



# Conversational Image Generation: Towards Multi-Round Personalized Generation

## with Multi-Modal Language Models

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### Introduction

**Conversational image generation is non-Markovian:** many user requests depend on visual states or bindings introduced several turns earlier.

**Existing benchmarks and models exploit a Markov shortcut,** leading to systematic failures in multi-round editing and identity consistency [1, 2].

**We address this with non-Markov datasets and a history-conditioned generative framework**

- Non-Markov multi-round data:
  - Rollback-style editing dataset
  - Name-based personalization dataset
- token-level caching
- high-fidelity detokenization
- staged personalization training

### Non-Markov Multi-round Image Generation

We represent a conversation up to turn  $t$  as an interleaved history

$$H_t = \{(T_1, I_1), (T_2, I_2), \dots, (T_t, I_t)\}$$

where  $T_i$  is the user instruction at round  $i$  and  $I_i$  is the model-generated image at that round. Given  $H_t$  and a new instruction  $T_{t+1}$ , model generates next image:

$$I_{t+1} \sim p_\theta(I | T_{t+1}, H_t)$$

Many existing multi-turn editing benchmarks [1, 2] are *effectively Markov*

$$p_\theta(I | T_{t+1}, H_t) \approx p_\theta(I | T_{t+1}, I_t)$$

**Markov multi-turn Existing multi-round editing**

Change the color of the plate to blue  $T_1$  Remove the steak and add a grilled salmon fillet  $T_2$  Convert the image to resemble a 19th-century still life painting  $T_3$

$P_\theta(I_2 | I_1, T_1)$   $P_\theta(I_3 | I_2, T_2)$   $P_\theta(I_4 | I_3, T_3)$

**Non-Markov multi-turn Rollback-style editing**

Change the color of the plate to blue  $T_1$  Remove the steak and add a grilled salmon fillet  $T_2$  Backtrack 1 times, Convert the image to resemble a 19th-century still life painting  $T_3$

$P_\theta(I_2 | I_1, T_1)$   $P_\theta(I_3 | I_2, T_2)$   $P_\theta(I_4 | I_2, T_3)$

**Name-based reference**

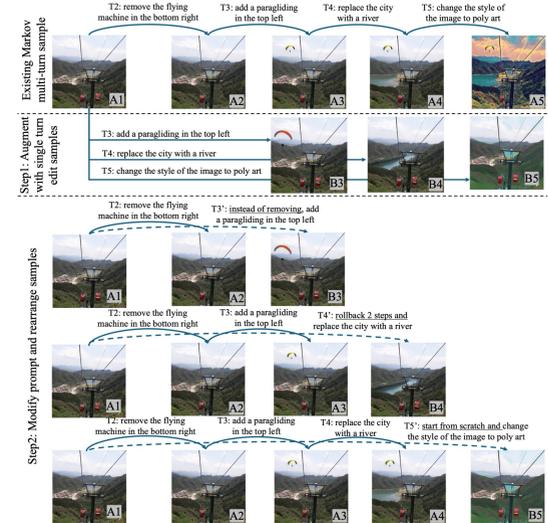
Text-to-image  $T_1$  Generate a close-up photo of Jasper  $T_2$  Create a detailed portrait of Mia  $T_3$

Jasper and Mia sitting on a couch with their eyes closed. Jasper has gray hair and a gray beard ... Mia sits to his right with her head resting against Jasper's chest. She has long brown hair ...

$P_\theta(I_2 | T_1)$   $P_\theta(I_3 | I_2, T_2)$   $P_\theta(I_4 | I_2, T_3)$

### Non-Markov Dataset Construction

#### Rollback-Style Non-Markov Multi-Round Editing



#### Name-Based Non-Markov Multi-Round Personalization

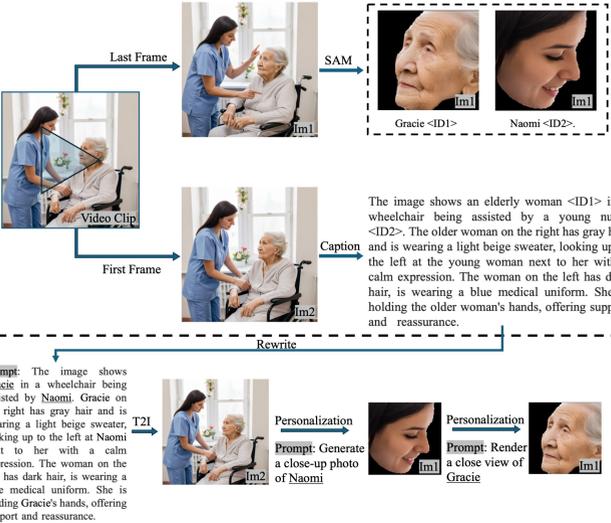
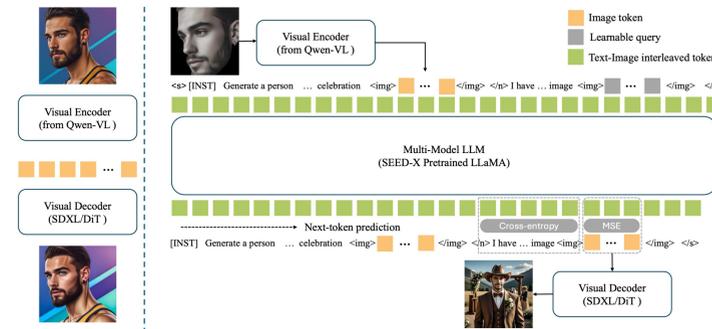


Image-level:  $p_\theta(I | T_{t+1}, H_t) \approx p_\theta(I | T_{t+1}, I_{base})$       token-level:  $p_\theta(I_3 | T_3, H_2) \approx p_\theta(I_3 | T_3, T_1^{(e)}, I_1^{(e)})$

### MLLM and Enabling Components



#### SEED-X [1] Framework

- It treats images as a visual language via a tokenizer [3] – detokenizer [4] interface.
  - However, vanilla framework suffers from reconstruction drift and identity degradation.
- Token-Level Caching**  $H_t = \{(T_1, \hat{I}_1), (T_2, \hat{I}_2), \dots, (T_t, \hat{I}_t)\}$  not  $\Phi(I_t)$
- At round  $t$ , the model produces image tokens  $\hat{I}_t$  (before detokenization)
- We cache  $\hat{I}_t$  and reuse it as the history representation for later rounds

**Reconstruction-Based DiT Detokenizer**

Input	DiT (Ours) FT on Person	DiT (Ours)	SDXL stage1	SDXL stage2	Condition of stage2
PSNR	14.50dB	14.74dB	10.72dB	11.02dB	

**Multi-Stage Instruction Fine-Tuning**

Condition face	Baseline	+ Prompt	Stage1 copy input	Stage2 face2image	Stage3 paired data
Arcface	0.114	0.151	0.597	0.327	0.293

#### Multi-Stage Instruction Fine-Tuning:

- Stage1: Who it is
- Stage2: Where it is
- Stage3: Who it remains

### Non-Markov Multi-Round Experimental Results

(Left: Multi-turn editing results) Finetuned on our dataset, MLLM supports both Markov and non-Markov editing ✓  
 (Middle: Multi-turn personalization results, ours vs baseline) → Ours: Correctly generates two distinct individuals and preserves name-identity bindings across rounds. ✓  
 SEED-X: Fails at two-person generation and defaults to text-to-image behavior, ignoring prior visual context.  
 (Right: Further explorations on full-body multi-turn personalization.)

**Full-body personalization:** Fine-tuning enables multi-round full-body generation, though face fidelity is lower than in close-up portraits  
 This is due to noisier, diffusion-synthesized supervision and a smaller dataset.

**Non-Markov evidence:** When early rounds leave attributes implicit (e.g., age), the model infers a plausible identity and consistently preserves it across later rounds—even with identical text prompts. ✓

**Markov Multi-Turn**

Source Image Round1 Round2 Round3

**Markov:** T1: Replace the shore with a mountain range; T2: Change the horse to a white horse; T3: Convert the image into a watercolor painting

**Non-Markov:** T3': Step back 2 times, Convert the image into a watercolor painting

**Markov Multi-Turn**

Source Image Round1 Round2 Round3

**Markov:** T1: Change the background to a sunny beach scene; T2: Replace the parking meters with palm trees; T3: Convert the image into a Comic Book style

**Non-Markov:** T3': Instead of Replace the parking meters with palm trees, Convert the image into a Comic Book style

**Prompt for full-body personalization**

Round1: Generate a image shows Henry and Lucas sitting at a table together. Henry has white hair and a white beard, and he is wearing a blue-and-white checkered button-up shirt. He is looking down at his hands as he holds two small pots with brown dirt in them. There is a hand protruding from the bottom left corner of the image holding a handful of seeds that are spilling out into the pots. Lucas is on the right side of the table. He has blond hair and he is wearing a navy-blue button-up shirt. He is looking down at the table with a neutral expression. There are gardening tools on the table in front of him. The background shows a kitchen with light-brown wood panel walls. There is a white sink on the left edge of the image. Above it, there is a white countertop with a white faucet. On the back wall, there is a white electrical outlet with a white switch above it. There is a white cabinet underneath the countertop on the right side of the image.

Round2: Henry is sitting on a light-green metal folding chair at an outdoor cafe. They wear a red beanie, a yellow long-sleeve shirt with a white checkered pattern, black pants, white socks, and black and white Nike shoes. Their left leg is bent upward and their right leg is stretched out behind them. They hold a phone in their left hand and look at the camera with a neutral expression. In front of them are two light-blue chairs and one light-yellow chair. The background is a gray sidewalk with green grass growing between it and a building. On the other side of the sidewalk is a glass wall with tall red spikes protruding from the ground.

Round3: Lucas is sitting on a black bench. They are wearing a black pacoat over a black shirt and blue jeans with holes in the knees. They look at the camera with a neutral expression. The background is a white wall with a shadow falling on the left side.

### Conclusions

**In summary,** conversational image generation requires explicit history conditioning to resolve rollback edits and identity references across multiple turns. Our non-Markov datasets and history-aware modeling pipeline can improve multi-round editing reliability and personalization consistency.

#### Future Directions:

- Standardized non-Markov conversational benchmarks for image generation.
- More diverse and complex non-Markov multi-round datasets.
- Memory mechanisms for long-horizon dialogue and visual state retrieval.
- Improved image token- and detokenization for stable long-term generation.

Please also refer to our extended arXiv version:



**References**

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4. D. Podell, Z. English, K. Lacey, A. Blattmann, T. Dockhorn, J. M'uller, J. Penna, and R. Rombach, "SDXL: Improving latent diffusion models for high-resolution image synthesis," arXiv preprint arXiv:2307.01952, 2023.