Diffusion Models-2

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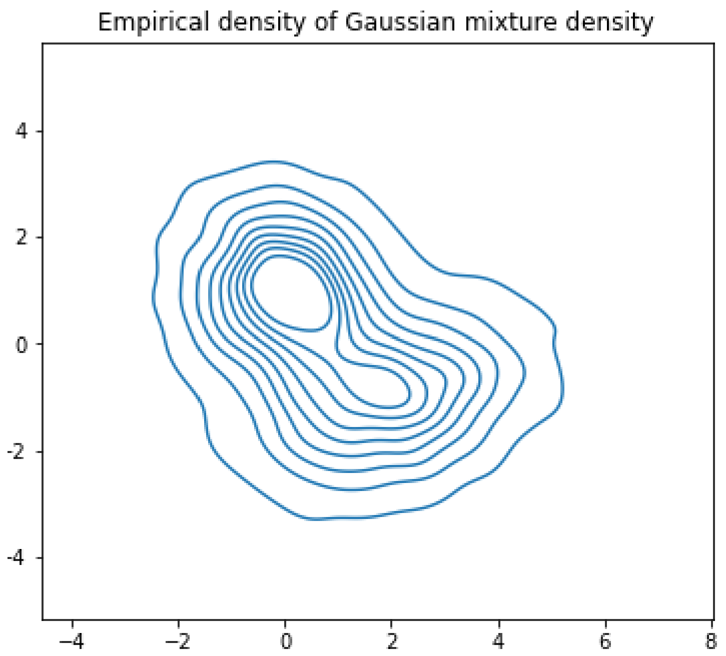
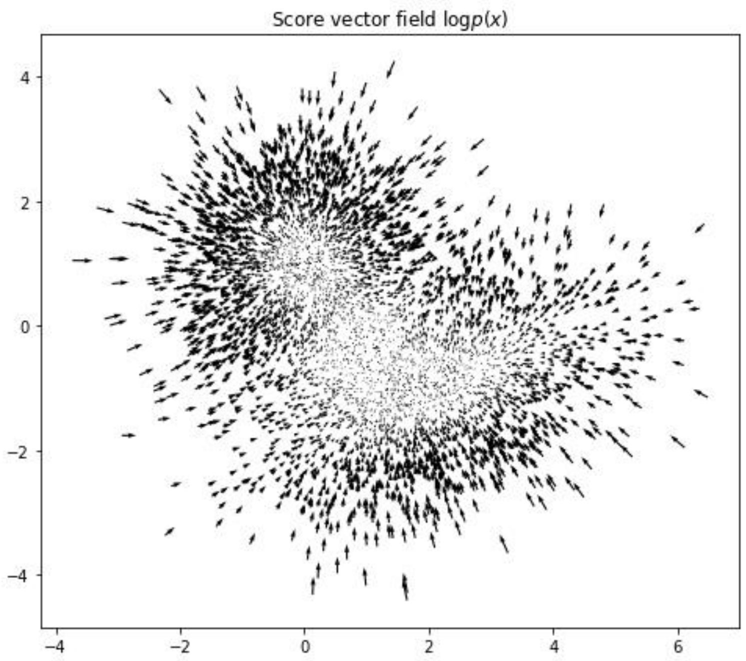
Score Function

The score function is a vector field that represents the gradient of the log-probability density of the data with respect to the data itself.

Mathematically, if $p(x)$ is the probability density function of the data x, the score function $\nabla_{\mathrm{x}} \log p(x)$ points in the direction of the steepest increase in log-density.





[MLFS_GMM_Diffusion_Day1_Student.ipynb - Colab (google.com)]

Score Vector Function

The score vector field in diffusion models is the collection of these score functions across different noise levels. During the forward diffusion process, noise is gradually added to the data. The score vector field, denoted as $s_\theta(x_t, t)$, is a neural network trained to approximate the true score function $\nabla_{\mathrm{x}_t} \log p(x_t \mid t)$ where x_t is the noisy data at time step t.

Role in diffusion models

1. **Training Phase**:
    1. The model learns to predict the score function at various noise levels.
    2. This involves training a neural network to minimize the difference between the predicted score $s\theta(xt,t)s\vartheta(xt,t)$ and the true score, often using denoising score matching techniques.
2. **Sampling Phase**:
    1. To generate new data, the model uses the learned score vector field to reverse the diffusion process.
    2. Starting from pure noise, the model iteratively denoises the sample by following the gradients indicated by the score vector field, effectively navigating back through the diffusion process to obtain a sample from the data distribution.

Importance

The score vector field is crucial because it provides the necessary information to reverse the noise addition process. By learning the gradients of the log-density, the model can effectively denoise samples and generate high-quality data that resembles the original training data.

Class conditioned diffusion models

```python
class ClassConditionedUnet(nn.Module):
  def __init__(self, num_classes=10, class_emb_size=4):
    super().__init__()

    # The embedding layer will map the class label to a vector of size class_emb_size
    self.class_emb = nn.Embedding(num_classes, class_emb_size)

    # Self.model is an unconditional UNet with extra input channels to accept the conditioning information (the class embedding)
    self.model = UNet2DModel(
        sample_size=28,           # the target image resolution
        in_channels=1 + class_emb_size, # Additional input channels for class cond.
        out_channels=1,           # the number of output channels
        layers_per_block=2,       # how many ResNet layers to use per UNet block
        block_out_channels=(32, 64, 64),
        down_block_types=(
            "DownBlock2D",        # a regular ResNet downsampling block
            "AttnDownBlock2D",    # a ResNet downsampling block with spatial self-attention
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        up_block_types=(
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          ),
    )

  # Our forward method now takes the class labels as an additional argument
  def forward(self, x, t, class_labels):
    # Shape of x:
    bs, ch, w, h = x.shape

    # class conditioning in right shape to add as additional input channels
    class_cond = self.class_emb(class_labels) # Map to embedding dimension
    class_cond = class_cond.view(bs, class_cond.shape[1], 1, 1).expand(bs, class_cond.shape[1], w, h)
    # x is shape (bs, 1, 28, 28) and class_cond is now (bs, 4, 28, 28)

    # Net input is now x and class cond concatenated together along dimension 1
    net_input = torch.cat((x, class_cond), 1) # (bs, 5, 28, 28)

    # Feed this to the UNet alongside the timestep and return the prediction
    return self.model(net_input, t).sample # (bs, 1, 28, 28)
```

[02_class_conditioned_diffusion_model_example.ipynb - Colab (google.com)]()

Class conditioned diffusion models

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These are the changes for the conditional model

[02_class_conditioned_diffusion_model_example.ipynb - Colab (google.com)]

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Why did we make this choice ?

[02_class_conditioned_diffusion_model_example.ipynb - Colab (google.com)]

Fine-Tuning and Guidance

There are two main approaches for adapting existing diffusion models:
•With **fine-tuning**, we'll re-train existing models on new data to change the type of output they produce

•With **guidance**, we'll take an existing model and steer the generation process at inference time for additional control

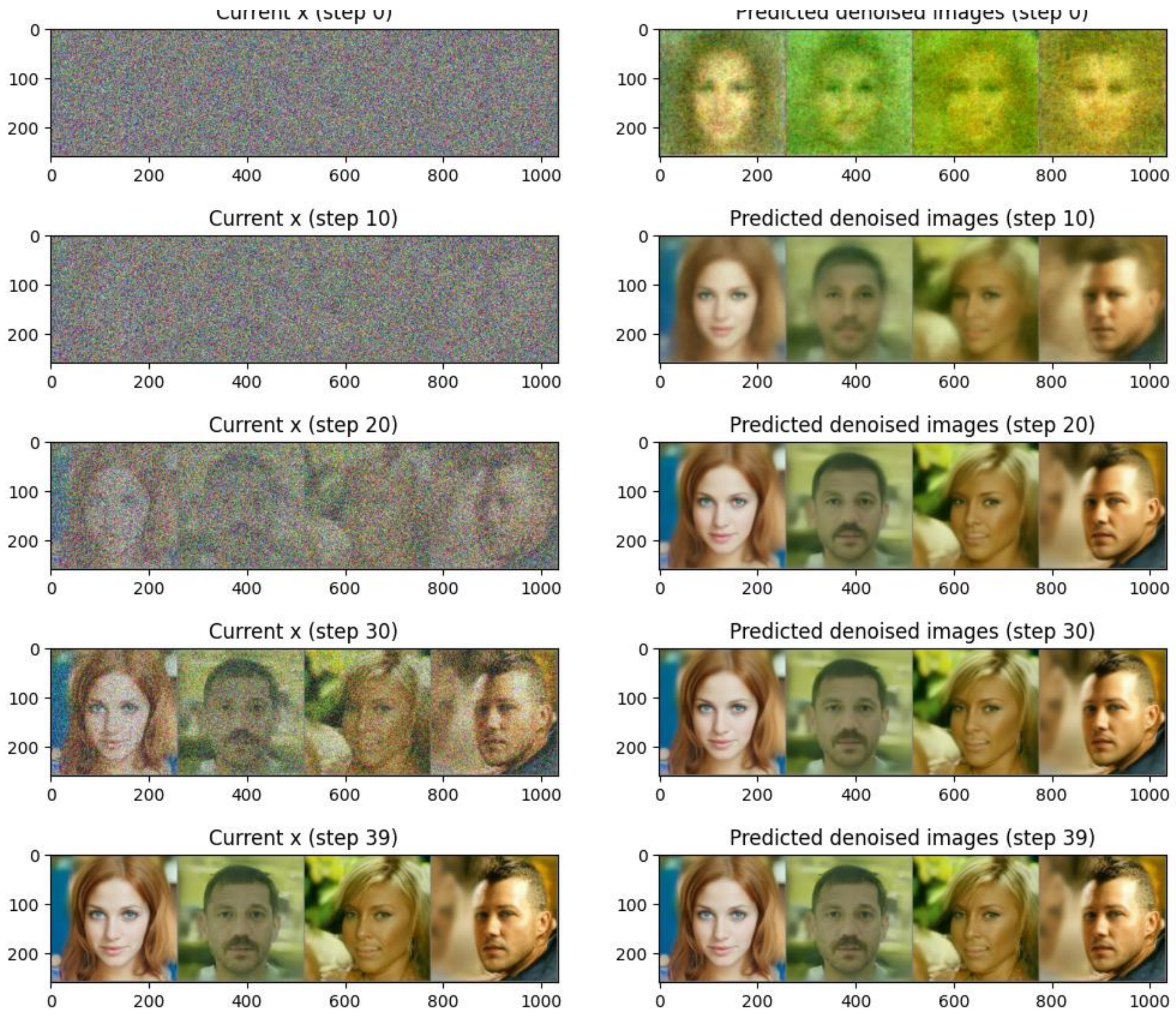
01_finetuning_and_guidance.ipynb - Colab (google.com)

Fine-Tuning and Guidance: image denoising overview

1. Model Process:
   - The model is fed a noisy input and tasked with predicting the noise, thereby estimating the denoised image.
   - Initial predictions are inaccurate, necessitating a multi-step process.
   - Recent research shows that using over 1000 steps is unnecessary; efficient sampling can be achieved with fewer steps.

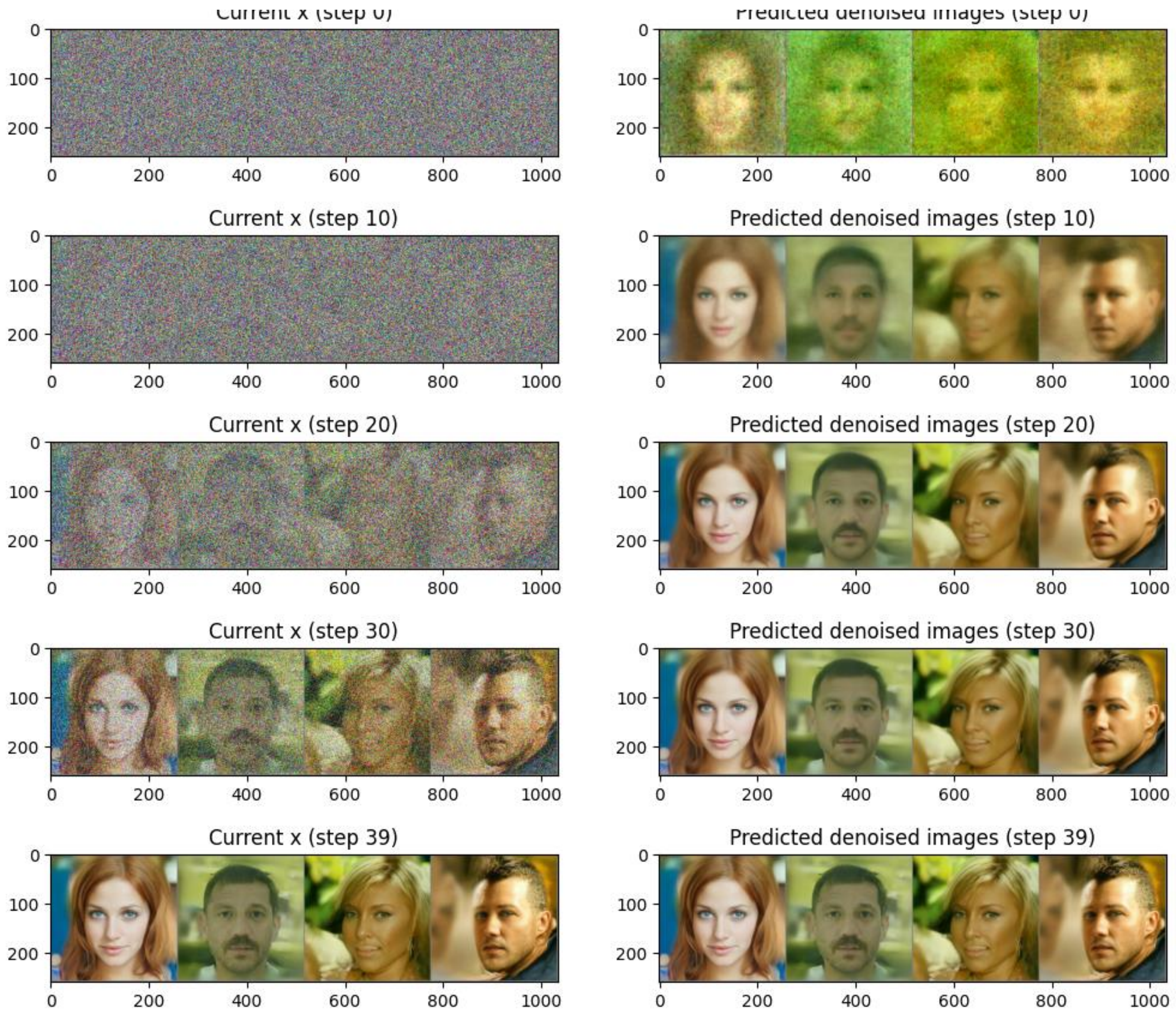
2. Sampling Methods in 🤗 Diffusers Library:
   - Scheduler: Handles sampling methods, performing updates via the `step()` function.
   - **Image Generation**:
     - Start with random noise (x).
     - For each timestep in the noise schedule, feed the noisy input (x) to the model.
     - Pass the prediction to the `step()` function.
     - The function returns an output with a `prev_sample` attribute, indicating the denoised image at that step.

Fine-Tuning and Guidance: image denoising overview



Schedulers allow to sample in reasonable time

Fine-Tuning and Guidance: image denoising overview



Schedulers allow to sample in reasonable time

```python
image_pipe.scheduler = scheduler
images = image_pipe(num_inference_steps=40).images
images[0]
```

```
0%|          | 0/40 [00:00<?, ?it/s]
```

40 steps instead of 1000

Training a diffusor

```python
import matplotlib.pyplot as plt

fig, axs = plt.subplots(1, 4, figsize=(16, 4))
for i, image in enumerate(dataset[:4]["image"]):
    axs[i].imshow(image)
    axs[i].set_axis_off()
fig.show()
```

[diffusers_training_example.ipynb - Colab (google.com)](#)

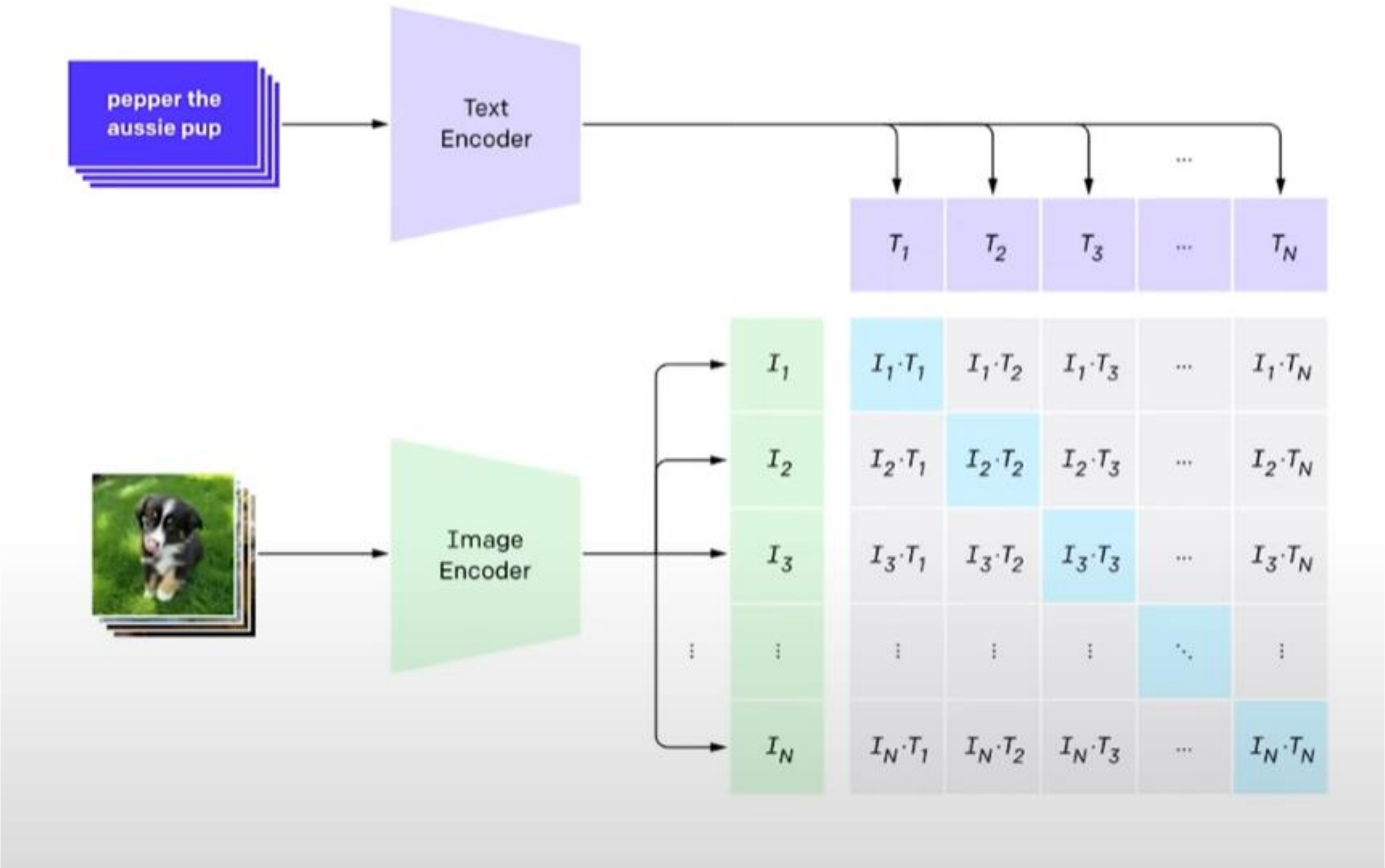
Stable Diffusion

01_stable_diffusion_introduction.ipynb - Colab (google.com)

diffusion-nbs/Stable Diffusion Deep Dive.ipynb at master · fastai/diffusion-nbs (github.com)

Grokking Stable Diffusion.ipynb - Colab (google.com)

Stable Diffusion



Stable Diffusion