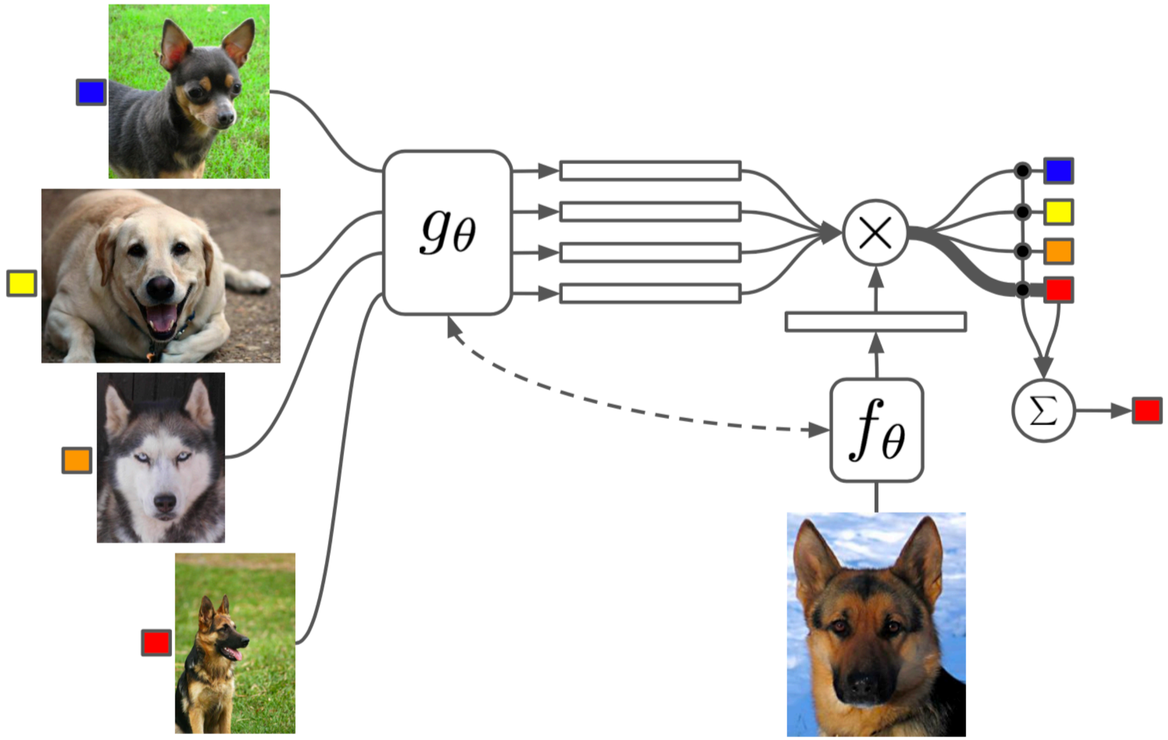

$$a(\mathbf{x}, \mathbf{x}_i) = \frac{\exp(\text{cosine}(f(\mathbf{x}), g(\mathbf{x}_i))}{\sum_{j=1}^{k} \exp(\text{cosine}(f(\mathbf{x}), g(\mathbf{x}_j))}$$

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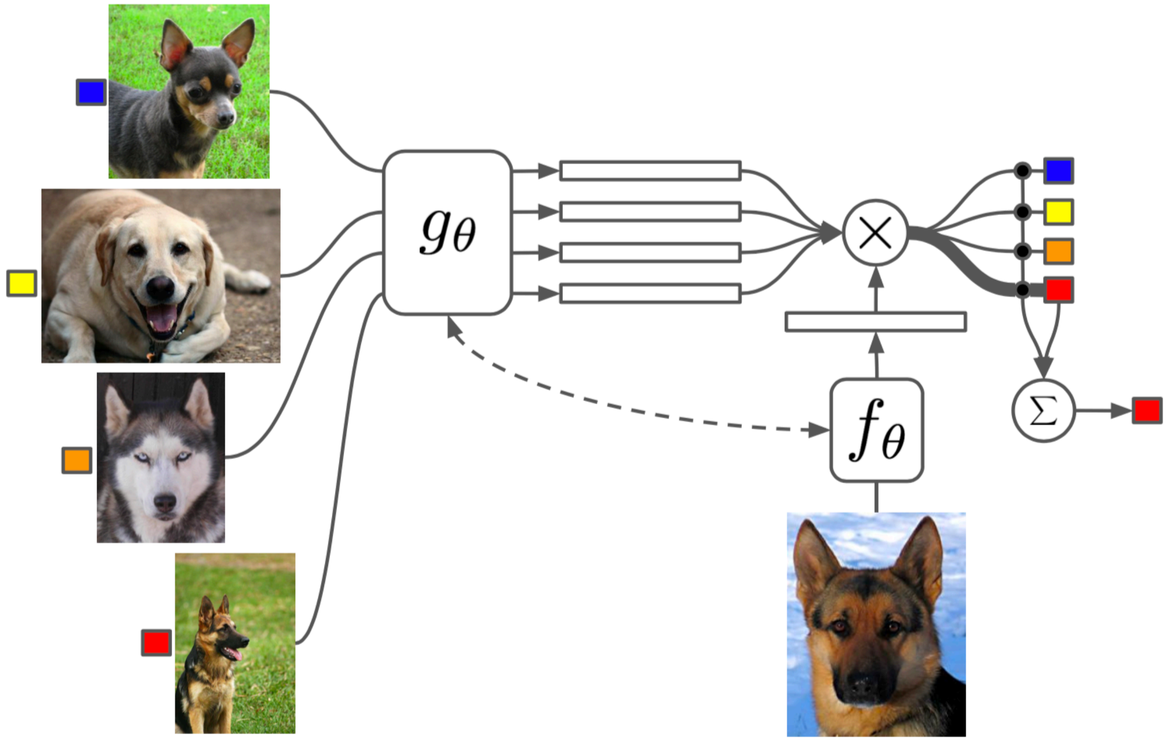

$$a(\mathbf{x}, \mathbf{x}_i) = \frac{\exp(\text{cosine}(f(\mathbf{x}), g(\mathbf{x}_i))}{\sum_{j=1}^{k} \exp(\text{cosine}(f(\mathbf{x}), g(\mathbf{x}_j))}$$

Simple version: $f = g$

+ soft-attention

Key = features of support set images
Value = labels of support set images
Query = features of test image

https://lilianweng.github.io/posts/2018-11-30-meta-learning/

[Vinyals et al.. 2016]

Metric-Based Meta-Learning — Marching Networks

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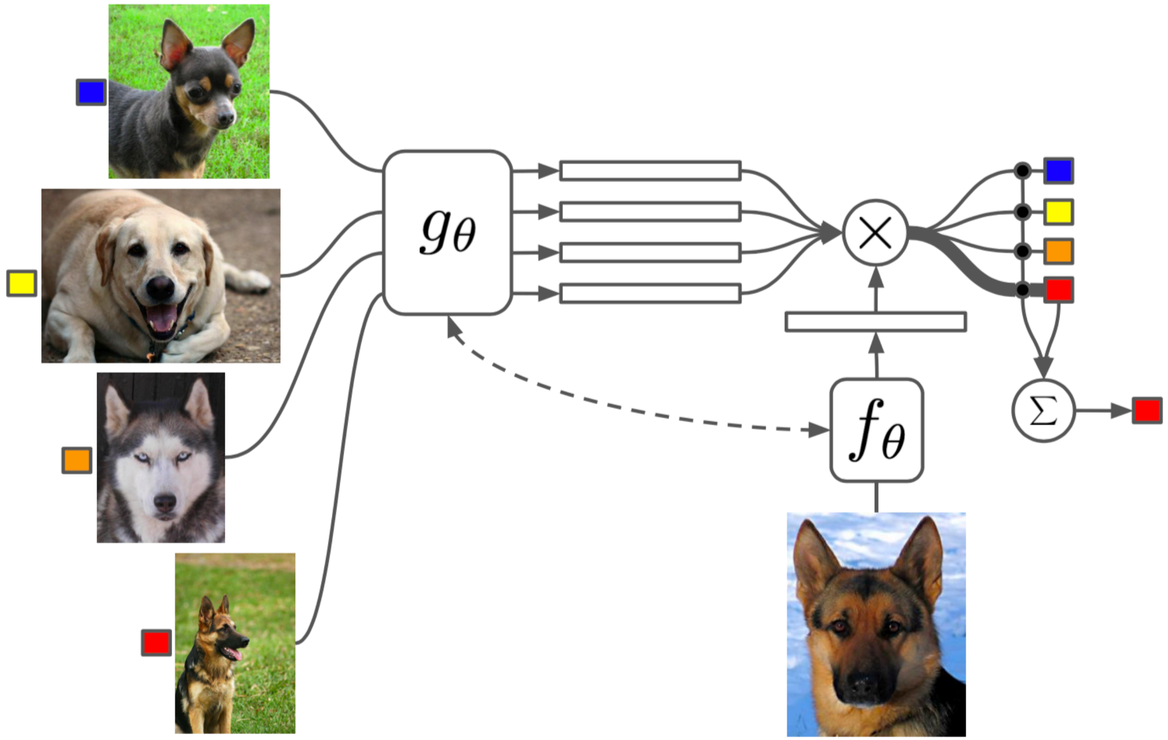

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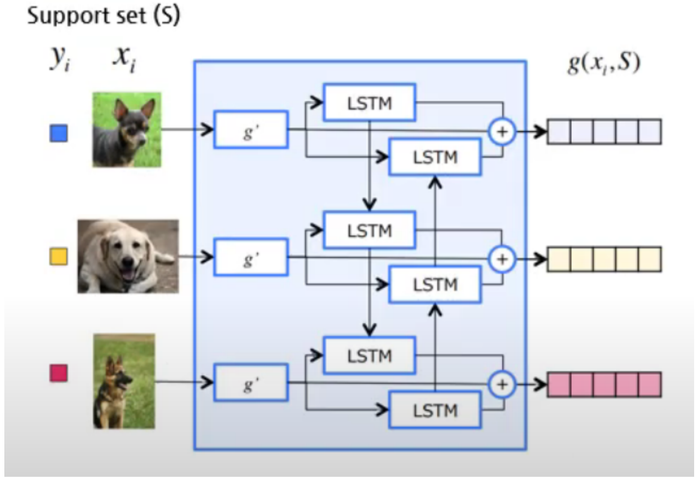
$g = \text{Bi-LSTM}$



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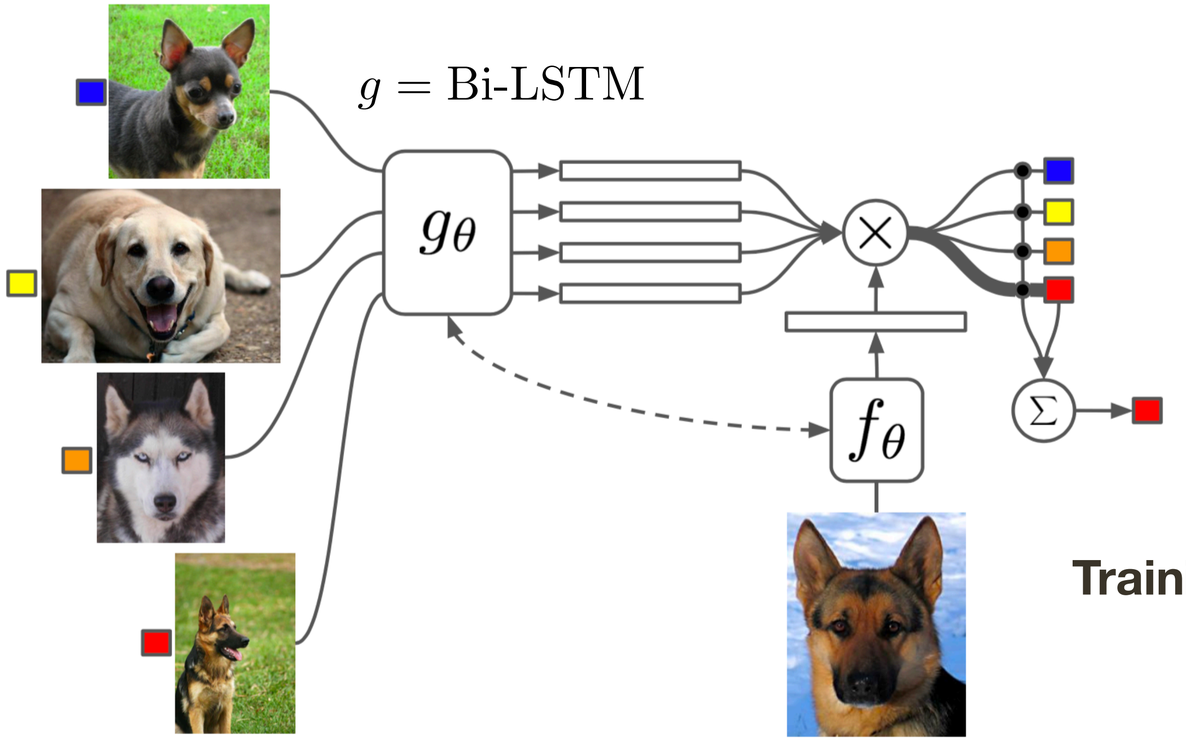

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Training Objective: correct classification of query examples

$$\theta^* = \arg\max_\theta \mathbb{E}_{L \subset \mathcal{L}}[\mathbb{E}_{S^L \subset \mathcal{D}, B^L \subset \mathcal{D}}[\sum_{(\mathbf{x}, y) \in B^L} P_\theta(y|\mathbf{x}, S^L)]]$$

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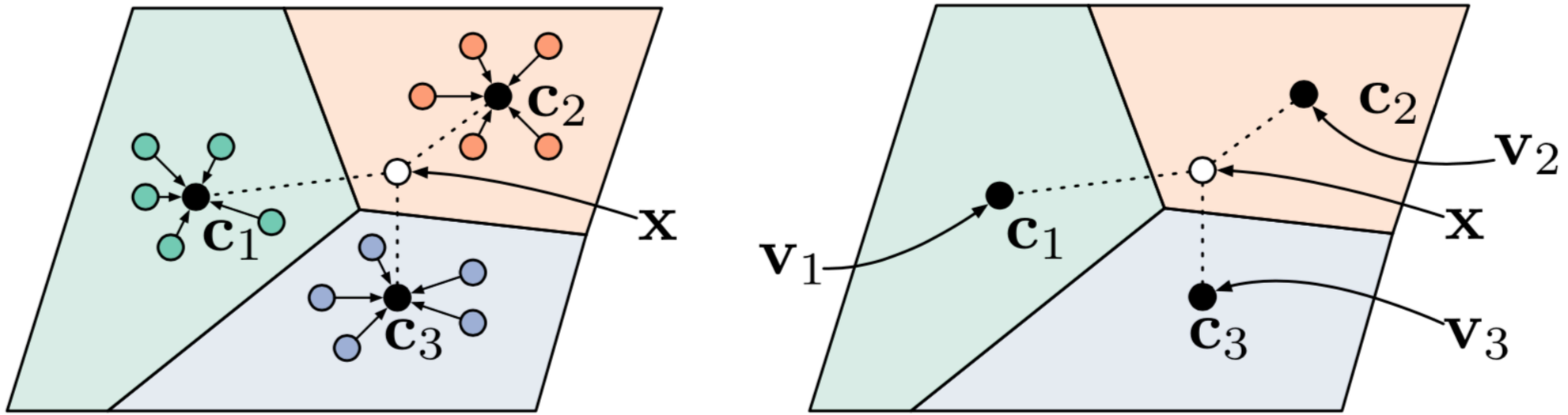
[Vinyals et al.. 2016]

Metric-Based Meta-Learning — **Prototypical** Networks

$$\mathbf{v}_c = \frac{1}{|S_c|} \sum_{(\mathbf{x}_i, y_i) \in S_c} f_\theta(\mathbf{x}_i)$$



(a) Few-shot (b) Zero-shot

$$P(y = c|\mathbf{x}) = \text{softmax}(-d_\varphi(f_\theta(\mathbf{x}), \mathbf{v}_c)) = \frac{\exp(-d_\varphi(f_\theta(\mathbf{x}), \mathbf{v}_c))}{\sum_{c' \in \mathcal{C}} \exp(-d_\varphi(f_\theta(\mathbf{x}), \mathbf{v}_{c'}))}$$

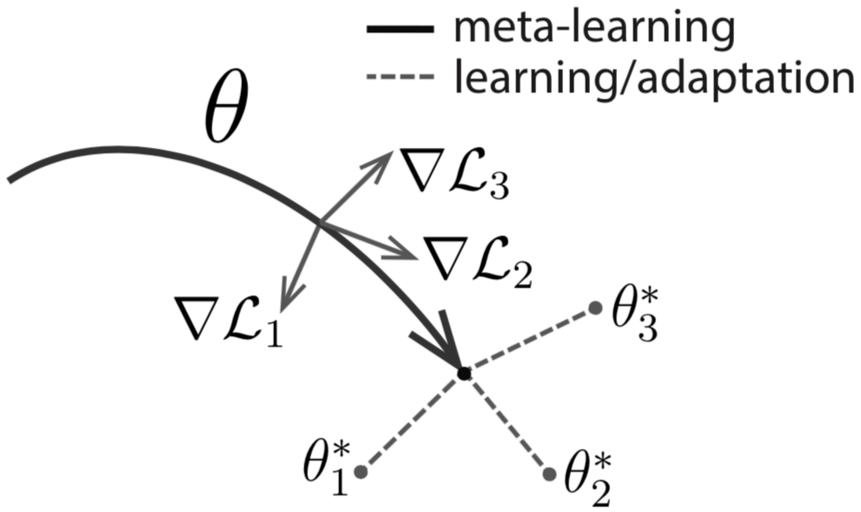
$$\mathcal{L}(\theta) = -\log P_\theta(y = c|\mathbf{x})$$

https://lilianweng.github.io/posts/2018-11-30-meta-learning/

[Snell et al., 2017]

Optimization-Based Meta-Learning — **MAML**

Idea: learn model initialization from which one can rapidly adopt to ANY meta-task



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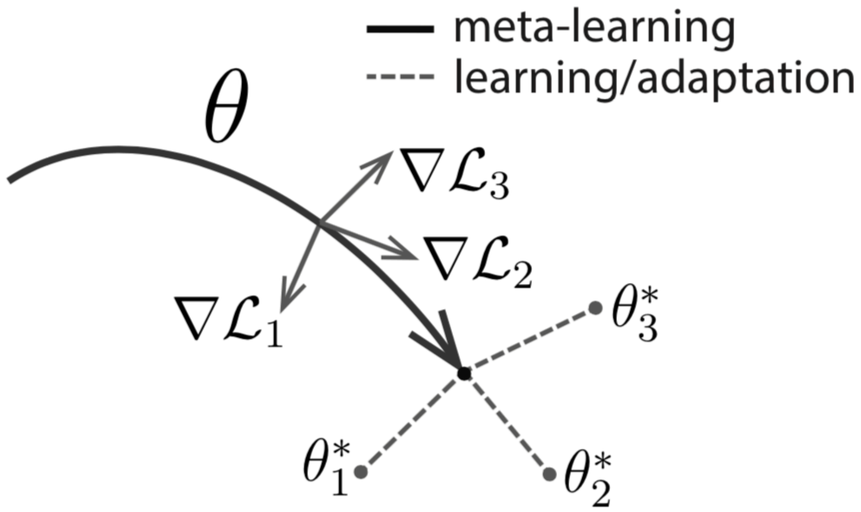
[Finn et al., 2017]

Optimization-Based Meta-Learning — **MAML**

Idea: learn model initialization from which one can rapidly adopt to ANY meta-task

Means: find model parameters that are sensitive to changes in the task



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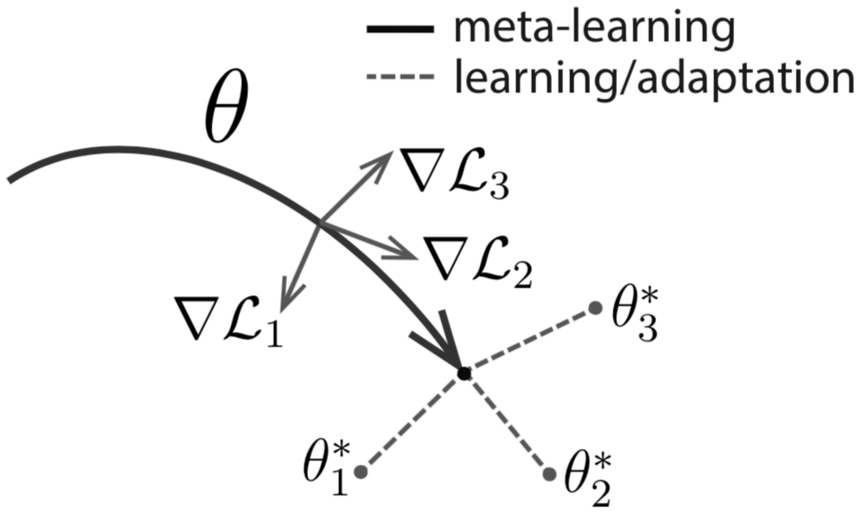

Adapting parameters for one task for k steps:

$$\theta_0 = \theta_{\text{meta}}$$
$$\theta_1 = \theta_0 - \alpha\nabla_\theta\mathcal{L}^{(0)}(\theta_0)$$
$$\theta_2 = \theta_1 - \alpha\nabla_\theta\mathcal{L}^{(0)}(\theta_1)$$
$$\dots$$
$$\theta_k = \theta_{k-1} - \alpha\nabla_\theta\mathcal{L}^{(0)}(\theta_{k-1})$$

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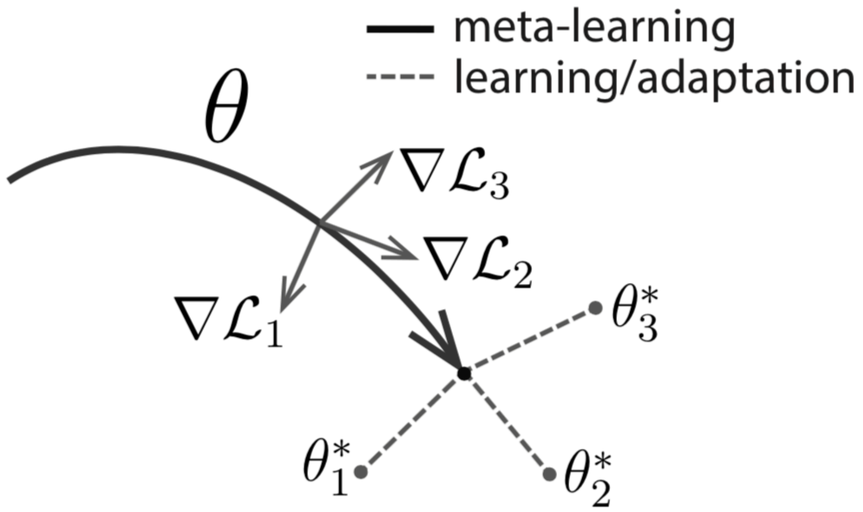

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Optimizing meta-parameters:

$$\theta_{\text{meta}} \leftarrow \theta_{\text{meta}} - \beta g_{\text{MAML}}$$

https://lilianweng.github.io/posts/2018-11-30-meta-learning/

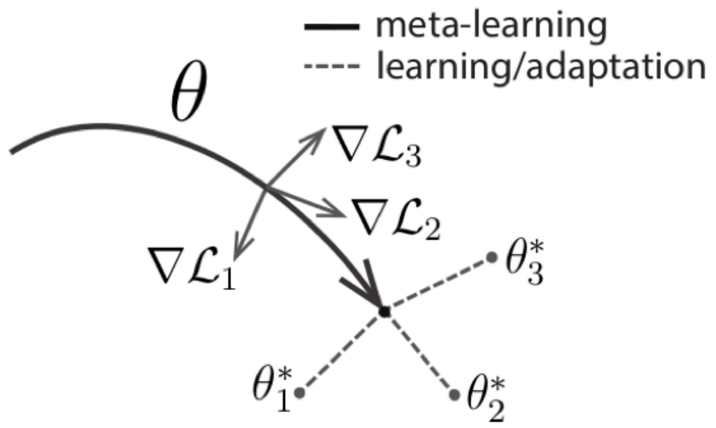
[Finn et al., 2017]

Optimization-Based Meta-Learning — **MAML**

Inner Loop: Update the model for a task from an initialization

Outer Loop: Optimize for the performance of all **inner loop** models on **all tasks**

Intuition: We want achieve a low loss after only a few updates on a task



https://dvl.in.tum.de/slides/automl-ss21/MAML.pdf

[Finn et al., 2017]

MAML — Algorithm

Algorithm 1 Model-Agnostic Meta-Learning

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: step size hyperparameters
1: randomly initialize θ
2: **while** not done **do**
3: Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$

https://dvl.in.tum.de/slides/automl-ss21/MAML.pdf

MAML — Inner Loop

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1: randomly initialize θ
2: **while** not done **do**
3: Sample batch of tasks $\mathcal{T}_i \sim p(\mathcal{T})$
4: **for all** $\mathcal{T}_i$ **do**
5: Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples
6: Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$
7: **end for**

Inner Loop: Update the model for a task from an initialization

$$\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$$

Simple gradient update on the sampled task

https://dvl.in.tum.de/slides/automl-ss21/MAML.pdf

MAML — Outer Loop

Algorithm 1 Model-Agnostic Meta-Learning

Require: $p(\mathcal{T})$: distribution over tasks

Require: α, β: step size hyperparameters

1: randomly initialize θ

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4: **for all** $\mathcal{T}_i$ **do**

5: Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$ with respect to K examples

6: Compute adapted parameters with gradient descent: $\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)$

7: **end for**

8: Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})$

9: **end while**

Meta-objective:

$$\min_\theta \underbrace{\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})}_{\text{Total loss of all updated models}} = \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta)})$$

Meta-update:

$$\theta \leftarrow \theta - \beta \nabla_\theta \underbrace{\sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta_i'})}_{\text{Total loss of all updated models}}$$

https://dvl.in.tum.de/slides/automl-ss21/MAML.pdf

MAML — Issues

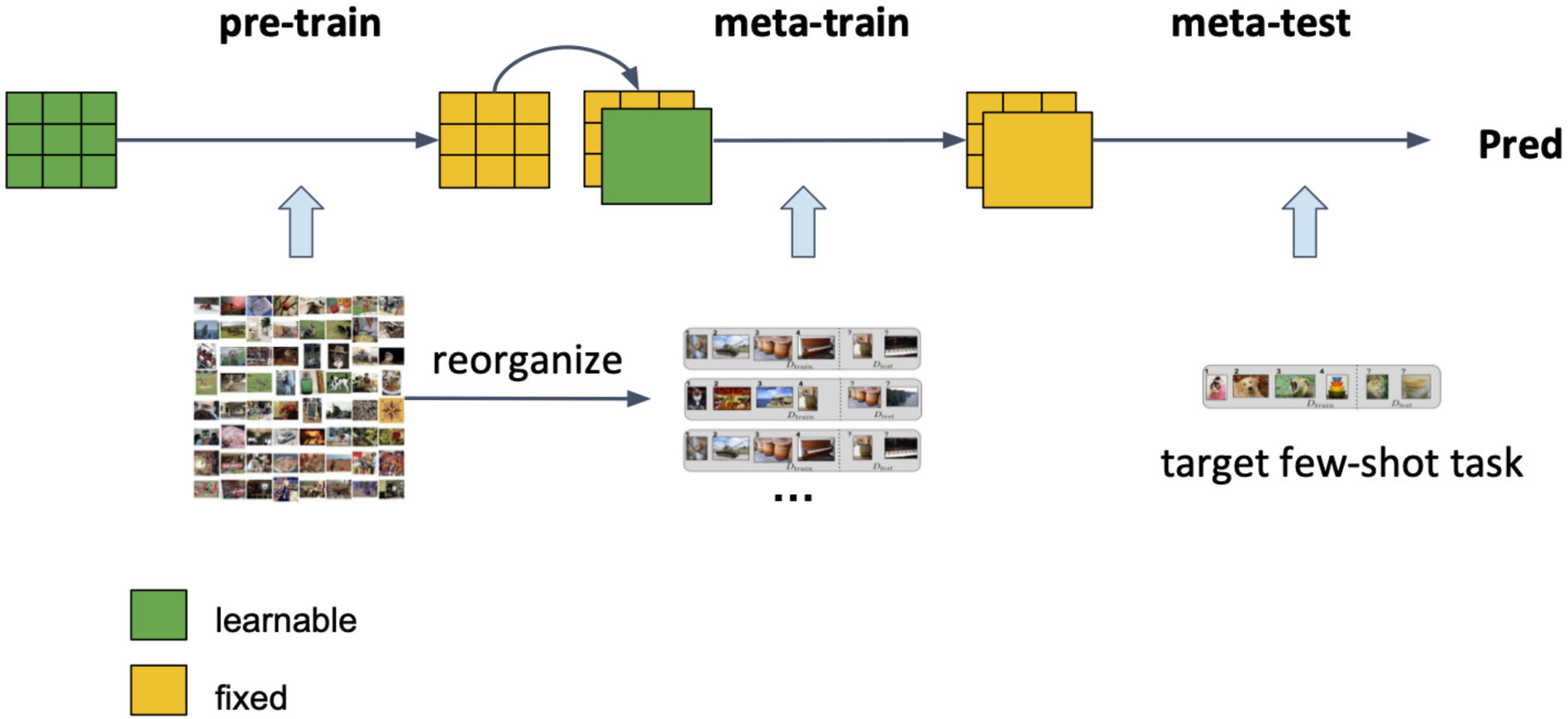
— Hard to train with deep feature extractor networks

Solution: Meta-transfer learning

— Slow training

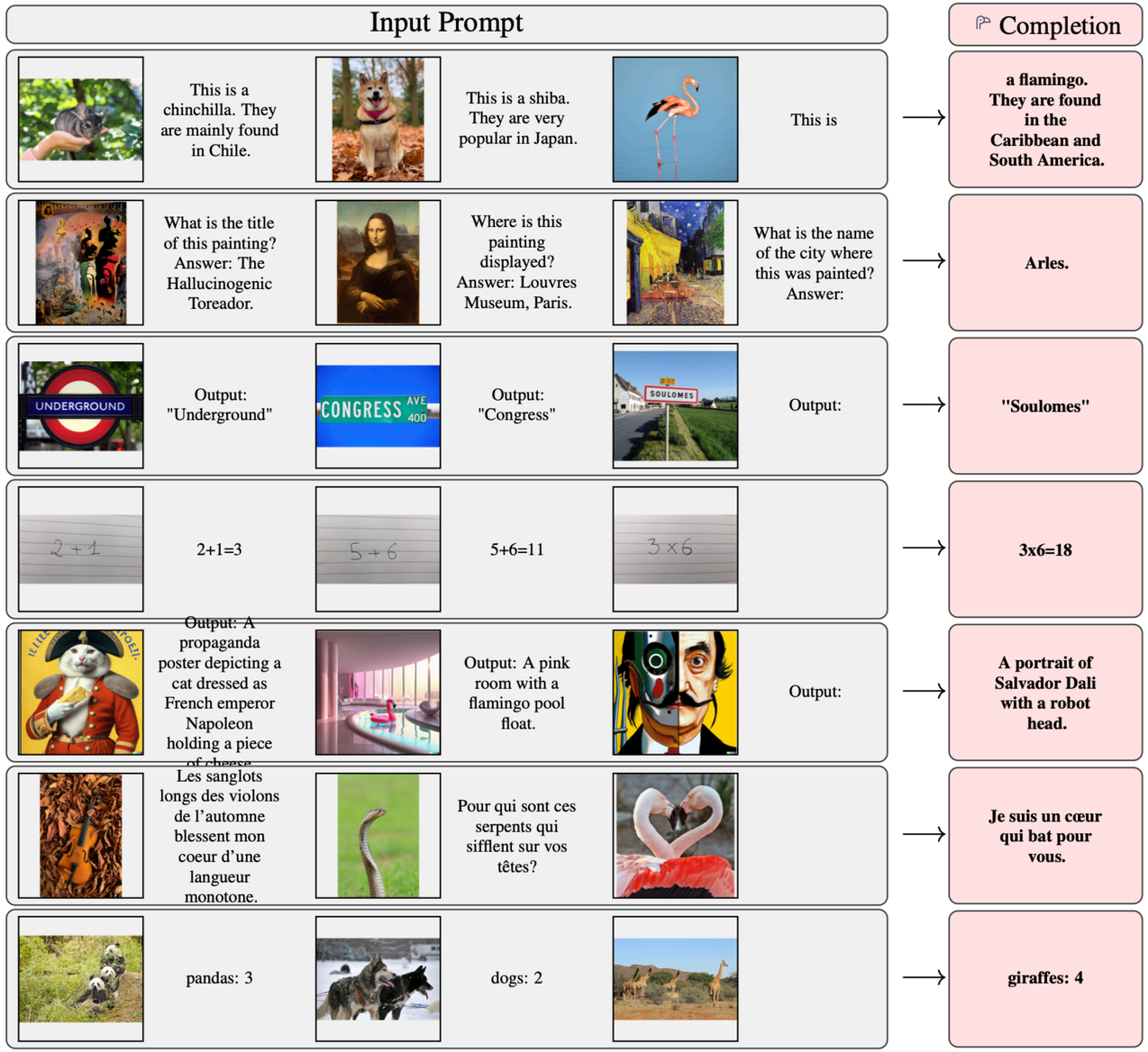
Solution: Hard task sampling (will not cover)

A more typical pipeline …



https://people.mpi-inf.mpg.de/~yaliu/files/meta-transfer-learning-slides.pdf

Multi-modal Few-shot Learners — **Flamingo**



[Alayrac et al., 2022]