Lab 1, Sampling

In [1]:
```
from typing import Dict, Tuple
from tqdm import tqdm
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader
from torchvision import models, transforms
from torchvision.utils import save_image, make_grid
import matplotlib.pyplot as plt
from matplotlib.animation import FuncAnimation, PillowWriter
import numpy as np
from IPython.display import HTML
from diffusion_utilities import *
```

Setting Things Up

In [2]:
```
class ContextUnet(nn.Module):
    def __init__(self, in_channels, n_feat=256, n_cfeat=10, heigh
        super(ContextUnet, self).__init__()

        # number of input channels, number of intermediate featu
        self.in_channels = in_channels
        self.n_feat = n_feat
        self.n_cfeat = n_cfeat
        self.h = height  #assume h == w. must be divisible by 4,

        # Initialize the initial convolutional layer
        self.init_conv = ResidualConvBlock(in_channels, n_feat, i

        # Initialize the down-sampling path of the U-Net with two
        self.down1 = UnetDown(n_feat, n_feat)        # down1 #[1
        self.down2 = UnetDown(n_feat, 2 * n_feat)    # down2 #[1

         # original: self.to_vec = nn.Sequential(nn.AvgPool2d(7),
        self.to_vec = nn.Sequential(nn.AvgPool2d((4)), nn.GELU())

        # Embed the timestep and context labels with a one-layer
        self.timeembed1 = EmbedFC(1, 2*n_feat)
        self.timeembed2 = EmbedFC(1, 1*n_feat)
        self.contextembed1 = EmbedFC(n_cfeat, 2*n_feat)
        self.contextembed2 = EmbedFC(n_cfeat, 1*n_feat)

        # Initialize the up-sampling path of the U-Net with three
        self.up0 = nn.Sequential(
            nn.ConvTranspose2d(2 * n_feat, 2 * n_feat, self.h//4,
            nn.GroupNorm(8, 2 * n_feat), # normalize
            nn.ReLU(),
        )
        self.up1 = UnetUp(4 * n_feat, n_feat)
        self.up2 = UnetUp(2 * n_feat, n_feat)

        # Initialize the final convolutional layers to map to the
```

```
        self.out = nn.Sequential(
            nn.Conv2d(2 * n_feat, n_feat, 3, 1, 1), # reduce numl
            nn.GroupNorm(8, n_feat), # normalize
            nn.ReLU(),
            nn.Conv2d(n_feat, self.in_channels, 3, 1, 1), # map i
        )

    def forward(self, x, t, c=None):
        """
        x : (batch, n_feat, h, w) : input image
        t : (batch, n_cfeat)      : time step
        c : (batch, n_classes)    : context label
        """
        # x is the input image, c is the context label, t is the

        # pass the input image through the initial convolutional
        x = self.init_conv(x)
        # pass the result through the down-sampling path
        down1 = self.down1(x)       #[10, 256, 8, 8]
        down2 = self.down2(down1)   #[10, 256, 4, 4]

        # convert the feature maps to a vector and apply an activ
        hiddenvec = self.to_vec(down2)

        # mask out context if context_mask == 1
        if c is None:
            c = torch.zeros(x.shape[0], self.n_cfeat).to(x)

        # embed context and timestep
        cemb1 = self.contextembed1(c).view(-1, self.n_feat * 2, 1
        temb1 = self.timeembed1(t).view(-1, self.n_feat * 2, 1, 1
        cemb2 = self.contextembed2(c).view(-1, self.n_feat, 1, 1)
        temb2 = self.timeembed2(t).view(-1, self.n_feat, 1, 1)
        #print(f"uunet forward: cemb1 {cemb1.shape}. temb1 {temb1


        up1 = self.up0(hiddenvec)
        up2 = self.up1(cemb1*up1 + temb1, down2)  # add and multi
        up3 = self.up2(cemb2*up2 + temb2, down1)
        out = self.out(torch.cat((up3, x), 1))
        return out
```

In [3]:

```
# hyperparameters

# diffusion hyperparameters
timesteps = 500
beta1 = 1e-4
beta2 = 0.02

# network hyperparameters
device = torch.device("cuda:0" if torch.cuda.is_available() else
n_feat = 64 # 64 hidden dimension feature
n_cfeat = 5 # context vector is of size 5
height = 16 # 16x16 image
save_dir = './weights/'
```

In [4]:

```
# construct DDPM noise schedule
b_t = (beta2 - beta1) * torch.linspace(0, 1, timesteps + 1, devic
```

```
a_t = 1 - b_t
ab_t = torch.cumsum(a_t.log(), dim=0).exp()
ab_t[0] = 1
```

In [5]:
```
# construct model
nn_model = ContextUnet(in_channels=3, n_feat=n_feat, n_cfeat=n_cf
```

Sampling

In [6]:
```
# helper function; removes the predicted noise (but adds some noi
def denoise_add_noise(x, t, pred_noise, z=None):
    if z is None:
        z = torch.randn_like(x)
    noise = b_t.sqrt()[t] * z
    mean = (x - pred_noise * ((1 - a_t[t]) / (1 - ab_t[t]).sqrt()
    return mean + noise
```

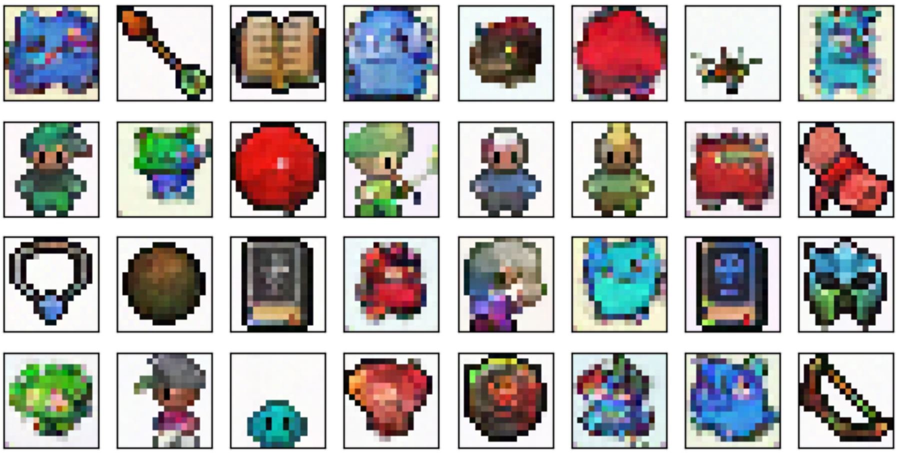
In [7]:
```
# load in model weights and set to eval mode
nn_model.load_state_dict(torch.load(f"{save_dir}/model_trained.pt
nn_model.eval()
print("Loaded in Model")
```

```
Loaded in Model
```

In [12]:
```
# sample using standard algorithm
@torch.no_grad()
def sample_ddpm(n_sample, save_rate=20):
    # x_T ~ N(0, 1), sample initial noise
    samples = torch.randn(n_sample, 3, height, height).to(device)

    # array to keep track of generated steps for plotting
    intermediate = []
    for i in range(timesteps, 0, -1):
        print(f'sampling timestep {i:3d}', end='\r')

        # reshape time tensor
        t = torch.tensor([i / timesteps])[:, None, None, None].to

        # sample some random noise to inject back in. For i = 1,
        z = torch.randn_like(samples) if i > 1 else 0

        eps = nn_model(samples, t)    # predict noise e_(x_t,t)
        samples = denoise_add_noise(samples, i, eps, z)
        if i % save_rate ==0 or i==timesteps or i<8:
            intermediate.append(samples.detach().cpu().numpy())

    intermediate = np.stack(intermediate)
    return samples, intermediate
```

In [13]:
```
# visualize samples
plt.clf()
samples, intermediate_ddpm = sample_ddpm(32)
animation_ddpm = plot_sample(intermediate_ddpm,32,4,save_dir, "ar
HTML(animation_ddpm.to_jshtml())
```

gif animating frame 31 of 32



Once Loop Reflect

<Figure size 640x480 with 0 Axes>

Demonstrate incorrectly sample without adding the 'extra noise'

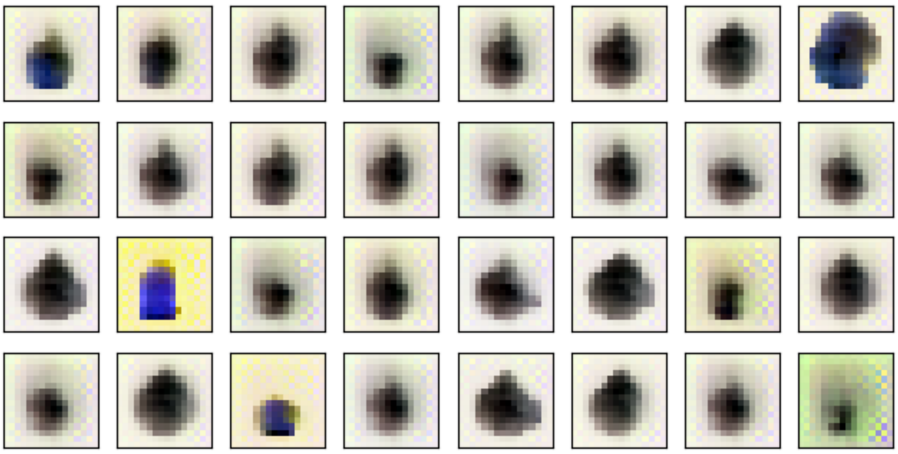
In [*]:

```
# incorrectly sample without adding in noise
@torch.no_grad()
def sample_ddpm_incorrect(n_sample):
    # x_T ~ N(0, 1), sample initial noise
    samples = torch.randn(n_sample, 3, height, height).to(device)

    # array to keep track of generated steps for plotting
    intermediate = []
    for i in range(timesteps, 0, -1):
        print(f'sampling timestep {i:3d}', end='\r')

        # reshape time tensor
        t = torch.tensor([i / timesteps])[:, None, None, None].tc

        # don't add back in noise
        z = 0

        eps = nn_model(samples, t)    # predict noise e_(x_t,t)
        samples = denoise_add_noise(samples, i, eps, z)
        if i%20==0 or i==timesteps or i<8:
            intermediate.append(samples.detach().cpu().numpy())

    intermediate = np.stack(intermediate)
    return samples, intermediate
```

In [11]:

```
# visualize samples
plt.clf()
samples, intermediate = sample_ddpm_incorrect(32)
animation = plot_sample(intermediate,32,4,save_dir, "ani_run", Nc
HTML(animation.to_jshtml())
```

```
gif animating frame 31 of 32
```



Once Loop Reflect

```
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```

Acknowledgments

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Diffusion model is based on Denoising Diffusion Probabilistic Models (https://arxiv.org/abs/2006.11239) and Denoising Diffusion Implicit Models (https://arxiv.org/abs/2010.02502)

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