自回归-扩散混合式大模型

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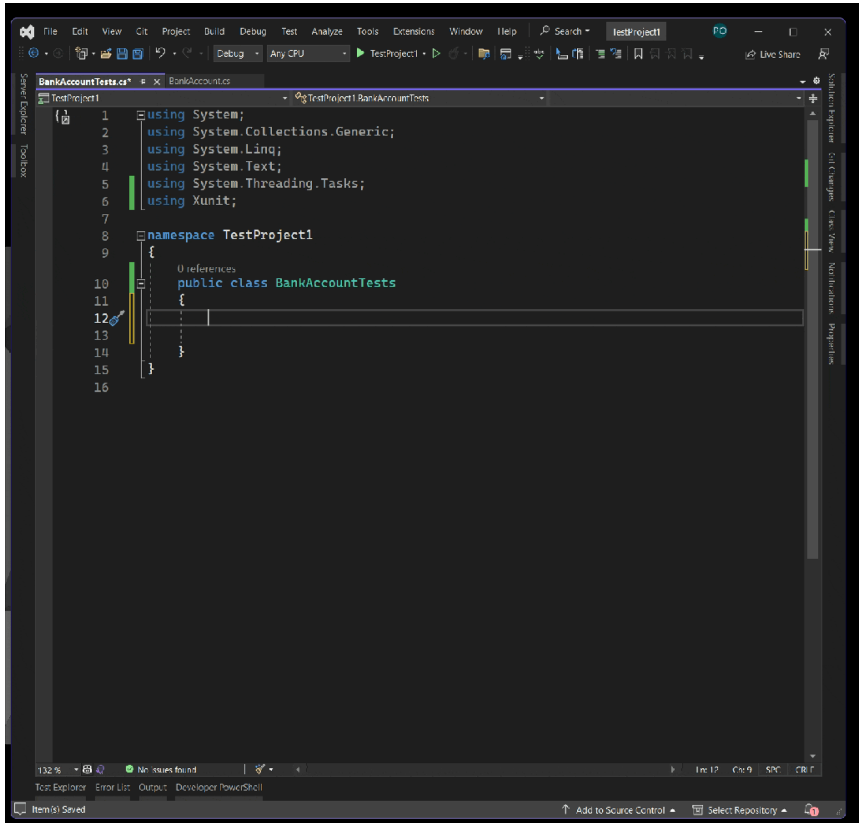
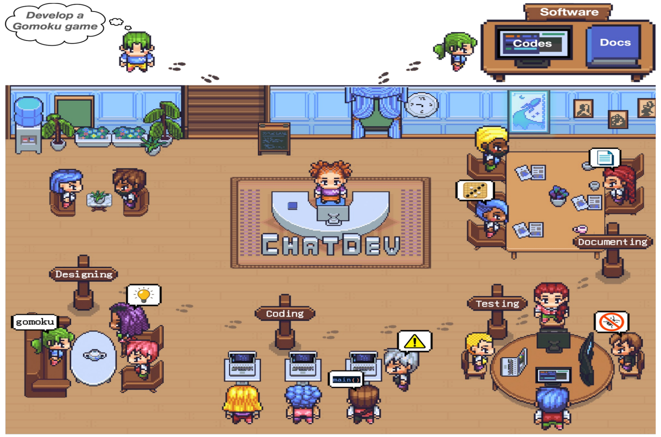
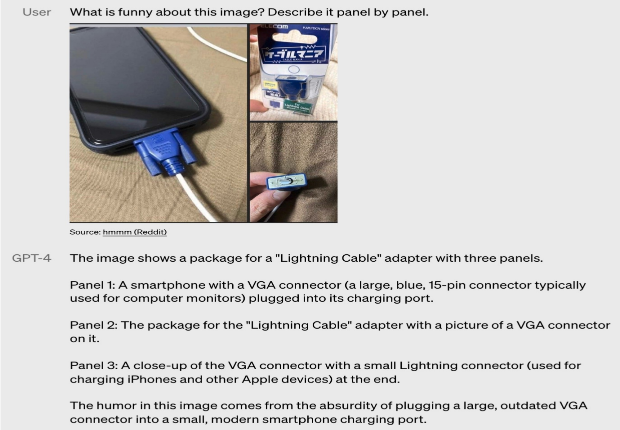
自回归模型（AR models）：从语言生成到智能体Agent，激发广泛应用



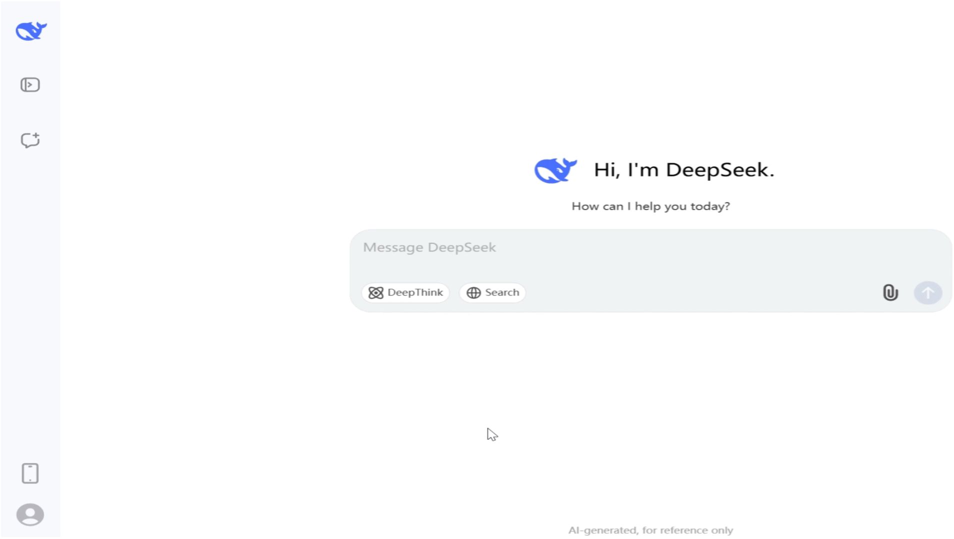
Coding assistant



Software development

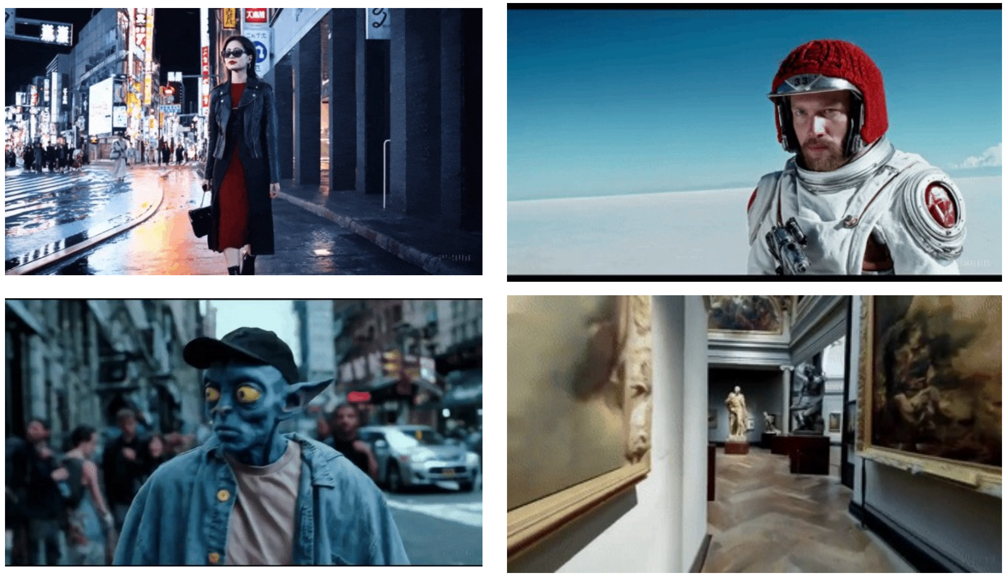


Multimodal understanding



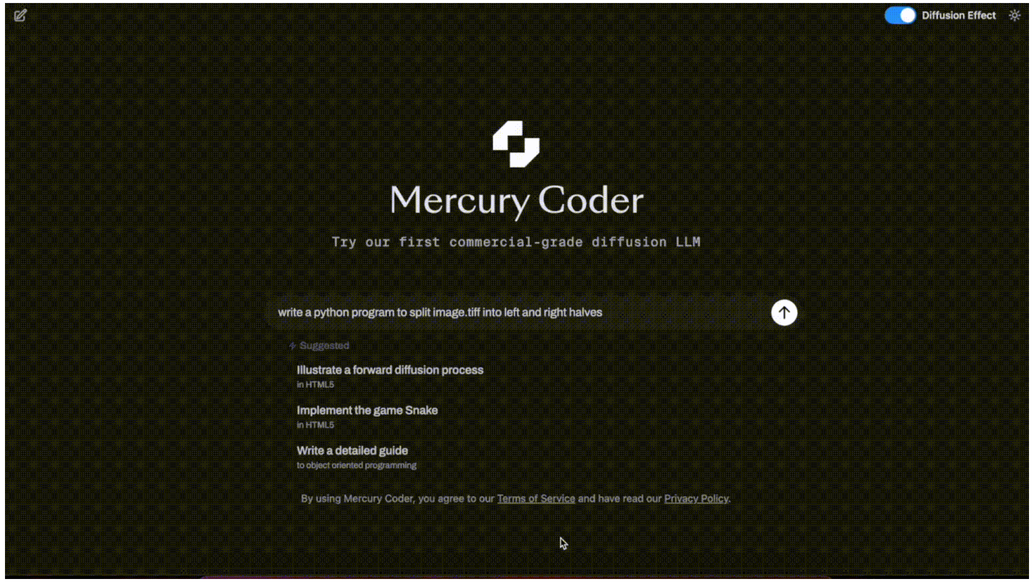
Reasoning

扩散模型（diffusion models）：兼顾连续/离散信号建模



Sora by OpenAI

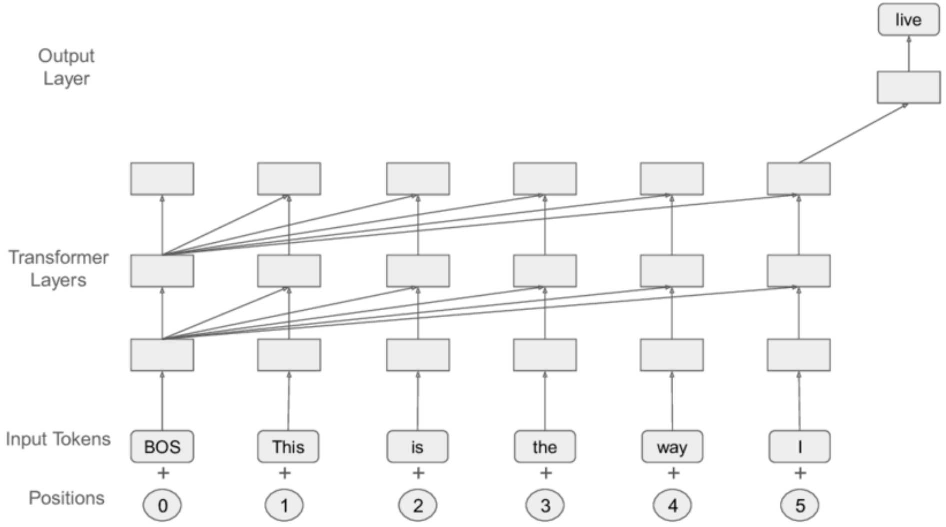
生成长视频等连续视觉信号



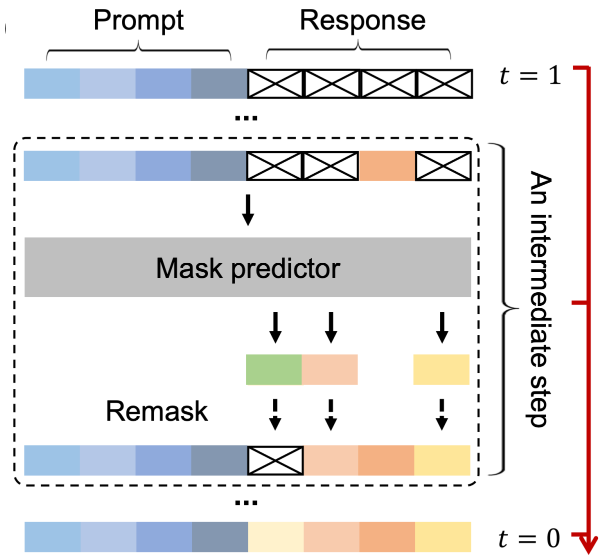
Mercury Coder by Inception Labs

比同性能自回归语言模型快5-10倍

AR和Diffusion各自具有不同的特性



VS.

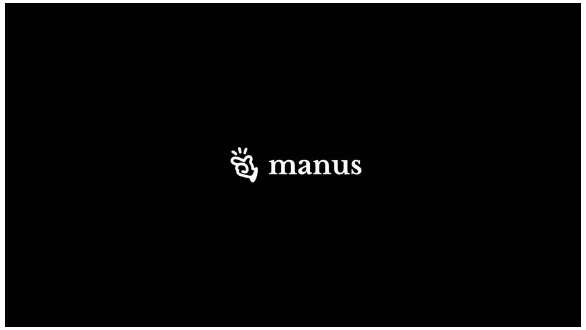


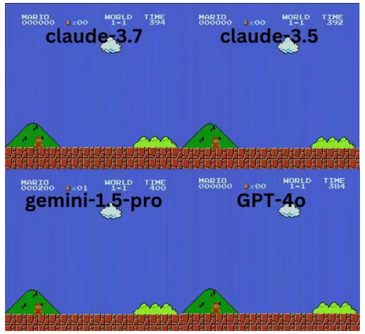
- **AR**：离散
  - 因果注意力
    - 每一步预测下一个**token**：$p(x_t|x_{<t})$
- **Diffusion**：离散/连续
  - 双向注意力
    - 每一步预测整条数据：$p(x_0|x_t)$

未来大模型架构

AR or diffusion?

AR仍然应该作为大模型的主干





Agent (跨模态、复杂任务)

VLA （实时性、强泛化）

AR模型可以提供：世界知识、推理规划、人机交互、研究基础、开源社区、**etc.**

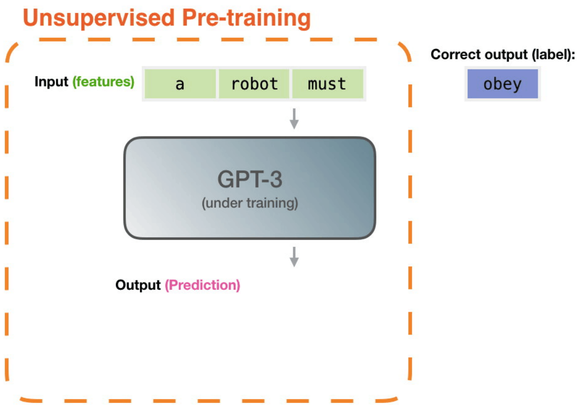
- 以上场景对于计算高效、扩模态高效、数据高效等方面有很高的要求，然而
  - **AR**是计算效率、跨模态效率和数据效率最优吗？

未来大模型架构

纯AR存在计算效率、扩模态效率等方面的问题

AR模型顺序推理（逐token生成），低效昂贵

AR模型依赖离散token，但离散化产生信息损失



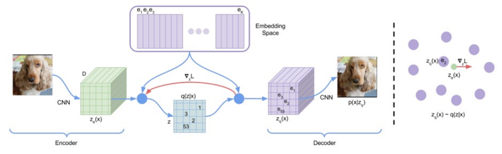


Figure 1: Left: A figure describing the VQ-VAE. Right: Visualisation of the embedding space. The output of the encoder $z(x)$ is mapped to the nearest point e_2. The gradient $\nabla_z L$ (in red) will push the encoder to change its output, which could alter the configuration in the next forward pass.

解决方案：自回归-扩散混合模型（AR-Diffusion Hybrid Models）

从解决**AR**模型的问题的角度

AR+discrete diffusion

- **动机：diffusion每一步都进行全局推理**

将AR语言模型生成tokens数和推理步数解耦

（高效并行解码）

AR+continuous diffusion

- **动机：diffusion可以直接生成连续信号**

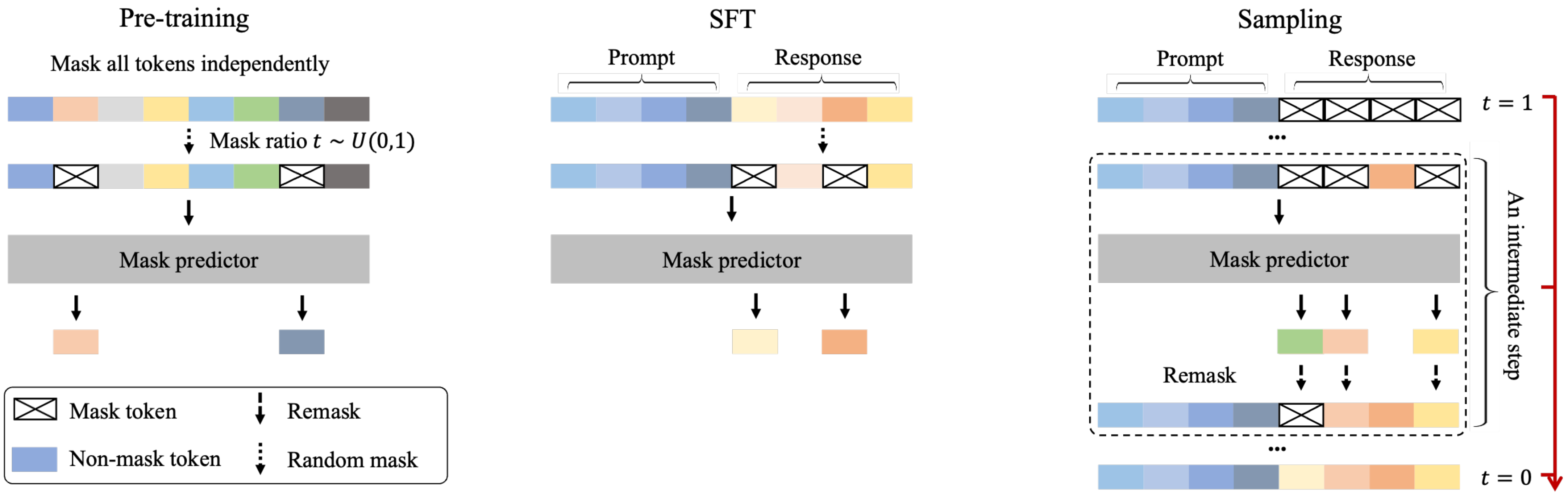
为AR语言模型提供生成多模态内容的能力

（跨模态生成）

自回归-扩散混合的高效推理语言模型

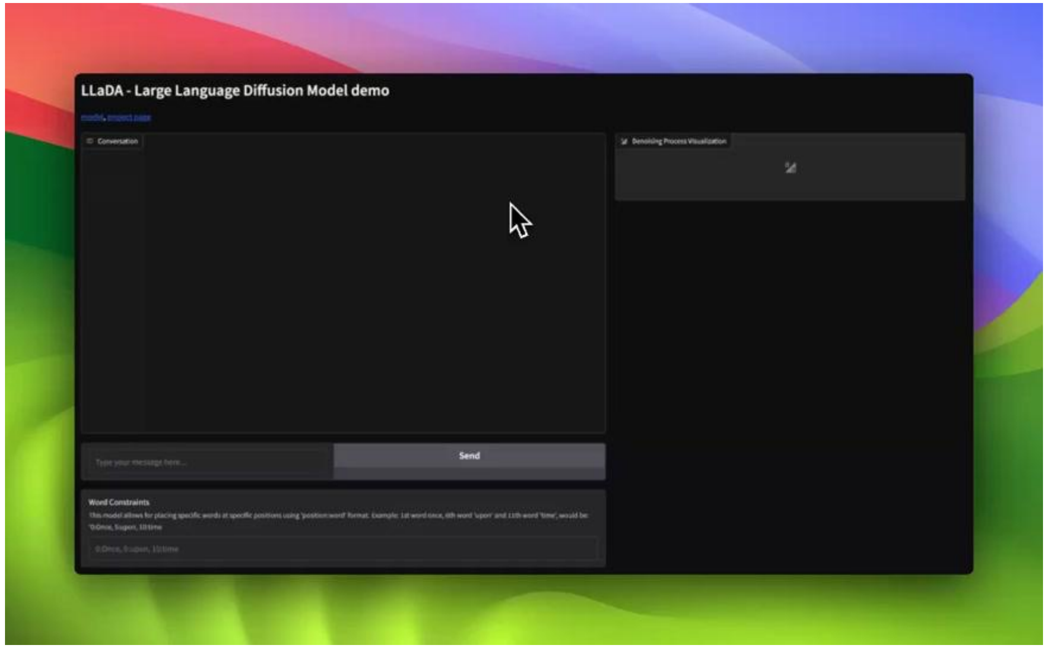
扩散语言模型

离散扩散模型（**discrete diffusion models**）

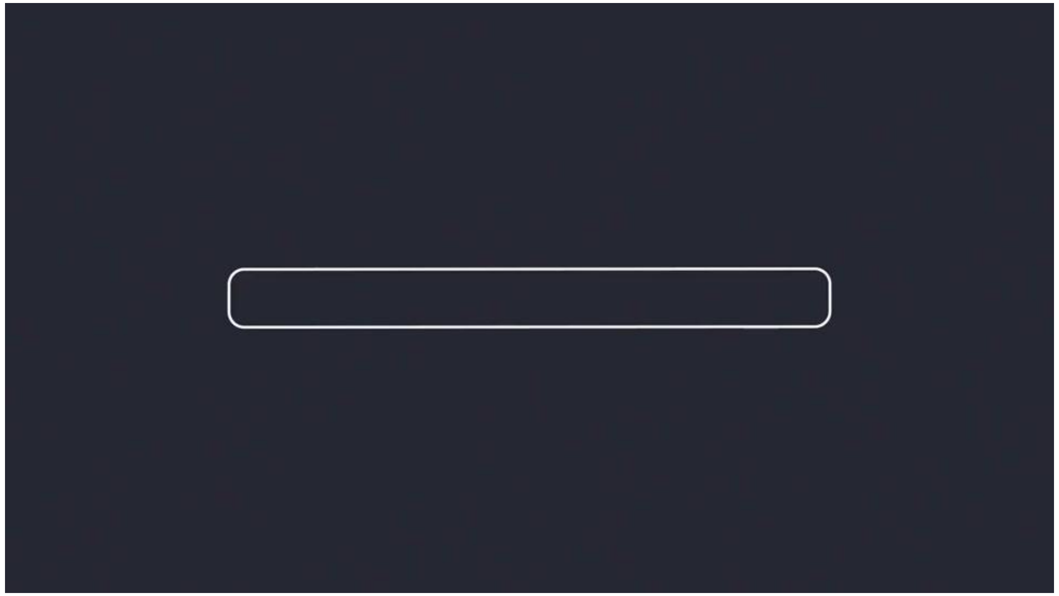


Nie et al., Large Language Diffusion Models. ArXiv 2502.09992

对扩散语言模型的期待：并行生成、推理加速

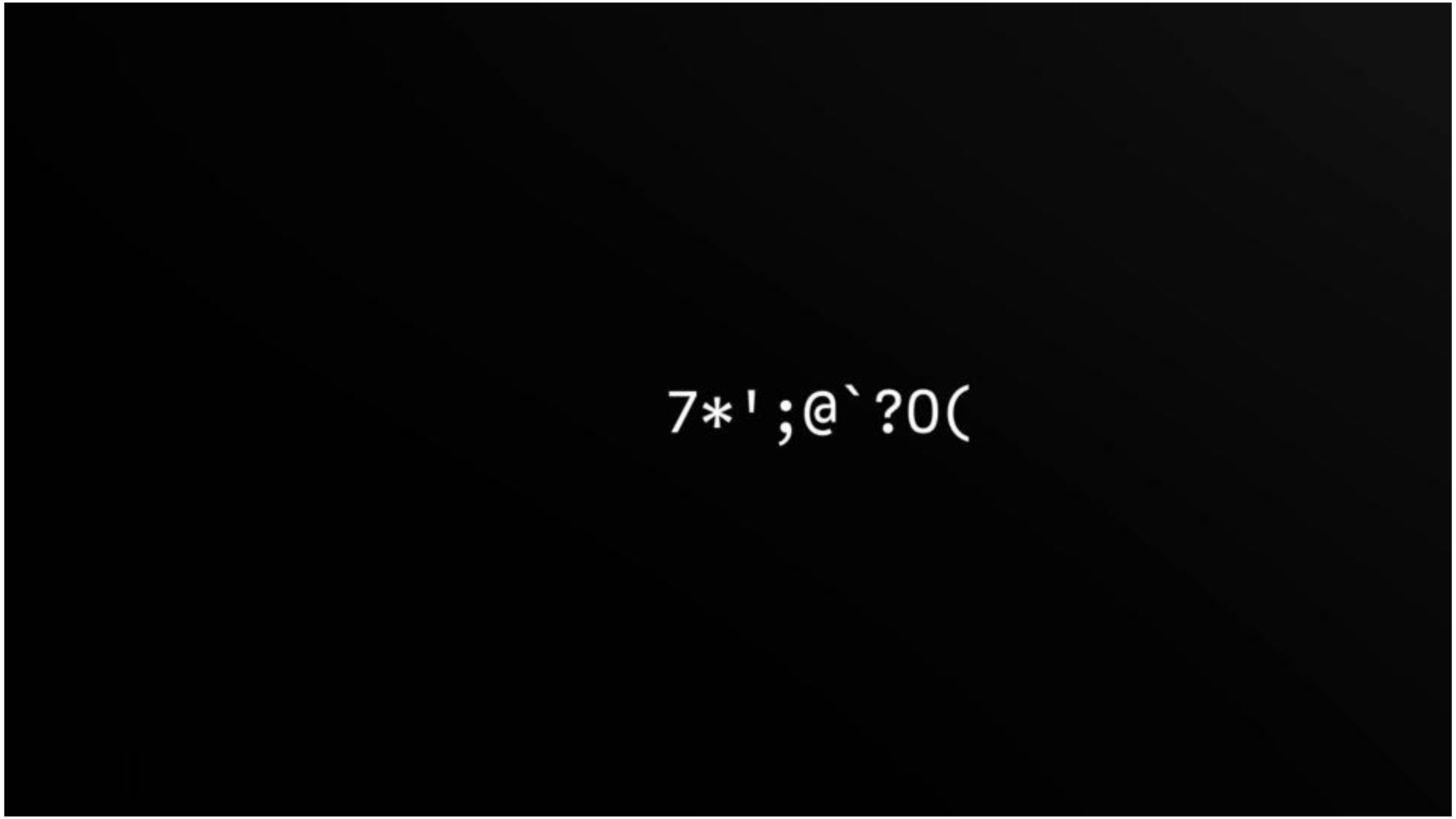


LLaDA (The first Large Language Diffusion Model, RUC)，可达LLaMA3级水平



Mercury, 5-10x快的代码生成, InceptionAI Labs (co-founded by Stefano Ermon)

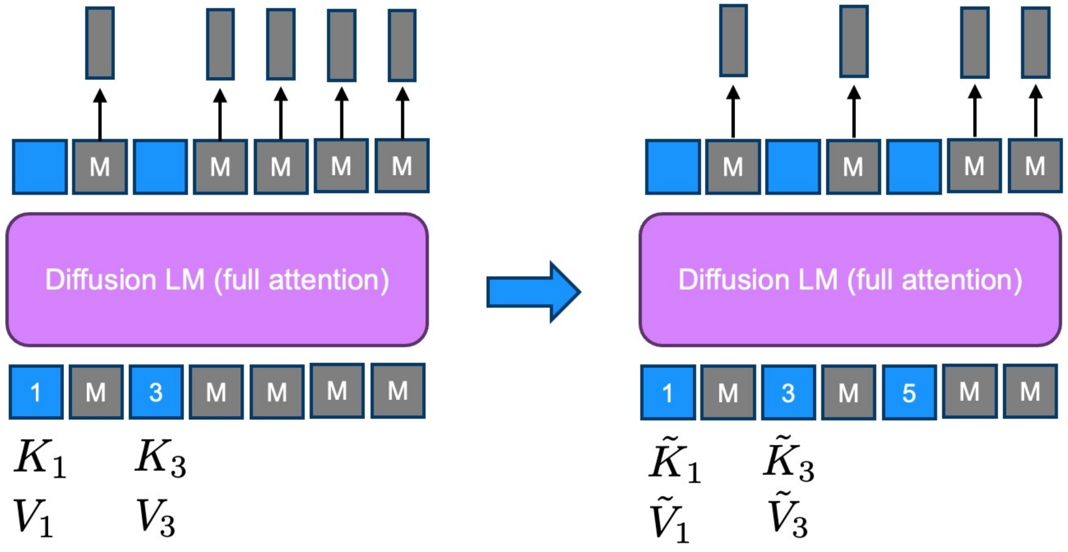
对扩散语言模型的期待：并行生成、推理加速



Seed Diffusion Preview: A large scale language model based on discrete-state diffusion, specializing in code generation, achieves an inference speed of 2,146 token/s, a 5.4x improvement over autoregressive models of comparable size.

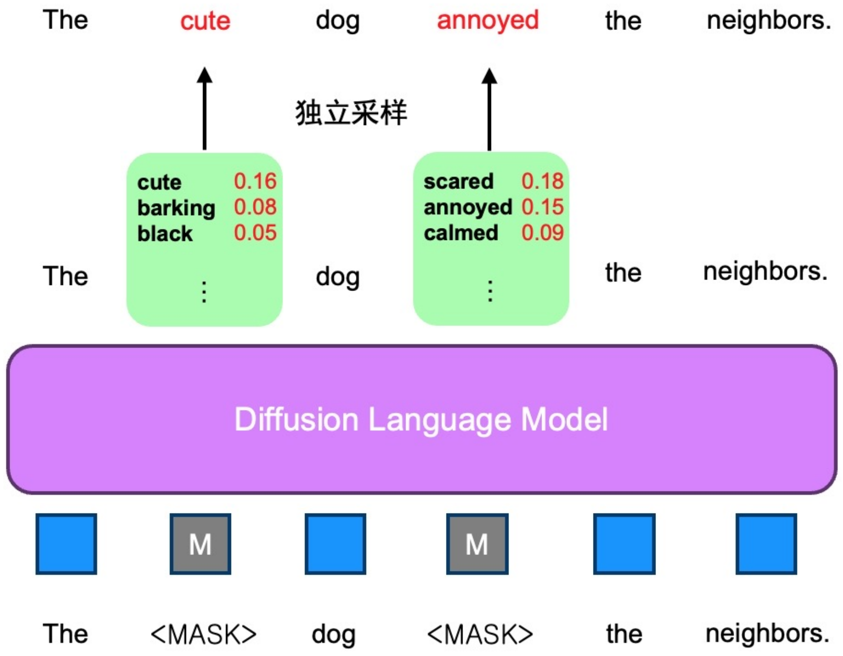
然而，对扩散语言模型的期待在开源社区并未兑现

- 无法应用**KV cache**：已经被解码的**token**的**key**和**value**始终会在去噪过程中发生变化



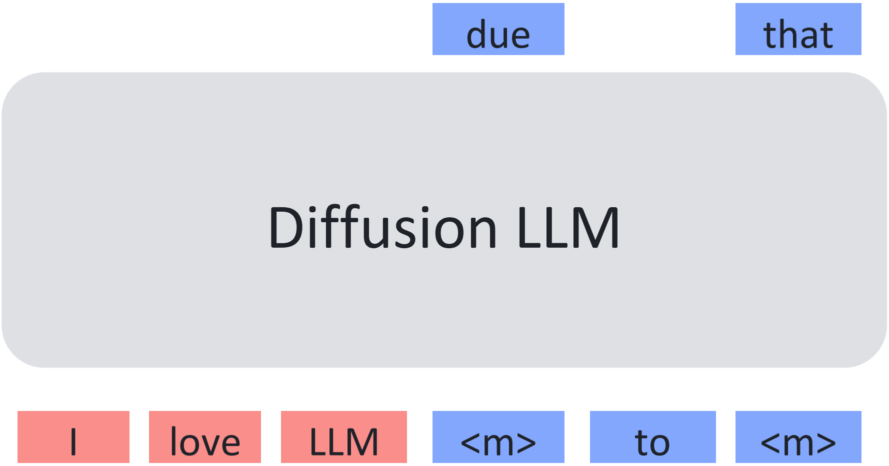
由于扩散模型的全局注意力机制，已经被解码的token的key和value依旧会在生成过程中产生变化，每一步迭代都需重新计算

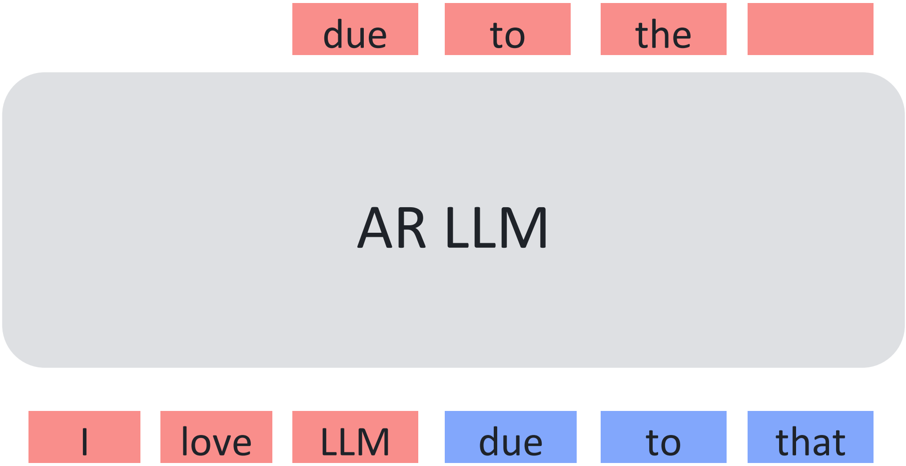
- 同时解码多个**token**时会产生潜在的训练-推理不一致的风险



虽然diffusion LM可以一次预测多个token的logits，其采样相互独立，同时解码相关性强的多个token可能会产生冲突

自回归语言模型 vs 扩散语言模型





- ✅ 有并行潜力
- ❌ 不能用**KV Cache**
- ❌ 固定长度
- ❌ 目前性能稍逊

- ❌ 串行生成
- ✅ 可以用**KV Cache**
- ✅ 任意长度
- ✅ 性能更强

构建自回归-扩散混合的语言高效生成新范式?

自回归-扩散混合的语言生成

Autoregression: ✓ High quality ✓ Arbitrary-length ✓ KV caching ✗ Not Parallelizable

Generation steps

```
There are three categories of the average
There are three categories of the average rate
There are three categories of the average rate of...
```

Diffusion: ✗ Lower quality ✗ Fixed-length ✗ No KV caching ✓ Parallelizable

```
      the reusability                        will continue to        the
Repeal the reusability cuts and       the law will continue to reduce the
Repeal the reusability cuts and prove the law will continue to reduce the deficit.
```

Block Diffusion (Ours): ✓ High quality ✓ Arbitrary-length ✓ KV caching ✓ Parallelizable

```
On September 17,       we      be
On September 17, 2016, we will be giving the      release of
On September 17, 2016, we will be giving the beta-release of the      to our server      testing ...
```

Block diffusion

- teacher forcing

分块的语言生成：

✅ 块间自回归：复用**KV cache**

✅ 块内扩散：并行生成

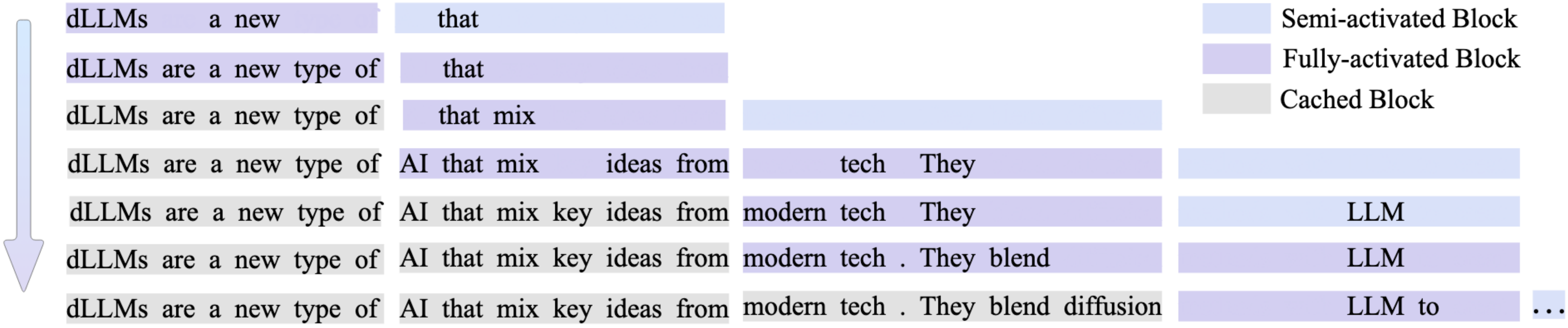
✅ 任意生成长度

❌ 然而，完全杜绝了块间并行

Arriola et al. Block Diffusion: Interpolating Between Autoregressive and Diffusion Language Models

自回归-扩散混合的语言模型

Discrete Diffusion Forcing (D2F): block-wise顺序生成 + **inter-block** 并行



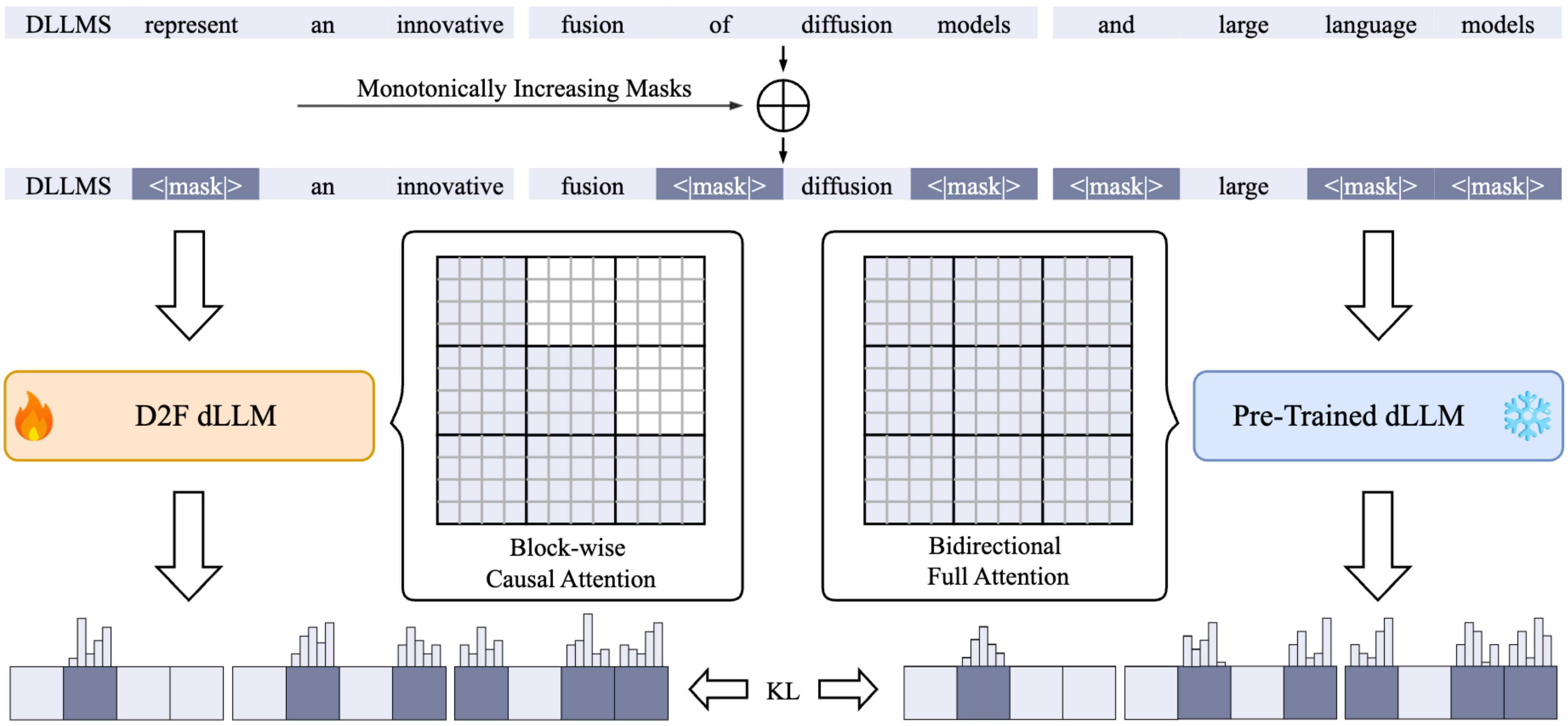
分块的语言生成：

- ✅ 块间自回归：复用**KV cache**
- ✅ 块内扩散：并行生成
- ✅ 任意生成长度
- ✅ 允许块间并行生成

Wang, Xu, Jin, Jin, Hu, Zhang, & Deng. D2F: Diffusion LLMs Can Do Faster-Than-AR Inference via Discrete Diffusion Forcing. https://zhijie-group.github.io/Discrete-Diffusion-Forcing/

自回归-扩散混合的语言模型

Discrete Diffusion Forcing (D2F)：通过非对称蒸馏进行训练



Wang, Xu, Jin, Jin, Hu, Zhang, & Deng. D2F: Diffusion LLMs Can Do Faster-Than-AR Inference via Discrete Diffusion Forcing. https://zhijie-group.github.io/Discrete-Diffusion-Forcing/

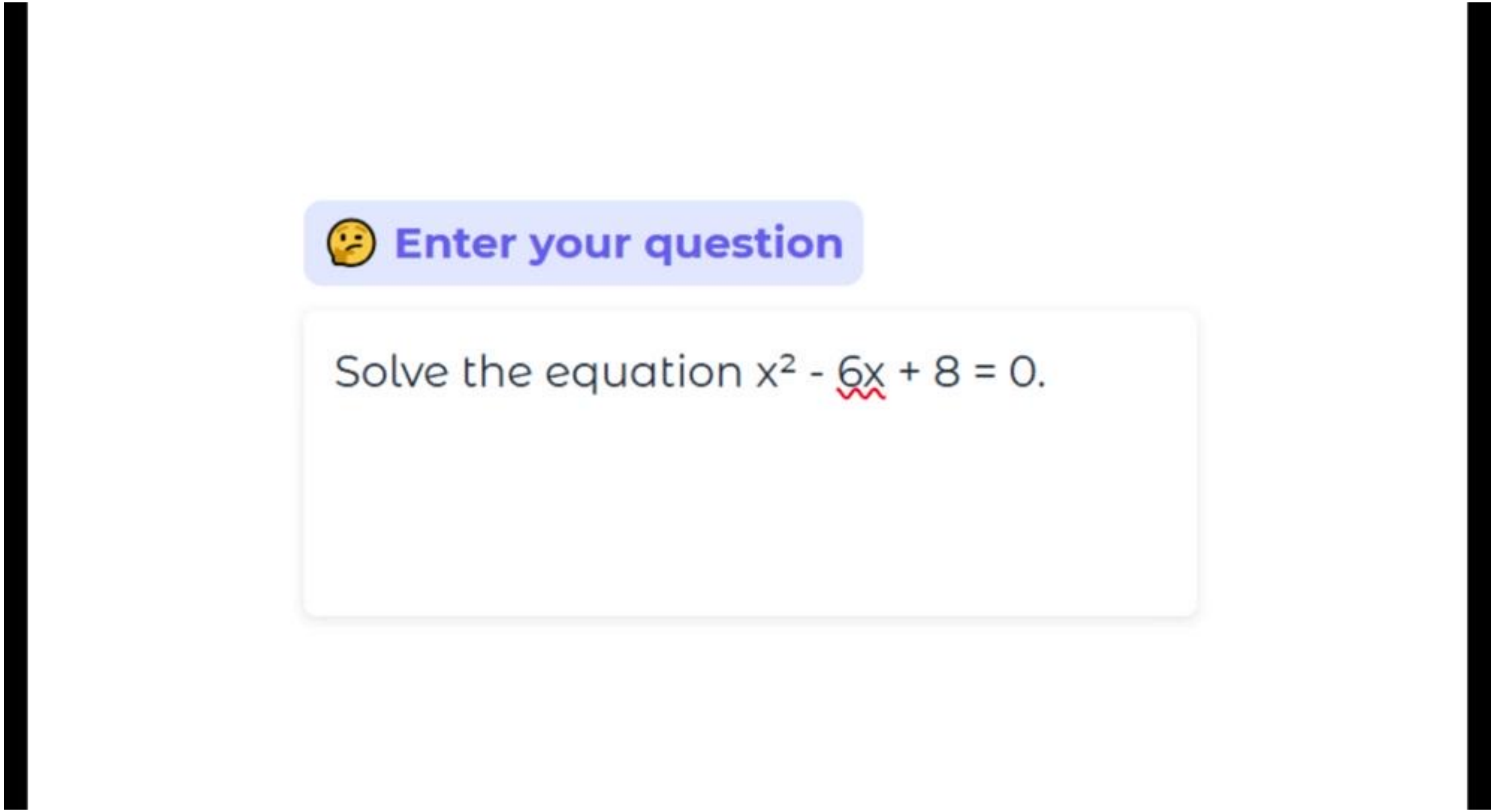
自回归-扩散混合的语言模型

Discrete Diffusion Forcing (D2F)：demo

Wang, Xu, Jin, Jin, Hu, Zhang, & Deng. D2F: Diffusion LLMs Can Do Faster-Than-AR Inference via Discrete Diffusion Forcing. https://zhijie-group.github.io/Discrete-Diffusion-Forcing/

自回归-扩散混合的语言模型

Discrete Diffusion Forcing (D2F)： demo



Wang, Xu, Jin, Jin, Hu, Zhang, & Deng. D2F: Diffusion LLMs Can Do Faster-Than-AR Inference via Discrete Diffusion Forcing. https://zhijie-group.github.io/Discrete-Diffusion-Forcing/

自回归-扩散混合的语言模型

Discrete Diffusion Forcing (D2F)：第一个大幅超越AR模型速度的开源扩散语言模型

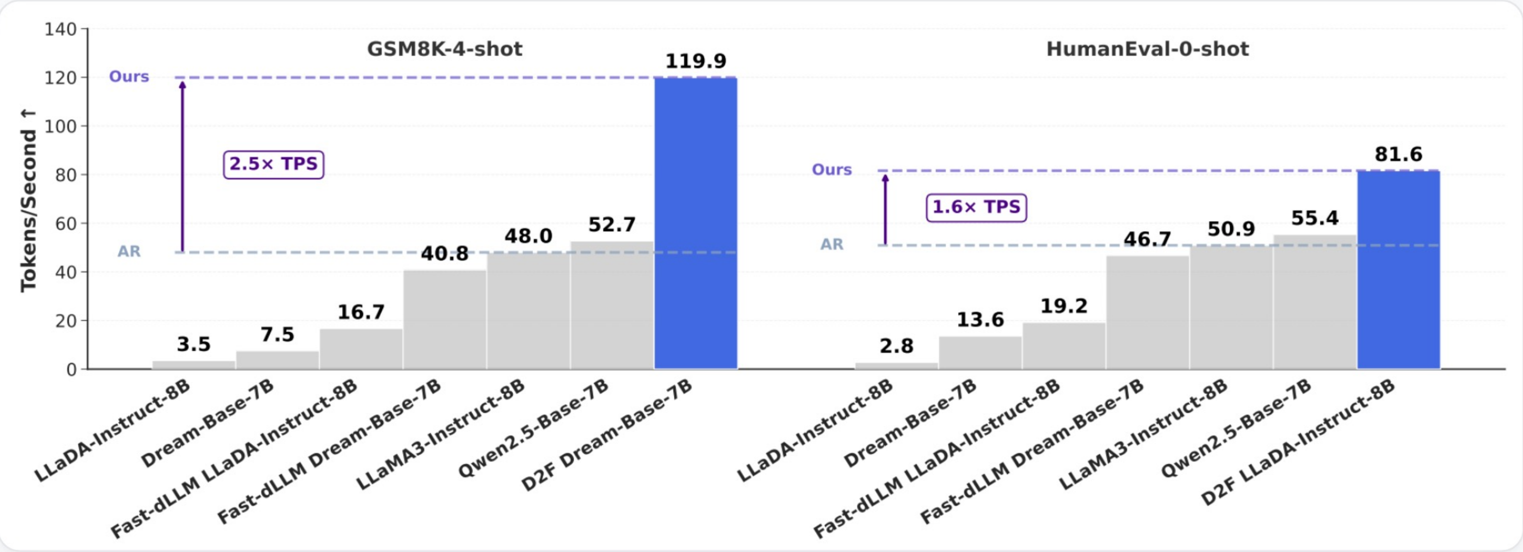
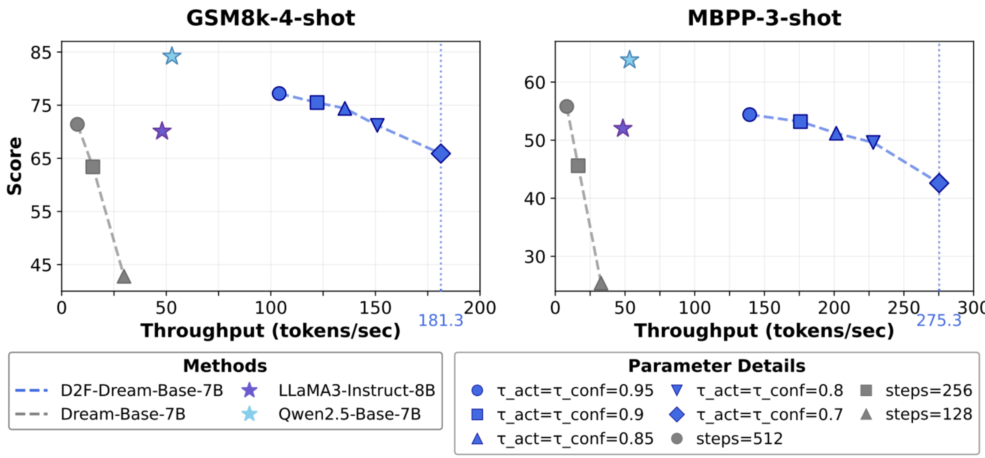


Figure 1. D2F dLLMs surpass similarly-sized autoregressive (AR) models in inference speed for the first time, achieving up to **2.5x** higher throughput than LLaMA3 and Qwen2.5. This comparison includes vanilla dLLMs, previous acceleration methods, and AR baselines.



提供了宝贵的Throughput vs. performance trade-off

Wang, Xu, Jin, Jin, Hu, Zhang, & Deng. D2F: Diffusion LLMs Can Do Faster-Than-AR Inference via Discrete Diffusion Forcing. https://zhijie-group.github.io/Discrete-Diffusion-Forcing/

自回归-扩散混合的语言模型

Discrete Diffusion Forcing (D2F)：效果

Test Set	Method	TPS ↑	Latency (s) ↓	Gen. Length	Score ↑
GSM8K 4-shot	LLaDA-Instruct	7.2 (1.0x)	32.3 (1.0x)	231	77.4
	dLLM-Cache	20.1 (2.8x)	11.5 (2.8x)	231	77.5
	Fast-dLLM (Prefix-Cache)	33.3 (4.6x)	7.0 (4.6x)	232	77.8
	Fast-dLLM (Dual-Cache)	35.2 (4.9x)	6.6 (4.9x)	232	**78.9**
	D2F-LLaDA	**52.5** (7.3x)	**2.8** (11.5x)	144	77.3
MBPP 3-shot	LLaDA-Instruct	0.9 (1.0x)	71.4 (1.0x)	65	**39.0**
	dLLM-Cache	2.3 (2.6x)	28.3 (2.5x)	66	37.0
	Fast-dLLM (Prefix-Cache)	13.0 (14.4x)	4.9 (14.6x)	64	37.6
	Fast-dLLM (Dual-Cache)	15.3 (17.0x)	3.8 (18.8x)	58	36.4
	D2F-LLaDA	**47.6** (52.9x)	**1.4** (51.0x)	68	38.0
HumanEval 0-shot	LLaDA-Instruct	2.8 (1.0x)	38.8 (1.0x)	107	36.0
	dLLM-Cache	4.5 (1.6x)	23.3 (1.7x)	104	39.0
	Fast-dLLM (Prefix-Cache)	13.7 (4.9x)	7.4 (5.2x)	102	38.4
	Fast-dLLM (Dual-Cache)	19.2 (6.9x)	5.2 (7.5x)	100	35.4
	D2F-LLaDA	**81.6** (29.1x)	**1.6** (24.3x)	133	**40.2**
Math 4-shot	LLaDA-Instruct	21.1 (1.0x)	11.5 (1.0x)	243	23.7
	dLLM-Cache	26.9 (1.3x)	9.1 (1.3x)	246	23.2
	Fast-dLLM (Prefix-Cache)	47.7 (2.3x)	5.2 (2.2x)	246	22.4
	Fast-dLLM (Dual-Cache)	42.5 (2.0x)	5.8 (2.0x)	246	22.4
	D2F-LLaDA	**90.2** (4.3x)	**4.3** (2.7x)	384	**29.1**

Table 1: Performance comparison of various acceleration methods on the **LLaDA-Instruct** model. Speedup ratios relative to the baseline are shown in (green). All baseline methods use the default sampling configuration from the original LLaDA implementation.

相对于原始的**DLLMs**，在代码生成上达到超过50倍的加速

Wang, Xu, Jin, Jin, Hu, Zhang, & Deng. D2F: Diffusion LLMs Can Do Faster-Than-AR Inference via Discrete Diffusion Forcing. https://zhijie-group.github.io/Discrete-Diffusion-Forcing/

自回归-扩散混合的语言模型

Discrete Diffusion Forcing (D2F)：与主流推理引擎vLLM兼容

HumanEval:

Baseline: 73.2 tok/s

0.95/0.95: 85.3 tok/s 214 steps

0.7/0.7: 142.2 tok/s 123 steps 峰值 200 tok/s 上下

自回归-扩散混合的语言模型

Discrete Diffusion Forcing (D2F)

GitHub

https://github.com/zhijie-group/Discrete-Diffusion-Forcing

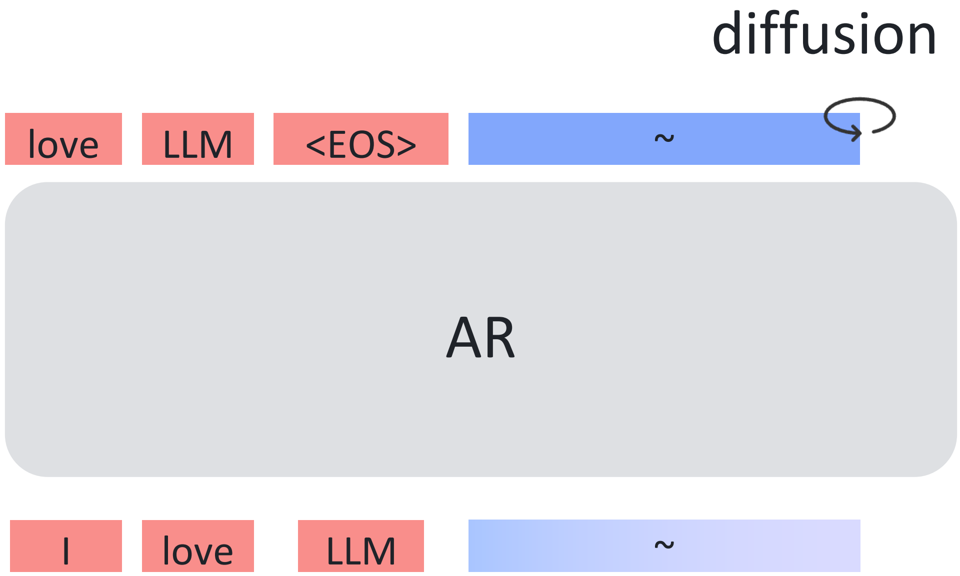
Demo

https://huggingface.co/spaces/zhijie3/D2F-LLaDA-Instruct-8B

自回归-扩散混合的多模态内容生成

“统一生成模型”

基于任意组合的**condition**，生成多模态内容（如：图像、文本、视频、声音、...）



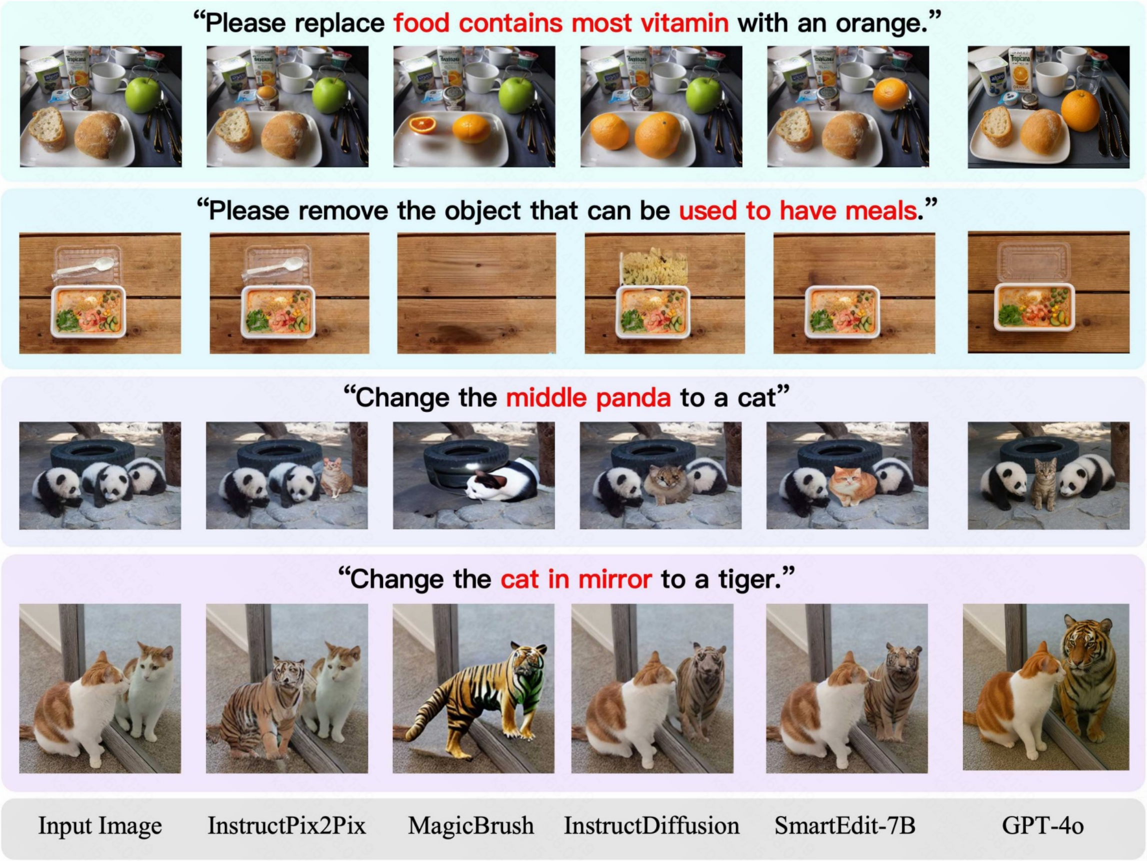
建模复杂的联合分布

- 提供各种条件生成能力

动机：GPT-4o代表的“统一生成模型”（面向图文）

相较于专用的图像生成模型，统一语言和视觉建模有助于建立世界知识

在传统编辑任务中的指令理解与跟随能力显著增强

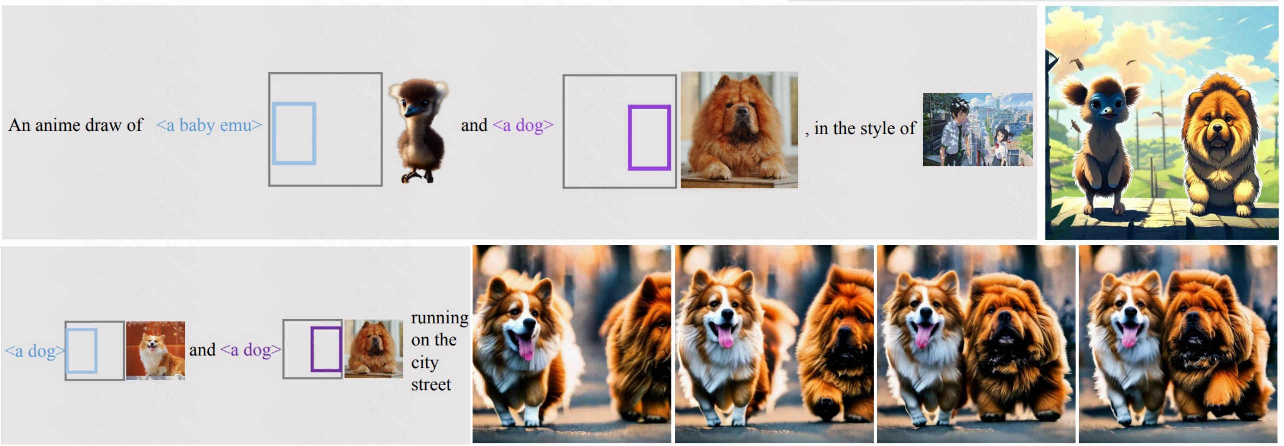


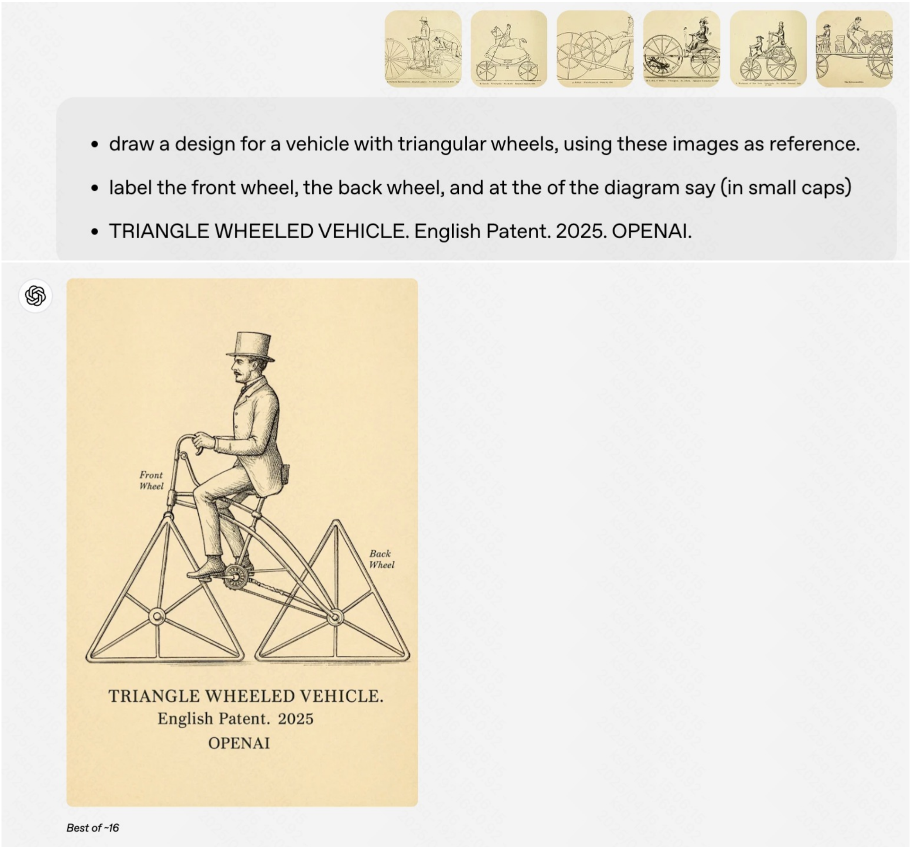
Yan, Zhiyuan, et al. "Gpt-imgeval: A comprehensive benchmark for diagnosing gpt4o in image generation." *arXiv:2504.02782* (2025).

动机：GPT-4o代表的“统一生成模型”（面向图文）

天然具备长上下文学习能力

处理多图与文本混合输入时，统一模型能够有效整合多模态信息，展现了控制精准、主体一致性强的生成效果





Sun, Quan, et al. "Generative multimodal models are in-context learners." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2024.
https://openai.com/index/introducing-4o-image-generation/

如何构建“统一生成模型”

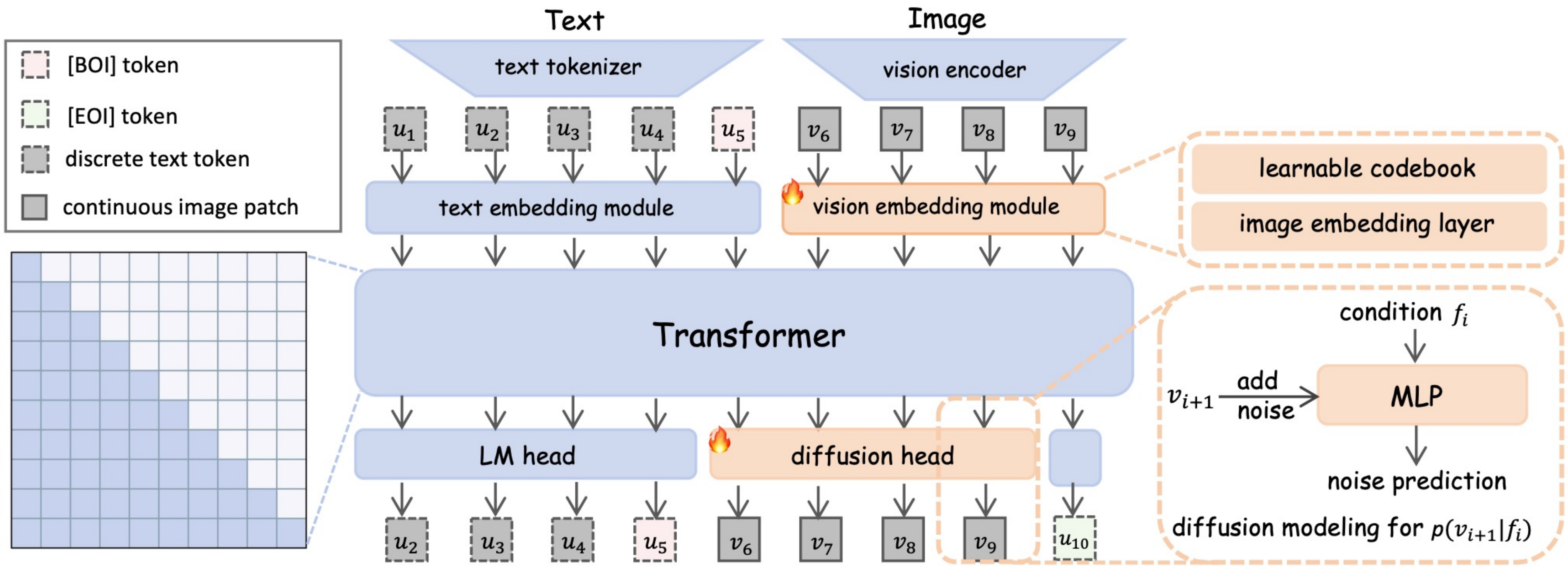
AR-diffusion hybrid的统一模型中，**AR**和**diffusion**分别起什么作用？

AR来“统一”，建立全局关联

- 文：预测下一个离散**token**
- 图：预测下一个图像单元的语义表示

- **Diffusion**来“适配”，链接各种连续模态
  - 图：以语义表示为条件生成连续的**pixels**

Orthus：自回归主干+扩散头



- 自回归**Transformer**主干（拥抱**KV Cache**）
- 处理离散的文本**token**和连续的图像**feature**（基于连续**VAE**）
- 基于线性层定义的**language head**和**diffusion MLP**来分别生成文和图（逐**token/patch**）

Kou, Jin, Liu, Ma, Jia, Chen, Jiang, Deng. Orthus: Autoregressive Interleaved Image-Text Generation with Modality-Specific Heads. ICML 2025

Orthus：自回归主干+扩散头

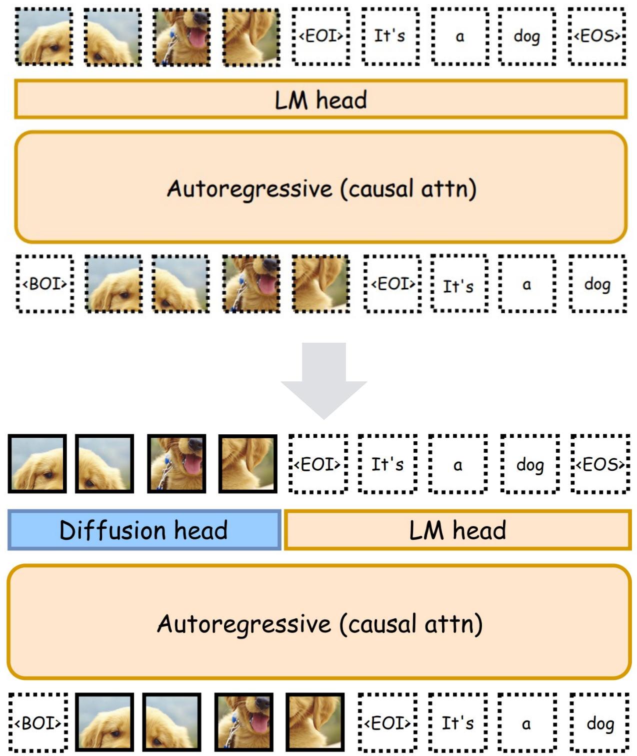
- 从离散图像特征到连续特征：

$$\boldsymbol{h}_i = \sum_j \boldsymbol{w}_j \mathbb{1}_{\tilde{v}_i=j},\ \tilde{v}_i = \underset{j\in\{1,\dots,K\}}{\arg\min}\ d(\boldsymbol{v}_i, \boldsymbol{c}_j)$$

=>

$$\boldsymbol{h}_i = \sum_j \boldsymbol{w}_j \frac{e^{-d(\boldsymbol{v}_i,\boldsymbol{c}_j)/\tau}}{\sum_{k=1}^{K} e^{-d(\boldsymbol{v}_i,\boldsymbol{c}_k)/\tau}}$$

- 自回归统一模型（如：**Chameleon**）： τ =0
- **Orthus: τ = 1**



- 从 τ =0的模型冷启动
  - 72个A100 GPU hours即可得到Orthus-7B-base
- 将涉及的**VQ-VAE**调成了**VAE**

Model	**PSNR**↑	**SSIM** [63]↑
VQ-VAE	23.7	0.80
Ours	26.1	0.84

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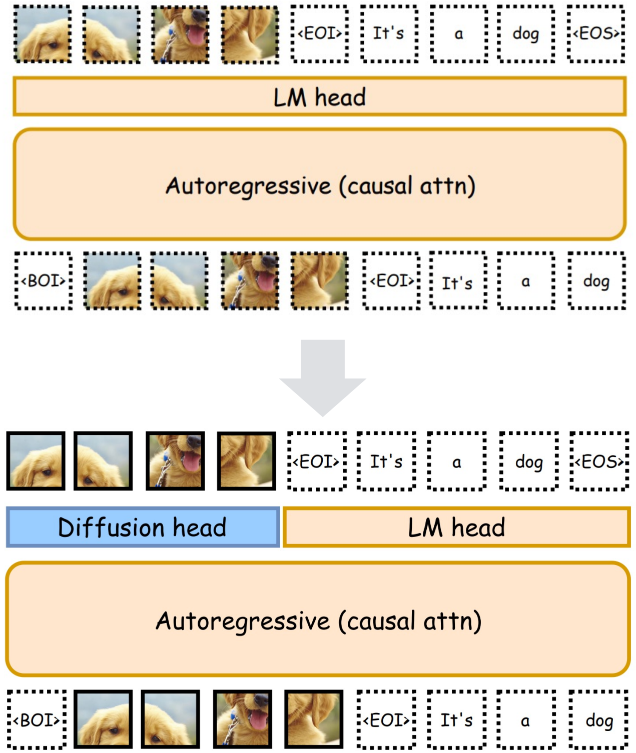
Orthus：自回归主干+扩散头

- **Diffusion head**训练：

$$\mathcal{L}_{\text{diff}} = \mathbb{E}_{\boldsymbol{\epsilon},t}[\|\boldsymbol{\epsilon} - \epsilon_\theta(\sqrt{\overline{\alpha}_t}\boldsymbol{v}_{i+1} + \sqrt{1-\overline{\alpha}_t}\boldsymbol{\epsilon}, t, \boldsymbol{f}_i)\|_2^2]$$

- 从文到图/图到文等不同任务学习有价值信号
  - 1:1混合LlaVA-v1.5-665K指令微调数据和高质量文生图数据JourneyDB、LAION-COCO-aesthetic (recaptioned from ShareGPT-4v)

$$\mathcal{L}_{Orthus} = \mathcal{L}_{\text{ar}} + \lambda\mathcal{L}_{\text{diff}}$$



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Orthus：ablation结果

Table 4. Comparisons of the performance of Orthus via separate training and unified training across multimodal benchmarks.

Type	$\mathcal{L}_{\text{diff}}$	$\mathcal{L}_{\text{ar}}$	POPE↑	MME-P↑	GQA↑	GenEval↑
Und. only	✗	✓	78.7	1244.2	51.9	-
Gen. only	✓	✗	-	-	-	0.56
Und. & Gen.	✓	✓	**79.6**	**1265.8**	**52.8**	**0.58**

同时从文到图和图到文数据学习可以实现1+1>2

Table 5. Ablation study on the choice of vision embedding modules on visual understanding tasks.

Type	POPE↑	MME-P↑	VQAv2↑	GQA↑	MMMU↑
softmax	**78.7**	**1244.2**	**60.8**	**51.9**	**28.0**
argmin	77.6	1064.8	57.9	50.1	26.7
linear	70.4	800.7	50.3	44.5	22.3

连续的图像特征对于视觉理解任务必要，但要避免冷启动

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Orthus：文生图/图生文量化结果

- 在多个图像理解指标上超越了现有混合理解生成模型**Chameleon**和**Show-o**，并在文到图生成的**GenEval** 指标上超过**SDXL**

Table 3. **Comparison with state-of-the-arts on visual generation benchmarks.** Model using external pre-trained diffusion model is marked with * and Chameleon† is post-trained with the same dataset as Orthus. The results in **bold** and underline are the best and second-best results, respectively.

Type	Model	Res.	GenEval	HPS
Gen. Only	SDv1.5 (Rombach et al., 2022)	512	0.43	27.0
	SDv2.1 (Rombach et al., 2022)	512	0.50	27.2
	DALL-E (Ramesh et al., 2022)	512	0.52	26.9
	Emu3-Gen (Wang et al., 2024)	512	0.54	-
	SDXL (Podell et al., 2023)	512	0.55	30.9
	SD3(d=30) (Esser et al., 2024)	512	0.64	-
Und. & Gen.	SEED-X* (Ge et al., 2024)	448	0.49	-
	LWM (Liu et al., 2024e)	256	0.47	26.1
	Show-o (Xie et al., 2024)	256	0.53	27.3
	Transfusion (Zhou et al., 2024)	256	**0.63**	-
	Chameleon†	512	0.43	26.9
	Orthus (Ours)	512	0.58	**28.2**

Table 2. **Evaluation on visual understanding benchmarks.** Und. and Gen. denote "understanding" and "generation", respectively. Models using external pre-trained diffusion models are marked with * and Chameleon† is post-trained with the same dataset as Orthus. The results in **bold** and underline are the best and second-best results, respectively. The results correspond to the exact match accuracy.

Type	Model	# Params	POPE↑	MME-P↑	VQAv2↑	GQA↑	MMMU↑
Und. Only	LlaVa (Liu et al., 2024d)	7B	76.3	809.6	-	-	-
	LlaVA-v1.5 (Liu et al., 2024b)	7B	85.9	1510.7	78.5	62.0	35.4
	InstructBLIP (Dai et al., 2023)	7B	-	-	-	49.2	-
	Qwen-VL-Chat (Bai et al., 2023)	7B	-	1487.5	78.2	57.5	-
	Emu3-Chat (Wang et al., 2024)	8B	85.2	1243.8	75.1	60.3	31.6
	InstructBLIP (Dai et al., 2023)	13B	78.9	1212.8	-	49.5	-
Und. and Gen.	Emu* (Sun et al., 2023)	13B	-	-	52.0	-	-
	NExT-GPT* (Wu et al., 2013)	13B	-	-	**66.7**	-	-
	Gemini-Nano-1 (Team et al., 2023)	1.8B	-	-	62.7	-	26.3
	Show-o (Xie et al., 2024)	1.3B	73.8	948.4	59.3	48.7	25.1
	LWM (Liu et al., 2024e)	7B	75.2	-	55.8	44.8	-
	Chameleon†	7B	77.8	1056.9	57.8	49.6	26.7
	Orthus (Ours)	7B	**79.6**	**1265.8**	63.2	**52.8**	**28.2**

Model	Res.	GenEval↑	HPSv2↑	POPE↑	MME↑	GQA↑
Orthus	512	0.58	28.2	79.6	1265.8	52.8
VILA-U	256	0.40	25.3	83.9	1336.2	58.3
Janus	384	0.61	27.8	87.0	1338.0	59.1

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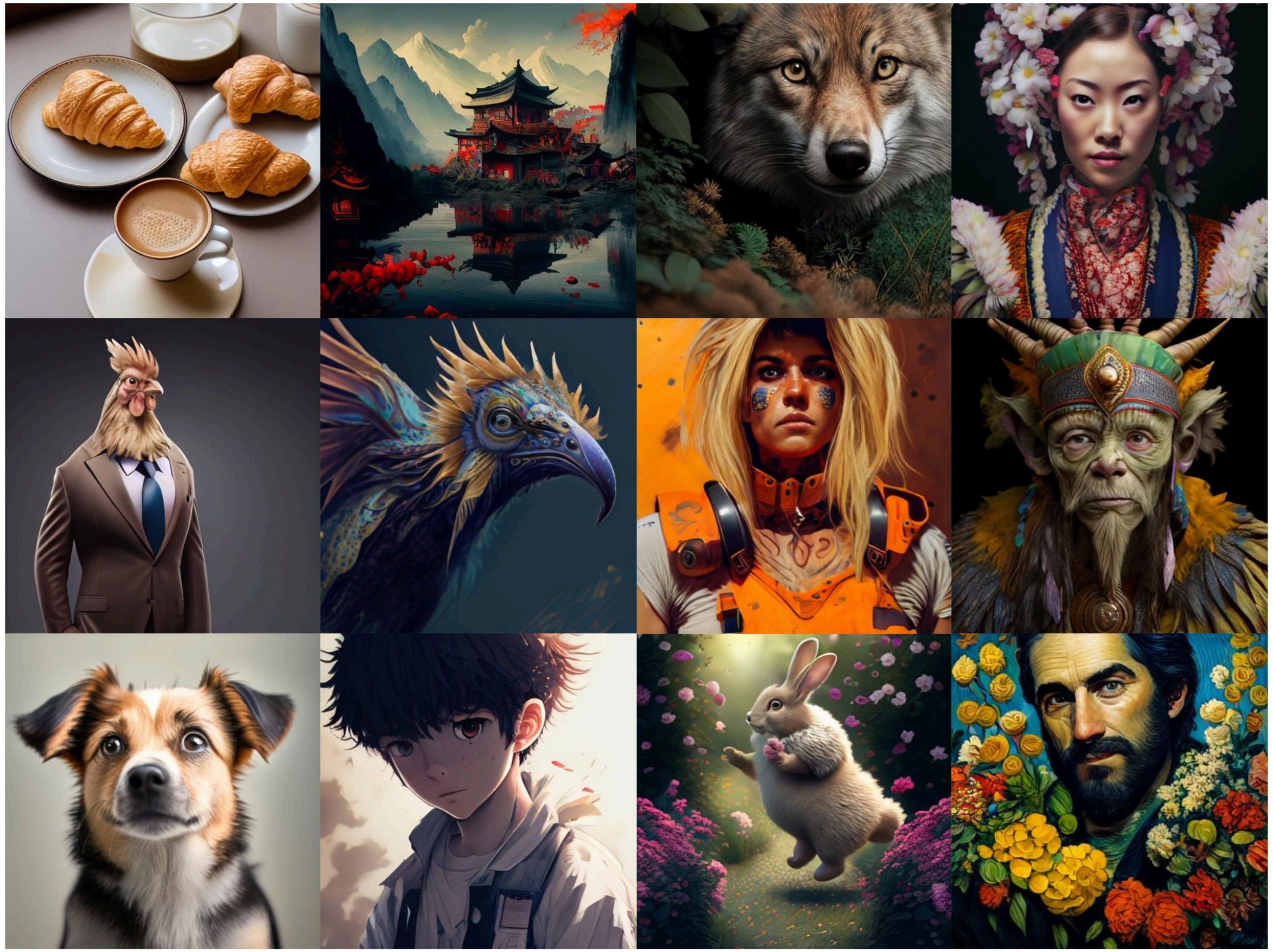
Orthus：文生图可视化结果



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Orthus：图文交错生成结果（图文->图、demo+图->图、图文->图文图文）

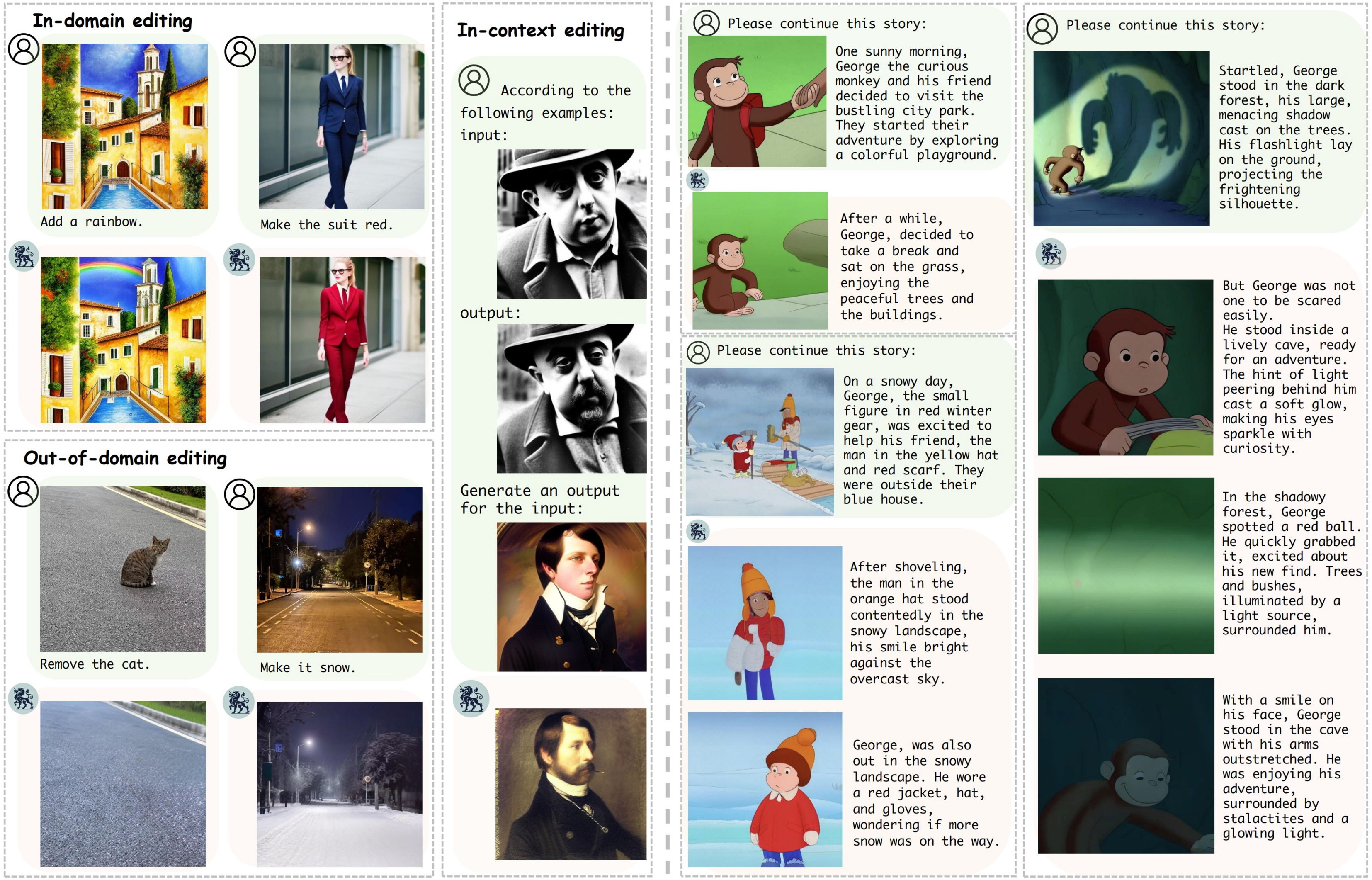

Table 1. Comparisons of CLIP similarities (Ruiz et al., 2023; Gal et al., 2022) between editing-specific diffusion models and Orthus on the test dataset of Instruct-Pix2Pix.

Model	-T↑	-I↑	-D↑
PnP (Tumanyan et al., 2023)	0.156	0.76	0.023
SDEdit (Meng et al.)	0.229	0.84	0.047
I-Pix2Pix (Brooks et al., 2023)	0.233	**0.88**	0.045
Orthus (Ours)	**0.238**	0.87	**0.049**

图像编辑能力指标

	Orthus	Show-o	NExT-GPT	MiniGPT-5	GILL	SEED-X
OpenING-IVD ↑	6.3	5.1	5.2	5.3	6.2	8.0

图文交错生成指标

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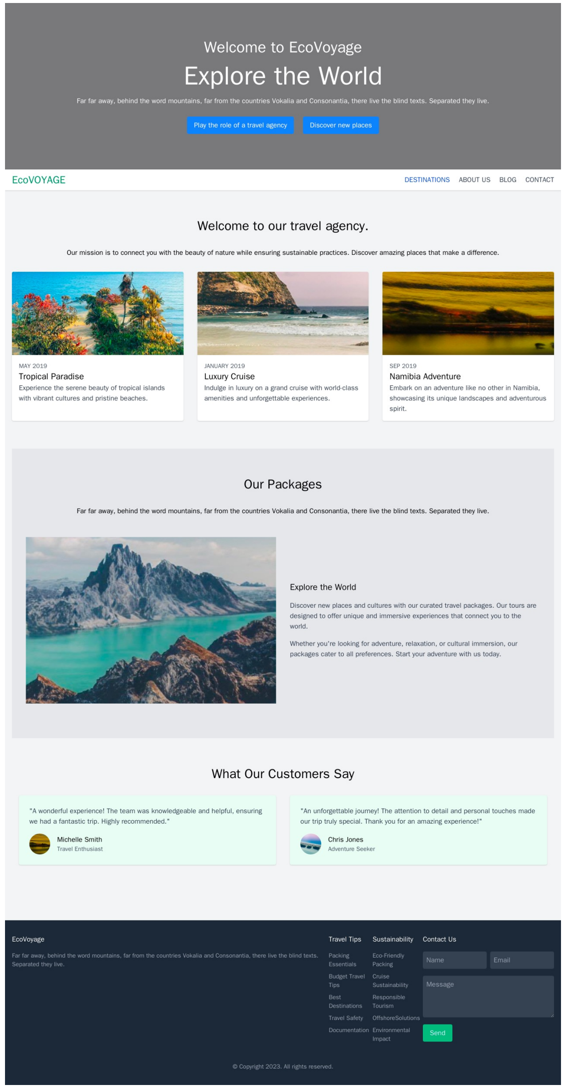
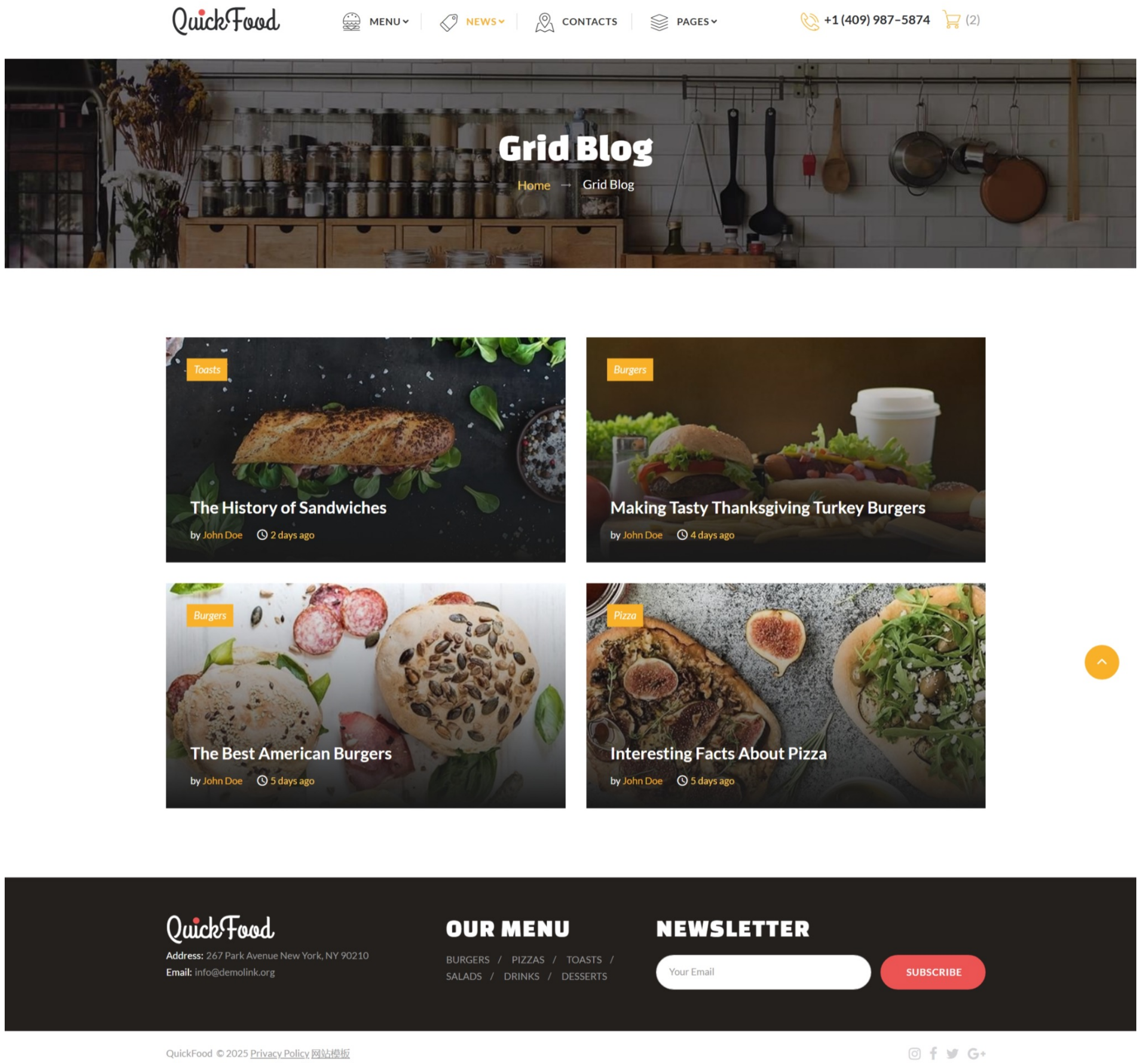
Orthus：图文交错的HTML网页生成





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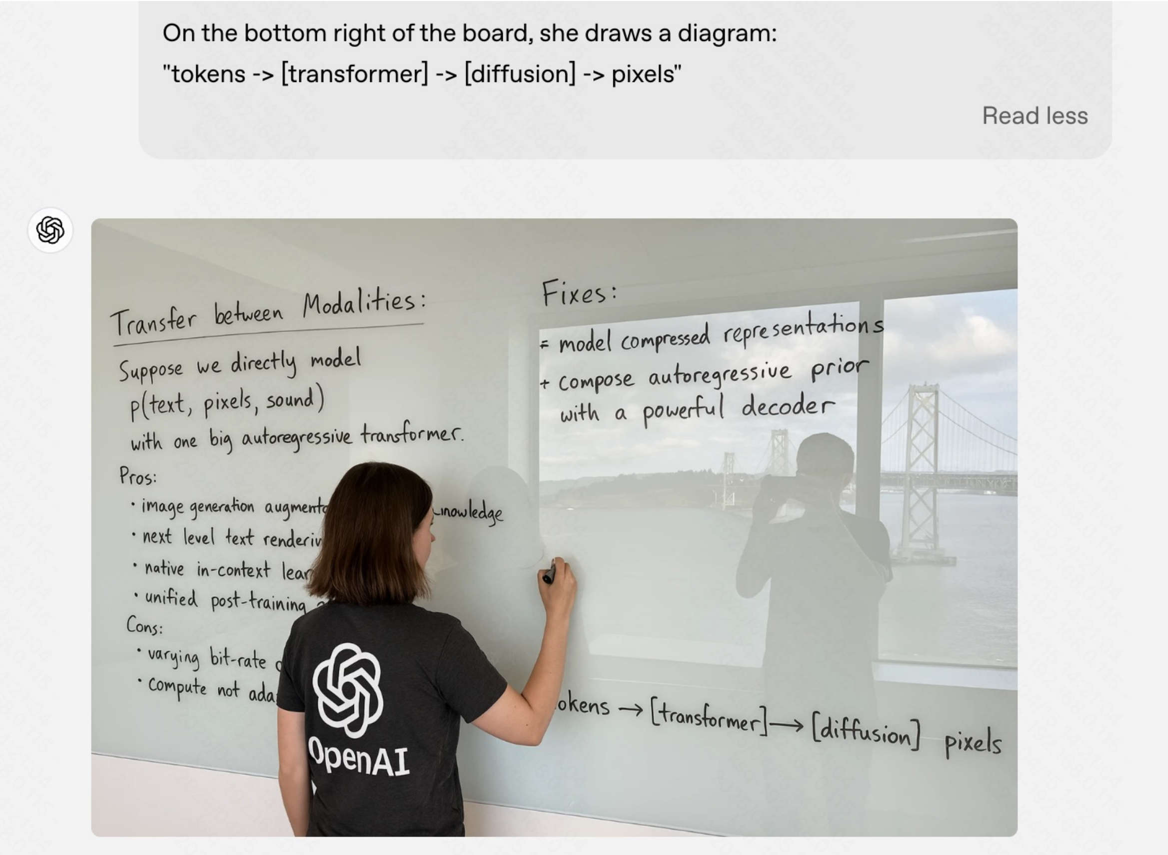
如何将多模态生成理解统一？

GPT-4o的彩蛋：tokens -> [transformer] -> [diffusion] -> pixels

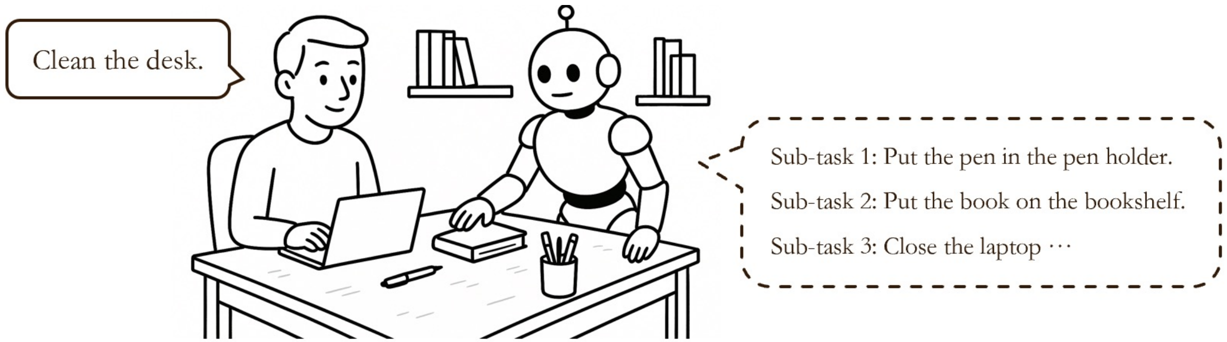
结合自回归模型的语义建模优势和扩散模型的细节建模优势

- 与Orthus (2024.12) 大思路一致
- 未来研究
  - 如何改进生成效率？
  - CLIP feature和VAE feature的选择



多模态内容生成在文/图数据外的应用

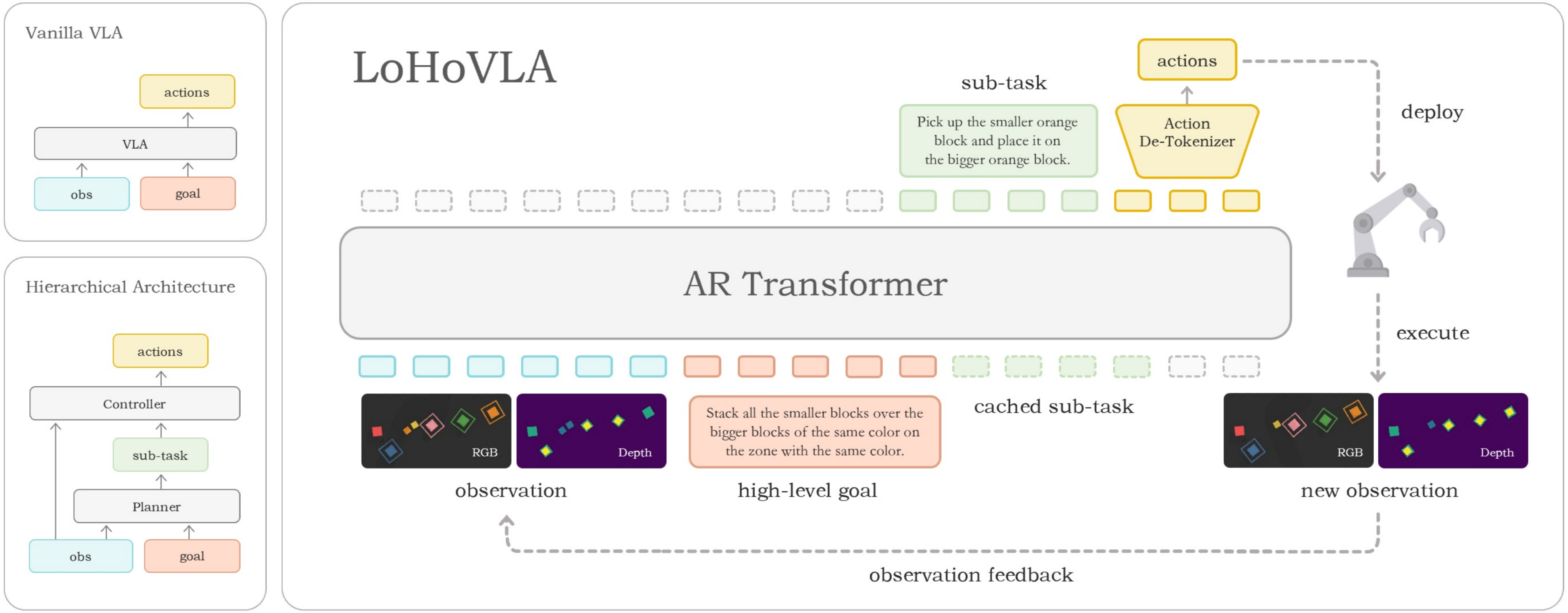
- **Vision-language-action (VLA)！**
- **VLA**为什么需要离散-连续信号交错生成？
  - **long-horizon**任务：高层次目标，需要多个步骤的解决方案



- 要求兼顾高层任务规划（目标->子任务）与低层动作控制（子任务->动作）
- 子任务（文本/图像）和动作（末端执行器位置、夹持器开合）模态不同

LoHoVLA：面向长时程具身任务的统一VLA模型

- 普通**VLA**模型：只能生成动作，隐式规划子任务（规划能力弱）
- 层次化架构：**Planner**规划子任务，**Controller**生成动作（模块冗余，次优协调）
- **LoHoVLA**：使用同一个模型完成子任务规划和动作控制（规划能力强，泛化性好）

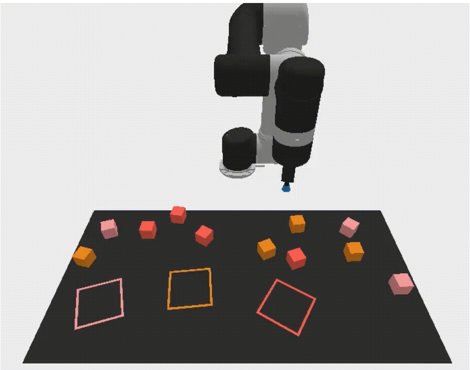


闭环控制

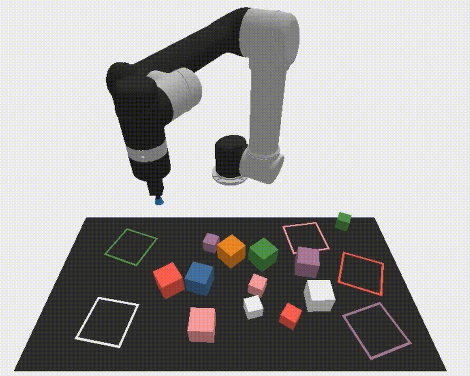
LoHoVLA：显著提高模型的规划能力和未见任务的泛化性能

Table 2: Comparison of the average award (%) and success rate (%) on LoHoRavens benchmark. Bold entries indicate the highest success rates, underlined entries indicate the second-highest.

Tasks		Vanilla VLA	LoHoRavens		LoHoVLA
			Explicit feedback	Implicit feedback	
Seen Tasks	A	**79.0** / 79.0	67.3 / -	67.3 / -	77.5 / 77.5
	B	14.9 / 0.0	31.4 / -	37.0 / -	**97.8** / 91.5
	C	26.8 / 0.5	18.0 / -	22.1 / -	**34.9** / 22.5
	D	32.3 / 3.0	30.4 / -	33.2 / -	**35.8** / 11.5
	E	22.1 / 3.5	9.6 / -	8.2 / -	**85.1** / 81.0
Unseen Tasks	F	52.1 / 9.0	28.5 / -	21.1 / -	**86.1** / 41.0
	G	6.8 / 0.0	21.9 / -	14.7 / -	**40.1** / 25.0
	H	7.3 / 0.0	13.2 / -	5.2 / -	**16.7** / 7.5
	I	43.1 / 1.5	12.8 / -	11.7 / -	**77.2** / 52.0
	J	38.6 / 10.5	27.4 / -	27.2 / -	**43.6** / 22.0
	K	58.2 / 33.0	4.0 / -	6.8 / -	**73.8** / 54.5



"Move all blocks of a color that occur in even numbers to the same colored zone."



"Stack blocks of the same color in the zone with same color, with bigger blocks underneath."

感谢各位专家！敬请批评指正！

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