

CSF: Black-box Fingerprinting via Compositional Semantics for Text-to-Image Models

Junhoo Lee Mijin Koo Nojun Kwak
Seoul National University

{mrjunoo, starmj09, nojunk}@snu.ac.kr

Abstract

Text-to-image models are commercially valuable assets often distributed under restrictive licenses, but such licenses are enforceable only when violations can be detected. Existing methods require pre-deployment watermarking or internal model access, which are unavailable in commercial API deployments. We present Compositional Semantic Fingerprinting (CSF), the first black-box method for attributing fine-tuned text-to-image models to protected lineages using only query access. CSF treats models as semantic category generators and probes them with compositional under-specified prompts that remain rare under fine-tuning. This gives IP owners an asymmetric advantage: new prompt compositions can be generated after deployment, while attackers must anticipate and suppress a much broader space of fingerprints. Across 6 model families (FLUX, Kandinsky, SD1.5/2.1/3.0/XL) and 13 fine-tuned variants, our Bayesian attribution framework enables controlled-risk lineage decisions, with all variants satisfying the dominance criterion.

1. Introduction

Text-to-Image models are deployed at scale and have gained huge success commercially [8, 23, 24, 36, 41, 43], now offering their services to millions of users. As the models themselves have become valuable assets, intellectual property (IP) protection for these models has become urgent. Consequently, many diffusion models are now distributed under restrictive licenses (e.g., non-commercial license for Flux.1 [dev] [22], research-only license for SDXL Turbo [2]) to prevent unauthorized commercial distribution of fine-tuned derivatives. However, these licenses are only effective when violations can be detected. The problematic scenario arises when an infringer fine-tunes a protected model and distributes it exclusively through an API. To address this challenge, we need a method that can attribute a suspect model to a

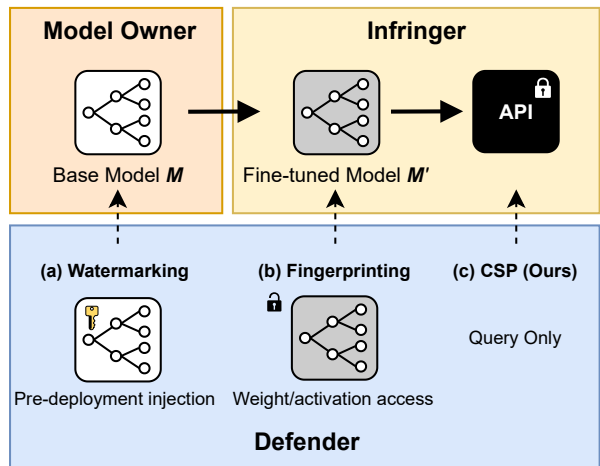


Figure 1. Comparison of model identification scenarios. (a) **Watermarking** requires pre-deployment access to inject a trigger into the base model. (b) **Traditional Fingerprinting** relies on white-box or gray-box ‘Internal Access’ (e.g., weights or activations), which is not available in commercial API. (c) **Our approach (CSF)** is designed for the most restrictive ‘Query Only’ black-box setting, where the defender only has access to the final T2I generation API, reflecting real-world infringement scenarios.

protected lineage under minimal access.

This problem reduces to finding a signature that attributes a suspect model to its root IP lineage. Existing approaches either inject identifiers into models (watermarking) or discover intrinsic fingerprints (fingerprinting). Watermarking works well in black-box, query-only settings because trigger inputs induce detectable patterns in outputs that survive typical fine-tuning [6, 16, 56, 60]. But watermarking requires pre-deployment training, can degrade model quality [4, 15, 25, 62], and, once known, can be removed by infringers [3, 14, 26, 30]. Fingerprinting instead passively extracts characteristics from deployed models, but these signals are subtle. Existing methods either do not address preservation under fine-tuning [55], or require internal activations or fine-

grained generation control [18, 27, 47, 53, 59], which commercial APIs typically do not provide (Figure 1). This leaves the restricted-access setting with only text-image pairs largely unsolved.

In this work, we present Compositional Semantic Fingerprinting (CSF), a fingerprinting method that statistically determines whether a suspect model belongs to a model lineage in the restrictive black-box setting using only text-to-image API access. CSF reverses the logic of watermarking for fingerprinting. Just as watermarks persist after fine-tuning because rare trigger inputs are unlikely to be overwritten, CSF exploits semantic compositions that sparsely appear in fine-tuning data. Rather than relying on visual artifacts, it probes semantics that persist through downstream modification. This gives IP owners an asymmetry advantage, since compositions can be generated at detection time. Moreover, CSF allows lineage decisions to be made statistically under controlled risk. The method is training-free and requires no model modification before deployment.

However, this query-only setting cannot be solved by per-model classifiers, representation-space clustering, or direct output matching alone. Fine-tuning can dramatically alter image style, color palette, and overall composition, overwhelming subtle pixel-level signals and making highly reliable output-space discrimination virtually impossible (Fig. 2). It can also substantially change naive surface biases, for example through Direct Preference Optimization (DPO) [39], while preserving deeper semantics inherited from pre-training.

CSF addresses this by moving the problem from visual space to semantic space and reducing it to text-to-class inference. Specifically, we probe models with compositional semantic combinations that are rare in fine-tuning data, using conditioning inspired by formal semantics, and sample multiple generations for each underspecified prompt. The resulting interpretation distributions reveal pre-training biases inherited from the base model lineage and preserved after fine-tuning. We then convert these outputs into category distributions via zero-shot classification, compare suspect and reference models through distances between the resulting semantic distributions, and aggregate evidence across prompts to make statistical lineage decisions with quantified uncertainty. We validate this on Stable Diffusion (v1.5, v2.1, XL, v3), Flux, Kandinsky, and fine-tuned variants from style transfer, LoRA [13], model merging, and DPO, covering 19 models in total.

2. Related Work

Model identification is a research area aimed at identifying the IP owner of a model from generated content. These methods reduce to the problem of mapping each

model M to a unique identifier ϕ_M . The approaches to obtaining identifiers are broadly divided into two categories: (1) methods that *inject* identifiers into models during training, and (2) methods that *discover* intrinsic identifiers that models inherently possess.

2.1. Watermarking: Identifier Injection

Watermarking injects a backdoor trigger (identifier) into the model during training, such that the model produces a predetermined output for specific trigger inputs [1, 17, 50]. This approach is promising as it can provide statistically rigorous evidence. It has been applied to various models, from classical classification models [1, 45] and large language models [19, 20, 35, 61] to recent diffusion models [6, 42, 56, 62]. For diffusion models, approaches have been proposed that embed watermarks in the denoising process [16, 42, 56, 58] or inject specific patterns into the latent space [5, 9, 14].

However, watermarking has fundamental limitations. First, adding heterogeneous triggers to training data inevitably degrades the model’s overall performance. Second, it cannot be applied to models already deployed without watermarks. Third, watermarks can be diluted through fine-tuning [9, 14, 55], or if the watermark becomes known, it can be neutralized by watermark defense techniques [57].

2.2. Fingerprinting: Identifier Discovery

Fingerprinting leverages intrinsic characteristics that models inherently possess as identifiers, requiring no additional tuning. Representative approaches include model weight-based methods that measure the distance between the suspect model’s weights and the original model’s weights [18, 28, 49]. Representation-based methods use kernels defined in the model’s latent feature space as identifiers, distinguishing models by distances between kernels [21, 59].

While these methods are effective, the major limitation is the requirement for white-box access. When suspect models are distributed as commercial APIs, weights and hidden representations are inaccessible. For diffusion models, methods that train classifiers on generated images are commonly used [33, 54], but these studies are limited to toy datasets or synthetic setups, with insufficient research on actually deployed foundational models (e.g., DALL-E [40], Stable Diffusion). Moreover, most assume white-box access. For example, [48] claims one-shot attribution but only identify cases where training data matches and does not address fine-tuned variants.

2.3. Our Approach

This work follows the fingerprinting approach of discovering intrinsic identifiers, but with the following distinctions. First, we assume a complete black-box set-

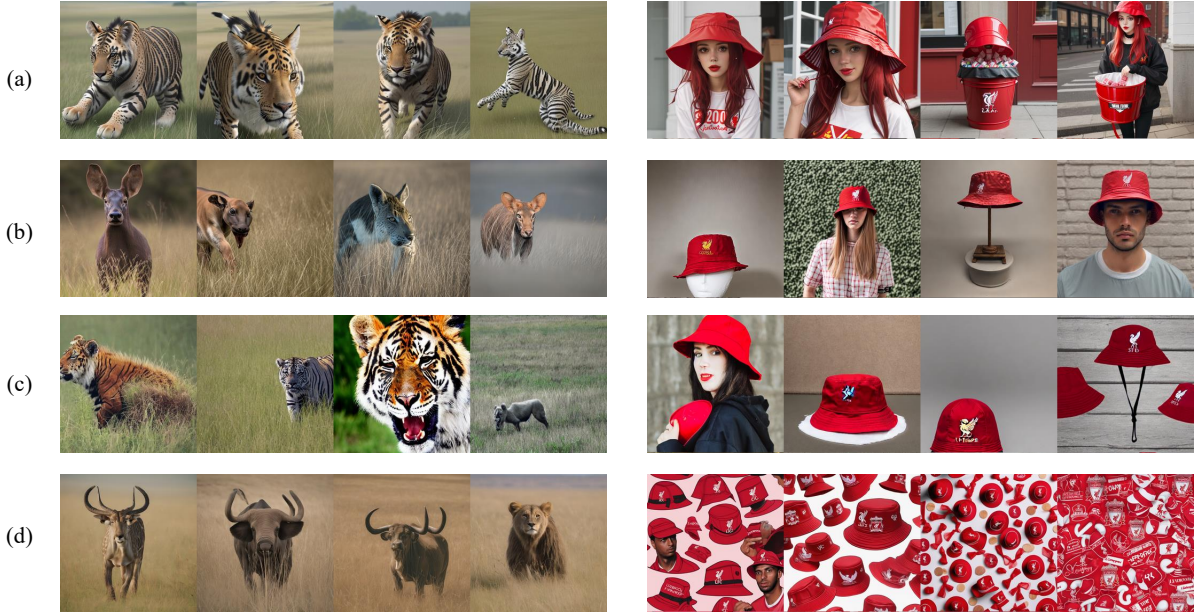


Figure 2. The “Name That Dataset” game [52] in Diffusion Fingerprinting. Image (a) is from a fine-tuned model (SD1.5-DreamShaper). One of the images (b, c, d) is its base model. This figure illustrates how difficult it is to identify the base model using a **naive prompt** (right column, randomly sampled from LAION-2B [46]), compared to **our CSF prompt** (left column). All images are uncensored results generated with different random seeds. **Can you specify which model (b, c, or d) is the base model for (a)?** Answer: (a) SD1.5-DreamShaper (fine-tuned), (b) SD2.1-DPO (fine-tuned), (c) SD1.5 Base, and (d) SDXL Base. The correct base model for (a) is (c).

ting. That is, only the API of currently deployed models is available, generation processes cannot be controlled, and only text prompts can be provided as conditions. Second, our method is train-free. Unlike existing methods, no separate model training or training data collection is required. Third, we target fine-tuned scenarios and foundational models. Reflecting the reality that commercial models are continuously fine-tuned, we propose a robust identifier that preserves the base model’s identity even after fine-tuning.

3. Problem Formulation

Task definition. For each text-to-image model M , the goal is to generate an identifier ϕ_M that uniquely identifies M . The identifier must satisfy two conditions:

- **Discriminability:** Different base models must be distinguishable. That is, for base models M_i and M_j ($i \neq j$), $\phi_{M_i} \neq \phi_{M_j}$.
- **Robustness:** Fine-tuned variants M' should be attributed to the same base model M . That is, for M' obtained by fine-tuning M , $\phi_{M'} \approx \phi_M$.

Key challenge. Fine-tuning dramatically alters generation style (photorealistic vs. anime), content bias (subject preferences), and generation quality—yet the base

model identity must remain recoverable. Existing visual features (CLIP [38] embeddings, ResNet [12] features) are highly sensitive to these stylistic variations, causing fine-tuned variants to cluster by style rather than base model (Fig. 3). This necessitates an alternative representation that isolates semantic interpretation from visual appearance.

Our setting. This work addresses the most extreme black-box setting. We assume that for a suspect model, we can only provide text prompts T as queries and observe the generated images $I = M(T)$, with the ability to perform multiple sampling for the same prompt. We have no access to any internal state such as model weights, gradients, internal activations, or diffusion trajectories used in prior work. This corresponds to the query-only interface commonly provided by commercial APIs.

4. Method

CSF abstracts text-to-image models as semantic category generators rather than pixel-level synthesizers, isolating interpretive biases from stylistic variations that change during fine-tuning (Section 4.1). We construct compositional underspecified prompts (e.g., “a danger-

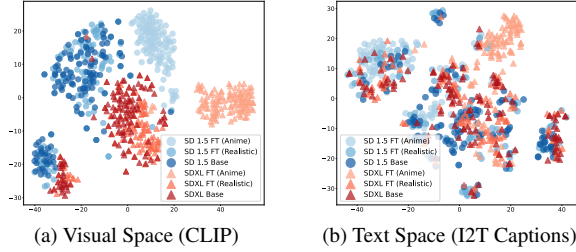


Figure 3. **Challenges in naive fingerprinting approaches.** (a) **Visual space:** t-SNE visualization of CLIP embeddings shows no family clustering. (b) **Text space:** Even when images are converted to captions via I2T models, style information leaks into the text, causing models from different families (e.g., SD1.5 DPO and SD2.1) to cluster together due to similar style descriptors.

ous urban nocturnal animal”) that combine individually common semantic components into exponentially rare compositions, exploiting the same robustness principle as backdoor watermarks—fine-tuning preserves model behavior on rare conditions absent from training data (Section 4.2). For each prompt, we generate $N = 30$ images, extract categorical distributions via CLIP zero-shot classification, and perform Bayesian attribution by computing Wasserstein distances between suspect and base model fingerprints across 42 prompts, yielding statistically rigorous confidence intervals (Section 4.5).

4.1. Semantic Fingerprinting

To isolate semantic interpretation from stylistic variations, we abstract text-to-image models as text-to-category generators. Rather than modeling pixel distributions, we model the semantic category distributions they implicitly define.

Naively, one might use image captions to extract semantic content. However, captions encode not just *what* is depicted but *how it is described*—the linguistic framing itself is model-dependent. Different models may describe the same semantic concept using different phrases, levels of detail, or contextual emphasis.

To eliminate this confound, we constrain the semantic space to a predefined set of categories (e.g., the category of animal). Rather than generating free-form descriptions, we ask: *which category does the model’s generation correspond to?* This reduces the problem to a distribution over discrete semantic choices.

We formalize this abstraction as follows. Given an underspecified prompt C (e.g., “a photo of animal”), model M produces images whose semantic content varies stochastically. Let \mathcal{Y}_C denote the space of semantically plausible categories for prompt C . Model M induces a categorical distribution:

$$P(Y|C, M), \quad Y \in \mathcal{Y}_C \quad (1)$$

where Y represents the semantic category (e.g., tiger, lion, wolf) of the generated image.

Due to stochastic image generation, each generation of $M(C)$ produces a different categorical vector $\phi \in \Delta^{K-1}$:

$$\mathbf{p} \sim P(\cdot|C, M), \quad \mathbf{p} \in \Delta^{K-1} \quad (2)$$

where \mathbf{p}_i represents the probability assigned to category i by a vision-language classifier, and Δ^{K-1} denotes the $(K-1)$ -dimensional probability simplex.

The model fingerprint is the distribution $P(\mathbf{p}|C, M)$ over these categorical vectors. We estimate this distribution via N i.i.d. samples $\{\mathbf{p}_1, \dots, \mathbf{p}_N\}$ obtained by generating N images and classifying each independently. Two models are compared via the Wasserstein distance between their empirical distributions over categorical vectors.

4.2. Compositional Semantic Fingerprinting

While semantic abstraction isolates interpretive biases from stylistic variations, a critical question remains: *which prompts preserve base model fingerprints through fine-tuning?*

To extract distributional fingerprints, prompts must be underspecified, admitting multiple semantic interpretations that vary across generations. However, naive broad prompts (e.g., “an animal”) face a fundamental problem: they correspond to common categories in fine-tuning datasets. Fine-tuning data frequently contains animal images with diverse species, allowing fine-tuning to overwrite the base model’s semantic biases. The base model fingerprint is lost.

We resolve this through *compositional underspecification*: prompts that produce semantic variation yet remain rare in fine-tuning data. We construct prompts by combining (1) a superordinate category T (e.g., “animal”) and (2) multiple semantic attributes $\{c_1, c_2, \dots\}$ (e.g., “dangerous”, “dimmed studio”). Each prompt follows the template:

$$C = \text{“A photo of } c_1 c_2 \dots c_k T \text{”} \quad (3)$$

Fingerprint extraction. For each compositional prompt C , we generate N images and extract their categorical distributions via zero-shot classification. The aggregated distribution characterizes how model M interprets underspecified conditions, independent of visual style.

Asymmetry characteristics. Unlike watermarking methods where known triggers can be targeted and removed, our compositional prompts exploit combinatorial explosion. Infringers cannot remove specific prompts without knowing which combinations will be

tested, and defending against all possible compositions is intractable—the exponential space of attribute combinations makes exhaustive removal infeasible. Verifiers maintain the advantage: they can freely construct new rare compositions post-deployment.

4.3. Robustness Principles

CSF as watermarks The robustness of our method follows the same principle as backdoor watermarks. Fine-tuning updates model parameters based on the training data distribution \mathcal{D}_{FT} . For input-output pairs (x, y) that appear in \mathcal{D}_{FT} , fine-tuning modifies the model’s behavior: $P(y|x, M') \neq P(y|x, M)$. However, for rare conditions not present in the fine-tuning data, where $P((x, y) \in \mathcal{D}_{FT}) \approx 0$, the model receives little update signal on those behaviors. As a result, the base model’s response to rare conditions is preserved: $P(y|x_{rare}, M') \approx P(y|x_{rare}, M)$.

This explains why backdoor watermarks persist: the specific trigger-watermark pair $(X_{trigger}, Y_{watermark})$ is engineered to be absent from natural fine-tuning data, leaving the embedded behavior intact.

Our compositional prompts exploit this mechanism through combinatorial rarity. By composing semantic components that may each be common in fine-tuning datasets, their joint condition becomes progressively rarer. For a compositional prompt built from a target concept T and contextual conditions $\{c_1, c_2, \dots\}$, we do not assume strict independence among components. Instead, we assume a monotonic decrease in occurrence as additional conditions are composed:

$$P(T) \gg P(T \cap c_1) \gg P(T \cap c_1 \cap c_2) \gg \dots \gtrsim 0. \quad (4)$$

This monotonic reduction is sufficient for our purpose: as more semantic conditions are composed, the resulting prompt enters an effectively rare regime under \mathcal{D}_{FT} . In that regime, fine-tuning provides little update pressure on the induced semantic behavior. Consequently, the base model’s semantic biases are preserved:

$$P(\mathbf{p} | C, M') \approx P(\mathbf{p} | C, M) \quad (5)$$

maintaining model fingerprints through fine-tuning.

Linguistic grounding. Our design exploits how language models resolve ambiguous descriptions. When encountering underspecified prompts like “a dangerous animal,” models must resolve ambiguity using their learned priors, just as humans invoke different referents based on their experiences. This is the principle of **underspecification** [7, 10, 37]: semantic constraints reduce but do not determine the referent space, forcing models to reveal their semantic biases. By combining this with compositional rarity, we create prompts that

are both discriminative (revealing model-specific interpretations) and robust (preserved through fine-tuning).

4.4. Implementation

Category extraction. For each compositional prompt C , we generate $N = 30$ images using the suspect model with different random seeds. Each image I_i is classified via CLIP [38] zero-shot classification:

$$\phi_i = \text{softmax}(\text{CLIP}_{\text{visual}}(I_i) \cdot \text{CLIP}_{\text{text}}(\{y_1, \dots, y_K\})) \quad (6)$$

where $\{y_1, \dots, y_K\}$ are subordinate categories for superordinate T , sourced from: (1) Wikipedia taxonomies for common domains, (2) existing dataset labels when available, or (3) LLM generation for specialized domains.

Prompt design. Each prompt follows a controlled three-component structure: (1) an underspecified semantic attribute that admits multiple interpretations, (2) a superordinate category defining the domain, and (3) a specific contextual condition. The underspecified attribute forces models to make subjective semantic choices, revealing their learned biases. The specific condition serves a critical role: it constrains non-semantic factors (composition, object count, scene complexity) to ensure each generation contains exactly one identifiable subject. This design prevents ambiguity in CLIP classification that would arise from multi-object scenes or empty backgrounds, isolating model-specific semantic interpretation as the sole source of distributional variation. We systematically vary the underspecified attributes across multiple semantic dimensions while maintaining fixed specific conditions within each domain, yielding 42 compositional prompts.

Sampling protocol. Each prompt-model pair produces 30 categorical distributions, yielding 1260 total samples per model. This demonstrates the practical affordability of our method, even using commercial APIs, the cost is only approximately **\$50** per model.¹

4.5. Bayesian Attribution Framework

Statistical inference problem. Model attribution is inherently probabilistic: each compositional prompt constitutes an independent trial, and we must infer the true base model from multiple noisy observations. We formalize this as Bayesian inference over model identity.

¹For example, OpenAI DALL-E 3 charges \$0.04 per 1024×1024 image (<https://openai.com/api/pricing>), yielding $42 \times 30 \times \$0.04 \approx \50 per model. Similar pricing applies to other commercial T2I APIs.

	Base Models					
	Flux-Base	Kandinsky-Base	SD1.5-Base	SD2.1-Base	SD3-Medium-Base	SDXL-Base
<i>Flux Family</i>						
Flux-LoRA	0.932*	0.023	0.023	0.023	0.023	0.068
Flux-Turbo-Alpha	0.977*	0.023	0.023	0.023	0.023	0.023
<i>Kandinsky Family</i>						
Kandinsky-Naruto	0.023	0.977*	0.023	0.023	0.023	0.023
Kandinsky-Pokemon-LoRA	0.049	0.829*	0.049	0.098	0.024	0.049
<i>SD1.5 Family</i>						
SD1.5-1.2-Base	0.023	0.023	0.841*	0.114	0.023	0.068
SD1.5-1.4-Base	0.023	0.023	0.977*	0.023	0.023	0.023
SD1.5-DreamShaper	0.091	0.068	0.659*	0.045	0.068	0.159
<i>SD2.1 Family</i>						
SD2.1-DPO	0.023	0.023	0.023	0.977*	0.023	0.023
SD2.1-LAION-Art	0.023	0.023	0.023	0.977*	0.023	0.023
<i>SD3 Family</i>						
SD3-Reality-Mix	0.136	0.091	0.023	0.045	0.705*	0.091
SD3-VAE-Anime	0.023	0.023	0.023	0.023	0.977*	0.023
<i>SDXL Family</i>						
SDXL-DPO	0.023	0.023	0.023	0.023	0.023	0.977*
SDXL-Lightning-4Step	0.023	0.091	0.023	0.068	0.023	0.864*

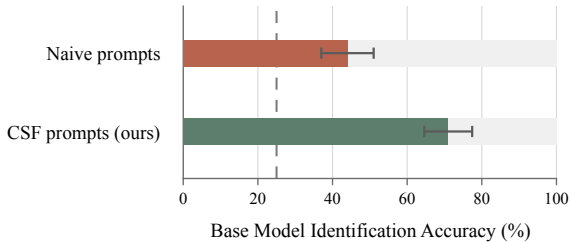


Figure 4. User study results for the “Name That Dataset” game (Fig. 2). Participants attempted to identify the correct base model using naive prompts (LAION-2B [46]) vs. our CSF prompts.

actionable only when the lower bound of the posterior interval exceeds 0.5, indicating dominance under controlled uncertainty.

5. Experiments

5.1. Model Selection

Base model We evaluate on 6 base families representing all major open-source text-to-image architectures: FLUX [23], Kandinsky [41], and Stable Diffusion 1.5/2.1/3.0/XL [8, 36, 43]. This covers fundamental architectural diversity - different noise schedules (cosine vs. rectified flow), backbones (2D U-Net [44] vs. DiT [34] vs. Flow Transformer [29]), text encoders (CLIP-only [38] vs. CLIP+T5 [31]), and latent resolutions. Critically, several families pose deliberate challenges: SD1.5 and SD2.1 share nearly identical architectures from the same company, with SD2.1’s training data being a *superset* of SD1.5’s. Similarly, SD3 and FLUX adopt the same T5-XXL + CLIP-L text encoders and 128×128 latent resolution, differing primarily in backbone design. These architectural overlaps make families exceptionally difficult to distinguish based on data-driven semantic biases alone. These architectural overlaps make lineage-level attribution exceptionally difficult from semantic behavior alone.

Lineage definition and attribution target. We study attribution at the level of model lineage rather than exact checkpoint identity. This matches the practical commercial setting, where the key forensic question is whether a deployed model derives from a restricted base family, since licensing and redistribution constraints typically extend to derivative models as well. We therefore define a lineage as a base model together with its intermediate checkpoints, continued-pretraining descendants, and downstream fine-tuned variants that inherit the same underlying family. Under this threat model, successful attribution means recovering the correct source lineage de-

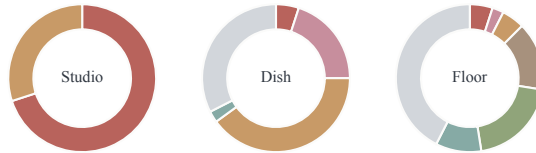


Figure 5. Generated category distributions vary substantially with scene context. Compared with the dimmed-studio setting, the dish and wooden-floor settings produce broader and systematically shifted category mixtures. Each donut summarizes 40 samples, and the same color denotes the same category across scenes.

spite substantial post-training modifications.

Fine-tuning variants We select variants spanning all major adaptation types to ensure comprehensive evaluation. These include: (1) LoRA [13] fine-tuning for style transfer and preference alignment, (2) full model fine-tuning on domain-specific datasets, (3) model merging (“cocktails”) that blend multiple fine-tuned models and dilute base fingerprints, (4) preference optimization (DPO [39]/RLHF [32]) that actively rewrites semantic biases toward human preferences, (5) distillation to few-step models that compress generation while potentially discarding subtle biases, and (6) component replacement (e.g., VAE swapping) that alters the generation pathway. Several variants combine multiple perturbations (e.g., merging + DPO), representing near-worst-case scenarios for fingerprint preservation.

5.2. Attribution Performance

Main results. Table 1 presents Bayesian attribution results for all 13 fine-tuned variants. Every model achieves posterior mean accuracy exceeding 50%, with 95% credible interval lower bounds consistently above this Dominance test. This demonstrates that for each suspect model, the correct base family is predicted more frequently than all other families *combined*, providing actionable attribution confidence. In contrast, using only base prompts without compositional constraints achieves fls, with several models showing significant confusion (e.g., sd15-dreamshaper → kandinsky, sd12 posterior: 0.429 for sdx1). This drop validates that compositional underspecification is necessary for reliable attribution.

Robustness and practical advantages. *Resistant to extreme perturbations.* Even the most challenging cases succeed. SD3-Reality-Mix undergoes full retraining on curated photorealistic datasets, fundamentally rewriting semantic priors beyond typical fine-tuning. Model merg-

Table 2. Attribution confidence: Wasserstein vs. JSD

Fine-tuned Model	Wasserstein (Ours)	JSD (Baseline)	Confidence Gap
Flux-LoRA	93.2%	77.3%	+15.9%
Kandinsky-Naruto	97.7%	43.2%	+54.5%
SD3-Reality-Mix	70.5%	56.8%	+13.7%
SDXL-DPO	97.7%	70.5%	+27.2%

Table 3. Attribution results under adversarial concept removal. Posterior mean attribution scores computed from 9 animal-specific probes after removing animal-related concepts using UCE.

Model	Base Models					
	Flux	Kandinsky	SD1.5	SD2.1	SD3-Med	SDXL
LoRA	0.714	0.143	0.143	0.143	0.143	0.286
Turbo-Alpha	0.857	0.143	0.143	0.143	0.143	0.143
Naruto	0.143	0.857	0.143	0.143	0.143	0.143
Pokemon-LoRA	0.143	0.857	0.143	0.143	0.143	0.143
I.2-Base	0.143	0.143	0.857	0.143	0.143	0.143
I.4-Base	0.143	0.143	0.857	0.143	0.143	0.143
Animal-Erase	0.143	0.143	0.857	0.143	0.143	0.143
DreamShaper	0.143	0.143	0.714	0.143	0.286	0.143
DPO	0.143	0.143	0.143	0.857	0.143	0.143
LAION-Art	0.143	0.143	0.143	0.857	0.143	0.143
Reality-Mix	0.286	0.143	0.143	0.143	0.714	0.143
VAE-Anime	0.143	0.143	0.143	0.143	0.857	0.143
DPO	0.143	0.143	0.143	0.143	0.143	0.857
Lightning-4Step	0.143	0.143	0.143	0.286	0.143	0.714

ing combined with DPO (e.g., Dreamshaper) layers preference re-biasing atop already-diluted cocktail fingerprints. Distillation compresses generation into few steps, potentially discarding subtle biases. Yet all variants maintain Dominance test at 95% confidence, demonstrating that compositional semantic biases persist even under aggressive adaptations.

Black-box advantages. Our method successfully attributes distilled models (SDXL-Lightning, FLUX-Turbo), which white-box methods [51] cannot handle due to altered generation trajectories. Similarly, gray-box methods requiring intermediate activations [59] fail in true API-only settings. By operating at the semantic level, our approach achieves robustness unavailable to architecture-dependent fingerprinting.

Human Study While our statistical framework provides quantitative attribution confidence, practical IP disputes require evidence that is not only mathematically sound but also perceptually interpretable. To address this, we validate that CSF-isolated biases align with human perception through a “Name That Dataset” [52] experiment on Amazon Mechanical Turk, as illustrated in Fig. 2.

We tasked 50 participants with identifying the base model for a given fine-tuned model (e.g., SD1.5-DreamShaper) from three candidate base models. Each participant completed 11 trials: 1 screening question for quality control, 5 using our CSF prompts, and 5 using naive baseline prompts (from LAION-2B [46]). In both conditions, participants were instructed to “ignore the visual style” and match only the “content distribution

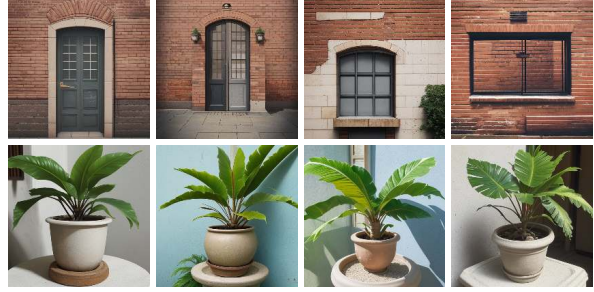


Figure 6. Failure cases of CSF. Top: prompts for baked goods in front of a brick wall. Bottom: prompts for tropical flowers on a pot. In both cases, models failed to generate identifiable objects within the target categories.

pattern,” simulating our method’s abstraction from style to semantics.

The results (Fig. 4), based on the 10 non-screening trials, confirm our hypothesis. Participant accuracy with naive prompts was 18% far below random chance for 95% confidence (33.3% for 3-way classification). This demonstrates that naive prompts fail to generate perceptually distinct semantic patterns, rendering the model’s lineage ambiguous even when style is disregarded. In contrast, our CSF prompts yielded 71% accuracy *i.e.*, meets Dominance test. This significant gap confirms that CSF-isolated biases are not mere statistical artifacts but are perceptually robust signals that align with human intuition, strengthening their credibility as circumstantial evidence for IP attribution.

5.3. Analysis

Robustness to adversarial concept removal. A natural question is whether CSF can be neutralized by semantic erasure or unlearning methods that deliberately remove target concepts from a model. To test this attack scenario, we evaluate CSF under adversarial concept removal settings, using concept-editing methods to suppress specific semantic concepts, with Unified Concept Editing (UCE) [11] as a representative example. We find that attribution remains stable even after targeted concept removal. This is because CSF operates on broad semantic categories, such as animals or flowers, combined with compositional contextual conditions, rather than on a single narrow concept. Consequently, defeating CSF would require erasing broad semantic capabilities, which is difficult without significantly harming general model utility. Note that this robustness is orthogonal from the asymmetric advantage discussed earlier: even under explicit post-hoc semantic removal, CSF remains effective because it relies on broad semantic capabilities rather than isolated concept triggers.

Failure modes. Our method occasionally fails when models cannot follow the compositional prompt, generating objects outside the target category (Figure 6). For instance, “a savory baked good against a brick wall” or “a tropical flower on a pot” produces unidentifiable objects in some models, preventing meaningful categorical classification. These generation failures are detectable via entropy thresholding, allowing automatic filtering of unreliable prompts.

Distance metric comparison. We validate the usage of Wasserstein distance by comparing Jensen-Shannon Divergence (JSD) as attribution metrics (Table 2). While both achieve correct attribution, JSD shows weaker confidence, particularly for some models. However, Wasserstein maintains consistently high confidence, as it captures geometric structure in the probability simplex rather than treating categories independently.

Prompt design validation. Figure 5 validates our compositional prompt design by demonstrating that underspecification elicits model-specific semantic biases. Varying only one contextual component, the categorical distributions shift dramatically across contexts. This context-dependent variation confirms that underspecified prompts force models to resolve ambiguity using their learned priors, revealing the semantic biases that constitute model fingerprints.

6. Conclusion

We present CSF, the first black-box fingerprinting method for text-to-image models that operates under the most restrictive query-only setting. Unlike prior fingerprinting approaches that rely on architectural access or heuristic similarity metrics, CSF provides statistical guarantees through a Bayesian attribution framework. Critically, CSF reverses the asymmetry inherent in watermarking approaches. While watermarks can be removed once discovered, IP owners can generate infinitely many new compositional prompts post-deployment. This defender-favorable asymmetry, combined with training-free deployment and modest query costs (\$50 per model), establishes CSF as a practical solution for intellectual property protection in the era of API-distributed generative models.

Acknowledgments

This work was supported by the Korean Government through the grants from IITP (RS-2021-II211343, RS-2022-II220320, RS-2025-25442338).

References

- [1] Yossi Adi, Carsten Baum, Moustapha Cisse, Benny Pinkas, and Joseph Keshet. Turning your weakness into a strength: Watermarking deep neural networks by back-dooring. In *27th USENIX security symposium (USENIX Security 18)*, pages 1615–1631, 2018. 2
- [2] Stability AI. Sdxl turbo. <https://huggingface.co/stabilityai/sdxl-turbo>, 2023. Accessed: 2025-11-12. 1
- [3] Xinyun Chen, Wenxiao Wang, Chris Bender, Yiming Ding, Ruoxi Jia, Bo Li, and Dawn Song. Refit: a unified watermark removal framework for deep learning systems with limited data. In *Proceedings of the 2021 ACM Asia Conference on Computer and Communications Security*, pages 321–335, 2021. 1
- [4] Yunzhuo Chen, Jordan Vice, Naveed Akhtar, Nur Al Hasan Haldar, and Ajmal Mian. Image watermarking of generative diffusion models. *arXiv preprint arXiv:2502.10465*, 2025. 1
- [5] Hai Ci, Yiren Song, Pei Yang, Jinheng Xie, and Mike Zheng Shou. Wmadapter: Adding watermark control to latent diffusion models. *arXiv preprint arXiv:2406.08337*, 2024. 2
- [6] Yingqian Cui, Jie Ren, Han Xu, Pengfei He, Hui Liu, Lichao Sun, Yue Xing, and Jiliang Tang. Diffusionshield: A watermark for copyright protection against generative diffusion models. *arXiv preprint arXiv:2306.04642*, 2023. 1, 2
- [7] Markus Egg. Semantic underspecification. *Language and Linguistics Compass*, 4(3):166–181, 2010. 5
- [8] Patrick Esser, Sumith Kulal, Andreas Blattmann, Rahim Entezari, Jonas Müller, Harry Saini, Yam Levi, Dominik Lorenz, Axel Sauer, Frederic Boesel, et al. Scaling rectified flow transformers for high-resolution image synthesis. In *ICML*, 2024. 1, 7
- [9] Pierre Fernandez, Guillaume Couairon, Hervé Jégou, Matthijs Douze, and Teddy Furon. The stable signature: Rooting watermarks in latent diffusion models. In *ICCV*, pages 22466–22477, 2023. 2
- [10] Steven Frisson. Semantic underspecification in language processing. *Language and linguistics compass*, 3(1): 111–127, 2009. 5
- [11] Rohit Gandikota, Hadas Orgad, Yonatan Belinkov, Joanna Materzyńska, and David Bau. Unified concept editing in diffusion models. *arXiv preprint arXiv:2308.14761*, 2023. 8
- [12] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016. 3
- [13] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. Lora: Low-rank adaptation of large language models. *ICLR*, 1(2):3, 2022. 2, 7, 1
- [14] Yuepeng Hu, Zhengyuan Jiang, Moyang Guo, and Neil Gong. Stable signature is unstable: Removing image watermark from diffusion models. *arXiv preprint arXiv:2405.07145*, 2024. 1, 2
- [15] Guang Hua and Andrew Beng Jin Teoh. Deep fidelity in dnn watermarking: A study of backdoor watermarking for classification models. *Pattern Recognition*, 144: 109844, 2023. 1
- [16] Huayang Huang, Yu Wu, and Qian Wang. Robin: Robust and invisible watermarks for diffusion models with adversarial optimization. *NeurIPS*, 37:3937–3963, 2024. 1, 2
- [17] Hengrui Jia, Christopher A Choquette-Choo, Varun Chandrasekaran, and Nicolas Papernot. Entangled watermarks as a defense against model extraction. In *30th USENIX security symposium (USENIX Security 21)*, pages 1937–1954, 2021. 2
- [18] Changhoon Kim, Kyle Min, Maitreya Patel, Sheng Cheng, and Yezhou Yang. Wouaf: Weight modulation for user attribution and fingerprinting in text-to-image diffusion models. In *CVPR*, pages 8974–8983, 2024. 2
- [19] John Kirchenbauer, Jonas Geiping, Yuxin Wen, Jonathan Katz, Ian Miers, and Tom Goldstein. A watermark for large language models. In *ICML*, pages 17061–17084. PMLR, 2023. 2
- [20] John Kirchenbauer, Jonas Geiping, Yuxin Wen, Manli Shu, Khalid Saifullah, Kezhi Kong, Kasun Fernando, Aniruddha Saha, Micah Goldblum, and Tom Goldstein. On the reliability of watermarks for large language models. *arXiv preprint arXiv:2306.04634*, 2023. 2
- [21] Simon Kornblith, Mohammad Norouzi, Honglak Lee, and Geoffrey Hinton. Similarity of neural network representations revisited. In *ICML*, pages 3519–3529. PMIR, 2019. 2
- [22] Black Forest Labs. Flux.1 [dev]. <https://huggingface.co/black-forest-labs/FLUX.1-dev>, 2023. Hugging Face model card; Accessed: 2025-11-12. 1
- [23] Black Forest Labs. Flux. <https://github.com/black-forest-labs/flux>, 2024. 1, 7
- [24] Black Forest Labs, Stephen Batifol, Andreas Blattmann, Frederic Boesel, Saksham Consul, Cyril Diagne, Tim Dockhorn, Jack English, Zion English, Patrick Esser, Sumith Kulal, Kyle Lacey, Yam Levi, Cheng Li, Dominik Lorenz, Jonas Müller, Dustin Podell, Robin Rombach, Harry Saini, Axel Sauer, and Luke Smith. Flux.1 kon-text: Flow matching for in-context image generation and editing in latent space, 2025. 1
- [25] Liangqi Lei, Keke Gai, Jing Yu, and Liehuang Zhu. Diffustrace: A transparent and flexible watermarking scheme for latent diffusion model. *arXiv preprint arXiv:2405.02696*, 2024. 1
- [26] Xinyu Li. Diffwa: Diffusion models for watermark attack. In *2023 International Conference on Integrated Intelligence and Communication Systems (ICIICS)*, pages 1–8. IEEE, 2023. 1

- [27] Zhuoling Li, Haoxuan Qu, Jason Kuen, Jiuxiang Gu, Qihong Ke, Jun Liu, and Hossein Rahmani. Diffip: Representation fingerprints for robust ip protection of diffusion models. In *ICCV*, pages 17035–17045, 2025. 2
- [28] Thibault Maho, Teddy Furon, and Erwan Le Merrer. Model fingerprinting with benign inputs. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2023. 2
- [29] Liam Daly Manocchio, Siamak Layeghy, Wai Weng Lo, Gayan K Kulatilleke, Mohanad Sarhan, and Marius Portmann. Flowtransformer: A transformer framework for flow-based network intrusion detection systems. *Expert Systems with Applications*, 241:122564, 2024. 7
- [30] Andreas Müller, Denis Lukovnikov, Jonas Thietke, Asja Fischer, and Erwin Quiring. Black-box forgery attacks on semantic watermarks for diffusion models. In *CVPR*, pages 20937–20946, 2025. 1
- [31] Jianmo Ni, Gustavo Hernandez Abrego, Noah Constant, Ji Ma, Keith Hall, Daniel Cer, and Yinfei Yang. Sentence-t5: Scalable sentence encoders from pre-trained text-to-text models. In *Findings of the association for computational linguistics: ACL 2022*, pages 1864–1874, 2022. 7
- [32] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *NeurIPS*, 35:27730–27744, 2022. 7
- [33] Jeongsoo Park and Andrew Owens. Community forensics: Using thousands of generators to train fake image detectors. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 8245–8257, 2025. 2
- [34] William Peebles and Saining Xie. Scalable diffusion models with transformers. In *ICCV*, pages 4195–4205, 2023. 7, 1
- [35] Wenjun Peng, Jingwei Yi, Fangzhao Wu, Shangxi Wu, Bin Bin Zhu, Lingjuan Lyu, Binxing Jiao, Tong Xu, Guangzhong Sun, and Xing Xie. Are you copying my model? protecting the copyright of large language models for eaas via backdoor watermark. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7653–7668, 2023. 2
- [36] Dustin Podell, Zion English, Kyle Lacey, Andreas Blattmann, Tim Dockhorn, Jonas Müller, Joe Penna, and Robin Rombach. Sdxl: Improving latent diffusion models for high-resolution image synthesis. *arXiv preprint arXiv:2307.01952*, 2023. 1, 7
- [37] James Pustejovsky. The semantics of lexical underspecification. *Folia linguistica*, 51(s1000):1–25, 2017. 5
- [38] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *ICML*, pages 8748–8763. Pmlr, 2021. 3, 5, 7
- [39] Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. *NeurIPS*, 36:53728–53741, 2023. 2, 7, 1
- [40] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. In *ICML*, pages 8821–8831. Pmlr, 2021. 2
- [41] Anton Razzhigaev, Arseniy Shakhmatov, Anastasia Maltseva, Vladimir Arkhipkin, Igor Pavlov, Ilya Ryabov, Angelina Kuts, Alexander Panchenko, Andrey Kuznetsov, and Denis Dimitrov. Kandinsky: an improved text-to-image synthesis with image prior and latent diffusion. *arXiv preprint arXiv:2310.03502*, 2023. 1, 7
- [42] Ahmad Rezaei, Mohammad Akbari, Saeed Ranjbar Alvar, Arezou Fatemi, and Yong Zhang. Lawa: Using latent space for in-generation image watermarking. In *ECCV*, pages 118–136. Springer, 2024. 2
- [43] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *CVPR*, pages 10684–10695, 2022. 1, 7
- [44] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015. 7
- [45] Bitá Darvish Rouhani, Huili Chen, and Farinaz Koushanfar. Deepsigns: A generic watermarking framework for ip protection of deep learning models. *arXiv preprint arXiv:1804.00750*, 2018. 2
- [46] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. Laion-5b: An open large-scale dataset for training next generation image-text models. *NeurIPS*, 35:25278–25294, 2022. 3, 7, 8, 1
- [47] Gowthami Somepalli, Vasu Singla, Micah Goldblum, Jonas Geiping, and Tom Goldstein. Diffusion art or digital forgery? investigating data replication in diffusion models. In *CVPR*, pages 6048–6058, 2023. 2
- [48] Hae Jin Song and Laurent Itti. Riemannian-geometric fingerprints of generative models. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 11425–11435, 2025. 2
- [49] Yuchen Sun, Tianpeng Liu, Panhe Hu, Qing Liao, Shaojing Fu, Nenghai Yu, Deke Guo, Yongxiang Liu, and Li Liu. Deep intellectual property protection: A survey. *arXiv preprint arXiv:2304.14613*, 2023. 2
- [50] Sebastian Szyller, Buse Gul Atli, Samuel Marchal, and N Asokan. Dawn: Dynamic adversarial watermarking of neural networks. In *Proceedings of the 29th ACM international conference on multimedia*, pages 4417–4425, 2021. 2
- [51] Huan Teng, Yuhui Quan, Chengyu Wang, Jun Huang, and Hui Ji. Fingerprinting denoising diffusion probabilistic models. In *CVPR*, pages 28811–28820, 2025. 8

- [52] Antonio Torralba and Alexei A Efros. Unbiased look at dataset bias. In *CVPR 2011*, pages 1521–1528. IEEE, 2011. [3](#), [8](#)
- [53] Subarna Tripathi et al. Paladin: Robust neural fingerprinting for text-to-image diffusion models. *arXiv preprint arXiv:2506.03170*, 2025. [2](#)
- [54] Zhendong Wang, Jianmin Bao, Wengang Zhou, Weilun Wang, Hezhen Hu, Hong Chen, and Houqiang Li. Dire for diffusion-generated image detection. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 22445–22455, 2023. [2](#)
- [55] Zilan Wang, Junfeng Guo, Jiacheng Zhu, Yiming Li, Heng Huang, Muhao Chen, and Zhengzhong Tu. Sleep-ermark: Towards robust watermark against fine-tuning text-to-image diffusion models. In *CVPR*, pages 8213–8224, 2025. [1](#), [2](#)
- [56] Yuxin Wen, John Kirchenbauer, Jonas Geiping, and Tom Goldstein. Tree-ring watermarks: Fingerprints for diffusion images that are invisible and robust. *arXiv preprint arXiv:2305.20030*, 2023. [1](#), [2](#)
- [57] Dongxian Wu and Yisen Wang. Adversarial neuron pruning purifies backdoored deep models. *Advances in Neural Information Processing Systems*, 34:16913–16925, 2021. [2](#)
- [58] Zijin Yang, Kai Zeng, Kejiang Chen, Han Fang, Weiming Zhang, and Nenghai Yu. Gaussian shading: Provable performance-lossless image watermarking for diffusion models. In *CVPR*, pages 12162–12171, 2024. [2](#)
- [59] Jie Zhang, Dongrui Liu, Chen Qian, Linfeng Zhang, Yong Liu, Yu Qiao, and Jing Shao. Reef: Representation encoding fingerprints for large language models. *arXiv preprint arXiv:2410.14273*, 2024. [2](#), [8](#)
- [60] Lijun Zhang, Xiao Liu, Antoni V Martin, Cindy X Bearfield, Yuriy Brun, and Hui Guan. Attack-resilient image watermarking using stable diffusion. *NeurIPS*, 37: 38480–38507, 2024. [1](#)
- [61] Xuandong Zhao, Prabhanjan Ananth, Lei Li, and Yu-Xiang Wang. Provable robust watermarking for ai-generated text. *arXiv preprint arXiv:2306.17439*, 2023. [2](#)
- [62] Yunqing Zhao, Tianyu Pang, Chao Du, Xiao Yang, Ngai-Man Cheung, and Min Lin. A recipe for watermarking diffusion models. *arXiv preprint arXiv:2303.10137*, 2023. [1](#), [2](#)

CSF: Black-box Fingerprinting via Compositional Semantics for Text-to-Image Models

Supplementary Material

A. Model Selection

A.1. Base Models

We include 6 base models representing the most prominent open-source diffusion model families. These models are selected due to their widespread adoption in both research and production environments, making them the primary targets for practical fingerprinting applications.

Stable Diffusion Family. The Stable Diffusion series (SD1.5-Base, SD2.1-Base, SD3-Medium-Base, SDXL-Base) represents the dominant lineage in open-source text-to-image generation. SD1.5 [43] established the standard U-Net architecture with latent diffusion, becoming the foundation for thousands of derivatives. SD2.1 introduced architectural improvements including a larger U-Net and OpenCLIP text encoder. SD3 [8] marked a major paradigm shift by adopting a transformer-based backbone similar to DiT [34], while SDXL [36] scaled up model capacity for higher-resolution generation. These four models share the same latent diffusion framework but differ in architecture scale, training data, and design choices, presenting a challenging test for distinguishing models within the same lineage. We additionally include SD1.5-1.2-Base and SD1.5-1.4-Base, intermediate checkpoints from SD1.5’s training trajectory, to evaluate whether fingerprints can differentiate between temporally close versions that share nearly identical architectures and overlapping training data.

Flux Family. Flux-Base [23] represents a recent shift toward fully transformer-based architectures, departing from the U-Net paradigm. Its adoption of attention-based processing throughout the model challenges whether fingerprinting methods designed for convolutional architectures can generalize to transformer-native designs.

Kandinsky Family. Kandinsky-Base [41] employs a unique two-stage pipeline with separate prior and decoder models, where the prior maps text to image embeddings before the decoder generates pixels. This architectural distinction from single-stage models like Stable Diffusion tests whether fingerprints can adapt to multi-stage generation processes.

The diversity across these base models—spanning U-Net vs. transformer architectures, single-stage vs. two-stage pipelines, and different capacity scales—provides a comprehensive testbed for evaluating cross-architecture fingerprint generalization.

A.2. Fine-tuned and Adapted Models

We include 13 fine-tuned variants spanning diverse adaptation strategies to test fingerprint persistence under practical model modifications:

Parameter-Efficient Fine-Tuning. Flux-LoRA, Kandinsky-Pokemon-LoRA, SD2.1-DPO, and SDXL-DPO apply LoRA [13] for low-rank adaptation, testing whether fingerprints survive when only a small fraction ($<1\%$) of parameters are modified. The latter two additionally incorporate Direct Preference Optimization [39] for alignment with human preferences, combining parameter efficiency with RLHF-style objectives that may disrupt learned semantic biases.

Domain-Specific Fine-Tuning. Kandinsky-Naruto (anime style), SD1.5-DreamShaper (aesthetic quality optimization), and SD2.1-LAION-Art (artistic style from LAION-Aesthetics [46]) undergo substantial fine-tuning on domain-specific data. These models challenge fingerprint robustness under significant distribution shift, where the semantic space may deviate considerably from the base model’s training distribution.

Model Merging. SD1.5-DreamShaper and SD3-Reality-Mix represent community-created models that interpolate or merge weights from multiple checkpoints to achieve desired aesthetic or photorealistic qualities. Weight merging presents a unique challenge as the resulting model’s semantic space is a non-linear combination of its constituent models, potentially diluting or obscuring individual model fingerprints.

Component-Specific Modification. SD3-VAE-Anime fine-tunes only the VAE decoder while keeping the diffusion model frozen, isolating the impact of decoder modifications on fingerprinting. This tests whether fingerprints embedded in the semantic (latent) space persist when only the pixel-space decoder is modified.

Inference Optimization. Flux-Turbo-Alpha and SDXL-Lightning-4Step are distilled for few-step inference (4-8 steps vs. 50+ steps), representing the most extreme adaptation scenario. These models undergo aggressive knowledge distillation and inference optimization that fundamentally alters the denoising trajectory. Crucially, such distillation has been shown to defeat even white-box watermarking methods [56], making it the hardest case for any fingerprinting approach. Our evaluation on these models tests whether semantic fingerprints can survive optimization pressures that eliminate traditional cryptographic signatures.

This comprehensive selection ensures our evaluation covers the practical challenges faced in real-world model fingerprinting, from lightweight adaptations to aggressive compression and merging strategies.

B. Results with Alternative Metrics

We evaluate our fingerprinting approach using alternative distance metrics to validate robustness. Results are reported at 95% confidence intervals.

B.1. Baseline Clustering Methods

Table A3 and Table A4 show results for hierarchical clustering on raw fingerprint vectors. Without model specifications (Table A3), naive clustering fails to achieve reliable fingerprinting due to high false positive rates. Incorporating specifications (Table A4) improves performance but still underperforms our compositional approach, confirming that how we structure semantic biases matters.

B.2. Jensen-Shannon Divergence

Table A7, Table A6, and Table A5 present JSD-based fingerprinting results. While JSD is a principled distribution metric, it struggles to capture the subtle compositional structure of semantic biases:

- JSD treats all fingerprint dimensions equally, missing compositionally-structured patterns
- Smoothing in JSD computation reduces discriminability at decision boundaries
- Higher variance in confidence intervals suggests less stable matching

These results explain why LPIPS, designed for perceptual differences, outperforms distribution-based metrics. Our compositional prompts produce semantically meaningful visual variations that may appear statistically minor under symmetric divergence measures.

C. Fingerprinting Prompt Templates

C.1. Prompt Design Rationale

Our 42 fingerprinting prompts are designed to systematically probe semantic biases across multiple dimensions:

Compositional structure All prompts follow the template "A photo of a [ADJECTIVE] [OBJECT] [LOCATION]", which allows independent manipulation of each semantic component. This compositionality is crucial for isolating specific bias sources and measuring their persistence through fine-tuning.

Attribute variation Each object category includes three semantically distinct adjectives that probe different semantic associations. For example, baked goods vary along the savory-sweet spectrum (savory, cheesy, sweet), while animals vary in perceived threat level (dangerous, wild, peaceful). This diversity ensures we capture a broad range of potential semantic biases.

Context variation We systematically vary background settings across three types: controlled studio environments (dimmed studio), natural contexts (grassland, forest, grass, savana), and textured surfaces (dark wood, brick wall, pot, vase, dish, wooden floor). The dimmed studio setting appears across all categories to provide a consistent baseline for cross-category comparison, while category-specific contexts test bias robustness in semantically appropriate settings.

Coverage and efficiency The resulting 42 prompts (5 categories \times 3 attributes \times 2-3 contexts) provide sufficient coverage to establish reliable fingerprints while remaining computationally tractable for fingerprinting verification in black-box settings.

C.2. Prompt Template Structure

Table A8 summarizes the compositional structure of our fingerprinting prompts. The full enumeration of all 42 prompts is provided in Section G.3.

D. Hyperparameter Settings

- **Standard Diffusion Models (SD1.5, SD2.1, SDXL Base):** We used a unified setting of **30 inference steps** and a **guidance scale (CFG) of 7.5**. This applies to the majority of fine-tuned models in our benchmark (e.g., DreamShaper, LAION-Art).
- **SDXL-Lightning:** As this model is distilled for extreme speed, we used **4 inference steps** with a **guidance scale of 0.0**, utilizing the `EulerDiscreteScheduler` with trailing timesteps.
- **Stable Diffusion 3 (SD3):** For the base medium model, we used **28 steps** with a CFG of **7.0**. For the *Reality Mix* variant, we lowered the CFG to **5.5** and set the guidance rescale to 0.0 to prevent artifacts.
- **Flux.1-dev:** We utilized the `FluxPipeline` with **50 inference steps** and a **guidance scale of 3.5**. The generation resolution was explicitly set to 512×512 , and for LoRA variants (e.g., RealismLora), adapter weights were loaded with a scale of 1.0.
- **DPO-Adapted Models:** For SD2.1-DPO and SDXL-DPO, we switched the scheduler to `DPMSolverMultistepScheduler` (SDE-DPM++ with Karras sigmas) to better handle the preference-aligned weights. The LoRA adapter strength was set to **0.9**.
- **Kandinsky 2.2:** We employed the specific `KandinskyV22PriorPipeline` for embedding generation (CFG 1.0), followed by the decoder pipeline.

E. Visualization

Figures B3 to B6 present example questions used in the human study. Additional qualitative grids for the prompt templates are provided below.

F. Heatmap

In Table A2, similar to other fingerprinting methods, our method can also be evaluated by visualizing a heatmap. We visualized the results by averaging each column.

G. Details of the Analysis experiments

G.1. Details of the Scene-Context Validation Experiment

We provide the full protocol for the scene-context validation experiment shown in Figure 5. The goal of this experiment was to verify that the semantic signal isolated by CSF changes systematically when only the contextual component of an underspecified prompt is modified.

Task. We instantiated the validation experiment in the fruit domain. For each trial, we fixed the superordinate category and the underspecified component of the prompt, and varied only the scene context. We considered three contextual settings: *dimmed studio*, *dish*, and *wooden floor*.

Prompt conditions. All prompt components other than the scene phrase were kept unchanged across conditions. This design isolates the effect of context alone, allowing us to test whether a single contextual modification can induce a measurable shift in the generated semantic category distribution.

Protocol. For each context, we generated 40 images using the same model and identical sampling settings. The generation pipeline, including the prompt template and all sampling hyperparameters, was kept fixed across the three conditions.

Category extraction. Each generated image was mapped to a fixed fruit-category vocabulary using the same zero-shot CLIP-based category extraction procedure used throughout the main experiments. The category set consisted of Apple, Nectarine, Grapefruit, Lime, Coconut, Honeydew, and Others.

Interpretation. As shown in Figure 5, changing only the scene context produces a substantial and systematic shift in the generated category distribution. Compared with the dimmed-studio setting, the dish and wooden-floor settings yield broader and differently redistributed mixtures over categories. This supports our claim that compositional underspecification reveals model-dependent semantic biases, and that contextual variation alone is sufficient to alter how the model resolves semantic ambiguity.

G.2. Details of the Human Perceptual Study

We provide the full protocol for the human perceptual validation experiment used in Figure 4. The goal of this study was to test whether the semantic signal isolated by CSF is also accessible to human observers, rather than being an artifact of the computational attribution procedure.

Task. We ran a four-way forced-choice “Name That Dataset” experiment on Amazon Mechanical Turk. In each trial, a participant was shown a fine-tuned model and asked to identify its underlying base model from four candidates. To mirror the abstraction used by CSF, participants were explicitly instructed to ignore visual style and rely only on recurring content-distribution cues.

Prompt conditions. We compared two prompt sources: (i) naive prompts randomly sampled from LAION-2B, and (ii) CSF prompts generated by our method. The candidate set size was fixed across conditions, yielding a chance level of 25%.

Protocol. For each condition, we collected responses from 50 independent participants under the same interface and instruction template. Candidate ordering was randomized to reduce position bias, while the task format was kept identical across conditions.

Metric and error bars. We report identification accuracy for each condition. Since each response is a binary correct/incorrect outcome, we model the measured accuracy under a binomial distribution and compute the error bars as

$$100\sqrt{\frac{p(1-p)}{n}},$$

where p is the observed accuracy and $n = 50$ is the number of independent participant responses.

Interpretation. Naive prompts lead to substantially weaker identification performance, whereas CSF prompts noticeably improve human recognition of the correct model lineage. This supports our claim that the signal captured by CSF is not merely machine-readable, but also perceptually robust.

Table A1. Model details for fingerprinting evaluation. All models are available at [https://huggingface.co/\[model-path\]](https://huggingface.co/[model-path]).

Model Name	HuggingFace Path
<i>Flux Family</i>	
Flux-Base	black-forest-labs/FLUX.1-dev
Flux-LoRA	XLabs-AI/flux-RealismLora
Flux-Turbo-Alpha	alimama-creative/FLUX.1-Turbo-Alpha
<i>Kandinsky Family</i>	
Kandinsky-Base	kandinsky-community/kandinsky-2-2-prior
Kandinsky-Naruto	JeonghyunLee/kandi2-prior-naruto-model
Kandinsky-Pokemon-LoRA	YiYiXu/pokeman_kandinsky_decoder_lora
<i>SD1.5 Family</i>	
SD1.5-Base	stable-diffusion-v1-5/stable-diffusion-v1-5
SD1.5-1.2-Base	CompVis/stable-diffusion-v1-2
SD1.5-1.4-Base	CompVis/stable-diffusion-v1-4
SD1.5-DreamShaper	Lykon/dreamshaper-8
<i>SD2.1 Family</i>	
SD2.1-Base	stabilityai/stable-diffusion-2-1
SD2.1-DPO	radames/sd-21-DPO-LoRA
SD2.1-LAION-Art	Vishnou/sd-laion-art
<i>SD3 Family</i>	
SD3-Medium-Base	stabilityai/stable-diffusion-3-medium-diffusers
SD3-Reality-Mix	terminusresearch/stable-diffusion-3.0-medium-reality-mix
SD3-VAE-Anime	Disty0/sd3.vae.anime.ft
<i>SDXL Family</i>	
SDXL-Base	stabilityai/stable-diffusion-xl-base-1.0
SDXL-DPO	radames/sd-xl-DPO-LoRA
SDXL-Lightning-4Step	ByteDance/SDXL-Lightning

Table A2. Average Normalized Wasserstein Distance Matrix across all prompts. Each value is the mean of column-normalized distances across all 42 prompts. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

	AVERAGE ACROSS ALL PROMPTS																		
	Flux			Kand			SD1.5				SD2.1		SD3			SDXL			
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Medium	SD3-Anime	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.34	0.25	0.71	0.71	0.71	0.85	0.84	0.84	0.77	0.81	0.83	0.83	0.63	0.65	0.66	0.78	0.79	0.73
F-LoRA	0.33	0.00	0.41	0.71	0.71	0.75	0.86	0.83	0.82	0.81	0.80	0.81	0.81	0.68	0.73	0.73	0.74	0.74	0.70
F-Turbo	0.24	0.41	0.00	0.73	0.78	0.73	0.78	0.78	0.79	0.77	0.76	0.77	0.77	0.67	0.69	0.69	0.78	0.78	0.72
K-Base	0.67	0.70	0.71	0.00	0.18	0.34	0.79	0.83	0.83	0.78	0.81	0.79	0.79	0.78	0.78	0.78	0.65	0.65	0.63
K-Naru	0.67	0.70	0.73	0.15	0.00	0.35	0.80	0.84	0.84	0.78	0.81	0.80	0.79	0.74	0.76	0.77	0.63	0.64	0.62
K-Poke	0.69	0.76	0.75	0.36	0.36	0.00	0.87	0.88	0.80	0.78	0.82	0.82	0.82	0.71	0.74	0.74	0.64	0.66	0.66
1.5-v1.2	0.91	0.95	0.86	0.89	0.91	0.91	0.00	0.41	0.46	0.58	0.80	0.74	0.74	0.96	0.95	0.95	0.81	0.84	0.86
1.5-v1.4	0.81	0.82	0.79	0.83	0.84	0.81	0.57	0.00	0.34	0.51	0.67	0.63	0.63	0.73	0.81	0.81	0.77	0.75	0.79
1.5-Base	0.78	0.79	0.77	0.80	0.80	0.81	0.39	0.33	0.00	0.50	0.66	0.62	0.62	0.76	0.79	0.79	0.74	0.72	0.75
1.5-Dream	0.80	0.85	0.82	0.84	0.85	0.81	0.55	0.55	0.56	0.00	0.80	0.80	0.80	0.77	0.84	0.84	0.82	0.80	0.80
2.1-DPO	0.75	0.77	0.74	0.79	0.78	0.76	0.69	0.65	0.66	0.72	0.00	0.26	0.28	0.64	0.71	0.72	0.74	0.73	0.78
2.1-Base	0.79	0.79	0.77	0.80	0.80	0.79	0.65	0.63	0.64	0.73	0.25	0.00	0.02	0.67	0.74	0.74	0.75	0.74	0.80
2.1-Art	0.79	0.79	0.77	0.79	0.79	0.78	0.65	0.62	0.63	0.72	0.26	0.02	0.00	0.67	0.74	0.74	0.75	0.74	0.79
SD3-Real	0.73	0.78	0.80	0.97	0.92	0.87	0.84	0.86	0.97	0.85	0.82	0.84	0.84	0.00	0.54	0.53	0.81	0.82	0.87
SD3-Base	0.59	0.67	0.63	0.73	0.72	0.68	0.78	0.75	0.76	0.73	0.68	0.68	0.68	0.40	0.00	0.00	0.64	0.65	0.67
SD3-Anime	0.59	0.68	0.63	0.73	0.72	0.67	0.78	0.75	0.76	0.73	0.67	0.68	0.68	0.40	0.00	0.00	0.64	0.65	0.67
XL-DPO	0.68	0.67	0.71	0.59	0.57	0.56	0.70	0.71	0.71	0.70	0.69	0.68	0.68	0.59	0.62	0.63	0.00	0.18	0.36
XL-Base	0.71	0.69	0.74	0.61	0.59	0.61	0.69	0.71	0.71	0.71	0.71	0.70	0.70	0.62	0.66	0.66	0.19	0.00	0.36
XL-Light	0.67	0.67	0.70	0.60	0.59	0.63	0.70	0.75	0.75	0.72	0.77	0.75	0.75	0.67	0.69	0.69	0.37	0.36	0.00





































































































Prompt: "A photo of a cheesy baked good on a dimmed studio"										
Model	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>Flux Family</i>										
Flux-Base										
Flux-LoRA										
Flux-Turbo-Alpha										
<i>Kandinsky Family</i>										
Kandinsky-Base										
Kandinsky-Naruto										
Kandinsky-Pokemon-LoRA										
<i>SD1.5 Family</i>										
SD1.5-Base										
SD1.5-1.2-Base										
SD1.5-1.4-Base										
SD1.5-DreamShaper										

Figure B1. Qualitative results (Part 1): Flux, Kandinsky, and SD1.5 families.

























































































Model	Prompt: "A photo of a cheesy baked good on a dimmed studio"									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>SD2.1 Family</i>										
SD2.1-Base										
SD2.1-DPO										
SD2.1-LAION-Art										
<i>SD3 Family</i>										
SD3-Medium-Base										
SD3-Reality-Mix										
SD3-VAE-Anime										
<i>SDXL Family</i>										
SDXL-Base										
SDXL-DPO										
SDXL-Lightning-4Step										

Figure B2. Qualitative results (Part 2): SD2.1, SD3, and SDXL families.

Table A3. 95% Confidence Interval Lower Bound of the Derived Models with base method

	Base Models					
	Flux-Base	Kandinsky-Base	SD1.5-Base	SD2.1-Base	SD3-Medium-Base	SDXL-Base
<i>Flux Family</i>						
Flux-LoRA	0.541	0.004	0.004	0.004	0.004	0.004
Flux-Turbo-Alpha	0.541	0.004	0.004	0.004	0.004	0.004
<i>Kandinsky Family</i>						
Kandinsky-Naruto	0.004	0.541	0.004	0.004	0.004	0.004
Kandinsky-Pokemon-LoRA	0.004	0.541	0.004	0.004	0.004	0.004
<i>SD1.5 Family</i>						
SD1.5-1.2-Base	0.004	0.004	0.223	0.004	0.004	0.118
SD1.5-1.4-Base	0.004	0.004	0.541	0.004	0.004	0.004
SD1.5-DreamShaper	0.004	0.223	0.043	0.004	0.004	0.043
<i>SD2.1 Family</i>						
SD2.1-DPO	0.004	0.004	0.004	0.541	0.004	0.004
SD2.1-LAION-Art	0.004	0.004	0.004	0.541	0.004	0.004
<i>SD3 Family</i>						
SD3-Reality-Mix	0.004	0.004	0.004	0.043	0.359	0.004
SD3-VAE-Anime	0.004	0.004	0.004	0.004	0.541	0.004
<i>SDXL Family</i>						
SDXL-DPO	0.004	0.004	0.004	0.004	0.004	0.541
SDXL-Lightning-4Step	0.004	0.043	0.004	0.004	0.004	0.359

Table A4. 95% Confidence Posterior mean of the Derived Models with base method

	Base Models					
	Flux-Base	Kandinsky-Base	SD1.5-Base	SD2.1-Base	SD3-Medium-Base	SDXL-Base
<i>Flux Family</i>						
Flux-LoRA	0.857	0.143	0.143	0.143	0.143	0.143
Flux-Turbo-Alpha	0.857	0.143	0.143	0.143	0.143	0.143
<i>Kandinsky Family</i>						
Kandinsky-Naruto	0.143	0.857	0.143	0.143	0.143	0.143
Kandinsky-Pokemon-LoRA	0.143	0.857	0.143	0.143	0.143	0.143
<i>SD1.5 Family</i>						
SD1.5-1.2-Base	0.143	0.143	0.571	0.143	0.143	0.429
SD1.5-1.4-Base	0.143	0.143	0.857	0.143	0.143	0.143
SD1.5-DreamShaper	0.143	0.571	0.286	0.143	0.143	0.286
<i>SD2.1 Family</i>						
SD2.1-DPO	0.143	0.143	0.143	0.857	0.143	0.143
SD2.1-LAION-Art	0.143	0.143	0.143	0.857	0.143	0.143
<i>SD3 Family</i>						
SD3-Reality-Mix	0.143	0.143	0.143	0.286	0.714	0.143
SD3-VAE-Anime	0.143	0.143	0.143	0.143	0.857	0.143
<i>SDXL Family</i>						
SDXL-DPO	0.143	0.143	0.143	0.143	0.143	0.857
SDXL-Lightning-4Step	0.143	0.286	0.143	0.143	0.143	0.714

Table A5. 95% Confidence Interval Lower Bound of the Derived Models with our method

	Base Models					
	Flux-Base	Kandinsky-Base	SD1.5-Base	SD2.1-Base	SD3-Medium-Base	SDXL-Base
<i>Flux Family</i>						
Flux-LoRA	0.842	0.001	0.001	0.001	0.001	0.015
Flux-Turbo-Alpha	0.918	0.001	0.001	0.001	0.001	0.001
<i>Kandinsky Family</i>						
Kandinsky-Naruto	0.001	0.918	0.001	0.001	0.001	0.001
Kandinsky-Pokemon-LoRA	0.006	0.702	0.006	0.028	0.001	0.006
<i>SD1.5 Family</i>						
SD1.5-1.2-Base	0.001	0.001	0.721	0.039	0.001	0.015
SD1.5-1.4-Base	0.001	0.001	0.918	0.001	0.001	0.001
SD1.5-DreamShaper	0.026	0.015	0.515	0.006	0.015	0.068
<i>SD2.1 Family</i>						
SD2.1-DPO	0.001	0.001	0.001	0.918	0.001	0.001
SD2.1-LAION-Art	0.001	0.001	0.001	0.918	0.001	0.001
<i>SD3 Family</i>						
SD3-Reality-Mix	0.053	0.026	0.001	0.006	0.563	0.026
SD3-VAE-Anime	0.001	0.001	0.001	0.001	0.918	0.001
<i>SDXL Family</i>						
SDXL-DPO	0.001	0.001	0.001	0.001	0.001	0.918
SDXL-Lightning-4Step	0.001	0.026	0.001	0.015	0.001	0.749

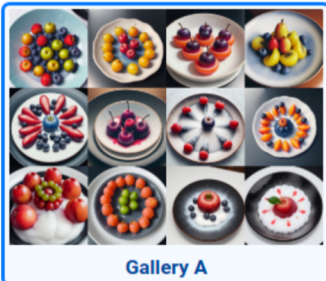
Table A6. 95% Confidence Interval Lower Bound of the Derived Models in jsd

	Base Models					
	Flux-Base	Kandinsky-Base	SD1.5-Base	SD2.1-Base	SD3-Medium-Base	SDXL-Base
<i>Flux Family</i>						
Flux-LoRA	0.640	0.001	0.015	0.006	0.026	0.026
Flux-Turbo-Alpha	0.842	0.006	0.001	0.001	0.001	0.006
<i>Kandinsky Family</i>						
Kandinsky-Naruto	0.015	0.291	0.118	0.053	0.015	0.068
Kandinsky-Pokemon-LoRA	0.015	0.842	0.001	0.001	0.001	0.001
<i>SD1.5 Family</i>						
SD1.5-1.2-Base	0.006	0.001	0.721	0.026	0.001	0.015
SD1.5-1.4-Base	0.006	0.001	0.809	0.015	0.001	0.001
SD1.5-DreamShaper	0.026	0.026	0.515	0.039	0.001	0.039
<i>SD2.1 Family</i>						
SD2.1-DPO	0.026	0.001	0.001	0.809	0.001	0.001
SD2.1-LAION-Art	0.006	0.001	0.001	0.877	0.001	0.001
<i>SD3 Family</i>						
SD3-Reality-Mix	0.053	0.006	0.015	0.026	0.421	0.084
SD3-VAE-Anime	0.026	0.001	0.001	0.001	0.779	0.006
<i>SDXL Family</i>						
SDXL-DPO	0.100	0.006	0.001	0.015	0.006	0.563
SDXL-Lightning-4Step	0.053	0.006	0.006	0.026	0.006	0.588

Table A7. Posterior mean of JSD


	Base Models					
	Flux-Base	Kandinsky-Base	SD1.5-Base	SD2.1-Base	SD3-Medium-Base	SDXL-Base
<i>Flux Family</i>						
Flux-LoRA	0.773	0.023	0.068	0.045	0.091	0.091
Flux-Turbo-Alpha	0.932	0.045	0.023	0.023	0.023	0.045
<i>Kandinsky Family</i>						
Kandinsky-Naruto	0.068	0.432	0.227	0.136	0.068	0.159
Kandinsky-Pokemon-LoRA	0.068	0.932	0.023	0.023	0.023	0.023
<i>SD1.5 Family</i>						
SD1.5-1.2-Base	0.045	0.023	0.841	0.091	0.023	0.068
SD1.5-1.4-Base	0.045	0.023	0.909	0.068	0.023	0.023
SD1.5-DreamShaper	0.091	0.091	0.659	0.114	0.023	0.114
<i>SD2.1 Family</i>						
SD2.1-DPO	0.091	0.023	0.023	0.909	0.023	0.023
SD2.1-LAION-Art	0.045	0.023	0.023	0.955	0.023	0.023
<i>SD3 Family</i>						
SD3-Reality-Mix	0.136	0.045	0.068	0.091	0.568	0.182
SD3-VAE-Anime	0.091	0.023	0.023	0.023	0.886	0.045
<i>SDXL Family</i>						
SDXL-DPO	0.205	0.045	0.023	0.068	0.045	0.705
SDXL-Lightning-4Step	0.136	0.045	0.045	0.091	0.045	0.727

Question 9 of 11




Gallery A


Which gallery (B, C, or D) has the most similar content distribution to Gallery A?



Gallery B



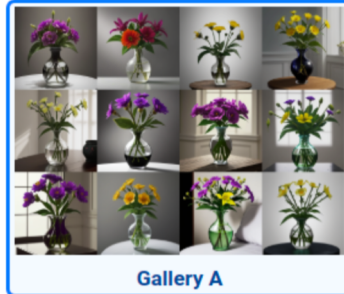
Gallery C



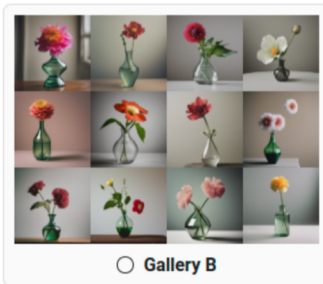
Gallery D

Figure B3. Example of human study

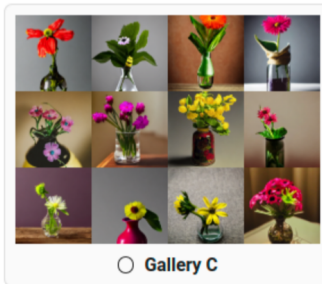
Question 10 of 11



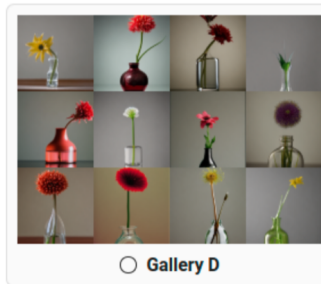
Which gallery (B, C, or D) has the most similar content distribution to Gallery A?



Gallery B



Gallery C



Gallery D

Figure B4. Example of human study

Task Instructions

You will be shown 11 questions. For each question, you will see one image gallery (Gallery A) and three other galleries (B, C, D).

Gallery A shares a similar 'content distribution pattern' with **only one** of the other galleries (B, C, or D).

Your Task:

For each of the 11 questions, please find the gallery (B, C, or D) that has the **most similar 'content distribution pattern'** to Gallery A.

A 'content distribution pattern' means **what is being shown** (e.g., the class of objects/animals) and **their ratios**.

Please ignore the visual style (e.g., photo vs. painting, color, mood).

Note: This survey includes one screening question (attention check) to ensure data quality. Please read all instructions carefully to ensure your work is approved.

Figure B5. An instruction of human study

Task Instructions

You will be shown 11 questions. For each question, you will see one image gallery (Gallery A) and three other galleries (B, C, D). Gallery A shares a similar 'content distribution pattern' with **only one** of the other galleries (B, C, or D).

Your Task:

For each of the 11 questions, please find the gallery (B, C, or D) that has the **most similar 'content distribution pattern'** to Gallery A. A 'content distribution pattern' means **what is being shown** (e.g., the class of objects/animals) and **their ratios**. Please ignore the visual style (e.g., photo vs. painting, color, mood).

Note: This survey includes one screening question (attention check) to ensure data quality. Please read all instructions carefully to ensure your work is approved.

Figure B6. Example of human study for comparison

Object Category	Adjectives	Locations
Baked good	savory, cheesy, sweet	dimmed studio, dark wood surface, brick wall
Animal	dangerous, wild, peaceful	grassland, forest, dimmed studio
Flower	vibrant, tropical	pot, dimmed studio, vase
Bird	peaceful, dangerous, flightless	grass, savana, dimmed studio
Fruit	sweet, frozen, savory	dish, wooden floor, dimmed studio

Table A8. Compositional structure of fingerprinting prompts. Each category systematically varies semantic attributes and visual contexts, yielding 42 total prompts (9+9+6+9+9). The dimmed studio setting appears across all categories to enable cross-category comparison.

Table A9. Average Normalized Wasserstein Distance Matrix across all prompts. Each value is the mean of column-normalized distances across all 42 prompts. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

	AVERAGE ACROSS ALL PROMPTS																		
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.34	0.25	0.71	0.71	0.71	0.85	0.84	0.84	0.77	0.81	0.83	0.83	0.63	0.65	0.66	0.78	0.79	0.73
F-LoRA	0.33	0.00	0.41	0.71	0.71	0.75	0.86	0.83	0.82	0.81	0.80	0.81	0.81	0.68	0.73	0.73	0.74	0.74	0.70
F-Turbo	0.24	0.41	0.00	0.73	0.74	0.73	0.78	0.78	0.79	0.77	0.76	0.77	0.77	0.67	0.69	0.69	0.78	0.79	0.73
K-Base	0.67	0.70	0.73	0.00	0.14	0.34	0.79	0.83	0.83	0.78	0.81	0.79	0.79	0.78	0.78	0.78	0.65	0.65	0.63
K-Naru	0.67	0.70	0.73	0.15	0.00	0.35	0.80	0.84	0.84	0.78	0.81	0.80	0.79	0.74	0.76	0.77	0.63	0.64	0.62
K-Poke	0.69	0.76	0.75	0.36	0.36	0.00	0.87	0.88	0.89	0.78	0.82	0.82	0.82	0.71	0.74	0.74	0.64	0.66	0.66
1.5-v1.2	0.91	0.95	0.88	0.89	0.91	0.93	0.00	0.41	0.46	0.58	0.80	0.74	0.74	0.96	0.95	0.95	0.87	0.84	0.86
1.5-v1.4	0.81	0.82	0.79	0.83	0.84	0.83	0.37	0.00	0.34	0.51	0.67	0.63	0.63	0.78	0.81	0.81	0.77	0.75	0.79
1.5-Base	0.78	0.79	0.77	0.80	0.80	0.81	0.39	0.33	0.00	0.50	0.66	0.62	0.62	0.76	0.79	0.79	0.74	0.72	0.75
1.5-Dream	0.80	0.85	0.82	0.84	0.85	0.81	0.55	0.55	0.56	0.00	0.80	0.80	0.80	0.77	0.84	0.84	0.82	0.80	0.80
2.1-DPO	0.75	0.77	0.74	0.79	0.78	0.76	0.69	0.65	0.66	0.72	0.00	0.26	0.26	0.64	0.71	0.72	0.74	0.73	0.78
2.1-Base	0.79	0.79	0.77	0.80	0.80	0.79	0.65	0.63	0.64	0.73	0.26	0.00	0.02	0.67	0.74	0.74	0.75	0.74	0.80
2.1-Art	0.79	0.79	0.77	0.79	0.79	0.78	0.65	0.62	0.63	0.72	0.26	0.02	0.00	0.67	0.74	0.74	0.75	0.74	0.79
SD3-Real	0.73	0.78	0.80	0.97	0.92	0.87	1.04	0.96	0.97	0.85	0.82	0.84	0.84	0.00	0.54	0.53	0.81	0.82	0.87
SD3-Base	0.59	0.67	0.63	0.73	0.72	0.68	0.78	0.75	0.76	0.73	0.68	0.68	0.68	0.40	0.00	0.00	0.64	0.65	0.67
SD3-Anim	0.59	0.68	0.63	0.73	0.72	0.67	0.78	0.75	0.76	0.73	0.67	0.68	0.68	0.40	0.00	0.00	0.64	0.65	0.67
XL-DPO	0.68	0.67	0.71	0.59	0.57	0.56	0.70	0.71	0.71	0.70	0.69	0.69	0.69	0.59	0.62	0.63	0.00	0.18	0.36
XL-Base	0.71	0.69	0.74	0.61	0.59	0.61	0.69	0.71	0.71	0.71	0.71	0.70	0.70	0.62	0.66	0.66	0.19	0.00	0.36
XL-Light	0.67	0.67	0.70	0.60	0.59	0.63	0.70	0.75	0.75	0.72	0.77	0.75	0.75	0.67	0.69	0.69	0.37	0.36	0.00

Table A10. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Cheesy Baked Good Against A Brick Wall																				
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL			
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light	
F-Base	0.00	0.15	0.15	0.96	0.96	0.96	0.47	0.30	0.36	0.29	0.93	0.94	0.94	0.35	0.39	0.42	0.50	0.42	0.37	
F-LoRA	0.14	0.00	0.19	0.86	0.87	0.83	0.46	0.29	0.35	0.32	0.75	0.79	0.79	0.26	0.32	0.34	0.40	0.36	0.29	
F-Turbo	0.15	0.21	0.00	0.98	0.99	0.97	0.40	0.27	0.33	0.30	0.93	0.92	0.93	0.34	0.39	0.43	0.49	0.40	0.35	
K-Base	1.00	1.00	1.00	0.00	0.05	0.25	1.00	1.00	1.00	1.00	0.87	0.55	0.59	1.00	1.00	1.00	1.00	1.00	1.00	
K-Naru	0.94	0.94	0.94	0.05	0.00	0.22	0.93	0.94	0.93	0.93	0.80	0.52	0.56	0.93	0.92	0.92	0.90	0.92	0.92	
K-Poke	0.68	0.65	0.66	0.17	0.16	0.00	0.68	0.66	0.67	0.67	0.44	0.33	0.35	0.60	0.61	0.61	0.55	0.59	0.57	
1.5-v1.2	0.43	0.47	0.36	0.88	0.88	0.89	0.00	0.20	0.18	0.25	0.90	0.86	0.86	0.50	0.62	0.64	0.51	0.40	0.44	
1.5-v1.4	0.33	0.35	0.28	1.04	1.04	1.02	0.23	0.00	0.17	0.20	0.99	1.00	1.00	0.46	0.60	0.63	0.51	0.38	0.38	
1.5-Base	0.37	0.41	0.33	1.00	1.00	1.00	0.20	0.16	0.00	0.18	1.00	1.00	1.00	0.47	0.63	0.66	0.48	0.36	0.38	
1.5-Dream	0.39	0.47	0.39	1.27	1.27	1.28	0.36	0.25	0.23	0.00	1.36	1.38	1.40	0.57	0.79	0.83	0.64	0.46	0.48	
2.1-DPO	0.42	0.38	0.41	0.37	0.37	0.28	0.44	0.41	0.43	0.46	0.00	0.20	0.19	0.38	0.38	0.38	0.35	0.36	0.36	
2.1-Base	0.53	0.50	0.51	0.30	0.30	0.27	0.53	0.52	0.54	0.59	0.25	0.00	0.03	0.50	0.48	0.47	0.50	0.52	0.50	
2.1-Art	0.51	0.48	0.49	0.31	0.31	0.27	0.51	0.50	0.52	0.57	0.23	0.03	0.00	0.48	0.45	0.45	0.48	0.49	0.48	
SD3-Real	0.28	0.24	0.27	0.77	0.77	0.68	0.44	0.34	0.36	0.34	0.67	0.71	0.71	0.00	0.24	0.25	0.26	0.25	0.19	
SD3-Base	0.26	0.23	0.26	0.63	0.63	0.58	0.45	0.37	0.40	0.39	0.56	0.56	0.55	0.20	0.00	0.00	0.32	0.31	0.26	
SD3-Anim	0.27	0.24	0.27	0.61	0.60	0.55	0.45	0.37	0.40	0.40	0.54	0.53	0.53	0.20	0.00	0.00	0.32	0.31	0.27	
XL-DPO	0.32	0.28	0.30	0.60	0.59	0.49	0.35	0.30	0.29	0.30	0.49	0.56	0.55	0.21	0.31	0.32	0.00	0.14	0.18	
XL-Base	0.32	0.30	0.30	0.73	0.71	0.64	0.33	0.26	0.26	0.26	0.62	0.69	0.69	0.23	0.36	0.37	0.17	0.00	0.19	
XL-Light	0.29	0.26	0.27	0.75	0.74	0.64	0.38	0.28	0.28	0.28	0.63	0.69	0.69	0.19	0.31	0.33	0.22	0.19	0.00	

Table A11. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Cheesy Baked Good On A Dark Wood Surface																				
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL			
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light	
F-Base	0.00	0.14	0.14	1.00	1.00	1.00	0.68	0.26	0.31	0.22	0.74	0.78	0.77	0.27	0.54	0.55	1.00	1.00	1.00	
F-LoRA	0.12	0.00	0.19	0.86	0.86	0.82	0.65	0.27	0.31	0.28	0.67	0.67	0.67	0.29	0.43	0.44	0.84	0.82	0.86	
F-Turbo	0.12	0.19	0.00	0.85	0.85	0.86	0.58	0.27	0.31	0.27	0.67	0.68	0.68	0.32	0.51	0.52	0.83	0.82	0.85	
K-Base	1.00	1.00	1.00	0.00	0.04	0.27	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.38	0.50	0.71	
K-Naru	1.02	1.03	1.02	0.04	0.00	0.29	1.00	1.00	0.99	1.00	1.00	1.01	1.01	1.00	0.99	0.99	0.38	0.50	0.71	
K-Poke	0.59	0.57	0.59	0.16	0.16	0.00	0.66	0.59	0.60	0.63	0.43	0.45	0.45	0.63	0.57	0.57	0.24	0.28	0.38	
1.5-v1.2	0.42	0.47	0.42	0.61	0.60	0.68	0.00	0.32	0.31	0.40	0.59	0.55	0.55	0.56	0.65	0.65	0.54	0.54	0.62	
1.5-v1.4	0.24	0.30	0.30	0.93	0.91	0.94	0.48	0.00	0.18	0.20	0.60	0.63	0.63	0.29	0.53	0.54	0.83	0.82	0.88	
1.5-Base	0.28	0.34	0.33	0.92	0.89	0.93	0.46	0.17	0.00	0.21	0.57	0.61	0.60	0.33	0.60	0.61	0.81	0.80	0.85	
1.5-Dream	0.34	0.48	0.48	1.50	1.46	1.61	0.97	0.32	0.34	0.00	1.10	1.24	1.22	0.21	0.87	0.89	1.47	1.51	1.59	
2.1-DPO	0.36	0.38	0.38	0.48	0.47	0.35	0.47	0.31	0.30	0.36	0.00	0.18	0.18	0.39	0.44	0.44	0.35	0.35	0.35	
2.1-Base	0.36	0.36	0.37	0.46	0.46	0.35	0.42	0.31	0.31	0.38	0.17	0.00	0.01	0.42	0.44	0.44	0.33	0.32	0.32	
2.1-Art	0.36	0.37	0.37	0.47	0.46	0.36	0.42	0.31	0.31	0.38	0.18	0.01	0.00	0.42	0.44	0.44	0.33	0.32	0.32	
SD3-Real	0.45	0.57	0.63	1.69	1.65	1.81	1.58	0.52	0.61	0.24	1.36	1.54	1.83	0.00	0.86	0.88	1.71	1.78	1.80	
SD3-Base	0.34	0.32	0.38	0.63	0.61	0.62	0.67	0.36	0.42	0.37	0.58	0.60	0.60	0.32	0.00	0.00	0.50	0.51	0.55	
SD3-Anim	0.34	0.32	0.38	0.62	0.60	0.61	0.66	0.36	0.41	0.37	0.57	0.59	0.59	0.33	0.00	0.00	0.49	0.51	0.54	
XL-DPO	0.61	0.59	0.59	0.23	0.22	0.25	0.53	0.54	0.54	0.60	0.44	0.43	0.44	0.62	0.48	0.48	0.00	0.09	0.28	
XL-Base	0.54	0.52	0.53	0.27	0.27	0.26	0.48	0.48	0.47	0.55	0.39	0.38	0.38	0.57	0.44	0.44	0.08	0.00	0.27	
XL-Light	0.48	0.48	0.47	0.34	0.33	0.31	0.48	0.45	0.44	0.51	0.34	0.33	0.33	0.51	0.41	0.41	0.22	0.23	0.00	

Table A12. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Cheesy Baked Good On A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.43	0.45	0.74	0.69	0.61	0.80	0.68	0.70	0.56	0.53	0.64	0.62	0.50	0.65	0.65	0.55	0.59	0.55
F-LoRA	0.42	0.00	0.61	0.63	0.61	0.65	0.74	0.71	0.72	0.64	0.54	0.58	0.58	0.57	0.71	0.71	0.55	0.58	0.60
F-Turbo	0.45	0.63	0.00	0.74	0.70	0.67	0.70	0.72	0.69	0.64	0.65	0.76	0.74	0.57	0.65	0.65	0.65	0.70	0.59
K-Base	1.00	0.87	1.00	0.00	0.20	0.69	0.77	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
K-Naru	0.89	0.81	1.00	0.19	0.00	0.63	0.85	0.98	0.96	0.89	0.88	0.95	0.96	0.83	0.90	0.90	0.82	0.83	0.81
K-Poke	0.56	0.61	0.61	0.47	0.45	0.00	0.80	0.71	0.68	0.55	0.55	0.66	0.64	0.52	0.65	0.65	0.55	0.61	0.58
1.5-v1.2	1.12	1.05	0.97	0.79	0.91	1.22	0.00	0.67	0.65	0.86	1.01	0.95	0.95	1.03	0.96	0.97	1.10	1.05	1.01
1.5-v1.4	0.82	0.88	0.86	0.90	0.91	0.94	0.58	0.00	0.36	0.46	0.64	0.67	0.70	0.70	0.88	0.89	0.67	0.66	0.67
1.5-Base	0.94	1.00	0.92	1.00	1.00	1.00	0.63	0.40	0.00	0.41	0.66	0.68	0.71	0.65	0.82	0.83	0.69	0.69	0.69
1.5-Dream	1.16	1.36	1.32	1.54	1.43	1.24	1.28	0.78	0.62	0.00	0.75	1.16	1.19	0.57	1.07	1.09	0.68	0.71	0.79
2.1-DPO	0.59	0.61	0.72	0.82	0.75	0.67	0.81	0.59	0.54	0.40	0.00	0.41	0.43	0.44	0.65	0.66	0.38	0.42	0.46
2.1-Base	0.58	0.54	0.68	0.67	0.67	0.65	0.62	0.50	0.46	0.51	0.34	0.00	0.06	0.55	0.63	0.64	0.50	0.52	0.54
2.1-Art	0.55	0.53	0.66	0.66	0.67	0.63	0.61	0.52	0.47	0.51	0.34	0.06	0.00	0.52	0.59	0.60	0.51	0.53	0.53
SD3-Real	0.80	0.93	0.90	1.18	1.02	0.90	1.18	0.93	0.76	0.44	0.63	0.96	0.93	0.00	0.50	0.50	0.51	0.56	0.60
SD3-Base	0.74	0.83	0.74	0.85	0.79	0.82	0.79	0.83	0.69	0.59	0.67	0.80	0.76	0.36	0.00	0.00	0.65	0.71	0.67
SD3-Anim	0.73	0.82	0.73	0.84	0.78	0.80	0.78	0.83	0.69	0.59	0.67	0.79	0.75	0.35	0.00	0.00	0.65	0.71	0.67
XL-DPO	0.72	0.75	0.85	0.97	0.84	0.79	1.03	0.72	0.67	0.43	0.45	0.72	0.75	0.42	0.75	0.75	0.00	0.22	0.43
XL-Base	0.78	0.78	0.92	0.98	0.84	0.88	1.00	0.72	0.68	0.45	0.50	0.76	0.78	0.47	0.82	0.83	0.23	0.00	0.42
XL-Light	0.67	0.74	0.70	0.89	0.75	0.76	0.87	0.67	0.61	0.46	0.49	0.72	0.72	0.46	0.71	0.71	0.39	0.38	0.00

Table A13. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Dangerous Animal In A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.60	0.25	0.88	0.90	0.90	0.95	0.96	0.95	0.98	0.61	0.56	0.57	0.45	0.43	0.44	0.88	0.89	0.79
F-LoRA	0.57	0.00	0.66	0.76	0.75	0.83	0.85	0.86	0.87	0.89	0.92	0.90	0.91	0.66	0.83	0.83	0.79	0.75	0.65
F-Turbo	0.24	0.68	0.00	0.85	0.87	0.85	0.91	0.92	0.92	0.92	0.50	0.50	0.50	0.46	0.44	0.44	0.91	0.93	0.80
K-Base	0.88	0.80	0.87	0.00	0.10	0.32	0.51	0.53	0.56	0.52	0.89	0.95	0.94	0.87	0.89	0.89	0.70	0.56	0.58
K-Naru	0.93	0.82	0.94	0.11	0.00	0.34	0.50	0.53	0.55	0.51	0.93	0.98	0.97	0.91	0.95	0.95	0.69	0.56	0.57
K-Poke	0.92	0.89	0.89	0.32	0.33	0.00	0.50	0.51	0.53	0.41	0.86	0.97	0.95	0.95	0.92	0.92	0.79	0.65	0.62
1.5-v1.2	1.15	1.09	1.14	0.62	0.59	0.60	0.00	0.28	0.34	0.37	1.13	1.15	1.16	1.18	1.13	1.13	0.89	0.66	0.59
1.5-v1.4	1.08	1.01	1.06	0.59	0.57	0.56	0.26	0.00	0.28	0.38	1.03	1.06	1.06	1.07	1.04	1.05	0.83	0.62	0.57
1.5-Base	1.00	0.97	1.00	0.59	0.56	0.54	0.29	0.26	0.00	0.38	1.00	1.00	1.00	1.00	1.00	1.00	0.81	0.64	0.58
1.5-Dream	1.34	1.29	1.30	0.72	0.68	0.55	0.41	0.47	0.50	0.00	1.16	1.26	1.25	1.41	1.31	1.30	1.13	0.82	0.73
2.1-DPO	0.61	0.97	0.52	0.89	0.90	0.85	0.93	0.93	0.95	0.85	0.00	0.22	0.22	0.48	0.55	0.55	0.97	0.98	0.97
2.1-Base	0.59	1.00	0.55	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.23	0.00	0.03	0.45	0.53	0.53	1.00	1.00	1.00
2.1-Art	0.59	0.98	0.53	0.96	0.96	0.95	0.97	0.97	0.97	0.93	0.23	0.03	0.00	0.46	0.53	0.54	0.98	0.98	0.98
SD3-Real	0.58	0.90	0.61	1.13	1.13	1.21	1.25	1.23	1.22	1.32	0.62	0.54	0.58	0.00	0.52	0.53	1.00	1.09	1.07
SD3-Base	0.46	0.92	0.48	0.94	0.96	0.95	0.97	0.98	1.00	1.00	0.57	0.52	0.55	0.43	0.00	0.00	0.82	0.84	0.77
SD3-Anim	0.46	0.92	0.48	0.93	0.95	0.95	0.97	0.98	0.99	0.99	0.57	0.53	0.55	0.43	0.00	0.00	0.82	0.83	0.76
XL-DPO	0.71	0.67	0.76	0.56	0.53	0.62	0.59	0.60	0.62	0.67	0.78	0.76	0.78	0.63	0.63	0.63	0.00	0.25	0.34
XL-Base	0.87	0.77	0.93	0.55	0.52	0.62	0.52	0.54	0.59	0.58	0.95	0.92	0.93	0.82	0.77	0.77	0.30	0.00	0.30
XL-Light	0.89	0.77	0.93	0.65	0.63	0.69	0.55	0.58	0.62	0.60	1.09	1.07	1.08	0.94	0.83	0.83	0.48	0.35	0.00

Table A14. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of A Dangerous Animal In A Forest																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.70	0.32	0.77	0.70	0.77	0.90	0.86	0.74	0.98	0.86	0.98	0.98	0.78	0.57	0.57	0.45	0.58	0.35
F-LoRA		0.77	0.00	1.18	0.81	0.87	0.81	1.05	0.99	1.03	1.03	1.04	1.08	1.07	1.05	0.84	0.86	0.47	0.44	0.51
F-Turbo		0.30	1.01	0.00	0.89	0.79	0.87	0.90	0.88	0.76	0.95	0.85	0.93	0.93	0.81	0.89	0.88	0.76	0.89	0.67
K-Base		0.73	0.70	0.89	0.00	0.14	0.27	0.71	0.59	0.67	0.70	0.72	0.79	0.78	1.00	0.93	0.94	0.62	0.62	0.55
K-Naru		0.63	0.72	0.76	0.13	0.00	0.28	0.69	0.56	0.63	0.70	0.69	0.76	0.75	0.91	0.90	0.90	0.59	0.60	0.51
K-Poke		0.83	0.79	0.99	0.31	0.32	0.00	0.75	0.58	0.73	0.71	0.74	0.78	0.77	1.13	1.06	1.07	0.76	0.76	0.63
1.5-v1.2		0.84	0.88	0.89	0.69	0.71	0.65	0.00	0.36	0.49	0.47	0.53	0.53	0.54	0.84	0.91	0.91	0.82	0.84	0.78
1.5-v1.4		0.85	0.88	0.91	0.61	0.61	0.53	0.38	0.00	0.45	0.47	0.50	0.51	0.50	0.93	0.97	0.97	0.85	0.86	0.78
1.5-Base		0.64	0.81	0.69	0.61	0.59	0.59	0.46	0.40	0.00	0.56	0.56	0.58	0.58	0.78	0.85	0.85	0.69	0.73	0.65
1.5-Dream		1.04	0.99	1.06	0.79	0.82	0.70	0.54	0.51	0.69	0.00	0.50	0.60	0.60	0.87	1.04	1.03	0.93	0.95	0.97
2.1-DPO		0.82	0.89	0.85	0.72	0.72	0.66	0.54	0.48	0.62	0.44	0.00	0.35	0.36	0.86	0.93	0.93	0.84	0.85	0.85
2.1-Base		1.00	1.00	1.00	0.85	0.84	0.74	0.58	0.52	0.69	0.57	0.38	0.00	0.02	0.88	1.00	1.00	1.00	1.00	1.00
2.1-Art		1.00	0.99	1.00	0.84	0.84	0.73	0.59	0.52	0.69	0.58	0.38	0.02	0.00	0.91	1.00	1.01	1.00	0.99	0.99
SD3-Real		1.14	1.39	1.25	1.54	1.45	1.54	1.32	1.37	1.32	1.20	1.32	1.27	1.30	0.00	1.15	1.11	1.21	1.35	1.31
SD3-Base		0.58	0.78	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.80	0.00	0.00	0.51	0.66	0.46
SD3-Anim		0.57	0.79	0.95	1.01	1.01	1.01	0.99	1.00	1.00	0.99	0.99	1.00	1.00	0.77	0.00	0.00	0.51	0.67	0.47
XL-DPO		0.47	0.44	0.83	0.68	0.67	0.73	0.91	0.89	0.83	0.91	0.92	1.02	1.02	0.86	0.52	0.53	0.00	0.16	0.21
XL-Base		0.58	0.40	0.94	0.65	0.65	0.71	0.90	0.87	0.85	0.89	0.89	0.98	0.97	0.92	0.64	0.66	0.15	0.00	0.26
XL-Light		0.40	0.52	0.80	0.65	0.64	0.67	0.95	0.89	0.86	1.03	1.02	1.11	1.10	1.01	0.51	0.53	0.22	0.29	0.00

Table A15. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of A Dangerous Animal In A Grassland																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.28	0.18	0.88	0.84	0.97	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.93	0.74	0.69	0.78
F-LoRA		0.36	0.00	0.50	0.98	0.93	1.19	1.19	1.08	1.09	1.12	1.17	1.18	1.17	1.17	1.32	1.33	0.71	0.66	0.69
F-Turbo		0.16	0.35	0.00	0.87	0.85	0.97	0.88	0.88	0.89	0.90	0.87	0.90	0.90	0.85	0.79	0.79	0.75	0.74	0.81
K-Base		0.85	0.74	0.94	0.00	0.09	0.27	0.66	0.63	0.61	0.61	0.64	0.63	0.62	0.92	1.00	1.00	0.47	0.53	0.73
K-Naru		0.82	0.71	0.94	0.09	0.00	0.28	0.68	0.65	0.63	0.62	0.65	0.65	0.64	0.94	1.01	1.02	0.46	0.52	0.72
K-Poke		0.80	0.76	0.89	0.23	0.24	0.00	0.64	0.62	0.63	0.57	0.57	0.58	0.58	0.82	0.84	0.84	0.53	0.59	0.80
1.5-v1.2		1.02	0.94	1.00	0.69	0.70	0.79	0.00	0.23	0.27	0.24	0.49	0.53	0.53	0.70	0.80	0.78	0.80	0.84	0.91
1.5-v1.4		1.15	0.97	1.14	0.74	0.76	0.88	0.26	0.00	0.24	0.26	0.53	0.54	0.53	0.66	0.85	0.84	0.80	0.84	0.95
1.5-Base		1.00	0.85	1.00	0.63	0.64	0.77	0.27	0.21	0.00	0.29	0.48	0.48	0.46	0.68	0.83	0.82	0.69	0.72	0.82
1.5-Dream		1.18	1.03	1.19	0.74	0.75	0.82	0.28	0.27	0.34	0.00	0.67	0.68	0.68	0.85	1.04	1.02	0.92	0.95	1.04
2.1-DPO		0.93	0.85	0.91	0.61	0.61	0.64	0.45	0.42	0.45	0.52	0.00	0.33	0.33	0.46	0.52	0.51	0.63	0.67	0.76
2.1-Base		0.86	0.79	0.86	0.56	0.57	0.61	0.45	0.41	0.41	0.49	0.30	0.00	0.02	0.53	0.58	0.58	0.59	0.61	0.78
2.1-Art		0.87	0.79	0.88	0.56	0.57	0.62	0.45	0.40	0.40	0.50	0.31	0.02	0.00	0.54	0.60	0.59	0.60	0.63	0.78
SD3-Real		1.30	1.18	1.24	1.23	1.23	1.30	0.89	0.75	0.88	0.93	0.65	0.80	0.80	0.00	0.41	0.40	1.17	1.19	1.12
SD3-Base		0.90	1.00	0.86	1.00	1.00	1.00	0.76	0.71	0.80	0.85	0.54	0.65	0.66	0.31	0.00	0.00	1.00	1.00	1.00
SD3-Anim		0.93	1.03	0.88	1.02	1.03	1.02	0.77	0.72	0.81	0.86	0.55	0.66	0.67	0.30	0.00	0.00	1.03	1.03	1.02
XL-DPO		0.65	0.49	0.74	0.43	0.41	0.58	0.69	0.62	0.61	0.69	0.60	0.61	0.61	0.80	0.91	0.92	0.00	0.17	0.47
XL-Base		0.60	0.44	0.72	0.47	0.46	0.62	0.71	0.64	0.62	0.70	0.62	0.62	0.62	0.80	0.90	0.90	0.17	0.00	0.46
XL-Light		0.72	0.49	0.82	0.69	0.67	0.90	0.82	0.75	0.75	0.81	0.75	0.83	0.82	0.79	0.94	0.94	0.49	0.48	0.00

Table A16. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of A Frozen Single Fruit On A Dimmed Studio																				
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL				
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light		
F-Base		0.00	0.18	0.20	0.48	0.50	0.48	1.00	1.00	1.00	0.99	0.92	0.92	0.91	0.83	0.81	0.80	0.73	0.81	0.55		
F-LoRA		0.16	0.00	0.25	0.46	0.45	0.50	0.94	0.91	0.89	0.96	0.89	0.85	0.83	0.79	0.87	0.86	0.67	0.74	0.48		
F-Turbo		0.17	0.24	0.00	0.44	0.48	0.49	0.88	0.90	0.85	0.86	0.80	0.79	0.78	0.79	0.82	0.82	0.62	0.69	0.47		
K-Base		0.34	0.37	0.37	0.00	0.14	0.17	0.75	0.70	0.70	0.64	0.80	0.75	0.74	0.35	0.49	0.50	0.41	0.48	0.37		
K-Naru		0.40	0.40	0.45	0.16	0.00	0.22	0.86	0.78	0.76	0.75	0.92	0.83	0.82	0.38	0.67	0.68	0.41	0.56	0.42		
K-Poke		0.40	0.47	0.48	0.20	0.22	0.00	0.84	0.75	0.81	0.71	0.93	0.86	0.85	0.27	0.34	0.35	0.50	0.58	0.49		
1.5-v1.2		0.85	0.89	0.87	0.88	0.90	0.85	0.00	0.40	0.40	0.86	0.74	0.67	0.66	0.92	0.78	0.77	0.81	0.86	0.84		
1.5-v1.4		0.88	0.90	0.93	0.86	0.86	0.79	0.42	0.00	0.36	0.85	0.81	0.71	0.71	0.81	0.73	0.73	0.77	0.81	0.82		
1.5-Base		1.00	1.00	1.00	0.98	0.94	0.97	0.47	0.41	0.00	0.91	0.75	0.64	0.64	0.96	0.92	0.91	0.83	0.88	0.91		
1.5-Dream		0.57	0.61	0.57	0.51	0.53	0.49	0.58	0.55	0.52	0.00	0.59	0.55	0.54	0.51	0.59	0.60	0.51	0.57	0.54		
2.1-DPO		0.91	0.98	0.92	1.00	1.13	1.10	0.86	0.90	0.74	1.02	0.00	0.26	0.25	1.15	1.02	1.02	1.03	0.98	1.02		
2.1-Base		0.89	0.92	0.89	1.00	1.00	1.00	0.76	0.78	0.62	0.92	0.25	0.00	0.01	1.00	1.00	1.00	0.85	0.89	0.87		
2.1-Art		0.88	0.90	0.88	0.98	0.98	0.98	0.75	0.77	0.62	0.90	0.25	0.01	0.00	0.99	1.00	1.00	0.83	0.87	0.86		
SD3-Real		0.55	0.58	0.61	0.32	0.31	0.22	0.71	0.61	0.63	0.59	0.76	0.68	0.67	0.00	0.34	0.35	0.46	0.56	0.55		
SD3-Base		0.78	0.94	0.92	0.66	0.81	0.39	0.89	0.80	0.88	1.00	1.00	1.00	1.00	0.50	0.00	0.00	1.00	1.00	1.00		
SD3-Anim		0.79	0.95	0.94	0.69	0.84	0.41	0.90	0.81	0.90	1.03	1.02	1.02	1.02	0.53	0.00	0.00	1.04	1.03	1.03		
XL-DPO		0.50	0.51	0.49	0.39	0.35	0.41	0.66	0.60	0.57	0.61	0.71	0.60	0.59	0.48	0.71	0.72	0.00	0.27	0.33		
XL-Base		0.50	0.51	0.50	0.41	0.42	0.43	0.62	0.57	0.54	0.61	0.61	0.57	0.55	0.52	0.64	0.64	0.24	0.00	0.39		
XL-Light		0.39	0.38	0.38	0.36	0.37	0.41	0.70	0.66	0.64	0.67	0.73	0.63	0.63	0.59	0.73	0.73	0.34	0.45	0.00		

Table A17. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of A Frozen Single Fruit On A Dish																				
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL				
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light		
F-Base		0.00	0.28	0.21	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.90	1.00	1.00	0.94	1.00	1.00	1.00	0.97	1.00		
F-LoRA		0.22	0.00	0.33	0.81	0.79	0.78	0.80	0.84	0.80	0.83	0.89	0.94	0.95	0.81	0.84	0.84	0.81	0.83	0.80		
F-Turbo		0.20	0.41	0.00	0.96	1.03	1.10	0.97	0.96	0.99	0.89	0.90	1.03	1.02	1.10	1.15	1.15	1.08	1.07	1.06		
K-Base		0.65	0.66	0.64	0.00	0.27	0.42	0.53	0.54	0.54	0.55	0.83	0.81	0.79	1.00	0.85	0.85	0.83	0.90	0.70		
K-Naru		0.65	0.64	0.68	0.27	0.00	0.36	0.53	0.57	0.57	0.57	0.89	0.87	0.85	0.96	0.85	0.84	0.82	0.89	0.63		
K-Poke		0.84	0.82	0.93	0.54	0.47	0.00	0.57	0.61	0.53	0.71	1.08	1.04	1.02	0.87	0.73	0.73	0.80	0.94	0.71		
1.5-v1.2		0.97	0.97	0.95	0.79	0.79	0.66	0.00	0.35	0.34	0.55	1.06	0.99	0.99	0.99	1.00	0.99	1.05	1.08	0.83		
1.5-v1.4		0.95	1.00	0.92	0.78	0.83	0.69	0.34	0.00	0.29	0.54	0.98	0.96	0.96	0.92	0.94	0.93	0.98	1.00	0.82		
1.5-Base		1.00	1.00	1.00	0.82	0.88	0.63	0.35	0.30	0.00	0.58	1.00	0.94	0.93	0.87	0.94	0.93	0.97	1.00	0.81		
1.5-Dream		0.78	0.81	0.70	0.66	0.69	0.66	0.45	0.44	0.46	0.00	0.95	0.96	0.94	1.04	0.95	0.94	1.02	1.05	0.74		
2.1-DPO		0.67	0.83	0.68	0.95	1.03	0.96	0.82	0.77	0.75	0.91	0.00	0.44	0.43	0.72	0.88	0.88	1.03	0.98	0.94		
2.1-Base		0.69	0.81	0.72	0.85	0.92	0.85	0.70	0.70	0.64	0.84	0.40	0.00	0.03	0.73	0.82	0.82	1.00	0.99	0.85		
2.1-Art		0.69	0.81	0.71	0.83	0.90	0.84	0.70	0.70	0.64	0.83	0.40	0.03	0.00	0.73	0.82	0.82	1.00	0.98	0.84		
SD3-Real		0.81	0.88	0.95	1.32	1.27	0.90	0.88	0.83	0.75	1.15	0.83	0.91	0.92	0.00	0.56	0.57	0.94	0.91	0.97		
SD3-Base		0.68	0.71	0.79	0.89	0.89	0.60	0.70	0.68	0.64	0.83	0.80	0.81	0.81	0.44	0.00	0.00	0.87	0.89	0.76		
SD3-Anim		0.67	0.71	0.78	0.87	0.87	0.58	0.69	0.66	0.63	0.81	0.79	0.81	0.80	0.45	0.00	0.00	0.87	0.88	0.75		
XL-DPO		0.55	0.55	0.59	0.70	0.69	0.52	0.59	0.57	0.53	0.71	0.75	0.79	0.80	0.59	0.70	0.70	0.00	0.34	0.60		
XL-Base		0.54	0.58	0.59	0.76	0.76	0.62	0.62	0.58	0.55	0.74	0.72	0.80	0.79	0.59	0.72	0.72	0.34	0.00	0.65		
XL-Light		0.58	0.58	0.62	0.63	0.57	0.50	0.50	0.50	0.47	0.55	0.73	0.72	0.71	0.66	0.65	0.65	0.64	0.69	0.00		

Table A18. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of A Frozen Single Fruit On A Wooden Floor																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.18	0.26	0.32	0.34	0.30	0.86	0.87	0.88	0.67	0.88	0.87	0.86	0.76	0.77	0.76	0.38	0.39	0.38
F-LoRA		0.18	0.00	0.30	0.32	0.31	0.32	0.96	0.94	0.93	0.66	0.91	0.89	0.89	0.67	0.86	0.86	0.38	0.39	0.38
F-Turbo		0.25	0.27	0.00	0.37	0.39	0.37	0.98	0.97	1.02	0.69	0.85	0.82	0.82	0.66	1.05	1.04	0.42	0.44	0.40
K-Base		0.37	0.36	0.45	0.00	0.13	0.18	1.00	0.95	1.00	0.61	1.00	1.00	1.00	0.61	1.00	1.00	0.32	0.32	0.39
K-Naru		0.40	0.36	0.48	0.13	0.00	0.18	1.06	0.96	1.02	0.59	1.05	1.03	1.02	0.58	0.98	0.98	0.37	0.35	0.45
K-Poke		0.41	0.43	0.54	0.21	0.21	0.00	1.12	1.02	1.10	0.60	1.20	1.18	1.18	0.65	1.04	1.03	0.34	0.32	0.42
1.5-v1.2		0.75	0.82	0.91	0.76	0.78	0.72	0.00	0.48	0.48	0.80	0.70	0.70	0.69	1.09	1.05	1.04	0.71	0.68	0.76
1.5-v1.4		0.68	0.71	0.80	0.64	0.63	0.58	0.43	0.00	0.41	0.68	0.72	0.68	0.67	0.92	0.91	0.90	0.60	0.59	0.68
1.5-Base		0.76	0.78	0.93	0.75	0.74	0.69	0.47	0.45	0.00	0.74	0.68	0.66	0.65	1.00	0.94	0.93	0.70	0.70	0.79
1.5-Dream		0.64	0.61	0.70	0.50	0.48	0.42	0.87	0.83	0.81	0.00	0.83	0.83	0.82	0.51	0.98	0.99	0.65	0.61	0.72
2.1-DPO		1.00	1.01	1.04	0.99	1.01	1.01	0.92	1.05	0.91	1.00	0.00	0.24	0.24	0.88	1.05	1.04	0.99	1.00	0.98
2.1-Base		1.00	1.00	1.00	1.00	1.00	1.00	0.92	1.00	0.88	1.00	0.24	0.00	0.01	0.87	1.00	1.00	1.00	1.00	1.00
2.1-Art		1.01	1.01	1.01	1.01	1.00	1.01	0.92	1.00	0.88	1.01	0.24	0.01	0.00	0.88	1.01	1.00	1.01	1.01	1.02
SD3-Real		1.00	0.86	0.91	0.69	0.64	0.62	1.63	1.54	1.52	0.70	1.01	1.00	0.99	0.00	1.51	1.53	0.88	0.86	0.96
SD3-Base		0.51	0.56	0.74	0.58	0.55	0.51	0.81	0.78	0.73	0.69	0.61	0.58	0.58	0.77	0.00	0.00	0.66	0.63	0.73
SD3-Anim		0.51	0.56	0.74	0.58	0.55	0.51	0.79	0.76	0.72	0.69	0.61	0.58	0.57	0.78	0.00	0.00	0.65	0.63	0.73
XL-DPO		0.40	0.39	0.47	0.29	0.33	0.26	0.85	0.81	0.86	0.71	0.91	0.91	0.91	0.70	1.03	1.02	0.00	0.18	0.29
XL-Base		0.40	0.39	0.47	0.28	0.30	0.24	0.79	0.77	0.83	0.65	0.89	0.88	0.88	0.67	0.97	0.96	0.17	0.00	0.30
XL-Light		0.40	0.38	0.44	0.35	0.39	0.32	0.90	0.89	0.95	0.78	0.89	0.90	0.90	0.75	1.13	1.13	0.29	0.30	0.00

Table A19. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of A Peaceful Animal In A Dimmed Studio																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.43	0.27	0.71	0.74	0.72	0.92	1.00	1.00	0.97	0.69	0.69	0.69	0.66	0.70	0.69	0.85	0.81	0.88
F-LoRA		0.44	0.00	0.43	0.67	0.69	0.73	0.77	0.88	0.90	0.88	0.70	0.70	0.70	0.77	0.83	0.83	0.72	0.67	0.79
F-Turbo		0.27	0.42	0.00	0.71	0.76	0.74	0.91	1.03	1.02	0.99	0.69	0.67	0.68	0.69	0.70	0.69	0.82	0.80	0.83
K-Base		0.86	0.79	0.88	0.00	0.11	0.51	0.68	0.86	0.90	0.69	1.00	1.00	1.00	0.95	0.94	0.94	0.59	0.54	0.81
K-Naru		0.87	0.78	0.91	0.11	0.00	0.45	0.64	0.82	0.84	0.67	0.97	0.96	0.96	0.93	0.91	0.91	0.55	0.51	0.77
K-Poke		0.81	0.80	0.85	0.47	0.44	0.00	0.78	0.98	1.01	0.71	0.94	0.93	0.93	0.84	0.87	0.87	0.60	0.58	0.78
1.5-v1.2		1.06	0.87	1.07	0.64	0.63	0.80	0.00	0.60	0.64	0.49	0.99	0.95	0.95	0.98	0.91	0.92	0.54	0.52	0.72
1.5-v1.4		0.84	0.73	0.89	0.60	0.60	0.74	0.44	0.00	0.42	0.50	0.70	0.70	0.69	0.70	0.65	0.65	0.55	0.50	0.67
1.5-Base		0.85	0.74	0.88	0.63	0.61	0.76	0.47	0.42	0.00	0.50	0.68	0.64	0.64	0.66	0.64	0.64	0.54	0.52	0.67
1.5-Dream		1.26	1.13	1.32	0.74	0.75	0.82	0.56	0.77	0.77	0.00	1.10	1.08	1.07	0.91	0.89	0.90	0.69	0.64	0.99
2.1-DPO		0.82	0.82	0.85	0.99	1.00	1.00	1.03	1.00	0.96	1.01	0.00	0.24	0.24	0.43	0.55	0.54	0.88	0.83	0.92
2.1-Base		0.83	0.83	0.83	1.00	1.00	1.00	1.00	1.00	0.92	1.00	0.24	0.00	0.01	0.41	0.52	0.52	0.88	0.83	0.90
2.1-Art		0.84	0.83	0.84	1.00	1.00	1.00	1.00	1.00	0.91	0.99	0.24	0.01	0.00	0.41	0.52	0.52	0.88	0.83	0.90
SD3-Real		0.94	1.08	1.00	1.12	1.14	1.06	1.22	1.18	1.10	0.99	0.51	0.48	0.48	0.00	0.36	0.36	1.20	1.15	1.26
SD3-Base		0.86	1.00	0.88	0.96	0.97	0.96	0.98	0.96	0.93	0.84	0.56	0.53	0.53	0.31	0.00	0.00	1.00	1.00	1.00
SD3-Anim		0.86	1.00	0.87	0.96	0.97	0.96	0.99	0.96	0.94	0.85	0.56	0.53	0.53	0.31	0.00	0.00	1.00	1.00	1.00
XL-DPO		0.98	0.81	0.97	0.56	0.55	0.61	0.55	0.75	0.73	0.61	0.85	0.84	0.84	0.98	0.94	0.94	0.00	0.20	0.49
XL-Base		1.00	0.80	1.00	0.55	0.54	0.64	0.55	0.74	0.76	0.60	0.86	0.85	0.84	1.00	1.00	1.00	0.21	0.00	0.51
XL-Light		0.79	0.69	0.76	0.60	0.60	0.62	0.56	0.71	0.72	0.68	0.70	0.67	0.67	0.80	0.73	0.73	0.38	0.37	0.00

Table A20. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

	Prompt: A Photo Of A Peaceful Animal In A Forest																		
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.65	0.28	0.57	0.57	0.58	0.94	1.00	0.96	0.86	0.92	1.00	1.00	0.91	0.79	0.79	0.84	0.89	0.84
F-LoRA	0.56	0.00	0.58	0.66	0.67	0.81	0.84	0.84	0.82	0.76	0.85	0.83	0.82	0.86	0.71	0.72	0.71	0.68	0.59
F-Turbo	0.26	0.63	0.00	0.60	0.59	0.54	0.85	0.89	0.88	0.82	0.87	0.94	0.93	0.79	0.66	0.66	0.77	0.84	0.78
K-Base	0.69	0.93	0.77	0.00	0.14	0.45	0.91	0.93	0.92	0.80	0.95	0.98	0.97	1.00	1.00	1.00	0.86	0.89	0.88
K-Naru	0.65	0.89	0.71	0.13	0.00	0.40	0.84	0.85	0.81	0.71	0.91	0.94	0.94	0.88	0.94	0.94	0.81	0.85	0.84
K-Poke	0.64	1.04	0.64	0.41	0.39	0.00	0.93	0.92	0.87	0.66	0.98	1.02	1.01	0.84	0.91	0.90	0.85	0.92	0.92
1.5-v1.2	0.83	0.85	0.80	0.66	0.65	0.75	0.00	0.57	0.55	0.62	0.82	0.70	0.71	0.66	0.73	0.72	0.88	0.88	0.83
1.5-v1.4	0.88	0.86	0.83	0.68	0.65	0.73	0.57	0.00	0.50	0.62	0.73	0.68	0.69	0.58	0.71	0.70	0.88	0.88	0.87
1.5-Base	0.96	0.95	0.93	0.76	0.70	0.78	0.62	0.57	0.00	0.62	0.91	0.82	0.82	0.65	0.82	0.81	0.97	0.95	0.93
1.5-Dream	0.90	0.91	0.91	0.69	0.64	0.62	0.73	0.74	0.65	0.00	0.93	0.81	0.81	0.61	0.86	0.84	0.81	0.81	0.84
2.1-DPO	0.81	0.86	0.81	0.69	0.70	0.78	0.81	0.73	0.80	0.78	0.00	0.47	0.48	0.73	0.72	0.72	0.96	0.95	0.94
2.1-Base	1.00	0.95	1.00	0.81	0.82	0.92	0.80	0.77	0.82	0.78	0.54	0.00	0.01	0.69	0.68	0.68	1.00	1.00	1.00
2.1-Art	1.01	0.95	1.00	0.80	0.82	0.92	0.81	0.78	0.83	0.78	0.55	0.01	0.00	0.70	0.69	0.69	1.00	1.00	1.01
SD3-Real	1.42	1.55	1.31	1.28	1.19	1.18	1.16	1.02	1.02	0.90	1.29	1.07	1.08	0.00	0.76	0.72	1.32	1.37	1.47
SD3-Base	0.96	1.00	0.86	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.83	0.84	0.59	0.00	0.00	0.75	0.79	0.81
SD3-Anim	0.97	1.02	0.86	1.01	1.00	0.99	1.00	0.98	0.99	0.99	1.01	0.83	0.84	0.57	0.00	0.00	0.76	0.80	0.82
XL-DPO	0.65	0.63	0.63	0.55	0.55	0.60	0.77	0.78	0.76	0.60	0.85	0.78	0.77	0.66	0.48	0.48	0.00	0.20	0.31
XL-Base	0.69	0.60	0.69	0.57	0.57	0.65	0.78	0.78	0.74	0.60	0.84	0.78	0.77	0.68	0.50	0.50	0.20	0.00	0.28
XL-Light	0.68	0.55	0.67	0.58	0.59	0.67	0.76	0.80	0.75	0.65	0.86	0.81	0.81	0.76	0.53	0.54	0.32	0.29	0.00

Table A21. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

	Prompt: A Photo Of A Peaceful Animal In A Grassland																		
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.36	0.21	0.80	0.78	0.82	0.98	0.92	0.87	1.00	1.00	1.00	1.00	0.68	0.47	0.49	0.68	0.62	0.66
F-LoRA	0.35	0.00	0.36	0.94	0.93	1.06	1.02	0.85	0.87	1.04	0.98	0.96	0.96	0.77	0.65	0.67	0.73	0.63	0.58
F-Turbo	0.22	0.39	0.00	0.86	0.86	0.85	0.99	0.95	0.88	1.03	1.04	1.03	1.02	0.70	0.46	0.47	0.72	0.67	0.67
K-Base	0.80	0.97	0.83	0.00	0.14	0.54	1.00	1.00	1.00	0.77	0.98	0.99	0.98	1.00	1.00	1.00	1.00	1.00	1.00
K-Naru	0.73	0.91	0.78	0.13	0.00	0.54	0.94	0.94	0.94	0.74	0.94	0.94	0.93	0.95	0.93	0.93	0.94	0.94	0.95
K-Poke	0.70	0.94	0.71	0.46	0.49	0.00	0.85	0.88	0.83	0.72	0.80	0.86	0.86	0.65	0.68	0.68	0.80	0.85	0.98
1.5-v1.2	0.93	1.00	0.91	0.95	0.94	0.94	0.00	0.57	0.55	0.54	0.71	0.73	0.74	0.65	0.90	0.89	1.00	0.87	1.08
1.5-v1.4	0.89	0.85	0.90	0.97	0.97	0.99	0.58	0.00	0.40	0.64	0.60	0.60	0.62	0.53	0.81	0.81	0.81	0.71	0.83
1.5-Base	0.87	0.90	0.86	1.00	0.99	0.97	0.58	0.42	0.00	0.64	0.62	0.66	0.67	0.51	0.78	0.77	0.85	0.77	0.90
1.5-Dream	1.26	1.36	1.27	0.98	0.99	1.06	0.73	0.84	0.81	0.00	0.84	0.83	0.85	0.89	1.19	1.19	1.32	1.23	1.42
2.1-DPO	1.12	1.14	1.13	1.10	1.12	1.04	0.85	0.69	0.70	0.74	0.00	0.36	0.37	0.54	0.91	0.90	0.84	0.77	0.97
2.1-Base	1.00	1.00	1.00	0.99	1.00	1.00	0.77	0.63	0.66	0.66	0.32	0.00	0.03	0.58	0.86	0.85	0.85	0.78	0.95
2.1-Art	1.00	1.00	1.00	0.98	0.99	1.01	0.79	0.64	0.68	0.67	0.33	0.03	0.00	0.60	0.88	0.88	0.88	0.80	0.96
SD3-Real	0.84	0.99	0.84	1.25	1.25	0.95	0.86	0.68	0.64	0.88	0.60	0.73	0.75	0.00	0.51	0.49	0.79	0.73	0.96
SD3-Base	0.45	0.64	0.42	0.96	0.95	0.76	0.90	0.80	0.75	0.90	0.77	0.82	0.84	0.39	0.00	0.00	0.61	0.60	0.68
SD3-Anim	0.47	0.66	0.44	0.96	0.95	0.75	0.90	0.80	0.74	0.90	0.76	0.81	0.83	0.38	0.00	0.00	0.60	0.60	0.68
XL-DPO	0.49	0.54	0.50	0.72	0.72	0.67	0.76	0.60	0.61	0.75	0.54	0.61	0.63	0.45	0.46	0.45	0.00	0.25	0.45
XL-Base	0.50	0.53	0.53	0.81	0.81	0.81	0.75	0.60	0.62	0.79	0.56	0.63	0.64	0.47	0.51	0.51	0.28	0.00	0.45
XL-Light	0.54	0.49	0.53	0.82	0.82	0.94	0.93	0.71	0.74	0.92	0.70	0.78	0.78	0.63	0.58	0.59	0.51	0.45	0.00

Table A22. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Savory Baked Good Against A Brick Wall																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.11	0.11	1.00	1.00	1.00	1.00	0.56	0.66	0.71	0.76	1.00	1.00	0.34	0.48	0.51	0.93	0.91	1.00
F-LoRA	0.13	0.00	0.18	1.16	1.17	1.12	1.16	0.65	0.76	0.94	0.79	1.07	1.06	0.27	0.38	0.41	0.94	0.93	1.08
F-Turbo	0.09	0.14	0.00	0.87	0.87	0.84	0.85	0.46	0.55	0.68	0.64	0.82	0.82	0.32	0.43	0.45	0.81	0.79	0.83
K-Base	1.00	1.00	1.00	0.00	0.06	0.31	0.95	1.00	1.00	0.86	1.00	0.56	0.59	1.00	1.00	1.00	1.00	1.00	0.67
K-Naru	0.94	0.95	0.94	0.06	0.00	0.30	0.89	0.94	0.94	0.80	0.96	0.56	0.58	0.97	0.96	0.96	0.96	0.96	0.64
K-Poke	0.72	0.69	0.69	0.23	0.23	0.00	0.75	0.64	0.69	0.78	0.54	0.36	0.38	0.62	0.62	0.61	0.52	0.51	0.32
1.5-v1.2	0.43	0.43	0.42	0.41	0.41	0.45	0.00	0.28	0.27	0.39	0.54	0.44	0.43	0.46	0.46	0.47	0.50	0.47	0.43
1.5-v1.4	0.30	0.29	0.28	0.53	0.53	0.47	0.34	0.00	0.21	0.43	0.49	0.49	0.48	0.34	0.39	0.40	0.45	0.42	0.42
1.5-Base	0.33	0.33	0.32	0.50	0.50	0.48	0.31	0.20	0.00	0.36	0.50	0.48	0.48	0.38	0.41	0.42	0.48	0.46	0.44
1.5-Dream	0.46	0.52	0.50	0.55	0.54	0.70	0.59	0.52	0.47	0.00	0.98	0.87	0.88	0.73	0.78	0.80	1.02	0.98	0.84
2.1-DPO	0.38	0.34	0.37	0.50	0.51	0.38	0.63	0.46	0.50	0.76	0.00	0.20	0.20	0.25	0.30	0.30	0.36	0.36	0.37
2.1-Base	0.56	0.51	0.52	0.31	0.33	0.28	0.57	0.51	0.54	0.75	0.22	0.00	0.01	0.41	0.41	0.41	0.39	0.38	0.32
2.1-Art	0.55	0.50	0.52	0.32	0.34	0.29	0.55	0.50	0.53	0.75	0.21	0.01	0.00	0.39	0.39	0.39	0.39	0.38	0.32
SD3-Real	0.31	0.21	0.33	0.91	0.94	0.78	0.97	0.60	0.70	1.03	0.45	0.67	0.66	0.00	0.17	0.18	0.55	0.57	0.69
SD3-Base	0.40	0.27	0.41	0.83	0.84	0.71	0.89	0.61	0.68	1.00	0.49	0.61	0.60	0.15	0.00	0.00	0.57	0.59	0.66
SD3-Anim	0.41	0.28	0.42	0.81	0.82	0.69	0.88	0.61	0.67	1.00	0.48	0.59	0.58	0.16	0.00	0.00	0.56	0.58	0.64
XL-DPO	0.42	0.37	0.42	0.46	0.46	0.33	0.53	0.39	0.44	0.72	0.32	0.32	0.32	0.27	0.32	0.31	0.00	0.17	0.25
XL-Base	0.42	0.37	0.41	0.46	0.47	0.32	0.49	0.36	0.42	0.69	0.33	0.31	0.32	0.28	0.32	0.32	0.17	0.00	0.24
XL-Light	0.53	0.49	0.50	0.35	0.36	0.24	0.52	0.42	0.47	0.69	0.39	0.30	0.31	0.40	0.42	0.42	0.29	0.28	0.00

Table A23. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Savory Baked Good On A Dark Wood Surface																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.20	0.18	1.00	1.00	0.93	1.00	0.87	1.00	0.32	1.00	1.00	1.00	0.35	0.81	0.82	1.00	1.00	1.00
F-LoRA	0.16	0.00	0.22	0.84	0.86	0.68	0.81	0.65	0.75	0.30	0.79	0.77	0.76	0.32	0.59	0.59	0.78	0.79	0.86
F-Turbo	0.14	0.22	0.00	0.74	0.77	0.69	0.78	0.69	0.77	0.37	0.80	0.76	0.76	0.42	0.67	0.68	0.79	0.78	0.81
K-Base	0.80	0.85	0.76	0.00	0.09	0.78	0.43	1.00	0.90	0.94	0.68	0.52	0.51	0.96	1.00	1.00	0.32	0.31	0.28
K-Naru	0.89	0.98	0.87	0.10	0.00	0.99	0.49	1.18	1.07	1.06	0.77	0.61	0.60	1.07	1.16	1.17	0.35	0.33	0.28
K-Poke	0.39	0.36	0.37	0.41	0.46	0.00	0.39	0.42	0.46	0.38	0.39	0.37	0.36	0.48	0.47	0.47	0.41	0.42	0.49
1.5-v1.2	0.71	0.73	0.71	0.39	0.39	0.67	0.00	0.56	0.54	0.65	0.41	0.35	0.35	0.78	0.64	0.63	0.21	0.21	0.27
1.5-v1.4	0.38	0.37	0.39	0.55	0.58	0.44	0.35	0.00	0.34	0.31	0.39	0.36	0.36	0.46	0.46	0.45	0.43	0.44	0.52
1.5-Base	0.40	0.38	0.40	0.45	0.48	0.44	0.31	0.31	0.00	0.38	0.34	0.34	0.33	0.52	0.48	0.48	0.38	0.39	0.45
1.5-Dream	0.29	0.34	0.42	1.05	1.07	0.82	0.82	0.63	0.86	0.00	0.81	0.88	0.86	0.24	0.73	0.72	0.89	0.90	0.91
2.1-DPO	0.49	0.49	0.51	0.42	0.43	0.47	0.29	0.43	0.42	0.45	0.00	0.20	0.20	0.60	0.50	0.50	0.30	0.31	0.39
2.1-Base	0.54	0.53	0.52	0.35	0.37	0.47	0.26	0.44	0.45	0.53	0.22	0.00	0.03	0.66	0.54	0.54	0.28	0.28	0.35
2.1-Art	0.54	0.52	0.52	0.35	0.36	0.47	0.26	0.44	0.45	0.52	0.21	0.03	0.00	0.66	0.53	0.53	0.27	0.27	0.35
SD3-Real	0.52	0.62	0.82	1.80	1.81	1.73	1.66	1.86	1.96	0.41	1.82	1.86	1.84	0.00	1.35	1.32	1.52	1.51	1.48
SD3-Base	0.40	0.37	0.42	0.62	0.64	0.56	0.44	0.51	0.59	0.40	0.50	0.49	0.48	0.44	0.00	0.00	0.40	0.41	0.55
SD3-Anim	0.41	0.37	0.43	0.62	0.65	0.56	0.44	0.51	0.59	0.40	0.50	0.50	0.49	0.43	0.00	0.00	0.39	0.41	0.55
XL-DPO	0.95	0.94	0.96	0.38	0.37	0.93	0.28	0.93	0.89	0.95	0.58	0.49	0.48	0.96	0.76	0.76	0.00	0.07	0.18
XL-Base	1.00	1.00	1.00	0.39	0.36	1.00	0.30	0.99	0.96	1.00	0.63	0.51	0.51	1.00	0.83	0.82	0.07	0.00	0.17
XL-Light	1.44	1.57	1.48	0.51	0.44	1.69	0.55	1.68	1.61	1.45	1.13	0.94	0.93	1.41	1.60	1.59	0.28	0.24	0.00

Table A24. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Savory Baked Good On A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.43	0.37	1.00	1.00	0.82	1.00	1.00	1.00	0.63	0.82	1.00	1.00	0.38	0.57	0.57	1.00	1.00	1.00
F-LoRA	0.29	0.00	0.41	0.71	0.74	0.56	0.65	0.63	0.65	0.56	0.51	0.61	0.60	0.39	0.48	0.47	0.55	0.57	0.65
F-Turbo	0.26	0.43	0.00	0.63	0.64	0.54	0.69	0.68	0.71	0.61	0.64	0.67	0.68	0.44	0.53	0.53	0.72	0.70	0.67
K-Base	0.95	1.00	0.84	0.00	0.14	0.43	0.47	0.92	0.97	0.91	1.00	0.71	0.70	1.00	1.00	1.00	0.59	0.49	0.39
K-Naru	0.96	1.05	0.87	0.15	0.00	0.51	0.52	0.97	1.06	0.93	1.08	0.80	0.78	1.00	1.02	1.02	0.65	0.56	0.41
K-Poke	0.62	0.63	0.58	0.34	0.40	0.00	0.47	0.66	0.68	0.70	0.67	0.51	0.49	0.78	0.83	0.83	0.50	0.45	0.43
1.5-v1.2	1.15	1.11	1.13	0.57	0.62	0.71	0.00	0.68	0.75	1.06	0.78	0.49	0.48	0.96	0.85	0.85	0.37	0.28	0.27
1.5-v1.4	0.54	0.51	0.53	0.53	0.55	0.47	0.32	0.00	0.37	0.64	0.43	0.36	0.36	0.51	0.52	0.52	0.37	0.36	0.41
1.5-Base	0.51	0.50	0.51	0.53	0.57	0.46	0.33	0.35	0.00	0.55	0.40	0.35	0.36	0.50	0.50	0.50	0.39	0.39	0.40
1.5-Dream	0.48	0.63	0.65	0.72	0.73	0.69	0.69	0.88	0.81	0.00	0.77	0.86	0.86	0.52	0.64	0.63	0.74	0.75	0.62
2.1-DPO	0.46	0.43	0.51	0.60	0.64	0.50	0.38	0.44	0.44	0.58	0.00	0.27	0.27	0.42	0.43	0.43	0.38	0.38	0.44
2.1-Base	0.67	0.60	0.64	0.50	0.56	0.45	0.28	0.44	0.46	0.77	0.32	0.00	0.02	0.60	0.54	0.55	0.35	0.31	0.35
2.1-Art	0.69	0.61	0.66	0.51	0.56	0.44	0.28	0.45	0.48	0.79	0.32	0.02	0.00	0.62	0.56	0.57	0.35	0.31	0.35
SD3-Real	0.40	0.61	0.66	1.11	1.09	1.08	0.87	0.98	1.02	0.72	0.79	0.94	0.95	0.00	0.27	0.27	0.93	0.94	0.95
SD3-Base	0.52	0.65	0.69	0.96	0.96	1.00	0.67	0.87	0.89	0.78	0.70	0.74	0.75	0.23	0.00	0.00	0.79	0.74	0.80
SD3-Anim	0.52	0.64	0.69	0.97	0.97	1.00	0.68	0.88	0.89	0.77	0.70	0.75	0.76	0.23	0.00	0.00	0.79	0.75	0.80
XL-DPO	0.84	0.68	0.86	0.52	0.57	0.55	0.27	0.56	0.63	0.82	0.57	0.43	0.42	0.74	0.72	0.72	0.00	0.11	0.25
XL-Base	1.00	0.84	1.00	0.52	0.58	0.59	0.24	0.67	0.76	1.00	0.67	0.46	0.45	0.89	0.82	0.82	0.13	0.00	0.22
XL-Light	1.17	1.13	1.11	0.48	0.50	0.67	0.28	0.88	0.92	0.96	0.91	0.61	0.59	1.05	1.02	1.02	0.35	0.26	0.00

Table A25. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Savory Single Fruit On A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.29	0.23	1.00	1.00	1.00	0.75	0.86	1.00	1.00	1.00	1.00	1.00	0.83	0.74	0.73	1.00	1.00	1.00
F-LoRA	0.25	0.00	0.28	0.78	0.80	0.89	0.73	0.79	0.89	0.90	0.84	0.83	0.84	0.72	0.65	0.66	0.89	0.85	0.92
F-Turbo	0.24	0.34	0.00	1.16	1.20	1.16	0.58	0.77	0.92	1.09	1.20	1.20	1.20	1.13	0.91	0.90	1.03	0.98	0.98
K-Base	0.91	0.83	1.00	0.00	0.21	0.54	1.00	1.00	0.96	0.71	0.56	0.56	0.59	0.69	0.92	0.98	0.71	0.70	0.96
K-Naru	0.87	0.82	0.99	0.20	0.00	0.50	1.01	1.00	0.96	0.72	0.53	0.51	0.54	0.63	0.88	0.93	0.69	0.69	0.93
K-Poke	1.70	1.78	1.87	1.02	0.97	0.00	1.79	1.86	1.78	1.25	0.66	0.80	0.82	1.14	1.58	1.70	0.98	1.04	1.58
1.5-v1.2	1.12	1.27	0.82	1.63	1.72	1.56	0.00	0.39	0.59	1.13	1.70	1.74	1.76	1.79	1.56	1.54	1.11	0.96	1.19
1.5-v1.4	0.93	1.00	0.79	1.19	1.24	1.19	0.29	0.00	0.44	0.78	1.20	1.23	1.25	1.26	1.13	1.12	0.85	0.75	0.95
1.5-Base	0.89	0.94	0.78	0.95	0.99	0.94	0.36	0.37	0.00	0.63	0.92	0.94	0.95	1.00	1.00	1.00	0.66	0.57	0.77
1.5-Dream	0.83	0.88	0.85	0.65	0.68	0.61	0.64	0.60	0.58	0.00	0.52	0.58	0.59	0.52	0.57	0.59	0.41	0.46	0.63
2.1-DPO	0.86	0.85	0.97	0.53	0.52	0.33	0.99	0.95	0.88	0.53	0.00	0.23	0.23	0.43	0.63	0.68	0.48	0.52	0.73
2.1-Base	0.81	0.80	0.92	0.51	0.48	0.38	0.96	0.93	0.86	0.57	0.22	0.00	0.01	0.48	0.70	0.75	0.50	0.55	0.76
2.1-Art	0.79	0.79	0.90	0.52	0.49	0.38	0.95	0.92	0.85	0.57	0.21	0.01	0.00	0.48	0.69	0.74	0.49	0.54	0.74
SD3-Real	0.59	0.60	0.75	0.54	0.51	0.47	0.86	0.82	0.79	0.44	0.36	0.42	0.42	0.00	0.30	0.32	0.51	0.54	0.72
SD3-Base	0.50	0.51	0.58	0.68	0.67	0.62	0.71	0.70	0.75	0.46	0.49	0.58	0.58	0.28	0.00	0.01	0.58	0.57	0.73
SD3-Anim	0.48	0.51	0.56	0.71	0.70	0.66	0.68	0.68	0.74	0.47	0.52	0.61	0.61	0.30	0.01	0.00	0.59	0.59	0.74
XL-DPO	0.93	0.98	0.91	0.72	0.74	0.54	0.70	0.73	0.68	0.46	0.52	0.57	0.58	0.67	0.80	0.84	0.00	0.23	0.54
XL-Base	1.00	1.00	0.92	0.77	0.79	0.61	0.65	0.70	0.64	0.56	0.60	0.67	0.68	0.77	0.86	0.89	0.25	0.00	0.56
XL-Light	0.73	0.79	0.67	0.77	0.78	0.68	0.59	0.64	0.62	0.55	0.62	0.68	0.68	0.74	0.79	0.82	0.42	0.41	0.00

Table A26. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Savory Single Fruit On A Dish																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.28	0.33	0.76	0.90	1.00	0.63	0.98	0.91	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
F-LoRA	0.22	0.00	0.29	0.65	0.79	0.79	0.58	0.81	0.79	0.79	0.79	0.75	0.76	0.82	0.77	0.77	0.81	0.80	0.85
F-Turbo	0.27	0.30	0.00	0.60	0.72	0.70	0.54	0.80	0.74	0.79	0.80	0.81	0.80	0.86	0.83	0.83	0.85	0.82	0.88
K-Base	0.51	0.54	0.49	0.00	0.25	0.49	0.43	0.60	0.56	0.63	0.59	0.60	0.60	0.73	0.71	0.71	0.65	0.60	0.69
K-Naru	0.52	0.57	0.50	0.22	0.00	0.48	0.55	0.72	0.62	0.74	0.54	0.57	0.58	0.65	0.61	0.61	0.57	0.53	0.65
K-Poke	0.70	0.69	0.60	0.51	0.58	0.00	0.68	0.81	0.79	0.88	0.51	0.61	0.62	0.68	0.62	0.61	0.52	0.53	0.78
1.5-v1.2	0.64	0.73	0.67	0.66	0.98	0.99	0.00	0.45	0.48	0.54	0.93	0.86	0.87	1.00	1.09	1.08	1.05	0.93	1.02
1.5-v1.4	0.68	0.70	0.67	0.62	0.87	0.80	0.30	0.00	0.32	0.40	0.62	0.60	0.61	0.68	0.73	0.73	0.68	0.61	0.75
1.5-Base	0.64	0.68	0.63	0.58	0.75	0.79	0.33	0.32	0.00	0.49	0.64	0.61	0.61	0.69	0.74	0.74	0.68	0.61	0.72
1.5-Dream	0.59	0.62	0.61	0.59	0.81	0.79	0.34	0.37	0.44	0.00	0.60	0.59	0.61	0.65	0.67	0.67	0.67	0.60	0.67
2.1-DPO	0.89	0.87	0.87	0.78	0.83	0.65	0.81	0.80	0.81	0.84	0.00	0.25	0.25	0.31	0.31	0.32	0.26	0.25	0.54
2.1-Base	0.74	0.70	0.73	0.66	0.74	0.65	0.62	0.64	0.65	0.69	0.21	0.00	0.03	0.39	0.36	0.36	0.39	0.35	0.56
2.1-Art	0.74	0.70	0.72	0.66	0.75	0.66	0.63	0.65	0.65	0.71	0.21	0.03	0.00	0.38	0.37	0.37	0.40	0.36	0.55
SD3-Real	1.22	1.24	1.27	1.34	1.39	1.19	1.19	1.20	1.21	1.25	0.43	0.63	0.63	0.00	0.29	0.30	0.42	0.40	1.06
SD3-Base	0.94	0.91	0.95	1.00	1.00	0.83	1.00	1.00	1.00	1.00	0.33	0.46	0.47	0.23	0.00	0.00	0.37	0.36	0.82
SD3-Anim	0.93	0.89	0.94	0.98	0.98	0.82	0.99	0.99	0.98	0.99	0.33	0.45	0.47	0.23	0.00	0.00	0.37	0.36	0.81
XL-DPO	0.95	0.96	0.98	0.93	0.94	0.70	0.97	0.93	0.93	1.00	0.28	0.50	0.51	0.32	0.37	0.38	0.00	0.14	0.57
XL-Base	1.00	1.00	1.00	0.90	0.92	0.76	0.91	0.88	0.88	0.95	0.29	0.47	0.49	0.33	0.38	0.38	0.15	0.00	0.60
XL-Light	0.54	0.57	0.58	0.56	0.61	0.61	0.54	0.58	0.56	0.58	0.33	0.41	0.40	0.47	0.47	0.47	0.33	0.33	0.00

Table A27. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Savory Single Fruit On A Wooden Floor																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.27	0.28	0.64	0.64	0.50	0.58	0.65	0.80	1.00	0.96	0.77	0.77	0.81	0.78	0.78	0.89	1.00	0.69
F-LoRA	0.27	0.00	0.28	0.72	0.69	0.64	0.64	0.69	0.77	0.96	0.93	0.78	0.78	0.64	0.56	0.56	0.83	0.91	0.66
F-Turbo	0.29	0.30	0.00	0.94	0.91	0.81	0.49	0.56	0.71	1.10	0.89	0.69	0.69	0.86	0.83	0.83	0.85	0.94	0.81
K-Base	0.60	0.67	0.82	0.00	0.11	0.21	0.62	0.62	0.69	0.57	0.78	0.73	0.71	0.66	0.60	0.60	0.93	0.93	0.73
K-Naru	0.65	0.70	0.87	0.12	0.00	0.24	0.69	0.69	0.78	0.64	0.85	0.79	0.77	0.63	0.58	0.58	1.01	0.98	0.75
K-Poke	0.54	0.69	0.82	0.24	0.25	0.00	0.68	0.70	0.78	0.65	0.93	0.84	0.83	0.68	0.64	0.63	1.02	1.06	0.79
1.5-v1.2	1.15	1.28	0.92	1.33	1.35	1.25	0.00	0.23	0.46	1.10	0.67	0.41	0.41	1.37	1.56	1.55	1.28	1.33	1.60
1.5-v1.4	1.02	1.08	0.82	1.05	1.06	1.02	0.18	0.00	0.28	0.78	0.54	0.37	0.37	1.12	1.23	1.22	0.99	1.02	1.19
1.5-Base	0.91	0.88	0.76	0.85	0.87	0.83	0.26	0.20	0.00	0.54	0.44	0.36	0.37	0.86	0.89	0.89	0.76	0.77	0.87
1.5-Dream	0.94	0.91	0.97	0.58	0.59	0.57	0.52	0.47	0.45	0.00	0.56	0.57	0.56	0.60	0.57	0.56	0.85	0.80	0.80
2.1-DPO	0.92	0.90	0.80	0.80	0.81	0.83	0.32	0.33	0.37	0.57	0.00	0.17	0.17	0.80	0.75	0.75	0.65	0.64	0.82
2.1-Base	0.98	1.00	0.83	1.00	1.00	1.00	0.26	0.30	0.41	0.77	0.22	0.00	0.02	1.00	1.00	1.00	0.78	0.79	1.00
2.1-Art	0.99	1.02	0.85	0.99	0.98	1.00	0.27	0.30	0.42	0.77	0.22	0.02	0.00	1.01	1.01	1.01	0.80	0.81	1.02
SD3-Real	1.96	1.56	1.97	1.74	1.52	1.54	1.68	1.73	1.84	1.54	2.03	1.90	1.89	0.00	0.37	0.37	2.00	1.70	1.57
SD3-Base	1.00	0.72	1.00	0.83	0.73	0.76	1.00	1.00	1.00	0.77	1.00	1.00	1.00	0.19	0.00	0.00	1.00	0.88	0.77
SD3-Anim	1.00	0.73	1.00	0.82	0.73	0.75	1.00	1.00	1.00	0.76	1.00	1.00	1.00	0.19	0.00	0.00	1.00	0.88	0.77
XL-DPO	0.65	0.61	0.58	0.73	0.73	0.69	0.47	0.46	0.49	0.66	0.50	0.44	0.45	0.60	0.57	0.57	0.00	0.26	0.45
XL-Base	0.79	0.72	0.70	0.80	0.76	0.78	0.53	0.52	0.54	0.68	0.53	0.49	0.50	0.55	0.55	0.55	0.28	0.00	0.51
XL-Light	0.53	0.50	0.58	0.60	0.56	0.56	0.61	0.58	0.59	0.65	0.65	0.60	0.60	0.49	0.46	0.46	0.47	0.49	0.00

Table A28. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Sweet Baked Good Against A Brick Wall																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.22	0.23	1.00	0.70	0.51	1.00	1.00	1.00	0.90	1.00	1.00	1.00	0.41	0.71	0.74	0.88	1.00	0.68
F-LoRA	0.22	0.00	0.34	1.05	0.85	0.64	0.97	1.01	1.01	0.93	0.89	0.88	0.89	0.30	0.52	0.55	0.96	1.03	0.79
F-Turbo	0.19	0.28	0.00	0.78	0.62	0.50	0.84	0.84	0.83	0.83	0.80	0.79	0.79	0.42	0.67	0.69	0.67	0.76	0.51
K-Base	0.68	0.71	0.63	0.00	0.32	0.54	0.59	0.63	0.67	0.83	0.85	0.66	0.66	0.75	0.82	0.81	0.70	0.70	0.61
K-Naru	0.56	0.67	0.60	0.38	0.00	0.36	0.77	0.77	0.80	0.77	1.08	0.97	0.98	0.71	0.93	0.94	0.76	0.81	0.60
K-Poke	0.55	0.68	0.64	0.85	0.49	0.00	0.97	1.04	1.05	1.03	1.40	1.33	1.33	0.79	1.17	1.19	0.99	1.13	0.76
1.5-v1.2	1.57	1.51	1.58	1.37	1.51	1.43	0.00	0.24	0.28	0.81	1.16	0.75	0.73	1.46	1.39	1.38	1.45	1.16	1.55
1.5-v1.4	1.05	1.05	1.06	0.98	1.00	1.02	0.16	0.00	0.14	0.42	0.84	0.60	0.59	1.00	1.01	1.00	1.01	0.79	1.00
1.5-Base	1.00	1.00	1.00	0.99	1.00	0.98	0.18	0.14	0.00	0.42	0.83	0.59	0.59	1.00	1.00	1.00	1.00	0.78	1.00
1.5-Dream	0.82	0.84	0.90	1.11	0.88	0.88	0.47	0.36	0.38	0.00	0.94	0.83	0.84	0.81	1.10	1.13	1.13	0.92	0.98
2.1-DPO	0.60	0.53	0.58	0.75	0.81	0.79	0.44	0.48	0.49	0.62	0.00	0.24	0.23	0.50	0.53	0.53	0.76	0.63	0.73
2.1-Base	0.80	0.70	0.76	0.79	0.98	1.00	0.38	0.46	0.47	0.73	0.32	0.00	0.01	0.65	0.58	0.57	0.84	0.66	0.86
2.1-Art	0.81	0.71	0.77	0.80	0.99	1.02	0.38	0.46	0.48	0.75	0.32	0.01	0.00	0.65	0.58	0.57	0.85	0.67	0.87
SD3-Real	0.41	0.30	0.50	1.12	0.90	0.75	0.94	0.96	1.01	0.90	0.84	0.82	0.81	0.00	0.36	0.38	0.84	0.87	0.72
SD3-Base	0.59	0.43	0.67	1.00	0.96	0.91	0.73	0.79	0.83	1.00	0.73	0.59	0.59	0.29	0.00	0.00	0.77	0.76	0.72
SD3-Anim	0.60	0.44	0.68	0.97	0.96	0.91	0.72	0.78	0.82	1.01	0.72	0.58	0.58	0.31	0.00	0.00	0.77	0.76	0.72
XL-DPO	0.57	0.62	0.53	0.67	0.62	0.61	0.60	0.63	0.65	0.81	0.83	0.69	0.69	0.54	0.61	0.62	0.00	0.28	0.31
XL-Base	0.67	0.68	0.61	0.69	0.68	0.71	0.50	0.50	0.52	0.68	0.70	0.55	0.56	0.57	0.62	0.62	0.28	0.00	0.39
XL-Light	0.47	0.55	0.43	0.62	0.53	0.50	0.69	0.66	0.69	0.75	0.84	0.75	0.74	0.50	0.60	0.61	0.33	0.41	0.00

Table A29. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Sweet Baked Good On A Dark Wood Surface																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.13	0.12	1.00	1.00	1.00	1.00	1.00	0.77	0.24	0.60	0.67	0.67	0.27	0.47	0.46	1.00	1.00	1.00
F-LoRA	0.11	0.00	0.14	0.85	0.85	0.82	0.82	0.77	0.63	0.26	0.50	0.56	0.55	0.30	0.37	0.36	0.85	0.84	0.83
F-Turbo	0.10	0.14	0.00	0.77	0.78	0.76	0.79	0.74	0.62	0.25	0.45	0.52	0.52	0.32	0.42	0.41	0.83	0.83	0.80
K-Base	0.52	0.52	0.48	0.00	0.11	0.28	0.43	0.65	0.73	0.61	0.64	0.62	0.63	0.61	0.49	0.48	0.33	0.34	0.31
K-Naru	0.55	0.55	0.51	0.12	0.00	0.30	0.43	0.67	0.77	0.58	0.69	0.66	0.67	0.59	0.50	0.50	0.30	0.30	0.27
K-Poke	0.55	0.54	0.50	0.29	0.31	0.00	0.66	0.90	0.95	0.63	0.91	0.89	0.90	0.57	0.63	0.61	0.47	0.48	0.43
1.5-v1.2	0.67	0.65	0.64	0.56	0.53	0.80	0.00	0.39	0.52	0.69	0.55	0.52	0.53	0.81	0.61	0.61	0.20	0.19	0.20
1.5-v1.4	0.40	0.36	0.36	0.50	0.49	0.65	0.23	0.00	0.27	0.38	0.32	0.33	0.33	0.56	0.38	0.38	0.33	0.33	0.31
1.5-Base	0.35	0.33	0.33	0.63	0.63	0.77	0.35	0.30	0.00	0.33	0.27	0.28	0.28	0.51	0.38	0.39	0.45	0.45	0.42
1.5-Dream	0.20	0.26	0.25	0.98	0.90	0.95	0.86	0.80	0.63	0.00	0.54	0.63	0.62	0.26	0.44	0.44	0.84	0.84	0.83
2.1-DPO	0.30	0.30	0.27	0.61	0.63	0.81	0.40	0.39	0.30	0.32	0.00	0.17	0.16	0.51	0.36	0.36	0.51	0.50	0.47
2.1-Base	0.33	0.32	0.31	0.58	0.59	0.78	0.38	0.40	0.30	0.36	0.16	0.00	0.02	0.54	0.35	0.35	0.50	0.49	0.46
2.1-Art	0.32	0.32	0.31	0.59	0.59	0.79	0.38	0.41	0.30	0.36	0.16	0.02	0.00	0.55	0.36	0.35	0.50	0.49	0.46
SD3-Real	0.45	0.60	0.64	1.98	1.81	1.72	2.02	2.35	1.93	0.52	1.73	1.89	1.89	0.00	1.11	1.08	1.71	1.68	1.81
SD3-Base	0.28	0.26	0.30	0.57	0.55	0.68	0.55	0.57	0.52	0.32	0.44	0.44	0.44	0.40	0.00	0.00	0.61	0.60	0.58
SD3-Anim	0.28	0.26	0.30	0.57	0.56	0.68	0.56	0.58	0.53	0.32	0.44	0.44	0.45	0.39	0.00	0.00	0.62	0.61	0.59
XL-DPO	0.90	0.90	0.90	0.57	0.49	0.77	0.26	0.75	0.91	0.90	0.93	0.92	0.92	0.91	0.91	0.91	0.00	0.04	0.12
XL-Base	1.00	1.00	1.00	0.65	0.55	0.86	0.28	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.05	0.00	0.14
XL-Light	0.78	0.77	0.75	0.46	0.39	0.61	0.23	0.60	0.73	0.78	0.74	0.74	0.75	0.84	0.76	0.76	0.10	0.11	0.00

Table A30. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Sweet Baked Good On A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.16	0.14	0.77	0.76	0.68	1.00	1.00	0.55	0.38	0.27	0.42	0.41	0.14	0.23	0.23	0.99	1.00	0.96
F-LoRA	0.13	0.00	0.15	0.70	0.72	0.69	0.67	0.65	0.35	0.33	0.30	0.32	0.32	0.19	0.22	0.22	0.77	0.77	0.74
F-Turbo	0.10	0.14	0.00	0.59	0.61	0.55	0.72	0.69	0.39	0.30	0.23	0.31	0.30	0.19	0.26	0.25	0.74	0.75	0.70
K-Base	0.45	0.53	0.46	0.00	0.10	0.23	0.56	0.75	0.61	0.49	0.47	0.55	0.53	0.50	0.59	0.58	0.35	0.36	0.34
K-Naru	0.47	0.57	0.49	0.10	0.00	0.26	0.64	0.83	0.66	0.49	0.45	0.56	0.54	0.50	0.61	0.61	0.37	0.39	0.38
K-Poke	0.36	0.47	0.38	0.21	0.23	0.00	0.73	0.86	0.64	0.45	0.39	0.53	0.51	0.41	0.52	0.52	0.47	0.49	0.47
1.5-v1.2	0.57	0.50	0.55	0.55	0.60	0.79	0.00	0.33	0.41	0.60	0.62	0.51	0.51	0.57	0.46	0.46	0.28	0.27	0.26
1.5-v1.4	0.38	0.32	0.35	0.49	0.52	0.62	0.22	0.00	0.22	0.35	0.37	0.31	0.31	0.39	0.36	0.36	0.34	0.34	0.30
1.5-Base	0.27	0.22	0.25	0.50	0.52	0.60	0.35	0.28	0.00	0.27	0.26	0.22	0.22	0.26	0.26	0.26	0.48	0.49	0.44
1.5-Dream	0.22	0.26	0.23	0.50	0.48	0.51	0.63	0.55	0.32	0.00	0.21	0.27	0.27	0.23	0.33	0.33	0.58	0.59	0.57
2.1-DPO	0.18	0.26	0.21	0.53	0.49	0.50	0.72	0.65	0.35	0.23	0.00	0.18	0.18	0.21	0.32	0.32	0.65	0.66	0.60
2.1-Base	0.23	0.23	0.23	0.51	0.50	0.55	0.49	0.45	0.24	0.25	0.15	0.00	0.01	0.23	0.28	0.28	0.54	0.55	0.50
2.1-Art	0.23	0.23	0.22	0.50	0.49	0.54	0.50	0.46	0.24	0.25	0.15	0.01	0.00	0.23	0.28	0.28	0.55	0.55	0.50
SD3-Real	0.16	0.28	0.29	0.98	0.94	0.90	1.14	1.18	0.60	0.44	0.36	0.49	0.47	0.00	0.16	0.16	1.13	1.14	1.14
SD3-Base	0.23	0.29	0.34	1.00	1.00	1.00	0.81	0.96	0.53	0.56	0.49	0.51	0.51	0.14	0.00	0.00	1.00	1.00	1.00
SD3-Anim	0.23	0.29	0.34	0.99	0.99	0.99	0.81	0.95	0.52	0.56	0.49	0.51	0.50	0.14	0.00	0.00	1.00	1.00	1.00
XL-DPO	0.96	0.96	0.95	0.57	0.58	0.87	0.48	0.86	0.96	0.95	0.95	0.96	0.96	0.96	0.97	0.97	0.00	0.04	0.12
XL-Base	1.00	1.00	1.00	0.61	0.64	0.93	0.48	0.89	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.04	0.00	0.13
XL-Light	0.78	0.78	0.76	0.48	0.51	0.73	0.37	0.65	0.74	0.78	0.75	0.74	0.74	0.81	0.81	0.81	0.10	0.10	0.00

Table A31. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Sweet Single Fruit On A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.31	0.33	0.27	0.24	0.26	0.80	0.97	0.94	0.61	0.96	1.00	1.00	0.58	0.54	0.54	0.82	0.97	0.80
F-LoRA	0.29	0.00	0.42	0.44	0.39	0.38	0.84	0.88	0.95	0.73	0.75	0.77	0.77	0.59	0.63	0.65	0.75	0.84	0.77
F-Turbo	0.35	0.47	0.00	0.60	0.57	0.57	0.64	0.93	0.88	0.57	1.03	1.06	1.06	0.88	0.76	0.75	0.89	1.04	0.82
K-Base	0.25	0.43	0.52	0.00	0.08	0.17	0.92	0.96	0.93	0.66	0.78	0.85	0.85	0.42	0.46	0.46	0.78	0.91	0.82
K-Naru	0.25	0.43	0.56	0.09	0.00	0.16	0.99	1.04	1.05	0.72	0.78	0.85	0.85	0.41	0.48	0.48	0.81	0.96	0.90
K-Poke	0.30	0.46	0.63	0.22	0.18	0.00	1.11	1.12	1.18	0.84	0.79	0.87	0.88	0.34	0.38	0.38	0.83	0.94	0.89
1.5-v1.2	1.07	1.19	0.80	1.33	1.27	1.27	0.00	0.80	0.73	0.65	1.38	1.34	1.33	1.44	1.40	1.39	1.31	1.38	1.31
1.5-v1.4	0.95	0.91	0.86	1.02	0.97	0.94	0.59	0.00	0.51	0.67	0.87	0.89	0.88	0.96	1.04	1.05	0.94	0.98	0.97
1.5-Base	0.93	1.00	0.82	1.00	1.00	1.00	0.54	0.51	0.00	0.60	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.5-Dream	0.66	0.85	0.59	0.78	0.76	0.79	0.54	0.75	0.66	0.00	1.10	1.09	1.11	0.90	0.79	0.77	0.90	1.02	0.91
2.1-DPO	1.08	0.89	1.09	0.95	0.84	0.77	1.16	1.00	1.13	1.13	0.00	0.30	0.29	0.53	0.73	0.77	0.66	0.68	0.96
2.1-Base	1.00	0.82	1.00	0.91	0.81	0.75	1.00	0.91	1.00	1.00	0.27	0.00	0.02	0.53	0.70	0.74	0.61	0.65	0.90
2.1-Art	1.00	0.81	1.00	0.92	0.82	0.75	0.99	0.90	1.01	1.01	0.26	0.02	0.00	0.53	0.69	0.74	0.60	0.66	0.90
SD3-Real	0.60	0.64	0.85	0.47	0.41	0.30	1.11	1.01	1.04	0.84	0.49	0.55	0.55	0.00	0.17	0.19	0.54	0.64	0.81
SD3-Base	0.51	0.63	0.67	0.47	0.43	0.31	0.99	1.00	0.95	0.68	0.61	0.66	0.66	0.16	0.00	0.01	0.49	0.60	0.77
SD3-Anim	0.50	0.65	0.66	0.47	0.43	0.31	0.98	1.01	0.95	0.66	0.64	0.69	0.69	0.17	0.01	0.00	0.50	0.63	0.77
XL-DPO	0.63	0.61	0.64	0.64	0.60	0.54	0.75	0.74	0.77	0.63	0.45	0.47	0.46	0.40	0.39	0.41	0.00	0.37	0.59
XL-Base	0.75	0.68	0.76	0.76	0.71	0.62	0.80	0.77	0.78	0.72	0.47	0.50	0.51	0.48	0.49	0.51	0.38	0.00	0.64
XL-Light	0.56	0.57	0.54	0.62	0.61	0.54	0.69	0.69	0.71	0.58	0.60	0.63	0.63	0.55	0.57	0.57	0.54	0.58	0.00

Table A32. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Sweet Single Fruit On A Dish																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.26	0.49	0.33	0.33	0.37	0.96	0.97	0.94	0.98	0.65	0.78	0.77	0.43	0.49	0.50	0.51	0.52	0.56
F-LoRA	0.27	0.00	0.62	0.43	0.43	0.40	0.96	0.97	0.98	1.03	0.62	0.75	0.74	0.46	0.57	0.57	0.48	0.51	0.63
F-Turbo	0.37	0.46	0.00	0.56	0.55	0.59	0.73	0.76	0.72	0.74	0.68	0.77	0.78	0.62	0.59	0.60	0.70	0.70	0.67
K-Base	0.35	0.44	0.78	0.00	0.12	0.18	1.00	1.00	1.00	1.00	0.47	0.66	0.65	0.27	0.39	0.39	0.31	0.36	0.38
K-Naru	0.37	0.47	0.81	0.13	0.00	0.24	1.03	1.04	1.05	1.06	0.51	0.67	0.66	0.32	0.45	0.45	0.36	0.42	0.41
K-Poke	0.50	0.53	1.06	0.23	0.29	0.00	1.26	1.24	1.28	1.30	0.67	0.86	0.87	0.31	0.50	0.50	0.28	0.39	0.58
1.5-v1.2	1.34	1.30	1.34	1.32	1.30	1.29	0.00	0.28	0.37	0.51	1.27	1.33	1.31	1.26	1.19	1.20	1.37	1.34	1.31
1.5-v1.4	1.18	1.13	1.21	1.15	1.13	1.11	0.25	0.00	0.30	0.51	1.11	1.10	1.10	1.09	1.05	1.05	1.15	1.14	1.14
1.5-Base	1.00	1.00	1.00	1.00	1.00	1.00	0.28	0.26	0.00	0.45	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.5-Dream	0.88	0.89	0.87	0.84	0.84	0.85	0.33	0.37	0.38	0.00	0.81	0.87	0.86	0.80	0.76	0.76	0.86	0.84	0.84
2.1-DPO	0.61	0.56	0.82	0.41	0.43	0.46	0.84	0.85	0.88	0.85	0.00	0.32	0.32	0.37	0.44	0.44	0.41	0.40	0.53
2.1-Base	0.63	0.58	0.82	0.50	0.49	0.51	0.77	0.73	0.76	0.79	0.28	0.00	0.04	0.45	0.47	0.47	0.48	0.46	0.60
2.1-Art	0.61	0.57	0.81	0.48	0.47	0.50	0.74	0.71	0.74	0.76	0.28	0.04	0.00	0.43	0.45	0.45	0.46	0.44	0.56
SD3-Real	0.52	0.53	0.98	0.31	0.34	0.27	1.08	1.07	1.13	1.07	0.48	0.67	0.65	0.00	0.29	0.29	0.34	0.34	0.49
SD3-Base	0.48	0.55	0.77	0.36	0.40	0.37	0.84	0.85	0.93	0.84	0.46	0.58	0.57	0.24	0.00	0.01	0.49	0.44	0.52
SD3-Anim	0.49	0.54	0.77	0.36	0.40	0.36	0.84	0.85	0.93	0.84	0.46	0.57	0.56	0.23	0.01	0.00	0.49	0.44	0.52
XL-DPO	0.55	0.50	0.99	0.31	0.35	0.23	1.06	1.02	1.02	1.04	0.48	0.64	0.64	0.31	0.54	0.53	0.00	0.16	0.49
XL-Base	0.52	0.49	0.91	0.33	0.38	0.28	0.95	0.93	0.94	0.93	0.43	0.56	0.55	0.28	0.45	0.45	0.14	0.00	0.45
XL-Light	0.44	0.47	0.69	0.28	0.29	0.34	0.74	0.74	0.74	0.74	0.44	0.58	0.56	0.32	0.41	0.41	0.35	0.36	0.00

Table A33. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Sweet Single Fruit On A Wooden Floor																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.17	0.35	0.34	0.33	0.36	0.71	0.77	0.74	0.88	0.87	0.84	0.84	0.43	0.34	0.34	0.45	0.51	0.37
F-LoRA	0.21	0.00	0.50	0.36	0.34	0.43	0.86	0.93	0.94	1.14	1.03	0.97	0.98	0.33	0.37	0.36	0.62	0.67	0.40
F-Turbo	0.30	0.34	0.00	0.63	0.60	0.62	0.55	0.63	0.62	1.00	0.88	0.81	0.82	0.55	0.52	0.52	0.55	0.62	0.47
K-Base	0.46	0.39	1.00	0.00	0.06	0.15	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.33	0.42	0.41	0.62	0.70	0.43
K-Naru	0.49	0.39	1.04	0.06	0.00	0.16	1.07	1.09	1.09	1.11	1.12	1.11	1.11	0.31	0.44	0.43	0.65	0.73	0.42
K-Poke	0.50	0.47	1.01	0.15	0.15	0.00	1.00	1.06	1.03	0.96	1.14	1.13	1.13	0.37	0.41	0.41	0.52	0.61	0.39
1.5-v1.2	1.24	1.19	1.13	1.29	1.27	1.25	0.00	0.39	0.32	1.26	0.94	0.69	0.69	1.20	1.29	1.28	1.30	1.31	1.25
1.5-v1.4	0.85	0.81	0.81	0.81	0.81	0.84	0.25	0.00	0.26	0.84	0.62	0.49	0.49	0.85	0.88	0.88	0.82	0.82	0.82
1.5-Base	1.00	1.00	0.98	1.00	1.00	1.00	0.25	0.32	0.00	0.97	0.60	0.49	0.48	1.00	1.00	1.00	1.00	1.00	1.00
1.5-Dream	0.60	0.61	0.80	0.50	0.51	0.47	0.49	0.52	0.49	0.00	0.59	0.56	0.56	0.59	0.46	0.46	0.55	0.55	0.65
2.1-DPO	0.74	0.69	0.87	0.63	0.65	0.69	0.46	0.48	0.38	0.73	0.00	0.19	0.20	0.65	0.61	0.61	0.73	0.71	0.78
2.1-Base	0.86	0.78	0.96	0.75	0.77	0.83	0.40	0.46	0.37	0.84	0.23	0.00	0.01	0.75	0.73	0.73	0.83	0.81	0.89
2.1-Art	0.86	0.78	0.97	0.75	0.77	0.83	0.40	0.45	0.36	0.83	0.24	0.01	0.00	0.76	0.73	0.73	0.83	0.81	0.89
SD3-Real	1.07	0.65	1.61	0.60	0.52	0.66	1.71	1.93	1.84	2.15	1.91	1.83	1.86	0.00	0.61	0.60	1.32	1.42	0.83
SD3-Base	0.38	0.32	0.68	0.35	0.33	0.33	0.82	0.89	0.82	0.74	0.79	0.80	0.80	0.27	0.00	0.00	0.38	0.39	0.40
SD3-Anim	0.38	0.32	0.67	0.34	0.33	0.33	0.82	0.89	0.82	0.74	0.79	0.80	0.81	0.27	0.00	0.00	0.38	0.39	0.39
XL-DPO	0.37	0.41	0.54	0.39	0.37	0.31	0.62	0.62	0.62	0.67	0.72	0.68	0.68	0.44	0.29	0.28	0.00	0.13	0.28
XL-Base	0.39	0.41	0.56	0.40	0.39	0.34	0.58	0.58	0.57	0.62	0.65	0.62	0.62	0.44	0.27	0.27	0.12	0.00	0.30
XL-Light	0.41	0.35	0.61	0.35	0.31	0.31	0.79	0.82	0.81	1.05	1.01	0.96	0.96	0.37	0.39	0.38	0.36	0.42	0.00

Table A34. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Tropical Single Flower In A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.39	0.11	0.53	0.63	0.49	0.69	1.00	0.92	0.56	1.00	1.00	1.00	1.00	0.70	0.73	0.64	0.73	0.58
F-LoRA	0.28	0.00	0.28	0.59	0.62	0.62	0.91	1.14	1.00	0.79	0.72	0.71	0.71	0.67	0.74	0.76	0.65	0.68	0.62
F-Turbo	0.11	0.38	0.00	0.57	0.66	0.52	0.70	1.00	0.91	0.57	0.96	0.96	0.96	0.93	0.72	0.75	0.61	0.67	0.57
K-Base	0.39	0.61	0.43	0.00	0.15	0.25	0.56	0.80	0.78	0.54	0.73	0.73	0.74	0.87	0.64	0.66	0.57	0.67	0.39
K-Naru	0.43	0.60	0.47	0.14	0.00	0.29	0.63	0.84	0.79	0.62	0.65	0.68	0.67	0.78	0.61	0.63	0.60	0.68	0.44
K-Poke	0.39	0.70	0.43	0.28	0.35	0.00	0.59	0.88	0.85	0.53	0.76	0.80	0.81	0.94	0.67	0.69	0.71	0.80	0.47
1.5-v1.2	0.73	1.34	0.76	0.81	0.97	0.77	0.00	0.55	0.68	0.37	1.06	1.05	1.05	1.55	0.96	0.99	1.04	1.09	0.68
1.5-v1.4	0.68	1.10	0.72	0.75	0.85	0.75	0.36	0.00	0.42	0.46	0.72	0.68	0.68	1.04	0.78	0.80	0.86	0.89	0.64
1.5-Base	0.57	0.88	0.59	0.66	0.72	0.65	0.40	0.38	0.00	0.49	0.65	0.62	0.62	0.86	0.66	0.68	0.69	0.73	0.53
1.5-Dream	0.81	1.59	0.85	1.06	1.32	0.94	0.51	0.95	1.14	0.00	1.50	1.43	1.44	2.07	1.32	1.37	1.15	1.23	0.78
2.1-DPO	1.04	1.06	1.05	1.04	1.00	0.99	1.06	1.10	1.10	1.09	0.00	0.18	0.19	0.70	0.98	0.98	1.16	1.15	1.10
2.1-Base	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.17	0.00	0.01	0.68	1.00	1.00	1.00	1.00	1.00
2.1-Art	0.99	1.00	0.99	1.00	0.99	1.00	0.99	0.99	0.99	1.00	0.18	0.01	0.00	0.67	0.98	0.98	1.00	1.00	1.00
SD3-Real	0.58	0.55	0.56	0.69	0.67	0.68	0.86	0.88	0.80	0.84	0.39	0.39	0.39	0.00	0.61	0.62	0.63	0.63	0.65
SD3-Base	0.43	0.64	0.46	0.54	0.55	0.52	0.56	0.70	0.66	0.57	0.58	0.61	0.61	0.65	0.00	0.00	0.61	0.64	0.56
SD3-Anim	0.44	0.64	0.47	0.54	0.55	0.51	0.56	0.70	0.65	0.57	0.56	0.60	0.59	0.64	0.00	0.00	0.61	0.64	0.57
XL-DPO	0.44	0.62	0.43	0.54	0.61	0.61	0.68	0.86	0.77	0.55	0.76	0.68	0.69	0.75	0.67	0.70	0.00	0.13	0.31
XL-Base	0.48	0.64	0.47	0.60	0.66	0.67	0.69	0.86	0.78	0.57	0.73	0.66	0.67	0.73	0.69	0.72	0.13	0.00	0.32
XL-Light	0.50	0.76	0.52	0.47	0.57	0.51	0.56	0.81	0.75	0.47	0.92	0.87	0.88	0.98	0.80	0.83	0.39	0.43	0.00

Table A35. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Tropical Single Flower On A Pot																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.49	0.23	0.80	0.78	0.59	0.93	0.93	0.97	0.91	0.85	0.89	0.89	0.66	0.48	0.49	0.63	0.68	0.70
F-LoRA	0.52	0.00	0.60	1.04	0.93	0.75	1.19	1.03	1.04	1.16	0.81	0.87	0.88	0.47	0.73	0.72	0.77	0.84	0.80
F-Turbo	0.21	0.50	0.00	0.72	0.71	0.55	0.84	0.83	0.88	0.77	0.75	0.78	0.78	0.66	0.44	0.45	0.60	0.64	0.67
K-Base	0.57	0.69	0.57	0.00	0.23	0.41	0.63	0.66	0.65	0.63	0.64	0.61	0.61	0.77	0.65	0.65	0.62	0.63	0.68
K-Naru	0.62	0.69	0.62	0.26	0.00	0.45	0.60	0.60	0.60	0.62	0.60	0.58	0.57	0.78	0.72	0.72	0.68	0.68	0.73
K-Poke	0.56	0.66	0.57	0.55	0.54	0.00	0.90	0.90	0.85	0.82	0.82	0.86	0.85	0.63	0.49	0.49	0.42	0.46	0.52
1.5-v1.2	1.19	1.41	1.17	1.13	0.95	1.22	0.00	0.44	0.52	0.50	0.86	0.71	0.73	1.49	1.15	1.17	1.11	1.09	1.18
1.5-v1.4	1.04	1.07	1.02	1.04	0.83	1.06	0.39	0.00	0.36	0.52	0.65	0.54	0.55	1.08	1.01	1.01	1.02	1.01	1.07
1.5-Base	1.00	1.00	1.00	0.95	0.78	0.93	0.42	0.34	0.00	0.55	0.65	0.57	0.57	1.00	0.94	0.94	0.86	0.87	0.92
1.5-Dream	0.95	1.12	0.88	0.91	0.81	0.90	0.41	0.48	0.55	0.00	0.76	0.64	0.65	1.20	0.94	0.96	0.91	0.92	1.03
2.1-DPO	0.88	0.78	0.86	0.94	0.78	0.90	0.71	0.60	0.65	0.76	0.00	0.28	0.28	0.80	0.93	0.93	0.95	0.94	0.91
2.1-Base	0.98	0.90	0.95	0.94	0.80	1.00	0.62	0.53	0.61	0.68	0.30	0.00	0.01	0.91	1.00	1.00	1.00	1.00	1.00
2.1-Art	0.96	0.89	0.94	0.93	0.78	0.98	0.62	0.53	0.60	0.68	0.29	0.01	0.00	0.89	0.98	0.98	0.99	0.99	0.99
SD3-Real	0.89	0.59	0.98	1.46	1.32	0.89	1.59	1.31	1.31	1.56	1.04	1.11	1.11	0.00	0.70	0.68	0.73	0.83	0.77
SD3-Base	0.53	0.75	0.54	1.00	1.00	0.57	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.57	0.00	0.00	0.35	0.41	0.43
SD3-Anim	0.52	0.72	0.53	0.99	0.98	0.56	0.99	0.98	0.98	0.99	0.96	0.98	0.97	0.54	0.00	0.00	0.36	0.41	0.43
XL-DPO	0.75	0.85	0.78	1.02	1.00	0.53	1.04	1.09	0.98	1.04	1.08	1.07	1.07	0.64	0.38	0.39	0.00	0.23	0.36
XL-Base	0.75	0.86	0.77	0.98	0.93	0.54	0.95	1.00	0.92	0.98	1.00	1.00	1.00	0.67	0.41	0.42	0.21	0.00	0.36
XL-Light	0.79	0.84	0.83	1.08	1.04	0.63	1.05	1.08	1.01	1.13	1.00	1.03	1.03	0.64	0.44	0.45	0.34	0.37	0.00

Table A36. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

	Prompt: A Photo Of A Tropical Single Flower On A Vase																		
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.41	0.27	0.50	0.51	0.44	0.75	0.77	0.70	0.63	0.46	0.47	0.47	0.60	0.51	0.51	0.68	0.72	0.65
F-LoRA	0.52	0.00	0.61	0.59	0.47	0.64	1.08	1.00	0.84	0.94	0.39	0.42	0.42	0.65	0.65	0.64	0.73	0.76	0.75
F-Turbo	0.27	0.48	0.00	0.51	0.53	0.38	0.73	0.74	0.68	0.55	0.51	0.51	0.52	0.57	0.47	0.46	0.64	0.67	0.63
K-Base	0.49	0.46	0.50	0.00	0.22	0.32	0.82	0.79	0.64	0.77	0.41	0.42	0.42	0.52	0.51	0.50	0.50	0.52	0.60
K-Naru	0.60	0.43	0.61	0.25	0.00	0.36	0.97	0.92	0.74	0.93	0.41	0.44	0.44	0.61	0.60	0.59	0.56	0.58	0.68
K-Poke	0.49	0.57	0.43	0.36	0.35	0.00	0.83	0.82	0.70	0.66	0.49	0.50	0.51	0.66	0.57	0.57	0.60	0.63	0.69
1.5-v1.2	1.06	1.21	1.04	1.18	1.18	1.06	0.00	0.38	0.61	0.46	0.71	0.68	0.69	1.11	0.73	0.74	1.04	1.05	0.77
1.5-v1.4	1.10	1.14	1.06	1.15	1.13	1.06	0.39	0.00	0.48	0.50	0.67	0.61	0.62	1.05	0.74	0.74	1.00	1.00	0.77
1.5-Base	0.82	0.78	0.80	0.76	0.74	0.73	0.50	0.39	0.00	0.55	0.50	0.44	0.44	0.74	0.60	0.60	0.65	0.65	0.60
1.5-Dream	1.09	1.30	0.96	1.55	1.39	1.04	0.56	0.61	0.82	0.00	0.93	0.90	0.91	1.08	0.65	0.66	1.09	1.11	0.78
2.1-DPO	0.96	0.65	1.07	0.88	0.74	0.93	1.05	0.98	0.89	1.12	0.00	0.17	0.17	1.07	1.08	1.08	1.09	1.11	1.07
2.1-Base	0.90	0.65	1.00	0.82	0.73	0.88	0.93	0.83	0.74	1.00	0.16	0.00	0.01	1.00	1.00	1.00	1.00	1.00	1.00
2.1-Art	0.91	0.65	1.02	0.82	0.73	0.89	0.95	0.84	0.73	1.01	0.15	0.01	0.00	1.00	1.00	1.00	1.01	0.99	1.00
SD3-Real	0.80	0.69	0.77	0.71	0.70	0.79	1.04	0.98	0.84	0.82	0.68	0.68	0.68	0.00	0.30	0.30	0.50	0.48	0.50
SD3-Base	1.00	1.00	0.91	1.00	1.00	1.00	1.00	1.00	1.00	0.73	1.00	1.00	1.00	0.43	0.00	0.00	0.62	0.62	0.49
SD3-Anim	0.97	0.97	0.88	0.96	0.97	0.97	0.99	0.98	0.98	0.72	0.98	0.97	0.97	0.42	0.00	0.00	0.59	0.60	0.48
XL-DPO	0.77	0.66	0.73	0.58	0.54	0.61	0.83	0.79	0.63	0.71	0.59	0.58	0.59	0.43	0.36	0.36	0.00	0.15	0.29
XL-Base	0.84	0.70	0.77	0.61	0.58	0.66	0.85	0.81	0.64	0.73	0.61	0.59	0.59	0.42	0.37	0.37	0.15	0.00	0.29
XL-Light	0.97	0.89	0.94	0.90	0.87	0.92	0.81	0.81	0.77	0.67	0.76	0.77	0.77	0.56	0.38	0.38	0.39	0.37	0.00

Table A37. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

	Prompt: A Photo Of A Vibrant Single Flower In A Dimmed Studio																		
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.34	0.15	0.32	0.36	0.35	0.97	0.93	0.94	0.94	0.93	0.90	0.90	0.50	0.39	0.40	0.86	0.91	0.72
F-LoRA	0.30	0.00	0.40	0.58	0.62	0.65	1.19	1.06	1.02	0.92	0.86	0.79	0.78	0.69	0.68	0.70	0.76	0.78	0.83
F-Turbo	0.14	0.42	0.00	0.35	0.38	0.36	0.84	0.81	0.83	0.87	0.87	0.85	0.85	0.50	0.39	0.39	0.80	0.84	0.72
K-Base	0.36	0.73	0.41	0.00	0.08	0.10	0.96	1.00	1.00	1.00	1.00	1.00	1.00	0.42	0.26	0.26	1.00	1.00	0.62
K-Naru	0.39	0.75	0.44	0.07	0.00	0.14	0.92	0.89	0.93	1.01	0.95	0.97	0.97	0.38	0.29	0.29	0.92	0.93	0.66
K-Poke	0.37	0.78	0.41	0.10	0.14	0.00	0.89	0.92	0.93	0.89	0.98	0.95	0.95	0.43	0.22	0.22	0.95	0.97	0.54
1.5-v1.2	0.70	0.97	0.65	0.63	0.62	0.61	0.00	0.45	0.44	0.71	0.65	0.65	0.66	0.78	0.72	0.72	0.70	0.71	0.79
1.5-v1.4	0.78	1.00	0.72	0.76	0.70	0.73	0.52	0.00	0.35	0.74	0.55	0.58	0.58	0.81	0.82	0.83	0.62	0.66	0.92
1.5-Base	0.82	1.00	0.77	0.79	0.75	0.77	0.53	0.36	0.00	0.68	0.56	0.56	0.57	0.85	0.88	0.87	0.67	0.68	0.88
1.5-Dream	0.88	0.98	0.87	0.85	0.88	0.79	0.92	0.83	0.74	0.00	0.84	0.67	0.67	1.11	1.05	1.04	0.74	0.74	0.62
2.1-DPO	0.93	0.97	0.93	0.91	0.88	0.93	0.90	0.65	0.65	0.90	0.00	0.20	0.21	0.88	0.89	0.90	0.61	0.66	1.04
2.1-Base	1.00	0.99	1.00	1.00	1.00	1.00	1.00	0.77	0.72	0.79	0.23	0.00	0.00	1.00	1.00	1.00	0.64	0.72	1.00
2.1-Art	1.00	0.98	1.00	1.00	1.00	1.00	1.00	0.77	0.72	0.79	0.23	0.00	0.00	1.00	1.00	1.00	0.64	0.72	0.99
SD3-Real	0.38	0.58	0.40	0.29	0.26	0.31	0.81	0.73	0.74	0.89	0.66	0.68	0.68	0.00	0.26	0.27	0.63	0.67	0.69
SD3-Base	0.33	0.65	0.35	0.20	0.23	0.18	0.83	0.83	0.85	0.94	0.75	0.76	0.76	0.29	0.00	0.00	0.77	0.82	0.64
SD3-Anim	0.33	0.65	0.35	0.19	0.23	0.17	0.82	0.82	0.84	0.93	0.75	0.75	0.75	0.30	0.00	0.00	0.77	0.83	0.63
XL-DPO	0.66	0.65	0.65	0.69	0.65	0.68	0.74	0.57	0.59	0.60	0.47	0.44	0.44	0.63	0.70	0.71	0.00	0.21	0.65
XL-Base	0.68	0.66	0.67	0.67	0.65	0.69	0.74	0.59	0.58	0.59	0.49	0.49	0.49	0.67	0.73	0.74	0.20	0.00	0.63
XL-Light	0.52	0.68	0.55	0.40	0.44	0.37	0.78	0.79	0.73	0.48	0.75	0.65	0.65	0.66	0.55	0.54	0.61	0.61	0.00

Table A38. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Vibrant Single Flower On A Pot																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.31	0.21	0.34	0.34	0.43	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.47	0.86	0.86	0.86	0.90	0.85
F-LoRA	0.31	0.00	0.39	0.51	0.52	0.60	1.01	1.03	1.00	1.05	1.05	1.05	1.05	0.47	0.81	0.81	0.80	0.87	0.90
F-Turbo	0.19	0.36	0.00	0.33	0.35	0.39	0.95	0.95	0.94	0.95	0.89	0.90	0.90	0.47	0.72	0.73	0.76	0.81	0.69
K-Base	0.31	0.47	0.32	0.00	0.15	0.23	0.95	0.93	0.91	0.91	0.73	0.76	0.77	0.41	0.72	0.72	0.65	0.74	0.65
K-Naru	0.30	0.46	0.33	0.15	0.00	0.25	0.93	0.92	0.89	0.91	0.76	0.78	0.79	0.42	0.70	0.71	0.63	0.71	0.61
K-Poke	0.40	0.55	0.39	0.23	0.26	0.00	1.00	0.97	0.93	0.94	0.77	0.76	0.77	0.32	0.65	0.65	0.56	0.65	0.54
1.5-v1.2	1.15	1.15	1.16	1.19	1.20	1.24	0.00	0.33	0.32	0.41	1.08	0.98	0.97	1.31	1.19	1.19	1.31	1.27	1.21
1.5-v1.4	0.94	0.96	0.95	0.96	0.97	0.98	0.27	0.00	0.24	0.44	0.79	0.73	0.72	1.01	0.96	0.96	1.00	0.99	0.97
1.5-Base	1.00	1.00	1.00	1.00	1.00	1.00	0.28	0.26	0.00	0.46	0.81	0.75	0.74	1.00	1.00	1.00	1.00	1.00	1.00
1.5-Dream	0.95	0.99	0.96	0.95	0.98	0.96	0.34	0.44	0.44	0.00	1.00	0.88	0.87	1.11	0.86	0.87	1.04	1.01	0.91
2.1-DPO	0.77	0.80	0.74	0.62	0.66	0.64	0.73	0.65	0.63	0.81	0.00	0.26	0.27	0.60	0.91	0.91	0.81	0.82	0.80
2.1-Base	0.87	0.91	0.84	0.72	0.76	0.71	0.75	0.67	0.65	0.80	0.30	0.00	0.02	0.64	0.95	0.94	0.87	0.83	0.86
2.1-Art	0.85	0.90	0.82	0.72	0.76	0.71	0.73	0.66	0.63	0.78	0.30	0.02	0.00	0.64	0.94	0.93	0.87	0.84	0.85
SD3-Real	0.58	0.58	0.62	0.56	0.59	0.42	1.41	1.33	1.24	1.44	0.96	0.91	0.93	0.00	0.84	0.84	0.69	0.83	0.85
SD3-Base	0.67	0.62	0.60	0.61	0.62	0.54	0.81	0.80	0.78	0.70	0.91	0.85	0.85	0.53	0.00	0.00	0.50	0.55	0.47
SD3-Anim	0.66	0.62	0.59	0.60	0.61	0.53	0.79	0.78	0.76	0.70	0.90	0.83	0.84	0.52	0.00	0.00	0.50	0.54	0.47
XL-DPO	0.64	0.60	0.60	0.53	0.53	0.45	0.85	0.79	0.75	0.82	0.78	0.74	0.76	0.42	0.48	0.49	0.00	0.26	0.43
XL-Base	0.63	0.61	0.61	0.57	0.56	0.49	0.78	0.75	0.71	0.75	0.74	0.68	0.69	0.48	0.50	0.50	0.25	0.00	0.45
XL-Light	0.69	0.73	0.60	0.58	0.56	0.48	0.86	0.84	0.81	0.78	0.84	0.80	0.81	0.56	0.49	0.50	0.47	0.52	0.00

Table A39. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Vibrant Single Flower On A Vase																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.41	0.20	0.54	0.56	0.89	1.00	1.00	1.00	0.95	1.00	1.00	1.00	0.79	0.76	0.76	1.00	1.00	1.00
F-LoRA	0.38	0.00	0.46	0.77	0.65	1.01	1.02	1.00	0.96	1.01	0.94	0.90	0.90	0.73	0.65	0.65	0.89	0.89	0.91
F-Turbo	0.18	0.45	0.00	0.51	0.55	0.78	0.90	0.90	0.91	0.86	0.91	0.92	0.92	0.70	0.72	0.72	0.90	0.90	0.89
K-Base	0.41	0.62	0.42	0.00	0.17	0.31	0.73	0.69	0.73	0.64	0.75	0.75	0.75	0.65	0.64	0.63	0.60	0.59	0.62
K-Naru	0.44	0.55	0.47	0.17	0.00	0.33	0.84	0.79	0.81	0.81	0.77	0.77	0.77	0.52	0.53	0.52	0.60	0.59	0.68
K-Poke	0.72	0.89	0.68	0.34	0.34	0.00	0.82	0.77	0.84	0.78	0.84	0.77	0.77	0.60	0.69	0.68	0.47	0.50	0.69
1.5-v1.2	1.15	1.26	1.13	1.12	1.23	1.16	0.00	0.38	0.48	0.48	0.91	0.81	0.80	1.28	1.29	1.30	0.79	0.76	0.88
1.5-v1.4	1.05	1.13	1.03	0.97	1.06	0.99	0.35	0.00	0.35	0.49	0.83	0.68	0.68	1.09	1.12	1.12	0.63	0.61	0.74
1.5-Base	0.97	1.00	0.97	0.94	1.00	1.00	0.41	0.32	0.00	0.54	0.78	0.67	0.67	1.00	1.00	1.00	0.67	0.61	0.80
1.5-Dream	1.13	1.29	1.11	1.02	1.24	1.15	0.49	0.55	0.67	0.00	1.11	1.01	0.99	1.55	1.41	1.41	0.94	0.87	0.79
2.1-DPO	0.85	0.85	0.83	0.84	0.83	0.88	0.67	0.67	0.68	0.79	0.00	0.25	0.25	0.81	0.89	0.89	0.66	0.67	0.86
2.1-Base	1.00	0.96	1.00	1.00	0.97	0.94	0.70	0.65	0.69	0.85	0.29	0.00	0.00	0.83	0.95	0.95	0.60	0.65	0.87
2.1-Art	1.01	0.98	1.01	1.01	0.98	0.95	0.70	0.65	0.69	0.84	0.30	0.00	0.00	0.85	0.96	0.97	0.60	0.65	0.88
SD3-Real	0.75	0.75	0.73	0.82	0.64	0.70	1.07	0.99	0.98	1.24	0.91	0.79	0.80	0.00	0.43	0.43	0.61	0.67	1.04
SD3-Base	0.65	0.59	0.66	0.72	0.57	0.72	0.95	0.90	0.87	1.00	0.90	0.81	0.81	0.38	0.00	0.00	0.65	0.64	0.79
SD3-Anim	0.64	0.59	0.65	0.70	0.56	0.70	0.94	0.89	0.86	0.99	0.88	0.80	0.80	0.38	0.00	0.00	0.64	0.63	0.78
XL-DPO	0.89	0.86	0.87	0.71	0.68	0.51	0.62	0.53	0.61	0.70	0.70	0.54	0.53	0.57	0.68	0.68	0.00	0.18	0.55
XL-Base	0.88	0.84	0.86	0.68	0.66	0.54	0.58	0.51	0.56	0.64	0.69	0.57	0.57	0.62	0.66	0.66	0.17	0.00	0.52
XL-Light	0.77	0.75	0.75	0.63	0.67	0.65	0.59	0.54	0.63	0.51	0.78	0.67	0.67	0.83	0.72	0.72	0.47	0.46	0.00

Table A40. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of A Wild Animal In A Dimmed Studio																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.51	0.17	1.00	1.00	0.98	1.00	1.00	1.00	1.00	0.62	0.56	0.55	0.43	0.72	0.70	1.00	1.00	0.98
F-LoRA		0.40	0.00	0.42	0.79	0.71	0.91	0.79	0.79	0.79	0.81	0.53	0.51	0.52	0.49	0.84	0.83	0.65	0.67	0.70
F-Turbo		0.18	0.58	0.00	1.18	1.17	1.08	1.09	1.09	1.09	1.12	0.71	0.64	0.63	0.49	0.80	0.78	1.09	1.14	1.07
K-Base		0.60	0.60	0.65	0.00	0.13	0.50	0.47	0.49	0.53	0.46	0.53	0.58	0.57	0.55	0.53	0.52	0.64	0.51	0.82
K-Naru		0.62	0.56	0.67	0.13	0.00	0.54	0.44	0.47	0.49	0.43	0.54	0.60	0.60	0.55	0.55	0.55	0.59	0.47	0.76
K-Poke		0.68	0.80	0.69	0.58	0.61	0.00	0.63	0.71	0.70	0.59	0.41	0.48	0.46	0.51	0.58	0.56	0.94	0.79	1.24
1.5-v1.2		1.11	1.10	1.12	0.86	0.78	1.00	0.00	0.19	0.22	0.23	1.06	1.06	1.06	1.10	1.00	1.00	1.00	0.84	1.07
1.5-v1.4		1.05	1.06	1.06	0.86	0.79	1.08	0.18	0.00	0.18	0.27	1.07	1.05	1.05	1.07	1.02	1.02	1.01	0.85	0.99
1.5-Base		1.00	1.00	1.00	0.88	0.79	1.00	0.20	0.17	0.00	0.30	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.79	0.93
1.5-Dream		0.98	1.01	1.01	0.75	0.68	0.83	0.20	0.25	0.30	0.00	0.89	0.94	0.94	0.99	0.80	0.81	0.92	0.72	1.00
2.1-DPO		0.47	0.52	0.51	0.68	0.67	0.45	0.73	0.78	0.77	0.70	0.00	0.19	0.18	0.32	0.58	0.56	0.71	0.64	0.97
2.1-Base		0.47	0.54	0.49	0.81	0.81	0.57	0.80	0.84	0.84	0.81	0.20	0.00	0.01	0.33	0.64	0.62	0.75	0.73	1.00
2.1-Art		0.47	0.55	0.49	0.80	0.81	0.56	0.80	0.84	0.84	0.81	0.20	0.01	0.00	0.33	0.63	0.61	0.76	0.74	1.01
SD3-Real		0.36	0.53	0.39	0.78	0.76	0.62	0.84	0.86	0.85	0.86	0.36	0.34	0.33	0.00	0.57	0.55	0.77	0.75	0.92
SD3-Base		0.46	0.67	0.47	0.56	0.56	0.53	0.57	0.61	0.63	0.52	0.47	0.48	0.47	0.42	0.00	0.00	0.68	0.59	0.73
SD3-Anim		0.45	0.67	0.46	0.56	0.57	0.52	0.58	0.63	0.64	0.53	0.47	0.48	0.47	0.41	0.00	0.00	0.68	0.60	0.74
XL-DPO		0.54	0.44	0.54	0.57	0.51	0.73	0.48	0.52	0.50	0.50	0.49	0.48	0.49	0.49	0.57	0.57	0.00	0.26	0.47
XL-Base		0.61	0.52	0.63	0.51	0.46	0.69	0.46	0.49	0.48	0.45	0.50	0.53	0.53	0.54	0.57	0.56	0.30	0.00	0.48
XL-Light		0.55	0.50	0.55	0.77	0.69	1.00	0.54	0.53	0.52	0.57	0.71	0.67	0.68	0.61	0.65	0.65	0.49	0.45	0.00

Table A41. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of A Wild Animal In A Forest																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.38	0.25	0.74	0.69	0.53	1.00	0.97	1.00	1.00	1.00	1.00	1.00	0.93	0.86	0.87	0.80	0.72	0.60
F-LoRA		0.39	0.00	0.51	0.63	0.65	0.58	1.08	0.97	0.92	1.12	1.01	1.00	1.01	1.02	1.10	1.11	0.83	0.72	0.54
F-Turbo		0.24	0.48	0.00	0.80	0.74	0.53	0.97	0.93	0.99	0.92	0.95	0.96	0.96	0.88	0.77	0.76	0.77	0.77	0.64
K-Base		0.70	0.57	0.78	0.00	0.17	0.33	0.90	0.81	0.78	0.88	0.86	0.91	0.92	1.00	1.00	1.00	0.94	0.86	0.61
K-Naru		0.60	0.53	0.65	0.15	0.00	0.30	0.81	0.75	0.72	0.76	0.79	0.84	0.85	0.84	0.91	0.90	0.79	0.75	0.56
K-Poke		0.52	0.54	0.53	0.34	0.34	0.00	0.92	0.88	0.91	0.83	0.99	1.02	1.02	1.05	1.03	1.03	1.01	0.96	0.70
1.5-v1.2		1.09	1.11	1.07	1.02	1.02	1.02	0.00	0.35	0.47	0.40	0.57	0.52	0.51	0.59	0.61	0.60	1.13	1.17	1.25
1.5-v1.4		1.03	0.98	1.00	0.90	0.92	0.95	0.34	0.00	0.41	0.53	0.54	0.48	0.46	0.68	0.65	0.65	1.17	1.18	1.14
1.5-Base		1.00	0.88	1.00	0.82	0.83	0.92	0.43	0.39	0.00	0.60	0.52	0.49	0.47	0.59	0.67	0.67	0.92	0.91	0.94
1.5-Dream		0.97	1.04	0.91	0.90	0.85	0.83	0.36	0.49	0.59	0.00	0.54	0.60	0.59	0.53	0.57	0.56	0.93	1.01	1.06
2.1-DPO		0.85	0.82	0.81	0.77	0.78	0.86	0.45	0.43	0.44	0.47	0.00	0.32	0.32	0.54	0.54	0.53	0.83	0.85	0.81
2.1-Base		0.92	0.88	0.90	0.88	0.90	0.95	0.44	0.41	0.45	0.57	0.35	0.00	0.01	0.61	0.57	0.57	1.00	1.00	0.95
2.1-Art		0.92	0.89	0.90	0.89	0.91	0.96	0.43	0.40	0.44	0.56	0.34	0.01	0.00	0.59	0.55	0.56	0.99	1.00	0.96
SD3-Real		1.13	1.18	1.09	1.28	1.18	1.30	0.66	0.78	0.72	0.66	0.78	0.80	0.78	0.00	0.73	0.73	0.78	0.91	1.13
SD3-Base		0.82	1.00	0.74	1.00	1.00	1.00	0.54	0.59	0.64	0.56	0.61	0.59	0.57	0.57	0.00	0.00	0.93	0.99	1.00
SD3-Anim		0.83	1.01	0.74	1.00	1.00	1.00	0.53	0.59	0.64	0.55	0.60	0.59	0.58	0.57	0.00	0.00	0.93	0.98	1.00
XL-DPO		0.75	0.74	0.73	0.92	0.86	0.97	0.98	1.04	0.86	0.90	0.92	1.02	1.01	0.60	0.92	0.91	0.00	0.29	0.44
XL-Base		0.64	0.61	0.70	0.81	0.77	0.88	0.97	1.00	0.81	0.93	0.90	0.97	0.97	0.67	0.93	0.92	0.28	0.00	0.37
XL-Light		0.54	0.46	0.59	0.58	0.58	0.64	1.03	0.97	0.84	0.98	0.85	0.93	0.94	0.83	0.94	0.94	0.42	0.37	0.00

Table A42. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of A Wild Animal In A Grassland																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.23	0.15	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.88	0.92	1.00	1.00	1.00
F-LoRA	0.22	0.00	0.21	1.10	1.04	1.07	1.00	0.96	0.96	1.02	0.88	0.90	0.90	0.98	1.07	1.11	0.93	0.90	0.82
F-Turbo	0.14	0.21	0.00	1.03	1.01	1.01	0.96	0.95	0.95	0.98	0.94	0.95	0.95	0.94	0.86	0.90	0.99	0.99	0.96
K-Base	0.62	0.71	0.68	0.00	0.22	0.31	0.70	0.61	0.60	0.61	0.63	0.57	0.55	0.79	0.75	0.78	0.45	0.45	0.66
K-Naru	0.64	0.69	0.67	0.23	0.00	0.34	0.69	0.60	0.61	0.63	0.61	0.56	0.54	0.74	0.76	0.79	0.45	0.44	0.65
K-Poke	0.62	0.72	0.69	0.32	0.34	0.00	0.72	0.62	0.65	0.63	0.69	0.62	0.61	0.80	0.73	0.77	0.44	0.51	0.78
1.5-v1.2	1.09	1.13	1.09	1.22	1.18	1.20	0.00	0.25	0.29	0.26	0.52	0.60	0.58	0.70	1.03	1.01	0.80	0.87	0.95
1.5-v1.4	1.00	0.99	0.99	0.97	0.94	0.95	0.22	0.00	0.20	0.28	0.47	0.48	0.46	0.66	0.89	0.88	0.56	0.64	0.81
1.5-Base	1.00	1.00	1.00	0.95	0.96	1.00	0.26	0.20	0.00	0.27	0.49	0.47	0.46	0.75	1.00	1.00	0.61	0.66	0.80
1.5-Dream	1.05	1.12	1.09	1.02	1.04	1.01	0.25	0.30	0.28	0.00	0.58	0.62	0.60	0.79	1.00	0.99	0.71	0.81	0.91
2.1-DPO	1.01	0.92	0.99	1.02	0.97	1.07	0.48	0.47	0.49	0.55	0.00	0.28	0.28	0.49	0.86	0.86	0.61	0.62	0.47
2.1-Base	0.86	0.81	0.85	0.78	0.75	0.82	0.47	0.42	0.41	0.50	0.24	0.00	0.03	0.56	0.79	0.80	0.45	0.46	0.49
2.1-Art	0.87	0.82	0.87	0.77	0.75	0.82	0.47	0.41	0.40	0.50	0.24	0.03	0.00	0.55	0.81	0.82	0.46	0.46	0.49
SD3-Real	0.79	0.80	0.78	0.99	0.91	0.96	0.50	0.52	0.59	0.59	0.38	0.51	0.49	0.00	0.53	0.51	0.67	0.69	0.61
SD3-Base	0.53	0.66	0.54	0.72	0.71	0.67	0.57	0.53	0.60	0.57	0.51	0.55	0.55	0.40	0.00	0.00	0.52	0.59	0.66
SD3-Anim	0.54	0.68	0.56	0.74	0.73	0.69	0.55	0.52	0.59	0.56	0.50	0.55	0.55	0.38	0.00	0.00	0.54	0.61	0.67
XL-DPO	0.86	0.84	0.90	0.62	0.62	0.59	0.64	0.48	0.52	0.58	0.52	0.46	0.46	0.73	0.75	0.79	0.00	0.22	0.58
XL-Base	0.82	0.77	0.85	0.59	0.57	0.64	0.65	0.53	0.54	0.63	0.50	0.44	0.43	0.72	0.81	0.85	0.21	0.00	0.52
XL-Light	0.99	0.85	1.00	1.05	1.02	1.18	0.86	0.81	0.79	0.86	0.47	0.57	0.55	0.77	1.10	1.12	0.66	0.64	0.00

Table A43. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of An Dangerous Bird In A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.23	0.20	0.47	0.46	1.00	0.97	0.85	0.89	0.73	0.94	0.91	0.92	0.68	0.56	0.56	0.70	0.74	0.51
F-LoRA	0.38	0.00	0.49	0.58	0.57	1.45	1.41	1.37	1.42	1.17	1.52	1.52	1.53	1.28	1.05	1.06	1.31	1.34	0.98
F-Turbo	0.18	0.26	0.00	0.45	0.43	0.91	0.92	0.79	0.82	0.70	0.84	0.82	0.84	0.62	0.52	0.52	0.62	0.68	0.46
K-Base	0.52	0.38	0.54	0.00	0.12	0.80	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.81
K-Naru	0.48	0.36	0.50	0.12	0.00	0.83	0.96	0.94	0.95	0.93	0.94	0.96	0.96	0.91	0.88	0.88	0.92	0.91	0.75
K-Poke	1.03	0.89	1.03	0.75	0.81	0.00	0.82	0.54	0.70	0.87	0.54	0.56	0.56	0.91	1.14	1.14	0.97	1.10	1.09
1.5-v1.2	1.07	0.93	1.12	1.00	1.01	0.88	0.00	0.49	0.42	0.61	0.68	0.63	0.63	0.89	1.22	1.23	1.24	1.20	1.28
1.5-v1.4	1.14	1.09	1.17	1.21	1.19	0.70	0.59	0.00	0.38	0.63	0.46	0.41	0.41	0.59	1.09	1.11	0.90	0.95	1.14
1.5-Base	0.95	0.91	0.97	0.97	0.96	0.73	0.41	0.30	0.00	0.51	0.50	0.46	0.45	0.63	0.95	0.96	0.90	0.91	1.00
1.5-Dream	0.65	0.62	0.69	0.81	0.79	0.76	0.49	0.42	0.42	0.00	0.60	0.55	0.55	0.54	0.75	0.75	0.72	0.72	0.70
2.1-DPO	1.08	1.05	1.06	1.05	1.02	0.61	0.71	0.39	0.54	0.78	0.00	0.29	0.28	0.65	0.96	0.97	0.82	0.91	1.10
2.1-Base	1.00	1.00	1.00	1.00	1.00	0.60	0.63	0.34	0.47	0.67	0.28	0.00	0.02	0.55	0.93	0.94	0.75	0.82	1.00
2.1-Art	1.02	1.02	1.03	1.01	1.01	0.60	0.64	0.34	0.47	0.69	0.27	0.02	0.00	0.55	0.94	0.95	0.78	0.84	1.02
SD3-Real	0.69	0.77	0.70	0.93	0.87	0.90	0.82	0.45	0.60	0.61	0.58	0.51	0.50	0.00	0.71	0.73	0.44	0.45	0.56
SD3-Base	0.39	0.43	0.39	0.63	0.58	0.75	0.77	0.57	0.62	0.58	0.58	0.58	0.58	0.49	0.00	0.00	0.53	0.60	0.49
SD3-Anim	0.39	0.43	0.39	0.62	0.57	0.74	0.76	0.57	0.62	0.58	0.58	0.58	0.58	0.49	0.00	0.00	0.53	0.60	0.48
XL-DPO	0.55	0.61	0.54	0.71	0.68	0.75	0.88	0.53	0.66	0.63	0.56	0.54	0.55	0.34	0.60	0.61	0.00	0.21	0.32
XL-Base	0.57	0.61	0.57	0.69	0.65	0.82	0.83	0.54	0.65	0.61	0.60	0.56	0.57	0.34	0.66	0.67	0.20	0.00	0.33
XL-Light	0.37	0.42	0.37	0.53	0.51	0.76	0.84	0.61	0.67	0.56	0.69	0.65	0.66	0.40	0.50	0.51	0.29	0.31	0.00

Table A44. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

	Prompt: A Photo Of An Dangerous Bird On A Grass																		
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.45	0.32	0.88	0.91	0.96	0.93	0.92	0.93	1.00	0.97	1.00	1.00	0.60	0.55	0.54	0.60	0.56	0.68
F-LoRA	0.41	0.00	0.51	0.81	0.87	1.04	0.94	0.93	0.87	0.98	0.99	0.99	0.99	0.76	0.71	0.71	0.70	0.65	0.76
F-Turbo	0.27	0.47	0.00	0.75	0.78	0.83	0.83	0.85	0.85	0.90	0.85	0.87	0.87	0.56	0.49	0.49	0.58	0.58	0.66
K-Base	1.00	1.00	1.00	0.00	0.21	0.41	1.00	1.00	1.00	0.97	0.80	0.87	0.86	1.00	1.00	1.00	1.00	1.00	1.00
K-Naru	0.92	0.97	0.93	0.19	0.00	0.41	0.95	0.92	0.95	0.90	0.82	0.87	0.85	0.89	0.86	0.86	0.88	0.89	0.93
K-Poke	1.13	1.34	1.15	0.42	0.48	0.00	1.19	1.24	1.29	1.20	0.83	0.95	0.93	0.99	0.99	0.99	1.00	1.03	0.92
1.5-v1.2	0.82	0.91	0.87	0.78	0.84	0.90	0.00	0.58	0.59	0.47	0.65	0.59	0.59	0.62	0.76	0.75	0.72	0.69	0.70
1.5-v1.4	0.79	0.87	0.86	0.76	0.79	0.91	0.56	0.00	0.46	0.49	0.82	0.75	0.73	0.62	0.68	0.68	0.72	0.71	0.81
1.5-Base	0.82	0.84	0.89	0.78	0.84	0.97	0.59	0.47	0.00	0.51	0.82	0.74	0.73	0.70	0.77	0.77	0.77	0.73	0.86
1.5-Dream	1.02	1.09	1.08	0.87	0.91	1.04	0.54	0.57	0.58	0.00	0.86	0.78	0.77	0.69	0.84	0.83	0.90	0.86	0.95
2.1-DPO	0.90	1.02	0.94	0.66	0.76	0.67	0.68	0.90	0.87	0.79	0.00	0.29	0.30	0.81	0.86	0.86	0.85	0.83	0.76
2.1-Base	0.90	0.97	0.92	0.69	0.77	0.72	0.59	0.78	0.75	0.69	0.28	0.00	0.02	0.74	0.81	0.81	0.80	0.77	0.72
2.1-Art	0.90	0.98	0.92	0.68	0.76	0.71	0.60	0.77	0.74	0.69	0.29	0.02	0.00	0.75	0.81	0.81	0.80	0.78	0.74
SD3-Real	0.65	0.90	0.72	0.96	0.95	0.91	0.76	0.78	0.85	0.74	0.94	0.90	0.91	0.00	0.32	0.32	0.39	0.39	0.49
SD3-Base	0.58	0.83	0.61	0.94	0.91	0.90	0.91	0.85	0.93	0.89	0.98	0.96	0.96	0.32	0.00	0.00	0.42	0.43	0.58
SD3-Anim	0.58	0.83	0.61	0.94	0.91	0.90	0.90	0.84	0.93	0.86	0.98	0.96	0.96	0.32	0.00	0.00	0.41	0.43	0.58
XL-DPO	0.61	0.78	0.70	0.90	0.89	0.87	0.83	0.86	0.89	0.90	0.93	0.91	0.90	0.37	0.40	0.40	0.00	0.17	0.37
XL-Base	0.64	0.80	0.78	1.00	1.00	1.00	0.88	0.94	0.93	0.96	1.00	0.98	0.98	0.41	0.46	0.46	0.18	0.00	0.39
XL-Light	0.79	0.95	0.89	1.02	1.06	0.91	0.90	1.09	1.12	1.07	0.94	0.92	0.94	0.52	0.63	0.63	0.42	0.39	0.00

Table A45. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

	Prompt: A Photo Of An Dangerous Bird On A Savana																		
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.49	0.27	0.56	0.56	0.55	0.66	0.58	0.72	0.71	0.55	0.52	0.53	0.53	0.58	0.59	0.55	0.53	0.49
F-LoRA	0.51	0.00	0.39	0.60	0.62	0.61	0.47	0.39	0.48	0.51	0.51	0.51	0.52	0.75	0.72	0.73	0.57	0.56	0.54
F-Turbo	0.44	0.61	0.00	0.84	0.82	0.79	0.71	0.57	0.85	0.72	0.45	0.41	0.43	0.61	0.76	0.76	0.87	0.86	0.82
K-Base	0.85	0.87	0.78	0.00	0.12	0.20	0.84	0.85	0.91	0.81	0.79	0.81	0.81	0.71	0.77	0.78	0.27	0.25	0.25
K-Naru	0.81	0.86	0.73	0.11	0.00	0.20	0.84	0.84	0.91	0.83	0.77	0.76	0.77	0.64	0.69	0.70	0.28	0.25	0.25
K-Poke	0.89	0.95	0.79	0.21	0.22	0.00	0.95	0.94	1.08	0.88	0.83	0.86	0.87	0.70	0.81	0.81	0.29	0.29	0.28
1.5-v1.2	0.85	0.58	0.57	0.71	0.75	0.75	0.00	0.34	0.47	0.38	0.45	0.44	0.45	0.96	0.94	0.95	0.69	0.68	0.70
1.5-v1.4	0.89	0.58	0.54	0.87	0.90	0.89	0.41	0.00	0.45	0.42	0.46	0.46	0.48	1.01	0.96	0.98	0.81	0.82	0.80
1.5-Base	0.83	0.53	0.61	0.70	0.73	0.77	0.42	0.33	0.00	0.44	0.54	0.52	0.53	1.00	0.85	0.86	0.61	0.61	0.62
1.5-Dream	1.06	0.73	0.66	0.80	0.87	0.82	0.45	0.41	0.57	0.00	0.51	0.50	0.52	1.22	1.19	1.20	0.78	0.80	0.81
2.1-DPO	0.98	0.88	0.50	0.93	0.95	0.92	0.63	0.53	0.84	0.61	0.00	0.21	0.22	0.82	0.92	0.92	0.96	0.95	0.96
2.1-Base	0.97	0.91	0.48	1.00	1.00	1.00	0.64	0.57	0.85	0.63	0.22	0.00	0.02	0.85	1.00	1.00	1.00	1.00	1.00
2.1-Art	0.95	0.89	0.48	0.96	0.96	0.96	0.63	0.56	0.82	0.62	0.22	0.02	0.00	0.83	0.96	0.96	0.95	0.95	0.96
SD3-Real	0.60	0.81	0.43	0.53	0.50	0.49	0.85	0.74	0.98	0.93	0.52	0.52	0.52	0.00	0.42	0.42	0.54	0.51	0.51
SD3-Base	0.63	0.74	0.50	0.55	0.52	0.54	0.79	0.67	0.80	0.86	0.55	0.57	0.58	0.40	0.00	0.00	0.40	0.40	0.43
SD3-Anim	0.63	0.74	0.50	0.55	0.52	0.54	0.79	0.68	0.80	0.85	0.55	0.57	0.57	0.39	0.00	0.00	0.41	0.41	0.43
XL-DPO	1.05	1.03	1.02	0.34	0.36	0.34	1.02	1.00	1.00	0.99	1.01	1.01	1.01	0.90	0.70	0.72	0.00	0.09	0.18
XL-Base	1.00	1.00	1.00	0.31	0.33	0.34	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.85	0.70	0.72	0.09	0.00	0.18
XL-Light	0.82	0.85	0.84	0.28	0.29	0.29	0.89	0.86	0.89	0.90	0.88	0.88	0.88	0.74	0.66	0.67	0.16	0.16	0.00

Table A46. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of An Flightless Bird In A Dimmed Studio																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.59	0.17	0.86	0.87	0.81	0.43	0.42	0.68	0.44	0.45	0.39	0.39	0.62	0.81	0.81	0.84	0.84	0.80
F-LoRA		0.36	0.00	0.38	0.53	0.51	0.56	0.44	0.48	0.53	0.43	0.51	0.48	0.48	0.73	0.85	0.87	0.71	0.68	0.61
F-Turbo		0.26	0.90	0.00	1.26	1.29	1.24	0.54	0.52	0.94	0.72	0.37	0.36	0.36	1.11	1.36	1.36	1.37	1.37	1.33
K-Base		1.00	1.00	1.00	0.00	0.12	0.19	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.85	0.93	0.96	0.56	0.59	0.53
K-Naru		0.88	0.83	0.89	0.11	0.00	0.21	0.87	0.86	0.85	0.83	0.88	0.87	0.86	0.78	0.85	0.87	0.52	0.53	0.48
K-Poke		1.15	1.28	1.20	0.23	0.29	0.00	1.17	1.19	1.19	1.05	1.27	1.22	1.23	0.86	0.83	0.86	0.55	0.58	0.60
1.5-v1.2		0.50	0.83	0.43	1.00	1.00	0.96	0.00	0.28	0.39	0.58	0.50	0.46	0.47	0.94	1.16	1.16	1.01	0.99	1.04
1.5-v1.4		0.45	0.82	0.38	0.92	0.91	0.90	0.26	0.00	0.39	0.53	0.35	0.34	0.34	0.87	1.01	1.02	0.91	0.89	0.94
1.5-Base		0.57	0.72	0.54	0.72	0.71	0.71	0.28	0.31	0.00	0.54	0.57	0.54	0.54	0.79	0.97	0.98	0.81	0.79	0.77
1.5-Dream		0.34	0.54	0.38	0.67	0.64	0.58	0.39	0.38	0.50	0.00	0.51	0.45	0.45	0.58	0.59	0.60	0.60	0.58	0.57
2.1-DPO		0.54	0.98	0.30	1.02	1.04	1.07	0.51	0.39	0.80	0.78	0.00	0.17	0.18	1.12	1.16	1.15	1.06	1.09	1.06
2.1-Base		0.45	0.91	0.28	1.00	1.00	1.00	0.46	0.37	0.75	0.67	0.17	0.00	0.02	1.00	1.00	1.00	1.00	1.00	1.00
2.1-Art		0.44	0.88	0.28	0.97	0.97	0.98	0.45	0.36	0.72	0.66	0.17	0.02	0.00	0.97	0.98	0.98	0.98	0.98	0.98
SD3-Real		0.46	0.88	0.57	0.55	0.57	0.45	0.60	0.61	0.70	0.56	0.70	0.64	0.64	0.00	0.46	0.47	0.45	0.43	0.49
SD3-Base		0.52	0.89	0.59	0.52	0.54	0.37	0.64	0.61	0.74	0.49	0.63	0.55	0.56	0.40	0.00	0.00	0.33	0.36	0.40
SD3-Anim		0.51	0.89	0.59	0.52	0.55	0.38	0.63	0.60	0.74	0.49	0.61	0.54	0.55	0.40	0.00	0.00	0.34	0.36	0.40
XL-DPO		0.65	0.89	0.72	0.37	0.40	0.30	0.67	0.65	0.74	0.60	0.69	0.66	0.67	0.46	0.40	0.41	0.00	0.13	0.22
XL-Base		0.62	0.81	0.69	0.37	0.38	0.30	0.63	0.62	0.69	0.55	0.68	0.63	0.64	0.42	0.41	0.42	0.13	0.00	0.24
XL-Light		0.55	0.69	0.63	0.32	0.33	0.29	0.62	0.61	0.63	0.51	0.62	0.60	0.60	0.46	0.43	0.44	0.19	0.23	0.00

Table A47. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of An Flightless Bird On A Grass																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.22	0.18	0.86	0.87	0.86	0.49	0.53	0.56	0.58	0.38	0.40	0.40	0.83	0.85	0.86	0.92	0.91	0.87
F-LoRA		0.34	0.00	0.20	1.14	1.19	1.15	0.69	0.78	0.81	0.88	0.52	0.55	0.55	1.35	1.25	1.27	1.45	1.41	1.32
F-Turbo		0.26	0.18	0.00	1.05	1.10	1.05	0.63	0.69	0.74	0.78	0.43	0.45	0.45	1.15	1.14	1.14	1.29	1.27	1.21
K-Base		0.85	0.74	0.75	0.00	0.11	0.25	1.00	1.00	1.00	1.00	0.90	0.91	0.90	0.97	0.72	0.77	0.62	0.58	0.59
K-Naru		0.96	0.85	0.86	0.12	0.00	0.23	1.06	1.06	1.06	1.04	1.00	1.00	1.00	1.02	0.81	0.85	0.54	0.49	0.57
K-Poke		1.44	1.24	1.26	0.42	0.35	0.00	1.56	1.65	1.64	1.46	1.55	1.52	1.53	1.51	1.28	1.37	0.78	0.67	0.84
1.5-v1.2		0.52	0.48	0.48	1.07	1.03	1.00	0.00	0.33	0.34	0.32	0.44	0.45	0.45	0.82	1.02	1.03	0.83	0.81	0.85
1.5-v1.4		0.46	0.44	0.43	0.87	0.84	0.86	0.27	0.00	0.28	0.32	0.42	0.42	0.41	0.62	0.79	0.80	0.69	0.68	0.68
1.5-Base		0.49	0.46	0.46	0.88	0.85	0.87	0.28	0.29	0.00	0.31	0.45	0.46	0.46	0.69	0.84	0.85	0.68	0.67	0.69
1.5-Dream		0.55	0.54	0.54	0.96	0.91	0.84	0.29	0.35	0.34	0.00	0.50	0.51	0.51	0.56	0.84	0.85	0.60	0.59	0.59
2.1-DPO		0.41	0.37	0.34	1.00	1.00	1.02	0.45	0.53	0.56	0.58	0.00	0.16	0.16	0.99	1.00	0.99	0.99	1.00	1.02
2.1-Base		0.44	0.39	0.35	1.00	1.00	1.00	0.46	0.53	0.57	0.58	0.15	0.00	0.01	1.00	1.00	1.00	1.00	1.00	1.00
2.1-Art		0.44	0.39	0.35	0.99	0.99	0.99	0.46	0.51	0.57	0.57	0.16	0.01	0.00	0.98	0.99	0.99	0.99	0.99	0.99
SD3-Real		0.50	0.53	0.50	0.59	0.56	0.54	0.46	0.43	0.47	0.35	0.55	0.55	0.55	0.00	0.40	0.40	0.39	0.41	0.40
SD3-Base		0.53	0.51	0.51	0.46	0.46	0.48	0.60	0.57	0.60	0.55	0.57	0.57	0.57	0.42	0.00	0.00	0.50	0.50	0.46
SD3-Anim		0.52	0.50	0.50	0.47	0.47	0.50	0.58	0.55	0.58	0.54	0.55	0.55	0.55	0.40	0.00	0.00	0.50	0.50	0.46
XL-DPO		0.90	0.92	0.91	0.60	0.48	0.46	0.76	0.77	0.76	0.61	0.88	0.89	0.89	0.64	0.77	0.81	0.00	0.09	0.28
XL-Base		1.00	1.00	1.00	0.64	0.49	0.44	0.84	0.86	0.84	0.68	1.00	1.00	1.00	0.74	0.87	0.91	0.10	0.00	0.32
XL-Light		0.78	0.77	0.79	0.53	0.47	0.46	0.72	0.71	0.71	0.56	0.83	0.82	0.82	0.59	0.66	0.69	0.26	0.26	0.00

Table A48. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of An Flightless Bird On A Savana																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.38	0.28	0.39	0.39	0.38	0.53	0.50	0.45	0.40	0.55	0.54	0.54	0.42	0.46	0.46	0.37	0.37	0.31
F-LoRA	0.38	0.00	0.40	0.53	0.57	0.52	0.62	0.58	0.55	0.52	0.58	0.54	0.54	0.68	0.68	0.69	0.60	0.60	0.49
F-Turbo	0.28	0.40	0.00	0.54	0.54	0.52	0.56	0.56	0.53	0.49	0.48	0.46	0.46	0.51	0.54	0.55	0.52	0.51	0.43
K-Base	0.72	0.98	1.00	0.00	0.08	0.15	0.96	0.74	0.77	0.50	1.00	1.00	1.00	0.61	0.48	0.49	0.29	0.30	0.29
K-Naru	0.70	1.01	0.97	0.08	0.00	0.15	0.93	0.74	0.74	0.49	0.96	0.97	0.97	0.53	0.44	0.44	0.26	0.26	0.26
K-Poke	0.71	0.96	0.97	0.15	0.16	0.00	0.94	0.77	0.80	0.43	1.01	1.01	1.01	0.58	0.47	0.48	0.28	0.30	0.26
1.5-v1.2	0.50	0.59	0.54	0.50	0.49	0.49	0.00	0.36	0.37	0.31	0.55	0.52	0.51	0.52	0.61	0.62	0.45	0.43	0.41
1.5-v1.4	0.49	0.58	0.56	0.40	0.41	0.41	0.37	0.00	0.34	0.33	0.55	0.54	0.54	0.54	0.53	0.54	0.41	0.40	0.38
1.5-Base	0.43	0.52	0.51	0.40	0.40	0.41	0.37	0.32	0.00	0.32	0.54	0.52	0.51	0.48	0.48	0.48	0.38	0.37	0.35
1.5-Dream	0.51	0.66	0.63	0.34	0.35	0.29	0.41	0.42	0.42	0.00	0.72	0.69	0.69	0.46	0.48	0.49	0.32	0.30	0.26
2.1-DPO	0.88	0.93	0.78	0.88	0.87	0.88	0.94	0.90	0.91	0.92	0.00	0.17	0.17	0.85	0.83	0.83	0.86	0.86	0.88
2.1-Base	1.00	1.00	0.86	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.19	0.00	0.01	1.00	1.00	1.00	1.00	1.00	1.00
2.1-Art	1.00	1.00	0.86	1.01	1.01	1.01	0.99	1.00	0.99	1.00	0.19	0.01	0.00	1.00	1.00	1.00	1.00	1.00	1.00
SD3-Real	0.46	0.73	0.55	0.35	0.32	0.34	0.59	0.59	0.54	0.39	0.57	0.58	0.58	0.00	0.34	0.35	0.29	0.29	0.27
SD3-Base	0.48	0.71	0.58	0.27	0.25	0.26	0.67	0.56	0.52	0.40	0.54	0.57	0.57	0.33	0.00	0.00	0.23	0.25	0.25
SD3-Anim	0.48	0.71	0.57	0.28	0.26	0.27	0.67	0.57	0.52	0.40	0.53	0.56	0.56	0.33	0.00	0.00	0.23	0.25	0.25
XL-DPO	0.53	0.85	0.74	0.22	0.20	0.21	0.67	0.58	0.56	0.35	0.76	0.77	0.76	0.37	0.31	0.31	0.00	0.05	0.16
XL-Base	0.53	0.86	0.74	0.23	0.21	0.23	0.66	0.58	0.55	0.34	0.77	0.78	0.78	0.39	0.34	0.35	0.05	0.00	0.16
XL-Light	0.47	0.75	0.67	0.24	0.22	0.21	0.65	0.59	0.55	0.31	0.82	0.82	0.82	0.38	0.36	0.37	0.17	0.17	0.00

Table A49. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

Prompt: A Photo Of An Peaceful Bird In A Dimmed Studio																			
	Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
	F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base	0.00	0.64	0.35	0.86	0.86	0.87	0.88	0.73	0.68	0.66	0.86	0.86	0.86	0.73	0.64	0.65	0.94	0.84	0.86
F-LoRA	0.68	0.00	0.63	0.67	0.72	0.80	0.94	0.86	0.83	0.69	0.96	0.94	0.96	0.75	0.86	0.87	0.66	0.59	0.62
F-Turbo	0.39	0.65	0.00	0.75	0.76	0.82	0.91	0.76	0.67	0.83	0.81	0.86	0.86	0.84	0.62	0.62	0.94	0.92	0.90
K-Base	0.96	0.71	0.77	0.00	0.33	0.46	0.93	0.91	0.85	0.89	0.99	1.00	1.00	1.00	0.66	0.68	0.78	0.77	0.71
K-Naru	0.85	0.67	0.68	0.29	0.00	0.43	0.90	0.83	0.74	0.82	0.84	0.88	0.88	0.86	0.56	0.57	0.69	0.68	0.68
K-Poke	0.88	0.77	0.75	0.41	0.44	0.00	0.87	0.89	0.80	0.74	0.85	0.90	0.89	0.79	0.65	0.66	0.63	0.62	0.60
1.5-v1.2	1.09	1.11	1.03	1.03	1.13	1.07	0.00	0.76	0.73	0.83	1.14	0.97	0.97	1.09	0.88	0.90	1.22	1.05	0.96
1.5-v1.4	0.87	0.98	0.83	0.97	1.00	1.06	0.73	0.00	0.53	0.90	0.73	0.71	0.72	0.88	0.69	0.69	1.03	1.01	1.00
1.5-Base	0.75	0.88	0.68	0.83	0.83	0.88	0.65	0.49	0.00	0.76	0.74	0.71	0.71	0.89	0.57	0.57	0.96	0.93	0.92
1.5-Dream	0.74	0.74	0.85	0.89	0.93	0.83	0.75	0.85	0.78	0.00	1.11	1.00	0.98	0.62	0.84	0.85	0.59	0.48	0.54
2.1-DPO	0.91	0.97	0.78	0.93	0.91	0.90	0.97	0.65	0.71	1.04	0.00	0.38	0.38	0.76	0.60	0.59	0.90	0.89	0.86
2.1-Base	0.97	1.00	0.88	1.00	1.00	1.00	0.87	0.66	0.73	1.00	0.41	0.00	0.04	0.76	0.71	0.71	0.93	0.86	0.80
2.1-Art	0.96	1.03	0.88	1.00	1.00	0.99	0.87	0.67	0.72	0.97	0.41	0.04	0.00	0.76	0.70	0.70	0.92	0.85	0.79
SD3-Real	0.88	0.85	0.92	1.06	1.05	0.94	1.04	0.88	0.96	0.66	0.86	0.81	0.81	0.00	0.95	0.95	0.61	0.54	0.54
SD3-Base	0.77	0.97	0.68	0.70	0.67	0.77	0.84	0.69	0.61	0.89	0.67	0.75	0.74	0.95	0.00	0.00	1.00	1.00	1.00
SD3-Anim	0.78	0.98	0.68	0.71	0.68	0.78	0.86	0.69	0.61	0.90	0.66	0.75	0.74	0.94	0.00	0.00	1.00	1.00	1.00
XL-DPO	0.92	0.61	0.84	0.68	0.68	0.62	0.96	0.84	0.85	0.51	0.83	0.81	0.80	0.50	0.82	0.82	0.00	0.21	0.28
XL-Base	1.00	0.67	1.00	0.81	0.83	0.74	1.00	1.00	1.00	0.51	1.00	0.91	0.91	0.54	1.00	1.00	0.25	0.00	0.26
XL-Light	1.44	0.99	1.38	1.07	1.16	1.00	1.29	1.41	1.40	0.81	1.36	1.20	1.19	0.76	1.41	1.42	0.49	0.36	0.00

Table A50. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of An Peaceful Bird On A Grass																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.36	0.52	0.67	0.70	0.78	0.74	0.81	0.70	0.95	0.74	0.77	0.77	1.00	0.85	0.85	0.87	0.76	0.66
F-LoRA		0.39	0.00	0.47	0.65	0.71	0.80	0.80	0.87	0.77	1.01	0.84	0.84	0.84	1.06	0.94	0.93	0.85	0.73	0.66
F-Turbo		0.52	0.44	0.00	0.78	0.79	0.79	0.71	0.74	0.72	0.93	0.77	0.73	0.72	0.89	0.84	0.83	0.76	0.66	0.56
K-Base		0.87	0.78	1.00	0.00	0.13	0.26	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	0.84	0.81	1.00	1.00	1.00
K-Naru		0.92	0.86	1.02	0.13	0.00	0.22	0.96	0.95	1.00	0.97	1.01	1.01	1.00	0.86	0.78	0.75	0.96	0.98	0.98
K-Poke		1.09	1.04	1.10	0.28	0.23	0.00	1.08	0.98	1.13	1.05	1.11	1.08	1.08	0.79	0.67	0.63	0.98	1.02	1.04
1.5-v1.2		0.98	0.97	0.93	1.01	0.97	1.01	0.00	0.45	0.52	0.47	0.61	0.53	0.53	0.75	0.96	0.96	0.71	0.63	0.57
1.5-v1.4		0.93	0.92	0.84	0.88	0.83	0.80	0.39	0.00	0.43	0.53	0.69	0.58	0.58	0.59	0.71	0.70	0.57	0.54	0.51
1.5-Base		0.79	0.79	0.80	0.87	0.86	0.90	0.45	0.42	0.00	0.66	0.66	0.55	0.55	0.84	0.89	0.90	0.73	0.63	0.57
1.5-Dream		1.14	1.12	1.11	0.93	0.89	0.90	0.43	0.55	0.70	0.00	0.80	0.71	0.70	0.57	0.91	0.90	0.66	0.63	0.51
2.1-DPO		0.84	0.87	0.86	0.87	0.87	0.89	0.52	0.68	0.67	0.75	0.00	0.29	0.29	0.88	0.93	0.94	0.82	0.69	0.60
2.1-Base		1.00	1.00	0.94	1.00	1.00	1.00	0.53	0.66	0.63	0.77	0.33	0.00	0.01	0.92	1.00	1.00	0.84	0.74	0.60
2.1-Art		0.99	0.99	0.93	1.00	0.99	0.99	0.52	0.65	0.63	0.76	0.33	0.01	0.00	0.91	0.99	0.99	0.83	0.74	0.60
SD3-Real		1.06	1.03	0.93	0.75	0.69	0.59	0.60	0.54	0.78	0.50	0.82	0.75	0.74	0.00	0.41	0.39	0.55	0.57	0.56
SD3-Base		0.84	0.85	0.82	0.64	0.58	0.47	0.72	0.61	0.78	0.75	0.81	0.76	0.76	0.38	0.00	0.00	0.58	0.61	0.60
SD3-Anim		0.86	0.86	0.83	0.63	0.57	0.45	0.73	0.62	0.80	0.76	0.83	0.78	0.77	0.38	0.00	0.00	0.58	0.62	0.62
XL-DPO		0.80	0.72	0.69	0.71	0.68	0.64	0.50	0.46	0.60	0.51	0.67	0.60	0.60	0.48	0.54	0.54	0.00	0.18	0.39
XL-Base		0.82	0.73	0.71	0.83	0.80	0.78	0.52	0.51	0.61	0.56	0.66	0.62	0.62	0.58	0.67	0.66	0.21	0.00	0.39
XL-Light		0.85	0.79	0.72	1.01	0.98	0.97	0.56	0.58	0.66	0.55	0.69	0.60	0.60	0.69	0.80	0.81	0.55	0.47	0.00

Table A51. Normalized Wasserstein Distance Matrix. Each column normalized by max distance to base models. ■ Short, ■ Medium-low, ■ Medium-high, ■ Long distance.

		Prompt: A Photo Of An Peaceful Bird On A Savana																		
		Flux			Kand			SD1.5				SD2.1			SD3			SDXL		
		F-Base	F-LoRA	F-Turbo	K-Base	K-Naru	K-Poke	1.5-v1.2	1.5-v1.4	1.5-Base	1.5-Dream	2.1-DPO	2.1-Base	2.1-Art	SD3-Real	SD3-Base	SD3-Anim	XL-DPO	XL-Base	XL-Light
F-Base		0.00	0.40	0.27	0.37	0.37	0.32	0.83	0.84	0.92	0.90	0.82	0.82	0.81	0.73	0.80	0.80	0.30	0.30	0.37
F-LoRA		0.37	0.00	0.45	0.45	0.46	0.51	0.78	0.78	0.79	0.78	0.96	0.89	0.88	0.91	0.90	0.89	0.36	0.35	0.37
F-Turbo		0.25	0.45	0.00	0.40	0.38	0.40	0.78	0.76	0.84	0.92	0.76	0.72	0.70	0.63	0.72	0.71	0.38	0.36	0.43
K-Base		0.37	0.48	0.44	0.00	0.14	0.28	0.90	0.89	0.90	1.00	0.86	0.88	0.88	0.89	0.98	0.97	0.32	0.31	0.34
K-Naru		0.36	0.47	0.40	0.14	0.00	0.26	0.87	0.86	0.88	0.98	0.80	0.82	0.82	0.82	0.91	0.90	0.31	0.30	0.35
K-Poke		0.37	0.63	0.51	0.32	0.31	0.00	1.03	1.07	1.06	1.07	0.94	0.98	0.97	0.96	1.02	1.02	0.29	0.27	0.30
1.5-v1.2		0.78	0.79	0.80	0.85	0.86	0.84	0.00	0.43	0.44	0.56	0.67	0.52	0.52	0.66	0.61	0.61	0.84	0.86	0.83
1.5-v1.4		0.93	0.91	0.91	0.98	0.98	1.02	0.50	0.00	0.38	0.66	0.65	0.48	0.48	0.59	0.57	0.57	1.01	1.01	0.97
1.5-Base		1.00	0.93	1.00	0.99	1.00	1.00	0.51	0.38	0.00	0.66	0.71	0.56	0.56	0.76	0.71	0.70	1.00	1.00	0.94
1.5-Dream		0.75	0.69	0.83	0.84	0.85	0.77	0.50	0.50	0.50	0.00	0.77	0.64	0.64	0.80	0.69	0.69	0.74	0.74	0.72
2.1-DPO		0.73	0.91	0.74	0.77	0.75	0.73	0.64	0.52	0.58	0.83	0.00	0.26	0.26	0.54	0.60	0.60	0.83	0.82	0.81
2.1-Base		0.86	1.00	0.83	0.92	0.90	0.89	0.58	0.46	0.54	0.81	0.30	0.00	0.02	0.56	0.58	0.57	0.99	0.96	0.97
2.1-Art		0.85	0.99	0.81	0.92	0.89	0.88	0.58	0.46	0.54	0.81	0.30	0.02	0.00	0.55	0.56	0.56	0.98	0.96	0.96
SD3-Real		0.77	1.02	0.72	0.93	0.89	0.87	0.73	0.56	0.73	1.01	0.63	0.56	0.54	0.00	0.37	0.36	0.99	0.96	1.03
SD3-Base		0.81	0.98	0.80	1.00	0.96	0.90	0.66	0.53	0.66	0.84	0.68	0.56	0.55	0.36	0.00	0.00	0.98	0.93	1.00
SD3-Anim		0.81	0.98	0.79	1.00	0.96	0.90	0.66	0.53	0.66	0.85	0.69	0.56	0.54	0.36	0.00	0.00	0.99	0.94	1.00
XL-DPO		0.30	0.38	0.41	0.32	0.33	0.25	0.90	0.92	0.92	0.88	0.94	0.94	0.93	0.95	0.97	0.97	0.00	0.13	0.21
XL-Base		0.33	0.41	0.43	0.34	0.34	0.26	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00	1.00	0.14	0.00	0.25
XL-Light		0.38	0.42	0.49	0.36	0.38	0.27	0.91	0.92	0.89	0.90	0.93	0.96	0.95	1.02	1.02	1.02	0.22	0.24	0.00





































































































Prompt: "A photo of a savory single fruit on a dish"										
Model	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>Flux Family</i>										
Flux-Base										
Flux-LoRA										
Flux-Turbo-Alpha										
<i>Kandinsky Family</i>										
Kandinsky-Base										
Kandinsky-Naruto										
Kandinsky-Pokemon										
<i>SD1.5 Family</i>										
SD1.5-Base										
SD1.5-1.2-Base										
SD1.5-1.4-Base										
SD1.5-DreamShaper										

Figure B7. Qualitative results (Part 1): Flux, Kandinsky, and SD1.5 families.










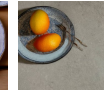









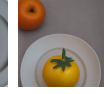









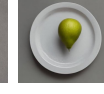









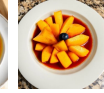









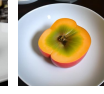









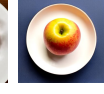









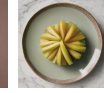









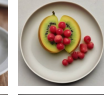









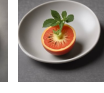
Prompt: "A photo of a savory single fruit on a dish"										
Model	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>SD2.1 Family</i>										
SD2.1-Base										
SD2.1-DPO										
SD2.1-LAION-Art										
<i>SD3 Family</i>										
SD3-Medium-Base										
SD3-Reality-Mix										
SD3-VAE-Anime										
<i>SDXL Family</i>										
SDXL-Base										
SDXL-DPO										
SDXL-Lightning-4Step										

Figure B8. Qualitative results (Part 2): SD2.1, SD3, and SDXL families.

Prompt: "A photo of a dangerous animal in a forest"										
Model	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>Flux Family</i>										
Flux-Base										
Flux-LoRA										
Flux-Turbo-Alpha										
<i>Kandinsky Family</i>										
Kandinsky-Base										
Kandinsky-Naruto										
Kandinsky-Pokemon										
<i>SD1.5 Family</i>										
SD1.5-Base										
SD1.5-1.2-Base										
SD1.5-1.4-Base										
SD1.5-DreamShaper										

Figure B9. Qualitative results (Part 1): Flux, Kandinsky, and SD1.5 families.

Model	Prompt: "A photo of a dangerous animal in a forest"									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>SD2.1 Family</i>										
SD2.1-Base										
SD2.1-DPO										
SD2.1-LAION-Art										
<i>SD3 Family</i>										
SD3-Medium-Base										
SD3-Reality-Mix										
SD3-VAE-Anime										
<i>SDXL Family</i>										
SDXL-Base										
SDXL-DPO										
SDXL-Lightning-4Step										

Figure B10. Qualitative results (Part 2): SD2.1, SD3, and SDXL families.































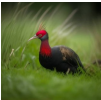


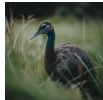
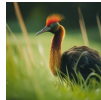
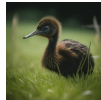
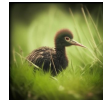


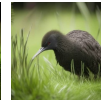
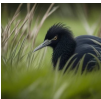


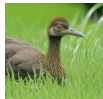
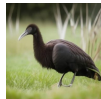


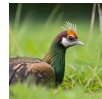

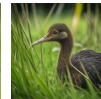

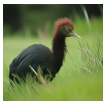

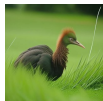


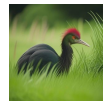
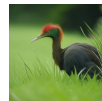
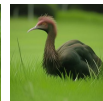
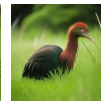
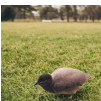


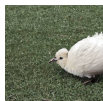


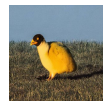

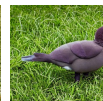
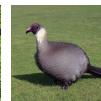





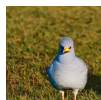






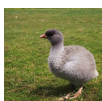
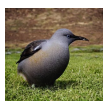


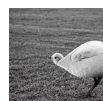

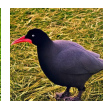



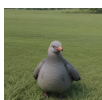

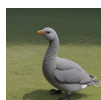


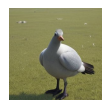


Prompt: "A photo of a dangerous animal in a grassland"										
Model	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>Flux Family</i>										
Flux-Base										
Flux-LoRA										
Flux-Turbo-Alpha										
<i>Kandinsky Family</i>										
Kandinsky-Base										
Kandinsky-Naruto										
Kandinsky-Pokemon										
<i>SD1.5 Family</i>										
SD1.5-Base										
SD1.5-1.2-Base										
SD1.5-1.4-Base										
SD1.5-DreamShaper										

Figure B11. Qualitative results (Part 1): Flux, Kandinsky, and SD1.5 families.

















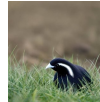














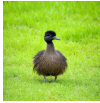
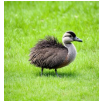
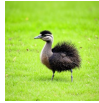
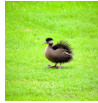
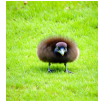




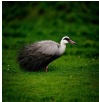
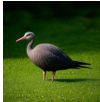
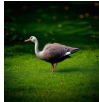
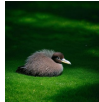
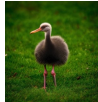

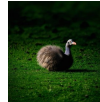
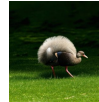
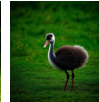
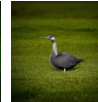

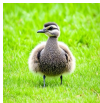
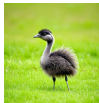
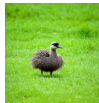

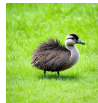
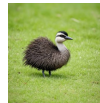

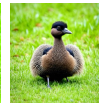
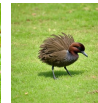



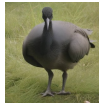



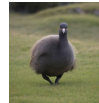


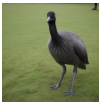

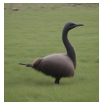



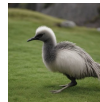

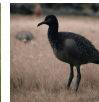
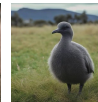





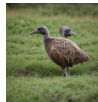




Model	Prompt: "A photo of a dangerous animal in a grassland"									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>SD2.1 Family</i>										
SD2.1-Base										
SD2.1-DPO										
SD2.1-LAION-Art										
<i>SD3 Family</i>										
SD3-Medium-Base										
SD3-Reality-Mix										
SD3-VAE-Anime										
<i>SDXL Family</i>										
SDXL-Base										
SDXL-DPO										
SDXL-Lightning-4Step										

Figure B12. Qualitative results (Part 2): SD2.1, SD3, and SDXL families.















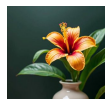

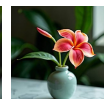



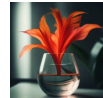
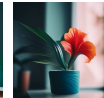



















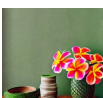


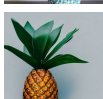
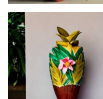
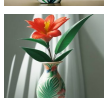

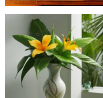

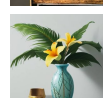
Prompt: "A photo of a tropical single flower on a vase"										
Model	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>Flux Family</i>										
Flux-Base										
Flux-LoRA										
Flux-Turbo-Alpha										
<i>Kandinsky Family</i>										
Kandinsky-Base										
Kandinsky-Naruto										
Kandinsky-Pokemon-LoRA										
<i>SD1.5 Family</i>										
SD1.5-Base										
SD1.5-1.2-Base										
SD1.5-1.4-Base										
SD1.5-DreamShaper										

Figure B13. Qualitative results (Part 1): Flux, Kandinsky, and SD1.5 families.







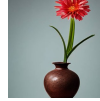
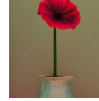
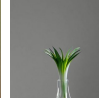
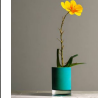








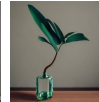
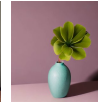



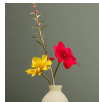

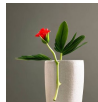















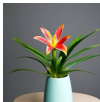

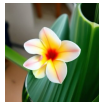
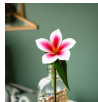

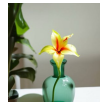




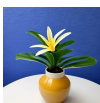
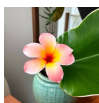





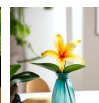
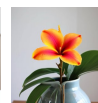








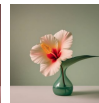




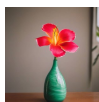

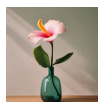
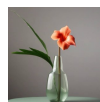

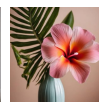

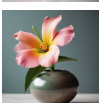
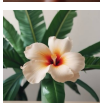
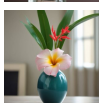
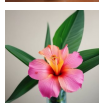
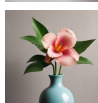



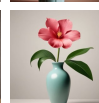
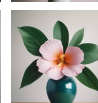
Model	Prompt: "A photo of a tropical single flower on a vase"									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
<i>SD2.1 Family</i>										
SD2.1-Base										
SD2.1-DPO										
SD2.1-LAION-Art										
<i>SD3 Family</i>										
SD3-Medium-Base										
SD3-Reality-Mix										
SD3-VAE-Anime										
<i>SDXL Family</i>										
SDXL-Base										
SDXL-DPO										
SDXL-Lightning-4Step										

Figure B14. Qualitative results (Part 2): SD2.1, SD3, and SDXL families.

G.3. Complete Prompt Enumeration

Baked Goods (9 prompts)

1. A photo of a savory baked good on a dimmed studio.
2. A photo of a savory baked good on a dark wood surface.
3. A photo of a savory baked good against a brick wall.
4. A photo of a cheesy baked good on a dimmed studio.
5. A photo of a cheesy baked good on a dark wood surface.
6. A photo of a cheesy baked good against a brick wall.
7. A photo of a sweet baked good on a dimmed studio.
8. A photo of a sweet baked good on a dark wood surface.
9. A photo of a sweet baked good against a brick wall.

Animals (9 prompts)

1. A photo of a dangerous animal in a grassland.
2. A photo of a dangerous animal in a forest.
3. A photo of a dangerous animal in a dimmed studio.
4. A photo of a wild animal in a grassland.
5. A photo of a wild animal in a forest.
6. A photo of a wild animal in a dimmed studio.
7. A photo of a peaceful animal in a grassland.
8. A photo of a peaceful animal in a forest.
9. A photo of a peaceful animal in a dimmed studio.

Flowers (6 prompts)

1. A photo of a vibrant single flower on a pot.
2. A photo of a vibrant single flower in a dimmed studio.
3. A photo of a vibrant single flower on a vase.
4. A photo of a tropical single flower on a pot.
5. A photo of a tropical single flower in a dimmed studio.
6. A photo of a tropical single flower on a vase.

Birds (9 prompts)

1. A photo of an peaceful bird on a grass.
2. A photo of an peaceful bird on a savana.
3. A photo of an peaceful bird in a dimmed studio.
4. A photo of an dangerous bird on a grass.
5. A photo of an dangerous bird on a savana.
6. A photo of an dangerous bird in a dimmed studio.
7. A photo of an flightless bird on a grass.
8. A photo of an flightless bird on a savana.
9. A photo of an flightless bird in a dimmed studio.

Fruits (9 prompts)

1. A photo of a sweet single fruit on a dish.
2. A photo of a sweet single fruit on a wooden floor.
3. A photo of a sweet single fruit on a dimmed studio.
4. A photo of a frozen single fruit on a dish.
5. A photo of a frozen single fruit on a wooden floor.
6. A photo of a frozen single fruit on a dimmed studio.
7. A photo of a savory single fruit on a dish.
8. A photo of a savory single fruit on a wooden floor.
9. A photo of a savory single fruit on a dimmed studio.