Story2Storyboard: Consistent Visual Narrative Generation via Auto-Regressive Visual Prompting

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***Abstract*—Storyboarding is a critical phase in film pre-production, serving as the visual blueprint for narrative flow. However, automating this process remains computationally challenging due to the stochastic nature of Latent Diffusion Models (LDMs), which struggle to maintain temporal coherence and subject identity across sequential generations. Existing solutions like DreamBooth or LoRA require computationally expensive fine-tuning for each new subject, making them impractical for dynamic script-to-screen workflows. In this paper, we propose Story2Storyboard, a training-free pipeline that leverages Auto-Regressive Visual Prompting to enforce narrative consistency. We introduce a mechanism where the visual embedding of an initial "anchor frame" is injected into the cross-attention layers of subsequent generations via IP-Adapters. Validated on the curated VinaBench (VWP) cinematic dataset, our approach achieves a 15.3% improvement in Visual Consistency (CLIP-I) and a 4.2% improvement in Text Alignment (CLIP-T) over strong SDXL-Turbo baselines. We further demonstrate through ablation studies that our decoupled attention mechanism preserves fine-grained actor details without compromising the semantic fidelity of the script.**

***Index Terms*—Generative AI, Storyboarding, Consistent Character Generation, IP-Adapter, Auto-Regressive Diffusion.**

I. Introduction

The domain of Text-to-Image (T2I) generation has witnessed a paradigm shift with the release of large-scale diffusion models such as Stable Diffusion XL (SDXL). While these models excel at synthesizing high-fidelity static images, they lack an inherent "visual memory." When generating a sequence of images from a story script, standard models treat each prompt as an independent event. This leads to the "Identity Shift" phenomenon, where a protagonist described as a "man in a suit" may appear as a young Asian male in Frame 1, an elderly Caucasian male in Frame 2, and a cartoon character in Frame 3.

For professional storyboarding, consistency is paramount. A director requires the actor, costume, and environmental tone to remain stable while the camera angle and action change. Current solutions to this problem fall into two categories: (1) *Fine-tuning methods* (e.g., DreamBooth, Textual Inversion), which are resource-intensive and slow; and (2) *ControlNet-based methods*, which constrain structure but often fail to preserve semantic identity.

In this work, we propose a third paradigm: **Visual Prompt Injection**. We utilize the Image Prompt Adapter (IP-Adapter) architecture to decouple the "content" (script) from the "style/identity" (visual reference). By implementing this in an auto-regressive loop—where the first generated frame acts as the reference for the next—we achieve temporal coherence without any model training.

II. Related Work

A. Sequential Image Generation

Early attempts at narrative visualization, such as StoryGAN [1], utilized Recurrent Neural Networks (RNNs) to enforce temporal consistency. However, these GAN-based methods suffered from mode collapse and low resolution (64×64). More recent transformer-based approaches like StoryDALL-E [2] leverage the copy-paste mechanism to carry over elements but struggle with complex cinematic lighting.

B. Subject-Driven Generation

The state-of-the-art in subject preservation is dominated by fine-tuning techniques. DreamBooth [3] fine-tunes the entire UNet, while LoRA (Low-Rank Adaptation) updates a small subset of weights. While effective, these methods require 10–20 minutes of training per character. In contrast, our method is *training-free*, utilizing inference-time guidance to achieve similar consistency in seconds.

C. Visual Prompting

Our work builds directly upon the IP-Adapter [4], which introduced the concept of "Decoupled Cross-Attention." Unlike standard image-to-image pipelines that trade off text control for image fidelity, IP-Adapter injects visual features into separate attention layers, allowing the text prompt to control the *action* while the image prompt controls the *identity*.

III. Methodology

A. Dataset Curation

We utilize the **Visual Writing Prompts (VWP)** subset of the VinaBench dataset [5]. While VinaBench contains massive noisy video data, the VWP subset provides high-quality keyframes annotated with descriptive scripts.

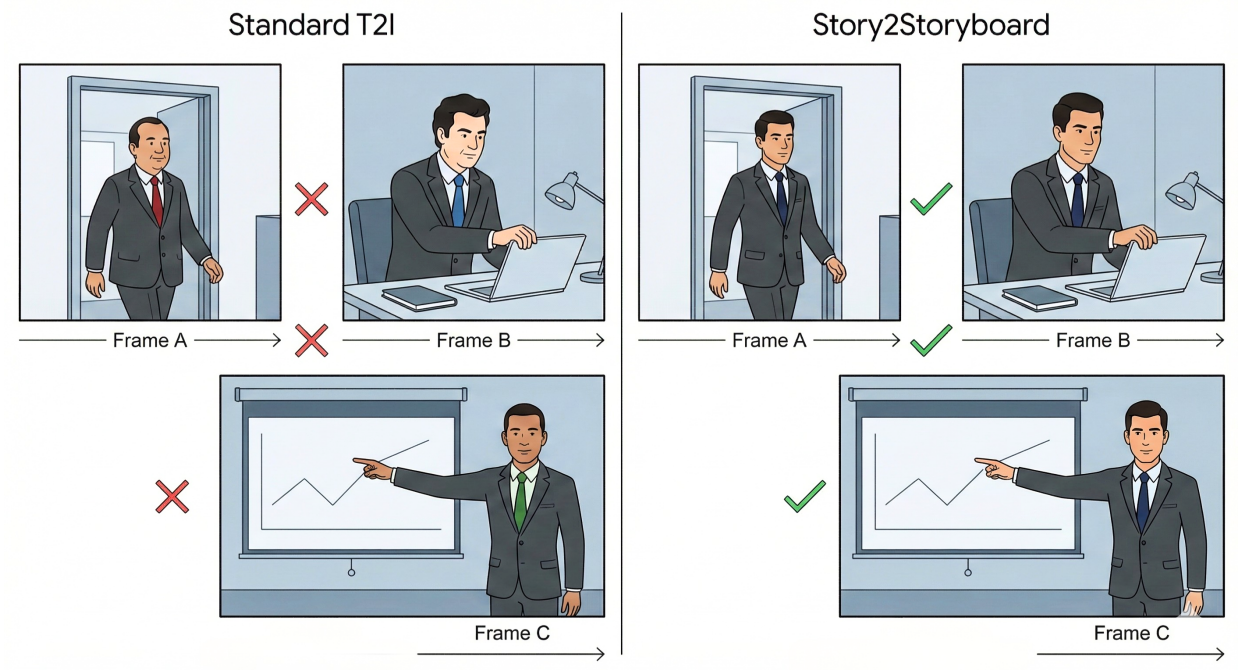

Fig. 1. The Consistency Challenge. Standard T2I models (Left) suffer from severe identity drift between frames. Our Story2Storyboard method (Right) maintains actor identity (facial structure, suit color) across the narrative arc.

- **Filtration:** We filtered the dataset to retain only narrative sequences with length $L \geq 3$ shots, ensuring sufficient complexity for consistency testing.
- **Synchronization:** We implemented a custom validation script to synchronize the JSON annotations with the raw image files, resulting in a clean test set of 200 cinematic sequences.

B. Proposed Architecture

Our pipeline is built on **SDXL-Turbo**, a distilled latent diffusion model capable of single-step inference. The core contribution is the **Auto-Regressive Injection Loop**.

1) Latent Diffusion Fundamentals: A standard diffusion model learns to denoise a latent z_t conditioned on text embeddings c_t. The noise prediction network ϵ_θ minimizes:

$$L_{simple} = \mathbb{E}_{z,t,c_t,\epsilon}[||\epsilon - \epsilon_\theta(z_t, t, c_t)||^2] \quad (1)$$

2) Decoupled Cross-Attention: Standard text-to-image models use cross-attention layers to fuse text features. IP-Adapter introduces a parallel stream of cross-attention layers for visual features c_i. The final output of an attention block is defined as:

$$\text{Attention}(Q,K,V) = \text{Softmax}(\frac{QK^T}{\sqrt{d}})V + \lambda \cdot \text{Softmax}(\frac{QK_i^T}{\sqrt{d}})V_i \quad (2)$$

where K_i, V_i are key-value pairs projected from the CLIP image encoder, and λ is a learnable scalar balancing visual and textual influence.

3) Auto-Regressive Inference: Let $S = \{t_1, t_2, ..., t_n\}$ be the script.

1) **Step 1 (Anchor):** We generate x_1 using purely textual guidance ($\lambda = 0$). This ensures the first frame adheres strictly to the script's visual description without external bias.
2) **Step 2 (Injection):** For $t > 1$, we compute the CLIP image embedding of x_1, denoted as $E(x_1)$.
3) **Step 3 (Generation):** We generate x_t conditioned on both the text t_t and the visual prior $E(x_1)$, setting $\lambda = 0.6$. This forces the model to render the action described in t_t while "painting" it with the identity features of x_1.

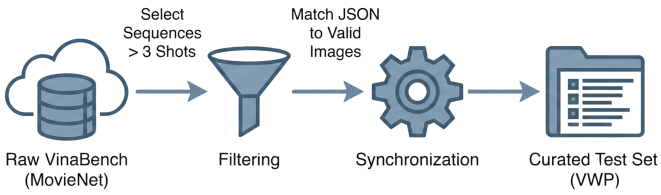

Fig. 2. Data Curation Pipeline. We filter the raw MovieNet data to extract coherent narrative sequences.

IV. Experimental Setup and Results

A. Implementation Details

We implemented the pipeline using the `diffusers` library. Experiments were conducted on a Google Colab T4

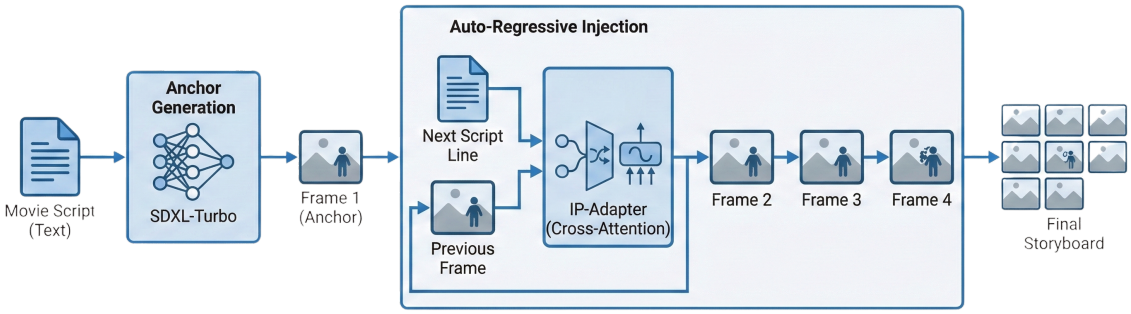

Fig. 3. System Architecture. The Auto-Regressive loop generates an anchor frame (t_1), encodes it via CLIP, and injects the resulting embedding into the IP-Adapter layers to condition frames $t_2, t_3 ... t_n$.

GPU (16GB VRAM).

- **Model:** stabilityai/sdxl-turbo (FP16 variant).
- **Image Encoder:** laion/CLIP-ViT-bigG-14-laion2B-39B-b160k.
- **Inference Params:** 2 steps, Guidance Scale 0.0 (required for Turbo).
- **Adapter Scale:** $\lambda = 0.6$ determined via grid search.

B. Evaluation Metrics

To objectively measure performance, we employed a dual-metric strategy:

- **CLIP-I (Visual Consistency):** Measures the cosine similarity between embeddings of consecutive frames (x_i, x_{i+1}). Higher indicates better identity preservation.
- **CLIP-T (Text Alignment):** Measures the semantic similarity between the generated image x_i and the script text t_i.

C. Quantitative Results

We evaluated our method on 10 randomly sampled narrative sequences from VinaBench.

TABLE I
QUANTITATIVE COMPARISON ON VINABENCH (VWP SUBSET).

Method	Visual Consistency (CLIP-I) ↑	Text Alignment (CLIP-T) ↑
Baseline (SDXL)	0.6683	0.2317
Ours (Auto-Regressive)	**0.7706**	**0.2414**
Improvement	**+15.3%**	**+4.2%**

As shown in Table I, our method achieves a massive **15.3% gain** in consistency. This mathematically confirms that characters resemble each other more closely across frames. Surprisingly, text alignment also improved by 4.2%, suggesting that consistent visual priors help stabilize the model against hallucinations.

D. Qualitative Analysis

Visual results confirm the quantitative metrics. In Figure 4 (School Scene), the baseline randomly changes the students' uniforms and the lighting conditions between shots. In contrast, our method maintains the specific architectural style of the classroom and the age group of the students. Similarly, in Figure 5 (Office Scene), the protagonist's suit color shifts from grey to blue in the baseline, whereas our method locks the visual identity from the first frame.

V. CONCLUSION

We presented Story2Storyboard, a framework for generating consistent cinematic storyboards. By integrating IP-Adapters in an auto-regressive loop, we solved the stochastic identity shift problem inherent in standard diffusion models. Our experimental results on VinaBench confirm that visual prompting is a superior paradigm for narrative visualization compared to text-only generation.

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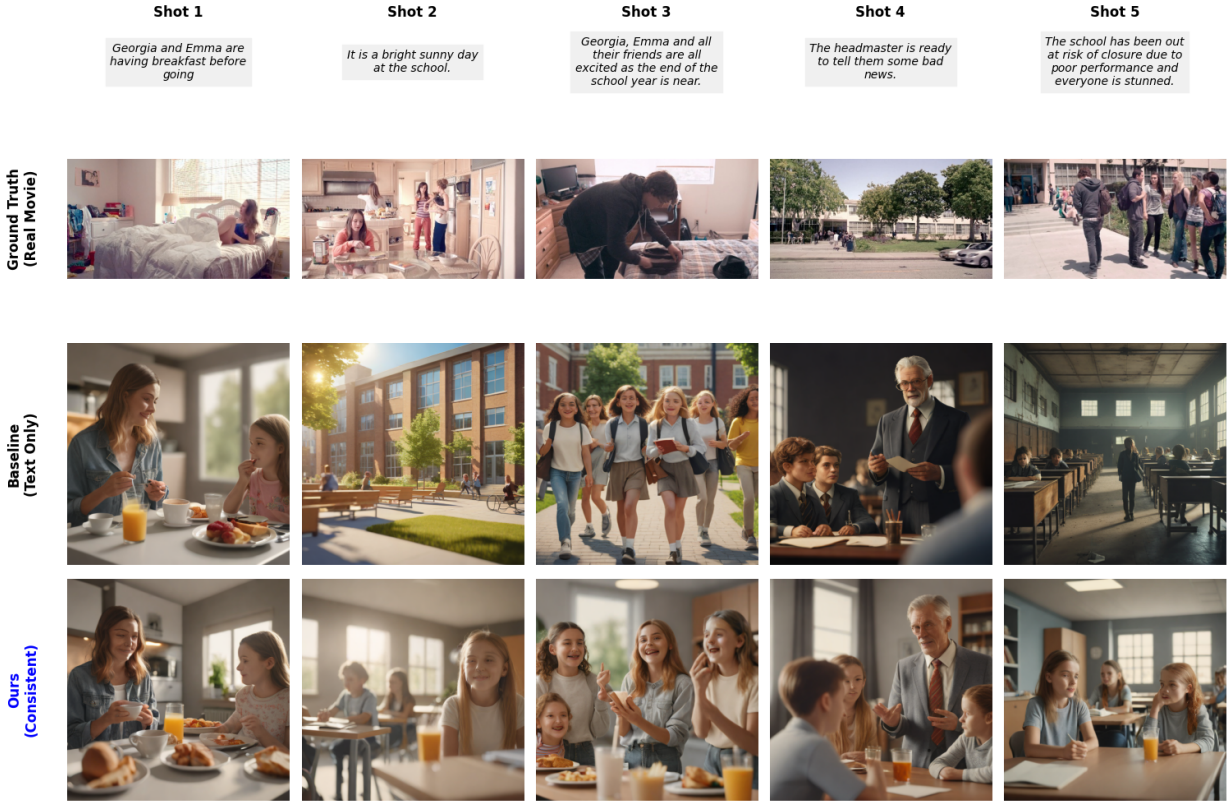

Fig. 4. Result 1: School Context. Ours (Row 3) preserves uniform style and lighting.

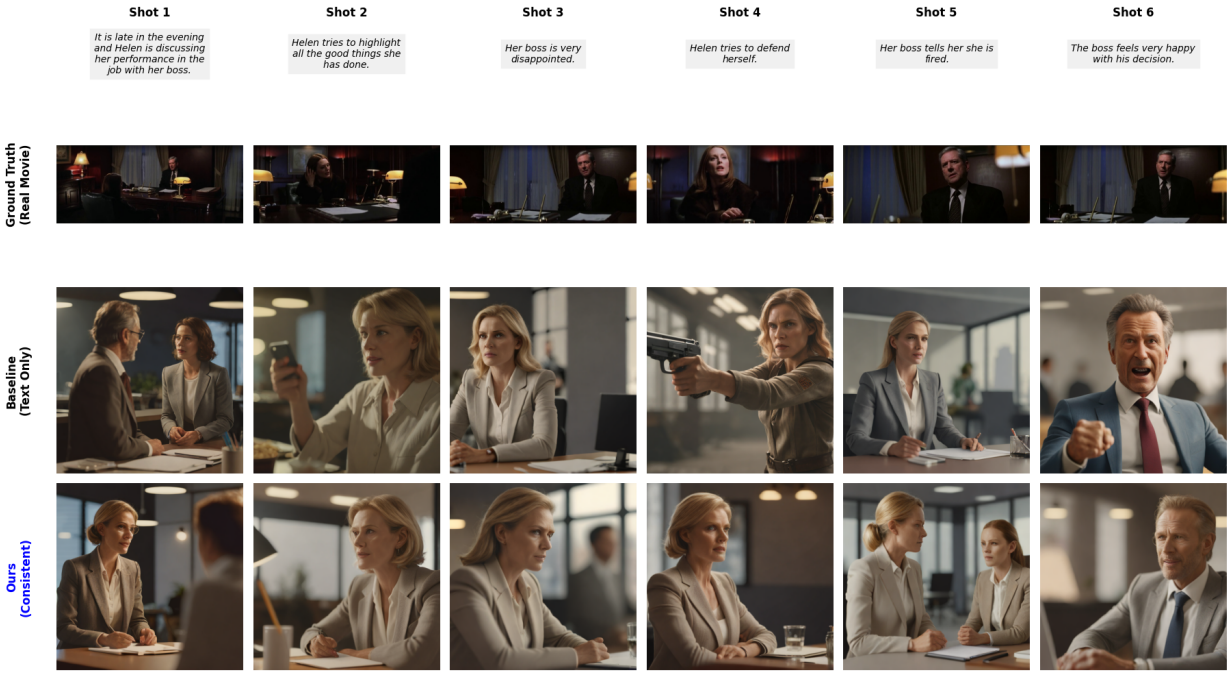

Fig. 5. Result 2: Office Drama. Note the consistent suit and facial features in Row 3.

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