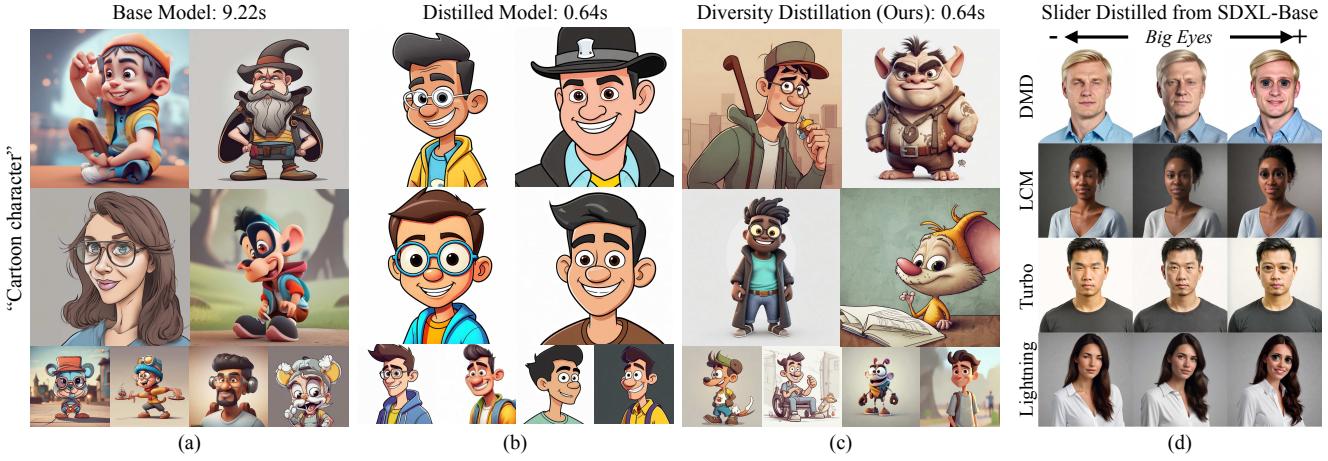


# Distilling Diversity and Control in Diffusion Models

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**Figure 1. Diversity Distillation:** (a) a base diffusion model is very slow and has good diversity (b) a distilled model is fast but sacrifices diversity (c) we show how the diversity of the base model can be distilled into the fast model by substituting the first timestamp. **Control Distillation:** (d) Control methods like Concept sliders can be transferred from a base model to distilled models, effectively distilling control

## Abstract

Distilled diffusion models suffer from a critical limitation: reduced sample diversity compared to their base counterparts. In this work, we uncover that despite this diversity loss, distilled models retain the fundamental concept representations of base models. We demonstrate control distillation - where control mechanisms like Concept Sliders and LoRAs trained on base models can be seamlessly transferred to distilled models and vice-versa, effectively distilling control without any retraining. This preservation of representational structure prompted our investigation into the mechanisms of diversity collapse during distillation. To understand how distillation affects diversity, we introduce Diffusion Target (DT) Visualization, an analysis and debugging tool that reveals how models predict final outputs at intermediate steps. Through DT-Visualization, we identify generation artifacts, inconsistencies, and demonstrate that initial diffusion timesteps disproportionately determine output diversity, while later steps primarily refine details. Based on these insights, we introduce diversity distillation - a hybrid inference approach that strategically employs the base model for only the first critical timestep before transitioning to the efficient distilled model. Our experiments demon-

strate that this simple modification not only restores the diversity capabilities from base to distilled models but surprisingly exceeds it, while maintaining nearly the computational efficiency of distilled inference, all without requiring additional training or model modifications. Our code and data are available at [distillation.baulab.info](https://distillation.baulab.info)

## 1. Introduction

Distilled diffusion models generate images in far fewer timesteps but lack the sample diversity of their original base model counterparts. In this paper we ask: *How can we distill both diversity and control capabilities from base diffusion models to their efficient distilled variants?*

Diffusion models demonstrate unprecedented quality [4, 13, 17, 24, 25], but their computational demands, requiring dozens or hundreds of sequential denoising steps, present significant deployment challenges. Diffusion distillation techniques [17, 18, 21, 29, 34, 35] address this by modifying base model weights to reduce required inference steps. However, this efficiency comes at a critical cost: mode col-

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lapse, where different initial noise seeds produce visually similar outputs, creating a fundamental trade-off between computational efficiency and generation diversity.

Our analysis reveals a surprising property: distilled diffusion models maintain consistent concept representations with their base counterparts, independent of the distillation procedure. We empirically verify this through concept transfer experiments, where control mechanisms like Concept Sliders [8, 10], LoRA adaptations [14, 16, 26] that are trained on base models can be seamlessly applied to distilled variants and vice versa without retraining. This preservation of representational structure despite the model weights modification suggests that the fundamental capabilities of base models remain intact in their distilled versions, enabling a form of “CONTROL DISTILLATION” from base to efficient models. This raises an intriguing question: if representations are preserved, why does diversity collapse during distillation?

To answer this question, we introduce a novel analysis and debugging technique called DT-Visualization (Diffusion Target) that reveals what a diffusion model “thinks” the final image will be at any intermediate timestep. Through DT-Visualization, we conduct a detailed analysis of latent representations across timesteps and discover that the initial diffusion steps disproportionately determine structural composition and diversity, while subsequent steps primarily refine details. This critical insight connects our findings: while distilled models preserve concept representations, they fail to maintain the diversity-generating behavior of early timesteps, affecting both sample-level variation and distribution-level coverage.

This observation motivates a simple hybrid inference approach that achieves “DIVERSITY DISTILLATION” by strategically employing the base model for only the first critical timestep before transitioning to the distilled model for efficient completion of the generation process. By leveraging the representational compatibility between models, this approach aims to directly address the mode collapse in distilled models during the diversity-critical early denoising steps.

Our experimental results reveal a counterintuitive finding: this hybrid approach not only restores the diversity lost during distillation but exceeds the diversity of the original base model while maintaining nearly the computational efficiency of distilled inference.

These results demonstrate that the traditional trade-off between computational efficiency and generation diversity can be mitigated through timestep-specific model selection. This work has implications for both theoretical understanding of diffusion model distillation and practical applications in model deployment.

## 2. Related Works

**Diffusion Distillation:** While diffusion models [13, 30, 31] excel at high-quality image synthesis, their requirement for 20-100 sampling steps creates significant computational bottlenecks. Diffusion distillation techniques address this limitation by finetuning base models that maintain quality with fewer steps. Progressive distillation [27] established the foundation by iteratively training student models to match teacher outputs with half the sampling steps. Recent approaches have further improved efficiency through distinct methodologies: Adversarial Diffusion Distillation [29], implemented in SDXL-Turbo, integrates score distillation with adversarial training to enable high-fidelity generation in just 1-4 steps, effectively combining diffusion guidance with GAN-like discriminators. Distribution Matching Distillation [34], featured in SDXL-DMD2, takes a different approach by focusing on matching output distributions rather than specific trajectories, eliminating regression loss and implementing a two time-scale update rule that significantly improves training stability. For balancing quality and mode coverage, Progressive Adversarial Diffusion Distillation [18] in SDXL-Lightning employs staged training with specialized latent-space discriminators, offering flexibility through checkpoints optimized for 1-8 step inference. Latent Consistency Models [21], applied in SDXL-LCM, ensure consistency in latent representations across noise levels for distillation, reducing steps to 4-8 while preserving generation quality. Despite these advances in efficiency, the relationship between model distillation and sample diversity has remained largely unexplored.

**Concept Representation:** Research in concept representation for diffusion models has evolved from basic personalization to sophisticated control mechanisms [2, 3, 8, 22, 33, 36]. Textual Inversion [6] captures the semantics of a concept with learnable embeddings in text space without modifying model weights, allowing personalization with just a few images. DreamBooth [26] advanced this approach by fine-tuning models with unique identifiers and a specialized prior preservation loss. Custom Diffusion [16] streamlined this process by optimizing only cross-attention layers, reducing storage requirements to just 3% of model weights while enabling multi-concept customization simultaneously. For precise attribute manipulation, Concept Sliders [8] introduced low-rank adaptors that create interpretable controls over specific visual attributes like age or weather conditions. This technique was expanded in Slider-Space [10], which decomposes visual capabilities into multiple controllable dimensions from a single prompt, enhancing creative exploration. Complementary to these control mechanisms, hierarchical concept trees [1, 32] were developed to enable intuitive exploration of related visual concepts. Recent work has also addressed ethical concerns

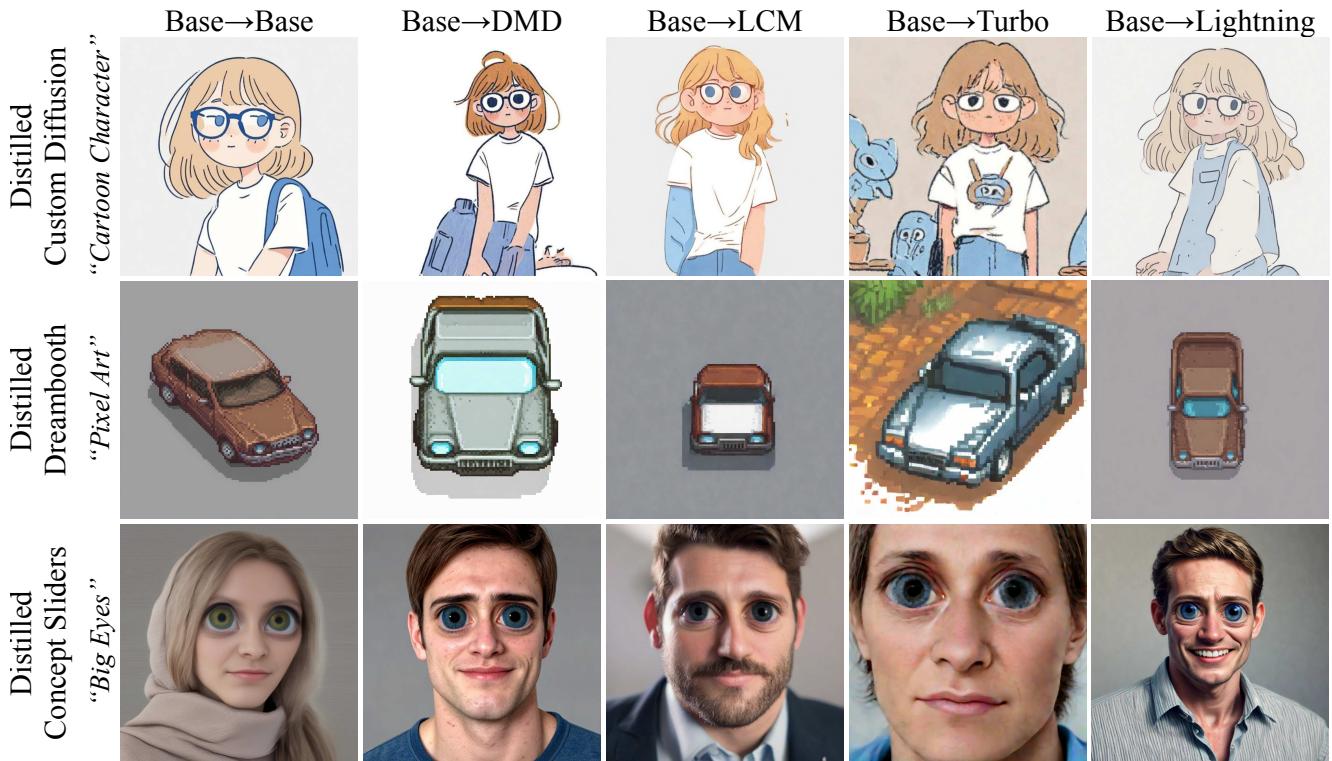


Figure 2. Customization adapters (custom diffusion [16] and dreambooth [26]) and concept control adapters (concept sliders [8]) trained on SDXL-base model can be transferred to all the distilled modeled without any additional finetuning. This demonstrates that concept representations are preserved through the diffusion distillation process

through targeted concept removal techniques by editing selective weights [7, 9, 20], redirecting concept representations [15, 23]. Since distillation modifies the UNet model of diffusion, in this work, we mainly focus on custom concept and control representations that are captured in UNet modules. Our work uniquely explores whether such control mechanisms can be distilled from base to efficient models without additional training.

### 3. Control Distillation

Diffusion distillation reduces computational requirements by modifying model weights to generate images in fewer timesteps, but introduces a well-known limitation: mode collapse. While the diversity reduction is established, the state of internal representations during distillation remains unexplored. We investigate whether distilled models, despite producing less diverse outputs, still preserve the same concept representations as their base counterparts.

To answer these questions, we investigate whether control mechanisms trained on base models can be directly applied to distilled models. Our investigation focuses on three distinct approaches for modifying diffusion models: **Concept Sliders** [8, 10], which are low-rank adaptors enabling fine-grained control over specific visual attributes

such as age, weather, and eye size; **Custom Diffusion** [16], which optimizes cross-attention layers for efficient multi-concept customization; and **DreamBooth** [26], which enables subject-driven generation through unique identifiers and prior preservation loss.

For each mechanism, we perform two types of transfer experiments. In *Base → Distilled Transfer*, we train the control mechanism on the base model and apply it to the distilled model. Conversely, in *Distilled → Base Transfer*, we train the control mechanism on a distilled model and apply it to the base model.

#### 3.1. Experimental Setup

We experiment with multiple distilled model variants: SDXL-Turbo [29], SDXL-Lightning [18], SDXL-LCM [21], and SDXL-DMD2 [34] — each representing different distillation techniques. We train Concept Sliders, Custom Diffusion and DreamBooth using LoRA [14] optimization according to their official implementation.

#### 3.2. Results

To quantify transfer effectiveness, we evaluate control mechanisms both qualitatively and quantitatively. Figure 2 shows qualitative examples of how concept representations

| Method                 | Concept          | Base→Base | Base→DMD | Base→LCM | Base→Turbo | Base→Lightning |
|------------------------|------------------|-----------|----------|----------|------------|----------------|
| Concept Sliders [8]    | Age              | 20.4      | 17.8     | 27.1     | 19.0       | 24.8           |
|                        | Smile            | 19.7      | 21.4     | 19.5     | 33.5       | 14.0           |
|                        | Muscular         | 34.6      | 26.7     | 33.8     | 39.0       | 33.2           |
| Customization [16, 26] | Lego             | 32.2      | 26.8     | 26.0     | 30.3       | 29.7           |
|                        | Watercolor style | 34.3      | 31.4     | 29.6     | 27.5       | 39.2           |
|                        | Crayon style     | 32.7      | 27.8     | 24.7     | 29.5       | 32.5           |

Table 1. We show the percentage change in CLIP score from the original image and the LoRA edited image. Higher values indicate stronger attribute change or style transfer. Control effectiveness is largely preserved when transferring from base to different distilled models, with only minor variations across distillation techniques.

can be transferred seamlessly from base model to distilled models. For example, the “comical big eyes” slider trained on SDXL controls Turbo’s generations, despite latter being a distilled model requiring 1-4 steps compared to SDXL’s 20-100.

Table 1 presents quantitative results showing CLIP scores [11] for various attributes. The transfer effectiveness remains consistently high across all tested combinations, confirming our hypothesis that concept representations are preserved during distillation. We show more experiments for the Distillation→Base evidence in Appendix.

This representational compatibility raises an intriguing question: *if concept representations are preserved during distillation, why do distilled models exhibit reduced diversity?*. To analyze this question, we introduce a visualization technique to better understand diffusion generation in the next section.

## 4. DT: Diffusion Target Visualization

To better analyze the information at each denoising step, we introduce DT-Visualization (Diffusion Target Visualization), a technique that allows us to interpret what the model “thinks” the final image will be at any intermediate timestep, without actually completing the full denoising process.

Let  $\mathbf{x}_0$  be an initial image and  $\mathbf{x}_T$  be pure Gaussian noise. The forward diffusion process gradually adds noise to the image. The generative process aims to reverse this diffusion, starting from  $\mathbf{x}_T$  and progressively denoising to reconstruct  $\mathbf{x}_0$ . At a timestep  $t$ , the model takes  $\mathbf{x}_t$  as input and predicts a noise  $\epsilon_\theta(\mathbf{x}_t, t)$  to compute the next step  $\mathbf{x}_{t-1}$ :

$$\mathbf{x}_{t-1} = \frac{\mathbf{x}_t - \sqrt{1 - \alpha_t} \epsilon_\theta(\mathbf{x}_t, t)}{\sqrt{\alpha_t}} \quad (1)$$

We can estimate the final image  $\tilde{\mathbf{x}}_{0,t}$  by taking the same direction  $\epsilon_\theta(\mathbf{x}_t, t)$  for all remaining diffusion steps. This can be achieved by recursively applying the denoising from Equation 1 with the same noise prediction. We label this approach “DT-Visualization”:

$$\tilde{\mathbf{x}}_{0,t} = \frac{\mathbf{x}_t - \sqrt{1 - \bar{\alpha}_t} \epsilon_\theta(\mathbf{x}_t, t)}{\sqrt{\bar{\alpha}_t}} \quad (2)$$

where  $\bar{\alpha}_t$  is the cumulative noise schedule parameter. This enables us to visualize the final image  $\tilde{\mathbf{x}}_{0,t}$  that the diffusion model is implicitly planning at each timestep  $t$  without actually running denoising forward passes through all remaining timesteps.

By computing  $\tilde{\mathbf{x}}_{0,t}$  at various timesteps throughout the denoising process and comparing the results, we can assess the contribution of each step to the final output.

### 4.1. DT for Investigating Generation Artifacts

DT-Visualization serves as a debugging tool for investigating artifacts and inconsistencies in diffusion model outputs. Figure 3 demonstrates this capability when analyzing a generation prompted with “Image of dog and cat sitting on sofa.” While the final image appears to contain only a dog, DT-Visualization at intermediate timestep  $T = 10$  reveals that the model initially conceptualized a cat face (red box), but later retracted this decision by the final generation step. This insight exposes how diffusion models can “change their mind” during the denoising process, sometimes discarding semantic elements present in the prompt. By comparing visualizations across different timesteps, we can pinpoint exactly when and how these decisions occur, providing valuable insights for model developers to address inconsistencies between prompts and generations. This visualization technique helps explain why models sometimes produce outputs that lack requested elements despite properly understanding the prompt’s semantics.

### 4.2. DT for Investigating Mode Collapse

Building on DT-Visualization’s effectiveness for uncovering generation artifacts, we extend this technique to examine the mechanisms underlying mode collapse in distilled diffusion models. By applying this visualization approach to both base and distilled model generations, we can directly observe differences in how these models develop image structure throughout the denoising process. Through both qualitative examples and quantitative analysis, we demon-

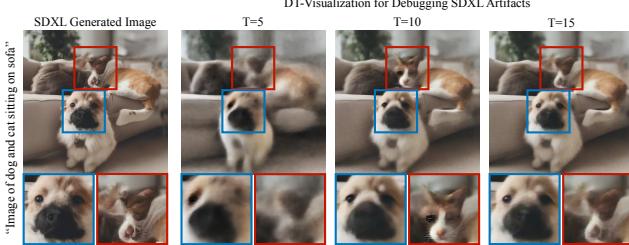


Figure 3. DT-Visualization reveals generation inconsistencies. When prompted with “Image of dog and cat sitting on sofa,” the SDXL model produces an image with only a dog. However, DT-Visualization at  $T = 10$  shows the model initially conceptualizing a cat face (red box) before abandoning this element in the final generation. This demonstrates how diffusion models can discard semantic elements during the denoising process.

strate how DT-Visualization provides critical insights into the diversity reduction phenomenon. Figure 4 presents qualitative DT-Visualization results for the prompt “picture of a dog”.

Standard diffusion denoising visualizations (left) show minimal differences between model variants, but our DT-Visualization technique (right) suggests a potential explanation for mode collapse: distilled models appear to commit to final image structure almost immediately after the first denoising step, while base models progressively develop structural elements across multiple steps. This observation suggests that early timesteps might play a disproportionate role in determining output diversity. If distilled models make critical structural decisions in a single timestep, this could explain their tendency to produce similar outputs across different random seeds. Base models, with their gradual structural refinement, might maintain greater output diversity precisely because they distribute these decisions, as shown in Figure 6.

Figure 5 quantifies this phenomenon by plotting the DreamSim similarity [5] distance between intermediate DT-visualizations and final images across COCO-10k [19] prompts. The data indicates that distilled models establish significant structural composition within a single timestep, whereas base models require approximately 30% of their total inference steps to achieve comparable structural definition.

These observations raise an intriguing question: if concept representations are preserved during distillation but diversity is reduced, could the first timestep be the critical factor? In the next section, we conduct causal experiments to determine whether the first timestep is indeed responsible for mode collapse, and explore how this insight might lead to solutions that preserve both efficiency and diversity.

## 5. Diversity Distillation

Our DT-Visualization analysis established a notable correlation between early timesteps and structural diversity in diffusion outputs. This motivates our investigation into whether initial denoising steps causally determine the diversity characteristics of generated samples. To empirically test this hypothesis, we propose a hybrid inference approach that selectively combines base and distilled models during generation, enabling systematic examination of the mechanisms underlying mode collapse.

We implement this approach in Algorithm 1, which uses the base model for the critical first timestep(s) to establish diverse structural compositions, then transitions to the distilled model for efficient refinement of details. This method leverages complementary strengths of both models while addressing their respective weaknesses, effectively distilling diversity from the base model into the distilled model’s generation process without requiring additional training or model modifications.

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### Algorithm 1 Hybrid Inference for Diversity Distillation

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**Require:** Base model  $f_{\text{base}}$ , distilled model  $f_{\text{distil}}$ , total timesteps  $T$ , transition point  $k$   
**Ensure:** Generated image  $\mathbf{x}_0$

- 1: Initialize  $\mathbf{x}_T \sim \mathcal{N}(0, \mathbf{I})$
- 2: **for**  $t = T, T - 1, \dots, 1$  **do**
- 3:     **if**  $t > T - k$  **then**  $\triangleright$  Critical timesteps for diversity
- 4:          $\mathbf{x}_{t-1} \leftarrow f_{\text{base}}(\mathbf{x}_t, t, \text{prompt})$
- 5:     **else**  $\triangleright$  Efficient refinement timesteps
- 6:          $\mathbf{x}_{t-1} \leftarrow f_{\text{distil}}(\mathbf{x}_t, t, \text{prompt})$
- 7:     **end if**
- 8: **end for**
- 9: **return**  $\mathbf{x}_0$

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### 5.1. Experimental Results

We evaluate our method on two distinct dimensions of diversity: distributional diversity and sample diversity. Distributional diversity measures how well the generated distribution matches the real training data distribution. It evaluates whether the model can generate outputs across the full spectrum of the training data when given various prompts, assessed primarily through FID [12] (lower is better). Sample diversity measures the variation among outputs generated from the same prompt with different random seeds, quantified by average pairwise DreamSim distance [5] (higher is better).

**Distributional Diversity.** Table 2 presents a comparison of our diversity distillation approach against base and distilled models. We measure the FID between the generated samples from baselines against the real COCO-30k

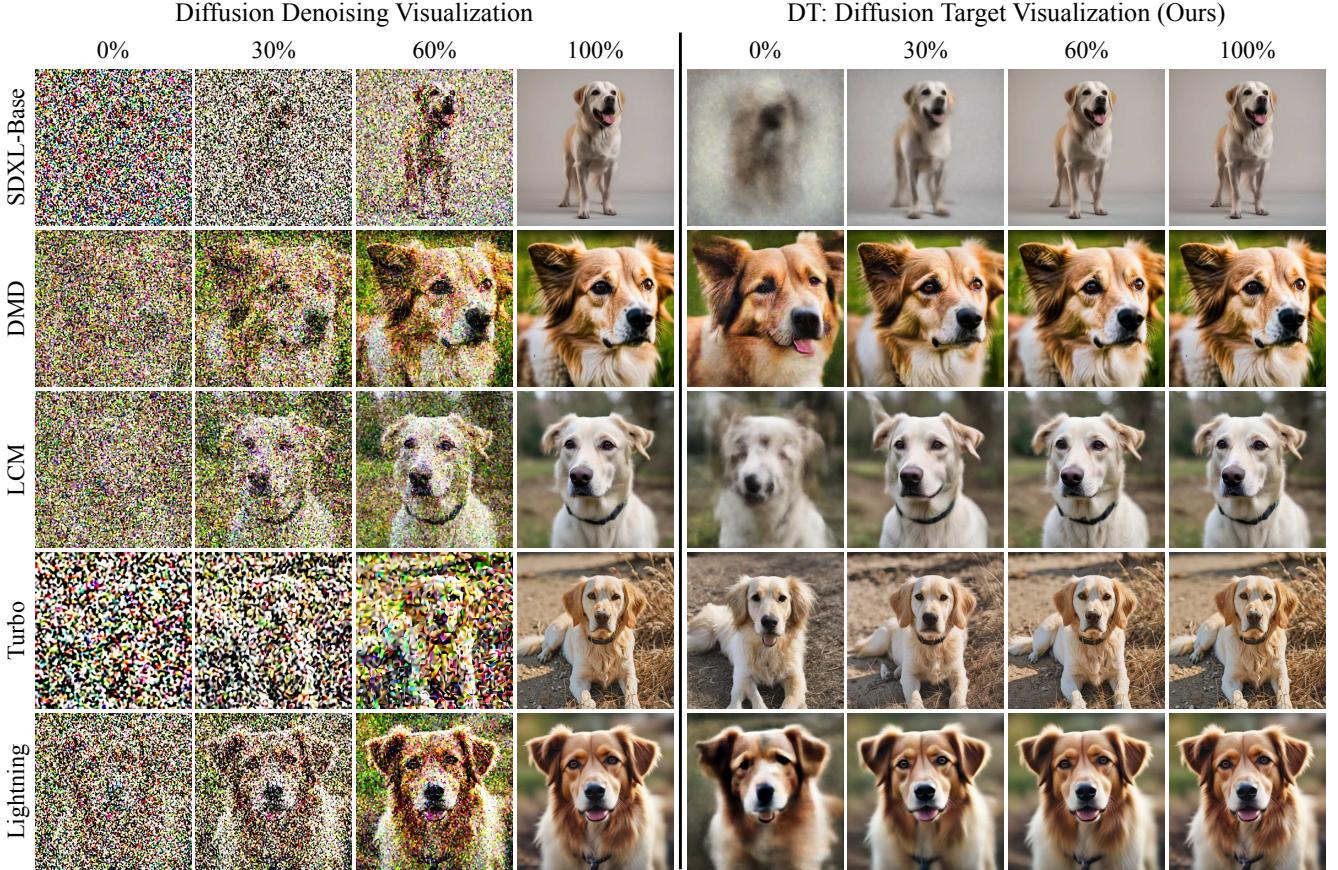


Figure 4. Comparison of standard diffusion visualization vs. our Diffusion Target (DT) visualization. Left: Standard visualization of intermediate latents shows subtle differences between base and distilled models. Right: Our DT visualization technique reveals dramatic differences in how models predict the final output. Distilled models commit to final image structure in the first timestep, while base models gradually refine structure across multiple steps, explaining the observed mode collapse in distilled models.

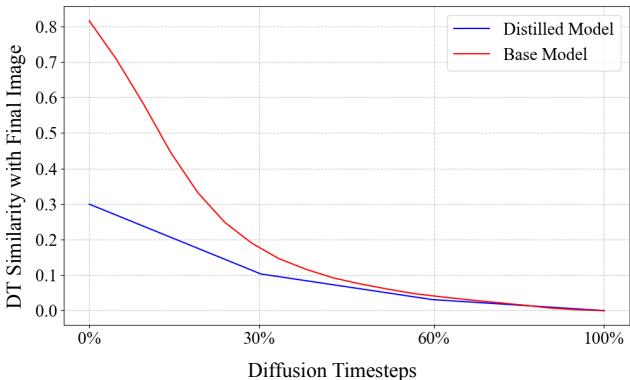


Figure 5. Measuring the dreamsim distance between intermediate DT-visualization and final image reveals that distilled models establish structural image composition within the initial diffusion step, whereas base models require approximately 30% of steps to achieve comparable structural definition.

Table 2. Comparing the distributional diversity using FID shows that our diversity distillation approach achieves diversity comparable to or better than the base model (SDXL-Base [24]) while maintaining nearly the computational efficiency of the distilled model (SDXL-DMD [34]).

dataset as a proxy for training dataset. We find that our approach has a better FID (lower) and CLIP (higher) scores on COCO-30k dataset than both the distilled and base models while being as fast as a distilled model.

**Sample Diversity.** To specifically measure the diversity of samples for a given prompt, we utilize a sample diversity metric [10] based on DreamSim distance. For each baseline variant, we generate 100 images for the same prompt and

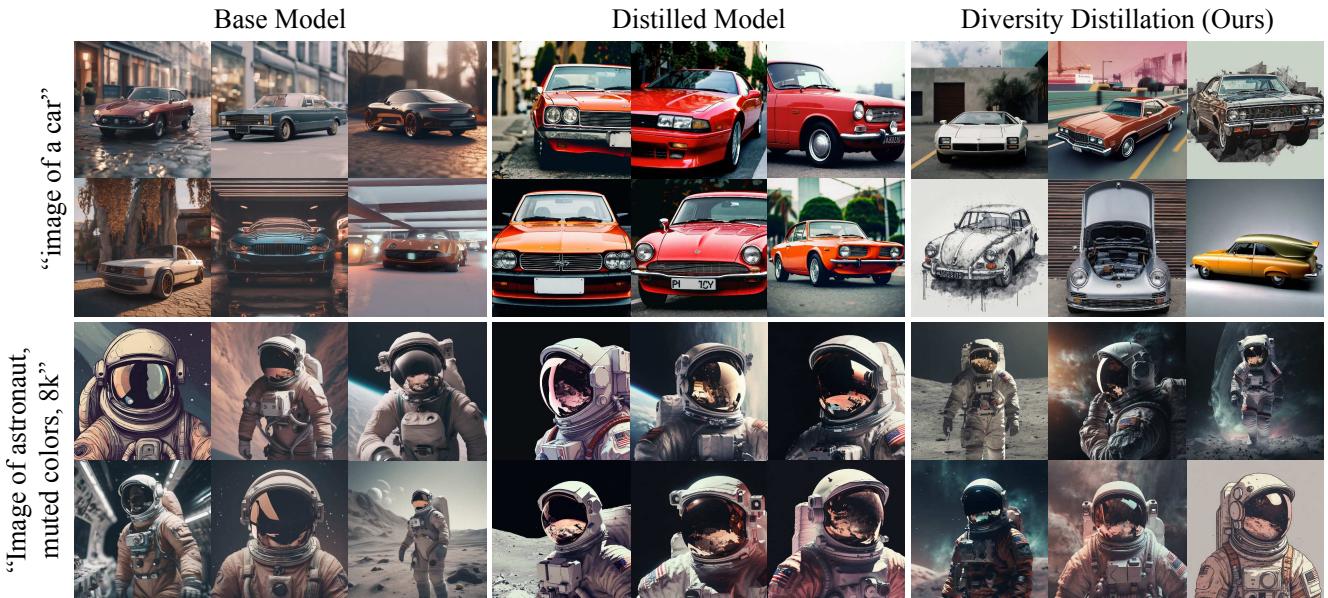


Figure 6. **Visual comparison of generation diversity.** Each row shows three different generations (different random seeds) for the same prompt using: (left) base model, (middle) distilled model, and (right) our diversity distillation approach. Note how the distilled model produces visually similar outputs across seeds, while our approach restores diversity comparable to the base model while maintaining similar inference speed as distilled model.

| Prompt          | Base         | Distilled | Hybrid (Ours) |
|-----------------|--------------|-----------|---------------|
| Sunset beach    | <b>0.396</b> | 0.271     | 0.373         |
| Cute puppy      | 0.233        | 0.199     | <b>0.265</b>  |
| Futuristic city | 0.237        | 0.198     | <b>0.283</b>  |
| Person          | <b>0.484</b> | 0.347     | 0.461         |
| Van Gogh art    | 0.337        | 0.305     | <b>0.366</b>  |
| Average         | 0.337        | 0.264     | <b>0.350</b>  |

Table 3. Sample diversity measured by average pairwise DreamSim distance (higher is more diverse). Our hybrid approach not only restores diversity lost during distillation but exceeds the diversity of the base model.

calculate the average pairwise DreamSim distance between samples. Table 3 shows that our approach restores the lost sample diversity in the distilled models.

Figure 6 provides a visual comparison of generation diversity across methods. The distilled model clearly exhibits less structural diversity across random seeds compared to the base model, while our hybrid approach successfully distills this diversity while maintaining faster inference speeds.

These results demonstrate that the traditional trade-off between computational efficiency and generation diversity can be effectively mitigated through our proposed diversity distillation approach. By strategically combining the strengths of base and distilled models, we achieve diversity distillation without requiring additional training or model modifications.

## 5.2. Hyperparameter Analysis

We conduct an analysis of different hyperparameters and variations of our approach to understand their impact on diversity and quality. Figure 7 presents our findings across multiple dimensions.

First, as shown in Figure 7(a), the guidance scale from the base model significantly impacts diversity, with optimal performance occurring around zero guidance. This suggests that minimal guidance from the base model preserves the natural diversity of outputs.

Figure 7(b) demonstrates the effect of varying  $k$ , the number of distilled model steps replaced by base model inference. Notably, even using the base model for just the first timestep ( $k=1$ ) provides substantial diversity gains with minimal computational overhead. This confirms our hypothesis that the earliest timesteps are particularly critical for establishing output diversity in diffusion models.

The computational efficiency of our approach is analyzed in Figure 7(c), which compares the total computational cost when replacing the first timestep of the distilled model with varying numbers of base model steps. Our results indicate that a 1:1 replacement ratio achieves the optimal balance between diversity enhancement and computational efficiency. More extensive use of the base model provides diminishing returns while significantly increasing inference time.

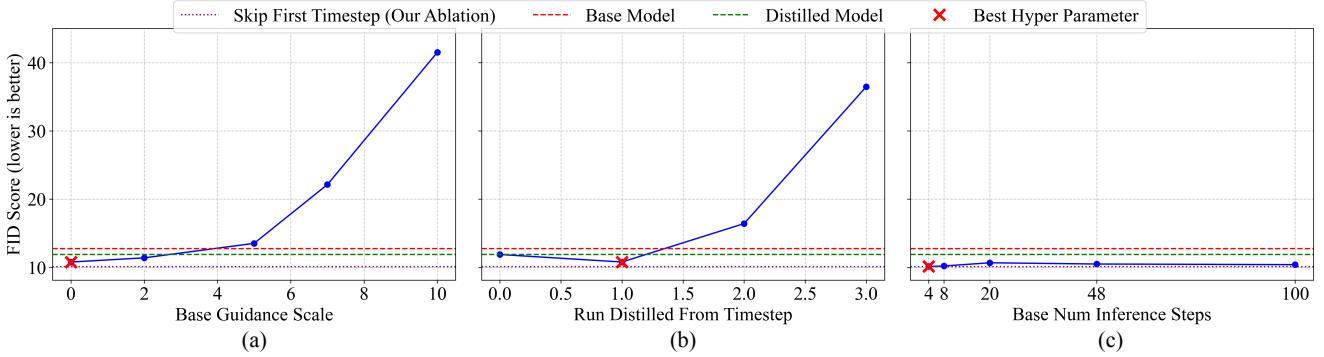


Figure 7. (a) Impact of guidance scale from the base model on diversity shows optimal performance around 0 guidance. (b) Effect of the number of distilled model steps ( $k$ ) being replaced by base model inference. Running distilled model from first timestep ( $k = 1$ ) provides diversity gains with minimal computational overhead. (c) Comparing the total timesteps of base model when replacing the first timestep of distilled model shows that replacing 1-1 timesteps of distilled with base is most ideal.

| Method              | Steps | FID( $\downarrow$ ) | IS( $\uparrow$ ) | CLIP( $\uparrow$ ) | Time (s)( $\downarrow$ ) |
|---------------------|-------|---------------------|------------------|--------------------|--------------------------|
| Hybrid (Ours)       | 4     | 10.79               | <b>26.13</b>     | <b>32.12</b>       | 0.64                     |
| Skip First Timestep | 3     | <b>10.12</b>        | 24.69            | 31.71              | <b>0.53</b>              |

Table 4. Skipping first timestep demonstrates superior FID scores and faster inference time but underperforms on generative quality as indicated by CLIP [11] and Inception [28] scores.

**Resource-Efficient Alternative:** For scenarios where loading both models simultaneously is not feasible [17], we explore an alternative approach: skipping the first step altogether in distilled model inference. This approach, compared in Figure 7 and Table 4 alongside our diversity distillation method and baselines, shows that simply skipping the first timestep in distilled inference provides a significant boost in diversity. This suggests that the first timestep in distilled models constrains diversity, and removing its influence allows for more varied outputs. While this approach is more resource-efficient than loading both models, our hybrid method still achieves superior results in terms of quality, as shown by CLIP and IS scores. We provide qualitative examples in Appendix.

## 6. Limitations

While our approach significantly improves diversity without substantial computational overhead, several limitations remain. First, our method requires maintaining both base and distilled models in memory, increasing resource requirements compared to distillation-only approaches. Future distillation works could explore our insights to design a diversity preserving model into a single distilled model.

Second, our analysis focused primarily on image diversity metrics, but further investigation is needed to understand the impact on semantic diversity—the range of concepts and compositions the model can generate. Developing

more sophisticated diversity metrics that capture both visual and semantic variation would provide deeper insights into the distillation process.

Finally, our approach treats all prompts uniformly, but different content types may benefit from different base/distilled step allocations. Adaptive inference strategies that dynamically adjust the transition point based on prompt characteristics could further optimize the quality-efficiency trade-off.

## 7. Conclusion

This work addresses a fundamental limitation of distilled diffusion models: the trade-off between computational efficiency and sample diversity. Our contributions are three-fold: (1) We demonstrate that distilled models preserve the concept representations of base models, enabling seamless transfer of control mechanisms like Concept Sliders and LoRAs without retraining; (2) We introduce DT-Visualization, revealing that initial timesteps disproportionately determine structural composition in the generation process; and (3) Based on these insights, we present diversity distillation, a hybrid inference approach that strategically employs the base model for only the first critical timestep before switching to the efficient distilled model.

Our experimental results challenge the conventional diversity-efficiency trade-off. Diversity distillation not only restores but exceeds the diversity of the original base model while maintaining the computational efficiency of distilled inference (0.64s vs. 9.22s per image). By eliminating this traditional trade-off without additional training or model modifications, our approach bridges the gap between high-quality, diverse generations and fast inference, opening new possibilities for real-time creative applications.

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## Code

Our methods are available as open-source code. Source code, and data sets for reproducing our results can be found at [sliderspace.baulab.info](https://sliderspace.baulab.info) and at our GitHub repo [github.com/rohitgandikota/sliderspace](https://github.com/rohitgandikota/sliderspace)

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# Distilling Diversity and Control in Diffusion Models

## Supplementary Material

### A. Control Distillation: Reverse Transfer

In the main paper, we demonstrated that control mechanisms trained on base models can be seamlessly transferred to distilled models. Here, we present additional results for the reverse direction: transferring control mechanisms trained on distilled models to base models. This bidirectional transfer capability further validates our hypothesis that concept representations are preserved during the distillation process.

We note that while most control mechanisms transferred effectively, we encountered difficulties training LoRA adaptations on LCM due to its specialized architecture and training procedure. These challenges highlight potential avenues for future research in developing more universally transferable control mechanisms.

### B. Mode Collapse and Diversity

The main paper introduced our finding that distilled diffusion models suffer from reduced sample diversity (mode collapse) compared to their base counterparts. We provide additional qualitative examples in Figure B.1-B.4 that visually demonstrate this phenomenon across various prompts and model variants.

These examples highlight the significant diversity loss in distilled models. While the distilled models produce high-quality images, they often converge to similar structural compositions regardless of random seed initialization. Our diversity distillation approach effectively addresses this limitation, restoring the variety of outputs comparable to the base model while maintaining computational efficiency.

### C. Extended DT-Visualization Analysis

The main paper introduced our DT-Visualization technique for analyzing how diffusion models develop structural information during the denoising process. We present additional visualizations in Figures C.1, C.2 that further illuminate the differences between base and distilled models.

These visualizations reinforce our key finding: distilled models compress the diversity-generating behavior distributed across early timesteps in base models into a single initial step, explaining the observed mode collapse. This insight directly informed our hybrid inference approach, which strategically leverages the diversity-generating capabilities of base models in critical early steps.

### D. Skip Step Approach

In the main paper, we introduced a resource-efficient alternative to our hybrid approach: skipping the first timestep altogether in distilled model inference. We provide additional qualitative comparisons between this approach and our hybrid method in Figure D.1.

The skip-first-step approach provides a reasonable compromise when resource constraints prevent loading both models simultaneously. However, our quantitative analysis in the main paper and these qualitative examples demonstrate that the hybrid approach consistently achieves superior results in terms of both diversity and quality.



Figure A.1. Reverse Control Transfer: Control mechanisms (Custom Diffusion [16] and Concept Sliders [8]) trained on distilled models can be effectively transferred to base models without retraining. This bidirectional transferability confirms that concept representations are preserved during diffusion distillation. Note: LCM LORA transfers were excluded due to training difficulties with the LCM architecture.

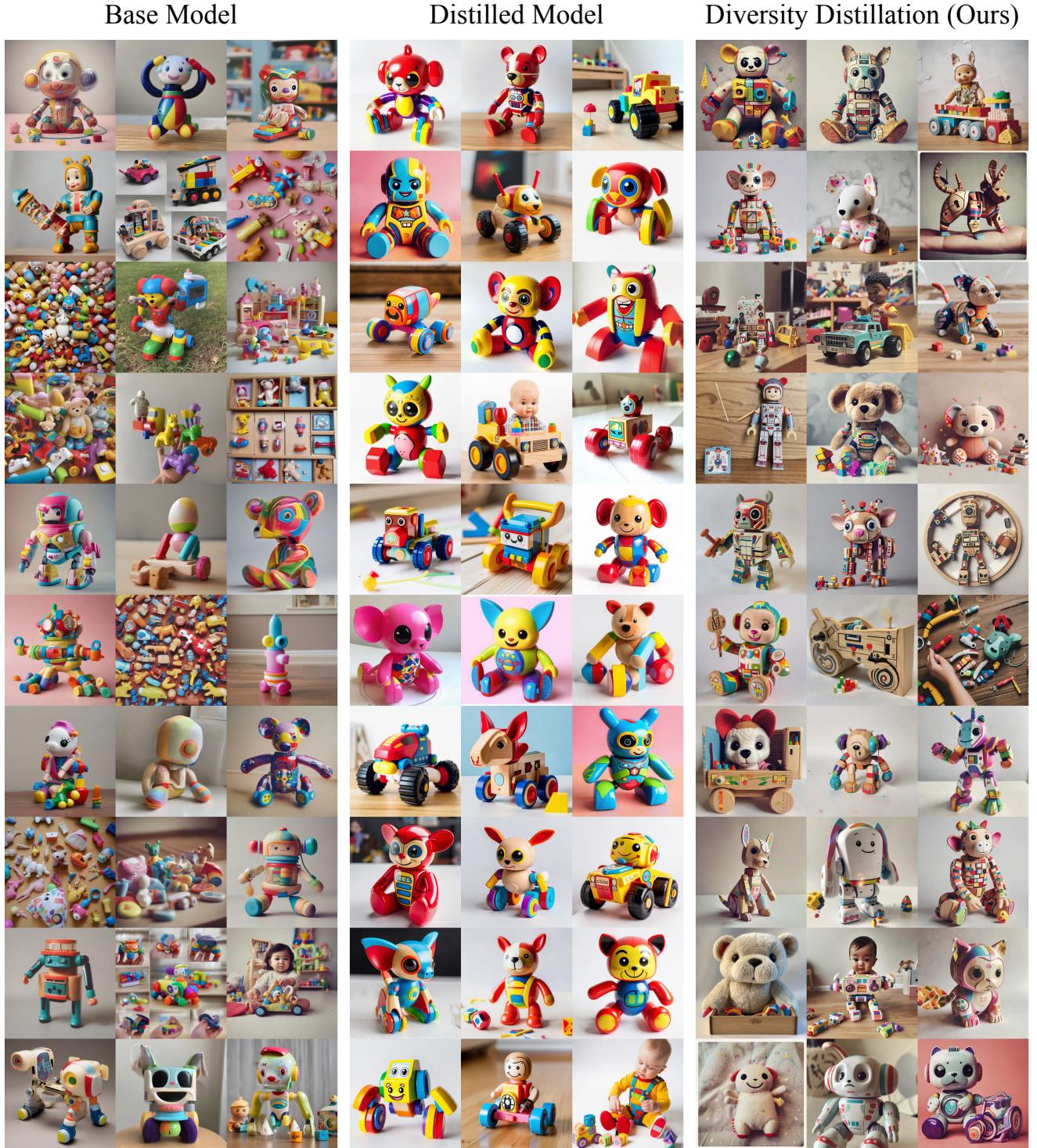


Figure B.1. Comparison of generation diversity across different models for the prompt "image of a toy." Each image shows different seeds for the same model. Note the structural similarity in distilled model outputs compared to the greater variation in base model and our hybrid approach.



Figure B.2. Comparison of generation diversity for "image of a flower". Distilled models (middle column) produce structurally similar outputs across different seeds, while our approach (right column) restores diversity comparable to the base model (left column) while maintaining the speed advantage of distilled models.



Figure B.3. Additional diversity comparison for "city street" Distilled models (middle column) produce structurally similar outputs across different seeds, while our approach (right column) restores diversity comparable to the base model (left column) while maintaining the speed advantage of distilled models.

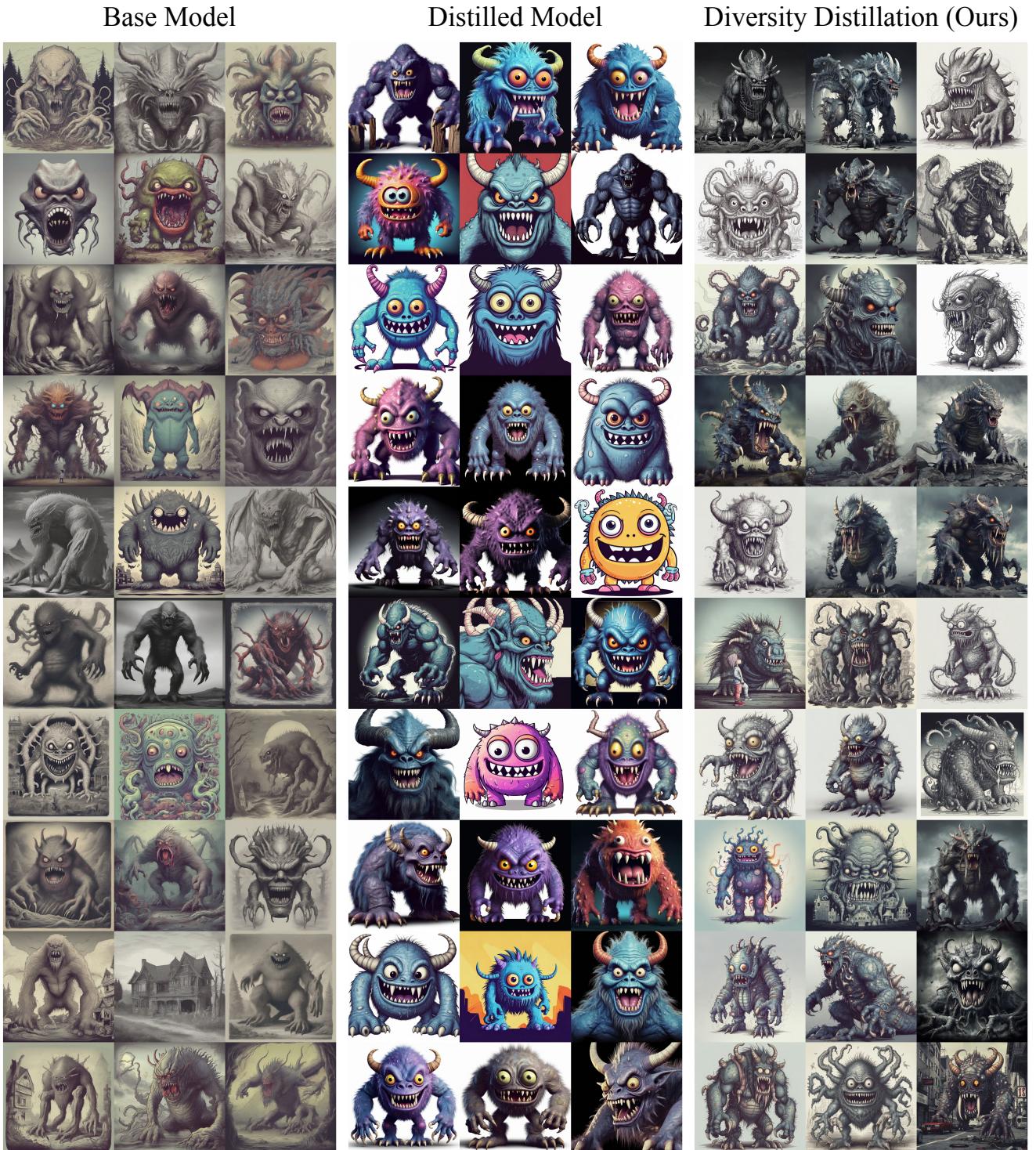


Figure B.4. Diversity comparison for abstract prompt: "picture of a monster" Distilled models (middle column) produce structurally similar outputs across different seeds, while our approach (right column) restores diversity comparable to the base model (left column) while maintaining the speed advantage of distilled models.

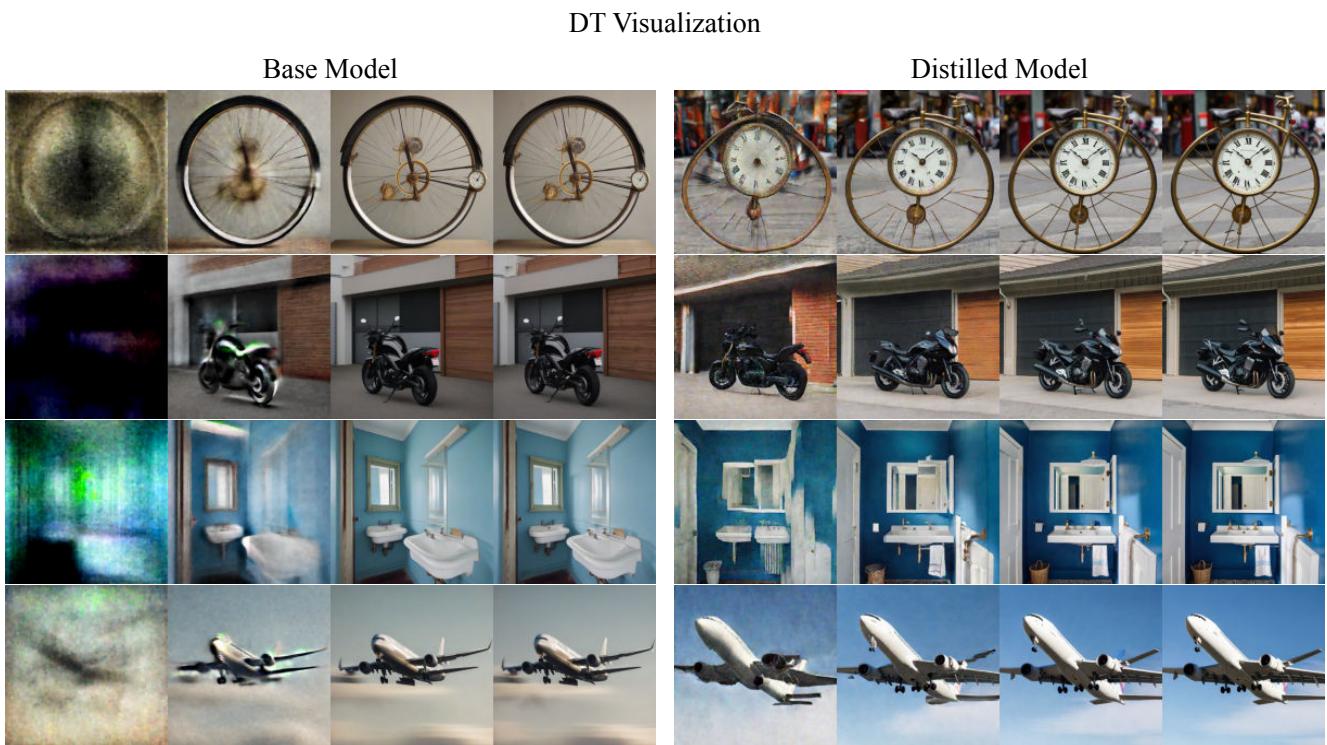


Figure C.1. Extended DT-Visualization comparison between SDXL-Base and SDXL-DMD for the prompt. The visualization reveals that DMD commits to final structural composition within the first timestep, while Base gradually develops structure across multiple steps. This pattern is consistent across different content types and prompts.

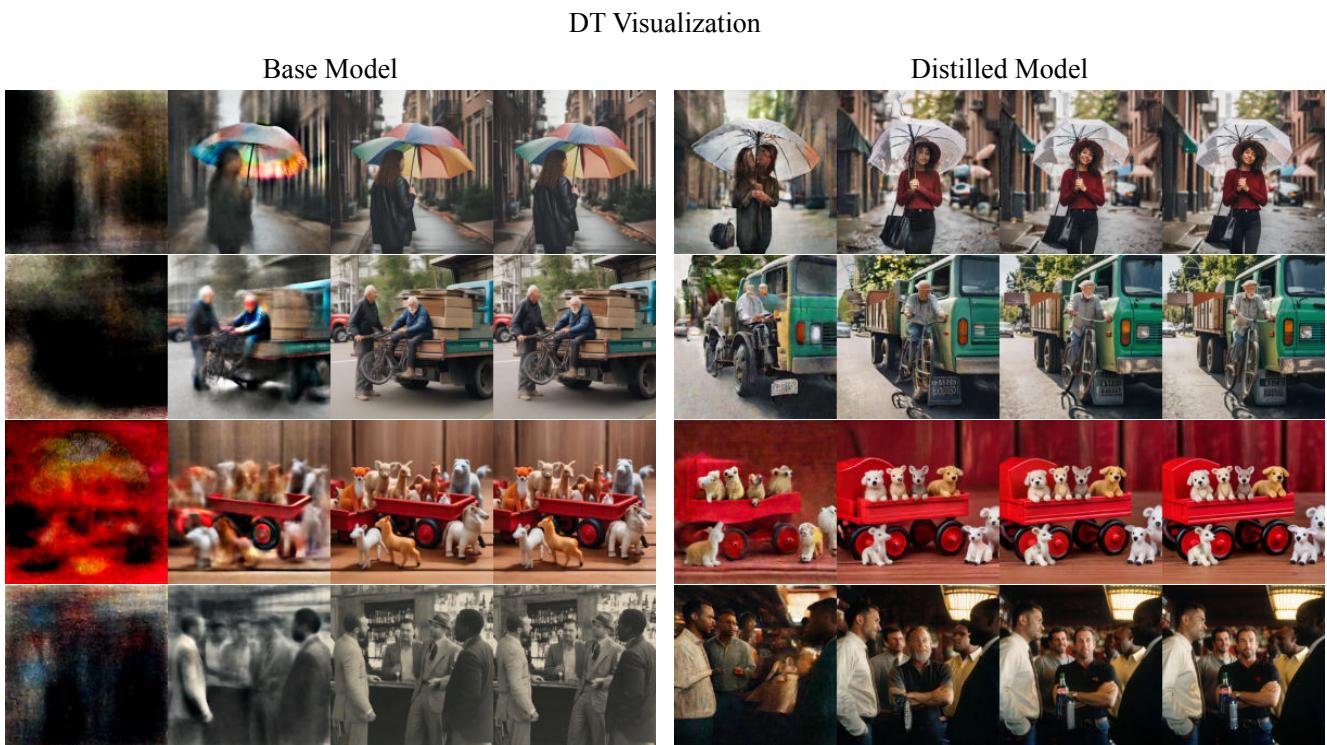


Figure C.2. Extended DT-Visualization comparison between SDXL-Base and SDXL-DMD for the prompt. The visualization reveals that DMD commits to final structural composition within the first timestep, while Base gradually develops structure across multiple steps. This pattern is consistent across different content types and prompts

“Image of a dog”

Diversity Distillation (Ours)



Skipping First Timestep (Ablation)



Figure D.1. Qualitative comparison between (left) our hybrid approach, (right) skip-first-step approach. The skip-first-step approach improves diversity over the standard distilled model but exhibits reduced quality compared to our hybrid method, particularly in fine details and coherence.