Project - Stable Diffusion

Team Members:

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Problem Statement:

The project focuses on pre-training a Stable Diffusion model from scratch to generate conditional color images based on inputs such as numbers, classes, tokens, or text. Using the U-Net architecture with skip connections, the model will learn to iteratively denoise noisy samples, transforming random noise into meaningful images.

The goal is to adapt and train the model on a selected color image dataset entirely in PyTorch, using the provided codebase without relying on pre-trained weights, fine-tuning, or external frameworks. Challenges include implementing the diffusion process, designing a custom loss function to predict and remove noise effectively, and ensuring the generated images are accurate and high-quality based on the given conditions. This project will deepen the understanding of training diffusion models from scratch while demonstrating their generative capabilities.

Dataset: (https://www.cs.toronto.edu/~kriz/cifar.html)

The CIFAR-10 and CIFAR-100 datasets are popular benchmarks in machine learning and computer vision, featuring 32x32 color images for tasks like classification and generation.

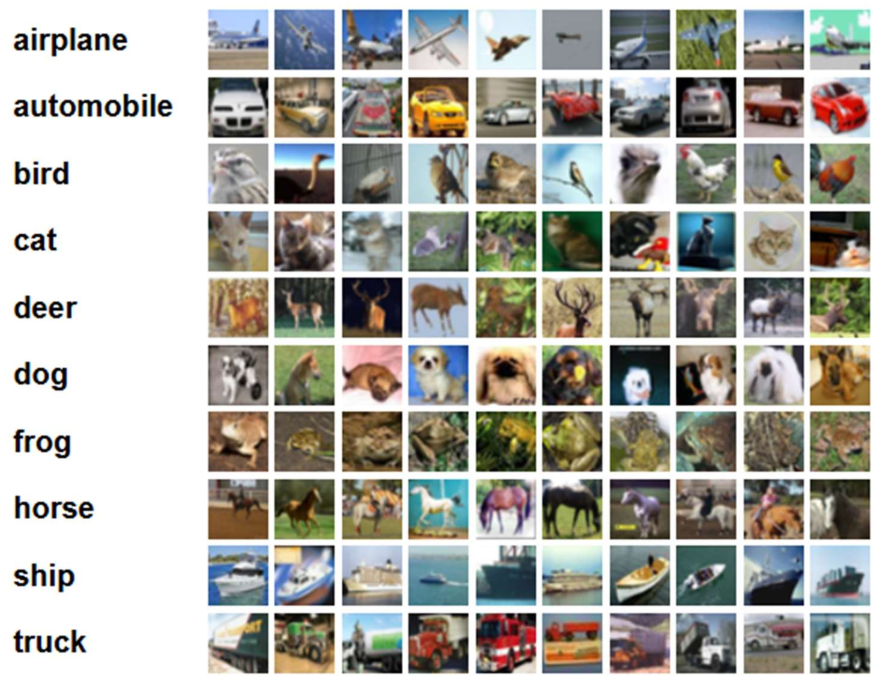
Dataset Overview:

CIFAR-10: 60,000 images (32x32 color) across 10 classes (e.g., airplane, car, dog). Divided into 50,000 training images and 10,000 testing images.

CIFAR-100: 60,000 images (32x32 color) across 100 classes, grouped into 20 superclasses. Each image has a "fine" (specific) and "coarse" (group) label.

The CIFAR-10 and CIFAR-100 datasets are well-suited for this project due to their manageable size, diverse classes, and efficient 32x32 color images, ideal for training a Stable Diffusion model from scratch. Their variety of objects, animals, and scenes provides rich visual features for the model to learn, while the class labels serve as conditions for generating specific images, such as "dog" or "airplane" in CIFAR-10 or more detailed classes like "tulip" in CIFAR-100.

These datasets align with the project's goals of generating conditional color images. Their small resolution enables efficient training and quick iterations, making them practical for validating the U-Net-based Stable Diffusion architecture. This ensures the model can effectively predict and remove noise while generating high-quality, conditioned outputs.



Code:

```
import torch

import torchvision

from torchvision import transforms

import matplotlib.pyplot as plt

import torchvision.datasets as datasets

import torchvision.transforms as transforms


# Define transformations for CIFAR-10

transform = transforms.Compose([

    transforms.Resize((32, 32)),  # Ensure images are resized to 32x32

    transforms.ToTensor(),        # Convert images to PyTorch tensors

    transforms.Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))  # Normalize to [-1, 1]

])


# Load CIFAR-10 dataset

train_dataset = datasets.CIFAR10(root='./data', train=True, transform=transform, download=True)
```

```
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=64, shuffle=True, num_workers=4, pin_memory=True)


# Denormalization function
def denormalize(img):
    img = (img * 0.5) + 0.5  # Reverse the normalization (assuming mean=0.5, std=0.5)
    return img


unique_images, unique_labels = next(iter(train_loader))
unique_images = unique_images.permute(0, 2, 3, 1).numpy()  # Permute to (batch, height, width, channels)
unique_images = denormalize(unique_images)  # Denormalize to [0, 1]


fig, axes = plt.subplots(4, 16, figsize=(16, 4), sharex=True, sharey=True)  # Create a 4x16 grid of subplots with a wider figure


for i in range(4):  # Loop over rows
    for j in range(16):  # Loop over columns
        index = i * 16 + j  # Calculate the index in the batch
        axes[i, j].imshow(unique_images[index])  # Show the image
        axes[i, j].axis('off')  # Turn off axis labels and ticks


plt.tight_layout()
plt.show()


%%capture


# Install the 'einops' library for easy manipulation of tensors
!pip install einops


# Install the 'lpips' library for computing perceptual similarity between images
```

```
!pip install lpips
# Import the PyTorch library for tensor operations.
import torch

# Import the neural network module from PyTorch.
import torch.nn as nn

# Import functional operations from PyTorch.
import torch.nn.functional as F

# Import the 'numpy' library for numerical operations.
import numpy as np

# Import the 'functools' module for higher-order functions.
import functools

# Import the Adam optimizer from PyTorch.
from torch.optim import Adam

# Import the DataLoader class from PyTorch for handling datasets.
from torch.utils.data import DataLoader

# Import data transformation functions from torchvision.
import torchvision.transforms as transforms

# Import the CIFAR10 dataset from torchvision.
from torchvision.datasets import CIFAR10

# Import 'tqdm' for creating progress bars during training.
import tqdm
```

```
# Import 'trange' and 'tqdm' specifically for notebook compatibility.
from tqdm.notebook import trange, tqdm

# Import the learning rate scheduler from PyTorch.
from torch.optim.lr_scheduler import MultiplicativeLR, LambdaLR

# Import the 'matplotlib.pyplot' library for plotting graphs.
import matplotlib.pyplot as plt

# Import the 'make_grid' function from torchvision.utils for visualizing image grids.
from torchvision.utils import make_grid

# Importing the rearrange function from the einops library
from einops import rearrange

# Importing the math module for mathematical operations
import math
# Forward diffusion for N steps in 1D.
def forward_diffusion_1D(x0, noise_strength_fn, t0, nsteps, dt):
    """
    Parameters:
    - x0: Initial sample value (scalar)
    - noise_strength_fn: Function of time, outputs scalar noise strength
    - t0: Initial time
    - nsteps: Number of diffusion steps
    - dt: Time step size

    Returns:
    - x: Trajectory of sample values over time
```

```
    - t: Corresponding time points for the trajectory
    """

    # Initialize the trajectory array
    x = np.zeros(nsteps + 1)

    # Set the initial sample value
    x[0] = x0

    # Generate time points for the trajectory
    t = t0 + np.arange(nsteps + 1) * dt

    # Perform Euler-Maruyama time steps for diffusion simulation
    for i in range(nsteps):

        # Get the noise strength at the current time
        noise_strength = noise_strength_fn(t[i])

        # Generate a random normal variable
        random_normal = np.random.randn()

        # Update the trajectory using Euler-Maruyama method
        x[i + 1] = x[i] + random_normal * noise_strength

    # Return the trajectory and corresponding time points
    return x, t
# Example noise strength function: always equal to 1
def noise_strength_constant(t):
    """
    Example noise strength function that returns a constant value (1).
```

```
    Parameters:
    - t: Time parameter (unused in this example)

    Returns:
    - Constant noise strength (1)
    """
    return 1
# Number of diffusion steps
nsteps = 100

# Initial time
t0 = 0

# Time step size
dt = 0.1

# Noise strength function
noise_strength_fn = noise_strength_constant

# Initial sample value
x0 = 0

# Number of tries for visualization
num_tries = 5

# Setting larger width and smaller height for the plot
plt.figure(figsize=(15, 3))

# Loop for multiple trials
```

```
for i in range(num_tries):

    # Simulate forward diffusion
    x, t = forward_diffusion_1D(x0, noise_strength_fn, t0, nsteps, dt)

    # Plot the trajectory
    plt.plot(t, x, label=f'Trial {i+1}')  # Adding a label for each trial

# Labeling the plot
plt.xlabel('Time', fontsize=20)
plt.ylabel('Sample Value ($x$)', fontsize=20)



# Title of the plot
plt.title('Forward Diffusion Visualization', fontsize=20)

# Adding a legend to identify each trial
plt.legend()

# Show the plot
plt.show()

# Reverse diffusion for N steps in 1D.
def reverse_diffusion_1D(x0, noise_strength_fn, score_fn, T, nsteps, dt):
    """
    Parameters:
    - x0: Initial sample value (scalar)
    - noise_strength_fn: Function of time, outputs scalar noise strength
    - score_fn: Score function
    - T: Final time
```

```
    - nsteps: Number of diffusion steps
    - dt: Time step size

    Returns:
    - x: Trajectory of sample values over time
    - t: Corresponding time points for the trajectory
    """

    # Initialize the trajectory array
    x = np.zeros(nsteps + 1)

    # Set the initial sample value
    x[0] = x0
    # Generate time points for the trajectory
    t = np.arange(nsteps + 1) * dt

    # Perform Euler-Maruyama time steps for reverse diffusion simulation
    for i in range(nsteps):

        # Calculate noise strength at the current time
        noise_strength = noise_strength_fn(T - t[i])

        # Calculate the score using the score function
        score = score_fn(x[i], 0, noise_strength, T - t[i])

        # Generate a random normal variable
        random_normal = np.random.randn()

        # Update the trajectory using the reverse Euler-Maruyama method
        x[i + 1] = x[i] + score * noise_strength**2 * dt + noise_strength * random_normal *
np.sqrt(dt)
```

```
    # Return the trajectory and corresponding time points
    return x, t
# Example score function: always equal to 1
def score_simple(x, x0, noise_strength, t):
    """
    Parameters:
    - x: Current sample value (scalar)
    - x0: Initial sample value (scalar)
    - noise_strength: Scalar noise strength at the current time
    - t: Current time


Returns:
    - score: Score calculated based on the provided formula
    """

    # Calculate the score using the provided formula
    score = - (x - x0) / ((noise_strength**2) * t)

    # Return the calculated score
    return score
# Number of reverse diffusion steps
nsteps = 100

# Initial time for reverse diffusion
t0 = 0

# Time step size for reverse diffusion
dt = 0.1
```

```
# Function defining constant noise strength for reverse diffusion
noise_strength_fn = noise_strength_constant

# Example score function for reverse diffusion
score_fn = score_simple

# Initial sample value for reverse diffusion
x0 = 0

# Final time for reverse diffusion
T = 11

# Number of tries for visualization
num_tries = 5

# Setting larger width and smaller height for the plot
plt.figure(figsize=(15, 3))

# Loop for multiple trials
for i in range(num_tries):
    # Draw from the noise distribution, which is diffusion for time T with noise strength 1
    x0 = np.random.normal(loc=0, scale=T)

    # Simulate reverse diffusion
    x, t = reverse_diffusion_1D(x0, noise_strength_fn, score_fn, T, nsteps, dt)

    # Plot the trajectory
    plt.plot(t, x, label=f'Trial {i+1}')  # Adding a label for each trial
```

```
# Labeling the plot
plt.xlabel('Time', fontsize=20)
plt.ylabel('Sample Value ($x$)', fontsize=20)

# Title of the plot
plt.title('Reverse Diffusion Visualized', fontsize=20)

# Adding a legend to identify each trial
plt.legend()

# Show the plot
plt.show()
# Define a module for Gaussian random features used to encode time steps.
class GaussianFourierProjection(nn.Module):
  def _init_(self, embed_dim, scale=30.):
    """
    Parameters:
    - embed_dim: Dimensionality of the embedding (output dimension)
    - scale: Scaling factor for random weights (frequencies)
    """
    super()._init_()

    # Randomly sample weights (frequencies) during initialization.
    # These weights (frequencies) are fixed during optimization and are not trainable.
    self.W = nn.Parameter(torch.randn(embed_dim // 2) * scale, requires_grad=False)

  def forward(self, x):
    """
    Parameters:
    - x: Input tensor representing time steps
```

```
        """
        # Calculate the cosine and sine projections: Cosine(2 pi freq x), Sine(2 pi freq x)
        x_proj = x[:, None] * self.W[None, :] * 2 * np.pi

        # Concatenate the sine and cosine projections along the last dimension
        return torch.cat([torch.sin(x_proj), torch.cos(x_proj)], dim=-1)
# Define a module for a fully connected layer that reshapes outputs to feature maps.
class Dense(nn.Module):
    def _init_(self, input_dim, output_dim):
        """
        Parameters:
        - input_dim: Dimensionality of the input features
        - output_dim: Dimensionality of the output features
        """
        super()._init_()

        # Define a fully connected layer
        self.dense = nn.Linear(input_dim, output_dim)

    def forward(self, x):
        """
        Parameters:
        - x: Input tensor

        Returns:
        - Output tensor after passing through the fully connected layer
          and reshaping to a 4D tensor (feature map)
        """

        # Apply the fully connected layer and reshape the output to a 4D tensor
```

```
        return self.dense(x)[..., None, None]
        # This broadcasts the 2D tensor to a 4D tensor, adding the same value across space.
# Define a time-dependent score-based model built upon the U-Net architecture.
class UNet(nn.Module):
    def _init_(self, marginal_prob_std, channels=[32, 64, 128, 256], embed_dim=256):
        """
        Initialize a time-dependent score-based network.

        Parameters:
        - marginal_prob_std: A function that gives the standard deviation
          of the perturbation kernel p_{0t}(x(t) | x(0)).
        - channels: The number of channels for feature maps of each resolution.
        - embed_dim: The dimensionality of Gaussian random feature embeddings.
        """
        super()._init_()

        # Gaussian random feature embedding layer for time
        self.time_embed = nn.Sequential(
            GaussianFourierProjection(embed_dim=embed_dim),
            nn.Linear(embed_dim, embed_dim)
        )

        # Encoding layers where the resolution decreases
        self.conv1 = nn.Conv2d(3, channels[0], kernel_size=3, stride=1, padding=1, bias=False)
        self.dense1 = Dense(embed_dim, channels[0])
        self.gnorm1 = nn.GroupNorm(4, num_channels=channels[0])

        self.conv2 = nn.Conv2d(channels[0], channels[1], kernel_size=3, stride=2, padding=1, bias=False)
        self.dense2 = Dense(embed_dim, channels[1])
        self.gnorm2 = nn.GroupNorm(32, num_channels=channels[1])
```

self.conv3 = nn.Conv2d(channels[1], channels[2], kernel_size=3, stride=2, padding=1, bias=False)

self.dense3 = Dense(embed_dim, channels[2])

self.gnorm3 = nn.GroupNorm(32, num_channels=channels[2])

self.conv4 = nn.Conv2d(channels[2], channels[3], kernel_size=3, stride=2, padding=1, bias=False)

self.dense4 = Dense(embed_dim, channels[3])

self.gnorm4 = nn.GroupNorm(32, num_channels=channels[3])

Decoding layers where the resolution increases

self.tconv4 = nn.ConvTranspose2d(channels[3], channels[2], kernel_size=3, stride=2, padding=1, output_padding=1, bias=False)

self.dense5 = Dense(embed_dim, channels[2])

self.tgnorm4 = nn.GroupNorm(32, num_channels=channels[2])

self.tconv3 = nn.ConvTranspose2d(channels[2] * 2, channels[1], kernel_size=3, stride=2, padding=1, output_padding=1, bias=False)

self.dense6 = Dense(embed_dim, channels[1])

self.tgnorm3 = nn.GroupNorm(32, num_channels=channels[1])

self.tconv2 = nn.ConvTranspose2d(channels[1] * 2, channels[0], kernel_size=3, stride=2, padding=1, output_padding=1, bias=False)

self.dense7 = Dense(embed_dim, channels[0])

self.tgnorm2 = nn.GroupNorm(32, num_channels=channels[0])

self.tconv1 = nn.ConvTranspose2d(channels[0] * 2, 1, kernel_size=3, stride=1, padding=1)

The swish activation function

self.act = lambda x: x * torch.sigmoid(x)

```
    self.marginal_prob_std = marginal_prob_std

def forward(self, x, t, y=None):
  """
  Forward pass of the UNet model.

  Parameters:
  - x: Input tensor.
  - t: Time tensor.
  - y: Optional target tensor.

  Returns:
  - h: Output tensor after passing through the UNet architecture.
  """
  # Obtain the Gaussian random feature embedding for time t
  embed = self.act(self.time_embed(t))

  # Encoding path
  h1 = self.conv1(x) + self.dense1(embed)
  h1 = self.act(self.gnorm1(h1))
  h2 = self.conv2(h1) + self.dense2(embed)
  h2 = self.act(self.gnorm2(h2))
  h3 = self.conv3(h2) + self.dense3(embed)
  h3 = self.act(self.gnorm3(h3))
  h4 = self.conv4(h3) + self.dense4(embed)
  h4 = self.act(self.gnorm4(h4))

  # Decoding path
  h = self.tconv4(h4) + self.dense5(embed)
  h = self.act(self.tgnorm4(h))
```

```
        # Ensure matching dimensions before concatenating h and h3
        if h.size(-1) != h3.size(-1) or h.size(-2) != h3.size(-2):
            h3 = F.interpolate(h3, size=(h.size(-2), h.size(-1)), mode="nearest")

        h = self.tconv3(torch.cat([h, h3], dim=1)) + self.dense6(embed)
        h = self.act(self.tgnorm3(h))

        # Ensure matching dimensions before concatenating h and h2
        if h.size(-1) != h2.size(-1) or h.size(-2) != h2.size(-2):
            h2 = F.interpolate(h2, size=(h.size(-2), h.size(-1)), mode="nearest")

        h = self.tconv2(torch.cat([h, h2], dim=1)) + self.dense7(embed)
        h = self.act(self.tgnorm2(h))

        # Ensure matching dimensions before concatenating h and h1
        if h.size(-1) != h1.size(-1) or h.size(-2) != h1.size(-2):
            h1 = F.interpolate(h1, size=(h.size(-2), h.size(-1)), mode="nearest")

        h = self.tconv1(torch.cat([h, h1], dim=1))

        # Normalize the output
        h = h / self.marginal_prob_std(t)[:, None, None, None]
        return h
class UNet_res(nn.Module):
    def _init_(self, marginal_prob_std, channels=[32, 64, 128, 256], embed_dim=256):
        """
        Initialize the alternate UNet model.

        Parameters:
```

```
- marginal_prob_std: A function that gives the standard deviation
  of the perturbation kernel p_{0t}(x(t) | x(0)).
- channels: The number of channels for feature maps of each resolution.
- embed_dim: The dimensionality of Gaussian random feature embeddings.
"""
super()._init_()

# Gaussian random feature embedding layer for time
self.time_embed = nn.Sequential(
   GaussianFourierProjection(embed_dim=embed_dim),
   nn.Linear(embed_dim, embed_dim)
)

# Encoding layers where the resolution decreases
self.conv1 = nn.Conv2d(3, channels[0], kernel_size=3, stride=1, padding=1, bias=False)
# Update input channels
self.dense1 = Dense(embed_dim, channels[0])
self.gnorm1 = nn.GroupNorm(4, num_channels=channels[0])

self.conv2 = nn.Conv2d(channels[0], channels[1], kernel_size=3, stride=2, padding=1,
bias=False)
self.dense2 = Dense(embed_dim, channels[1])
self.gnorm2 = nn.GroupNorm(32, num_channels=channels[1])

self.conv3 = nn.Conv2d(channels[1], channels[2], kernel_size=3, stride=2, padding=1,
bias=False)
self.dense3 = Dense(embed_dim, channels[2])
self.gnorm3 = nn.GroupNorm(32, num_channels=channels[2])

self.conv4 = nn.Conv2d(channels[2], channels[3], kernel_size=3, stride=2, padding=1,
bias=False)
self.dense4 = Dense(embed_dim, channels[3])
```

```
        self.gnorm4 = nn.GroupNorm(32, num_channels=channels[3])

        # Decoding layers where the resolution increases
        self.tconv4 = nn.ConvTranspose2d(channels[3], channels[2], kernel_size=3, stride=2, padding=1, output_padding=1, bias=False)
        self.dense5 = Dense(embed_dim, channels[2])
        self.tgnorm4 = nn.GroupNorm(32, num_channels=channels[2])

        self.tconv3 = nn.ConvTranspose2d(channels[2], channels[1], kernel_size=3, stride=2, padding=1, output_padding=1, bias=False)
        self.dense6 = Dense(embed_dim, channels[1])
        self.tgnorm3 = nn.GroupNorm(32, num_channels=channels[1])

        self.tconv2 = nn.ConvTranspose2d(channels[1], channels[0], kernel_size=3, stride=2, padding=1, output_padding=1, bias=False)
        self.dense7 = Dense(embed_dim, channels[0])
        self.tgnorm2 = nn.GroupNorm(32, num_channels=channels[0])

        self.tconv1 = nn.ConvTranspose2d(channels[0], 1, kernel_size=3, stride=1, padding=1)

        # The swish activation function
        self.act = lambda x: x * torch.sigmoid(x)
        self.marginal_prob_std = marginal_prob_std

    def forward(self, x, t, y=None):
        """
        Parameters:
        - x: Input tensor
        - t: Time tensor
        - y: Target tensor (not used in this forward pass)
```

```
Returns:
- h: Output tensor after passing through the U-Net architecture
"""

# Obtain the Gaussian random feature embedding for t
embed = self.act(self.time_embed(t))

# Encoding path
h1 = self.conv1(x) + self.dense1(embed)
h1 = self.act(self.gnorm1(h1))
h2 = self.conv2(h1) + self.dense2(embed)
h2 = self.act(self.gnorm2(h2))
h3 = self.conv3(h2) + self.dense3(embed)
h3 = self.act(self.gnorm3(h3))
h4 = self.conv4(h3) + self.dense4(embed)
h4 = self.act(self.gnorm4(h4))

# Decoding path
h = self.tconv4(h4)
h += self.dense5(embed)
h = self.act(self.tgnorm4(h))
h = self.tconv3(h + h3)
h += self.dense6(embed)
h = self.act(self.tgnorm3(h))
h = self.tconv2(h + h2)
h += self.dense7(embed)
h = self.act(self.tgnorm2(h))
h = self.tconv1(h + h1)

# Normalize output
```

```
        h = h / self.marginal_prob_std(t)[:, None, None, None]
        return h
# Using GPU
device = "cuda"

# Marginal Probability Standard Deviation Function
def marginal_prob_std(t, sigma):
    """
    Compute the mean and standard deviation of $p_{0t}(x(t) | x(0))$.

    Parameters:
    - t: A vector of time steps.
    - sigma: The $\sigma$ in our SDE.

    Returns:
    - The standard deviation.
    """
    # Convert time steps to a PyTorch tensor
    t = torch.tensor(t, device=device)
    #t = t.clone().detach().to(device)

    # Calculate and return the standard deviation based on the given formula
    return torch.sqrt((sigma**(2 * t) - 1.) / 2. / np.log(sigma))
# Using GPU
device = "cuda"

def diffusion_coeff(t, sigma):
    """
    Compute the diffusion coefficient of our SDE.
```

```
    Parameters:
    - t: A vector of time steps.
    - sigma: The $\sigma$ in our SDE.

    Returns:
    - The vector of diffusion coefficients.
    """
    # Calculate and return the diffusion coefficients based on the given formula
    return torch.tensor(sigma**t, device=device)

# Sigma Value
sigma =  25.0

# marginal probability standard
marginal_prob_std_fn = functools.partial(marginal_prob_std, sigma=sigma)

# diffusion coefficient
diffusion_coeff_fn = functools.partial(diffusion_coeff, sigma=sigma)
def loss_fn(model, x, marginal_prob_std, eps=1e-5):
    """
    The loss function for training score-based generative models.

    Parameters:
    - model: A PyTorch model instance that represents a time-dependent score-based model.
    - x: A mini-batch of training data.
    - marginal_prob_std: A function that gives the standard deviation of the perturbation kernel.
    - eps: A tolerance value for numerical stability.
    """
    # Sample time uniformly in the range (eps, 1-eps)
    random_t = torch.rand(x.shape[0], device=x.device) * (1. - 2 * eps) + eps
```

```
    # Find the noise std at the sampled time t
    std = marginal_prob_std(random_t)

    # Generate normally distributed noise
    z = torch.randn_like(x)

    # Perturb the input data with the generated noise
    perturbed_x = x + z * std[:, None, None, None]

    # Get the score from the model using the perturbed data and time
    score = model(perturbed_x, random_t)

    # Ensure score and noise have matching dimensions
    if score.size() != z.size():
        z = F.interpolate(z, size=score.shape[2:], mode='bilinear', align_corners=False)

    # Calculate the loss based on the score and noise
    loss = torch.mean(torch.sum((score * std[:, None, None, None] + z)**2, dim=(1, 2, 3)))

    return loss

def Euler_Maruyama_sampler(score_model,
                           marginal_prob_std,
                           diffusion_coeff,
                           batch_size=64,
                           x_shape=(3, 32, 32),
                           num_steps=1000,
                           device='cuda',
                           eps=1e-3,
                           y=None):
```

```
    """
    Generate samples using Euler-Maruyama sampler with corrected sqrt() usage.
    """
    t = torch.ones(batch_size, device=device)
    init_x = torch.randn(batch_size, *x_shape, device=device) * marginal_prob_std(t)[:, None, None, None]
    time_steps = torch.linspace(1., eps, num_steps, device=device)
    step_size = time_steps[0] - time_steps[1]
    x = init_x

    with torch.no_grad():
        for time_step in time_steps:
            batch_time_step = torch.ones(batch_size, device=device) * time_step
            g = diffusion_coeff(batch_time_step)
            mean_x = x + (g**2)[:, None, None, None] * score_model(x, batch_time_step, y=y) * step_size
            noise = torch.randn_like(x)
            x = mean_x + torch.sqrt(torch.tensor(step_size, device=device)) * g[:, None, None, None] * noise

    return x

# Define the score-based model and move it to the specified device
score_model = torch.nn.DataParallel(UNet(marginal_prob_std=marginal_prob_std_fn))
score_model = score_model.to(device)

# Number of training epochs
n_epochs = 150
# Size of a mini-batch
batch_size = 256
# Learning rate
```

```
lr = 1e-4


# Load the CIFAR10 dataset and create a data loader
dataset = CIFAR10('.', train=True, transform=transforms.Compose([transforms.Resize((32, 32)), transforms.ToTensor(), transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))]), download=True)
data_loader = DataLoader(dataset, batch_size=batch_size, shuffle=True, num_workers=2)


# Define the Adam optimizer for training the model
optimizer = Adam(score_model.parameters(), lr=lr)


# Progress bar for epochs
tqdm_epoch = trange(n_epochs)
for epoch in tqdm_epoch:
    avg_loss = 0.
    num_items = 0
    # Iterate through mini-batches in the data loader
    for x, y in tqdm(data_loader):
        x = x.to(device)
        # Calculate the loss and perform backpropagation
        loss = loss_fn(score_model, x, marginal_prob_std_fn)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        avg_loss += loss.item() * x.shape[0]
        num_items += x.shape[0]
    # Print the averaged training loss for the current epoch
    tqdm_epoch.set_description('Average Loss: {:5f}'.format(avg_loss / num_items))
    # Save the model checkpoint after each epoch of training
    torch.save(score_model.state_dict(), 'ckpt.pth')
# Load the pre-trained checkpoint from disk
```

```
device = 'cuda'

# Load the pre-trained model checkpoint
ckpt = torch.load('ckpt.pth', map_location=device, weights_only=True)  # Set weights_only=True
score_model.load_state_dict(ckpt)

# Set sample batch size and number of steps
sample_batch_size = 64
num_steps = 1000

# Choose the Euler-Maruyama sampler
sampler = Euler_Maruyama_sampler

# Generate samples using the specified sampler
samples = sampler(
    score_model,
    marginal_prob_std_fn,
    diffusion_coeff_fn,
    sample_batch_size,
    num_steps=num_steps,
    device=device,
    y=None
)

# Clip samples to be in the range [0, 1]
samples = samples.clamp(0.0, 1.0)

# Visualize the generated samples
%matplotlib inline
import matplotlib.pyplot as plt
```

```
sample_grid = make_grid(samples, nrow=int(np.sqrt(sample_batch_size)))

# Plot the sample grid
plt.figure(figsize=(6, 6))
plt.axis('off')
plt.imshow(sample_grid.permute(1, 2, 0).cpu(), vmin=0., vmax=1.)
plt.show()

# Initialize the alternate U-Net model for training.
score_model = torch.nn.DataParallel(UNet_res(marginal_prob_std=marginal_prob_std_fn))
score_model = score_model.to(device)

# Set the number of training epochs, mini-batch size, and learning rate.
n_epochs = 150
batch_size = 256
lr = 1e-4

# Load the CIFAR10 dataset for training.
dataset = CIFAR10('.', train=True, transform=transforms.Compose([transforms.Resize((32, 32)), transforms.ToTensor(), transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))]), download=True)
data_loader = DataLoader(dataset, batch_size=batch_size, shuffle=True, num_workers=4)

# Initialize the Adam optimizer with the specified learning rate.
optimizer = Adam(score_model.parameters(), lr=lr)
# Learning rate scheduler to adjust the learning rate during training.
scheduler = LambdaLR(optimizer, lr_lambda=lambda epoch: max(0.2, 0.98 ** epoch))

# Training loop over epochs.
tqdm_epoch = trange(n_epochs)
for epoch in tqdm_epoch:
```

```
    avg_loss = 0.
    num_items = 0
    # Iterate over mini-batches in the training data loader.
    for x, y in data_loader:
        #x = x.to(device)
        x, y = x.to(device), y.to(device)
        # Compute the loss for the current mini-batch.
        loss = loss_fn(score_model, x, marginal_prob_std_fn)
        # Zero the gradients, backpropagate, and update the model parameters.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        # Accumulate the total loss and the number of processed items.
        avg_loss += loss.item() * x.shape[0]
        num_items += x.shape[0]

    # Adjust the learning rate using the scheduler.
    scheduler.step()
    lr_current = scheduler.get_last_lr()[0]

    # Print the average loss and learning rate for the current epoch.
    print('{} Average Loss: {:5f} lr {:.1e}'.format(epoch, avg_loss / num_items, lr_current))
    tqdm_epoch.set_description('Average Loss: {:5f}'.format(avg_loss / num_items))

    # Save the model checkpoint after each epoch of training.
    torch.save(score_model.state_dict(), 'ckpt_res.pth')
# Load the pre-trained checkpoint from disk.
device = 'cuda'

# Load the pre-trained model checkpoint
```

```
ckpt = torch.load('ckpt_res.pth', map_location=device)
score_model.load_state_dict(ckpt)

# Set sample batch size and number of steps
sample_batch_size = 64
num_steps = 1000

# Choose the Euler-Maruyama sampler
sampler = Euler_Maruyama_sampler

# Generate samples using the specified sampler
samples = sampler(score_model,
                  marginal_prob_std_fn,
                  diffusion_coeff_fn,
                  sample_batch_size,
                  num_steps=num_steps,
                  device=device,
                  y=None)

# Clip samples to be in the range [0, 1]
samples = samples.clamp(0.0, 1.0)

# Visualize the generated samples
%matplotlib inline
import matplotlib.pyplot as plt
sample_grid = make_grid(samples, nrow=int(np.sqrt(sample_batch_size)))

# Plot the sample grid
plt.figure(figsize=(6, 6))
plt.axis('off')
```

```
plt.imshow(sample_grid.permute(1, 2, 0).cpu(), vmin=0., vmax=1.)
plt.show()
class CrossAttention(nn.Module):
    def _init_(self, embed_dim, hidden_dim, context_dim=None, num_heads=1):
        """
        Initialize the CrossAttention module.

        Parameters:
        - embed_dim: The dimensionality of the output embeddings.
        - hidden_dim: The dimensionality of the hidden representations.
        - context_dim: The dimensionality of the context representations (if not self attention).
        - num_heads: Number of attention heads (currently supports 1 head).

        Note: For simplicity reasons, the implementation assumes 1-head attention.
        Feel free to implement multi-head attention using fancy tensor manipulations.
        """
        super(CrossAttention, self)._init_()

        self.hidden_dim = hidden_dim
        self.context_dim = context_dim
        self.embed_dim = embed_dim



        # Linear layer for query projection
        self.query = nn.Linear(hidden_dim, embed_dim, bias=False)

        # Check if self-attention or cross-attention
        if context_dim is None:
            self.self_attn = True
            self.key = nn.Linear(hidden_dim, embed_dim, bias=False)
```

```
            self.value = nn.Linear(hidden_dim, hidden_dim, bias=False)
        else:
            self.self_attn = False
            self.key = nn.Linear(context_dim, embed_dim, bias=False)
            self.value = nn.Linear(context_dim, hidden_dim, bias=False)

    def forward(self, tokens, context=None):
        """
        Forward pass of the CrossAttention module.

        Parameters:
        - tokens: Input tokens with shape [batch, sequence_len, hidden_dim].
        - context: Context information with shape [batch, context_seq_len, context_dim].
                   If self_attn is True, context is ignored.

        Returns:
        - ctx_vecs: Context vectors after attention with shape [batch, sequence_len, embed_dim].
        """

        if self.self_attn:
            # Self-attention case
            Q = self.query(tokens)
            K = self.key(tokens)
            V = self.value(tokens)
        else:
            # Cross-attention case
            Q = self.query(tokens)
            K = self.key(context)
            V = self.value(context)
```

```
        # Compute score matrices, attention matrices, and context vectors
        scoremats = torch.einsum("BTH,BSH->BTS", Q, K)  # Inner product of Q and K, a tensor
        attnmats = F.softmax(scoremats / math.sqrt(self.embed_dim), dim=-1)  # Softmax of scoremats
        ctx_vecs = torch.einsum("BTS,BSH->BTH", attnmats, V)  # Weighted average value vectors by attnmats

        return ctx_vecs
class TransformerBlock(nn.Module):
    """The transformer block that combines self-attn, cross-attn, and feed forward neural net"""
    def _init_(self, hidden_dim, context_dim):
        """
        Initialize the TransformerBlock.

        Parameters:
        - hidden_dim: The dimensionality of the hidden state.
        - context_dim: The dimensionality of the context tensor.

        Note: For simplicity, the self-attn and cross-attn use the same hidden_dim.
        """

        super(TransformerBlock, self)._init_()

        # Self-attention module
        self.attn_self = CrossAttention(hidden_dim, hidden_dim)

        # Cross-attention module
        self.attn_cross = CrossAttention(hidden_dim, hidden_dim, context_dim)

        # Layer normalization modules
        self.norm1 = nn.LayerNorm(hidden_dim)
```

```
    self.norm2 = nn.LayerNorm(hidden_dim)
    self.norm3 = nn.LayerNorm(hidden_dim)

    # Implement a 2-layer MLP with K * hidden_dim hidden units, and nn.GELU nonlinearity
    self.ffn = nn.Sequential(
        nn.Linear(hidden_dim, 3 * hidden_dim),
        nn.GELU(),
        nn.Linear(3 * hidden_dim, hidden_dim)
    )

def forward(self, x, context=None):
    """
    Forward pass of the TransformerBlock.

    Parameters:
    - x: Input tensor with shape [batch, sequence_len, hidden_dim].
    - context: Context tensor with shape [batch, context_seq_len, context_dim].

    Returns:
    - x: Output tensor after passing through the TransformerBlock.
    """

    # Apply self-attention with layer normalization and residual connection
    x = self.attn_self(self.norm1(x)) + x

    # Apply cross-attention with layer normalization and residual connection
    x = self.attn_cross(self.norm2(x), context=context) + x

    # Apply feed forward neural network with layer normalization and residual connection
    x = self.ffn(self.norm3(x)) + x
```

```
        return x
class SpatialTransformer(nn.Module):
    def _init_(self, hidden_dim, context_dim):
        """
        Initialize the SpatialTransformer.

        Parameters:
        - hidden_dim: The dimensionality of the hidden state.
        - context_dim: The dimensionality of the context tensor.
        """
        super(SpatialTransformer, self)._init_()

        # TransformerBlock for spatial transformation
        self.transformer = TransformerBlock(hidden_dim, context_dim)

    def forward(self, x, context=None):
        """
        Forward pass of the SpatialTransformer.

        Parameters:
        - x: Input tensor with shape [batch, channels, height, width].
        - context: Context tensor with shape [batch, context_seq_len, context_dim].

        Returns:
        - x: Output tensor after applying spatial transformation.
        """
        b, c, h, w = x.shape
        x_in = x
```

```
        # Combine the spatial dimensions and move the channel dimension to the end
        x = rearrange(x, "b c h w -> b (h w) c")

        # Apply the sequence transformer
        x = self.transformer(x, context)

        # Reverse the process
        x = rearrange(x, 'b (h w) c -> b c h w', h=h, w=w)

        # Residue connection
        return x + x_in
class UNet_Tranformer(nn.Module):
    """A time-dependent score-based model built upon U-Net architecture."""
    def _init_(self, marginal_prob_std, channels=[32, 64, 128, 256], embed_dim=256,
                text_dim=256, nClass=10):
        """
        Initialize a time-dependent score-based network.

        Parameters:
        - marginal_prob_std: A function that gives the standard deviation
          of the perturbation kernel p_{0t}(x(t) | x(0)).
        - channels: The number of channels for feature maps of each resolution.
        - embed_dim: The dimensionality of Gaussian random feature embeddings of time.
        - text_dim: The embedding dimension of text/digits.
        - nClass: Number of classes to model.
        """
        super()._init_()

        # Gaussian random feature embedding layer for time
        self.time_embed = nn.Sequential(
```

```
            GaussianFourierProjection(embed_dim=embed_dim),
            nn.Linear(embed_dim, embed_dim)
        )

        # Encoding layers where the resolution decreases
        self.conv1 = nn.Conv2d(3, channels[0], kernel_size=3, stride=1, padding=1, bias=False)
# Updated to 3 channels
        self.dense1 = Dense(embed_dim, channels[0])
        self.gnorm1 = nn.GroupNorm(4, num_channels=channels[0])

        self.conv2 = nn.Conv2d(channels[0], channels[1], kernel_size=3, stride=2, padding=1,
bias=False)
        self.dense2 = Dense(embed_dim, channels[1])
        self.gnorm2 = nn.GroupNorm(32, num_channels=channels[1])

        self.conv3 = nn.Conv2d(channels[1], channels[2], kernel_size=3, stride=2, padding=1,
bias=False)
        self.dense3 = Dense(embed_dim, channels[2])
        self.gnorm3 = nn.GroupNorm(32, num_channels=channels[2])
        self.attn3 = SpatialTransformer(channels[2], text_dim)

        self.conv4 = nn.Conv2d(channels[2], channels[3], kernel_size=3, stride=2, padding=1,
bias=False)
        self.dense4 = Dense(embed_dim, channels[3])
        self.gnorm4 = nn.GroupNorm(32, num_channels=channels[3])
        self.attn4 = SpatialTransformer(channels[3], text_dim)

        # Decoding layers where the resolution increases
        self.tconv4 = nn.ConvTranspose2d(channels[3], channels[2], kernel_size=3, stride=2,
padding=1, output_padding=1, bias=False)
        self.dense5 = Dense(embed_dim, channels[2])
        self.tgnorm4 = nn.GroupNorm(32, num_channels=channels[2])
```

```
        self.tconv3 = nn.ConvTranspose2d(channels[2], channels[1], kernel_size=3, stride=2, padding=1, output_padding=1, bias=False)
        self.dense6 = Dense(embed_dim, channels[1])
        self.tgnorm3 = nn.GroupNorm(32, num_channels=channels[1])

        self.tconv2 = nn.ConvTranspose2d(channels[1], channels[0], kernel_size=3, stride=2, padding=1, output_padding=1, bias=False)
        self.dense7 = Dense(embed_dim, channels[0])
        self.tgnorm2 = nn.GroupNorm(32, num_channels=channels[0])

        self.tconv1 = nn.ConvTranspose2d(channels[0], 3, kernel_size=3, stride=1, padding=1) # Fixed to output 3 channels



        # The swish activation function
        self.act = nn.SiLU()
        self.marginal_prob_std = marginal_prob_std
        self.cond_embed = nn.Embedding(nClass, text_dim)

    def forward(self, x, t, y=None):
        """
        Forward pass of the UNet_Transformer model.

        Parameters:
        - x: Input tensor.
        - t: Time tensor.
        - y: Target tensor.

        Returns:
        - h: Output tensor after passing through the UNet_Transformer architecture.
```

```
"""
# Obtain the Gaussian random feature embedding for t
embed = self.act(self.time_embed(t))
y_embed = self.cond_embed(y).unsqueeze(1)

# Encoding path
h1 = self.conv1(x) + self.dense1(embed)
h1 = self.act(self.gnorm1(h1))
h2 = self.conv2(h1) + self.dense2(embed)
h2 = self.act(self.gnorm2(h2))
h3 = self.conv3(h2) + self.dense3(embed)
h3 = self.act(self.gnorm3(h3))
h3 = self.attn3(h3, y_embed)
h4 = self.conv4(h3) + self.dense4(embed)
h4 = self.act(self.gnorm4(h4))
h4 = self.attn4(h4, y_embed)

# Decoding path
h = self.tconv4(h4) + self.dense5(embed)
h = self.act(self.tgnorm4(h))
h = self.tconv3(h + h3) + self.dense6(embed)
h = self.act(self.tgnorm3(h))
h = self.tconv2(h + h2) + self.dense7(embed)
h = self.act(self.tgnorm2(h))
h = self.tconv1(h + h1)

# Normalize output
h = h / self.marginal_prob_std(t)[:, None, None, None]
return h
```

```
def loss_fn_cond(model, x, y, marginal_prob_std, eps=1e-5):
    """
    The loss function for training score-based generative models with conditional information.

    Parameters:
    - model: A PyTorch model instance that represents a time-dependent score-based model.
    - x: A mini-batch of training data.
    - y: Conditional information (target tensor).
    - marginal_prob_std: A function that gives the standard deviation of the perturbation kernel.
    - eps: A tolerance value for numerical stability.

    Returns:
    - loss: The calculated loss.
    """
    # Sample time uniformly in the range [eps, 1-eps]
    random_t = torch.rand(x.shape[0], device=x.device) * (1. - eps) + eps
    # Generate random noise with the same shape as the input
    z = torch.randn_like(x)
    # Compute the standard deviation of the perturbation kernel at the sampled time
    std = marginal_prob_std(random_t)
    # Perturb the input data with the generated noise and scaled by the standard deviation
    perturbed_x = x + z * std[:, None, None, None]
    # Get the model's score for the perturbed input, considering conditional information
    score = model(perturbed_x, random_t, y=y)
    # Calculate the loss using the score and perturbation
    loss = torch.mean(torch.sum((score * std[:, None, None, None] + z)**2, dim=(1, 2, 3)))
    return loss
# Specify whether to continue training or initialize a new model

continue_training = False # Either True or False
```

```
if not continue_training:

    # Initialize a new UNet with Transformer model
    score_model = torch.nn.DataParallel(UNet_Tranformer(marginal_prob_std=marginal_prob_std_fn))
    score_model = score_model.to(device)

# Set training hyperparameters
n_epochs =   200   #{'type':'integer'}
batch_size =  256 #{'type':'integer'}
lr = 1e-4         #{'type':'number'}



# Load the CIFAR10 dataset and create a data loader
dataset = CIFAR10('.', train=True, transform=transforms.Compose([transforms.Resize((32, 32)), transforms.ToTensor(), transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))]), download=True)
data_loader = DataLoader(dataset, batch_size=batch_size, shuffle=True, num_workers=4)

# Define the optimizer and learning rate scheduler
optimizer = Adam(score_model.parameters(), lr=lr)
scheduler = LambdaLR(optimizer, lr_lambda=lambda epoch: max(0.2, 0.98 ** epoch))

# Use tqdm to display a progress bar over epochs
tqdm_epoch = trange(n_epochs)
for epoch in tqdm_epoch:
    avg_loss = 0.
    num_items = 0
```

```
    # Iterate over batches in the data loader
    for x, y in tqdm(data_loader):
        #x = x.to(device)
        x, y = x.to(device), y.to(device)

        # Compute the loss using the conditional score-based model
        loss = loss_fn_cond(score_model, x, y, marginal_prob_std_fn)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        avg_loss += loss.item() * x.shape[0]
        num_items += x.shape[0]

    # Adjust learning rate using the scheduler
    scheduler.step()
    lr_current = scheduler.get_last_lr()[0]

    # Print epoch information including average loss and current learning rate
    print('{} Average Loss: {:5f} lr {:.1e}'.format(epoch, avg_loss / num_items, lr_current))
    tqdm_epoch.set_description('Average Loss: {:5f}'.format(avg_loss / num_items))

    # Save the model checkpoint after each epoch of training
    torch.save(score_model.state_dict(), 'ckpt_transformer.pth')
# Load model and generate samples
score_model = torch.nn.DataParallel(UNet_Tranformer(marginal_prob_std=marginal_prob_std_fn))
ckpt = torch.load('ckpt_transformer.pth', map_location=device)
score_model.load_state_dict(ckpt)
score_model.eval()

target_class = 3
```

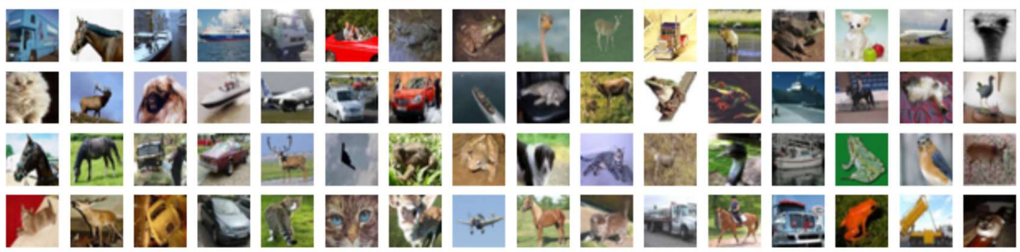
```
samples = Euler_Maruyama_sampler(
    score_model,
    marginal_prob_std_fn,
    diffusion_coeff_fn,
    batch_size=64,
    x_shape=(3, 32, 32),
    num_steps=250,
    device=device,
    y=target_class * torch.ones(64, dtype=torch.long, device=device)
)

# Visualize samples
samples = samples.clamp(0.0, 1.0)
sample_grid = make_grid(samples, nrow=8)
plt.figure(figsize=(8, 8))
plt.axis('off')
plt.imshow(sample_grid.permute(1, 2, 0).cpu(), vmin=0., vmax=1.)
plt.title(f"Generated Samples for Class {target_class}")
plt.show()
```

Output:

Latest_diffusion.ipynb | Final_Stable_Diffusion_CIFAR

Code | Python 3.9 (Default)

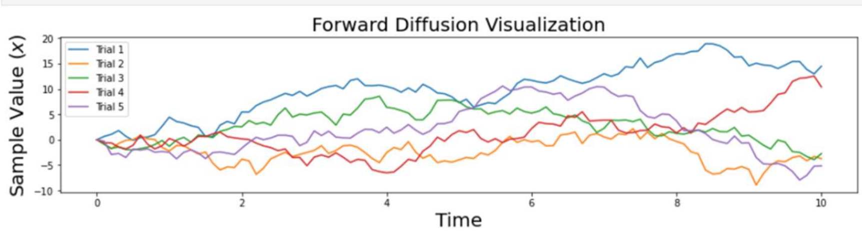
```python
def denormalize(img):
    img = (img * 0.5) + 0.5  # Reverse the normalization (assuming mean=0.5, std=0.5)
    return img

unique_images, unique_labels = next(iter(train_loader))
unique_images = unique_images.permute(0, 2, 3, 1).numpy()  # Permute to (batch, height, width, channels)
unique_images = denormalize(unique_images)  # Denormalize to [0, 1]

fig, axes = plt.subplots(4, 16, figsize=(16, 4), sharex=True, sharey=True)  # Create a 4x16 grid of subplots with a wider figure

for i in range(4):  # Loop over rows
    for j in range(16):  # Loop over columns
        index = i * 16 + j  # Calculate the index in the batch
        axes[i, j].imshow(unique_images[index])  # Show the image
        axes[i, j].axis('off')  # Turn off axis labels and ticks

plt.tight_layout()
plt.show()
```



Latest_diffusion.ipynb | Final_Stable_Diffusion_CIFAR

Code | Python 3.9 (Default)

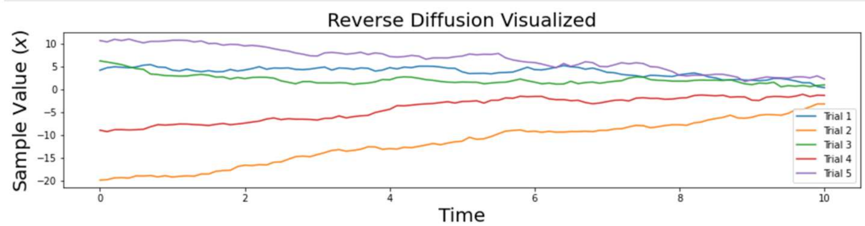
```python
for i in range(num_tries):

    # Simulate forward diffusion
    x, t = forward_diffusion_1D(x0, noise_strength_fn, t0, nsteps, dt)

    # Plot the trajectory
    plt.plot(t, x, label=f'Trial {i+1}')  # Adding a label for each trial

# Labeling the plot
plt.xlabel('Time', fontsize=20)
plt.ylabel('Sample Value ($x$)', fontsize=20)

# Title of the plot
plt.title('Forward Diffusion Visualization', fontsize=20)

# Adding a legend to identify each trial
plt.legend()

# Show the plot
plt.show()
```



Latest_diffusion.ipynb | Final_Stable_Diffusion_CIFAR

Code | Python 3.9 (Default)

```python
    # Draw from the noise distribution, which is diffusion for time T with noise strength 1
    x0 = np.random.normal(loc=0, scale=T)

    # Simulate reverse diffusion
    x, t = reverse_diffusion_1D(x0, noise_strength_fn, score_fn, T, nsteps, dt)

    # Plot the trajectory
    plt.plot(t, x, label=f'Trial {i+1}')  # Adding a label for each trial

# Labeling the plot
plt.xlabel('Time', fontsize=20)
plt.ylabel('Sample Value ($x$)', fontsize=20)

# Title of the plot
plt.title('Reverse Diffusion Visualized', fontsize=20)

# Adding a legend to identify each trial
plt.legend()

# Show the plot
plt.show()
```



Latest_diffusion.ipynb | Final_Stable_Diffusion_CIFAR

Code | Python 3.9 (Default)

```python
# Progress bar for epochs
tqdm_epoch = trange(n_epochs)
for epoch in tqdm_epoch:
    avg_loss = 0.
    num_items = 0
    # Iterate through mini-batches in the data loader
    for x, y in tqdm(data_loader):
        x = x.to(device)
        # Calculate the loss and perform backpropagation
        loss = loss_fn(score_model, x, marginal_prob_std_fn)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
        avg_loss += loss.item() * x.shape[0]
        num_items += x.shape[0]
    # Print the averaged training loss for the current epoch
    tqdm_epoch.set_description('Average Loss: {:5f}'.format(avg_loss / num_items))
    # Save the model checkpoint after each epoch of training
    torch.save(score_model.state_dict(), 'ckpt.pth')
```

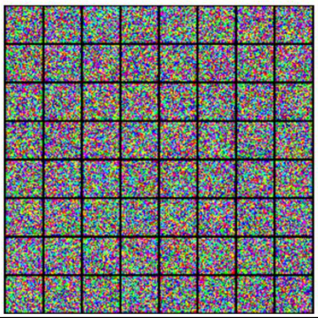
```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./cifar-10-python.tar.gz
100%|██████████| 170M/170M [00:02<00:00, 70.5MB/s]
Extracting ./cifar-10-python.tar.gz to .
Average Loss: 2132.388699: 100% 150/150 [21:29<00:00, 8.39s/it]
100% 196/196 [00:12<00:00, 13.70it/s]
/tmp/ipykernel_100942/3893175082.py:17: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourceTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  t = torch.tensor(t, device=device)
100% 196/196 [00:08<00:00, 25.11it/s]
100% 196/196 [00:08<00:00, 23.55it/s]
```

Latest_diffusion.ipynb | Final_Stable_Diffusion_CIFAR

Code | Python 3.9 (Default)

```python
# Plot the sample grid
plt.figure(figsize=(6, 6))
plt.axis('off')
plt.imshow(sample_grid.permute(1, 2, 0).cpu(), vmin=0., vmax=1.)
plt.show()
```

```
/tmp/ipykernel_100942/3893175082.py:17: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourc
eTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  t = torch.tensor(t, device=device)
/tmp/ipykernel_100942/1259072587.py:16: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourc
eTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  return torch.tensor(sigma**t, device=device)
/tmp/ipykernel_100942/890849440.py:25: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or source
Tensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  x = mean_x + torch.sqrt(torch.tensor(step_size, device=device)) * g[:, None, None, None] * noise
```



Latest_diffusion.ipynb | Final_Stable_Diffusion_CIFAR

Code | Python 3.9 (Default)

```python
    # Adjust the learning rate using the scheduler.
    scheduler.step()
    lr_current = scheduler.get_last_lr()[0]

    # Print the average loss and learning rate for the current epoch.
    print('{} Average Loss: {:5f} lr {:.1e}'.format(epoch, avg_loss / num_items, lr_current))
    tqdm_epoch.set_description('Average Loss: {:5f}'.format(avg_loss / num_items))

    # Save the model checkpoint after each epoch of training.
    torch.save(score_model.state_dict(), 'ckpt_res.pth')
```

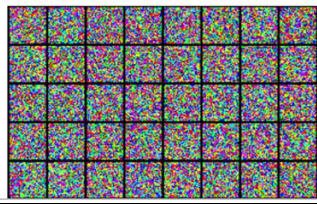
```
Files already downloaded and verified
Average Loss: 2138.495873: 100% 150/150 [12:13<00:00, 4.77s/it]
/tmp/ipykernel_100942/3893175082.py:17: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourc
eTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  t = torch.tensor(t, device=device)
0 Average Loss: 6686.901018 lr 9.8e-05
1 Average Loss: 3368.707142 lr 9.6e-05
2 Average Loss: 2822.383275 lr 9.4e-05
3 Average Loss: 2567.415416 lr 9.2e-05
4 Average Loss: 2431.749631 lr 9.0e-05
5 Average Loss: 2353.175866 lr 8.9e-05
6 Average Loss: 2304.296937 lr 8.7e-05
7 Average Loss: 2272.783301 lr 8.5e-05
8 Average Loss: 2249.709676 lr 8.3e-05
9 Average Loss: 2232.534809 lr 8.2e-05
10 Average Loss: 2220.365502 lr 8.0e-05
11 Average Loss: 2209.351641 lr 7.8e-05
12 Average Loss: 2201.922295 lr 7.7e-05
13 Average Loss: 2194.210076 lr 7.5e-05
14 Average Loss: 2190.505753 lr 7.4e-05
15 Average Loss: 2186.416438 lr 7.2e-05
16 Average Loss: 2183.188976 lr 7.1e-05
17 Average Loss: 2178.986962 lr 7.0e-05
```

Latest_diffusion.ipynb | Final_Stable_Diffusion_CIFAR

Code | Python 3.9 (Default)

```python
# Plot the sample grid
plt.figure(figsize=(6, 6))
plt.axis('off')
plt.imshow(sample_grid.permute(1, 2, 0).cpu(), vmin=0., vmax=1.)
plt.show()
```

```
/tmp/ipykernel_100942/3196970592.py:5: FutureWarning: You are using `torch.load` with `weights_only=False` (the current default value), which uses th
e default pickle module implicitly. It is possible to construct malicious pickle data which will execute arbitrary code during unpickling (See http
s://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for more details). In a future release, the default value for `weights_only` wi
ll be flipped to `True`. This limits the functions that could be executed during unpickling. Arbitrary objects will no longer be allowed to be loaded
via this mode unless they are explicitly allowlisted by the user via `torch.serialization.add_safe_globals`. We recommend you start setting `weights_
only=True` for any use case where you don't have full control of the loaded file. Please open an issue on GitHub for any issues related to this exper
imental feature.
  ckpt = torch.load('ckpt_res.pth', map_location=device)
/tmp/ipykernel_100942/3893175082.py:17: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourc
eTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  t = torch.tensor(t, device=device)
/tmp/ipykernel_100942/1259072587.py:16: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourc
eTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  return torch.tensor(sigma**t, device=device)
/tmp/ipykernel_100942/890849440.py:25: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or source
Tensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  x = mean_x + torch.sqrt(torch.tensor(step_size, device=device)) * g[:, None, None, None] * noise
```

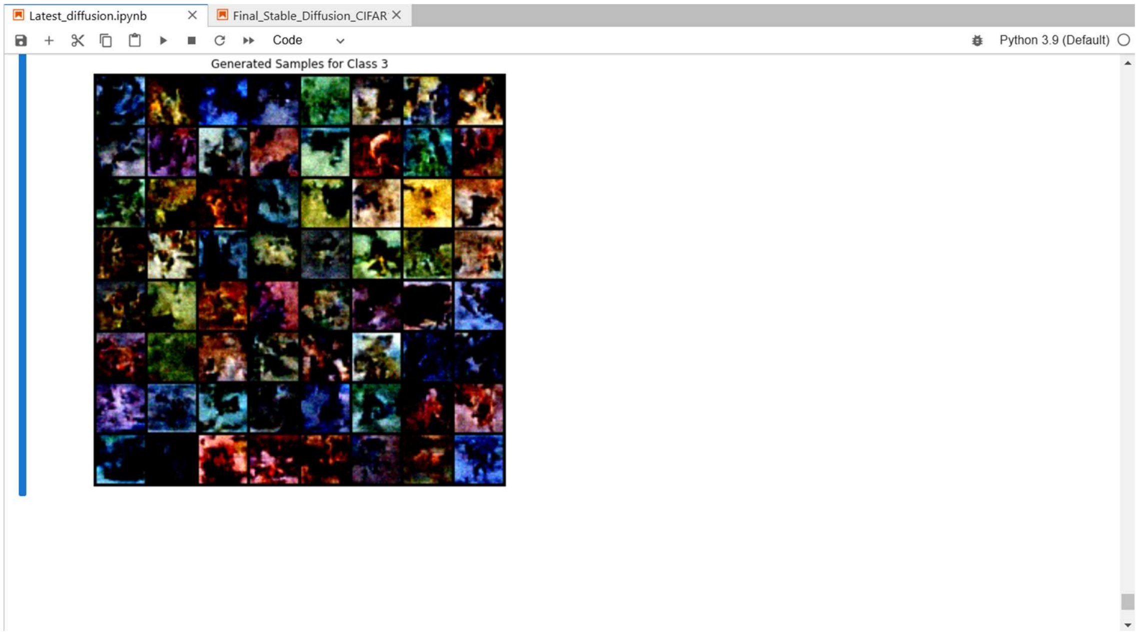


Latest_diffusion.ipynb | Final_Stable_Diffusion_CIFAR

Code | Python 3.9 (Default)

```python
    # Adjust learning rate using the scheduler
    scheduler.step()
    lr_current = scheduler.get_last_lr()[0]

    # Print epoch information including average loss and current learning rate
    print('{} Average Loss: {:5f} lr {:.1e}'.format(epoch, avg_loss / num_items, lr_current))
    tqdm_epoch.set_description('Average Loss: {:5f}'.format(avg_loss / num_items))

    # Save the model checkpoint after each epoch of training
    torch.save(score_model.state_dict(), 'ckpt_transformer.pth')
```

```
Files already downloaded and verified
Average Loss: 115.624652: 100% 200/200 [21:32<00:00, 6.36s/it]
100% 196/196 [00:06<00:00, 36.24it/s]
/tmp/ipykernel_100942/3893175082.py:17: UserWarning: To copy construct from a tensor, it is recommended to use sourceTensor.clone().detach() or sourc
eTensor.clone().detach().requires_grad_(True), rather than torch.tensor(sourceTensor).
  t = torch.tensor(t, device=device)
0 Average Loss: 3306.254765 lr 9.8e-05
100% 196/196 [00:05<00:00, 35.69it/s]
1 Average Loss: 1123.250744 lr 9.6e-05
100% 196/196 [00:06<00:00, 34.60it/s]
2 Average Loss: 775.076693 lr 9.4e-05
100% 196/196 [00:05<00:00, 36.15it/s]
3 Average Loss: 605.974069 lr 9.2e-05
100% 196/196 [00:06<00:00, 35.08it/s]
4 Average Loss: 503.167865 lr 9.0e-05
100% 196/196 [00:05<00:00, 36.72it/s]
```


Latest_diffusion.ipynb
Final_Stable_Diffusion_CIFAR
Code
Python 3.9 (Default)
Generated Samples for Class 3