Notebook to explore DiffEdit

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Notebook to try out the DiffEdit methodology

This follows the paper: http://arxiv.org/abs/2210.11427

The first part of the notebook is setup to generate image masks based upon the differences in images generated by starting with the same noised image and denoising it with two different prompts, the first one the prompt that goes with the image, the second a prompt related to a "target" image, which is what it is desired to change some aspect of the image into.

The methodology in the paper is not very well described and so a few alternative approaches are considered

```
from pathlib import Path
from PIL import Image
from tqdm.auto import tqdm
import numpy as np
import matplotlib.pyplot as plt

import torch
from torchvision import transforms as tfms
from torch import autocast

from diffusers import DDIMScheduler, LMSDiscreteScheduler
from transformers import CLIPTextModel, CLIPTokenizer
```

```python
from diffusers import AutoencoderKL, UNet2DConditionModel
from transformers import logging
```

```python
#!pip install accelerate
```

```python
# Note that this step is helpful to avoid verbose warnings when loading the text encoder
logging.set_verbosity_error()
```

```python
# Set device
torch_device = "cuda" if torch.cuda.is_available() else "cpu"
```

```python
# Load the tokenizer and text encoder
tokenizer = CLIPTokenizer.from_pretrained("openai/clip-vit-large-patch14", torch_dtype=torch.fl
text_encoder = CLIPTextModel.from_pretrained("openai/clip-vit-large-patch14", torch_dtype=torch
```

```python
# Load the VAE and Unet
vae = AutoencoderKL.from_pretrained("stabilityai/sd-vae-ft-ema", torch_dtype=torch.float16).to(
unet = UNet2DConditionModel.from_pretrained("CompVis/stable-diffusion-v1-4", subfolder="unet",
```

```python
# Create a DDIM scheduler
ddim_sched = DDIMScheduler(beta_start=0.00085,
                                    beta_end=0.012,
                                    beta_schedule='scaled_linear',
                                    clip_sample=False,
                                    set_alpha_to_one=False)
```

```python
# Create a LMS scheduler
scheduler = LMSDiscreteScheduler(beta_start=0.00085, beta_end=0.012, beta_schedule="scaled_line
```

Add Functions

```python
def prompt_to_embedding(prompt: str, torch_device):
    text_input = tokenizer(prompt, padding="max_length", max_length=tokenizer.model_max_length,
    with torch.no_grad():
        embeddings = text_encoder(text_input.input_ids.to(torch_device))[0]
    return embeddings
```

```python
def pil_to_latent(input_im):
    # Single image -> single latent in a batch (so size 1, 4, 64, 64)
    with torch.no_grad():
        latent = vae.encode(tfms.ToTensor()(input_im).unsqueeze(0).half().to(torch_device)*2-1)
    return 0.18215 * latent.latent_dist.sample()
```

```python
def latents_to_array(latents):
    latents = 1 / 0.18215 * latents
    with torch.no_grad():
        image = vae.decode(latents).sample

    # Create image array
    image = (image / 2 + 0.5).clamp(0, 1)
    image = image.detach().cpu().permute(0, 2, 3, 1).numpy()
    images = (image * 255).round().astype("uint8")
    # At this point, this is a single-item array of image data, so return only the item
    # to remove the extra diemension from the returned data
    return images[0]
```

```python
def latents_to_pil(latents):
    # bath of latents -> list of images
    image = latents_to_array(latents)
    pil_imagea = Image.fromarray(image)
    return pil_imagea
```

```python
def show_latents(latents):
    fig, axs = plt.subplots(1, 4, figsize=(16, 4))
    for c in range(4):
        axs[c].imshow(latents[0][c].cpu(), cmap='Greys')
        axs[c].axis('off')
```

```python
def load_image(path_to_image, size):
    path_to_img = Path(path_to_image)
    assert path_to_img.is_file(), f"No file found {path_to_image}"
    image = Image.open(path_to_img).convert('RGB')
    return image
```

```python
def denoising_loop(latents, text_emb, scheduler, g=7.5, strength=0.5, steps=50, dim=512, start_
    with autocast(torch_device):
        noise_preds = torch.tensor([], device=torch_device)
        for i, t in enumerate(scheduler.timesteps):
```

```
            if i > start_step:
                #print(f"step: {i}")
                latent_model_input = torch.cat([latents] * 2)
                latent_model_input = scheduler.scale_model_input(latent_model_input, t)
                with torch.no_grad():
                    noise_u,noise_t = unet(latent_model_input, t, encoder_hidden_states=text_em
                noise_pred = noise_u + g*(noise_t - noise_u)
                noise_preds = torch.concat([noise_preds, noise_pred])
                latents = scheduler.step(noise_pred, t, latents).prev_sample
        return latents, noise_preds
```

```
def show_image(image, seed=None, scale_by=0.5):
    if seed is not None:
        print(f'Seed: {seed}')
    return image.resize(((int)(image.width * scale_by), (int)(image.height * scale_by)))
```

```
def add_noise_to_image(latents, seed, scheduler, start_step):
    torch.manual_seed(seed)
    noise = torch.randn_like(latents)
    noised_latents = scheduler.add_noise(
        original_samples=latents,
        noise=noise,
        timesteps=torch.tensor([scheduler.timesteps[start_step]]))
    return noised_latents
```

```
def show_images(nrows, ncols, images, titles=[], figsize=(16, 5)):
    num_axes = nrows*ncols
    num_images = len(images)
    num_titles = len(titles)
    fig, axs = plt.subplots(nrows, ncols, figsize=figsize)
    flt_ax = axs.flat
    for c in range(num_axes):
        if c == num_images: break
        flt_ax[c].imshow(images[c])
        flt_ax[c].axis('off')
        if c < num_titles:
            flt_ax[c].set_title(titles[c])
```

Define parameters for analysis

```
resolution = 512
def_steps = 70
def_g = 7.5
def_strength = 0.5
def_sch = scheduler
start_step = 20
```

Load base image and create latents

```
path_to_image = "/home/images/horse_1_512.jpg"
image = load_image(path_to_image, resolution)
latents = pil_to_latent(image)
```

```
# show the base image
show_image(image)
```

```
# Plot the latents
show_latents(latents)
```

Define Prompts and create embeddings

```
#base_prompt = "A horse running on grass under a cloudy blue sky"
#target_prompt = "A zebra running on grass under a cloudy blue sky"
base_prompt = "A horse"
target_prompt = "Zebra"
unguided_prompt = [""]
```

```
base_prompt_emb = prompt_to_embedding(base_prompt, torch_device)
target_prompt_emb = prompt_to_embedding(target_prompt, torch_device)
unguided_prompt = prompt_to_embedding(unguided_prompt, torch_device)
```

```
base_emb_pair = torch.concat([unguided_prompt, base_prompt_emb])
target_emb_pair = torch.concat([unguided_prompt, target_prompt_emb])
```

Set inference timesteps

```
def prepare_scheduler_noise_image_and_denoise(latents, text_emb, steps, start_step, scheduler,
    timesteps = scheduler.set_timesteps(steps)
    strength=0.5
    noised_latents = add_noise_to_image(latents, seed, scheduler, start_step)
    dn_latents, noise = denoising_loop(noised_latents, text_emb=text_emb, scheduler=scheduler,
                                       dim=dim, start_step=start_step, torch_device=device)
    return dn_latents, noise
```

```
dn_base, noise_base = prepare_scheduler_noise_image_and_denoise(latents,
                                                                text_emb=base_emb_pair,
                                                                steps=def_steps,
                                                                start_step=30,
                                                                scheduler=def_sch,
```

```
                                                                    seed=100,
                                                                    g=7.5,
                                                                    dim=resolution,
                                                                    device=torch_device)
```

```
/opt/conda/lib/python3.8/site-packages/diffusers/schedulers/scheduling_lms_discrete.py:155: Integ
  If increasing the limit yields no improvement it is advised to analyze
  the integrand in order to determine the difficulties.  If the position of a
  local difficulty can be determined (singularity, discontinuity) one will
  probably gain from splitting up the interval and calling the integrator
  on the subranges.  Perhaps a special-purpose integrator should be used.
  integrated_coeff = integrate.quad(lms_derivative, self.sigmas[t], self.sigmas[t + 1], epsrel=1e
```

```
latents_to_pil(dn_base)
```

```
dn_target, noise_target = prepare_scheduler_noise_image_and_denoise(latents,
                                                                    text_emb=target_emb_pair,
                                                                    steps=def_steps,
                                                                    start_step=30,
                                                                    scheduler=def_sch,
                                                                    seed=100,
                                                                    g=7.5,
                                                                    dim=resolution,
```

```
                                                   device=torch_device)
```

```
latents_to_pil(dn_target)
```

```
show_images(1, 3 , [np.asarray(image), latents_to_array(dn_base), latents_to_array(dn_target)],
            ["Original Image", "Denoised original", "Denoised Zebra", "Denoised Zebra with mask'
```


```
orig_img = np.asarray(image)
orig_img.shape
```

```
(512, 515, 3)
```

```
noise_base.shape
```

```
torch.Size([39, 4, 64, 64])
```

```
diff_noises = (noise_base - noise_target).mean(0, keepdim=True)
```

```
diff_noises.shape
```

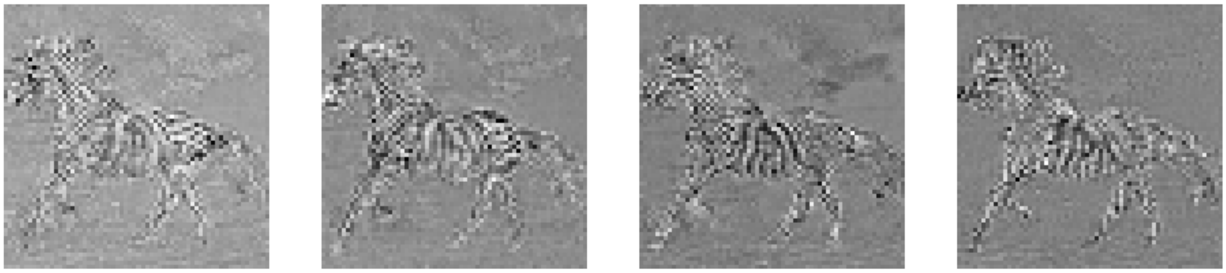
```
torch.Size([1, 4, 64, 64])
```

```
diff_noise_normed = (diff_noises - diff_noises.min())/(diff_noises - diff_noises.min()).max()
```

```
diff_noise_normed.shape
```

```
torch.Size([1, 4, 64, 64])
```

```
show_latents(diff_noise_normed)
```



```
diff_noise_normed.min(), diff_noise_normed.max(), diff_noise_normed.std(), diff_noise_normed.me
```

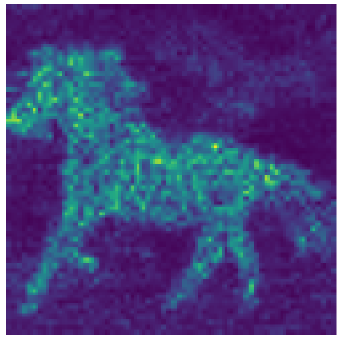
```
(tensor(0., device='cuda:0'),
 tensor(1., device='cuda:0'),
 tensor(0.0744, device='cuda:0'),
 tensor(0.5083, device='cuda:0'))
```

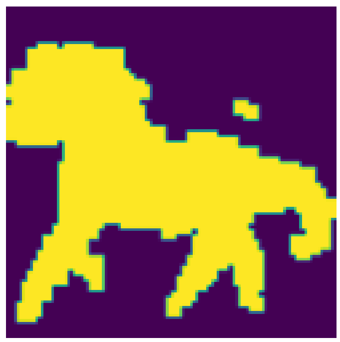
```
mask = ((diff_noise_normed-0.5).abs()+0.5).mean(dim=1).squeeze().cpu()
```

```
import cv2
```

```
def extract_channel_mask(img, do_inverse=False):
    kernel = np.ones((3,3),np.uint8)
    img = (img*255).squeeze().cpu().to(torch.uint8).numpy()
    if do_inverse:
        ret2,img2 = cv2.threshold(img,0,255,cv2.THRESH_BINARY_INV+cv2.THRESH_OTSU)
    else:
        ret2,img2 = cv2.threshold(img,0,255,cv2.THRESH_BINARY+cv2.THRESH_OTSU)
    opening = cv2.dilate(img2, kernel)
    return opening
```

```
show_images(2, 1, [mask, extract_channel_mask(mask, do_inverse=False)])
```





Now need to apply the mask to the generated zebra image and then run the decode function

```
binary_mask = torch.tensor(extract_channel_mask(mask, do_inverse=False)).bool()
```

```
def apply_mask_to_latents(original_latents, new_latents, mask):
    comp_lat = torch.where(mask, new_latents.cpu(), original_latents.cpu())
    return comp_lat
```

```
final_latents = apply_mask_to_latents(dn_base, dn_target, binary_mask)
```

```
latents_to_pil(final_latents.to(torch_device))
```

```
show_images(2, 2, [np.asarray(image), latents_to_array(dn_base), latents_to_array(dn_target), l
           ["Original Image", "Denoised original", "Denoised Zebra", "Denoised Zebra with mask'
```

In this case the final masked image is almost identical to that of the unmasked image since the background generated by the denoising process had almost no differene. In other cases this could clearly be more extreme. The issue of course would be that the mask would need to be carefully blended to facilitate a smooth merge.

Overall it seems to me that this is an approach that has very limited application an in many ways it is better to avoid using the mask