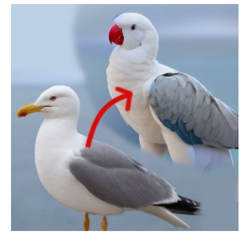
Introduction to Stable Diffusion's parameters



Description	Learning to use a pre-trained SD model.
Period	Fall 2022
Languages & Libs	Python, PyTorch
Tags	Computer Vision, Autoencoder, Stable Diffusion

Stable Diffusion is an image generation network, which was released to the public in 2022. It is based on a diffusion process, in which the model gets a noisy image as an input and it tries to generate a noise-free image as an output. This process can be guided by describing the target image in plain English (aka txt2img), and optionally even giving it a target image (aka. img2img). This article doesn't describe how the model works and how to run it yourself, instead this is more of a tutorial on how various parameters affect the resulting image. Non-technical people can use these image generating AIs via webpages such as Artistic.wtf (my and my friend's project), Craiyon.com, Midjourney.com and others.

This article shows how three different parameters (number of steps, "CFG" or classifier-free guidance scale, and img2img strength) affect the image. These may interact with each other in complex ways, but that isn't studied here. Experiments use five different input texts (aka "prompts"): "a white parrot sitting by the sea", "full length portrait of gorgeous goddess standing in field full of flowers", "panda movie poster with yellow background and red title text", "mountains by a river" and "an ancient yellow robot holding a sword on desert". In addition they contain "prompt-engineering" terms such as "cinematic, highly detailed, illustration, concept ar". These greatly improve the results, but that topic isn't covered here either. One can find prompt examples from sites such as lexica.art and huggingface.co's MagicPrompt.

Variations of the "same" image are generated by changing the seed of a random number generator. This affects the noise from which denoising steps are started (the diffusion process), and the algorithm will converge to quite different looking images. But they should still be conseptually similar. Here three different seeds are used for each experiment.

Each parameter is varied to eight different values, either on a linear or logarithmic scale. Thus each figure consists of 3×8 sub-images. Originally each image was generated on a resolution of 512×512 (except the panda poster, since it has a different aspect ratio), so the resulting image tile would have a resolution of 1536×4096, and there are 20 such images in total. This brings the total image size to 156 megapixels, which would make the file size relatively large. Original PNGs take 180 MB, but the used images here have a resolution of 2560×960, and with a JPG quality of 90% their total size is only 12 MB (93% less).

Figure 1: "a white parrot sitting by the sea", generated at varying number of denoising steps. Major details have converged by the 4th or 5th column (15 & 18 steps), but there is still a noticeable jump on the last two columns (21 & 50 steps). The "sea" background lacks any interesting details.

The default settings are 50 denoising steps, CFG scale of 7.5 and reference image strength of 0 (meaning no reference image). All other parameters are kept constant while one other parameter is varied. (Note: the commmon convention on img2img applications seems to specify the weight of the added random noise, not the weight of the input image! Here the "image strength" is 1 - "noise strength".) The results shown here are based on Stable Diffusion model version 1.4 and using the "DDIM" sampler.

The first varied parameter is the **number of denoising steps**. The used values are $[3, 6, 9, 12, 15, 18, 21, 50]$, and usually the image has converged by step 50. These results are shown in figures 1 - 5.

Figure 2: "an ancient yellow robot holding a sword on desert" at varying number of steps. The result is quite acceptable already by column four (12 steps), and by 24 steps it has converged so much that the result is very similar as when using 50 steps (the right-most column).

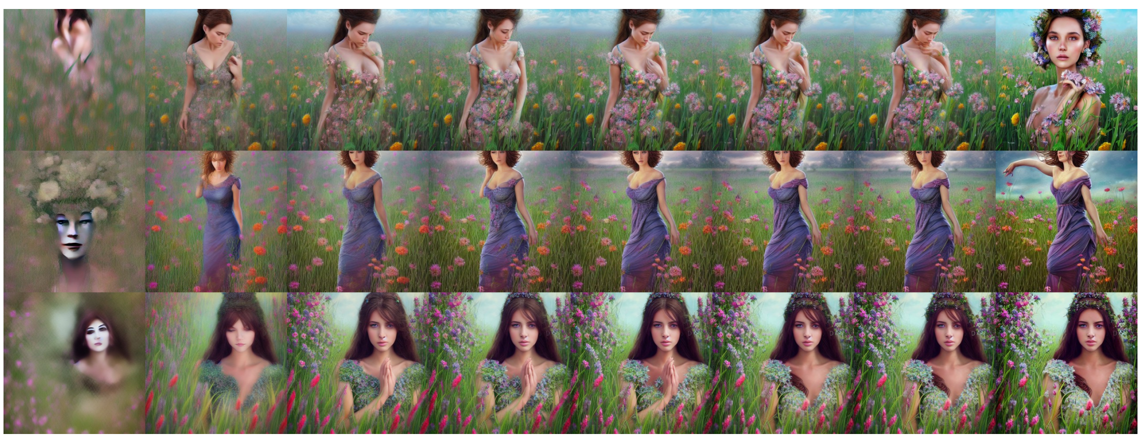


Figure 3: "full length portrait of gorgeous goddess standing in field full of flowers" at varying number of steps. Here the convergence is quite slow, and the pose keeps changing throughout the process. Depending on the seed, steps 24 and 50 may produce very different looking images. This means that using a lower step-count for previewing seeds doesn't always work.

All images have their major aspects defined already with just 10 - 15 denoising steps. Most of the time even going from 24 to 50 steps doesn't change the result in any major way, but of course there are exceptions. The most challenging inputs were "full length portrait of gorgeous goddess standing in field full of flowers" (Figure 3 and "panda movie poster with yellow background and red title text" (Figure 5). They don't have much in common, but the "goddess" has a complex foreground and background, and the "panda" has typography (seems to have either Chinese or English depending on the seed), high-contrasting colors and just a vague idea on how the composition should look like.

This is incontrast to the "a white parrot sitting by the sea" (Figure 1) and "an ancient yellow robot holding a sword on desert" (Figure 2), which have a somewhat constrained pose and a simpler background. Although the set of all possible robots has huge variety.

Figure 4: "mountains by a river" at varying number of steps. Initial images lack contrast and detail, but again the column 4 (12 steps) resembles the final result very much. Somehow the art style seems foggy and lacks detail, naturally this can be guided by changing the prompt by including terms like "sunshine".

Figure 5: "panda movie poster with yellow background and red title text" at varying number of steps. Even the column three (9 steps) could pass as a low-quality poster, but the contents continue to change until approximately column 6 (18 steps). And especially the top right corner's image benefits from "full" 50 steps, which adds detail to its hair and tunes the pose to look straight at the camera. It is plausible that original Kung Fu Panda movie posters were part of the training dataset.

Step parameter summary: This parameter is an easy one to tune, since the end result is almost always better with more steps. Sometimes the end result has converged after 30 steps, but it is better to let it run for 50 steps to be sure. And it is very rare that the end result would significantly change when going beyond that, at least when generating 512×512 resolution images.

The next studied parameter is the "CFG" or **classifier-free guidance scale**, or just "scale". It is described for example at diffusion-news.org, but the conclusions there are conflicting with experimental results which are shown in this article. According to the article, it "is a measure of how close you want the model to stick to your prompt when looking for a related image to show you. A Cfg Scale value of 0 will give you essentially a random image based on the seed, where as a Cfg Scale of 20 (the maximum on SD) will give you the closest match to your prompt that the model can produce." They even run the tests with various different **samplers**, but those aren't covered in this article for the sake of sticking to basics.

Tested CFG scales are from the formula $1 + 6.5 * 10^i$, where i is interpolated linearly between -1 and 1. This was chosen so that the default scale of 7.5 is in the middle. The values (rounded to two decimals) are $[1.65, 2.25, 3.42, 5.68, 10.03, 18.44, 34.67, 66.0]$. But the actual middle value 7.5 isn't present in the list, since there is an even number of samples. Examples are shown in figures 6 - 10.

Figure 6: "Parrot" at varying CFG scale between 1.65 and 66.0. Lower scale values produce an interesting hand-drawn style, but on the larger scales the results aren't very successful.

Figure 7: "Robot" at varying CFG scale between 1.65 and 66.0. Smallest values aren't really coherent, but larger values produce an interesting pop-art style.

The scale parameter has a very concrete impact on the resulting artistic style. Smaller numbers seem to cause the iteration to focus on smaller scale detail, and the overall contrast and saturation is fairly weak. But if such artistic style is desired, contrast and saturation can be easily fixed in post-processing. Parameters 6 - 8 give the most realistic and well-balanced results. Going beyond that, the results get progressively to the opposite direction. They have very vibrant colors, have high global contrast but are lacking in small details.

CFG scale parameter summary: Use smaller values for intricate hand-drawn style, the default 7.5 for realistic photos and larger values for pop-art style with high contrast and saturated colors. But going to either extreme may require further tweaking in a photo-editing software.

Figure 8: "Goddes" at varying CFG scale between 1.65 and 66.0. Smallest scales are well suited for this prompt, but larger values don't work that well.

Figure 9: "Mountains" at varying CFG scale between 1.65 and 66.0. Here all scales produce quite decent but very different results.

Figure 10: "Panda" at varying CFG scale between 1.65 and 66.0. Here smaller values produce interesting compositions with lots of detail, and larger values produce less interesting images.

The next studied parameter is the img2img **strength** (or "weight"), a value between 0% and 100%. The all previously described parameters still play a role, but here they are kept to their default values (running for 50 steps and the CFG scale is 7.5). Note that because of reasons, the strength has an opposite convention that original work such as source code at github.com/CompVis/stable-diffusion which says "strength is a value between 0.0 and 1.0, that controls the amount of noise that is added to the input image. Values that approach 1.0 allow for lots of variations but will also produce images that are not semantically consistent with the input." Basically it is a trade-off parameter between the image generated purely from the prompt, and the target image. 0% noise means that the output resembles the target 100%, and 100% noise means that the target image has no impact. Hopefully this isn't confusing anybody.

The weight is a very delicate parameter to tune, and if the two images (from the prompt and the target) are very different, then there might be a tipping point where changing the weight even a little bit will have a large change in the resulting image. However this depends very much on the context, and on many experiments the results had a nice gradular change. But because of this, the img2img exeperiments were run with two different parameter gradients. The first one uses weights $[0.03, 0.06, 0.09, 0.12, 0.15, 0.18, 0.21]$, and the second one uses $[0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7]$. The results are shwon in figures 11 - 20. Note that only seven different weights were used, but images consist of eight columns. This is because the right-most picture always shows the target image (corresponding to a strength of 1.0, or noise-level of zero).

Figure 11: "Parrot" turning into a seagull by the sea, using small strength values. All values (between 0.03 and 0.21) show interesting interpolation between the "source" and "target" images.

Figure 12: "Parrot" turning into a seagull by the sea, using large strength values. Columns 5 - 7 (strengths 0.5 - 0.7) resemble the target image too much, and very little "parrot" influence is present.

Figure 13: "Robot" on a desert, inspired by a yellowish stick-man drawing, using small strength values. In this case the target image isn't realistic at all, so at these strengths the image hasn't influenced the composition at all. It has only set the yellow color theme.

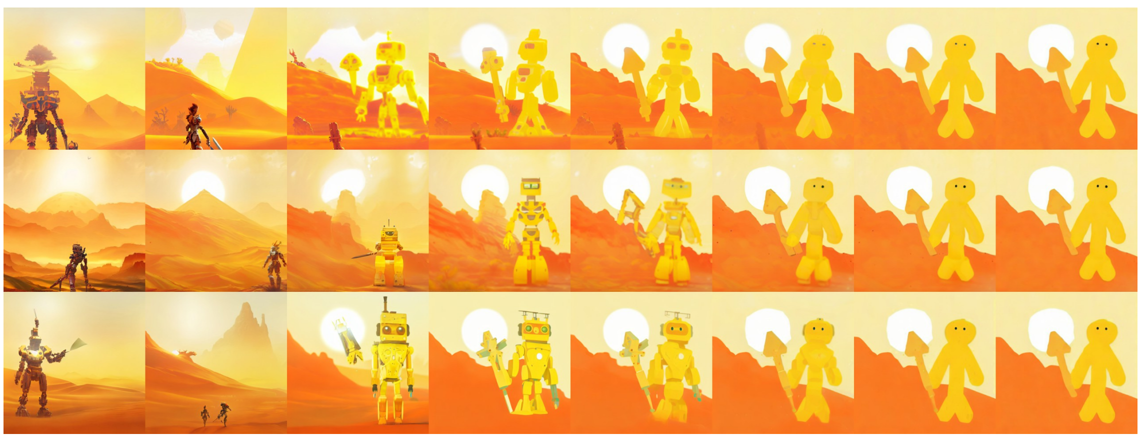


Figure 14: "Robot" on a desert, inspired by a yellowish stick-man drawin, using large strength values. Here strength values of 0.3 - 0.5 seem to produce the best results, going higher than this loses all details since they are absent from the target image.

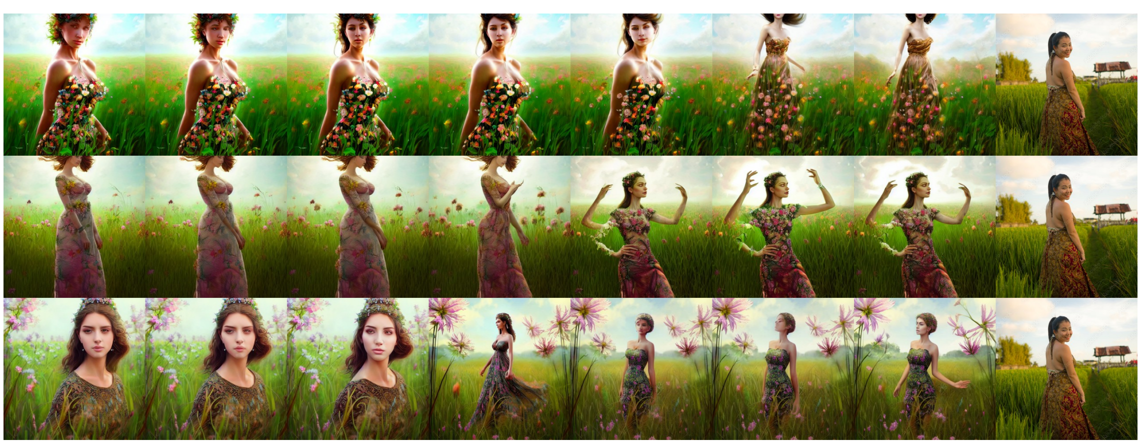


Figure 15: "Goddess" mimicking a woman on a grass field, using small strength values. Here all images are quite interesting, although the composition at the middle column isn't ideal since the face isn't visible.

Figure 16: "Goddess" mimicking a woman on a grass field, using large strength values. Images beyond the 2nd column (having the strength of 0.2) aren't that good, facial and other features are a mix-n-match with clearly visible artifacts.

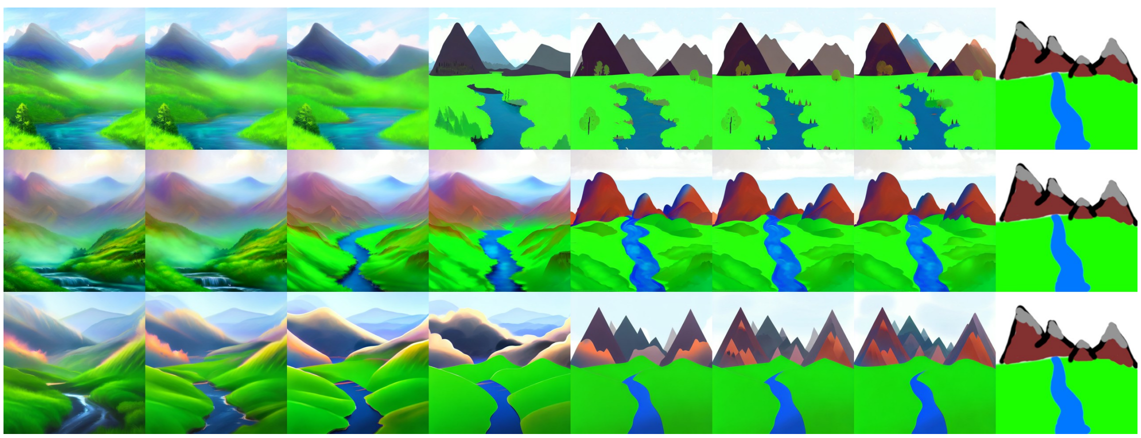


Figure 17: "Mountains" taking guidanse from a simple drawing, using small strength values. Only the first three columns (strengths 0.03 - 0.09) show interesting results. The taget image is so simplistic and unrealistic that it doesn't have a good impact on the resulting image.

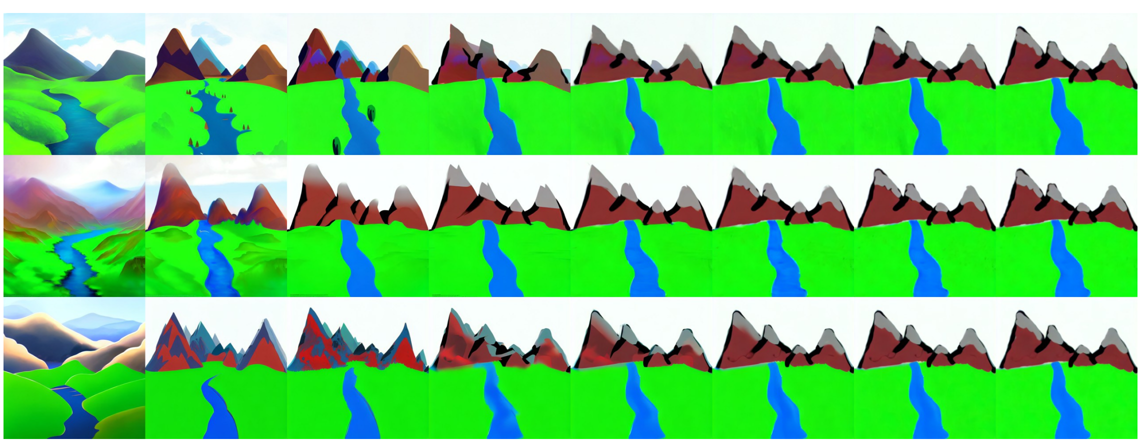


Figure 18: "Mountains" taking guidanse from a simple drawing, using large strength values. Clearly large strengths don't work well in this case.

Fiugres 13, 14 ("robot"), 17 and 18 ("mountains") show that one must use very low strengths if the target image is unrealistic, having lots regions with uniform color and lacks small-scale details. Better results could be obtained by running the img2img generation several times, using a low strength value each time and picking the most promising looking image as a starting point for the next iteration.

Other examples show that best results are obtained by using a realistic input image to begin with, if realistic results are desired. But since it is very context-dependent on which strength values produce resonable results, trial-and-error approach seems the easiest one. And one must not forget that CFG scale can be changed as well from the default 7.5, and it will have a major impact on the outcome as well.

Figure 19: "Panda" taking guidanse from the actual movie poster, using small strength values. Here all results look more or less reasonable.

Figure 20: "Panda" taking guidanse from the actual movie poster, using large strength values. By column 5 (strength 0.5) all of the results look very similar. Most interesting results are between columns 2 and 4 (strengths 0.2 - 0.4).

Img2img strength parameter summary: The results depend very much on the prompt and the target image. Some cases work best with a very small weight, while others require a larger one so trial-and-error must be used. But in general smaller weights work best when the target image is unrealistic and lacks detail, and larger weights can be used when the target image is aready realistic.

There are still many more topics to study, such as what kind of descriptions to append to the prompt, using different versions of the model (version 1.5 is alreayd out), using different samplers among others.