

LoRACLr: Contrastive Adaptation for Customization of Diffusion Models

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<https://loraclr.github.io>



Figure 1. **High-Fidelity Multi-Concept Image Generation.** Examples illustrating LoRACLr’s ability to generate unified scenes with multiple distinct characters and styles across diverse settings. Each scene demonstrates LoRACLr’s capability to combine varied concepts seamlessly, preserving the original identities of each character, as seen in concepts.

Abstract

Recent advances in text-to-image customization have enabled high-fidelity, context-rich generation of personalized images, allowing specific concepts to appear in a variety of scenarios. However, current methods struggle with combining multiple personalized models, often leading to attribute entanglement or requiring separate training to preserve concept distinctiveness. We present LoRACLr, a novel approach for multi-concept image generation that merges multiple LoRA models, each fine-tuned for a distinct concept, into a single, unified model without additional individual fine-tuning. LoRACLr uses a contrastive objective to align and merge the weight spaces of these models, ensuring compatibility while minimizing interference. By enforcing distinct yet cohesive representations for each concept, LoRACLr enables efficient, scalable model composition for high-quality, multi-concept image synthesis. Our results highlight the effectiveness of LoRACLr in accurately merging multiple concepts, advancing the capabilities of personalized image generation.

1. Introduction

Diffusion models for text-to-image generation [12] have revolutionized image synthesis from textual prompts, as demonstrated by major advancements forward from Stable Diffusion [30], Imagen [34], and DALL-E 2 [28]. Customization techniques for these models have further amplified their versatility, enabling the personalized image generation of specific concepts such as characters, objects, or artistic styles. Low-Rank Adaptation (LoRA) [13] has emerged as a powerful tool for customizing pre-trained models with minimal retraining, allowing for flexible, efficient personalization. By combining LoRA with advanced customization methods like DreamBooth [31], users can generate images that not only retain high-fidelity but also capture their unique creative vision.

However, combining multiple LoRA models to create a single composition remains a significant challenge. Current multi-concept models often struggle to maintain the quality of individual concepts, require simultaneous training on multiple concepts [21], or need per-image optimization [22]. Alternative methods face specific limitations: some can only merge style and content LoRAs [36],

while others become unstable as the number of combined LoRAs grows [14]. Methods like Mix-of-Show [10] require specialized LoRA variants, such as Embedding-Decomposed LoRAs (EDLoRAs), which diverge from the standard LoRA formats widely used in the community. More recent approaches, like OMG [20], employ segmentation methods to isolate subjects during generation, but these approaches rely heavily on the accuracy of the segmentation models used. These challenges limit the broader applicability of text-to-image models, particularly when multiple distinct concepts must coexist in a single output image.

To address these challenges, we propose LoRACLRL, a novel approach that combines multiple LoRA models into a single model capable of accurately generating multiple concepts simultaneously. Our method introduces a novel contrastive objective that aligns each model’s weight space, prevents interference, and preserves fidelity by ensuring that each model represents its respective concept distinctly within the joint composition. Importantly, our approach allows for the use of pre-existing LoRA models without the need for retraining or accessing original training data. By employing contrastive learning, LoRACLRL achieves scalable model composition, enabling high-quality multi-concept image generation without requiring additional fine-tuning or computational overhead.

Our extensive evaluations reveal that LoRACLRL achieves significant improvements in both visual quality and compositional coherence over baseline methods. Through qualitative and quantitative experiments, we demonstrate that our approach consistently preserves the fidelity and identity of each concept while avoiding the common issue of feature interference, even as complexity increases with additional concepts. LoRACLRL provides a practical and scalable solution to compositional customization in generative models, with promising implications for applications like virtual content creation, personalized storytelling, and digital art.

2. Related Work

Text-Conditioned Image Synthesis. Text-conditioned image synthesis has seen significant advances through the development of both GANs [2, 9, 17–19] and diffusion models [6, 11, 12, 23, 30, 39]. Early GAN-based methods focused on generating images conditioned on classes [2, 15, 17] or text attributes [1, 8, 24, 29]. More recently, the focus has shifted towards large-scale text-to-image diffusion models [28, 30, 34, 43], trained on large-scale datasets [35], enabling more nuanced and accurate image synthesis.

Personalized Image Generation and Customization. Personalized image generation aims to embed user-specific concepts that can be reused across different contexts, from distinct characters to unique styles. Early methods like Textual Inversion (TI) [7] and DreamBooth (DB) [31] laid the groundwork by learning representations from a lim-

ited set of images. TI optimizes text embedding to reconstruct target images using a diffusion-based loss, allowing for flexible and personalized image synthesis. DB, on the other hand, fine-tunes model weights to learn unique concept representations, using rare tokens to encode custom features for reliable reproduction. Subsequent works, such as $\mathcal{P}+$ [40], build upon Texture Inversion by incorporating a more expressive token representation, enhancing subject alignment and fidelity in generation. Further developments have aimed to improve the scalability and efficiency of customization. Custom Diffusion [21] advanced this goal by fine-tuning only the cross-attention layers, balancing customization precision and computational efficiency. Building on these foundations, DB-LoRA [33] introduces LoRA [13] to DB to enable more parameter-efficient tuning, reducing the need for extensive retraining. Recent approaches, such as StyleDrop [38], HyperDreamBooth [32], and a variety of feed-forward network-based techniques [16, 37, 41, 42], have further minimized computational demands by predicting adaptation parameters directly from data.

Merging Multiple Concepts. Combining LoRAs for style and subject control remains an open research challenge. Current methods for multi-concept synthesis often face notable limitations. Weighted summation [33] is a simple approach but suffers from feature interference. AnyDoor [3] enables zero-shot object replacement and composition without per-instance fine-tuning. Mix-of-Show [10] requires specialized Embedding-Decomposed LoRAs (ED-LoRAs) for each concept, which limits compatibility with standard LoRAs. ZipLoRA [36] can merge style and content LoRAs but struggles when multiple content LoRAs are needed. OMG [20] depends on off-the-shelf segmentation to isolate subjects, making its performance highly dependent on segmentation accuracy and the model’s ability to generate multiple objects. Recent advancements have focused on merging multiple specialized models into a unified generative framework. Mix-of-Show [10] effectively merges models using ED-LoRAs but requires access to the original training data, which limits compatibility with community LoRAs, such as those available on platforms like civit.ai [4]. Orthogonal Adaptation [25] introduces constraints to separate attributes across LoRAs, reducing interference; however, it increases training complexity by directly modifying the fine-tuning process, which also requires access to the original data.

Our approach, LoRACLRL, uses a contrastive objective to align the weight spaces of specialized LoRA models, enabling coherent multi-concept compositions with minimal interference. Unlike prior methods, LoRACLRL combines pre-existing LoRA models without retraining, preserving each model’s distinct attributes for scalable, high-fidelity multi-concept image synthesis.

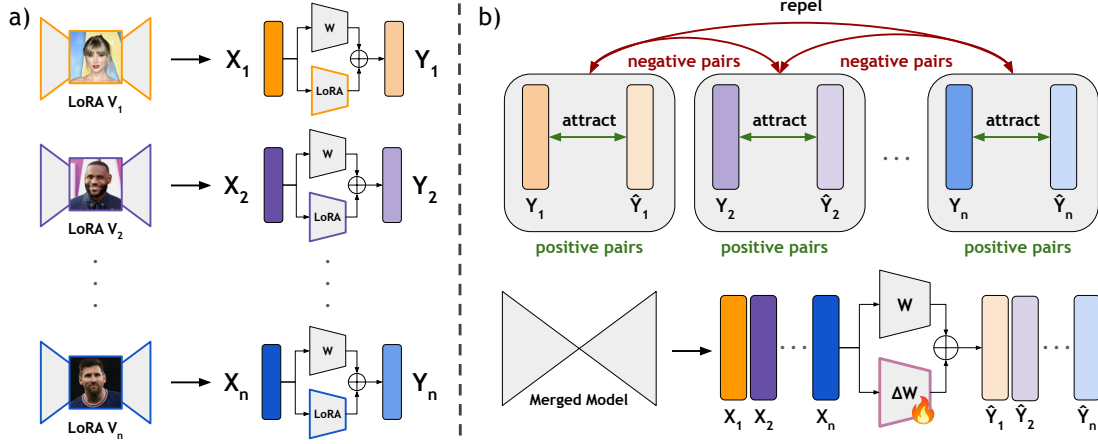


Figure 2. **Framework Overview.** The framework comprises two main stages: (a) generating concept-specific representations with individual pre-trained LoRA models and (b) merging these representations into a unified model using a novel contrastive objective. In (a), each LoRA model produces input-output pairs (X_i, Y_i) for distinct concepts $(V_1, V_2, \dots, V_n)$, establishing positive pairs (aligned concepts) and negative pairs (unrelated concepts). In (b), these representations are combined into a single model, ΔW , to enable multi-concept synthesis. LoRACLRL aligns attracting positive pairs to ensure identity retention and repelling negative pairs to prevent cross-concept interference.

3. Method

Our proposed approach, LoRACLRL, enables seamless multi-concept synthesis by merging independently trained LoRA models in a post-training phase. Instead of modifying or retraining each model for compatibility, LoRACLRL uses an optimization-based merging that adapts pre-existing LoRA models to function cohesively within a shared model, capable of generating all the target concepts. Leveraging contrastive learning, our method aligns the weight spaces of the models, ensuring each concept retains high-fidelity while remaining compatible in joint compositions. An overview of LoRACLRL is shown in Fig. 2.

3.1. Low-Rank Adaptation Models

LoRA [13] fine-tunes large models by adding low-rank matrices W_{in} and W_{out} to frozen base layers, allowing adaptation with minimal computation. Applied to cross-attention layers in Stable Diffusion [30], LoRA updates weights as $W' = W + W_{in}W_{out}$, where W_{in} and W_{out} are significantly smaller than W , reducing model storage to just 15-100 MB compared to the full model’s 3.44 GB. This fine-tuning embeds new styles or concepts efficiently within the diffusion model’s latent space.

3.2. LoRACLRL

LoRACLRL’s merging process relies on contrastive loss to ensure compatibility across independently trained LoRA models. Given a pre-trained LoRA V_i , we first create pairs of *input* and *output features*, denoted as X_i and Y_i , respectively, see Fig. 2 (a). Meanwhile, *predicted features* $\hat{Y}_i$ represent the merged model’s output for the same input features, X_i , i.e., $\hat{Y}_i = (W + \Delta W)X_i$. The intuition behind our contrastive objective is as follows: positive pairs gener-

ated by the same LoRA models should attract, while negative pairs generated by the different LoRAs should repel, see Fig. 2 (b). The contrastive loss objective is defined as:

$$\mathcal{L}_{\text{contrastive}} = \frac{1}{N} \sum_{i=1}^N (d_{p,i}^2 + \max(0, m - d_{n,i})^2), \quad (1)$$

where $d_{p,i}$ represents the positive distance for each pair, $d_{n,i}$ represents the negative distance, m is the margin parameter, which defines the minimum allowable distance for negative pairs to enforce separation and prevent feature overlap, and N is the number of concepts being combined. The positive and negative components are defined as:

$$d_{p,i} = \|Y_i - \hat{Y}_i\|_2, \quad (2)$$

where $d_{p,i}$ is the distance between the output features Y_i of the original LoRA model and the predicted features $\hat{Y}_i$ from the merged model for the same concept.

$$d_{n,i} = \min_{j \neq i} \|Y_i - \hat{Y}_j\|_2, \quad (3)$$

where $d_{n,i}$ is the negative distance, computed as the minimum distance between the output features Y_i for a given concept and the predicted features $\hat{Y}_j$ of unrelated concepts, with $j \neq i$. This contrastive objective keeps unrelated concepts distinct while aligning each concept’s output features with the merged model’s predictions, with negative pair loss d_n further preventing concept interference and ensuring distinct representations for similar concepts.

Delta-Based Merging. LoRACLRL uses an additive delta, ΔW , to merge LoRA models without altering the base weights directly. Initialized to zero, we learn ΔW to adjust the pre-trained weights, preserving the integrity of each

model while ensuring compatibility. An L2 regularization term is applied to ΔW to limit its magnitude, ensuring sparsity and minimal adjustments. The optimization objective combines the contrastive merging loss, $\mathcal{L}_{\text{contrastive}}$ and $\mathcal{L}_{\text{delta}}$:

$$\mathcal{L}_{\text{delta}} = \lambda_{\text{delta}} \|\Delta W\|_2, \quad (4)$$

where λ_{delta} controls the trade-off between effective merging of concepts and maintaining sparsity in ΔW . The total objective is:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{contrastive}} + \mathcal{L}_{\text{delta}}. \quad (5)$$

At each step, ΔW is updated to minimize $\mathcal{L}_{\text{total}}$ using gradient descent. Positive and negative samples contribute to the contrastive pairs, reinforcing distinct boundaries for each concept while ensuring cohesive alignment among merged concepts. This iterative process converges to an optimized weight configuration. By restricting updates to ΔW rather than altering base weights directly, LoRA achieves balanced adaptation, preserving the integrity of each concept’s features while enabling seamless multi-concept merging within a unified model.

4. Experiments

Implementation Details. In all our experiments, we use the Stable Diffusion model [30] with the ChilloutMix checkpoint¹ for its high-quality image generation capability. Our approach leverages pre-trained LoRA models, eliminating the need to train individual LoRA models from scratch and significantly reducing computational overhead. During the merging process, we use a learning rate of $1e^{-4}$, a margin parameter m of 0.5 to control separation between positive and negative pairs during contrastive learning, and a regularization coefficient λ_{delta} of 0.001 to ensure sparsity in the learned delta. All experiments, including model outputs, and processing, were conducted on an NVIDIA A100 GPU at Virginia Tech. Combining 12 concepts is highly efficient, typically taking about 5 minutes, which makes our approach scalable and practical for real-world applications that require seamless integration of multiple concepts. For our experiments, we utilize pre-trained single-concept LoRA and/or ED-LoRA models as the starting point.

Baselines. We evaluate our approach against several state-of-the-art baselines in multi subject customization, including: DB-LoRA [31], $\mathcal{P}+$ [40], Custom Diffusion [21], Mix-of-Show [10], and Orthogonal Adaptation [25]. For DB-LoRA, Federated Averaging (FedAvg) is used to merge models. Custom Diffusion utilizes its optimization-based method for merging, while Mix-of-Show merges using gradient fusion. Orthogonal Adaptation introduces orthogonal transformations to mitigate concept interference during merging. In the case of $\mathcal{P}+$, no fine-tuning of model

weights is performed; instead, merging is achieved by directly querying each concept’s token embedding.

Datasets & Metrics. For all evaluations, we use the same experimental setup and dataset proposed by [25], which includes 12 concept identities, each represented by 16 distinct images of the target concept across various contexts. Following prior work [10, 25], we evaluate our method using three key metrics: Text Alignment, Image Alignment, and Identity Alignment. Text Alignment measures text-image similarity using the CLIP [27] model to ensure that generated images match the input prompts. Image Alignment evaluates the similarity between generated and reference images in the CLIP feature space. Identity Alignment uses the ArcFace [5] model to assess how accurately the target human identity is preserved in the generated images.

4.1. Qualitative Results

We demonstrate the qualitative results of our method for both single and multiple subjects. Given a set of subjects, each represented by a personalized model—for instance, celebrities like Margot Robbie and Taylor Swift (see Fig. 3)—and a text prompt such as ‘<Margot> and <Taylor> in an ancient library with towering shelves,’ our objective is to generate a composite image that integrates these subjects according to the provided text prompt. Using 12 subjects identified by [25], we first merge them into a unified model through our novel contrastive-based objective, applied consistently across all experiments. Unlike methods that require individual fine-tuning for each concept [25], our approach can work with pre-trained models such as LoRA or ED-LoRA models.

Single Concepts. We first demonstrate our method’s ability to preserve individual identities. Figure 3 (bottom row) confirms that our approach maintains the integrity of each identity for single concepts. This capability extends to diverse settings. For example, the “<CONCEPT> Cyberpunk style” shows subjects portrayed as game-like characters, as seen in the fourth images of the bottom row in Fig. 3.

Multiple Concepts. Figure 3 showcases images generated with our method using varying numbers of concepts—6, 5, 4, 3, and 2. These visuals demonstrate that our method not only accurately captures each individual identity but also generates composite images guided by the text prompts. Notably, our approach excels by utilizing a single merged model to generate a wide range of concepts across diverse prompts, eliminating the need to train separate models for different concept counts. We also note that the original LoRA models for individual subjects are trained on various images of celebrities who may have different hairstyles or colors. As a result, variations such as different hairstyles or colors can appear even within generations of the same celebrity model (e.g., different generations of a Taylor Swift LoRA might show varying hair colors or styles, reflecting

¹<https://huggingface.co/windwhinny/chilloutmix>



Figure 3. **Qualitative Results.** LoRACLRL effectively combines different numbers of unique concepts across a wide range of scenes, producing high-fidelity compositions that capture the complexity and nuance of multi-concept prompts in diverse environments. LoRACLRL preserves the identity of each concept, ensuring accurate representation in composite scenes while also maintaining fidelity in single-concept generation, as demonstrated in the last row. Real images from the original concepts are shown on the left for reference.

her real-life changes). These variations are not inconsistencies in our model but rather reflect the diversity inherent in the original LoRA models. Importantly, despite these variations, our model maintains fidelity and identity to the celebrities' faces and ensures that details like hairstyles do not mix across different subjects.

Qualitative Comparisons. In Fig. 4, we visually compare our method against several state-of-the-art approaches, including Orthogonal Adaptation, MoS, and $\mathcal{P}+$, across various concepts. Figure 4 illustrate that our method successfully preserves individual identities without crossovers, whereas other methods encounter issues. For instance, Or-

thogonal Adaptation [25] inadvertently transfers features, such as the hair of female characters, to others, while MoS [10] and $\mathcal{P}+$ [40] struggle with precise identity depiction. Additionally, while these models perform adequately with two or three concepts, their ability to accurately represent more concepts diminishes as the concept count increases. For instance, in scenes with six concepts, see Fig. 4 first section, methods other than LoRACLRL fail to preserve the identity of Lionel Messi, highlighting their limitations as the number of concepts increases.

Style LoRA Integration. To showcase the flexibility of our approach, we integrate style-specific LoRA models to gen-



Figure 4. **Multi-Concept Comparison.** Composite images generated by our method (LoRACLR) and competing methods (Orthogonal Adaptation [25], Mix-of-Show [10], Prompt+ [40]) for multi-concept prompts. Each row depicts a different scene defined by the text prompts. Our method consistently preserves individual identities, while others struggle with identity preservation and concept interference.

erate scenes combining conceptual and stylistic elements, enabling outputs in styles like *comic art* or *oil painting*. As shown in Fig. 5, prompts such as “...in a city, in *comic style*” capture the vibrant aesthetic of comic art, while “...in a garden, holding flowers, in *oil painting style*” reflect the textured quality of oil painting. Complex scenes like “...in a castle, signing papers, in *oil painting style*” illustrate the model’s ability to maintain content coherence alongside stylistic adaptation. These results demonstrate

our method’s efficiency in preserving content accuracy and achieving high stylistic fidelity, making it practical for creative and artistic workflows.

Non-Human Examples. We present examples involving non-human concepts, including animals, objects, and monuments. Our model generalizes seamlessly to these scenarios while maintaining high-quality outputs and stylistic consistency. As shown in Fig. 7, our method effectively integrates diverse concepts into cohesive scenes. It excels

Table 1. **Quantitative Results.** Comparison of LoRACLR against state-of-the-art models, evaluated before and after merging. LoRACLR achieves competitive performance across all metrics, with notable improvements in image and identity alignment post-merging.

Method	Text Alignment $\uparrow$			Image Alignment $\uparrow$			Identity Alignment $\uparrow$		
	Single	Merged	Δ	Single	Merged	Δ	Single	Merged	Δ
P+ [40]	.643	$\rightarrow$.643	—	.683	$\rightarrow$.683	—	.515	$\rightarrow$.515	—
Custom Diffusion [21]	.668	$\rightarrow$.673	+0.005	.648	$\rightarrow$.623	-.025	.504	$\rightarrow$.408	-.096
DB-LoRA (FedAvg) [33]	.613	$\rightarrow$.682	+0.069	.744	$\rightarrow$.531	-.213	.683	$\rightarrow$.098	-.585
MoS (FedAvg) [10]	.625	$\rightarrow$.621	-.004	.745	$\rightarrow$.735	-.010	.728	$\rightarrow$.706	-.022
MoS (Grad Fusion) [10]	.625	$\rightarrow$.631	+0.006	.745	$\rightarrow$.729	-.016	.728	$\rightarrow$.717	-.011
Orthogonal Adaptation [25]	.624	$\rightarrow$.644	+0.020	.748	$\rightarrow$.741	-.007	.740	$\rightarrow$.745	+0.005
LoRACLR (Ours)	.668	$\rightarrow$.665	-.003	.766	$\rightarrow$.776	+0.010	.799	$\rightarrow$.828	+0.029



Figure 5. **Style LoRAs.** Our method combines styles like comic art and oil painting into multi-subject scenes, ensuring stylistic fidelity and content coherence and showcasing its flexibility.

with objects like tables, chairs, and vases, accurately capturing their distinct textures. Additionally, it demonstrates robustness with monumental elements such as pyramids and rocks, blending them seamlessly with other concepts. These results highlight the adaptability of our method in generating coherent and visually engaging compositions across a wide range of non-human concepts, including animals, objects, and landmarks. This versatility makes it suitable for both creative and practical applications, such as wildlife illustration, interior design, and architectural visualization.

4.2. Quantitative Results

In Tab. 1, we present the results for each approach before and after identity merging to illustrate their impact on the metrics. Our approach achieves the highest scores for image and identity alignment compared to other methods, as demonstrated by the qualitative examples in Fig. 4. While Custom Diffusion and DB-LoRA show superior Text Alignment, they fall short in Image and Identity Alignment, underscoring the versatility and balanced performance of our approach across all key aspects.

Effect of # Concepts. Unlike other methods, which struggle to maintain text alignment, image alignment, and identity preservation as the number of combined concepts increases, LoRACLR maintains these metrics, see Fig. 6.

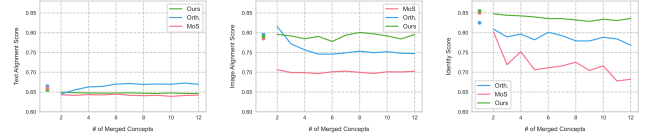


Figure 6. **Quantitative Results on Number of Concepts.** Text alignment, image alignment, and identity preservation scores remain high as merged concepts increase. Our method maintains identity and prompt adherence. Dots indicate baseline metrics for each LoRA model pre-merging for performance reference.

User Study. To supplement the findings in Tab. 1 and Fig. 6, we conduct a user study involving 50 participants on Prolific.com [26]. The study consisted of 40 questions where participants are shown reference images of individual concepts alongside composite images, with varying numbers of concepts, generated by our method and competing methods, presented in a randomized order. Participants are asked to evaluate each image pair based on: *Identity Alignment: Given the reference images on the left, how well does the image on the right capture the identity of these concepts?* (1 = Not at all, 5 = Very much). Our method received an average score of 3.42, while Orthogonal Adaptation received 2.41, Mix-of-Show received 2.21 and Prompt+ received 2.01, indicating superior preservation of concept identities by our method compared to competing methods.

Merging Time. In terms of time efficiency, our method demonstrates significant advantages. It takes only 5 minutes to combine 12 LoRA models. In contrast, [25] requires fine-tuning each LoRA model from scratch, each taking approximately 10-15 minutes. While the actual merging process of [25] takes only 1 second, it requires prior fine-tuning, which adds up to a total of 120 minutes to merge them. Meanwhile, Mix-of-Show requires 15 minutes to merge the models. After merging, generating the images takes approximately 10 seconds for all methods. This comparison clearly shows that our method is substantially faster than other methods in merging models. Once LoRACLR merges LoRA models into a unified model, it can generate composite images without any further need for retraining the individual concepts or access to original training data.

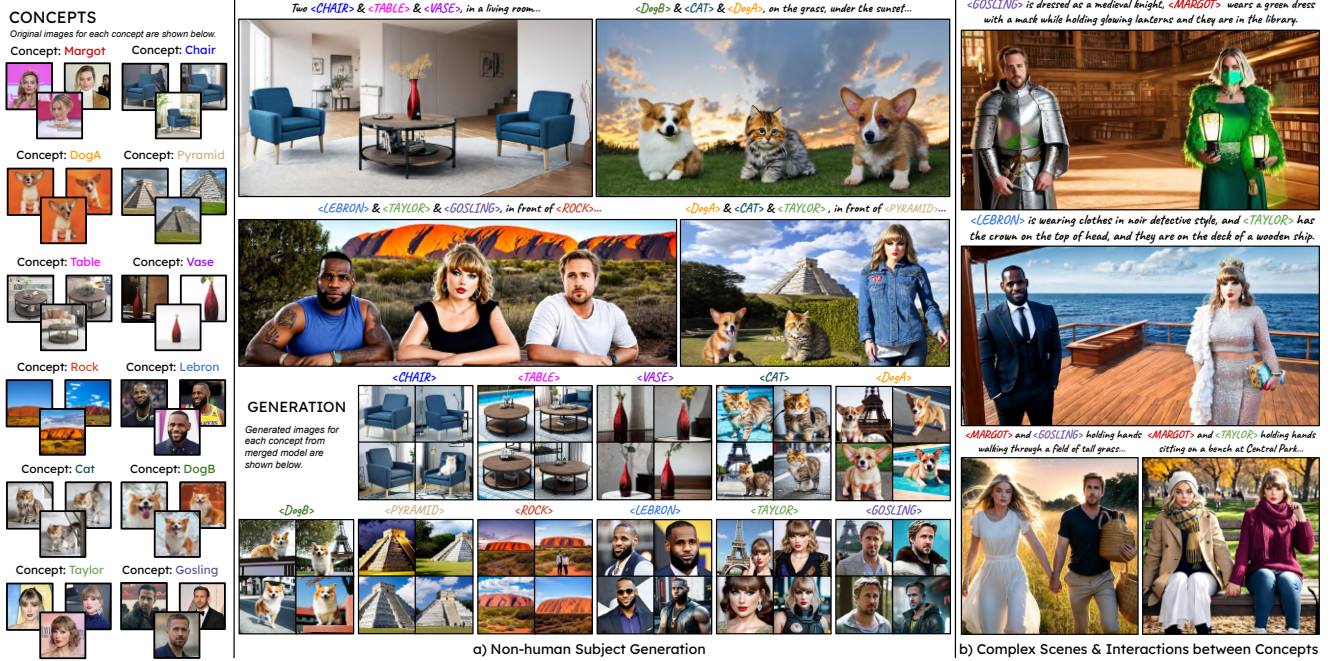


Figure 7. **Non-human subject & Complex Composition.** (a) Our method effectively integrates diverse concepts—including animals, objects (e.g., tables, chairs, vases), and landmarks (e.g., pyramids, rocks)—into visually coherent and semantically meaningful scenes. (b) LoRACLr also enables complex interactions between concepts, such as multiple subjects engaging in contextual activities.

Ablation Study We conduct ablation studies to evaluate the impact of key parameters such as the effects of margin, λ_{delta} , and concept count as follows:

- **Impact of Margin and λ_{delta} .** As shown in Fig. 8, we explore different values of margin and λ_{delta} . The results demonstrate that our method achieves robust identity preservation and visual coherence with margin values around 0.25–0.5 and λ_{delta} set at 0.001. Higher values for either parameter lead to diminished performance in maintaining individual identity and prompt coherence.
- **Effect of # Concepts.** Qualitative results in Fig. 8 further demonstrate that our model maintains identity and visual coherence even with complex multi-concept compositions, highlighting its scalability and robustness.

5. Discussion

Limitations. Similar to [10, 25], the performance of our method is inherently tied to the capabilities of the underlying LoRA models. Therefore, the success of LoRACLr in generating coherent and high-quality images depends on the robustness of these initial models. Moreover, given that our method enables sophisticated composition capabilities, it is crucial to consider the potential for misuse, such as deep-fakes. Thus, we advocate for the careful use of our method to prevent such applications and promote ethical use.

Conclusion. We introduce LoRACLr, a novel approach that merges multiple LoRA models using a contrastive learning objective. Our method preserves the distinct iden-

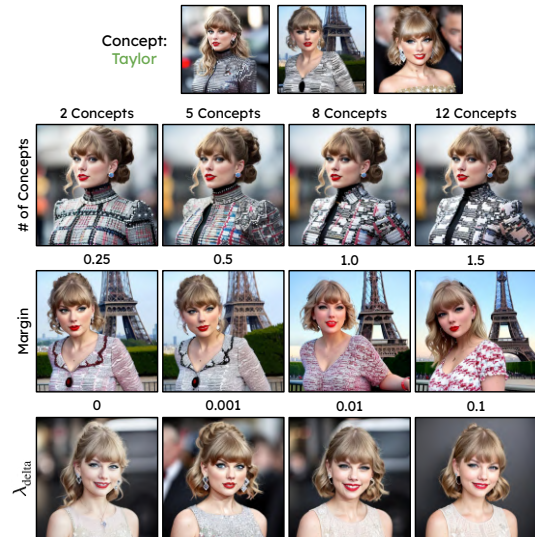


Figure 8. **Ablation Study on Margin, λ_{delta} , and Concept Count.** Effect of varying margin, λ_{delta} , and number of concepts (2, 5, 8, 12) on identity preservation and visual coherence.

ties of concepts while enabling the creation of composite images from multiple subjects. LoRACLr is designed to be compatible with any existing LoRA model, ensuring seamless integration with future, more advanced models. Operating as a post-training method, LoRACLr requires only a one-time merging process and can be used with any prompts, utilizing community-available LoRA models.

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