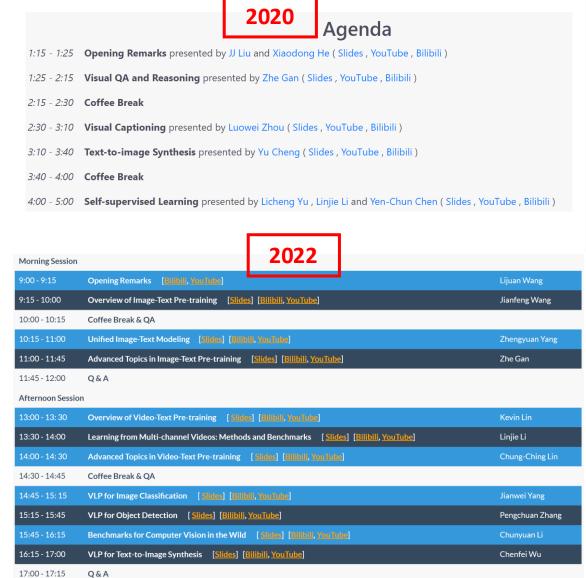
In conjunction with **CVPR 2024** June 17th 2024 (9 a.m. PDT — 5 p.m. PDT) Location: Summit 437- 439, Seattle Convention Center

Morning Sessio	n										
9:00 - 9:20	Opening Re	Opening Remarks									
9:20 - 10:10	Large Multi	Large Multimodal Models: Towards Building General-Purpose Multimodal Assistant Chunyuan Li									
10:10 - 11:00	Methods, A	Methods, Analysis & Insights from Multimodal LLM Pre-training									
11:00 - 11:50	LMMs with	LMMs with Fine-Grained Grounding Capabilities									
Afternoon Sess	Afternoon Session										
13:00 - 13:50	A Close Loo	k at Vision in Large	Multimodal Models	5			Jianwei	Yang			
13:50 - 14:40	Multimodal	Multimodal Agents Linjie Li									
14:40 - 15:00	Coffee Brea	Coffee Break & QA									
15:00 - 15: 50	Recent Adv	Recent Advances in Image Generative Foundation Models Zhengyuan Yang									
15:50 - 16: 40	Video and 3	Video and 3D Generation Kevin Lin									
16:40 - 17:00	Closing Ren	narks & QA									
Chunyuan Li	Zhe Gan	Haotian Zhang	Jianwei Yang	Linjie Li	Zhengyuan Yang	Kevin Lin	Jianfeng Gao	Lijuan Wang			
Tiktok	Apple	Apple	Microsoft	Microsoft	Microsoft	Microsoft	Microsoft	Microsoft			

Previous Tutorials (2020-2023)



	2021			
Prerecorded Ses	ssions 2021			
4min	Opening Remarks [Video]	Jingjing Liu and Xiaodong He		
50min	Representations and Training Strategies for VLP [Video] [Slides]	Zhe Gan		
40min	Robustness, Efficiency and Extensions for VLP [Video] [Slides]	Linjie Li		
40min	Video-and-Language Pre-training [Video] [Slides]	Luowei Zhou		
42min	Introduction to VLN [Video] [Slides]	Qi Wu		
55min	Generalizable VLN Methods [Video] [Slides]	Xin Eric Wang		
58min	Forward to Realistic VLN [Video] [Slides]	Yoav Artzi and Peter Anderson		
15min	VLN Summary [Video] [Slides]	Qi Wu		
Live Session				
16:00-17:00	Panel Discussion (o) LIVE on Zoom [Video]	All speakers		

	2023
9:00 - 9:40	Opening Remarks & Visual and Vision-Language Pre-training [Sildes] [Bithil, YouTube]
9:40 - 10:20	From Representation to Interface: The Evolution of Foundation for Vision Understanding [Slides] [Bilibili, YouTube]
10:20 - 11:00	Alignments in Text-to-Image Generation [Slides] [Ollivel, You Tube]
11:00 - 11:40	Large Multimodal Models [Slides, Notes] [Bilibili, YouTube]
11:40 - 12:10	Multimodal Agents: Chaining Multimodal Experts with LLMs [Sildes] [Billbill, YouTube]
12:10 - 12:30	Q&A

https://vlp-tutorial.github.io/

Check out our survey paper

Vision-Language Pre-training: Basics, Recent Advances, and Future Trends

2023

dog, grass, frisbee

Zhe Gan, Linjie Li, Chunyuan Li, Lijuan Wang, Zicheng Liu, Jianfeng Gao Microsoft Corporation {zhgan,linjli,chunyl,lijuanw,zliu,jfgao}@microsoft.com

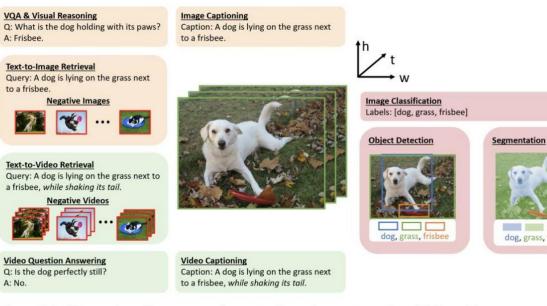
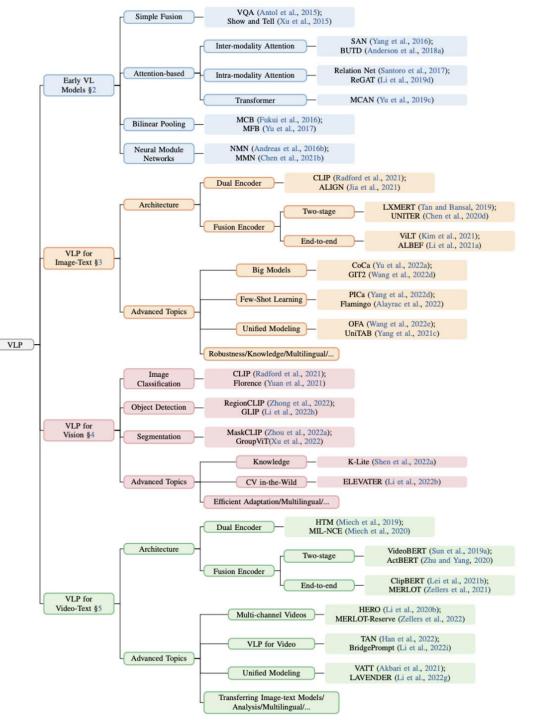
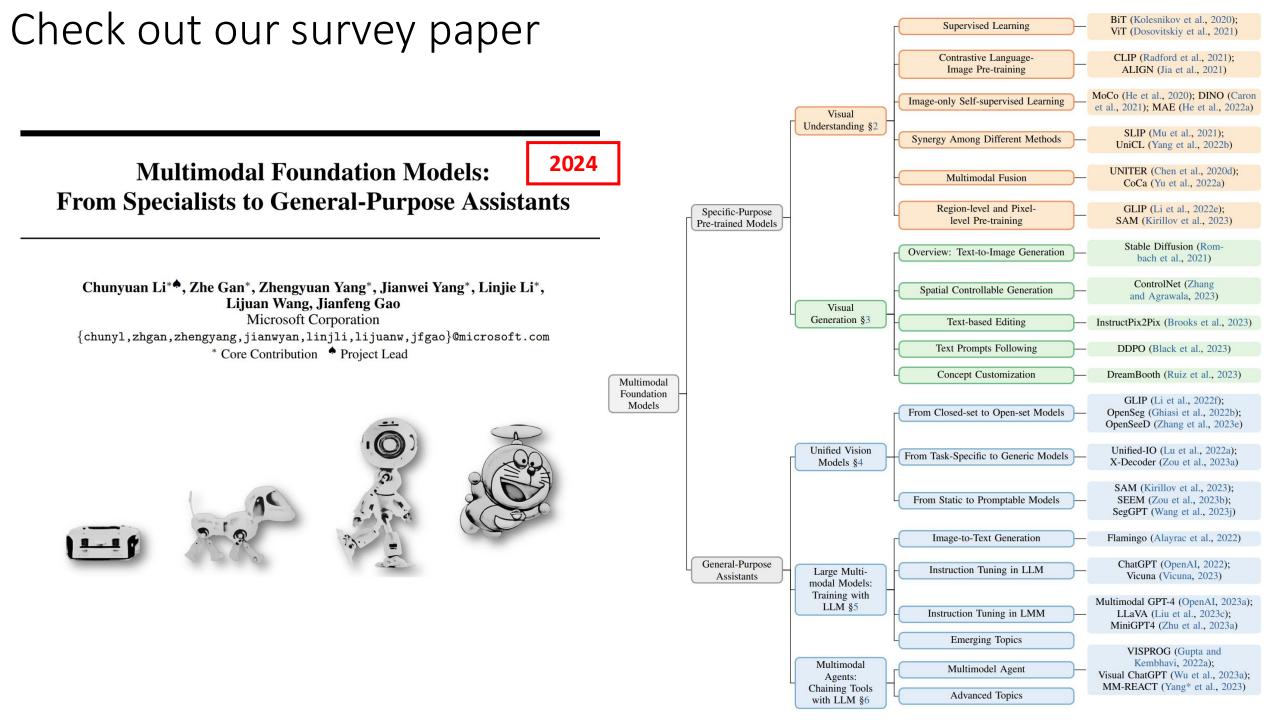


Figure 1.2: Illustration of representative tasks from three categories of VL problems covered in this paper: image-text tasks, vision tasks as VL problems, and video-text tasks.

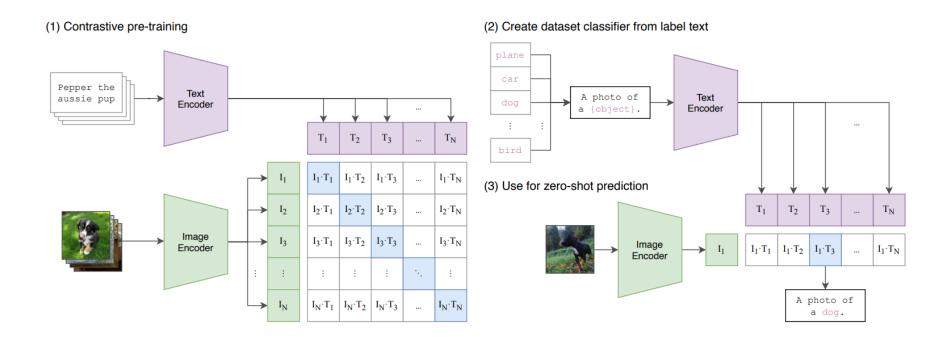




- Looking back, CLIP was a big paradigm shift
- LMMs extends LLMs with multi-sensory skill to achieve generic intelligence
 - Prelude of LMMs (Early Vision-Language Models, Flamingo, CoCa, GIT)
 - The era of LMMs starts from GPT-4V
 - Landscape of open-source and proprietary LMMs
 - New research areas: Grounding LMMs, Visual prompting, Multimodal Agent
- Diffusion model as a vision-centered representation learner
 - Your diffusion model is secretly a zero shot classifier
 - DALL-E 3: reconstruct image from ultra-descriptive caption
 - SORA: video generation models as world simulators

CLIP was a Big Paradigm Shift

Rather than needing handcrafted labels to train a good classifier for a given domain, we can leverage freeform text from the internet to learn a model that is a good classifier for *all* domains

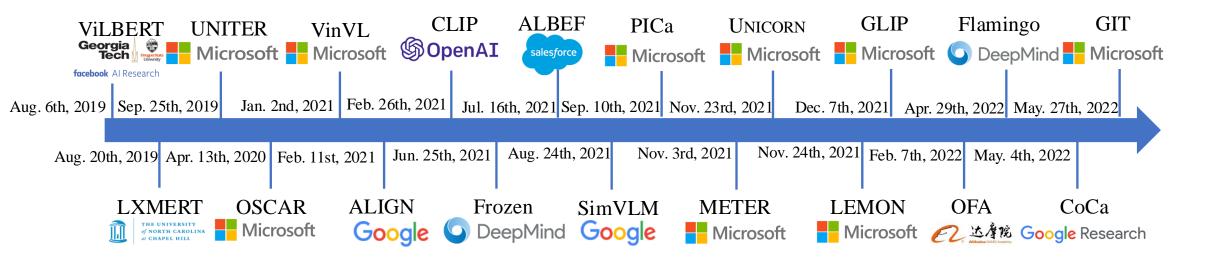


Alec Radford, etc. Learning Transferable Visual Models From Natural Language Supervision. <u>https://arxiv.org/abs/2103.00020</u> 26 Feb. 2021

- Looking back, CLIP was a big paradigm shift
- LMMs extends LLMs with multi-sensory skill to achieve generic intelligence
 - Prelude of LMMs (Early Vision-Language Models, Flamingo, CoCa, GIT)
 - The dawn of LMMs starts from GPT-4V
 - Landscape of open-source and proprietary LMMs
 - New research areas: Grounding LMMs, Visual prompting, Multimodal Agent
- Diffusion model as a vision-centered representation learner
 - Your diffusion model is secretly a zero shot classifier
 - DALL-E 3: reconstruct image from ultra-descriptive caption
 - SORA: video generation models as world simulators

Prelude of LMMs (Early Vision-Language Models)

- Early VLP models depend on pre-trained object detectors to extract visual features offline.
- Newer end-to-end VLP models achieve stronger performance with model and data scaling.
- Upscaled VLP models demonstrate new capabilities such as in-context learning and multimodal few shots.



The Era of LMMs starts from GPT-4V

The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision)

Zhengyuan Yang*, Linjie Li*, Kevin Lin*, Jianfeng Wang*, Chung-Ching Lin*, Zicheng Liu, Lijuan Wang* Microsoft Corporation

* Core Contributor * Project Lead

"The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision)" work from our colleagues at Microsoft covers a plethora of practical observations and strategies for using GPT-4V.

https://openai.com/contributions/gpt-4v/

2	GP	Γ-4V's Input Modes	10
	2.1	Text-only Inputs	10
	2.2	Single Image-text Pair	10
	2.3	Interleaved Image-text Inputs	11
3	GP	F-4V's Working Modes and Prompting Techniques	12
	3.1	Following Text Instructions	15
	3.2	Visual Pointing and Visual Referring Prompting	15
	3.3	Visual + Text Prompting	16
	3.4	In-context Few-shot Learning	19
4	Visi	on-Language Capability	26
	4.1	Image Description on Diverse Domains	26
	4.2	Object Localization, Counting, and Dense Captioning	38
	4.3	Multimodal Knowledge and Commonsense	43
	4.4	Scene Text, Table, Chart, and Document Reasoning	49
	4.5	Multilingual Multimodal Understanding	58
	4.6	Coding Capability with Vision	63
5	Inte	raction with Humans: Visual Referring Prompting	66
	5.1	Understand Pointing Inputs	66
	5.2	Visual Referring Prompting	69
	5.3	Generate Pointing Outputs	69
6	Tem	poral and Video Understanding	73
	6.1	Multi-image Sequencing	73
	6.2	Video Understanding	73
	6.3	Visual Referring Prompting for Grounded Temporal Understanding	79
7	Abs	tract Visual Reasoning and Intelligence Quotient Test	80
	7.1	Abstract Visual Stimuli	80
	7.2	Discovery and Association of Parts and Objects	80
	7.3	Wechsler Adult Intelligence Scale	80
	7.4	Raven's Progressive Matrices	80
8	Emo	otional Quotient Test	86
	8.1	Read Emotion from Facial Expressions	86
	8.2	Understand How Visual Content Arouses Emotions	87
	8.3	Emotion Conditioned Output	89
9	Eme	erging Application Highlights	90
	9.1	Spot the Difference	90

GPT-4V Emerging Capability Highlights

• LMM emergent capabilities

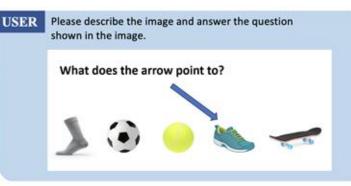
The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision)

Zhengyuan Yang*, Linjie Li*, Kevin Lin*, Jianfeng Wang*, Chung-Ching Lin*, Zicheng Liu, Lijuan Wang*♠ Microsoft Corporation

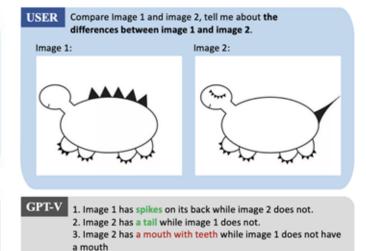
* Core Contributor * Project Lead

Abstract

Large multimodal models (LMMs) extend large language models (LLMs) with multi-sensory skills, such as visual understanding, to achieve stronger generic intelligence. In this paper, we analyze the latest model, GPT-4V(ision) [99-101, 1]1, to deepen the understanding of LMMs. The analysis focuses on the intriguing tasks that GPT-4V can perform, containing test samples to probe the quality and genericity of GPT-4V's capabilities, its supported inputs and working modes, and the effective ways to prompt the model. In our approach to exploring GPT-4V, we curate and organize a collection of carefully designed qualitative samples spanning a variety of domains and tasks. Observations from these samples demonstrate that GPT-4V's unprecedented ability in processing arbitrarily interleaved multimodal inputs and the genericity of its capabilities together make GPT-4V a powerful multimodal generalist system. Furthermore, GPT-4V's unique capability of understanding visual markers drawn on input images can give rise to new humancomputer interaction methods such as visual referring prompting. We conclude the report with in-depth discussions on the emerging application scenarios and the future research directions for GPT-4V-based systems. We hope that this preliminary exploration will inspire future research on the next-generation multimodal task formulation, new ways to exploit and enhance LMMs to solve real-world problems, and gaining better understanding of multimodal foundation models. Finally, we acknowledge that the model under our study is solely the product of OpenAI's innovative work, and they should be fully credited for its development. Please see the GPT-4V contributions paper [10] for the authorship and credit attribution: https://cdn.openai.com/contributions/gpt-4v.pdf.



GPT-V The image shows a sock, a soccer ball, a tennis ball, a running shoe, and a skateboard. The arrow is pointing to the running shoe. So, the answer is that the arrow points to a running shoe.



Spot the Difference

Visual Pointing

USER Describe and summarize what the circled person doing?



GPT-V The circled person is sitting on a bench and then stands up and adjusts his shirt.

Interleaved Image-text Sequence

GPT-4V Emerging Capability Highlights

• Genericity

The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision)

Zhengyuan Yang*, Linjie Li*, Kevin Lin*, Jianfeng Wang*, Chung-Ching Lin*, Zicheng Liu, Lijuan Wang* Microsoft Corporation

* Core Contributor * Project Lead

Abstract

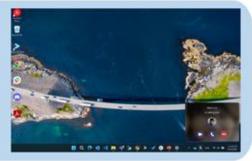
Large multimodal models (LMMs) extend large language models (LLMs) with multi-sensory skills, such as visual understanding, to achieve stronger generic intelligence. In this paper, we analyze the latest model, GPT-4V(ision) [99-101, 1]1, to deepen the understanding of LMMs. The analysis focuses on the intriguing tasks that GPT-4V can perform, containing test samples to probe the quality and genericity of GPT-4V's capabilities, its supported inputs and working modes, and the effective ways to prompt the model. In our approach to exploring GPT-4V, we curate and organize a collection of carefully designed qualitative samples spanning a variety of domains and tasks. Observations from these samples demonstrate that GPT-4V's unprecedented ability in processing arbitrarily interleaved multimodal inputs and the genericity of its capabilities together make GPT-4V a powerful multimodal generalist system. Furthermore, GPT-4V's unique capability of understanding visual markers drawn on input images can give rise to new humancomputer interaction methods such as visual referring prompting. We conclude the report with in-depth discussions on the emerging application scenarios and the future research directions for GPT-4V-based systems. We hope that this preliminary exploration will inspire future research on the next-generation multimodal task formulation, new ways to exploit and enhance LMMs to solve real-world problems, and gaining better understanding of multimodal foundation models. Finally, we acknowledge that the model under our study is solely the product of OpenAI's innovative work, and they should be fully credited for its development. Please see the GPT-4V contributions paper [10] for the authorship and credit attribution: https://cdn.openai.com/contributions/gpt-4v.pdf.

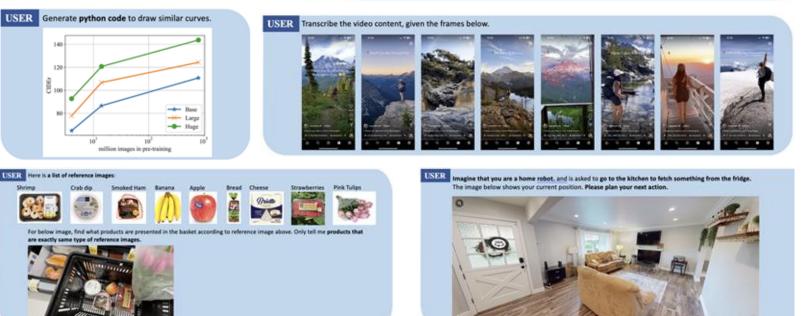
USER Please read the table in this image and return a markdown-style reconstructed table in text.

Country	Sales Volume	Revenue	Profit
USA	40.080	\$15.971.880	\$3.086.421
China	35.070	\$15.866.670	\$3.032.162
Australia	27.054	\$14.812.566	\$2.868.636
India	23.046	\$10.608.174	\$1.853.710
South Korea	16.032	\$10.494.948	\$1.975.844

USER Imagine that you are a robot operating a computer. Like how humans operate the computer, you can move the mouse, click an icon with the mouse, or type some texts with the keyboard.

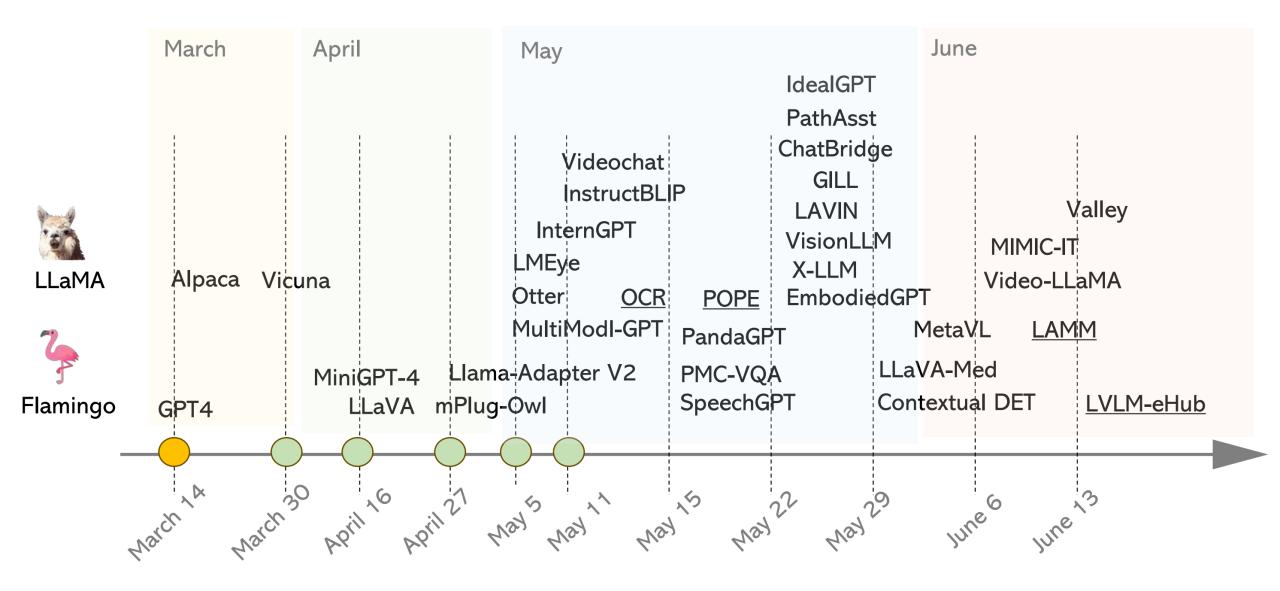
> Below is what you see on the computer screen. Describe the image and predict your next move. If the action involves moving the mouse, describe the location and the icon as detailed as possible.





Table, GUI, Coding, Video, Grocery, Embodied, etc.

Evolution of LMMs (a surge of Open Source LMMs since GPT-4V)



Landscape of LMMs (Open-Source LMMs and Proprietary LMMs)

			Indinanti		roource	rioprictar			
Reset	Size	Date	Overall	Art & Design	Business	Science	Health & Medicine	Human. & Social Sci.	Tech & Eng.
Human Expert (Best)	-	2024-01-31	88.6	89.2	90.7	90.0	87.3	89.2	86.2
Human Expert (Medium)	-	2024-01-31	82.6	84.2	86.0	84.7	78.8	85.0	79.1
Human Expert (Worst)	-	2024-01-31	76.2	80.8	78.0	78.0	73.3	74.2	74.3
GPT-4o*	-	2024-05-27	69.1	-	-	-	-	-	-
Gemini 1.5 Pro*	-	2024-05-31	<u>62.2</u>	-	-	-	-	-	-
Gemini 1.0 Ultra*	-	2023-12-11	59.4	70.0	56.7	48.0	67.3	78.3	47.1
Claude 3 Opus*	-	2024-03-05	59.4	67.5	67.2	48.9	61.1	70.0	50.6
GPT-4V(ision) (Playground)	-	2023-11-27	56.8	65.8	<u>59.3</u>	54.7	<u>64.7</u>	72.5	36.7
Reka Core*	-	2024-04-23	56.3	75.9	47.3	<u>49.3</u>	58.0	75.0	44.2
Gemini 1.5 Flah*	-	2024-05-31	56.1	-	-	-	-	-	-
SenseChat-Vision-0423-Preview*	-	2024-04-23	54.6	66.7	54.0	45.3	53.3	75.0	43.8
Reka Flash*	-	2024-04-23	53.3	61.7	42.7	47.3	59.3	74.2	44.3
Claude 3 Sonnet*	-	2024-03-05	53.1	61.7	58.2	37.1	57.1	68.7	45.0
HPT Pro*	-	2024-03-15	52.0	66.7	43.3	42.7	50.7	72.5	43.8
VILA1.5*	-	2024-05-04	51.9	60.8	43.3	36.0	57.3	73.3	<u>48.1</u>
InternVL-Chat-V1.2*	-	2024-02-23	51.6	62.5	40.7	39.3	58.7	70.0	46.2
Qwen-VL-MAX*	-	2024-01-27	51.4	72.5	43.3	40.0	58.0	69.2	38.6
Skywork-VL*	-	2024-05-30	51.4	66.7	41.3	38.7	55.3	68.3	46.7
LLaVA-1.6-34B *	34B	2024-02-01	51.1	67.5	46.0	39.3	52.0	67.5	43.8
Claude 3 Haiku*	-	2024-03-05	50.2	60.8	52.5	37.1	52.3	66.0	41.5
Adept Fuyu-Heavy*	-	2024-01-31	48.3	53.4	46.3	33.7	51.3	72.2	44.0
Gemini 1.0 Pro*	-	2023-12-11	47.9	-	-	-	-	-	-
Marco-VL-Plus*	-	2024-03-09	46.2	60.8	37.3	35.3	48.7	69.2	37.1

Open-Source

Proprietary

14

Human Expert

On MMMU leaderboard

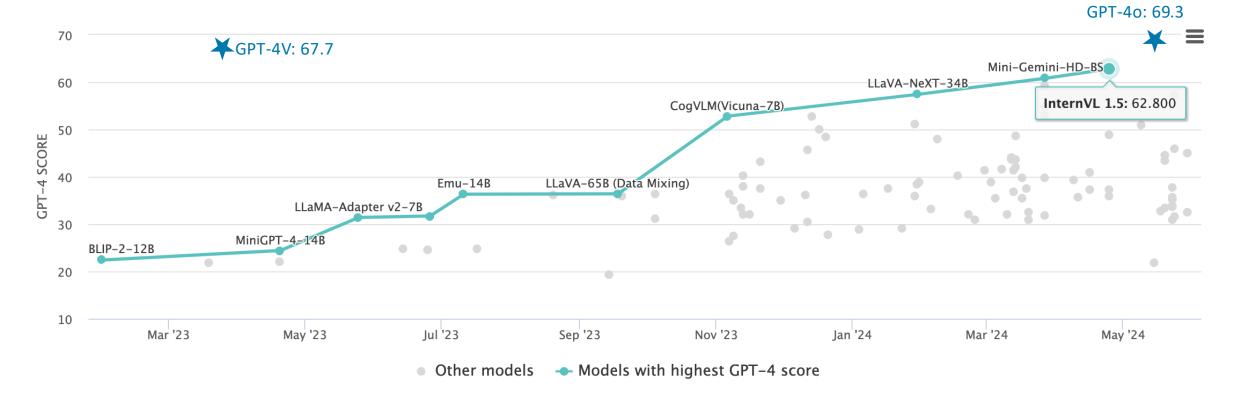
- 30 Open-Source LMMs
- 21 Proprietary LMMs

-- as of 6/13/2024

X. Yue, Y. Ni, K. Zhang, T. Zheng, R. Liu, G. Zhang, S. Stevens, etc. MMMU: A Massive Multi-discipline Multimodal Understanding and Reasoning Benchmark for Expert AGI, https://arxiv.org/abs/2311.16502

Rapid Progress in LMMs





[1] Yu, Weihao, et al. "Mm-vet: Evaluating large multimodal models for integrated capabilities." ICML 2024

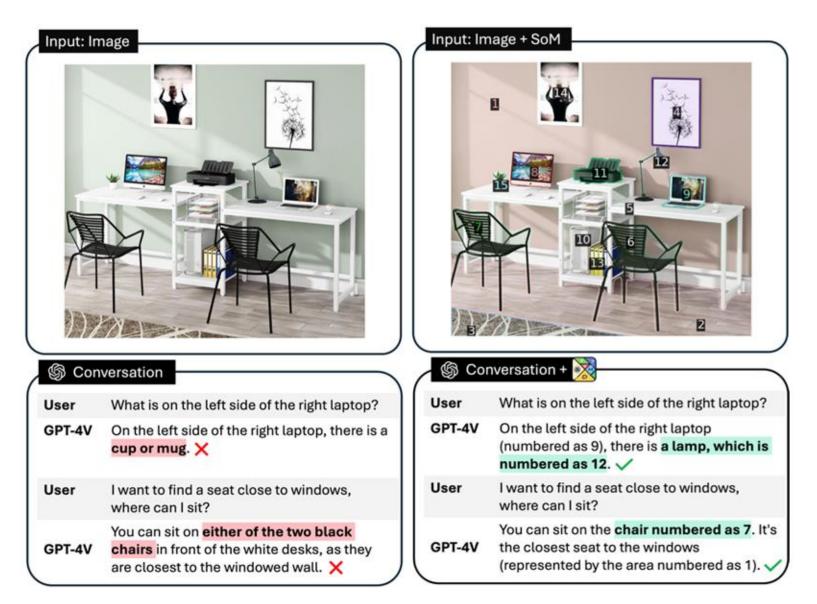
https://github.com/yuweihao/MM-Vet

I/O Modality of GPT-40 \$0penAI

GPT-4o ("o" for "omni") is a step towards much more natural human-computer interaction—it accepts as input any combination of text, audio, image, and video and generates any combination of text, audio, and image outputs.

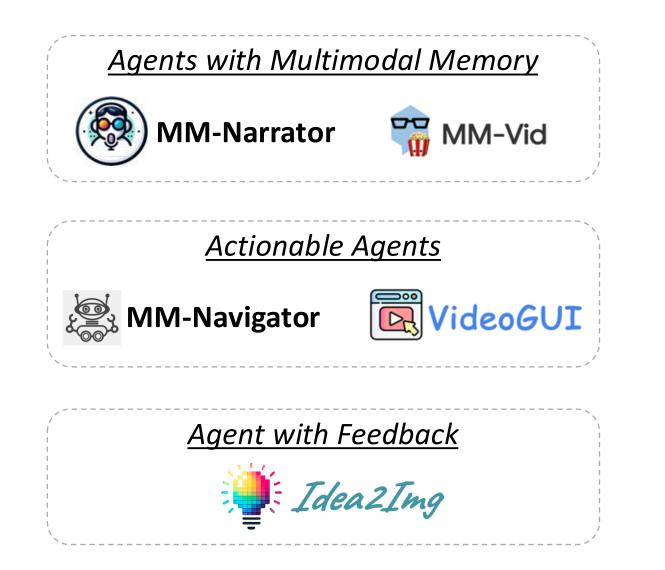
It would be interesting to investigate what additional capabilities a model combining all these modalities could achieve beyond current capabilities and how to make the native integration efficient so that different modalities enhance each other.

LMM inspired new research area -- Visual Prompting



[1] Yang, Jianwei, et al. "Set-of-Mark Prompting Unleashes Extraordinary Visual Grounding in GPT-4V"

LMM inspired new research area – Multimodal Agent





Audio Description



GUI Navigation



Visual Design & Creation

- Looking back, CLIP is a big paradigm shift
- The past year was the year of LMMs
 - Prelude of LMMs (Early Vision-Language Models, Flamingo, CoCa, GIT)
 - The era of LMMs starts from GPT-4V
 - Landscape of open-source and proprietary LMMs
 - Session 1: LLaVA and LMMs by Chunyuan Li
 - Session 2: LMMs pre-training by Zhe Gan



- New research areas: Grounding LMMs, Visual prompting, Multimodal Agent
 - Session 3: LMMs Grounding by Haotian Zhang
 - Session 4: Visual prompting by Jianwei Yang
 - Session 5: Multimodal agent by Linjie Li



- Looking back, CLIP was a big paradigm shift
- The past year was the year of LMMs
 - Prelude of LMMs (Early Vision-Language Models, Flamingo, CoCa, GIT)
 - The era of LMMs starts from GPT-4V
 - Landscape of open-source and proprietary LMMs
 - New research areas: Grounding LMMs, Visual prompting, Multimodal Agent
- Diffusion model as a vision-centered representation learner
 - Your diffusion model is secretly a zero shot classifier
 - DALL-E 3: reconstruct image from ultra-descriptive caption
 - SORA: video generation models as world simulators

Your Diffusion Model is Secretly a Zero-Shot Classifier

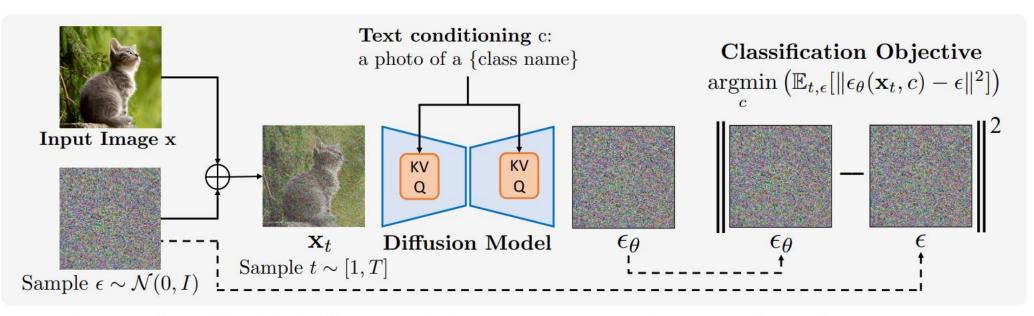
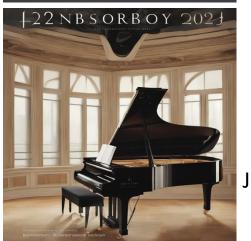


Figure 1. Overview of our Diffusion Classifier approach: Given an input image x and a set of possible conditioning inputs (e.g., text for Stable Diffusion or class index for DiT, an ImageNet class-conditional model), we use a diffusion model to choose the one that best fits this image. Diffusion Classifier is theoretically motivated through the variational view of diffusion models and uses the ELBO to approximate $\log p_{\theta}(\mathbf{x} \mid \mathbf{c})$. Diffusion Classifier chooses the conditioning \mathbf{c} that best predicts the noise added to the input image. Diffusion Classifier from Stable Diffusion and a standard classifier from DiT without any additional training.









SDXL

July 2023







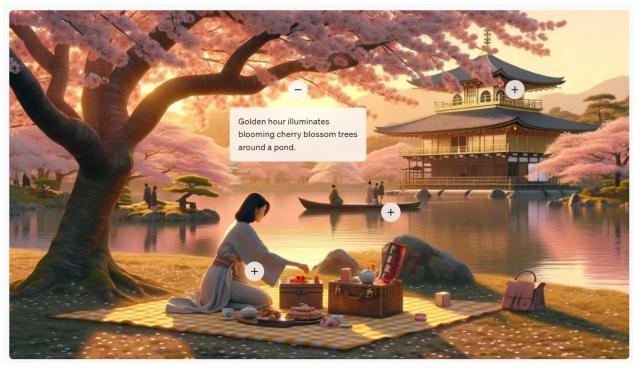






Dalle-3 Sept. 2023

DALL-E 3: Reconstruct Image from Ultra-descriptive Caption [©]OpenAI



Core research and execution

Gabriel Goh, James Betker, Li Jing, Aditya Ramesh

Research contributors—primary

Tim Brooks, Jianfeng Wang, Lindsey Li, Long Ouyang, Juntang Zhuang, Joyce Lee, Prafulla Dhariwal, Casey Chu, Joy Jiao

Research contributors—secondary

Jong Wook Kim, Alex Nichol, Yang Song, Lijuan Wang, Tao Xu

https://openai.com/index/dall-e-3/



"Golden hour illuminates blooming cherry blossom trees around a pond.

In the distance, a building with Japanese-inspired architecture is perched on the lake.

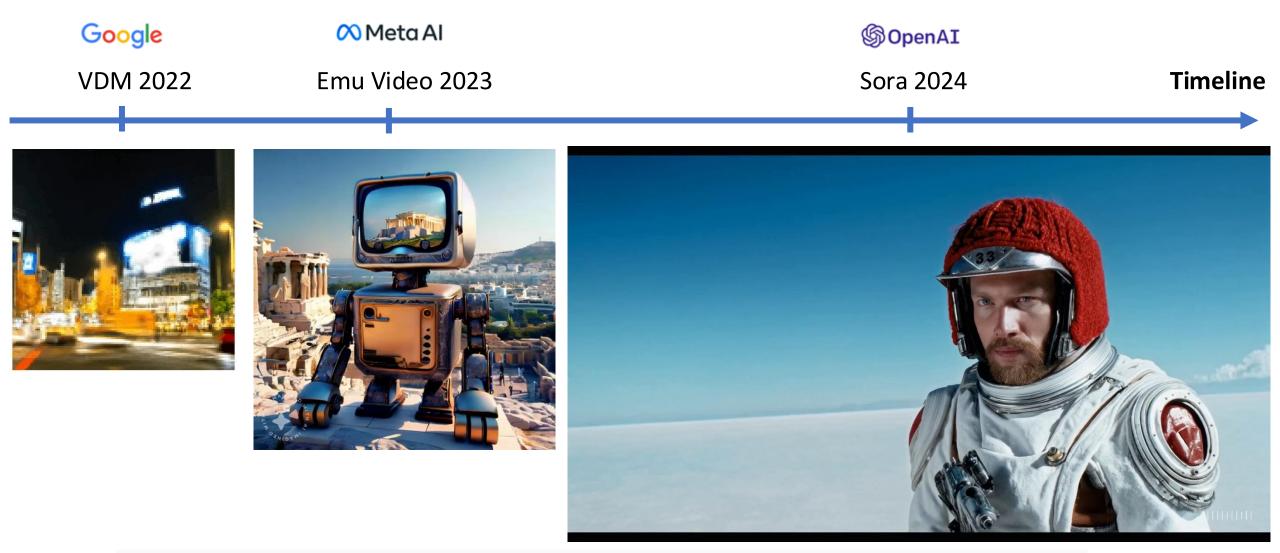
In the pond, a group of people enjoying the serenity of the sunset in a rowboat.

A woman underneath a cherry blossom tree is setting up a picnic on a yellow checkered blanket."

- Takeaway from DALL-E 3: training on ultradescriptive captions makes the model more compute-efficient, even when we measure the quality of samples produced with shorter captions
- Suggests that we can get better unconditional models by using UD captions as scaffolding, even if we don't use UD captions at inference

-- Aditya Ramesh

Video Generation Models as World Simulators



SORA: Our results suggest that scaling video generation models is a promising path towards building general purpose simulators of the physical world.

https://openai.com/index/video-generation-models-as-world-simulators/

- Looking back, CLIP was a big paradigm shift
- The past year was the year of LMMs
- Diffusion model as a vision-centered representation learner
 - Your diffusion model is secretly a zero shot classifier
 - DALL-E 3: reconstruct image from ultra-descriptive caption
 - SORA: video generation models as world simulators
 - Session 6: Image Generation by Zhengyuan Yang
 - Session 7: Video and 3D Generation by Kevin Lin



Morning Sessio	n										
9:00 - 9:20	Opening Re	Opening Remarks									
9:20 - 10:10	Large Multi	Large Multimodal Models: Towards Building General-Purpose Multimodal Assistant Chunyuan Li									
10:10 - 11:00	Methods, A	Methods, Analysis & Insights from Multimodal LLM Pre-training									
11:00 - 11:50	LMMs with	LMMs with Fine-Grained Grounding Capabilities									
Afternoon Sess	Afternoon Session										
13:00 - 13:50	A Close Loo	k at Vision in Large	Multimodal Models	5			Jianwei	Yang			
13:50 - 14:40	Multimodal	Multimodal Agents Linjie Li									
14:40 - 15:00	Coffee Brea	Coffee Break & QA									
15:00 - 15: 50	Recent Adv	Recent Advances in Image Generative Foundation Models Zhengyuan Yang									
15:50 - 16: 40	Video and 3	Video and 3D Generation Kevin Lin									
16:40 - 17:00	Closing Ren	narks & QA									
Chunyuan Li	Zhe Gan	Haotian Zhang	Jianwei Yang	Linjie Li	Zhengyuan Yang	Kevin Lin	Jianfeng Gao	Lijuan Wang			
Tiktok	Apple	Apple	Microsoft	Microsoft	Microsoft	Microsoft	Microsoft	Microsoft			

In conjunction with **CVPR 2024** June 17th 2024 (9 a.m. PDT — 5 p.m. PDT) Location: Summit 437- 439, Seattle Convention Center