

AMD

Model Training/Inference

PyTorch

CUDA

A100, H100

ROCm

MI250, MI300

AMD

Training Foundation Models from Scratch— Fully Open Source

- Show credibility
- Generate awareness
- Provide feedback

Foundation Models Released

- AMD-OLMo-1B
 - Introducing the First AMD 1B Language Models: AMD OLMo
- Instella-3B
 - Introducing Instella: New State-of-the-art Fully Open 3B Language Models ROCm Blogs
- Instella-VL-1B
 - Instella-VL-1B: First AMD Vision Language Model ROCm Blogs
- Instella-Long
 - Introducing Instella-Long: A Fully Open Language Model with Long-Context Capability — ROCm Blogs
- Instella-T2I
 - https://arxiv.org/abs/2506.21022
 - https://rocm.blogs.amd.com/artificial-intelligence/instella-t2i/README.html

We're hiring

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Features



Access to Powerful Computing Resources

Provides easy access to AMD GPUs enabling developers to run computationally intensive



Pre-Installed Docker Containers and Flexibility

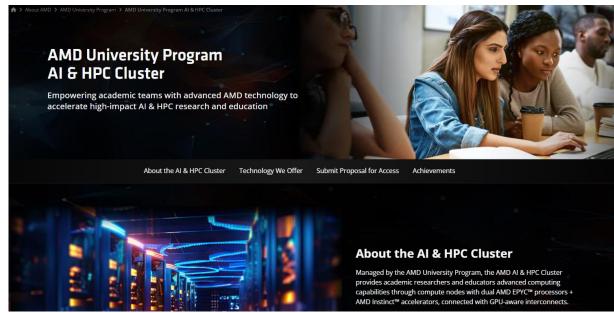
Docker containers preloaded with popular Al software, minimizing setup time, while giving



Zero Setup with Cloud-Based Convenience

A Jupyter Notebook environment running inside containers available upon VM launch,

AMD University Program AI & HPC Cluster

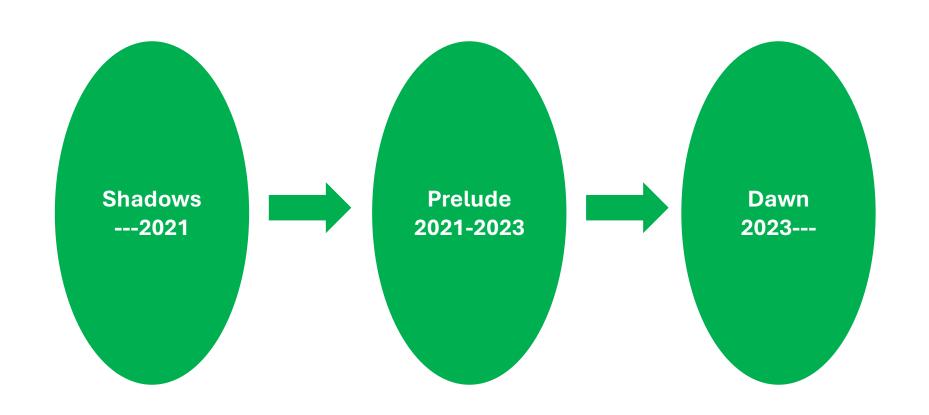


Outline

- A brief history of multimodality models
 - Understanding
 - Generation
 - Unification
 - Agentic
- Special topics
 - Does image help with reasoning?
 - Token compression
- Summary and future directions

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Shadows

---2021

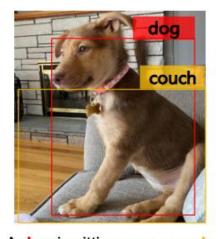
Research

Vision-Language was a niche area
Object detector as feature extractor
Not end-to-end
Multimodal encoder architecture

Industry

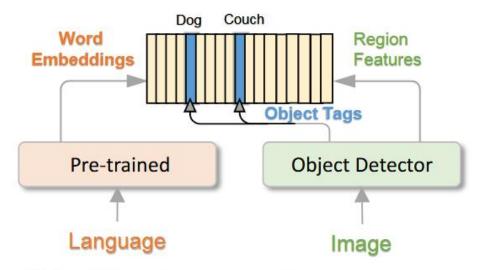
Limited vocabulary
Limited domain
Vocab expansion
Domain customization

Oscar: Object-Semantics Aligned Pre-Training for Vision-Language Tasks (2020)

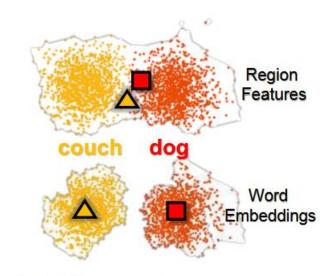


A dog is sitting on a couch

(a) Image-text pair

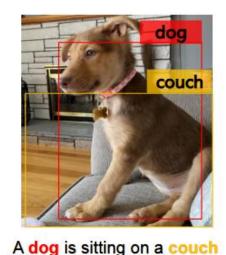


(b) Objects as anchor points

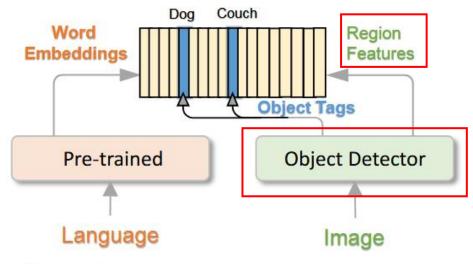


(c) Semantics spaces

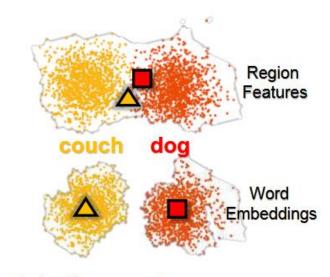
Oscar: Object-Semantics Aligned Pre-Training for Vision-Language Tasks (2020)



(a) Image-text pair



(b) Objects as anchor points



(c) Semantics spaces

VinVL MiniVLM Uniter Oscar **ViLT** UFO ViTCap Lemon 2019 2020 2021 2021 2021 2021 2021 2021

ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision

Modality

Interaction

Textual

Embed

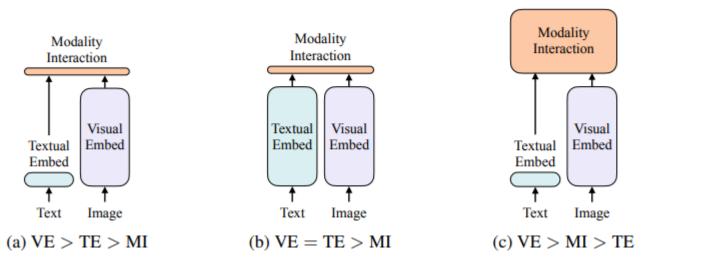
Text

Visual

Embed

Image

(d) MI > VE = TE



Prelude of LMMS 2021-2023

- Flamingo: April 29, 2022, https://arxiv.org/abs/2204.14198
- CoCa: May 4, 2022, https://arxiv.org/abs/2205.01917
- GIT: May 27, 2022, https://arxiv.org/abs/2205.14100

Flamingo: a Visual Language Model for Few-Shot Learning

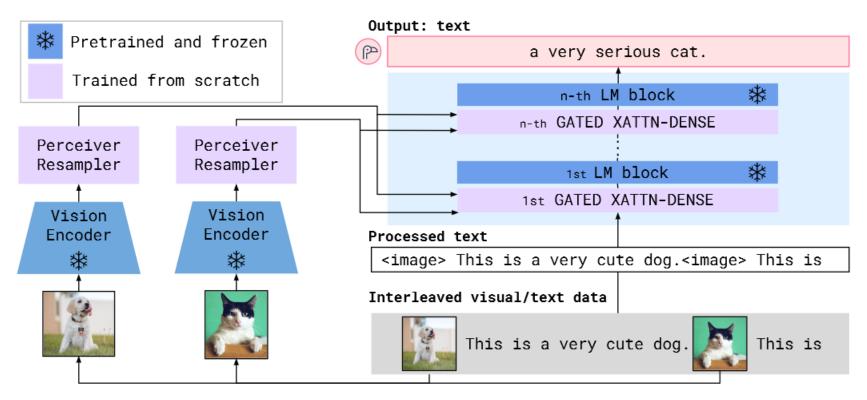
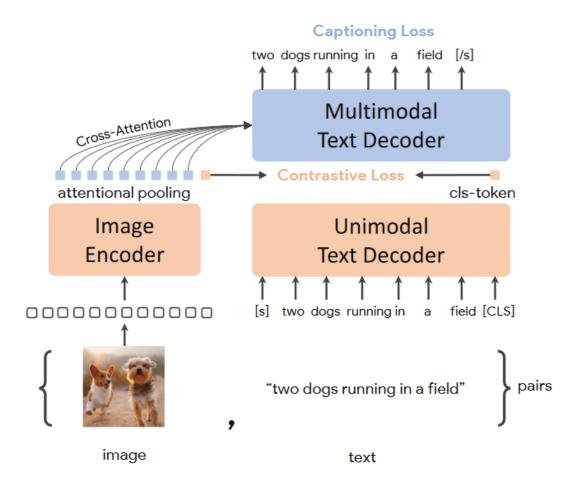


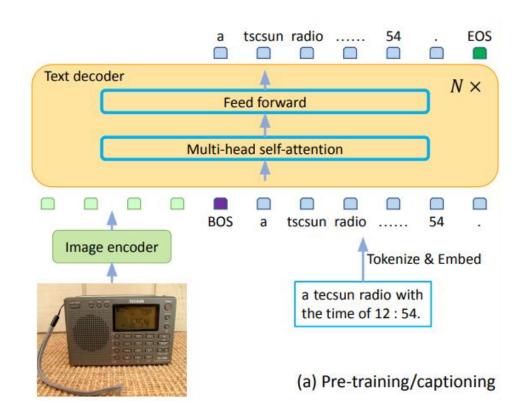
Figure 3: **Flamingo architecture overview.** Flamingo is a family of visual language models (VLMs) that take as input visual data interleaved with text and produce free-form text as output.

Alayrac, Donahue, Luc, Miech, Barr, Hasson, Lenc, Mensch, Millican, Reynolds, Ring, Rutherford, Cabi, Han, Gong, Samangooei, Monteiro, Menick, Borgeaud, Brock, Nematzadeh, Sharifzadeh, Binkowski, Barreira, Vinyals, Zisserman, Simonyan, 2022/04/29, https://arxiv.org/abs/2204.14198

CoCa: Contrastive Captioners are Image-Text Foundation Models



GIT: A Generative Image-to-text Transformer for Vision and Language



- Select/Unselect All
- ✓ a page that says probability theory is a central field of mathematics, widely applicable to scientific, technological, and human situations involving uncertainty.

Probability theory is a central field of mathematics, widely applicable to scientific, technological, and human situations involving uncertainty. The most obvious applications are to situations, such as games of chance

Dawn of LMMS 2023---September 2023

Dawn of LMMs

- GPT-4V(vision):
 - GPT-4V(ision) system card
 - https://openai.com/research/gpt-4v-system-card
 - GPT-4V(ision) technical work and authors
 - GPT-4V(ision) technical work and authors (openai.com)
 - The Dawn of LMMs: preliminary explorations with GPT-4V(ision)
 - https://arxiv.org/abs/2309.17421

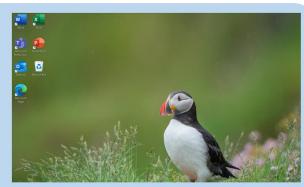
GUI-Navigation



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.

You are asked to find a detailed recipe of Mapo Tofu.

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



GPT-V My immediate next move would be to move the mouse to the Microsoft Edge icon located at the bottom left corner of the screen and click on it to open the web browser. From there, I can search for a detailed recipe of Mapo Tofu.



(c) Query:

I'm planning my trip to Mt. Rainier, and wish to check if there are road closures or other scenarios. Where should I click?









GPT-4V:

For information on road closures and other alerts at Mt. Rainier, you should click on "6 Alerts" at the top of the screen. This will likely provide you with current notifications and updates related to the park's conditions and any restrictions in place. Safe travels!

Open Source LMMs (December, 2023)

- BLIP2
- InstructBLIP
- MiniGPT-4
- LLaVA

• ...

Rank	Model	Score	
& W	BLIP-2	1293.84	
ě	InstructBLIP	1212.82	
ŏ	LLaMA-Adapter V2	972.67	
4	mPLUG-Owl	967.35	
5	LaVIN	963.61	
6	MiniGPT-4	866.58	
7	ImageBind_LLM	775.77	
8	VisualGLM-6B	705.31	
9	Multimodal-GPT	654.73	
10	PandaGPT	642.59	
11	LLaVA	502.82	
12	Otter	483.73	

× ×	MiniGPT-4	292.14	
ŏ	InstructBLIP	291.79	
ŏ	BLIP-2	290.00	
4	mPLUG-Owl	276.07	
5	LaVIN	249.64	
6	LLaMA-Adapter V2	248.93	
7	PandaGPT	228.57	
8	Multimodal-GPT	226.79	
9	LLaVA	214.64	
10	ImageBind_LLM 213.5		
11	VisualGLM-6B	181.79	
12	Otter	136.07	

Model

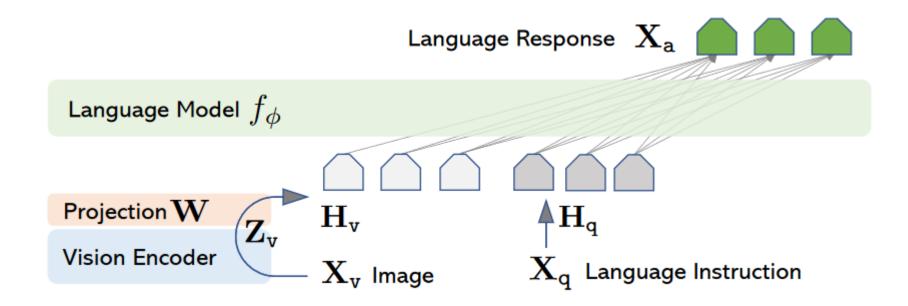
Rank

Score

(1) Perception

(2) Cognition

LLaVA: Visual Instruction Tuning

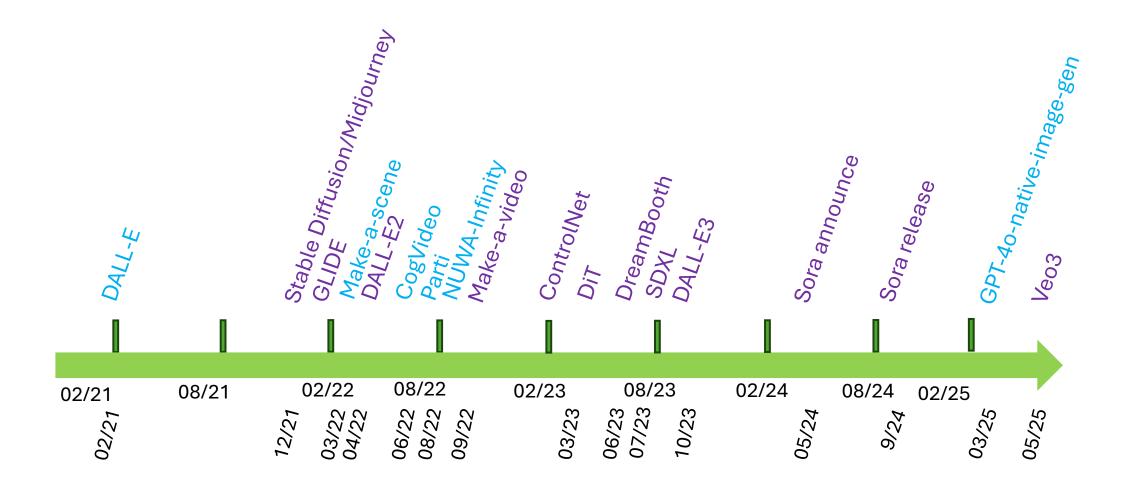


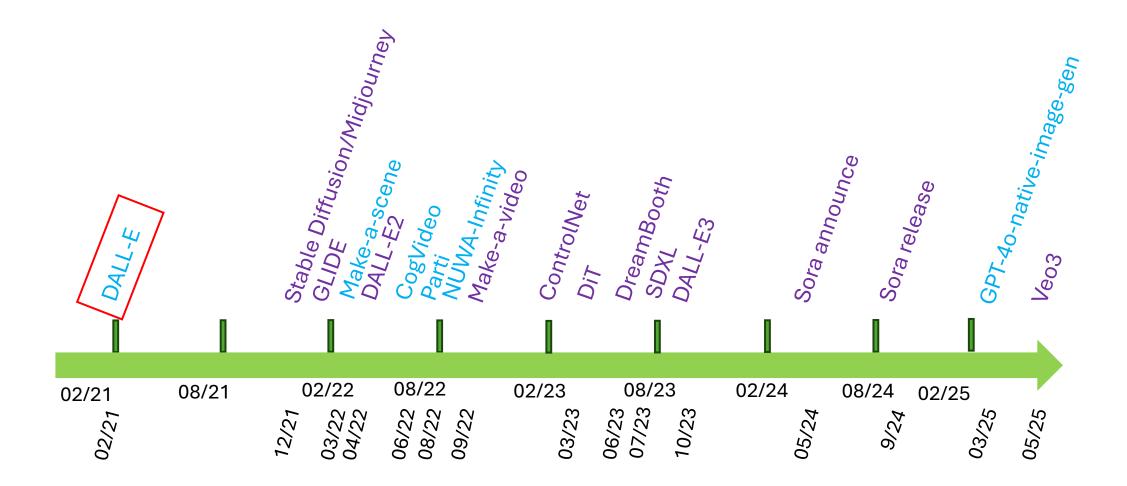
Looking Back

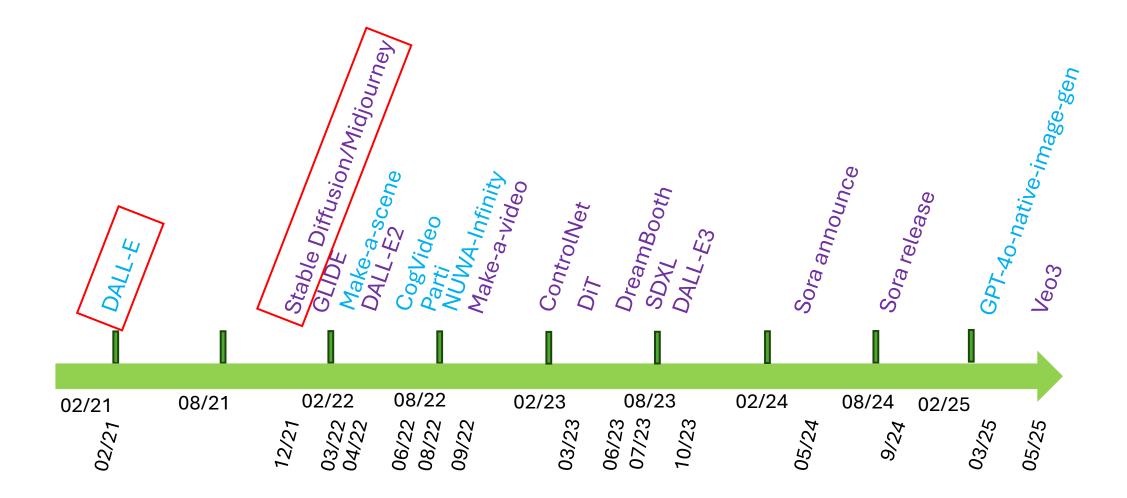
- Convergence of vision-language architecture
 - Vision encoder + language decoder
 - It was not obvious
 - Is it optimal?
- Benefits of leveraging language models for vision tasks
 - Open vocabulary
 - Task unification
 - Generalization

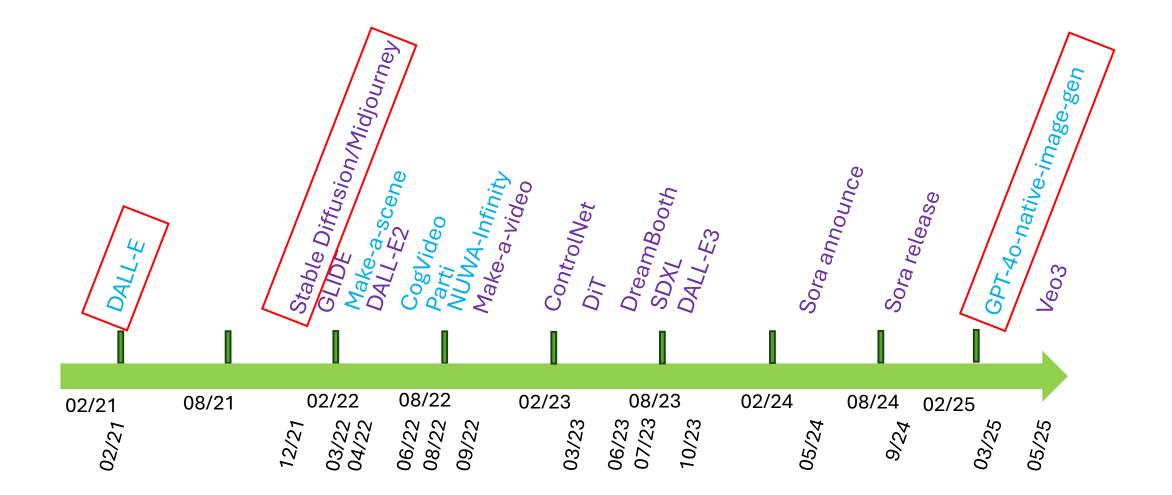
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- Special topics
 - Does image help with reasoning?
 - Token compression
- Future directions
 - 3D, embodied agents, robotics









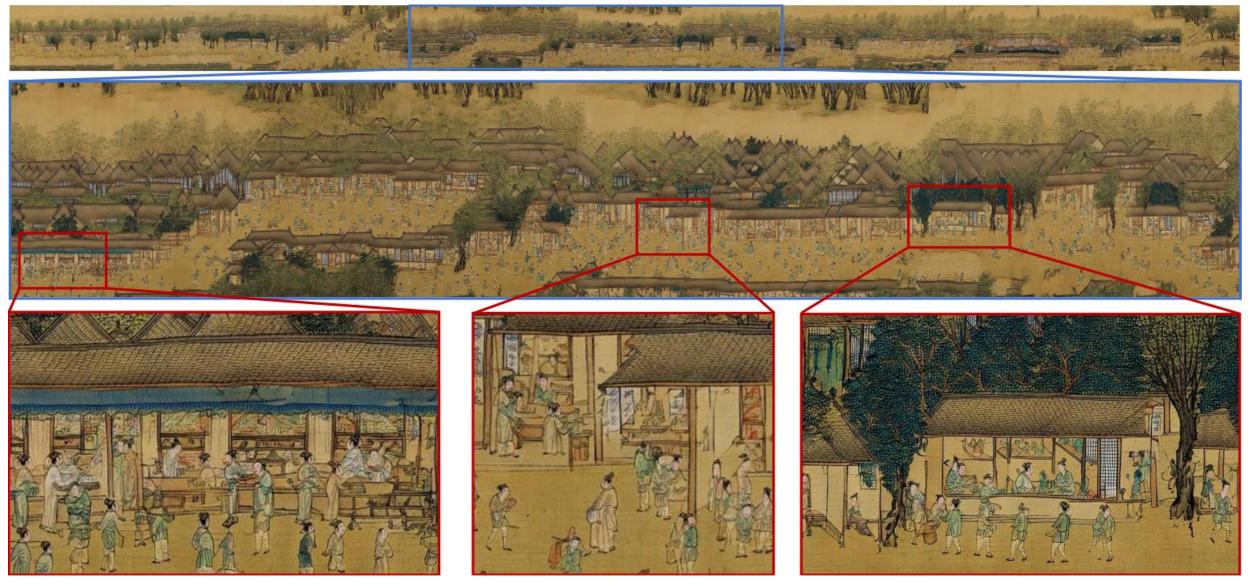
Diffusion vs Autoregressive

	Aesthetics	Spatial	Text	Semantic	Speed
	Aestrictics	relation	rendering	alignment	Speeu
DALL-E3					
GPT-4o					

Diffusion vs Autoregressive

- Diffusion
 - Better aesthetic quality
 - Faster especially with few-stop distillation
- Autoregressive
 - Leveraging pretrained LLM
 - Better semantic alignment
 - Text generation
 - Flexible in image size and video length expansion

AR: Flexibility in image size expansion 38912 x 2048

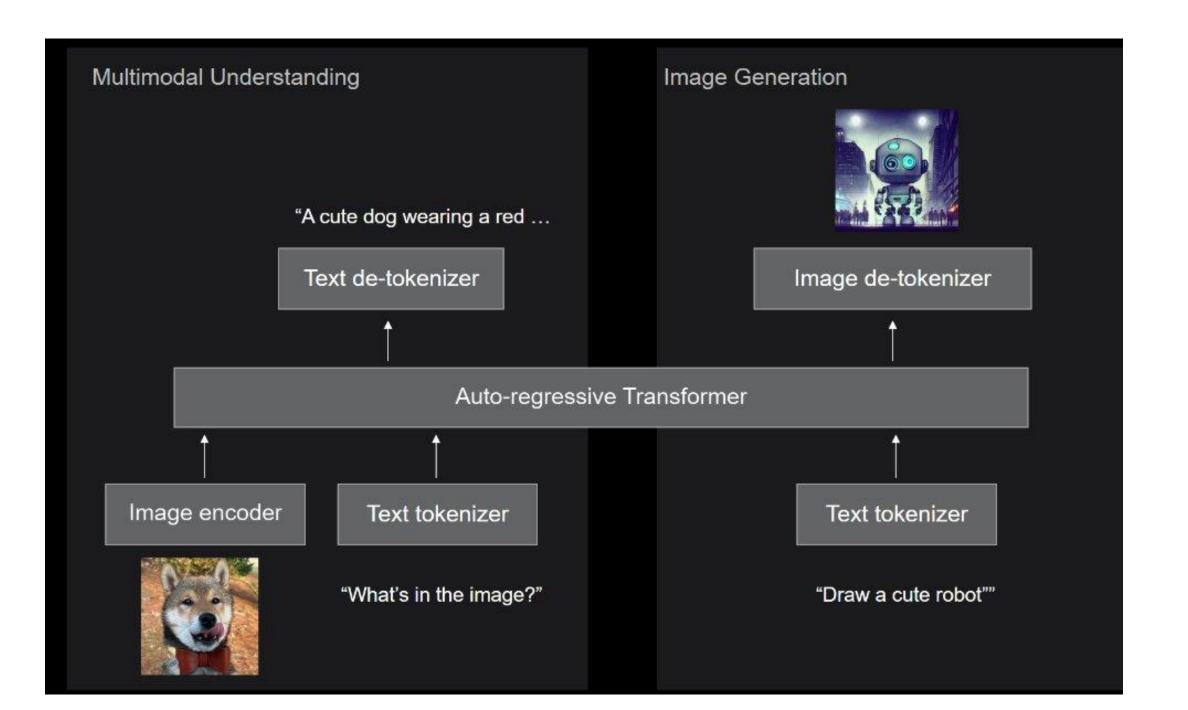


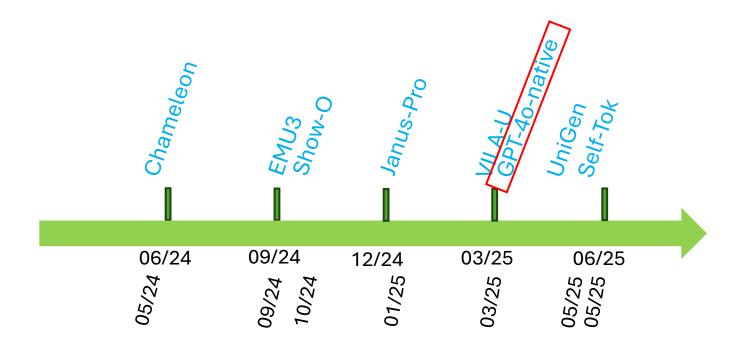
"Along the River During the Qingming Festival"

NUWA-Infinity: Autoregressive over Autoregressive Generation for Infinite Visual Synthesis Wu et al, arXiv 2207.09814, Oct. 2022

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- > All models are autoregressive except Show-O
- > Show-O: discrete diffusion
- > Janus-Pro and UniGen use separate tokenizers: better accuracy in understanding tasks
- > GPT-40 proves that unified model can excel in both understanding and generation
- Need more and performant open-source unified models

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Agentic model goes beyond perception

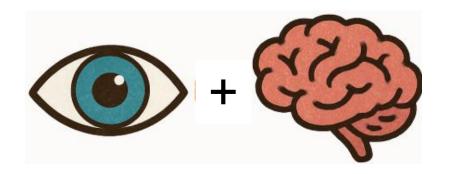


Two examples of agentic multimodality models

GUI Navigation Tool-Use

GUI Navigation: Computer-Using Agent

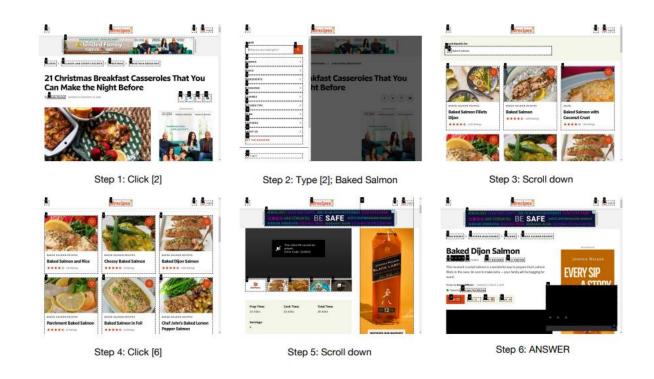
- OpenAl Operator
 - Vision + reasoning
 - Multi-turn RL



- Benchmarks
 - OSWorld
 - WebArena
 - WebVoyager
 - MageBench
 - ...

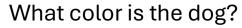
GUI Navigation: Computer-Using Agent

"Find a recipe for Baked Salmon that takes less than 30 minutes to prepare and has at least a 4-star rating based on user reviews."



Vision Tool-Use: O3/O3-Pro







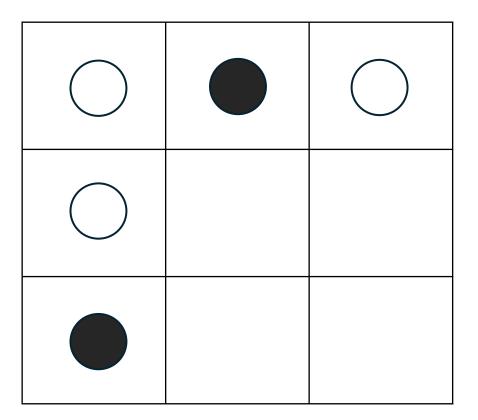
```
from PIL import Image
img = Image.open("input.jpg")
crop = img.crop(100,100,400,400)
crop.save("output.jpg")
```

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Does Image Help with Reasoning?

Tic-Tac-Toe game



Where should black play next?

Version 1: Text only

Alice and Bob are playing a game on a 3x3 grid. The points on the grid are labeled top to bottom, left to right, as A,B,C,D,E,F,G,H,I. Alice plays white. Bob plays black. At each turn, the player places a stone of the corresponding color onto one of the positions that have not been occupied. Whoever has three stones in a line (horizontal, vertical, or diagonal) wins.

Alice first places a white stone at A. Bob places a black stone at B. Then Alice at C. Then Bob at G. Alice D.

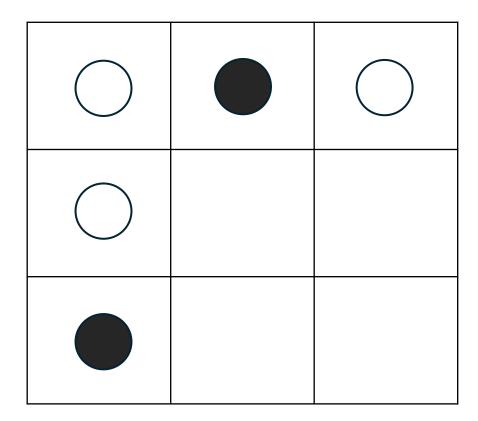
Where should Bob play next?

Version 2: Text + Image

Alice and Bob are playing a game on a 3x3 grid. The points on the grid are labeled top to bottom, left to right, as A,B,C,D,E,F,G,H,I. Alice plays white. Bob plays black. At each turn, the player places a stone of the corresponding color onto one of the positions that have not been occupied. Whoever has three stones in a line (horizontal, vertical, or diagonal) wins.

Alice first places a white stone at A. Bob places a black stone at B. Then Alice at C. Then Bob at G. Alice D.

Where should Bob play next?

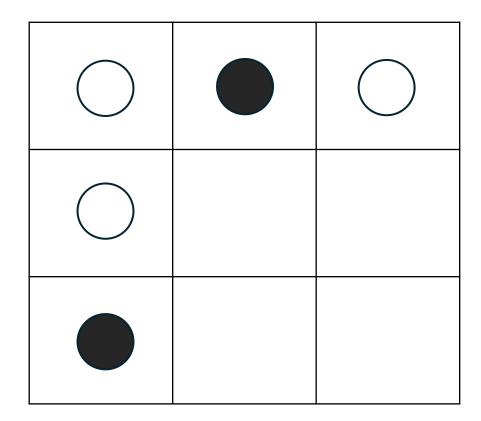


Version 2: Image Only

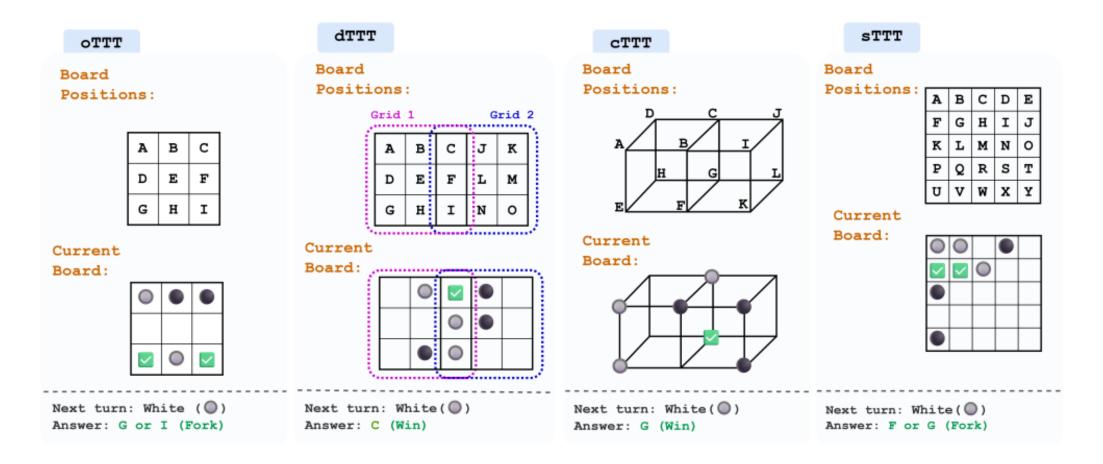
Alice and Bob are playing a game on a 3x3 grid. The points on the grid are labeled top to bottom, left to right, as A,B,C,D,E,F,G,H,I. Alice plays white. Bob plays black. At each turn, the player places a stone of the corresponding color onto one of the positions that have not been occupied. Whoever has three stones in a line (horizontal, vertical, or diagonal) wins.

Alice first places a white stone at A. Bob places a black stone at B. Then Alice at C. Then Bob at G. Alice D.

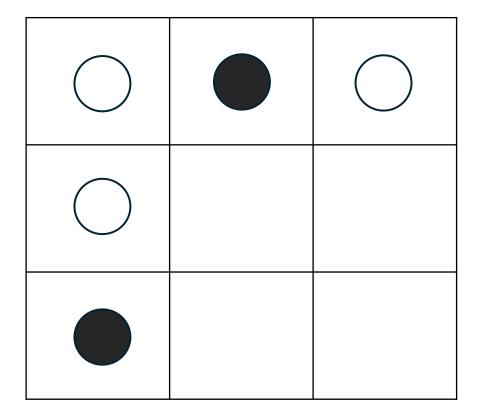
Where should Bob play next?



Tic-Tac-Toe Extensions (not seen by Frontier models)



Visual Is Helpful for Human



А	В	С
D	E	F
G	Н	I

Is Visual Helpful for LLMs?

Text > Text + Image > Image

Text Only						Text (Full description) + Image					Image (with general game description)					
Test Set Size:		102	100	90	120	412	102	100	90	120	412	102	100	90	120	412
TTTBench-V	Size	oTTT	dTTT	cTTT	sTTT	Averages	oTTT	dTTT	cTTT	sTTT	Averages	oTTT	dTTT	cTTT	sTTT	Averages
TTTBellCli-V		Pass@1 Pass@			Pass@1	Pass@1				Pass@1	Pass@1 Pa			Pass@1		
ChatGPT-40-latest	API	50.74	40.50	39.31	27.19	39.44	50.74	41.25	45.14	27.29	41.11	35.66	15.00	9.17	18.33	19.54
Llama4-Maverick	400B	49.51	40.50	40.69	32.81	40.88	45.34	35.38	41.39	31.56	38.42	34.19	11.50	12.36	17.19	18.81
Llama4-Scout	100B	32.35	30.12	31.25	24.06	29.45	34.56	24.88	27.78	8.96	24.05	21.08	8.38	6.81	1.88	9.54
Qwen2.5-VL-32B-Instruct	32B	42.41	30.30	40.00	40.27	38.25	42.23	29.70	42.08	39.06	38.27	20.22	7.86	16.67	5.81	12.64
VL-Rethinker-7B	7B	25.74	24.50	39.58	30.21	30.01	22.79	22.00	33.75	29.06	26.90	6.29	3.74	17.36	0.10	6.87

Is Visual Helpful for LLMs?

Text > Text + Image > Image

Text Only					Text (Full description) + Image Image (with general game descr						ription)					
Tes	t Set Size:	102	100	90	120	412	102	100	90	120	412	102	100	90	120	412
TTTBench-V	Size	oTTT	dTTT	cTTT	sTTT	Averages	oTTT	dTTT	cTTT	sTTT	Averages	oTTT	dTTT	cTTT	sTTT	Averages
TTTBellCli-V		Pass@1 Pa			Pass@1	Pass@1			Pass@1	Pass@1 Pa			Pass@1			
ChatGPT-40-latest	API	50.74	40.50	39.31	27.19	39.44	50.74	41.25	45.14	27.29	41.11	35.66	15.00	9.17	18.33	19.54
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Llama4-Scout	100B	32.35	30.12	31.25	24.06	29.45	34.56	24.88	27.78	8.96	24.05	21.08	8.38	6.81	1.88	9.54
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Token Compression

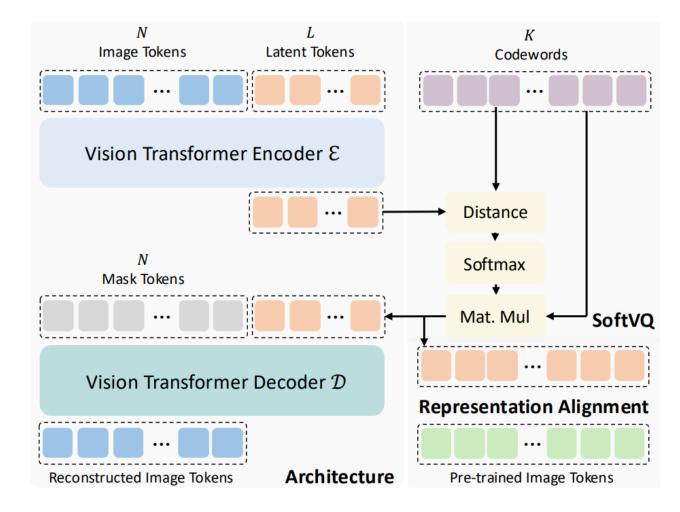
- Images are represented as tokens
- Too many tokens

$$w \times h \longrightarrow \frac{w}{f} \times \frac{h}{f}$$
 tokens $f = 8 \text{ or } 16$

EMU3:
$$1024 \times 1024 \rightarrow \frac{1024}{16} \times \frac{1024}{16} = 4096$$
 tokens

1D Tokenization

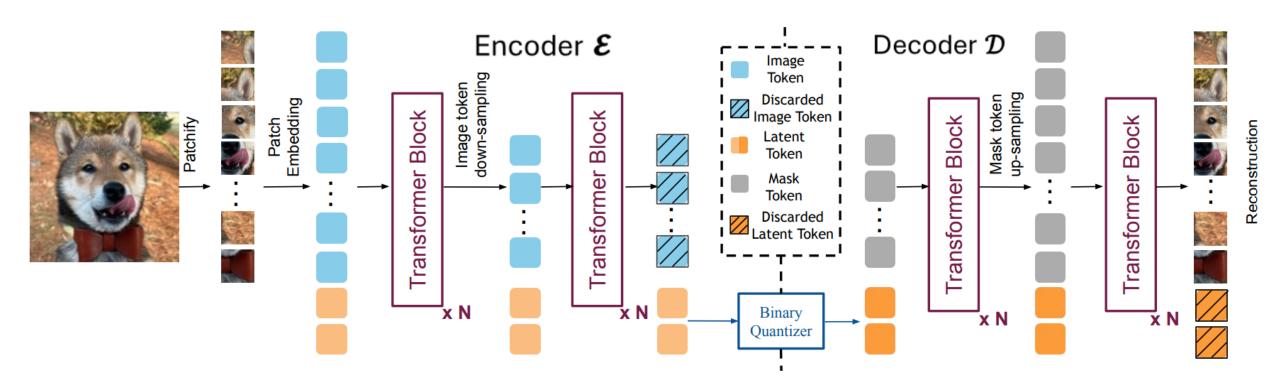
- 128 tokens for 1024x1024 image vs 4096 tokens in EMU3
- 32x tokens reduction



SoftVQ-VAE: Efficient 1-Dimensional Continuous Tokenizer, Chen et al, CVPR 2025 Masked autoencoders are effective tokenizers for diffusion models. Chen et al, ICML 2025

1D Binary Image Tokenizer (1D BiT)

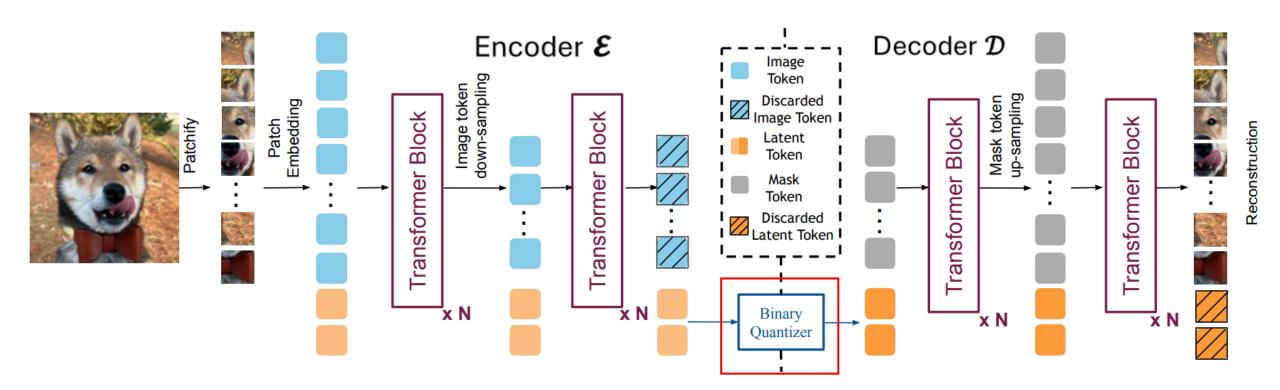
Enabling both diffusion and Autoregressive image generation



Instella-T2I: Pushing the Limits of 1D Discrete Latent Space Image Generation, Wang et al, 2025 https://arxiv.org/abs/2506.21022

1D Binary Image Tokenizer (1D BiT)

Enabling both diffusion and Autoregressive image generation



Instella-T2I: Pushing the Limits of 1D Discrete Latent Space Image Generation, Wang et al, 2025 https://arxiv.org/abs/2506.21022

T2I using 1D BiT (Instella-T2I)



Instella-T2I: Pushing the Limits of 1D Discrete Latent Space Image Generation, Wang et al, 2025 https://arxiv.org/abs/2506.21022

1024x1024 T2I Evaluation

- 128 tokens for both Instella-AR and Instella-Diff
- 32 times token reduction compared to EMU3
- Fully open public datasets for training
- Instella-Diff: competitive against SOTA models like SDXL that use in-house data

Model	Size	Reso.	Single Obj.	Two Obj.	Counting	Colors	Color Attr.	Position	Overall ↑	CLIP↑	IR↑
SDv1.5	0.9B	512	0.97	0.38	0.35	0.76	0.06	0.04	0.43	0.318	0.201
SDv2.1	0.9B	512	0.98	0.51	0.44	0.85	0.17	0.07	0.50	0.338	0.372
PixArt-α	0.6B	1024	0.98	0.50	0.44	0.80	0.07	0.08	0.48	0.321	0.871
PixArt-σ	0.6B	1024	0.98	0.59	0.50	0.80	0.15	0.10	0.52	0.325	0.872
SDXL	2.6B	1024	0.98	0.74	0.39	0.85	0.23	0.15	0.55	0.335	0.600
SD3-Medium	8.0B	1024	0.97	0.89	0.69	0.82	0.47	0.34	0.69	0.334	0.871
Chameleon	7.0B	512	-	-	-	-	-	-	0.39	-	-
Emu3	8.0B	1024	0.98	0.71	0.34	0.81	0.17	0.21	0.54	0.333	0.872
Instella AR	0.8B	1024	0.96	0.43	0.40	0.80	0.14	0.08	0.46	0.313	0.538
Instella Diff	1.2B	1024	0.99	0.78	0.66	0.85	0.45	0.12	0.64	0.332	0.900

GenEval

1024x1024 T2I Evaluation

- 128 tokens for both Instella-AR and Instella-Diff
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SDv2.1	0.9B	512	0.98	0.51	0.44	0.85	0.17	0.07	0.50	0.338	0.372
PixArt- α	0.6B	1024	0.98	0.50	0.44	0.80	0.07	0.08	0.48	0.321	0.871
PixArt- σ	0.6B	1024	0.98	0.59	0.50	0.80	0.15	0.10	0.52	0.325	0.872
SDXL	2.6B	1024	0.98	0.74	0.39	0.85	0.23	0.15	0.55	0.335	0.600
SD3-Medium	8.0B	1024	0.97	0.89	0.69	0.82	0.47	0.34	0.69	0.334	0.871
Chameleon	7.0B	512	-	-	-	-	-	-	0.39	-	-
Emu3	8.0B	1024	0.98	0.71	0.34	0.81	0.17	0.21	0.54	0.333	0.872
Instella AR	0.8B	1024	0.96	0.43	0.40	0.80	0.14	0.08	0.46	0.313	0.538
Instella Diff	1.2B	1024	0.99	0.78	0.66	0.85	0.45	0.12	0.64	0.332	0.900

GenEval

Outline

- A brief history of multimodality models
 - Understanding
 - Generation
 - Unification
 - Agentic
- Special topics
 - Does image help with reasoning?
 - Tokenization vs compression
- Summary and future directions

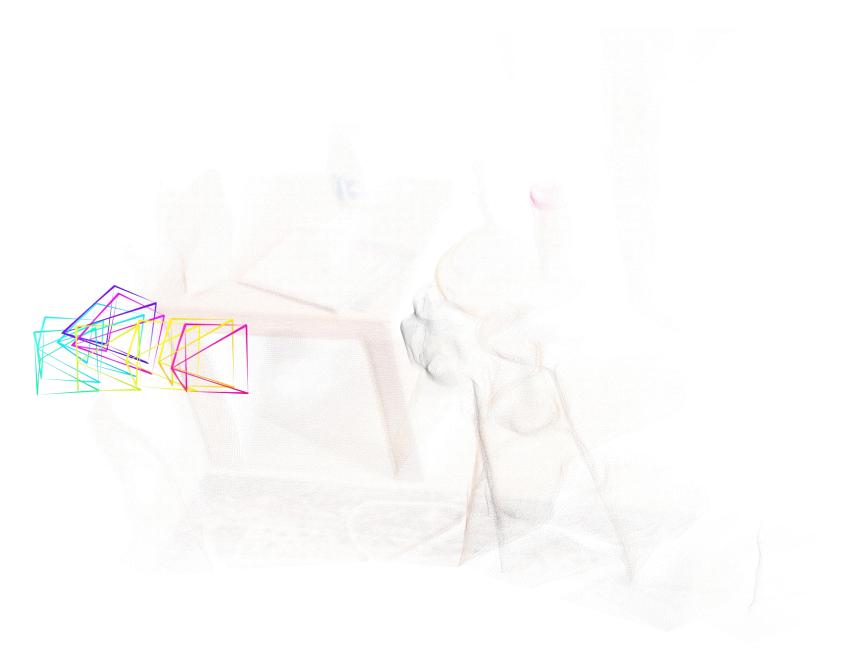
Summary

- By leveraging language models, multimodality field has been revolutionized
- Diffusion has been dominating on image/video generation, but AR is coming back, leading to unification where language model plays a central role for both understanding and generation
- Agentic models extend perception to reasoning+acting, leveraging language model's basic reasoning and tool-use capabilities and RL framework
- There is a large intelligence gap on reasoning with images
- Token compression has huge potential for image/video generation and understanding

Future Directions

- Unification
 - How to get visual understanding and generation to help each other
 - Can multimodal learning help improving language model?
- 3D
 - Hot topic in CVPR2025, VGGT
 - Need to inject semantics by integrating with language
 - Component semantics: dog->walk, car->run
- Image/Video compression vs. token compression
 - Token redundancy in both visual understanding and generation
 - Language-conditioned token compression
- Embodied agents and robotics
 - Robots need a brain:
 - Physical abilities are amazing, but Intelligence is lacking
 - Multimodal models to play a major role
 - Learning paradigm shift: learning from interaction in real time, persistent memory, personalization





vggt - a Hugging Face Space by facebook





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