BridgeTower: Building Bridges Between Encoders in Vision-Language Representation Learning

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Presenter: Xiao Xu

Work done during the internship of Microsoft Research Asia.

Vision-Language Pre-training Background

ViLBERT
Aug, 2019

B2T2
Aug, 2019

LXMERT
Aug, 2019

Unified VLP
Sep, 2019

12-in-1
Dec, 2019

PixelBERT
Apr, 2020

VILLA
June, 20

VisualBERT
Aug, 2019

Unicoder-VL
Aug, 2019

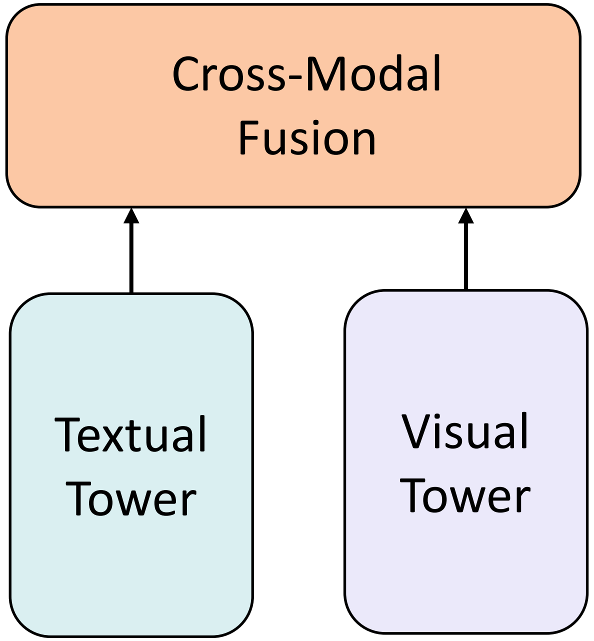
VL-BERT
Aug, 2019

UNITER
Sep, 2019

ImageBERT
Jan, 2020

Oscar
Apr, 2020

Traditional Two-Tower Architecture



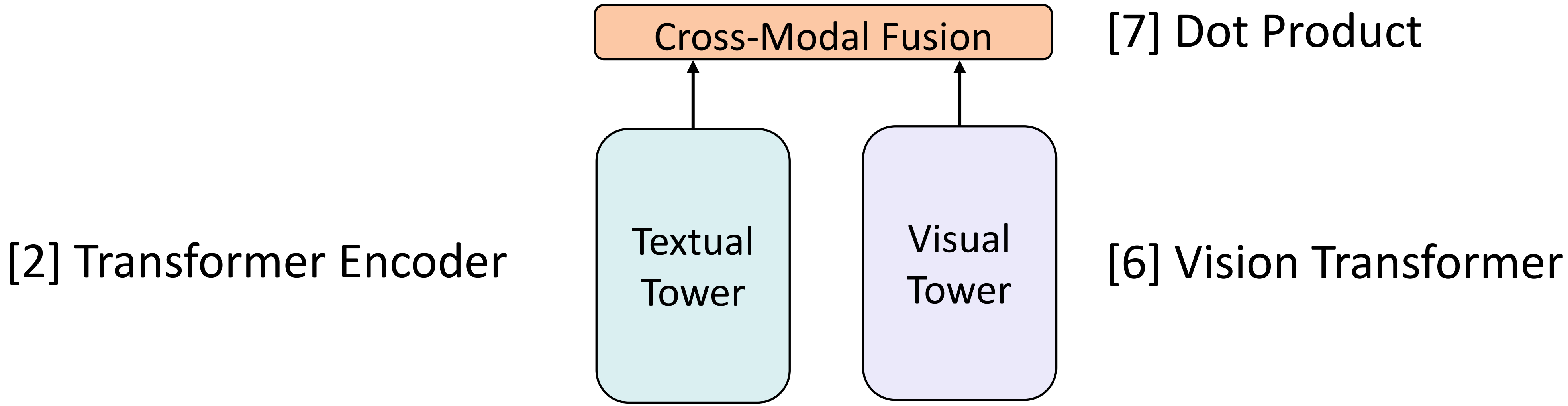
[7] Dot Product
[8] Transformer Encoder
[9] Transformer Decoder
[10] Transformer Encoder (MoME)

[1] Word Embedding
[2] Transformer Encoder

[3] Linear Projection
[4] CNN
[5] Object Detector
[6] Vision Transformer

	CLIP	**SOHO**	**Unicoder-VL**	**ViLT**	**VL-T5**	**METER**	**UniT**	**OFA**	**VLMo**	**BLIP**
Textual-Tower	[2]	[1]	[1]	[1]	[1]	[2]	[2]	[1]	[1]	[2]
Visual-Tower	[6]	[4]	[5]	[3]	[5]	[6]	[6]	[4]	[3]	[6]
Cross-Fusion	[7]	[8]	[8]	[8]	[8] + [9]	[8]	[9]	[8] + [9]	[10]	[8] + [9]

Traditional Two-Tower Architecture



	CLIP	SOHO	Unicoder-VL	ViLT	VL-T5	METER	UniT	OFA	VLMo	BLIP
Textual-Tower	[2]	[1]	[1]	[1]	[1]	[2]	[2]	[1]	[1]	[2]
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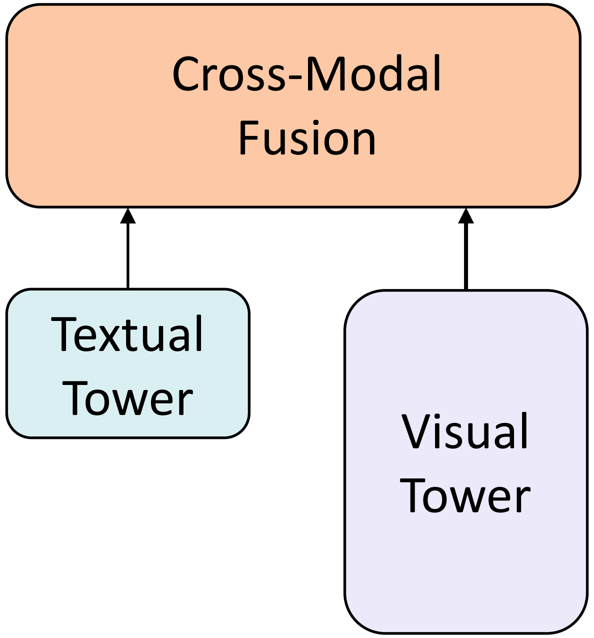
Cross-Fusion	[7]	[8]	[8]	[8]	[8] + [9]	[8]	[9]	[8] + [9]	[10]	[8] + [9]

Traditional Two-Tower Architecture



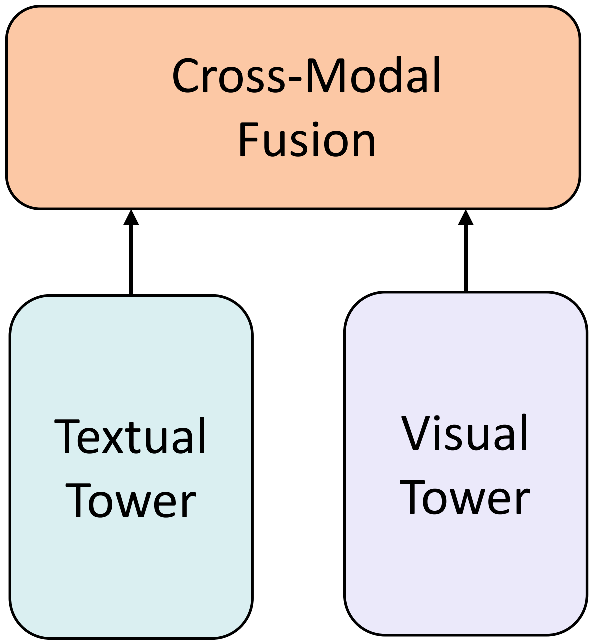
[8] Transformer Encoder

[1] Word Embedding

[5] Faster R-CNN

	CLIP	SOHO	Unicoder-VL	ViLT	VL-T5	METER	UniT	OFA	VLMo	BLIP
Textual-Tower	[2]	[1]	[1]	[1]	[1]	[2]	[2]	[1]	[1]	[2]
Visual-Tower	[6]	[4]	[5]	[3]	[5]	[6]	[6]	[4]	[3]	[6]
Cross-Fusion	[7]	[8]	[8]	[8]	[8] + [9]	[8]	[9]	[8] + [9]	[10]	[8] + [9]

Traditional Two-Tower Architecture



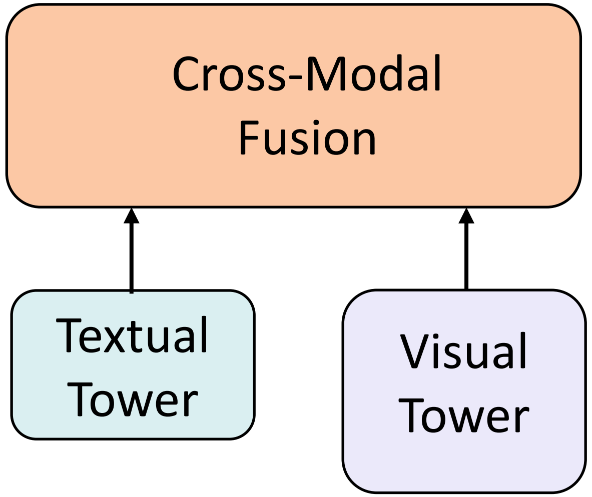
[8] Transformer Encoder

[2] RoBERTa

[6] CLIP-ViT / Swin Transformer

	CLIP	SOHO	Unicoder-VL	ViLT	VL-T5	METER	UniT	OFA	VLMo	BLIP
Textual-Tower	[2]	[1]	[1]	[1]	[1]	[2]	[2]	[1]	[1]	[2]
Visual-Tower	[6]	[4]	[5]	[3]	[5]	[6]	[6]	[4]	[3]	[6]
Cross-Fusion	[7]	[8]	[8]	[8]	[8] + [9]	[8]	[9]	[8] + [9]	[10]	[8] + [9]

Traditional Two-Tower Architecture



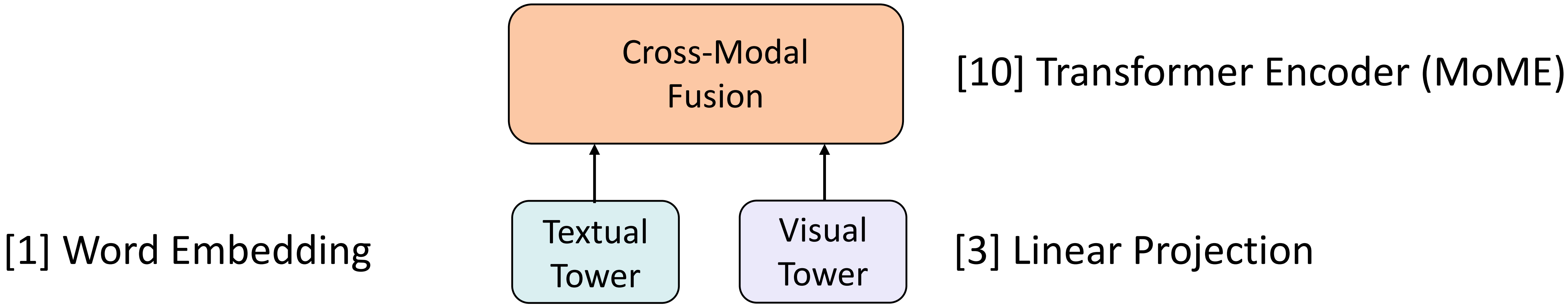
[8] Transformer Encoder
[9] Transformer Decoder

[1] Word Embedding

[4] ResNet (the first three blocks)

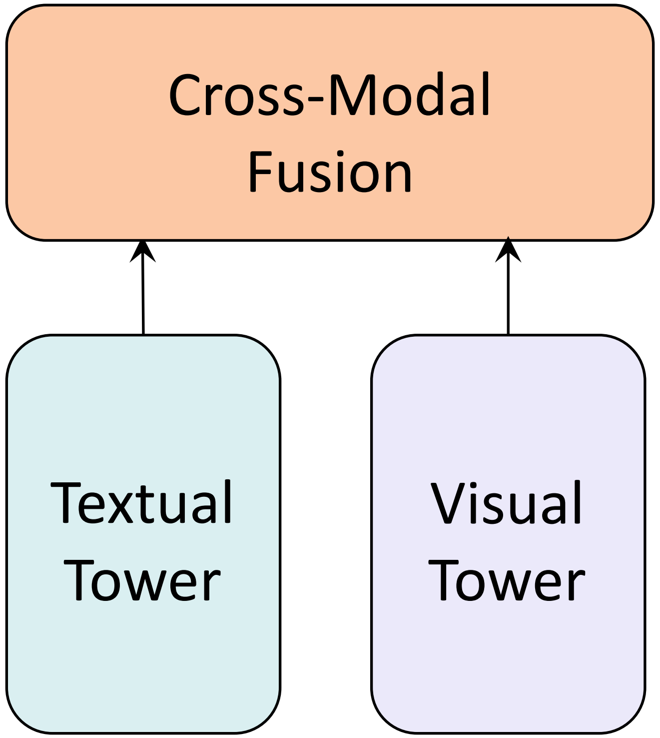
	CLIP	SOHO	Unicoder-VL	ViLT	VL-T5	METER	UniT	OFA	VLMo	BLIP
Textual-Tower	[2]	[1]	[1]	[1]	[1]	[2]	[2]	[1]	[1]	[2]
Visual-Tower	[6]	[4]	[5]	[3]	[5]	[6]	[6]	[4]	[3]	[6]
Cross-Fusion	[7]	[8]	[8]	[8]	[8] + [9]	[8]	[9]	[8] + [9]	[10]	[8] + [9]

Traditional Two-Tower Architecture

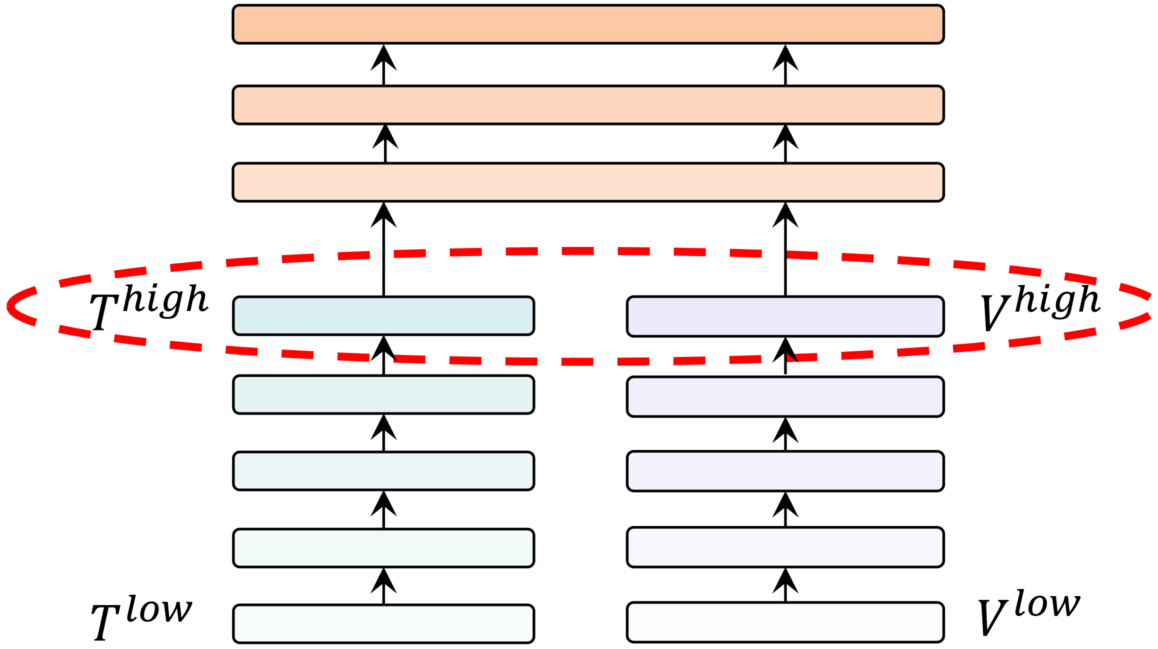


	CLIP	SOHO	Unicoder-VL	ViLT	VL-T5	METER	UniT	OFA	VLMo	BLIP
Textual-Tower	[2]	[1]	[1]	[1]	[1]	[2]	[2]	[1]	[1]	[2]
Visual-Tower	[6]	[4]	[5]	[3]	[5]	[6]	[6]	[4]	[3]	[6]
Cross-Fusion	[7]	[8]	[8]	[8]	[8] + [9]	[8]	[9]	[8] + [9]	[10]	[8] + [9]

Motivation



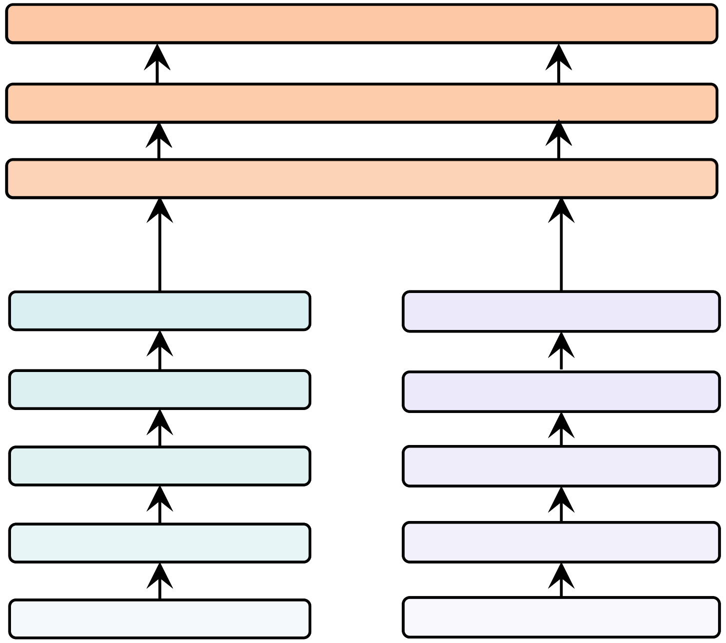
Two-Tower architecture
only use the last-layer uni-modal features.



Numerous works proved: different layers encode different types of semantic information.

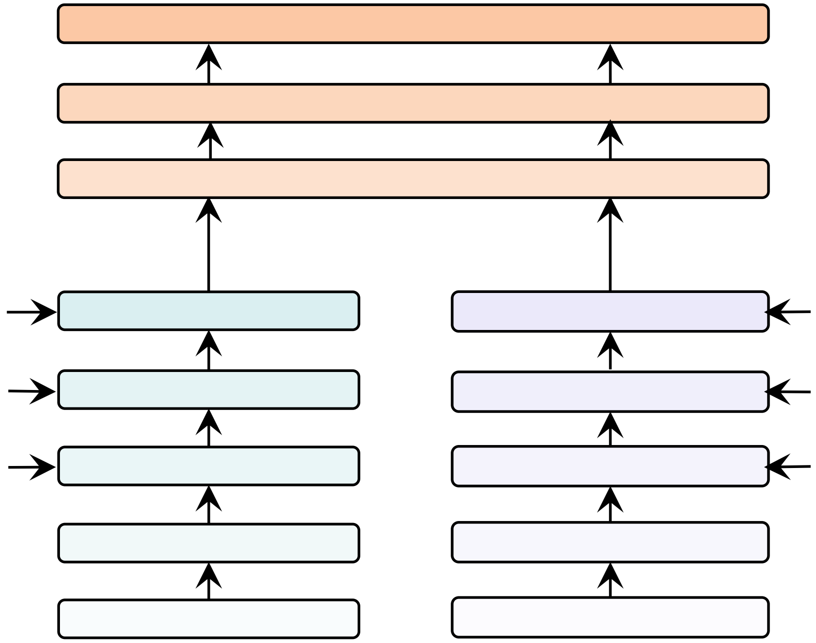
Question: can we build bridges between different layers of uni-modal towers and the cross-modal fusion module?

Two-Tower vs BridgeTower



Two-Tower

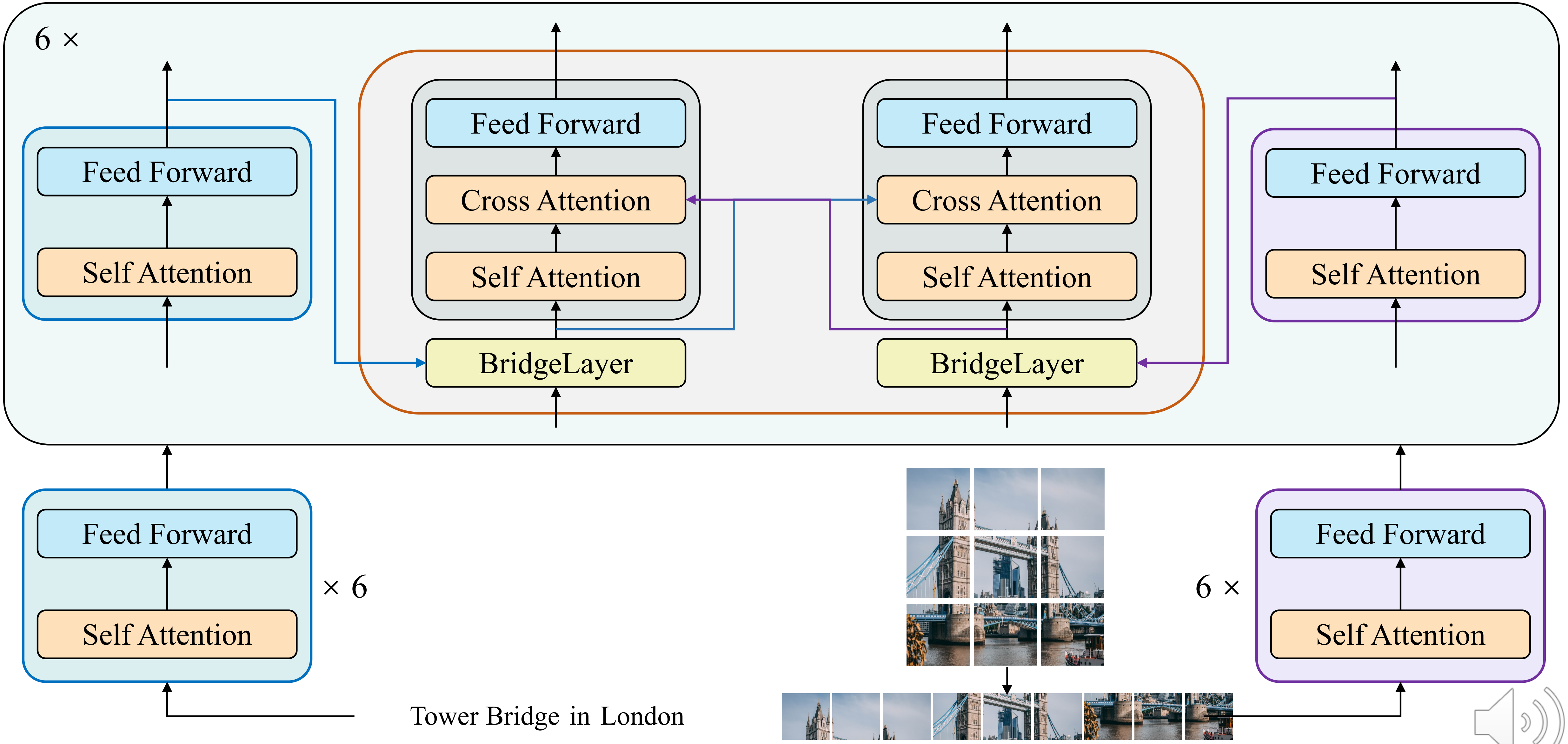
only fuse the
last layer features



BRIDGETOWER

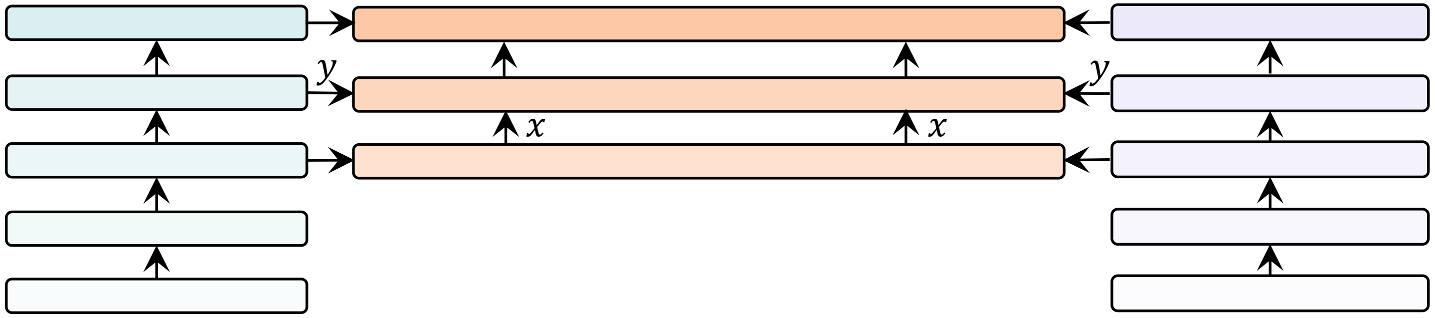
gradually fuse
multiple top layer features

Our BridgeTower Architecture

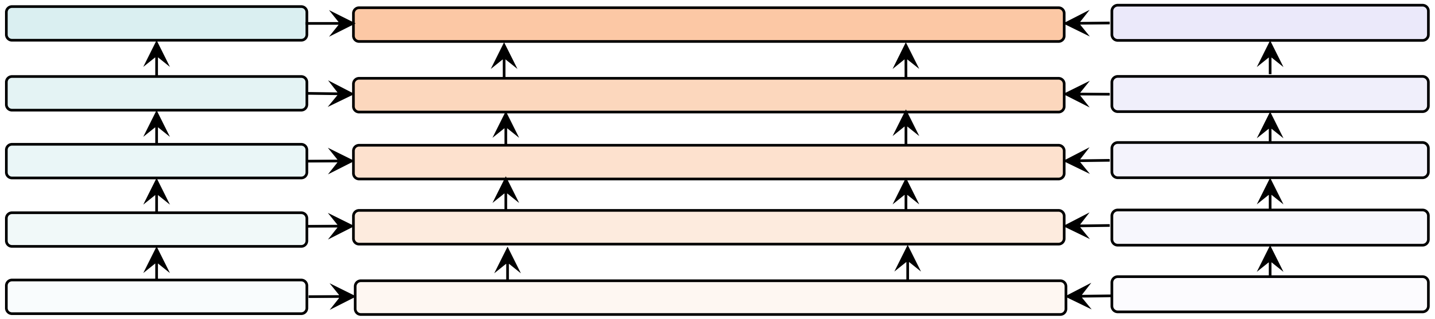


Textual Encoder
Cross-Modal Encoder
Visual Encoder

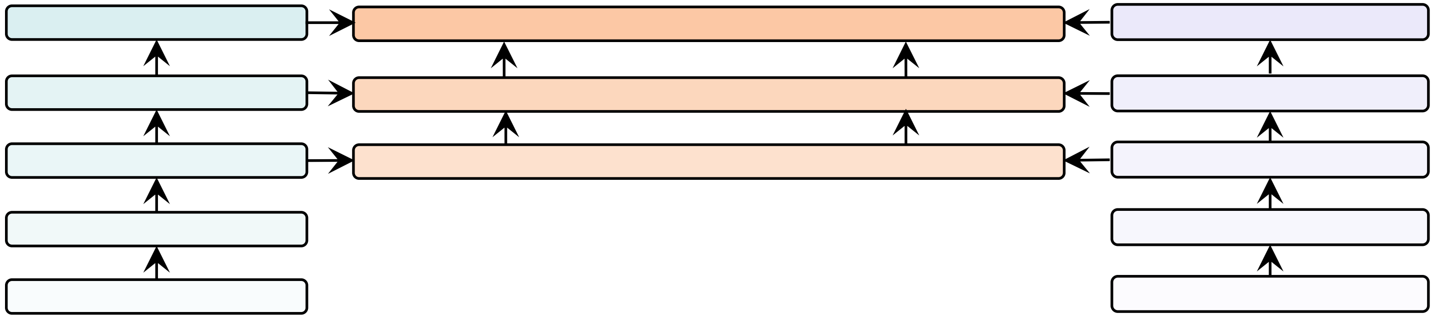
Ablation Study



Design I: Definition of Bridges

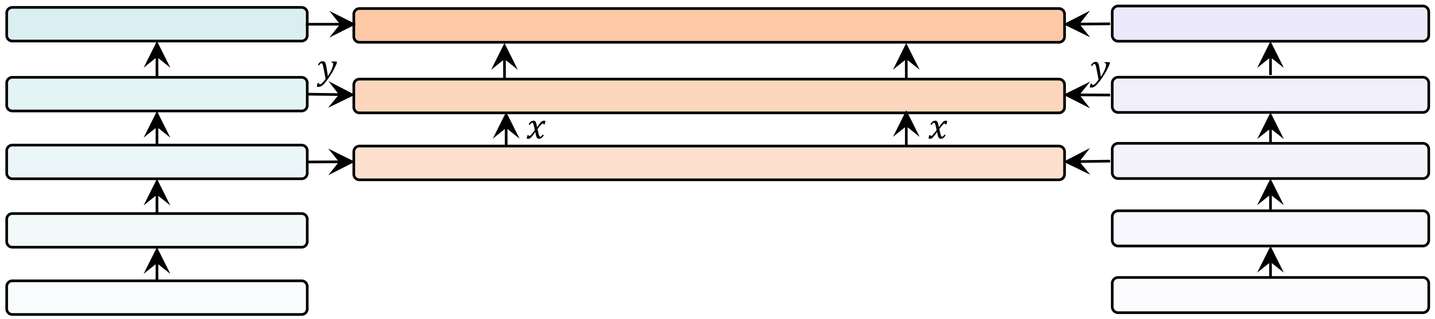


Design II: Number of Layers



Design III: Number of Bridges

Design I: Definition of Bridges

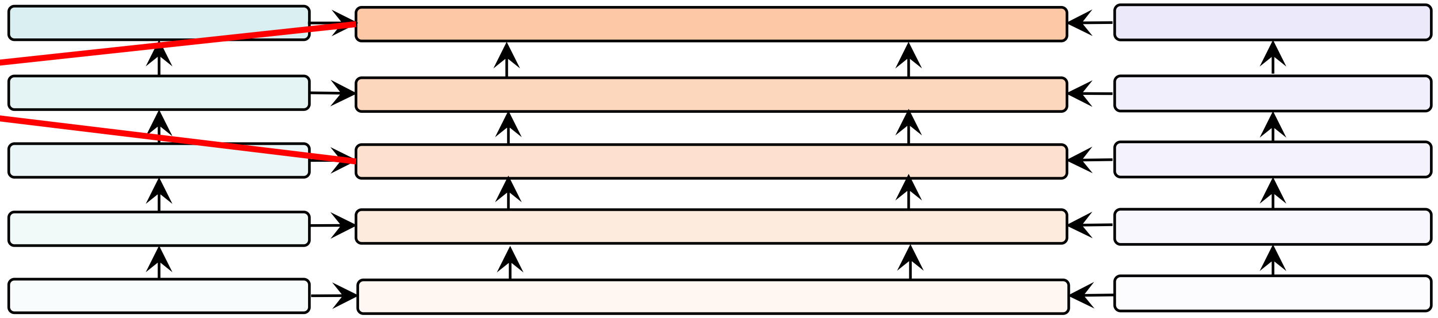


BridgeLayer(x, y)	# Params	Test-Dev	RSUM
(a) $x + y$	**18.4K**	**75.18**	**533.8**
(b) $x \odot y$	18.4K	73.41	530.4
(c) $\alpha x + (1-\alpha) y, \alpha \in \mathbb{R}^{D_Z}$	26.0K	75.09	532.9
(d) $\alpha x + (1-\alpha) y, \alpha = \sigma(\mathbf{W}[x; y])$	11.8M	75.13	533.1
(e) $\mathbf{W}[x; y]$	11.8M	74.55	532.2
(f) $\mathbf{W}_2(\mathrm{GeLU}(\mathbf{W}_1[x; y]))$	35.4M	74.26	530.2
(g) $\mathrm{MCA}(x, y)$	23.6M	73.67	514.3
(h) $\mathrm{FFN}(\mathrm{MCA}(x, y))$	70.8M	73.54	511.1
(i) $x + y + \mathbf{W}_*[x; y]$	11.8M	75.10	533.1

x: the output cross-modal representation of the previous layer

y: the corresponding uni-modal representation

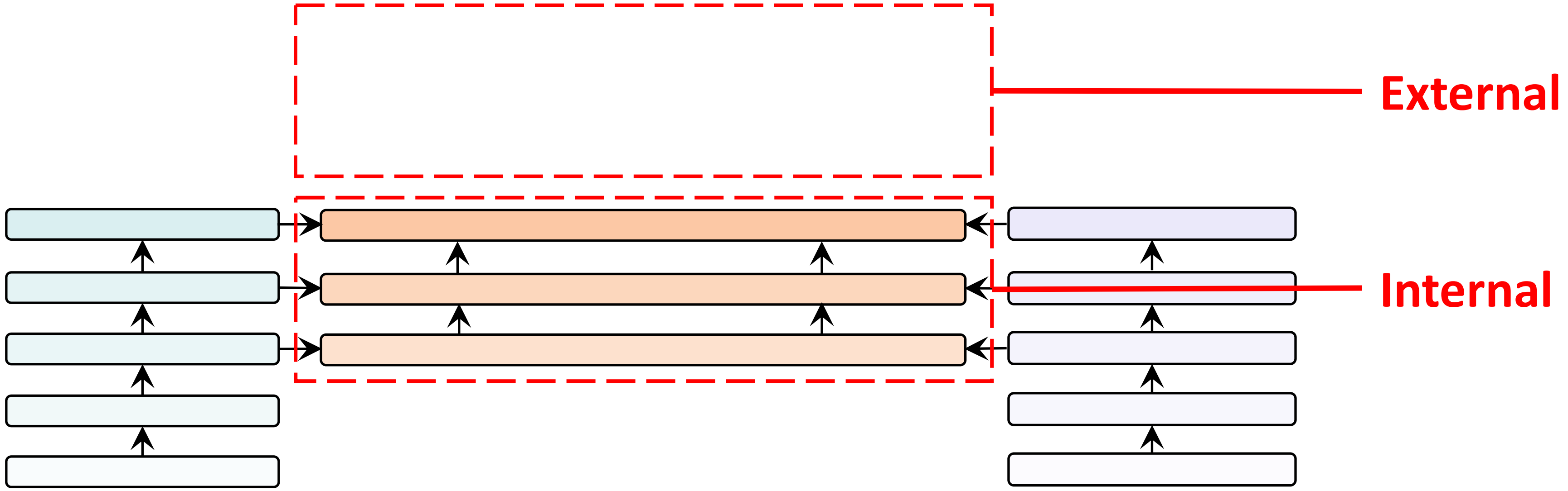
Design II: Number of Layers



L_Z
number of layers
starting from the top

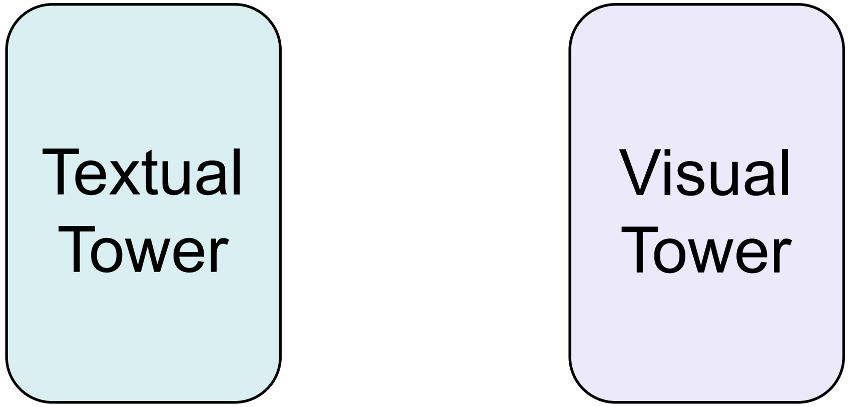
L_Z	# Params	VQAv2 Test-Dev		Flickr30K RSUM	
		METER	Ours	METER	Ours
2	37.8M	72.84	74.12 (↑ 1.28)	526.0	527.1 (↑ 1.1)
3	56.8M	73.47	74.36 (↑ 0.89)	526.5	528.6 (↑ 2.1)
4	75.6M	73.71	75.00 (↑ 1.29)	527.9	529.7 (↑ 1.8)
5	94.6M	73.80	74.98 (↑ 1.18)	528.8	531.8 (↑ 3.0)
6	113.4M	74.04	**75.18** (↑ 1.14)	530.7	**533.8** (↑ 3.1)
8	151.2M	73.97	75.07 (↑ 1.10)	530.0	531.6 (↑ 1.6)
10	189.0M	73.45	75.06 (↑ 1.61)	529.6	531.7 (↑ 2.1)
12	226.8M	71.88	74.94 (↑ 3.06)	528.7	531.4 (↑ 2.7)

Design III: Number of Bridges



	# Internal	# External	VQAv2 Test-Dev	Flickr30K RSUM
BridgeTower	6	0	**75.18**	**533.8**
	4	2	75.06 (↓ 0.12)	533.1 (↓ 0.7)
	3	3	74.97 (↓ 0.21)	532.8 (↓ 1.0)
	2	4	74.71 (↓ 0.47)	532.3 (↓ 1.5)
Two-Tower(METER)	0	6	74.04 (↓ 1.14)	530.7 (↓ 3.1)

Apply Different Uni-modal Backbones



Visual Backbone	Textual Backbone	VQAv2 Test-Dev		Flickr30K RSUM	
		METER	Ours	METER	Ours
DeiT B-224/16	RoBERTa	69.98	70.83 (↑ 0.85)	448.0	455.7 (↑ 7.7)
ViT B-224/16	RoBERTa	70.26	72.24 (↑ 1.98)	472.7	476.9 (↑ 4.2)
ViT B-384/16	RoBERTa	70.52	72.38 (↑ 1.86)	472.8	477.1 (↑ 4.3)
CLIP-VIT-B/32	RoBERTa	72.19	72.91 (↑ 0.72)	508.8	512.0 (↑ 3.2)
CLIP-VIT-B/16	BERT	74.09	74.89 (↑ 0.80)	522.1	526.5 (↑ 4.4)
CLIP-VIT-B/16	RoBERTa	74.04	**75.18** (↑ 1.14)	530.7	**533.8** (↑ 3.1)

Pre-training Settings

- **Pre-training Objectives**
  - Masked Language Modeling – MLM
  - Image-Text Matching – ITM
- **Pre-training Datasets**
  - 4M Images, ~9M Image-Text Pairs

	COCO	VG	CC	SBU
# Images	113K	108K	2.9M	860K
# Captions	567K	4.8M	2.9M	860K

Hyperparameters	BRIDGETOWER$_{BASE}$	BRIDGETOWER$_{LARGE}$
Number of Layers	6	6
Hidden size	768	1,024
FFN inner hidden size	3,072	4,096
Number of Attention heads	12	16
Dropout Ratio	0.1	0.1
Attention dropout	0.1	0.1
Total Steps	100k	100k
Batch Size	4,096	4,096
Textual Encoder	RoBERTa$_{BASE}$	RoBERTa$_{LARGE}$
Visual Encoder	CLIP-ViT-B	CLIP-ViT-L
Patch Size	16	14
Image Resolution	288	294

Results on VQAv2 Dataset

Model	# Pre-train Images	Visual Backbone	Test-Dev	Test-Standard			
			Overall	Yes/No	Number	Other	Overall
Base-Size Models							
ViLT$_{\text{BASE}}$ (Kim, Son, and Kim 2021)	4M	ViT-B-384/32	71.26	-	-	-	-
UNITER$_{\text{BASE}}$ (Chen et al. 2020) $*$	4M	Faster R-CNN	72.70	-	-	-	72.91
VILLA$_{\text{BASE}}$ (Gan et al. 2020) $*$	4M	Faster R-CNN	73.59	-	-	-	73.67
UNIMO$_{\text{BASE}}$ (Li et al. 2021b)	4M	Faster R-CNN	73.79	-	-	-	74.02
ALBEF$_{\text{BASE}}$ (Li et al. 2021a) $*$	4M	DeiT-B-224/16	74.54	-	-	-	74.70
ALBEF$_{\text{BASE}}$ (Li et al. 2021a) $*$	14M	DeiT-B-224/16	75.84	-	-	-	76.04
VinVL$_{\text{BASE}}$ (Zhang et al. 2021)	5.7M	ResNeXt-152	75.95	-	-	-	76.12
VLMO$_{\text{BASE}}$ (Wang et al. 2021a)	4M	BEiT-B-224/16	76.64	-	-	-	76.89
BLIP$_{\text{BASE}}$ (Li et al. 2022b) $*$	14M	DeiT-B-224/16	77.54	-	-	-	77.62
METER$_{\text{BASE}}$ (Dou et al. 2022)	4M	CLIP-ViT-B-224/16	77.68	92.49	58.07	69.20	77.64
mPLUG (Li et al. 2022a) $*$	4M	CLIP-ViT-B-224/16	77.94	-	-	-	77.96
OFA$_{\text{BASE}}$ (Wang et al. 2022b) $*\star$	54M	ResNet-101	77.98	-	-	-	78.07
SimVLM$_{\text{BASE}}$ (Wang et al. 2021c) $\star$	1.8B	ResNet-101	77.87	-	-	-	78.14
BLIP$_{\text{BASE}}$ (Li et al. 2022b) $*$	129M	DeiT-B-224/16	78.24	-	-	-	78.17
BRIDGETOWER$_{\text{BASE}}$ **(Ours)**	**4M**	CLIP-ViT-B-224/16	**78.66**	**92.92**	**60.69**	**70.51**	**78.73**
BRIDGETOWER$_{\text{BASE}}$ **(Ours)** $*$	**4M**	CLIP-ViT-B-224/16	**79.10**	**93.06**	**62.19**	**70.69**	**79.04**
Large-Size Models							
UNITER$_{\text{LARGE}}$ (Chen et al. 2020) $*$	4M	Faster R-CNN	73.82	-	-	-	74.02
VILLA$_{\text{LARGE}}$ (Gan et al. 2020) $*$	4M	Faster R-CNN	74.69	-	-	-	74.87
UNIMO$_{\text{LARGE}}$ (Li et al. 2021b)	4M	Faster R-CNN	75.06	-	-	-	75.27
VinVL$_{\text{LARGE}}$ (Zhang et al. 2021)	5.7M	ResNeXt-152	76.52	92.04	61.50	66.68	76.63
SimVLM$_{\text{LARGE}}$ (Wang et al. 2021c)	1.8B	ResNet-152	79.32	-	-	-	79.56
VLMO$_{\text{LARGE}}$ (Wang et al. 2021a)	4M	BEiT-L-224/16	79.94	-	-	-	79.98
OFA$_{\text{LARGE}}$ (Wang et al. 2022b) $*\star$	54M	ResNet-152	80.43	93.32	**67.31**	72.71	80.67
BRIDGETOWER$_{\text{LARGE}}$ **(Ours)**	**4M**	CLIP-ViT-L-224/14	**81.25**	**94.69**	64.58	**73.16**	**81.15**
BRIDGETOWER$_{\text{LARGE}}$ **(Ours)** $*$	**4M**	CLIP-ViT-L-224/14	**81.52**	**94.80**	66.01	**73.45**	**81.49**

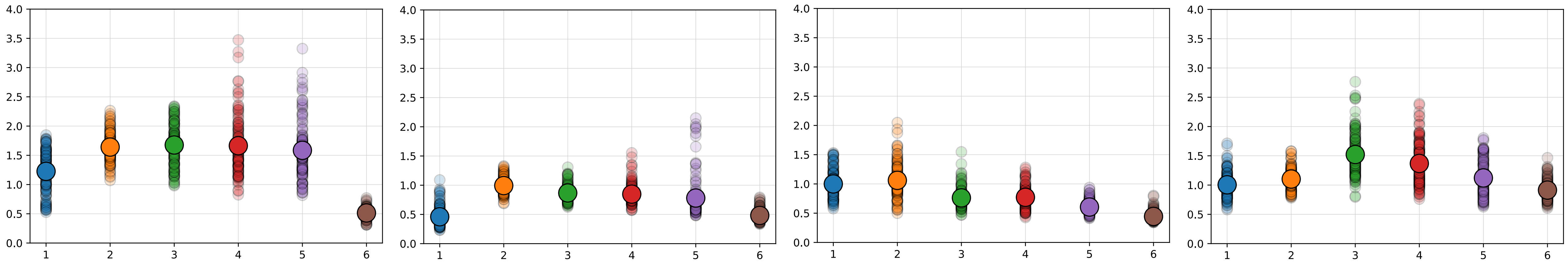
Results on VQAv2 Dataset

Model	# Pre-train Images	Visual Backbone	Test-Dev Overall	Test-Standard Yes/No	Test-Standard Number	Test-Standard Other	Test-Standard Overall
Large-Size Models							
UNITER$_{\text{LARGE}}$ (Chen et al. 2020) $*$	4M	Faster R-CNN	73.82	-	-	-	74.02
VILLA$_{\text{LARGE}}$ (Gan et al. 2020) $*$	4M	Faster R-CNN	74.69	-	-	-	74.87
UNIMO$_{\text{LARGE}}$ (Li et al. 2021b)	4M	Faster R-CNN	75.06	-	-	-	75.27
VinVL$_{\text{LARGE}}$ (Zhang et al. 2021)	5.7M	ResNeXt-152	76.52	92.04	61.50	66.68	76.63
SimVLM$_{\text{LARGE}}$ (Wang et al. 2021c)	1.8B	ResNet-152	79.32	-	-	-	79.56
VLMO$_{\text{LARGE}}$ (Wang et al. 2021a)	4M	BEiT-L-224/16	79.94	-	-	-	79.98
OFA$_{\text{LARGE}}$ (Wang et al. 2022b) $*\star$	54M	ResNet-152	80.43	93.32	**67.31**	72.71	80.67
BRIDGETOWER$_{\text{LARGE}}$ **(Ours)**	**4M**	CLIP-ViT-L-224/14	**81.25**	**94.69**	64.58	**73.16**	**81.15**
BRIDGETOWER$_{\text{LARGE}}$ **(Ours)** $*$	**4M**	CLIP-ViT-L-224/14	**81.52**	**94.80**	66.01	**73.45**	**81.49**
Huge or even Larger Size Models							
SimVLM$_{\text{HUGE}}$ (Wang et al. 2021c)	1.8B	ResNet-101	80.03	93.29	66.54	72.23	80.34
METER$_{\text{HUGE}}$ (Dou et al. 2022)	14M	Florence-CoSwin-H	80.33	94.25	64.37	72.30	80.54
mPLUG (Li et al. 2022a) $*$	14M	CLIP-ViT-L-224/14	81.27	-	-	-	81.26
GIT2 (Wang et al. 2022a) $*$	10.5B	DaViT(4.8B)	81.74	92.90	67.06	75.77	81.92
OFA$_{\text{HUGE}}$ (Wang et al. 2022b) $*\star$	54M	ResNet-152	82.0	94.66	71.44	73.35	81.98
Flamingo (Alayrac et al. 2022) $\star$	2.3B	NFNet-F6	82.0	-	-	-	82.1
CoCa (Yu et al. 2022) $\star$	4.8B	ViT-G-288/18	82.3	94.55	70.25	74.46	82.33
BEiT-3 (Wang et al. 2022c)	28M	BEiT-3	84.19	**96.43**	**73.63**	75.92	84.18
PaLI (Chen et al. 2022)	1.6B	ViT-E-224	**84.3**	96.13	69.07	**77.58**	**84.34**

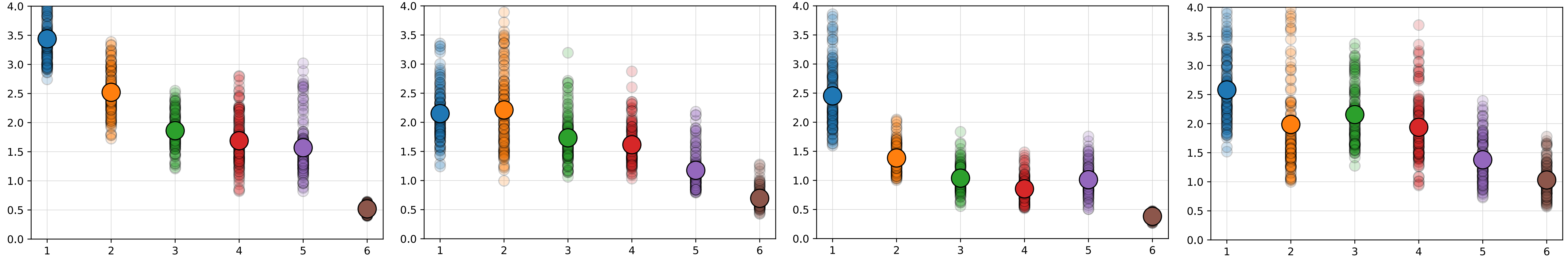
Results on SNLI-VE and Flickr30K Dataset

Model	# Pre-train Images	SNLI-VE		Flickr30K (1K test set)						
		dev	test	IR@1	IR@5	IR@10	TR@1	TR@5	TR@10	RSUM
Pre-trained on More Data										
ALIGN$_{BASE}$ (Jia et al. 2021)	1.8B	-	-	84.9	97.4	98.6	95.3	99.8	100.0	576.0
ALBEF$_{BASE}$ (Li et al. 2021a)	14M	80.80	80.91	85.6	97.5	98.9	95.9	99.8	100.0	577.7
Pre-trained on CC, SBU, MSCOCO and VG datasets										
ViLT$_{BASE}$ (Kim, Son, and Kim 2021)	4M	-	-	64.4	88.7	93.8	83.5	96.7	98.6	525.7
UNITER$_{LARGE}$ (Chen et al. 2020)	4M	79.30	79.38	75.6	94.1	96.8	87.3	98.0	99.2	550.9
VILLA$_{LARGE}$ (Gan et al. 2020)	4M	80.18	80.02	76.3	94.2	96.8	87.9	97.5	98.8	551.5
UNIMO$_{LARGE}$ (Li et al. 2021b)	4M	**81.11**	80.63	78.0	94.2	97.1	89.4	98.9	99.8	557.5
ALBEF$_{BASE}$ (Li et al. 2021a)	4M	80.14	80.30	82.8	96.7	98.4	94.3	99.4	99.8	571.4
METER-CLIP-ViT$_{BASE}$ (Dou et al. 2022)	4M	80.86	**81.19**	82.2	96.3	98.4	94.3	**99.6**	99.9	570.7
BRIDGETOWER$_{BASE}$ **(Ours)**	**4M**	**81.11**	**81.19**	**85.8**	**97.6**	**98.9**	**94.7**	**99.6**	**100.0**	**576.6**

KL Divergence Visualization



(a) METER, visual self-attention (c) METER, textual self-attention (e) METER, visual cross-attention (g) METER, textual cross-attention



(b) BRIDGETOWER, visual self-attention (d) BRIDGETOWER, textual self-attention (f) BRIDGETOWER, visual cross-attention (h) BRIDGETOWER, textual cross-attention

Higher/lower KL divergence means that different attention heads pay attention to different/similar tokens.

Conclusion & Future

- Conclusion:
  - We introduced BridgeTower, a simple but effective architecture for VL pre-training.
  - We studied different design choices for bridges.
  - We show that BridgeTower achieves SOTA results on multiple downstream tasks.
- Future:
  - More Pre-training Objectives (currently we only use two)
  - Larger-Scale Pre-training (currently only 4M data)
  - More Modalities (currently only two modalities)

Integrated into Hugging Face – Transformers

Transformers
Search documentation ⌘K
MAIN EN 78,811

Image Processor

MODELS
TEXT MODELS
VISION MODELS
AUDIO MODELS
MULTIMODAL MODELS

- AltCLIP
- BLIP
- BridgeTower
- Chinese-CLIP
- CLIP
- CLIPSeg
- Data2Vec
- Donut
- FLAVA
- GIT
- GroupViT
- LayoutLMV2
- LayoutLMV3
- LayoutXLM
- LXMERT
- OneFormer
- OWL-ViT
- Perceiver
- Speech Encoder Decoder Models
- TrOCR
- OWL-ViT
- Perceiver
- Speech Encoder Decoder Models
- TrOCR

BridgeTower

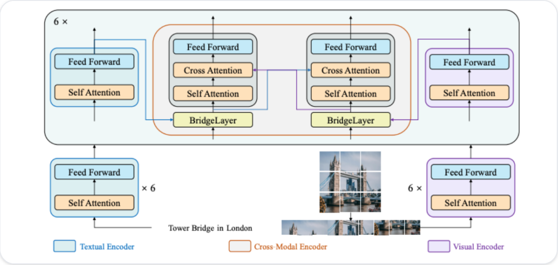
Overview

The BridgeTower model was proposed in 📎 BridgeTower: Building Bridges Between Encoders in Vision-Language Representative Learning by Xiao Xu, Chenfei Wu, Shachar Rosenman, Vasudev Lal, Wanxiang Che, Nan Duan. The goal of this model is to build a bridge between each uni-modal encoder and the cross-modal encoder to enable comprehensive and detailed interaction at each layer of the cross-modal encoder thus achieving remarkable performance on various downstream tasks with almost negligible additional performance and computational costs.

This paper has been accepted to the AAAI'23 conference.

The abstract from the paper is the following:

Vision-Language (VL) models with the TWO-TOWER architecture have dominated visual-language representation learning in recent years. Current VL models either use lightweight uni-modal encoders and learn to extract, align and fuse both modalities simultaneously in a deep cross-modal encoder, or feed the last-layer uni-modal representations from the deep pre-trained uni-modal encoders into the top cross-modal encoder. Both approaches potentially restrict vision-language representation learning and limit model performance. In this paper, we propose BRIDGETOWER, which introduces multiple bridge layers that build a connection between the top layers of uni-modal encoders and each layer of the crossmodal encoder. This enables effective bottom-up cross-modal alignment and fusion between visual and textual representations of different semantic levels of pre-trained uni-modal encoders in the cross-modal encoder. Pre-trained with only 4M images, BRIDGETOWER achieves state-of-the-art performance on various downstream vision-language tasks. In particular, on the VQAv2 test-std set, BRIDGETOWER achieves an accuracy of 78.73%, outperforming the previous state-of-the-art model METER by 1.09% with the same pre-training data and almost negligible additional parameters and computational costs. Notably, when further scaling the model, BRIDGETOWER achieves an accuracy of 81.15%, surpassing models that are pre-trained on orders-of-magnitude larger datasets.



- Source Code: https://github.com/huggingface/transformers/tree/main/src/transformers/models/bridgetower
- Documentation: https://huggingface.co/docs/transformers/main/en/model_doc/bridgetower

Integrated into Hugging Face – Transformers

- Pre-trained models released on Hugging Face – Model Hub
  - https://huggingface.co/BridgeTower

Models 4

⇅ Sort: Recently Updated

BridgeTower/bridgetower-large-itm-mlm-gaudi
Updated about 8 hours ago

BridgeTower/bridgetower-base
Updated about 8 hours ago • ↓ 550

BridgeTower/bridgetower-large-itm-mlm
Updated about 8 hours ago • ↓ 366

BridgeTower/bridgetower-base-itm-mlm
Updated about 8 hours ago • ↓ 300

- Model Variants
  - Number of parameters:

	Textual Encoder	Visual Encoder	Cross-Modal Encoder	Total
BridgeTower$_{\text{Base}}$	124M	86M	113M	323M
BridgeTower$_{\text{Large}}$	355M	304M	200M	859M

Usage – Image-Text Matching

```
from transformers import BridgeTowerProcessor, BridgeTowerForImageAndTextRetrieval
import requests
from PIL import Image

url = "http://images.cocodataset.org/val2017/000000039769.jpg"
image = Image.open(requests.get(url, stream=True).raw)
texts = ["An image of two cats chilling on a couch", "A football player scoring a goal"]

processor = BridgeTowerProcessor.from_pretrained("BridgeTower/bridgetower-base-itm-mlm")
model = BridgeTowerForImageAndTextRetrieval.from_pretrained("BridgeTower/bridgetower-base-itm-mlm")

# forward pass
scores = dict()
for text in texts:
    # prepare inputs
    encoding = processor(image, text, return_tensors="pt")
    outputs = model(**encoding)
    scores[text] = outputs.logits[0,1].item()
# {'An image of two cats chilling on a couch': 4.843737125396728,
#  'A football player scoring a goal': -6.897047996520996}
```

Usage – Masked Language Modeling

```
from transformers import BridgeTowerProcessor, BridgeTowerForMaskedLM
from PIL import Image
import requests

url = "http://images.cocodataset.org/val2017/000000360943.jpg"
image = Image.open(requests.get(url, stream=True).raw).convert("RGB")
text = "a <mask> looking out of the window"

processor = BridgeTowerProcessor.from_pretrained("BridgeTower/bridgetower-base-itm-mlm")
model = BridgeTowerForMaskedLM.from_pretrained("BridgeTower/bridgetower-base-itm-mlm")

# prepare inputs
encoding = processor(image, text, return_tensors="pt")

# forward pass
outputs = model(**encoding)

results = processor.decode(outputs.logits.argmax(dim=-1).squeeze(0).tolist())

print(results)
# a cat looking out of the window.
```

Next Steps

- ❑ Pre-training and Fine-tuning scripts

- ❑ Checkpoints and notebooks for more downstream tasks

- Notably, code and model checkpoints for pre-training and all downstream tasks are available in https://github.com/microsoft/BridgeTower.

Thanks & QA

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Presenter: Xiao Xu

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Slides and more in https://looperxx.github.io/.