计图挑战赛实验报告

Method

Dreambooth

Dreambooth 即为 Baseline 提供的方法，报告希望将讲述重点放在本组额外使用的方法上

StyleID (Style Injection with Diffusion)

1. 整体思路：
   - StyleID 有两个输入了，其一为风格图片，其二为待转换风格的图片（我们用 Baseline 的输出作为待转换风格的图片，以进一步加强输出和参考风格的关联）
   - 首先，将两张图片分别进行 DDIM Inversion, 在进行加噪的过程中，将每一步 unet 中计算 self-attention 所用的 q, k, v 的值提取出来
   - 随后，将加噪得到的两个 latent noise 进行叠加
   - 最后，利用前面所得的 q, k, v 的值，引导对叠加得到的 latent noise 的 DDIM Reversion, 得到最终输出
   - 每个风格我们随机抽取了一张作为 StyleID 的 style image 输入
2. 在加噪和降噪两个过程中，只需要对 unet 的 up_blocks 的后六个 Spatial Transformer 块的 Self-Attention 块进行修改，为如下部分：

```
list_attn =
['up_blocks.2.attentions.0.transformer_blocks.0.attn1.processor',
            'up_blocks.2.attentions.1.transformer_blocks.0.attn1.processor',
            'up_blocks.2.attentions.2.transformer_blocks.0.attn1.processor',
            'up_blocks.3.attentions.0.transformer_blocks.0.attn1.processor',
            'up_blocks.3.attentions.1.transformer_blocks.0.attn1.processor',
            'up_blocks.3.attentions.2.transformer_blocks.0.attn1.processor']
```

3. DDIM Inversion
   - 在 SD21 上使用 DDIMScheduler 进行加噪

- 原理
  - 加噪过程基于如下公式：

$$\varepsilon_t = \sqrt{\alpha_t} v_t + \sqrt{1-\alpha_t} z_t$$

$$z_{t+1} = \sqrt{\alpha_{t+1}} \left(\frac{z_t - \sqrt{1-\alpha_t}\varepsilon_t}{\sqrt{\alpha_t}} \right) + \sqrt{1-\alpha_{t+1}}\varepsilon_t$$

  - 其中，使用`v`是因为 SD21 的 unet 为`v_prediction`模式，需要额外计算，将其转换为预测的噪声
- Code：

```
def ddim_inversion(img: jt.Var) -> jt.Var:
    timesteps = jt.Var(np.flip(pipeline.scheduler.timesteps))

    # abtain initial noise of the inpur image
    latents = 0.1875 * 
pipeline.vae.encode(img).latent_dist.sample()
    # using empty string as text_embdding
    text_embeddings = pipeline._encode_prompt(prompt='', 
device=device, num_images_per_prompt=1, 
do_classifier_free_guidance=True)

    for i in tqdm(range(0, arguments.step_num), desc='DDIM 
Inversion', total=arguments.step_num):
        t = timesteps[i]

        latent_model_input = jt.cat([latents] * 2)
        latent_model_input = 
pipeline.scheduler.scale_model_input(latent_model_input, t)

        # prediction type of SD21 is 'v_prediction'
        v_pred = pipeline.unet(latent_model_input, t, 
encoder_hidden_states=text_embeddings).sample

        t_cur = max(1, t.item() - (1000 // arguments.step_num))
        t_nxt = t
        a_cur = pipeline.scheduler.alphas_cumprod[t_cur]
        a_nxt = pipeline.scheduler.alphas_cumprod[t_nxt]

        # using 'v_prediction' to compute predicted noise
        noise_pred = a_cur.sqrt() * v_pred.chunk(2)[0] + (1.0 - 
a_cur).sqrt() * latents
        latents = a_nxt.sqrt() * (latents - (1.0 - a_cur).sqrt() * 
noise_pred) / a_cur.sqrt() + (1.0 - a_nxt).sqrt() * noise_pred

    return latents
```

- 使用 AttnProcessor 修改 unet 部分结构的 Attention 块

- 原理：继承`diffusers.attention_processors.AttnProcessor`类，重写`__call__`函数，在计算出 q, k, v 值的时候进行保存即可

- Code：

```python
class SaveFeatureAttnProcessor(AttnProcessor):
    def __init__(self, is_sty_img=True):
        super().__init__()
        self.sty_img = is_sty_img
        # for style images, we need to save 'key' and 'value'
        if self.sty_img:
            self.ft_dict = [[],[]]
        # for content images, save 'query' only
        else:
            self.ft_dict = []

    def __call__(
        self,
        attn: Attention,
        hidden_states: jt.Var,
        encoder_hidden_states: Optional[jt.Var] = None,
        attention_mask: Optional[jt.Var] = None,
        temb: Optional[jt.Var] = None,
        scale: float = 1.0,
    ) -> jt.Var:
        residual = hidden_states

        args = () if USE_PEFT_BACKEND else (scale,)

        if attn.spatial_norm is not None:
            hidden_states = attn.spatial_norm(hidden_states, temb)

        input_ndim = hidden_states.ndim

        if input_ndim == 4:
            batch_size, channel, height, width = hidden_states.shape
            hidden_states = hidden_states.view(batch_size, channel, height * width).transpose(1, 2)

        batch_size, sequence_length, _ = (
            hidden_states.shape if encoder_hidden_states is None else encoder_hidden_states.shape
        )
        attention_mask = attn.prepare_attention_mask(attention_mask, sequence_length, batch_size)

        if attn.group_norm is not None:
            hidden_states = attn.group_norm(hidden_states.transpose(1, 2)).transpose(1, 2)
```

```
        query = attn.to_q(hidden_states, *args)

        if encoder_hidden_states is None:
            encoder_hidden_states = hidden_states
        elif attn.norm_cross:
            encoder_hidden_states = 
attn.norm_encoder_hidden_states(encoder_hidden_states)

        key = attn.to_k(encoder_hidden_states, *args)
        value = attn.to_v(encoder_hidden_states, *args)

        # save q, k, v features
        if self.sty_img:
            self.ft_dict[0].append(key)
            self.ft_dict[1].append(value)
        else:
            self.ft_dict.append(query)

        query = attn.head_to_batch_dim(query)
        key = attn.head_to_batch_dim(key)
        value = attn.head_to_batch_dim(value)

        attention_probs = attn.get_attention_scores(query, key, 
attention_mask)
        hidden_states = torch.bmm(attention_probs, value)
        hidden_states = attn.batch_to_head_dim(hidden_states)

        # linear proj
        hidden_states = attn.to_out[0](hidden_states, *args)
        # dropout
        hidden_states = attn.to_out[1](hidden_states)

        if input_ndim == 4:
            hidden_states = hidden_states.transpose(-1, 
-2).reshape(batch_size, channel, height, width)

        if attn.residual_connection:
            hidden_states = hidden_states + residual

        hidden_states = hidden_states / attn.rescale_output_factor

        return hidden_states
```

4. 噪音叠加：AdaIN

    - 对于噪音的叠加，需要考虑两方面的因素，其一，需要保证输出图片的色调信息和 Style image 一致；其二，需要保证输出图片的内容和 content image 一致

    - 采用名为`AdaIN`的方法进行叠加：

$$z_T^{cs} = \sigma(z_T^s)\left(\frac{z_T^c - \mu(z_T^c)}{\sigma(z_T^c)}\right) + \mu(z_T^s)$$

其中，μ 为均值，σ 为标准差，c 代表 content image，s 代表 style image

- Code：

```
def adain(sty_latent: jt.Var, cnt_latent: jt.Var) -> jt.Var:
    sty_np = np.asarray(sty_latent)
    cnt_np = np.asarray(cnt_latent)

    sty_mean = sty_np.mean(axis=2, keepdims=True).mean(axis=3,
keepdims=True)
    cnt_mean = cnt_np.mean(axis=2, keepdims=True).mean(axis=3,
keepdims=True)
    sty_std = sty_np.std(axis=2, keepdims=True).mean(axis=3,
keepdims=True)
    cnt_std = cnt_np.std(axis=2, keepdims=True).mean(axis=3,
keepdims=True)

    sty_mean = jt.Var(sty_mean)
    cnt_mean = jt.Var(cnt_mean)
    sty_std = jt.Var(sty_std)
    cnt_std = jt.Var(cnt_std)

    return sty_std * (cnt_latent - cnt_mean) / cnt_std + sty_mean
```

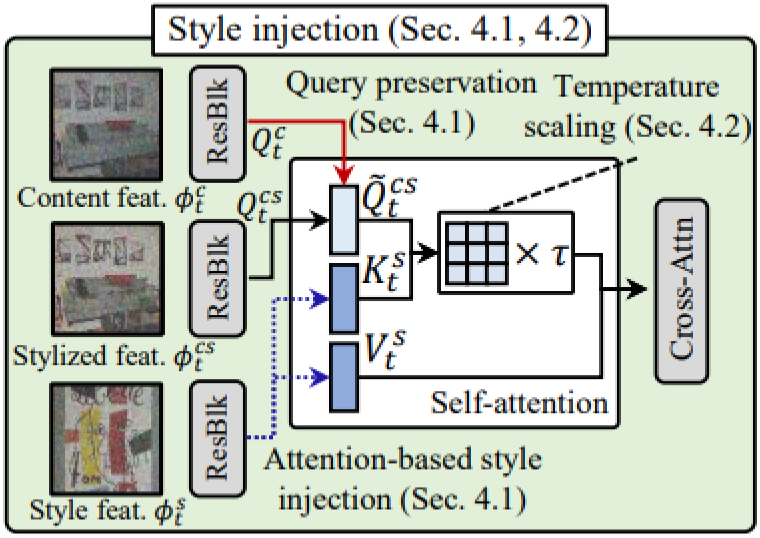
5. DDIM Reversion

- 降噪过程基于如下公式：

$$\varepsilon_t = \sqrt{\alpha_t} v_t + \sqrt{1-\alpha_t} z_t$$

$$z_{t-1} = \sqrt{\alpha_{t-1}}\left(\frac{z_t - \sqrt{1-\alpha_t}\varepsilon_t}{\sqrt{\alpha_t}}\right) + \sqrt{1-\alpha_{t-1}}\varepsilon_t$$

- 对于降噪过程，self-attention 计算修改为如下方式：



- 在上图中，由 style image 提供 k, v, 由 content image 和 stylized image 共同提供 q，用公式表达如下：

$$\tilde{Q}_t^{cs} = \gamma \times Q_t^c + (1-\gamma) \times Q_t^{cs}$$

$$\text{Attn\_output} = \text{softmax}\left(\frac{T\tilde{Q}_t^{cs}\left(K_t^s\right)^T}{\sqrt{d}}\right)V_t^s, T > 1$$

- 其中，T 用于提高锐度，防止输出图像过于模糊
- 对于代码实现，继承`diffusers.attention_processors.AttnProcessor`类，在`__init__()`函数中加载 Inversion 过程中计算的特征；随后重写`__call__`函数，按照上文的公式，进行计算即可
- Code：

```
class StyleInjectAttnProcessor(AttnProcessor):
    def __init__(self, _sty_ft: list[list], _cnt_ft: list):
        super().__init__()
        self.sty_ft = _sty_ft
        self.cnt_ft = _cnt_ft
        self.gamma = 0.75
        self.T = 1.8
        self.reverse_step = 0

    def __call__(
        self,
        attn: Attention,
        hidden_states: jt.Var,
        encoder_hidden_states: Optional[jt.Var] = None,
        attention_mask: Optional[jt.Var] = None,
        temb: Optional[jt.Var] = None,
        scale: float = 1.0,
    ) -> jt.Var:
        residual = hidden_states
```

```
        args = () if USE_PEFT_BACKEND else (scale,)

        if attn.spatial_norm is not None:
            hidden_states = attn.spatial_norm(hidden_states, temb)

        input_ndim = hidden_states.ndim

        if input_ndim == 4:
            batch_size, channel, height, width = hidden_states.shape
            hidden_states = hidden_states.view(batch_size, channel,
height * width).transpose(1, 2)

        batch_size, sequence_length, _ = (
            hidden_states.shape if encoder_hidden_states is None else
encoder_hidden_states.shape
        )
        attention_mask = attn.prepare_attention_mask(attention_mask,
sequence_length, batch_size)

        if attn.group_norm is not None:
            hidden_states = attn.group_norm(hidden_states.transpose(1,
2)).transpose(1, 2)

        # q~ = gamma * q_load + (1 - gamma) * q
        query = self.gamma * self.cnt_ft[len(self.cnt_ft) - 1 -
self.reverse_step] + (1.0 - self.gamma) * attn.to_q(hidden_states,
*args)
        query = query * self.T

        if encoder_hidden_states is None:
            encoder_hidden_states = hidden_states
        elif attn.norm_cross:
            encoder_hidden_states =
attn.norm_encoder_hidden_states(encoder_hidden_states)

        # load k and v
        key = self.sty_ft[0][len(self.sty_ft) - 1 - self.reverse_step]
        value = self.sty_ft[1][len(self.sty_ft) - 1- self.reverse_step]

        query = attn.head_to_batch_dim(query)
        key = attn.head_to_batch_dim(key)
        value = attn.head_to_batch_dim(value)
        self.reverse_step += 1

        attention_probs = attn.get_attention_scores(query, key,
attention_mask)
        hidden_states = torch.bmm(attention_probs, value)
        hidden_states = attn.batch_to_head_dim(hidden_states)

        # linear proj
        hidden_states = attn.to_out[0](hidden_states, *args)
        # dropout
        hidden_states = attn.to_out[1](hidden_states)
```

```
        if input_ndim == 4:
            hidden_states = hidden_states.transpose(-1,
-2).reshape(batch_size, channel, height, width)

        if attn.residual_connection:
            hidden_states = hidden_states + residual

        hidden_states = hidden_states / attn.rescale_output_factor

        return hidden_states

def ddim_reversion(start_latents: jt.Var, device=device) -> jt.Var:
    dict_attn = {}
    attn_processors = pipeline.unet.attn_processors
    j = 0
    for i in attn_processors.keys():
        if i in list_attn:
            dict_attn[i] = StyleInjectAttnProcessor(_sty_ft=sty_ft[j],
_cnt_ft=cnt_ft[j])
            j += 1
        else:
            dict_attn[i] = AttnProcessor()
    pipeline.unet.set_attn_processor(dict_attn)

    timesteps = pipeline.scheduler.timesteps

    latents = start_latents.clone()
    text_embeddings = pipeline._encode_prompt(prompt='', device=device,
num_images_per_prompt=1, do_classifier_free_guidance=True)

    for i in tqdm(range(0, arguments.step_num), desc='DDIM Reversion',
total=arguments.step_num):
        t = timesteps[i]

        latent_model_input = jt.cat([latents] * 2)
        latent_model_input =
pipeline.scheduler.scale_model_input(latent_model_input, t)

        v_pred = pipeline.unet(latent_model_input, t,
encoder_hidden_states=text_embeddings).sample

        prev_t = max(0, t.item() - (1000 // arguments.step_num))
        a_cur = pipeline.scheduler.alphas_cumprod[t.item()]
        a_pre = pipeline.scheduler.alphas_cumprod[prev_t]

        noise_pred = a_pre.sqrt() * v_pred.chunk(2)[0] + (1.0 -
a_pre).sqrt() * latents
        pred_x0 = (latents - (1 - a_cur).sqrt() * noise_pred) /
a_cur.sqrt()
        drc_xt = (1 - a_pre).sqrt() * noise_pred

        latents = a_pre.sqrt() * pred_x0 + drc_xt

    return latents
```

Summerize

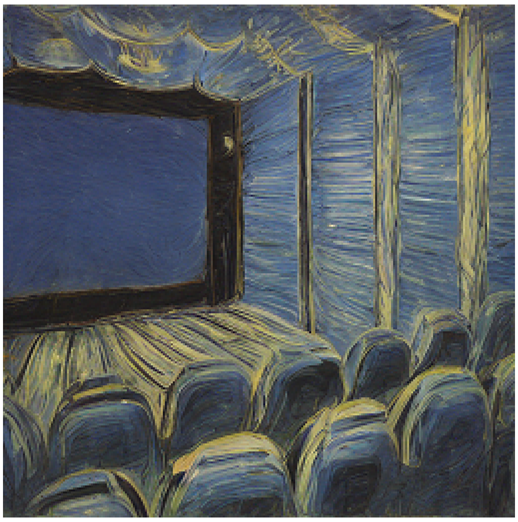
1. 对于 Dreambooth，我们尝试过通过优化 prompt, 调整微调训练迭代次数来优化不同类的生成结果
    - 其中，前者作用并不是很大，在很多情况下，生成内容和提示词并不吻合（如提示词为芒果，但是生成的是瓶子，在生成 park, school 等场景类的词的时候尤为明显），我们猜测可能是由于 SD21 的文意理解能力有限，需要通过其他方法进行输出的指导
    - 后者在 style11 (石头浮雕风格)取得了很好的效果：在迭代次数为 1000 的情况下，由于 style11 的训练图片均为动物，故训练微调导致 overfitting，输入任何提示词，输出基本均为动物；将迭代次数降至 250 后，生成效果明显更优，既保留了风格，又保留了生成不同内容的能力
2. 对于 StyleID
    - 原作者 StyleID 是在 SD14 上实现的，其 unet 和 SD21 的 unet 结构虽一致，但是预测模式不同，前者为`epsilon`模式，后者为`v_prediction`模式；在最初实现的时候，由于忽略了这一点，加噪和降噪过程进行失败
    - 原作者 StyleID 没有用任何库，手写的 ldm，导致在移植的时候查阅代码极度痛苦，不过好在还是成功了，也通过这个更进一步了解了 SD 的网络结构和细节
3. 在后续工作中，我们计划使用额外的方法微调训练 SD，保证输出和 style 和 prompt 同时对齐

Result

1. 截止 6.30 23:30，小组提交的结果排名如下，位列第三

2. 部分生成结果展示

   - style00：cinema

   - style02：bamboo

   - style05：beach

   - style07：eagle

- style11：ship

- style13：scooter

Members

1. 孙昌勖 2021012754（队长）：
   - baseline 调试
   - Style Align 方法测试（计划后续使用于 B 榜）

    - StyleID 方法测试并使用 Jittor 实现
2. 汪钰涵 2022012241：
    - baseline 调试
    - 针对不同类和图片，生成合适的 prompt (positive and negative)，优化 baseline 输出效果
3. 方奔皓 2021012747：
    - baseline 调试
    - baseline 结果生成
    - Style Align 方法测试

Reference

Websites

1. JDiffusion and Baseline here
2. Stable Diffusion 2-1 here
3. An Interpretion to SD here
4. Style Align Project Page here
5. StyleID github repository here, this is our `important reference` for JStyleID based on this code.
6. `DDIMScheduler` here
7. Attention blocks of the U-Net of SD here

Paper

1. Denosing Diffusion Probabilistic Models
2. Denoising Diffusion Implicit Models
3. High-Resolution Image Synthesis with Latent Diffusion Models
4. Style Align Image Generation via Shared Attention
5. Style Injection in Diffusion: A Training-free Approach for Adapting Large-scale Diffusion Models for Style Transfer
6. Imagen Video: High Definition Video Generation with Diffusion Models