The Silent Brush: Artistic Style Leakage in AI Art Generation

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Abstract

Generative text-to-image models often produce outputs that appear novel yet reflect stylistic patterns learned from training data. While prior work suggests these models internalize style as statistical regularities, systematic methods to measure such influence remain limited. We introduce *Art Arena*, a protocol for quantifying stylistic influence through three stages: *Entry Trials* test for stored stylistic traces under explicit attribution, *Motif Duels* probe interactions and hybridization under controlled prompts, and the *Influence Ledger* ranks styles by their likelihood to reappear when style is not mentioned—a phenomenon we term ***"The Silent Brush"***. By converting influence into an empirical signal, *Art Arena* enables auditing of stylistic leakage and provides insight into how training data shapes generative behavior. While developed for text-to-image systems, the approach generalizes to other modalities and encourage transparency in creative AI.

1 Introduction

Every artwork carries a unique stylistic fingerprint shaped by choices in color, composition, and technique (Jafarpour et al., 2009; Dangeti et al., 2024). These fingerprints form recognizable patterns that generative models often learn and reproduce (Chen et al., 2025; Wan & Jing, 2024). As these models become widely used in creative workflows, their outputs appear novel yet remain deeply connected to existing artistic traditions. This raises a central question for our work: ***how can we reveal and measure stylistic influence within generative models?***

Creativity research suggests that innovation typically arises through exploration within structured conceptual spaces, involving recombination of prior ideas rather than complete novelty (Boden, 2004; Koestler, 1964). Art theory aligns with this view, describing artworks as intertextual—embedded in networks of references and influences rather than isolated acts of originality (Barthes, 1977; Kristeva, 1980). Cognitive psychology provides a mechanism for such intertextuality: motifs and stylistic cues activate schemas and prototypes, shaping perception and similarity judgments through category-based expectations (Rosch, 1975; Barsalou, 1985). Aesthetic philosophy further notes that reproducibility, mechanical in Benjamin's era and algorithmic today, alters notions of aura and authorship, raising ethical questions around originality and consent in generative systems (Benjamin, 1935).

Furthermore, recent machine learning studies indicate that generative models trained on large-scale image datasets can internalize stylistic patterns as statistical regularities, such as texture correlations and color distributions, within their learned representations (Everaert et al., 2023; Arias et al., 2025). Analyses of diffusion models suggest that as model capacity and data scale increase, learned representations capture global covariance structures, which can support style-consistent generation under weak or ambiguous prompts (Li et al., 2024; Gu et al., 2023a). Theoretical work modeling these systems as associative memories suggests that high-capacity models can form attractor states reflecting stylistic priors, which may appear during sampling and contribute to unintended stylistic persistence across motifs (Pham et al., 2025). Empirical studies on zero-shot style transfer demonstrate that such priors can be activated without explicit conditioning, indicating that memorized stylistic features can generalize beyond their original context (Deng et al., 2024). A detailed discussion of the models and training datasets is presented in Section A.1 of the Appendix.

Despite these converging insights, the dynamics of stylistic influence in generative models remain largely unexamined. Existing evaluations prioritize prompt fidelity or perceptual quality, leaving unanswered questions about how styles interact, compete, and hybridize within the latent spaces of these systems. Styles embedded in training data can exert asymmetric pull on outputs, shaping cultural hierarchies and creative possibilities. Recent evidence of memorization and leakage in large-scale models underscores the urgency of this inquiry, revealing that stylistic traces can be reactivated under targeted prompts (Shokri et al., 2017; Carlini et al., 2021). Yet the field lacks a principled framework to measure influence, to distinguish diffuse inspiration from targeted recall, and to make these intertextual relations computationally legible for ethical governance.

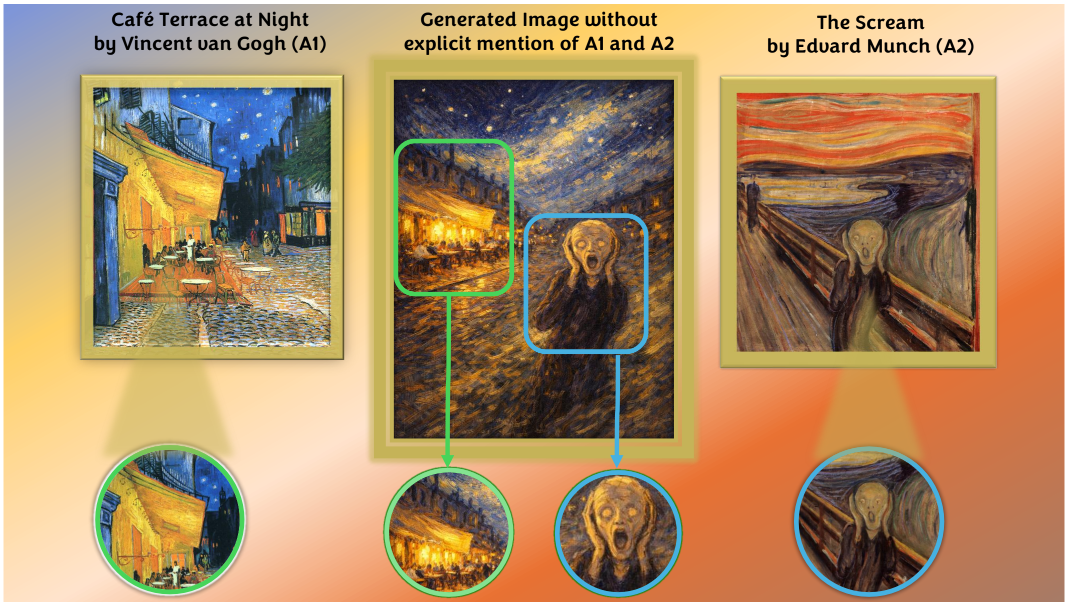


Figure 1: **Artistic Style Leakage.** An image generated by a text-to-image model that, without explicitly prompting *Café Terrace at Night* or *The Scream*, visibly incorporates elements from both artworks. **Prompt used for generation:** "A solitary, androgynous figure stands rigid in the foreground, clutching its head in a silent scream as golden café light spills onto the street behind. The glowing awning and receding tables stretch into the night, while the sky above churns in agitated waves of blue and yellow. Loose, directional brushstrokes bind figure, architecture, and sky into a single nocturnal field of anxiety, light, and distorted perception."

To address this gap, we introduce ***Art Arena***, a protocol that formalizes stylistic influence as a measurable construct. *Art Arena* consists of three stages. The first, *Early Trials*, tests whether a model can reproduce an artwork's style when explicitly attributed, indicating the presence of stored stylistic traces. The second, *Motif Duels* , uses controlled prompts to examine how styles interact and whether hybridization occurs. The third, *Influence Ledger*, aggregates results into a ranked structure that ***identifies styles most likely to appear silently without explicit mention of their stylistic cues***. These stages convert influence from an abstract notion into an empirical signal using structured comparisons. By making influence computationally observable, *Art Arena* provides a basis for auditing stylistic leakage and understanding how training data shapes generative behavior. While designed for text-to-image models, the approach generalizes to other modalities.

Ethical Considerations: Our work aims to make stylistic influence measurable, but studying this phenomenon introduces challenges. Quantifying style can oversimplify complex artistic practices and may reveal patterns that reflect biases in training data. Influence scores could be misinterpreted or used in unintended ways, such as ranking styles or encouraging appropriation. There is also a possibility that analysis might indirectly expose characteristics of underlying datasets. To mitigate these risks, *Art Arena* is designed as a diagnostic tool for transparency and governance rather than enforcement. Its purpose is to support informed discussion about attribution, consent, and cultural equity while avoiding prescriptive judgments about artistic value.

2 Related Work

2.1 Imitation, Memorization, and Data Leakage

Modern image generation models have been empirically shown to reproduce specific training examples, as well as localized fragments of those examples. Retrieval-based audits report near-duplicate generations and show that replication rates increase with duplicated or strongly aligned image–caption pairs in training data (Somepalli et al., 2023; Carlini et al., 2021). Complementary analyses connect optimization regimes, overparameterization, and data duplication to a transition from generalization toward memorization in generative models (Zhang et al., 2017; Feldman, 2020; Gu et al., 2023b). Privacy-focused work further establishes membership inference and related attacks against diffusion systems in white-, gray-, and black-box settings, underscoring persistent leakage risks in practical deployments (Shokri et al., 2017; Hayes et al., 2019; Matsumoto et al., 2023; Pang et al., 2025; Pang & Wang, 2023).

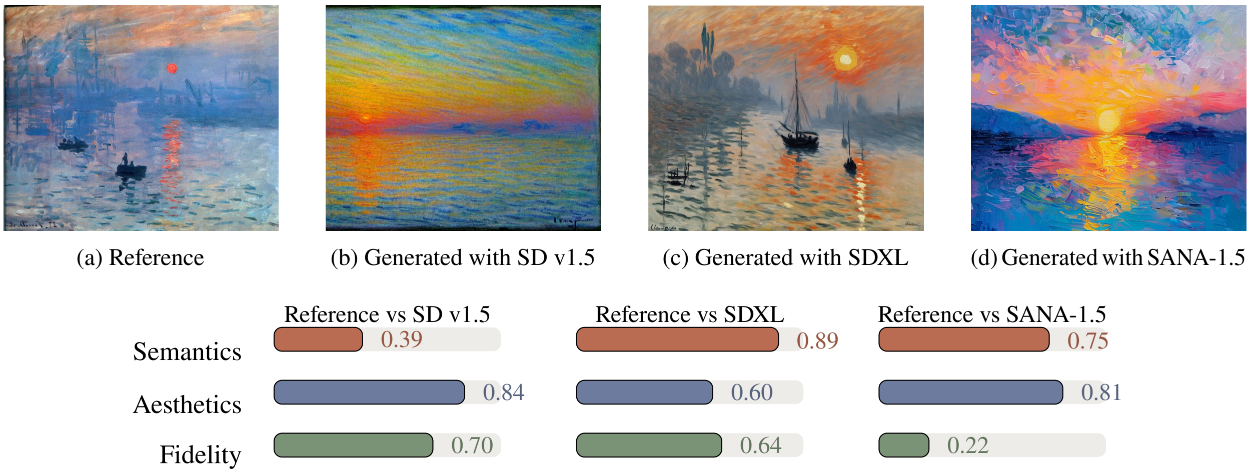


Figure 2: **Imitation of the artwork** *Impression, Sunrise* by Claude Monet using the SDXL, SD v1.5, and SANA-1.5 text-to-image models. The prompt used for imitation was: "Impression, Sunrise in the style of Claude Monet." We evaluate the degree of imitation using CLIP (Semantics), LPIPS (Aesthetics), and CSD (Fidelity). *Higher CLIP and CSD scores indicate stronger imitation, whereas lower LPIPS scores indicate stronger imitation.* Among the generated samples, image (c) appears visually closest to the reference image (a), exhibiting similar structural and stylistic characteristics, including color palette, objects placement, and finer details such as the reflection of the sun on the water, as collectively captured by the proximity-based metrics.

Methodologically, instance-level leakage is typically operationalized via semantic and perceptual pipelines: CLIP-space nearest neighbors (Radford et al., 2021), perceptual similarity metrics such as LPIPS (Zhang et al., 2018b), and other embedding-based retrieval scores that capture close matches between generated samples and training instances (Somepalli et al., 2023; Carlini et al., 2021). These tools are effective for detecting direct or near-direct reproductions. However, these pipelines are ill suited to detect *distributed, feature-level* re-expression. Most existing memorization audits stylistic influence through a retrieval criterion that searches for near duplicates in an embedding or perceptual space. This effectively tests whether the model can reproduce a specific training sample with high confidence and do so reliably across regenerations. Modern text to image models often synthesize images by blending features from many artworks, including textures, color palettes, and composition. These instance-level memorization techniques fail to consider pairwise artwork interaction that arises from the joint contribution of multiple samples.

2.2 Style Representation and Generative Control

The computational study of style predates diffusion. Neural style transfer formalized style through Gram matrices of deep features, linking style to texture statistics and correlations (Gatys et al., 2015), with antecedents in classical texture modeling (Portilla & Simoncelli, 2000). Vision research further documents a pervasive texture/style bias in deep networks, indicating that learned representations privilege specific appearance regularities (Geirhos et al., 2018). With style-based GANs and latent diffusion, explicit control and disentanglement of style became core design goals, enabling fine-grained modulation via latent manipulation and conditional denoising (Karras et al., 2019; Rombach et al., 2022a; Saharia et al., 2022a).

Personalization methods demonstrate that models can acquire subject- and style-specific keys from a handful of examples, rapidly specializing via token binding or fine-tuning (Ruiz et al., 2023; Gal et al., 2022). Although these methods focus on *intentional* style replication, they also suggest that large and diverse training datasets filled with distinctive artistic content can embed strong stylistic patterns that later appear even without explicit style prompts. Emerging evidence of zero-shot or weak-prompt style emergence in diffusion systems reinforces this view, suggesting that stylistic priors can be activated even when style is not requested (Deng et al., 2024).

3 *Art Arena* — A Protocol for Revealing Stylistic Influence

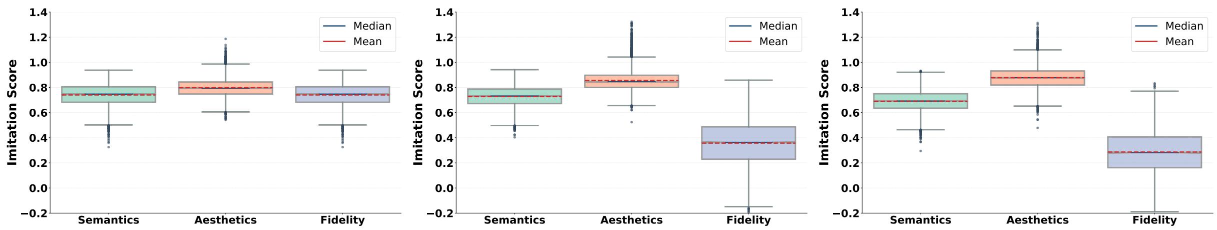
Notations summary. *Art Arena* is a protocol that makes stylistic influence in text-to-image systems measurable through controlled interactions between artworks. We present the pseudocode of *Art Arena* in Algorithm 1. The input `Artworks` is a list of records {`title`, `artist`, `reference_image`}. The text-to-image generator is `Model` M. The comparator

Algorithm 1: *Art Arena*

```
Input  : Artworks: list of {title, artist, reference_image}.
         Model M: text-to-image generator.
         Proximity: calibrated comparator for generated vs. reference images.
         Params: K (generations), R (rounds), τ_f (fitness threshold), δ (margin).
Output : FitSet, Matches, Leaderboard

Step 1: Early Trials (Fitness Test)
foreach w in Artworks do
    Prompt ← "<title(w)> in the style of <artist(w)>";
    Images ← Generate K samples via M(Prompt);
    Fit ← Average(Proximity(Images, reference_image(w)));
    if Fit ≥ τ_f then
        FitSet.add(w)

Step 2: Motif Duels (Battleground)
foreach w in FitSet do
    Score[w] ← 0;
    Motifs ← ExtractMotifs(w);
    MotifSet[w] ← sample r motifs from Motifs;
foreach ordered pair c, d in FitSet, c ≠ d do
    DefenderTemplate ← "<title(e)> in the style of <artist(e)>";
    wins_c ← 0; wins_d ← 0;
    for r ← 0 to R do
        Selected ← select r^th motif from MotifSet[c];
        Prompt_r ← "<Selected as phrases>" DefenderTemplate;
        Images_r ← Generate K samples via M(Prompt_r);
        prox_c ← Average(Proximity(Images_r, reference_image(c)));
        prox_d ← Average(Proximity(Images_r, reference_image(d)));
        if (prox_c − prox_d) > δ then
            wins_c++
        if (prox_d − prox_c) > δ then
            wins_d++
    if wins_c > wins_d then
        Matches.append({pair: c, d, winner: c}); Score[c]++
    else
        if wins_c > wins_d then
            Matches.append({pair: c, d, winner: d}); Score[d]++
        else
            Matches.append({pair: c, d, winner: "draw"})

Step 3: Influence Ledger (Leaderboard)
Ledger ← SortByDescendingScore(Score);
return {FitSet, Matches, Ledger};
```

`Proximity` is any measure that compares generated images to a `reference_image`; we denote its evaluation generically by $\mathrm{prox}\,(\cdot,\cdot)$. Global parameters are K (samples per prompt), R (rounds per duels), *fitness_threshold* τ_f for entry, and *margin_delta* δ for round outcomes. The algorithm outputs `FitSet` (artworks passing the fitness test), `Matches` (pairwise results with scores), and `Leaderboard` (a ranked map of stylistic influence). Motifs for a challenger c are obtained by `ExtractMotifs`(c) as an ordered list of phrases; the defender template for artwork d is the string: `DefenderTemplate`(d) = "$\langle\mathrm{title}(d)\rangle$ `in the style of` $\langle\mathrm{artist}(d)\rangle$".

Step 1: Entry Trials (Fitness Test). This stage assesses whether M can faithfully imitate an artwork's distinctive style when attribution is explicit, indicating that the model is reactivating learned stylistic patterns rather than generating from diffuse influence. For each artwork $w \in$ `Artworks`: `Prompt`(w) = "$\langle\mathrm{title}(w)\rangle$ `in the style of` $\langle\mathrm{artist}(w)\rangle$".



(a) Stable Diffusion v1.5 (b) Stable Diffusion XL (c) SANA-1.5

Figure 3: We present the distribution of fitness scores for SD v1.5, SDXL, and SANA-1.5 across three proximity metrics, evaluated on 8,737 artworks from twenty popular artists. For the Semantics and Fidelity metrics, a higher mean indicates better performance, whereas for Aesthetics, a lower mean indicates better performance. A tighter interquartile range reflects more concentrated scores, while a wider range indicates greater variability. Outliers correspond to artworks whose scores deviate substantially from the overall distribution, suggesting that the models strongly or weakly recall a small subset of artworks with extreme confidence levels.

Generate K sample $\texttt{Images} = \{x_1, \ldots, x_K\}$ via $M(\texttt{Prompt}(w))$. Compute

$$\mathrm{Fit}(w) = \frac{1}{K}\Sigma_{k=1}^{K}\,\mathrm{prox}\big(x_k, \texttt{reference\_image}(w)\big)$$

If $\mathrm{Fit}(w) \geq \tau_f$, the artwork is added to `FitSet`. A high proximity score under explicit prompting indicates that the model is likely recalling stored stylistic traces rather than generating from diffuse influence, a behavior consistent with memory and priming effects (Tulving, 1985; Stevens et al., 2008) and supported by evidence of memorization and leakage in generative models (Shokri et al., 2017; Carlini et al., 2021). When a model imitates with high accuracy, it signals that the style is strongly encoded in its parameters, increasing the likelihood of unintentional appearance in other generated images. The artworks comprising the FitSet are presented in the in the Appendix (refer Tables 5, 6, and 7).

Step 2: Motif Duels (Battleground). In this stage, artworks admitted to `FitSet` compete in a round-robin interactions, where each artwork faces every other as challenger and defender. The defender's identity is anchored by its title and artist, while the challenger contributes motifs drawn from its own stylistic vocabulary. For each match, we sample combinations of motifs from the challenger and blend them with the defender's template to compose prompts (see Figure 4). Across R rounds, the model generates K images per prompt, and proximity scores are computed against both reference artworks:

$$\texttt{prox}_c(r) = \frac{1}{K}\Sigma_{k=1}^{K}\,\mathrm{prox}\big(x_{r,k}, \texttt{reference\_image}(c)\big), \qquad \texttt{prox}_d(r) = \frac{1}{K}\Sigma_{k=1}^{K}\,\mathrm{prox}\big(x_{r,k}, \texttt{reference\_image}(d)\big)$$

A round is awarded to the challenger if $\texttt{prox}_c(r) - \texttt{prox}_d(r) > \delta$ and round is awarded to the defender if $\texttt{prox}_d(r) - \texttt{prox}_c(r) > \delta$. The artwork that secures the majority of rounds claims the match, and its `Score` is incremented in the `Leaderboard`. Unlike the prior methods reviewed in Section 2.1, proposed round-robin setup captures pairwise artwork interactions when assessing stylistic influence.

> If the challenger consistently outperforms the defender in Motif Duels, it suggests that the defender's stylistic representation is relatively shallow within the model's parameter space. As a result, unintentional leakage of the defender's style in generalized prompts is less likely, since its influence is weak and rarely activated without explicit cues. In such cases, the challenger demonstrates a behavior akin to a "silent brush," dominating without direct mention of stylistic triggers such as the artwork name or the artist. Conversely, if the defender dominates the Motif Duels, this indicates that its stylistic signature is deeply embedded and broadly distributed across the model's parameter space. Such styles exhibit high "accommodation," meaning they blend easily with other motifs and persist under hybridization. In practical generation scenarios, this deep embedding makes them more likely to appear unintentionally, acting as a "silent brush" in generated images.

Step 3: Influence Ledger. After all pairwise matches are complete, the results are aggregated into a `Leaderboard` by ranking artworks according to their cumulative `Score`, computed as the number of matches won across all roles in the round-robin interactions. This ranking serves not only as a summary of outcomes but as a structural map of influence within the model, identifying which styles exert dominant pull.

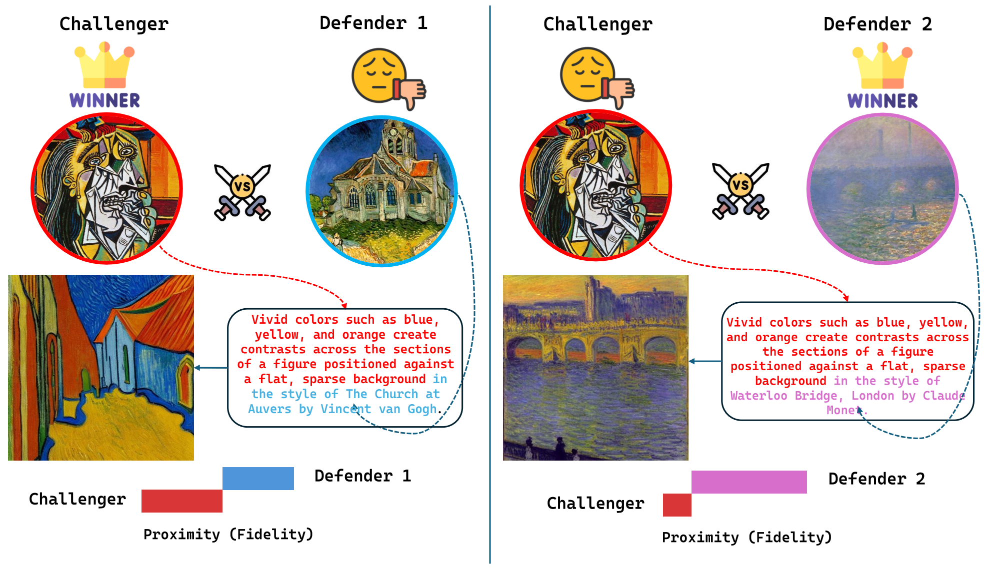


Figure 4: Motif Duel for **SD v1.5** evaluated under the fidelity based proximity (CSD). The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.

4 Experiments

Dataset and generative models: We select the top twenty most popular artists from WikiArt (wik, 2026) and collect all associated artworks, totaling 8,737 images. This choice ensures that we consider artworks likely present in large-scale web corpora such as LAION (Schuhmann et al., 2022), commonly used to train text-to-image models. We evaluate three widely adopted text to image generation models: `stable-diffusion-xl-base-1.0` (SDXL) (AI, 2023), Stable Diffusion v1.5 (SD v1.5) (Rombach et al., 2022b), and SANA-1.5 (Xie et al., 2025).

Proximity metrics: We measure proximity with three complementary metrics: CLIP cosine similarity (Radford et al., 2021; Hessel et al., 2021), Learned Perceptual Image Patch Similarity (LPIPS) (Zhang et al., 2018a), and Contrastive Style Descriptors (CSD) (Somepalli et al., 2024). The presented set of proximity targets to capture distinct aspect of style. CLIP similarity captures high-level semantics and composition. It supports content level recall and text–image alignment (Radford et al., 2021; Hessel et al., 2021). It has also been used for data attribution through embedding-space distribution analysis (Joshi et al., 2026). It is used widely but is known to have limitations such as sensitivity to prompt wording, dataset biases, and weaker performance on fine-grained differences (Shao et al., 2023). LPIPS measures perceptual closeness via deep feature distances. It reflects aesthetics properties such as structure and texture (Zhang et al., 2018a). LPIPS is often included in training objectives for diffusion and restoration to improve realism and to probe the perception–distortion tradeoff (Ho et al., 2022; Saharia et al., 2022b). Recent studies have shown that it can be vulnerable to adversarial perturbations and may misalign with human judgments under distribution shift (Kettunen et al., 2019; Ghazanfari et al., 2023). CSD encodes content-invariant style cues such as color palettes, texture statistics, and stroke patterns (Somepalli et al., 2024). It serves as a style fidelity metric for image-driven style transfer (Xing et al., 2024) and as a pre-trained style embedding for cosine-similarity scoring against reference image to maintain style consistency (Mou et al., 2025). The quality of the proximity score, depends on how diverse and well-covered the curated training dataset is, which was built by finding style tags in high-aesthetic LAION captions, removing overly common tags, dropping broken URLs, and deduplicating near-duplicate images while merging their tags.

Motif extraction and blending: We construct challenger template via a two-stage pipeline. First, we perform motif extraction by analyzing each artwork to identify content elements (objects, structures, and spatial components). This is done by retrieving commonly referenced names and descriptions from art-historical sources (e.g., museum and curatorial references), ensuring the motif reflects established descriptive conventions.

Second, we generate challenger template by blending motifs at varying levels. For an artwork with R motifs, we enumerate all non-empty motif combinations and convert each combination into a coherent, style-neutral scene description. From this pool, we sample k challenger template. We keep this k-sized set fixed per artwork for the entire

(a) Challenger Artwork | (b) Without defender template (DT) | (c) DT: The Three Trees, Autumn by Claude Monet | (d) DT: Autumn Effect at Argenteuil by Claude Monet | (e) DT: Number 3 by Jackson Pollock | (f) DT: Number 48 by Jackson Pollock

Figure 5: Representative Motif Duel instance for **SD v1.5** under semantics-based proximity, with a challenger artwork tested against four distinct defenders. The challenger artwork is *Sunset on the Seine at Lavacourt, Winter Effect* by Claude Monet and the motif-derived prompt is given by: "The scene features muted winter sunset light with pastel tones, a river reflecting shimmering light, a hazy softness over structures, and a winter landscape with sparse, bare trees." Column (a) shows the challenger artwork. Column (b) shows the image generated using only the motif-derived prompt without any defender template (DT). Columns (c) to (f) show images generated by combining the motif-derived prompt with different defender templates, where each defender template specifies a particular artwork and artist (refer Algorithm 1, step 2).

tournament to ensure consistent and comparable matchups across rounds. We present an example of motifs description that were extracted and prompts after blending them in Tables 3 and 4. Prompt templates for motif extraction and motif blending, along with the source list used for motif descriptions, are provided in the Appendix (refer Figures 7, 8 and 9). All stages of this pipeline are executed using GPT-4o. Additional details are provided in the Appendix (refer Section A.2).

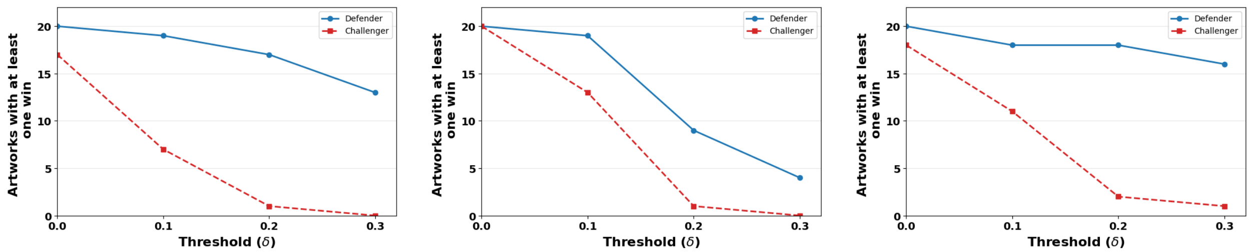
Style learning: After the tournament, we perform stylistic fine-tuning of SD v1.5, SDXL, and SANA-1.5 on the bottom five artworks for each model, and again conduct tournament under the same conditions. This tests whether repeated exposure strengthens the internal style embedding of these weak samples and increases their chances to win duels, i.e., whether prior losers can climb to the top by defeating previous leaders.

Experimental setup: We follow Algorithm 1 and run it three times, once per proximity metric: CLIP, LPIPS, and CSD. For Early Trials, prompts of the form "<title(w)> in the style of <artist(w)>" generate $K = 1$ image per artwork using SD v1.5, Stable Diffusion XL, and SANA-1.5. Due to computational complexity and noise from weak imitations, we set the fitness threshold τ_f to select the top twenty artworks by each metric, forming the FitSet. Motif duels are then run in a round robin fashion on FitSet with $R = 5$ rounds per pair, blending challenger motifs with defender templates and computing proximity using the same metric. The threshold (δ) is set to 0, so the winner is the artwork with the higher score. Finally, outcomes are aggregated into Influence Ledgers.

Imitation–Motif Duel consistency: We jointly analyze outcomes from *imitation* measured in Early Trials and from Motif Duels for artworks in the FitSet to see if they point to the same winner. Here, consistency means the winner under imitation matches the winner in the corresponding Motif Duel for the same challenger–defender pair. We then summarize these matches in the matrix over the FitSet, with rows treating artworks as the challenger and columns as the defender. The artworks are arranged as per their imitation rank with A1 being the highest ranked artwork. Each cell records agreement or disagreement between the two outcomes. We count two symmetric types of agreement: **Challenger agreement** when the row artwork wins in both imitation and Motif Duel, and **Defender agreement** when the column artwork wins in both imitation and Motif Duel. We also count **Disagreement** when neither row artwork nor column artwork wins in both imitation and Motif Duel. These counts indicate where imitation strength aligns with duel performance across the matrix.

5 Results and Analysis

1. **Motif Duels reveals the unpredictable influence of artistic priors**: Figure 5 (see also Figures 18 and 19 in the Appendix) illustrates how generated outputs evolve when challenger and defender signals are combined within the prompt. The visual variations observed across images (c)–(f) indicate that the challenger contributes elements of content, while each defender imparts distinct stylistic characteristics. These combinations exhibit inherent unpredictability, as the challenger and defender signals interact with varying intensities across different pairings.
   For instance, in Figure 5, image (c) preserves only a limited set of texture-based elements from the challenger artwork, whereas image (d) retains aspects of the challenger's color composition. Similarly, Figure 4 demonstrates that introducing a new defender injects its own stylistic priors, even when most of the prompt remains unchanged.



(a) Semantics (b) Aesthetics (c) Fidelity

Figure 6: **Sensitivity analysis of threshold** (δ) used to award rounds for **SD v1.5** with proximity (a) Semantics, (b) Aesthetics, and (c) Fidelity. The x-axis represents the different threshold values and the y-axis represent the number of artworks (defender and challenger) with at least one win.

This further reinforces that generative outputs can shift in unexpected ways due to the complex interplay between content and stylistic signals.

2. **Stylistic leakage is multi-dimensional, requiring multiple proximity metrics for a holistic view**: Tables 1, 8, and 9 show that the model captures stylistic dimensions in a differentiated manner, with distinct strengths across semantic, aesthetic, and fidelity aspects. *Entry Trials* show minimal overlap among artworks, with no single piece consistently added to `FitSet` across all three proximity metrics (refer Table 5, 6, and 7). Moreover, we observe that for some artworks, the model captures specific attribute more strongly than the others (refer to Figures 2 and 3). This variation reflects the multi-faceted nature of style representation. Different proximity metrics capture distinct aspects of how the model internalizes artistic features. Together, these complementary signals highlight why style leakage must be examined from multiple perspectives.
3. **Models tend to have liking towards some artists** : An interesting pattern across the influence ledgers is that models tend to develop likings toward certain artists whose styles repeatedly dominate their proximity-based rankings. In **SDXL**, for instance, Vincent van Gogh is among the top performers across the Semantic, Aesthetic, and Fidelity ledgers. (See Figure 1 and Table 8). **SANA-1.5** shows a similar tendency, with Andy Warhol frequently appearing among the leading positions (refer to Table 9), while Jackson Pollock exhibits strong performance in Fidelity and Aesthetics. In contrast, **SD v1.5** does not exhibit such a pronounced preference; instead, its influence ledgers display a relatively balanced distribution of stylistic leakage. This indicates that SD v1.5's leakage potential is shared across multiple artists (see Table 1). This difference may stem from model size, as larger models are likely to internalize and surface strongly represented stylistic features.
4. **Leakage potential of an artwork tends to influence the win as challenger or defender**: Leakage potential influences whether an artwork succeeds as a challenger or a defender in pairwise evaluations. Artworks with higher leakage potential tend to achieve wins in both roles, indicating that their representations can be activated through both motif or explicit textual references. As can be seen in Table 8, *Still Life – Vase with Twelve Sunflowers* records 36 total wins (17 as challenger, 19 as defender), while *Wheat Fields at Auvers Under Clouded Sky* records 32 wins (16 in each role) under the SDXL (CSD) setup. In contrast, artworks with lower leakage potential exhibit a more asymmetric pattern. *Waterloo Bridge, London* records 12 defender wins but only 3 challenger wins, and *Weeping Woman* shows 13 defender wins and none as a challenger prior to fine-tuning (refer Table 1). This suggests that while all evaluated artworks are relatively reproducible under explicit attribution, only those with higher leakage potential generalize reliably from motif-level cues, whereas artworks with lower leakage potential depend more strongly on explicit mention of stylistic cues to influence generation. We also notice an opposite trend: in SDXL, wins as challenger often exceed wins as defender (refer Table 8). This indicates that SDXL has a higher leakage potential than SD v1.5, as it can activate style representations from motifs more effectively without relying on stylistic cues.
5. **Stylistic fine-tuning tends to impact leakage potential**: Table 1 highlights the shift in the raking post fine-tuning. We observe notable shifts in all three influence ledgers—Semantic, Aesthetics, and Fidelity. Most interestingly, the artist whose work was used for fine-tuning often moves to the top positions. For example, in the Fidelity ledger, Picasso's *Weeping Woman* jumps from Rank 18 (0 challenger wins, 13 defender wins) to Rank 1 after fine-tuning, in Aesthetics ledger Andy Wahrol's *Spam* climbs to Rank 1 and Claude Monet's *Pool with Waterlilies* climbs up 3 places to claim the top spot in the Semantic ledger. Also, the reshuffling in the lower half of the ledger confirms that targeted fine-tuning strengths the representation of that artwork in the model's parameter space. For example, Jackson Pollock's *Number 3* and *Number 48* improve by two ranks each in the Semantic ledger and Van Gogh's *Daubigny's Garden* climbs from Rank 16 to Rank 8. For SANA-1.5 (refer Table 9), we observe more competitive shifts. For example, in Semantic ledger artwork *A Corner of the Garden at Montegron* by Claude Monet climbs six places to move to 11th place from 17th whereas *After Marilyn Pink* by Andy Warhol rose from 18 to 13th place

Table 1: Influence Ledgers from Motif Duels for **SD v1.5**. Each table presents results in the order **Semantic**, **Aesthetics**, and **Fidelity** (top to bottom). Ranks are assigned by total wins, with challenger wins used as a tie-breaker. The tables on the right show rankings after fine-tuning, where ▲+x denotes improvements and ▼-x denotes declines in rank. Lower ranks indicate greater leakage potential. In the pre-trained setting (tables on the left), we display the top-3 and bottom-5 artworks, and we report their updated ranks following stylistic fine-tuning in the corresponding tables on the right.

Rank	Artwork (Pre-trained)	Wins as Challenger	Wins as Defender
1	Leonardo da Vinci, *Madonna Litta (Madonna and the Child)*	16	13
2	Vincent van Gogh, *Wheat Fields at Auvers Under Clouded Sky*	13	15
3	Claude Monet, *Pool with Waterlilies*	13	15
16	Claude Monet, *Yachts at Argenteuil*	4	7
17	Claude Monet, *Small Branch of the Seine*	4	6
18	Jackson Pollock, *Number 3*	1	10
19	Jackson Pollock, *Number 48*	1	8
20	Raphael, *The Fall on the Road to Calvary*	0	9

Rank	Artwork (Post stylistic fine-tuning)
1	Claude Monet, *Pool with Waterlilies* ▲+3
2	Leonardo da Vinci, *Madonna Litta (Madonna and the Child)* ▼-1
4	Vincent van Gogh, *Wheat Fields at Auvers Under Clouded Sky* ▼-2
16	Jackson Pollock, *Number 3* ▲+2
17	Jackson Pollock, *Number 48* ▲+2
18	Claude Monet, *Yachts at Argenteuil* ▼-2
19	Claude Monet, *Small Branch of the Seine* ▼-2
20	Raphael, *The Fall on the Road to Calvary*

Rank	Artwork (Pre-trained)	Wins as Challenger	Wins as Defender
1	Vincent van Gogh, *Olive Grove*	19	12
2	Vincent van Gogh, *A Group of Cottages*	14	12
3	Vincent van Gogh, *Wheat Field at Auvers with White House*	14	12
16	Vincent van Gogh, *Daubigny's Garden*	7	8
17	Claude Monet, *Waterloo Bridge, London*	3	12
18	Pablo Picasso, *Weeping Woman*	0	13
19	Claude Monet, *The Sea Seen from the Cliffs of Fecamp*	0	12
20	Vincent van Gogh, *Flowering Garden*	0	7

Rank	Artwork (Post stylistic fine-tuning)
1	Pablo Picasso, *Weeping Woman* ▲+17
3	Vincent van Gogh, *Olive Grove* ▼-2
6	Vincent van Gogh, *Wheat Field at Auvers with White House* ▼-3
8	Vincent van Gogh, *Daubigny's Garden* ▲+9
9	Vincent van Gogh, *A Group of Cottages* ▼-7
15	Vincent van Gogh, *Flowering Garden* ▲+5
16	Claude Monet, *The Sea Seen from the Cliffs of Fecamp* ▲+3
17	Claude Monet, *Waterloo Bridge, London* ▼-1

Rank	Artwork (Pre-trained)	Wins as Challenger	Wins as Defender
1	Jackson Pollock, *Circumcision January*	17	15
2	Jackson Pollock, *Number 17*	17	15
3	Andy Warhol, *Spam*	19	12
16	Jackson Pollock, *Enchanted Forest*	8	3
17	Claude Monet, *Houses of Parliament, Fog Effect*	8	2
18	Claude Monet, *Lavacourt, Sun and Snow*	7	5
19	Jackson Pollock, *Number 4*	6	4
20	Andy Warhol, *Rorschach*	2	0

Rank	Artwork (Post stylistic fine-tuning)
1	Andy Warhol, *Spam* ▲+2
2	Jackson Pollock, *Circumcision January* ▼-1
3	Jackson Pollock, *Number 17* ▼-1
11	Jackson Pollock, *Enchanted Forest* ▲+5
16	Jackson Pollock, *Number 4* ▲+3
17	Andy Warhol, *Rorschach* ▲+3
19	Claude Monet, *Lavacourt, Sun and Snow*
20	Claude Monet, *Houses of Parliament, Fog Effect* ▼-2

(refer Table 9). Such large jumps are again observed in Aesthetics ledger where Sunny Lawn in a Public Park jumped 10 places to move to Top-10. This suggests that SANA-1.5 demonstrates comparatively high sensitivity to stylistic fine-tuning.

6. **Effect of stylistic fine-tuning on the top contenders is minimal**: Across the Influence Ledgers, we observe that the artworks which occupy top ranks before stylistic fine-tuning show little to no movement after stylistic fine-tuning. A likely reason is that these leaders are deeply embedded in the model's parameter space as a result of the pre-training data containing more duplicates or near-duplicates of these works. This deep embedding makes their representations strong and unlikely to be disturbed with a small amount of stylistic fine-tuning. Since the stylistic fine-tuning is applied only to the bottom five contenders, the model does not see these artworks enough times to reliably overtake the top contenders. Interestingly, in Table 1, *Weeping Woman* by Pablo Picasso exhibits a rank jump of 17 after stylistic fine-tuning, yet the top contender, *Olive Grove* by Vincent van Gogh, shifts down by only two ranks. This pattern suggests that targeted stylistic fine-tuning can primarily redistributes positions within the middle and lower tiers rather than overturning leaders, and even when a bottom contender makes a large gain the effect on the very top is modest, so the impact on top contenders is minimal even in extreme cases.
7. **Motif Duel reveals the limits of imitation to capture the stylistic influence**: In Table 2 (and in Tables 10 to 17 in the appendix), the entries below the diagonal correspond to lower-ranked challengers competing against higher-ranked defenders, while entries above the diagonal correspond to higher-ranked challengers facing lower-ranked defenders. We observe relatively few disagreements below the diagonal and a consistent presence of defender agreements in this region, indicating that higher-ranked artworks reliably win when acting as defenders. In contrast, above the diagonal, we observe significantly more disagreements, showing that higher-ranked artworks do not consistently dominate as challengers against lower-ranked defenders. This asymmetry implies that high imitation rank artworks exert stronger influence as defenders under style preservation than as challengers under motif injection. For Aesthetics, we observe the highest agreement on both sides of the diagonal, suggesting that the models capture aesthetic abstraction more faithfully. Therefore, imitation rank provides a useful signal for stylistic influence.
The expected trend suggests that the top ranked artworks should win in both roles and win count would fall roughly linearly with rank. Yet the analysis shows that this relationship is not strictly linear across models and proximities. For example, in the Table 2, artwork A18 records 2 wins despite being ranked below A5, A10, and A13, which achieve zero wins as challenger. Such irregularities are observed consistently across other models and proximity.

Table 2: Imitation–Motif Duel consistency for **SD v1.5 under Semantics-based proximity**. Rows index FitSet artworks (refer Table 5) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: ✓ if the challenger wins in both, ✔ if the defender wins in both, and ✗ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		Defender																				Win Count	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Challenger	A1	-	✗	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✓	✗	✓	✓	✓	✗	✓	8	0
	A2	✔	-	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗	✗	✓	✗	✗	✓	5	1
	A3	✔	✔	-	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	✓	✗	✗	✓	✗	✗	✗	4	2
	A4	✔	✔	✔	-	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	1	3
	A5	✔	✗	✗	✗	-	✗	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	13	1
	A6	✔	✔	✔	✔	✔	-	✗	✓	✗	✓	✓	✓	✗	✗	✓	✗	✓	✗	✗	✗	6	5
	A7	✗	✔	✗	✔	✔	✔	-	✗	✓	✓	✗	✓	✗	✓	✗	✗	✓	✗	✓	✗	6	4
	A8	✔	✔	✔	✔	✔	✔	✔	-	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	0	7
	A9	✔	✔	✔	✔	✔	✔	✔	✔	-	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✓	3	8
	A10	✔	✔	✗	✔	✔	✔	✔	✔	✗	-	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	0	7
	A11	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	-	✓	✗	✓	✗	✗	✓	✓	✓	✓	6	9
	A12	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	-	✗	✗	✗	✗	✓	✓	✗	✗	2	11
	A13	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	-	✗	✗	✗	✗	✗	✗	✗	0	12
	A14	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	-	✗	✗	✓	✗	✗	✗	1	12
	A15	✔	✔	✗	✗	✗	✔	✔	✗	✔	✔	✔	✗	✔	✗	-	✓	✓	✓	✗	✗	3	8
	A16	✔	✗	✗	✔	✔	✔	✔	✔	✔	✗	✔	✗	✔	✗	✔	-	✓	✗	✗	✗	1	10
	A17	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✗	✗	✔	-	✗	✗	✗	0	13
	A18	✗	✗	✗	✗	✔	✗	✗	✗	✔	✔	✗	✗	✗	✗	✔	✔	✗	-	✓	✓	2	5
	A19	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	-	✓	1	18
	A20	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	-	0	18
Win Count	Challenger	0	0	2	0	1	0	1	3	2	3	3	6	1	6	2	4	12	5	4	7	209	
	Defender	17	15	11	14	14	13	12	10	9	9	8	4	6	2	4	4	2	2	0	0		

These deviations indicate that imitation fails to capture how styles interact during generation and strictly evaluates how well an artwork can be reproduced. In practice, generated images are influenced by multiple training artworks, and their stylistic properties emerge from such interactions rather than from a single source. This limitation is also reflected in the larger number of disagreements above the diagonal. Strong imitation does not guarantee dominance in Motif Duels. Motif Duels address this gap by introducing pairwise artwork interaction through motif blending in a round-robin setting, enabling a more direct evaluation of how styles compete and combine. This highlights that interaction-based evaluation is necessary for studying stylistic influence beyond imitation evaluation.

8. **Win margin in Motif Duel tends to indicate the strength of stylistic influence**: In Figure 6 (a) and (c) (see also Figure 20 (a) and (b), and Figure 21 (c) in the Appendix), the number of artworks with at least one win as a defender does not decrease as rapidly with increasing threshold (δ) as it does for challengers. This suggests that defenders tend to outperform challengers across rounds with a larger margin. The result indicates that the model possesses a stronger abstract understanding of the artworks, enabling it to render challenger's motif content in the defender's style more effectively using the defender template.
   In contrast, for Semantics and Fidelity proximity (Figure 6 (b) Figure 20 (c), and Figure 21 (a) and (b) in the Appendix) the number of artworks with at least one win as both defender and challenger as the threshold increases shows a similar trend. This indicates closely matched competition between defenders and challengers, where the challenger motif composition along with the defender template yield generated outputs that are comparably influenced by both styles.
   Interestingly, for SANA-1.5 with aesthetics-based proximity (Figure 21 (b)), the number of artworks with at least one defender win decreases more sharply than that of challengers as the threshold increases. This observation supports our earlier finding with imitation-Motif Duel consistency, where the model is shown to capture aesthetic abstraction more faithfully.

6 Conclusion

This work shows that stylistic influence in text-to-image models is a measurable outcome of training on large and loosely curated datasets. Our experiments reveal that certain styles reappear consistently and asymmetrically across prompts, indicating that stylistic patterns can persist even in the absence of explicit cues. To capture this behavior, we introduced Art Arena, a simple and structured protocol that tests style recall and examines style interactions across controlled settings. In doing so, the framework highlights how stylistic traces behave more like diffuse statistical regularities than isolated memorized examples. Art Arena provides a practical way to observe how training data shapes generative outputs and offers a foundation for more transparent analysis of stylistic behavior in modern diffusion models. Our work also outlines a path toward dataset-aware governance, since the protocol can be integrated into model evaluation pipelines, inform dataset documentation, and support clearer communication around the influence of training data on model outputs.

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A Appendix

A.1 Image Generation Models and Training Datasets

Large-scale text-to-image diffusion models such as Stable Diffusion v1.5 and Stable Diffusion XL (SDXL) are publicly documented to have been trained on subsets of the LAION-5B dataset, a web-scale corpus of image–text pairs constructed from Common Crawl URLs (Rombach et al., 2022a; Schuhmann et al., 2022). Official model documentation confirms that Stable Diffusion v1.x models were trained on filtered subsets including LAION-2B-en, LAION-high-resolution, and LAION-Aesthetics (Rombach et al., 2022a). The use of LAION-derived data has also been acknowledged in legal proceedings, including *Andersen et al. v. Stability AI* in the United States and *Getty Images v. Stability AI* in the United Kingdom, where it was treated as undisputed that Stable Diffusion models were trained on large-scale web-scraped image–text datasets containing copyrighted material (Andersen et al., 2023; Lindberg, 2024; High Court of Justice of England and Wales, 2025; Coulter, 2024). While SDXL does not release a granular dataset manifest, Stability AI has stated that SDXL follows the same large-scale LAION-based data curation paradigm as earlier Stable Diffusion models (Stability AI, 2023). In contrast, newer models such as SANA-1.5 do not publicly disclose their training datasets, reflecting a broader lack of dataset transparency in contemporary foundation model research rather than contradicting the established role of LAION-style corpora.

The LAION datasets were constructed through automated scraping of publicly accessible web images and associated text using Common Crawl, followed by weakly supervised filtering based on CLIP similarity, language detection, resolution constraints, and heuristic classifiers for aesthetic quality and NSFW content. Although LAION distributes only URLs and captions rather than hosting images directly, multiple studies note that semantic and stylistic information from the underlying images is nonetheless absorbed into model parameters during training (Rombach et al., 2022a; Carlini et al., 2023). This emphasis on scale and diversity over manual curation results in datasets containing artworks, illustrations, photographs, stock imagery, and user-generated content spanning a wide range of artistic styles and creators.

Subsequent analyses and investigations have highlighted significant issues with this data collection strategy. Empirical audits and journalistic investigations have shown that LAION subsets contain copyrighted artworks, recognizable characters, and works attributable to living artists, often without consent or licensing (Jiang, 2025; Wiggers, 2024). These findings underpin ongoing copyright litigation against Stability AI and related entities (Andersen et al., 2023; High Court of Justice of England and Wales, 2025). More critically, independent researchers and watchdog organizations reported the presence of harmful and illegal material, including suspected child sexual abuse material (CSAM), within portions of LAION-5B (Thiel, 2023; Cole, 2023). In response, LAION removed known CSAM hashes, introduced stricter filtering, and released revised dataset versions with enhanced safety measures (LAION e.V., 2024). However, these interventions occurred after earlier diffusion models had already been trained and cannot retroactively remove learned representations embedded in model parameters.

This dataset lineage motivates the need for systematic auditing of stylistic behavior in generative models. Training on large-scale, weakly curated datasets such as LAION exposes diffusion models to dense concentrations of artworks and recurring stylistic patterns, which prior work suggests are internalized as distributed statistical regularities rather than explicit memorization (Rombach et al., 2022a; Carlini et al., 2023). These *stored stylistic traces* may reappear during generation even when stylistic cues are not explicitly requested, leading to the silent appearance of recognizable stylistic features. Because such influence is neither directly observable in model parameters nor reliably captured by prompt-based qualitative analysis, existing evaluation approaches remain insufficient for disentangling explicit attribution, interaction, and unprompted stylistic re-emergence. To address this gap, *Art Arena* formalizes stylistic influence as a measurable construct, converting it into an empirical signal through structured comparisons. By doing so, *Art Arena* enables systematic auditing of stylistic leakage and provides insight into how large-scale training data shapes generative behavior, with applicability beyond text-to-image models to other generative modalities.

A.2 Motif Extraction

This section describes the process used to extract motifs for running **Motif Duels**, an essential evaluation method in *ArtArena*. For every artwork in the `FitSet`, we generate a *content-only* list of motifs using structured prompts (Figure 7) given to GPT-4o. These prompts instruct the model to identify only the concrete, visible elements in the image, such as objects, structures, symbols, and spatial components, while avoiding any references to style, artist identity, mood, medium, or lighting. The result is a clean, style-neutral motif list that represents the artwork's content in a consistent and comparable way.

Motifs Extraction Prompt

Instruction. Analyze the artwork "{artwork_name}" by "{artist_name}" and identify the most important motifs present in it. Consult reliable sources ({source}) to obtain the commonly used motif names and concise descriptions. Return the output in the following structure:

```
[
  {artwork_name}:  [
     {motif1:  description},
     {motif2:  description},
     ...
  ]
]
```

Figure 7: **Motif-Extraction Prompt**: Prompt used to extract motif names and natural-language motif descriptions for an artwork, based on terminology commonly used in reliable art-historical sources. The sources used are mentioned in Figure 8.

Museum & Institutional Sources for Motifs Extraction

Museum & Institutional Sources for Motifs Extraction
Best for authoritative descriptions, curatorial language, and visual motifs

1. **The Metropolitan Museum of Art (The Met) — Heilbrunn Timeline of Art History**
   `https://www.metmuseum.org`
   Strengths: clear visual descriptions; motif-level analysis of gesture, composition, light, and material; especially strong for Caravaggio, Raphael, Warhol, and Monet.

2. **Van Gogh Museum (Amsterdam)**
   `https://www.vangoghmuseum.nl`
   Strengths: exceptionally detailed analysis of brushwork, colour, and rhythm; explicit ground, sky, and vegetation motifs; ideal for prompt-oriented extraction.

3. **National Gallery (London) & National Gallery of Art (Washington)**
   `https://www.nationalgallery.org.uk | https://www.nga.gov`
   Strengths: balanced formal and emotional descriptions; strong for portraits, interiors, and compositional motifs.

4. **Musée d'Orsay (Paris)**
   `https://www.musee-orsay.fr`
   Strengths: Impressionist & Post-Impressionist motif language; atmosphere, light, and seasonal landscape descriptions.

High-Quality Secondary Art Databases
Best for concise motif phrasing and comparative analysis

5. **WikiArt**
   `https://www.wikiart.org`
   Strengths: aggregated descriptions across styles; quick identification of recurring motifs; good cross-artist consistency.

6. **Artchive**
   `http://www.artchive.com`
   Strengths: short, prompt-friendly summaries; emphasis on composition and movement.

7. **WahooArt**
   `https://www.wahooart.com`
   Strengths: plain-language visual descriptions; helpful for classical and Renaissance works.

Scholarly / Curatorial Commentary
Best for deeper motif interpretation

8. **Tate (UK)**
   `https://www.tate.org.uk`
   Strengths: excellent for modern and contemporary art; clear explanations of abstraction, repetition, and symbolism.

9. **MoMA (Museum of Modern Art)**
   `https://www.moma.org`
   Strengths: essential for Pollock and Warhol; focus on process, material, and conceptual motifs.

10. **Kröller-Müller Museum**
    `https://krollermuller.nl`
    Strengths: landscape-focused Van Gogh analysis; strong treatment of ground, vegetation, and sky motifs.

Art History & Analysis Sites
Best for motif phrasing usable directly in prompts

11. **The Collector**
`https://www.thecollector.com`
Strengths: accessible yet rigorous analysis; frequent discussion of symbolic and compositional motifs.

12. **ArtUK**
`https://artuk.org`
Strengths: British collections with strong descriptive metadata.

13. **Google Arts & Culture**
`https://artsandculture.google.com`
Strengths: high-resolution imagery with curatorial summaries; useful for spatial organisation and colour-field understanding.

Figure 8: Sources used to extract motif names and descriptions as commonly referenced by curators, art historians, and authoritative museum databases.

Motifs Blending Prompt (Challenger)

Input: You need to generate prompts by blending the motifs from {content}. Motifs represent **CONTENT ONLY** (objects, structures, symbols, spatial elements). They do **NOT** represent style, artist identity, mood, or medium.

Task:

- Generate **ALL** non-empty combinations of the given motifs. If there are N motifs, generate exactly $2^N - 1$ combinations.
- Each combination must be used to construct **ONE** prompt.

Constraints:

- The prompt MUST describe ONLY the motifs as visible scene content.
- The prompt MUST be compatible with later injection of external style or artist tokens.
- The prompt must be content-complete but stylistically neutral.

Prompt Construction Rules: For each motif combination:

- Describe a single coherent scene that includes all motifs.
- Use literal, concrete, observational language.
- No references to famous artists, art movements, or mediums.
- No mood words (e.g., dramatic, surreal, expressive).
- No composition embellishment beyond spatial relations strictly required to place motifs.
- Do NOT infer symbolism beyond what is visually explicit.
- Do not exceed 70 tokens per prompt.

Output Format: Return STRICT JSON ONLY with the following structure.

```
{
  "num_motifs": N,
  "expected_combinations": 2^N - 1,
  "items": [
    {
      "combo_id": integer,
      "motifs": [exact motif strings],
      "content_prompt": "A single neutral content-only scene description suitable for
      style leakage testing.",
      "style_injection_slot": "{{STYLE_OR_ARTIST_TO_BE_INJECTED_LATER}}"
    }
  ]
}
```

Ordering Constraints:

- Sort combinations by increasing number of motifs (1 → N).
- Preserve the original motif order inside each combination.
- Do not repeat or merge combinations.

```
Generate the output now
```

Figure 9: **Motif-based challenger prompt construction**: We enumerate motif combinations and blend them into coherent, style-neutral scene descriptions used as challenger prompts in Motif Duels

Including clear **Style Influence Constraints** and **Prompt Construction Rules** in this process is important for separating content from style. Without these rules, extra clues like artistic terms, emotional language, or medium descriptors could unintentionally influence the behavior of image generation models, making it harder to tell whether the model understands the actual content of the scene. Our framework prevents this in three ways. First, it enforces a strict content-only vocabulary, ensuring that motifs are free of stylistic hints. Second, for a motif set of size N, the method generates prompts for all non-empty combinations of motifs, producing exactly $2^N - 1$ prompts. This full combinatorial coverage helps reveal how models handle different content combinations without style interference. Third, the prompt rules require short, neutral descriptions that use only minimal spatial details, keeping the phrasing simple and style-free while also allowing later style injection when needed.

Together, this motif extraction process and the controlled prompting rules create a reliable testing setup for Motif Duels. Each prompt acts as a focused test of whether a model can represent and combine content correctly, while style remains fully separated. This enables precise measurement of style influence, consistent comparison across artworks, and a stable foundation for later experiments where style can be introduced independently of content.

The following detailed sources (Figure 8) were used to retrieve the necessary motifs. In the above mentioned prompt, the agent is not just provided with the artwork name and the artist name but also with the artwork image for better capturing of motifs.

A.3 Artworks and their extracted motifs

In this section, we provide examples of the extracted motif corresponding to two of the most famous artworks namely "The Starry Night by Vincent Van Gogh" and "The Scream by Edvard Munch". The table 3 describes the types of motifs extracted and the corresponding motifs descriptions for each of the motif. The table 4 represent the crafted prompts corresponding to various combinations using the extracted motifs. The above mentioned tables help us better understand how different motifs of the same artworks can be carefully combined, such that they semantically are correct.

In the above visual results of the various motifs, their combinations illustrate that simply adding more motifs does not monotonically strengthen an artwork's stylistic influence. Instead, the influence saturates, plateaus, or can even weaken depending on how well the model has internalized that artwork's stylistic schema. This reinforces why the proposed Motif Duel setup is necessary: pairwise battleground evaluations reveal whether an artwork's style genuinely exerts a deep, distributed pull on the model's parameter space, or whether its influence collapses once motifs are hybridized with competing styles. By forcing artworks to confront one another as both challenger and defender, the duel framework exposes these asymmetric and nonlinear behaviors—showing which styles survive aggressive recombination and which dissipate under motif blending. Consequently, motif duels provide a more faithful measure of leakage potential than raw motif similarity alone, capturing how style representations behave when activated indirectly, competitively, and compositionally.

Table 3: Examples of the extracted motif for different artworks.

Artwork	Motifs
The Starry Night by Vincent Van Gogh	Night sky Swirling cloud band Village Church steeple Cypress tree
Pool with Waterlilies by Claude Monet	Water lilies Water reflections Natural vegetation
The Scream by Vincent van Gogh	Figure on bridge Bridge railing Two distant figures Waterbody Horizon and landform
The Fall on the Road to Calvary by Raphael	The Cross The Fallen Christ The Mourning Women Roman Soldiers
The Ascension Of Christ by Rembrandt	Central figure of Christ Cherubic angels Group of observers Vegetative motifs

Table 4: **Motifs extraction and blending**. Extracted motifs and their blending to construct the prompt for the artwork. The list of extracted motifs and prompts for different artworks is provided in the Table 3.

Artwork	Motifs	Prompt
The Starry Night by Vincent Van Gogh	Night sky, Village	A dark sky with many stars above a small cluster of buildings at the base of the hills.
	Cypress tree, Swirling cloud band	A tall tree mass in the foreground with a broad curved band of clouds crossing behind it.
	Church steeple, Night sky, Village	A pointed steeple rising above clustered houses beneath a star-filled sky.
	Swirling cloud band, Night sky, Cypress tree	A curved band of clouds moving across a starry sky with a tall tree mass in the foreground.
	Village, Cypress tree, Church steeple, Night sky	A group of small buildings and a narrow steeple near a tall foreground tree under a dark starry sky.
The Scream by Edvard Munch	Figure on bridge, Waterbody	A central figure standing on a bridge with a stretch of water visible beyond it.
	Bridge railing, Two distant figures, Horizon and landform	A walkway with railings receding into depth and two small figures near a low horizon with landforms.
	Figure on bridge, Bridge railing, Horizon and landform	A main figure on a bridge with horizontal planks and a distant low horizon of landmasses.
	Waterbody, Bridge railing	A wide body of water seen past the receding railings of a wooden bridge.
	Figure on bridge, Two distant figures, Waterbody, Horizon and landform	A central figure with two smaller figures farther back on a bridge overlooking water and a low horizon of landforms.

Table 5: Artworks in the FitSet for **SD v1.5** for proximity: Semantics (CLIP), Fidelity (CSD), and Aesthetics (LPIPS).

Rank	Semantics (CLIP)	Fidelity (CSD)	Aesthetics (LPIPS)
1	Sunset on the Seine at Lavacourt, Winter Effect by Claude Monet	Olive Grove by Vincent van Gogh	Spam by Andy Warhol
2	The Three Trees, Autumn by Claude Monet	A Group of Cottages by Vincent van Gogh	Number 17 by Jackson Pollock
3	Autumn Effect at Argenteuil by Claude Monet	Entrance to the Public Garden in Arles by Vincent van Gogh	Circumcision January by Jackson Pollock
4	Crucifixion by Raphael	Le Mas de Saint-Paul (A Meadow in the Mountains) by Vincent van Gogh	Untitled (Green Silver) by Jackson Pollock
5	Madonna Litta (Madonna and the Child) by Leonardo da Vinci	The Garden of Saint-Paul Hospital by Vincent van Gogh	Mural by Jackson Pollock
6	Water Lilies Red by Claude Monet	Waterloo Bridge, London by Claude Monet	Sibyl Erithraea by Michelangelo Sistine Chapel Ceiling
7	Wheat Fields at Auvers Under Clouded Sky by Vincent van Gogh	Wheat Field at Auvers with White House by Vincent van Gogh	Ocean Greyness by Jackson Pollock
8	The Fall on the Road to Calvary by Raphael	Avenue in the Park by Vincent van Gogh	Birth by Jackson Pollock
9	Wheat Field with the Alpilles Foothills in the Background by Vincent van Gogh	Poppy Field in Giverny by Claude Monet	Chestnut Trees in Blossom by Vincent van Gogh (1887)
10	Olive Grove - Orange Sky by Vincent van Gogh	Flower Garden by Gustav Klimt	The Beach at Sainte-Adresse by Claude Monet
11	Pool with Waterlilies by Claude Monet	Green Wheat Fields by Vincent van Gogh	Number 48 by Jackson Pollock
12	Yachts At Argenteuil by Claude Monet	Public Garden with Couple and Blue Fir Tree (The Poet's Garden III) by Vincent van Gogh	Mask by Jackson Pollock
13	Nude woman with turkish bonnet by Pablo Picasso	The Sea Seen from the Cliffs of Fecamp by Claude Monet	Trees with Ivy by Vincent van Gogh
14	Small Branch of the Seine by Claude Monet	Flowers on the Banks of Seine near Vetheuil by Claude Monet	Lavacourt, Sun and Snow by Claude Monet
15	Poppy Field in Giverny by Claude Monet	The Church at Auvers by Vincent van Gogh	Chestnut Tree in Blossom by Vincent van Gogh (1890)
16	Vase with Carnations and Other Flowers by Vincent van Gogh	Weeping Woman by Pablo Picasso	Houses of Parliament, Fog Effect by Claude Monet
17	Waves Breaking by Claude Monet	Camille Monet and a Child in the Artist's Garden in Argenteuil by Claude Monet	Number 4 by Jackson Pollock
18	Vase of Peonies on a Small Pedestal by Edouard Manet	Daubigny's Garden by Vincent van Gogh	Enchanted Forest by Jackson Pollock
19	Number 3 by Jackson Pollock	Entrance to a Quarry near Saint Remy by Vincent van Gogh	Number 29 by Jackson Pollock
20	Number 48 by Jackson Pollock	Flowering Garden by Vincent van Gogh	Rorschach by Andy Warhol

Table 6: Artworks in the FitSet for **SDXL** for proximity: Semantics (CLIP), Fidelity (CSD), and Aesthetics (LPIPS).

Rank	Semantics (CLIP)	Fidelity (CSD)	Aesthetics (LPIPS)
1	Vincent's Bedroom in Arles by Vincent van Gogh	Wheat Fields at Auvers Under Clouded Sky by Vincent van Gogh	Sky Above Clouds IV by Georgia O'Keeffe
2	Water Lilies by Claude Monet	Wheat Field with Reaper and Sun by Vincent van Gogh	Black & White (Number 20) by Jackson Pollock
3	Irises by Vincent van Gogh	View of Vessenots near Auvers by Vincent van Gogh	Mademoiselle Gachet in her garden at Auvers-sur-Oise by Vincent van Gogh
4	Wheat Field with Reaper and Sun by Vincent van Gogh	The Garden of Saint-Paul Hospital by Vincent van Gogh	Slightly Open Clam Shell by Georgia O'Keeffe
5	Olive Grove by Vincent van Gogh	Campbell's Soup Cans by Andy Warhol	Wheat Field with Reaper and Sun by Vincent van Gogh
6	Olive Trees with Yellow Sky and Sun by Vincent van Gogh	Composition (White, Black, Blue and Red on White) by Jackson Pollock	Impression, sunrise by Claude Monet
7	Orchard in Bloom by Claude Monet	Mademoiselle Gachet in her garden at Auvers-sur-Oise by Vincent van Gogh	The Sea at Saint-Adresse by Claude Monet
8	Vase with Zinnias by Vincent van Gogh	The Kiss by Gustav Klimt	Tree with Ivy in the Asylum Garden by Vincent van Gogh
9	Blumengarten by Gustav Klimt	Vincent's Bedroom in Arles by Vincent van Gogh	Ice Floes on the Seine at Bougival by Claude Monet
10	Still Life - Vase with Twelve Sunflowers by Vincent van Gogh	Wheat Field at Auvers with White House by Vincent van Gogh	Lady with a Lap Dog by Rembrandt
11	Bouquet of Sunflowers by Claude Monet	A Group of Cottages by Vincent van Gogh	White Aphrodisiac Telephone by Salvador Dali
12	Number 4 by Jackson Pollock	Still Life - Vase with Twelve Sunflowers by Vincent van Gogh	Shadows on the Sea at Pourville by Claude Monet
13	Self Portrait with a Grey Felt Hat by Vincent van Gogh	Untitled (From Marilyn Monroe) by Andy Warhol	The Ploughed Field by Vincent van Gogh
14	The Fall on the Road to Calvary by Raphael	Starry Night Over the Rhone by Vincent van Gogh	Tomb of Giuliano de Medici by Michelangelo
15	Number 48 by Jackson Pollock	Field and Ploughman and Mill by Vincent van Gogh	Irises by Vincent van Gogh
16	Marilyn Monroe by Andy Warhol	Marilyn Monroe by Andy Warhol	Mulberry Tree by Vincent van Gogh
17	After Marilyn Pink by Andy Warhol	Three Marilyns by Andy Warhol	Eyes in the Heat by Jackson Pollock
18	David by Michelangelo	After Marilyn Pink by Andy Warhol	Three female heads with one sleeping by Rembrandt
19	Self Portrait with Felt Hat by Vincent van Gogh	Self Portrait with Pallette by Vincent van Gogh	Bust of Brutus by Michelangelo
20	Incredulity of Saint Thomas by Caravaggio	Number 4 by Jackson Pollock	Design for Julius II tomb (first version) by Michelangelo

Table 7: Artworks in the FitSet for **SANA-1.5** for proximity: Semantics (CLIP), Fidelity (CSD), and Aesthetics (LPIPS).

Rank	Semantics (CLIP)	Fidelity (CSD)	Aesthetics (LPIPS)
1	Green Coca Cola Bottles by Andy Warhol	Convergence (Number 10) by Jackson Pollock	Echo (Number 25) by Jackson Pollock
2	Christ on the Cross by Rembrandt	Marilyn Monroe by Andy Warhol	Black & White (Number 20) by Jackson Pollock
3	The Japanese Bridge (The Bridge in Monet's Garden) by Claude Monet	Cross by Andy Warhol	Number 32 by Jackson Pollock
4	Water Lilies by Claude Monet	Beatles by Andy Warhol	Portrait of a Man by Rembrandt
5	Pathway in Monet's Garden at Giverny by Claude Monet	Marilyn Blue by Andy Warhol	Tree with Ivy in the Asylum Garden by Vincent van Gogh
6	Portrait of Simonetta Vespucci (Portrait of a Young Woman) by Sandro Botticelli	Coca-Cola (3) by Andy Warhol	Daubigny's Garden by Vincent van Gogh
7	Apple Trees on the Chantemesle Hill by Claude Monet	Tree Trunks in the Grass by Vincent van Gogh	Sistine Chapel Ceiling by Michelangelo
8	Coca-Cola (3) by Andy Warhol	Orange Prince by Andy Warhol	A lute player by Caravaggio
9	Pathway in Monet's Garden at Giverny by Claude Monet	Three Marilyns by Andy Warhol	Saint Jerome in Meditation by Caravaggio
10	Portrait with Pink and Blue Face by Henri Matisse	After Marilyn Pink by Andy Warhol	Saskia Wearing A Veil by Rembrandt
11	Untitled (From Marilyn Monroe) pink by Andy Warhol	Haystacks in Provence by Vincent van Gogh	The Garden of Doctor Gachet at Auvers-sur-Oise by Vincent van Gogh
12	Galaxy by Jackson Pollock	The Garden of Doctor Gachet at Auvers-sur-Oise by Vincent van Gogh	Portrait of a Man Wearing a Black Hat by Rembrandt
13	Untitled (From Marilyn Monroe) blue by Andy Warhol	Marilyn Red by Andy Warhol	Portrait of a Man in the Hat Decorated with Pearls by Rembrandt
14	The Alpilles with Olive Trees in the Foreground by Vincent van Gogh	Trees in the Asylum Garden by Vincent van Gogh	Old Man in Prayer by Rembrandt
15	The Ascension Of Christ by Rembrandt	The Alpilles with Olive Trees in the Foreground by Vincent van Gogh	Cathedral by Jackson Pollock
16	Marilyn Monroe by Andy Warhol	Trees in the garden of the Hospital Saint-Paul by Vincent van Gogh	Lighting Study of an Elderly Woman in a White Cap by Rembrandt
17	A Corner of the Garden at Montgeron by Claude Monet	Daubigny's Garden by Vincent van Gogh	Crushed Campbell's Soup Can (Beef Noodle) by Andy Warhol
18	After Marilyn Pink by Andy Warhol	Mademoiselle Gachet in her garden at Auvers-sur-Oise by Vincent van Gogh	Portrait of a Bearded Man in Black Beret by Rembrandt
19	Marilyn Blue by Andy Warhol	Sunny Lawn in a Public Park by Vincent van Gogh	Portrait of a Woman Wearing a Gold Chain by Rembrandt
20	Mickey by Andy Warhol	Untitled (From Marilyn Monroe) by Andy Warhol	Portrait of a seated man rising from his chair by Rembrandt

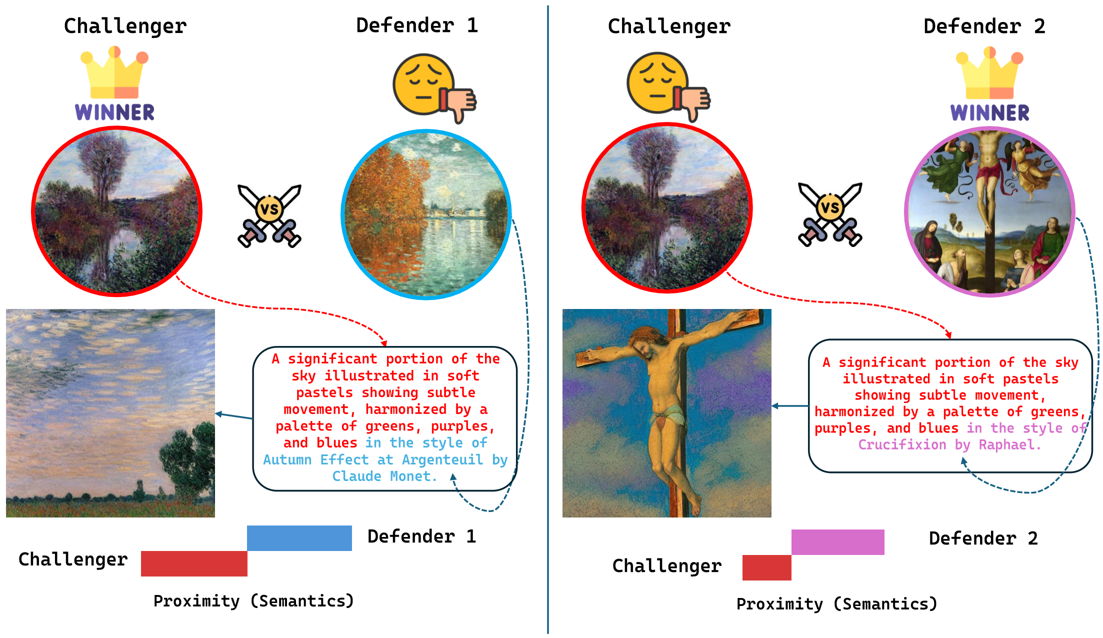


Figure 10: Motif Duel for **SD v1.5** evaluated under the semantic based proximity (CLIP). The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.

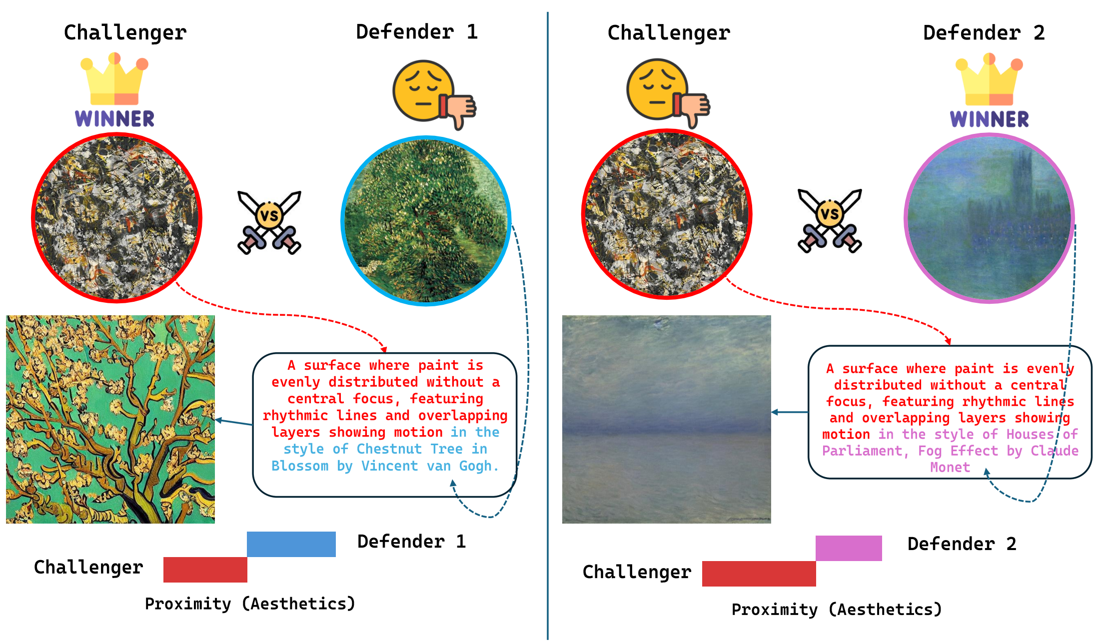


Figure 11: Motif Duel for **SD v1.5** evaluated under the aesthetics based proximity (LPIPS). Lower score indicates better performance. The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.

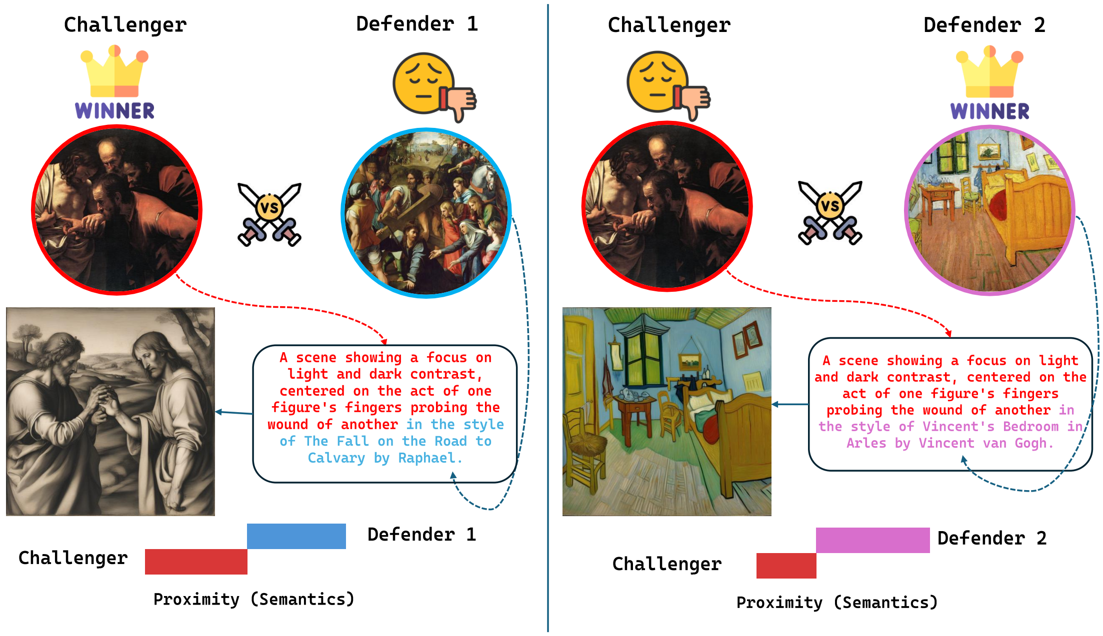


Figure 12: Motif Duel for **SDXL** evaluated under the semantic based proximity (CLIP). Higher score indicates better performance. The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.

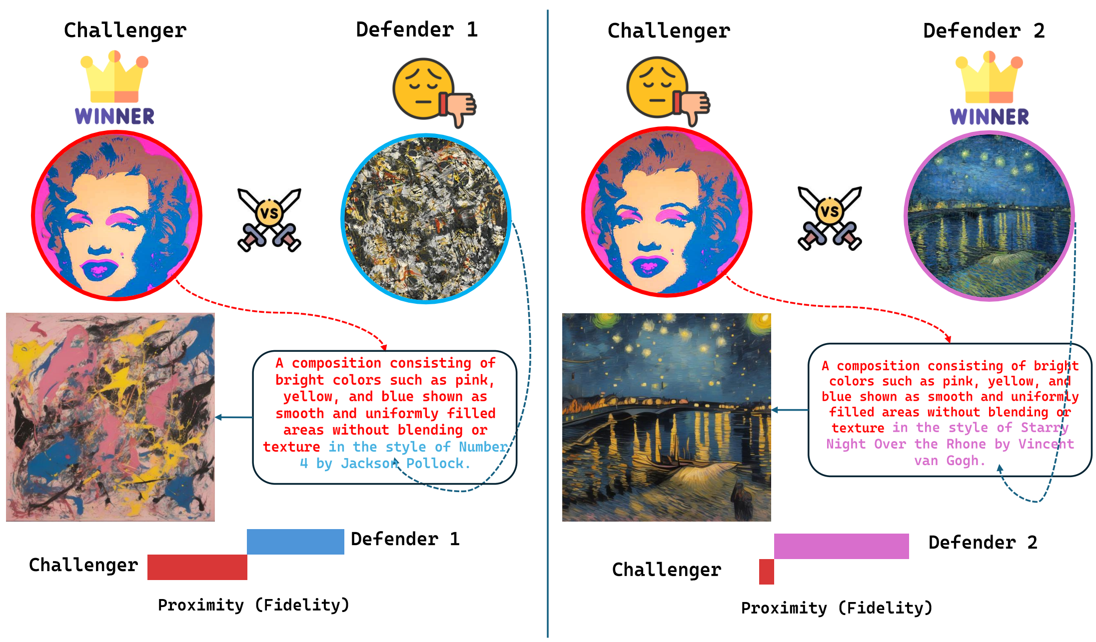


Figure 13: Motif Duel for **SDXL** evaluated under the fidelity based proximity (CSD). Higher score indicates better performance. The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.

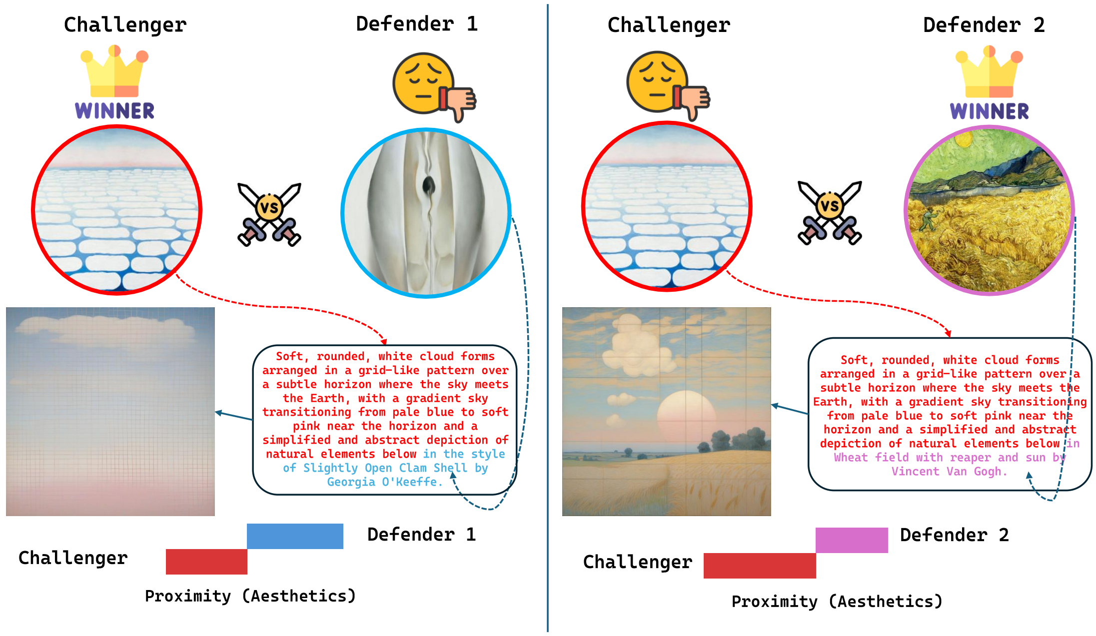


Figure 14: Motif Duel for **SDXL** evaluated under the aesthetics based proximity (LPIPS). Lower score indicates better performance. The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.

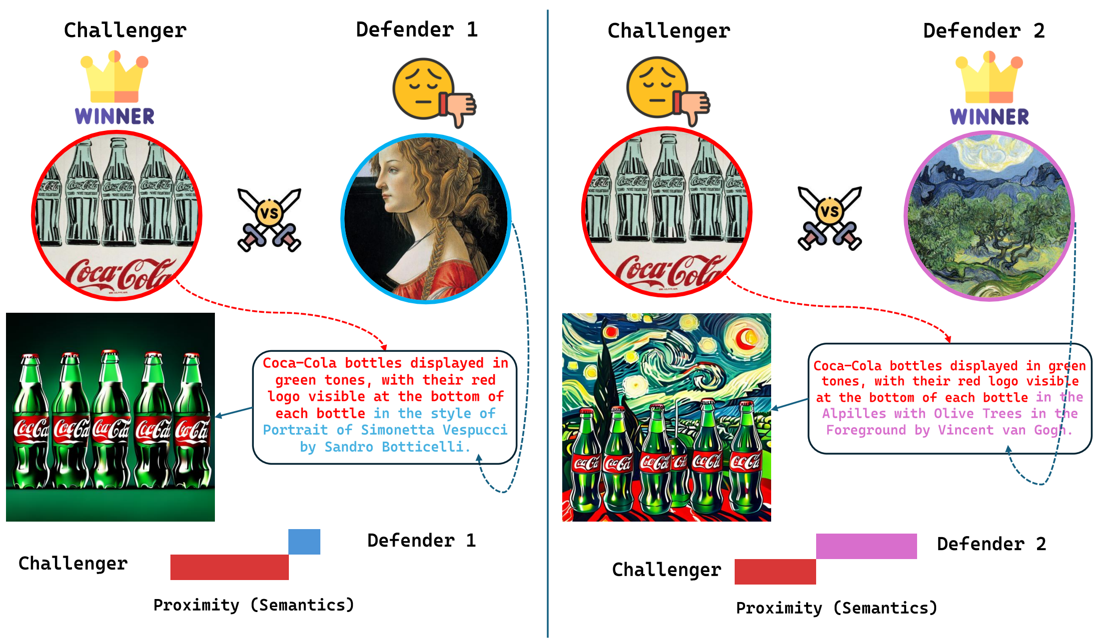


Figure 15: Motif Duel for **SANA-1.5** evaluated under the semantic based proximity (CLIP). Higher score indicates better performance. The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.

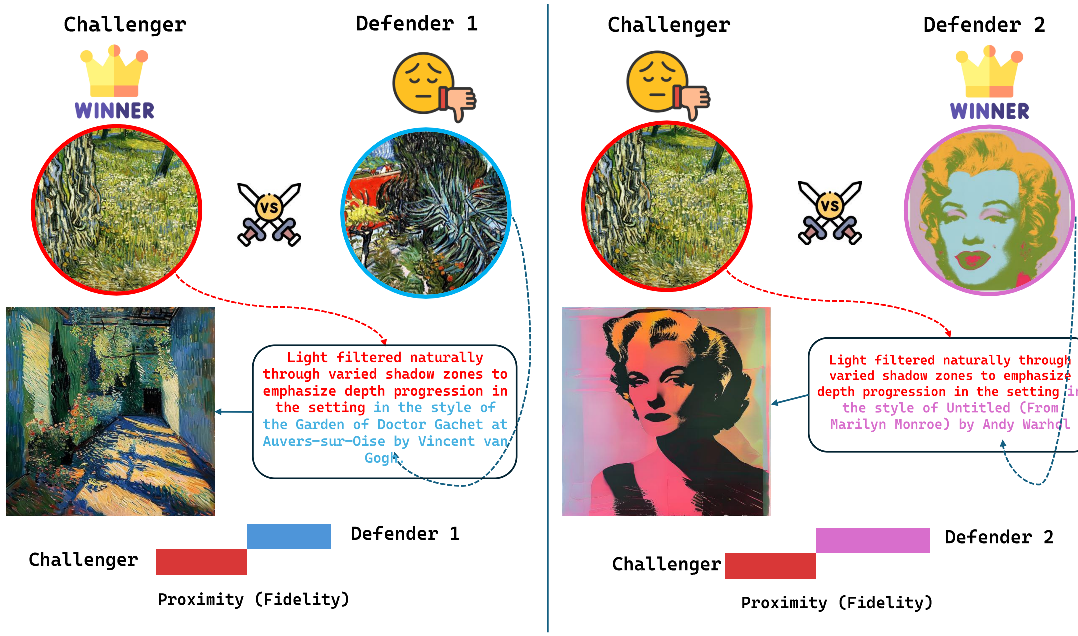


Figure 16: Motif Duel for **SANA-1.5** evaluated under the fidelity based proximity (CSD). Higher score indicates better performance. The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.

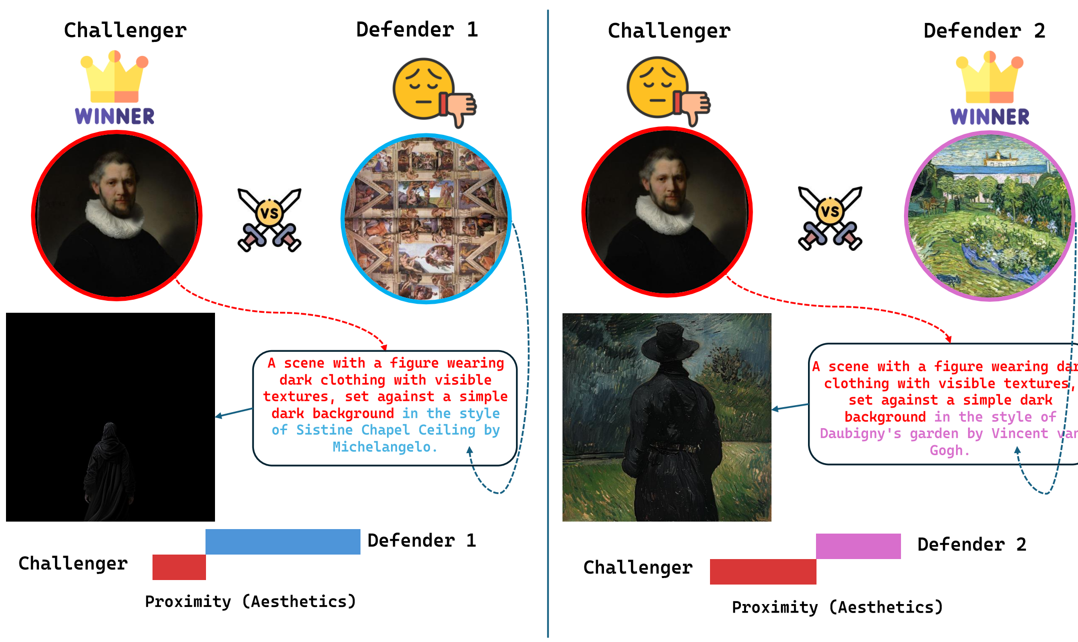
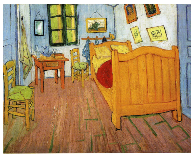


Figure 17: Motif Duel for **SANA-1.5** evaluated under the aesthetics based proximity (LPIPS). Lower score indicates better performance. The challenger contributes the motif which is paired with defender 1 and defender 2 to form two composite prompts. The generated images are then evaluated for proximity to both the challenger and the corresponding defender. The figure shows that the motif composed with different defenders yields stylistically distinct outputs as reflected in the proximity scores.


(a) Challenger Artwork


(b) Without defender template (DT)


(c) DT: Water Lilies by Claude Monet


(d) DT: Irises by Vincent van Gogh


(e) DT: Self Portrait with Felt Hat by Vincent van Gogh


(f) DT: Incredulity of Saint Thomas by Caravaggio

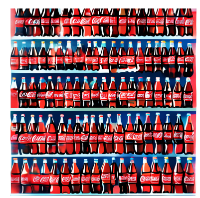
Figure 18: Representative Motif Duel instance for **SDXL** under semantics based proximity, with a challenger artwork tested against four distinct defenders. The challenger artwork is **Vincent's Bedroom in Arles** by Vincent van Gogh and the motif-derived prompt is given by: "A room with a prominent yellow bed, plain wooden chairs with green cushions, and framed pictures on the walls featuring portraits and landscapes." Column (a) shows the challenger artwork. Column (b) shows the image generated using only the motif-derived prompt without any defender template (DT). Columns (c) to (f) show images generated by combining the motif-derived prompt with different defender templates, where each defender template specifies a particular artwork and artist.

(a) Challenger Artwork


(b) Without defender template (DT)

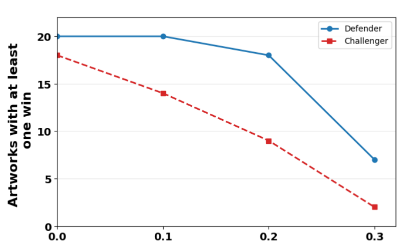

(c) DT: Christ on the Cross by Rembrandt


(d) DT: The Japanese Bridge by Claude Monet

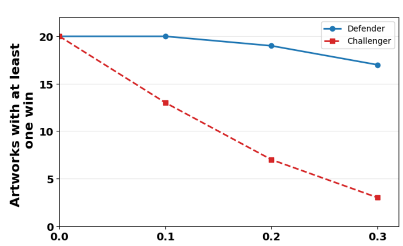

(e) DT: Marilyn Blue by Andy Warhol


(f) DT: Mickey by Andy Warhol

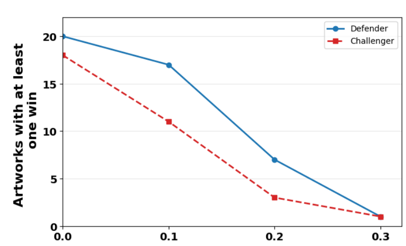
Figure 19: Representative Motif Duel instance for **SANA-1.5** under semantics-based proximity, with a challenger artwork tested against four distinct defenders. The challenger artwork is **Green Coca Cola Bottles** by Andy Warhol and the motif-derived prompt is given by: "Rows of repeating Coca-Cola bottles arranged in a flat layout, emphasizing a lack of visual depth or dimensional perspective." Column (a) shows the challenger artwork. Column (b) shows the image generated using only the motif-derived prompt without any defender template (DT). Columns (c) to (f) show images generated by combining the motif-derived prompt with different defender templates, where each defender template specifies a particular artwork and artist.



(a) Semantics

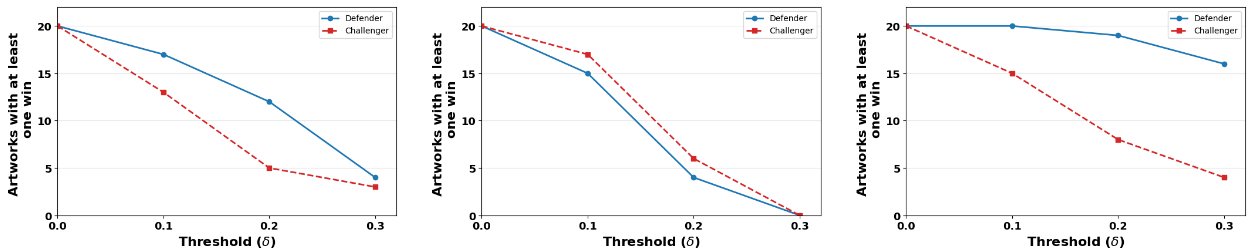


(b) Aesthetics



(c) Fidelity

Figure 20: Sensitivity analysis of threshold (δ) used to award rounds for **SDXL** with proximity (a) Semantics, (b) Aesthetics, and (c) Fidelity. The x-axis represents the value of the threshold and the y-axis represent the number of artworks (defender and challenger) with at least one win.



(a) Semantics (b) Aesthetics (c) Fidelity

Figure 21: Sensitivity analysis of threshold (δ) used to award rounds for **SANA-1.5** with proximity (a) Semantics, (b) Aesthetics, and (c) Fidelity. The x-axis represents the value of the threshold and the y-axis represent the number of artworks (defender and challenger) with at least one win.

Table 8: Influence Ledgers from Motif Duels for **SDXL**. Each table presents results in the order **Semantic**, **Aesthetics**, and **Fidelity** (top to bottom). Ranks are assigned by total wins, with challenger wins used as a tie-breaker. The tables on the right show rankings after fine-tuning, where ▲+x denotes improvements and ▼-x denotes declines in rank. Lower ranks indicate greater leakage potential. In the pre-trained setting (tables on the left), we display the top-3 and bottom-5 artworks, and we report their updated ranks following stylistic fine-tuning in the corresponding tables on the right.

Rank	Artwork (Pre-trained)	Wins as Challenger	Wins as Defender
1	Vincent van Gogh, *Vincent's Bedroom in Arles*	19	12
2	Claude Monet, *Water Lilies*	17	13
3	Vincent van Gogh, *Wheat Field with Reaper and Sun*	16	12
16	Andy Warhol, *Marilyn Monroe*	2	10
17	Michelangelo, *David*	4	7
18	Andy Warhol, *After Marilyn Pink*	2	9
19	Vincent van Gogh, *Self Portrait with Felt Hat*	1	10
20	Caravaggio, *Incredulity of Saint Thomas*	0	5

Rank	Artwork (Post stylistic fine-tuning)
1	Vincent van Gogh, *Vincent's Bedroom in Arles*
2	Claude Monet, *Water Lilies*
4	Vincent van Gogh, *Wheat Field with Reaper and Sun* ▼-1
15	Andy Warhol, *Marilyn Monroe* ▲+1
16	Michelangelo, *David* ▲+1
17	Vincent van Gogh, *Self Portrait with Felt Hat* ▲+2
19	Andy Warhol, *After Marilyn Pink* ▼-1
20	Caravaggio, *Incredulity of Saint Thomas*

Rank	Artwork (Pre-trained)	Wins as Challenger	Wins as Defender
1	Georgia O'Keeffe, *Sky Above Clouds IV*	17	18
2	Jackson Pollock, *Black & White (Number 20)*	15	17
3	Georgia O'Keeffe, *Slightly Open Clam Shell*	17	14
16	Vincent van Gogh, *Mulberry Tree*	1	10
17	Jackson Pollock, *Eyes in the Heat*	1	9
18	Rembrandt, *Three female heads with one sleeping*	2	7
19	Michelangelo, *Bust of Brutus*	0	7
20	Michelangelo, *Design for Julius II tomb (first version)*	0	4

Rank	Artwork (Post stylistic fine-tuning)
1	Georgia O'Keeffe, *Sky Above Clouds IV*
3	Jackson Pollock, *Black & White (Number 20)* ▼-1
4	Georgia O'Keeffe, *Slightly Open Clam Shell* ▼-1
15	Vincent van Gogh, *Mulberry Tree* ▲+1
16	Rembrandt, *Three female heads with one sleeping* ▲+2
18	Jackson Pollock, *Eyes in the Heat* ▼-1
19	Michelangelo, *Design for Julius II tomb (first version)* ▲+1
20	Michelangelo, *Bust of Brutus* ▼-1

Rank	Artwork (Pre-trained)	Wins as Challenger	Wins as Defender
1	Vincent van Gogh, *Wheat Fields at Auvers Under Clouded Sky*	14	18
2	Vincent van Gogh, *Wheat Field with Reaper and Sun*	11	14
3	Vincent van Gogh, *View of Vessenots near Auvers*	9	14
16	Andy Warhol, *Marilyn Monroe*	3	12
17	Andy Warhol, *Three Marilyns*	1	14
18	Andy Warhol, *After Marilyn Pink*	1	13
19	Vincent van Gogh, *Self Portrait with Palette*	2	12
20	Jackson Pollock, *Number 4*	1	12

Rank	Artwork (Post stylistic fine-tuning)
1	Vincent van Gogh, *Wheat Fields at Auvers Under Clouded Sky*
3	Vincent van Gogh, *View of Vessenots near Auvers*
5	Vincent van Gogh, *Wheat Field with Reaper and Sun* ▼-3
11	Vincent van Gogh, *Self Portrait with Palette* ▲+8
13	Andy Warhol, *Three Marilyns* ▲+4
14	Andy Warhol, *After Marilyn Pink* ▲+4
16	Jackson Pollock, *Number 4* ▲+4
18	Andy Warhol, *Marilyn Monroe* ▼-2

Table 9: Influence Ledgers from Motif Duels for **SANA-1.5**. Each table presents results in the order **Semantic**, **Aesthetics**, and **Fidelity** (top to bottom). Ranks are assigned by total wins, with challenger wins used as a tie-breaker. The tables on the right show rankings after fine-tuning, where ▲+x denotes improvements and ▼-x denotes declines in rank. Lower ranks indicate greater leakage potential. In the pre-trained setting (tables on the left), we display the top-3 and bottom-5 artworks, and we report their updated ranks following stylistic fine-tuning in the corresponding tables on the right.

Rank	**Artwork (Pre-trained)**	**Wins as Challenger**	**Wins as Defender**
1	Green Coca Cola Bottles by Andy Warhol	19	16
2	Christ on the Cross by Rembrandt	19	12
3	The Japanese Bridge by Claude Monet	14	16
16	Marilyn Monroe by Andy Warhol	5	9
17	A Corner of the Garden at Montgeron by Claude Monet	5	8
18	After Marilyn Pink by Andy Warhol	3	9
19	Marilyn Blue by Andy Warhol	4	5
20	Mickey by Andy Warhol	1	1

Rank	**Artwork (Post stylistic fine-tuning)**
1	Green Coca Cola Bottles by Andy Warhol
3	Christ on the Cross by Rembrandt ▼-1
4	The Japanese Bridge by Claude Monet ▼-1
18	Marilyn Monroe by Andy Warhol ▼-2
11	A Corner of the Garden at Montgeron by Claude Monet ▲+6
13	After Marilyn Pink by Andy Warhol ▲+5
19	Marilyn Blue by Andy Warhol
20	Mickey by Andy Warhol

Rank	**Artwork (Pre-trained)**	**Wins as Challenger**	**Wins as Defender**
1	Jackson Pollock, *Convergence (Number 10)*	19	13
2	Andy Warhol, *Marilyn Monroe*	17	13
3	Andy Warhol, *Cross*	19	9
16	Vincent van Gogh, *Trees in the garden of the Hospital Saint-Paul*	7	6
17	Vincent van Gogh, *Daubigny's Garden*	4	8
18	Andy Warhol, *Untitled (From Marilyn Monroe)*	1	10
19	Vincent van Gogh, *Sunny Lawn in a Public Park*	2	9
20	Vincent van Gogh, *Mademoiselle Gachet in her garden at Auvers-sur-Oise*	5	6

Rank	**Artwork (Post stylistic fine-tuning)**
1	Jackson Pollock, *Convergence (Number 10)*
2	Andy Warhol, *Cross* ▲+1
3	Andy Warhol, *Marilyn Monroe* ▼-1
9	Vincent van Gogh, *Sunny Lawn in a Public Park* ▲+10
15	Vincent van Gogh, *Mademoiselle Gachet in her garden at Auvers-sur-Oise* ▲+5
17	Vincent van Gogh, *Trees in the garden of the Hospital Saint-Paul* ▼-1
18	Andy Warhol, *Untitled (From Marilyn Monroe)*
19	Vincent van Gogh, *Daubigny's Garden* ▼-2

Rank	**Artwork (Pre-trained)**	**Wins as Challenger**	**Wins as Defender**
1	Jackson Pollock, *Echo (Number 25)*	19	15
2	Jackson Pollock, *Black & White (Number 20)*	17	15
3	Jackson Pollock, *Number 32*	17	13
16	Rembrandt, *Lighting Study of an Elderly Woman in a White Cap*	4	8
17	Rembrandt, *Portrait of a Bearded Man in Black Beret*	4	6
18	Andy Warhol, *Crushed Campbell's Soup Can (Beef Noodle)*	7	3
19	Rembrandt, *Portrait of a Woman Wearing a Gold Chain*	6	2
20	Rembrandt, *Portrait of a seated man rising from his chair*	6	1

Rank	**Artwork (Post stylistic fine-tuning)**
2	Jackson Pollock, *Number 32* ▲+1
3	Jackson Pollock, *Black & White (Number 20)* ▼-1
4	Jackson Pollock, *Echo (Number 25)* ▼-3
13	Rembrandt, *Portrait of a Bearded Man in Black Beret* ▲+4
14	Rembrandt, *Lighting Study of an Elderly Woman in a White Cap* ▲+2
15	Andy Warhol, *Crushed Campbell's Soup Can (Beef Noodle)* ▲+3
16	Rembrandt, *Portrait of a seated man rising from his chair* ▲+4
19	Rembrandt, *Portrait of a Woman Wearing a Gold Chain*

Table 10: Imitation–Motif Duel consistency for **SD v1.5 under Aesthetics-based proximity**. Rows index FitSet artworks (refer Table 5) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: ✓ if the challenger wins in both, ✓ if the defender wins in both, and ✗ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		**Defender**																				**Win Count**	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Challenger	A1	-	✓	✗	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	17	0
	A2	✗	-	✗	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	15	0
	A3	✗	✓	-	✗	✓	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	14	1
	A4	✓	✓	✓	-	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	15	3
	A5	✓	✓	✓	✓	-	✗	✗	✗	✓	✗	✓	✓	✓	✗	✓	✗	✓	✓	✓	✓	9	4
	A6	✓	✓	✓	✓	✗	-	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	13	4
	A7	✓	✓	✓	✓	✓	✗	-	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	12	5
	A8	✓	✓	✓	✓	✓	✗	✗	-	✓	✗	✓	✓	✓	✗	✓	✗	✓	✓	✓	✓	9	5
	A9	✗	✓	✓	✓	✓	✓	✓	✗	-	✓	✗	✗	✓	✓	✓	✓	✓	✓	✗	✓	8	6
	A10	✗	✓	✓	✗	✓	✓	✗	✓	✓	-	✓	✗	✗	✓	✓	✓	✓	✓	✓	✓	8	6
	A11	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	-	✓	✓	✓	✓	✗	✓	✓	✓	✓	8	9
	A12	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓	✗	-	✓	✓	✓	✗	✓	✓	✓	✓	7	8
	A13	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	-	✓	✓	✓	✓	✓	✗	✓	6	11
	A14	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✓	✗	✗	✗	✗	1	12
	A15	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✗	-	✓	✗	✗	✓	✓	3	12
	A16	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✓	1	14
	A17	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	-	✓	✓	✓	3	15
	A18	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✗	✗	✓	-	✗	✓	1	13
	A19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✗	✗	✓	-	✓	1	15
	A20	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	-	0	18
Win Count	Challenger	0	1	0	2	4	4	4	6	8	3	8	9	11	11	13	9	13	14	13	18	312	
	Defender	14	18	17	13	13	12	10	9	11	9	8	7	7	4	3	1	2	2	1	0		

Table 11: Imitation–Motif Duel consistency for **SD v1.5 under Fidelity-based proximity**. Rows index FitSet artworks (refer Table 5) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: ✓ if the challenger wins in both, ✓ if the defender wins in both, and ✗ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		Challenger																				Win Count	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Defender	A1	-	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	17	0
	A2	✗	-	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✗	✗	✓	✗	✗	✓	✓	✓	12	0
	A3	✓	✓	-	✓	✗	✗	✗	✓	✗	✗	✓	✓	✗	✗	✓	✗	✗	✓	✓	✓	8	2
	A4	✗	✓	✓	-	✗	✗	✗	✓	✗	✗	✓	✓	✗	✓	✗	✗	✗	✓	✓	✓	7	2
	A5	✓	✓	✓	✗	-	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗	✗	✗	✓	✓	✓	6	3
	A6	✓	✓	✓	✓	✓	-	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓	✗	✗	✗	2	5
	A7	✓	✓	✗	✗	✓	✓	-	✓	✗	✗	✓	✓	✓	✗	✓	✗	✗	✓	✓	✓	8	4
	A8	✓	✗	✓	✓	✓	✓	✓	-	✗	✗	✓	✗	✗	✗	✗	✗	✗	✓	✓	✓	4	6
	A9	✓	✓	✓	✓	✓	✗	✓	✓	-	✗	✗	✗	✓	✓	✗	✗	✓	✗	✗	✗	3	7
	A10	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	0	9
	A11	✓	✓	✗	✓	✓	✓	✓	✗	✓	✓	-	✓	✗	✗	✗	✗	✗	✗	✗	✓	2	8
	A12	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✗	-	✗	✗	✗	✗	✗	✓	✓	✓	3	9
	A13	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✗	✗	✗	✗	0	12
	A14	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✗	✗	✗	0	13
	A15	✓	✗	✗	✓	✗	✓	✗	✗	✓	✓	✗	✗	✓	✓	-	✗	✗	✗	✓	✓	2	7
	A16	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✗	0	15
	A17	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	0	16
	A18	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	-	✓	✓	2	16
	A19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	✓	✗	-	✓	1	15
	A20	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	0	19
Win Count	Challenger	0	1	2	3	2	2	2	6	1	0	7	7	4	3	4	1	2	8	10	12	245	
	Defender	17	15	14	14	14	13	12	10	11	10	6	6	7	5	5	4	3	1	1	0		

Table 12: Imitation–Motif Duel consistency for **SDXL under Semantics-based proximity**. Rows index FitSet artworks (refer Table 6) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: ✓ if the challenger wins in both, ✓ if the defender wins in both, and ✗ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		Defender																				Win Count	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Challenger	A1	-	✓	✓	✓	✗	✗	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	16	0
	A2	✗	-	✗	✗	✗	✗	✗	✗	✓	✗	✓	✗	✗	✓	✗	✗	✓	✗	✗	✓	5	0
	A3	✗	✓	-	✓	✗	✗	✓	✓	✓	✗	✗	✓	✗	✓	✓	✓	✓	✓	✗	✓	11	1
	A4	✗	✓	✗	-	✗	✗	✗	✓	✗	✗	✗	✗	✓	✓	✗	✓	✗	✓	✓	✓	7	1
	A5	✗	✓	✗	✗	-	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	12	1
	A6	✓	✓	✗	✓	✗	-	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓	✓	✓	✗	✓	5	3
	A7	✗	✓	✓	✓	✓	✓	-	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	12	5
	A8	✗	✗	✓	✗	✗	✓	✗	-	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗	✓	10	2
	A9	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	0	8
	A10	✗	✓	✓	✗	✗	✓	✓	✓	✓	-	✗	✗	✗	✗	✓	✗	✗	✓	✗	✓	3	6
	A11	✗	✓	✗	✗	✗	✓	✗	✓	✓	✓	-	✓	✓	✓	✗	✓	✗	✓	✓	✓	7	5
	A12	✓	✗	✓	✓	✓	✓	✓	✓	✗	✓	✓	-	✗	✗	✓	✗	✗	✗	✗	✗	1	9
	A13	✓	✓	✗	✓	✗	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✗	✗	✓	✗	1	10
	A14	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✓	✗	✗	1	13
	A15	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	-	✗	✓	✗	✗	✓	2	13
	A16	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	✗	✗	2	15
	A17	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	✗	✗	1	16
	A18	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	-	✗	✓	1	16
	A19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	0	18
	A20	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	0	19
Win Count	Challenger	0	1	1	2	0	0	2	5	6	1	5	6	5	9	7	8	9	12	6	12	258	
	Defender	11	16	12	12	10	14	11	12	10	10	9	7	7	5	5	4	3	2	1	0		

Table 13: Imitation–Motif Duel consistency for **SDXL under Aesthetics-based proximity**. Rows index FitSet artworks (refer Table 6) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: ✓ if the challenger wins in both, ✓ if the defender wins in both, and ✗ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		Defender																				Win Count	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Challenger	A1	-	✓	✓	✗	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	17	0
	A2	✓	-	✗	✗	✓	✗	✓	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	13	1
	A3	✓	✓	-	✗	✓	✗	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	14	2
	A4	✗	✗	✓	-	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	14	1
	A5	✓	✓	✓	✗	-	✗	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	11	3
	A6	✓	✓	✓	✓	✓	-	✓	✗	✗	✗	✗	✓	✗	✓	✓	✗	✗	✓	✓	✓	7	5
	A7	✓	✓	✓	✓	✓	✓	-	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓	✗	✓	✓	8	6
	A8	✓	✓	✓	✗	✓	✓	✗	-	✓	✗	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	10	5
	A9	✓	✓	✓	✓	✓	✓	✗	✓	-	✗	✗	✓	✗	✓	✗	✗	✗	✓	✓	✓	5	7
	A10	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✓	✗	✓	✗	✗	✗	✓	✓	✓	5	9
	A11	✓	✓	✓	✗	✓	✗	✗	✓	✓	✗	-	✓	✗	✗	✗	✗	✗	✗	✓	✓	3	6
	A12	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	-	✗	✓	✗	✗	✓	✗	✓	✓	4	10
	A13	✓	✓	✓	✓	✓	✓	✗	✗	✓	✓	✗	✓	-	✗	✓	✗	✓	✗	✗	✓	3	9
	A14	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	-	✗	✗	✓	✓	✓	✓	4	12
	A15	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✗	✓	✗	✓	✓	3	14
	A16	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✗	✓	✗	-	✗	✗	✗	✗	0	12
	A17	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	-	✗	✓	✓	2	15
	A18	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	-	✓	✓	2	16
	A19	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	1	18
	A20	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	0	15
Win Count	Challenger	0	1	1	0	3	2	6	3	4	3	5	10	7	10	9	7	11	10	16	18	295	
	Defender	18	17	17	13	15	13	7	11	11	7	6	8	6	6	4	4	3	2	1	0		

Table 14: Imitation–Motif Duel consistency for **SDXL under Fidelity-based proximity**. Rows index FitSet artworks (refer Table 6) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: ✓ if the challenger wins in both, ✔ if the defender wins in both, and ✗ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		Defender																				Win Count	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Challenger	A1	-	✓	✓	✓	✓	✗	✓	✗	✓	✓	✓	✗	✗	✓	✓	✓	✗	✗	✓	✓	13	0
	A2	✔	-	✗	✓	✓	✗	✗	✗	✓	✓	✗	✗	✗	✓	✗	✗	✗	✗	✗	✓	6	1
	A3	✗	✗	-	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗	✓	✓	✗	✗	✗	✗	✓	6	0
	A4	✔	✗	✗	-	✗	✗	✗	✗	✓	✗	✓	✗	✗	✗	✓	✗	✗	✗	✓	✓	5	1
	A5	✔	✔	✔	✔	-	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗	✗	3	4
	A6	✔	✔	✔	✔	✔	-	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	0	5
	A7	✔	✗	✗	✗	✔	✔	-	✗	✓	✓	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	3	3
	A8	✔	✔	✔	✔	✔	✔	✔	-	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	0	7
	A9	✔	✗	✗	✗	✔	✔	✗	✔	-	✓	✓	✗	✗	✓	✓	✗	✗	✗	✓	✓	6	4
	A10	✔	✔	✗	✔	✔	✔	✔	✔	✗	-	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓	2	7
	A11	✔	✔	✗	✗	✔	✔	✔	✔	✗	✔	-	✗	✗	✗	✓	✗	✗	✗	✗	✓	2	7
	A12	✗	✗	✗	✗	✔	✗	✗	✔	✗	✗	✗	-	✗	✓	✓	✓	✓	✗	✓	✓	6	2
	A13	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	-	✗	✗	✓	✗	✗	✗	✓	2	11
	A14	✗	✔	✗	✗	✔	✔	✔	✔	✗	✗	✗	✔	✔	-	✓	✗	✗	✗	✗	✓	2	7
	A15	✔	✗	✔	✗	✔	✔	✔	✔	✗	✔	✔	✔	✔	✔	-	✗	✗	✗	✗	✗	0	11
	A16	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	-	✓	✓	✗	✓	3	14
	A17	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	-	✓	✗	✗	1	15
	A18	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	-	✗	✗	0	16
	A19	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	-	✗	0	18
	A20	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	-	0	19
Win Count	Challenger	0	1	1	2	2	1	1	0	5	5	3	0	0	5	9	4	3	3	4	11	212	
	Defender	16	12	10	10	15	13	11	11	6	8	7	8	4	6	5	4	3	2	1	0		

Table 15: Imitation–Motif Duel consistency for **SANA-1.5 under Semantics-based proximity**. Rows index FitSet artworks (refer Table 7) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: ✓ if the challenger wins in both, ✔ if the defender wins in both, and ✗ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		Defender																				Win Count	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Challenger	A1	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	19	0
	A2	✗	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	18	0
	A3	✗	✔	-	✓	✓	✗	✓	✓	✓	✗	✓	✓	✗	✗	✓	✓	✓	✓	✓	✓	13	1
	A4	✗	✔	✔	-	✓	✗	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	14	2
	A5	✗	✗	✔	✔	-	✓	✓	✓	✗	✗	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	11	2
	A6	✔	✔	✔	✔	✗	-	✓	✓	✓	✗	✗	✗	✗	✗	✓	✗	✓	✗	✗	✓	6	4
	A7	✗	✔	✔	✔	✔	✔	-	✓	✓	✗	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓	10	5
	A8	✔	✔	✗	✗	✗	✗	✗	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	12	2
	A9	✔	✔	✔	✗	✗	✔	✗	✗	-	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	9	4
	A10	✔	✔	✔	✔	✗	✔	✔	✔	✗	-	✗	✗	✗	✗	✗	✗	✓	✗	✗	✓	2	7
	A11	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	-	✗	✓	✗	✗	✗	✗	✗	✓	✓	3	9
	A12	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✗	-	✓	✗	✗	✗	✗	✓	✓	✓	4	9
	A13	✔	✗	✔	✔	✔	✔	✔	✗	✗	✔	✔	✔	-	✗	✗	✗	✓	✗	✗	✓	2	9
	A14	✔	✗	✗	✔	✗	✔	✗	✗	✗	✔	✗	✔	✗	-	✓	✓	✓	✓	✓	✓	6	5
	A15	✔	✔	✔	✗	✗	✗	✗	✗	✗	✔	✔	✗	✔	✔	-	✗	✓	✗	✓	✓	3	7
	A16	✔	✔	✔	✗	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✗	-	✓	✗	✗	✓	2	12
	A17	✔	✗	✔	✔	✗	✔	✔	✗	✗	✗	✔	✔	✗	✔	✗	✗	-	✓	✓	✓	3	8
	A18	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✗	✔	✗	✔	✔	✔	✔	-	✓	✗	1	14
	A19	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	✗	-	✓	1	16
	A20	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	✔	✔	✔	✔	✔	-	0	18
Win Count	Challenger	0	1	2	3	4	3	6	7	7	4	6	8	9	4	10	9	13	11	14	18	273	
	Defender	14	14	15	12	8	12	9	5	6	7	6	7	2	6	3	3	3	1	1	0		

Table 16: Imitation–Motif Duel consistency for **SANA-1.5 under Aesthetics-based proximity**. Rows index FitSet artworks (refer Table 7) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: ✓ if the challenger wins in both, ✔ if the defender wins in both, and ✗ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		Defender																				Win Count	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Challenger	A1	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	19	0
	A2	✔	-	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	16	1
	A3	✔	✗	-	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	16	1
	A4	✗	✔	✗	-	✓	✗	✓	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	13	1
	A5	✔	✔	✔	✗	-	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	14	3
	A6	✔	✔	✔	✗	✗	-	✗	✗	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	11	3
	A7	✔	✔	✔	✗	✔	✔	-	✗	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	11	5
	A8	✔	✔	✔	✗	✔	✔	✔	-	✓	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	11	6
	A9	✔	✔	✔	✔	✔	✔	✔	✔	-	✓	✗	✓	✓	✓	✗	✓	✗	✓	✓	✓	8	8
	A10	✔	✔	✔	✔	✔	✔	✔	✔	✔	-	✗	✓	✓	✗	✗	✗	✓	✓	✓	✓	6	9
	A11	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	-	✗	✓	✓	✓	✗	✓	✗	✓	✗	5	9
	A12	✔	✔	✔	✔	✔	✔	✔	✔	✗	✗	✔	-	✓	✓	✗	✗	✗	✓	✓	✓	5	9
	A13	✗	✔	✗	✔	✗	✗	✗	✔	✗	✔	✗	✗	-	✗	✓	✓	✓	✗	✓	✓	5	4
	A14	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✗	-	✗	✓		✓	✓	✓	4	11
	A15	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✗	✗	-	✓	✓	✓	✓	✓	5	11
	A16	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	✗	✔	✔	-	✗	✗	✓	✓	2	13
	A17	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	-	✗	✗	✗	0	15
	A18	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	-	✓	✓	2	17
	A19	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	✗	✔	✔	✔	✗	✗	-	✓	1	14
	A20	✔	✔	✔	✔	✔	✔	✗	✔	✔	✔	✔	✔	✔	✔	✔	✔	✗	✔	✔	-	0	17
Win Count	Challenger	0	1	1	3	3	3	5	4	8	9	5	10	12	11	10	10	12	13	17	17	311	
	Defender	17	17	15	12	13	13	11	11	9	7	8	4	3	5	5	4	1	1	1	0		

Table 17: Imitation–Motif Duel consistency for **SANA-1.5 under Fidelity-based proximity**. Rows index FitSet artworks (refer Table 7) as challengers and columns index FitSet artworks as defenders. Each cell records whether the winner under imitation matches the winner under motif-duel for that pair: $\color{green}\checkmark$ if the challenger wins in both, $\color{blue}\checkmark$ if the defender wins in both, and $\color{red}✗$ if the outcomes disagree. Row, column, and total agreement counts are also reported for reference.

Matrix		**Defender**																				**Win Count**	
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	Challenger	Defender
Challenger	A1	-	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	19	0
	A2	$\color{red}✗$	-	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	17	0
	A3	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	9	2
	A4	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	-	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	14	0
	A5	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	-	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	4	2
	A6	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	-	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	12	0
	A7	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	4	6
	A8	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	-	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	6	3
	A9	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	3	4
	A10	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	2	7
	A11	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	6	9
	A12	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	-	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	5	9
	A13	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{green}\checkmark$	2	7
	A14	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	5	12
	A15	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	-	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{green}\checkmark$	$\color{red}✗$	4	10
	A16	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	0	15
	A17	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	$\color{red}✗$	$\color{green}\checkmark$	$\color{red}✗$	1	15
	A18	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	-	$\color{green}\checkmark$	$\color{red}✗$	1	12
	A19	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	-	$\color{red}✗$	0	11
	A20	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{red}✗$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	$\color{blue}\checkmark$	-	0	12
Win Count	Challenger	0	1	2	3	4	5	3	5	7	4	4	7	7	6	5	8	11	10	14	8	250	
	Defender	16	15	9	13	9	10	7	10	10	10	5	4	7	2	3	1	3	1	1	0		