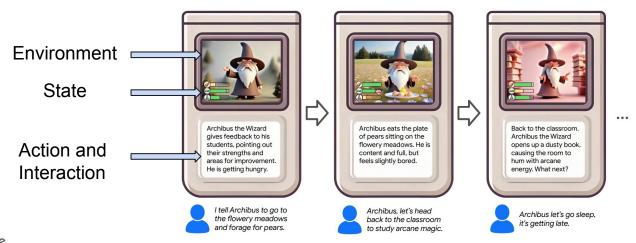


# Unbounded: A Generative Infinite Game of Character Life Simulation

Jialu Li, Yuanzhen Li, Neal Wadhwa, Yael Pritch, David E. Jacobs, Michael Rubinstein, Mohit Bansal, Nataniel Ruiz

#### What's generative infinite game?

 Generative: All the game environments, character states, character actions are encapsulated with generative models.



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- Generative: All the game environments, character states, character actions are encapsulated with generative models.
- Infinite: "played for the purpose of continuing the play", with no fixed boundaries and evolving rules.



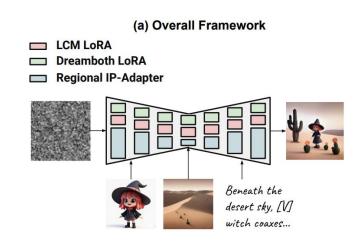
#### Main Components

 Real-time controllable text-to-image generation model capable of maintaining character consistency and environment consistency throughout the generative game

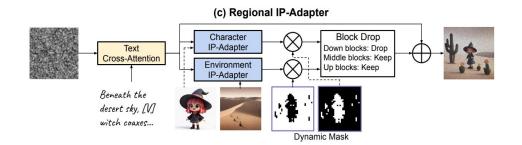
#### Main Components

- Real-time controllable text-to-image generation model capable of maintaining character consistency and environment consistency throughout the generative game
- A large language model acts as game engine for interactive user experience

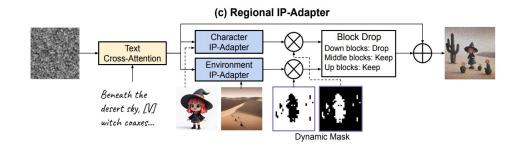
- Latent consistency model for few-step inference
- Dreambooth for character consistency



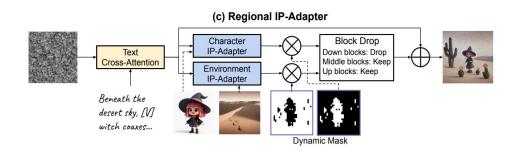
 Dynamic regional IP-Adapter with block drop to mitigate interference.

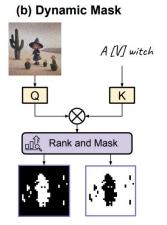


- Dynamic regional IP-Adapter with block drop to mitigate interference.
- Regional: Apply condition to relative region instead of full image.

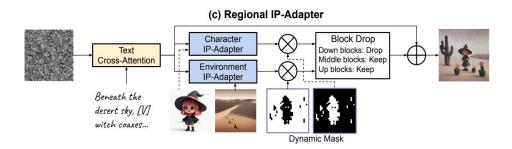


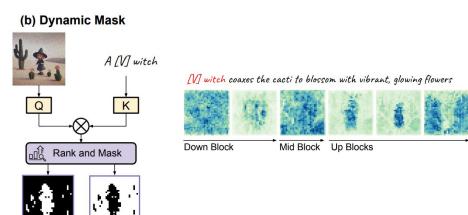
- Dynamic regional IP-Adapter with block drop to mitigate interference.
- Regional: Apply condition to relative region instead of full image.
- Dynamic: The region mask is dynamically extracted from cross-attention layers.



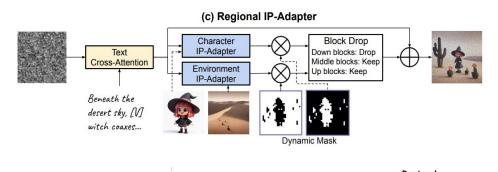


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- Block Drop: Drop blocks with low quality masks





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[V] dog cautiously ascends the creaky wooden steps, each one groaning louder as it climbs the narrow, winding staircase of the haunted castle.

#### Evaluation -- Comparison with Previous Approach

- Evaluation dataset: 5,000 (character image, environment description, text prompt) triplets
- Evaluation metrics: CLIP, DINO, DreamSim

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Methods	Envi	ronment Co	nsistency	Cha	racter Cons	Semantic Alignment		
	$CLIP-I^E \uparrow$	$DINO^E \uparrow$	$DreamSim^E\downarrow$	$CLIP-I^C \uparrow$	$DINO^C \uparrow$	$DreamSim^C\downarrow$	CLIP-T↑	
IP-Adapter (Ye et al., 2023)	0.470	0.381	0.595	0.366	0.139	0.832	0.168	
IP-Adapter-Instruct (Rowles et al., 2024)	0.334	0.151	0.832	0.246	0.124	0.872	0.098	
StoryDiffusion (Zhou et al., 2024c)	0.528	0.257	0.733	0.629	0.464	0.545	0.242	
Ours	0.563	0.322	0.675	0.676	0.470	0.488	0.242	

 Our approach consistently outperforms previous approach in maintaining environment consistency and character consistency, while achieving comparable performance in maintaining semantic alignment.

#### Evaluation -- Effectiveness of Regional IP-Adapter

No.	Block	Regional	Scale	Envi	ronment Co	nsistency	Cha	Alignment		
1101	Drop	IP-Adapter		$\text{CLIP-I}^E \uparrow$	$DINO^E \uparrow$	$DreamSim^E\downarrow$	CLIP-I $^C \uparrow$	$DINO^C \uparrow$	$DreamSim^C\downarrow$	CLIP-T↑
1.	Х	Х	1.0	0.123	0.111	0.885	0.073	0.024	0.973	0.034
2.	1	×	1.0	0.414	0.331	0.647	0.337	0.147	0.832	0.149
3.	/	<b>✓</b>	1.0	0.563	0.322	0.675	0.676	0.470	0.488	0.242
4.	Х	Х	0.5	0.470	0.381	0.595	0.366	0.139	0.832	0.168
5.	1	×	0.5	0.577	0.332	0.640	0.627	0.374	0.575	0.252
6.	1	✓	0.5	0.549	0.263	0.726	0.705	0.514	0.450	0.246

 Adding block drop improves both environment and character consistency compared with multi-IP-Adapter.

#### Evaluation -- Effectiveness of Regional IP-Adapter

No.	Block	Regional	Scale	<b>Environment Consistency</b>			Cha	Alignment		
2,00	Drop	IP-Adapter		CLIP-I $^E \uparrow$	$DINO^E \uparrow$	$DreamSim^E \downarrow$	$\overline{\text{CLIP-I}^C}\uparrow$	$DINO^C \uparrow$	$DreamSim^C \downarrow$	CLIP-T↑
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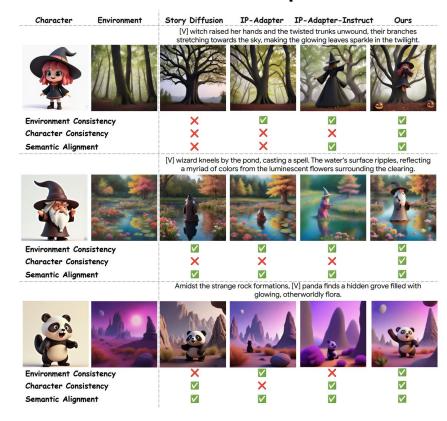
- Adding block drop improves both environment and character consistency compared with multi-IP-Adapter.
- Our regional IP-Adapter enhances character consistency and text alignment while maintaining comparable performance in environment consistency.

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 Injecting IP-Adapter with different scale can effectively balance character consistency and environment consistency.

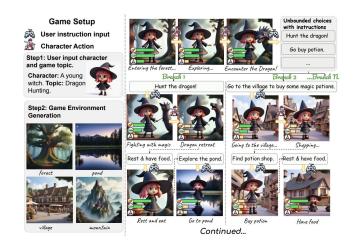
#### **Evaluation -- Qualitative Examples**



#### LLM as Game Engine

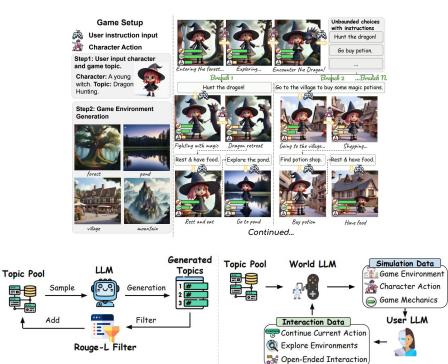
#### Game Engine

- Environment control
- Coherent story generation
- Game mechanics
- Prompt rewriting



#### LLM as Game Engine

- Game Engine
  - Environment control
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  - Prompt rewriting
- Distill Gemma-2B for real-time interactive response

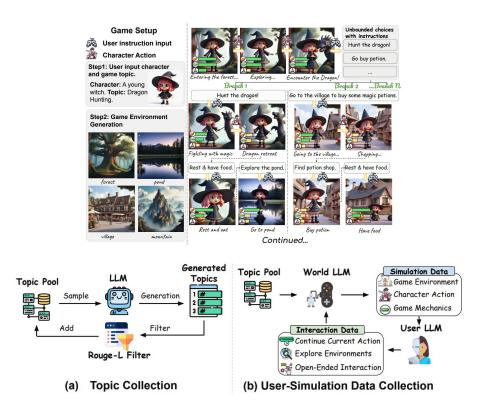


(b) User-Simulation Data Collection

**Topic Collection** 

#### LLM as Game Engine

- Game Engine
  - Environment control
  - Coherent story generation
  - Game mechanics
  - Prompt rewriting
- Distill Gemma-2B for real-time interactive response
- Data collection
  - Diverse topic collection
  - Multi-round interaction data between the world simulation LLM and the user LLM.



#### **Evaluation -- Comparison with Large Models**

- Evaluation dataset: 100 user-simulator interaction samples
- Evaluation metrics: GPT-4 as judge

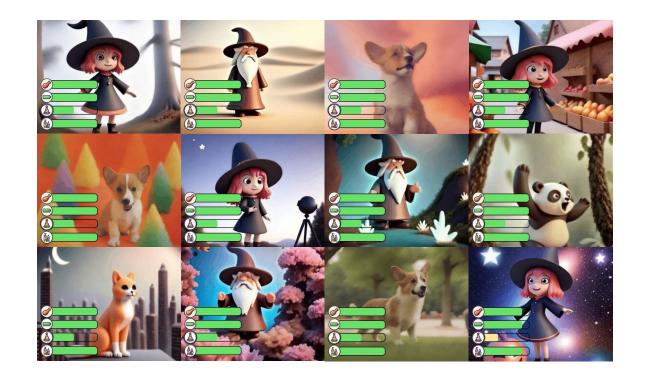
#### **Evaluation -- Comparison with Large Models**

- Evaluation dataset: 100 user-simulator interaction samples
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Model	Overall		State Update		Environment Relevance		Story Coherence		Instruction Following	
	Base	Ours	Base	Ours	Base	Ours	Base	Ours	Base	Ours
Gemma-2B (Team et al., 2024)	6.22	7.44	5.60	7.47	6.12	7.94	6.34	7.57	6.43	7.67
Gemma-7B (Team et al., 2024)	6.80	7.39	6.29	7.43	7.07	7.91	6.90	7.48	6.89	7.53
Llama3.2-3B (Meta, 2024)	7.21	7.50	6.86	7.38	7.63	7.93	7.36	7.56	7.31	7.67
Ours-1k	7.65	7.82	7.50	7.74	8.10	8.19	7.78	7.93	7.82	7.97
GPT-4o (OpenAI, 2023)	7.76	7.68	7.69	7.66	8.20	8.10	7.95	7.82	7.85	7.82

 Distillation with 5k data achieves comparable performance to GPT-4o.

## Summary



#### Thank you!

Project Website: <a href="https://generative-infinite-game.github.io/">https://generative-infinite-game.github.io/</a>

If you have any questions, please contact <a href="mailto:jialuli@cs.unc.edu">jialuli@cs.unc.edu</a>.