



# On Path to Multimodal Generalist: **General-Level** and **General-Bench**

## ICML'25 Spotlight/Oral

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# On Path To Multimodal Generalist: General-Bench & General-Level

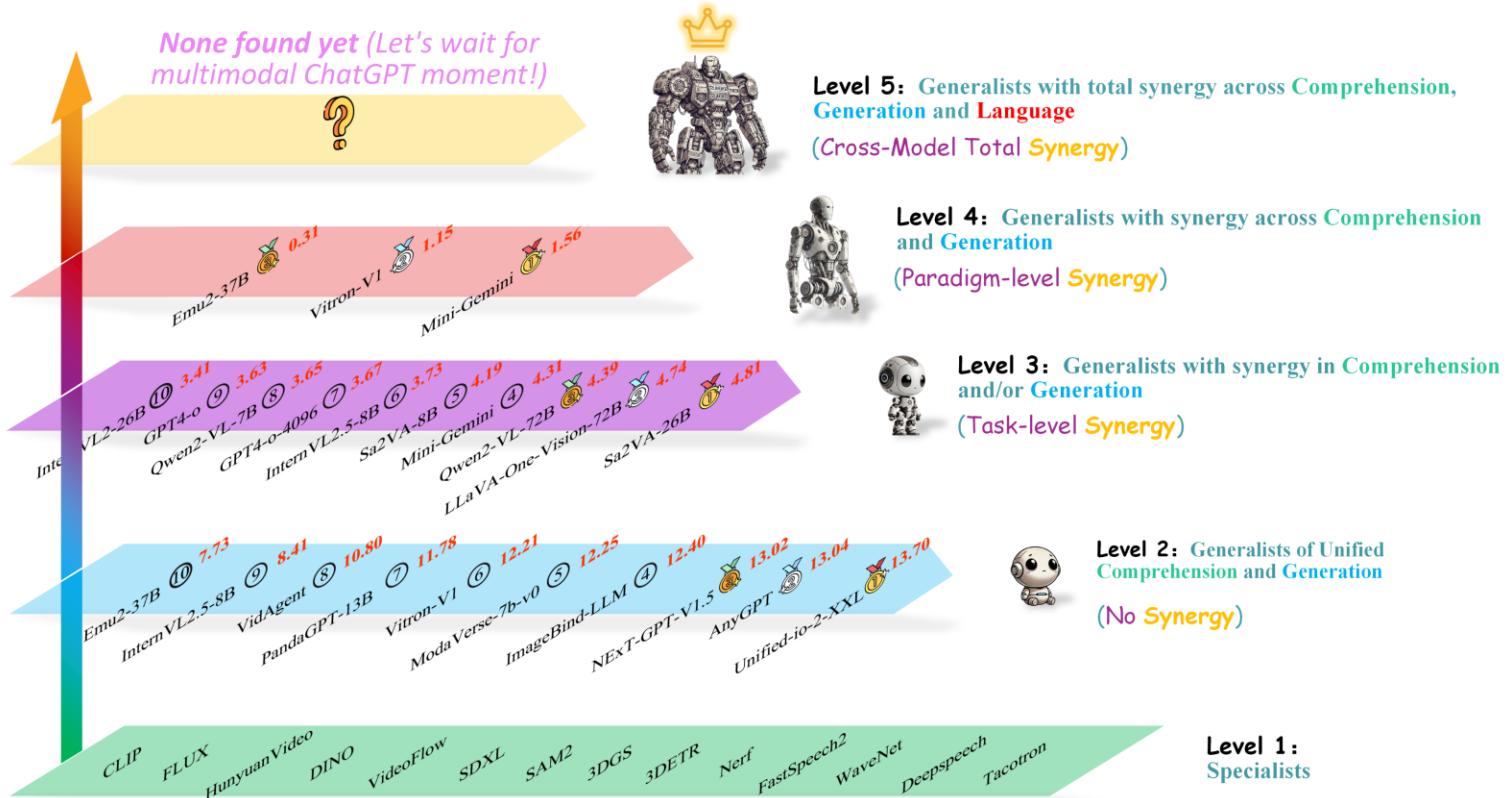


Project: <https://generalist.top/>

Paper: <https://arxiv.org/abs/2505.04620>

Benchmark: <https://generalist.top/leaderboard>

Is your MLLM a well-rounded generalist?



- Hao Fei, Yuan Zhou, ⋯, Jiebo Luo, Tat-Seng Chua, Shuicheng Yan, Hanwang Zhang. “On Path to Multimodal Generalist: General-Level and General-Bench” . ICML (Spotlight) . 2025



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Project: <https://generalist.top/>

Paper: <https://arxiv.org/abs/2505.04620>

Benchmark: <https://generalist.top/leaderboard>



**Jiebo Luo**

*University of Rochester*  
**Advisory**



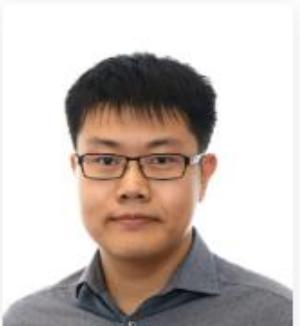
**Tat-Seng Chua**

*NUS*  
**Advisory**



**Shuicheng Yan**

*NUS*  
**Project Supervision**



**Hanwang Zhang**

*NTU*  
**Project Supervision**

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**Hao Fei,**  
**ICML (**

**Tao Zhang**  
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*NTU*  
**Image Group**



**Meng Luo**  
*NUS*  
**Video Group**

**ral-Bench” .**

# Content

1

**General-Level**

2

**General-Bench**

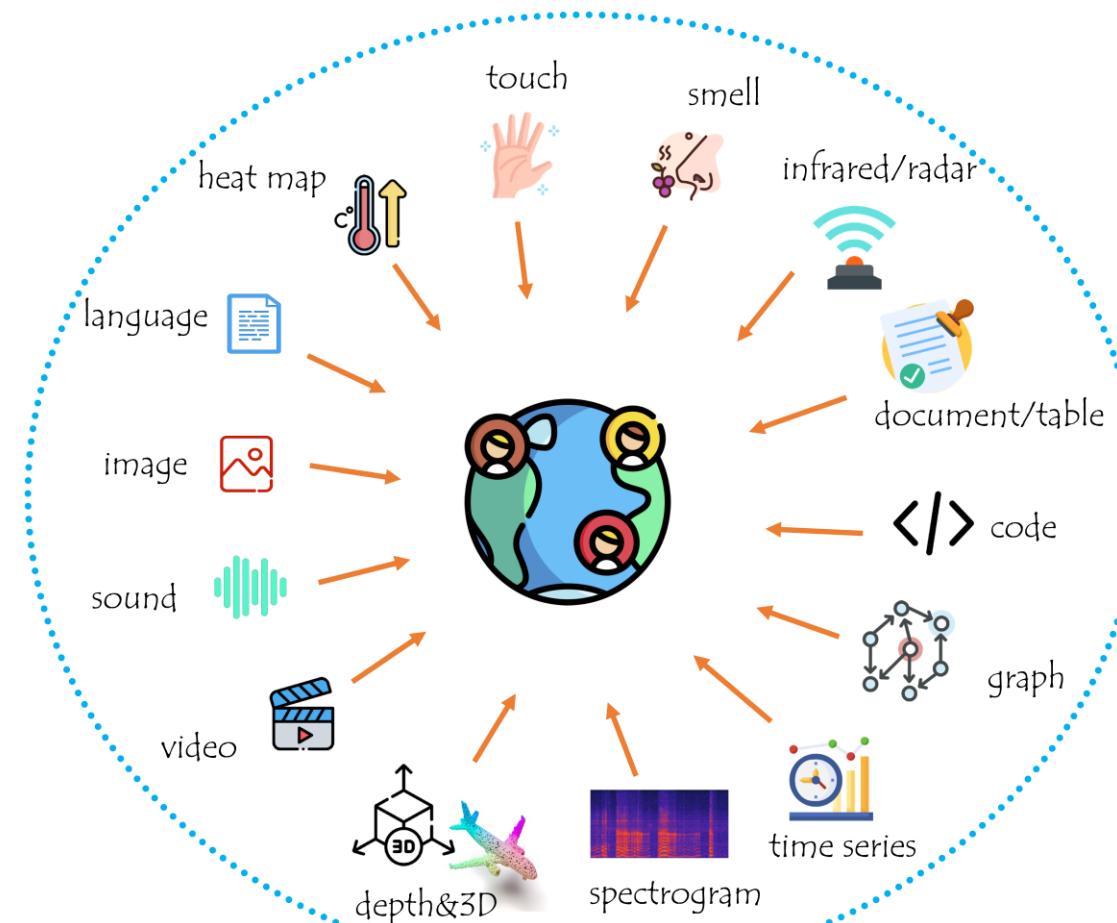
3

**What To Do Next**

# On Path to Multimodal Generalist: General-Level

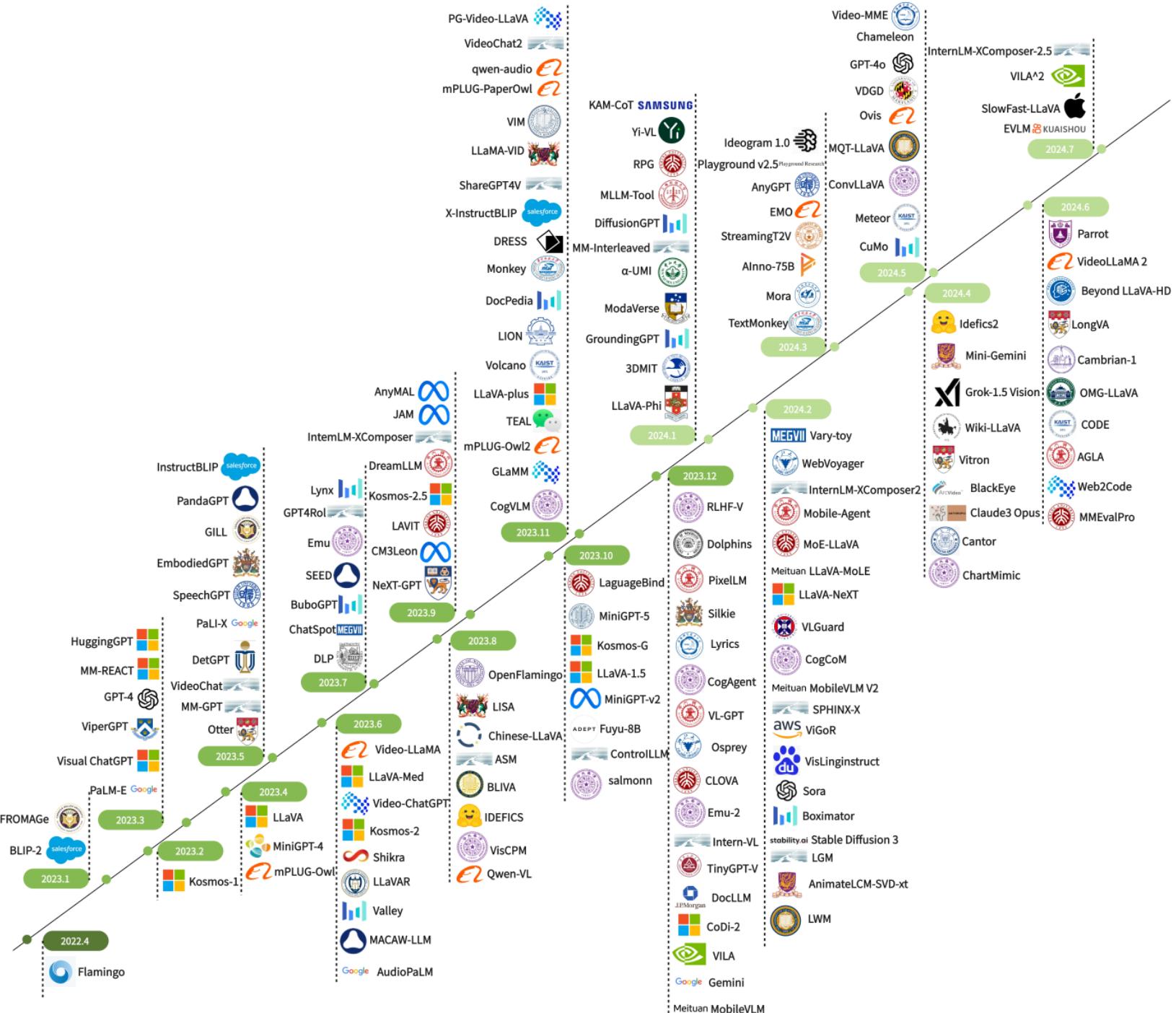
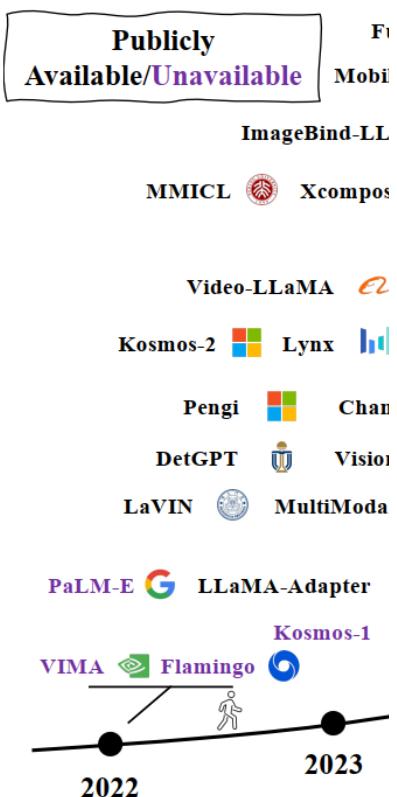
## Multimodal AI

👉 The world functions with varied multimodal information and signals



# On Path to Multi

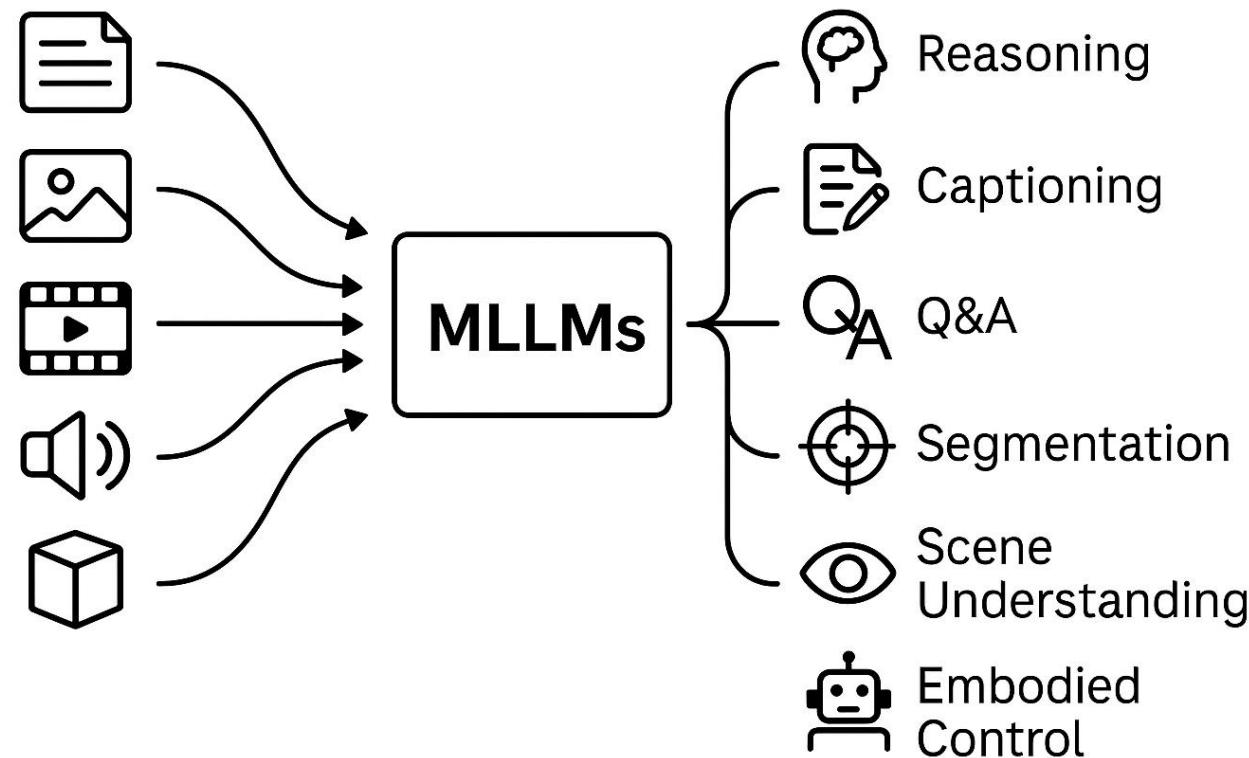
## Development of Multi-Hot Trends



# On Path to Multimodal Generalist: General-Level

## ■ Background

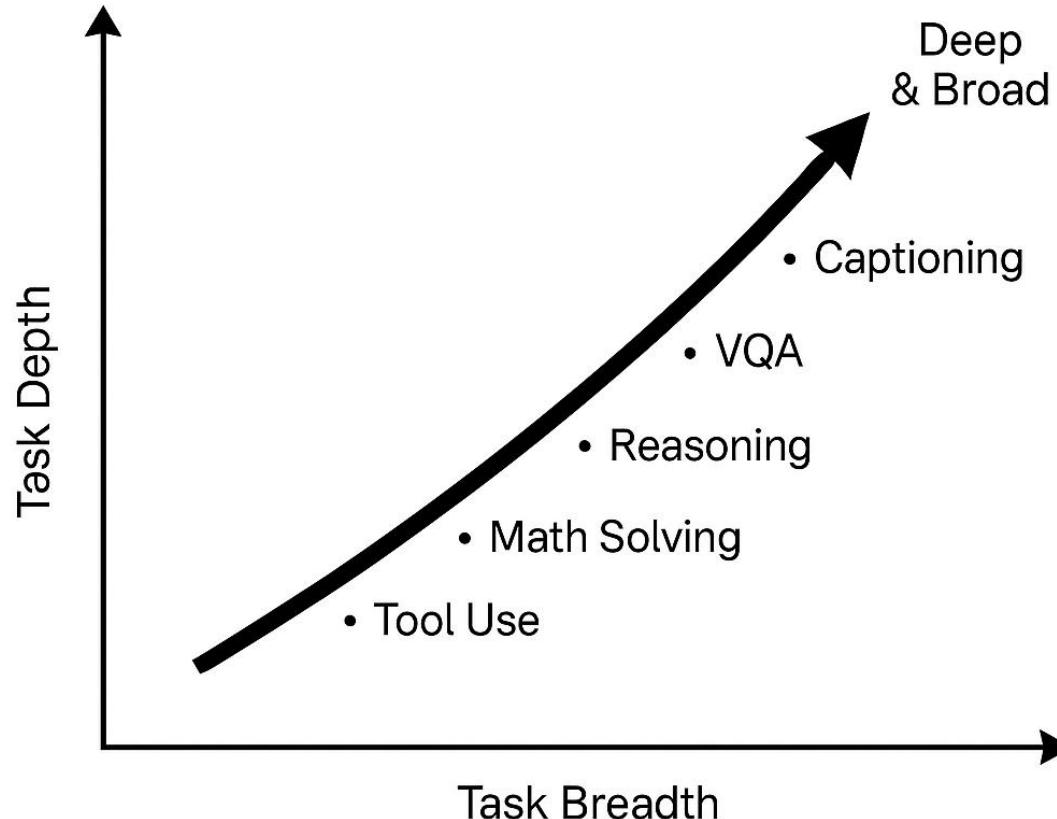
- Expansion of MLLMs: More modalities, More Tasks



# On Path to Multimodal Generalist: General-Level

## ■ Background

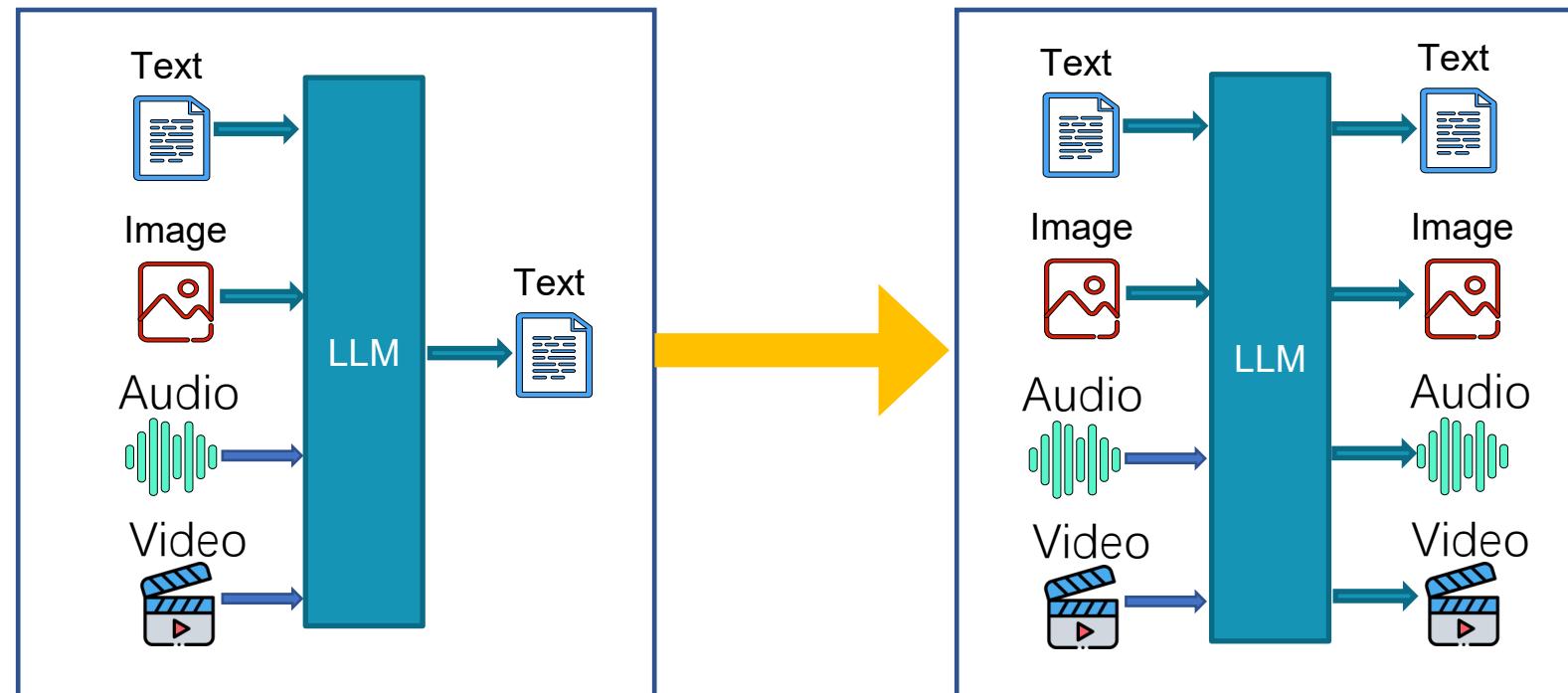
- Evolving with deeper capability



# On Path to Multimodal Generalist: General-Level

## ■ Background

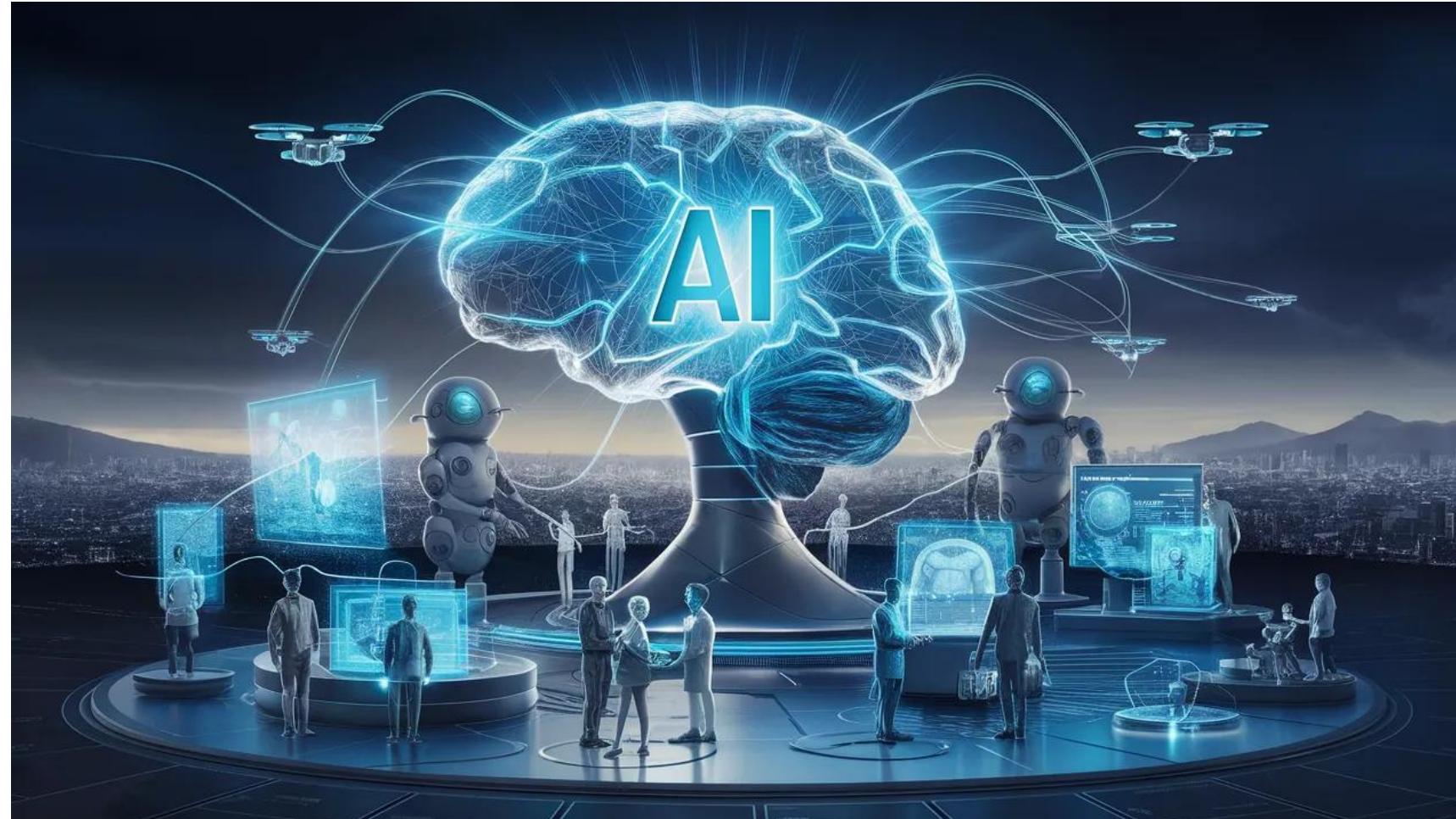
- Multimodal Comprehension vs. Unified Multimodal Comprehension & Generation



# On Path to Multimodal Generalist: General-Level

## ■ Ultimate Goal

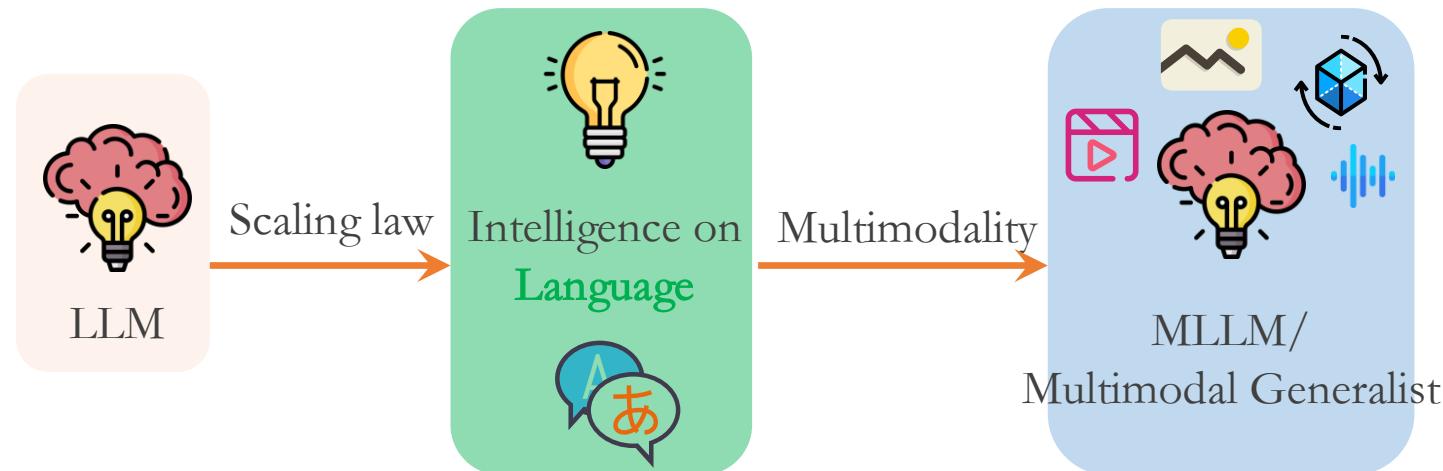
👉 What will the next-generation of **multimodal foundation models/agents** look like?



# On Path to Multimodal Generalist: General-Level

## Motivation

- Existing issue-I: *The language intelligence of LLMs empowers multimodal intelligence.*

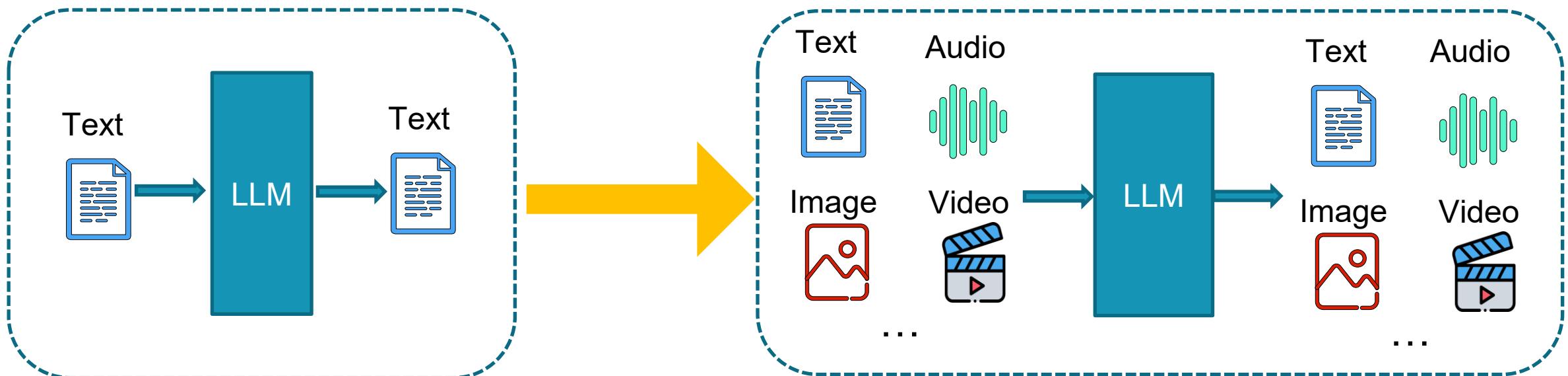


# On Path to Multimodal Generalist: General-Level

## Motivation

- Existing issue-I: *The language intelligence of LLMs empowers multimodal intelligence.*

Extending **Language** LLM to **Multimodal** LLM (MLLM)



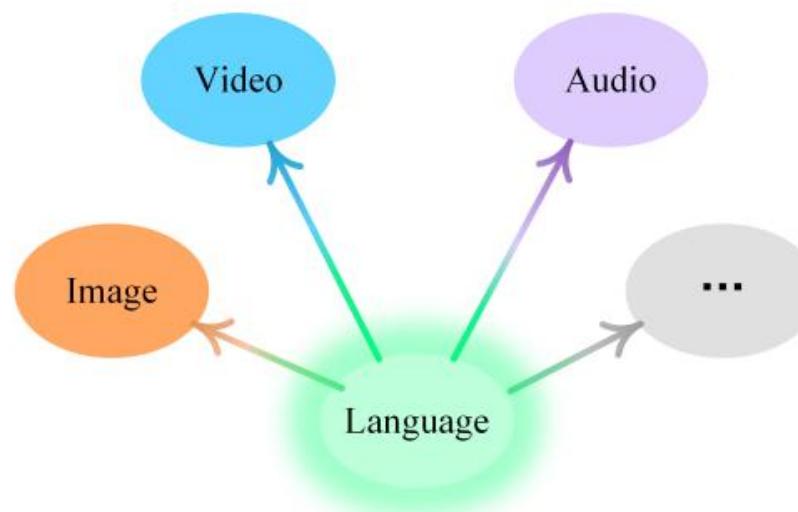
# On Path to Multimodal Generalist: General-Level

## Motivation

- Existing issue-I: *The language intelligence of LLMs empowers multimodal intelligence.*

*Existing* intelligent pattern in multimodal generalist

*Language intelligence supports unidirectionally  
"intelligence" of other modalities*



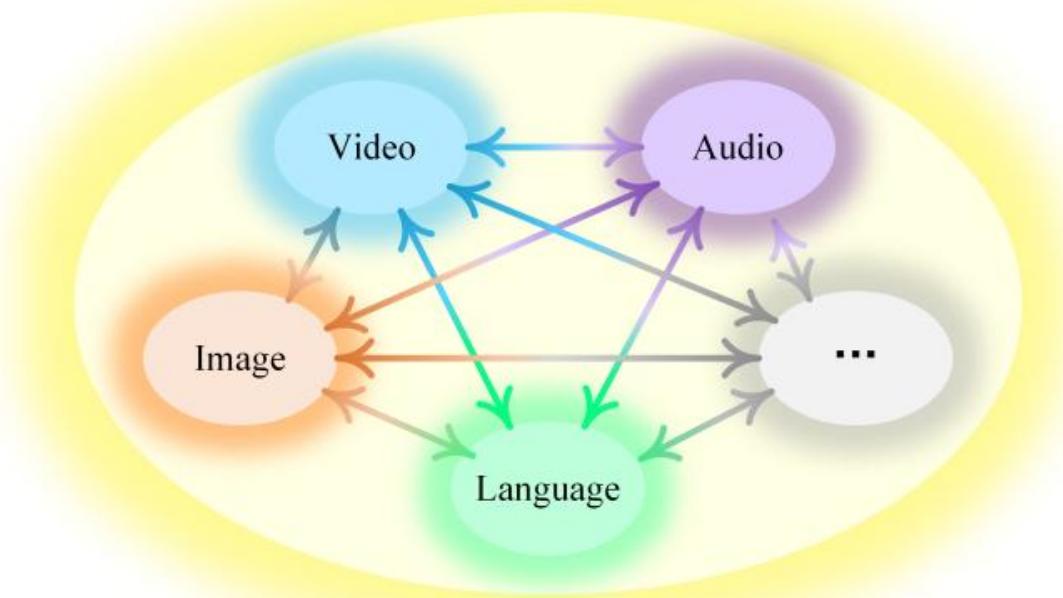
# On Path to Multimodal Generalist: General-Level

## Motivation

- Existing issue-I: *The language intelligence of LLMs empowers multimodal intelligence.*

Ideal intelligent pattern in multimodal generalist

Total synergy across any modalities, functions  
and tasks for authentic multimodal intelligence

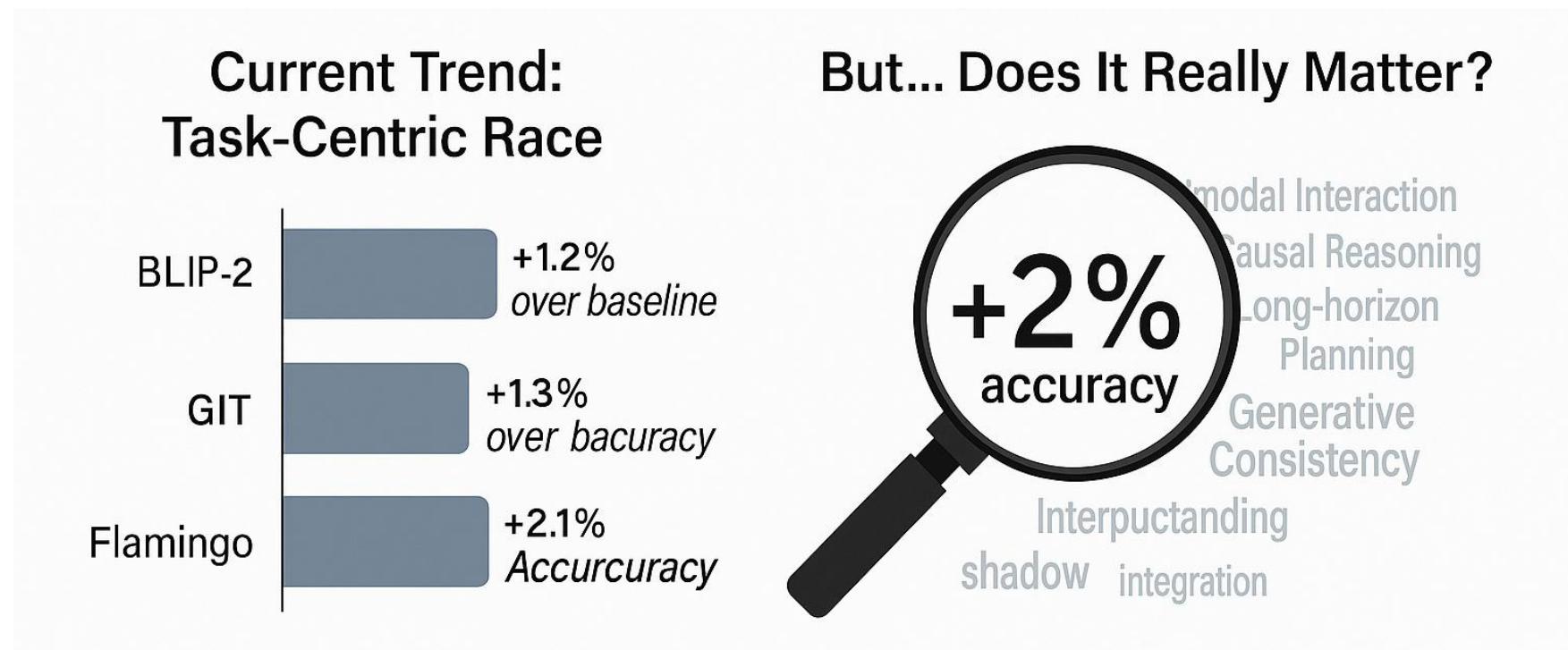


# On Path to Multimodal Generalist: General-Level

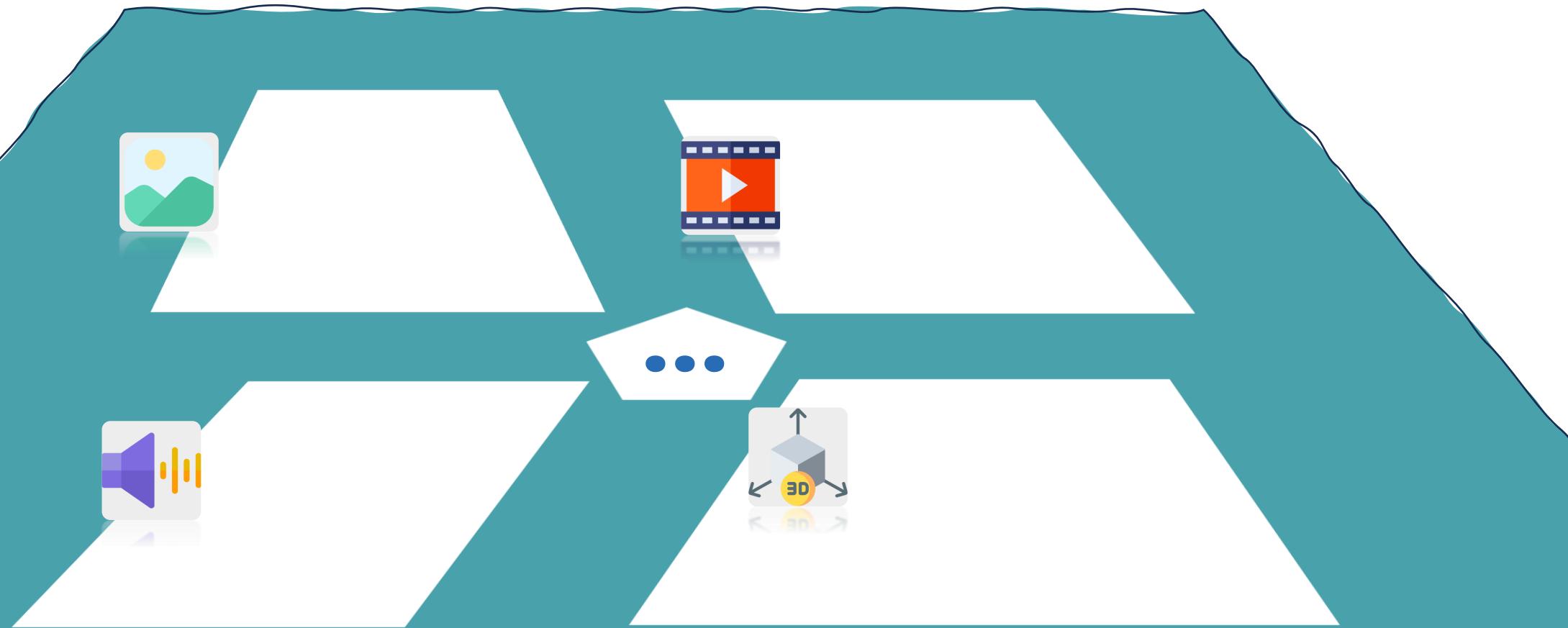
## Motivation

- Existing issue-II: *Rethinking MLLM evaluation beyond straightforward accuracy gains.*

*Most existing MLLMs madly race for task performance of single modality/task.*



# MLLM Task Performance



MLLM Task Performance

Most MLLMs madly race for *task performance* of separate Modality/**T**ask

MLLM Task Performance ↑

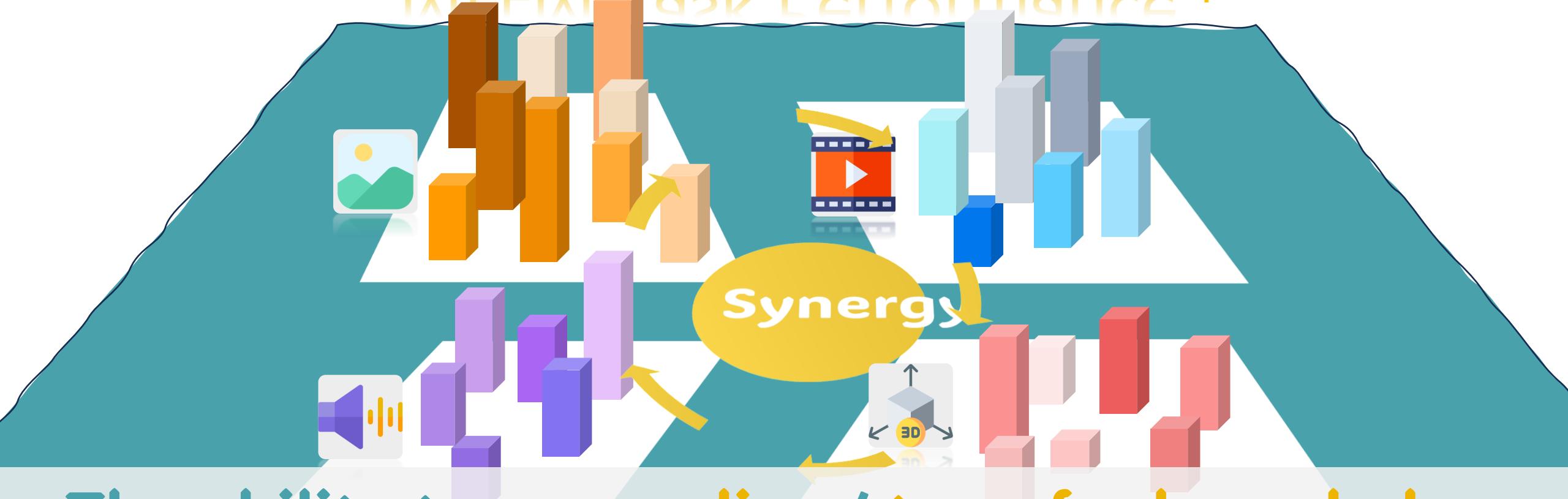
Does *higher results* simply mean  
*stronger intelligent multimodal AI*?

# Synergy Drives Intelligence: The Path Toward AGI

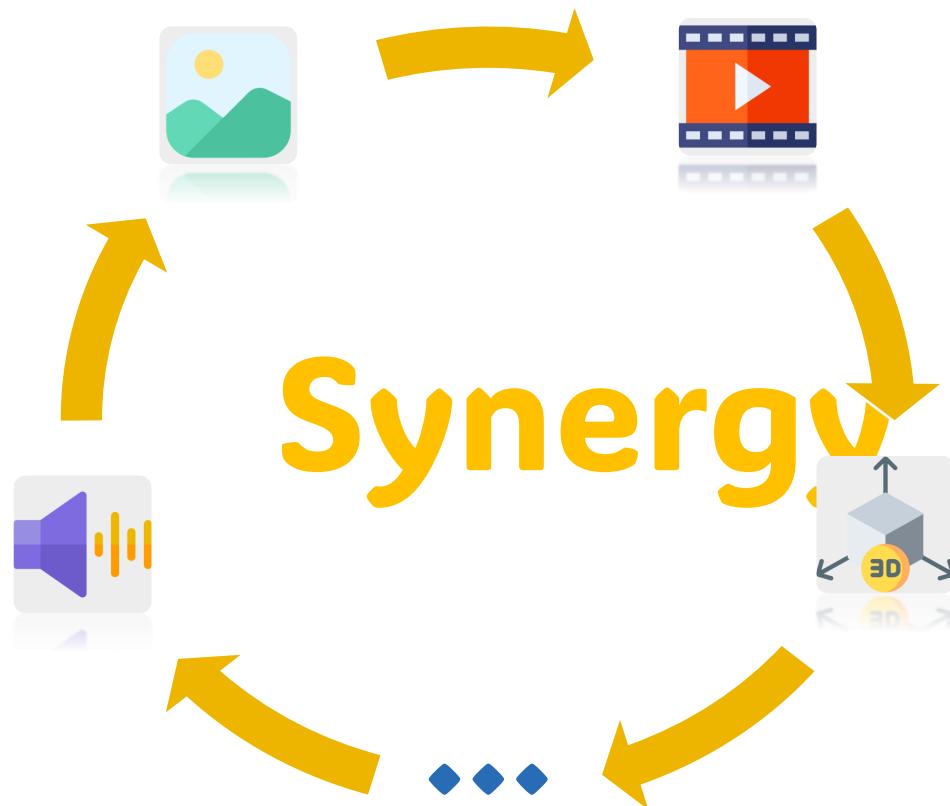


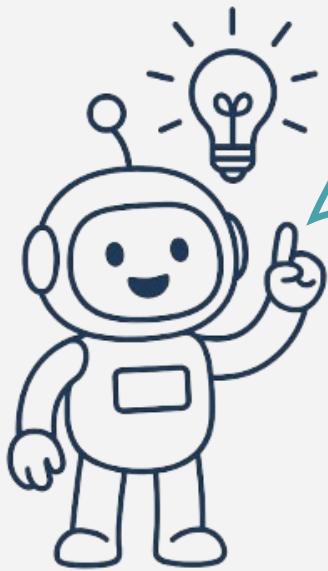
# Synergy

MLLM Task Performance ↑



The ability to generalize / transfer knowledge  
across Tasks, Modalities and Paradigm...





# General-Level

Positioning and assessing the capabilities of current MLLM generalists

Level-0  
No automation



Level-1  
Driver Assistance

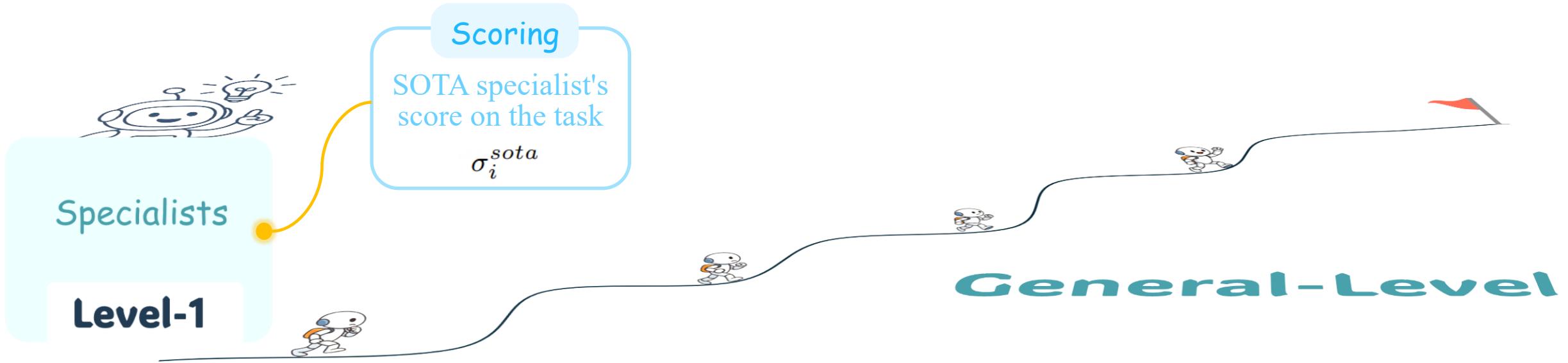
Level-2  
Partial Automation

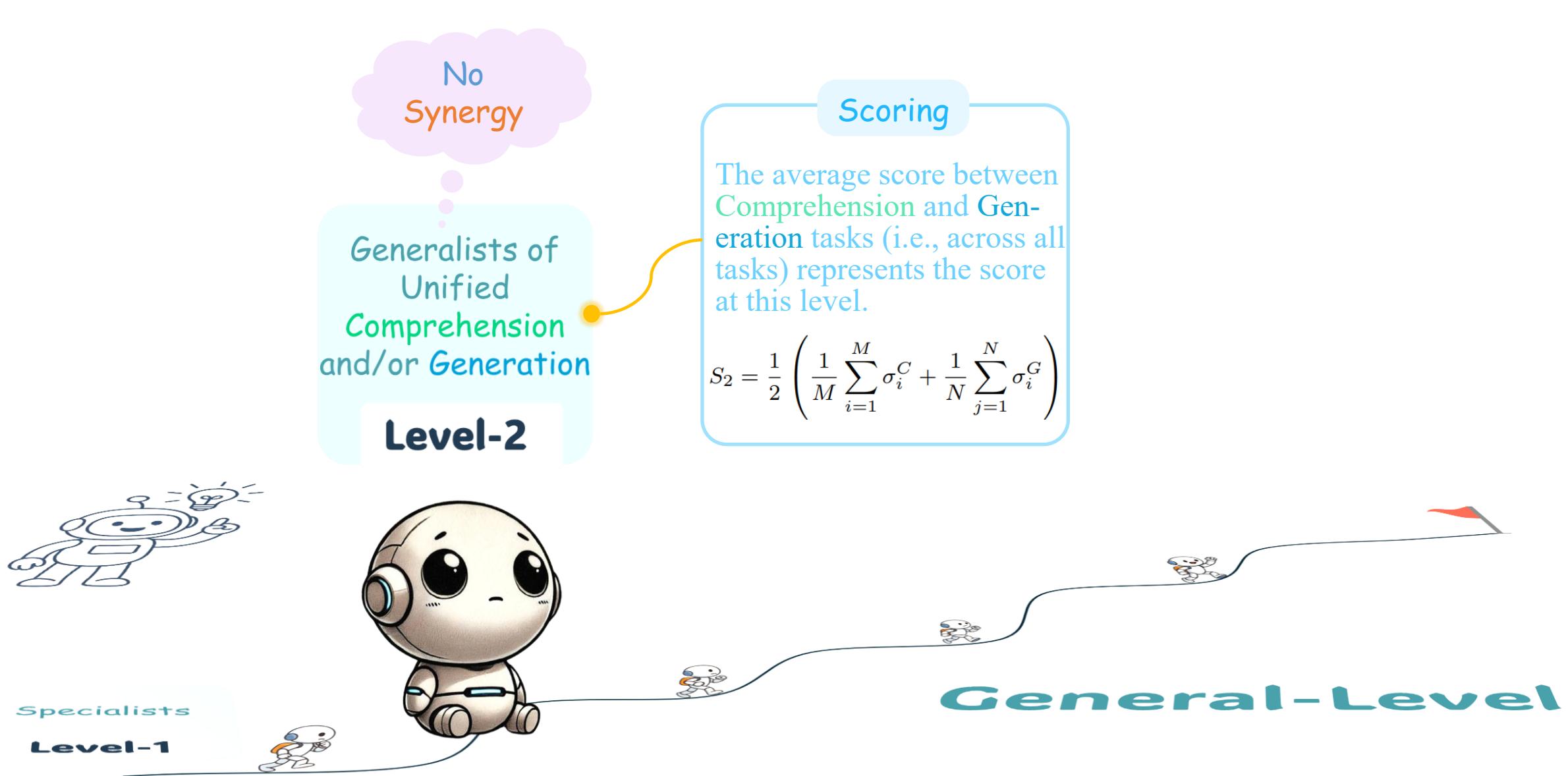
Level-3  
Conditional Automation

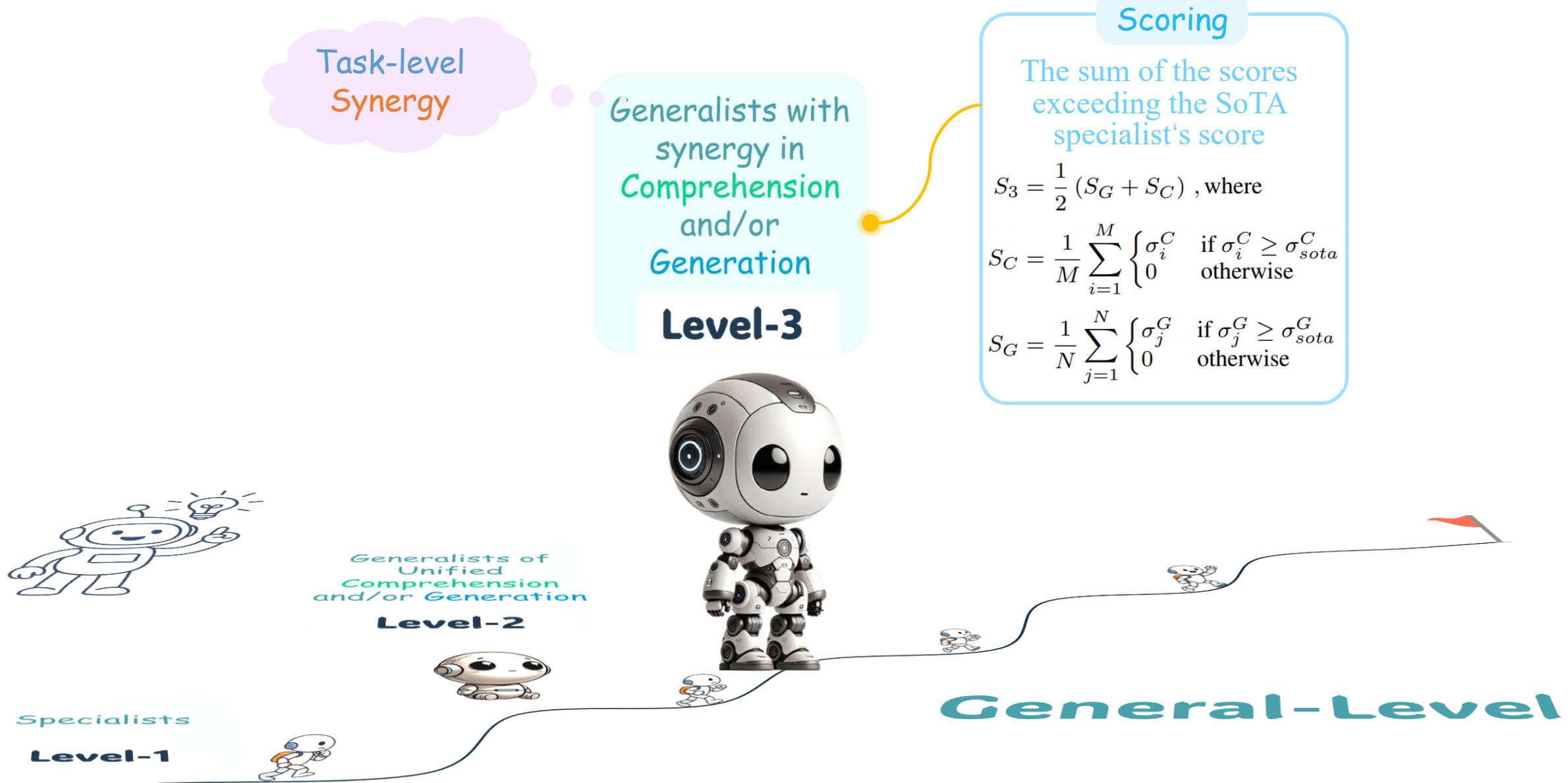
Level-4  
High Automation

Level-5  
Full Automation

Levels of  
Autonomous  
Driving







## Scoring

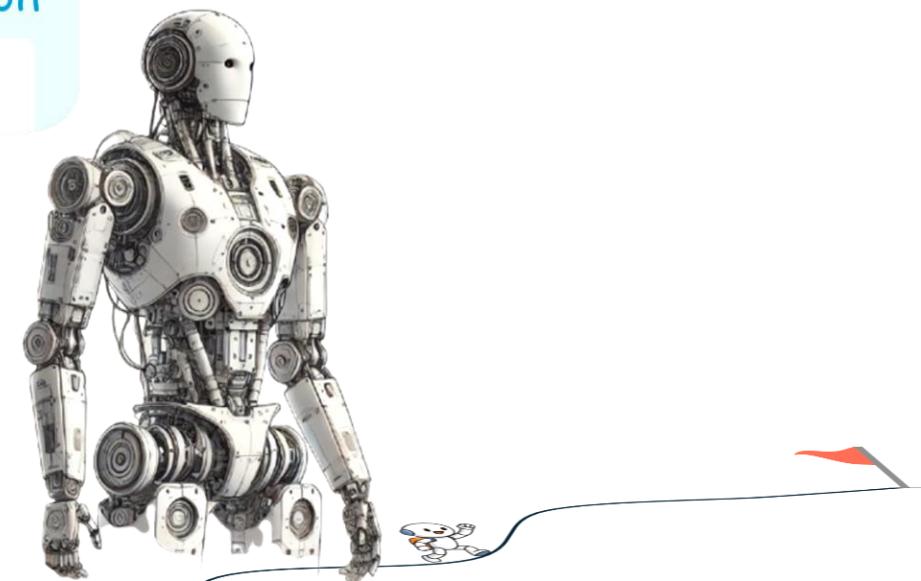
The harmonic mean between Comprehension and Generation scores

$$S_4 = \frac{2S_C S_G}{S_C + S_G}$$

Generalists with synergy across Comprehension and Generation

**Level-4**

Paradigm-level Synergy



Generalists of Unified Comprehension and/or Generation  
**Level-2**



Generalists with synergy in Comprehension and/or Generation  
**Level-3**



Specialists

**Level-1**



**General-Level**



Generalists of Unified Comprehension and/or Generation

**Level-2**

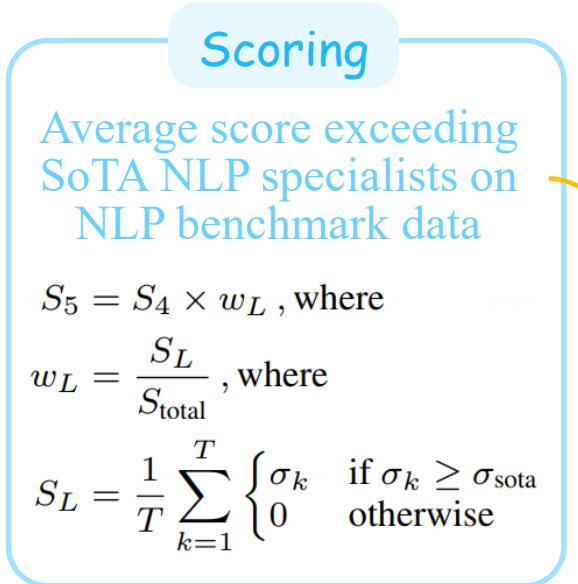


Generalists with synergy in Comprehension and/or Generation

**Level-3**



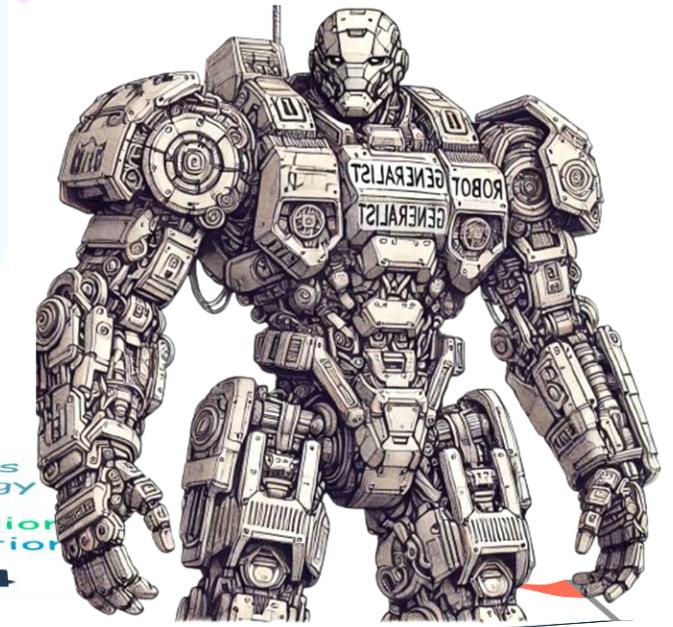
**General-Level**

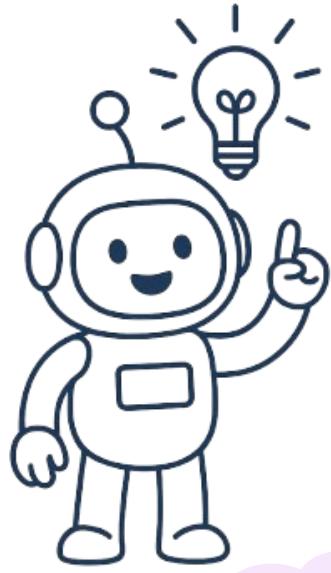


**Level-5**

Generalists with total synergy across **Comprehension**, **Generation** and **Language**

Cross-modal Total Synergy





Specialists

**Level-1**

Generalists of Unified Comprehension and/or Generation

**Level-2**



Task-level Synergy

Paradigm-level Synergy

Generalists with synergy in Comprehension and/or Generation

**Level-3**



Generalists with synergy across Comprehension and Generation

**Level-3**



**Level-5**

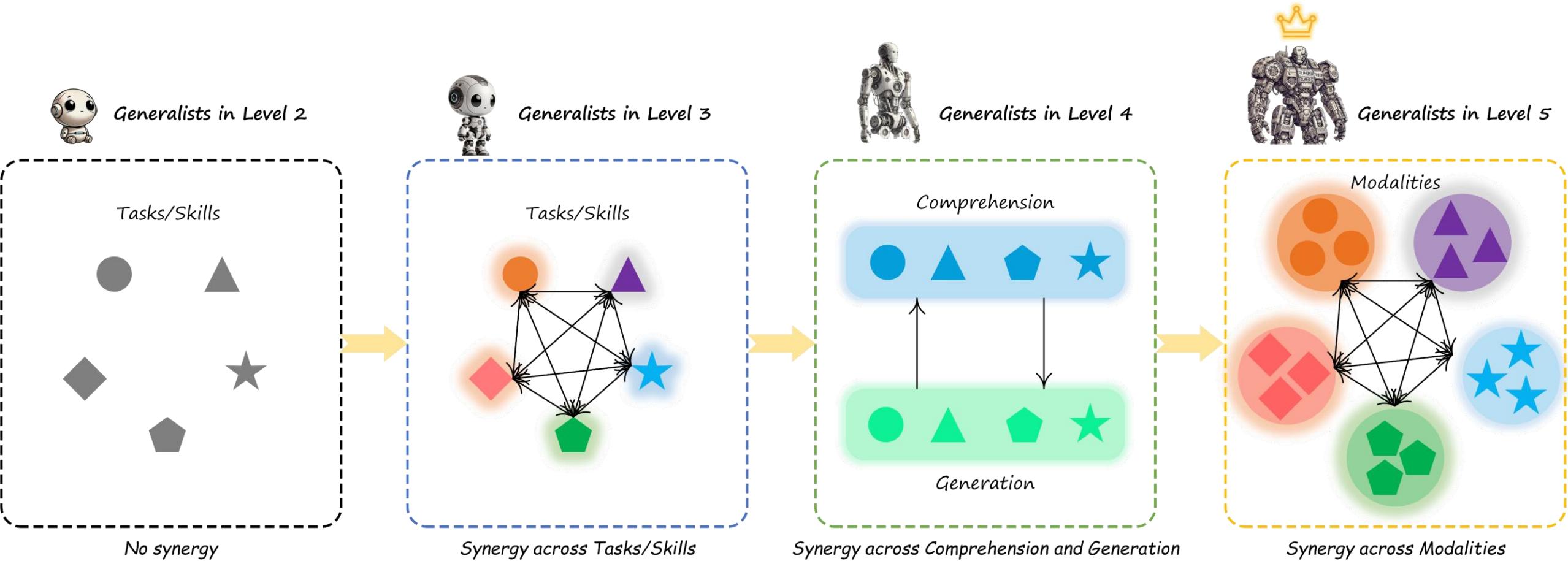
Generalists with total synergy across Comprehension, Generation and Language

Cross-modal Total Synergy

# General-Level

# On Path to Multimodal Generalist: General-Level

## ■ General-Level: Synergy-centered evaluation framework



# On Path to Multimodal Generalist: General-Level

## ■ What is a (Multimodal) Generalist?

- One single model is capable of handling multiple tasks
- In most cases, an LLM serves as the core intelligence component
- At the very least, can be prompted using natural language to express user intentions
- e.g., MLLMs, or large multimodal foundational models, as well as multimodal agents

GPT-4o

LLaVA

Gemini

Blip

NExT-GPT

...

# On Path to Multimodal Generalist: General-Level

## ■ What is a (Multimodal) Specialist?

- In most cases, a specialist model can — and only can — achieve SoTA performance on a specific task
- It is typically fine-tuned on the training set of that task
- In most cases, the model often has a smaller parameter size compared to generalist models
- It mostly does not incorporate an LLM as the core reasoning or intelligence engine

DINO

SDXL

SAM

WaveNet

Nerf

...

# On Path to Multimodal Generalist: General-Level

## ■ Relaxation of Scoring

- How to measure the synergy effect between on task-A & on task-B ?

*the performance of a generalist on joint modeling of tasks A and B  $P_\theta(y|A, B)$  should exceed its performance when modeling task A alone  $P_\theta(y|A)$  or task B alone  $P_\theta(y|B)$ .*

$$P_\theta(y|A, B) > P_\theta(y|A) \quad \& \quad P_\theta(y|A, B) > P_\theta(y|B)$$

# On Path to Multimodal Generalist: General-Level

## ■ Relaxation of Scoring

- How to measure the synergy effect between on **task-A** & on **task-B** ?

$$P_{\theta}(y|A, B)$$

$$\frac{P_{\theta}(y|A)}{P_{\theta}(y|B)}$$

# On Path to Multimodal Generalist: General-Level

## ■ Relaxation of Scoring

- How to measure the synergy effect between on **task-A** & on **task-B** ?

*the stronger a model's synergy capability, the more likely it is to surpass the task performance of SoTA specialists when there is a synergy.*

Let's simplify the rule:

*if a generalist **outperforms** a SoTA specialist in a specific task, we consider it as evidence of a synergy effect, i.e., leveraging the knowledge learned from other tasks or modalities to enhance its performance in the targeted task.*

# On Path to Multimodal Generalist: General-Level

## ■ One more notice

- There's never a fair comparisons for generalist with specialist

Specialist

*Fine-tuned on training set*

Generalist

*No task-specific fine-tuning*

*Hard!*

*Unfair!*

***But Necessary!***

# On Path to Multimodal Generalist: General-Level

## Modality-specific Scoring

👉 calculate the specific score component  $S_k^i$  of a generalist in the  $i$ -th modality (assuming there are  $N$  modalities in total) for the score  $S_k$ .

 $S_2^{img}$  $S_2^{vid}$  $S_2^{aud}$  $S_2^{3d}$ 

...

 $S_2$  $S_k$  $S_3^{img}$  $S_3^{vid}$  $S_3^{aud}$  $S_3^{3d}$ 

...

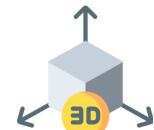
$$S_k = \sum_i \frac{1}{N} S_k^i$$

 $S_4^{img}$  $S_4^{vid}$  $S_4^{aud}$  $S_4^{3d}$ 

...

 $S_4$  $S_2^{3d}$  $S_5^{img}$  $S_5^{vid}$  $S_5^{aud}$  $S_5^{3d}$ 

...

 $S_5$ 

# On Path to Multimodal Generalist: General-Level

## ■ Independence from Peer Generalists



The scores of any generalist:

- ✓ • *depend solely on the data of the task and the reference score of SoTA specialist*
  
- ✗ • *without relying on the scores of other tested generalists*

# On Path to Multimodal Generalist: General-Level

## ■ Monotonicity Across Levels

Key Attribute:

- *If a generalist is rated at the highest level  $k$ , it should achieve valid scores at all levels from 2 to  $k$ .*
  - *As the level increases, the expected scores should decrease:  $S_{k-1} > S_k$*
- 
- *The monotonicity reflects increasing **task difficulty** and **stricter capability** demands at higher levels.*
  - *The property ensures that stronger generalists maintain consistent performance across multiple difficulty levels.*
  - *It provides a realistic and interpretable evaluation standard for generalist models.*

# On Path to Multimodal Generalist: General-Level

## ■ Encouraging Rich and Balanced Multimodal Task Support

Key Attribute:

- *More task, the better*
  
- *More balance, the better*

# On Path to Multimodal Generalist: General-Level

Receipt to Leveling Upper in General-Level



**Level-1  
Specialist**



**Level-2  
Generalist with  
No Synergy**

**Level-3  
Generalist with  
Task-level Synergy**

**Level-4  
Generalist with  
Paradigm-level Synergy**

**Level-5  
Generalist with  
Modality-level  
Synergy**

**Levels Up on  
General-Level**



## Level-2:

Generalists of Unified  
**Comprehension** and/or  
**Generation**

Models are task-unified players, e.g., MLLMs, capable of supporting different modalities and tasks. Such MLLMs can integrate various models through existing encoding and decoding technologies to achieve aggregation and unification of various modalities and tasks (such as comprehension and generation tasks).

The average score between **Comprehension** and **Generation** tasks (i.e., across all tasks) represents the score at this level. A model that can score non-zero on the data is considered capable of supporting that task. The more supported tasks and the higher the scores, the higher its overall score:

$$S_2 = \frac{1}{2} \left( \frac{1}{M} \sum_{i=1}^M \sigma_i^C + \frac{1}{N} \sum_{j=1}^N \sigma_j^G \right)$$

Unified-io-2 (Lu et al., 2024a), AnyGPT (Zhan et al., 2024), NExT-GPT (Wu et al., 2024a), SEED-LLaMA (Ge et al., 2023), GPT-4V (OpenAI, 2022b), ...



**Supporting as many tasks and functionalities as possible**

## Level-1: Specialists

Various current models, each fine-tuned on a specific task or dataset of specific modalities, are task-specific players (i.e., SoTA specialists). This includes various learning tasks, such as linguistic/visual recognition, classification, generation, segmentation, grounding, inpainting, and more.

For each task in the benchmark ( $i$ -th task), the current SoTA specialist's score is recorded as:

$$\sigma_i^{sota}$$

CLIP (Li et al., 2022), FLUX (Labs, 2023), FastSpeech2 (Ren et al., 2021), ...



### Level-3:

Generalists with **synergy** in **Comprehension** and/or **Generation**

Models are task-unified players, and synergy is in **Comprehension** and/or **Generation**. MLLMs enhance several tasks' performance beyond corresponding SoTA scores through joint learning across multiple tasks due to the synergy effect.

Assign a mask weight of 0 or 1 to each task; mask=1 only if the corresponding score ( $\sigma_i^C$  or  $\sigma_i^G$ ) exceeds the SoTA specialist's score, otherwise mask=0. Then, calculate the average score between  $S_C$  and  $S_G$ . The more tasks to surpass the SoTA specialist, the higher the  $S_3$ :

$$S_3 = \frac{1}{2} (S_G + S_C) , \text{ where}$$

$$S_C = \frac{1}{M} \sum_{i=1}^M \begin{cases} \sigma_i^C & \text{if } \sigma_i^C \geq \sigma_{sota}^C \\ 0 & \text{otherwise} \end{cases}$$

$$S_G = \frac{1}{N} \sum_{j=1}^N \begin{cases} \sigma_j^G & \text{if } \sigma_j^G \geq \sigma_{sota}^G \\ 0 & \text{otherwise} \end{cases}$$

GPT-4o (OpenAI, 2022b), Gemini-1.5 (Team et al., 2024a), Claude-3.5 (Team, 2024), DeepSeek-VL (Lu et al., 2024b), LLaVA-One-Vision (Li et al., 2024d), Qwen2-VL (Wang et al., 2024a), InternVL2.5 (Chen et al., 2024c), Phi-3.5-Vision (Abdin et al., 2024), ...



**Generalists achieving as stronger synergy and cross as many tasks as possible**

 <b>Level-3:</b>	Models are task-unified players, and synergy is across Comprehension and Generation.	Assign a mask weight of 0 or 1 to each task;	GPT-4o (OpenAI, 2023), ...
 <b>Level-4:</b> Generalists with synergy across Comprehension and Generation	Models are task-unified players, and synergy is across Comprehension and Generation.	Calculate the harmonic mean between Comprehension and Generation scores. The stronger synergy a model has between Comprehension and Generation tasks, the higher the score: $S_4 = \frac{2S_C S_G}{S_C + S_G}$	Mini-Gemini (Li et al., 2024c), Vitron-V1 (Fei et al., 2024a), Emu2-37B (Sun et al., 2024), ...
	<b>Generalists in unified comprehension and generation capability with synergy in between</b>	$S_C = \frac{1}{M} \sum_{i=1}^M \begin{cases} \sigma_i^C & \text{if } \sigma_i^C \geq \sigma_{sota}^C \\ 0 & \text{otherwise} \end{cases}$ $S_G = \frac{1}{N} \sum_{j=1}^N \begin{cases} \sigma_j^G & \text{if } \sigma_j^G \geq \sigma_{sota}^G \\ 0 & \text{otherwise} \end{cases}$	2024d), Qwen2-VL (Wang et al., 2024a), InternVL2.5 (Chen et al., 2024c), Phi-3.5-Vision (Abdin et al., 2024), ...



## Level-5:

Generalists with **total synergy** across **Comprehension**, **Generation** and **Language**

Models are task-unified players, preserving the synergy effect across **Comprehension**, **Generation**, and **Language**. In other words, the model not only achieves cross-modality synergy between **Comprehension** and **Generation** groups but also further realizes synergy with language. The **Language** intelligence can enhance multimodal intelligence and vice versa; understanding multimodal information can also aid in understanding language.

Calculate the model's average score exceeding SoTA NLP specialists on NLP benchmark data; normalize it to a [0,1] weight, and multiply it by the score from level-4 as the level-5 score:

$$S_5 = S_4 \times w_L, \text{ where}$$

$$w_L = \frac{S_L}{S_{\text{total}}}, \text{ where}$$

$$S_L = \frac{1}{T} \sum_{k=1}^T \begin{cases} \sigma_k & \text{if } \sigma_k \geq \sigma_{\text{sota}} \\ 0 & \text{otherwise} \end{cases}$$

*None found yet  
(Let's wait for  
multimodal Chat-  
GPT moment!)*



**Generalists achieving cross-modal synergy with abductive reasoning ability**

# Content

1

**General-Level**

2

**General-Bench**

3

**What To Do Next**

# On Path to Multimodal Generalist: General-Bench

## ■ Why General-Bench?

**So, where to evaluate generalist  
models across these five levels?**

**Using Existing Benchmark**



# Existing MLLM Benchmark

ScienceQA

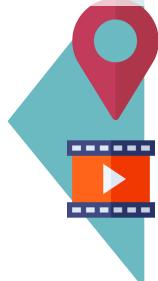


MME

MMMU



MM-Vet



MMAU

AudioBench

Limit Modalities

LiSkills

Limit Domains

LP paradigm



MLVU

VideoMME

MARBLE

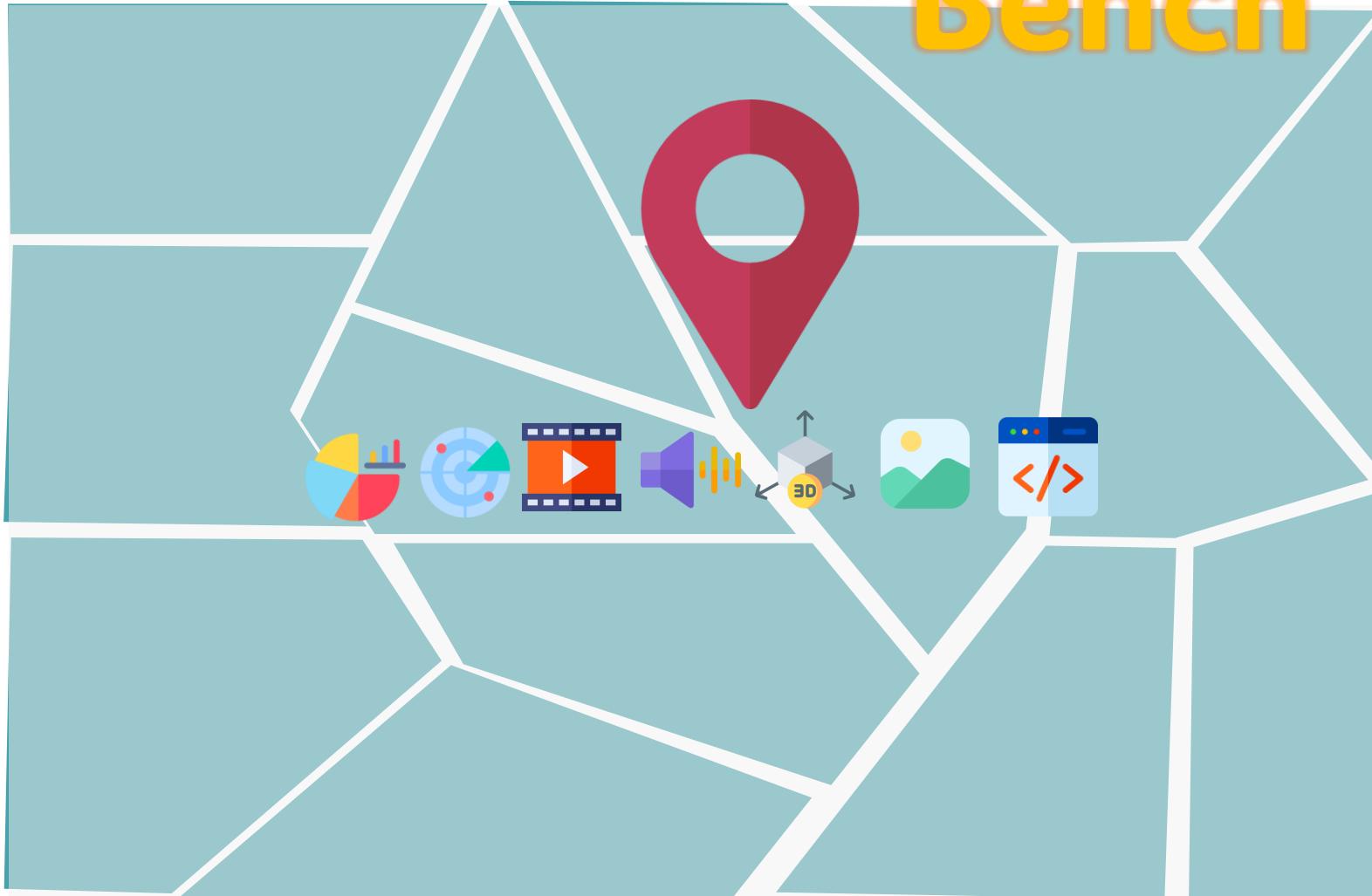
Mia-bench

3DBench

VideoBench

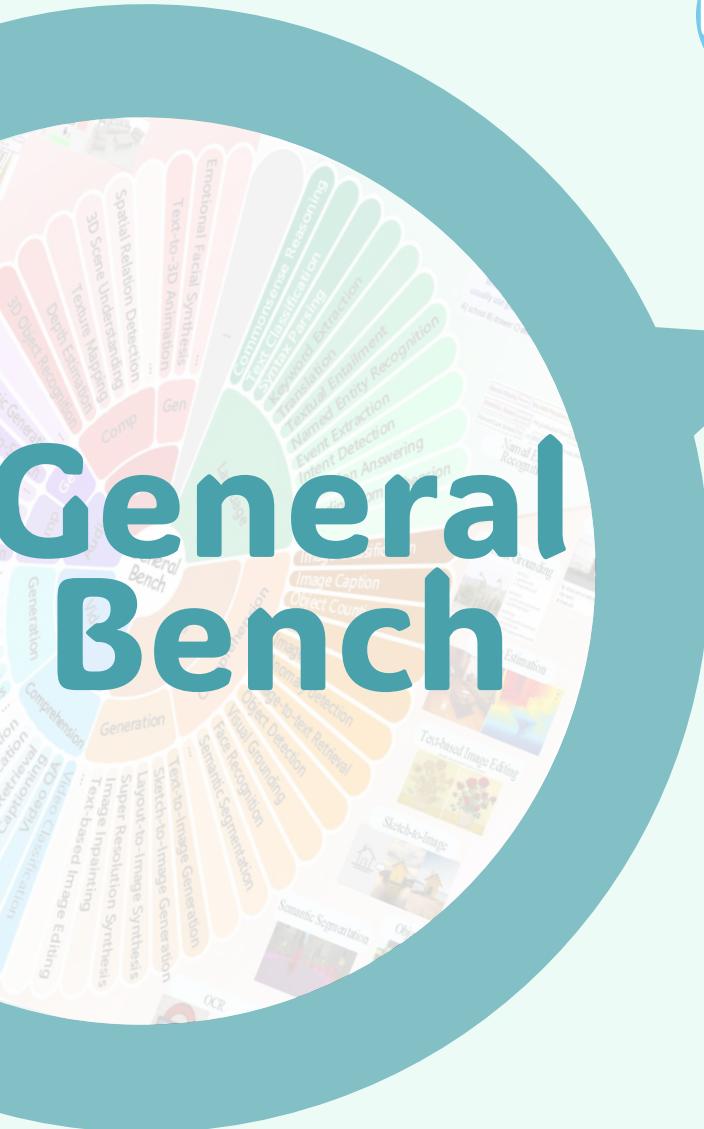
# We Propose

# General-Bench





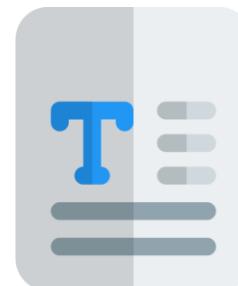
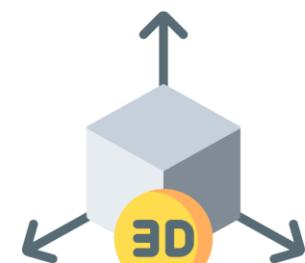
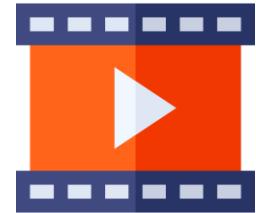
# General Bench

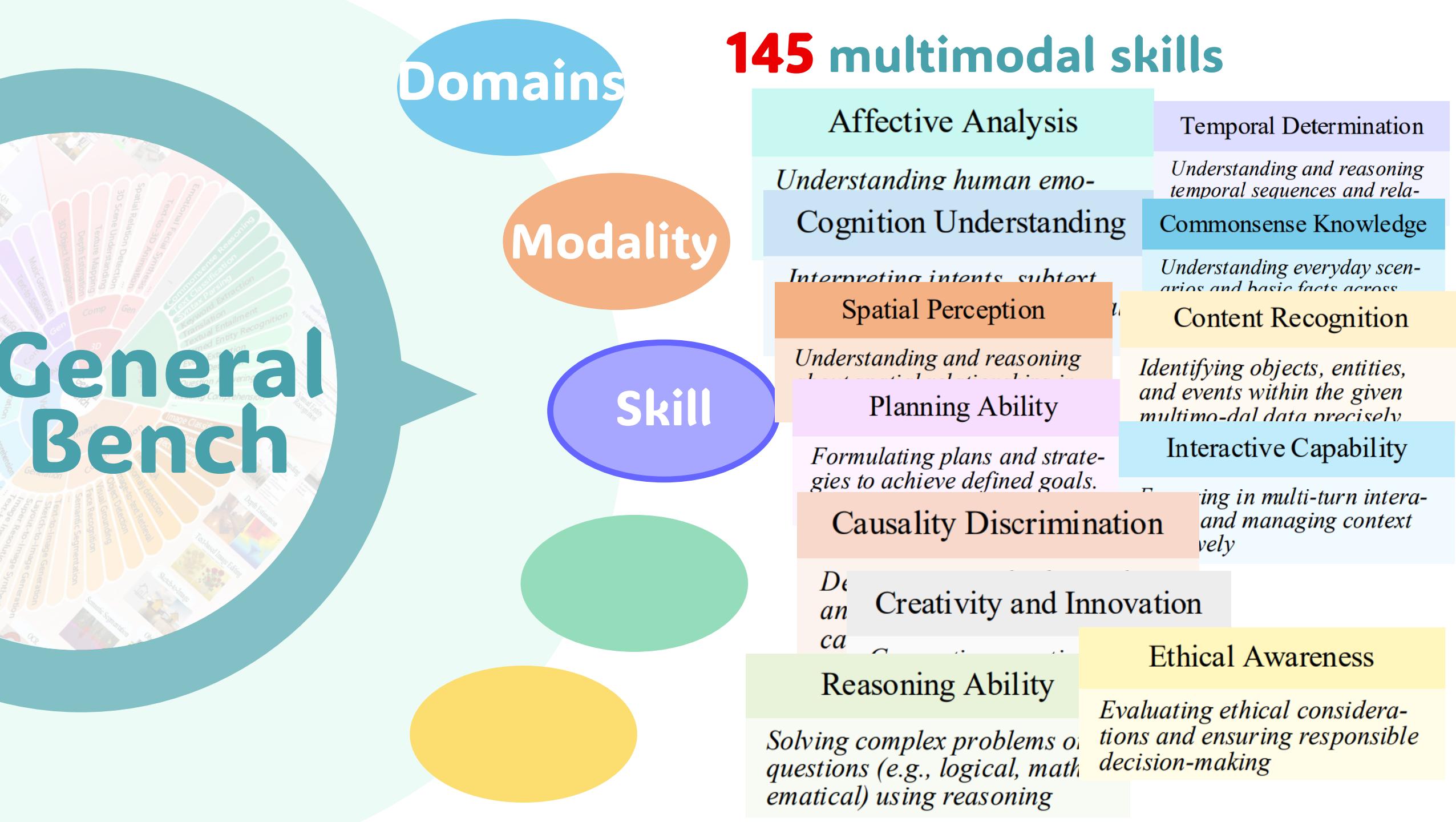


# Domains

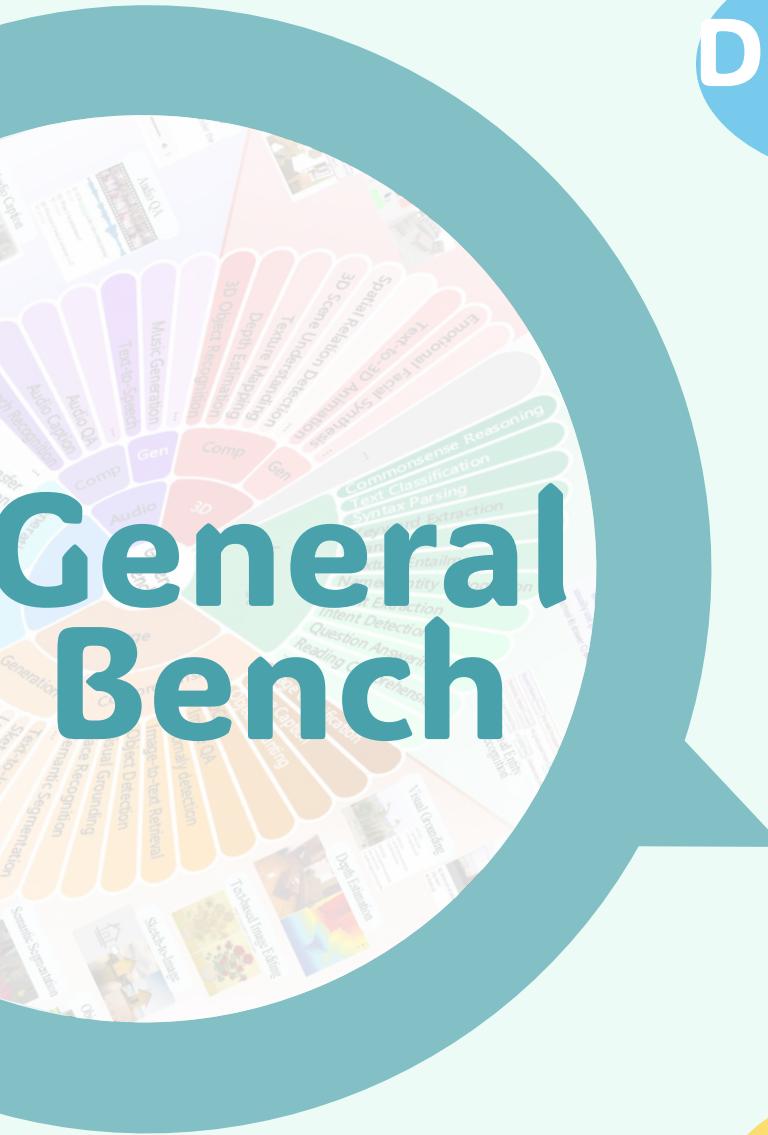
# Modality

## 5 major modalities





# General Bench



# Domains

# Modality

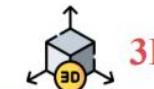
# Tasks

# 702 tasks



## Comprehension

- Audio QA
  - Animal Sound Analysis
  - Music Understanding
  - Audio Content Analysis
  - Environ Sound Analysis
  - Speech Accent Analysis
  - Speech Content Analysis
  - Speech Emotion Analysis



## Comprehension

- 3D Detection
  - 3D QA
  - 3D Motion Analysis
  - 3D Pose Estimation
  - 3D Tracking
  - 3D Human-related Object Classification
  - 3D Indoor Scene Semantic Segmentation
  - 3D Outdoor Scene Semantic Segmentation
  - ...





# Image

- I
  - I
  - R
  - P
  - T
  - V
  - S

## Comprehension

  - Image Captioning
  - Image Depth Estimation
  - Image OCR
  - Image Recognition
  - Semantic Segmentation
  - Image Visual Grounding
  - Image Visual QA
  - Scene Recognition
  - Multimodal Reasoning
  - Multi-image Visual QA
  - Object Detection
  - ...



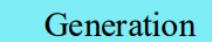
# Language

- Linguistic Parsing
  - Semantic Parsing
  - Affective Computing
  - Opinion Mining
  - Relation Extraction
  - Event Extraction
  - Behavioral Analysis
  - Named Entity Recognition



 **Video**

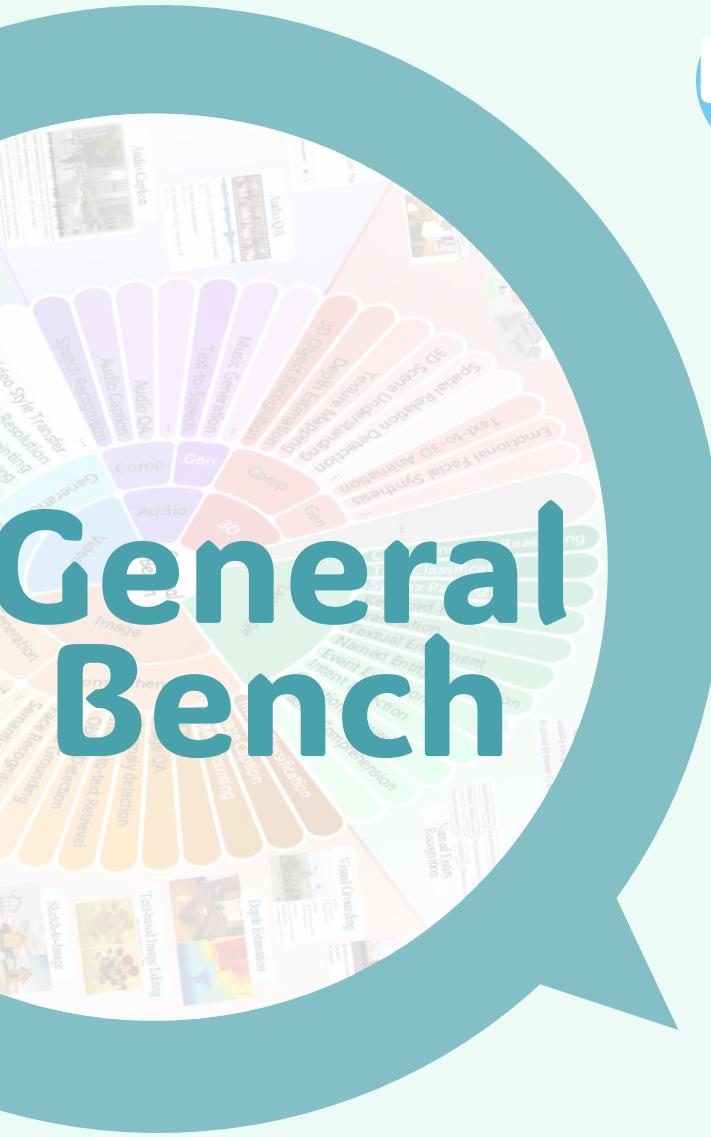
- Di ▪ Video Action Prediction
  - Ac ▪ Video QA
  - Etl ▪ Object Matching
  - Ma ▪ Object Tracking
  - Nu ▪ Video Grounding
  - So ▪ Long Video Tracking
  - Su ▪ Video Depth Estimation
  - Te ▪ Video Action Recog
  - Te ▪ Video Event Recog
  - Te ▪ Video Object Recog
  - Te ▪ Optical Flow



Generation

- Conditional Video Gen
  - Image2Video Generation
  - Text2Video Generation
  - Video Action Generation
  - Video Editing
  - Video Enhancement
  - ...

# General Bench



Sample

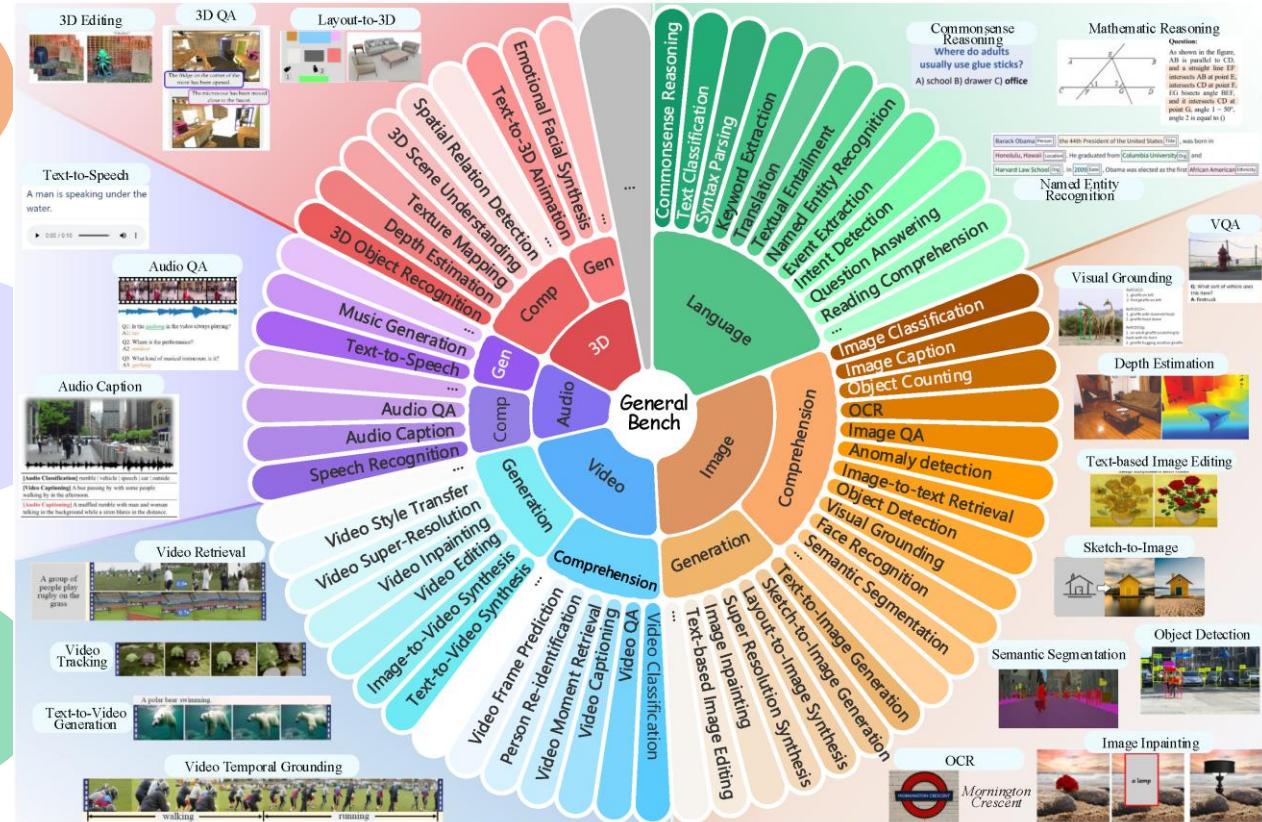
Domains

Modality

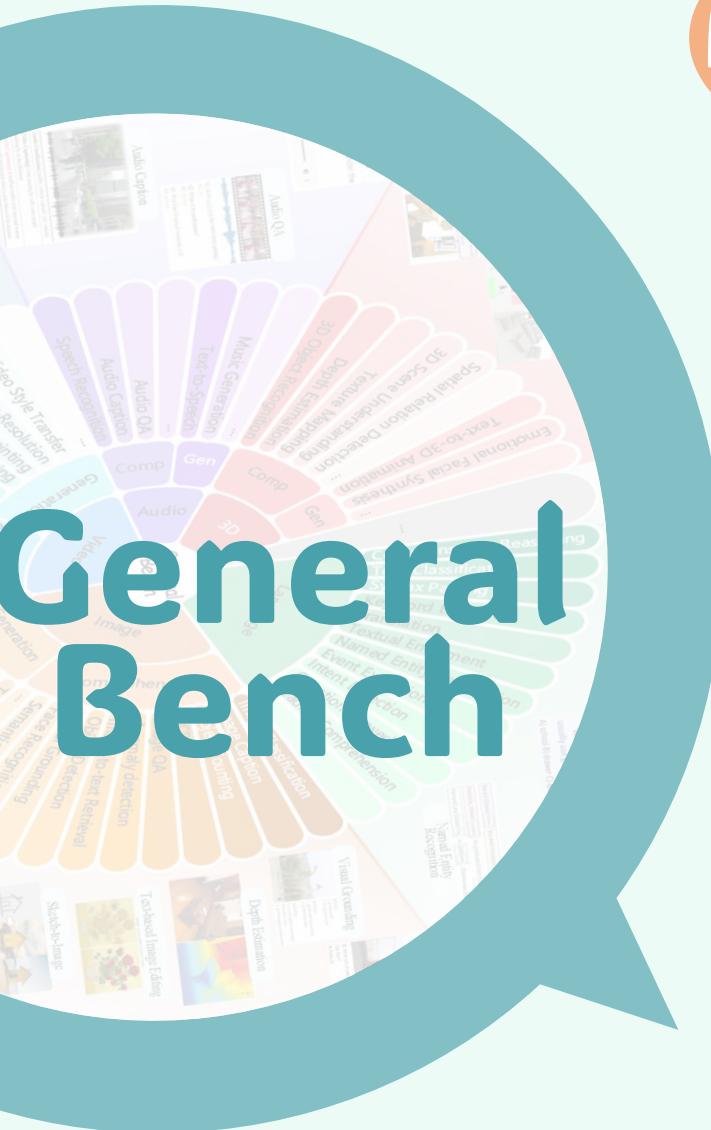
Skill

Tasks

325,876 samples



# General Bench



Modality

Skill

Tasks

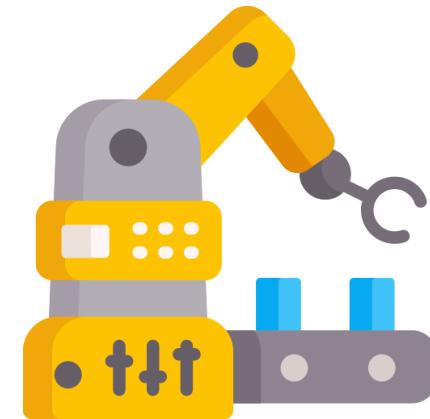
Sample

Paradigm

Comprehension



Generation



# On Path to Multimodal Generalist: General-Bench



## Statistics of General-Bench

	#Skill	Image		Video		Audio		3D		Language	TOTAL
		Comp	Gen	Comp	Gen	Comp	Gen	Comp	Gen		
	Single	40	15	20	6	9	11	13	9	-	22
	Sum	55	-	26	-	20	-	22	-	-	145
	#Task	271	45	126	46	24	20	30	22	-	118
	Sum	316	-	170	-	44	-	52	-	-	702
	#Instance	124,880	26,610	44,442	16,430	11,247	9,516	23,705	10,614	-	58,432
	Sum	151,490	-	60,872	-	20,763	-	34,319	-	-	325,876

# On Path to Multimodal Generalist: General-Bench

## Statistics of General-Bench

Benchmark	SEED-Bench	MMBench	MMMU	LVLM-eHub	MMIU	MMT-Bench	MEGA-Bench	General-Bench
Modality	Txt,Img,Vid	Txt,Img	Txt,Img	Txt,Img	Txt,Img,Vid, Point-Cloud,Depth	Txt,Img,Vid, Point-Cloud	Txt,Img,Vid	Txt,Img,Aud, Time,Depth,3D-RGB, Point-Cloud,Infrared, Spectrogram,Radar, Code,Doc,Graph,...
Task Scheme	Comp.	Comp.	Comp.	Comp.	Comp.	Comp.	Comp.	Comp.+Gen.
# Domain	1	1	6	1	1	4	5	<b>29</b>
# Skill	12	2	6	6	7	32	10	<b>145</b>
# Task	12	20	30	47	52	162	505	<b>702</b>
# Sample	19K	3K	11.5K	2.1K	11.7K	31K	8K	<b>325.8K</b>
Answer Form	MC-QA	MC-QA	MC-QA	MC-QA	MC-QA	MC-QA	Free-Form	Free-Form
# Metric	Acc.	Acc.	Acc.	Acc.	Acc.	Acc.	Origin (45)	Origin (58)
Annotation	Manual	Repurposed	Manual	Repurposed	Repurposed	Repurposed	Manual	Manual
# Tested Models	12	21	24	8	22	30	22	<b>172+102</b>

#	Metric	Range	Calculation	Representative Tasks
<b>• General</b>				
1	Acc↑	[0,1]	Accuracy is defined as the ratio of correctly classified instances to the total number of instances.	Classification
2	Macro-Acc↑	[0,1]	Macro-Acc evaluates how well a model performs on average across all classes, regardless of class imbalance.	Event Relation Prediction
3	EM-Acc↑	[0,1]	Exact Match Accuracy evaluates the percentage of predictions that are exactly the same as their corresponding references.	QA, machine translation, or summarization
4	AP↑	[0,1]	AP, Average Precision, is a metric used to evaluate the performance of object detection tasks, reflecting the overall precision-recall trade-off across multiple thresholds.	Anomaly Detection
5	mAP↑	[0,1]	mAP, Mean Average Precision, is the mean of Average Precision values across all queries or instances:	2D/3D Detection
6	F1↑	[0,1]	F1 score is the harmonic mean of Precision and Recall.	QA
7	Micro-F1↑	[0,1]	Micro-F1 score is the harmonic mean of the Micro-averaged precision and recall.	Classification
8	AUC↑	[0,1]	AUC is used in binary classification tasks and measures the area under the ROC curve. It represents the model's ability to distinguish between classes.	Image Generation
<b>• Ranking-related</b>				
9	R@k↑	[0,1]	R@k measures the Recall rate at the top k results in tasks like image retrieval, where the true positive must appear within the top k predicted results.	Image Scene Graph Parsing
10	AP@k↑	[0,1]	AP@k is the Average Precision calculated at an IoU threshold of k ( $k \geq 1$ ). This metric is typically used when higher overlap between retrieved items and ground truth items is required.	Object Detection
11	mAP@k↑	[0,1]	mAP@k refers to the mean Average Precision where the Intersection over Union (IoU) threshold is set to k ( $k \geq 1$ ).	Object Detection
12	EM@1↑	[0,1]	Exact Match at 1 evaluates the proportion of instances for which the model's top prediction exactly matches the correct answer.	3D Question Answering
13	ANLS↑	[0,1]	ANLS, Average Normalized Levenshtein Similarity, measures how well a model ranks items in a list based on their relevance to a query.	OCR
<b>• Regression-related</b>				
14	MAE ↓	[0,∞)	MAE, Mean Absolute Error, measures the average of the absolute differences between the predicted values and the actual values. It's typically used in regression tasks.	Object Counting
15	RMS ↓	[0,∞)	RMS, Root Mean Square, is a metric for regression tasks that measures the square root of the average squared differences between the predicted values and true values.	Image Depth Estimation
16	MSE ↓	[0,∞)	MSE, Mean Squared Error, is commonly used for regression tasks and measures the average squared differences between predicted values and actual values.	Object Matting
17	RMSE ↓	[0,∞)	RMSE, Root Mean Squared Error.	Time Series Prediction
<b>• Text Generation-related</b>				

On Path

How to

I-Bench

#	Metric	Range	Calculation	Representative Tasks
50	CLAP↑	[0,1]	CLAP (Contrastive Language-Audio Pretraining) evaluates the alignment between generated audio and text. It is derived from a contrastive learning framework where embeddings of audio and text are trained to be close in a shared latent space if they are semantically related.	Audio Editing
51	Style-CLAP ↑	[0,1]	Style-CLAP calculates the CLAP cosine similarity between the generated Mel spectrograms and the corresponding textual description of the style to evaluate style fit.	Music Style Transfer
52	MCD ↓	[0,∞)	Mel-cepstral distortion (MCD) measures the spectral distance between the mel-cepstral coefficients (MCCs) of generated speech and reference speech, providing an indication of how closely the generated speech resembles the reference in terms of acoustic characteristics.	Speech Synthesis
53	WER ↓	[0,1]	WER (Word Error Rate) measures the percentage of errors in the transcribed output compared to the reference transcription.	TTS
54	FAD ↓	[0,∞)	Frechet audio distance (FAD) evaluates the quality and realism of generated audio, and measures the similarity between the distribution of features obtained by VGGish in generated audio and those in a set of real (reference) audio samples.	Video-to-Audio
55	PCC ↑	[0,1]	Pitch-Class Consistency (PCC) is a metric used in the evaluation of generated music to assess how consistent the pitch classes (e.g., notes) are across pairs of bars in a piece of music. It measures the overlapping area between the pitch-class histograms of different bars, ensuring that the generated music maintains harmonic coherence.	Music Generation
<b>• Human-aware Evaluation</b>				
56	UPR ↑	[0,1]	UPR, User Preference Rates, UPR measures the proportion of times a particular system or model is preferred over alternatives in a set of user evaluations. It reflects the subjective preferences of users and is often derived from pairwise comparisons or ranking experiments.	Video Style Transfer
57	MOS ↑	[1,5]	Mean Opinion Score (MOS), in which human raters listen to synthesized speech and assess its naturalness, quality, and intelligibility using a 5-point Likert scale.	Speech Generation
58	GPT-Score ↑	[0,1]	GPT-Score evaluates the instruction following rate with GPT assistance, as an alternative to human evaluation.	Audio Question Answering

# On Path to Multimodal Generalist: General-Bench

## ■ How are the evaluation metrics?

### ➤ Mapping Functions of Scoring Metric

- Normalizing **MAE**:

$$y = 2 \times \text{sigmoid} \left( \frac{50}{x} \right) - 1, \quad \text{where } x \in [0, +\infty), \quad y \in (0, 1).$$

- Normalizing **RMS**:

$$y = 2 \times \text{sigmoid} \left( \frac{50}{x} \right) - 1, \quad \text{where } x \in [0, +\infty), \quad y \in (0, 1).$$

- Normalizing **MSE**:

$$y = 2 \times \text{sigmoid} \left( \frac{5}{x} \right) - 1, \quad \text{where } x \in [0, +\infty), \quad y \in (0, 1).$$

- Normalizing **RMSE**:

$$y = 2 \times \text{sigmoid} \left( \frac{5}{x} \right) - 1, \quad \text{where } x \in [0, +\infty), \quad y \in (0, 1).$$

- Normalizing **absRel**:

$$y = 2 \times \text{sigmoid} \left( \frac{0.1}{x} \right) - 1, \quad \text{where } x \in [0, +\infty), \quad y \in (0, 1).$$

# On Path to Multimodal Generalist: General-Bench

## ■ How are the evaluation metrics?

### ➤ Mapping Functions of Scoring Metric

- Normalizing **RTE**:

$$y = 2 \times \text{sigmoid} \left( \frac{0.5}{x} \right) - 1, \quad \text{where } x \in [0, +\infty), \quad y \in (0, 1).$$

- Normalizing **CD**:

$$y = 2 \times \text{sigmoid} \left( \frac{1}{x} \right) - 1, \quad \text{where } x \in [0, +\infty), \quad y \in (0, 1).$$

- Normalizing **MCD**:

$$y = 2 \times \text{sigmoid} \left( \frac{5}{x} \right) - 1, \quad \text{where } x \in [0, +\infty), \quad y \in (0, 1).$$

- Normalizing **WER**:

$$y = 1 - x, \quad \text{where } x \in [0, 1], \quad y \in [0, 1].$$

- Normalizing **MS-SSIM**:

$$y = \frac{(x + 1)}{2}, \quad \text{where } x \in [-1, 1], \quad y \in [0, 1].$$

- Normalizing **MOS**:

$$y = \frac{x - 1}{4}, \quad \text{where } x \in [1, 5], \quad y \in [0, 1].$$

# On Path to Multimodal Generalist: General-Bench

■ How many multimodal generalist are included?

#	Model	Backbone	Size	Modality Support	Paradigm
• Language-oriented (Closed/Open-sourced) Models					
1	Meta-Llama-3.1-8B-Instruct (Touvron et al., 2023)	Llama	8B	Language	/
2	Gemma-2-9b-it (Team Gemma et al., 2024b)	Gemma	9B	Language	/
3	GPT-J (Wang and Komatsuzaki, 2021)	GPT-J	6B	Language	/
4	ChatGLM-6B (GLM et al., 2024)	ChatGLM	6B	Language	/
5	Qwen2.5-7B-Instruct (Yang et al., 2024a)	Qwen2.5	7B	Language	/

# On Path to Multimodal Generalist: General-Bench

## ■ How many multimodal generalist are included?

6	InternLM2-Chat-7B (Cai et al., 2024)	InternLM2	7B	Language	/
7	Baichuan2-7B-Chat (Yang et al., 2023)	Baichuan2	7B	Language	/
8	Vicuna-7b-V1.5 (Chiang et al., 2023)	Vicuna	7B	Language	/
9	Falcon3-7B-Instruct (Almazrouei et al., 2023)	Falcon3	7B	Language	/
10	Minstral-8B-Instruct-2410 (Jiang et al., 2024a)	Minstral	8B	Language	/
11	Yi-lightning (Young et al., 2024)	Llama	6B	Language	/
12	GPT-3.5-turbo (OpenAI, 2022a)	GPT3.5	/	Language	/

# On Path to Multimodal Generalist: General-Bench

## ■ How many multimodal generalist are included?

• Multimodal Close-sourced Models					
1	GPT4-V ( <a href="#">OpenAI, 2022b</a> )	GPT4	/	Language, Image	Comprehension
2	GPT4-o-mini ( <a href="#">OpenAI, 2022b</a> )	GPT4	/	Language, Image	Comprehension
3	GPT4-o ( <a href="#">OpenAI, 2022b</a> )	GPT4	/	Language, Image	Comprehension
4	GPT4-o-4096 ( <a href="#">OpenAI, 2022b</a> )	GPT4	/	Language, Image	Comprehension
5	ChatGPT-o-latest ( <a href="#">OpenAI, 2022b</a> )	GPT4	/	Language, Image	Comprehension
6	Claude-3.5-Sonnet ( <a href="#">Team, 2024</a> )	Claude-3.5-Sonnet	/	Language, Image	Comprehension
7	Claude-3.5-Opus ( <a href="#">Team, 2024</a> )	Claude-3.5-Opus	/	Language, Image	Comprehension
8	Gemini-1.5-Pro ( <a href="#">Team et al., 2024a</a> )	Gemini	/	Language, Image	Comprehension
9	Gemini-1.5-Flash ( <a href="#">Team et al., 2024a</a> )	Gemini	/	Language, Image	Comprehension

# On Path to Multimodal Generalist: General-Bench

• Multimodal Open-sourced Models					
1	Yi-vision-v2 (Young et al., LLaVa 2024)		6B	Language, Image	Comprehension
2	Emu2-37B (Sun et al., LLaMA-33B 2024)		37B	Language, Image	Comprehension+Generation
3	InternVL2.5-2B (Chen internlm2.5-1.8b-chat et al., 2024c)		2B	Language, Image	Comprehension
4	InternVL2.5-4B (Chen Qwen2.5-3B-Instruct et al., 2024c)		4B	Language, Image	Comprehension
5	InternVL2.5-8B (Chen internlm2.5-7b-chat et al., 2024c)		8B	Language, Image	Comprehension
6	Mini-InternVL-Chat-2B-V1-5 (Gao et al., 2024)	InternLM2-Chat-1.8B	2B	Language, Image	Comprehension
7	Mini-InternVL-Chat-4B-V1-5 (Gao et al., 2024)	Phi-3-mini-128k-instruct	4B	Language, Image	Comprehension
8	InternLM-XComposer2-VL-1.8B (Dong et al., 2024)	InternLM2-Chat-1.8B	1.8B	Language, Image	Comprehension
9	MoE-LLAVA-Phi2-2.7B-4e-384 (Lin et al., 2024a)	Phi2	2.7B	Language, Image	Comprehension
10	Monkey-10B-chat (Li et al., 2024e)	Qwev-7B	10B	Language, Image	Comprehension

# On Path to Multimodal Generalist: General-Bench

## ■ How many multimodal generalist are included?

62	PointLLM-13B (Xu et al., LLaMA 2025)	13B	Language, 3D	Comprehension
63	3D-VisTA (Zhu et al., BERT 2023b)	1.3B	Language, 3D	Comprehension
64	AvatarGPT (Zhou et al., T5-large 2024a)	770M	Language, 3D	Comprehension
65	MotionGPT-T5 (Jiang et al., 2024b)	220M	Language, 3D	Generation
66	MotionGPT-LLaMA (Zhang et al., 2023e)	13B	Language, 3D	Generation
67	LLaMA-mesh (Zhang LLaMA et al., 2023e)	7B	Language, 3D	Generation
68	GAMA (Ghosh et al., Llama-2-7b-chat 2024)	7B	Language, Audio	Comprehension
69	Pengi (Deshmukh et al., GPT2-base 2023)	124M	Language, Audio	Comprehension
70	WavLLM (Hu et al., LLaMA-2-7B-chat 2024b)	7B	Language, Audio	Comprehension
71	SALMONN-7B (Tang Vicuna-7B et al., 2023)	7B	Language, Audio (Speech)	Comprehension

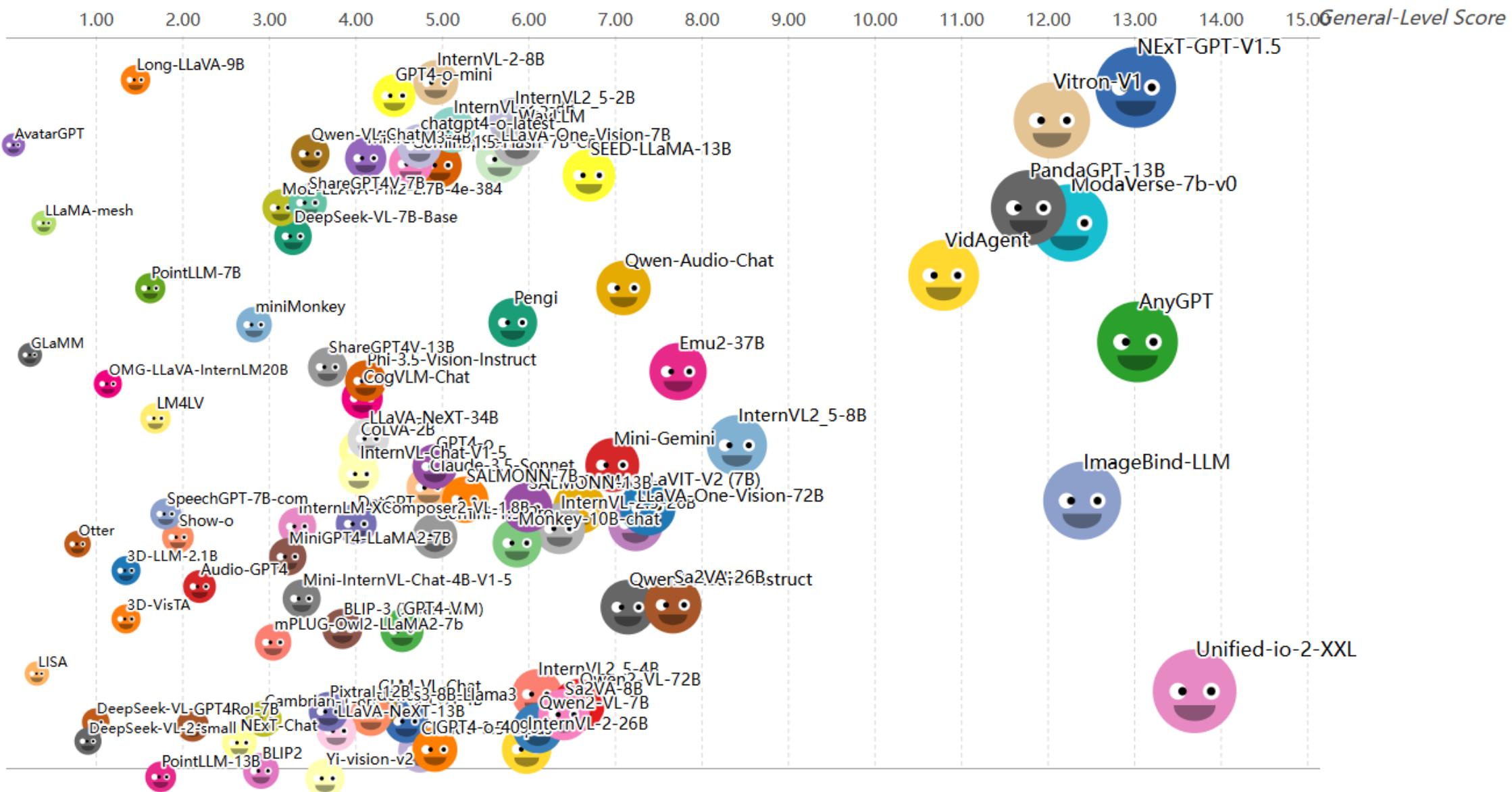
# On Path to Multimodal Generalist: General-Bench

■ What General-Bench Unveils? —— General-Level Leaderboards



## Hero at Level-2 Ranking in

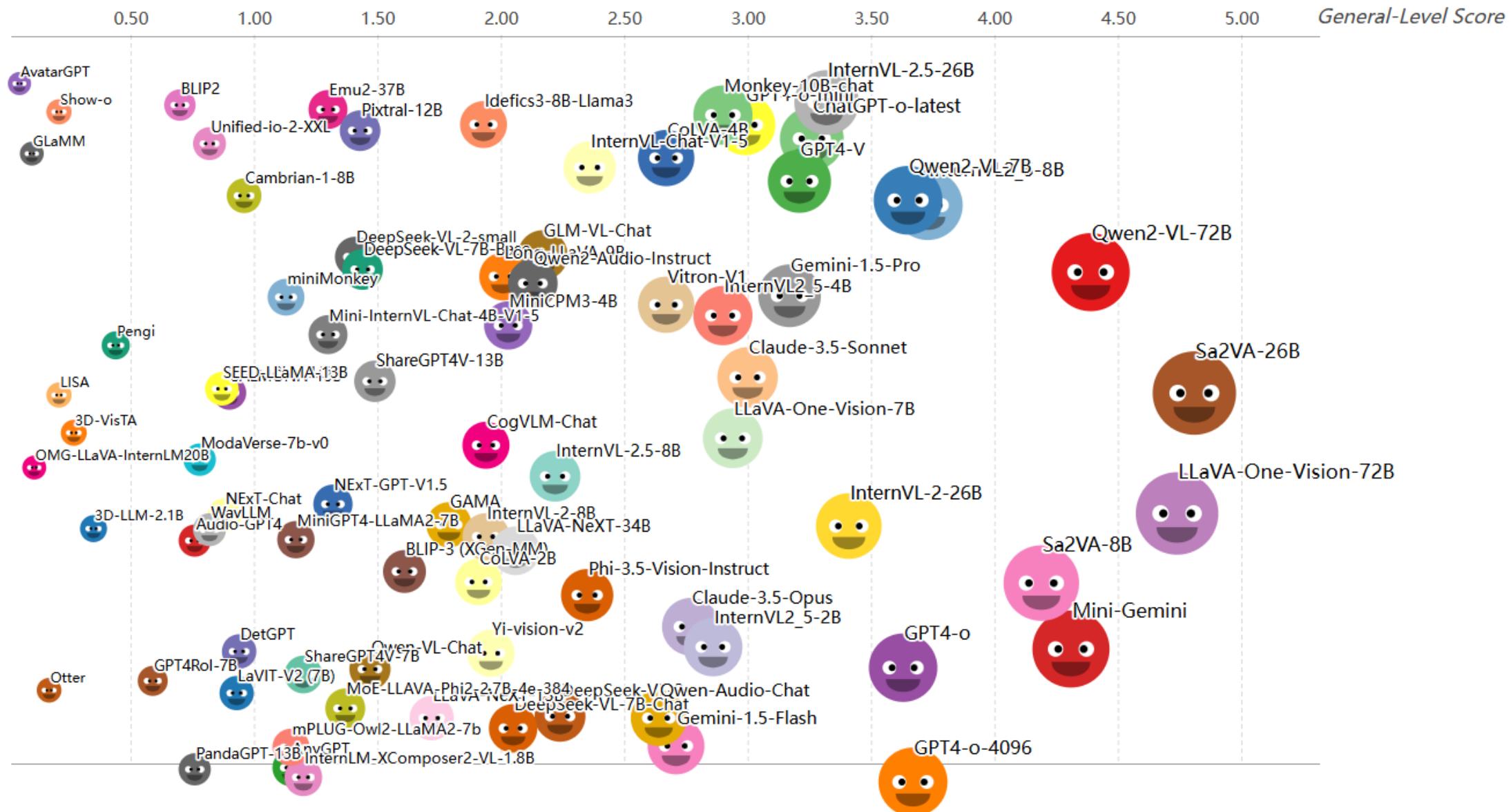
Plot View





## Hero at Level-3 Ranking in

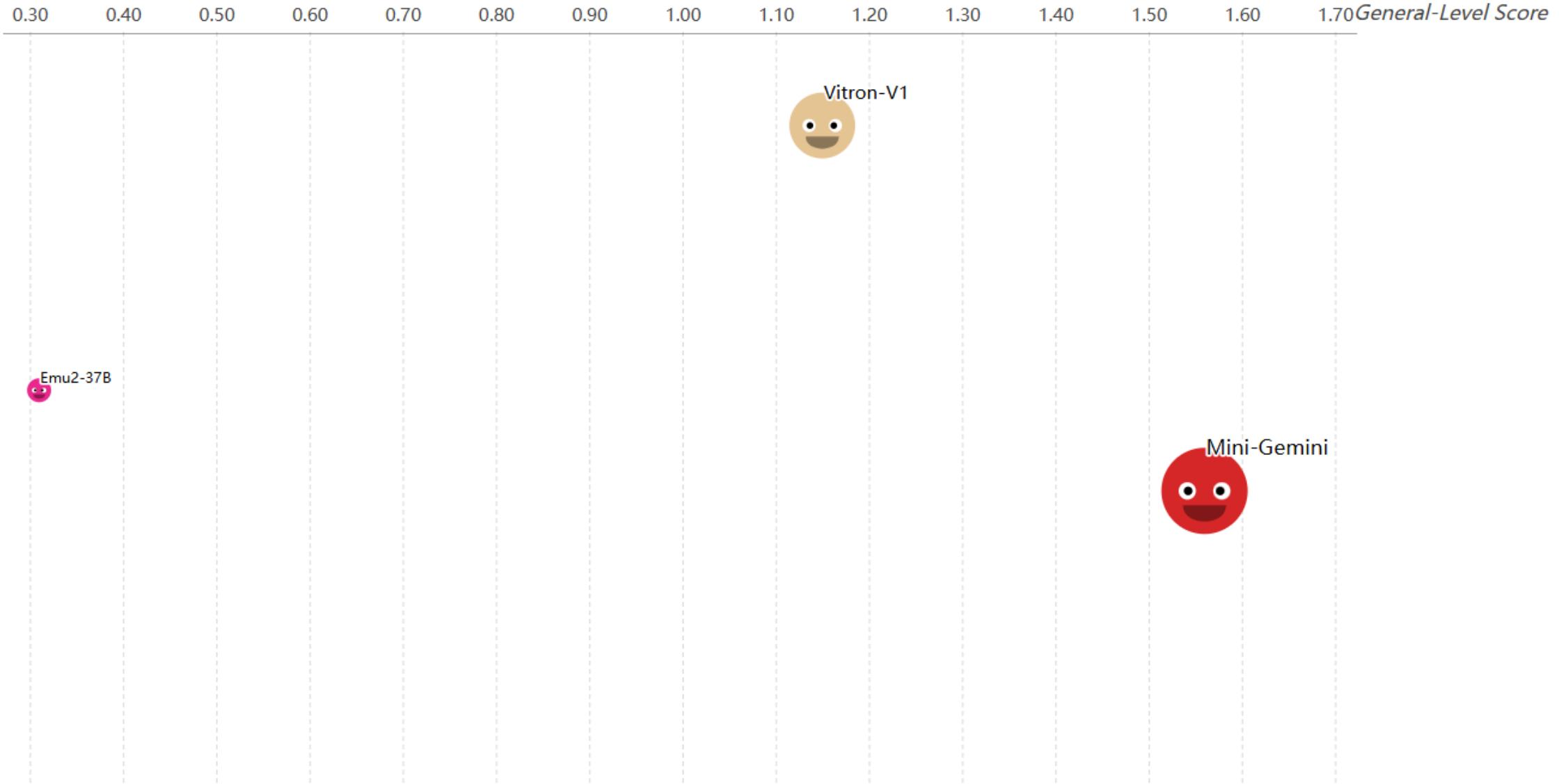
Plot View





## Hero at Level-4 Ranking in

Plot View





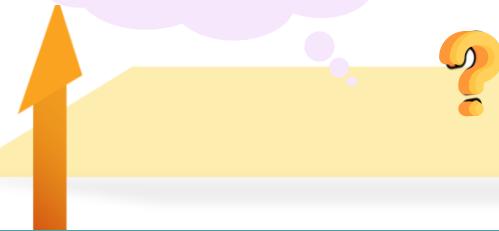
Hero at Level-5 Ranking in

Plot View

*Submit your multimodal generalist to the leaderboard!*



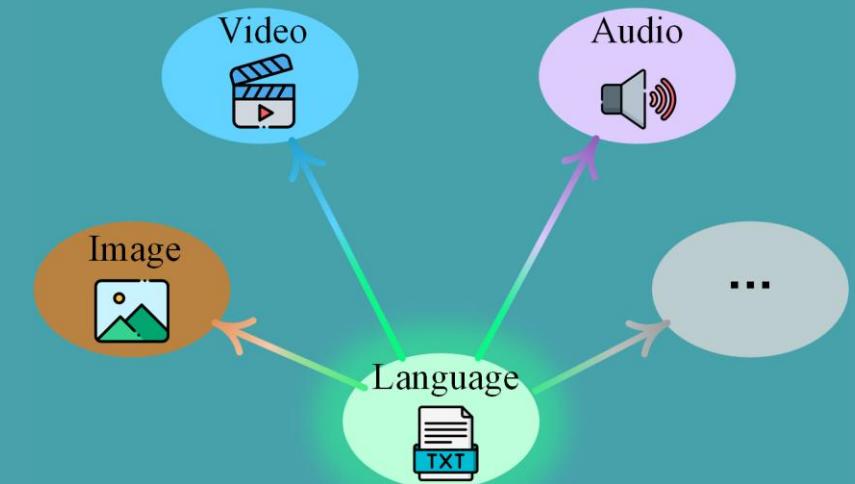
No Generalist  
found here



**Level 5:** Generalists with total synergy across  
Comprehension, Generation and Language

# General Bench

Engaging with modal Generalists (e.g. MLLMs)  
means developing agent-centric Architectures  
with integrated backbones of intelligence



No Generalist  
found here

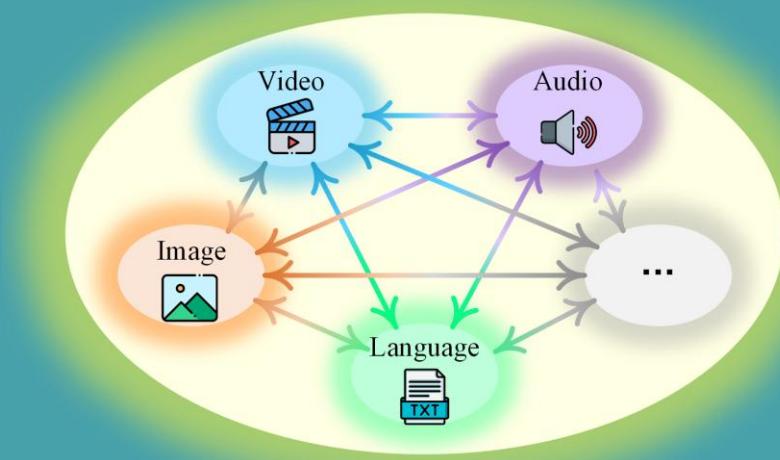


**Level 5:** Generalists with total synergy across  
Comprehension, Generation and Language

# General Bench

Toward Level-5:

Achieving Total Synergy Across  
Modalities, Tasks, Paradigms for  
Native Multimodal intelligence



# On Path to Multimodal Generalist: General-Bench

■ What General-Bench Unveils? — Quantitative Performances

Model	Image Comprehension Skill (Avg within each #I-C Group)										Task Completion		Level Score on Image		
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#Supported Task	#Win-over-Specialist	Level-2	Level-3	Level-4
	#11	#12	#13	#14	#15	#16	#17	#18	#19	#20					
	#21	#22	#23	#24	#25	#26	#27	#28	#29	#30					
	#31	#32	#33	#34	#35	#36	#37	#38	#39	#40					
SoTA Specialist	51.27	53.32	42.04	22.30	39.02	22.42	46.02	15.67	51.20	28.01	/	/	/	/	/
	36.40	65.15	43.78	58.90	63.73	87.84	58.66	72.25	34.51	95.70					
	70.00	50.40	65.97	16.60	78.00	50.48	19.90	53.55	64.10	35.90					
	39.80	57.20	54.60	63.27	29.60	87.10	98.00	39.60	36.42	82.02					
GPT-4V	69.42	58.64	39.54	0.00	66.18	36.08	61.74	0.00	16.90	20.88	177 (65.1%)	105 (38.6%)	18.16	12.85	0.00
	0.00	0.00	51.04	63.52	0.00	70.90	51.60	0.00	0.00	0.00					
	71.90	37.12	50.30	16.06	72.20	0.00	0.00	72.51	0.00	97.98					
	40.05	0.00	90.40	0.00	31.64	89.10	22.22	22.54	18.08	84.84					
GPT-4o	73.87	63.42	43.23	0.00	71.56	39.65	68.83	0.00	67.80	23.24	177 (65.1%)	112 (41.2%)	19.67	14.51	0.00
	0.00	0.00	71.23	61.54	0.00	79.38	55.25	0.00	0.00	0.00					
	81.30	39.61	48.63	15.12	93.00	0.00	0.00	77.53	0.00	98.79					
	44.30	0.00	90.40	0.00	33.47	91.20	35.56	24.80	21.12	87.88					
Gemini-1.5-Pro	72.33	23.41	39.39	0.00	62.38	34.30	66.25	0.00	59.20	23.79	177 (65.1%)	101 (37.1%)	19.67	12.66	0.00
	0.00	0.00	60.86	40.10	0.00	0.00	58.09	0.00	0.00	0.00					
	84.57	31.55	60.87	15.20	86.40	0.00	0.00	76.72	0.00	96.76					
	36.41	0.00	98.00	0.00	38.45	92.00	30.37	22.18	21.20	83.23					
Gemini-1.5-Flash	67.00	25.79	37.85	0.00	59.45	29.91	63.61	0.00	56.50	22.19	177 (65.1%)	94 (34.6%)	18.54	10.85	0.00
	0.00	0.00	55.22	32.92	0.00	0.00	54.57	0.00	0.00	0.00					
	80.63	28.97	56.91	16.57	82.60	0.00	0.00	73.57	0.00	93.42					
	28.53	0.00	96.40	0.00	29.97	90.20	27.96	20.64	18.22	80.40					
Claude-3.5-Opus	65.38	57.69	39.95	0.00	63.35	34.50	63.43	0.00	45.62	20.44	178 (65.4%)	93 (34.2%)	19.00	11.08	0.00
	0.00	0.00	60.21	58.15	0.00	66.57	51.23	0.00	0.00	0.00					
	70.39	41.19	54.75	13.87	77.80	0.00	0.00	73.04	0.00	94.65					
	38.28	0.00	91.38	0.00	0.00	87.31	23.87	28.71	25.75	84.65					
Emu2-32B	53.76	7.31	36.62	0.00	41.31	22.22	41.89	0.00	21.20	12.83	178 (65.4%)	52 (19.1%)	30.90	5.18	1.25
	0.00	0.00	39.47	12.20	0.00	0.00	44.51	5.28	0.00	0.00					
	56.33	29.43	45.46	21.45	64.20	0.00	0.00	54.59	0.00	70.34					
	17.73	0.00	72.80	0.00	0.00	73.40	31.72	14.09	18.73	56.97					
Phi-3.5-Vision-Instruct	55.32	3.44	34.16	0.00	42.61	42.04	51.34	0.00	0.00	24.35	179 (65.8%)	85 (31.3%)	16.46	9.39	0.00
	0.00	0.00	41.00	21.77	0.00	0.00	52.13	11.89	0.00	0.00					
	67.56	32.32	51.51	23.70	90.10	0.00	0.00	57.68	0.00	52.02					
	19.31	0.00	83.40	0.00	15.02	80.00	3.98	23.06	25.41	71.31					
Qwen2-VL-72B	66.98	5.74	35.64	0.00	56.58	40.50	48.79	0.00	43.18	25.32	177 (65.1%)	99 (36.4%)	19.41	12.34	0.00
	0.00	0.00	45.66	29.44	0.00	0.00	59.87	10.89	0.00	0.00					
	81.86	38.59	58.99	16.17	97.43	0.00	0.00	72.47	0.00	92.41					
	4.33	0.00	77.64	0.00	16.83	79.34	11.65	29.62	32.22	62.83					

Model	Image Generation Skill (Avg within each #I-G Group)								Task Completion		Level Score on Image		
	#1 #9	#2 #10	#3 #11	#4 #12	#5 #13	#6 #14	#7 #15	#8	#Supported Task	#Winning-Specialist	Level-2	Level-3	Level-4
SoTA Specialist	18.70 53.16	45.40 16.47	33.77 25.33	16.30 43.93	4.86 20.35	24.00 67.44	99.29 36.11	15.06	/	/	/	/	/
SEED-LLaMA-14B	127.10 30.18	0.00 87.90	37.10 14.58	7.51 175.33	127.42 0.00	98.33 51.82	0.00 62.60	0.00	35 (77.8%)	0 (0.0%)	26.81	3.49	0.00
Emu2-32B	93.52 40.51	0.00 118.55	34.85 15.43	8.53 154.26	101.80 0.00	81.95 57.09	0.00 58.17	0.00	34 (75.6%)	2 (4.4%)	30.90	5.18	1.25
AnyGPT	158.21 28.88	0.00 108.06	40.47 14.91	10.30 193.39	117.21 0.00	115.91 53.02	0.00 64.21	0.00	36 (80.0%)	0 (0.0%)	23.10	1.29	0.00
LaVIT-V2 (7B)	79.79 46.40	0.00 89.78	31.35 15.79	11.87 161.54	149.78 0.00	59.23 50.18	0.00 51.68	0.00	36 (80.0%)	0 (0.0%)	29.50	3.71	0.00
NExT-GPT-V1.5	49.71 28.19	0.00 86.45	6.00 6.53	3.91 53.42	75.71 12.45	41.20 38.98	0.00 72.72	47.30	41 (91.1%)	0 (0.0%)	18.69	3.24	0.00
Vitron-V1	19.78 37.88	0.00 24.89	21.17 17.95	7.45 31.04	32.15 0.00	35.33 48.30	86.53 58.87	23.47	42 (93.3%)	3 (6.7%)	30.13	7.65	4.59

Model	Video Comprehension Skill (Avg within each #V-C Group)												#Supported Task	#Win-over-Specialist	Level Score on Video		
	#1 #11	#2 #12	#3 #13	#4 #14	#5 #15	#6 #16	#7 #17	#8 #18	#9 #19	#10 #20	Level-2	Level-3	Level-4				
SoTA Specialist	37.43 45.84	49.64 13.92	21.31 0.14	23.06 48.06	81.85 68.96	85.43 63.62	54.53 77.02	64.83 75.08	40.65 37.20	30.80 44.00	/	/	/	/	/	/	/
InternVL-2.5-8B	33.15 0.00	27.54 0.00	14.51 0.00	18.83 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 4.85	55 (43.7%)	5 (4.0%)	5.76	1.24	0.00		
InternVL-2.5-26B	37.03 0.00	32.01 0.00	18.71 0.00	21.57 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 5.30	55 (43.7%)	26 (20.6%)	6.70	3.76	0.00		
Qwen2-VL-72B	38.22 0.00	32.32 0.00	19.35 0.00	22.70 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 5.70	55 (43.7%)	22 (17.5%)	6.89	5.22	0.00		
DeepSeek-VL-2	21.50 0.00	18.90 0.00	12.10 0.00	12.10 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 3.20	55 (43.7%)	5 (4.0%)	3.98	0.64	0.00		
LLaVA-One-Vision-72B	31.20 0.00	31.30 0.00	19.10 0.00	10.60 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 1.70	56 (44.4%)	21 (16.7%)	5.83	3.75	0.00		
Sa2VA-8B	33.19 0.00	25.11 60.28	16.75 0.00	8.67 0.00	0.00 19.85	0.00 37.83	0.00 46.36	71.03 42.58	50.95 48.02	0.00 1.48	91 (72.2%)	32 (25.4%)	8.31	4.38	0.00		
Sa2VA-26B	35.33 0.00	26.33 0.00	17.58 0.00	10.39 0.00	0.00 28.41	0.00 38.91	0.00 47.10	0.00 43.12	0.00 48.42	0.00 1.70	81 (64.3%)	27 (21.4%)	8.81	4.58	0.00		
CoLVA-4B	32.68 0.00	26.45 0.00	13.55 0.00	17.62 0.00	0.00 45.81	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 4.23	63 (50.0%)	8 (6.3%)	4.78	1.24	0.00		
InternVL-2-8B	32.69 0.00	27.09 0.00	14.24 0.00	17.61 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 4.85	55 (43.7%)	0 (0.0%)	5.64	0.46	0.00		
Long-LLaVA-9B	36.14 0.00	26.25 0.00	15.89 0.00	15.53 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 0.00	0.00 4.20	54 (42.9%)	22 (17.5%)	5.84	3.81	0.00		

Model	Video Generation Skill (Avg within each #V-G Group)						Task Completion		Level Score on Video		
	#1	#2	#3	#4	#5	#6	#Task-Suprt	#Win-Spclst	Level-2	Level-3	Level-4
<b>SoTA Specialist</b>	69.09	55.79	88.94	62.90	37.79	51.46	/	/	/	/	/
VidAgent	52.42	47.73	88.84	63.61	0.00	0.00	30 (65.2%)	0 (0.0%)	25.00	0.00	0.00
LM4LV	0.00	0.00	0.00	0.00	25.90	5.93	8 (17.4%)	0 (0.0%)	6.74	0.00	0.00
NExT-GPT-V1.5	26.78	6.72	130.22	16.03	0.08	0.06	40 (87.0%)	0 (0.0%)	8.34	0.71	0.00
Vitron-V1	36.74	19.32	116.31	25.09	0.08	0.06	40 (87.0%)	0 (0.0%)	18.72	3.04	0.00

Model	Audio Comprehension Skill (Avg within each #A-C Group)									Task Completion		Level Score on Audio		
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#Task-Suprt	#Win-Spclst	Level-2	Level-3	Level-4
SoTA Specialist	87.27	79.08	70.62	79.00	71.87	62.90	58.70	77.90	78.07	/	/	/	/	/
Qwen-Audio-Chat	56.93	68.77	76.80	37.70	47.71	19.79	56.44	85.15	78.50	30 (100.0%)	6 (25.0%)	28.39	10.57	0.00
Qwen2-Audio-Instru	72.65	74.80	61.40	36.80	45.82	13.45	61.68	78.95	67.99	24 (100.0%)	6 (25.0%)	28.61	8.53	0.00
GAMA	57.00	64.20	68.00	53.20	18.43	26.95	48.85	85.55	61.80	23 (95.8%)	4 (16.7%)	26.35	7.15	0.00
Pengi	52.88	60.07	56.70	36.78	19.77	19.55	42.95	77.40	61.17	23 (95.8%)	1 (4.2%)	23.29	1.74	0.00
SALMONN-13B	67.89	56.33	67.80	29.45	24.67	19.36	43.95	76.55	56.67	23 (95.8%)	2 (8.3%)	23.95	3.61	0.00
WavLLM	64.45	41.07	71.20	30.08	31.30	26.55	45.75	61.40	64.57	24 (100.0%)	2 (8.3%)	23.49	3.28	0.00
NExT-GPT-V1.5	43.23	29.13	65.80	26.70	14.47	25.65	47.95	70.20	69.43	24 (100.0%)	0 (0.0%)	25.05	1.34	0.00
PandaGPT (13B)	41.80	20.23	45.20	20.98	8.47	20.50	42.25	54.80	65.83	24 (100.0%)	0 (0.0%)	16.98	0.65	0.00
ModaVerse-7b-v0	34.10	16.37	32.80	15.20	6.60	8.90	35.05	49.20	60.13	23 (95.8%)	0 (0.0%)	26.10	1.14	0.00
Any-GPT	44.50	32.13	63.40	48.08	16.27	36.40	52.65	67.95	44.63	23 (95.8%)	1 (4.2%)	29.06	3.29	0.00
Unified-io-2-XXL	30.15	27.60	56.10	28.58	15.47	38.35	38.70	63.50	60.63	24 (100.0%)	0 (0.0%)	25.63	1.01	0.00

Model	Audio Generation Skill (Avg within each #A-G Group)											Task Completion		Level Score on Audio		
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#Task-Suprt	#Win-Spclst	Level-2	Level-3	Level-4
SoTA Specialist	31.50	3.82	3.64	4.68	41.54	51.40	11.52	6.80	8.33	22.88	20.33	/	/	/	/	/
Unified-io-2-XXL	18.36	2.03	5.11	40.52	16.41	24.31	16.97	86.23	94.52	0.25	2.24	17 (85.0%)	0 (0.0%)	25.63	1.01	0.00
Any-GPT	23.50	3.24	4.57	33.58	13.38	14.05	27.49	45.36	83.89	0.25	2.47	17 (85.0%)	1 (5.0%)	29.06	3.29	0.00
NExT-GPT-V1.5	13.60	1.15	4.07	50.51	34.51	1.35	12.36	96.70	99.23	0.25	7.77	17 (85.0%)	1 (5.0%)	25.05	1.34	0.00
AudioGPT	0.50	1.32	4.61	23.10	29.48	0.00	0.00	46.30	79.98	0.25	0.00	13 (65.0%)	1 (5.0%)	8.80	3.02	0.00
SpeechGPT	0.10	2.79	4.44	32.35	0.00	0.00	0.00	30.24	85.54	0.25	0.00	11 (55.0%)	0 (0.0%)	7.22	0.00	0.00
ModaVerse	12.30	1.15	4.29	50.50	28.99	1.05	16.45	100.00	100.00	0.25	4.17	17 (85.0%)	2 (10.0%)	26.10	1.14	0.00

Model	3D Comprehension Skill (Avg within each #D-C Group)													Task Completion		Level Score on 3D		
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#Task-Supprt	#Win-Spclst	Level-2	Level-3	Level-4
SoTA Specialist	96.24	98.35	97.78	78.50	70.02	81.20	55.00	88.28	75.20	9.96	68.52	47.14	22.30	/	/	/	/	/
3D-VisTA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	46.37	0.00	7 (23.3%)	2 (6.7%)	5.41	1.07	0.00
PointLLM-7B	46.16	7.50	72.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8 (26.7%)	0 (0.0%)	6.53	0.00	0.00
PointLLM-13B	48.79	10.00	78.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	9 (30.0%)	0 (0.0%)	7.00	0.00	0.00
3D-LLM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	46.34	0.00	7 (23.3%)	1 (3.3%)	5.41	1.38	0.00
AvatarGPT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	12.70	1 (3.3%)	0 (0.0%)	0.21	0.21	0.00

Model	3D Generation Skill (Avg within each #D-G Group)									Task Completion		Level Score on 3D		
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#Task-Suprt	#Win-Spclst	Level-2	Level-3	Level-4
<b>SoTA Specialist</b>	0.22	7.12E-5	24.42	25.69	78.06	83.64	6540.02	6540.02	0.23	/	/	/	/	/
MotionGPT-T5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.51	1 (4.5%)	0 (0.0%)	0.00	0.00	0.00
MotionGPT-LLaMA	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.60	1 (4.5%)	0 (0.0%)	0.00	0.00	0.00
LLaMA-Mesh	0.00	0.00	0.00	17.55	0.00	0.00	0.00	0.00	0.00	1 (4.5%)	0 (0.0%)	1.60	0.00	0.00

Model	Language Skill (Avg within each #L Group)												Task Completion		Level Score Level-5
	#1 #12	#2 #13	#3 #14	#4 #15	#5 #16	#6 #17	#7 #18	#8 #19	#9 #20	#10 #21	#11 #22	#Supported Task	#Win-over-Specialist		
SoTA Specialist	62.62 86.95	86.23 0.31	76.78 94.40	71.00 91.41	58.02 86.05	62.80 86.03	75.11 84.72	77.84 83.67	79.70 58.61	71.91 77.73	28.27 92.38	/	/	/	
Meta-Llama-3.1-8B-Instruct	39.75 45.34	56.76 7.95	54.21 76.40	60.52 51.80	20.01 65.90	37.17 41.10	36.23 24.49	29.12 30.70	53.23 8.08	44.49 32.40	14.80 54.35	113 (98.3%)	0 (0.0%)	0.00	
ChatGLM-6b	28.97 42.84	33.24 10.91	37.24 41.80	46.10 45.81	19.39 24.50	27.84 16.45	18.85 0.12	35.88 8.41	27.85 2.70	38.51 23.80	13.93 45.37	96 (83.5%)	0 (0.0%)	0.00	
Vicuna-7b-v1.5	24.78 43.98	11.18 11.41	33.44 0.00	41.19 0.00	4.51 0.00	13.25 0.96	19.94 0.07	35.27 0.47	54.81 0.00	40.58 23.13	5.06 15.40	72 (62.6%)	0 (0.0%)	0.00	
Falcon3-7B-Instruct	36.79 48.15	58.36 5.15	49.91 88.80	56.80 85.89	21.38 45.65	37.12 42.86	32.03 27.64	42.11 34.22	55.79 11.19	42.07 39.80	15.56 58.75	112 (97.4%)	0 (0.0%)	0.00	
Minstral-8B-Instruct-2410	41.74 23.39	54.21 11.08	49.53 84.80	51.92 72.60	39.32 56.70	40.49 37.14	13.00 6.28	22.86 31.38	56.87 9.37	43.46 25.53	13.73 40.44	112 (97.4%)	0 (0.0%)	0.00	
Yi-Lightning	41.73 52.68	60.54 5.37	55.39 72.60	60.51 56.24	20.53 64.75	39.83 43.59	22.45 28.27	43.57 42.84	62.52 25.34	42.03 29.27	15.29 60.49	113 (98.3%)	0 (0.0%)	0.00	
GPT-4V	27.55 44.56	62.40 3.16	34.57 86.20	32.55 83.23	14.43 65.10	27.84 53.82	27.79 54.14	36.07 45.45	65.36 33.86	42.11 26.46	13.96 24.24	113 (98.3%)	0 (0.0%)	0.00	
GPT-4o	26.25 46.41	62.57 2.58	33.98 85.40	31.50 86.30	16.20 67.50	26.26 56.10	27.14 57.42	36.64 46.97	66.86 39.52	42.69 32.07	14.49 28.50	113 (98.3%)	0 (0.0%)	0.00	
Emu2-32B	32.91 50.15	45.43 9.53	47.04 57.54	39.56 48.78	27.74 43.76	31.24 36.67	39.04 19.84	41.72 24.01	45.48 13.78	46.35 26.47	13.05 31.72	113 (98.3%)	0 (0.0%)	0.00	
DeepSeek-VL-7B	29.97 79.68	44.39 83.00	55.55 62.20	20.36 50.60	40.49 62.30	57.93 46.87	49.85 4.12	48.73 28.46	27.03 8.11	56.76 31.80	10.37 40.97	114 (99.1%)	0 (0.0%)	0.00	
Qwen2-VL-7B	23.91 37.23	27.51 6.48	37.68 64.00	46.40 37.00	17.84 3.50	20.96 20.50	36.25 0.24	29.29 4.87	35.42 6.00	35.58 20.87	12.62 21.79	94 (81.7%)	0 (0.0%)	0.00	
LLaVA-One-Vision-72B	50.44 43.81	41.98 3.55	54.55 84.80	61.13 10.43	29.87 59.35	56.99 34.91	35.24 42.94	43.27 28.63	55.23 19.26	41.49 52.20	17.73 71.95	110 (95.7%)	0 (0.0%)	0.00	
InternVL2.5-8B	42.93 71.96	47.76 75.20	59.54 55.40	31.17 68.40	42.86 56.75	32.72 55.60	50.98 22.12	43.02 36.48	30.85 9.80	51.23 32.13	9.07 53.67	114 (99.1%)	0 (0.0%)	0.00	

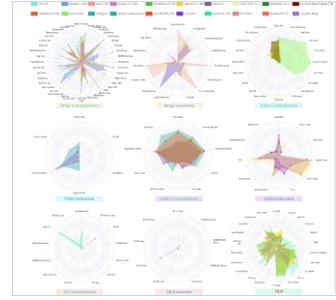
# On Path to Multimodal Generalist: General-Bench

## ■ What General-Bench Unveils? —— Quantitative Performances

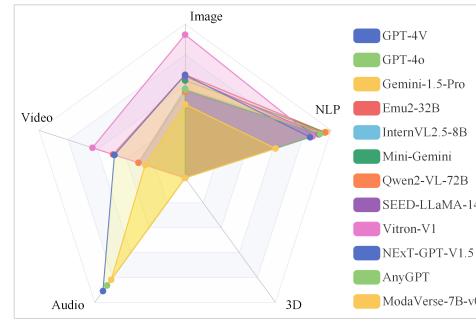
- *Observation-1: Lack of task support.*
- *Observation-2: Few generalists surpass the SoTA specialist.*
- *Observation-3: Focus more on content comprehension than supporting generation.*
- *Observation-4: Insufficient support for all modalities.*
- *Observation-5: Multimodality does NOT really enhance language.*

# On Path to Multimodal Generalist: General-Bench

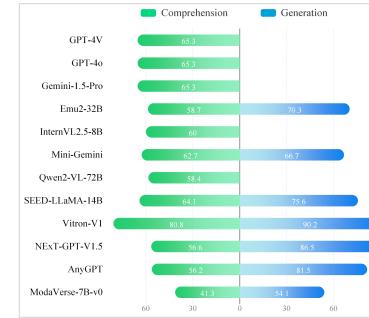
## ■ What General-Bench Unveils? —— In-depth Analysis



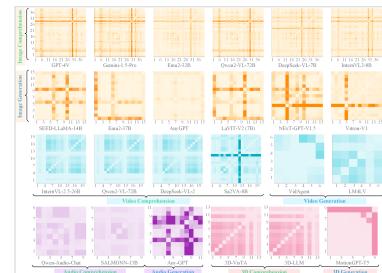
Task Supporting



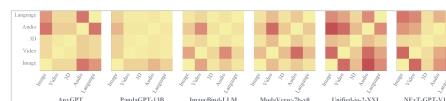
Modality Supporting



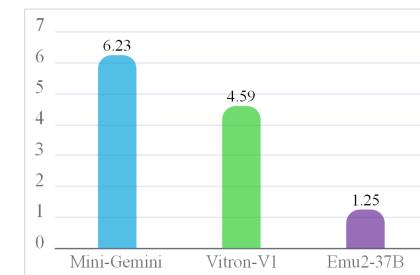
Capabilities on  
Comprehension vs. Generation



Synergy Across Skills



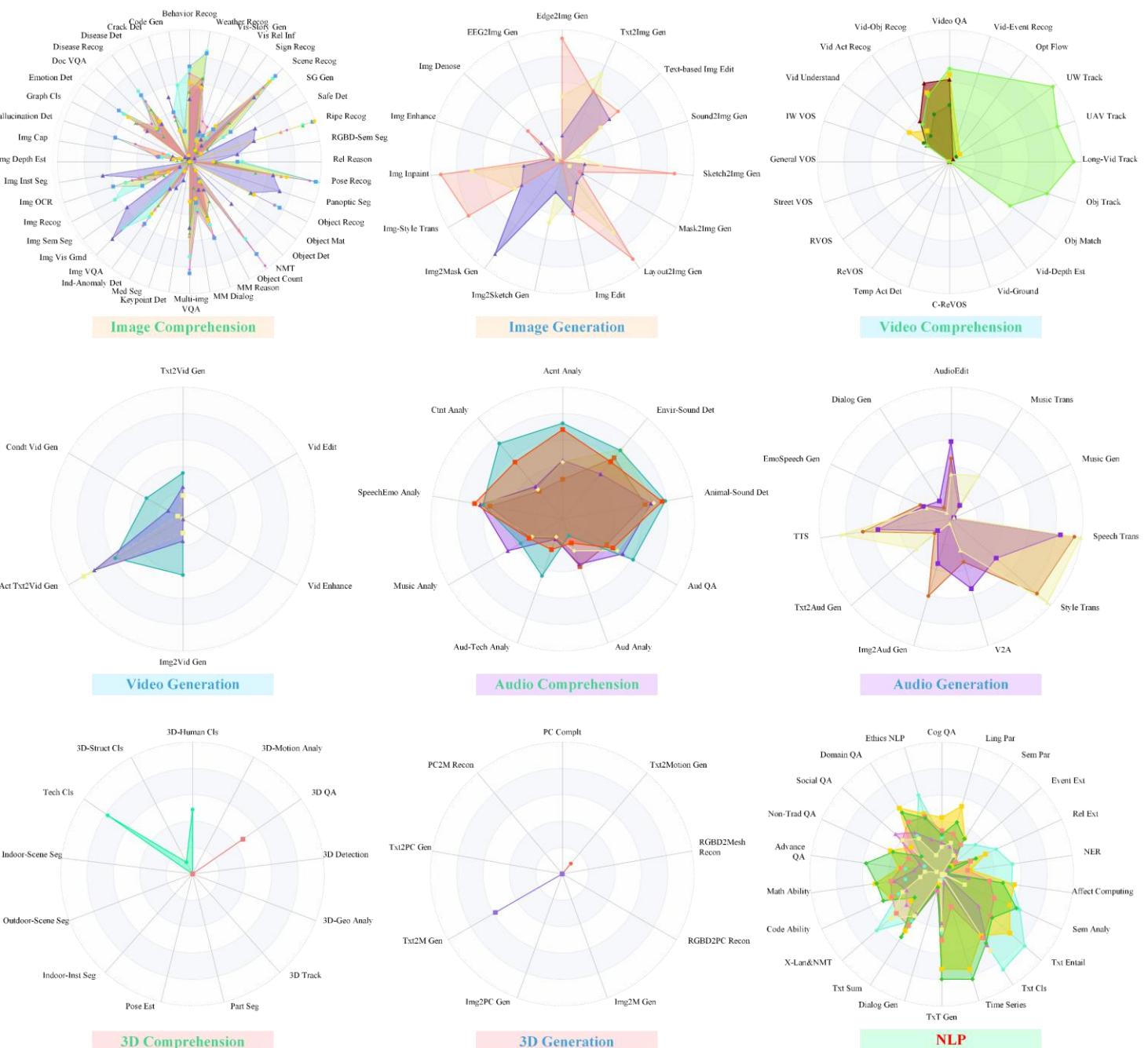
Synergy Across Modalities



Synergy Across  
Comprehension and Generation

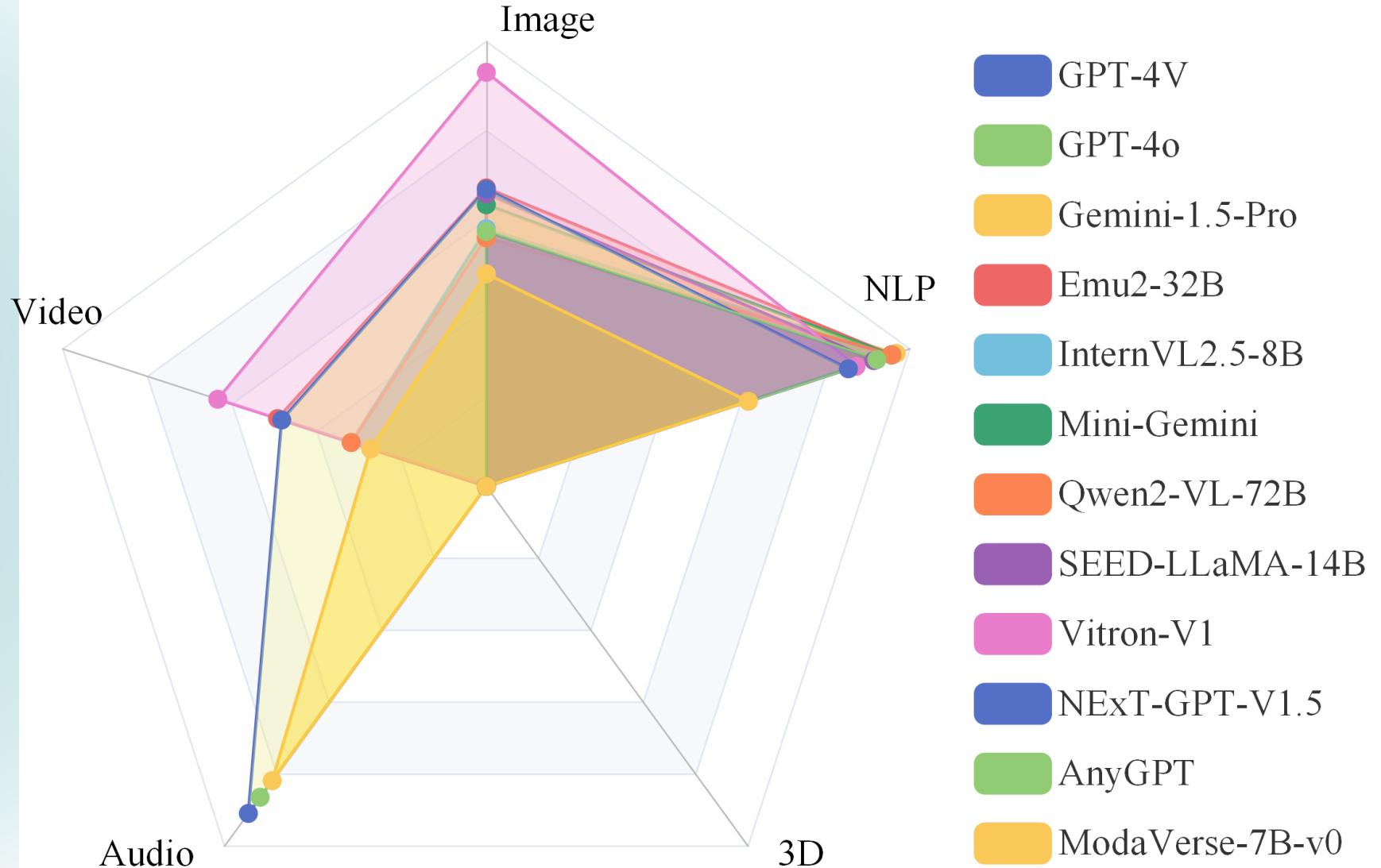
# Task Supporting

Current MLLMs generally exhibit limited task support, with a strong bias toward simpler comprehension tasks and significant challenges in covering diverse and complex generation skills across modalities.



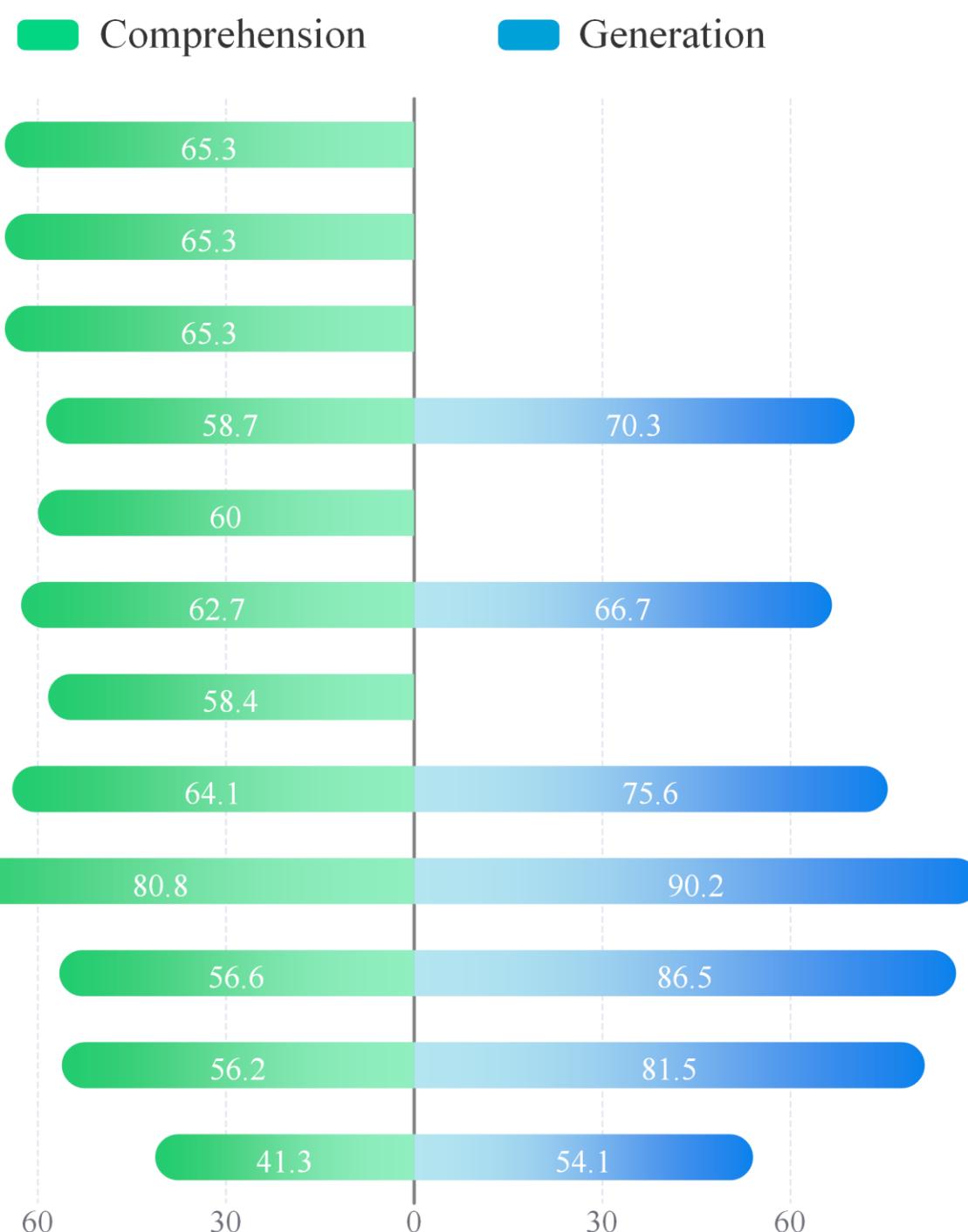
# Modality Supporting

Most MLLMs support only a Single Non-language Modality, while only a few-like NExT-GPT-1.5 or Unified-IO-2 demonstrate truly broad, all-modality capabilities.



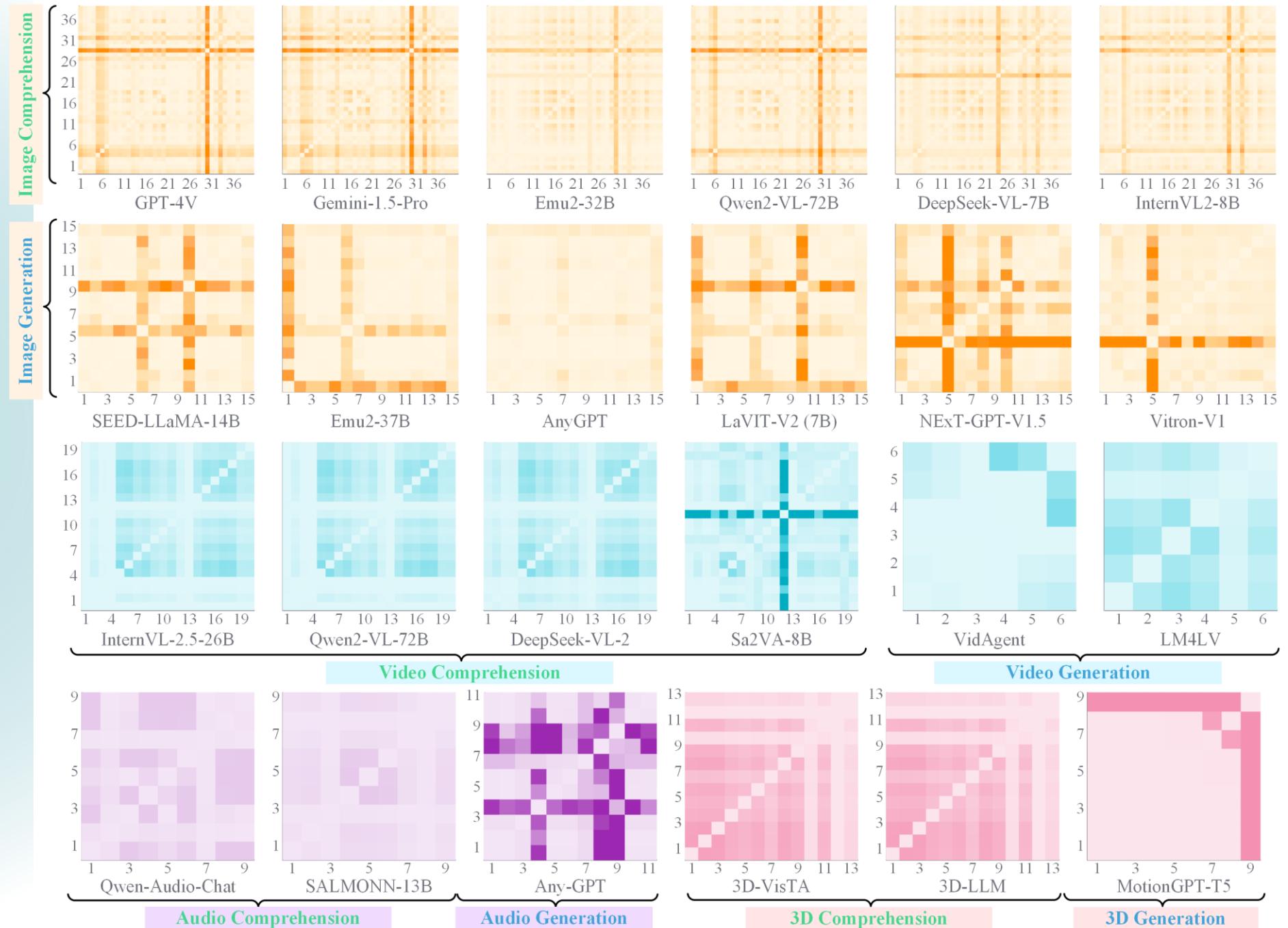
# Comprehension vs. Generation

Most MLLMs are Stronger at Comprehension than generation, due to the greater complexity and training cost of generation; only a few models, like Vitron-V1, demonstrate balanced capabilities across both paradigms.



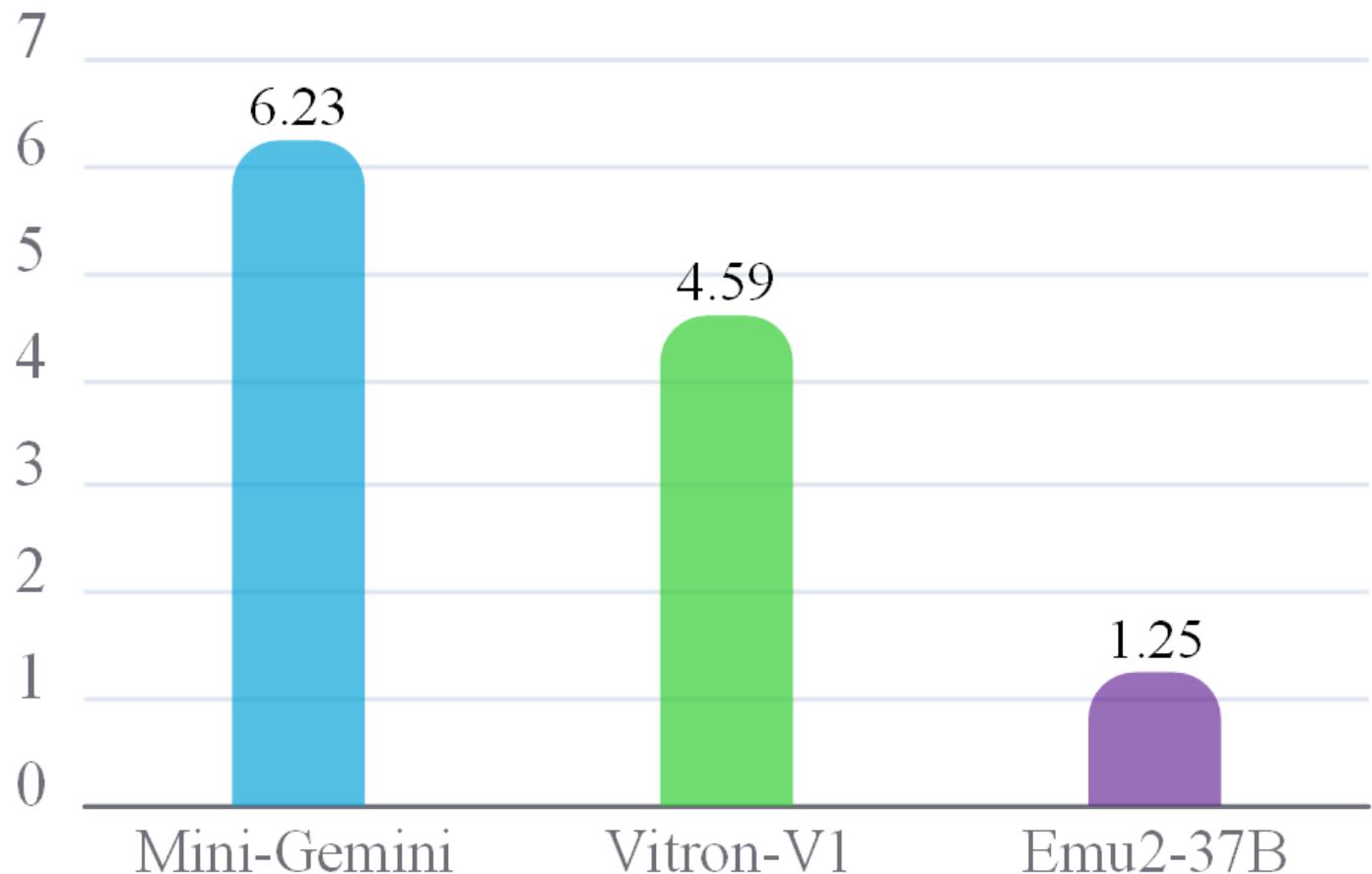
# Synergy Across Skills

Synergy effects in MLLMs are uneven across skills, with stronger synergy observed in generation tasks and among closely related skills, particularly in models with higher Level3 scores.



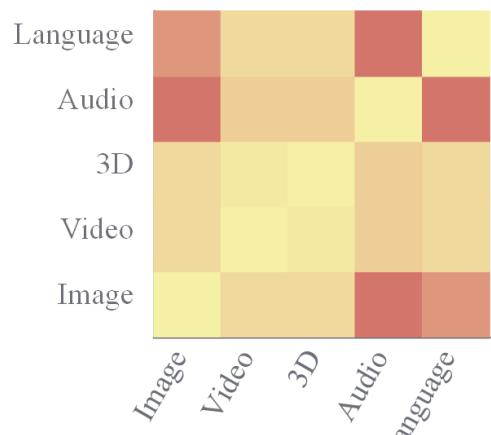
# Synergy Across Comprehension & Generation

Only a few MLLMs exhibit synergy between comprehension and generation, with Mini-Gemini showing the strongest effect-mainly within the image modality.

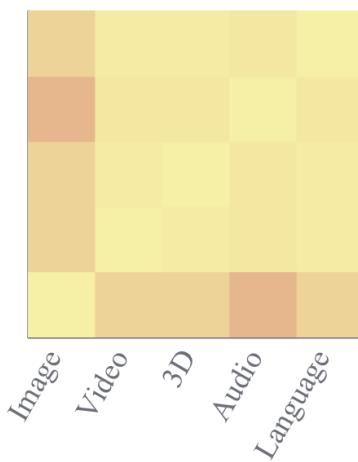


# Synergy Across Modalities

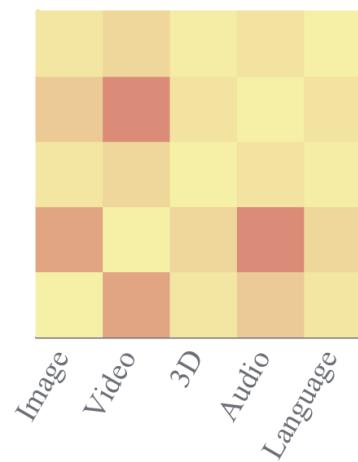
Synergy is strongest between image and video modalities, while language shows only one-way synergy toward other modalities; no modalities really-significantly enhance language tasks- highlighting a key limitation of current MLLMs.



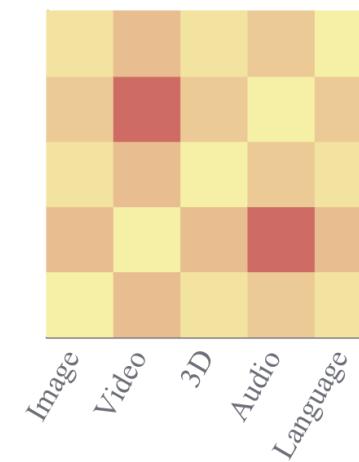
AnyGPT



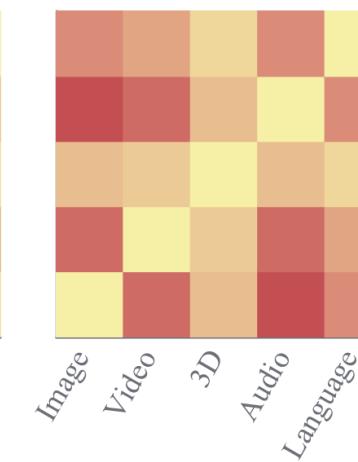
PandaGPT-13B



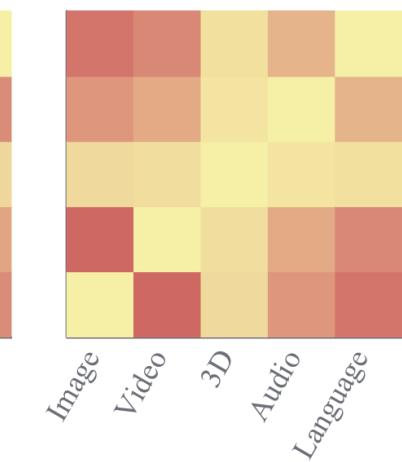
ImageBind-LLM



ModaVerse-7b-v0



Unified-io-2-XXL



NEiT-GPT-V1.5

# On Path to Multimodal Generalist: General-Bench

## ■ How to use General-Bench?

### General-Level Open Set



With inputs and labels of samples all publicly open, for open-world use (e.g. academic experiment).

### General-Level Close Set



With only sample inputs available, which participants can use for ranking in our leaderboard.

# On Path to Multimodal Generalist: General-Bench

- How to participate the Leaderboard?

# General Bench

## Scope-A: Full-spectrum Hero

Difficulty: ★★★★★★

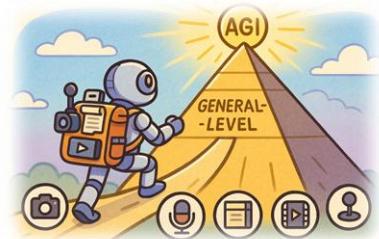
Number of leaderboards: ★

Details:

- ✓ Covers all General-Level tasks and modalities.
- ✓ Most challenging track; requires high model capacity and resource commitment.

Highlights:

- ✓ Evaluates holistic generalization and cross-modal synergy.
- ✓ Suitable for near-AGI or foundation-level multimodal generalists.



## Four-scoped leaderboard



# General Bench

Scope-A: Full-spectrum Hero

Scope-B: Modality-specific Unified Hero

Difficulty: ★★★★

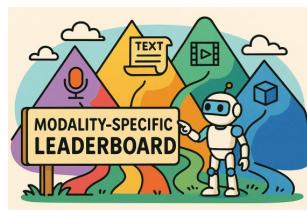
Number of leaderboards: ★★★

Details:

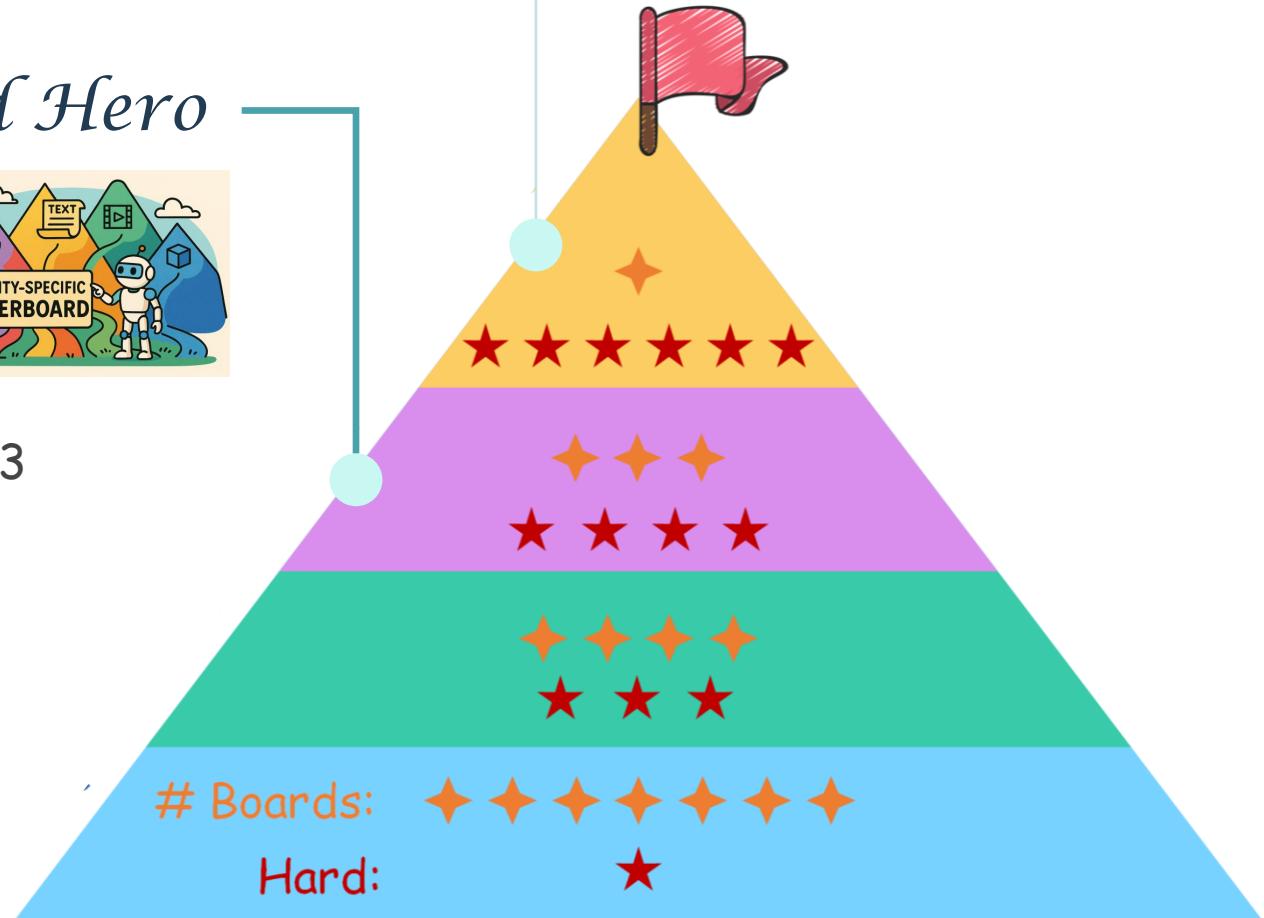
- ✓ 7 separate leaderboards (4 single modality + 3 combined modality).
- ✓ Focuses on mastering diverse tasks within a single modality.

Highlights:

- ✓ Measures within-modality generalization.
- ✓ Suited for intermediate-level models with cross-task transferability.



# Four-scoped leaderboard



# General Bench

Scope-A: Full-spectrum Hero

Scope-B: Modality-specific Unified Hero

Scope-C: Comprehension/Generation Hero

Difficulty: ★★★

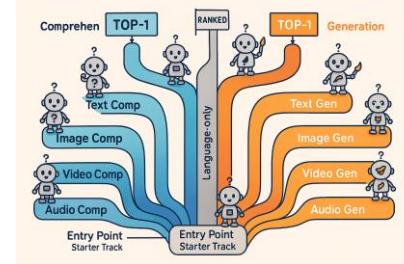
Number of leaderboards: ★★★★

Details:

- ✓ 8 leaderboards:  $2 \times 4$  for multimodal comprehension/generation under different modalities.
- ✓ Supports entry-level model evaluation or teams with limited resources.

Highlights:

- ✓ Assesses task-type specialization: understanding or generation.
- ✓ Reflects generalization across task types.



# Four-scoped leaderboard



# General Bench

*Scope-A: Full-spectrum Hero*

*Scope-B: Modality-specific Unified Hero*

*Scope-C: Comprehension/Generation Hero*

*Scope-D: Skill-specific Hero*

 **Difficulty:** ★ ★ ★



 **Number of leaderboards:** ★ ★ ★ ★ ★ ★

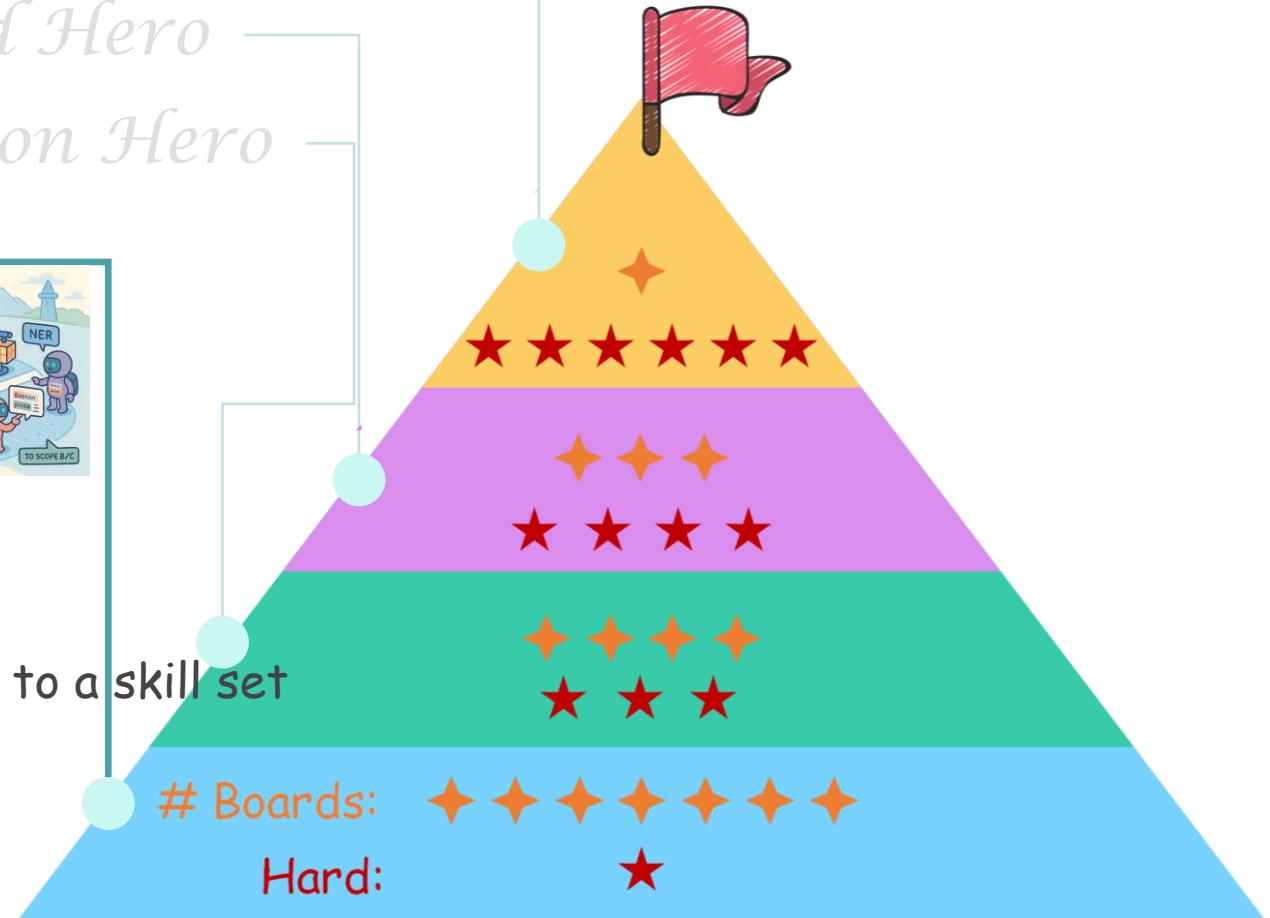
 **Details:**

- ✓ Large number of sub-leaderboards, each scoped to a skill set
- ✓ Easiest to participate; lowest cost.

 **Highlights:**

- ✓ Evaluates fine-grained skill performance.
- ✓ Helps identify model strengths and specialization areas.

# Four-scoped leaderboard



# General Bench

## Four-scoped leaderboard

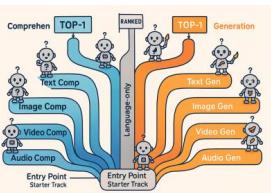
Scope-A: Full-spectrum Hero



Scope-B: Modality-specific Unified Hero



Scope-C: Comprehension/Generation Hero



Scope-D: Skill-specific Hero



# On Path to Multimodal Generalist: General-Bench

## ■ Model Diagnostics

### Model Diagnostics



In this page, we present a comprehensive diagnostic analysis of multimodal generalist models that are included in our General-Bench 🏆 leaderboard. Built upon an exceptionally large-scale, multi-dimensional 📊 evaluation benchmark, General-Bench enables broad and in-depth assessment across diverse modalities, tasks, and paradigms 🔍.

While leaderboard rankings 🏆 offer a high-level view of overall performance, they often mask the nuanced strengths and weaknesses exhibited by each model across different dimensions. To bridge this gap, our Model Diagnostics aims to unpack these subtleties—identifying where each model excels 💪 and where it struggles ⚠️ across modalities, capabilities, and task types.

We believe such fine-grained diagnostics are essential for guiding the future development of stronger and more robust multimodal models 🚀. We believe this effort plays a critical role in advancing the field toward truly universal multimodal generalists—and ultimately, Artificial General Intelligence (AGI) 🤖.

# Submission and Contribution

Welcome to submit your Multimodal Generalist to General-Level leaderboard, or contribute your dataset to General-Bench to maximize the visibility.

## 💡 Guidelines for Submitting Model to Leaderboard

- Please first download the corresponding [close-set data](#) for your selected leaderboard (based on its unique identifier).
- You are also encouraged to download the [open-set data](#) for model debugging and development purposes.
- Based on the close-set data, conduct inference using your model, and save the output results into a single [\[model\]-\[leaderboard-id\].zip](#) file.
- In the following submission process, in addition to uploading the evaluation result file, please fill in the following [required information fields](#) to help us properly process your submission on the backend.
- Please refer to the [documentation](#) for more detailed instructions.
- To ensure fairness of the evaluations, General-Level have implemented the following restrictions:
  1. A maximum of submitting 2 results past 24 hours (excluding exceptions);
  2. A maximum of submitting 4 results past 7 days (excluding exceptions);
  3. Before the evaluation of the latest submission finished (evaluation results / error logs generated), users are not allowed to start a new submission.

[Submit to Leaderboard](#)

[Contribute to General-Bench](#)



Click or drag file here to upload an evaluation result file (.zip)

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# Submission and Contribution

Welcome to submit your Multimodal Generalist to General-Level leaderboard, or contribute your dataset to General-Bench to maximize the visibility.

## 💡 Guidelines for Contributing Data to General-Bench

- **General-Bench is open and non-commercial.** A key feature of this project for evaluating multimodal generalist models is the need for broad coverage—including diverse modalities, tasks, paradigms, domains, and capabilities. We greatly appreciate your contributions of new data and tasks 😊, which will also benefit the whole community. Once your data is included in General-Bench, your contribution will be **acknowledged on the website homepage** to increase its visibility, and it will also be **cited** in our technical paper.
- We especially welcome datasets that feature 1) **highly challenging** tasks, or (2) task definitions involving **multiple modalities** simultaneously.
- Please fill in the required information fields. Refer to the [documentation](#) for detailed instructions. This includes:
  1. The name of the dataset (or task), the number of instances (including Open/Close set split);
  2. The task's modality, paradigm, domain, and targeted evaluation capabilities;
  3. A description of the evaluation methodology used for the task.
- Please submit your data as a single [\[data-name\].zip](#) file, together with an evaluation manual (might be `txt`, `doc`, `md` etc., all zipped in [\[data-name\]-\[eval-instruction\].zip](#)).

### Submit to Leaderboard



Click or drag file to this area to upload the dataset file (.zip)

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### Contribute to General-Bench



Click or drag file to this area to upload the data instruction file (.zip)

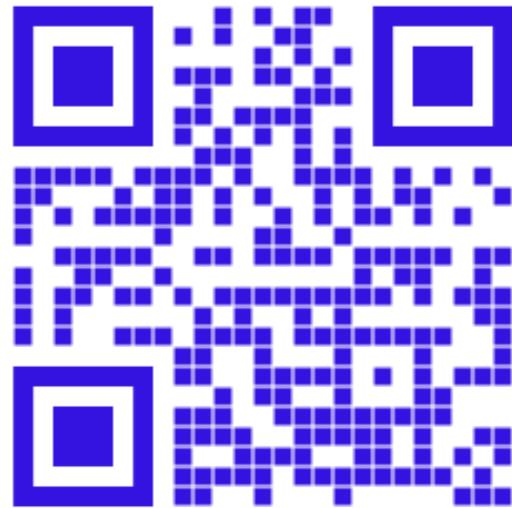
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# Content

- 1 General-Level**
- 2 General-Bench**
- 3 What To Do Next**

# On Path to Multimodal Generalist: What's Next

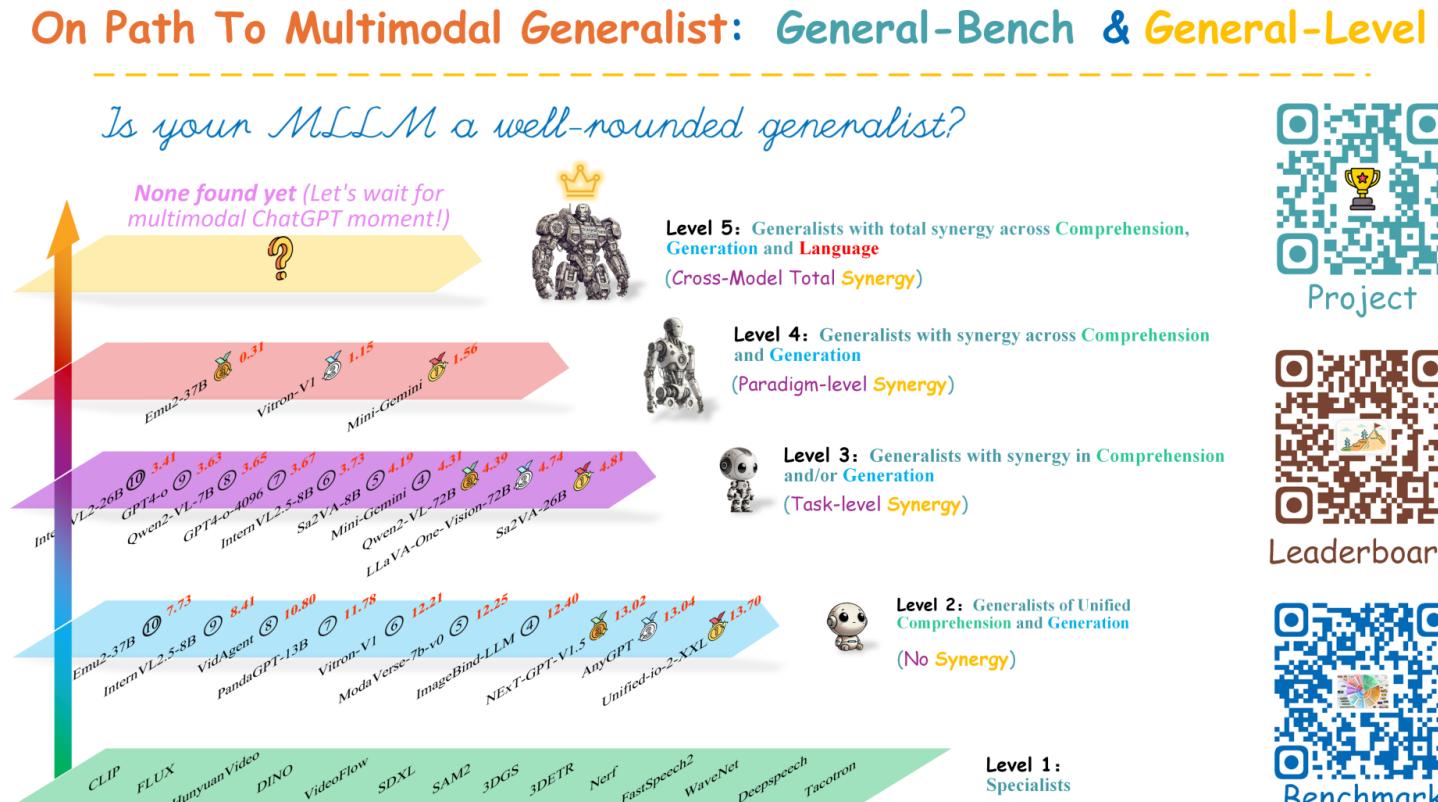
## Overview



Project: <https://generalist.top/>

Paper: <https://arxiv.org/abs/2505.04620>

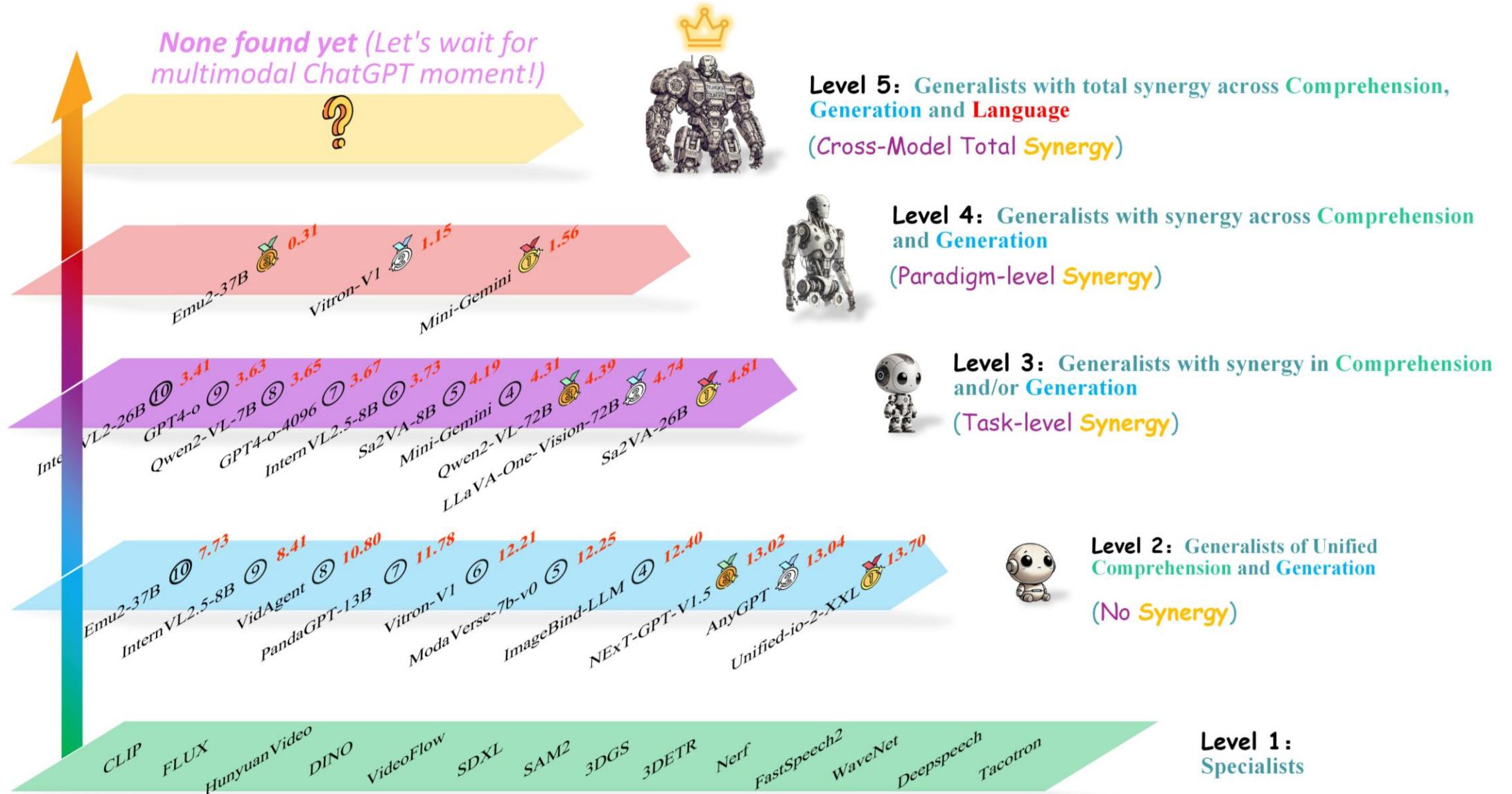
Benchmark: <https://generalist.top/leaderboard>



# On Path to Multimodal Generalist: What's Next

- Improving from **Generalist Model** perspective

# On Path to Multimodal Generalist: What's Next



# On Path to Multimodal Generalist: What's Next

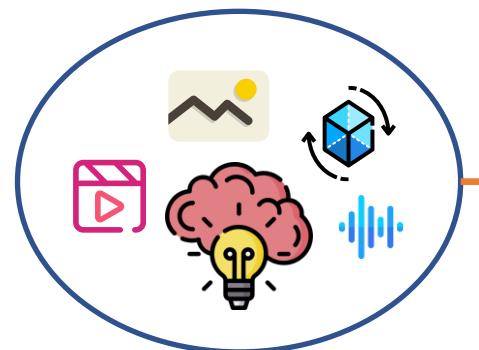
## ■ Goals to Next-generation **Multimodal Generalist**

- **Multimodality**   
*supporting diverse modalities and tasks, enabling models to seamlessly process and reason across language, vision, audio, and more—much like human cognition*
- **Unification**   
*integrating both perception and generation capabilities into a single architecture*
- **Advancement**   
*enabling higher-order functionalities with advanced capability, such as fine-grained advanced reasoning in complex contexts*
- **Generalizability**   
*achieving cross-modality and cross-task generalization, where knowledge learned in one modality or task can transfer to others*

# On Path to Multimodal Generalist: What's Next

## ■ Angle-I: Multimodal Generalists with in-depth **Modality&Task** Unification

- Enhance **breadth** capability.



MLLM/  
Multimodal Generalist

Breadth: More Unified

- { ✓ Supporting More Tasks
- ✓ Supporting More Modalities

# On Path to Multimodal Generalist: What's Next

	Modality (w/ Language)			
	Image	Video	Audio	3D
Input-side Perceiving	Flamingo, Kosmos-1, Blip2, mPLUG-Owl, Mini-GPT4, LLaVA, InstructBLIP, VPGTrans, CogVLM, Monkey, Chameleon, Otter, Qwen-VL, GPT-4v, SPHINX, Yi-VL, Fuyu, ...	VideoChat, Video-ChatGPT, Video-LLaMA, PandaGPT, MovieChat, Video-LLaVA, LLaMA-VID, Momentor, ...	AudioGPT, SpeechGPT, VIOLA, AudioPaLM, SALMONN, MU-LLaMA, ...	3D-LLM, 3D-GPT, LL3DA, SpatialVLM, PointLLM, PointBind, ...
	[Pixel-wise] GPT4RoI, LION, MiniGPT-v2, NExT-Chat, Kosmos-2, GLaMM, LISA, DetGPT, Osprey, PixelLM, ...	[Pixel-wise] PG-Video-LLaVA, Merlin, MotionEpic, ...	-	-
	Video-LLaVA, Chat-UniVi, LLaMA-VID		-	-
	Panda-GPT, Video-LLaMA, AnyMAL, Macaw-LLM, Gemini, VideoPoet, ImageBind-LLM, LLMBind, LLaMA-Adapter, ...			-
Perceiving + Generating	GILL, EMU, MiniGPT-5, DreamLLM, LLaVA-Plus, InternLM-XComposer2, SEED-LLaMA, LaVIT, Mini-Gemini, ...	GPT4Video, Video-LaVIT, VideoPoet, ...	AudioGPT, SpeechGPT, VIOLA, AudioPaLM, ...	-
	[Pixel-wise] Vitron		-	-
	NExT-GPT, Unified-IO 2, AnyGPT, CoDi-2, Modaverse, ViT-Lens, ...			-

# On Path to Multimodal Generalist: What's Next

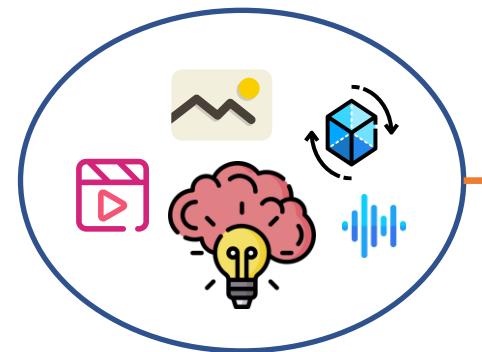
## Angle-I: Multimodal Generalists with in-depth **Modality&Task** Unification



# On Path to Multimodal Generalist: What's Next

## ■ Angle-II: Unified Comprehension & Generation

- Further enhance **breadth** capability.



MLLM/  
Multimodal Generalist

Breadth: More Unified

- Supporting More Tasks
- Supporting More Modalities
- Supporting More Paradigm

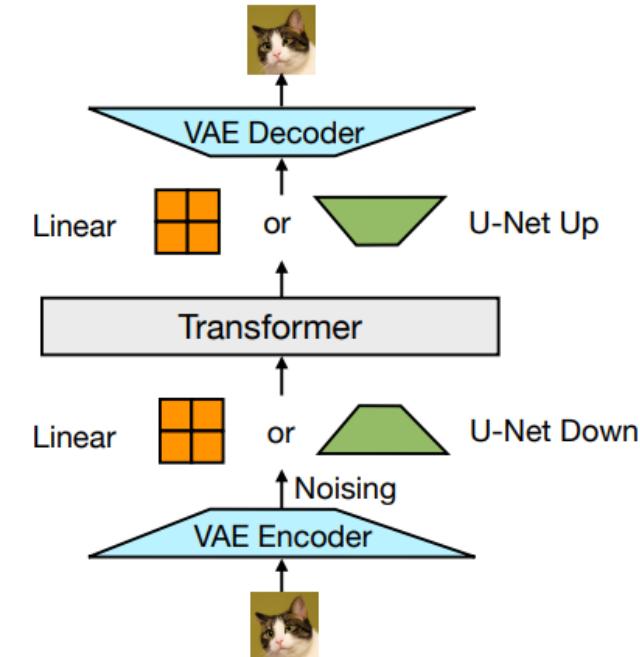
# On Path to Multimodal Generalist: What's Next

## ■ Angle-II: Unified Comprehension & Generation



What is the optimal model architecture under unified MLLM?

- Pipeline Agent
- Joint Encoder+LLM+Diffusion
- Joint LLM<sup>AR</sup> Tokenization (VQ-VAE)
- Joint LLM<sup>AR</sup>+Diffusion



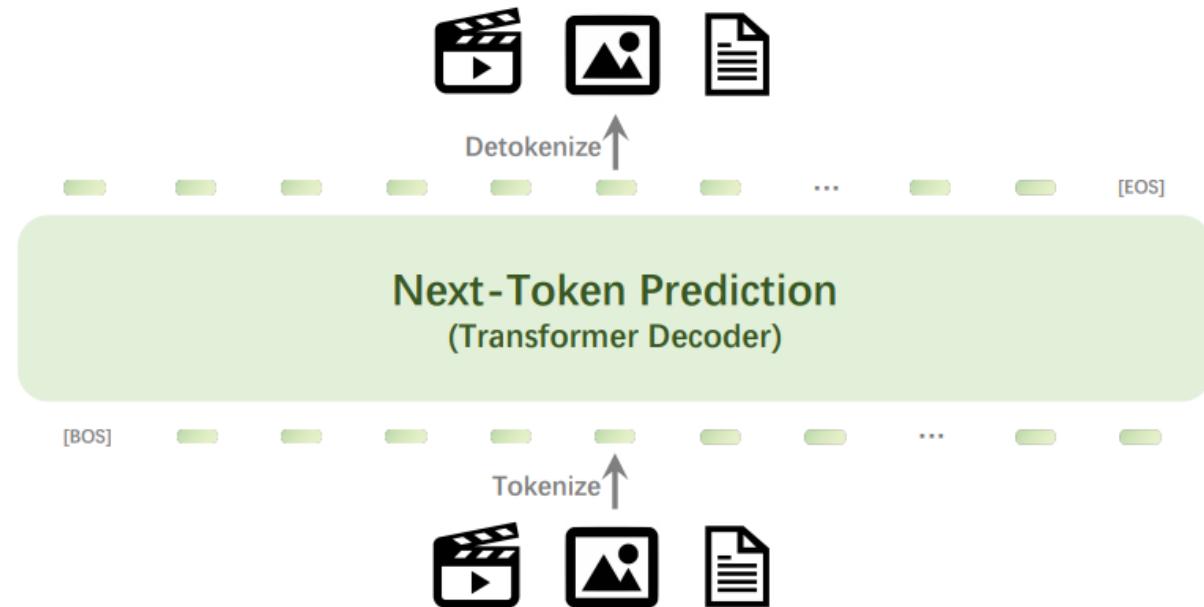
- Tianhong Li, Yonglong Tian, He Li, Mingyang Deng, Kaiming He. [Autoregressive Image Generation without Vector Quantization](#). 2024.
- Boyuan Chen, Diego Marti Monso, Yilun Du, Max Simchowitz, Russ Tedrake, Vincent Sitzmann. [Diffusion Forcing: Next-token Prediction Meets Full-Sequence Diffusion](#). 2024.
- Zhou, Chunting, et al. [Transfusion: Predict the Next Token and Diffuse Images with One Multi-Modal Model](#). 2024.

# On Path to Multimodal Generalist: What's Next

## ■ Angle-II: Unified Comprehension & Generation

➤ Emu3

- *Image/Video/Text*
- *AR loss*



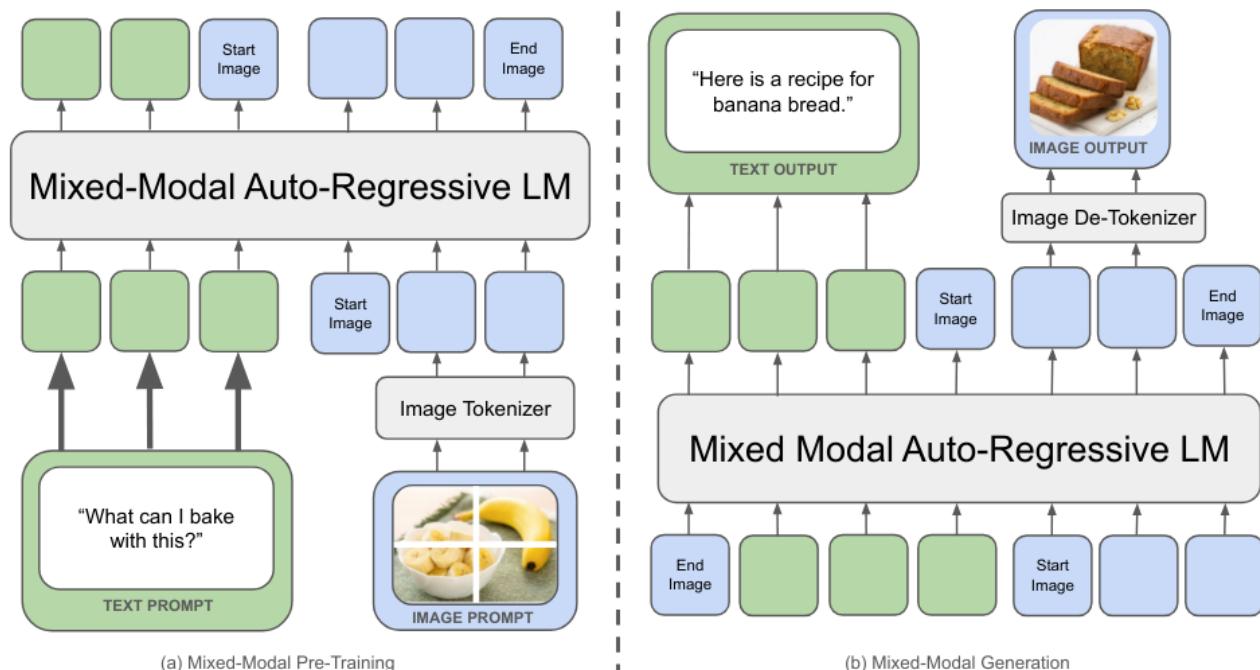
- Xinlong Wang ⋯. [Emu3: Next-Token Prediction is All You Need. 2024.](#)

# On Path to Multimodal Generalist: What's Next

## ■ Angle-II: Unified Comprehension & Generation

### ➤ Chameleon

- *Image/Text*
- *AR loss*



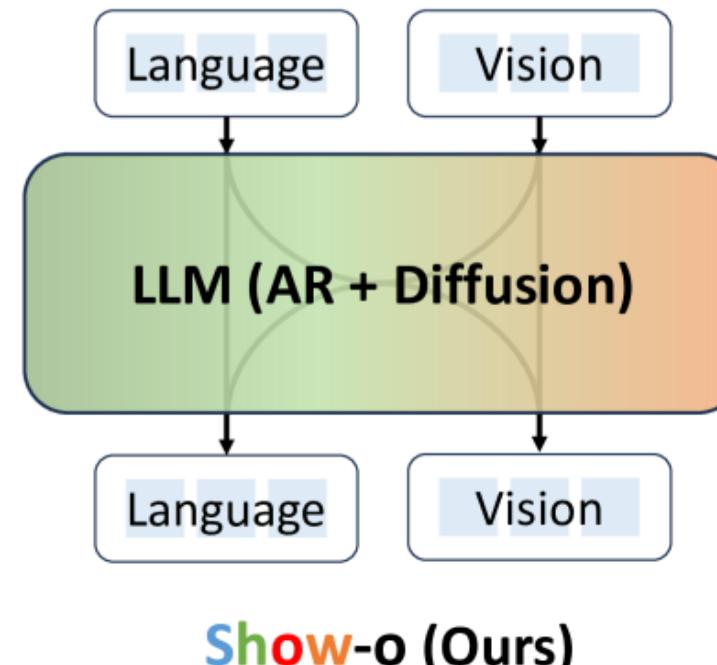
- META AI. Chameleon: Mixed-Modal Early-Fusion Foundation Models. 2024.

# On Path to Multimodal Generalist: What's Next

## ■ Angle-II: Unified Comprehension & Generation

### ➤ Show-o

- *Image/Text*
- *Image: Diffusion with bidirectional Loss*
- *Text: AR Loss*



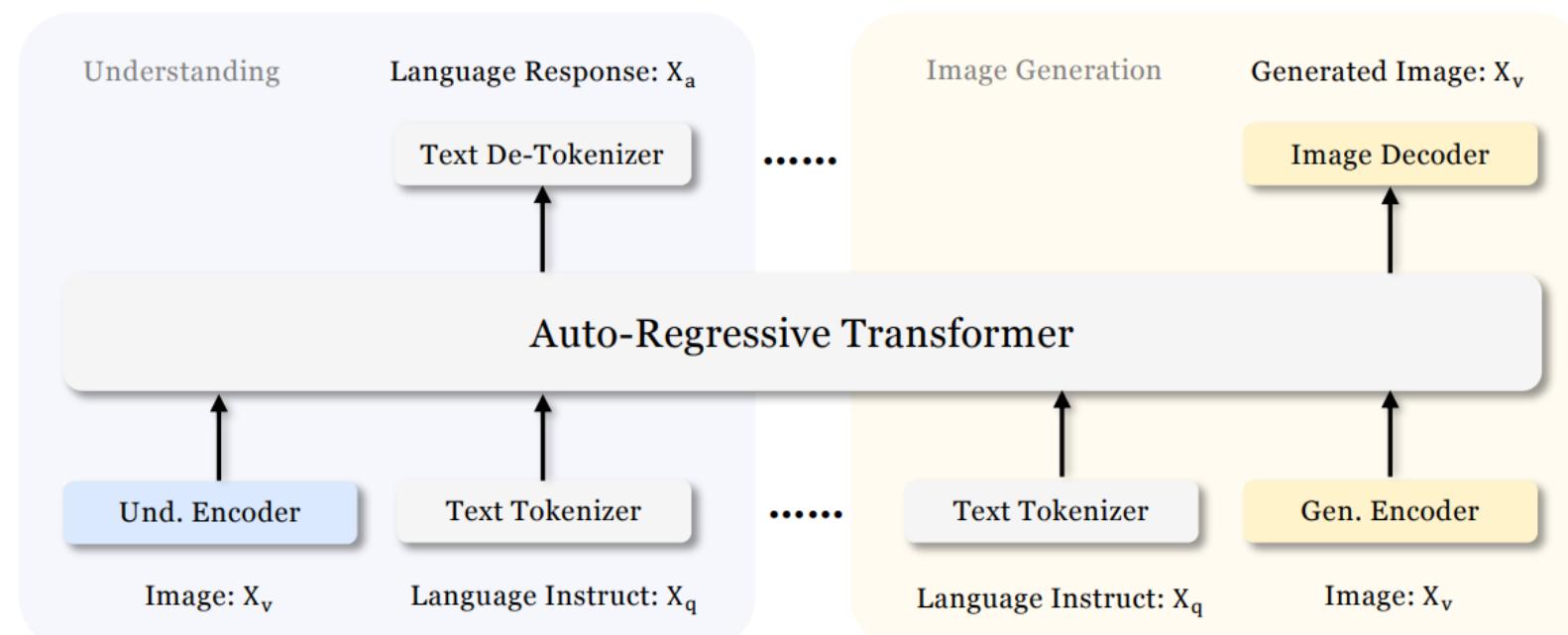
- Jinheng Xie, etc. [Show-o: One Single Transformer to Unify Multimodal Understanding and Generation](#). 2024.

# On Path to Multimodal Generalist: What's Next

## ■ Angle-II: Unified Comprehension & Generation

➤ Janus

- *Image/Text*
- *ViT: Comprehension*
- *VAE: Generation*
- *Both AR loss*



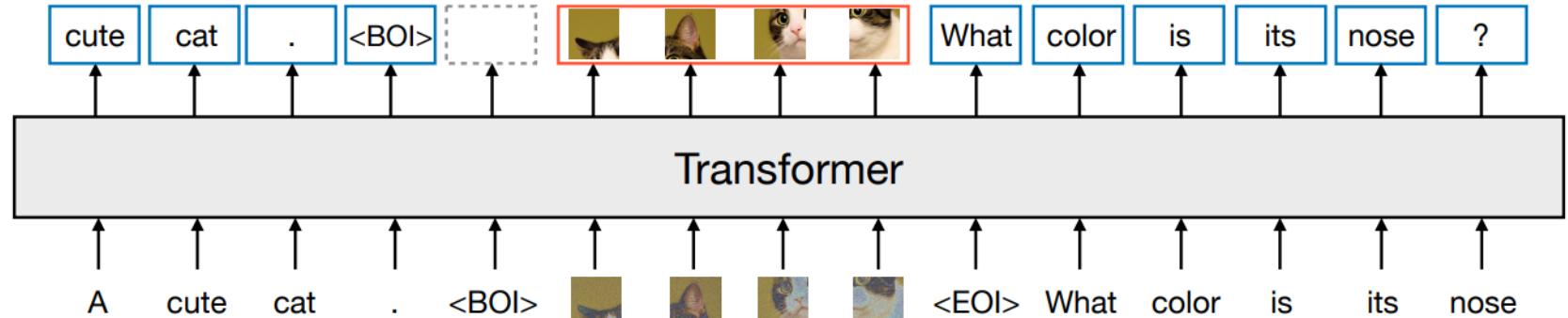
- Janus-Series: Unified Multimodal Understanding and Generation Models. 2024.

# On Path to Multimodal Generalist: What's Next

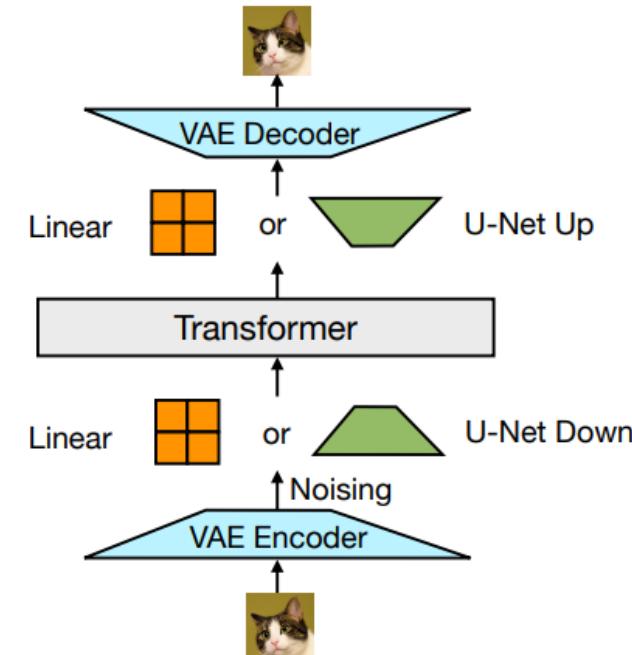
## ■ Angle-II: Unified Comprehension & Generation

### ➤ TransFusion

- *Image/Text*
- *Text: AR Loss*
- *Vision: DDPM Loss*

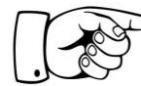


- Transfusion: Predict the Next Token and Diffuse Images with One Multi-Modal Model. 2024.



# On Path to Multimodal Generalist: What's Next

## ■ Angle-II: Unified Comprehension & Generation



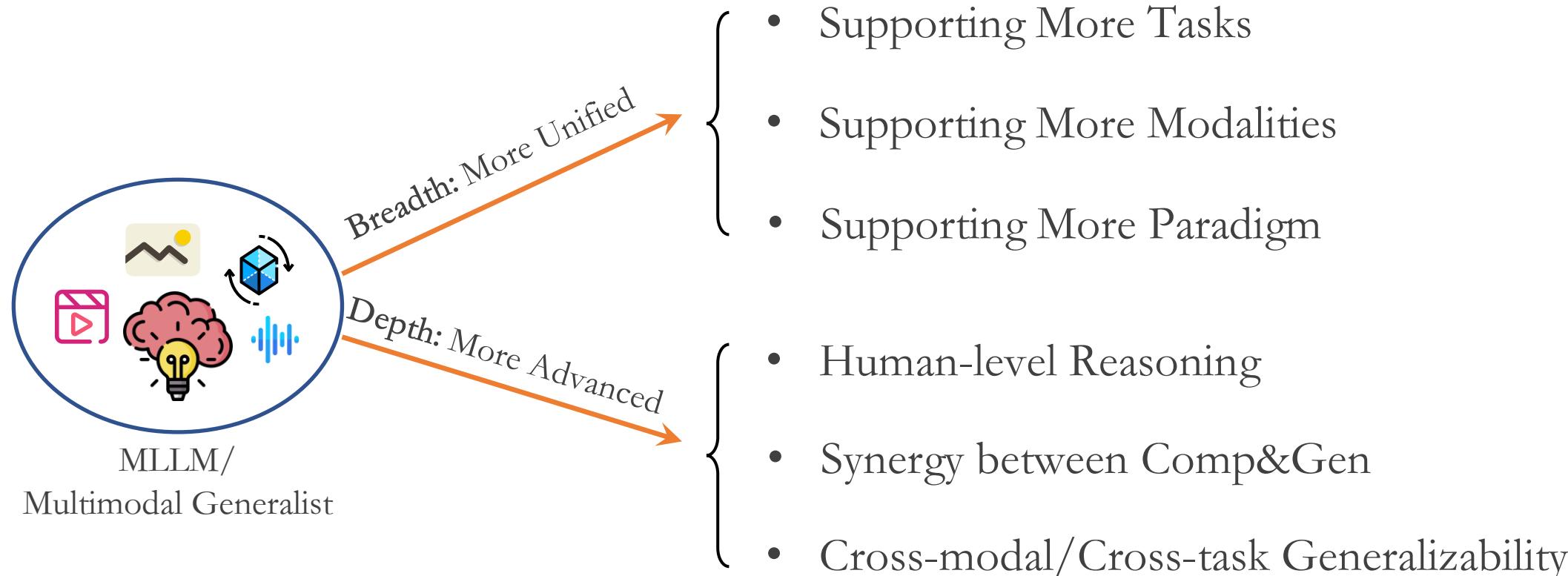
Still much room to explore

- *Generation hurt comprehension? Can both two enhance others?*
- *How to obtain better tokenizer? How to handle Video tokenizer?*
- *How far to beat SoTA specialist?*
- *What's the best architecture for other modalities?*
- ...

# On Path to Multimodal Generalist: What's Next

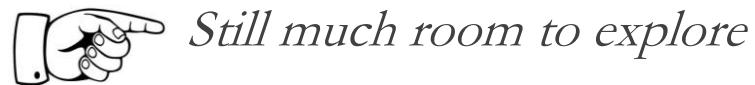
## ■ Angle-III: Native Multimodal Intelligence

- Further enhance capabilities both in **breadth** and **depth**.



# On Path to Multimodal Generalist: What's Next

## ■ Angle-III: Native Multimodal Intelligence



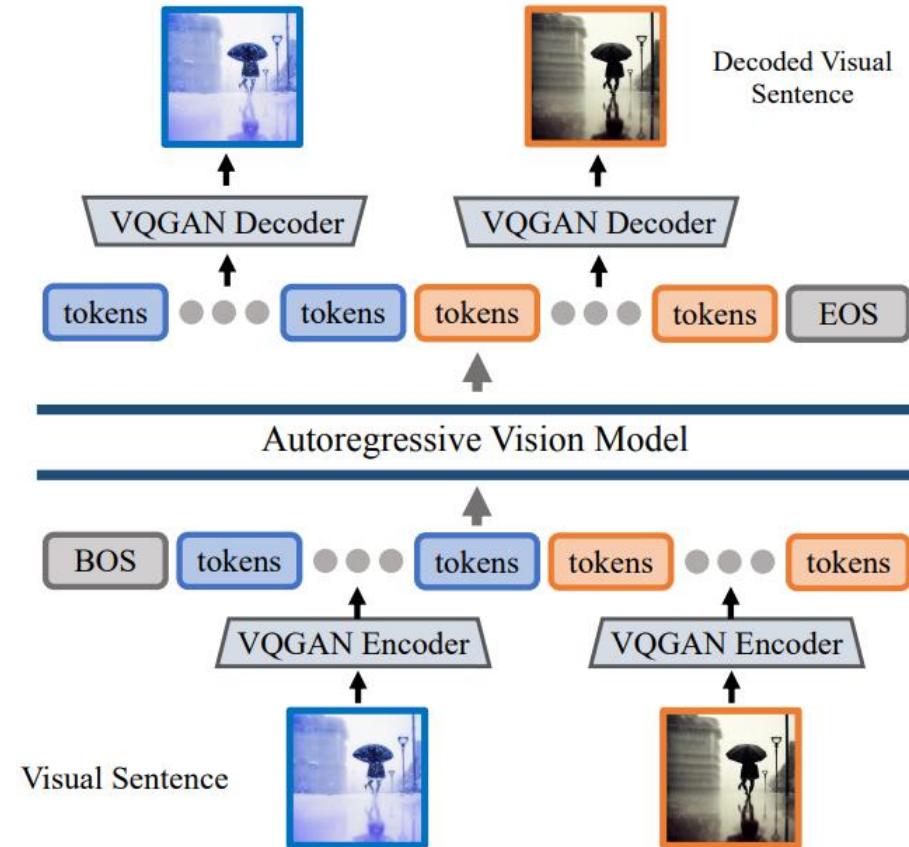
- *Architecture*
- *Data Scale*
- *Training/Learning*
- ...

# On Path to Multimodal Generalist: What's Next

## ■ Angle-III: Native Multimodal Intelligence

### ➤ Large Vision Model (LVM)

- mimicking LLM pretraining
- next visual token prediction

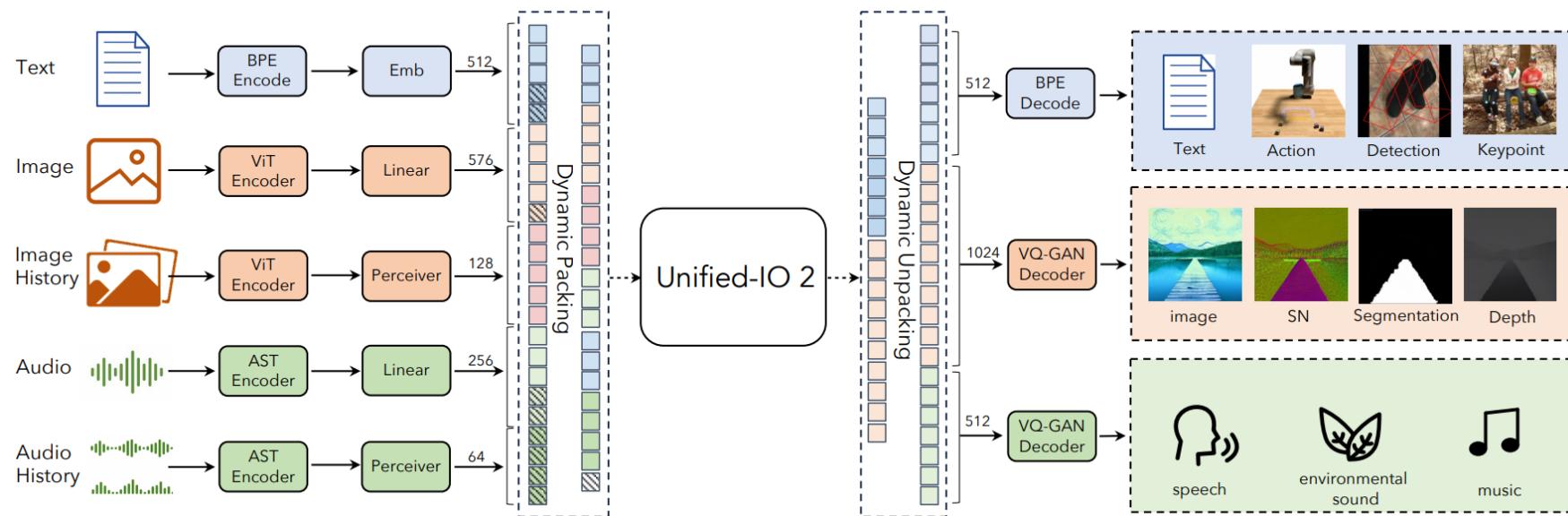


# On Path to Multimodal Generalist: What's Next

## ■ Angle-III: Native Multimodal Intelligence

### ➤ Unified IO-2

- mimicking LLM pretraining
- next visual token prediction



- Lu, J., Clark, C., Lee, S., Zhang, Z., Khosla, S., Marten, R., ... & Kembhavi, A. [Unified-IO 2: Scaling Autoregressive Multimodal Models with Vision Language, Audio and Action](#). CVPR. 2024

# On Path to Multimodal Generalist: What's Next

## ■ Angle-III: Native Multimodal Intelligence



What scale of dataset is required for pre-training from scratch?

Modality	LLM/MLLM	Amount
Language	Chat-GPT4	13 Trillion text tokens
Vision	LVM	420 Billion visual tokens
Multimodalities	Unified-IO 2	1 Trillion text tokens, 1 Billion image-text pairs, 180 Million video clips, 130 Million interleaved image & text, 3 Million 3D assets, 1 Million agent trajectories

# On Path to Multimodal Generalist: What's Next

## ■ Angle-III: Native Multimodal Intelligence

- Training/Learning
  - *Synergistic Training*

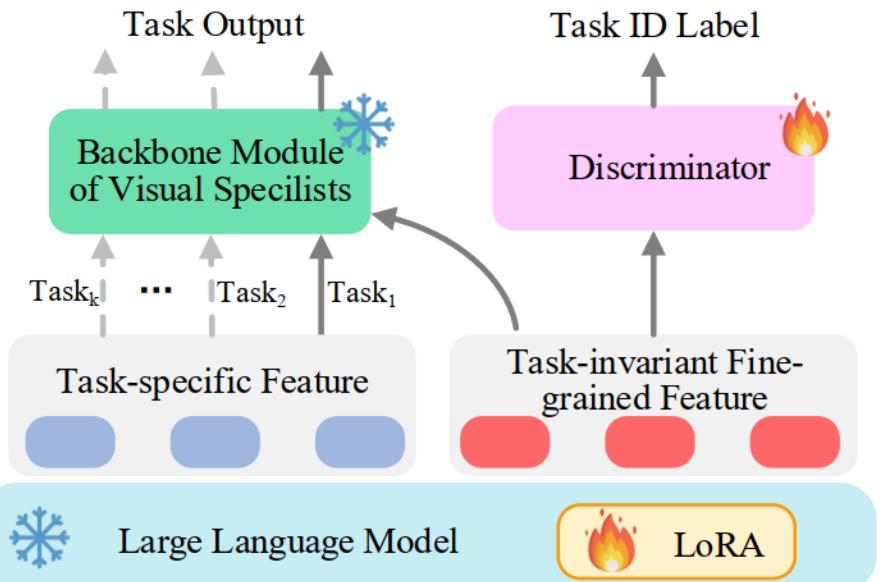


Figure 3: Illustration of the synergy module.

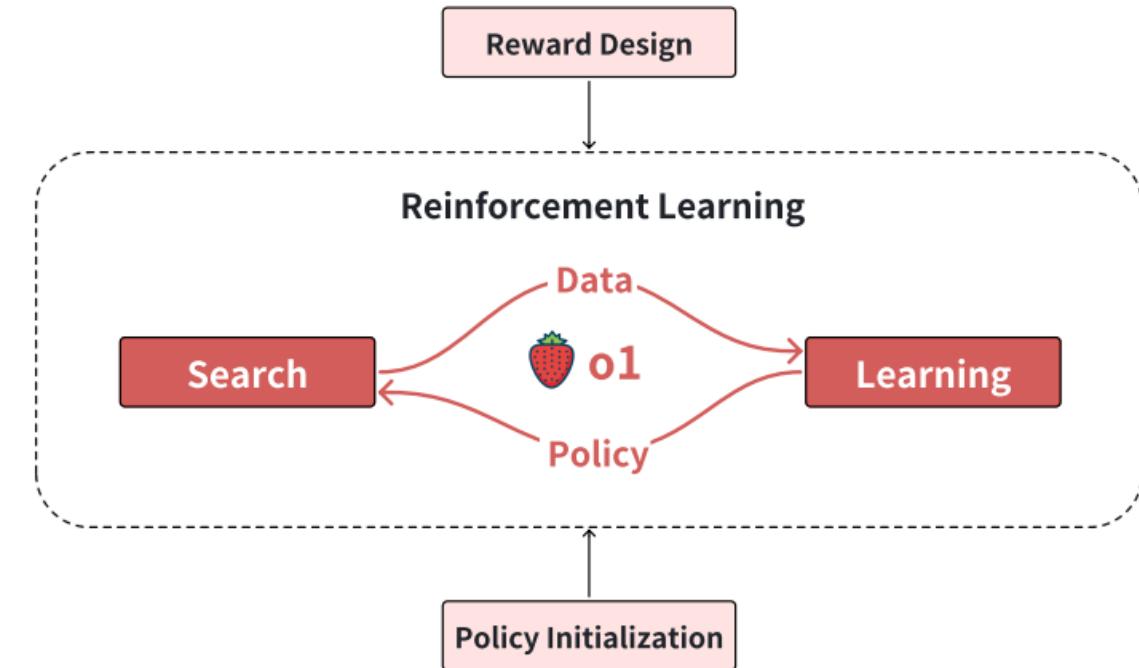
- Hao Fei, Shengqiong Wu, Hanwang Zhang, Tat-Seng Chua, Shuicheng Yan. “[ViTRON: A Unified Pixel-level Vision LLM for Understanding, Generating, Segmenting, Editing](#)” . NeurIPS. 2024

# On Path to Multimodal Generalist: What's Next

## ■ Angle-III: Native Multimodal Intelligence

### ➤ Training/Learning

- *R1/O1 for interleaved multimodality?*
- *RL Scaling*



- Zeng, etc. “Scaling of Search and Learning: A Roadmap to Reproduce o1 from Reinforcement Learning Perspective” . Arxiv. 2024

# On Path to Multimodal Generalist: What's Next

- Improving from **Evaluation Framework** perspective

# On Path to Multimodal Generalist: What's Next

## ■ Angle-I: Further refinement of the General-Level framework

- *The synergy measurement is simplified by assuming performance beyond SoTA specialists implies synergy, avoiding direct modeling.*
- *There is room for improving algorithmic design to better reflect true multimodal coordination and synergy.*

# On Path to Multimodal Generalist: What's Next

## ■ Angle-II: Expanding the General-Bench

- *Expanding to cover more comprehensive tasks and modalities for fair and complete evaluation.*
- *Imbalance exists — image tasks dominate, while audio and 3D modalities are underrepresented.*
- *True multimodal generalists should handle modality-switching and interleaved reasoning.*
- *Incorporate tasks that involve multi-turn, cross-modal interactions for both comprehension and generation.*

# On Path to Multimodal Generalist: What's Next

## ■ Angle-III: Rethinking Evaluation Paradigm for Model Capabilities

- *Many current evaluation still follow traditional paradigms*
  - work well for simple tasks (e.g., multiple-choice, classification)
  - but fail on format-free multimodal generation tasks, metrics like **FID/FVD** are increasingly viewed as inadequate for evaluating video or 3D generation quality.
- *There is a growing reliance on human evaluation, but it lacks scalability.*
  - use LLMs as judges, but face challenges in evaluation stability and reproducibility.
  - adopts a single metric per task, which may introduce bias; should incorporate multiple complementary metrics for more holistic assessment.
- *Should also assess interpretability and reasoning traceability.*

# Thank you!

Q&A

