





In this repo, we present **R-4B**, a multimodal large language model designed for general-purpose auto-thinking, autonomously switching between step-by-step thinking and direct response generation based on task complexity. This capability enables R-4B to deliver high-quality responses while significantly improving inference efficiency and reducing computational costs.

The development of R-4B follows a two-stage training paradigm: (1) Bi-mode Annealing, which establishes both thinking and non-thinking capabilities for VQA; and (2) Bi-mode Policy Optimization (BPO), which enables the model to adaptively switch between thinking and non-thinking modes based on input demands.

- Think Smart, Act Fast: Adaptive & Controllable Thinking! Our model provides three-mode control over the response process.
 - Auto-thinking Mode: Unleash auto-thinking that works across general topics, from simple Q&A to complex scientific analysis. It saves time and computation by thinking only when it matters.
 - **Support Manual Control:** Explicitly command the model to use its thinking or non-thinking capabilities, enabling you to make your choices for every job.

• **Strong Performance, Open for Everyone!** Our model is now **fully open-source**. It achieves **state-of-the-art performance** among models of comparable size.

- [2025.08.20] vLLM Support is Here! Our R-4B model is now fully compatible with <u>vLLM</u> for high-performance inference.
- [2025.08.18] Top Rank Achieved! We are thrilled to announce that R-4B is now ranked #1 among all open-source models on the OpenCompass Multi-modal Reasoning Leaderboard!
- [2025.08.11] Rank #1! R-4B ranks first under 20B parameters on the OpenCompass Multimodal Academic Leaderboard!
- [2025.08.05] R-4B is Released! Our model is now publicly available. You can download it from <u>Hugging Face</u>.

Quickstart

Below, we provide simple examples to show how to use R-4B with A Transformers.

Using Transformers to Chat

Users can dynamically control the model's response by selecting one of three modes (autothinking, thinking, or non-thinking) with thinking_mode. thinking_mode=auto for autothinking mode; thinking_mode=long for thinking mode; thinking_mode=short for non-thinking mode. Default is auto-thinking.

```
import requests
from PIL import Image
import torch
from transformers import AutoModel, AutoProcessor

model_path = "YannQi/R-4B"

# Load model
model = AutoModel.from_pretrained(
```

```
model_path,
    torch_dtype=torch.float32,
    trust_remote_code=True,
).to("cuda")
# Load processor
processor = AutoProcessor.from_pretrained(model_path, trust_remote_code=True)
# Define conversation messages
messages = [
    {
        "role": "user",
        "content": [
            Ę
                "type": "image",
                "image": "http://images.cocodataset.org/val2017/000000039769.jpg",
            3,
            {"type": "text", "text": "Describe this image."},
        ],
    }
]
# Apply chat template
text = processor.apply_chat_template(
    messages,
    tokenize=False,
    add_generation_prompt=True,
    thinking_mode="auto"
)
# Load image
image_url = "http://images.cocodataset.org/val2017/000000039769.jpg"
image = Image.open(requests.get(image_url, stream=True).raw)
# Process inputs
inputs = processor(
    images=image,
    text=text,
    return_tensors="pt"
).to("cuda")
```

```
# Generate output
generated_ids = model.generate(**inputs, max_new_tokens=16384)
output_ids = generated_ids[0][len(inputs.input_ids[0]):]

# Decode output
output_text = processor.decode(
    output_ids,
    skip_special_tokens=True,
    clean_up_tokenization_spaces=False
)

# Print result
print("Auto-Thinking Output:", output_text)
```

- - We recommend using vLLM for fast R-4B deployment and inference.

The code of R-4B requires the newest vllm now. Please install from local source:

```
git clone https://github.com/vllm-project/vllm.git
cd vllm
VLLM_USE_PRECOMPILED=1 uv pip install --editable .
```

Online Serving

The thinking_mode switch is also available in APIs created by vLLM. Default is auto-thinking.

Serve

```
vllm serve \
yannqi/R-4B \
```

```
--served-model-name r4b \
--tensor-parallel-size 8 \
--gpu-memory-utilization 0.8 \
--host 0.0.0.0 \
--port 8000 \
--trust-remote-code
```

Openai Chat Completion Client

```
import base64
from PIL import Image
from openai import OpenAI
# Set OpenAI's API key and API base to use vLLM's API server.
openai_api_key = "EMPTY"
openai_api_base = "http://localhost:8000/v1"
client = OpenAI(
    api_key=openai_api_key,
   base_url=openai_api_base,
)
# image url
image_messages = [
    Ę
        "role": "user",
        "content": [
            Ę
                "type": "image_url",
                "image_url": {
                    "url": "http://images.cocodataset.org/val2017/000000039769.jpg
                },
            3,
            {"type": "text", "text": "Describe this image."},
        ],
    3,
]
```

```
chat_response = client.chat.completions.create(
    model="r4b",
    messages=image_messages,
    max_tokens=16384,
    extra_body={
        "chat_template_kwargs": {"thinking_mode": "auto"},
     },
)
print("Chat response:", chat_response)
```

Experimental Results

Capability	Benchmark	Qwen2.5-VL -7B	InternVL3 -8B	InternVL3.5 -4B	Kimi-VL-A3B -Thinking	Keye-VL -8B	R-4B-Base	R-4B-RL
		(N-T)	(N-T)	(T)	(T)	(A-T)	(T)	(A-T)
General Visual QA	$MMMU_{val}$	58.6	62.7	66.6	64.0	<u>66.8</u>	63.2	68.1
	MMMU-Pro	34.7	45.6	-	49.2	<u>47.5</u>	46.7	46.5
	MMStar	64.1	68.7	65.0	70.4	<u>72.8</u>	70.8	73.1
	MMBenchV1.1-EN _{dev}	82.1	84.7	-	82.6	89.7	81.9	84.9
	MMBenchV1.1-CN _{dev}	81.3	83.6	-	80.7	89.8	83.2	84.7
	MMVet	69.7	<u>82.8</u>	76.6	81.9	65.5	85.9	81.9
	HallusionBench	55.7	49.4	44.8	57.2	<u>57.3</u>	53.9	58.9
	VLMs are Blind	37.4	36.8	-	<u>60.8</u>	61.0	47.0	52.3
	MMVP	73.3	79.3	-	<u>80.3</u>	79.0	79.3	80.7
	VisuLogic	20.0	26.1	-	25.0	21.1	22.5	<u>25.1</u>
	RealWorldQA	68.2	70.6	66.3	66.1	66.3	<u>70.5</u>	69.1
Table & Chart & OCR	AI2D	83.9	85.2	83.9	82.7	85.8	84.8	86.2
	CharXiv (DQ)	73.9	73.6	71.1	75.4	74.5	82.8	82.9
	CharXiv (RQ)	42.5	37.6	39.6	47.7	40.0	<u>55.4</u>	56.8
	DocVQA _{val}	95.5	89.4	<u>92.4</u>	69.0	86.3	89.6	91.0
Visual Perception & Counting	OCRBench	89.7	88.0	81.5	86.2	85.3	82.8	83.6
	BLINK _{val}	<u>56.4</u>	55.5	58.1	56.2	52.5	54.8	56.3
	CountBench	74.1	80.0	-	<u>91.4</u>	75.4	92.6	90.2
Math & Reasoning	MathVision	26.2	28.8	26.2	56.8	42.4	45.7	<u>47.8</u>
	MathVista _{MINI}	66.8	70.7	77.1	80.1	75.2	76.8	<u>78.0</u>
	MathVerse-vision	41.2	32.4	61.7	57.4	40.8	65.0	<u>64.9</u>
	OlympiadBench	19.4	25.9	-	33.9	45.2	<u>47.0</u>	49.6
	WeMath	37.7	38.5	50.1	47.0	58.6	<u>54.1</u>	52.8
	LogicVista	44.5	43.6	56.4	51.0	50.6	<u>58.8</u>	59.1
	DynaMath	20.1	23.9	35.7	27.1	35.3	<u>36.3</u>	39.5

- 1. R-4B establishes itself with powerful, state-of-the-art perceptual abilities that are competitive with larger models.
- 2. In evaluation sets that require complex logical reasoning and mathematical problem-solving, such as WeMath, MathVerse, and LogicVista, R-4B displays a strong performance curve. This highlights its advanced adaptive thinking capacity for logical deduction and solving complex quantitative problems.

Citation

```
@misc{yang2025r4bincentivizinggeneralpurposeautothinking,
    title={R-4B: Incentivizing General-Purpose Auto-Thinking Capability in MLLMs
    author={Qi Yang and Bolin Ni and Shiming Xiang and Han Hu and Houwen Peng ar
    year={2025},
    eprint={2508.21113},
    archivePrefix={arXiv},
    primaryClass={cs.CV},
    url={https://arxiv.org/abs/2508.21113},
}
```


R-4B is developed based on the codebases of the following projects: <u>LLaVA-Next</u>, <u>SigLIP2</u>, <u>Qwen3</u>, <u>Qwen2.5-VL</u>, <u>VLMEvalKit</u>. We sincerely thank these projects for their outstanding work.