DLP LAB7

Let’s play DDPM

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1. Introduction

這次的 lab 需要實作 DDPM 對影像中的積木進行分類。

DDPM 是近年提出的 generation network，通過迭代將 diffusion process 應用於高斯分佈等 base distribution。過程中逐漸將基礎分佈轉變為 target data distribution。在每個擴散步驟中，將 noise 從當前分佈注入樣本，並使用稱為 diffusion model 對樣本進行 denoise，使其更接近 target data distribution。

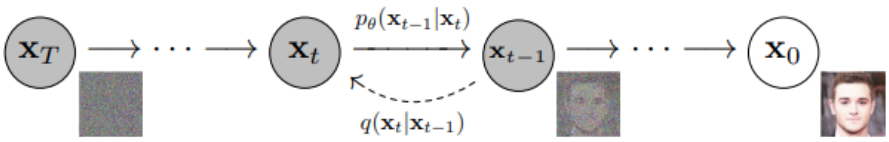


Figure 2: The directed graphical model considered in this work.

2. Implementation details

2.1 DDPM

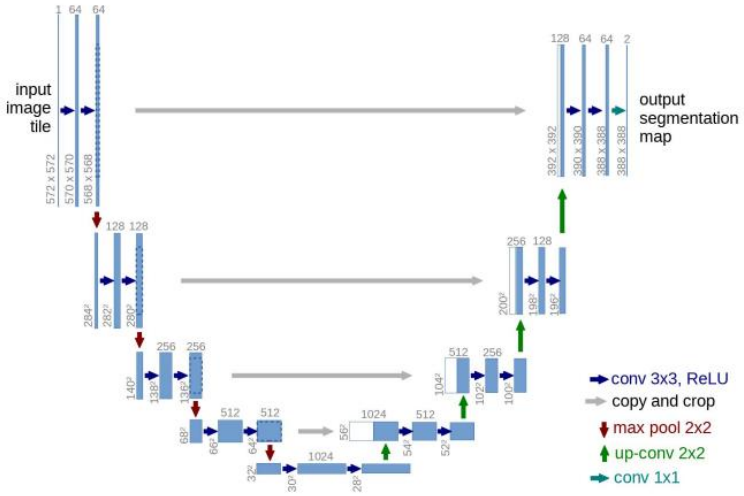
用 diffusers.DDPMScheduler 進行 noising 及 denoising。

DDPMScheduler 可以在經過一段時間之後，在影像上加入 gaussian noise，設定如下:

noise_scheduler = DDPMScheduler (num_train_timesteps=1000, beta_schedule='squaredcos_cap_v2')，每張影像最多傳遞 1000 次，也就是 T={0~999}，beta_schedule 控制 denoising 的方法。

2.2 U-Net

架構如圖，用 diffusers.UNet2DModel 可以快速建立 U-Net



```
net = UNet2DModel(
    sample_size = 64,
    in_channels = 3,
    out_channels = 3,
    layers_per_block = 2,
    class_embed_type = None,
    block_out_channels = (128, 128, 256, 256, 512, 512),
    down_block_types=(
    "DownBlock2D",  # a regular ResNet downsampling block
    "DownBlock2D",
    "DownBlock2D",
    "DownBlock2D",
    "AttnDownBlock2D",  # a ResNet downsampling block with spatial self-attention
    "DownBlock2D",
    ),
    up_block_types=(
        "UpBlock2D",  # a regular ResNet upsampling block
        "AttnUpBlock2D",  # a ResNet upsampling block with spatial self-attention
        "UpBlock2D",
        "UpBlock2D",
        "UpBlock2D",
        "UpBlock2D",
    ),
)
```

2.3 noise schedule

如圖，noise 和迭代次數都是 random，然後再用 2.1 定義的 noise_scheduler 加上 noise

```
noise = torch.randn_like(img)
timesteps = torch.randint(0, 999, (img.shape[0],)).long().to(device)
noisy_img = noise_scheduler.add_noise(img, noise, timesteps)
```

2.4 loss function

因為影像都是積木，所以只需要簡單判斷 predict 和 ground truth 的差異即可，所以選用 MSELoss 作為 loss function。

2.5 hyper-parameters

epochs = 200，但是當 test acc 和 new_test acc 大於 0.85 時會跳出迴圈

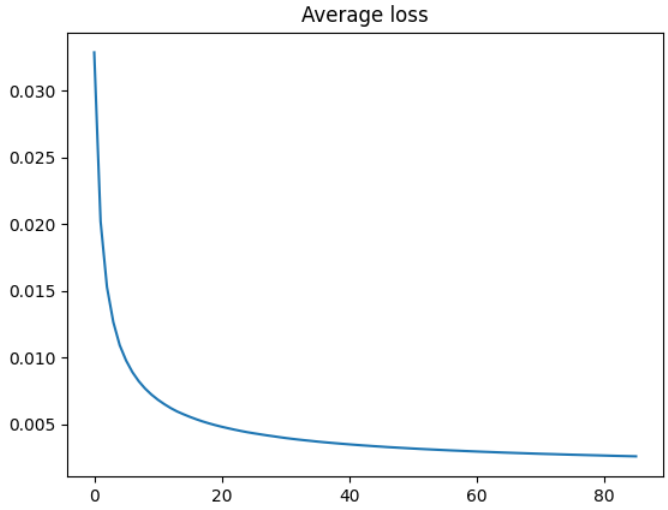
batch size = 32

3. Dataset Descriptions

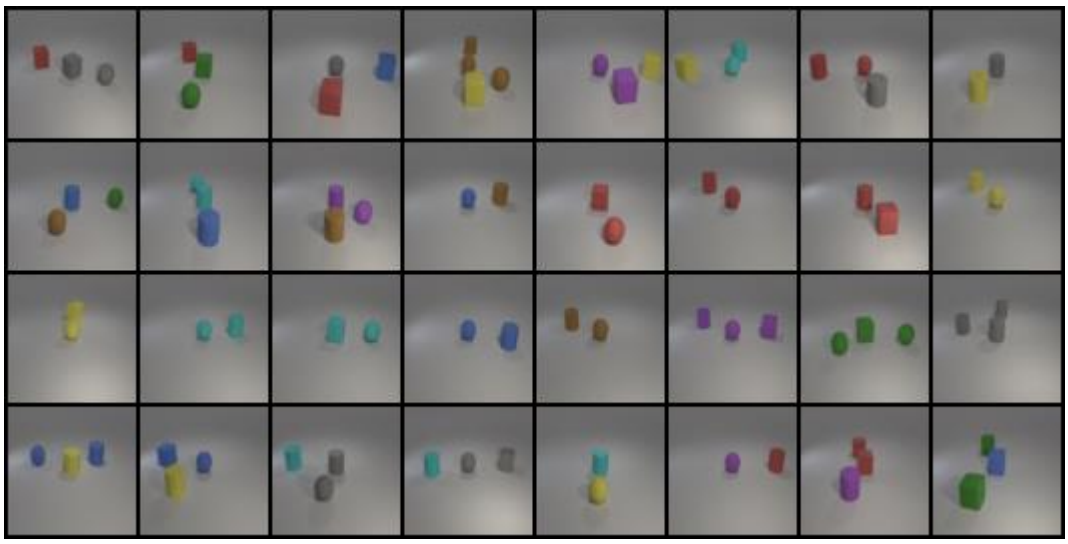
讀取影像後，會重新設定成(64, 64, 3)的影像，且 label 會轉成 one_hot_encoding

4. Result

```
epoch 85: Average loss = 0.002609
==test.json==
1000it [01:04, 15.52it/s]
Test Result: 0.875
==test_new.json==
1000it [01:04, 15.52it/s]
Test Result: 0.8690476190476191
```

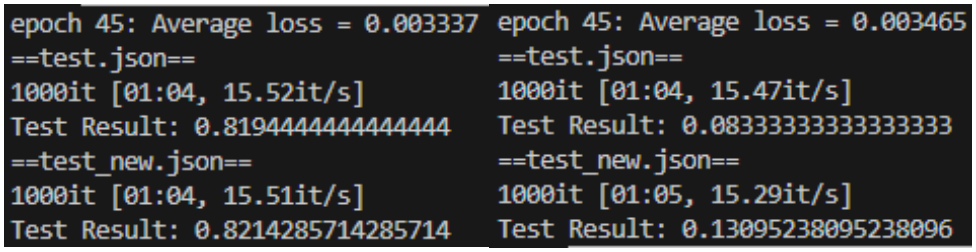


Test F1-score = 0.875



New_Test F1-score = 0.869

利用 embedding 對資料進行降維，減少運算量，加快收斂。在沒有 embedding 的情況下，經過相同的 epochs 得到的 accuracy 遠低於有 embedding 得到的 accuracy。



有 embedding　　無 embedding