Multimodal Learning

对比学习、多模态生成式模型（语言生成）

高鑫　2023.6.6

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IMAGEBIND: One Embedding Space To Bind Them

2023,5,9

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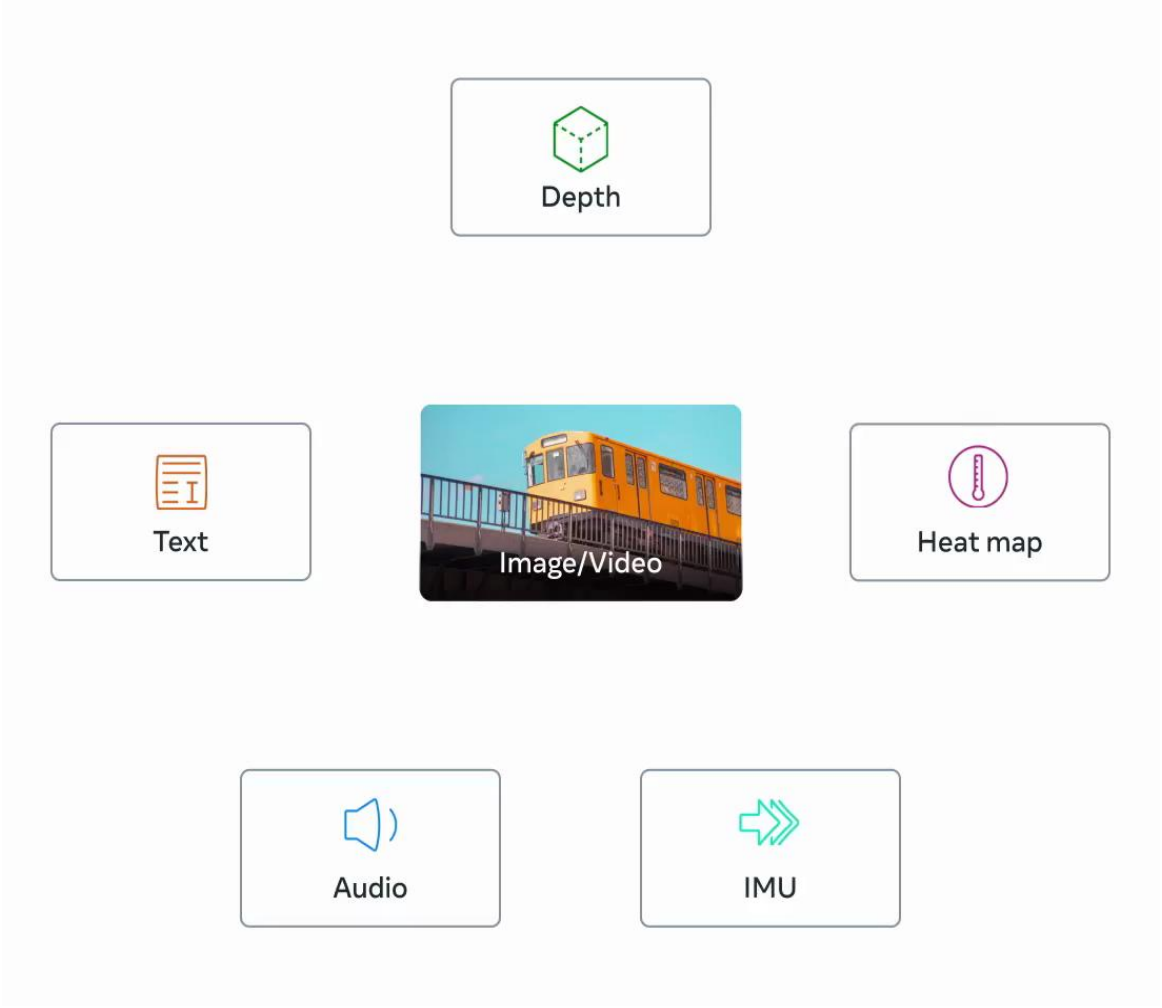
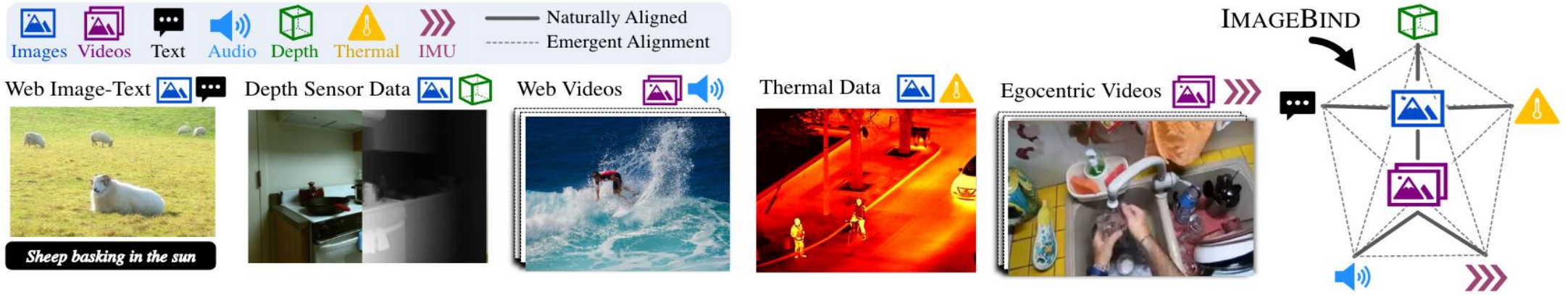
FAIR, Meta AI
https://facebookresearch.github.io/ImageBind



- The 'binding' property of images offers many sources of supervision to learn visual features

!! the absence of large quantities of multimodal data where all modalities are present together !!

- **IMAGEBIND:** multiple types of image-paired data ==> a single shared representation space



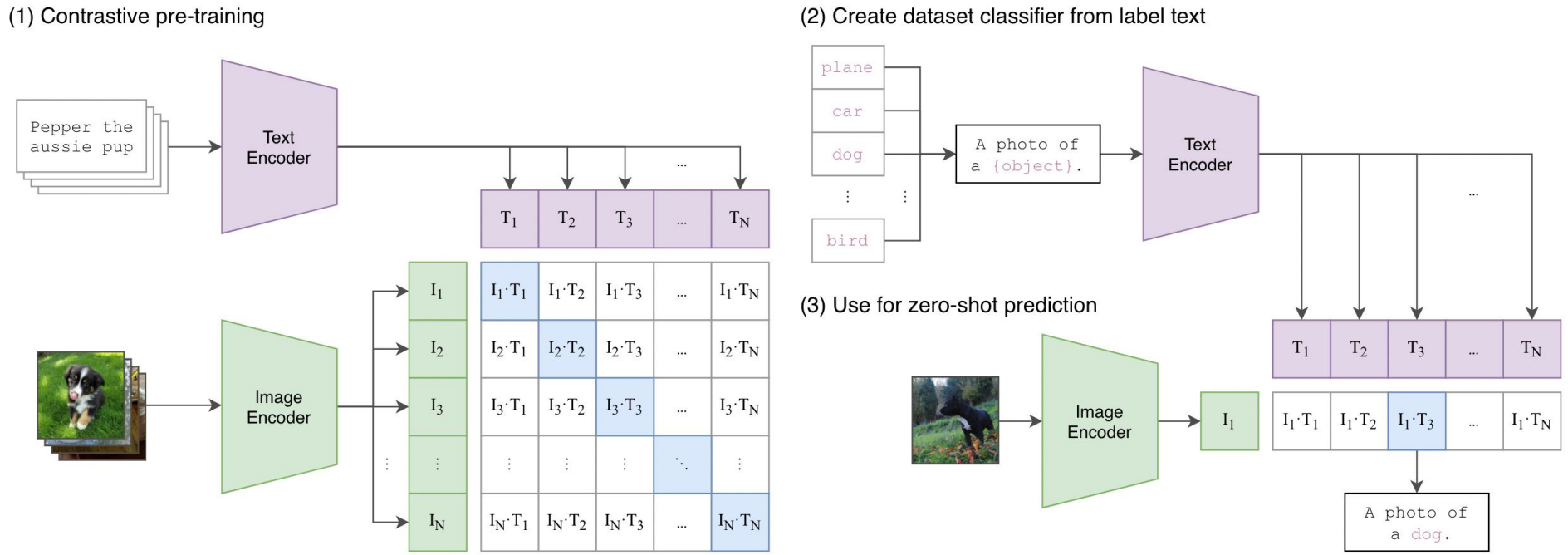
an emergent alignment across all of the modalities

IMAGEBIND's emergent zero-shot classification matches or outperforms specialist models trained with direct audio-text supervision on benchmarks

an image I_i, its corresponding observation in the other modality M_i
encode them: $q_i = f(I_i)$ and $k_i = g(M_i)$ (f, g are deep networks)

InfoNCE loss: $L_{\mathcal{I},\mathcal{M}} = -\log \frac{\exp(\mathbf{q}_i^\top \mathbf{k}_i/\tau)}{\exp(\mathbf{q}_i^\top \mathbf{k}_i/\tau)+\sum_{j\neq i}\exp(\mathbf{q}_i^\top \mathbf{k}_j/\tau)}$, $L_{\mathcal{I},\mathcal{M}} + L_{\mathcal{M},\mathcal{I}}$

an emergent behavior in the embedding space that aligns two pairs of modalities (M_1, M_2) (only train using the pairs (I, M_1) and (I, M_2))

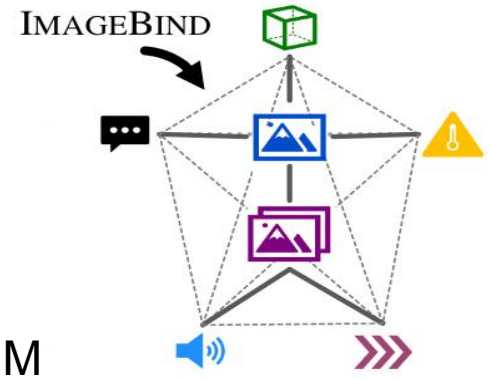


Architecture:

images(videos), text encoder: pretrained OpenCLIP

audio, depth, thermal, IMU: “2D images”, ViT

32GB V100 or 40GB A100



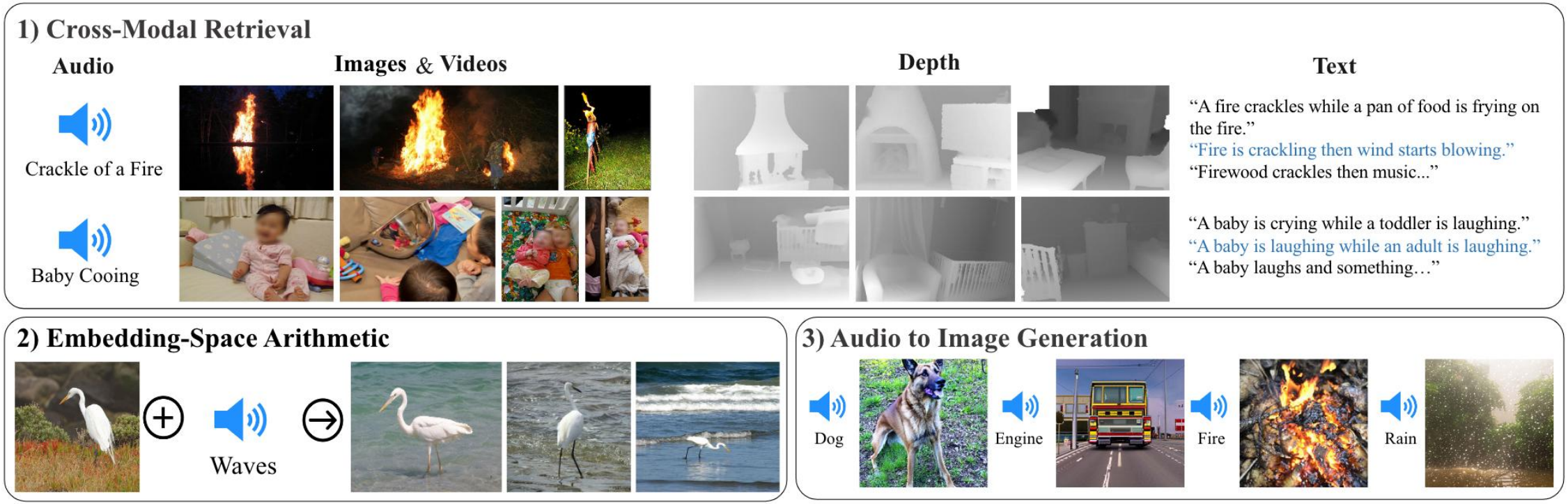
Training dataset:

videos&audio	Audioset	2M
images&depth	SUN	~5K
images&thermal	LLVIP	12025，3463
videos&IMU	Ego4D	510142，68865

✖50

Config	AS	SUN	LLVIP	Ego4D
Vision encoder	ViT-Huge			
embedding dim.	768	384	768	512
number of heads	12	8	12	8
number of layers	12	12	12	6
Optimizer	AdamW			
Optimizer Momentum	$\beta_1 = 0.9, \beta_2 = 0.95$			
Peak learning rate	1.6e-3	1.6e-3	5e-4	5e-4
Weight decay	0.2	0.2	0.05	0.5
Batch size	2048	512	512	512
Gradient clipping	1.0	1.0	5.0	1.0
Warmup epochs	2			
Sample replication	1.25	50	25	1.0
Total epochs	64	64	64	8
Stoch. Depth [28]	0.1	0.0	0.0	0.7
Temperature	0.05	0.2	0.1	0.2
Augmentations:				
`RandomResizedCrop`				
`size`	-	224px		-
`interpolation`	-	Bilinear	Bilinear	-
`RandomHorizontalFlip`	-	$p = 0.5$	$p = 0.5$	-
`RandomErase`	-	$p = 0.25$	$p = 0.25$	-
`RandAugment`	-	9/0.5	9/0.5	-
`Color Jitter`	-	0.4	0.4	-
`Frequency masking`	12	-	-	-

IMAGEBIND's joint embedding space enables novel multimodal capabilities



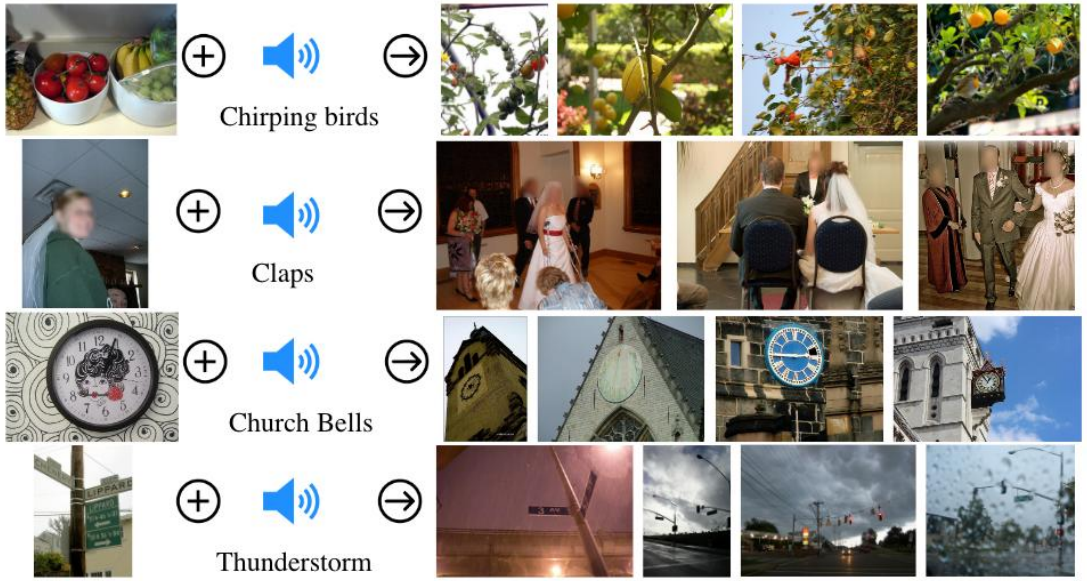
Emergent zero-shot classification and retreival

Dataset	Task	#cls	Metric	#test
Audioset Audio-only (AS-A) [18]	Audio cls.	527	mAP	19048
ESC 5-folds (ESC) [58]	Audio cls.	50	Acc	400
Clotho (Clotho) [16]	Retrieval	-	Recall	1045
AudioCaps (AudioCaps) [36]	Retrieval	-	Recall	796
VGGSound (VGGS) [8]	Audio cls.	309	Acc	14073
SUN Depth-only (SUN-D) [67]	Scene cls.	19	Acc	4660
NYU-v2 Depth-only (NYU-D) [64]	Scene cls.	10	Acc	653
LLVIP (LLVIP) [31]	Person cls.	2	Acc	15809
Ego4D (Ego4D) [22]	Scenario cls.	108	Acc	68865

	Emergent	Clotho		AudioCaps		ESC
		R@1	R@10	R@1	R@10	Top-1
Uses audio and text supervision						
AudioCLIP [26]	✗	-	-	-	-	**68.6**
Uses audio and text loss						
AVFIC [50]	✗	3.0	17.5	8.7	37.7	-
No audio and text supervision						
IMAGEBIND	✓	**6.0**	**28.4**	**9.3**	**42.3**	66.9
Supervised						
AVFIC finetuned [50]	✗	8.4	38.6	-	-	-
ARNLQ [52]	✗	12.6	45.4	24.3	72.1	-

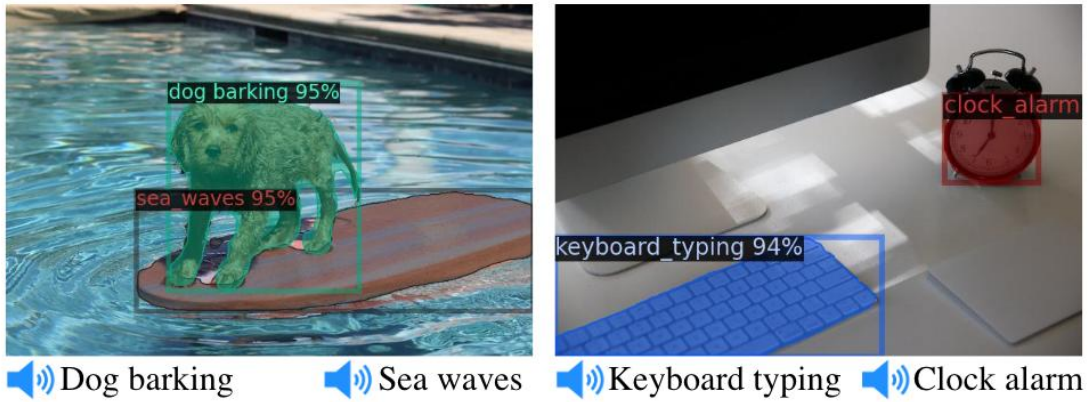
	IN1K	P365	K400	MSR-VTT	NYU-D	SUN-D	AS-A	VGGS	ESC	LLVIP	Ego4D
Random	0.1	0.27	0.25	0.1	10.0	5.26	0.62	0.32	2.75	50.0	0.9
IMAGEBIND	77.7	45.4	50.0	36.1	54.0	35.1	17.6	27.8	66.9	63.4	25.0
Text Paired	-	-	-	-	41.9*	25.4*	28.4† [26]	-	68.6† [26]	-	-
Absolute SOTA	91.0 [80]	60.7 [65]	89.9 [78]	57.7 [77]	76.7 [20]	64.9 [20]	49.6 [38]	52.5 [35]	97.0 [9]	-	-

Embedding space arithmetic: image retrievals obtained by adding together image and audio embeddings.



Without training

haven't seen (audio, text) pairs



a pretrained **text-based detection model, Detic,** and simply replace its CLIP-based 'class' (text) embeddings with IMAGEBIND's audio embeddings

a pretrained **DALLE-2 diffusion model** (private reimplementation) and replace its prompt embeddings by audio embeddings

Scaling the Image Encoder

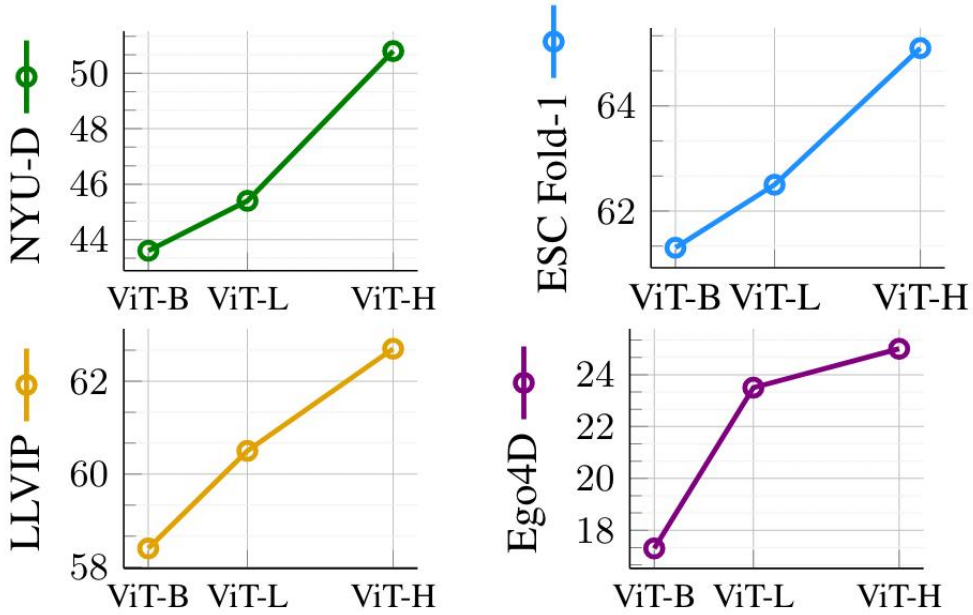
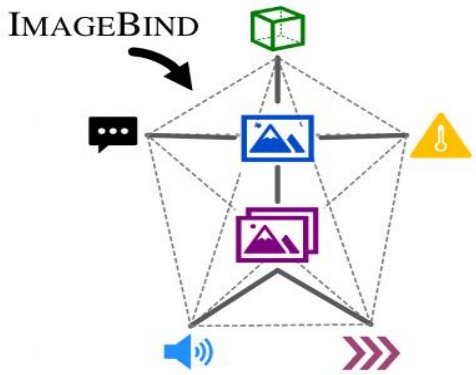


Figure 6. Scaling the image encoder size while keeping the other modality encoders' size fixed. We measure the performance on the emergent zero-shot classification of depth, audio, thermal, and IMU modalities. Scaling the image encoder significantly improves the zero-shot classification results suggesting that a stronger visual representation improves the 'binding' of modalities.

- **No improvement in the ability to extract visual features;**
- **Excessive reliance on the ability of image encoders;**
- **Imbalances between different modalities, the dataset sizes vary greatly**
- **How to further train and enhance the representation ability with other modalities in pairs**



MEDICAL IMAGE UNDERSTANDING WITH PRETRAINED VISION LANGUAGE MODELS: A COMPREHENSIVE STUDY

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ICLR 2023

Can pre-trained VLMs learned from a large number of natural text-image pairs help with the understanding of medical images?

Well-designed medical prompts are the key to elicit knowledge from pre-trained VLMs

domain gap between medical images and natural images

With the help of well-designed text prompts, the model can be equipped with **high-level semantics** describing the characteristic of target objects instead of only providing **object names**.

expressive attributes that are shared between domains: **Color**, **Shape**, **Location**

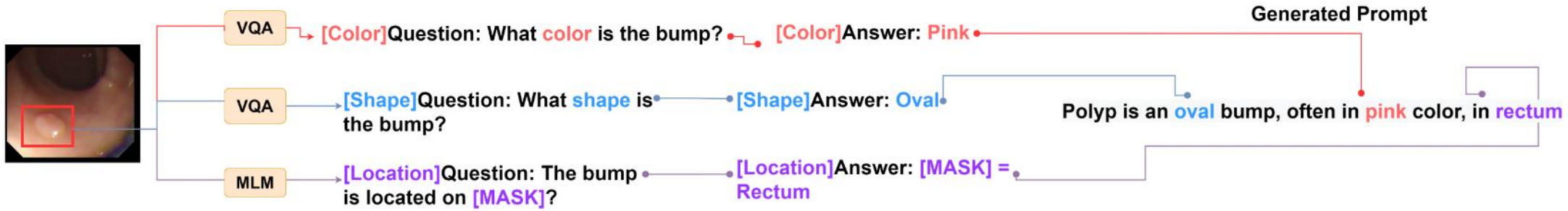
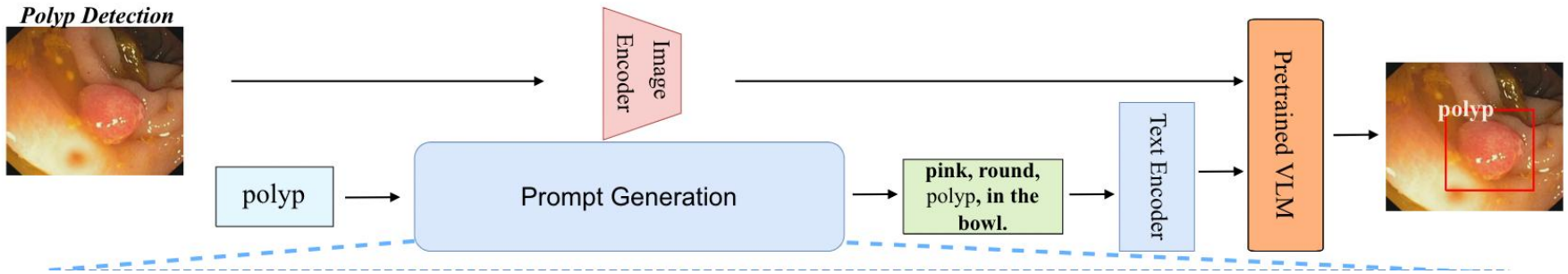
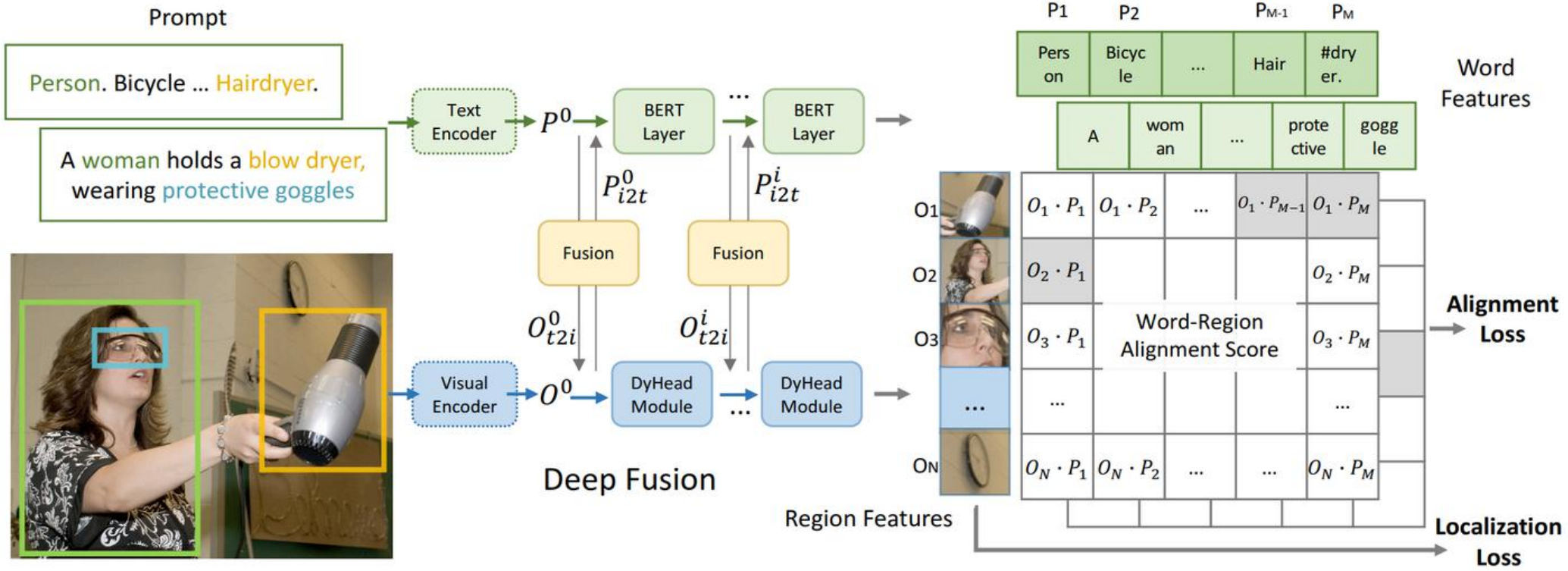


Figure 4: Auto-prompt generation show case.

Overall goal:

Transfer pre-trained VLMs to the medical field, and use them for downstream object detection.

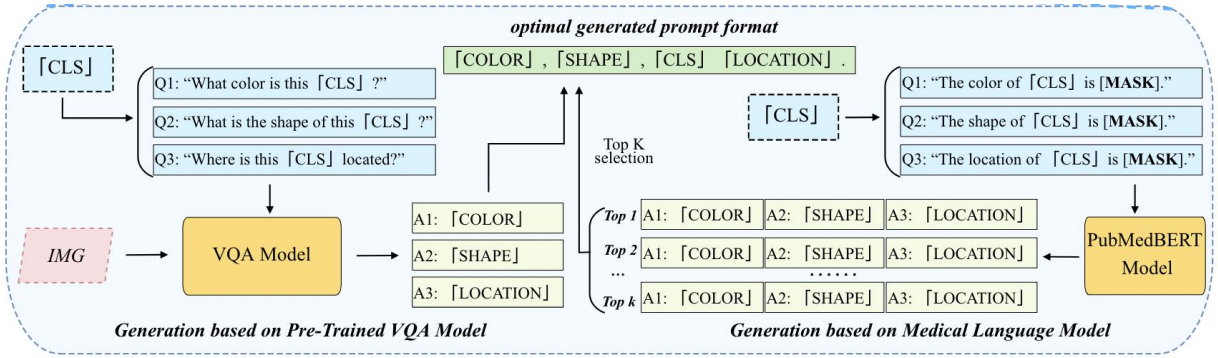

Polyp Detection
Image Encoder
polyp
Prompt Generation
pink, round, polyp, in the bowl.
Text Encoder
Pretrained VLM
polyp


Prompt
Person. Bicycle ... Hairdryer.
A woman holds a blow dryer, wearing protective goggles
Text Encoder
Visual Encoder
BERT Layer
BERT Layer
Fusion
Fusion
DyHead Module
DyHead Module
Deep Fusion
P1 P2 PM-1 PM
Person
Bicycle
...
Hair
#dryer.
A
woman
...
protective
goggle
Word Features
O1
O2
O3
ON
Word-Region Alignment Score
Alignment Loss
Region Features
Localization Loss

- manually designing an effective prompt requires expert-level knowledge and a lot of effort;
- in the current vision-language models, the prompts are normally fixed for all samples during inference, i.e., not image-specific, which is not ideal for grounding novel objects that may have varying appearances.

generate knowledge-rich and image-specific prompts

【PubMedBERT】 Masked Language Model Driven Auto-Prompt Generation
'The [Attr] of an [Object] is [MASK]'
top-k predicted words for the [MASK] token



【OFA】 Image Specific Auto-Prompt Generation
"What color is this wound?".

hybrid prompts

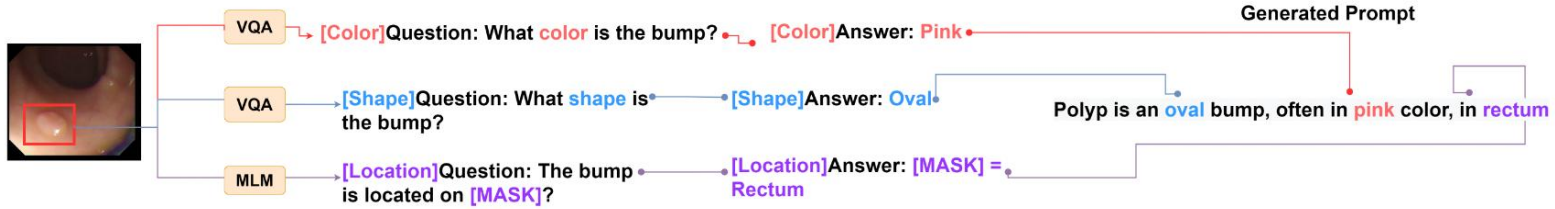


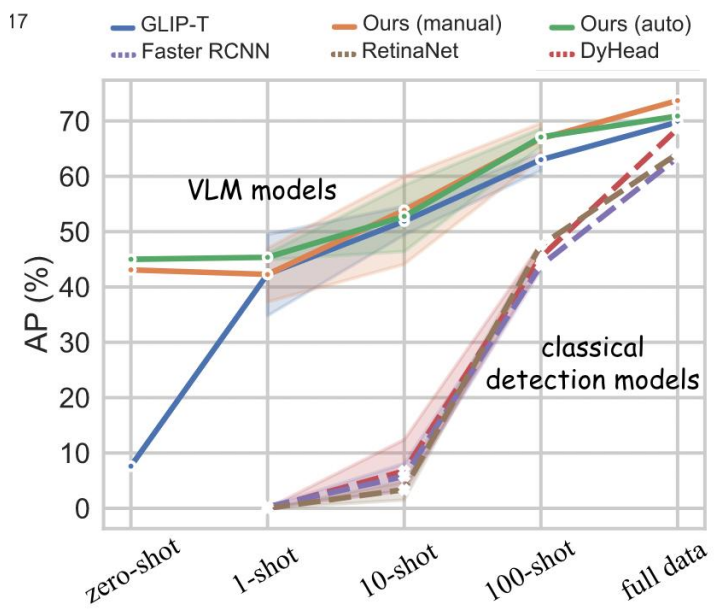
Figure 4: Auto-prompt generation show case.

Table 1: Dataset overview (13 datasets in total).

	Photography images		Endoscopy images	Microscopy images		Radiology images			
				Cytology	Histopathology	X ray	CT	MRI	Ultrasound
Dataset	ISIC 2016	DFUC 2020	Ployp Benchmark (×5)⋆	BCCD	CPM-17	TBX11K	Luna16	ADNI	TN3k

⋆ includes CVC-300, CVC-ClinicDB, CVC-ColonDB, Kvasir, and ETIS

1. Transfer performance surpassing supervised methods



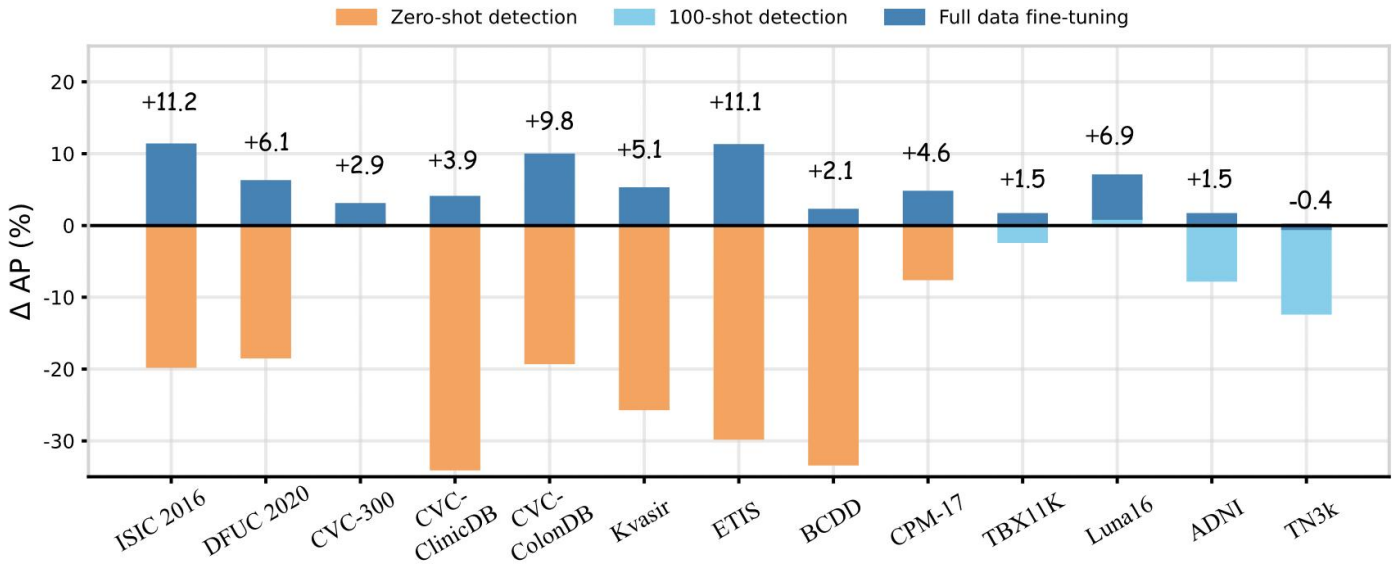


Figure 2: Comparisons with a fully supervised baseline (the horizontal line). The y-axis shows ΔAP compared to the supervised baseline. For non-radiology datasets, we exhibit zero-shot and full data results; we show 100-shot and full data results for the radiology datasets (from TBX11K to TN3k).

2. Superior zero-shot transfer performance compared to the baseline

our approaches can empower the pre-trained VLM with remarkable zero-shot capability in the medical domain.

Table 3: Our approaches v.s. supervised models on non-radiology datasets (AP%).

	Method	Backbone	ISIC 2016	DFUC 2022	Polyp (×5)	BCCD	CPM-17
Full Data	Faster RCNN	RN50	50.3	42.3	56.6	56.9	39.8
	RetinaNet	RN50	54.0	43.1	58.8	56.7	35.7
	DyHead	Swin-T	52.9	44.2	62.9	60.1	38.8
	GLIP-T(default cls)	Swin-T	62.4	**50.3**	68.1	62.5	43.9
	Ours (Manual)	Swin-T	**64.1**	**50.3**	**69.4**	62.2	43.4
	Ours (Auto)	Swin-T	61.6	50.1	68.8	**63.1**	**44.2**
100-Shot	Faster RCNN	RN50	44.6	27.0	44.9	38.6	–
	RetinaNet	RN50	41.7	28.4	41.7	54.3	–
	DyHead	Swin-T	42.5	27.8	42.5	40.5	–
	GLIP-T(default cls)	Swin-T	55.9	41.4	57.6	59.8	–
	Ours (Manual)	Swin-T	58.0	**43.7**	**60.8**	60.1	–
	Ours (Auto)	Swin-T	**58.8**	42.4	**60.8**	**60.2**	–
Zero-Shot	GLIP-T(default cls)	Swin-T	20.1	0.1	4.1	0.7	7.6
	GLIP-L(default cls)	Swin-L	20.4	3.6	11.9	10.4	11.6
	Ours (with MLM)	Swin-T	25.1	24.8	38.4	24.1	20.3
	Ours (with VQA)	Swin-T	23.5	12.9	27.1	14.3	26.2
	Ours (with Hybrid)	Swin-T	24.5	22.5	35.1	14.3	24.8
	Ours (Manual)	Swin-T	**33.3**	**25.9**	**41.3**	**26.9**	**31.4**

3. The effectiveness of attribution injection and auto-prompts

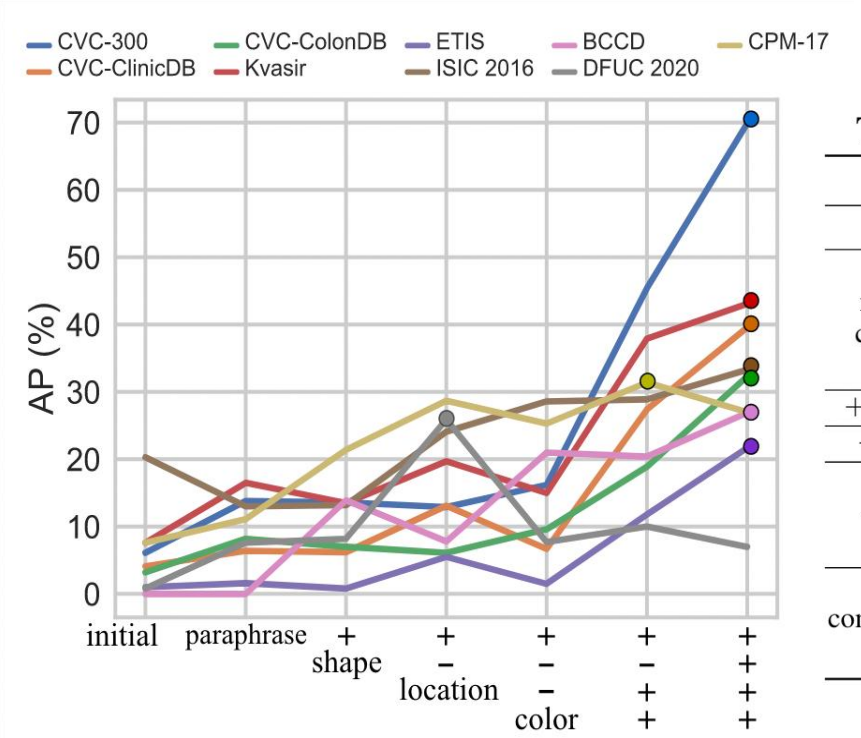


Table 4: Examples of prompts for BCDD (zero-shot performance on the validation and test set)

	Prompt	AP	AP50
initial	platelet. red blood cell. white blood cell	0.4	0.9
medical concepts	thrombocyte. erythrocyte. leukocyte	0.1	0.1
	blood platelet. red blood corpuscle. white blood corpuscle	3.1	7.0
	thrombocyte, blood platelet. erythrocyte, red blood corpuscle. leukocyte, white blood corpuscle	6.8	15.5
	thrombocyte or blood platelet. **erythrocyte or** red blood **corpuscle**. **leukocyte or** white blood **corpuscle**	8.6	17.9
+ location	platelet **in blood**. red blood cell **in blood**. white blood cell **in blood**	6.9	14.4
+ shape	**small** platelet. **rounded** red blood cell. **irregular** white blood cell	7.7	14.9
+ color	colorless platelet. freshcolor red blood cell. blue white blood cell	18.3	32.3
	colorless platelet. freshcolor red blood cell. purple white blood cell	17.8	32.9
	colorless platelet. **freshcolor** red blood cell. **purple or blue** white blood cell	24.9	43.8
combinations	small, colorless platelet. rounded, freshcolor red blood cell. irregular , purple or blue white blood cell	26.6	47.1
	small, colorless blood platelet. rounded, freshcolor erythrocyte. irregular, purple or blue leukocyte	26.4	45.3
	small, **colorless** platelet. **rounded**, **freshcolor** red blood **corpuscle**. **irregular**, **purple or blue** white blood **corpuscle**	**27.1**	**47.6**

the overall performance increases as more attributes are integrated into the prompts

Multimodal Chain-of-Thought Reasoning in Language Models

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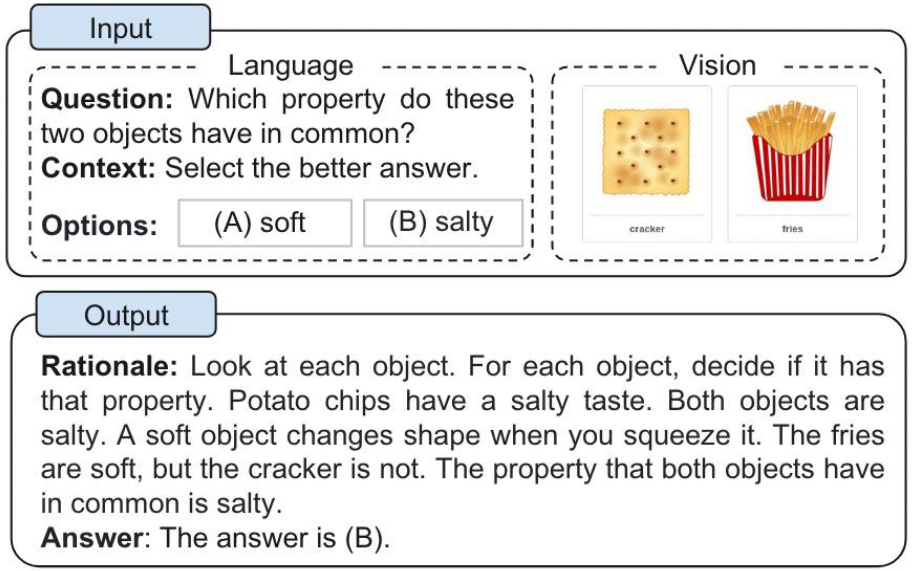
2023,2,17

[1]Shanghai Jiao Tong University [2]Amazon Web Services. Correspondence to: Zhuosheng Zhang (work done at Amazon Web Services) <zhangzs@sjtu.edu.cn>, Aston Zhang <az@astonzhang.com>.

[1]https://github.com/amazon-science/mm-cot



- Large language models (LLMs) have shown impressive performance on complex reasoning by leveraging chain-of-thought (CoT) prompting to generate intermediate reasoning chains as the rationale to infer the answer.

Why is chain-of-thought reasoning useful?

locality[1]

P (C|A) intermediate variable B (B,C) and (B,A) are often seen

- Direct prediction of conditional probabilities is inaccurate for some inferences because the relevant variables are rarely seen together in training. Chain-of-thought reasoning improves estimation because it can chain together local statistical dependencies that are frequently observed in training.

[1] Prystawski, B.; Goodman, N. D. Why Think Step-by-Step? Reasoning Emerges from the Locality of Experience. arXiv April 7, 2023. http://arxiv.org/abs/2304.03843 .

ScienceQA dataset [2] | IMAGEBIND | 华西 | MMCoT | LLaVA

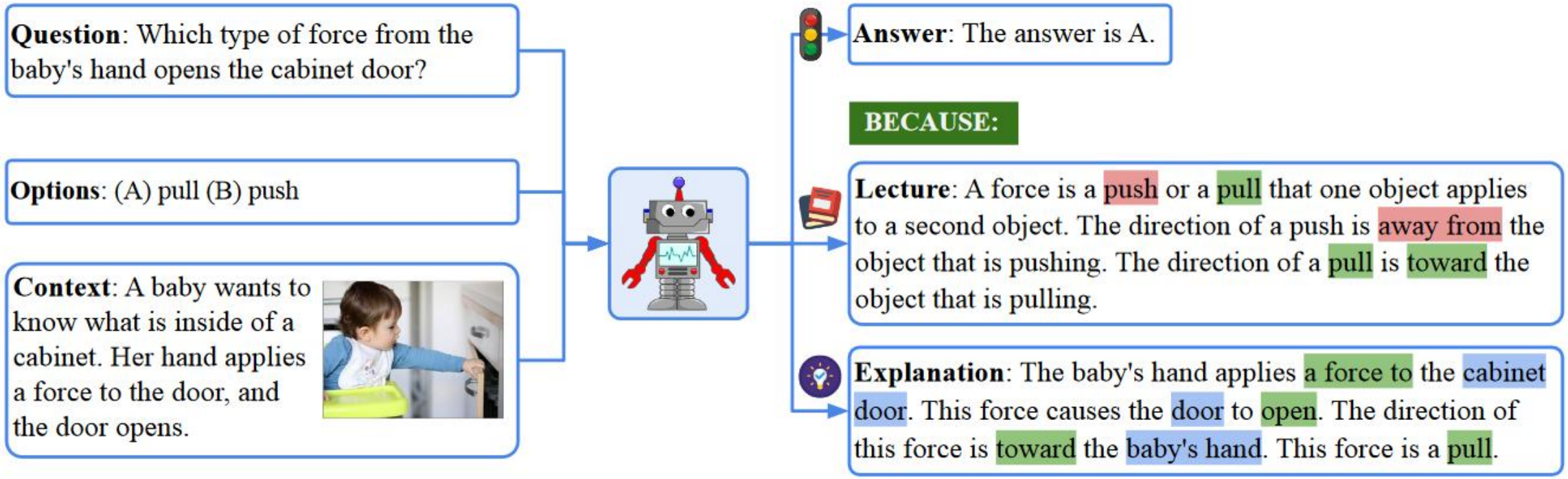


Figure 1: We construct the SCIENCEQA dataset where a data example consists of multimodal question answering information and the grounded lecture and explanation. We study if QA models can generate a reasonable explanation to reveal the chain-of-thought reasoning.

[2] Lu, P.; Mishra, S.; Xia, T.; Qiu, L.; Chang, K.-W.; Zhu, S.-C.; Tafjord, O.; Clark, P.; Kalyan, A. Learn to Explain: Multimodal Reasoning via Thought Chains for Science Question Answering.

- The first to study CoT reasoning in different modalities
- Two ways to elicit Multimodal-CoT reasoning:

prompting LLMs 将图像转化成文字(caption)，和问题一起输给大模型，大量的信息损失，缺少不同模态在某一共同表示空间的相互作用

fine-tuning small models 利用到不同模态之间的相互作用，问题是参数量太小的模型会产生错误的推理过程 (The key challenge is that language models under 100 billion parameters tend to generate hallucinated rationales that mislead the answer inference (Ho et al., 2022; Magister et al.,2022; Ji et al., 2022).

Table 2. Effects of CoT in the one-stage setting.

Method	Format	Accuracy
No-CoT	QCM→A	80.40
Reasoning	QCM→RA	67.86
Explanation	QCM→AR	69.77

The question text (Q), the context text (C), and multiple options (M) as the input; the rationale text(R), and answer(A) as the output

The rationales might not necessarily contribute to predicting the right answer

separate the CoT problem into two stages: rationale generation and answer inference

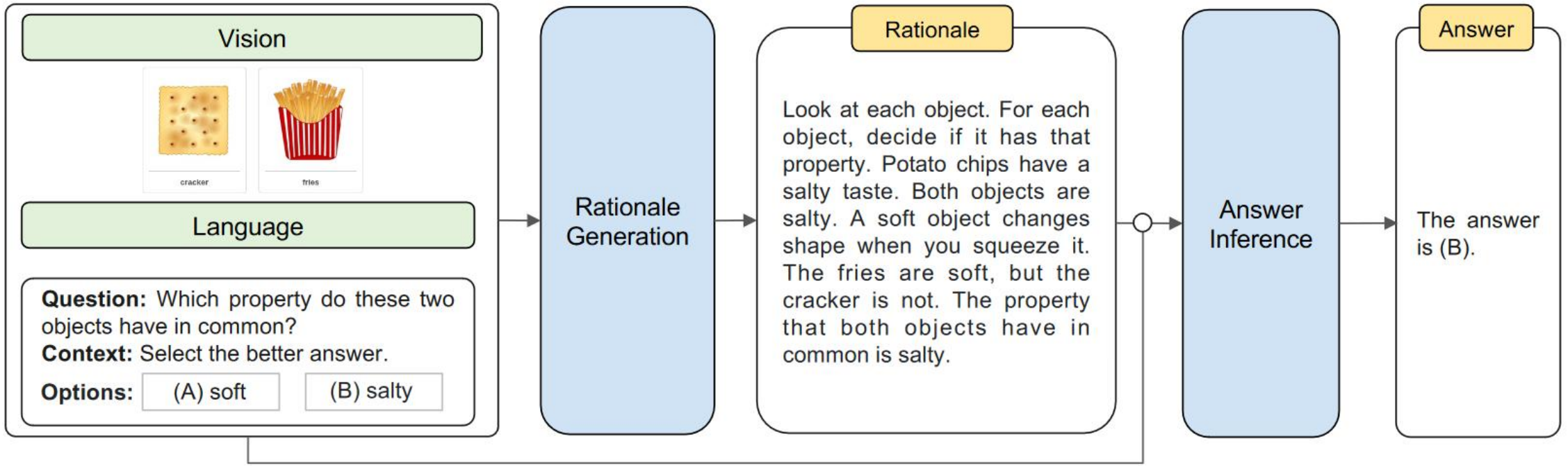


Figure 4. Overview of our Multimodal-CoT framework. Multimodal-CoT consists of two stages: (i) rationale generation and (ii) answer inference. Both stages share the same model architecture but differ in the input and output. In the first stage, we feed the model with language and vision inputs to generate rationales. In the second stage, we append the original language input with the rationale generated from the first stage. Then, we feed the updated language input with the original vision input to the model to infer the answer.

How the rationales affect the answer prediction?

Q: question, C: context, M: multiple options, R: rationale, A: answer

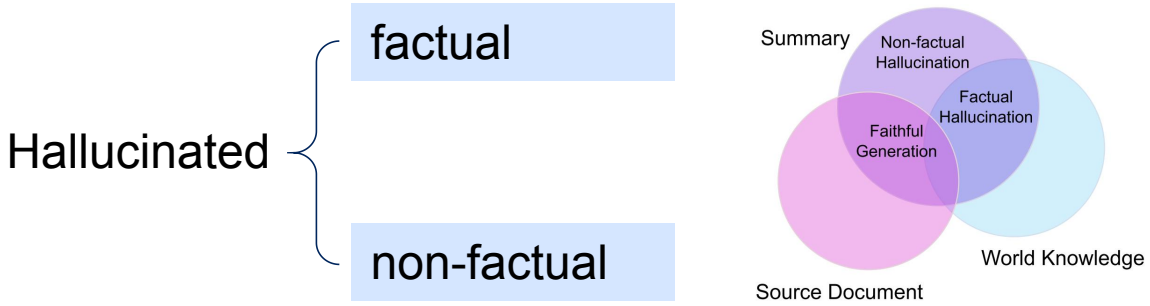


Table 3. Two-stage setting of (i) rationale generation (RougeL) and (ii) answer inference (Accuracy).

Method	(i) QCM→ R	(ii) QCMR→ A
Two-Stage Framework	91.76	70.53
w/ Captions	91.85	71.12
w/ Vision Features	96.97	84.91

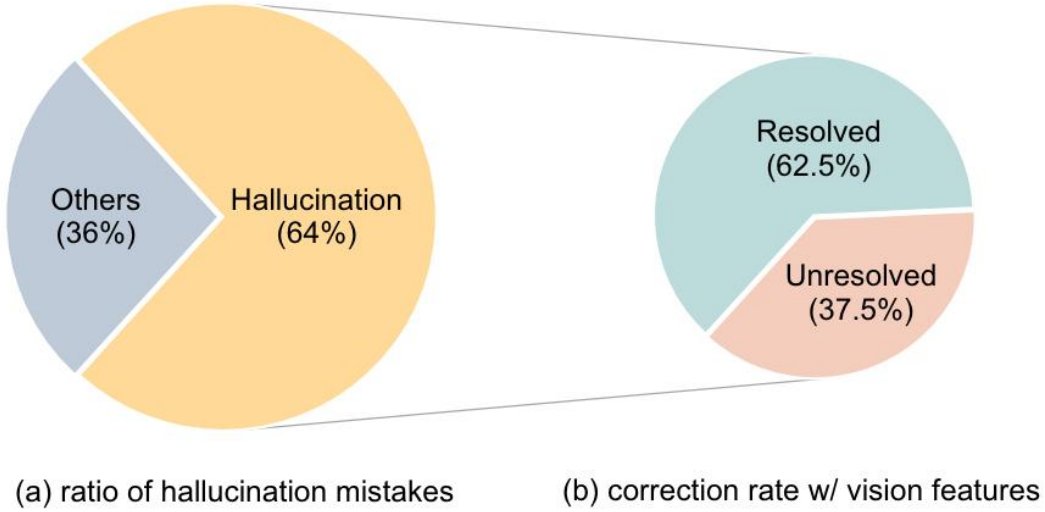


Figure 3. The ratio of hallucination mistakes (a) and correction rate w/ vision features (b).

Multimodality (Vision Features) Contributes to Effective Rationales

We speculate that such a phenomenon of hallucination is due to a lack of necessary vision contexts for performing effective Multimodal-CoT.

1. DETR model (Carion et al., 2020) to extract vision features

2. fuse the vision features with the encoded language representations

3. feed to the decoder

backbone language model: UnifiedQA (T5)

4 NVIDIA Tesla V100 32G GPUs

$$X = \{X^1_{\text{language}}, X_{\text{vision}}\} \Rightarrow R = F(X) \text{ where } R \text{ is the rationale}$$

$$X^2_{\text{language}} = X^1_{\text{language}} \circ R \quad \text{(concat)}$$

$$\Rightarrow X' = \{X^2_{\text{language}}, X_{\text{vision}}\} \Rightarrow A = F(X')$$

model	size
Mutimodal-CoT$_{\text{Base}}$	223M
Mutimodal-CoT$_{\text{Large}}$	738M

1. encoding

$$H_{\text{language}} = \text{LanguageEncoder}(X_{\text{language}}), \quad (2)$$

$$H_{\text{vision}} = W_h \cdot \text{VisionExtractor}(X_{\text{vision}}), \quad (3)$$

$H_{\text{language}} \in \mathbb{R}^{n \times d}$ where n denotes the length of the language input, and d is the hidden dimension. Meanwhile, patch-level vision features, we apply a learnable projection matrix W_h to convert the shape of $\text{VisionExtractor}(X_{\text{vision}})$ into that of H_{language}; thus we have $H_{\text{vision}} \in \mathbb{R}^{m \times d}$ where m is the number of patches.

2. interaction

we use a single-head attention network to correlate text tokens with image patches, where the query ($\mathcal{Q}$), key ($\mathcal{K}$) and value ($\mathcal{V}$) are H_{language}, H_{vision} and H_{vision},

$$H^{\text{attn}}_{\text{vision}} = \text{Softmax}(\frac{\mathcal{Q}\mathcal{K}^\top}{\sqrt{d_k}})\mathcal{V}, \quad (4)$$

$$H^{\text{attn}}_{\text{vision}} \in \mathbb{R}^{n \times d}$$

$$\lambda = \text{Sigmoid}(W_l H_{\text{language}} + W_v H^{\text{attn}}_{\text{vision}}), \quad (5)$$

$$H_{\text{fuse}} = (1 - \lambda) \cdot H_{\text{language}} + \lambda \cdot H^{\text{attn}}_{\text{vision}}, \quad (6)$$

3. decoding H_{fuse} is fed into the Transformer decoder to predict the target Y

Mutimodal-CoTLarge outperforms GPT-3.5 by 16.51% (75.17%→91.68%) and surpasses human performance

Table 4. Main results (%). Size = backbone model size. Question classes: NAT = natural science, SOC = social science, LAN = language science, TXT = text context, IMG = image context, NO = no context, G1-6 = grades 1-6, G7-12 = grades 7-12. Results except ours are taken from Lu et al. (2022a). Segment 1: Human performance; Segment 2: VQA baselines; Segment 3: UnifiedQA baselines; Segment 4: GPT-3.5 baselines; Segment 5: Our Multimodal-CoT results. Results in **bold** are the best performance.

Model	Size	NAT	SOC	LAN	TXT	IMG	NO	G1-6	G7-12	Avg
Human	-	90.23	84.97	87.48	89.60	87.50	88.10	91.59	82.42	88.40
MCAN (Yu et al., 2019)	95M	56.08	46.23	58.09	59.43	51.17	55.40	51.65	59.72	54.54
Top-Down (Anderson et al., 2018)	70M	59.50	54.33	61.82	62.90	54.88	59.79	57.27	62.16	59.02
BAN (Kim et al., 2018)	112M	60.88	46.57	66.64	62.61	52.60	65.51	56.83	63.94	59.37
DFAF (Gao et al., 2019)	74M	64.03	48.82	63.55	65.88	54.49	64.11	57.12	67.17	60.72
ViLT (Kim et al., 2021)	113M	60.48	63.89	60.27	63.20	61.38	57.00	60.72	61.90	61.14
Patch-TRM (Lu et al., 2021)	90M	65.19	46.79	65.55	66.96	55.28	64.95	58.04	67.50	61.42
VisualBERT (Li et al., 2019)	111M	59.33	69.18	61.18	62.71	62.17	58.54	62.96	59.92	61.87
UnifiedQA$_{\text{Base}}$ (Khashabi et al., 2020)	223M	68.16	69.18	74.91	63.78	61.38	77.84	72.98	65.00	70.12
UnifiedQA$_{\text{Base}}$ w/ CoT (Lu et al., 2022a)	223M	71.00	76.04	78.91	66.42	66.53	81.81	77.06	68.82	74.11
GPT-3.5 (Chen et al., 2020)	175B	74.64	69.74	76.00	74.44	67.28	77.42	76.80	68.89	73.97
GPT-3.5 w/ CoT (Lu et al., 2022a)	175B	75.44	70.87	78.09	74.68	67.43	79.93	78.23	69.68	75.17
Mutimodal-CoT$_{\text{Base}}$	223M	87.52	77.17	85.82	87.88	82.90	86.83	84.65	85.37	84.91
Mutimodal-CoT$_{\text{Large}}$	738M	**95.91**	**82.00**	**90.82**	**95.26**	**88.80**	**92.89**	**92.44**	**90.31**	**91.68**

Two stages?

VT-R ==> VTR-A **VS** **VT-RA**

Table 5. Ablation results of Multimodal-CoT.

Model	NAT	SOC	LAN	TXT	IMG	NO	G1-6	G7-12	Avg
Multimodal-CoT	87.52	77.17	85.82	87.88	82.90	86.83	84.65	85.37	84.91
w/o Two-Stage Framework	80.99	87.40	81.91	80.25	78.83	83.62	82.78	82.20	82.57
w/o Vision Features	71.09	70.75	69.18	71.16	65.84	71.57	71.00	69.68	70.53

Vision encoder?

Table 6. Accuracy (%) of using different vision features.

Method	One-stage	Two-Stage
w/ CLIP	81.21	84.81
w/ DETR	82.57	84.91
w/ ResNet	80.97	84.77

Table 8. Categorization analysis of Multimodal-CoT.

Answer	CoT Category	Percentage (%)
Correct	CoT is correct	90
	CoT is incorrect	10
Incorrect	Commonsense Mistake	82
	Logical Mistake	12
	CoT is correct	6

- injecting commonsense knowledge;
- incorporating more informative vision features and improving language-vision interaction to be capable of understanding maps and counting numbers;

Visual Instruction Tuning

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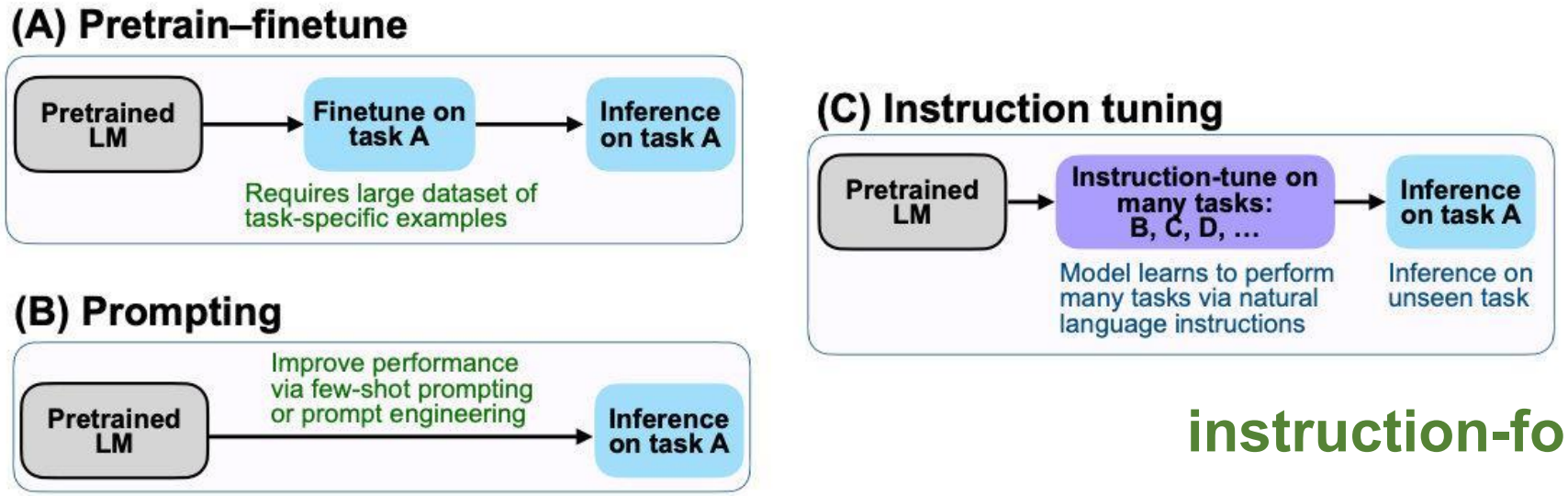
[1]University of Wisconsin–Madison [2]Microsoft Research [3]Columbia University
https://llava-vl.github.io

LLaVA: Large Language and Vision Assistant 2023,4,17

In this paper, we present the first attempt to use language-only GPT-4 to generate multimodal language-image instruction-following data.

Instruction tuning large language models (LLMs) using machine-generated instruction-following data has improved zero-shot capabilities on new tasks



instruction-following ability

In the natural language processing (NLP) community, to enable LLMs such as GPT-3, T5, PaLM, and OPT to follow natural language instructions and complete real-world tasks, researchers have explored methods for LLM instruction-tuning, leading to instruction-tuned counterparts such as InstructGPT/ChatGPT, FLAN-T5, FLANPaLM, and OPT-IML, respectively.

[3] Wei J, Bosma M, Zhao V Y, et al. Finetuned language models are zero—shot learners[J]. arXiv preprint arXiv:2109.01652, 2021.

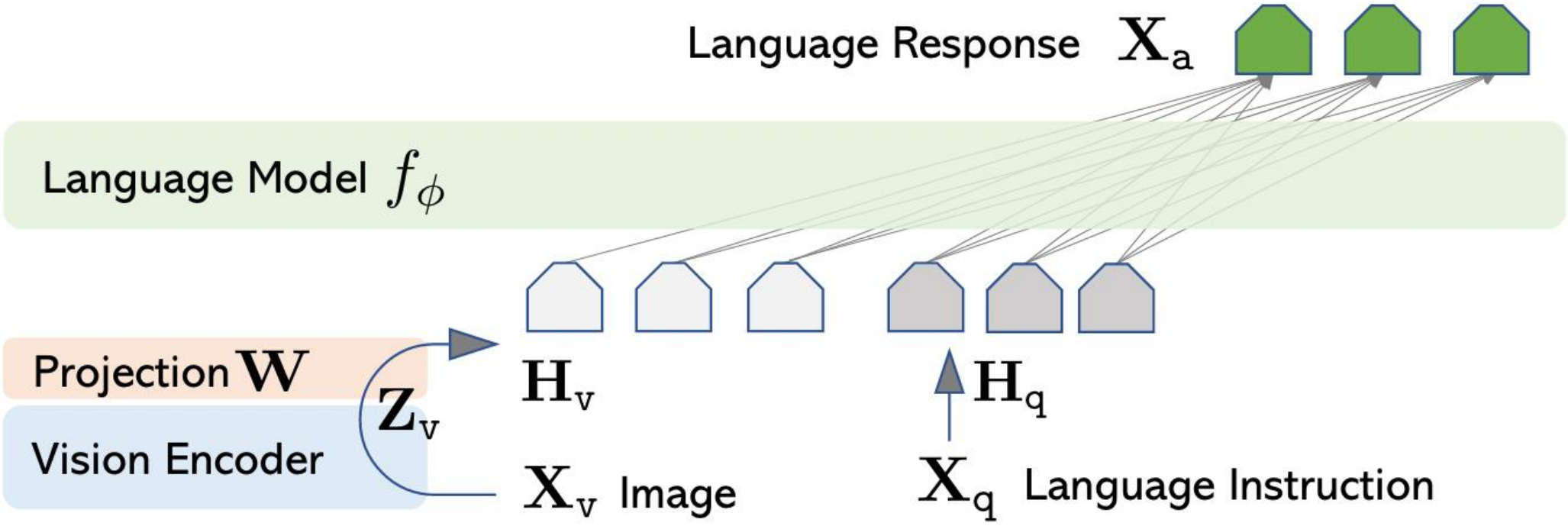
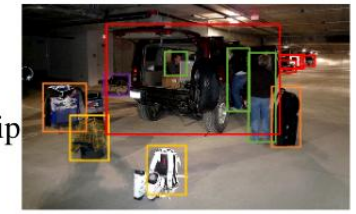


Figure 1: LLaVA network architecture.

We leave exploring possibly more effective and sophisticated architecture designs for LLaVA as future work.

158K unique language-image samples
- 23K in detailed description
- 58K in conversations
- 77k in complex reasoning

Context type 1: Captions
A group of people standing outside of a black vehicle with various luggage.
Luggage surrounds a vehicle in an underground parking area
People try to fit all of their luggage in an SUV.
The sport utility vehicle is parked in the public garage, being packed for a trip
Some people with luggage near a van that is transporting it.



Context type 2: Boxes
person: [0.681, 0.242, 0.774, 0.694], person: [0.63, 0.222, 0.686, 0.516], person: [0.444, 0.233, 0.487, 0.34], backpack: [0.384, 0.696, 0.485, 0.914], backpack: [0.755, 0.413, 0.846, 0.692], suitcase: [0.758, 0.413, 0.845, 0.69], suitcase: [0.1, 0.497, 0.173, 0.579], bicycle: [0.282, 0.363, 0.327, 0.442], car: [0.786, 0.25, 0.848, 0.322], car: [0.783, 0.27, 0.827, 0.335], car: [0.86, 0.254, 0.891, 0.3], car: [0.261, 0.101, 0.787, 0.626]

Response type 1: conversation
Question: What type of vehicle is featured in the image?
Answer: The image features a black sport utility vehicle (SUV).
Question: Where is the vehicle parked?
Answer: The vehicle is parked in an underground parking area, likely in a public garage.
Question: What are the people in the image doing?
Answer: The people are trying to fit all of their luggage into the SUV, likely preparing for a trip.

Response type 2: detailed description
The image is an underground parking area with a black sport utility vehicle (SUV) parked. There are three people in the scene, with one person standing closer to the left side of the vehicle, another person in the middle, and the third person on the right side. They are all working together to pack their luggage into the SUV for a trip.
In the parking area, various luggage items are scattered around the vehicle. There are two backpacks, one located near the left rear wheel and the other closer to the right side of the vehicle. Additionally, there are two suitcases, one on the right side of the car and another further away near the center of the parking area. A bicycle can also be seen on the left side of the vehicle.
Other cars are parked around the main SUV, with one car positioned behind it and slightly to the left, another behind and slightly to the right, and the third car further behind on the right side.

caption+bounding box => GPT4/3.5

Response type 3: complex reasoning
Question: What challenges do these people face?
Answer: In the image, a group of people is standing outside a black SUV in a parking area, surrounded by various pieces of luggage, including suitcases and backpacks. They are facing the challenge of fitting all their luggage into the black SUV. There are multiple suitcases and backpacks to be packed, which suggests that the group has a significant amount of belongings to accommodate. They might have to strategize and arrange the luggage efficiently to ensure that everything fits properly into the vehicle. Additionally, they need to consider the comfort of the passengers and visibility while driving, so the placement of the luggage must not obstruct the driver's view or make the passengers uncomfortable during the trip.

To get a rich and comprehensive description for an image,
ask GPT-4 to use the original image captions to generate the detailed description

- brief description question + image caption
- detailed description question + GPT-refined image caption

Instructions for brief image description. The list of instructions used to briefly describe the image content are shown in Table 8. They present the same meaning with natural language variance.

- "Describe the image concisely."
- "Provide a brief description of the given image."
- "Offer a succinct explanation of the picture presented."
- "Summarize the visual content of the image."
- "Give a short and clear explanation of the subsequent image."
- "Share a concise interpretation of the image provided."
- "Present a compact description of the photo's key features."
- "Relay a brief, clear account of the picture shown."
- "Render a clear and concise summary of the photo."
- "Write a terse but informative summary of the picture."
- "Create a compact narrative representing the image presented."

Table 8: The list of instructions for brief image description.

Instructions for detailed image description. The list of instructions used to describe the image content in detail are shown in Table 9. They present the same meaning with natural language variance.

- "Describe the following image in detail"
- "Provide a detailed description of the given image"
- "Give an elaborate explanation of the image you see"
- "Share a comprehensive rundown of the presented image"
- "Offer a thorough analysis of the image"
- "Explain the various aspects of the image before you"
- "Clarify the contents of the displayed image with great detail"
- "Characterize the image using a well-detailed description"
- "Break down the elements of the image in a detailed manner"
- "Walk through the important details of the image"
- "Portray the image with a rich, descriptive narrative"
- "Narrate the contents of the image with precision"
- "Analyze the image in a comprehensive and detailed manner"
- "Illustrate the image through a descriptive explanation"
- "Examine the image closely and share its details"
- "Write an exhaustive depiction of the given image"

Table 9: The list of instructions for detailed image description.

```
messages = [ {"role":"system", "content": f"""You are an AI visual assistant, and you are
seeing a single image. What you see are provided with five sentences, describing the same image you
are looking at. Answer all questions as you are seeing the image.

Design a conversation between you and a person asking about this photo. The answers should be in a
tone that a visual AI assistant is seeing the image and answering the question. Ask diverse questions
and give corresponding answers.

Include questions asking about the visual content of the image, including the object types, counting
the objects, object actions, object locations, relative positions between objects, etc. Only include
questions that have definite answers:
(1) one can see the content in the image that the question asks about and can answer confidently;
(2) one can determine confidently from the image that it is not in the image. Do not ask any question
that cannot be answered confidently.

Also include complex questions that are relevant to the content in the image, for example, asking
about background knowledge of the objects in the image, asking to discuss about events happening in
the image, etc. Again, do not ask about uncertain details. Provide detailed answers when answering
complex questions. For example, give detailed examples or reasoning steps to make the content more
convincing and well-organized. You can include multiple paragraphs if necessary."""}
]
for sample in fewshot_samples:
    messages.append({"role":"user", "content":sample['context']})
    messages.append({"role":"assistant", "content":sample['response']} )
messages.append({"role":"user", "content":'\n'.join(query)})
```

1. 假装你是一个AI视觉助手，正在看一张图片。caption和bounding box描述了这张图片的信息，但不能透露你看过caption和bounding box
2. 设计一段你和一个人关于这张图像的对话
3. 包含针对视觉内容的问题，如物体种类、物体数量、物体动作、物体位置、物体之间的相对位置等等。只设计有明确答案的问题
4. 包含与图片内容相关的复杂问题，例如物体的背景知识，对发生事件的讨论等等。

in-context learning seed examples

For each image $\mathbf{X}_\mathrm{v}$, we generate multi-turn conversation data $(\mathbf{X}_\mathrm{q}^1, \mathbf{X}_\mathrm{a}^1, \cdots, \mathbf{X}_\mathrm{q}^T, \mathbf{X}_\mathrm{a}^T)$, where T is the total number of turns. We organize them as a sequence, by treating all answers as the assistant's response, and the instruction $\mathbf{X}_\mathrm{instruct}^t$ at the t-th turn as:

$$\mathbf{X}_\mathrm{instruct}^t = \begin{cases} \text{Random choose } [\mathbf{X}_\mathrm{q}^1, \mathbf{X}_\mathrm{v}] \text{ or } [\mathbf{X}_\mathrm{v}, \mathbf{X}_\mathrm{q}^1], & \text{the first turn } t = 1 \\ \mathbf{X}_\mathrm{q}^t, & \text{the remaining turns } t > 1 \end{cases}$$

description => a single-turn conversation

$$\mathbf{X}_\mathrm{system\text{-}message} \texttt{<STOP>} \backslash\mathrm{n}$$
$$\text{Human : } \mathbf{X}_\mathrm{instruct}^1 \texttt{<STOP>} \backslash\mathrm{n} \text{ Assistant: } \mathbf{X}_\mathrm{a}^1 \texttt{<STOP>} \backslash\mathrm{n}$$
$$\text{Human : } \mathbf{X}_\mathrm{instruct}^2 \texttt{<STOP>} \backslash\mathrm{n} \text{ Assistant: } \mathbf{X}_\mathrm{a}^2 \texttt{<STOP>} \backslash\mathrm{n} \cdots$$

$$p(\mathbf{X}_\mathrm{a}|\mathbf{X}_\mathrm{v}, \mathbf{X}_\mathrm{instruct}) = \prod_{i=1}^{L} p_{\boldsymbol{\theta}}(\boldsymbol{x}_i|\mathbf{X}_\mathrm{v}, \mathbf{X}_{\mathrm{instruct},<i}, \mathbf{X}_{\mathrm{a},<i})$$

- Only **green sequence/tokens** are used to compute the loss in the auto-regressive model.
- X system-message = A chat between a curious human and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the human's questions.
- <STOP> = ###.

Stage 1 Pre-training for Feature Alignment: image + brief description question => image caption

Stage 2 Fine-tuning End-to-End: image + instruct_question => instruct_answer

- Multimodal Chatbot.
- Science QA： question & context as instruct_question, and reasoning & answer as instruct_answer

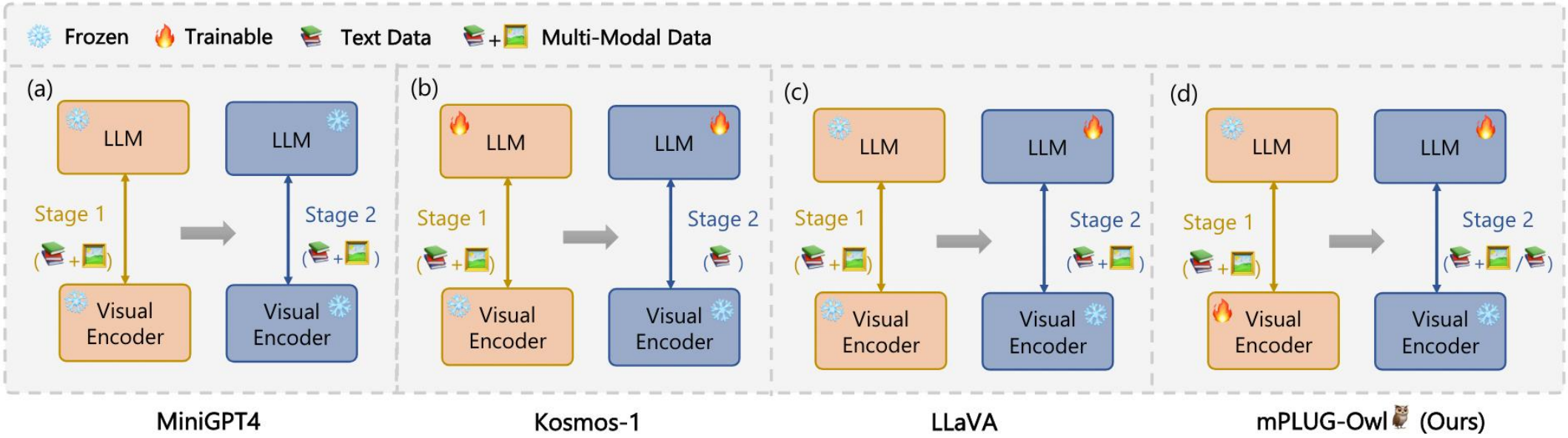


Figure 1: Comparison between different training paradigms. All of these methods are trained in a two-stage fashion. Stage 1 stands for pre-training and Stage 2 represents instruction tuning.

Visual input example, Extreme Ironing:

Source: https://www.barnorama.com/wp-content/uploads/2016/12/03-Confusing-Pictures.jpg

User	What is unusual about this image?
LLaVA	The unusual aspect of this image is a man ironing clothes on the back of a minivan or van. This is not a typical place to perform this activity, as one would usually iron clothes in a more stationary and safe location, such as a home, using a regular ironing board. The scene depicted in the image is peculiar as it involves a makeshift ironing setup on a vehicle, which can be both unsafe and unconventional. Additionally, it is not clear how the man is able to maintain balance and stability while ironing clothes in such an unstable environment.
	[*Start a new conversation, and clear the history*]
User	What's happening in the scene?
LLaVA	The image depicts a man standing on top of a yellow SUV in a busy city street. He is holding a portable ladder, seemingly ironing clothes while standing on the vehicle. Around the scene, there are other cars, a traffic light, and a fire hydrant. Additionally, there are two other people in the vicinity, one close to the man on the car and another further away. The man on the ladder appears to be attracting attention due to his unconventional choice of ironing his clothes on top of a moving car. The city street around him is bustling with activity, adding to the unique nature of the scene.
User	What is unusual about this image?
GPT-4 [32]	The unusual thing about this image is that a man is ironing clothes on an ironing board attached to the roof of a moving taxi.
User	Can you explain this meme in detail?
BLIP-2	a man is sitting on the back of a yellow cab
User	Can you explain this meme in detail?
OpenFlamingo	The man is drying his clothes on the hood of his car.

Case study

	Conversation	Detail description	Complex reasoning	**All**
Full data	83.1	75.3	96.5	85.1
Detail + Complex	81.5 (-1.6)	73.3 (-2.0)	90.8 (-5.7)	81.9 (-3.2)
Conv + 5% Detail + 10% Complex	81.0 (-2.1)	68.4 (-7.1)	91.5 (-5.0)	80.5 (-4.4)
Conversation	76.5 (-6.6)	59.8 (-16.2)	84.9 (-12.4)	73.8 (-11.3)
No Instruction Tuning	22.0 (-61.1)	24.0 (-51.3)	18.5 (-78.0)	21.5 (-63.6)

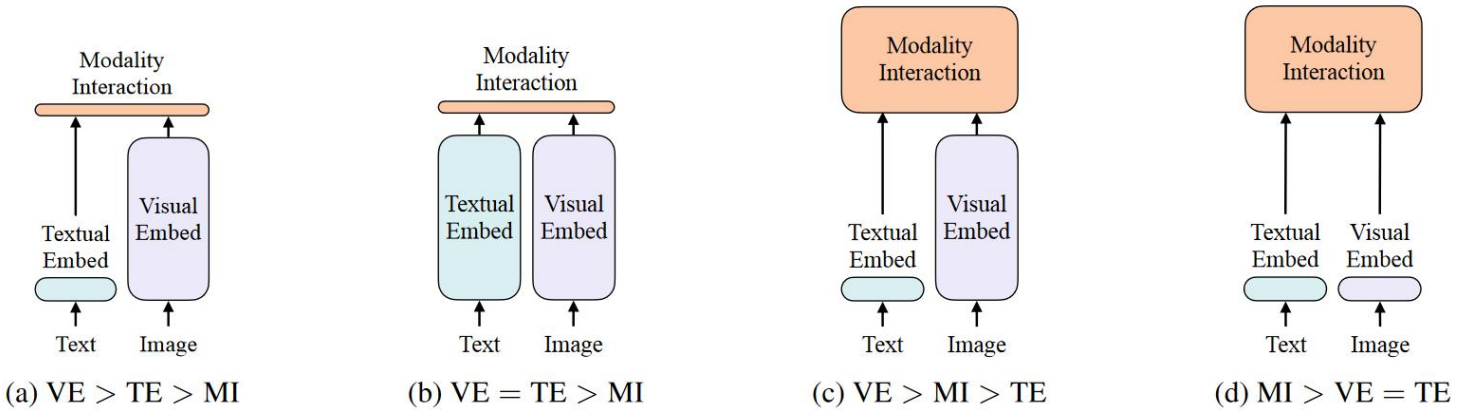
Adding a small amount of the detailed description and complex reasoning questions => model's capability ⬆

Results on ScienceQA

Method	Subject			Context Modality			Grade		Average
	NAT	SOC	LAN	TXT	IMG	NO	G1-6	G7-12	
Representative & SoTA methods with numbers reported in the literature									
Human [30]	90.23	84.97	87.48	89.60	87.50	88.10	91.59	82.42	88.40
GPT-3.5 [30]	74.64	69.74	76.00	74.44	67.28	77.42	76.80	68.89	73.97
GPT-3.5 w/ CoT [30]	75.44	70.87	78.09	74.68	67.43	79.93	78.23	69.68	75.17
LLaMA-Adapter [55]	84.37	88.30	84.36	83.72	80.32	86.90	85.83	84.05	85.19
MM-CoT$_{Base}$ [57]	87.52	77.17	85.82	87.88	82.90	86.83	84.65	85.37	84.91
MM-CoT$_{Large}$ [57]	95.91	82.00	90.82	95.26	88.80	92.89	92.44	90.31	91.68
Results with our own experiment runs									
GPT-4	84.06	73.45	87.36	81.87	70.75	90.73	84.69	79.10	82.69
LLaVA	90.36	95.95	88.00	89.49	88.00	90.66	90.93	90.90	90.92
LLaVA+GPT-4 (complement)	90.36	95.50	88.55	89.05	87.80	91.08	92.22	88.73	90.97
LLaVA+GPT-4 (judge)	91.56	96.74	91.09	90.62	88.99	93.52	92.73	92.16	**92.53**

Table 6: Results (accuracy %) on Science QA dataset. Question classes: NAT = natural science, SOC = social science, LAN = language science, TXT = text context, IMG = image context, NO = no context, G1-6 = grades 1-6, G7-12 = grades 7-12.

Conclusion



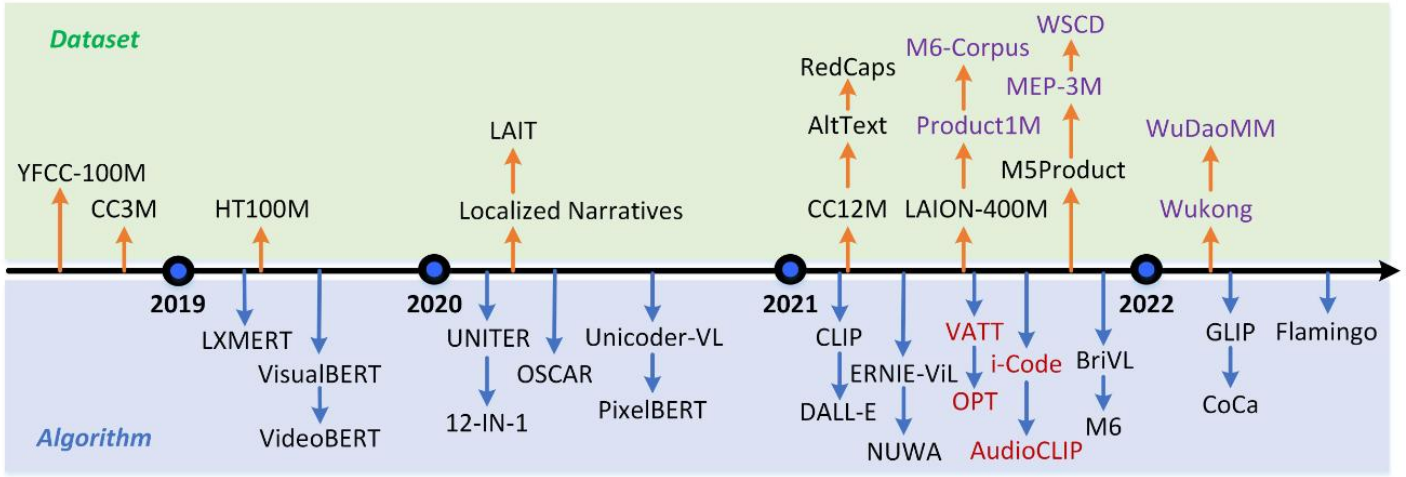


Fig. 1 The chronological milestones on multi-modal pre-trained big models from 2019 to the present (June 2022), including multi-modal datasets (as shown by the orange arrow) and representative models (as shown by the blue arrow). The purple font indicates that the dataset contains Chinese text (other datasets contain English text). The models highlighted in wine red are trained on more than two modalities.

Architecture:

Multimodality embed

Modality interaction

- Pretrained models
- Generative models

Techniques:

- contrastive learning
- prompt learning
- chain of thought
- instruct-tuning

谢谢观看

Work summary report