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# Research on the Generation of Ceramic Decorative Patterns from the Perspective of AIGC

--Taking Traditional Ornamentation as an Example

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**Abstract:** In traditional ceramic art, the design of decorative patterns is at the core of its aesthetic value. However, traditional design methods are limited due to their low efficiency and singular style. This study aims to promote the development of ceramic decorative pattern design through technological innovation, to meet the personalized and diversified aesthetic demands of modern people for ceramic decorative patterns. Researchers have proposed a method based on fine-tuning the Stable Diffusion large model with the LoRA model, combined with prompt optimization technology, to achieve high-quality generation of ceramic decorative patterns. This method not only significantly improves design efficiency but also breaks through the limitations of traditional styles, creating innovative and personalized decorative patterns. By introducing deep learning and artificial intelligence technologies, this study has brought revolutionary changes to the field of ceramic decorative pattern design, enabling designers to quickly respond to market changes and create works that meet contemporary aesthetics. This has not only propelled the development of ceramic art to a higher level and depth but also provided designers with a fast, flexible, and innovative design tool.

**Keywords:** LoRA Model, Stable Diffusion, Ceramic Decorative Pattern Design, Traditional Ornamentation, Generative Artificial Intelligence Design, Prompt Optimization

## 1. Introduction

Ceramic culture, as the essence of traditional Chinese culture, is not only a treasure of Huaxia civilization but also a shining pearl in the world's art treasury. It carries the sediment of thousands of years of history and also showcases unique artistic charm. In the creative process of ceramic art, decorative pattern design is the core element in enhancing its aesthetic appeal. However, traditional ceramic decorative pattern design is overly dependent on the personal experience and creativity of the designer, leading to a lengthy design cycle, low efficiency, and difficulty in keeping up with the market's rapid growth in demand for personalized products.

Internationally, scholars have begun to explore the application of Stable Diffusion (SD) in the fields of art and design, especially its advantages in pattern generation and creative design. Researchers such as Rombach[1] have pointed out that SD models, by learning from large-scale text and image data, can achieve high-quality text-to-image conversion. Their ability to depict details and expand creativity has brought revolutionary changes to the design field. Domestically, scholars like Li Li[2] have compared the performance of Style GAN and Stable Diffusion in the generation of traditional patterns, finding that Style GAN excels in realism, while Stable Diffusion is better at inheriting and innovating traditional patterns, more meeting the needs of cultural and artistic design. In this study, we innovatively use the LoRA model to generate ceramic decorative patterns. The advantage of this method is its ability to efficiently fine-tune large pre-trained models without updating the entire model's parameters, thereby maintaining design flexibility and innovation while reducing computational resource requirements and training time. The low computational complexity of the LoRA model allows it to operate efficiently in resource-limited environments, not only improving design efficiency and reducing costs but also enabling rapid adjustments according to market demands and user preferences, meeting the needs for personalized design.

## 2. Low-Rank Adaptation of Large Language Models

### 2.1. The principle of the Lora model

Edward Hu[3] proposed Low-Rank Adaptation, or LoRA, which freezes the pre-trained model weights and injects trainable rank decomposition matrices into each layer of the Transformer architecture, greatly reducing the number of trainable parameters for downstream tasks. It is primarily used for model fine-tuning in the field of Natural Language Processing (NLP). Its core concept is to automatically adjust the weights between layers of the neural network through learning to enhance the model's performance. LoRA can be seen as a plugin for the Stable Diffusion model, allowing users to customize their needs with a small amount of data without altering its architecture, thereby reducing the training resources required. The principle of the LoRA model is shown in the figure below.

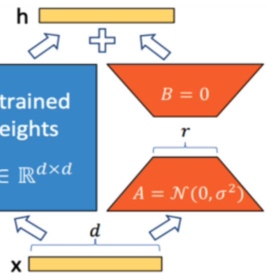



**Figure 1.** The principle of the LoRA model

In the field of AI art creation, using a fine-tuning training method that combines the Stable Diffusion (SD) model and LoRA technology allows for training to focus only on the LoRA part, which has fewer parameters, thereby achieving good results in some specific tasks.

## 2.2. Training process of Lora model

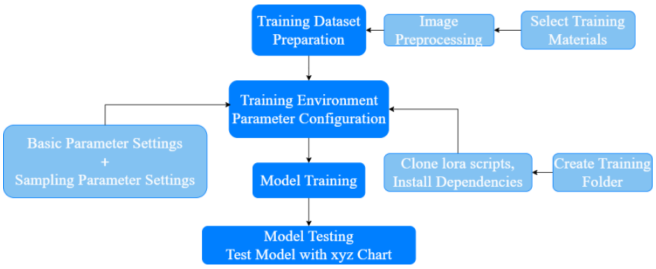



**Figure 2.** Training process of Lora model

# 3. Training dataset for traditional floral pattern Lora model

## 3.1. Dataset creation process

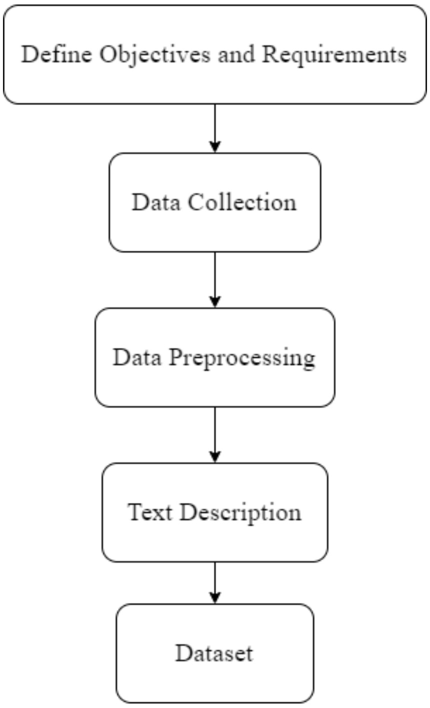



**Figure 3**. Dataset creation process

### 3.1.1. Clearly define goals and requirements

Clarify the goals you hope to achieve through fine-tuning, such as changing the style of generated images, optimizing the generation effects of specific characters or objects, etc.In this study, we need to collect ceramic pictures with traditional patterns.

### 3.1.2. Data Collection

In the process of constructing a dataset of ceramic decorative patterns, we adopt a multi-channel collection strategy, extensively gathering ceramic decorative patterns from various sources such as museums, archaeological excavations, private collections, and public databases. At the same time, we strictly adhere to copyright regulations to ensure that all used patterns have been legally authorized, or confirm that it belongs to the public domain, in order to avoid copyright infringement. Additionally, we focus on the diversity of samples, striving to cover a wide range of ceramic decorative patterns from different historical periods, regions and styles, to enhance the breadth and representativeness of the dataset. This ensures that the dataset can fully reflect the richness and diversity of ceramic decorative art.

### 3.1.3. Data Preprocessing

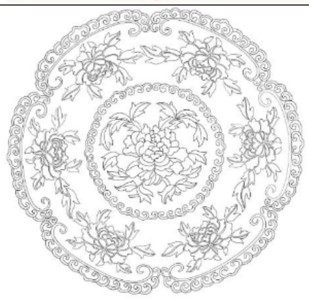
During the data preprocessing phase, we perform a series of image processing operations on the collected ceramic decorative pattern images, including cropping, image denoising and format conversion, to ensure the consistency of image quality. Additionally, to facilitate subsequent model training, we standardize the data by unifying key parameters such as image size and resolution. These steps are crucial for enhancing the usability of the dataset and the efficiency of model training.

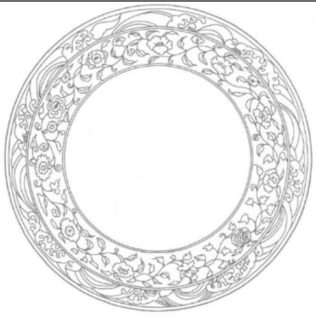
### 3.1.4. Text Description

In the process of constructing a multimodal dataset of ceramic decorative patterns, a key step is to write detailed textual descriptions for each pattern. This involves not only the visual characteristics of the pattern but also its deeper meanings and the details of its manufacturing process. Subsequently, conducting consistency checks is crucial to ensure that the textual descriptions accurately match the content of the images, thus avoiding the transmission of any potentially misleading information. This process not only enhances the accuracy of the dataset but also improves its practicality in academic research and artistic creation.

In practice, we need to provide textual descriptions for the ceramic patterns and select key words from these descriptions to serve as tags for the patterns. Table 1 shows some of the tags we have collected for the ceramic patterns. The text content of the tags describes the main content and some elemental features shown in the material images in the form of English words or short phrases.

**Table 1.** Some decorative motifs and their labels

| picture | tag |
|---|---|
|  | flower, no humans, blue flower, traditional media, white background, blue theme, simple background, Designs of composite flowers |
|  | Ink art, greyscale, monochrome, no humans, flower, peony |

| | |
|---|---|
|  | greyscale, monochrome, flower, traditional media, no humans, jewelry |
|  | monochrome, greyscale, lineart, no humans, flower, peony |

The ceramic surface ornamentation dataset we created for training the traditional ornamentation LoRa model is shown in Figure 4.

**Figure 4.** Ceramic surface ornamentation dataset

# 4. Training and testing of LoRa models of traditional ornamentation

## 4.1. Training Environment

The computer hardware configuration used in this model training: NVIDIA GeForce RTX 4090 Laptop GPU with 24 GB of video memory.

## 4.2. The main parameters of the training are set

1. After the dataset is ready, name the training dataset with the format: number_name, where the number represents the number of training steps for each image. 10 is selected for training steps here, so the total number of steps is 10 × 37=370

2.Set the basic model to a realistic large model: dreamshaper_8.

3.Adjust the training dataset path to the path where your training dataset is located.

4.Adjust the training image resolution to the resolution of the images in the dataset, and it must be a multiple of 64.

5.Modify train_batch_size to 1.

6.Modify max train epochs to 20. Therefore, the total number of training steps would be 20×370=7400 steps.

7.Set the learning rate to 0.0001.

The specific model training parameter settings are shown in Figure 5.

```
pretrained_model="E:\A stable-diffusion\sd-webui-aki-v4.7\models\Stable-diffusion\dreamshaper_8.saf
model_type="sd1.5"                    # option: sd1.5 sd2.0 sdxl | 可选 sd1.5 sd2.0 sdxl. SD2.0
parameterization=0                    # parameterization | 参数化 本参数需要在 model_type 为 sd

train_data_dir="E:\A stable-diffusion\Qiuye5.29-lora-scripts\train\10_tradition" # train dataset pa
reg_data_dir=""                # directory for regularization images | 正则化数据集路径, 默认不使用正

# Network settings | 网络设置
network_module="networks.lora" # 在这里将会设置训练的网络种类, 默认为 networks.lora 也就是 LoRA 训练
network_weights=""             # pretrained weights for LoRA network | 若需要从已有的 LoRA 模型上继
network_dim=32                 # network dim | 常用 4~128, 不是越大越好
network_alpha=32               # network alpha | 常用与 network_dim 相同的值或者采用较小的值, 如 ne

# Train related params | 训练相关参数
resolution="512,512"   # image resolution w,h. 图片分辨率, 宽,高。支持非正方形, 但必须是 64 倍数。
batch_size=1           # batch size
max_train_epoches=20   # max train epoches | 最大训练 epoch
save_every_n_epochs=2  # save every n epochs | 每 N 个 epoch 保存一次

train_unet_only=0            # train U-Net only | 仅训练 U-Net, 开启这个会牺牲效果大幅减少显存使用。
train_text_encoder_only=0    # train Text Encoder only | 仅训练 文本编码器
stop_text_encoder_training=0 # stop text encoder training | 在第N步时停止训练文本编码器

noise_offset="0" # noise offset | 在训练中添加噪声偏移来改良生成非常暗或者非常亮的图像, 如果启用, 推
keep_tokens=0    # keep heading N tokens when shuffling caption tokens | 在随机打乱 tokens 时, 保留
min_snr_gamma=0  # minimum signal-to-noise ratio (SNR) value for gamma-ray | 伽马射线事件的最小信噪

# Learning rate | 学习率
lr="1e-4"                            # learning rate | 学习率, 在分别设置下方 U-Net 和 文本编码器 的
unet_lr="1e-4"                       # U-Net learning rate | U-Net 学习率
text_encoder_lr="1e-5"               # Text Encoder learning rate | 文本编码器 学习率
lr_scheduler="cosine_with_restarts" # "linear", "cosine", "cosine_with_restarts", "polynomial", "co
lr_warmup_steps=0                    # warmup steps | 学习率预热步数, lr_scheduler 为 constant 或 ad
lr_restart_cycles=1                  # cosine_with_restarts restart cycles | 余弦退火重启次数, 仅在

# Optimizer settings | 优化器设置
optimizer_type="AdamW8bit" # Optimizer type | 优化器类型 默认为 AdamW8bit, 可选: AdamW AdamW8bit Li

# Output settings | 输出设置
output_name="aki"             # output model name | 模型保存名称
save_model_as="safetensors" # model save ext | 模型保存格式 ckpt, pt, safetensors

# Resume training state | 恢复训练设置
save_state=0 # save state | 保存训练状态 名称类似于 <output_name>-??????-state ?????? 表示 epoch 数
resume=""    # resume from state | 从某个状态文件夹中恢复训练 需配合上方参数同时使用 由于规范文件限

# 其他设置
min_bucket_reso=256                  # arb min resolution | arb 最小分辨率
max_bucket_reso=1024                 # arb max resolution | arb 最大分辨率
persistent_data_loader_workers=1 # persistent dataloader workers | 保留加载训练集的worker, 减少每个
clip_skip=2                          # clip skip | 玄学 一般用 2
multi_gpu=0                          # multi gpu | 多显卡训练 该参数仅限在显卡数 >= 2 使用
lowram=0                             # lowram mode | 低内存模式 该模式下会将 U-net 文本编码器 VAE 转移到

# LyCORIS 训练设置
algo="lora"   # LyCORIS network algo | LyCORIS 网络算法 可选 lora、loha、lokr、ia3、dylora。lora即为
conv_dim=4    # conv dim | 类似于 network_dim, 推荐为 4
conv_alpha=4 # conv alpha | 类似于 network_alpha, 可以采用与 conv_dim 一致或者更小的值
dropout="0"   # dropout | dropout 概率, 0 为不使用 dropout, 越大则 dropout 越多, 推荐 0~0.5. LoHa/L
```

**Figure 5.** The model training parameter settings page

## 4.3. The test effect of the invoked trained LoRA model

This study employs an xyz-plot for model testing: The basic prompts for generating traditional decorative patterns on porcelain are as follows: "Beautiful porcelain plate", "traditional ceramic design", "concentric floral and vine patterns"; the relevance of the prompts is set to 8; the resolution for the generated images is 512 by 512 pixels; the number of iterative steps for generation is 20;

The image generation effect with LoRA model weights ranging from 0 to 1 is shown in Figure 6.

**Figure 6.** The image generation effect

The results indicate that as the LoRA model weight increases, the blue and white floral patterns generated on the porcelain evolve from simpler designs to more complex and intricate ones, with the complexity of the patterns continuously increasing. The generation effect is optimal when the weight is set between 0.6 and 0.8, and setting the weight too high can lead to overfitting.

# 5. The practice of generating ceramic decorative images: taking traditional ornamentation as an example

When engaging in the practice of generating ceramic decorative patterns, we first used the LoRA (Low-Rank Adaptation) model to control the style of the pattern generation. Then, we conducted logical deduction of the prompts to determine the optimal prompts. After that, we varied some parameters to identify the best settings. Once the optimal parameters were determined, we generated several design drafts and ultimately selected the design with the highest quality.

In this study, taking a porcelain plate as an example and based on the sd1.5 model, used two LoRA models for generating traditional decorative patterns on porcelain plates. One is the B_lora model developed by our group, and the other is the Cyanware Pattern v1.0 model downloaded from the internet. The parameter settings for the practice are shown in Table 2.

**Table 2 .** Parameter value setting

| Parameter name | Meaning | Suggested value |
|---|---|---|
| Steps | Number of Iterative Steps | 20~40 |
| CFG scale | Prompt Relevance | 7~15 |
| Sampler | Sampling Method | dpm_2s_ancestral, dpmpp_2m_sde |
| Clip skip | Skip Layers | 2~4 |
| VAE | Variational Auto-encoder | vae-ft-mse-840000-ema-pruned |

## 5.1. Prompt word derivation

### 5.1.1. Derivation of positive prompts

In the process of generating ceramic works, positive prompts can be categorized into three types of keywords: style, shape, and quality. Here are the methods to write a prompt to generate ceramic images:

1. Style: First, select the desired style of the ceramic and use corresponding style keywords, such as "elegant," "traditional," etc.

2. Shape: Next, specify the category of the ceramic shape, like "vase," "plate," or other specific styles.

3. Pattern Elements: Then, describe the pattern elements you want, such as "floral," "vine," and you can add color details, for example, "red peony."

4. Detailed Description: If you have a clear image in your mind, you can further refine the description. For instance, specify the pattern style on the edge of the ceramic plate, or whether the ceramic requires special designs like "hollow-out" or "crackle glaze."

5. Scene Information: Describe scene information as well as angle and lighting effects. For example, add a slight reflection on the surface of the ceramic, or use "top lighting" to highlight the texture, and choose background colors with varying shades of light and dark.

These details can help enhance the overall quality and effect of the generated image.

### 5.1.2. Derivation of Negative prompts

Negative prompts encompass vocabulary that helps avoid the generation of discordant elements in images as well as terms related to quality. When generating images of ceramic ware, negative prompts can be continuously adjusted and optimized according to actual needs, with special attention required in several key areas:

1.Preventing Distortion and Incompleteness: It is crucial to avoid distortion, incompleteness, blurriness, and pixelation in the generated images. Negative prompts can include terms that directly address these issues, such as "distorted," "incomplete," "blurry," and "pixelated" to ensure that the images are clear and whole.

2.Color bias: Color bias is an important issue when generating ceramic images. For example, when generating an image of blue and white porcelain, there may be an abnormal blue tone deviation, in which case a specific reverse hint needs to be entered to ensure that the color of the blue and white porcelain of the generated image is close to the color accuracy of real blue and white porcelain in the real world to avoid such errors.

3.Quality Control: Negative prompts can also be used to enhance the overall quality of the images. Terms like "low quality," "poorly drawn," and "ugly" can be included to explicitly instruct the model to avoid generating images with these characteristics, thereby improving the quality of the output.

Figure 7 illustrates the logic behind the prompts used for generating ceramic decorative patterns.

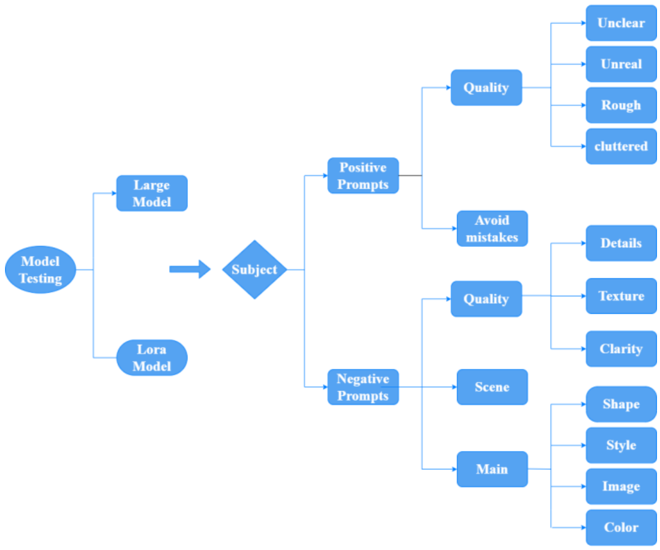



**Figure 7** Prompt word logic

### 5.1.3. Generate a cue word derivation of a traditional ornamented ceramic pattern

We first utilized the LoRA model trained by our group to deduce specific prompts for creating traditional decorative motifs. The positive prompts include the main subject plus style words. Input "an exquisite porcelain plate" and "traditional Chinese floral decorative patterns" as positive prompts. The negative prompt only included "unrealistic." However, during the generation process, it was found that the quality of the images produced was low, with the specific issues being the fusion of two stacked porcelain plates and deformation of shape, which failed to present a complete plate. Additionally, the lines of the patterns were rough, making it difficult to transform the design drafts into physical objects. To avoid the aforementioned problems, we enhanced the weight of the main subject in the positive prompts to make it more prominent during the generation process. At the same time, we added the following content to the negative prompts to improve the generation effect: "avoid rough patterns, blurriness, pixelation, low quality, deformities, distorted shapes, unrealistic patterns, dull colors, over-saturation, rough textures, chipped edges," etc.

If further refining the prompts, specific patterns, style words, and quality descriptions can be added to the positive prompts. For the negative prompts, stricter limitations can be set in terms of lighting, style, and design quality to enhance the overall texture of the ceramics. The following are the refined final prompts:

Positive: (an exquisite porcelain plate:1.3), traditional Chinese floral decorative patterns, delicate peonies, chrysanthemums, blooming lotus flowers, intricate and detailed floral patterns, soft traditional Chinese colors, fine brushwork, smooth porcelain surface, crafted in the style of traditional Chinese porcelain art, round with smooth edges, clear, exquisite pattern details, hand-painted, ensuring balance in floral elements, (4k).

Negative: (unrealistic:1.3), avoid rough patterns, blurriness, pixelation, low quality, deformities, distorted shapes, unrealistic patterns, dull colors, over-saturation, rough textures, chipped edges, misaligned geometry, flat design, excessive noise, cartoonish style, harsh lighting, unbalanced composition, messy details, unrealistic materials, overly simplified, avoid rough design.

### 5.2. Model effects

Based on the derived positive and negative prompts, we conducted a generation practice of decorative patterns on the surface of ceramics using two different LoRA models.

1. The effect of the LoRa model trained by our group is shown in Figure 8:

**Figure 8** The effect of the LoRa model trained by our group

2. The effect of the celadon pattern LoRa model which downloaded from the Internet is shown in Figure 9:

**Figure 9** The effect of the celadon pattern LoRa model which downloaded from the Internet

In terms of pattern layout, both models tend to adhere to the traditional aesthetic of symmetry, often featuring a large, central flower as the focal point, such as a majestic peony, surrounded by complementary flowers and intricate decorations. In more innovative outcomes, the floral patterns are thoughtfully arranged in harmony with the shape of the porcelain plate, spiraling outward or creating a continuous decorative border along the edge, which adds a unique rhythm to the design.

However, both models share similar shortcomings, such as a tendency to generate irregular and non-standard circular plates, which can detract from the overall visual appeal and often require multiple adjustments to the prompts for optimization. Furthermore, the generated image patterns also appear somewhat rough, and upon closer inspection, there still exists a certain gap compared to hand-drawn ones.

There are also distinct differences between the two models. The model trained by our group has a propensity for a more linear style, using fine lines to construct the patterns. Even in the stamen area, the lines are delicate, with less color fill, which can lead to a cluttered appearance due to the overlay of multiple lines, making the details appear rough to the naked eye. In contrast, the cyanware model typically fills the petals with color or uses thicker lines for embellishment, resulting in a more vibrant and enriched visual effect. The cyanware model also frequently uses gradient colors, contributing to a more harmonious color scheme and enhancing the pattern composition.

## 6. Conclusion

Ceramic art, as an essential component of Chinese traditional culture, carries profound historical and cultural connotations. In the design of traditional ceramic decorative patterns, designers have relied on personal experience and creativity, which has led to long design cycles and low efficiency, struggling to meet the modern market's rapid growth in demand for personalized and diverse products. However, the rapid advancement of artificial intelligence (AI) technology, particularly Generative artificial intelligence, has introduced innovative approaches to ceramic decorative pattern design.

By integrating intelligent generation algorithms into ceramic decorative pattern design, we can not only break through the limitations of traditional design to create a greater variety of personalized patterns but also significantly improve design efficiency and reduce costs. Furthermore, these intelligent generation algorithms can be flexibly adjusted according to market demands, further promoting innovation and development in ceramic art design. The combination of AI technology with traditional ceramic art facilitates a deep integration of technology and art, injecting new vitality into the inheritance and promotion of traditional arts.

Despite finding certain shortcomings in the shape and details of the generated images during the experimental process, such as non-standard circular porcelain plates and rough patterns, these issues can be effectively mitigated by optimizing prompt words and adjusting model training parameters. Overall, the application of intelligent generation algorithms in ceramic decorative pattern design provides strong technical support for the transformation and upgrading of the ceramic industry and opens new avenues for the innovative development of traditional arts. Looking ahead, as technology continues to evolve and optimize, there is every reason to believe that AI will play an increasingly significant role in promoting the prosperity and development of ceramic art.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