UNITER: UNiversal Image-TExt Representation Learning

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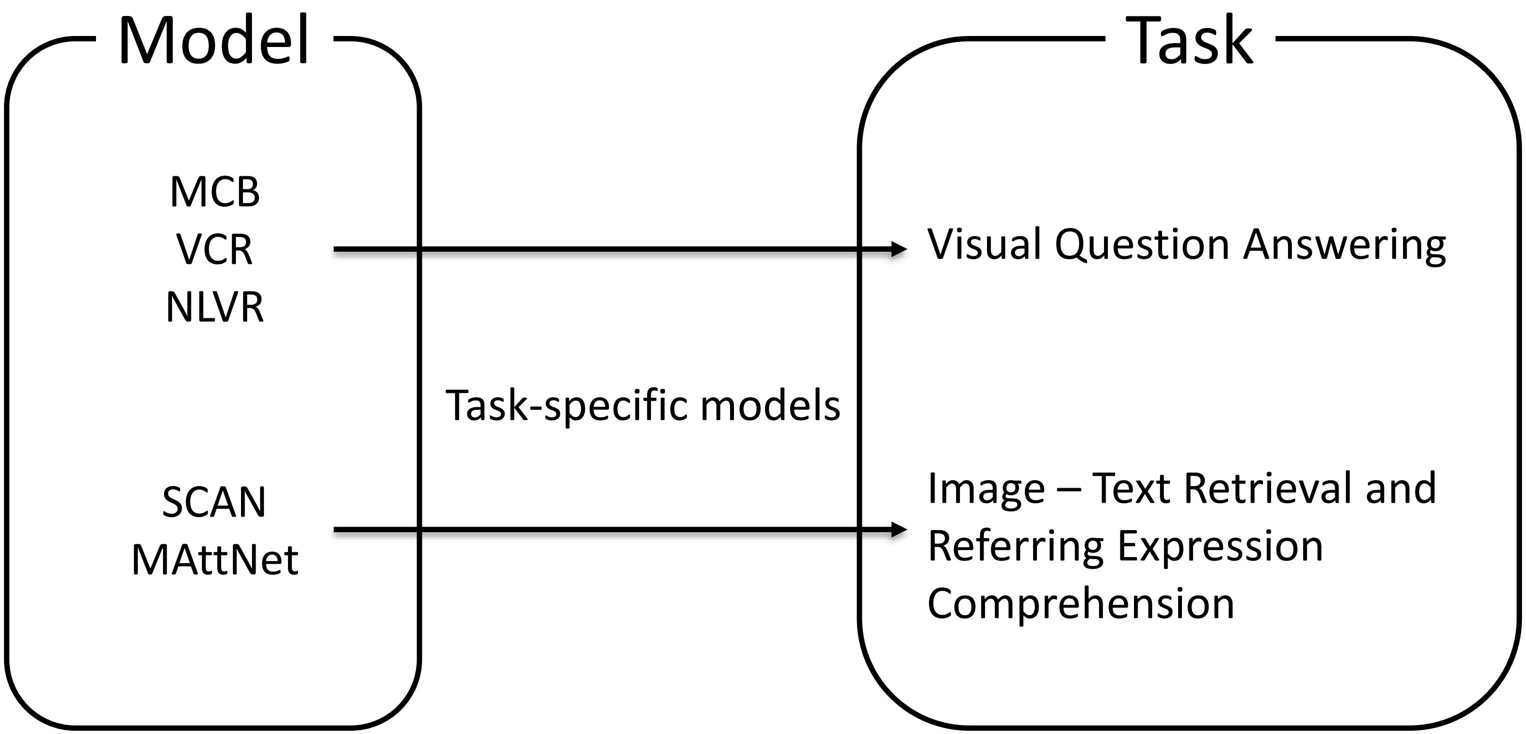
Problem Statement

How to learn a UNiversal Image-TExt Representation for all V + L tasks?

Motivation



Raising a million-dollar question :
Can we learn a universal image-text representation for all V+L tasks?

Motivation

+

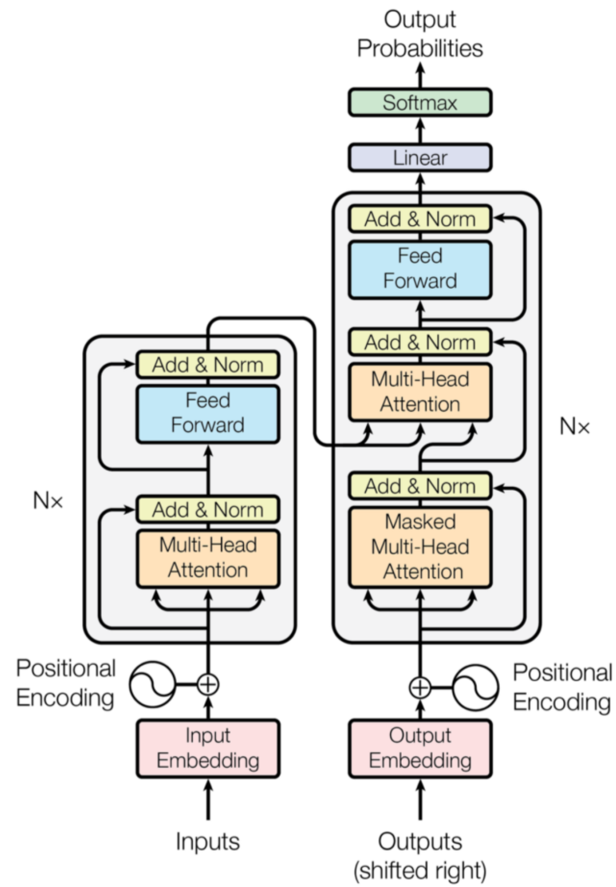


Figure 1: The Transformer - model architecture.

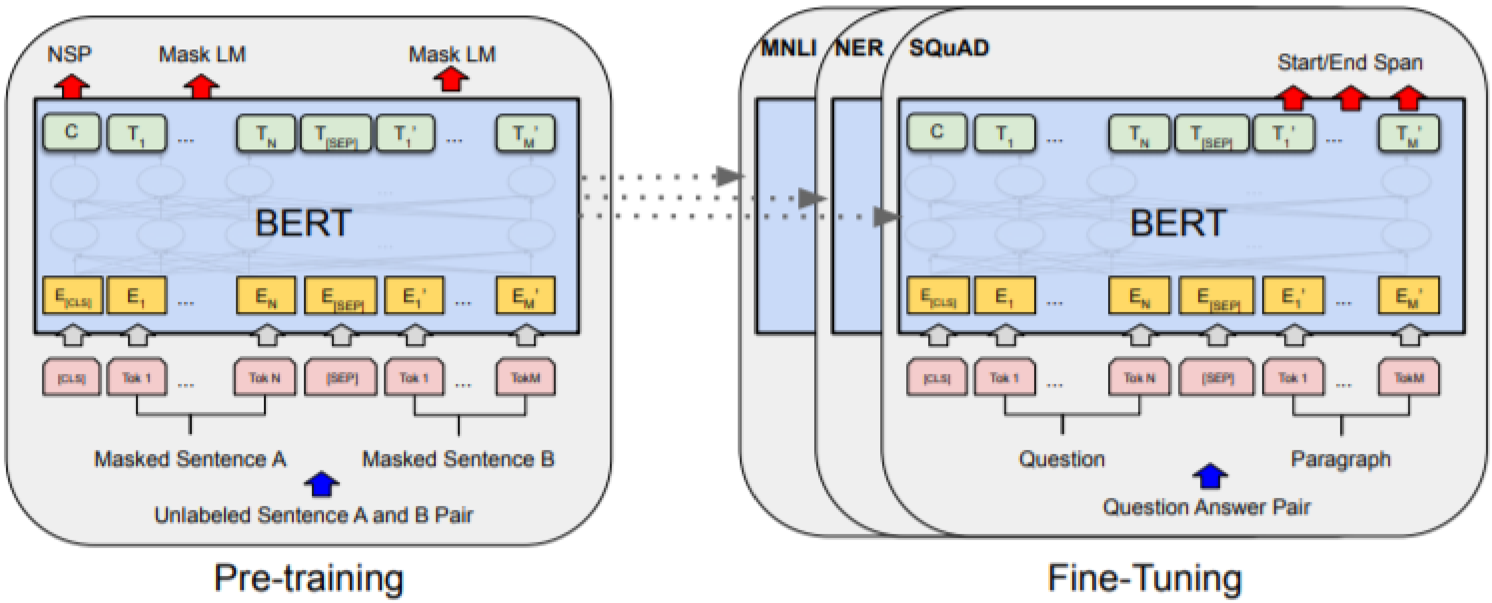
Two keys to great advance in NLP task

1. Effective pre-training task over large language corpus.
2. Use of Transformer for learning contextualized text representations.

Previous work

[Pretrain-then-transfer learning]

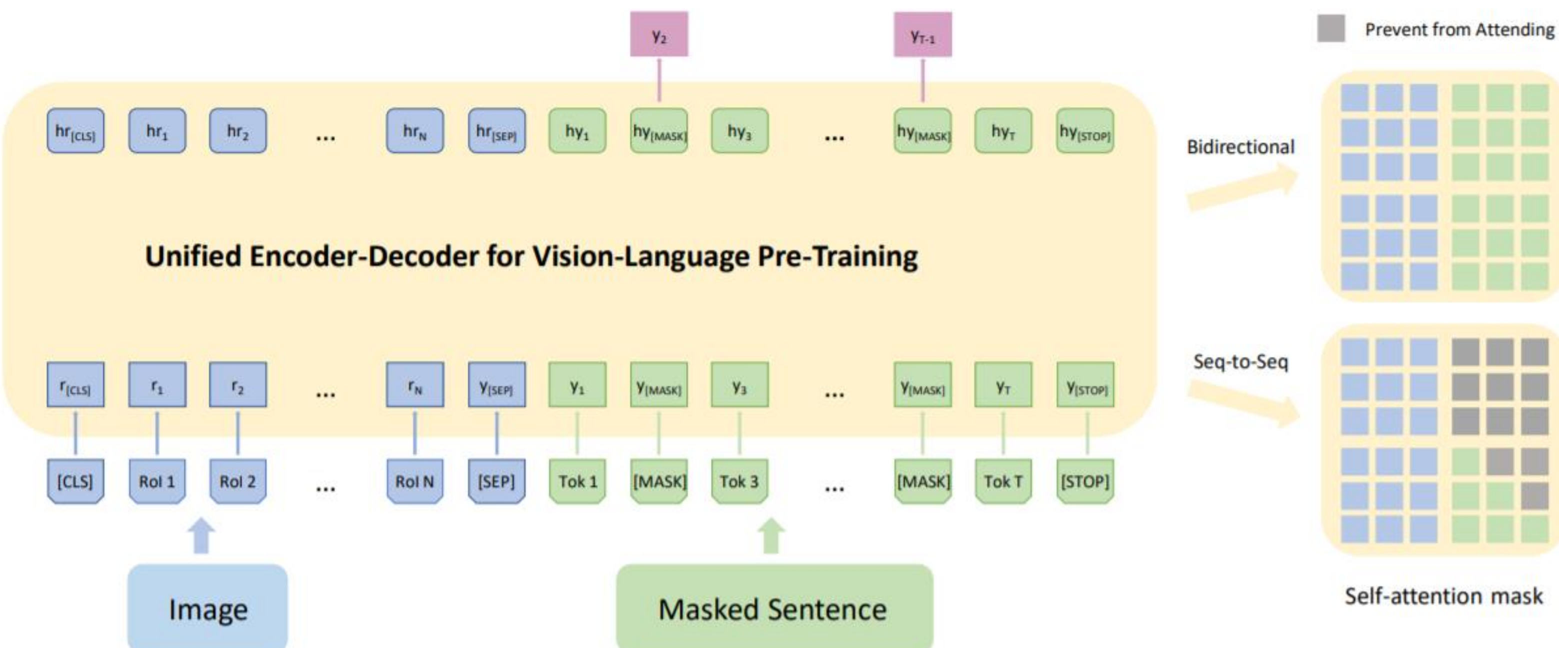
<BERT : Pre-training of Deep Bidirectional Transformers for Language Understanding>



Previous work

[Pretrained model for V + L tasks]

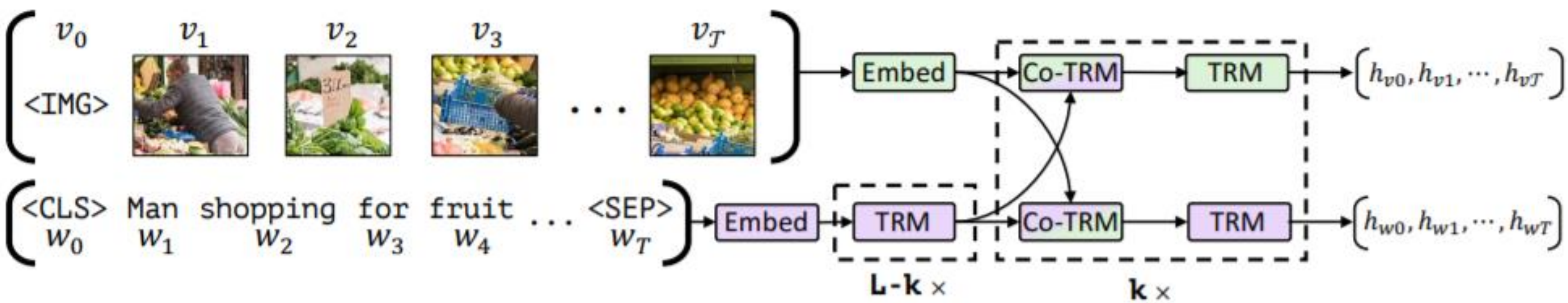
<Unified Vision-Language Pre-Training for Image Captioning and VQA>



VLP applied pre-trained models to both image captioning and VQA.

Related work

Two stream architecture – ViLBERT

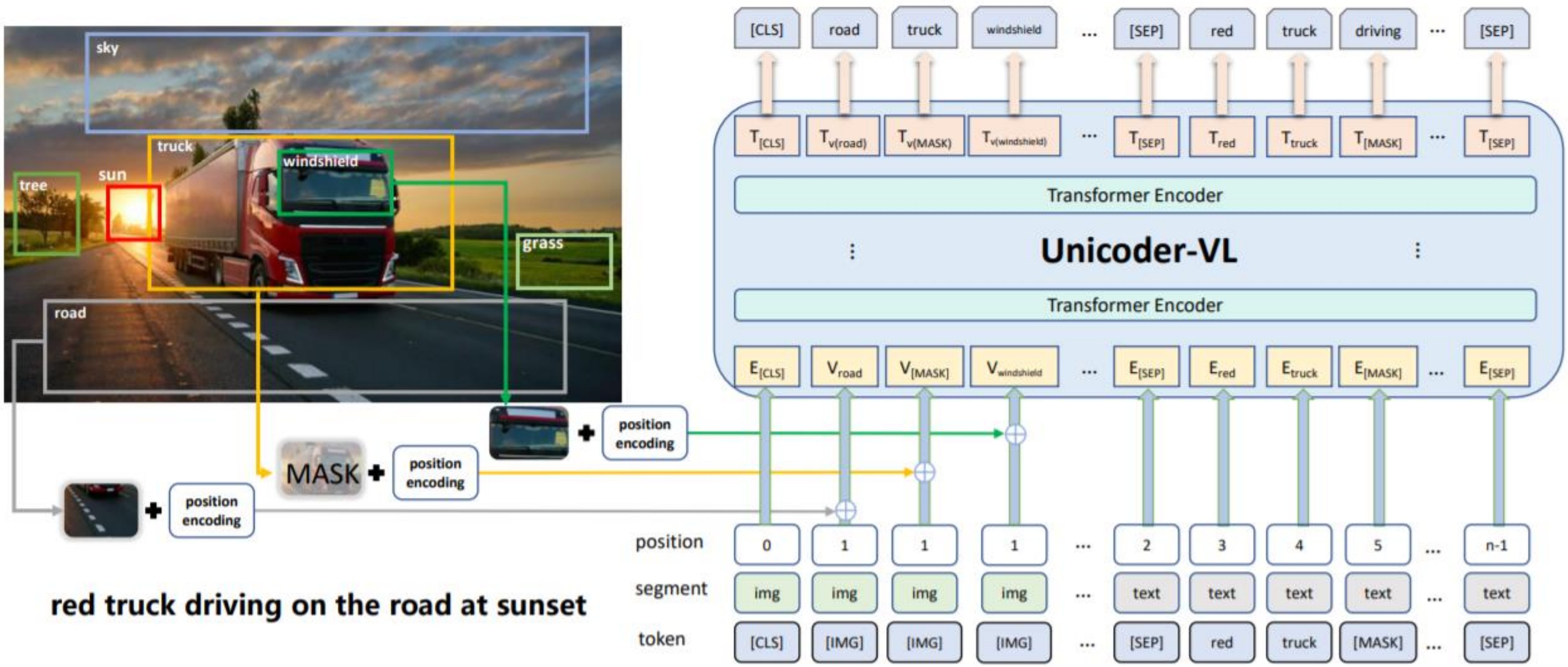


Two separate stream, interact through co-attentional transformer layer.

Pre-trained with Masked Multi-modal modeling and Multi-modal alignment prediction

Related work

Single stream architecture – Unicoder-VL



Pre-trained with Masked Language Modeling,
Masked Object Classification and Visual-linguistic Matching

Contribution

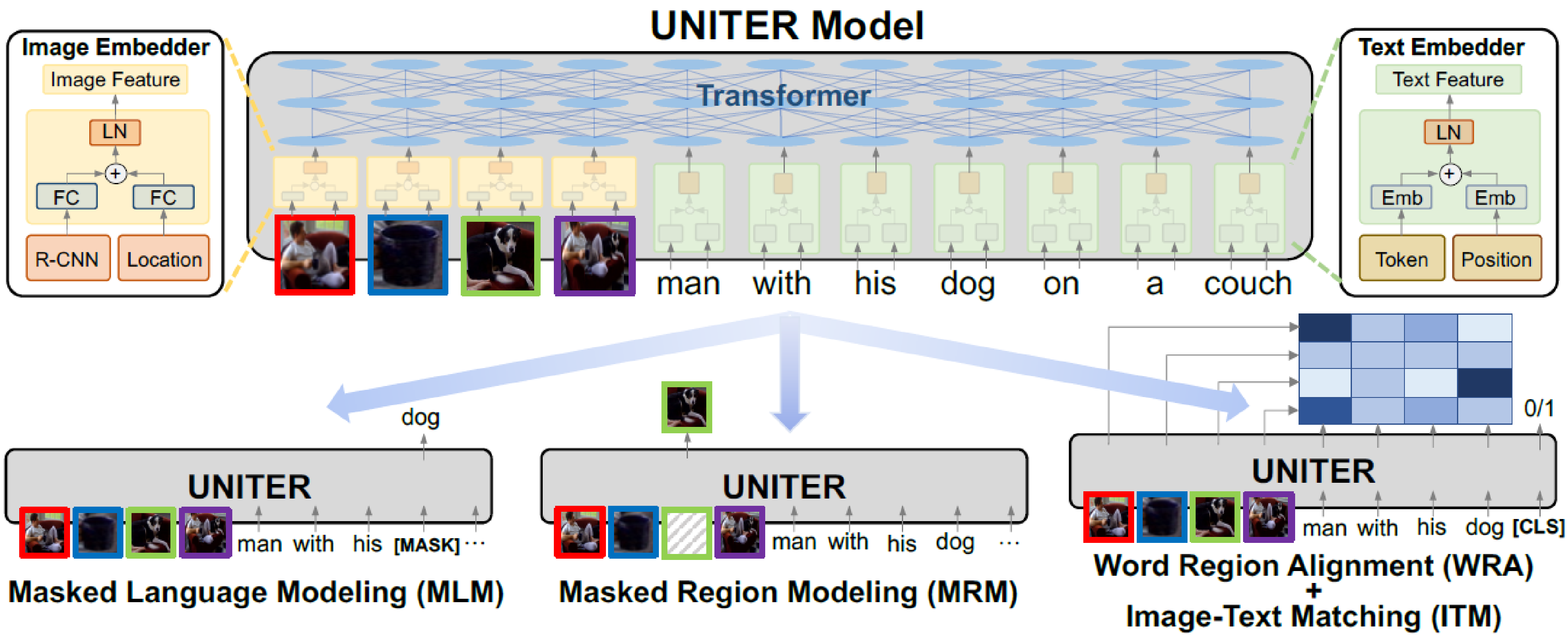
1. They Introduce powerful Universal Image-Text Representation for V + L task.

2. They present conditional Masking for masked language/region modeling and propose a novel optimal-Transport-based Word-region Alignment task for pre-training.

3. They achieve new SOTA on a wide range of V + L benchmarks, outperforming existing multimodal pre-training methods by a large margin.

Model

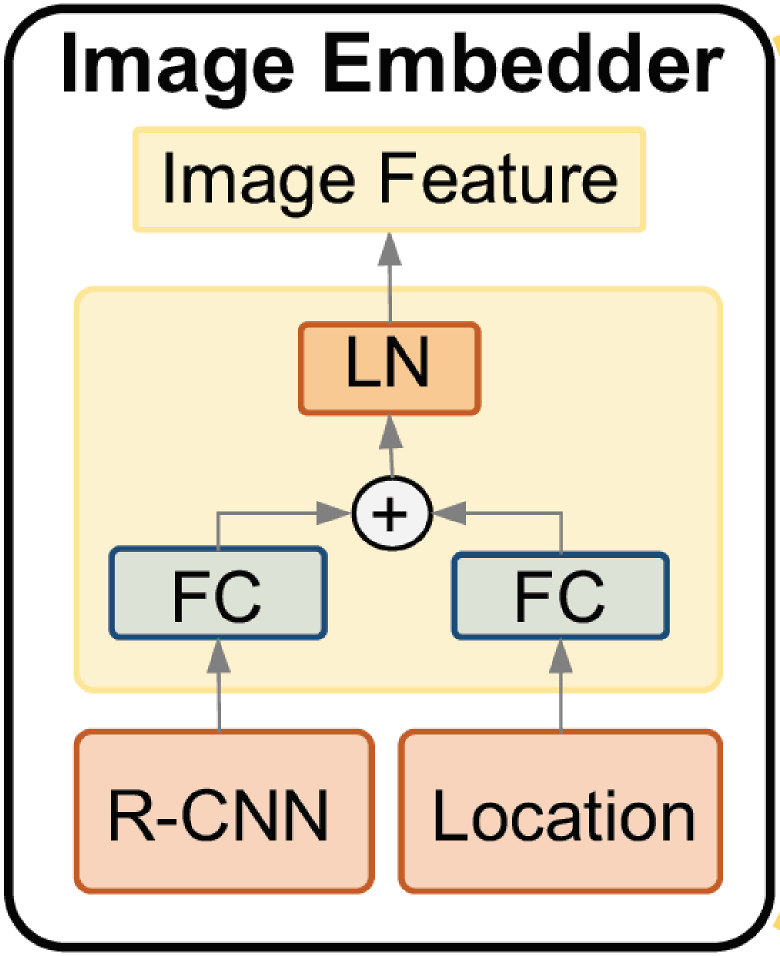
[The entire architecture]



Uniter model consists of Image Embedder, Text Embedder and Transformer module.
Input : image – sentence pair data, with region and words token

Model

[Image Embedder]



Represent location feature
via a 7-dimensional vector

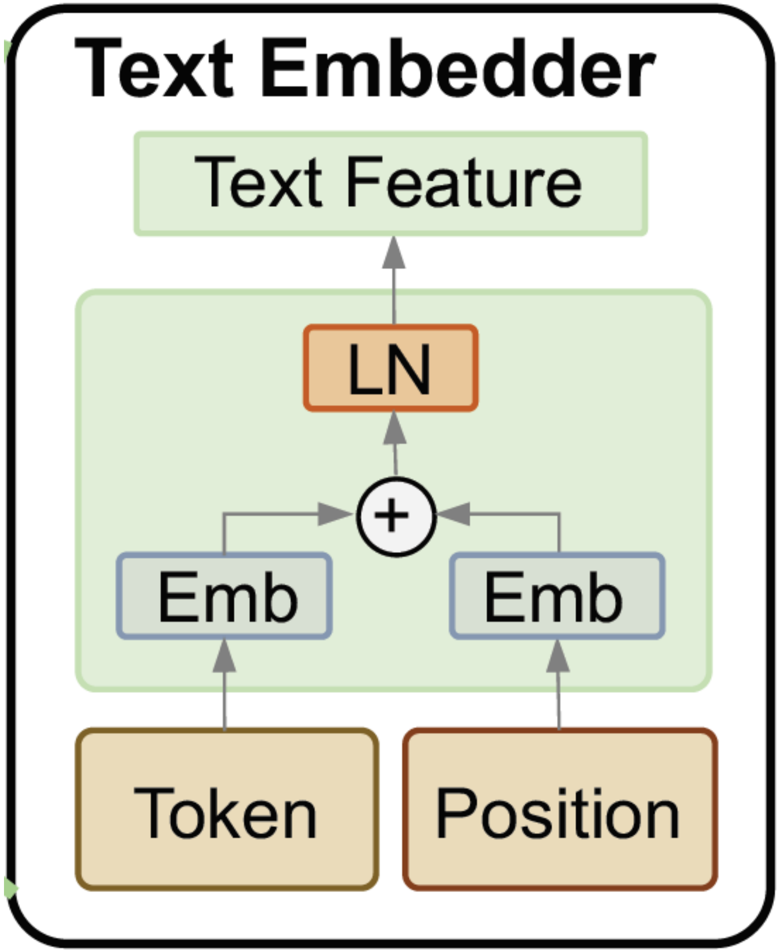
By Fully connected layer,
projected Same embedding space.

Passing through a layer
normalization layer.

Faster R-CNN was pre-trained on Visual
Genome object + attribute data

Model

[Text Embedder]

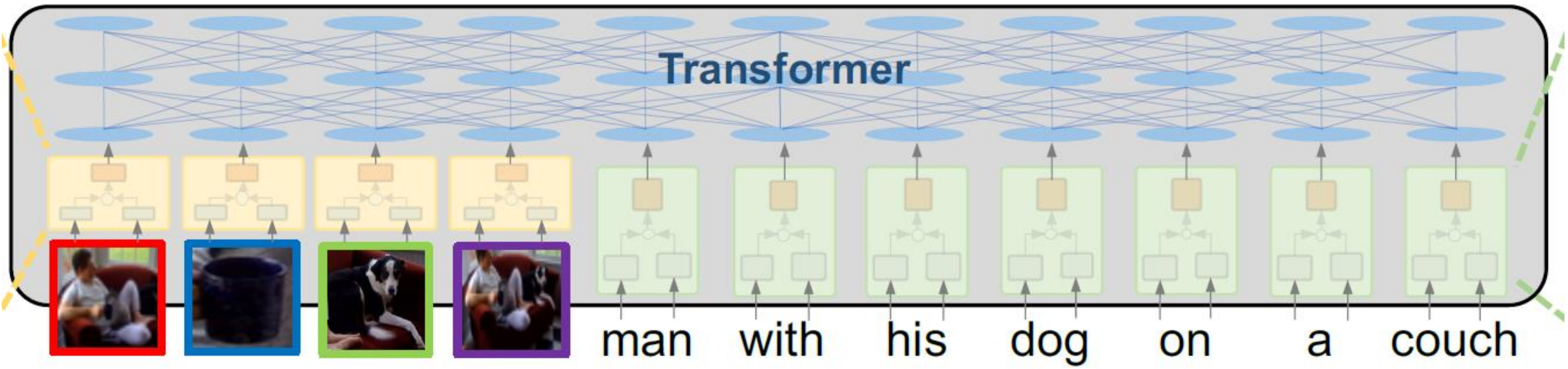


Tokenize the input sentence into Word-Pieces.

Use position feature because transformer is order-less.

Model

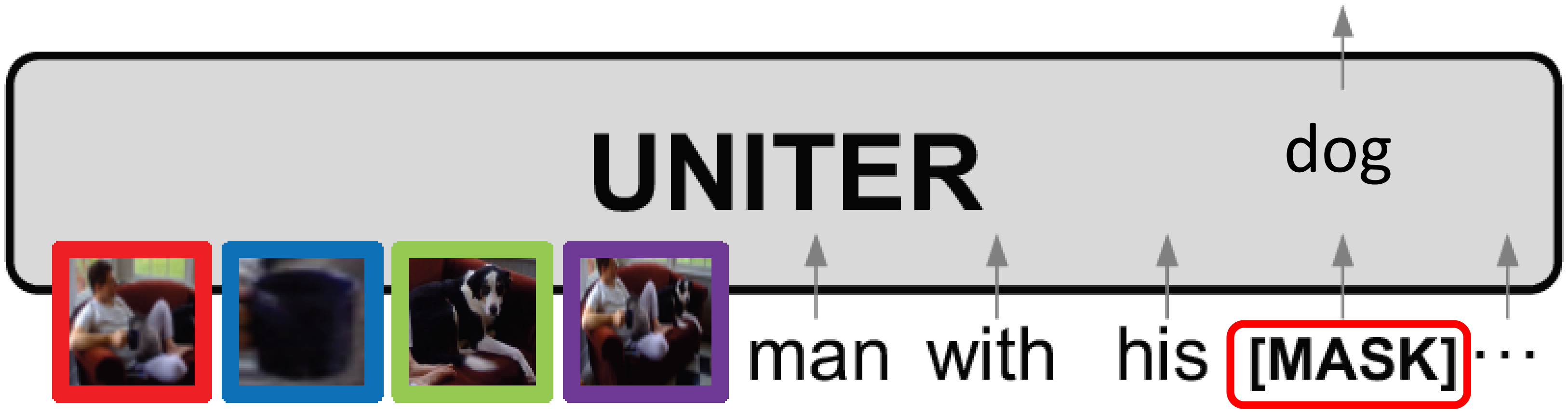
[Transformer]



Randomly sample one task for each mini-batch,
Train on only one objective per SGD update.

Model

[Pre-training Task : MLM]

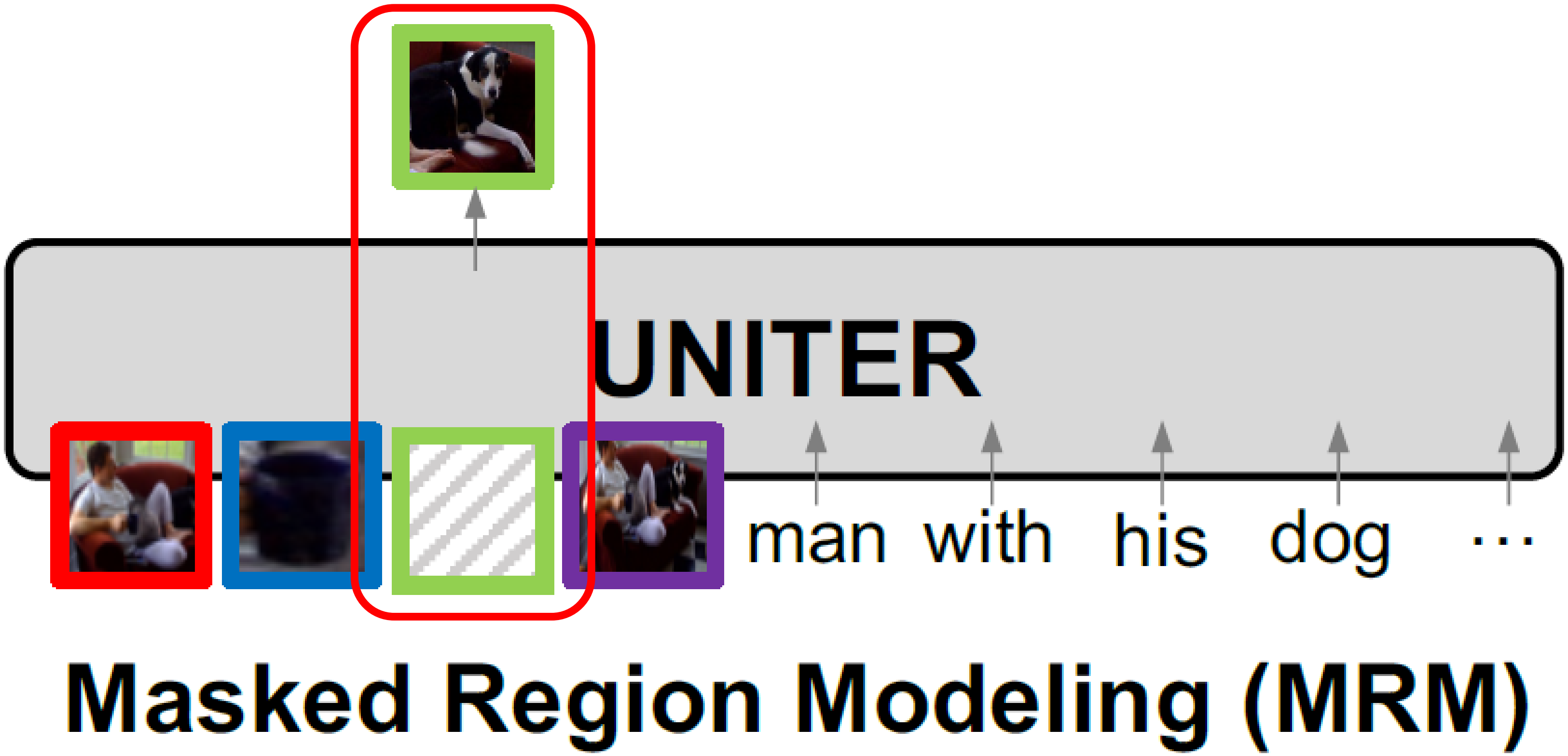


Masked Language Modeling (MLM)

Randomly mask with 15% probability

Model

[Pre-training Task : MRM]



Visual features are high-dimensional and continuous
-> Propose three variants for MRM

Model

[Pre-training Task : MRM]

1. Masked Region Feature Regression(MRFR)

- Predict region feature by L2 regression

2. Masked Region Classification(MRC)

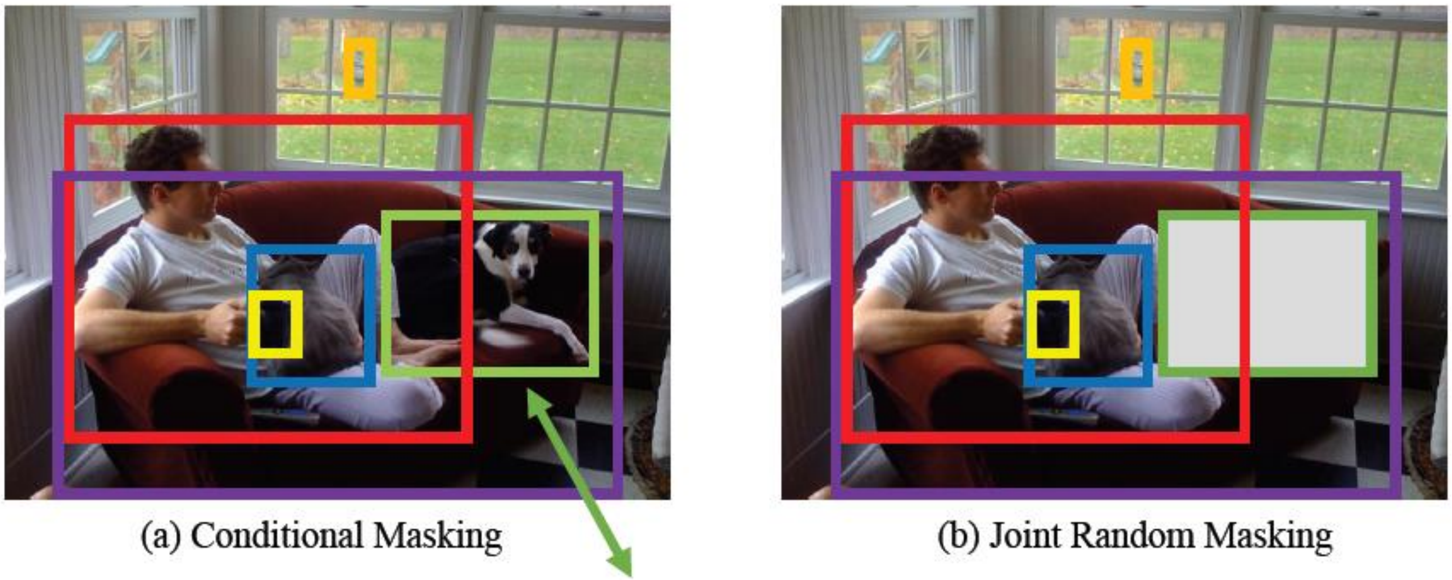
- Predicted as one of K object classes.

3. Masked Region Classification with KL-Divergence(MRC – kl)

- Similar with MRC, but not hard label – (1, 0)
- Minimize the real distribution and Predict distribution

Model

[Pre-training Task : MLM & MRM]



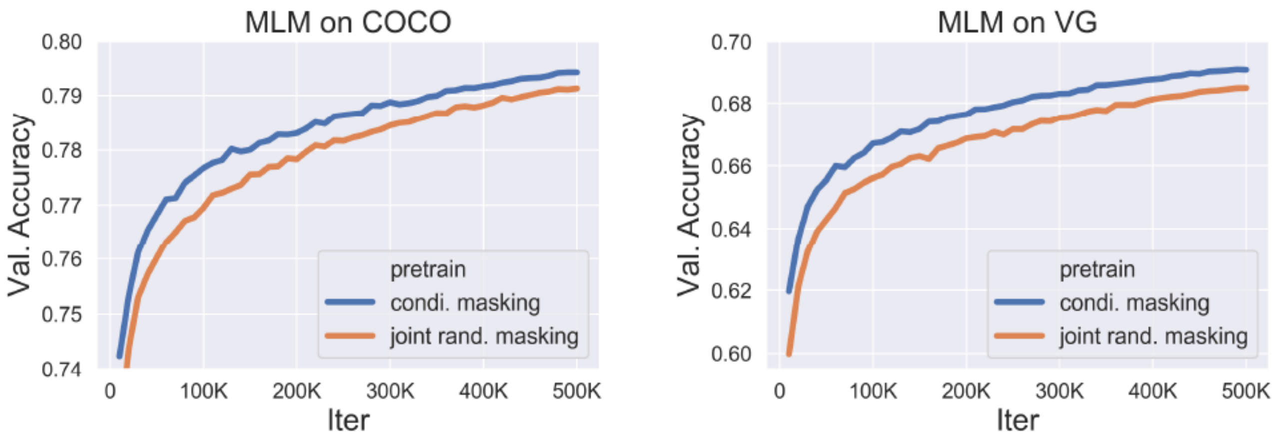
(a) Conditional Masking (b) Joint Random Masking

a man with his <MASK> and cat sitting on the sofa

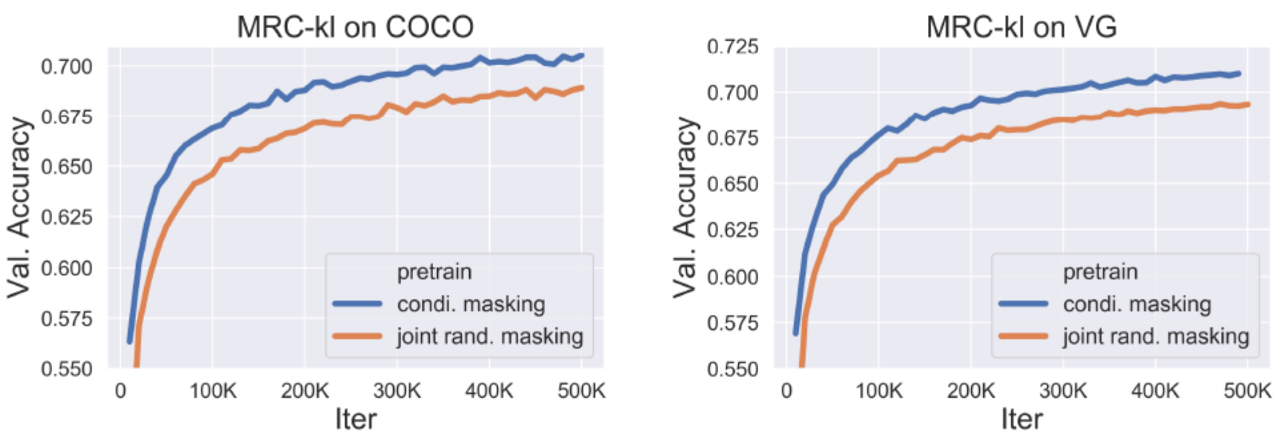
On joint mask random masking,
Problems arise when both the region and image are masked

Model

[Pre-training Task : MLM & MRM]



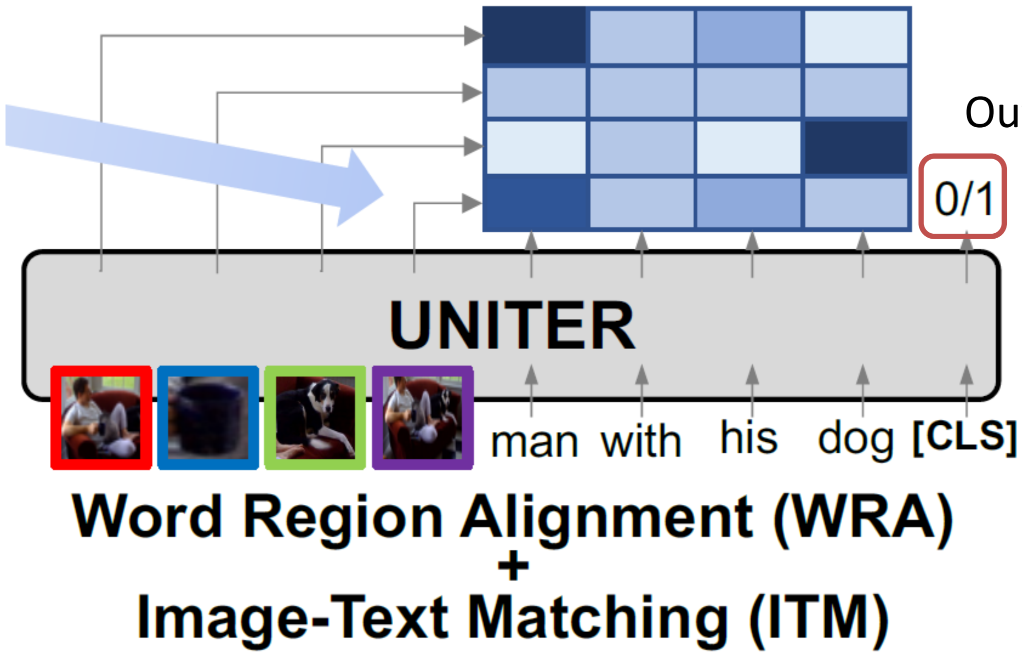
(a) Validation accuracy of MLM on COCO and VG datasets



Val accuracy is higher when using conditional masking.

Model

[Pre-training Task : ITM]



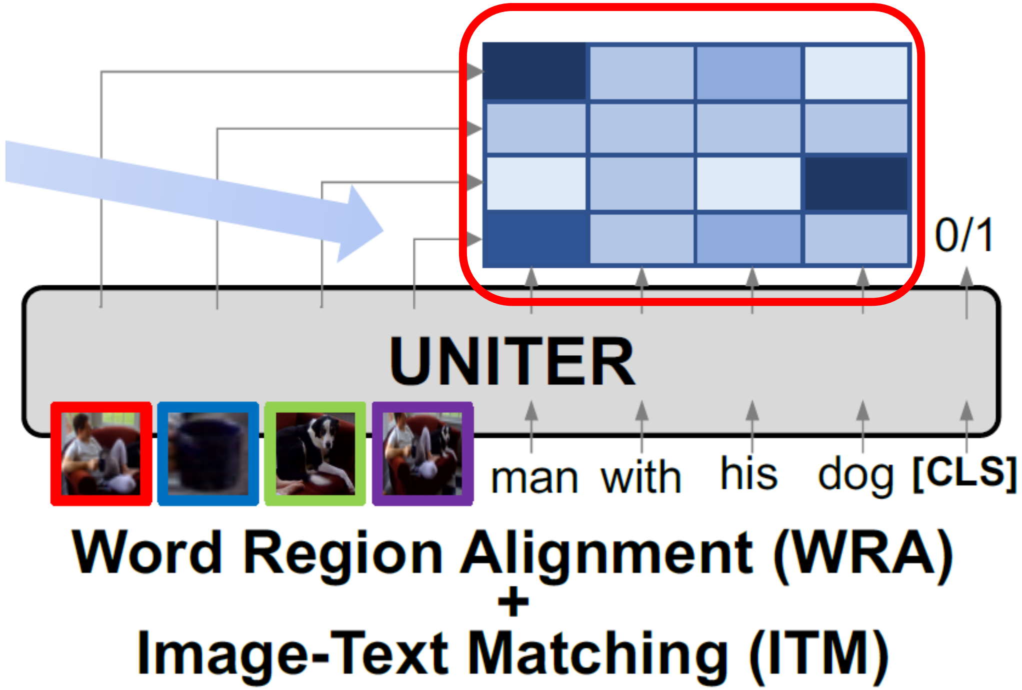
Make sure the given image and text fit well.

Classification as 0/1 across the sigmoid function.

An additional special token [CLS] fed into model.

Model

[Pre-training Task : WRA]



Optimal Transport for WRA

1) Self-normalization : sum of elements of matrix is 1

2) Robust : matrix contains (2r – 1) non – zero elements at most.

3) Efficiency : matrix vector product are efficiency for pre-train.

Q & A

Datasets / Code

[Dataset]

COCO	https://cocodataset.org/#home
Visual Genome	https://visualgenome.org/
Conceptual Captions	https://ai.google.com/research/ConceptualCaptions
SBU Captions	http://www.cs.virginia.edu/~vicente/sbucaptions/
Flickr30k	http://nlp.cs.illinois.edu/
VQA2.0	https://visualqa.org/
VCR	https://visualcommonsense.com/
NLVR	http://lil.nlp.cornell.edu/nlvr/
SNLI-VE	https://github.com/necla-ml/SNLI-VE

[Code]

Publicly available	https://github.com/ChenRocks/UNITER

Setting

1. UNITER-base

L = 12, H = 768, A = 12, Total Parameters = 86M

2. UNITER-large

L = 24, H = 1024, A = 16, Total Parameters = 303M

L : number of stacked Transformer blocks;

H: hidden activation dimension

A: number of attention heads

Baselines

1. ViLBERT

2. VLBERT(Large)
 - Faster R-CNN and Geometry Embedding.

3. Unicoder-VL

4. VisualBERT
 - Used CNN and BERT

5. LXMERT
- 2 stream architecture with cross-modality encoder

6. Task Specific SOTA Models

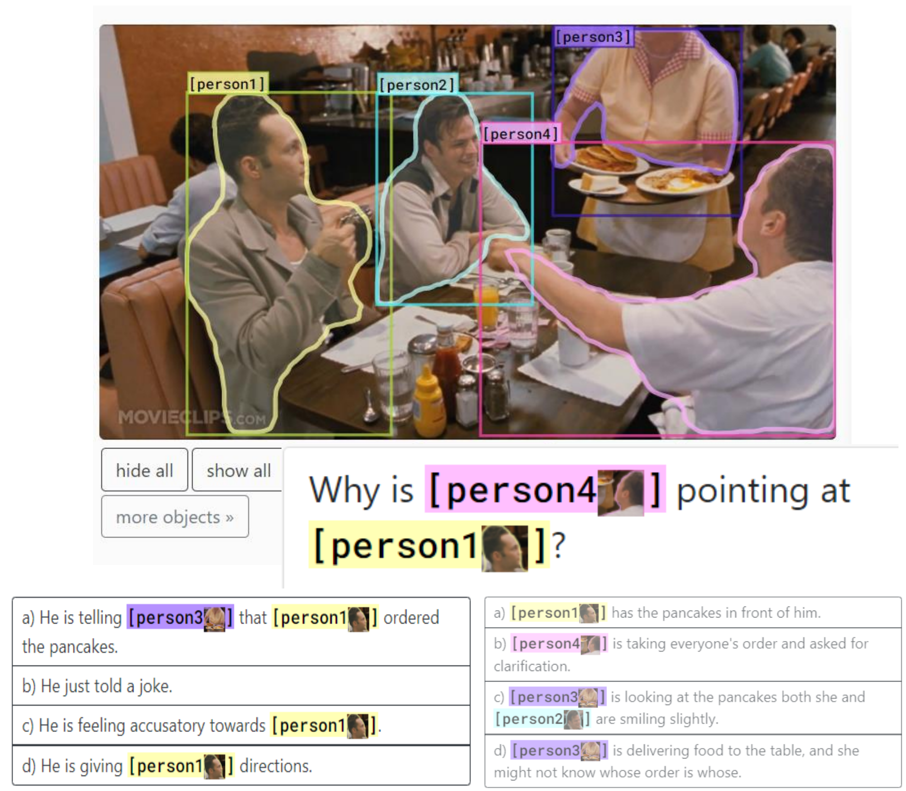
Tasks

[Task 1: Visual Question and Answering(VQA)]

Input : Image and Question

Output : Single word

[Task 2 : Visual Commonsense Reasoning (VCR)]

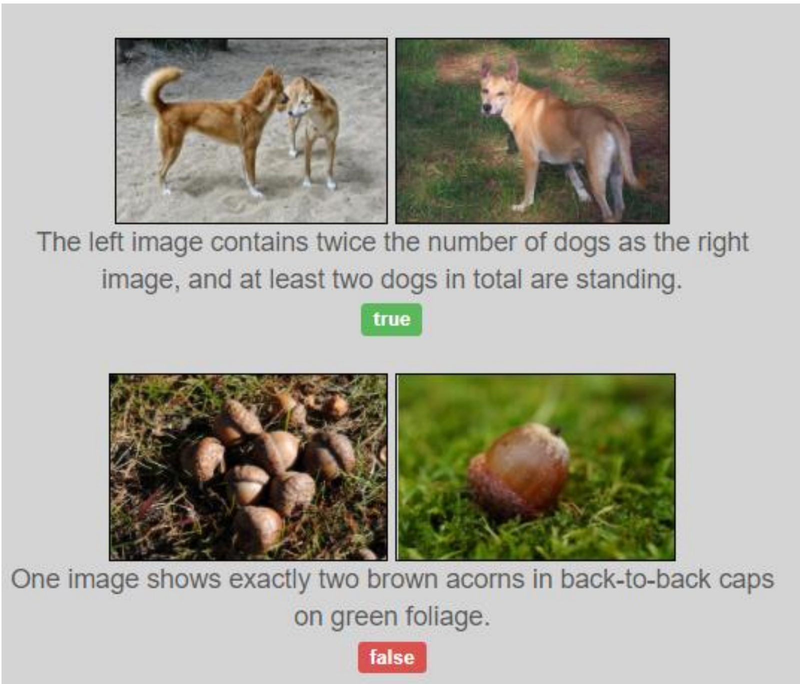


Input : Image + (Question or Q&A)

Output : Answer/Reason/A & R

Tasks

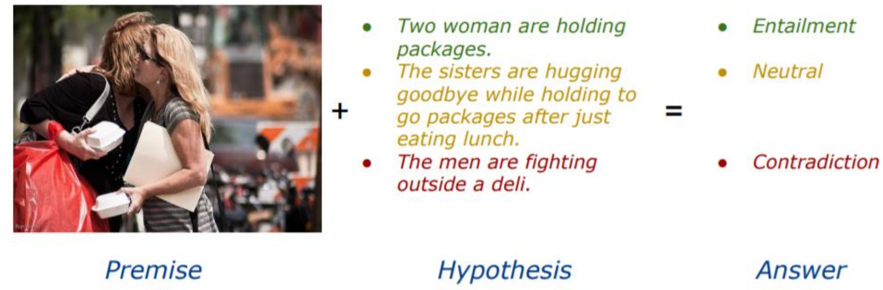
[Task 3 : Natural Language for Visual Reasoning(NLVR)]

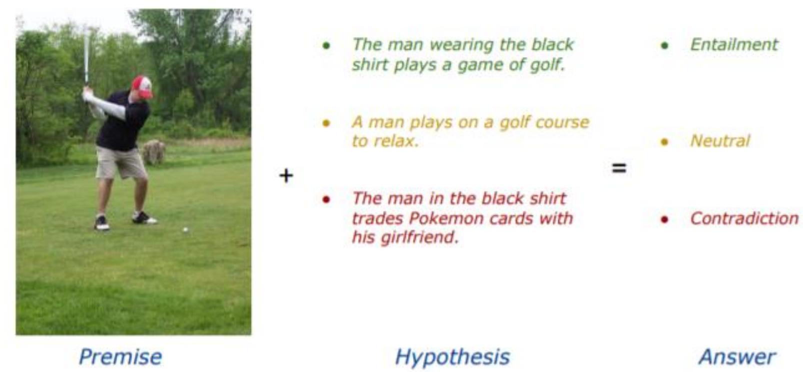


Input : Image and sentence

Output : Judge of correctness of description.

[Task 4 : Stanford Natural Language Inference Visual Entailment(SNLI - VE)]





Input : Image and hypothesis

Output : Answer

Tasks

[Task 5 : Image - Text retrieval]

(a)

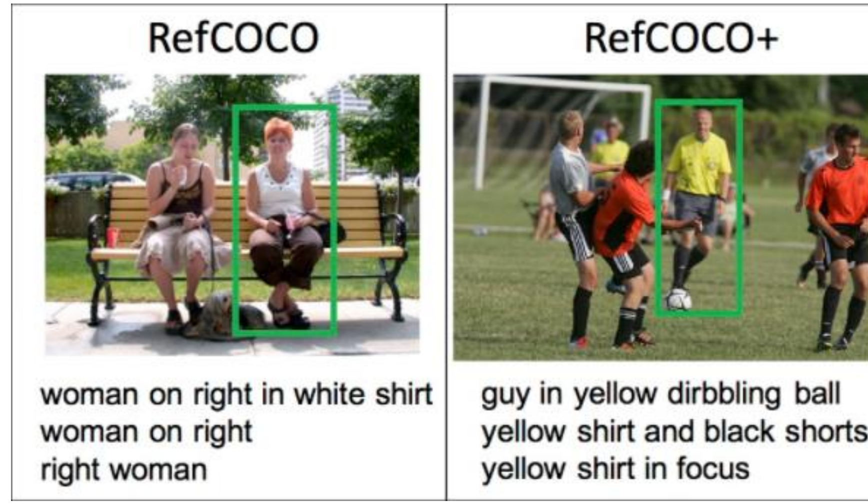
1:Older women and younger girl are opening presents up . ✓
2:Two ladies and a little girl in her pajamas opening gifts ✓
3:A family opening up their Christmas presents . ✓
4:A mother and two children opening gifts on a Christmas morning . ✓
5:A little girl opening a Christmas present . ✓

Query: *A man riding a motorcycle is performing a trick at a track .*

Input : Image and some sentences
Or Sentence and some Images

Output : Answer

[Task 6 : Referring Expression Comprehension]



Input : Reference and image regions

Output : The most relevant image region

Experiments

[Pre-training tasks]

Pre-training Data		Pre-training Tasks	Meta-Sum	VQA	IR (Flickr)	TR (Flickr)	NLVR^2	Ref-COCO+
				test-dev	val	val	dev	val^d
None	1	None	314.34	67.03	61.74	65.55	51.02	68.73
Wikipedia + BookCorpus	2	MLM (text only)	346.24	69.39	73.92	83.27	50.86	68.80
In-domain (COCO+VG)	3	MRFR	344.66	69.02	72.10	82.91	52.16	68.47
	4	ITM	385.29	70.04	78.93	89.91	74.08	72.33
	5	MLM	386.10	71.29	77.88	89.25	74.79	72.89
	6	MLM + ITM	393.04	71.55	81.64	91.12	75.98	72.75
	7	MLM + ITM + MRC	393.97	71.46	81.39	91.45	76.18	73.49
	8	MLM + ITM + MRFR	396.24	71.73	81.76	92.31	76.21	74.23
	9	MLM + ITM + MRC-kl	397.09	71.63	82.10	92.57	76.28	74.51
	10	MLM + ITM + MRC-kl + MRFR	399.97	71.92	83.73	92.87	76.93	74.52
	11	MLM + ITM + MRC-kl + MRFR + WRA	400.93	72.47	83.72	93.03	76.91	74.80
	12	MLM + ITM + MRC-kl + MRFR (w/o cond. mask)	396.51	71.68	82.31	92.08	76.15	74.29
Out-of-domain (SBU+CC)	13	MLM + ITM + MRC-kl + MRFR + WRA	396.91	71.56	84.34	92.57	75.66	72.78
In-domain + Out-of-domain	14	MLM + ITM + MRC-kl + MRFR + WRA	**405.24**	**72.70**	**85.77**	**94.28**	**77.18**	**75.31**

With Out of domain dataset, Meta-Sum score is larger than
When use only In-domain dataset.

Experiments

[Down-stream tasks]

Tasks		SOTA	ViLBERT	VLBERT (Large)	Unicoder -VL	VisualBERT	LXMERT	UNITER Base	UNITER Large
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**

UNITER achieve SOTA for all V+L Tasks.
UNITER-base model outperforms SOTA by approximately +2.8% for VCR on Q -> AR, +2.5% for NLVR$_2$, +7% for SNLI-VE, +4% on R@1 for Image-Text Retrieval (+15% for zero-shot setting), and +2% for RE Comprehension.

Experiments

[Down-stream tasks]

Tasks		SOTA	ViLBERT	VLBERT (Large)	Unicoder -VL	VisualBERT	LXMERT	UNITER Base	UNITER Large
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**

Despite that UNITER is single stream model with a fewer parameter than two-stream model, it achieved SOTA for many Tasks.

Conclusions

1. They present large-scale pre-trained model providing UNiversal Image-TExt Representations for Vision-and-Language tasks

2. Four main pre-training tasks are proposed and evaluated through extensive ablation studies.

3. Trained with both in-domain and out-of-domain datasets, UNITER outperforms state-of-the-art models over multiple V+L tasks by a significant margin.

Q & A