UniTune: Text-Driven Image Editing by Fine Tuning an Image Generation Model on a Single Image

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Figure 1: UniTune results showing edits preserving visual and semantic fidelity.

Abstract

We present UniTune, a simple and novel method for general text-driven image editing. UniTune gets as input an arbitrary image and a textual edit description, and carries out the edit while maintaining high semantic and visual fidelity to the input image. UniTune uses text, an intuitive interface for art-direction, and does not require additional inputs, like masks or sketches. At the core of our method is the observation that with the right choice of parameters, we can fine-tune a large text-to-image diffusion model on a single image, encouraging the model to maintain fidelity to the input image while still allowing expressive manipulations. We used Imagen as our text-to-image model, but we expect UniTune to work with...
other large-scale models as well. We test our method in a range of different use cases, and demonstrate its wide applicability.

Figure 2: Samples showing UniTune’s ability to maintain semantic details even across broad visual changes, and to place edits in a logical manner.

1 Introduction

High fidelity image manipulation via text commands is a long standing problem in computer graphics research. Using free-form commands to describe a desired edit, like “men wearing tuxedos”, “pixelart”, or “a blue house” (figures 1, 2, and 6) is significantly easier than carrying out the changes manually in an image editing software. Intuitive language based interfaces have the potential to make experts more efficient and to unlock graphic design capabilities for casual users. Despite amazing advancements in image generation methods [1] [2], general domain high-fidelity image editing is still an unsolved problem. In this work, we present UniTune, which takes a meaningful step towards that goal.

Revolutionary text-to-image models like Dall-E [1], Imagen [2, 3] and Stable Diffusion [4] excel at creating images from scratch, or at filling manually-removed parts of existing images in a context-aware fashion. However, for editing operations, these models usually require the user to specify masks and often struggle with edits that depend on the masked portion of the image.

UniTune is a novel method to edit images by simply supplying a textual description of the desired result preserving high fidelity to the entirety of the input image, including the edited portions. Fidelity is preserved both to visual details (e.g. shapes, colors, and textures) and to semantic details (e.g. objects, poses, and actions).

UniTune is able to edit arbitrary images in complex cross domain scenes. We tested it for localized edits as well as broad global edits (see section 4). To our knowledge, UniTune is unique in its ability to make image-wide stylistic changes that maintain only semantic details and in its ability to place complex local edits in a logical location.

UniTune performs expressive image editing by harnessing the power of large scale text-to-image diffusion models. We show a simple yet powerful technique for transferring their visual and semantic capabilities to the domain of image editing.

Our main observation is that, with the right parameters, fine-tuning large diffusion models on a single \((image, prompt)\) pair does not lead to complete catastrophic forgetting [5]. As expected, a
fine-tuned model will strongly prefer to associate the provided image and prompt together (see figure 3), and will strongly prefer to draw samples that are almost identical to the provided image given other prompts. However, the visual and semantic knowledge that the model acquired in its original training is still usable across a very wide variety of edit operations by simply using Classifier Free Guidance (see figure 4). The fidelity-expressiveness balance can be tuned by controlling the number of training steps and learning rate, or the amount of Classifier Free Guidance \[6\] and SDEdit \[7\] (see section 3).

Fine-tuning of diffusion models is a powerful technique, relevant to many use cases e.g. image-to-image translation \[8\] and topic-driven image generation \[9\] \[10\]. These approaches attempt to mitigate over-fitting at training time by data augmentation \[9\], using large data sets \[8\] \[11\] or limiting fine-tuning to the embedding of specific tokens \[10\]. This allows these techniques to learn e.g. the essence of a subject, without learning transient image-specific attributes, like pose, camera angle, background, etc. For our use case of image editing, some over-fitting is beneficial as we actually aim to maintain high fidelity to the source image. To our knowledge, UniTune is the first method to use fine tuning of a large diffusion model for the use case of image editing.

Figure 3: The images generated by the model conditioned on the rare tokens after different number of fine tuning iterations. It takes around 64 iterations for the model to be able to faithfully reproduce the original image.

Figure 4: Images for the prompt “minion” after fine-tuning on the image on the left, with various degrees of Classifier Free Guidance weights. With standard conditioned sampling (second from the left), the fine-tuned model tends to produce something very similar to the image it was fine-tuned on, ignoring the prompt, as if the model forgot the concept of a “minion”. Using Classifier Free Guidance (right) we observe that the knowledge of what a “minion” is, is preserved within the model’s weights.

2 Related work

Image editing is a fundamental problem in computer graphics research and finding intuitive interfaces for image manipulation has been an active research field for years. Natural language driven editing, arguably the most intuitive interface possible, had been out of reach until recent advancement in image generation models and in image-text alignment. Any solution needs to address and balance two problems: how to maintain fidelity to the base image and how to adhere to the edit instruction text.

**GAN based editors.** Early solutions used GANs \[12\] \[13\] as the image generation model and CLIP \[14\] as the image-text alignment mechanism. For base image fidelity they invert a user provided image into the GAN latent space \[15\] \[16\] \[17\] \[18\]. For text-based editing they transfer the image-text alignment capabilities of CLIP into the GAN framework in various techniques (e.g. by optimizing latent vectors \[19\] \[20\] \[21\], finding vectors that move in a certain direction \[22\] \[23\] or retraining the generator itself \[24\]). These methods achieve impressive results given a well organized latent space like StyleGAN. This means they are limited to the the domains that the GAN model is trained on (e.g. only faces).
VQGan-Clip [25] uses VQ-GAN [26] (broader cross-domain model) and CLIP-based optimization of latent vectors to enable text-guided editing of arbitrary images. The model can perform local color and texture changes as well as broad stylistic changes that maintain pixel-level details (e.g. changing the lighting). It cannot perform global changes that alter pixel structure completely but maintain semantic details. For localized object replacement it can only operate within a predefined mask.

**Text-driven diffusion models.** Even more recently, diffusion models [27, 28, 29] began to outperform GANs [30] while offering a simpler training setup. Earlier diffusion model based editing solutions continued to use CLIP for text-image alignment, either as a way to guide sampling [31, 32] or as a loss function for fine-tuning a model on a specific edit operation [33]. More advanced solutions (which we use in UniTune) train the diffusion model itself on extremely large text/image datasets directly with text that is either CLIP encoded (Dall-E2 [1], Stable Diffusion [4]) or T5 encoded (Imagen [2]).

**Sampling based fidelity techniques.** For image fidelity, diffusion models self-correcting sampling is extremely useful. SDEdit [7] addresses image fidelity by starting the sampling process from a noisy version of the base image. DiffusionClip [33] uses a noising deterministic DDIM process to find the exact noise that will result in the target image. ILVR [34] and Liu et al. [31] use classifier Guidance [30] to guide a DDPM sampler in a direction that is close to the base image, visually or semantically.

With regard to capabilities, earlier diffusion-based solutions (e.g. Liu et al. [31], ILVR [34], DiffusionClip [33]) are limited by the capabilities of the models they were trained on. They either work in limited domains (faces, buildings, single object) or with limited edit operations (e.g. texture and color changes that preserve pixel structure). More research is needed to see if image fidelity approaches like noising DDIM and Classifier Guidance can perform well with large text-to-image models.

Solutions like SDEdit [7], Blended Diffusion [32] that use a noisy version of the base image are easier to migrate to larger models[1] but also face challenges: since the model has never seen the user image, the noising process cannot recover missing details making it hard to balance between fidelity and adherence to the user edit prompt (see figure [10], leftmost column). To combat this, these methods usually use a predefined edit masks that limits the edited area throughout the sampling process. This mitigates the problem but it still exist within the edited portion. Moreover it’s sometimes hard to predict the size of the desired edit area.

**Model based fidelity techniques.** One possible improvement over inflexible edit masks is presented by Glide [11] that fine-tunes a diffusion model with additional inputs: base image and an edit mask, similar to Palette [35]. This approach lets the model treat the mask as a hint, rather than as a strict constraint. Glide performs better than other models in integrating objects in complex scenes, but still cannot perform modification that change the entire scene but maintain semantic similarities.

Another option is to familiarize the generative model directly with the base Image. Blended Latent Diffusion [36] implements mask-based editing using a latent diffusion model [37] (a diffusion model that operates on the latent space of an autoencoder like VQ-GAN [26]). To get inversion to work, they fine-tune the generator of the autoencoder on the base image. This means the generator can better reproduce the base image and fix distortions caused by the edit mask.

Prompt-to-Prompt [38] achieves high quality editing capabilities by operating on the outputs of a text-to-image model. This allows using visual-semantic information encoded in its intermediate attention matrices. Some limitations of relying on the attention weights is that it requires the image to have been generated by the diffusion model to begin with (they experimented with inverting arbitrary images using DDIM noising with mixed results), requires a base prompt, and only supports a limited set of editing operations (adding or changing a word).

Text2LIVE [39] trains a U-Net [40] (a common architecture in diffusion models) on the fly to perform the edit operation on the base image. The training data is the the image itself (in different crops and augmentations), and the loss function is CLIP based. The model excels on local, pixel structure preserving changes like adding effects (fire, smoke) or changing texture and color, but lacks visual and semantic richness in its training data which means it cannot perform complex operations like integrating complex objects into the scene or make global changes that maintain semantic details.

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[1] SDEdit is used in Stable Diffusion img2img mode; Dall-E 2 also has an in-painting feature but technical details are not yet published.
Subject-driven image generation. Two recent breakthroughs, DreamBooth [9] and Textual Inversion [10] solve a related but distinct problem of subject-driven image generation. In that setting the goal is to use a small number of images to teach a text-to-image model to generate novel renditions of a given subject in new contexts. The model should derive the details that are important to the subject, but avoid keeping details like background, position, and other objects in the images (as opposed to UniTune). Both methods use fine-tuning (either of the image generation model or of an entry in the embedding table of the textual encoder).

3 Method

Our goal is to convert an input of \((base\_image, edit\_prompt)\) into an \(edited\_image\). In a nutshell, our system fine-tunes a text-to-image and super-resolution Imagen models on pairs of \((base\_image, rare\_tokens)\) for a very low number of iterations, and then samples from the model while conditioning on text in the form "[rare\_tokens] edit\_prompt". Using Classifier Free Guidance ([6]) the fine-tuned model correctly takes the conditioning into account (see figure 4). When a higher visual fidelity is needed, we also use SDEdit [7] to maintain visual details in the original image. The user is presented with images that use combinations of the parameters mentioned (number of training steps, Classifier Free Guidance, SDEdit) allowing them to pick the most suitable version.

3.1 Edit prompts

In our experiments, \(edit\_prompt\) is a short description of the image after the editing process. Similarly to text-to-image models, prompt engineering is often useful to achieve better results (e.g. to emphasize that a certain detail should not be changed). In many of the examples in this paper the first simple prompt worked well (e.g. "a couple in front of a red train."). In some difficult cases a more detailed prompt was required. Also, like in standard text-to-image generations, sometimes repeating an important element in the prompt is helpful. See table 1 for examples of edit prompts.

3.2 Fine-tuning

Imagen is composed of a text-to-image model that generates 64x64 pixels output, and two super resolutions models that convert the 64x64 image to a 256x256 image and then to a 1024x1024 image.

64x64 model. To bias the models towards \(base\_image\) we fine-tune it on pairs of \((base\_image, rare\_tokens)\) for 128 iterations with a batch size of 4 (i.e. 4 different time values in each iteration), emitting weights after 16, 32, 64, and 128 iterations (rarely, for extremely high fidelity, we go up to 1024). We use Adafactor with a learning rate of 0.0001. We keep the T5 encoder weights frozen during training (same as when training Imagen). We use 3 rare tokens, following [9] (in all of our experiments these are the string "beikkpic"). As seen in figure 3, our fine-tuned model can faithfully reproduce \(base\_image\) after 64 iterations.

Super-resolution models. To improve fidelity in photo-realistic cases, we also fine-tune the 64x64 to 256x256 model, with a very similar procedure to the one outlined above for 64x64 models. We use the same noise augmentation procedure that was used to train the original Imagen super-resolution model [2]. We did not experiment with fine tuning the 256x256 to 1024x1024 models, though we expect it would have improved the quality further.

Variations. Inspired by [38], we also tested a different setting where we fine-tune with a pair of \((base\_image, base\_prompt)\). \(base\_prompt\) is a detailed description of the image before editing. However, we preferred "rare tokens to prompt" as it worked well and did not require an additional detailed prompt from the user. We also tried using Textual Inversion [10] training on \(base\_image\) which, as expected, resulted in too many missing or altered details. We tried using Dreambooth’s class-specific prior preservation loss [9] as well for varying number of training steps, with a \(base\_prompt\) used as the class name. For base image prompts we tried "[rare\_tokens]", "[rare\_tokens] base\_prompt" and both. We did not use SDEdit in these experiments. All of these variations performed worse and took longer to train than our chosen implementation.
3.3 Sampling

To perform the edit operation, we sample the fine-tuned models with the prompt "[rare_tokens] edit_prompt" (e.g. "beikkpic two dogs in a restaurant" or "beikkpic a minion"). We show to the user results from 16, 32, 64, and 128 fine-tuning steps along with various sampling configurations as detailed below. With naive sampling the model often ignores edit_prompt showing base_image instead (figure 4). To mitigate that and allow the user to tune fidelity and expressiveness we use a combination of methods.

**Classifier Free Guidance.** Classifier Free Guidance is a technique used by text-to-image models like Imagen to guide the model to align with the textual prompt. In this technique, a model is trained on unconditioned input as well as conditioned input. Then, given a guidance weight $w$ we adjust the conditioned $\epsilon_{\text{conditioned}}$ returned from the model to be $\epsilon_{\text{unconditioned}} + w(\epsilon_{\text{conditioned}} - \epsilon_{\text{unconditioned}})$. In our case, a fine-tuned model with no prompt will often output something very similar to the base image (see figure 4), so Classifier Free Guidance is essentially a way to guide the model away from base_image and towards edit_prompt. We use a guidance weight of 32.

**Initialization with SDEdit.** Following SDEdit [7], to further guide the sampling towards maintaining the visual details of the base image (e.g. maintaining the position of certain objects), we skip the first iterations of the sampling process and begin the sampling process with an appropriately noised version of the input image, instead of starting from random noise. We only use this technique for the text to 64x64 model, and didn’t experiment with it on the SR models, but we expect it to be useful there as well. In our experiments we start from $t = 1.0$ (i.e. no SDEdit) in cases where we want to only maintain semantic fidelity (e.g. turn a photo into pixel art) and up to $t = 0.89$ to cases where we want to maintain very high visual fidelity. Starting from $t \leq 0.8$ almost always results in just recreating the original image.

**Prompt Guidance.** In the "prompt to prompt" setting, we found that a technique we call Prompt Guidance is particularly helpful to tune fidelity and expressiveness. Prompt Guidance is similar to Classifier Free Guidance except that the baseline is a different prompt instead of the unconditioned model. This guides the model towards the delta between the two prompts. In our case we experimented with adjusting the model output to be $\epsilon_{\text{base_prompt}} + w(\epsilon_{\text{edit_prompt}} - \epsilon_{\text{base_prompt}})$. While Prompt Guidance was helpful in the prompt to prompt setting, in the rare tokens setting we ended up using standard Classifier Free Guidance was enough.

**Future Sampling Experiments.** There is a myriad of other methods to balance fidelity and expressiveness that we only partially explored. These include mixing (some of) the fine-tuned weights with the base model weights, scaling the T5 encoding of specific tokens, or initializing the sampling process with a sketch of the desired edit that can be obtained by low-fidelity methods. We leave an exploration of these methods for future work.

![Original](image1.png) ![Ours (without interpolation)](image2.png) ![Ours (with interpolation)](image3.png)

Figure 5: An extreme example of interpolation helping overall quality.
3.4 Interpolation

To improve fidelity even further in photo-realistic cases, especially in higher resolutions, we can take further advantage of the fact that our method outputs images that are extremely close to the source image. In these cases, we can use a naive interpolation between the generated image and the original image, basically interpolating with the pixels of the original image if their neighborhood is very similar in both the generated and original images. This technique was only needed in a couple of the images in the paper, but turned out extremely useful in those cases (see figure 5). We suspect it might not hurt performance in cases where we try to maintain not just semantic but also very high visual fidelity to the original image, so could be turned on by default in those cases, but we didn’t experiment extensively with that yet. Also, note that this simple technique won’t work if the objects moved a significant amount of distance, but it can be easily extended to support those cases as well.

4 Results

To demonstrate UniTune’s breadth of edit capabilities we tested the system in multiple scenarios, including adding or changing items in the scene, adding an accessory, changing hair-style or clothing, changing the background scene, and changing the overall look and style of the photo (see figures 1, 2, 6, 7, 8).

While all image-editing operations require some level of similarity to the base image, the desired level varies greatly between use cases. UniTune can make edits in a wide range of fidelity levels. Figures 1 and 2 show how different prompts result in localized changes (e.g., adding a turkey to an empty plate), changes that alter accessories, clothing or surroundings but keep the character’s visual appearance (e.g., changing plain clothes to tuxedos), changes in the characters themselves (e.g., changing people into dogs), and changes that transform the style of the image, keeping only semantic details intact (e.g., changing a realistic scene into a cartoon one).

Figure 2 demonstrates two unique capabilities of UniTune: deciding where to place complex edits without a predefined edit mask and allowing changes that only maintain semantics and not necessarily pixel-level details. The "red train in the background" column shows how UniTune correctly contextualizes and places edits within the photo. In the first row, UniTune positions the train on the bridge, as that is the most logical position for it within that context. In other columns note how semantic features like clothing, hairstyles, spatial orientation, weather, etc. are preserved. For example, the bridge in the first row has a different rendering style for each edit prompt, but its structural features are preserved.

UniTune can also perform localized edits, with or without edit masks. Figure 8 shows how UniTune can place new objects (bee, ladybug, hats) without an edit mask. When edit masks are used,

![Original](image1)
![Dog wearing red hat](image2)
![Dog standing on grass](image3)
![Dog wears a superhero cape](image4)
![Cat stands next to the ocean](image5)

![Original](image6)
![Blue house](image7)
![House and grass covered in snow](image8)
![Sunny day, green grass, red flowers, large sun in sky](image9)
![Thunderstorm at night time](image10)

Figure 6: UniTune works in multiple domains and can carry out a wide set of manipulations on photos of animals and inanimate objects with high quality.
UniTune strength is in scenarios where familiarity with the the details under the mask is required, as demonstrated in figures 14 and 15. Figures 1, 7 show some examples of accessorizing, which is a type of local edit operation that is hard to achieve without familiarity with the details of the edited portion.

We also wanted to check UniTune’s performance with simpler edits. Figure 6 (bottom) shows UniTune ability for pixel preserving global and local change: changing color of an object, or global feature like weather and light. Other models had demonstrated making pixel-preserving local changes, but UniTune is also able to combine different changes together. In the last two images we show how we can simultaneously change the weather, the color of the flowers and add a new object (sun in the sky). Figure 7 demonstrates complex edits in a narrow domain. While domain specific methods (e.g. GANs trained on portrait photos) show amazing performance in these cases, UniTune has comparable capabilities across numerous domains.

**Initialization with SDEdit.** UniTune is complementary with SDEdit [7], and we use SDEdit in many of the images we generate. Adjusting the starting iteration when rendering with SDEdit allows us to balance between fidelity (faithfulness to the input photo) and expressiveness (faithfulness to the given edit prompt). This trade-off can be seen in every column of figure 10 - expressiveness gets higher when going down the column, at a cost of a lower fidelity. As can be seen in the figure,
Figure 8: More UniTune examples. The last two rows illustrate UniTune working on the same cat input image, and being able to preserve both high visual fidelity (second from bottom row) and high semantic fidelity (bottom row) as appropriate. See table 1 for the full edit prompts and parameter setting used to generate the images in this figure.

Figure 9: Examples of UniTune performing local edits (adding objects) without masks.

fine-tuning on the input image (which corresponds to going right in the grid) allows us to reach a better mixture of fidelity and expressiveness.

5 Comparison to other methods

Prompt-to-Prompt. Similar to UniTune, Prompt-to-Prompt also explores the problem of editing an image via text manipulation. Prompt-to-Prompt works best on images created by the diffusion model, and shows mixed results with arbitrary images. Also, as the Prompt-to-Prompt technique requires fixing the attention weights, it is restricted to localized edits, and supports only a limited set of edit operations (adding or changing a word). Our method is inspired by Prompt-to-Prompt, and relaxes those restrictions. While we did not perform a thorough comparison, for many cases where both methods are applicable, UniTune is able to generate equally pleasing results (see figure 11).
Figure 10: UniTune results for the same input image and edit prompt, with different combinations of fine-tuning iterations (x-axis) and SDEdit start iteration (y-axis). The input image was the image on the left of figure 1. The edit prompt was “Homer and Bart Simpson sitting in a restaurant. Homer wears a red hoodie. Bart wears a blue shirt. Homer puts his hand on Bart’s shoulder. drawn in the style of the Simpsons”. We chose a very expressive query to maximize fidelity even for cases that ignore the input image (high $t_0$, no fine-tuning). The left-most column corresponds to using SDEdit without any fine-tuning, while the bottom row corresponds to fine-tuning on the input image without SDEdit.
In-painting methods. In-painting requires the user to specify an explicit mask to edit, allowing editing of a specific detail in the image. UniTune does not require a mask, allowing an edit operation specified only by a single textual prompt. However, this depends on the ability of the textual prompt to pinpoint the exact detail in the photo that needs to change, and in some cases can lead to interesting losses where unexpected parts of the image are changed. Figure 12 shows examples of in-painting operations shown in previous papers using in-painting [32, 11]. In most cases we found it relatively simple to use UniTune to reach similar results, but usually the query had to change in order to correctly pinpoint the exact part of the image we wanted to edit. As an example, “a cat jumping on a pink yarn ball” was used instead of “pink yarn ball”, to guide UniTune towards selecting the correct cat to turn into a yarn ball.

UniTune can also use edit masks as needed. Figures 15 and 14 show how UniTune can improve upon existing in-painting methods in cases where familiarity with the details under the edit mask is required.

Text2LIVE. Similar to UniTune, Text2LIVE [39] performs an edit operation given only a textual prompt, without an explicit mask. It shows impressive results, but mainly allows simpler changes like changing textures, or adding smaller effects like smoke, but not modifying complex structures and making more drastic changes. In our limited comparison on figures from their paper, UniTune was able to generate equally pleasing results (see example in figure 13).

6 Limitations

Quality. Like many other image editing solutions, UniTune capabilities are bounded to those of the underlying text-to-image model. Our choice in the experiments we’ve run was Imagen [2], which is a robust high quality generator, especially for photo-realistic images. Nevertheless, our biggest losses are in the rare cases where Imagen faces difficulties. We are hopeful that as the base model improves so will UniTune here. Also, there are frequent cases where subjects get mixed (e.g. the faces of two people are swapped) or cloned (e.g. the same face repeats more than once). For all quality issues we encountered, the trivial strategy of trying several seeds (usually 8 but sometimes up to 64 samples) and selecting the best one worked well. There is clearly more work for getting the system to output a single image that is always high quality.

Balancing fidelity and expressiveness. There are some instances where it was hard for us to find a good balance between fidelity and expressiveness, most notably when issuing small size edits, or when using edit masks (two cases that bias the model towards the base image). In those cases, the model transitions abruptly between copying the base image, and producing something too far from it. We believe sampling methods like sketching, weight averaging and token averaging will help here, but leave exploration for future work.

Latency. The first step of UniTune, fine tuning the base model, take around 3 minutes using TPUv4, and needs to be run once per input image. Then, generation with UniTune takes the same time as sampling from the original large model (~30 seconds). While workable, this is far from interactive, especially for a new image and given the system requires manual tuning. Note that when we run fine-tuning, we save the fine-tuned model a few times, allowing the user to try different levels of fine
Figure 12: Comparison of image editing in UniTune to in-painting in Glide and Blended Latent Diffusion. (1) Glide (implicit) [11] (2) Blended Latent Diffusion [36], both using the best sample out of 64 selected by CLIP. The top three rows of the figure were taken from the papers above. Since no mask is supplied to UniTune, edit prompts were altered to pinpoint the correct part of the figure to change. To generate the UniTune examples, we tried a few edit prompt phrasings, and manually selected the best result out of 64 variations generated with different UniTune configurations. Two images of people who appeared in the original paper were removed, as we did not want to show them without their direct consent.

Figure 13: Comparison of UniTune and Text2LIVE editing an image from the Text2LIVE paper. The Text2LIVE result is taken from the original paper [39]. The edit prompt for UniTune is "cup of coffee with heart latte art".

Parameter tuning. UniTune uses numerous parameters to tune the final output (most notably the prompt, as well as the strength of SDEdit, the amount of fine-tuning, and more, rarely the interpolation parameters or guidance strength). Finding the best combination often takes 3-4 attempts. In future versions we would like to automatically merge these parameters with a single knob that tunes fidelity against expressiveness.
7 Conclusion and discussion

In this paper we presented UniTune, a simple yet powerful approach for text-driven image editing. UniTune is unique in its abilities to intelligently place objects in the scene or make global edits that preserve semantic details, from only a text description. This makes UniTune useful by casual users e.g. by speaking to a mobile device. We showed that fine-tuning a diffusion model on a single image is a promising method to bias its output distribution towards that image, and that, surprisingly, editing capabilities are preserved when using the right sampling methods. That said, there is a lot of room for further research, including how to automatically adjust the fidelity-expressiveness knobs, how to increase the chances of a good result, and how to improve generation speed. We believe that fine-tuned text-to-image diffusion models with the sampling mechanisms we propose are a good starting point for followup research.

These capabilities raise some interesting questions. In the more general context of standard diffusion models - does the diffusion model create in its activations a useful semantic encoding of its input that may serve as useful latent vectors for image understanding use-cases (similar to the one achieved by Diffusion Autoencoders [41] or StyleGan [13] in limited domains). Understanding what information is encoded, and where, may also help us fine-tune on a smaller set of weights, fine-tune longer without losing editability, or even use Hypernetworks to modify the weights of the model without fine-tuning (which had recently been shown to work in GANs [42], [43]). Our work raises interesting questions even more broadly, beyond image generation, on whether we could use similar techniques to imbue large models in other domains (e.g. GPT) with preferences by fine tuning on a single example.

Societal impact

UniTune, like other image generation models, has a great potential to complement and augment human creativity by creating new tools for professionals and empowering non-professionals with the ability to edit images more easily and in a more intuitive manner. However, we recognize that applications of this research may impact individuals and society in complex ways (see [2] for an overview). In particular, this method illustrates the ease with which such models can be used to alter sensitive characteristics such as skin color, age and gender. Although this has long been possible by means of image editing software, text-to-image models can make it easier.

Another cause of concern is reproducing unfair bias that may be found in the underlying model training data. This is also relevant for our underlying model, Imagen (see discussion in [2]). Moreover, these unfair biases may make the performance of the model vary across people of different groups. While we did not see this effect in our qualitative experiments, more research into bias evaluation methods, both for image editing and generation will help address this concern.

We encourage future research to help mitigate and measure the potential negative impact of generative models if misused, and believe thoughtful consideration and further research in all of these matters is necessary prior to determining how such technologies can be made broadly available.

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References

[1] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents, 2022.
[2] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily Denton, Seyed Kamary Seyed Ghasempour, Burcu Karagol Ayan, S. Sara Mahdavi, Rapha Gontijo Lopes, Tim Salimans, Jonathan Ho, David J Fleet, and Mohammad Norouzi. Photorealistic text-to-image diffusion models with deep language understanding, 2022.

[3] Chitwan Saharia, Jonathan Ho, William Chan, Tim Salimans, David J. Fleet, and Mohammad Norouzi. Image super-resolution via iterative refinement, 2021.

[4] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models, 2021.

[5] Ian J. Goodfellow, Mehdi Mirza, Da Xiao, Aaron Courville, and Yoshua Bengio. An empirical investigation of catastrophic forgetting in gradient-based neural networks, 2013.

[6] Jonathan Ho and Tim Salimans. Classifier-free diffusion guidance, 2022.

[7] Chenlin Meng, Yutong He, Yang Song, Jiaming Song, Jiajun Wu, Jun-Yan Zhu, and Stefano Ermon. Sdedit: Guided image synthesis and editing with stochastic differential equations, 2021.

[8] Tengfei Wang, Ting Zhang, Bo Zhang, Hao Ouyang, Dong Chen, Qifeng Chen, and Fang Wen. Pretraining is all you need for image-to-image translation. In arXiv, 2022.

[9] Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. Dreambooth: Fine-tuning text-to-image diffusion models for subject-driven generation, 2022.

[10] Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit H. Bermano, Gal Chechik, and Daniel Cohen-Or. An image is worth one word: Personalizing text-to-image generation using textual inversion, 2022.

[11] Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. Glide: Towards photorealistic image generation and editing with text-guided diffusion models, 2021.

[12] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks, 2014.

[13] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks, 2018.

[14] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision, 2021.

[15] Weihao Xia, Yulun Zhang, Yujuu Yang, Jing-Hao Xue, Bolei Zhou, and Ming-Hsuan Yang. Gan inversion: A survey, 2021.

[16] Jun-Yan Zhu, Philipp Krähenbühl, Eli Shechtman, and Alexei A. Efros. Generative visual manipulation on the natural image manifold, 2016.

[17] Andrew Brock, Theodore Lim, J. M. Ritchie, and Nick Weston. Neural photo editing with introspective adversarial networks, 2016.

[18] Daniel Roich, Ron Mokady, Amit H. Bermano, and Daniel Cohen-Or. Pivotal tuning for latent-based editing of real images, 2021.

[19] Or Patashnik, Zongze Wu, Eli Shechtman, Daniel Cohen-Or, and Dani Lischinski. Styleclip: Text-driven manipulation of stylegan imagery, 2021.

[20] Weihao Xia, Yujuu Yang, Jing-Hao Xue, and Baoyuan Wu. Tedigan: Text-guided diverse face image generation and manipulation, 2020.

[21] David Bau, Alex Andonian, Audrey Cui, YeonHwan Park, Ali Jahanian, Aude Oliva, and Antonio Torralba. Paint by word, 2021.

[22] Rameen Abdal, Peihao Zhu, John Femiani, Niloy J. Mitra, and Peter Wonka. Clip2stylegan: Unsupervised extraction of stylegan edit directions, 2021.

[23] David Stap, Maurits Bleeker, Sarah Ibrahimi, and Maartje ter Hoeve. Conditional image generation and manipulation for user-specified content, 2020.
[24] Rinon Gal, Or Patashnik, Haggai Maron, Gal Chechik, and Daniel Cohen-Or. Stylegan-nada: Clip-guided domain adaptation of image generators, 2021.

[25] Katherine Crowson, Stella Biderman, Daniel Kornis, Dashiell Stander, Eric Hallahan, Louis Castricato, and Edward Raff. Vqgan-clip: Open domain image generation and editing with natural language guidance, 2022.

[26] Patrick Esser, Robin Rombach, and Björn Ommer. Taming transformers for high-resolution image synthesis, 2020.

[27] Jascha Sohl-Dickstein, Eric A. Weiss, Niru Maheswaranathan, and Surya Ganguli. Deep unsupervised learning using nonequilibrium thermodynamics, 2015.

[28] Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models, 2020.

[29] Yang Song and Stefano Ermon. Generative modeling by estimating gradients of the data distribution, 2019.

[30] Prafulla Dhariwal and Alex Nichol. Diffusion models beat gans on image synthesis, 2021.

[31] Xihui Liu, Dong Huk Park, Samaneh Azadi, Gong Zhang, Arman Chopikyan, Yuxiao Hu, Humphrey Shi, Anna Rohrbach, and Trevor Darrell. More control for free! image synthesis with semantic diffusion guidance, 2021.

[32] Omri Avrahami, Dani Lischinski, and Ohad Fried. Blended diffusion for text-driven editing of natural images, 2021.

[33] Gwanghyun Kim, Taesung Kwon, and Jong Chul Ye. Diffusionclip: Text-guided diffusion models for robust image manipulation, 2021.

[34] Jooyoung Choi, Sungwon Kim, Yonghyun Jeong, Youngjuane Gwon, and Sungroh Yoon. Ilvr: Conditioning method for denoising diffusion probabilistic models, 2021.

[35] Chitwan Saharia, William Chan, Huiwen Chang, Chris A. Lee, Jonathan Ho, Tim Salimans, David J. Fleet, and Mohammad Norouzi. Palette: Image-to-image diffusion models, 2021.

[36] Omri Avrahami, Ohad Fried, and Dani Lischinski. Blended latent diffusion, 2022.

[37] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models, 2021.

[38] Amir Hertz, Ron Mokady, Jay Tenenbaum, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. Prompt-to-prompt image editing with cross attention control, 2022.

[39] Omer Bar-Tal, Dolev Ofri-Amar, Rafail Fridman, Yoni Kasten, and Tali Dekel. Text2live: Text-driven layered image and video editing. arXiv preprint arXiv:2204.02491, 2022.

[40] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation, 2015.

[41] Konpat Preechakul, Nattanat Chatthee, Suttisak Wizadwongsa, and Supasorn Suwajanakorn. Diffusion autoencoders: Toward a meaningful and decodable representation. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2022.

[42] Yuval Alaluf, Omer Tov, Ron Mokady, Rinon Gal, and Amit H. Bermano. Hyperstyle: Stylegan inversion with hypernetworks for real image editing, 2021.

[43] Tan M. Dinh, Anh Tuan Tran, Rang Nguyen, and Binh-Son Hua. Hyperinverter: Improving stylegan inversion via hypernetwork. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022.
Figure 14: Adding glasses to faces with editing masks. UniTune is familiar with the details of the edited portion, and can use them when drawing the glasses to make the eyes more realistic and similar to the based image.

Figure 15: Turning people into fluffy monsters with editing masks. UniTune is able to maintain the posture and arm alignment even though it’s hidden behind the edit mask.
A Appendix

A.1 UniTune in-painting

Limiting edits to a predefined area is a common fidelity technique popularized by DALL-E’s in-painting and out-painting features. In diffusion models, masking works by replacing a non-edited portion of the image with an appropriately noised version of the base image at every sampling step, or by overriding the model output at every step as if it predicted the original image. Masking allows users to control the exact location and size of edits, offering a high level of control and fidelity. However, masking also limits the model’s expressiveness as it’s often hard to predict the right proportions of the edited section, especially when adding new objects (see figure 12 for comparison between UniTune and in-painting methods).

While UniTune works well without any masks, and is therefore usable by non-experts (e.g., on a mobile device by simply speaking commands), it is compatible with common masking techniques. UniTune is especially useful when a higher fidelity is needed within the masked area as it is familiar with the image details. This also allows imprecise large masks as UniTune can restore the unedited parts inside the mask correctly. Figure 14 demonstrate how UniTune in-painting can be used when adding transparent elements like eyeglasses, and figure 15 shows how it can be used when editing existing characters or objects within a photo while maintaining semantic fidelity.

A.2 Example UniTune Parameters

See table 1 for all edit prompts and parameters used to generate the images in figure 8.

| Edit Prompt                              | Fine-Tuning Steps | SDEdit Initialization |
|------------------------------------------|-------------------|-----------------------|
| Yellow flower                            | 64                | 0.94                  |
| A bee pollinating a flower               | 64                | 0.90                  |
| A ladybug on a flower                    | 64                | 0.88                  |
| Black and white pencil sketch of a flower| 32                | 1.00                  |
| Elephants wearing top hats               | 64                | 0.98                  |
| Elephants walking in the water           | 64                | 0.96                  |
| Elephants walking in the thick jungle, many trees | 64 | 0.98 |
| Framed oil painting of elephants         | 64                | 1.00                  |
| A vampire cat wearing a coat             | 64                | 0.94                  |
| A cat peeking out of a basket            | 64                | 0.98                  |
| A cat wearing sunglasses                 | 64                | 0.90                  |
| A brown cat with yellow eyes             | 64                | 0.94                  |
| A vampire cat wearing a coat, scary fangs| 32                | 0.98                  |
| Beautiful watercolor painting of a cat, on canvas | 32 | 1.00 |
| Birthday card, watercolor painting of a cat | 32 | 1.00 |
| Marble statue of a cat                   | 64                | 0.90                  |

Table 1: Prompts and parameters used to generate the images in figure 8. All figures used a classifier free guidance weight of 32. Super-resolution model was not fine tuned for these images.
Figure 16: Transforming artworks using UniTune.

Figure 17: Some more examples.