

COMP547

DEEP UNSUPERVISED LEARNING

Lecture #13 – Pretraining for Vision and Language



KOÇ
UNIVERSITY

Aykut Erdem // Koç University // Spring 2024

Good news, everyone!

- Midterm exam will be released on May 18 at 12:00 (36 hours to submit your answers)
- Final project presentations will be held on May 20-22, 2024
- Final project reports are due May 26, 2024



Previously on COMP547

- Motivation and introduction
- Introduction to language models
- History of neural language models
- A digression into Transformers
- Beyond standard LMs
- Why we need unsupervised learning



Lecture overview

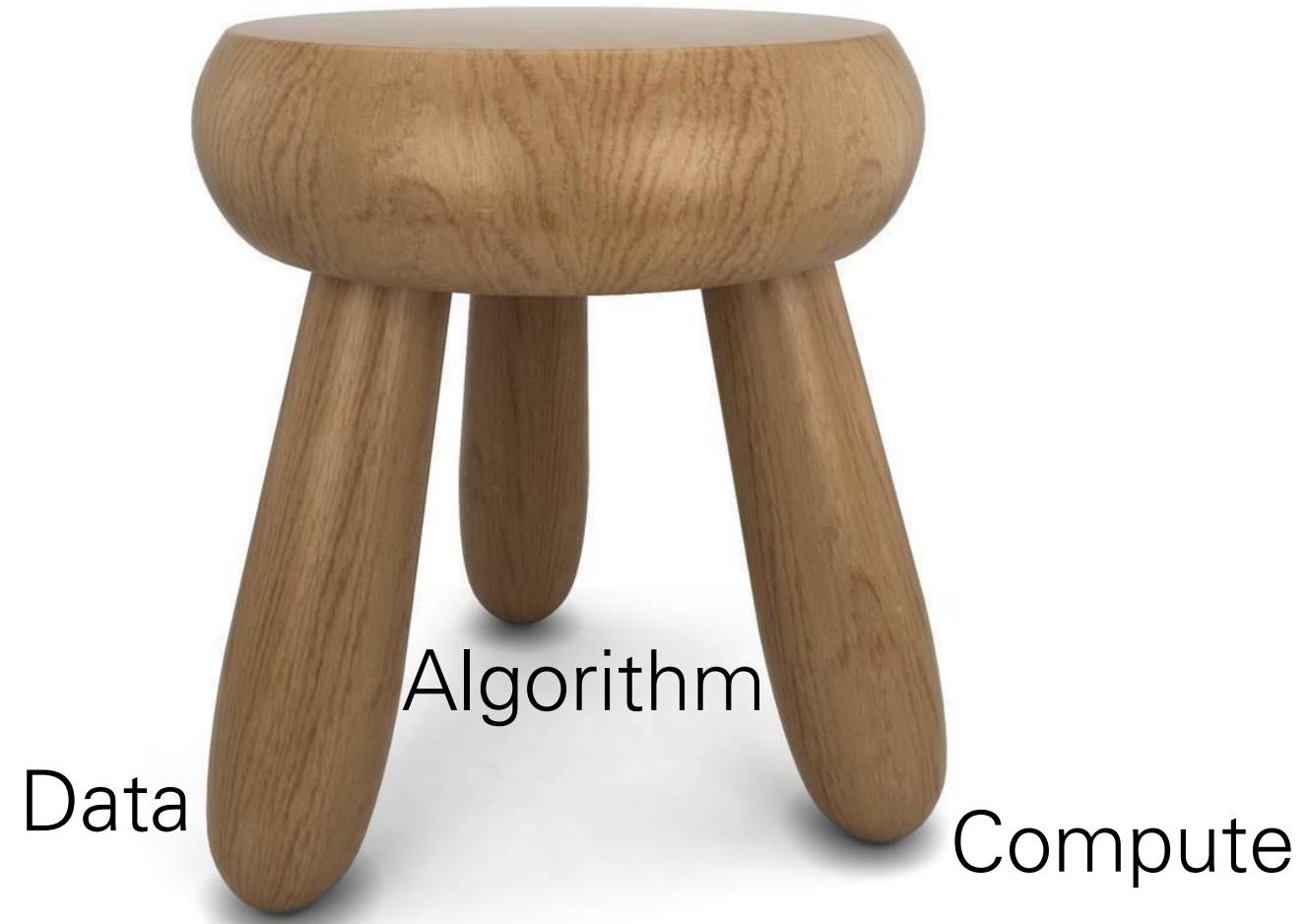
- Introduction
- Pre-training data
- Feature representations for vision and language
- Model architectures
- Pre-training tasks
- Downstream tasks
- Moving forward

Disclaimer: Much of the material and slides for this lecture were borrowed from
— Licheng Yu, Yen-Chun Chen, Linjie Li's tutorial on "Self-Supervised Learning for Vision-and-Text"

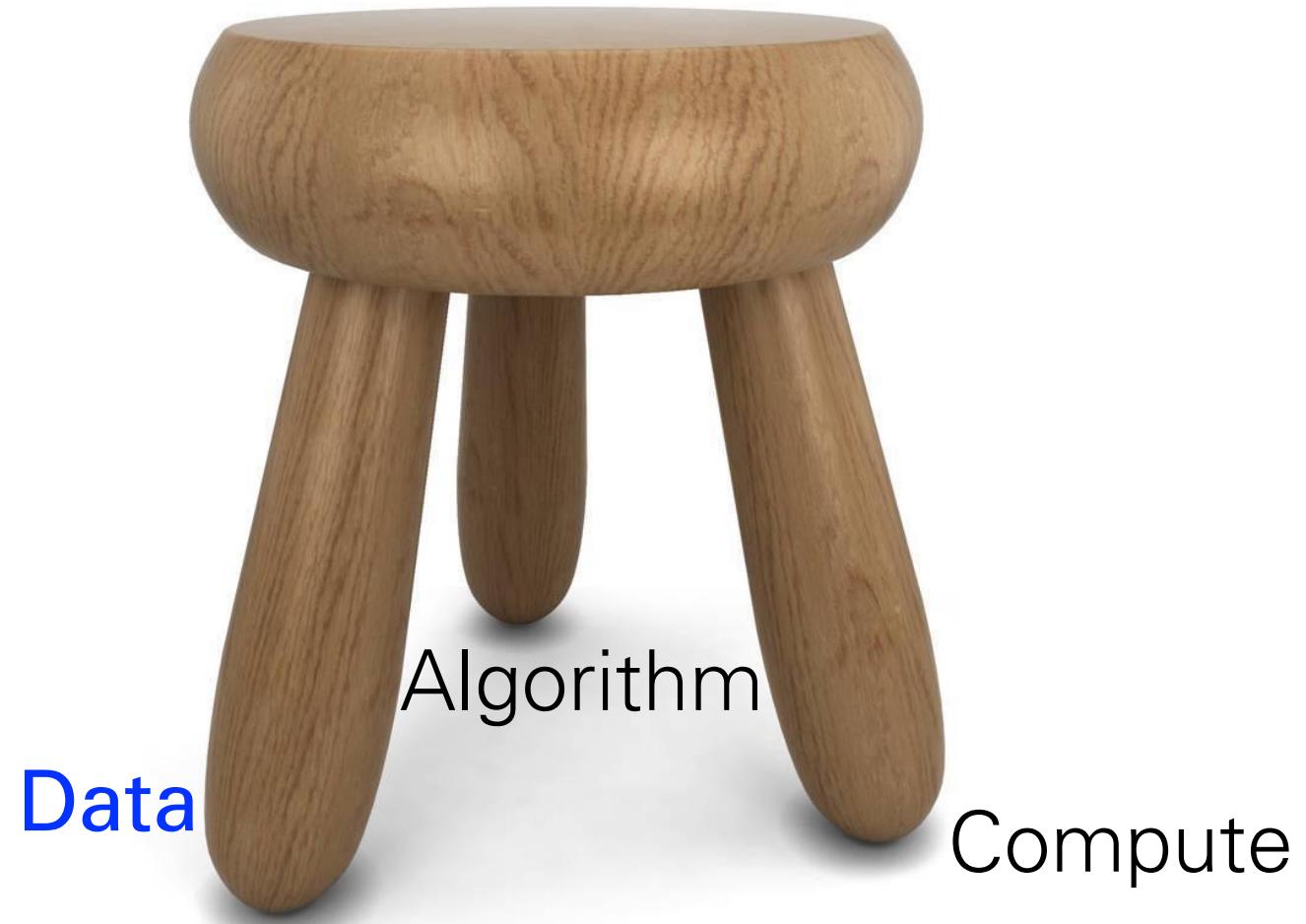
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Nowadays Machine Learning



Nowadays Machine Learning



Datasets + Labels



Please describe the image:

Enter description here

prev next

Instructions:

- Describe all the **important parts** of the scene.
- **Do not** start the sentences with "There is".
- **Do not** describe unimportant details.
- **Do not** describe things that might have happened in the future or past.
- **Do not** describe what a person might say.
- **Do not** give people proper names.
- The sentence should contain at least **8 words**.

- MS COCO's Image Captioning:
 - 120,000 images
 - 5 sentences / image
 - 15 cents / sentence
 - +20% AWS processing fee



\$108,000



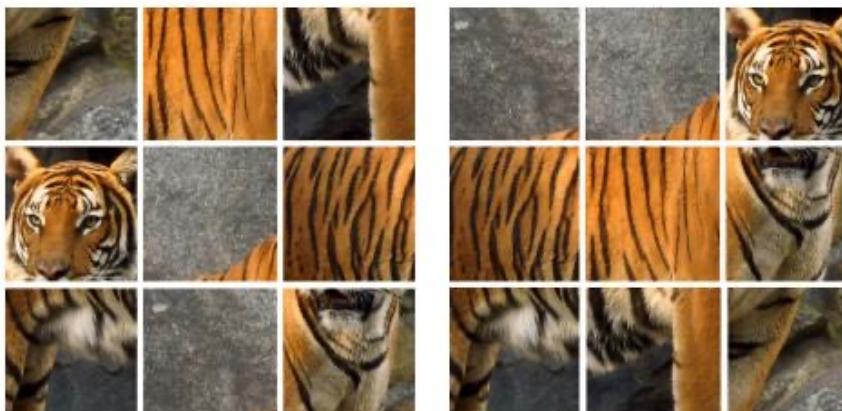
Datasets + Labels: Self-Supervised Learning for Vision

Image Colorization



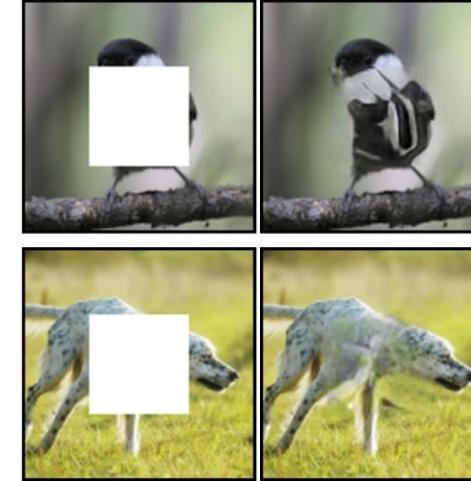
[Zhang et al. ECCV 2016]

Image Colorization



[Noroozi et al. ECCV 2016]

Image Inpainting



[Pathak et al. CVPR 2016]

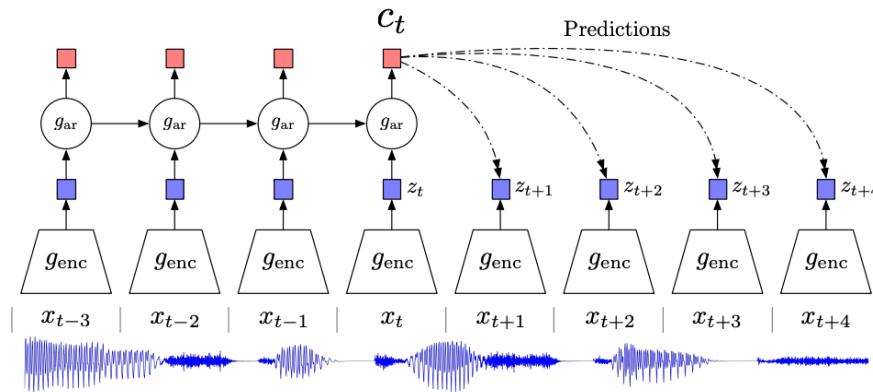
Relative Location Prediction

Example:

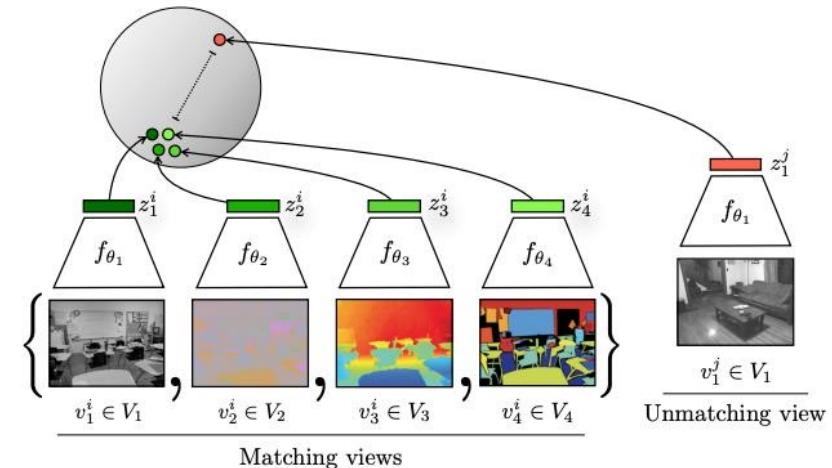


[Doersch et al. ICCV 2015]

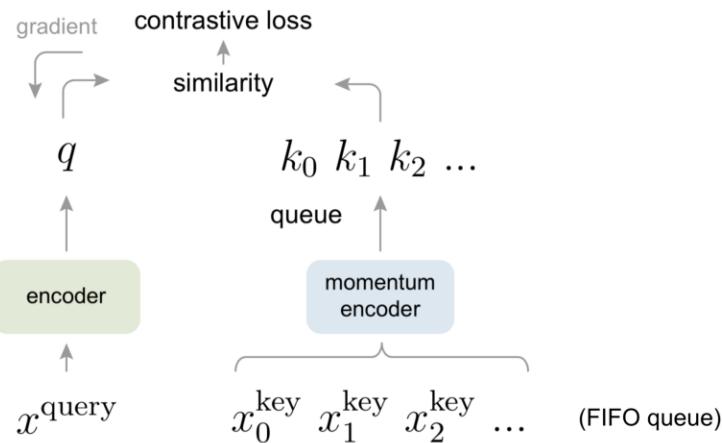
Datasets + Labels: Self-Supervised Learning for Vision



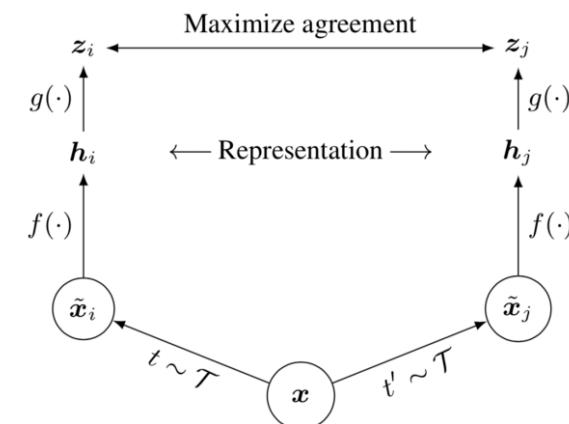
CPC [Ord et al. 2019]



CMC [Tian et al. 2019]

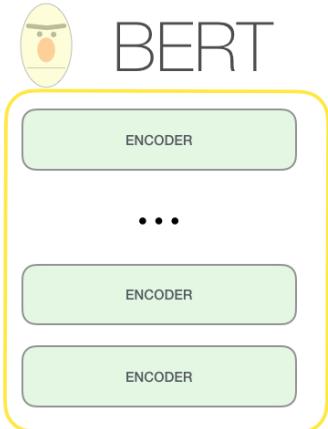


MoCo [He et al. 2019]



SimCLR [Chen et al. 2020]

Datasets + Labels: Self-Supervised Learning for NLP



Wikipedia
From Wikipedia, the free encyclopedia

This article is about the Internet encyclopedia. For Wikipedia's home page, see [Main Page](#). For other uses, see [Wikipedia \(disambiguation\)](#).

For Wikipedia's visitor introduction, see [Wikipedia:About](#).

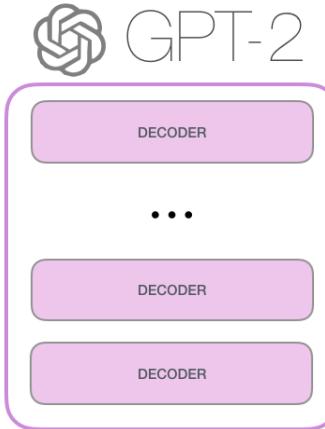
Wikipedia, (<https://en.wikipedia.org/>) or (<https://wikipedia.org/>) owned by the nonprofit organization [Wikimedia Foundation](#),^{[5][6][7]} is a free Internet encyclopedia that allows its users to edit almost any article accessible.^[8] Wikipedia is the largest and most popular general reference work on the Internet^{[9][10][11]} and is ranked among the ten most popular websites.^[4]

Wikipedia was launched on January 15, 2001 by Jimmy Wales and Larry Sanger. Sanger^[12] coined its name,^[13] a portmanteau of *wiki*^[notes 3] and *encyclopedia*. It was only in the English language initially, but it quickly developed similar versions in other languages which differ in content and in editing practices. With 5,203,037 articles, English Wikipedia is the largest out of more than 290 versions of encyclopedias on Wikipedia. Overall, Wikipedia consists of more than 40 million articles in more than 250 different languages^[15] and as of February 2014, it had 18 billion page views and nearly 500 million unique visitors each month.^[16]

In 2005, *Nature* published a peer review comparing 42 science articles from *Encyclopædia Britannica* and Wikipedia, and found that Wikipedia's level of accuracy approached *Encyclopædia Britannica's*.^[17] Criticism of Wikipedia includes claims that it exhibits systemic bias, presents a mixture of "truths, half truths, and some falsehoods",^[18] and that in controversial topics, it is subject to manipulation and spin.^[19]

Contents [hide]

- 1 History
- 1.1 Nupedia
- 1.2 Launch and early growth
- 1.3 Present milestones



BBC NEWS NORTHERN IRELAND

25 September 2013 Last updated at 11:20 GMT

Easter Rising: Trinity College Dublin launches letters appeal

A leading Irish university has launched an ambitious project aimed at understanding more about one of the most tumultuous periods in the country's history.

Trinity College Dublin is gathering letters and photographs from the year spanning the 1916 Easter Rising to build a new digital archive on ordinary life in the period.

It has appealed to the public - north and south of the border - for help by uploading old family letters and photographs to the archive.

The Letters of 1916: Creating History already includes letters from various public Irish institutions like the National Library of Ireland, the National Archives of Ireland, Trinity College itself and University College Dublin.

Dr Susan Schreiber, an associate professor at Trinity and the project's principal investigator, said: "When people write history it's the grand narrative, the big events, the important people, but people were living very ordinary lives through these extraordinary times."

"As we approach the centenary of the Easter Rising we want to try to get a sense of how ordinary people coped with one of the most disruptive periods in contemporary Irish history - from loved ones serving in the British Army and Dublin itself becoming a theatre of war, to the business of state carried out by government."

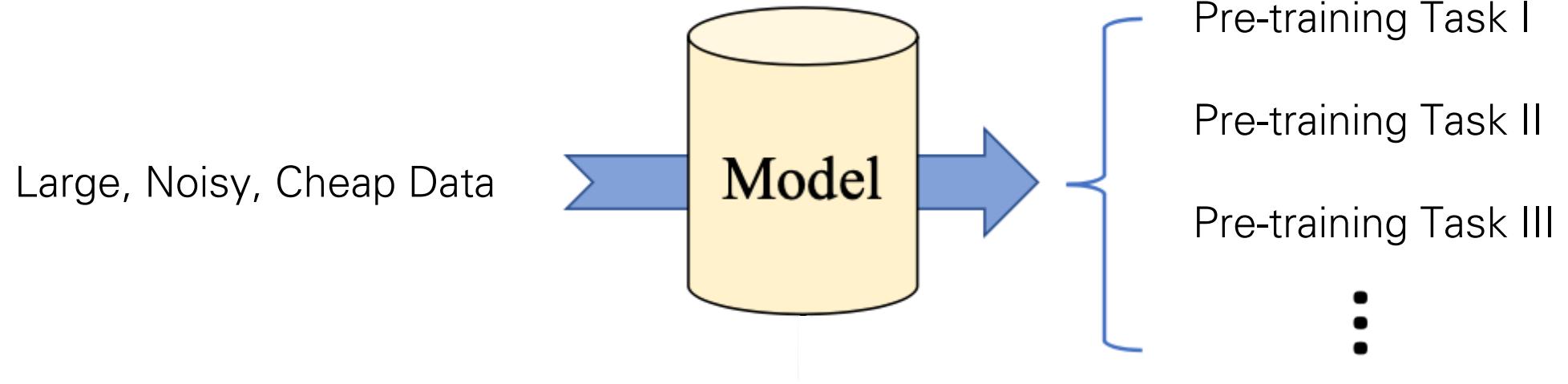
Top Stories

- Iran wants nuclear deal 'in months'
- China general's son jailed for rape
- Europe's key animals 'recovering'
- Foreign experts join Kenya clue hunt
- US spies targeted Martin Luther King

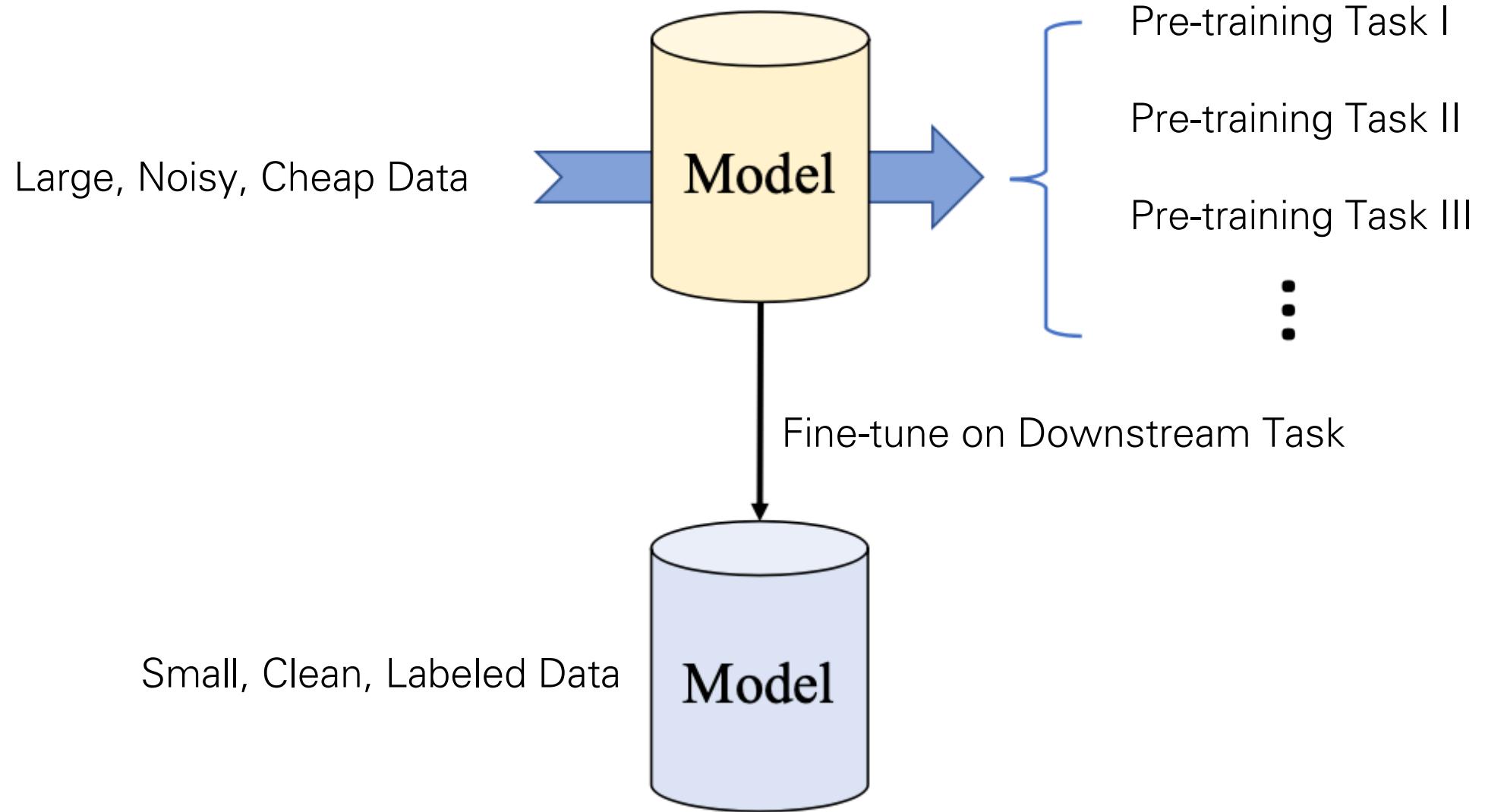
Features & Analysis

- In the cooler
- How yoga is helping prison stay calm
- Digital do-gooders

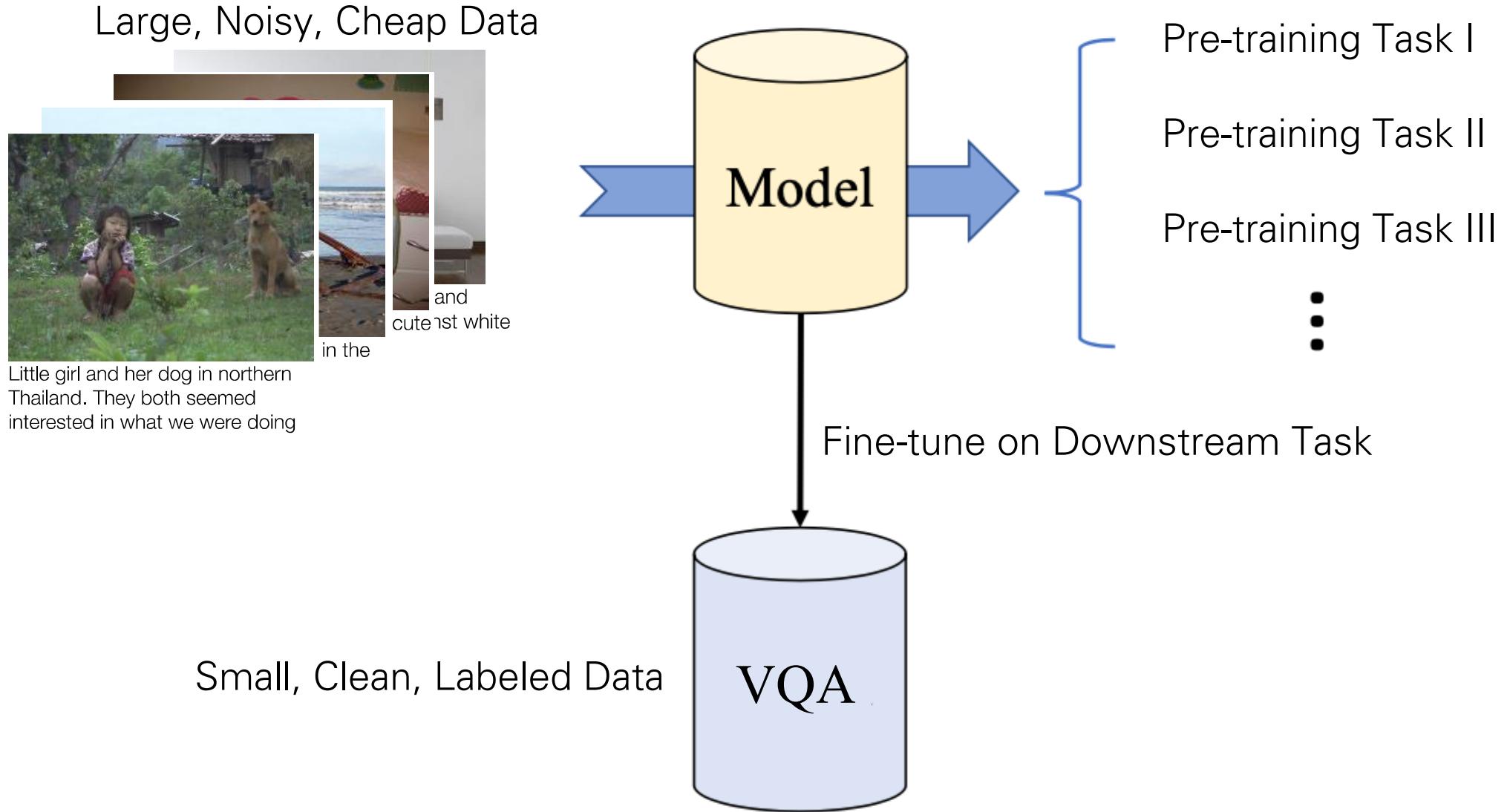
Pre-training + Finetuning



Pre-training + Finetuning

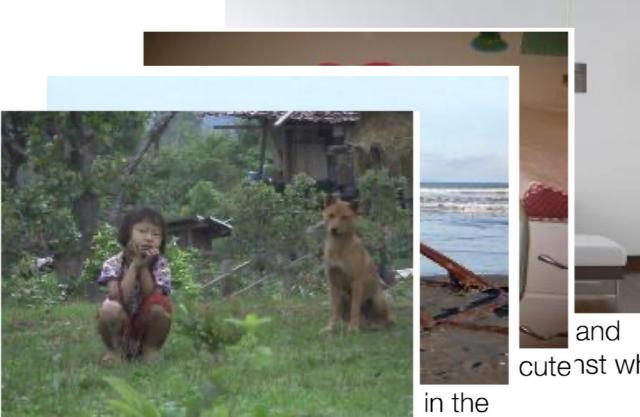


Self-Supervised Learning for V+L



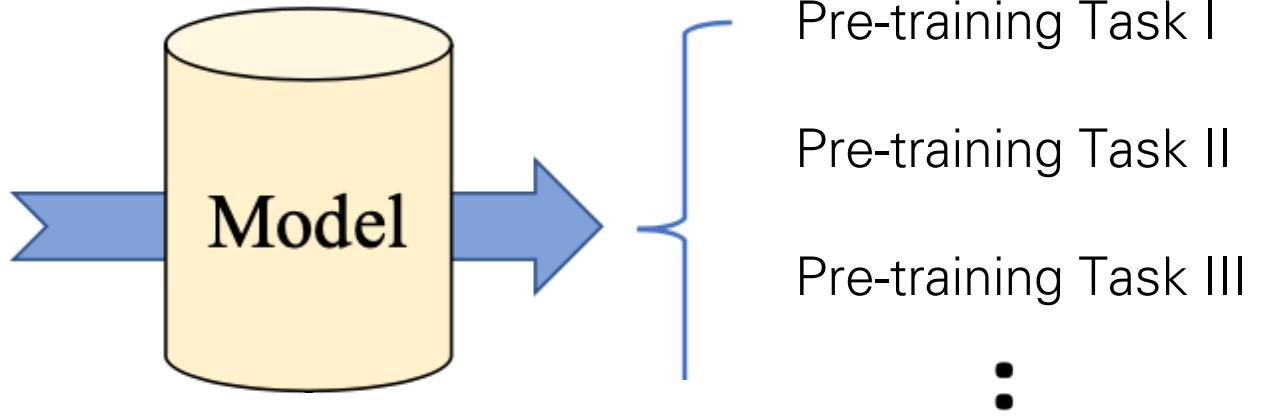
Generalization

Large, Noisy, Cheap Data

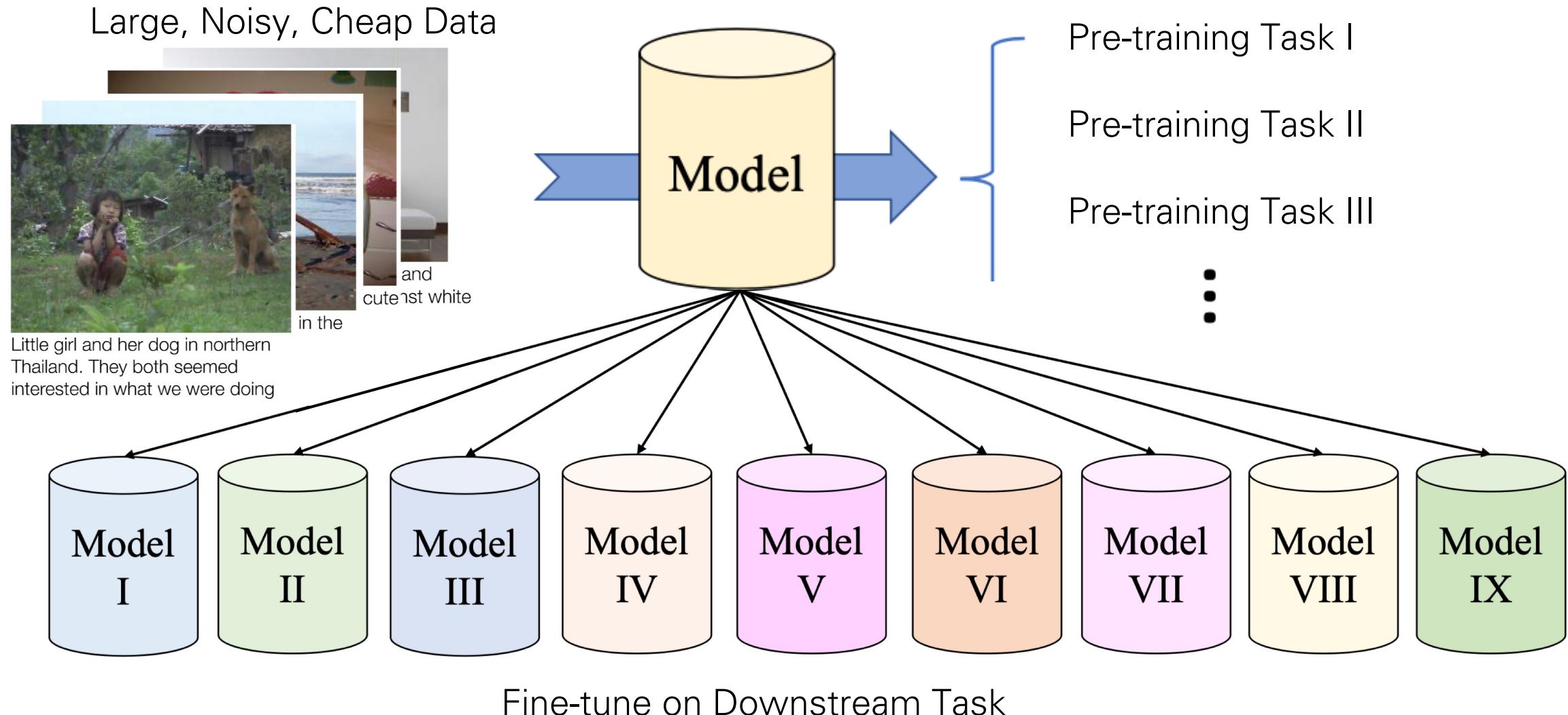


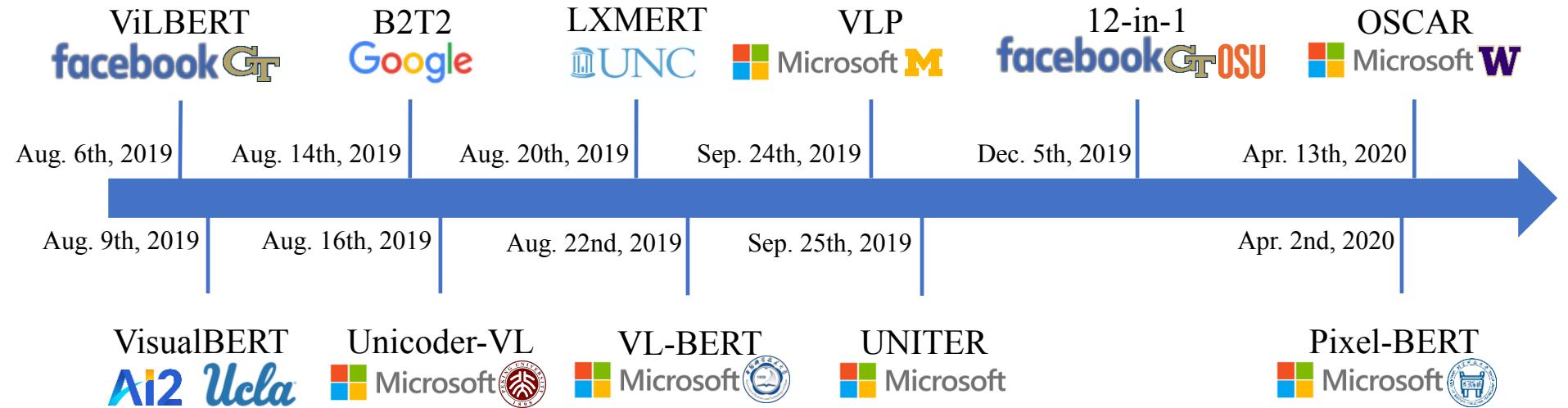
Little girl and her dog in northern Thailand. They both seemed interested in what we were doing

in the
and
cute&st white



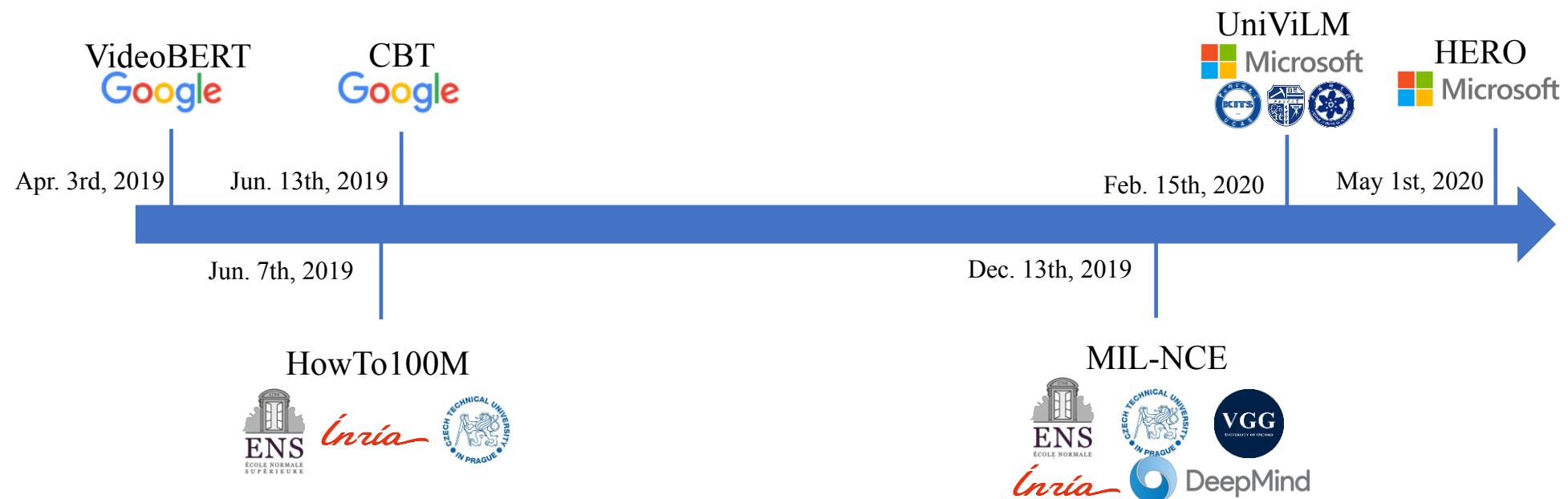
Generalization





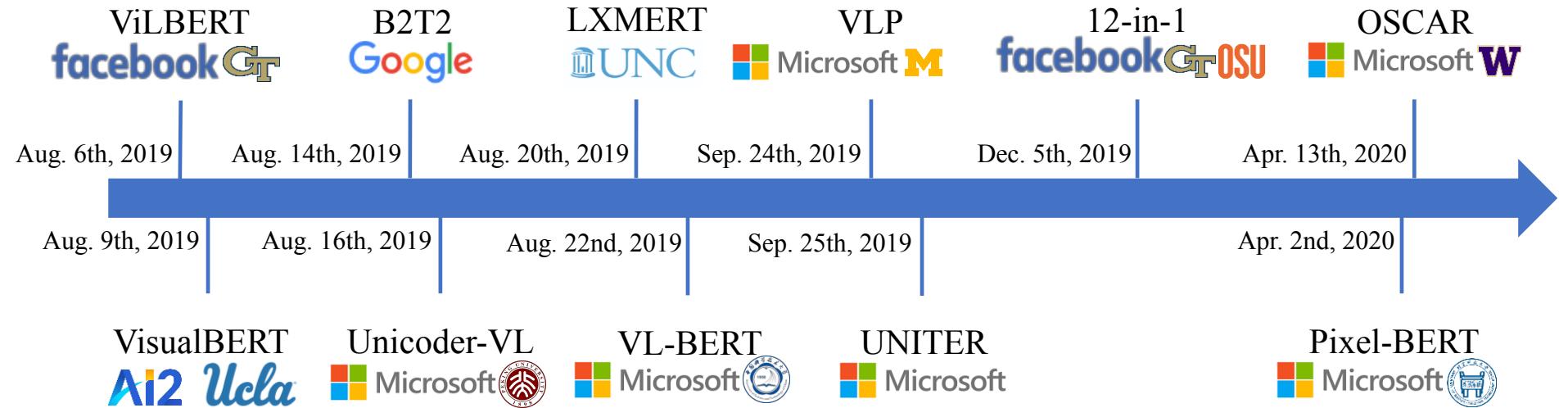
Downstream Tasks

- VQA • VCR • NLVR2
- Visual Entailment
- Referring Expressions
- Image-Text Retrieval
- Image Captioning



Downstream Tasks

- Video QA
- Video-and-Language Inference
- Video Captioning
- Video Moment Retrieval



Downstream Tasks

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Pre-training Vision+Language Data

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'man with his dog on a couch'

)

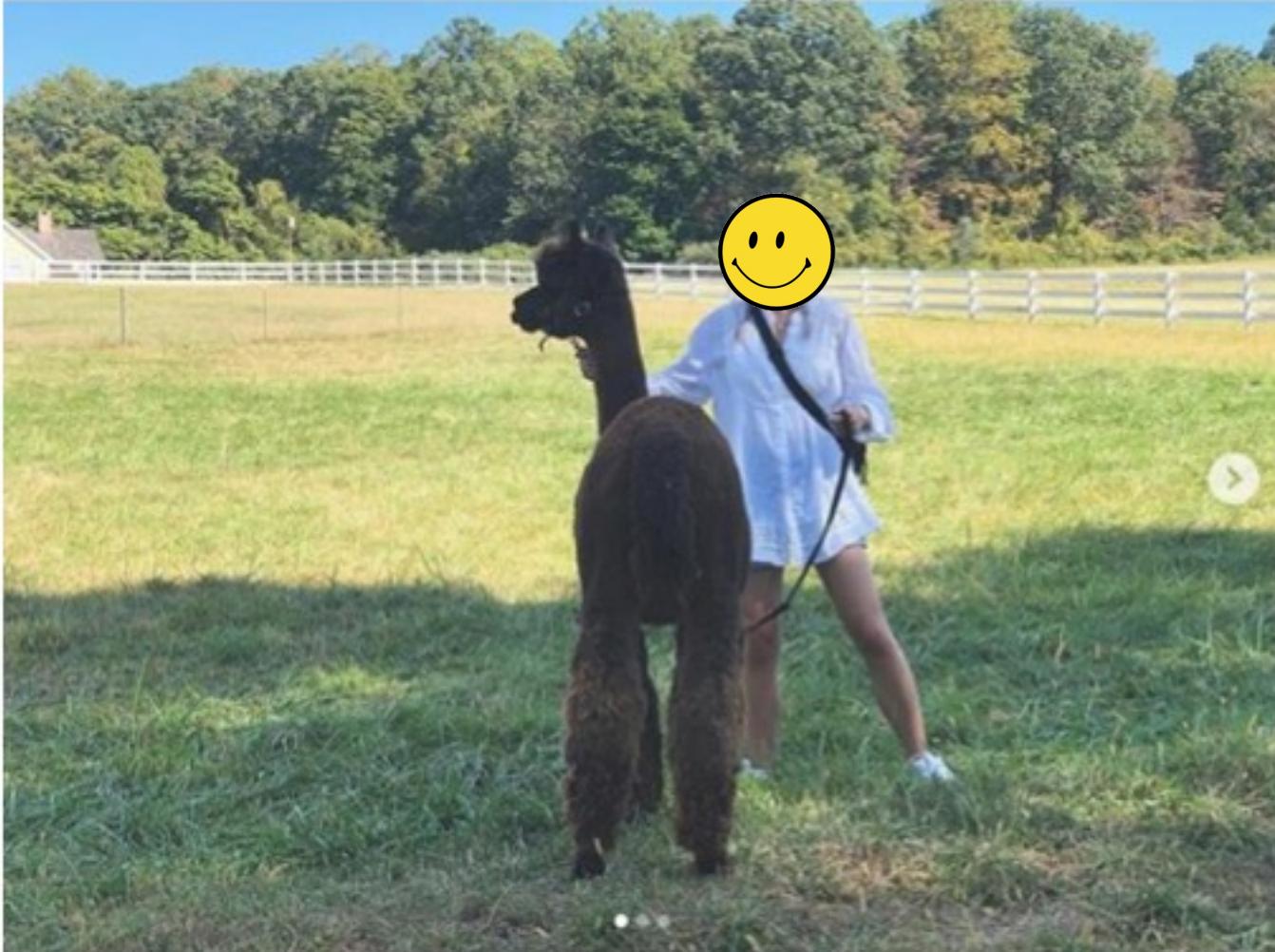
Free Data for Vision + Language



Free Data for Vision + Language



Free Data for Vision + Language



A photograph of a person in a blue shirt and shorts walking a dark brown alpaca on a leash in a grassy field. A yellow smiley face emoji is overlaid on the alpaca's head. In the background, there is a white fence and a line of trees under a clear blue sky.

• Follow
Bluebird Farm Alpacas

The alpaca was actually walking me, and I'm okay with that

#neverstopexploring #newyork
#alpaca #positivevibes #teamcozy
#shecozy #citylimitless
#portraitphotography #portrait
#vacationmode

144 likes

5 HOURS AGO

Add a comment... Post

Common Pre-training Data for VL

Split	In-domain		Out-of-domain	
	COCO Captions	VG Dense Captions	Conceptual Captions	SBU Captions
train	533K (106K)	5.06M (101K)	3.0M (3.0M)	990K (990K)
val	25K (5K)	106K (2.1K)	14K (14K)	10K (10K)

Conceptual Caption



Alt-text: A Pakistani worker helps to clear the debris from the Taj Maha Hotel November 7, 2005 in Balakot, Pakistan

Conceptual Captions: a worker helps to clear the debris.

SBU Caption



Little girl and her dog in northern Thailand. They both seemed interested in what we are doing

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Visual and Language Features

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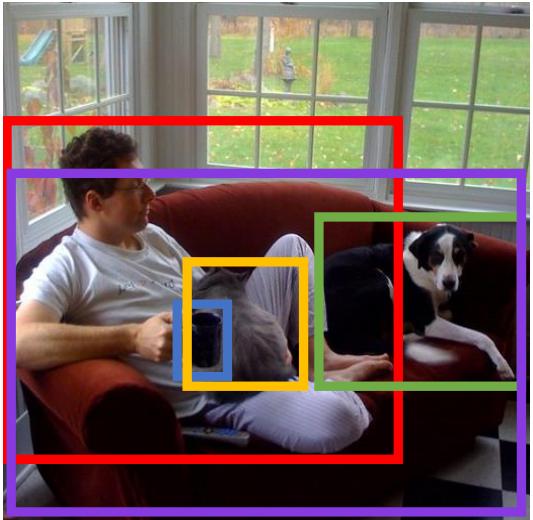
,

“man with his dog on a couch”

)

Visual and Language Features

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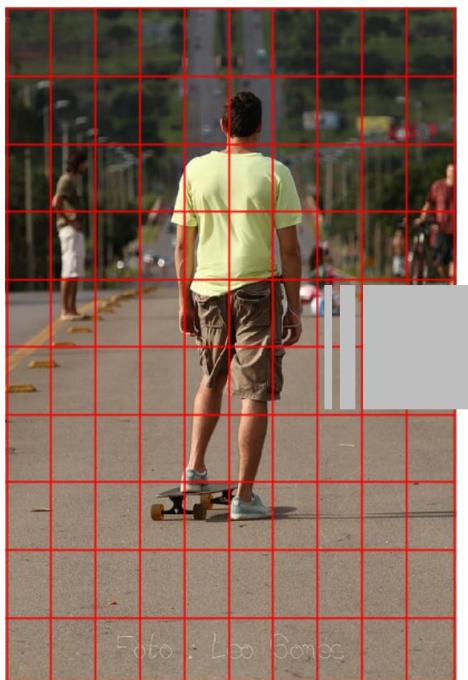


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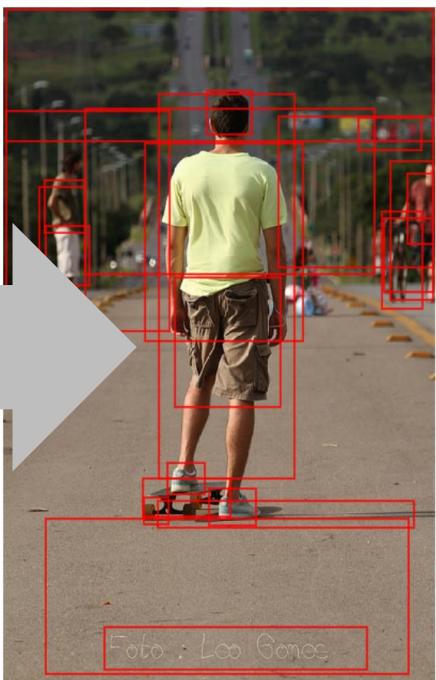
'man' 'with' 'his' 'dog' 'on' 'a' 'couch'

)

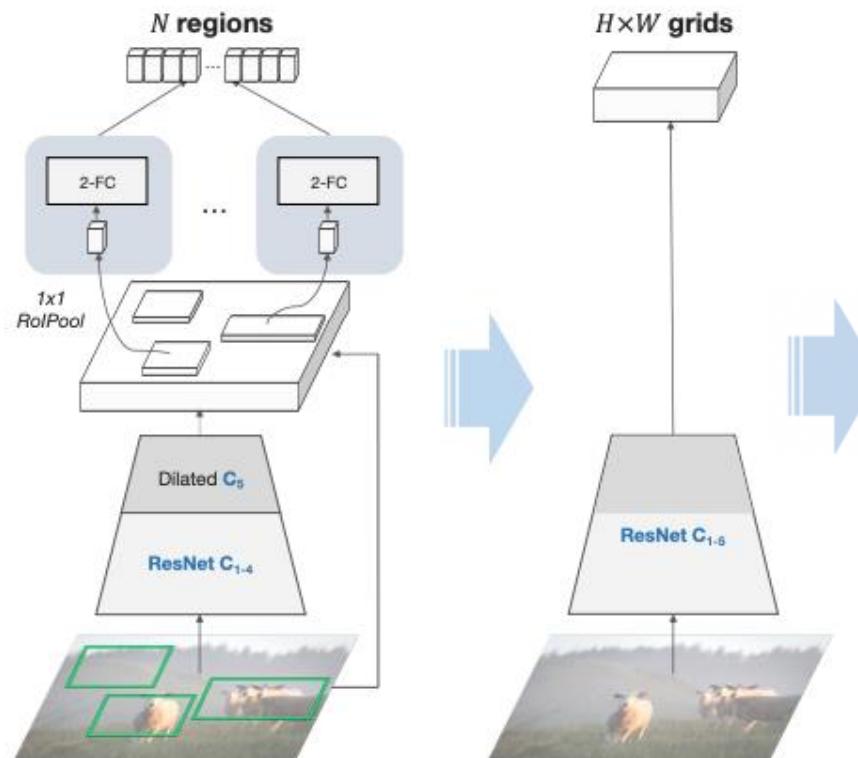
Visual Features



Pre-2017: grid feature maps
[Ren et al., NeurIPS 2015]

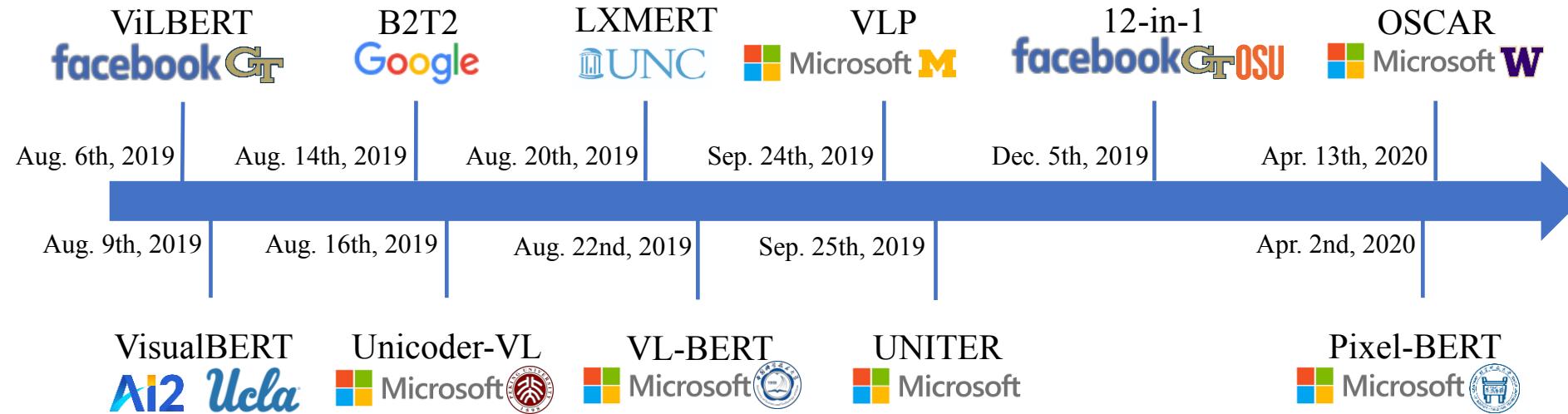


Post-2017: region features
[Anderson et al., CVPR 2018]



Lecture overview

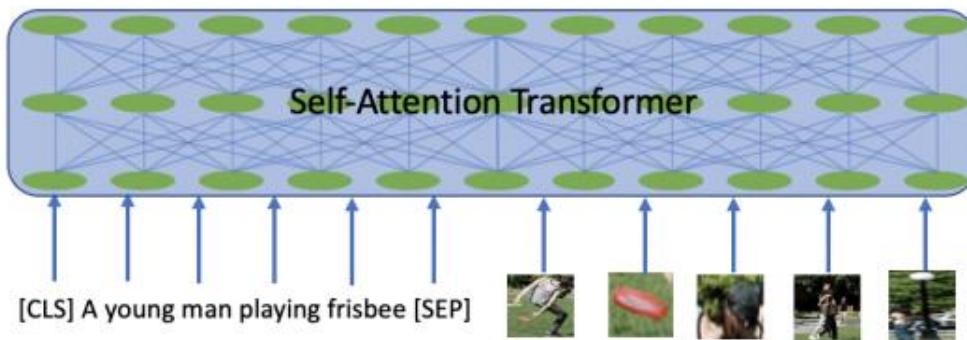
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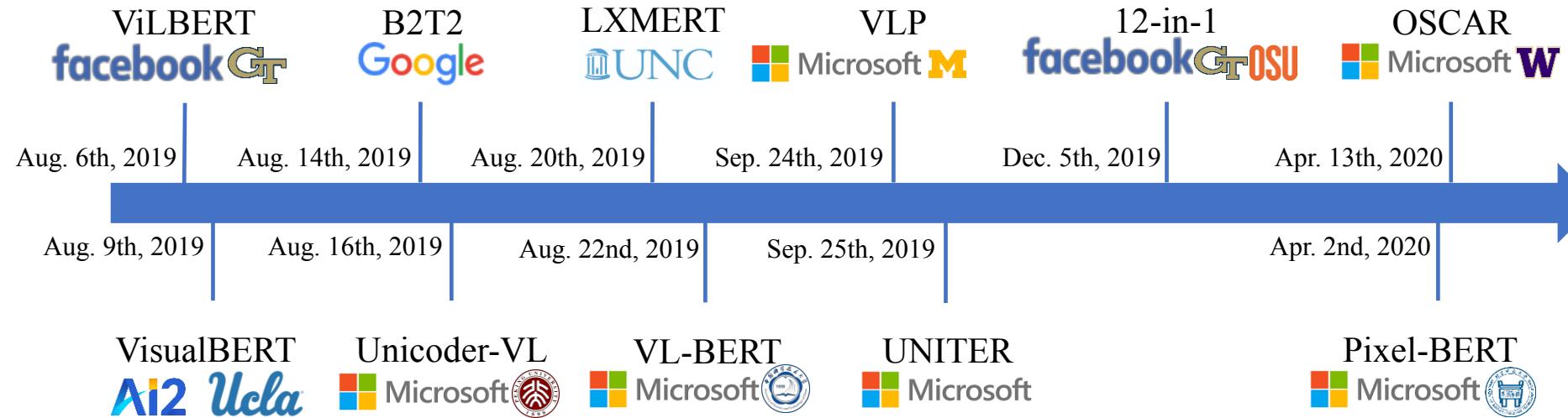
Downstream Tasks

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Model Architecture:



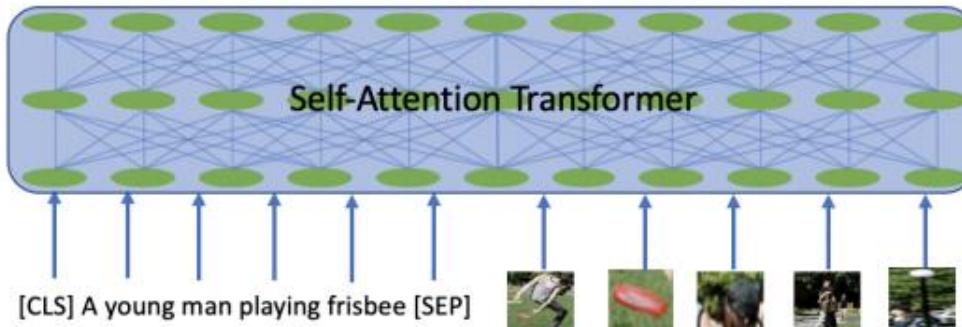
(a) Single-stream Model



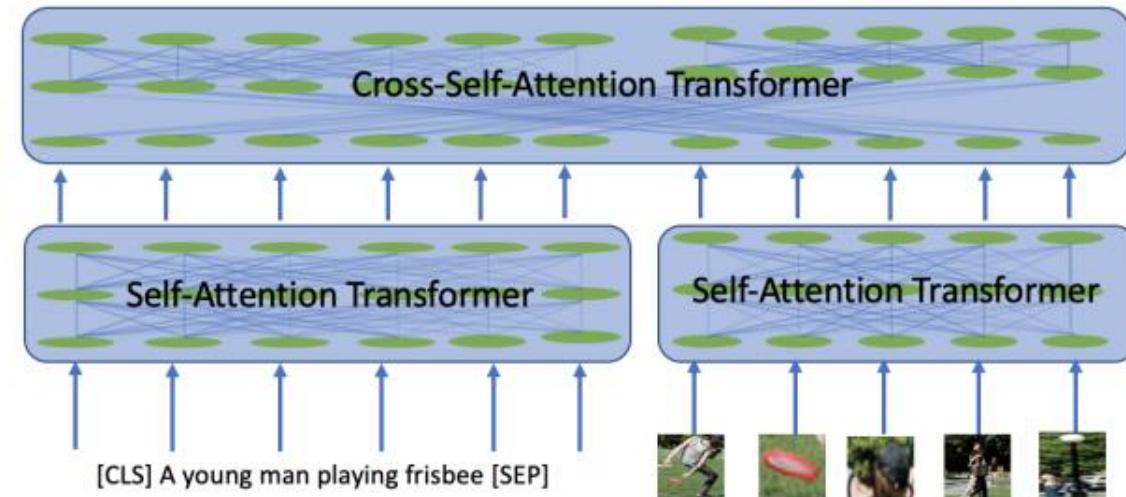
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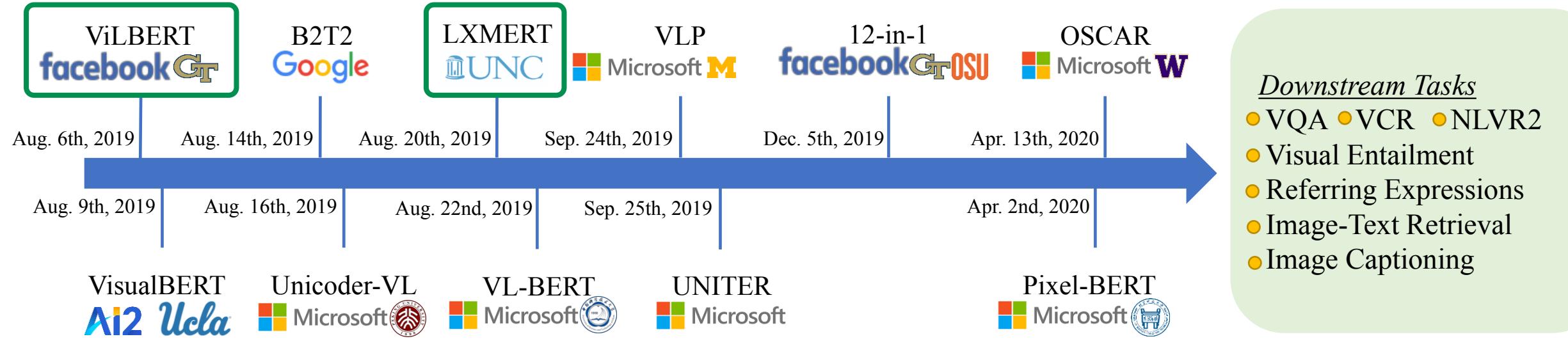
Model Architecture:



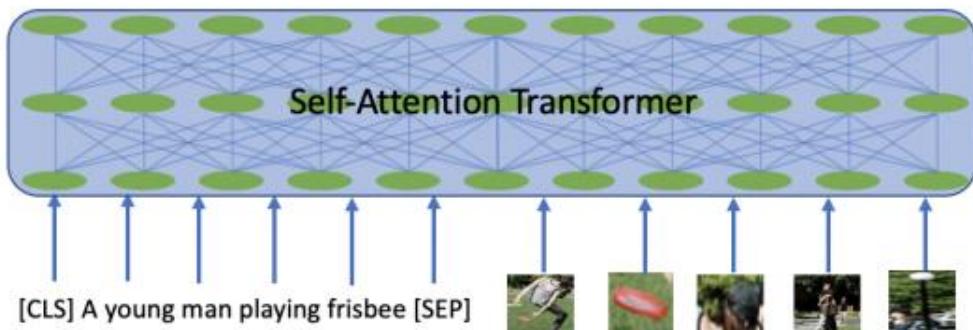
(a) Single-stream Model



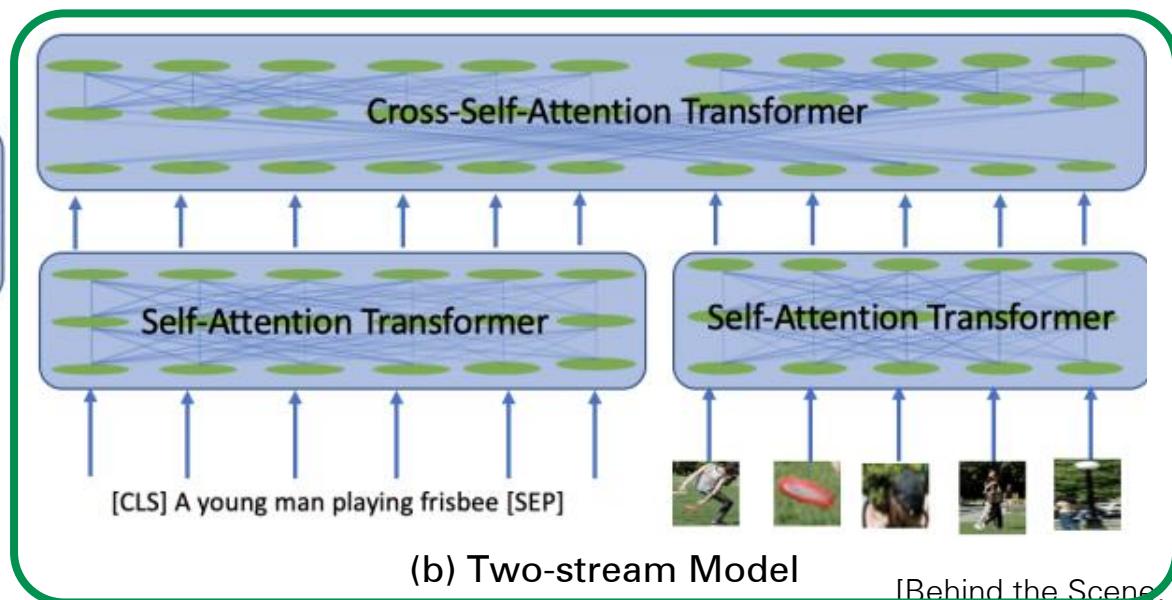
(b) Two-stream Model



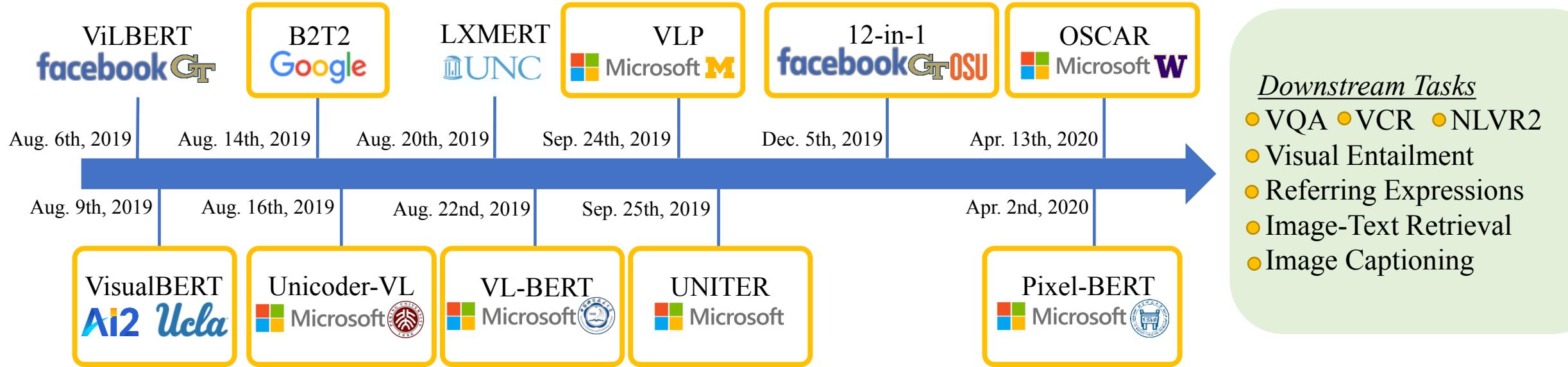
Model Architecture:



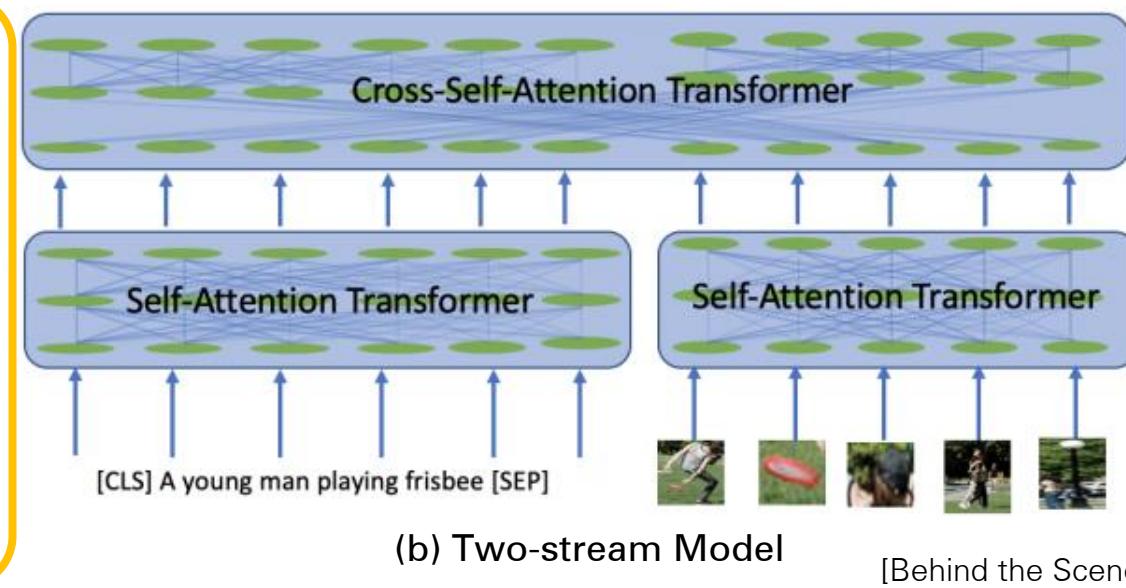
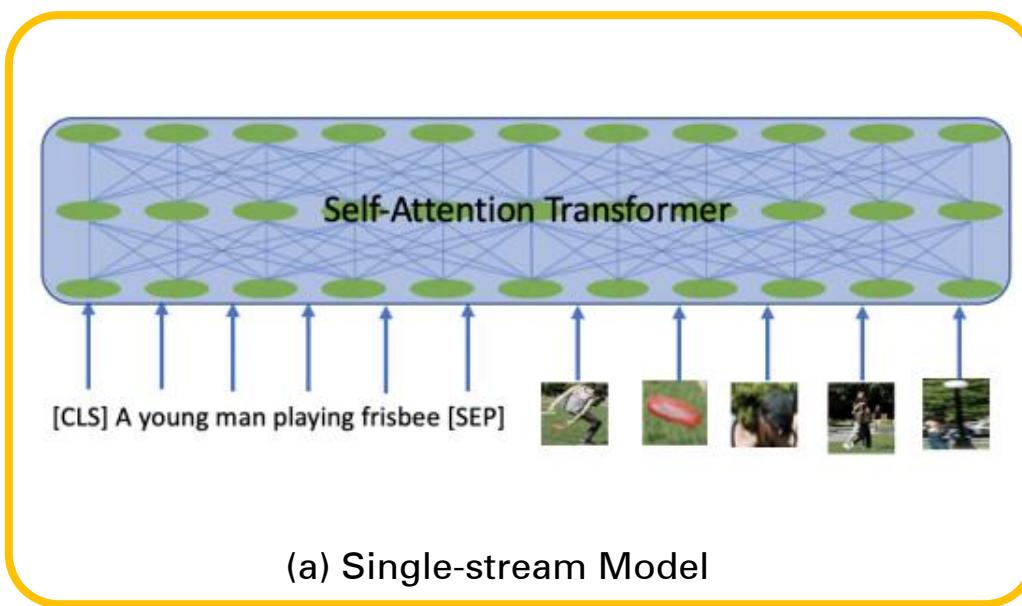
(a) Single-stream Model



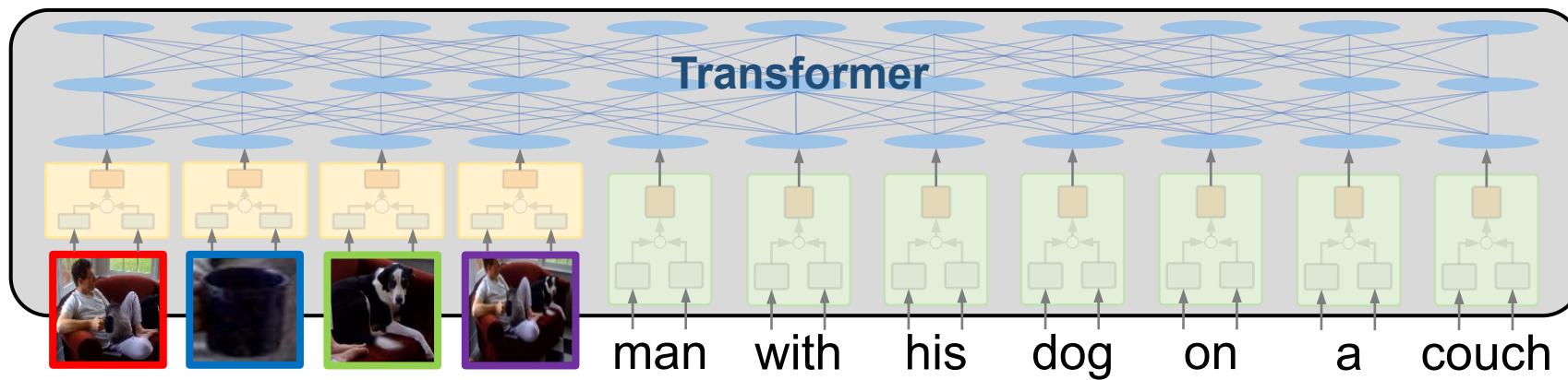
(b) Two-stream Model



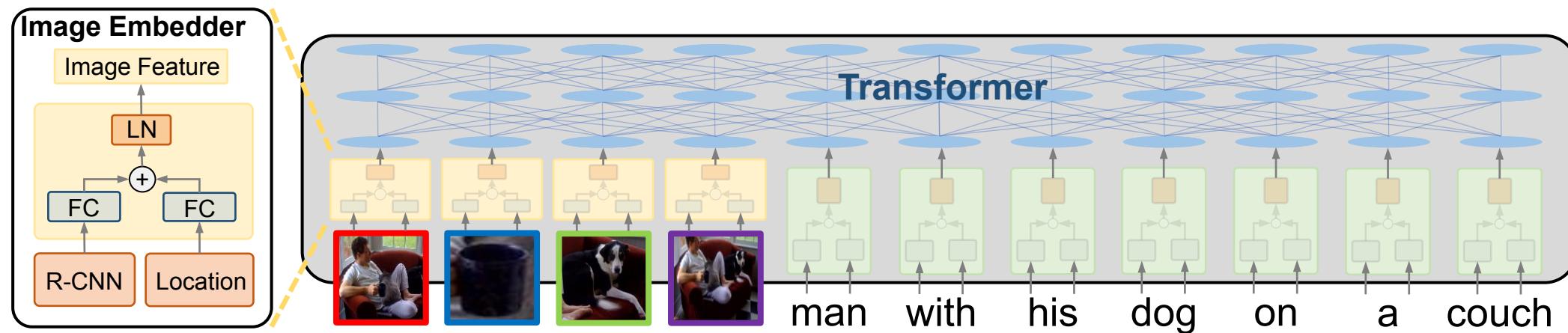
Model Architecture:



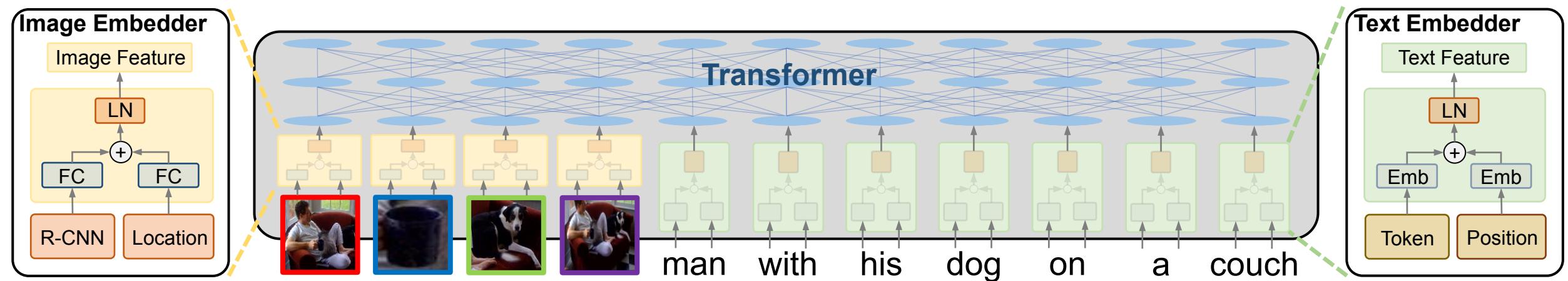
Single-Stream Architecture



Single-Stream Architecture



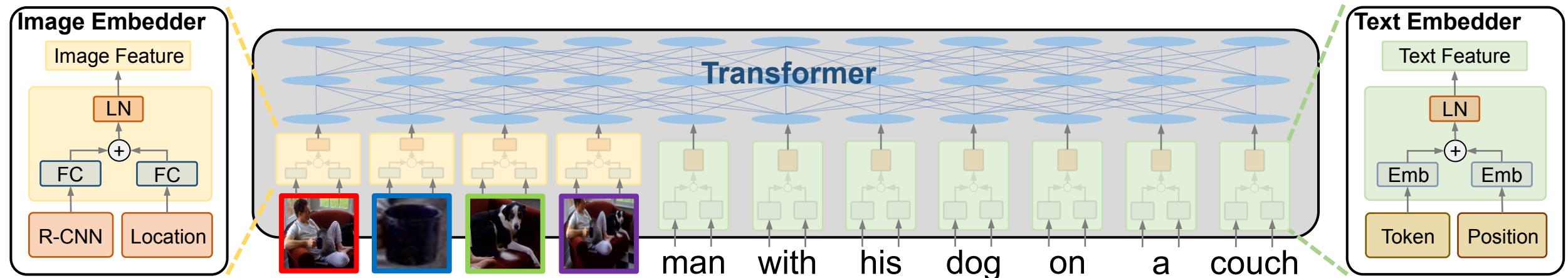
Single-Stream Architecture



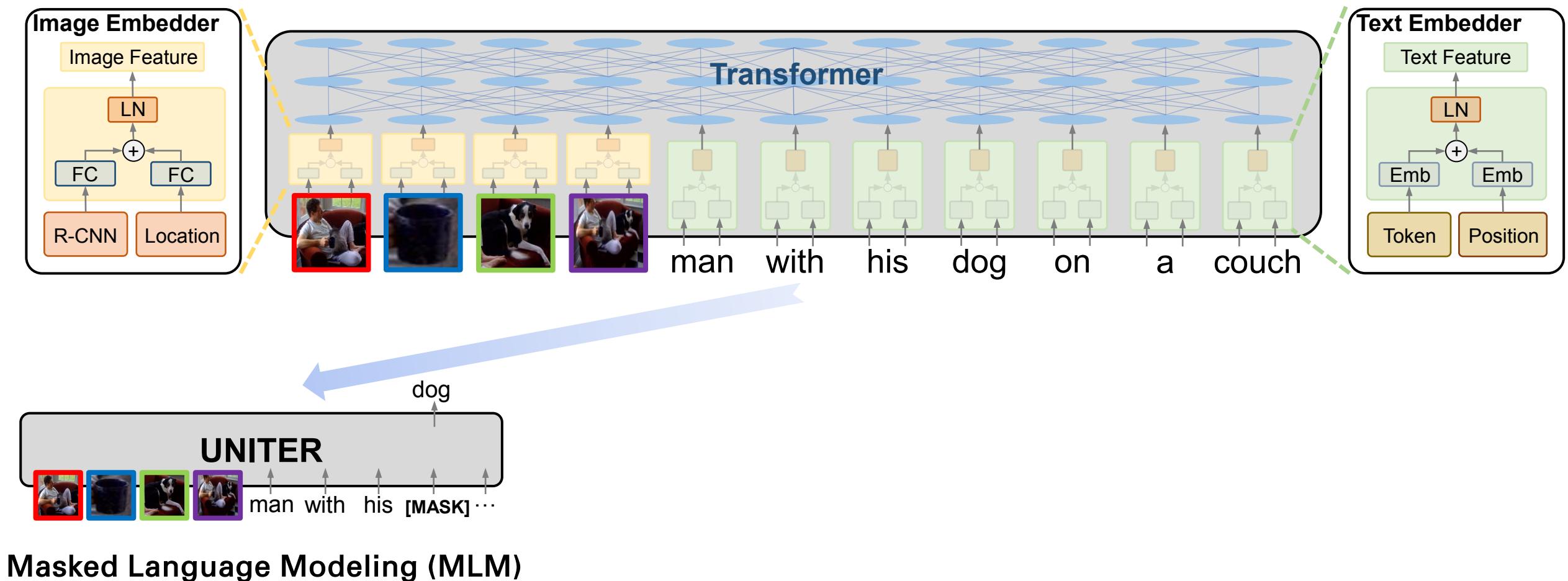
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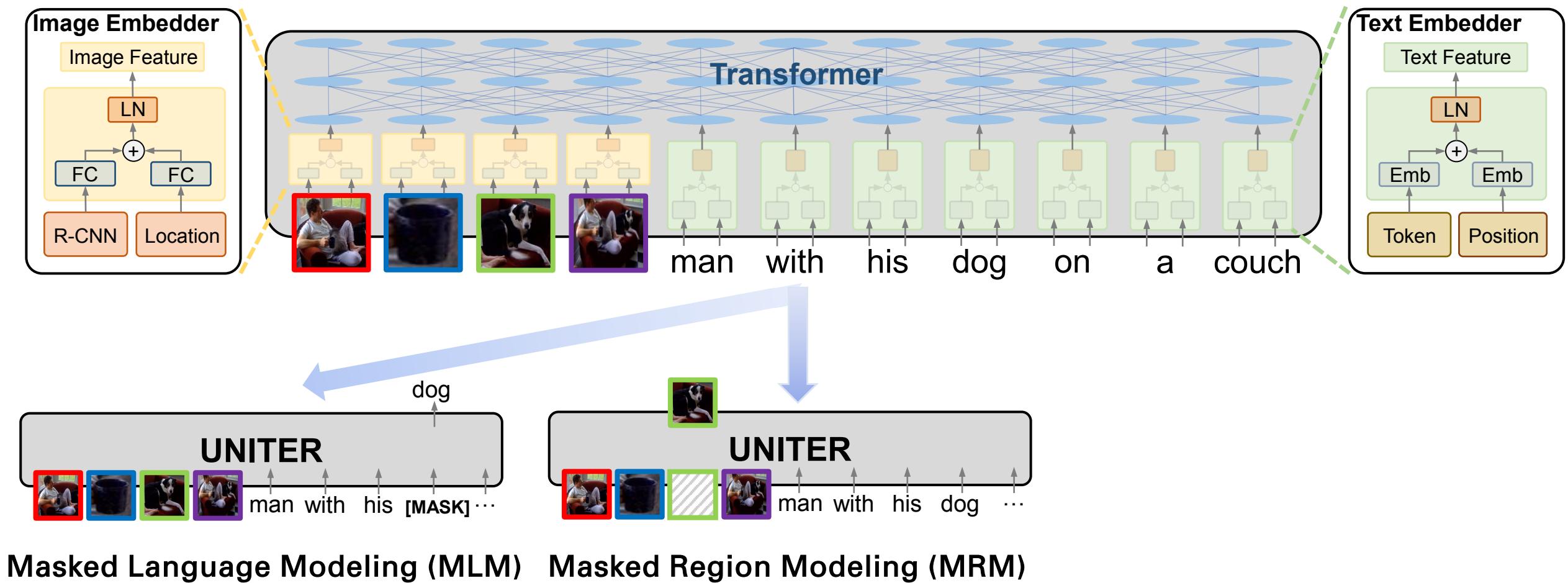
Pretraining Tasks



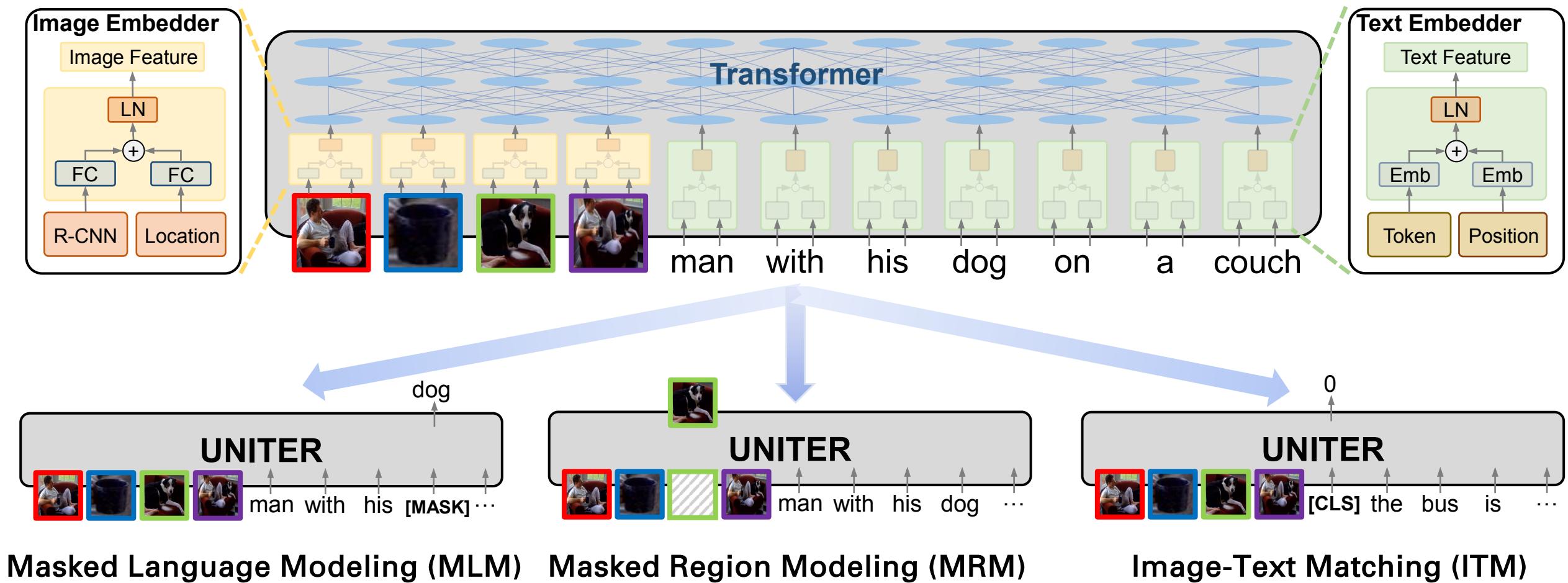
Pretraining Tasks



Pretraining Tasks



Pretraining Tasks



Pretraining Tasks



Masked Language Modeling (MLM)

Image Regions: $\mathbf{v} = \{v_1, \dots, v_K\}$

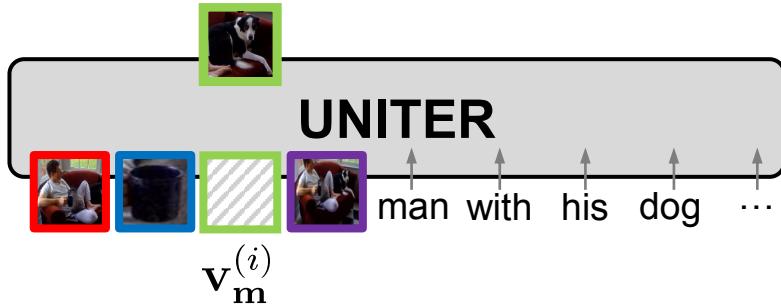
Sentence Tokens: $\mathbf{w} = \{w_1, \dots, w_T\}$

Masking Indices: $\mathbf{m} \in \mathbb{N}^M$

Loss Function of Masked Language Modeling (MLM):

$$\mathcal{L}_{\text{MLM}}(\theta) = -E_{(\mathbf{w}, \mathbf{v}) \sim D} \log P_\theta(\mathbf{w}_m | \mathbf{w}_{\setminus m}, \mathbf{v}).$$

Pretraining Tasks



Masked Region Modeling (MRM)

Image Regions: $\mathbf{v} = \{v_1, \dots, v_K\}$

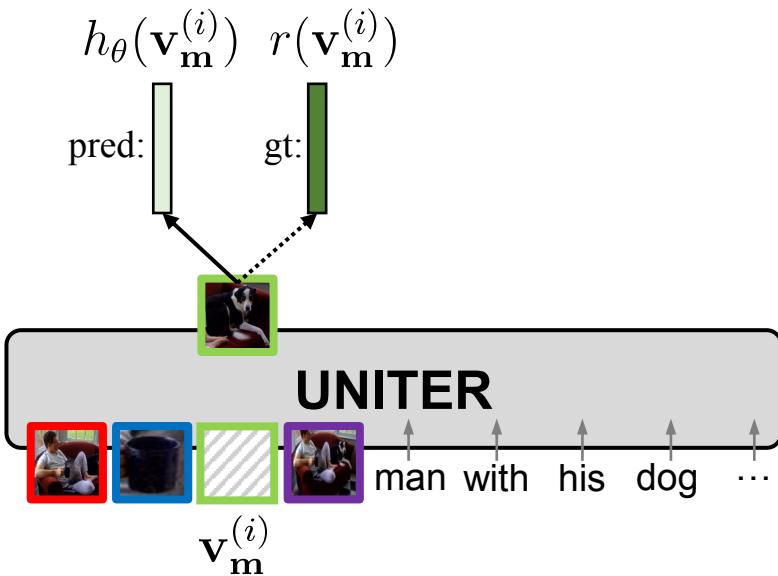
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Pretraining Tasks



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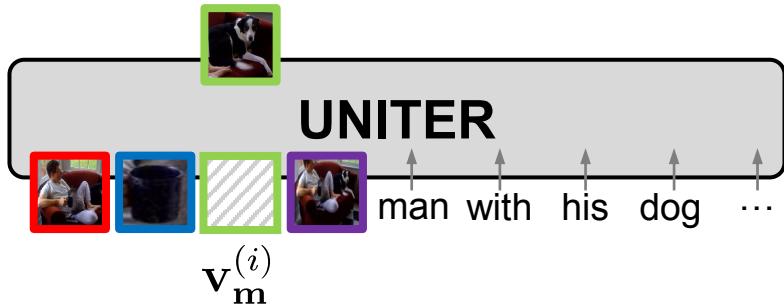
Loss Function of Masked Language Modeling (MLM):

$$\mathcal{L}_{\text{MLM}}(\theta) = -E_{(\mathbf{w}, \mathbf{v}) \sim D} \log P_\theta(\mathbf{w}_m | \mathbf{w}_{\setminus m}, \mathbf{v}).$$

1) Objective of Masked Region Feature Regression (MRFR)

$$f_\theta(\mathbf{v}_m | \mathbf{v}_{\setminus m}, \mathbf{w}) = \sum_{i=1}^M \|h_\theta(\mathbf{v}_m^{(i)}) - r(\mathbf{v}_m^{(i)})\|_2^2$$

Pretraining Tasks



Masked Region Modeling (MRM)

Image Regions: $\mathbf{v} = \{v_1, \dots, v_K\}$

Sentence Tokens: $\mathbf{w} = \{w_1, \dots, w_T\}$

Masking Indices: $\mathbf{m} \in \mathbb{N}^M$

Loss Function of Masked Language Modeling (MLM):

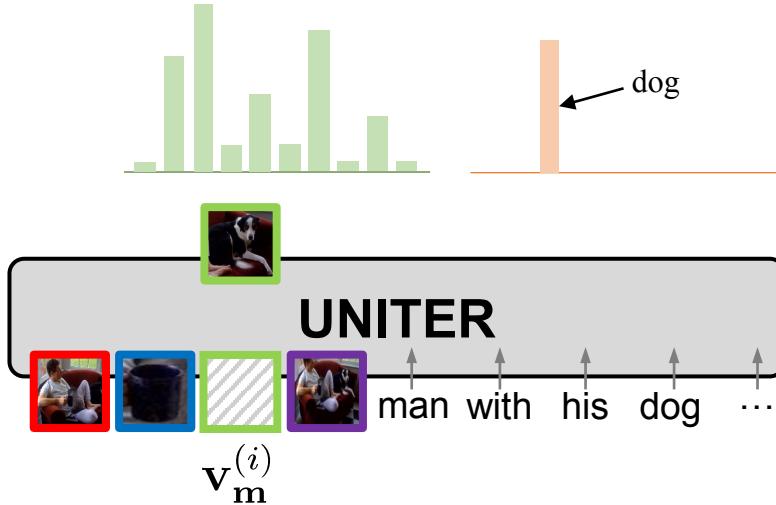
$$\mathcal{L}_{\text{MLM}}(\theta) = -E_{(\mathbf{w}, \mathbf{v}) \sim D} \log P_\theta(\mathbf{w}_m | \mathbf{w}_{\setminus m}, \mathbf{v}).$$

2) Objective of Masked Region Classification (MRC)

$$f_\theta(\mathbf{v}_m | \mathbf{v}_{\setminus m}, \mathbf{w}) = \sum_{i=1}^M \text{CE}(c(\mathbf{v}_m^{(i)}), g_\theta(\mathbf{v}_m^{(i)}))$$

Pretraining Tasks

$$g_{\theta}(\mathbf{v}_m^{(i)}) \in \mathbb{R}^K \quad c(\mathbf{v}_m^{(i)}) \in \mathbb{R}^K$$



Masked Region Modeling (MRM)

Image Regions: $\mathbf{v} = \{v_1, \dots, v_K\}$

Sentence Tokens: $\mathbf{w} = \{w_1, \dots, w_T\}$

Masking Indices: $\mathbf{m} \in \mathbb{N}^M$

Loss Function of Masked Language Modeling (MLM):

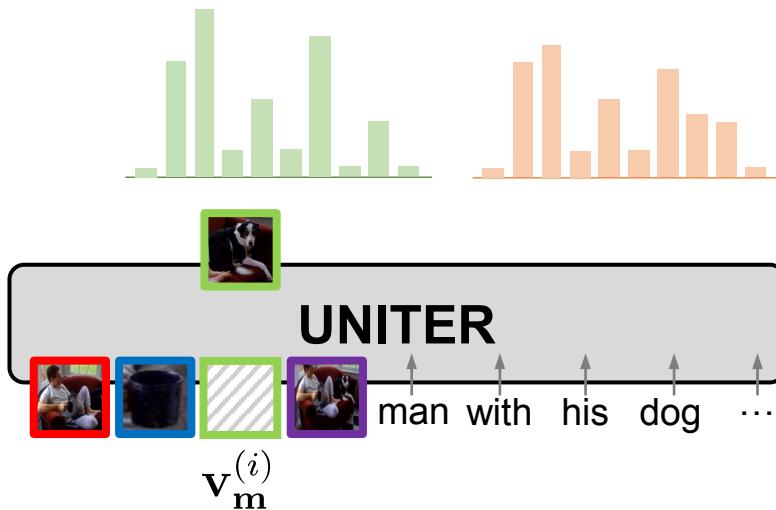
$$\mathcal{L}_{\text{MLM}}(\theta) = -E_{(\mathbf{w}, \mathbf{v}) \sim D} \log P_{\theta}(\mathbf{w}_m | \mathbf{w}_{\setminus m}, \mathbf{v}).$$

2) Objective of Masked Region Classification (MRC)

$$f_{\theta}(\mathbf{v}_m | \mathbf{v}_{\setminus m}, \mathbf{w}) = \sum_{i=1}^M \text{CE}(c(\mathbf{v}_m^{(i)}), g_{\theta}(\mathbf{v}_m^{(i)}))$$

Pretraining Tasks

$$g_{\theta}(\mathbf{v}_m^{(i)}) \in \mathbb{R}^K \quad \tilde{c}(\mathbf{v}_m^{(i)}) \in \mathbb{R}^K$$



Masked Region Modeling (MRM)

Image Regions: $\mathbf{v} = \{v_1, \dots, v_K\}$

Sentence Tokens: $\mathbf{w} = \{w_1, \dots, w_T\}$

Masking Indices: $\mathbf{m} \in \mathbb{N}^M$

Loss Function of Masked Language Modeling (MLM):

$$\mathcal{L}_{\text{MLM}}(\theta) = -E_{(\mathbf{w}, \mathbf{v}) \sim D} \log P_{\theta}(\mathbf{w}_m | \mathbf{w}_{\setminus m}, \mathbf{v}).$$

3) Objective of Masked Region Classification – KL Divergence (MRC-KL)

$$f_{\theta}(\mathbf{v}_m | \mathbf{v}_{\setminus m}, \mathbf{w}) = \sum_{i=1}^M D_{KL}(\tilde{c}(\mathbf{v}_m^{(i)}) || g_{\theta}(\mathbf{v}_m^{(i)}))$$

Pretraining Tasks

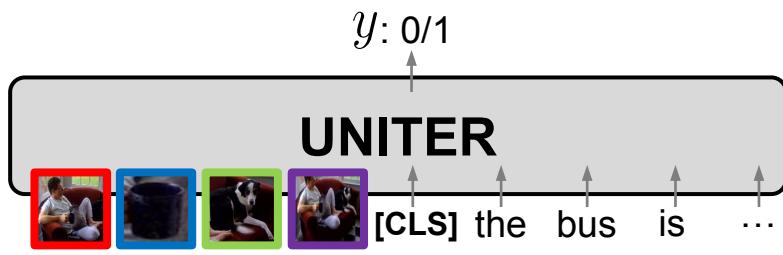


Image-Text Matching (ITM)

Image Regions: $\mathbf{v} = \{v_1, \dots, v_K\}$

Sentence Tokens: $\mathbf{w} = \{w_1, \dots, w_T\}$

Loss Function of Image-Text Matching (ITM)

$$\mathcal{L}_{\text{ITM}}(\theta) = -E_{(\mathbf{w}, \mathbf{v}) \sim D} [y \log s_\theta(\mathbf{w}, \mathbf{v}) + (1 - y) \log(1 - s_\theta(\mathbf{w}, \mathbf{v}))].$$

Pretraining Tasks

- UNITER: Word-Region Alignment [Chen et al., 2019]
- VLP: Left-to-Right Language Modeling [Zhou et al., AAAI 2019]
- 12-in-1: Multi-task Learning [Lu et al., CVPR 2020]
- LXMERT: Multi-task Learning [Tan and Bansal, EMNLP 2019]
- OSCAR: Multi-View Alignment (tokens, tags, regions) [Li et al., 2020]
- ...

Lecture overview

- Introduction
- Pre-training data
- Feature representations for vision and language
- Model architectures
- Pre-training tasks
- **Downstream tasks**
- Moving forward

Downstream Task 1: Visual Question Answering



What color are her eyes?
What is the mustache made of?



How many slices of pizza are there?
Is this a vegetarian pizza?

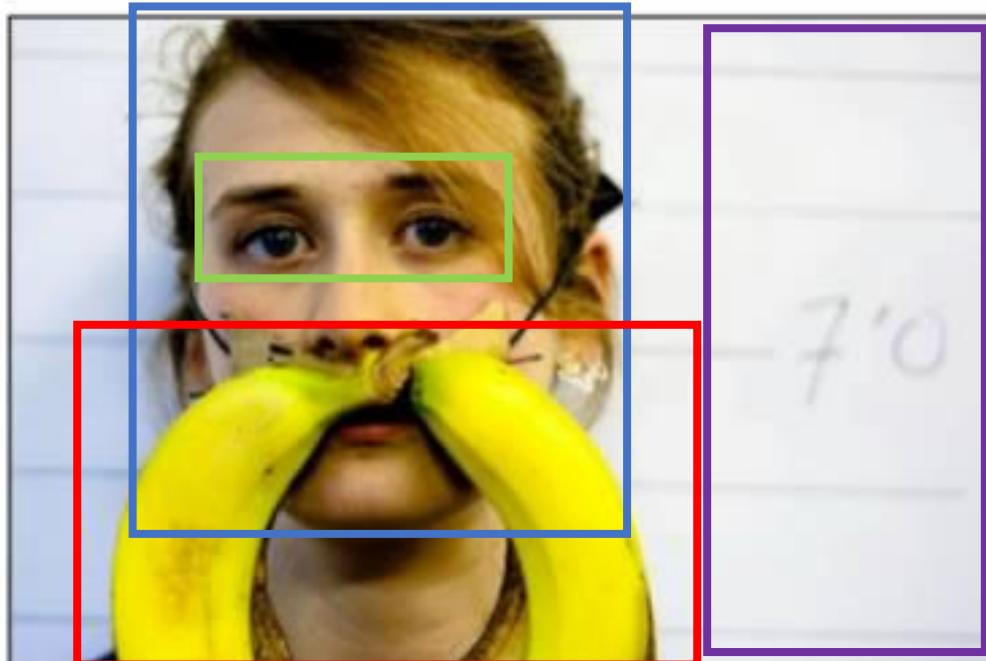


Is this person expecting company?
What is just under the tree?

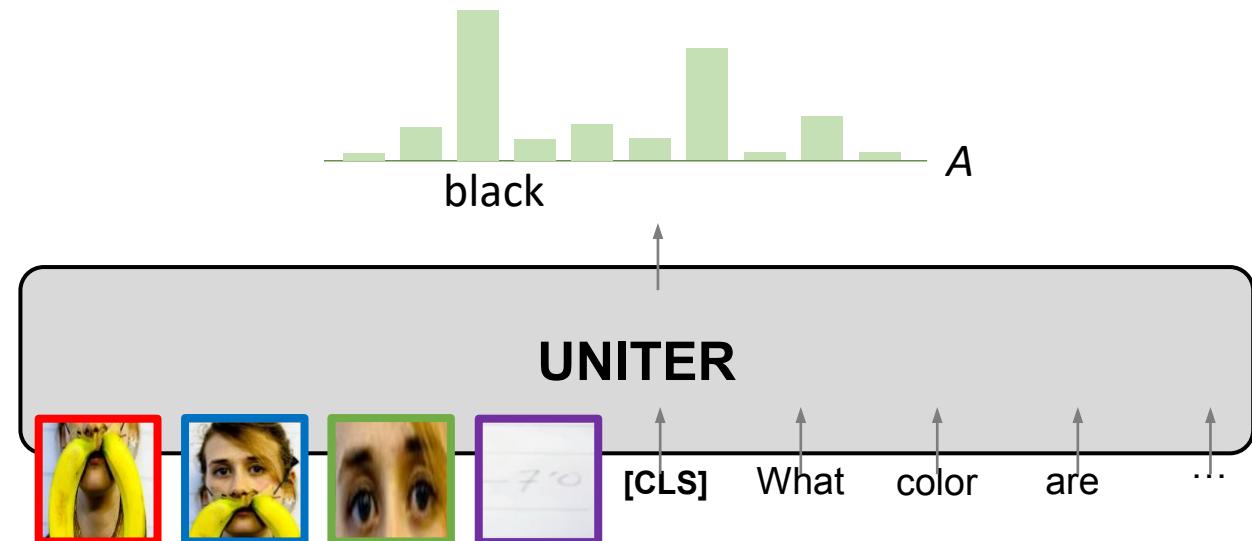


Does it appear to be rainy?
Does this person have 20/20 vision?

Downstream Task 1: Visual Question Answering



What color are her eyes?



Downstream Task 2: Visual Entailment



Premise

+

- 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.

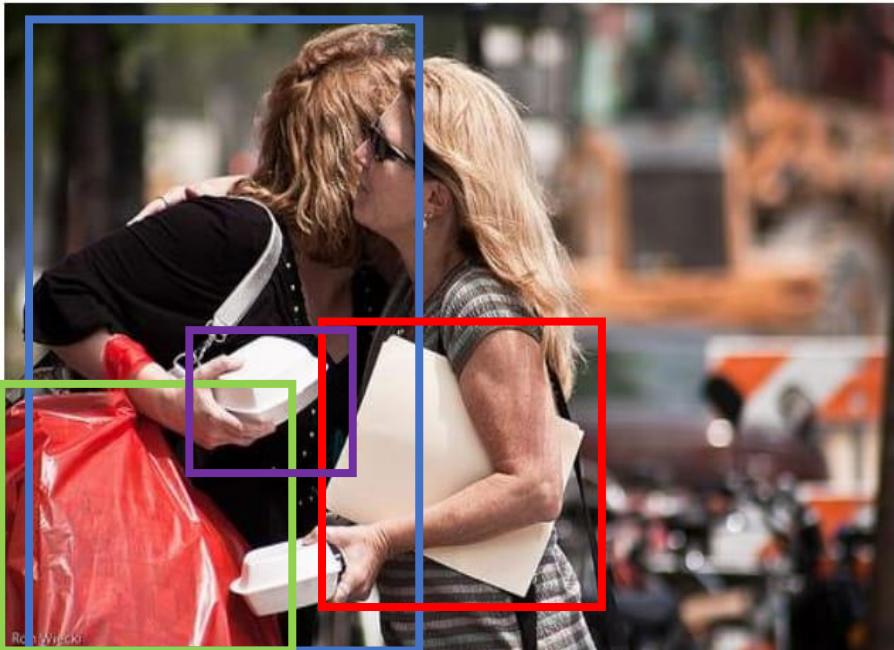
Hypothesis

=

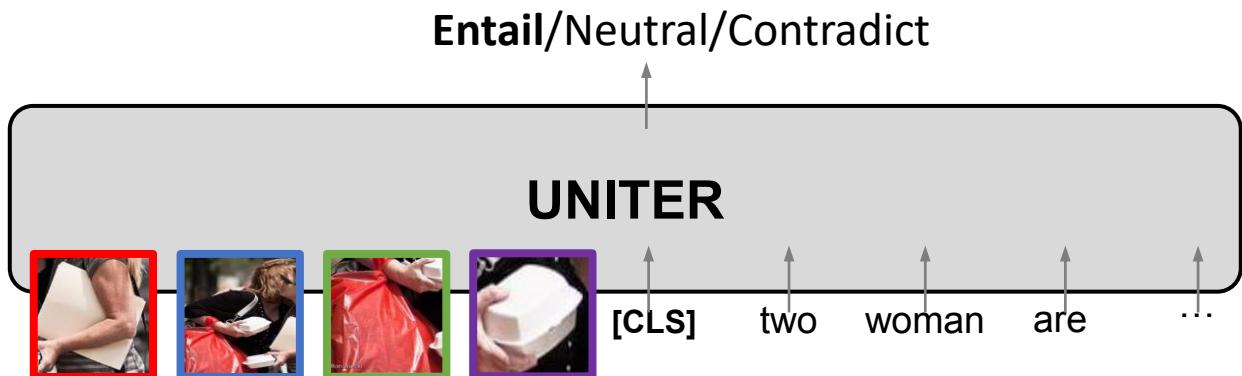
- Entailment
- Neutral
- Contradiction

Answer

Downstream Task 2: Visual Entailment



Two woman are holding
packages.



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.

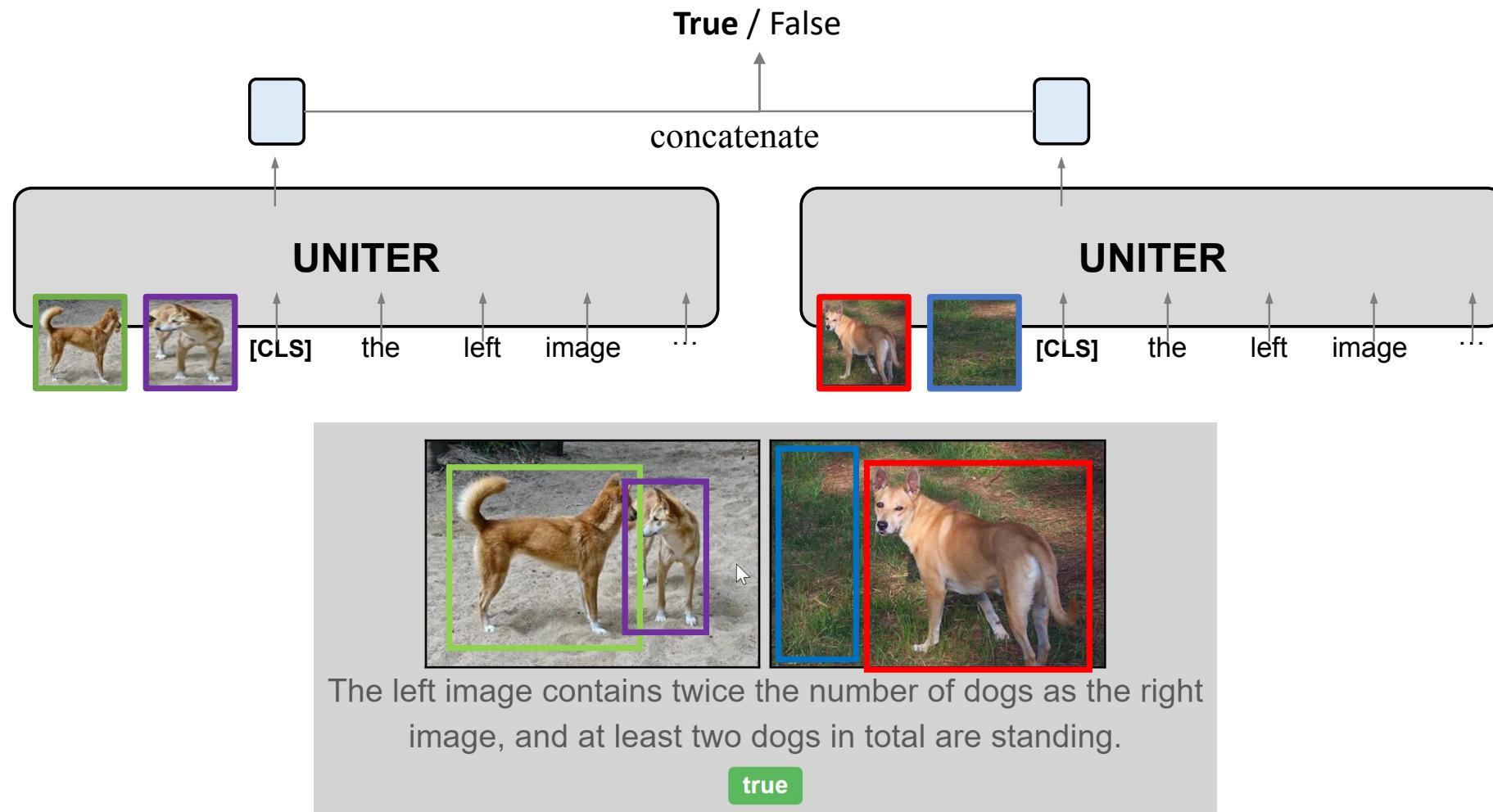
true



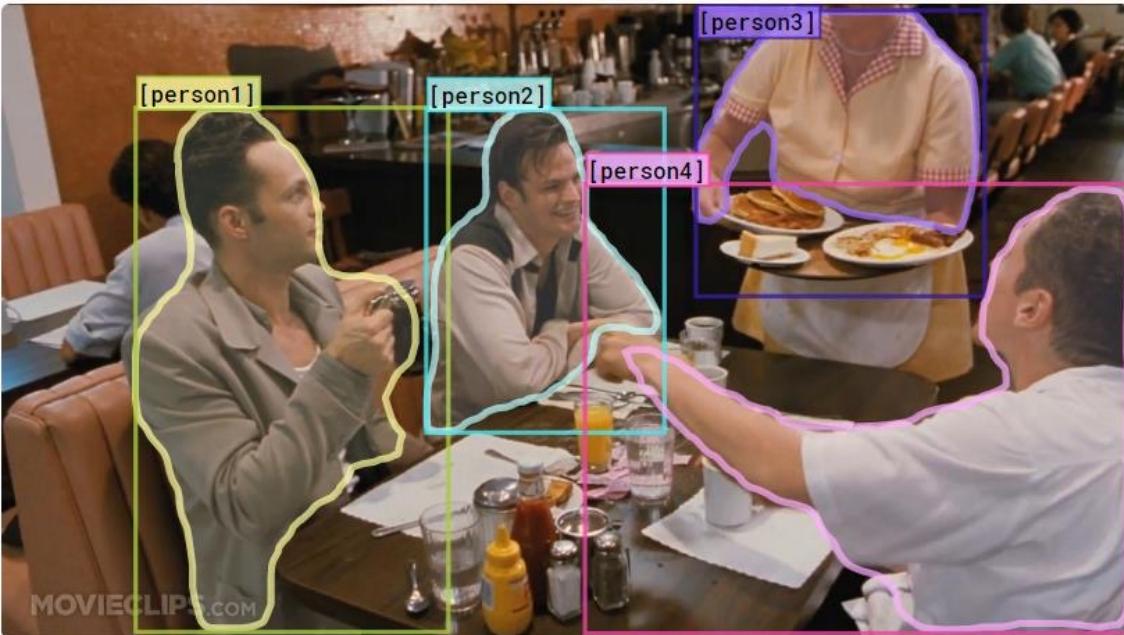
One image shows exactly two brown acorns in back-to-back caps on green foliage.

false

Downstream Task 3: Natural Language for Visual Reasoning



Downstream Task 4: Visual Commonsense Reasoning



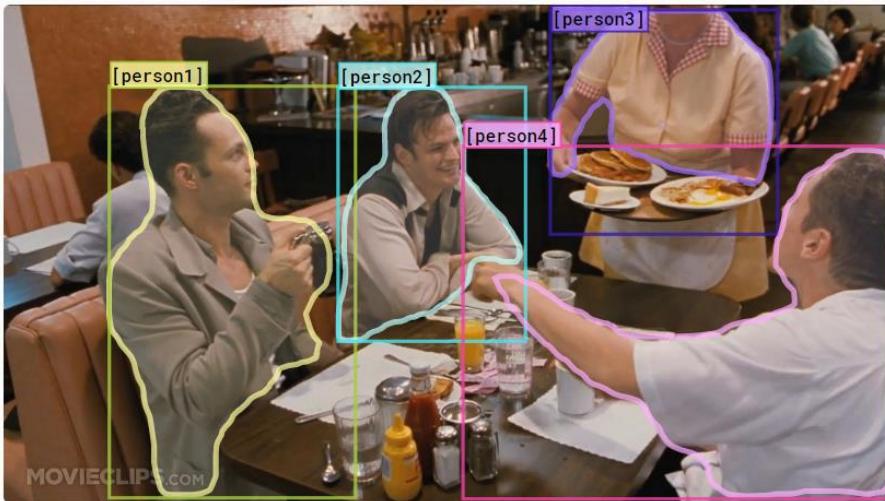
Why is [person4] pointing at [person1]?

- 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:

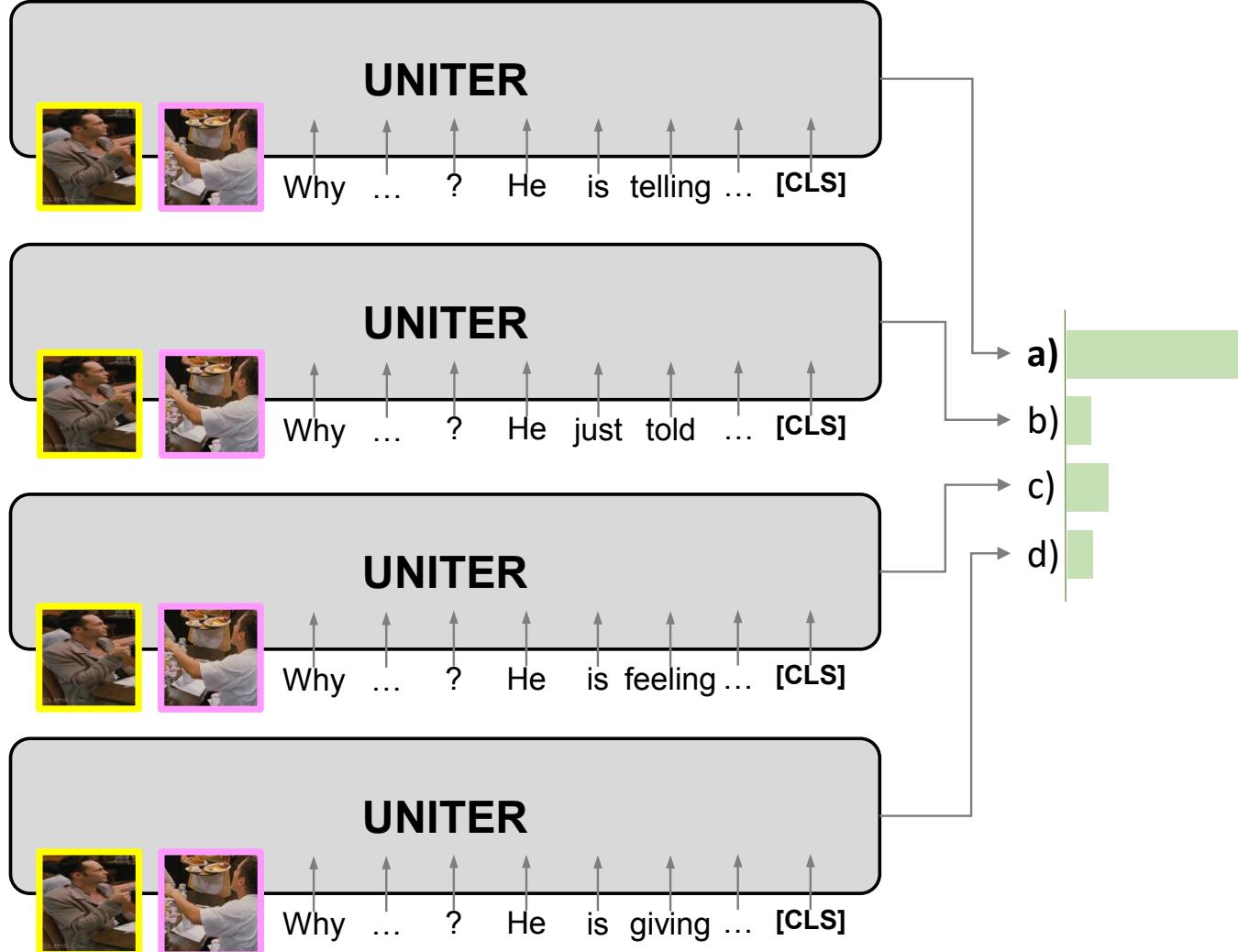
- a) [person1] has the pancakes in front of him.
- b) [person4] is taking everyone's order and asked for clarification.
- c) [person3] is looking at the pancakes and both she and [person2] are smiling slightly.
- d) [person3] is delivering food to the table, and she might not know whose order is whose.

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.

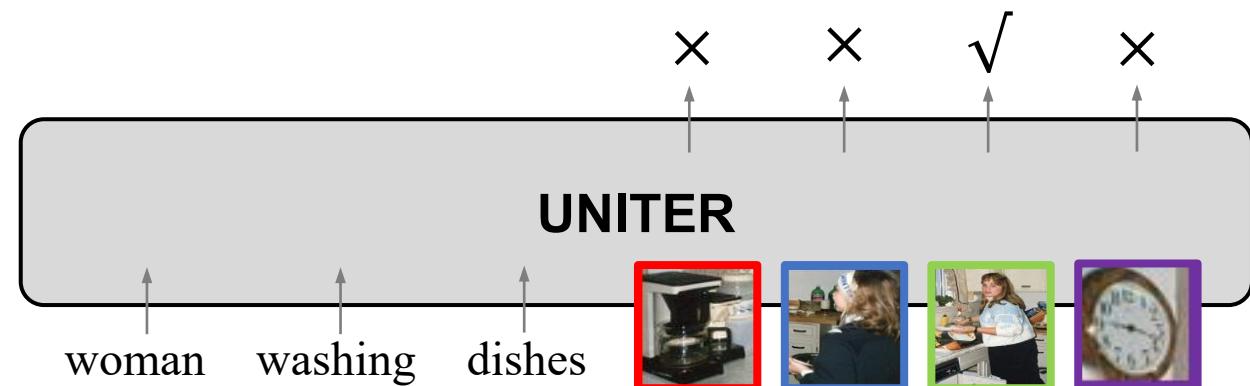
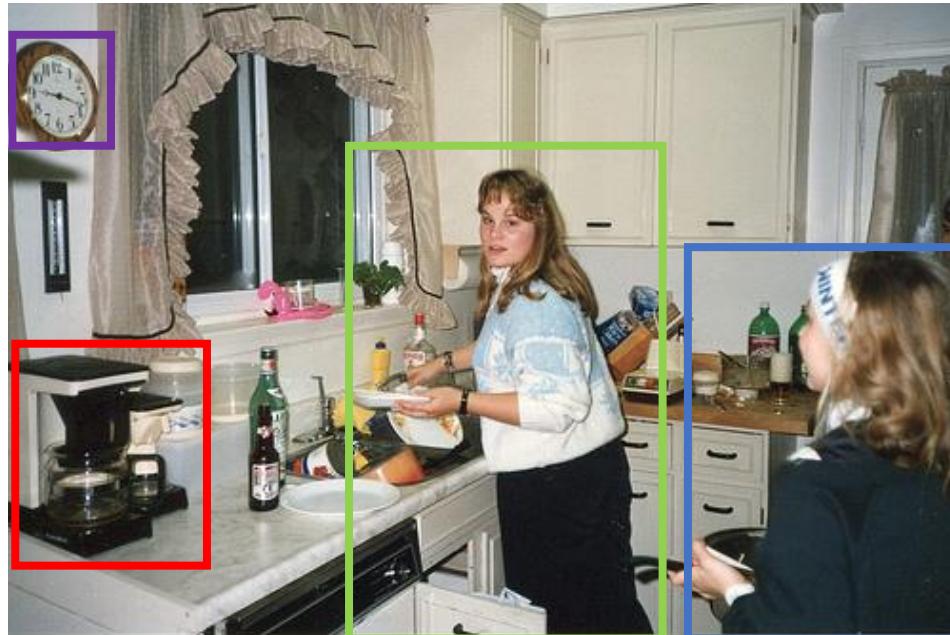


Downstream Task 5: Referring Expression Comprehension

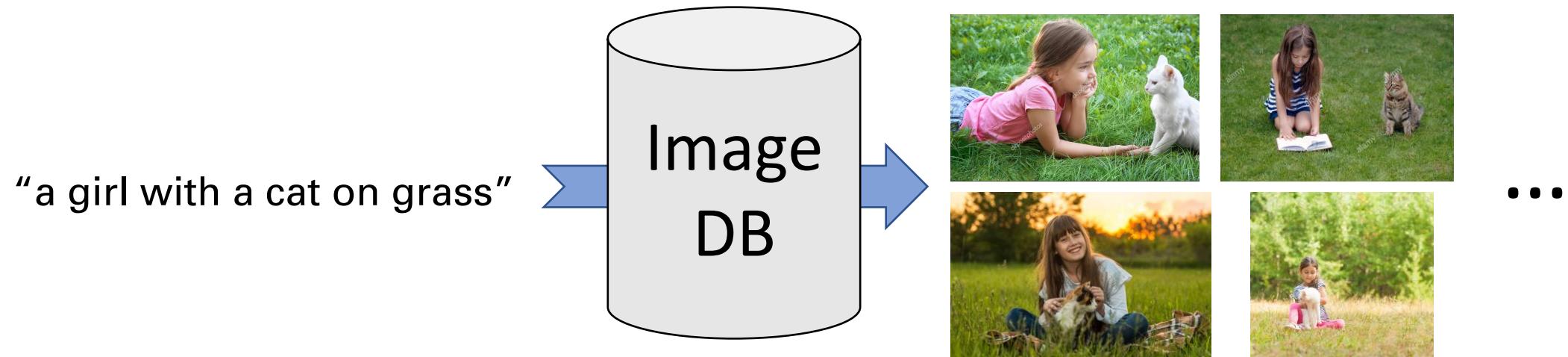


woman washing dishes

Downstream Task 5: Referring Expression Comprehension

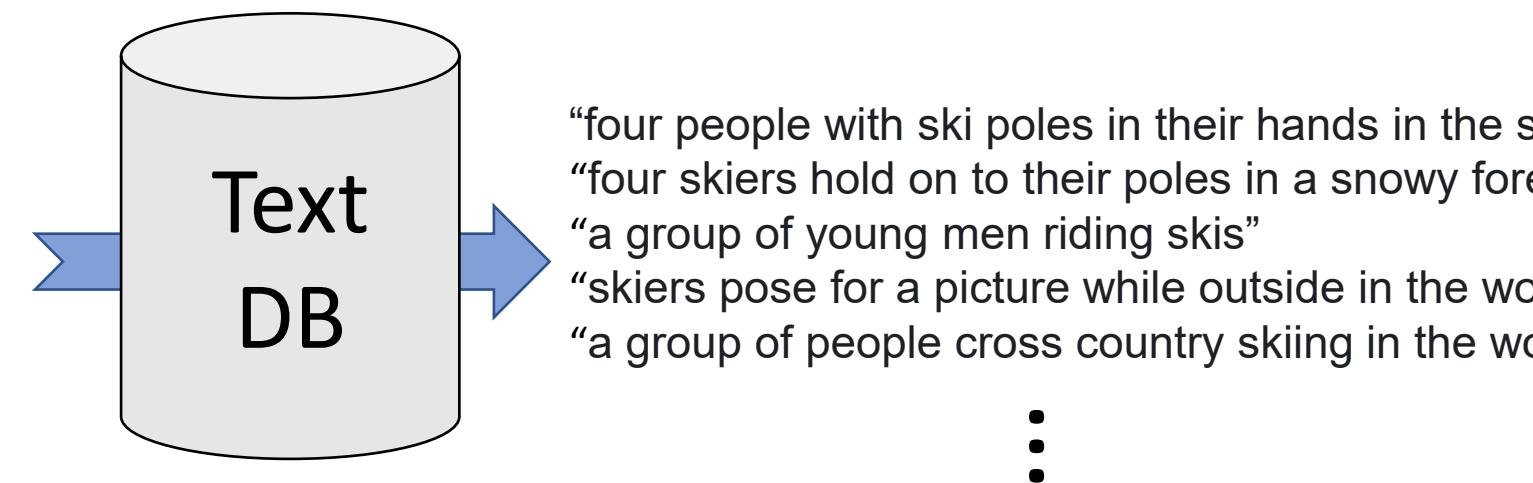
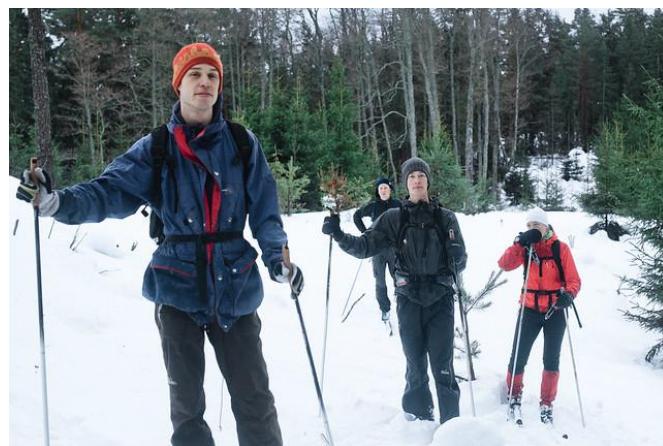
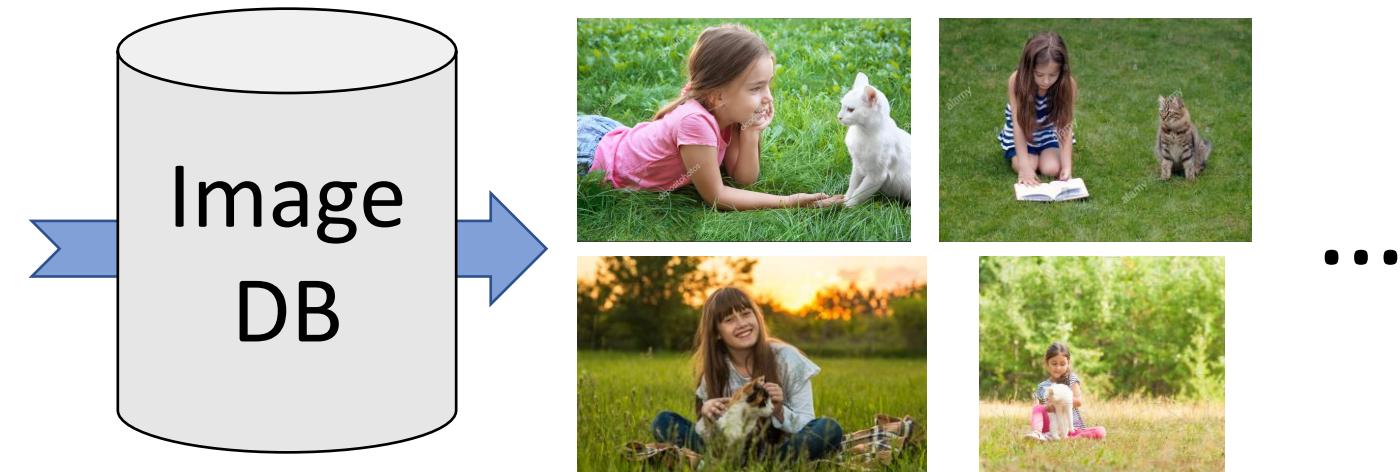


Downstream Task 6: Image-Text Retrieval

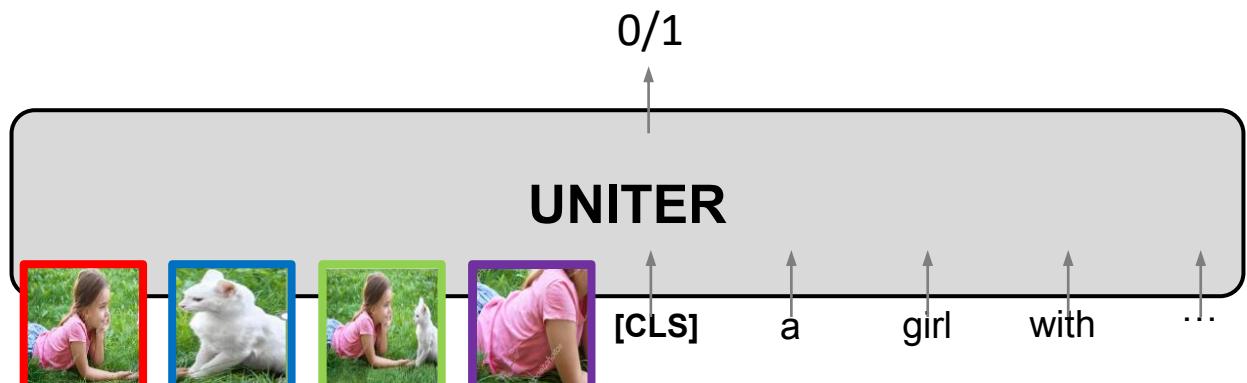
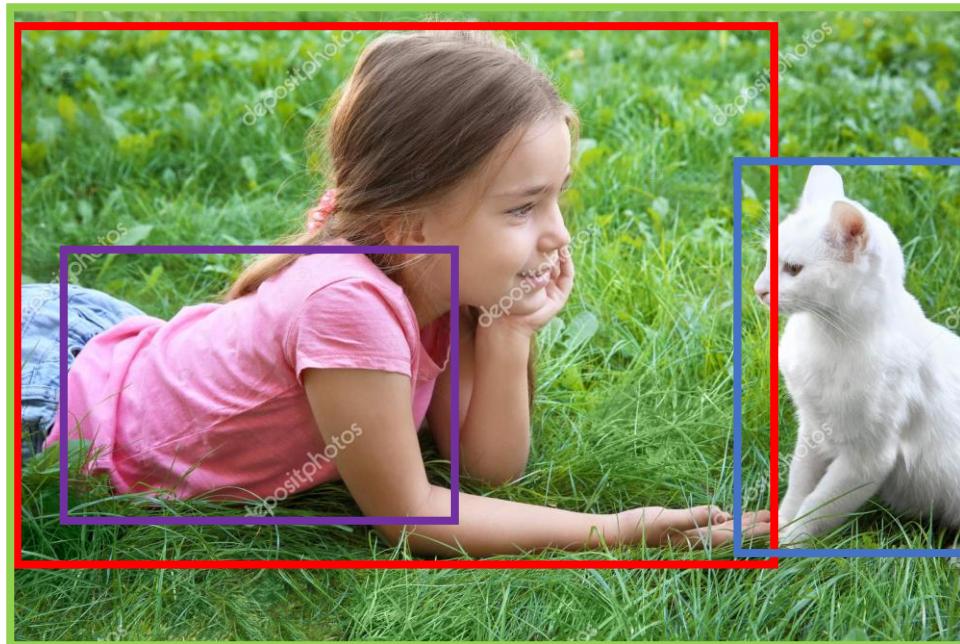


Downstream Task 6: Image-Text Retrieval

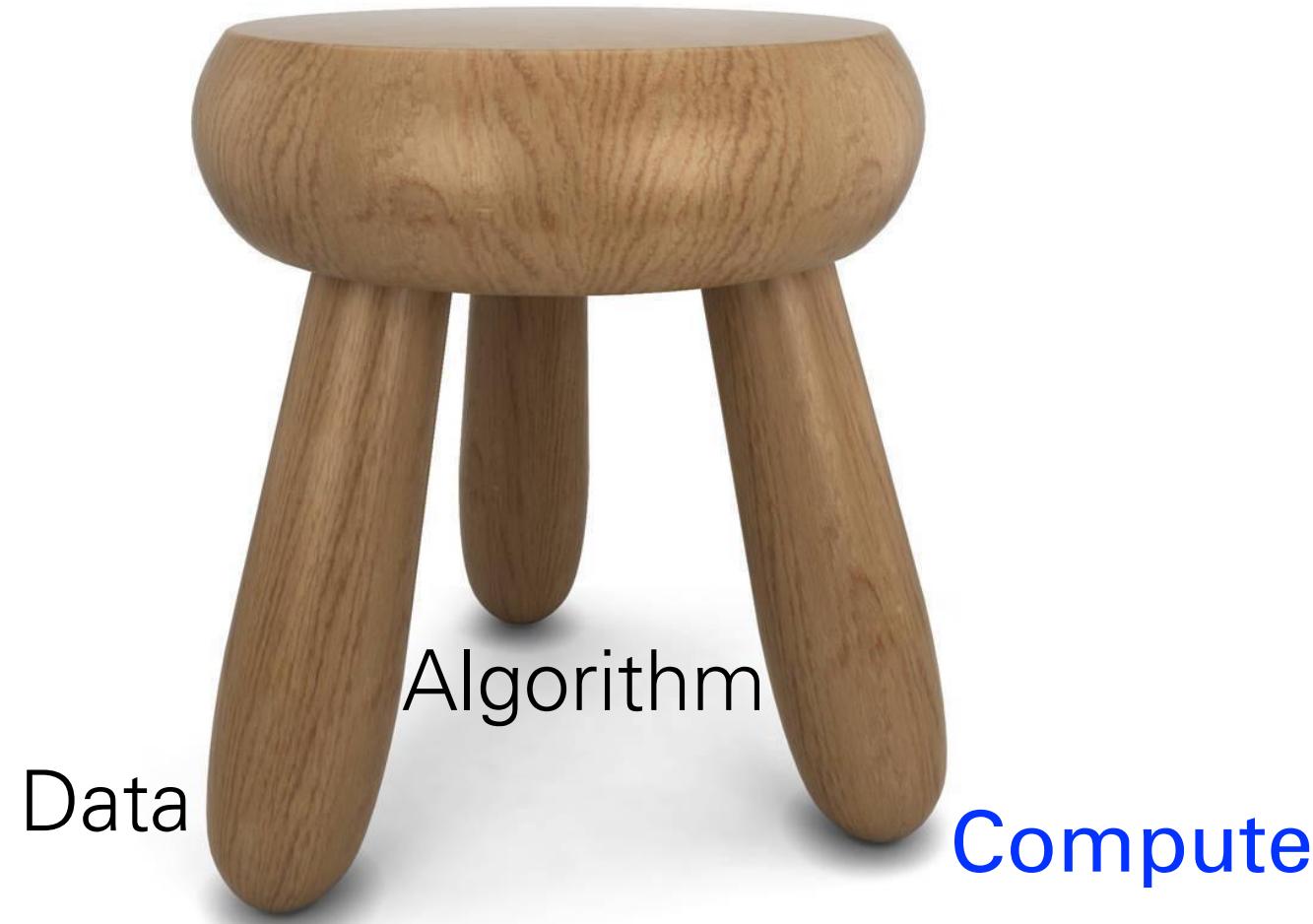
“a girl with a cat on grass”



Downstream Task 6: Image-Text Retrieval



SSL for Vision + Language

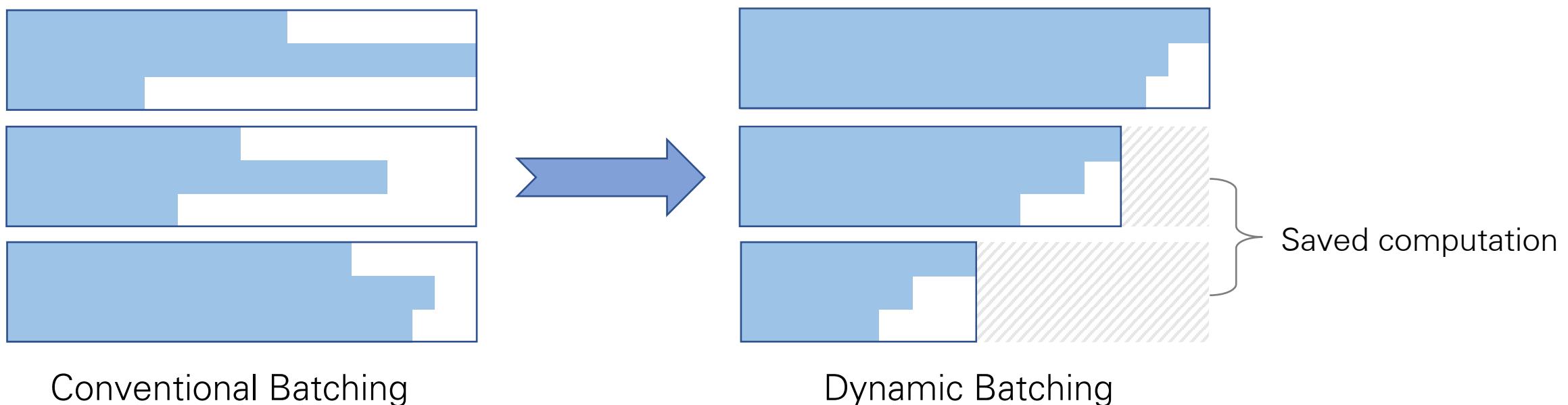


Optimization for Faster Training

- Dynamic Batching
- Gradient Accumulation
- Mixed-precision Training

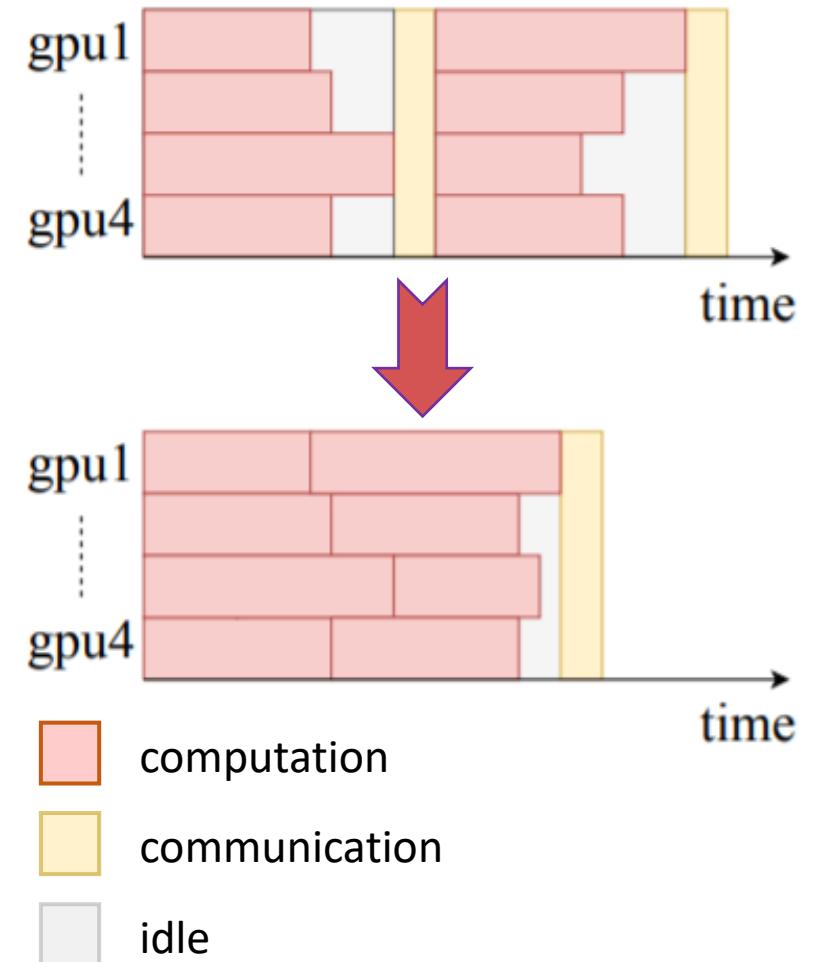
Optimization for Faster Training

- Dynamic Batching
 - Transformer (self-attention) is $O(L^2)$ (L : number of word + region)
 - Common practice: pad the input to the same maximum length (too long)
 - The solution: batch data by similar length and only do minimum padding



Optimization for Faster Training

- Dynamic Batching
- Gradient Accumulation
 - For large models, the main training bottleneck is **network communication overhead** between nodes
 - Reduce the communication frequency, hence increase overall throughput



Optimization for Faster Training

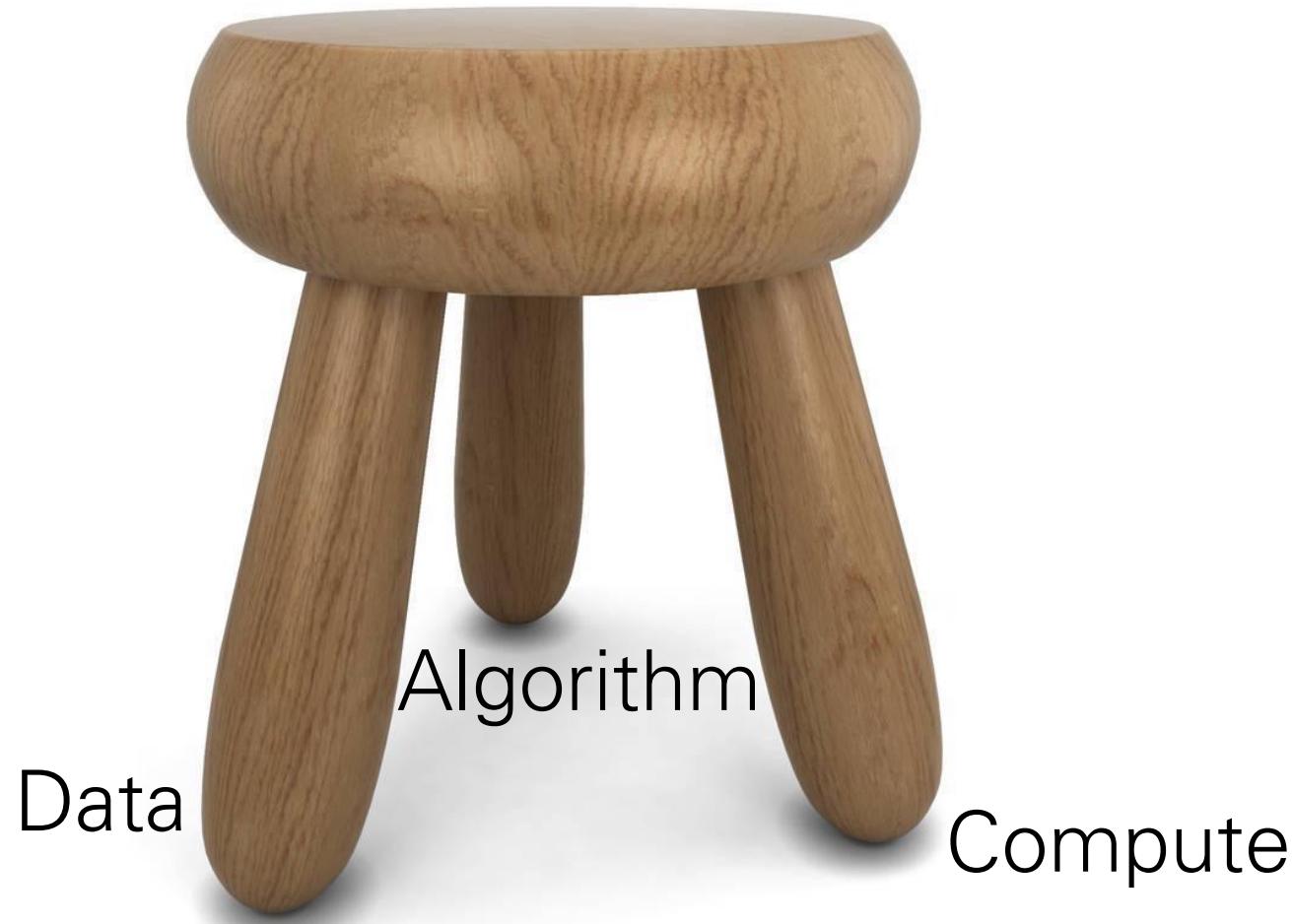
- Dynamic Batching
- Gradient Accumulation
- Mixed-precision Training
 - Bring in the benefits from both worlds of 16-bit and 32-bit
 - **2x~4x speedup** compared to standard training

	FP-16	FP-32
Speed	Fast	Slow
Memory	Low	High
Numerical Stability	Bad	Good

Lecture overview

- Introduction
- Pre-training data
- Feature representations for vision and language
- Model architectures
- Pre-training tasks
- Downstream tasks
- Moving forward

SSL for Vision + Language



SOTA of V+L Tasks (Early 2020)

- VQA: UNITER
- VCR: UNITER
- GQA: NSM* [Hudson et al., NeurIPS 2019]
- NLVR2: UNITER
- Visual Entailment: UNITER
- Image-Text Retrieval: UNITER
- Image Captioning: VLP
- Referring Expressions: UNITER

*: without V+L pre-training

Tasks	SOTA	ViLBERT	VLBERT (Large)	Unicoder -VL	VisualBERT	LXMERT	UNITER		
							Base	Large	Base
VQA	test-dev	70.63	70.55	71.79	-	70.80	72.42	72.70	73.82
	test-std	70.90	70.92	72.22	-	71.00	72.54	72.91	74.02
VCR	Q→A	72.60	73.30	75.80	-	71.60	-	75.00	77.30
	QA→R	75.70	74.60	78.40	-	73.20	-	77.20	80.80
	Q→AR	55.00	54.80	59.70	-	52.40	-	58.20	62.80
NLVR ²	dev	54.80	-	-	-	67.40	74.90	77.18	79.12
	test-P	53.50	-	-	-	67.00	74.50	77.85	79.98
SNLI- VE	val	71.56	-	-	-	-	-	78.59	79.39
	test	71.16	-	-	-	-	-	78.28	79.38
ZS IR (Flickr)	R@1	-	31.86	-	48.40	-	-	66.16	68.74
	R@5	-	61.12	-	76.00	-	-	88.40	89.20
	R@10	-	72.80	-	85.20	-	-	92.94	93.86
IR (Flickr)	R@1	48.60	58.20	-	71.50	-	-	72.52	75.56
	R@5	77.70	84.90	-	91.20	-	-	92.36	94.08
	R@10	85.20	91.52	-	95.20	-	-	96.08	96.76
IR (COCO)	R@1	38.60	-	-	48.40	-	-	50.33	52.93
	R@5	69.30	-	-	76.70	-	-	78.52	79.93
	R@10	80.40	-	-	85.90	-	-	87.16	87.95
ZS TR (Flickr)	R@1	-	-	-	64.30	-	-	80.70	83.60
	R@5	-	-	-	85.80	-	-	95.70	95.70
	R@10	-	-	-	92.30	-	-	98.00	97.70
TR (Flickr)	R@1	67.90	-	-	86.20	-	-	85.90	87.30
	R@5	90.30	-	-	96.30	-	-	97.10	98.00
	R@10	95.80	-	-	99.00	-	-	98.80	99.20
TR (COCO)	R@1	50.40	-	-	62.30	-	-	64.40	65.68
	R@5	82.20	-	-	87.10	-	-	87.40	88.56
	R@10	90.00	-	-	92.80	-	-	93.08	93.76
Ref- COCO	val	87.51	-	-	-	-	-	91.64	91.84
	testA	89.02	-	-	-	-	-	92.26	92.65
	testB	87.05	-	-	-	-	-	90.46	91.19
	val ^d	77.48	-	-	-	-	-	81.24	81.41
	testA ^d	83.37	-	-	-	-	-	86.48	87.04
	testB ^d	70.32	-	-	-	-	-	73.94	74.17
Ref- COCO+	val	75.38	-	80.31	-	-	-	83.66	84.25
	testA	80.04	-	83.62	-	-	-	86.19	86.34
	testB	69.30	-	75.45	-	-	-	78.89	79.75
	val ^d	68.19	72.34	72.59	-	-	-	75.31	75.90
	testA ^d	75.97	78.52	78.57	-	-	-	81.30	81.45
	testB ^d	57.52	62.61	62.30	-	-	-	65.58	66.70
Ref- COCOg	val	81.76	-	-	-	-	-	86.52	87.85
	test	81.75	-	-	-	-	-	86.52	87.73
	val ^d	68.22	-	-	-	-	-	74.31	74.86
	test ^d	69.46	-	-	-	-	-	74.51	75.77

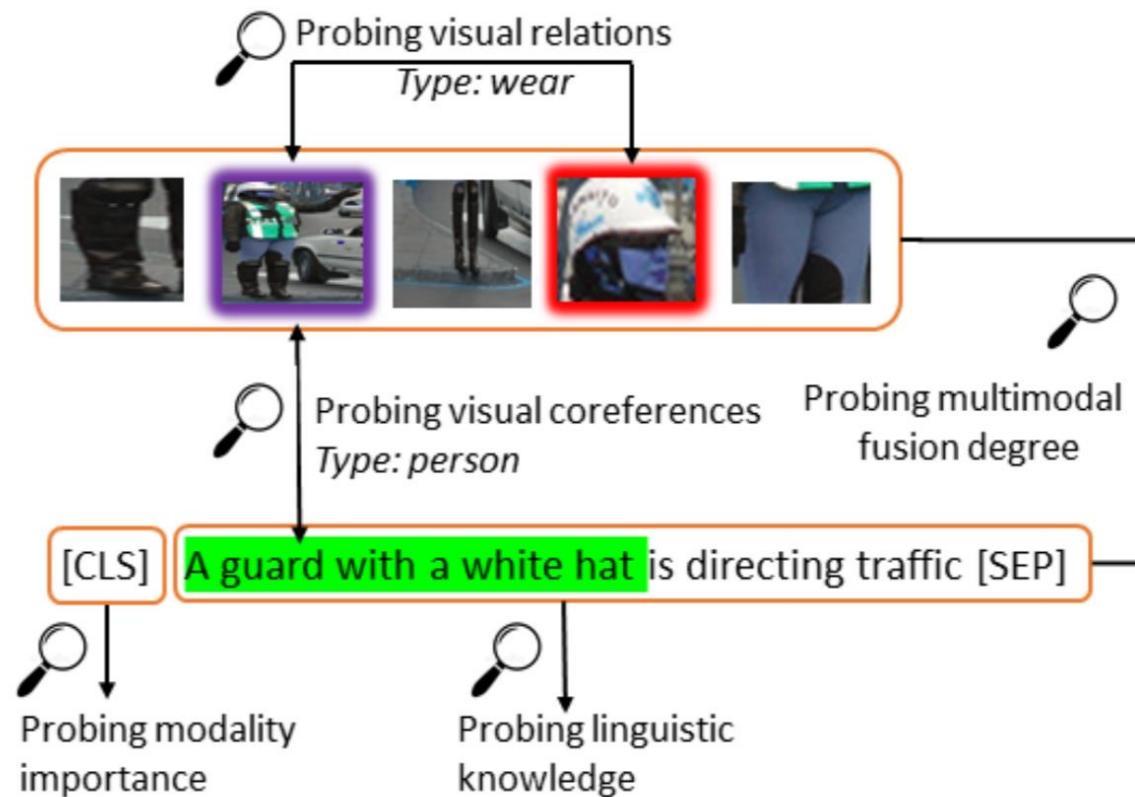
Moving Forward...

- Interpretability of VLP models
 - VALUE [Cao et al., 2020]
- Better visual features
 - Pixel-BERT [Huang et al., 2020]
 - OSCAR [Li et al., 2020]
- Adversarial (pre-)training for V+L
 - VILLA [Gan et al., 2020]

What do V+L pretrained models learn?

VALUE: Vision-And-Language Understanding Evaluation

Input Image

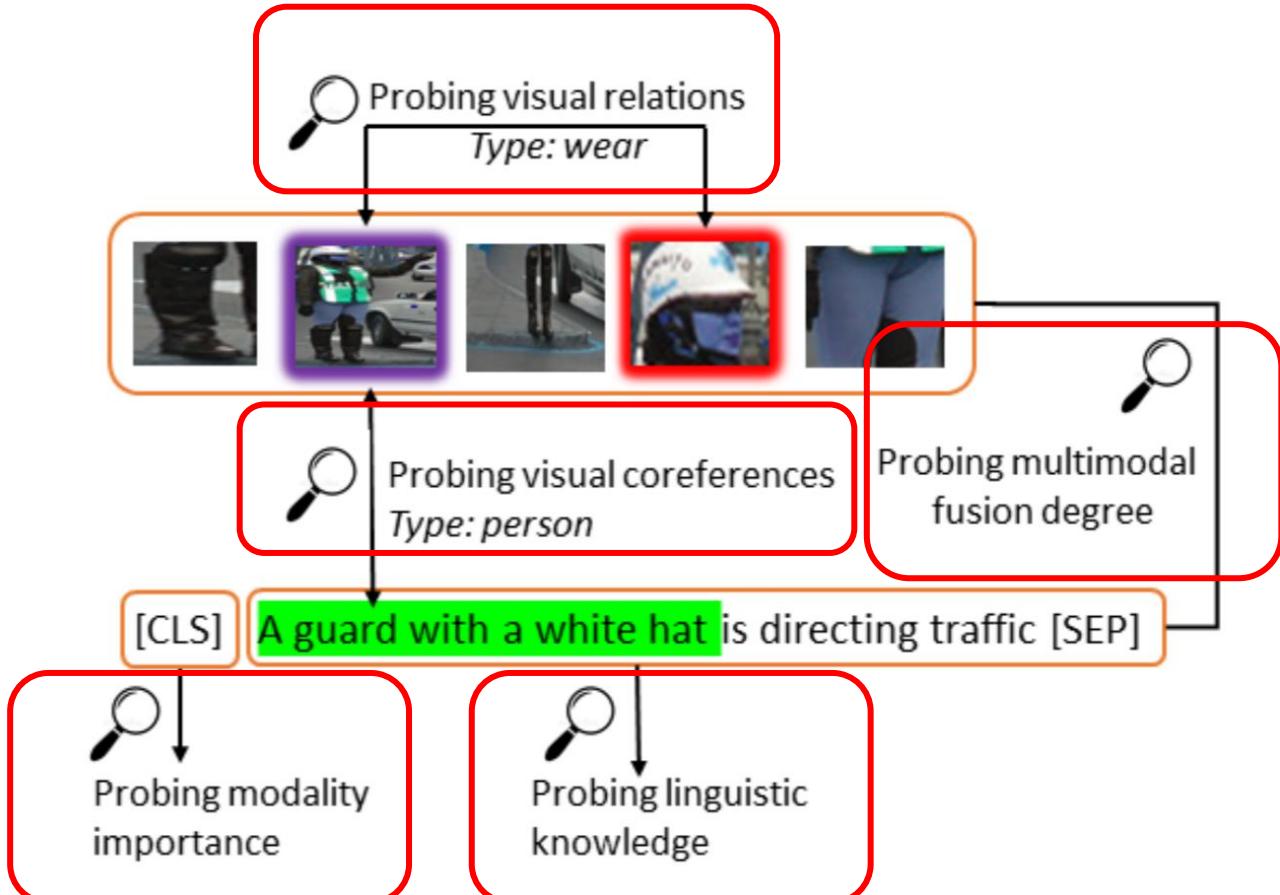


Probing Pre-Trained Models

- Single-stream vs. two-stream
- Attention weight probing
 - 12 layers x 12 heads = 144 attention weight matrices
- Embedding probing
 - 768-dim x 12 layers

Modality Probing

- Visual Probing
- Linguistic Probing
- Cross-Modality Probing



Modality Probing

- Visual Probing
 - Visual relation detection (existence, type)
 - Visual Genome dataset; top-32 frequent relations



Modality Probing

- Visual Probing
- Linguistic Probing
 - Surface tasks (sentence length)
 - Syntactic tasks (syntax tree, top constituents, ...)
 - Semantic tasks (tense, subject/object, ...)



A guard with a white hat is directing traffic [SEP] -
modality
ce

Probing linguistic
knowledge

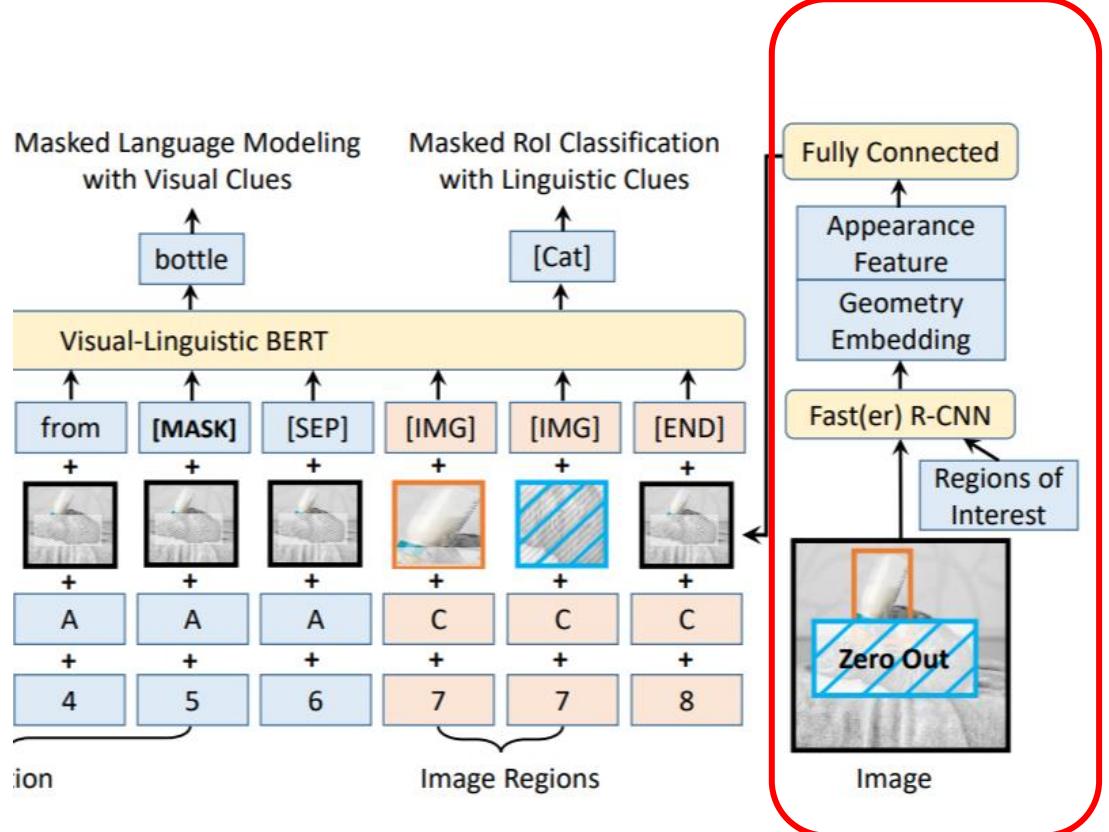
Modality Probing

- Visual Probing
- Linguistic Probing
- Cross-Modality Probing
 - Multimodal fusion degree
 - Modality importance
 - Visual coreference

VALUE: Vision-And-Language Understanding Evaluation

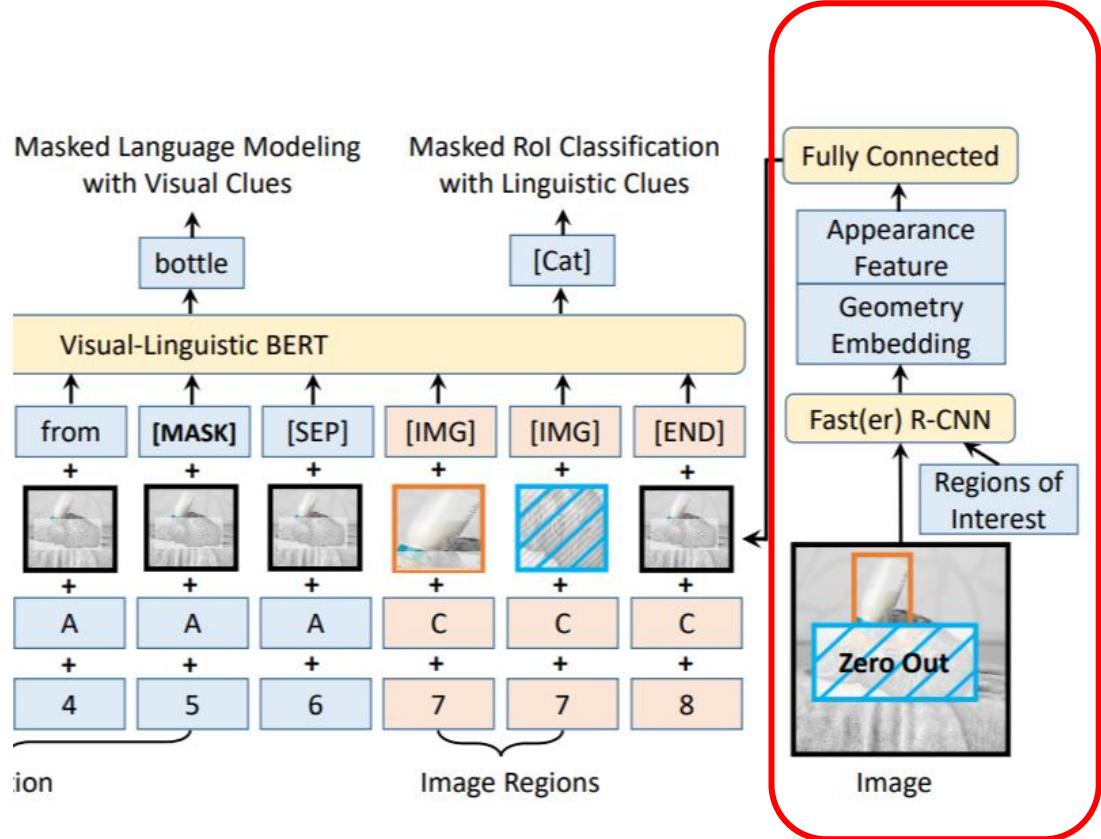
1. Cross-modal fusion:
 - a. In single-stream model (UNITER), deeper layers have more cross-modal fusion.
 - b. The opposite for two-stream model (LXMERT).
2. Text modality is more important than image.
3. In single-stream model, some heads only focus on cross-modal interaction.
4. Visual relations are learned in pre-training.
5. Linguistic knowledge can be found.

From Region Features to Grid Features

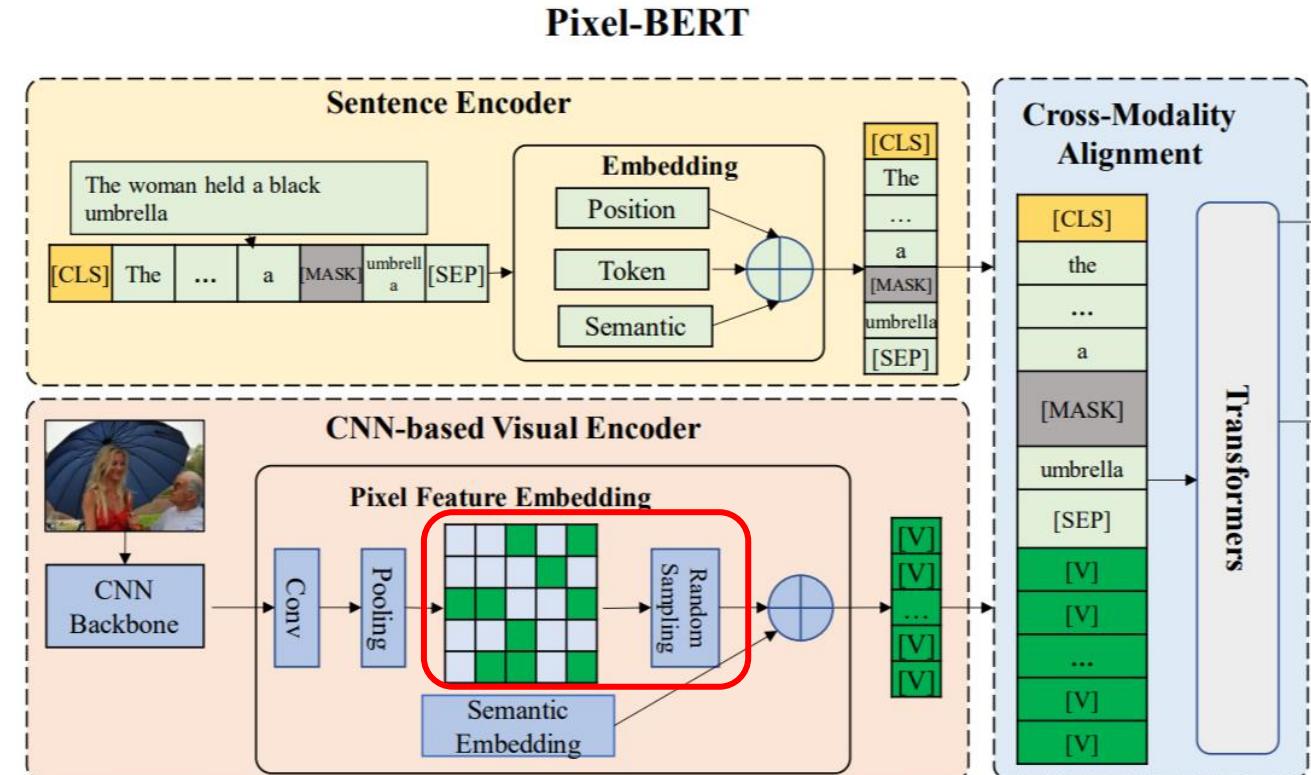


VL-BERT; Su et al., ICLR 2020]

From Region Features to Grid Features



VL-BERT; Su et al., ICLR 2020]

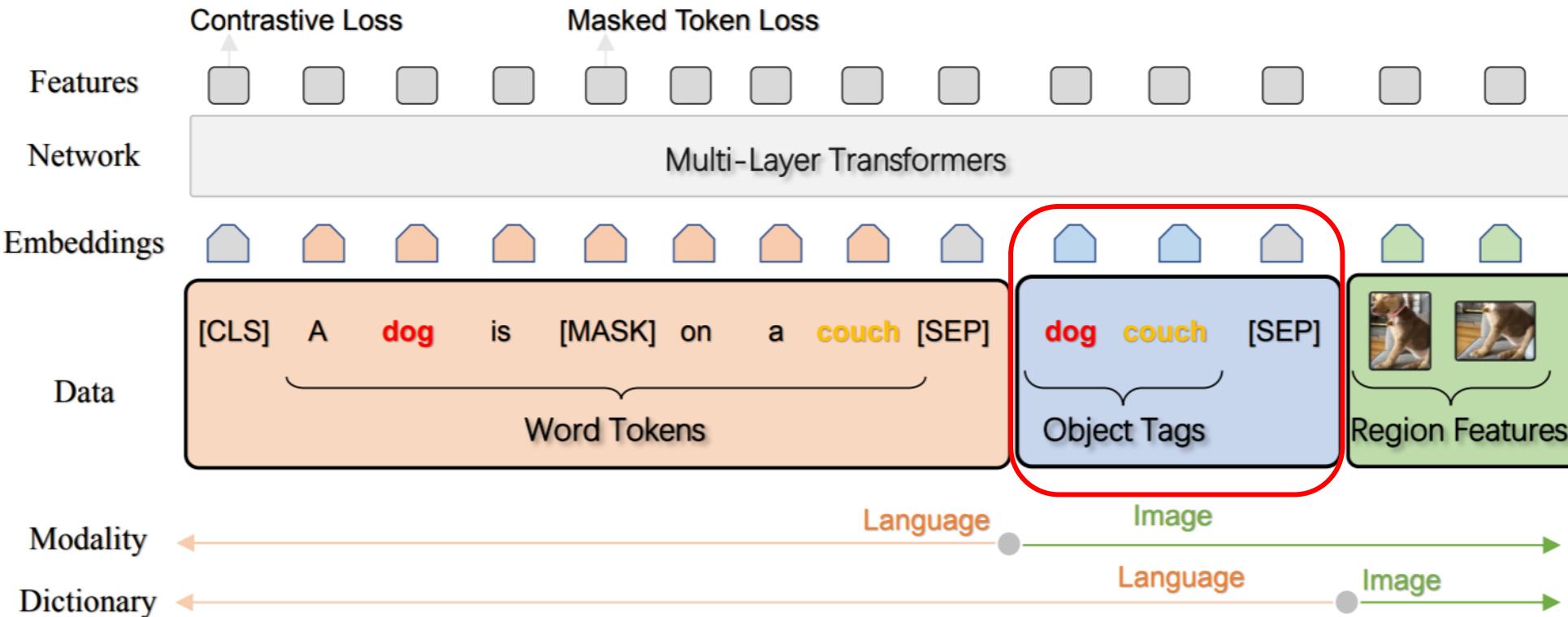


Pixel-BERT; Huang et al., 2020]

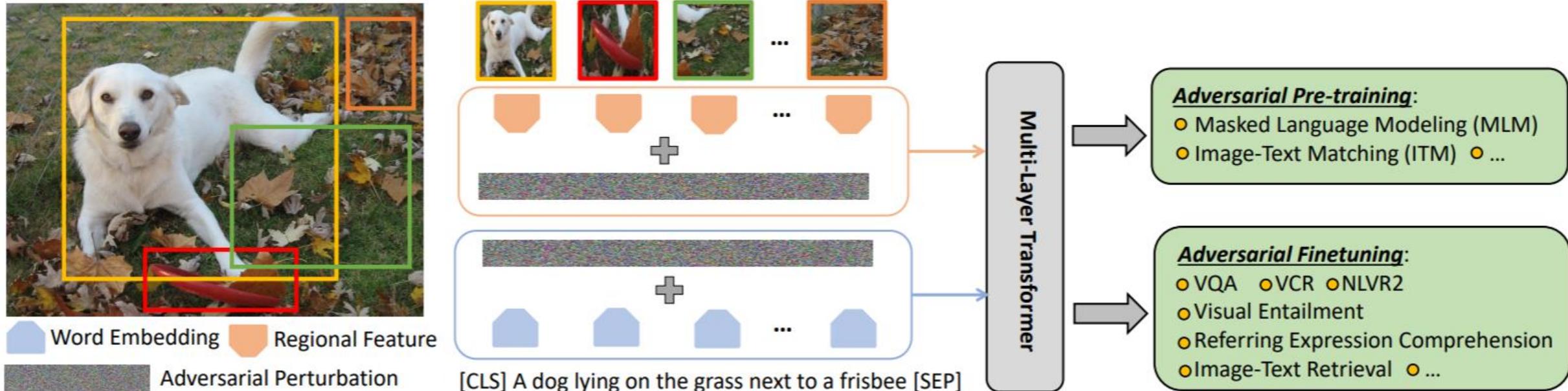
Object Tags as Input Features

OSCAR: Object-Semantics Aligned Pretraining

$$\mathbf{x} \triangleq [\underbrace{\mathbf{w}}_{\text{language}}, \underbrace{\mathbf{q}, \mathbf{v}}_{\text{image}}] = [\underbrace{\mathbf{w}, \mathbf{q}}_{\text{language}}, \underbrace{\mathbf{v}}_{\text{image}}] \triangleq \mathbf{x}'$$



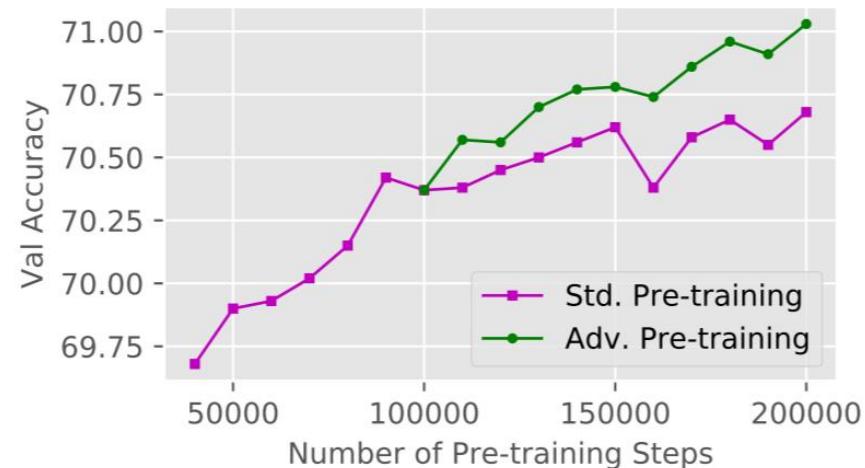
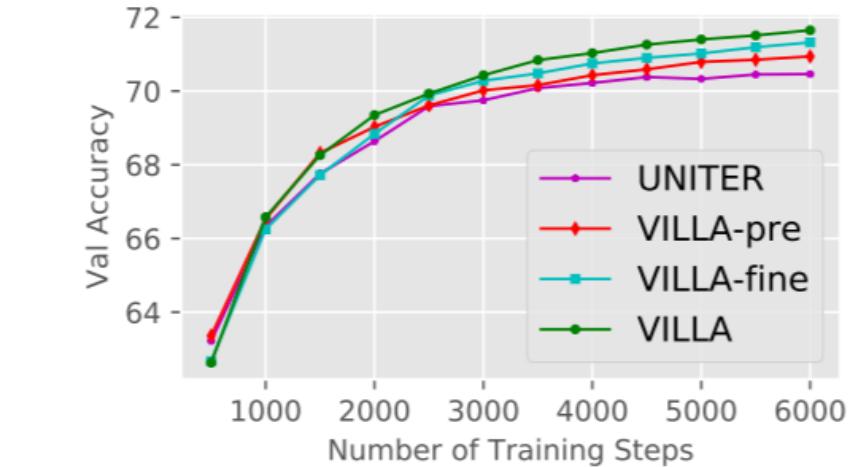
VILLA: Vision-and-Language Large-Scale Adversarial Training



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

1. Task-agnostic adversarial pre-training
2. Task-specific adversarial finetuning
3. “Free” adversarial training
 - FreeLB [Zhu et al., ICLR 2020]
 - KL-constraint
4. Improved generalization
 - No trade-off between accuracy and robustness.

Method	VQA		VCR			NLVR ²		SNLI-VE	
	test-dev	test-std	Q→A	QA→R	Q→AR	dev	test-P	val	test
VL-BERT _{LARGE}	71.79	72.22	75.5 (75.8)	77.9 (78.4)	58.9 (59.7)	-	-	-	-
Oscar _{LARGE}	73.61	73.82	-	-	-	79.12	80.37	-	-
UNITER _{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 _{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) Standard vs. adversarial pre-training.

SOTA of V+L Tasks

- VQA: UNITER
- VCR: UNITER
- GQA: NSM* [Hudson et al., NeurIPS 2019]
- NLVR2: UNITER
- Visual Entailment: UNITER
- Image-Text Retrieval: UNITER
- Image Captioning: VLP
- Referring Expressions: UNITER

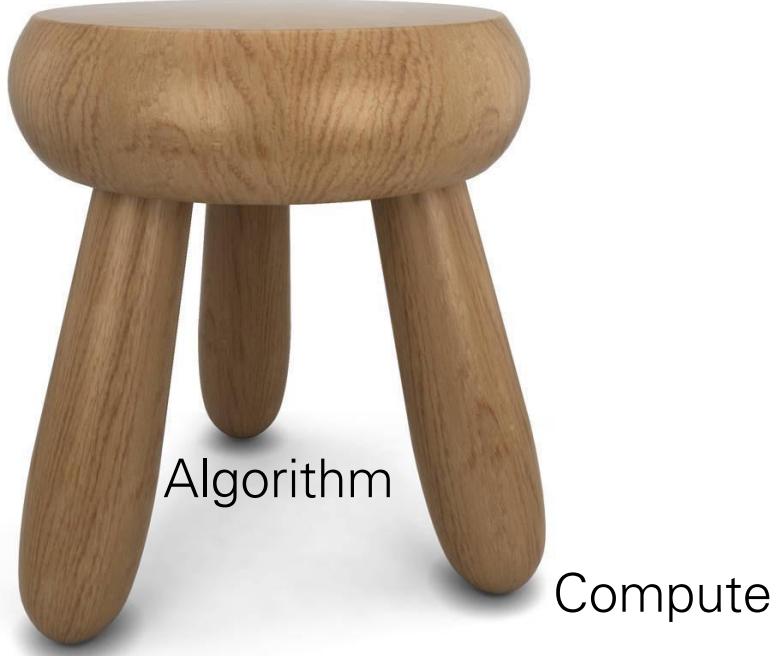
*: without V+L pre-training

SOTA of V+L Tasks

- VQA: VILLA (single), GridFeat+MoVie* (ensemble) [GridFeat; Jiang et al., CVPR 2020]
[MoVie; Nguyen et al., 2020]
- VCR: VILLA
- GQA: HAN* [Kim et al., CVPR 2020]
- NLVR2: VILLA
- Visual Entailment: VILLA
- Image-Text Retrieval: OSCAR
- Image Captioning: OSCAR
- Referring Expressions: VILLA

*: without V+L pre-training

Take-away

- SOTA pre-training for V+L
 - Available datasets
 - Model architecture
 - Pre-training tasks
 - Future directions
 - Study the representation learned by pre-training → pruning/compression
 - Better visual features → end-to-end training of CNN
 - Reasoning tasks (GQA)
- 
- The image shows a simple wooden stool with a circular seat and four legs. It is positioned on the right side of the slide. To the left of the stool, the word "Data" is written vertically. To the right, the words "Algorithm" and "Compute" are written vertically, with "Algorithm" above "Compute". This visual metaphor represents the three fundamental components that support machine learning models.

COMP547

DEEP UNSUPERVISED LEARNING

Lecture #13 – Pretraining for Vision and Language



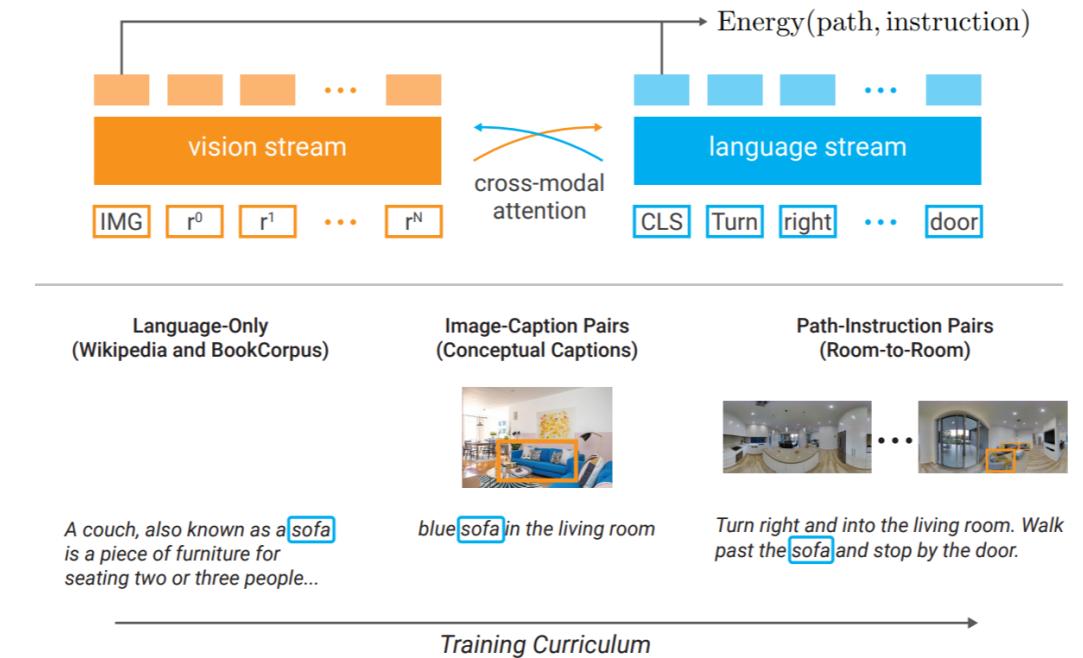
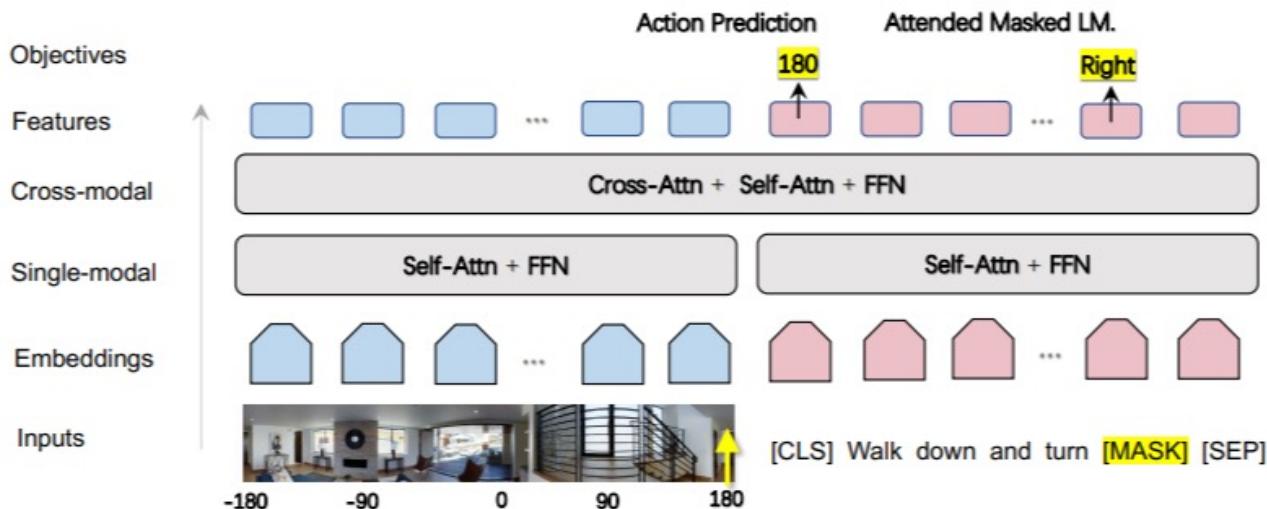
KOÇ
UNIVERSITY

Aykut Erdem // Koç University // Spring 2024

Beyond Image+Text Pre-Training

- Self-supervised learning for vision-and-language navigation (VLN)
 - PREVALENT [Hao et al., CVPR 2020]
 - VLN-BERT [Majumdar et al., 2020]
- Video+Language Pre-training
- Multilingual Multimodal Pre-training

Self-Supervised Learning for VLN



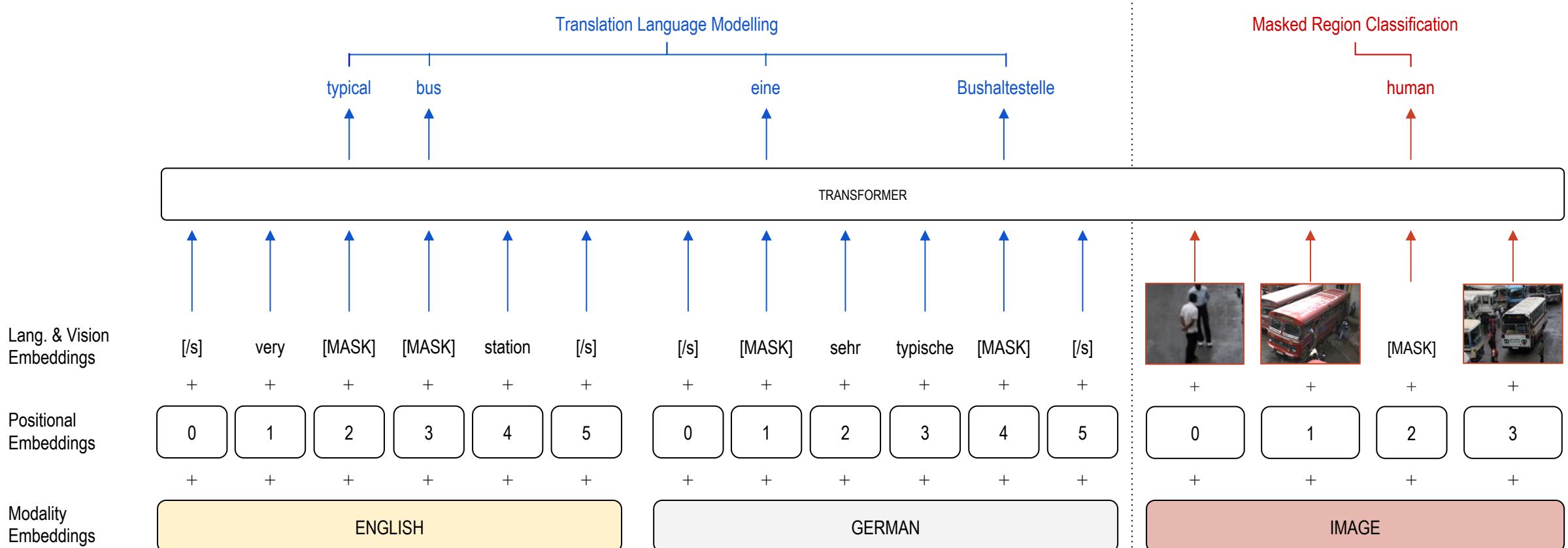
[PREVALENT; Hao et al., CVPR 2020]

[VLN-BERT; Majumdar et al., 2020]

Video + Language Pre-Training

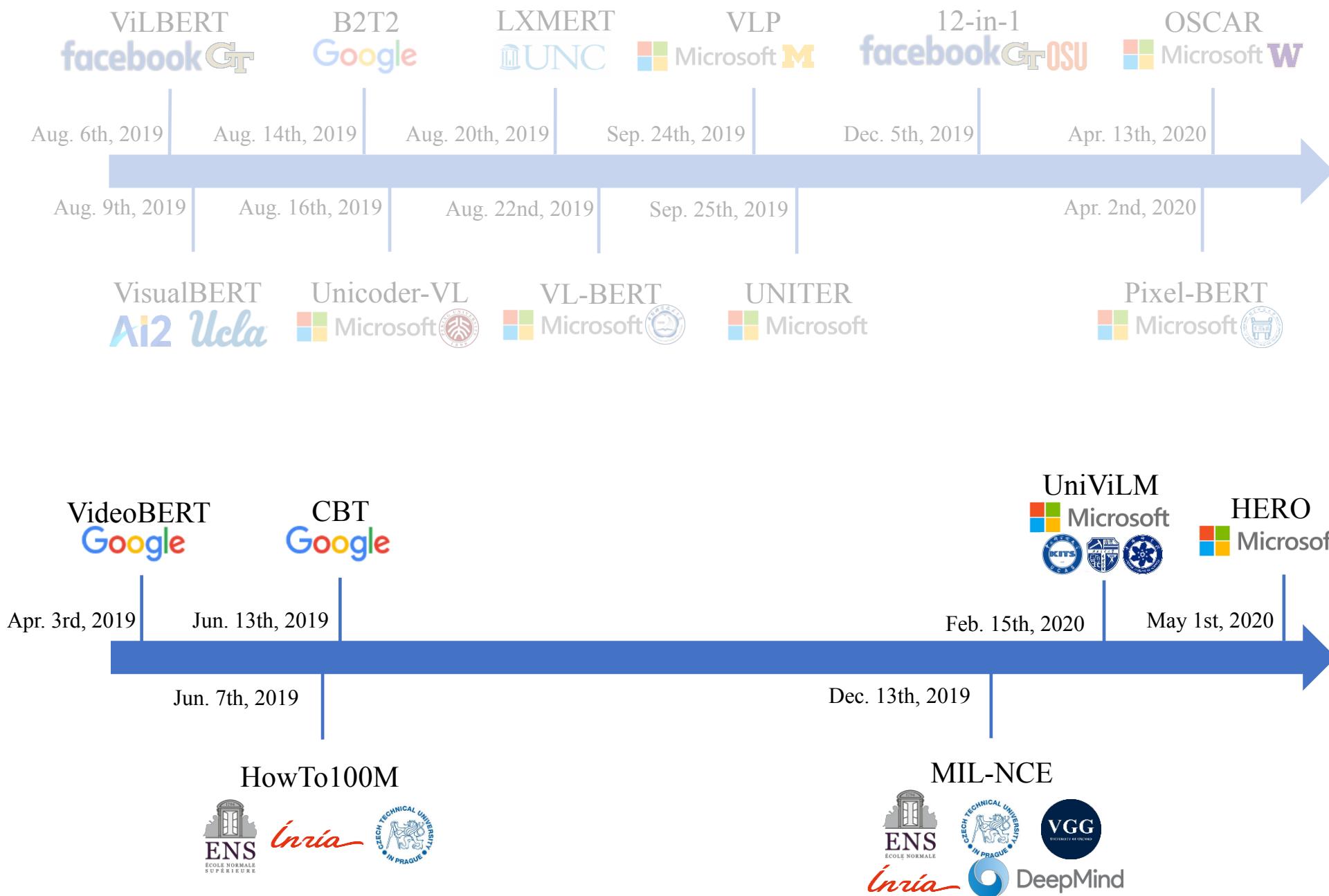


Multilingual Multimodal Pre-training



Lecture overview

- Introduction
- Pre-training data
- Feature representations for vision and language
- Model architectures
- Pre-training tasks
- Downstream tasks
- Moving forward
 - **Self-supervised learning for video + language**
 - Multilingual multimodal pre-training



Downstream Tasks

- VQA ● VCR ● NLVR2
- Visual Entailment
- Referring Expressions
- Image-Text Retrieval
- Image Captioning

Downstream Tasks

- Video QA
- Video-and-Language Inference
- Video Captioning
- Video Moment Retrieval

Video + Language Pre-training



*Keep rolling tight and squeeze the air out to its side
and you can kind of pull a little bit.*

Video + Language Pre-training

Video: Sequence of image frames

Language: Subtitles/Narrations

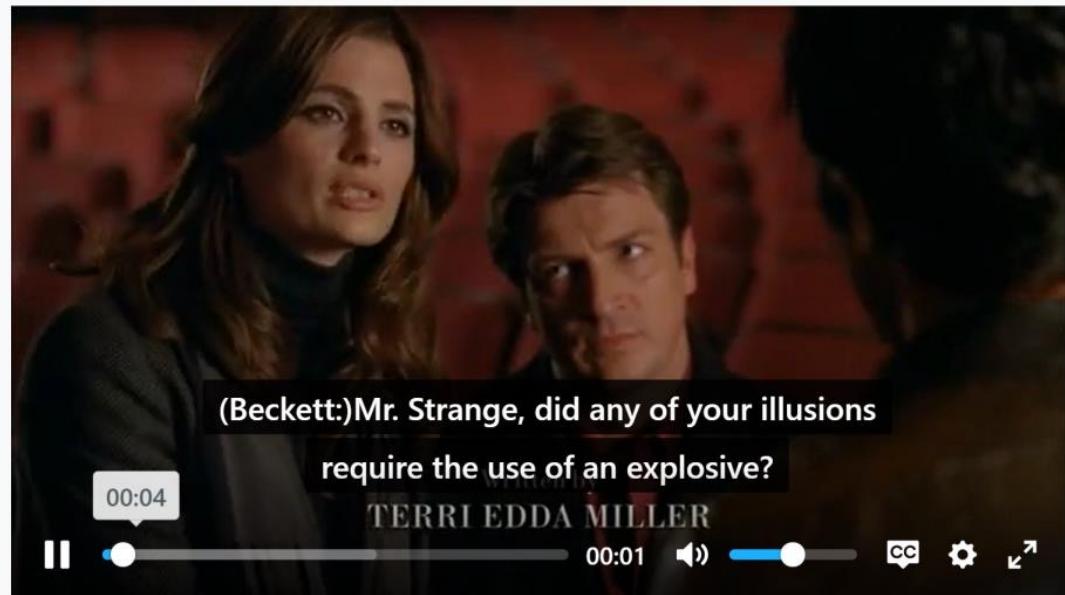


Keep rolling tight and squeeze the air out to its side and you can kind of pull a little bit.

Pre-training Data for Video + Language

TV Dataset

[Lei et al. EMNLP 2018]



- 22K video clips from 6 popular TV shows
- Each video clip is 60-90 seconds long
- Dialogue ("character name: subtitle") is provided

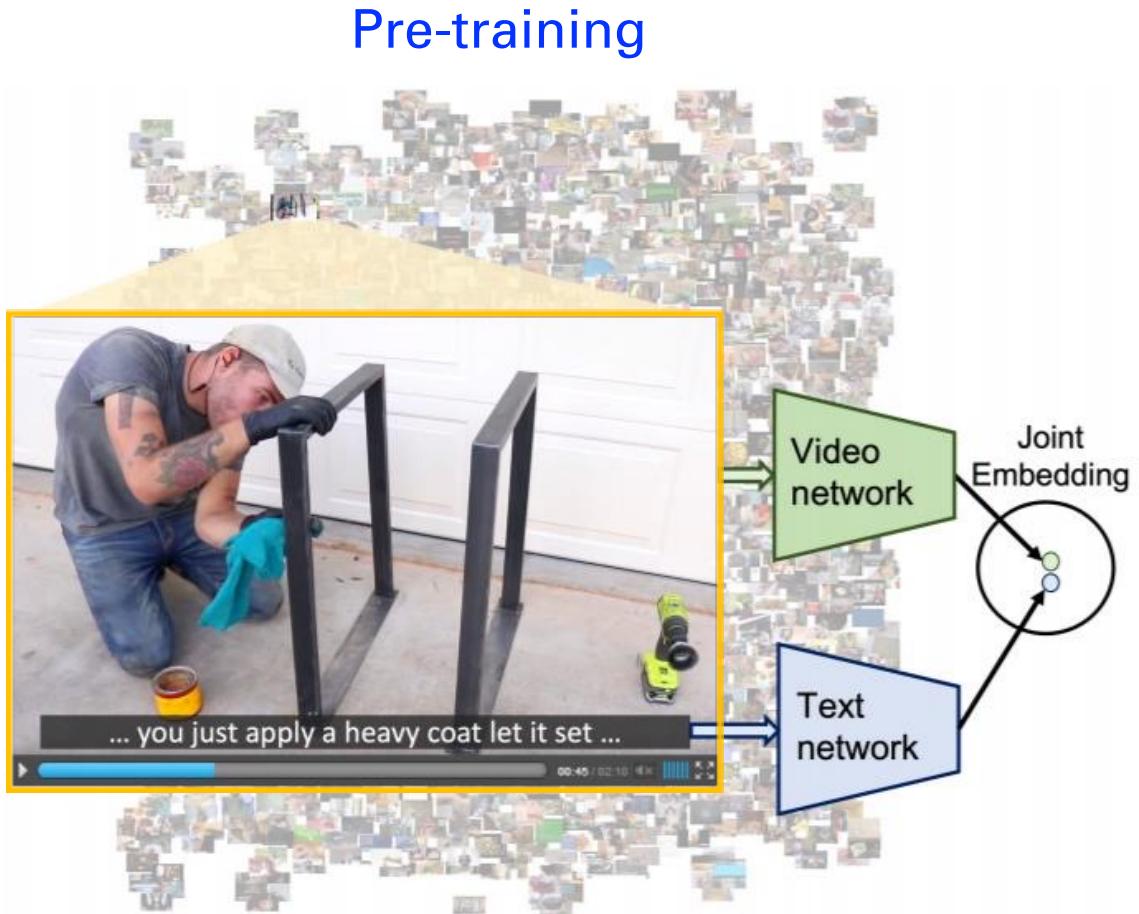
HowTo100M Dataset

[Miech et al. ICCV 2019]



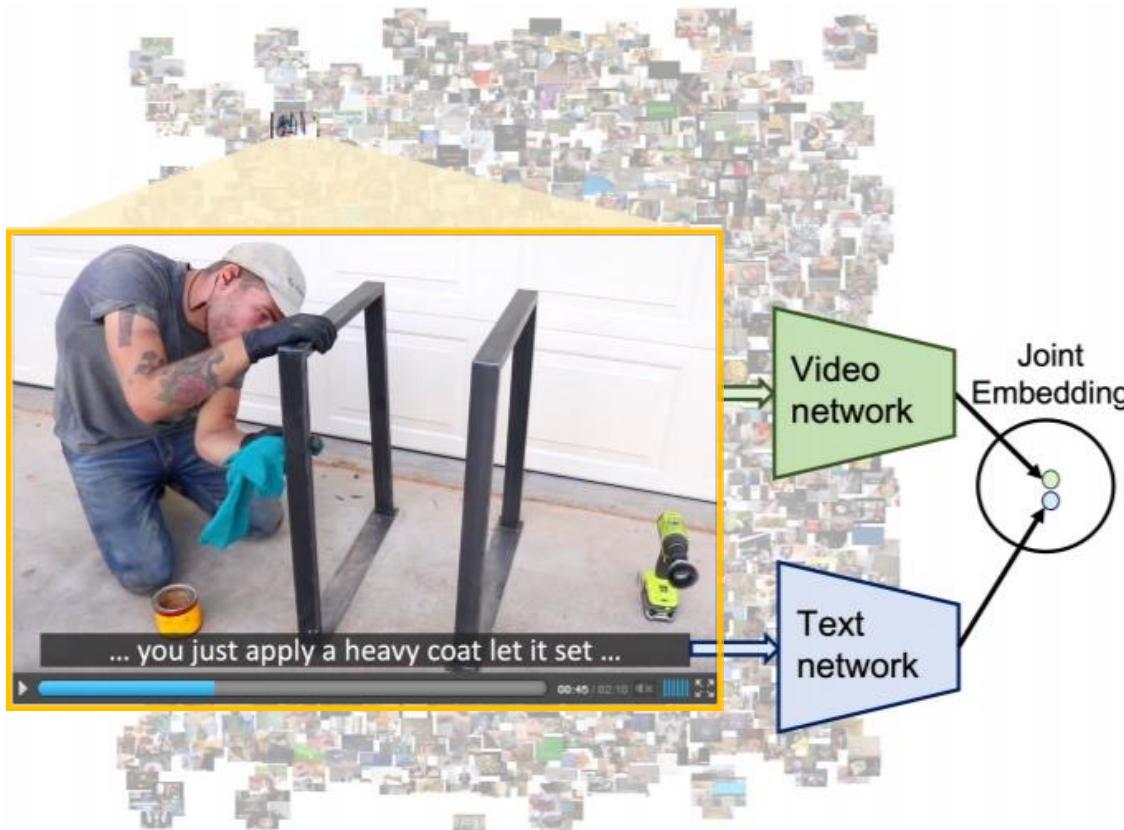
- 1.22M instructional videos from YouTube
- Each video is 6 minutes long on average
- Narrations in different languages

HowTo100M: Learning a Text-Video Embedding from Watching Hundred Million Narrated Video Clips



HowTo100M: Learning a Text-Video Embedding from Watching Hundred Million Narrated Video Clips

Pre-training

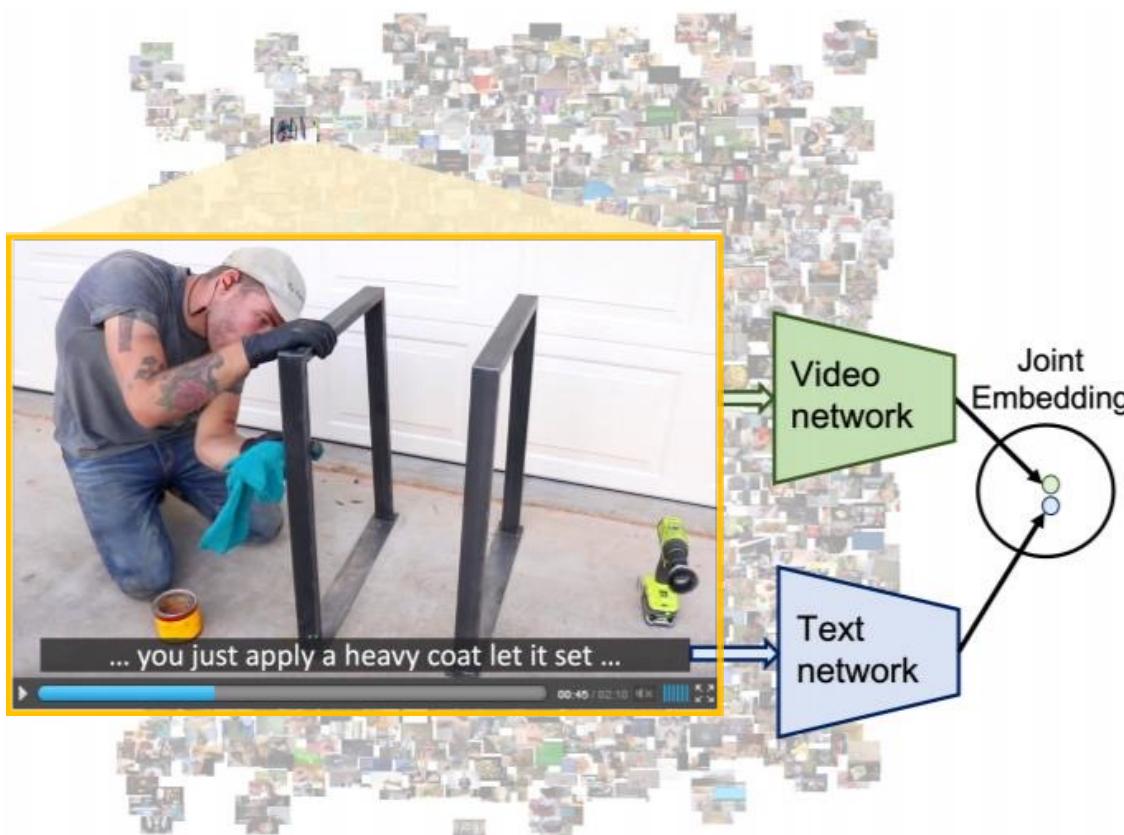


Large-scale Pre-training Dataset

- 136M video clips with narrations from 1.2M YouTube videos spanning 23K activities

HowTo100M: Learning a Text-Video Embedding from Watching Hundred Million Narrated Video Clips

Pre-training



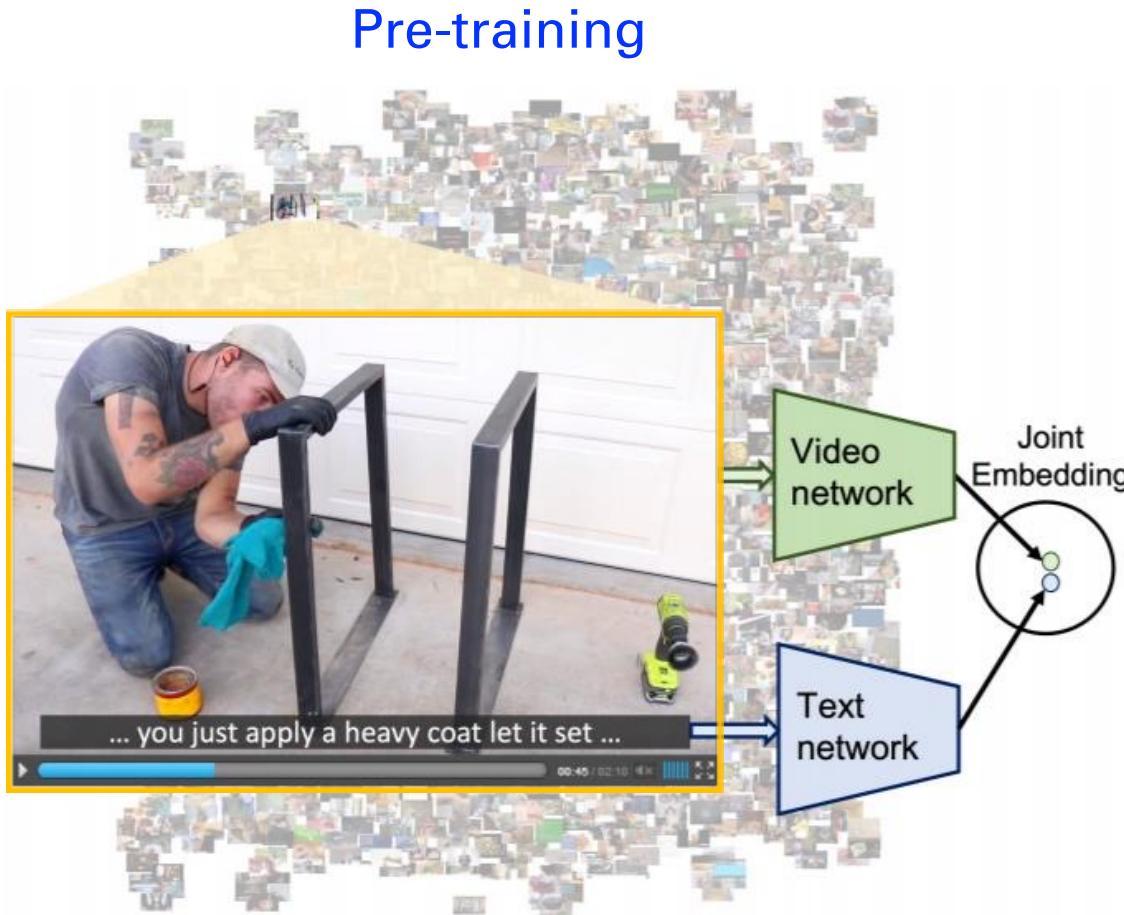
Large-scale Pre-training Dataset

- 136M video clips with narrations from 1.2M YouTube videos spanning 23K activities

Video Representations

- 2D features from ImageNet pretrained ResNet-152
- 3D features from Kinetics pretrained ResNeXt-101

HowTo100M: Learning a Text-Video Embedding from Watching Hundred Million Narrated Video Clips



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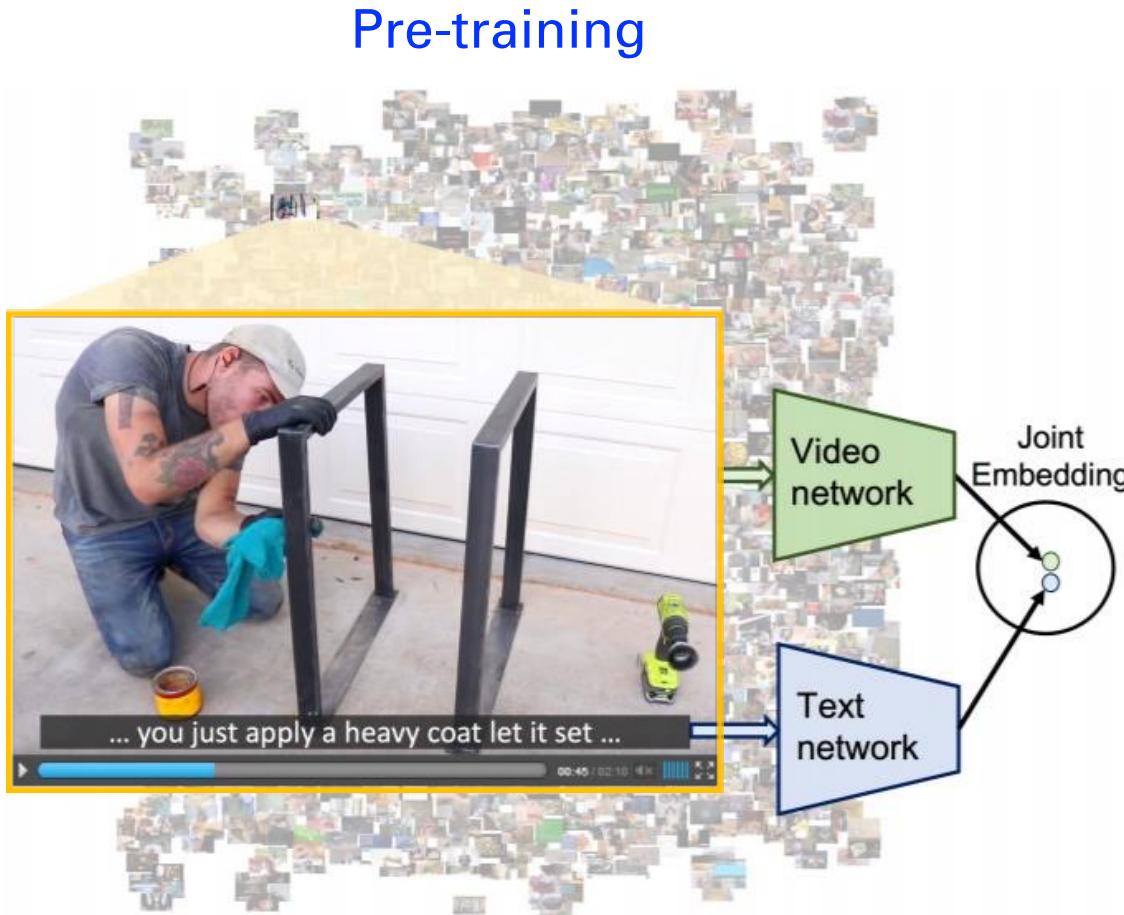
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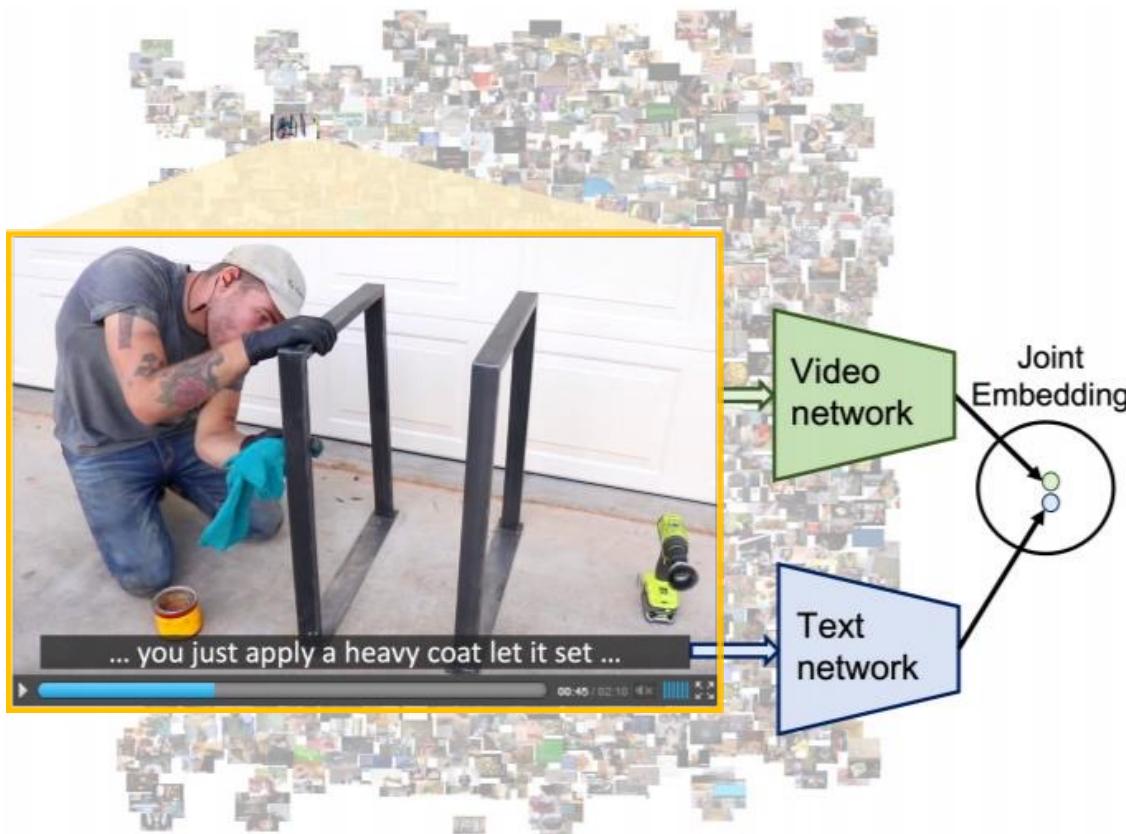
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Pre-training Joint Embedding

- Non-linear functions to embed both modalities to a common embedding space
- Supervise the training with max-margin ranking loss

HowTo100M: Learning a Text-Video Embedding from Watching Hundred Million Narrated Video Clips

Pre-training



Downstream Tasks

Weakly Supervised Step Localization



Step #1
Apply the jam Step #2
Assemble the sandwich

Retrieval

Query: Toast the bread slices in the toaster



HowTo100M: Learning a Text-Video Embedding from Watching Hundred Million Narrated Video Clips

Model	CrossTask (Averaged Recall)
Fully-supervised Upper-bound [1]	31.6
HowTo100M PT only (weakly supervised)	<u>33.6</u>

Step Localization

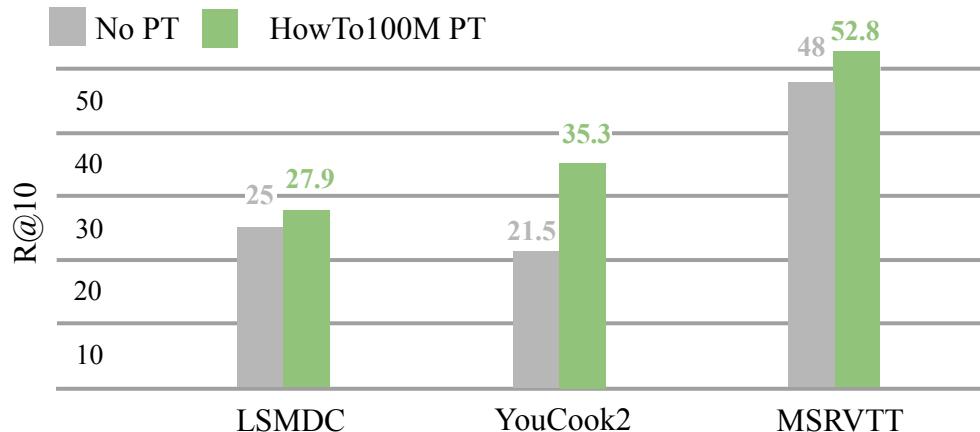
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Clip Retrieval

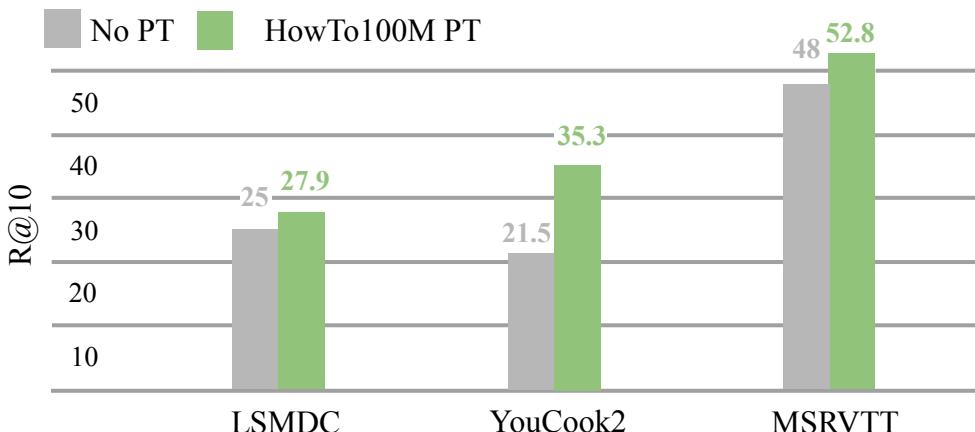
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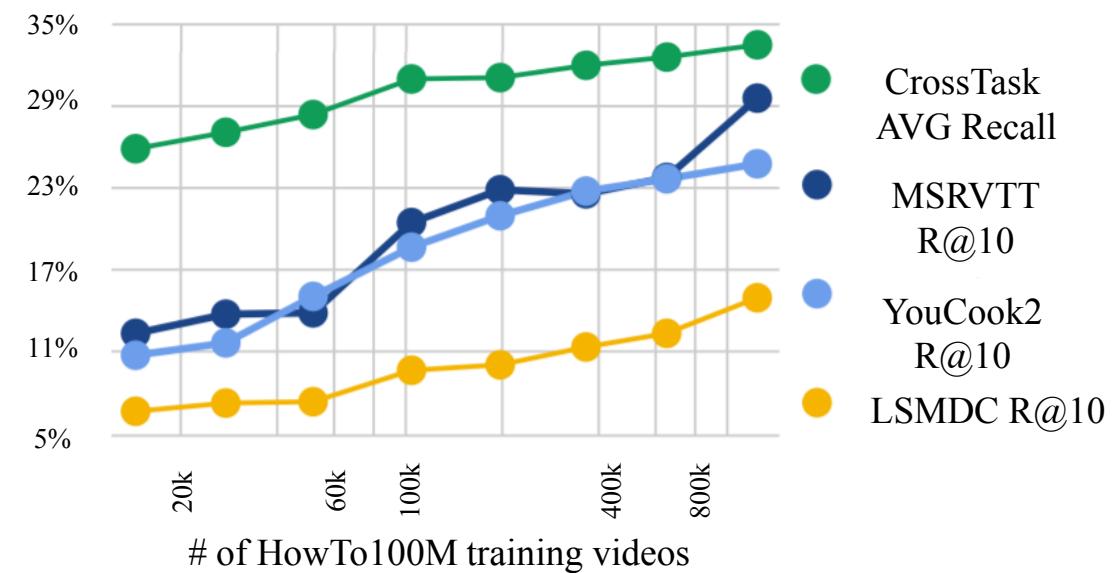
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Clip Retrieval

- HowTo100M PT largely boosts model performance despite the domain differences

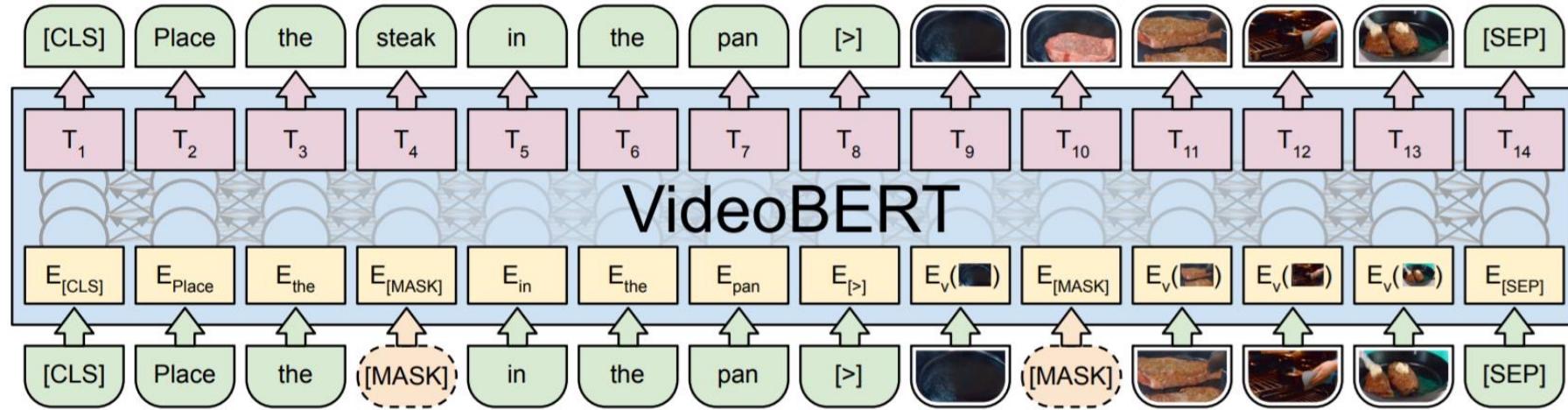
Downstream Performance vs. Pre-training Data Size



- Adding more data gives better results across all downstream tasks

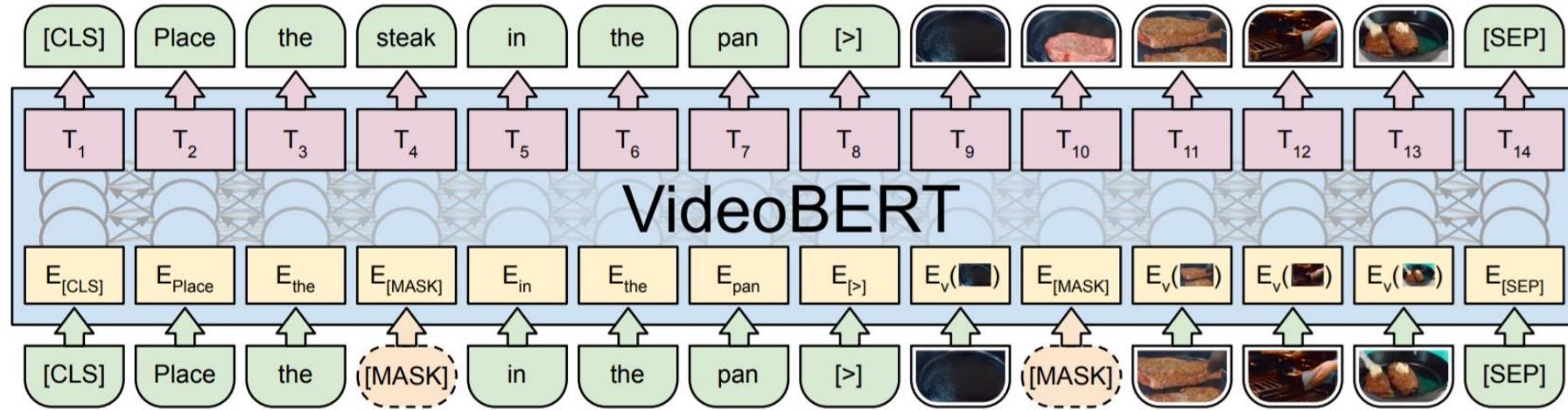
VideoBERT: A Joint Model for Video and Language Representation Learning

Pre-training



VideoBERT: A Joint Model for Video and Language Representation Learning

Pre-training

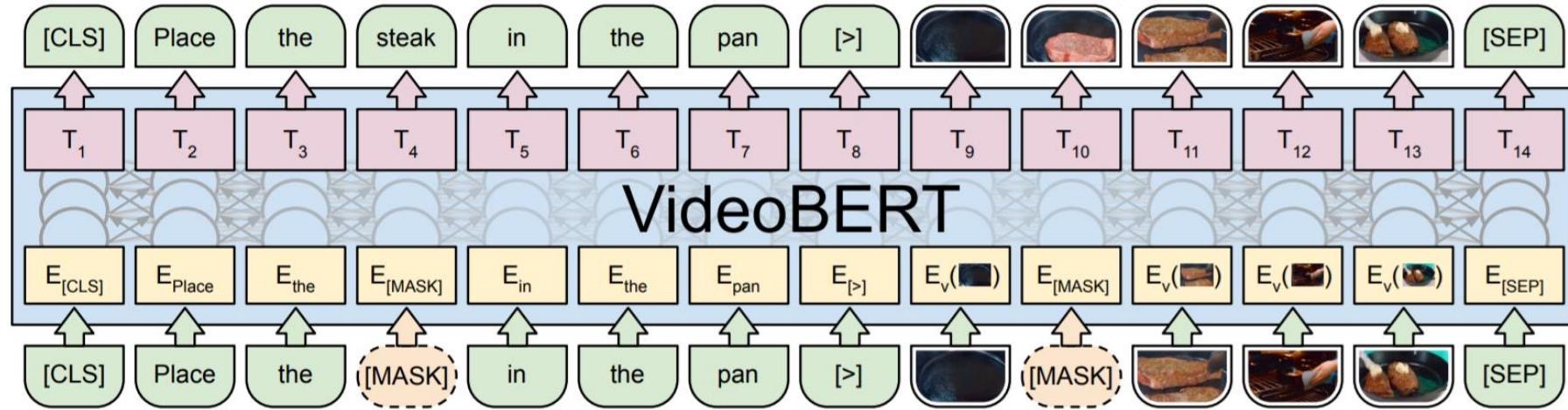


Large-scale Pre-training Dataset

- 312K cooking/recipe videos from YouTube

VideoBERT: A Joint Model for Video and Language Representation Learning

Pre-training



Large-scale Pre-training Dataset

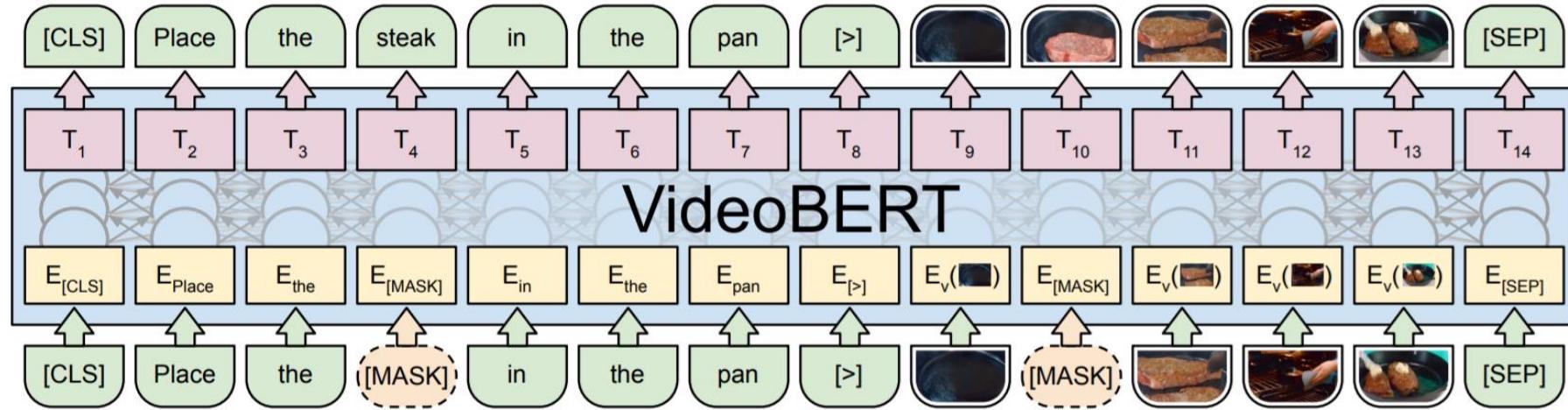
- 312K cooking/recipe videos from YouTube

Text Representations

- Tokenized into WordPieces, following BERT

VideoBERT: A Joint Model for Video and Language Representation Learning

Pre-training



Large-scale Pre-training Dataset

- 312K [cooking/recipe](#) videos from YouTube

Video Representations

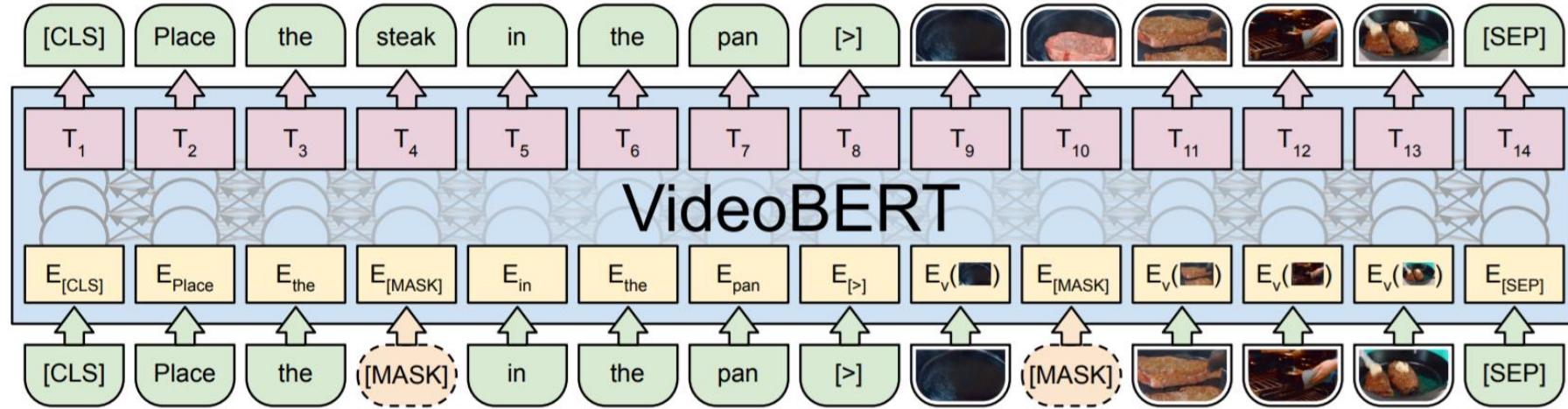
- 3D features from Kinetics pretrained S3D
- [Tokenized](#) into 21K clusters using hierarchical k-means

Text Representations

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VideoBERT: A Joint Model for Video and Language Representation Learning

Pre-training



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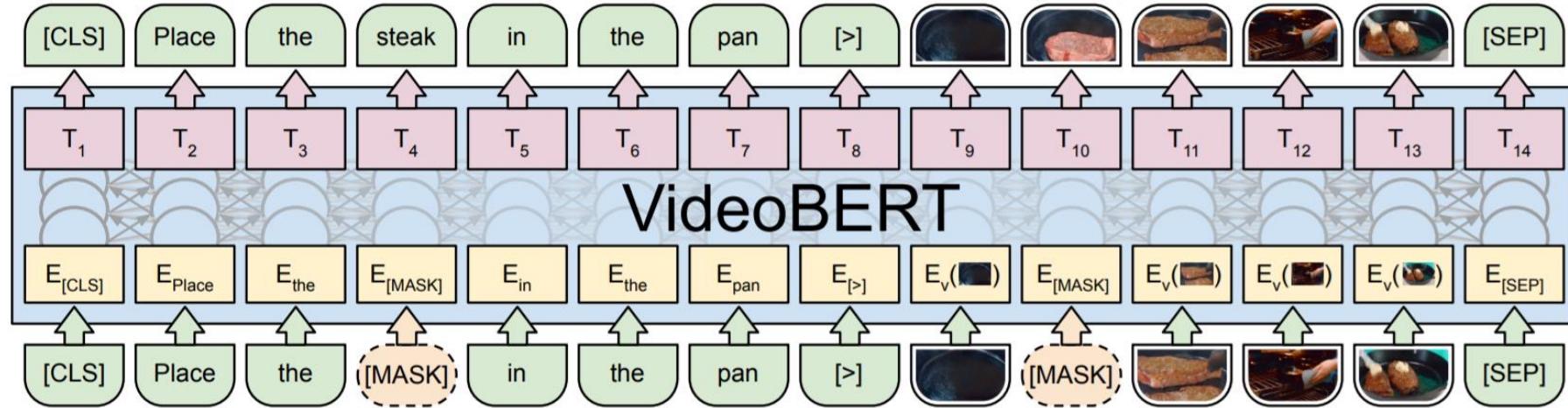
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Pre-training Joint Embedding

- Transformer-based Video-Text encoder
- Pre-training tasks: Masked Language Modeling (MLM) + Masked Frame Modeling (MFM)

VideoBERT: A Joint Model for Video and Language Representation Learning

Pre-training



Downstream Tasks

Captioning



Now, let's [MASK] the [MASK] to the [MASK] and [MASK] the [MASK].



Now, let's place the tomatoes to the cutting board and slice the tomatoes.

Zero-shot Action classification



Now, let's show you how to [MASK] the [MASK].



Top Verbs: make, assemble, prepare
Top Nouns: pizza, sauce, pasta

VideoBERT: A Joint Model for Video and Language Representation Learning

Model	Verb top-5	Object top-5
Fully-supervised Method [1]	<u>46.9</u>	30.9
VideoBERT (Zero-Shot)	43.3	<u>33.7</u>

YouCook2 Action Classification

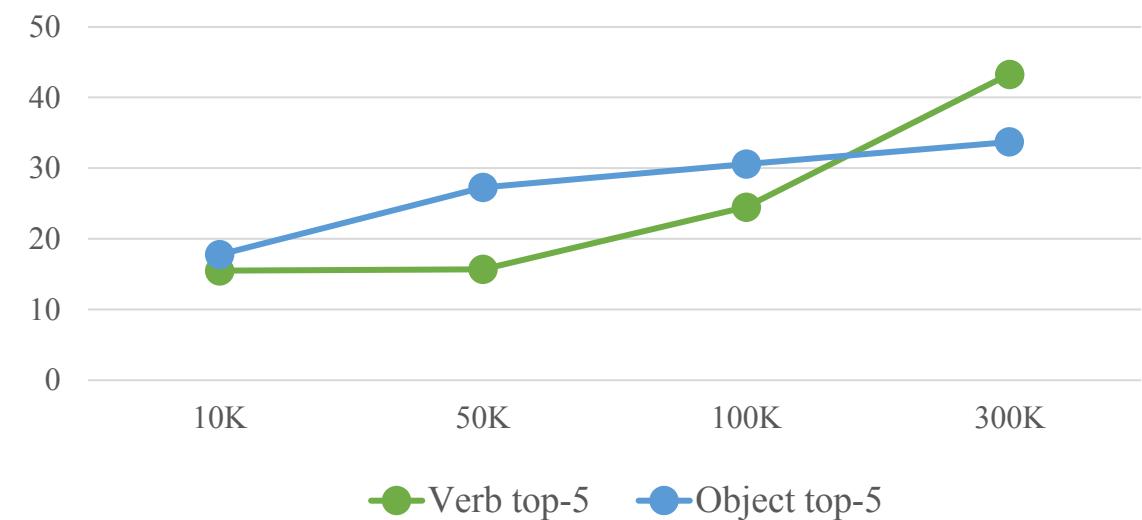
- VideoBERT (Zero-Shot) performs competitively to supervised method

Model	BLEU-4	METEOR	ROUGE-L	CIDEr
SOTA w/o PT [2]	3.84	11.55	27.44	0.38
VideoBERT	4.04	11.01	27.50	0.49
VideoBERT + S3D	<u>4.33</u>	<u>11.94</u>	<u>28.80</u>	<u>0.55</u>

YouCook2 Captioning

- VideoBERT outperforms SOTA
- Adding S3D features to visual tokens further boosts performance

YouCook2 Action Classification Performance
vs.
Pre-training Data Size

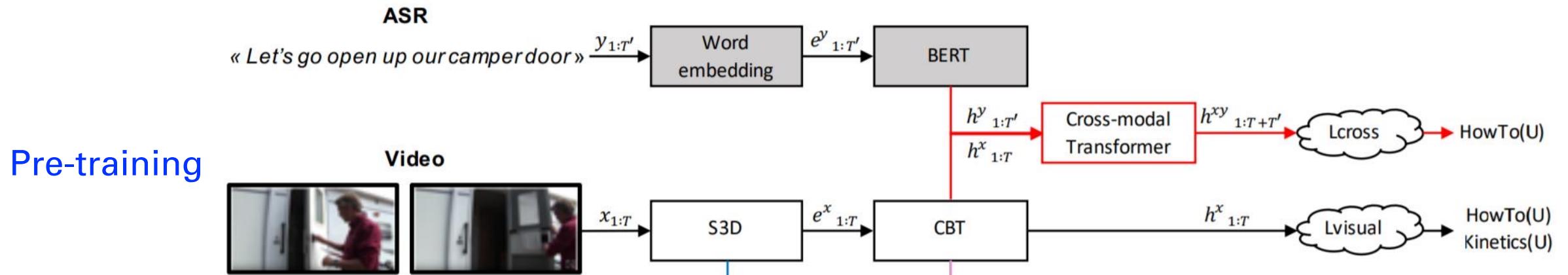


- Adding more data generally gives better results

[1] Xie, Saining, et al. "Rethinking spatiotemporal feature learning for video understanding." ECCV 2018

[2] Zhou, Luwei, et al. "End-to-end dense video captioning with masked transformer." CVPR 2018

CBT: Learning Video Representations using Contrastive Bidirectional Transformer



Large-scale Pre-training Dataset

- HowTo100M

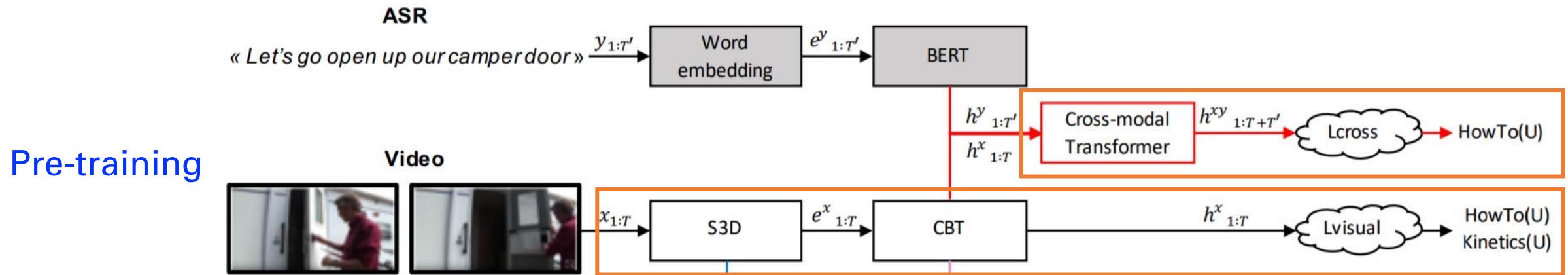
Text Representations

- Extract contextualized word embeddings from BERT

Video Representations

- 3D features from Kinetics pretrained S3D

CBT: Learning Video Representations using Contrastive Bidirectional Transformer



Large-scale Pre-training Dataset

- HowTo100M

Text Representations

- Extract contextualized word embeddings from BERT

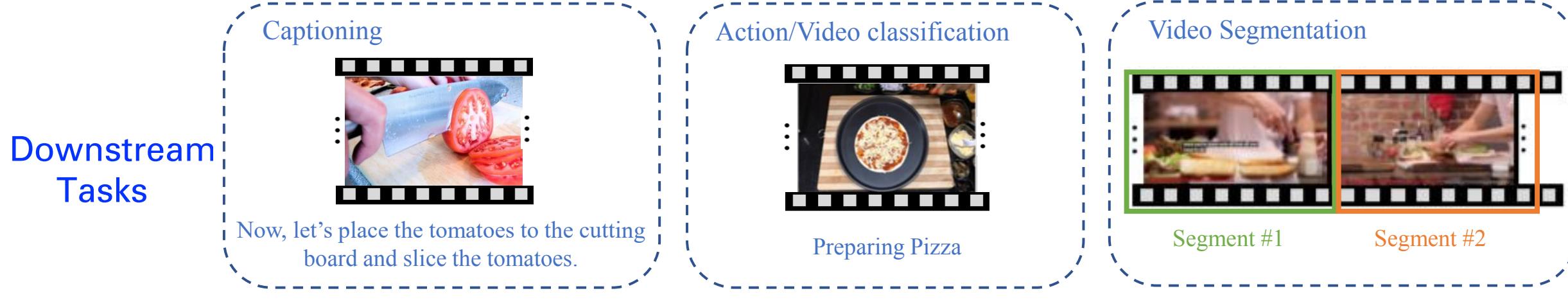
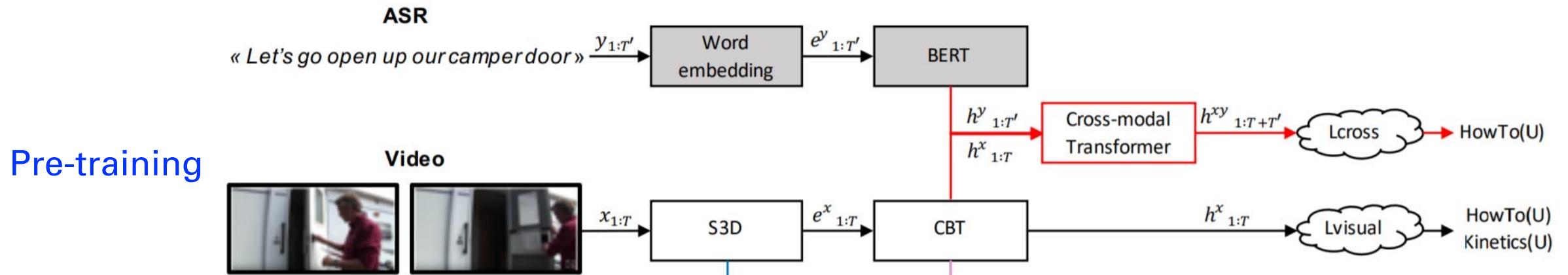
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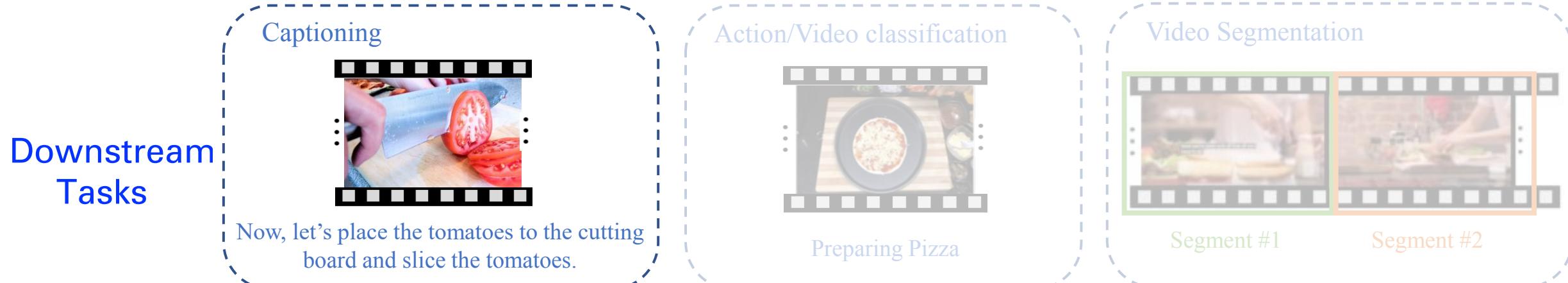
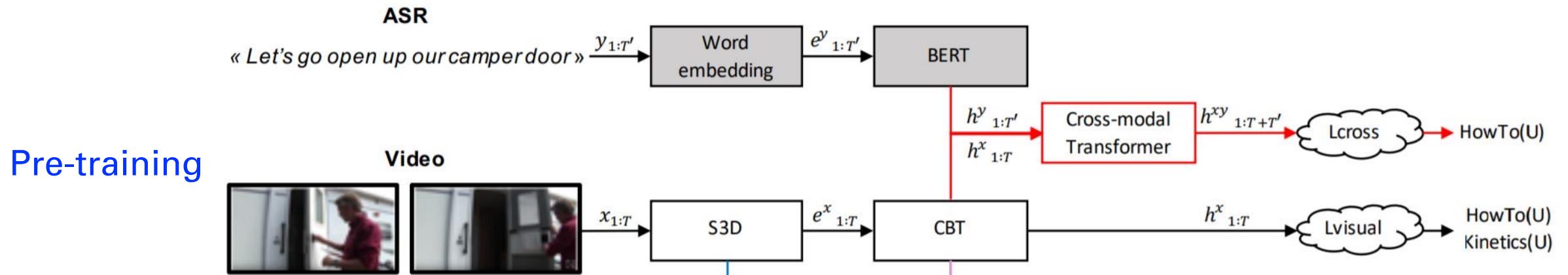
Pre-training for Better Video Representations

- 3 Transformers: BERT, CBT and Cross-modal Transformer
- Pre-train through Noise Contrastive Estimation (NCE)
 - Video-only Pre-training (end-to-end)
 - Video-Text Alignment (fixed S3D and BERT)

CBT: Learning Video Representations using Contrastive Bidirectional Transformer



CBT: Learning Video Representations using Contrastive Bidirectional Transformer



CBT: Learning Video Representations using Contrastive Bidirectional Transformer

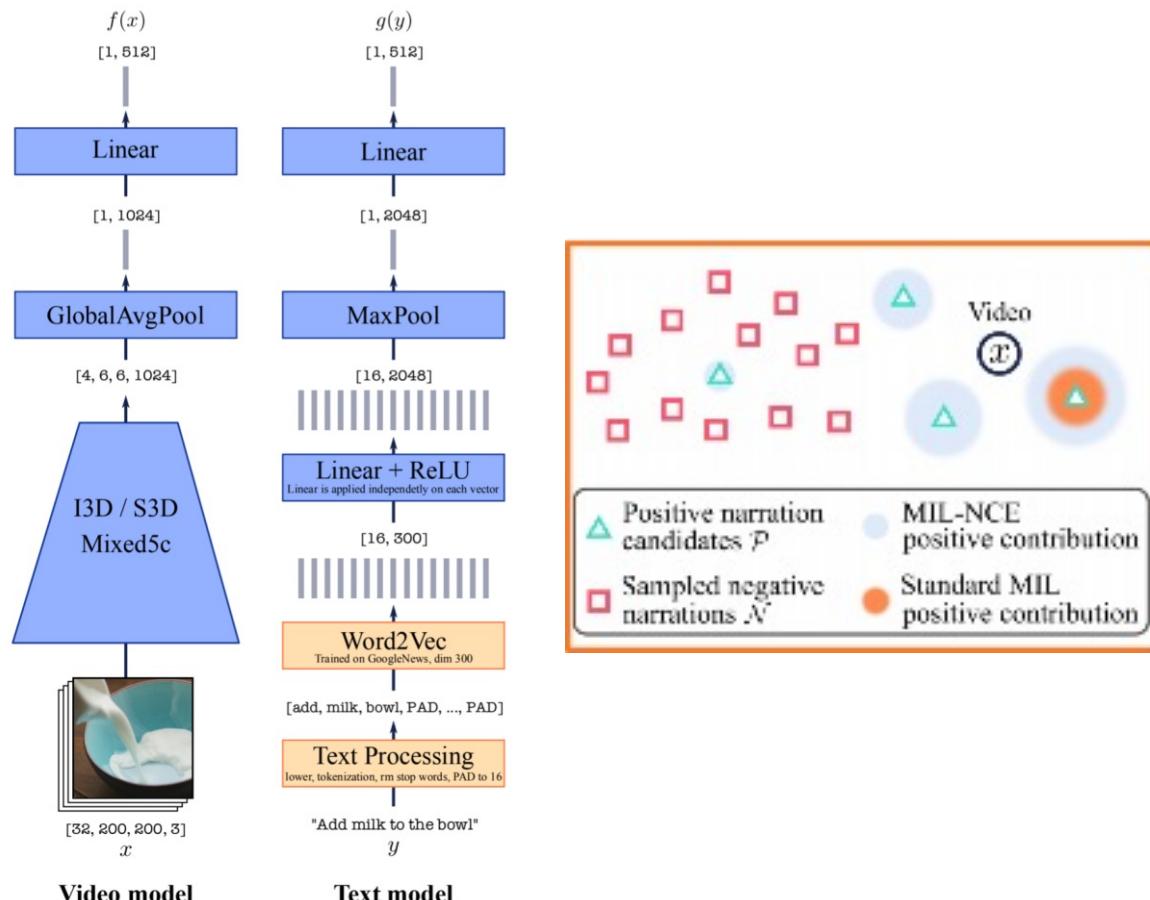
Model	BLEU-4	METEOR	ROUGE-L	CIDEr
SOTA w/o PT [1]	4.38	11.55	27.44	0.38
S3D	3.24	9.52	26.09	0.31
VideoBERT + S3D	4.33	11.94	28.80	0.55
CBT	<u>5.12</u>	<u>12.97</u>	<u>30.44</u>	<u>0.64</u>

YouCook2 Captioning

- CBT achieves the new state of the art, as contrastive learning encourages better video representations

MIL-NCE: End-to-End Learning of Visual Representations from Uncurated Instructional Videos

Pre-training



Large-scale Pre-training Dataset

- HowTo100M

Video Representations

- 3D features from I3D/S3D

Text Representations

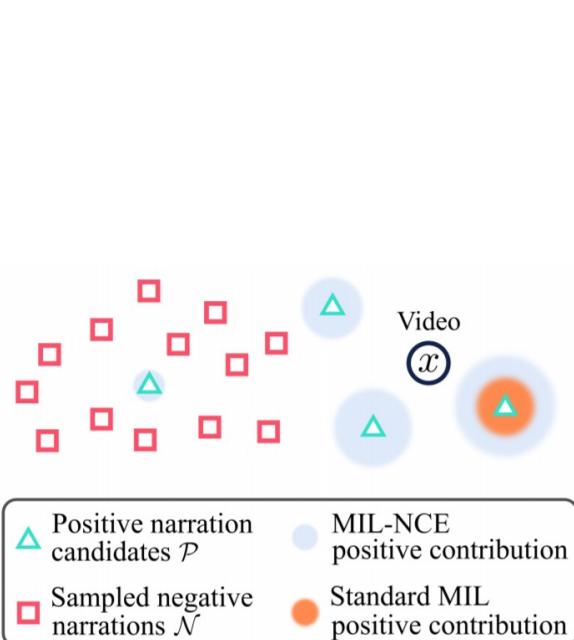
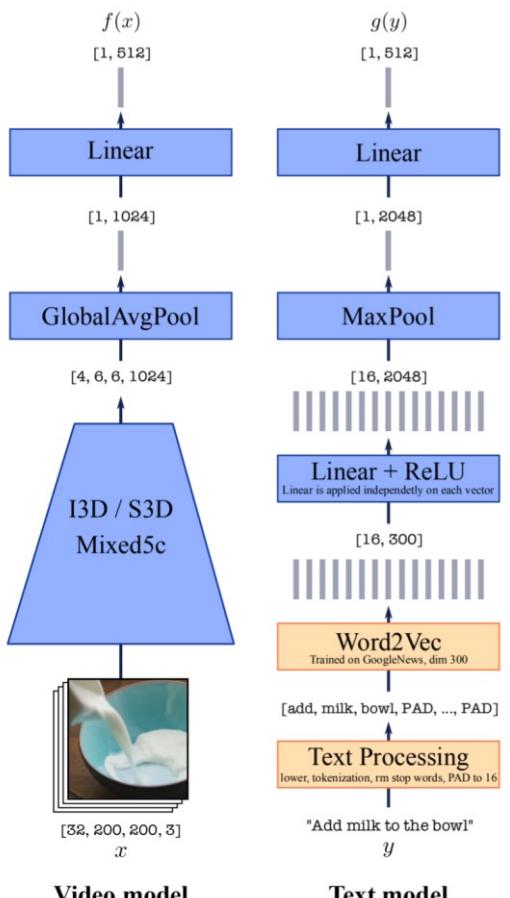
- GoogleNews pre-trained word2vec embeddings

Pre-training Joint Embedding

- MIL-NCE pre-training
 - Multiple Instance Learning (MIL)
 - Noise Contrastive Estimation (NCE)

MIL-NCE: End-to-End Learning of Visual Representations from Uncurated Instructional Videos

Pre-training



Downstream Tasks

Action Recognition



Preparing Pizza

Action (Step) Segmentation/Localization



Step #1
Apply the jam Step #2
Assemble the sandwich

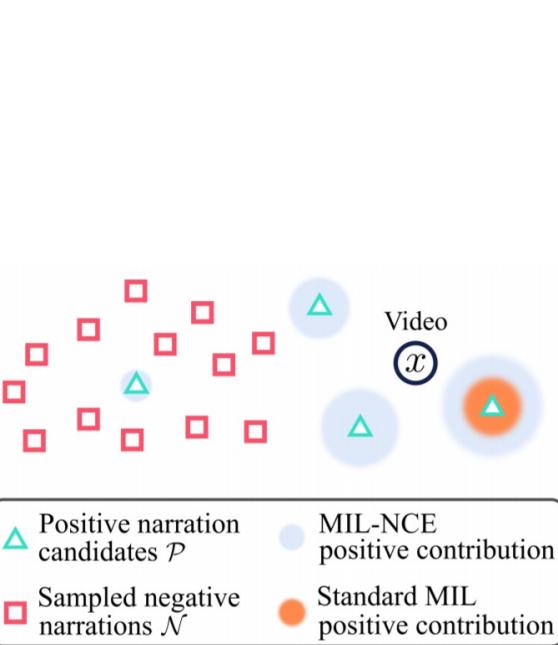
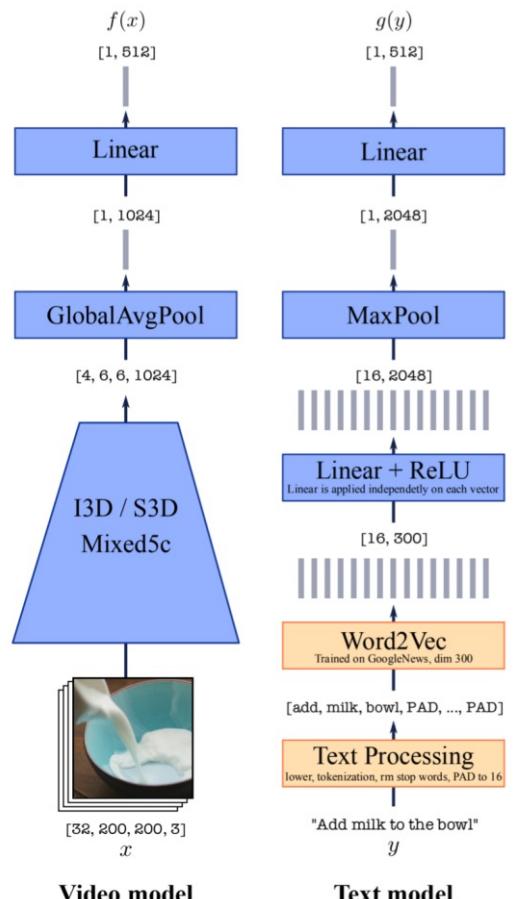
Retrieval

Query: Toast the bread slices in the toaster

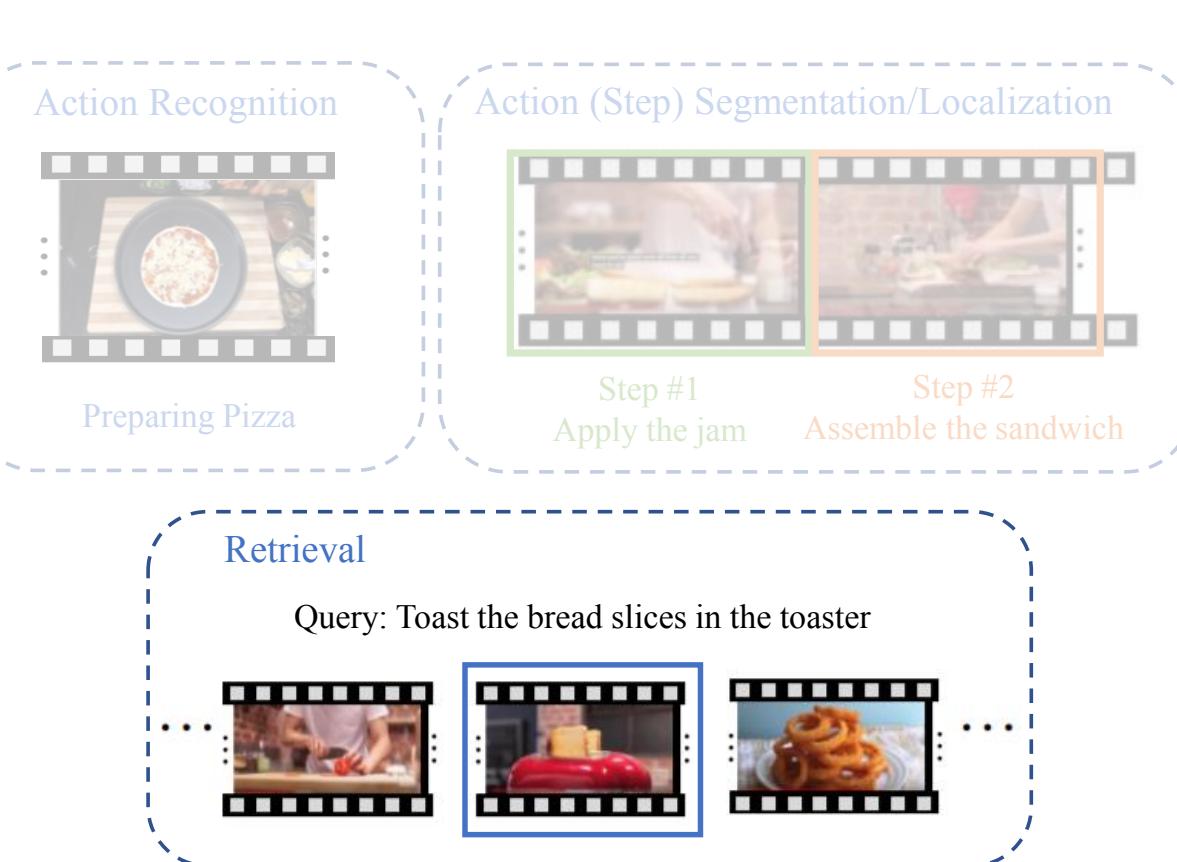


MIL-NCE: End-to-End Learning of Visual Representations from Uncurated Instructional Videos

Pre-training



Downstream Tasks



MIL-NCE: End-to-End Learning of Visual Representations from Uncurated Instructional Videos

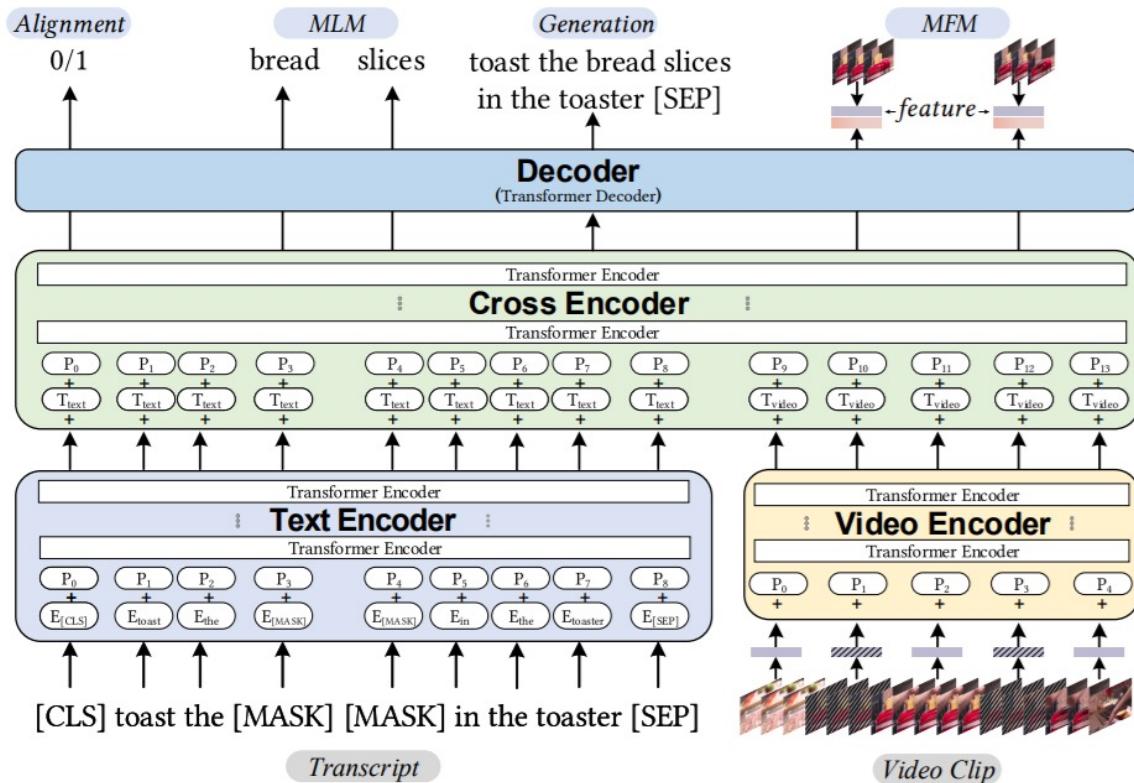
Model	Labeled Dataset Used	YouCook2 (Median R)	MSRVTT (Median R)
HowTo100M	ImageNet + Kinetics400	46	38
	ImageNet + Kinetics400 + YouCook2	24	-
MIL-NCE	None	<u>16</u>	<u>35</u>

Zero-shot Clip Retrieval

- On both datasets, MIL-NCE improves over HowTo100M without using any labeled data
- On YouCook2, MIL-NCE even surpasses supervised HowTo100M model

UniViLM: a Unified Video and Language pre-training Model for multimodal understanding and generation

Pre-training



Large-scale Pre-training Dataset

- 380K videos from HowTo100M
- All food domain related videos

Video Representations

- 2D features from ImageNet pre-trained ResNet-152
- 3D features from Kinetics pre-trained ResNeXt-101

Text Representations

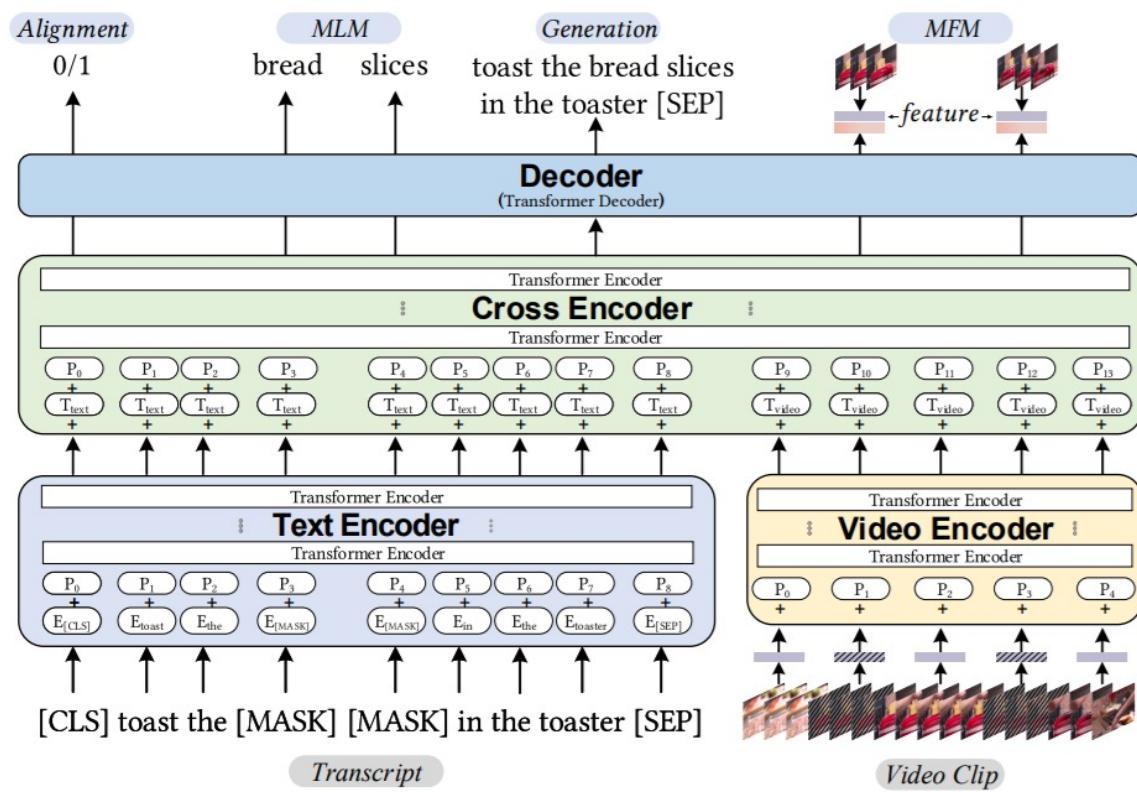
- Tokenized into WordPieces, following BERT

Pre-training Joint Embedding

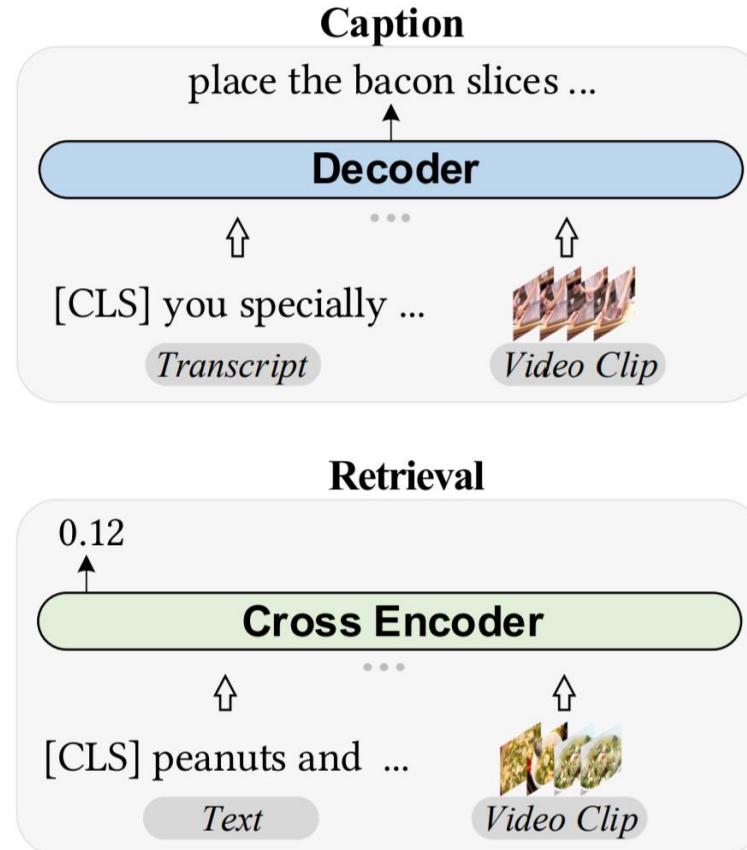
- Pre-training tasks: MLM + MFM + Video-Text Alignment

UniViLM: a Unified Video and Language pre-training Model for multimodal understanding and generation

Pre-training



Downstream Tasks



UniViLM: a Unified Video and Language pre-training Model for multimodal understanding and generation

Model	Pre-training Data Size	YouCook2 (Median R)	MSRVTT (Median R)
HowTo100M	1.2M	24	9
	380K	25	16
UniViLM	380K	<u>20</u>	9

Clip Retrieval

- On YouCook2 (in-domain), UniViLM improves over HowTo100M with less pre-training data
- On MSRVTT (out-of-domain), UniViLM surpasses HowTo100M with the same amount of pre-training data

YouCook2 Captioning

- UniViLM w/o pre-training achieves worse performance
- UniViLM w/ pre-training slightly outperforms SOTA

Model	Pre-training Data Size	BLEU-4	METEOR	ROUGE-L	CIDEr
SOTA [1]	0	9.01	<u>17.77</u>	36.65	1.12
UniViLM	0	8.67	15.38	35.18	1.00
UniViLM	380K	<u>10.42</u>	16.93	<u>38.04</u>	<u>1.20</u>

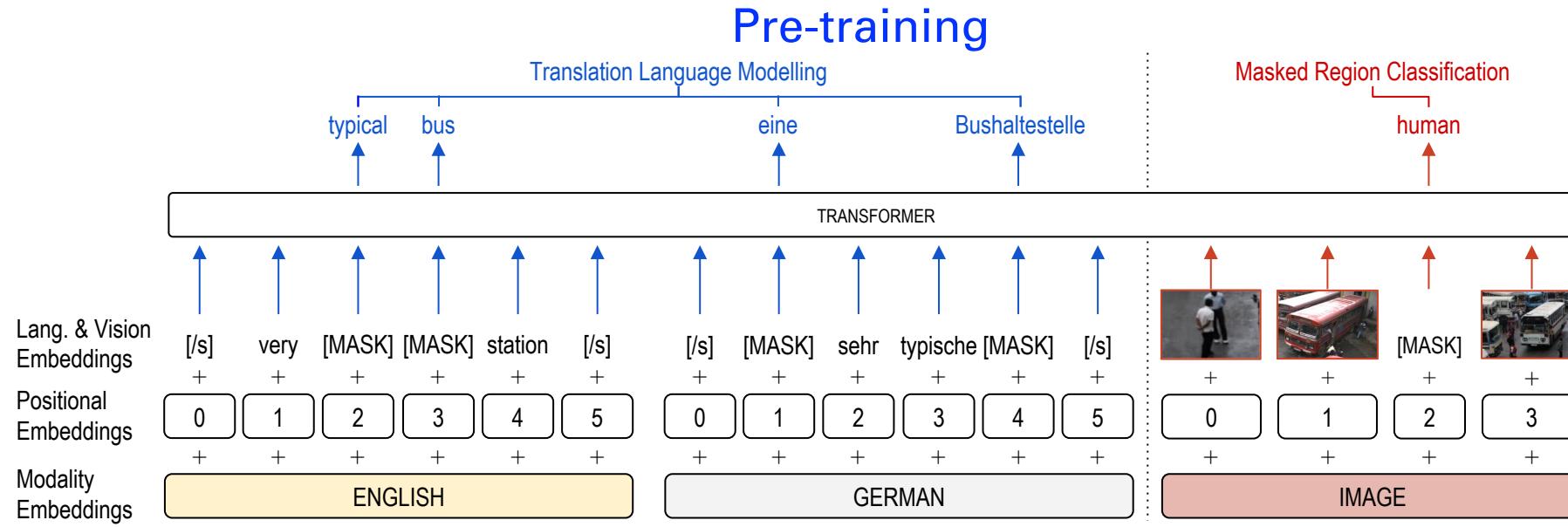
Summary: Self-Supervised Learning for V+L

- Video + Language Pre-training is still at its early stage
 - Video + Language inputs are directly concatenated, losing the temporal alignment
 - Pre-training tasks directly borrowed from Image + Text Pre-training
 - Pre-training datasets limited to narrated instructional videos from YouTube
- Video + Language downstream tasks are relatively “simple”
 - Mostly focus on visual clues only
 - Subtitles/Narrations contain a lot of information, but usually discarded

Lecture overview

- Introduction
- Pre-training data
- Feature representations for vision and language
- Model architectures
- Pre-training tasks
- Downstream tasks
- Moving forward
 - Self-supervised learning for video + language
 - **Multilingual multimodal pre-training**

VTLM: Cross-lingual Visual Pre-training for Multimodal Machine Translation



Large-scale Pre-training Dataset

- ~3.3M images from Conceptual Captions

Image Representations

- 2D features from Open Images pre-trained Faster R-CNN detections and full image

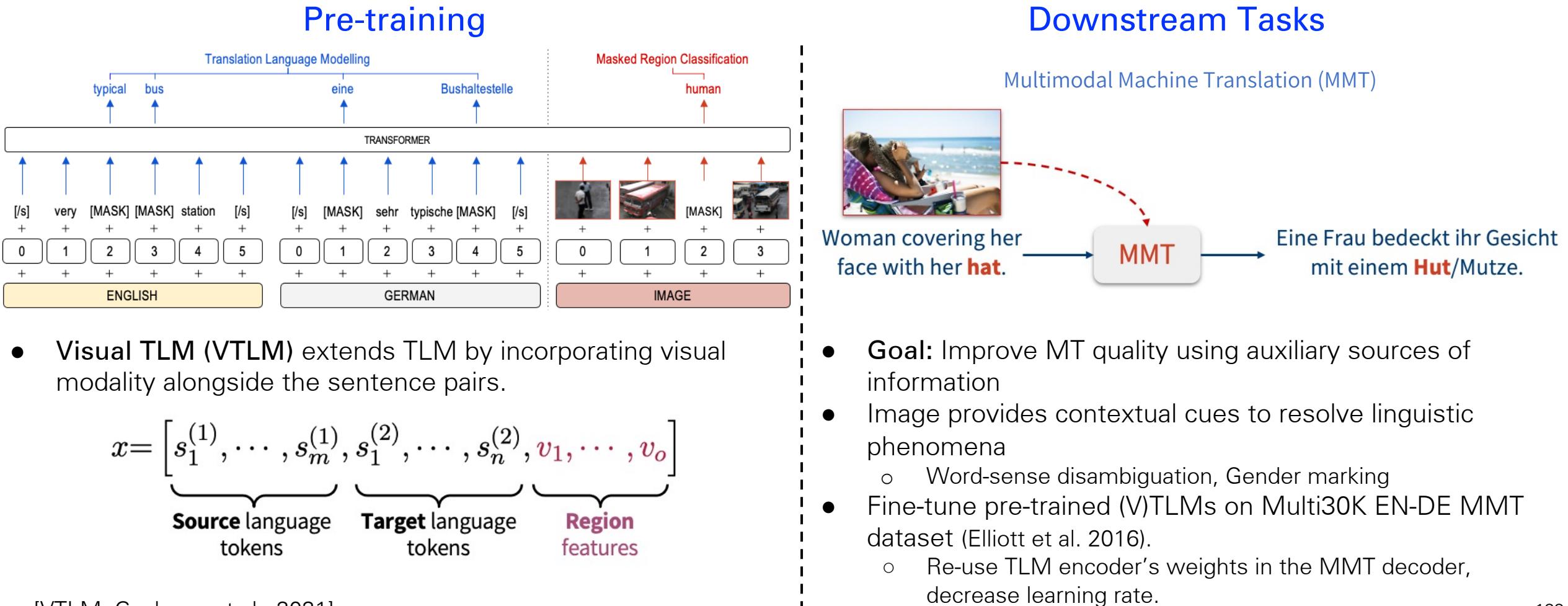
Text Representations

- Tokenized English and German descriptions

Pre-training Joint Embedding

- Pre-training tasks: Translation Language Modeling (**TLM**) + Masked Region Classification (**MRC**)

VTLM: Cross-lingual Visual Pre-training for Multimodal Machine Translation



VTLM: Cross-lingual Visual Pre-training for Multimodal Machine Translation

1. Pre-training on CC boosts all scores upwards substantially
(pre-training on Multi30k does not, cf. paper)
2. VTLM pre-training helps MMT more than TLM pre-training
3. Interestingly, not masking the visual regions (but keeping the MRC task) yields the best performance

2016		2017		coco	
METEOR	BLEU	METEOR	BLEU	METEOR	BLEU
Best RNN-MMT (Caglayan, 2019)					
58.7	39.4	52.9	32.6	-	-
Graph-based Transformers MMT (Yin et al., 2020)					
57.6	39.8	51.9	32.2	37.6	28.7
Ensemble RNN-MMT (Delbrouck and Dupont, 2018)					
59.6	40.3	-	-	-	-
Unconstrained Transformers MMT (Helcl et al., 2018)					
59.1	42.7	-	-	-	-
TLM-MMT: Pre-train on CC and Fine-tune on Multi30k					
60.3	41.9	56.7	37.6	53.3	34.3
60.2 ± 0.08	41.7 ± 0.18	56.5 ± 0.16	37.5 ± 0.1	53.0 ± 0.2	34.1 ± 0.14
VTLM-MMT: Pre-train on CC and Fine-tune on Multi30k					
60.8	42.7	57.1	38.1	53.1	34.2
60.6 ± 0.15	42.6 ± 0.14	56.9 ± 0.2	37.7 ± 0.43	53.0 ± 0.05	33.9 ± 0.19
VTLM-MMT: Alternative (0% visual masking during pre-training)					
61.3	44.0	57.2	38.0	53.8	35.2
60.9 ± 0.3	43.3 ± 0.6	57.1 ± 0.07	37.6 ± 0.3	53.6 ± 0.17	35.1 ± 0.1

THE END