Bounding-Box Experiment - Fashion Editing

The purpose of this experiment is to see how far we can push improvement in our fine-tuned fashion editing model. We want to see to what extent we can address some of the visual issues we are detecting in its edit - the most prevelant one being that it's editing outside the segmentation mask area. We want to confine the editing region stricter, so we incorporate a "hierarchial bounding" into our loss function.

The general structure of this notebook file remains the same as original, titled "Final_Project".

1. Imports and Background

```
# imports
import os
import json
import torch
from torch import nn
from torch.utils.data import DataLoader
import torch.nn.functional as F
import numpy as np
import PIL
from PIL import Image
import matplotlib.pyplot as plt
from tqdm import tqdm
from tqdm.auto import tqdm
import pandas as pd
import requests
from io import BytesIO
import random

# models and dataset
from datasets import load_dataset
from diffusers import StableDiffusionInstructPix2PixPipeline, DPMSolverMultistepScheduler
from transformers import CLIPProcessor, CLIPModel
from datasets import load_dataset
```

```
# cloning pix2pix, getting it in

!git clone https://github.com/huggingface/diffusers

%cd examples/instruct_pix2pix
!pip install -r requirements.txt
```

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```
# from pix2pix hf website

import PIL
import requests
import torch
from diffusers import StableDiffusionInstructPix2PixPipeline, EulerAncestralDiscreteScheduler
from accelerate.utils import write_basic_config
write_basic_config()
```

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2. Data Preparation

```
#Loading fashionpedia
dataset_fashionpedia = load_dataset("detection-datasets/fashionpedia", split="train", streaming=T
fashionpedia_samples = list(dataset_fashionpedia.take(100)) #just load 100 for now to see if poss
print(fashionpedia_samples[0]['image'])
```

```
5
6
7 #Define clip model to help us evaluate models
8 clip_model = CLIPModel.from_pretrained("openai/clip-vit-large-patch14").to("cuda")
9 clip_processor = CLIPProcessor.from_pretrained("openai/clip-vit-large-patch14")
```

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```
1 #load deepfashion2
2 dataset = load_dataset("SaffalPoosh/deepFashion-with-masks")
3
4 print(dataset)
5 print(dataset["train"].features)
6
7 sample = dataset["train"][0]
8 print(sample.keys())
9
```

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```
1 #building triples from same person pairs
2
3 from collections import defaultdict
4
5 # Group images by person ID
6 by_pid = defaultdict(list)
7 for i in range(len(dataset["train"])):
8   by_pid[dataset["train"][i]["pid"]].append(i)
9
10 multi_outfit = {k: v for k, v in by_pid.items() if len(v) >= 2}
11 print(f"Total unique people: {len(by_pid)}")
12 print(f"People with 2+ images: {len(multi_outfit)}")
13 print(f"Potential pairs: {sum(len(v) for v in multi_outfit.values())}")
```

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```
1 # visualizing same person pairs
2
3 multi_outfit_pids = [pid for pid, indices in by_pid.items() if len(indices) >= 3]
4
5 fig, axes = plt.subplots(3, 3, figsize=(12, 12))
6 for row, pid in enumerate(multi_outfit_pids[:3]):
7   indices = by_pid[pid][:3]
8   for col, idx in enumerate(indices):
9     sample = dataset["train"][idx]
10     axes[row, col].imshow(sample["images"])
11     axes[row, col].set_title(sample["caption"], fontsize=8)
12     axes[row, col].axis("off")
13
14 plt.suptitle("Same-person pairs from DeepFashion2", fontsize=14)
15 plt.tight_layout()
16 plt.show()
17
```

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```
1 def generate_instruction(caption1, caption2):
2   """Generate edit instruction from two captions."""
3   part2 = caption2.lower().split("in ")[-1] if "in " in caption2.lower() else caption2.lower()
4   return f"change to {part2}"
5
6 MAX_TRIPLETS = 8000
7
8 # Build triplets from same-person pairs
9 triplets = []
10 for pid, indices in tqdm(by_pid.items(), desc="Building triplets"):
11   if len(indices) < 2:
12       continue
13
```

```
  for i in range(len(indices)):
      for j in range(len(indices)):
          if i == j:
              continue

          triplets.append({
                  "src_idx": indices[i],
                  "tgt_idx": indices[j],
              })

          if len(triplets) >= MAX_TRIPLETS:
              break
      if len(triplets) >= MAX_TRIPLETS:
          break
  if len(triplets) >= MAX_TRIPLETS:
      break

print(f"Total triplets: {len(triplets)}")
print(f"Sample: {triplets[0]}")

```

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```
# Visualize a few triplets
fig, axes = plt.subplots(3, 2, figsize=(10, 12))

for row in range(3):
    t = triplets[row * 100]  # Sample from different parts

    # Load images from dataset using indices
    src = dataset["train"][t["src_idx"]]
    tgt = dataset["train"][t["tgt_idx"]]
    instruction = generate_instruction(src["caption"], tgt["caption"])

    axes[row, 0].imshow(src["images"])
    axes[row, 0].set_title(f"Original:\n{src['caption']}", fontsize=9)
    axes[row, 0].axis("off")

    axes[row, 1].imshow(tgt["images"])
    axes[row, 1].set_title(f"Target:\n{tgt['caption']}\n\nInstruction: {instruction}", fontsize=9
    axes[row, 1].axis("off")

plt.suptitle("Real Triplets from DeepFashion2", fontsize=14)
plt.tight_layout()
plt.show()
```

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```
import os
from tqdm import tqdm
from PIL import Image

CACHE_DIR = "deepfashion_cache"
os.makedirs(CACHE_DIR, exist_ok=True)

# Get unique indices we need
all_indices = set()
for t in triplets:
  all_indices.add(t["src_idx"])
  all_indices.add(t["tgt_idx"])

print(f"Caching {len(all_indices)} unique images...")

for idx in tqdm(all_indices, desc="Caching images"):
  cache_path = f"{CACHE_DIR}/{idx}.png"
  if not os.path.exists(cache_path):
      img = dataset["train"][idx]["images"]
      img.save(cache_path)

```

```
print("Caching complete!")

```

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```
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms
import torchvision.transforms.functional as TF

class TripletDataset(Dataset):
    def __init__(self, triplet_list, hf_data, size=512):
        self.data = triplet_list
        self.hf = hf_data
        self.size = size
        self.transform = transforms.Compose([
            transforms.Resize((size, size), interpolation=transforms.InterpolationMode.BILINEAR),
            transforms.ToTensor(),
            transforms.Normalize([0.5, 0.5, 0.5], [0.5, 0.5, 0.5])
        ])

        self.mask_transform = transforms.Compose([
            transforms.Resize((size, size), interpolation=transforms.InterpolationMode.NEAREST),
            transforms.ToTensor(),
        ])
        # Mild color jitter shared between conditioning and target (helps generalization)
        self.color_jitter = transforms.ColorJitter(
            brightness=0.1,
            contrast=0.1,
            saturation=0.1,
            hue=0.05,
        )

    def __len__(self):
        return len(self.data)

    def __getitem__(self, idx):
        t = self.data[idx]

        src = self.hf["train"][t["src_idx"]]
        tgt = self.hf["train"][t["tgt_idx"]]

        orig_img = src["images"]
        edit_img = tgt["images"]
        instruction = generate_instruction(src["caption"], tgt["caption"])
        src_mask = src["mask"]

        if orig_img.mode != "RGB":
            orig_img = orig_img.convert("RGB")
        if edit_img.mode != "RGB":
            edit_img = edit_img.convert("RGB")
        if src_mask.mode != "L":
          src_mask = src_mask.convert("L")

        if torch.rand(1).item() < 0.5:
            orig_img = TF.hflip(orig_img)
            edit_img = TF.hflip(edit_img)
            src_mask = TF.hflip(src_mask)

        # Mild color jitter applied consistently to both images (not the mask)
        orig_img = self.color_jitter(orig_img)
        edit_img = self.color_jitter(edit_img)

        conditioning_image = self.transform(orig_img)
        pixel_values = self.transform(edit_img)
        mask_tensor = self.mask_transform(src_mask)  # [1, H, W], values in [0,1]
        mask_tensor = (mask_tensor > 0.5).float()

        return {
            "conditioning_image": conditioning_image,
            "pixel_values": pixel_values,
```

```
            "prompt": instruction,
            "mask": mask_tensor,
        }

# Create dataset
full_ds = TripletDataset(triplets, dataset, size=512)

train_size = int(len(full_ds) * 0.8)
val_size = int(len(full_ds) * 0.1)
test_size = len(full_ds) - train_size - val_size

train_ds, val_ds, test_ds = torch.utils.data.random_split(
    full_ds,
    [train_size, val_size, test_size],
    generator=torch.Generator().manual_seed(42)
)

BATCH_SIZE = 1  # Small batch size
train_loader = DataLoader(train_ds, batch_size=BATCH_SIZE, shuffle=True, num_workers=0)
val_loader = DataLoader(val_ds, batch_size=BATCH_SIZE, shuffle=False, num_workers=0)
test_loader = DataLoader(test_ds, batch_size=BATCH_SIZE, shuffle=False, num_workers=0)

print(f"Train: {len(train_ds)}, Val: {len(val_ds)}, Test: {len(test_ds)}")

test_batch = next(iter(train_loader))
print(f"Conditioning shape: {test_batch['conditioning_image'].shape}")
print(f"Sample prompt: {test_batch['prompt'][0]}")
print("DataLoader working!")
```

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3. Model Preparation and Baseline

3.1 Calculating Clip Score and Directional Similarity Scores (Evaluation Metrics)

```
#Define evaluation metrics

#clip score, which tells us how similar text is to image.
def calculate_clip_score(image, text, clip_model, clip_processor):
    """Author: David Thai -- function to calculate the clip score."""
    inputs = clip_processor(
        text=[text],
        images=image,
        return_tensors="pt",
        padding=True
    ).to("cuda")
    with torch.no_grad(): #the following is cosine similarity
        outputs = clip_model(**inputs)
        image_embeds = outputs.image_embeds / outputs.image_embeds.norm(dim=-1, keepdim=True)
        text_embeds = outputs.text_embeds / outputs.text_embeds.norm(dim=-1, keepdim=True)
        clip_score = (image_embeds @ text_embeds.T).item()
    return clip_score * 100



#directional simularity
def calculate_clip_directional_similarity(original_img, edited_img, text, clip_model, clip_proces
   """Author: David Thai -- function to calculate the clip directional similarity"""
    with torch.no_grad():
        #original embeddings
        inputs_orig = clip_processor(images=original_img, return_tensors="pt").to("cuda")
        orig_embeds = clip_model.get_image_features(**inputs_orig)
        orig_embeds = orig_embeds / orig_embeds.norm(dim=-1, keepdim=True)
        #edit embeddings
        inputs_edit = clip_processor(images=edited_img, return_tensors="pt").to("cuda")
        edit_embeds = clip_model.get_image_features(**inputs_edit)
```

```
        edit_embeds = edit_embeds / edit_embeds.norm(dim=-1, keepdim=True)
        #text embeddings
        inputs_text = clip_processor(text=[text], return_tensors="pt", padding=True).to("cuda")
        text_embeds = clip_model.get_text_features(**inputs_text)
        text_embeds = text_embeds / text_embeds.norm(dim=-1, keepdim=True)
        #calculate direction
        img_direction = edit_embeds - orig_embeds
        img_direction = img_direction / (img_direction.norm(dim=-1, keepdim=True) + 1e-8)
        #neutral starting point
        null_text = clip_processor(text=[""], return_tensors="pt", padding=True).to("cuda")
        null_embeds = clip_model.get_text_features(**null_text)
        null_embeds = null_embeds / null_embeds.norm(dim=-1, keepdim=True)
        #determine direction
        text_direction = text_embeds - null_embeds
        text_direction = text_direction / (text_direction.norm(dim=-1, keepdim=True) + 1e-8)
        #calculate cosine similarity
        directional_sim = (img_direction @ text_direction.T).item()
    return directional_sim * 100
```

3.2 Evaluate Model

Now we prepare the model and use this baseline for InstructPix2Pix on fashionpedia, just to see how it performs as a baseline.

```
# Evaluating a baseline for InstructPix2Pix on fashionpedia

NUM_SAMPLES = 3  # num of images to test
NUM_INFERENCE_STEPS =50   # inference steps -- means lower = faster, higher = better quality
GUIDANCE_SCALE = 7.5
IMAGE_GUIDANCE_SCALE = 1.5

# this is the output directiory where the eval results are saved.
os.makedirs('evaluation_results', exist_ok=True)
os.makedirs('evaluation_results/images', exist_ok=True)

results = []
all_edits = []

for idx in range(3):
    sample = fashionpedia_samples[idx]
    original_image = sample['image']

    prompts = ['change the clothes this person is wearing to blue',
            'make the clothes this person is wearing red',
            'add stripes to the clothes',
            'change the clothes to a floral pattern']

    if max(original_image.size) > 1024:
      original_image.thumbnail((1024, 1024), Image.Resampling.LANCZOS)

    fig, ax = plt.subplots(1, 1, figsize=(8, 8))
    ax.imshow(original_image)
    ax.set_title(f'Original Image (Sample {idx + 1})', fontsize=14, fontweight='bold')
    ax.axis('off')
    plt.tight_layout()
    plt.show()

    for prompt_idx, text_prompt in enumerate(prompts):
      try:
          edited_images = pipe(
              prompt=text_prompt,
              image=original_image,
              num_inference_steps=NUM_INFERENCE_STEPS,
              guidance_scale=GUIDANCE_SCALE,
              image_guidance_scale=IMAGE_GUIDANCE_SCALE,
          ).images
          edited_image = edited_images[0]

          clip_score_original = calculate_clip_score(original_image, text_prompt, clip_model, cli
```

```
        clip_score_edited = calculate_clip_score(edited_image, text_prompt, clip_model, clip_pr
        clip_directional = calculate_clip_directional_similarity(
            original_image, edited_image, text_prompt, clip_model, clip_processor
        )

        fig, axes = plt.subplots(1, 2, figsize=(16, 8))

        axes[0].imshow(original_image)
        axes[0].set_title(f'Original CLIP Score: {clip_score_original:.2f}',
                          fontsize=12, fontweight='bold')
        axes[0].axis('off')

        axes[1].imshow(edited_image)
        axes[1].set_title(f'Edited LIP Score: {clip_score_edited:.2f} (Δ: {clip_score_edited - c
                          fontsize=12, fontweight='bold')
        axes[1].axis('off')

        metrics_text = f'Value of directional Similarity: {clip_directional:.2f}'
        plt.figtext(0.5, 0.02, metrics_text, ha='center', fontsize=11, bbox=dict(boxstyle='roun

        plt.suptitle(f'Prompt: "{text_prompt}"', fontsize=13, fontweight='bold', style='italic'
        plt.tight_layout()
        plt.subplots_adjust(bottom=0.08)
        plt.show()

        result = {
            'sample_id': f"{idx}_{prompt_idx}",
            'sample_num': idx + 1,
            'edit_num': prompt_idx + 1,
            'prompt': text_prompt,
            'clip_score_original': clip_score_original,
            'clip_score_edited': clip_score_edited,
            'clip_score_improvement': clip_score_edited - clip_score_original,
            'clip_directional_similarity': clip_directional,
        }
        results.append(result)

        all_edits.append({
            'original': original_image,
            'edited': edited_image,
            'prompt': text_prompt,
            'metrics': result
        })

        print(f"   CLIP Score: {clip_score_edited:.2f} | improvement: {clip_score_edited - clip_

    except Exception as e:
        print(f"   Error: {e}")
        continue
```

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4. Fine-Tuning

```
gc.collect()
torch.cuda.empty_cache()

pipe = StableDiffusionInstructPix2PixPipeline.from_pretrained(
    "timbrooks/instruct-pix2pix",
    torch_dtype=torch.float16,
    safety_checker=None,
)
pipe.to("cuda")

pipe.scheduler = DDPMScheduler.from_config(pipe.scheduler.config)

unet = pipe.unet
vae = pipe.vae
```

```
tokenizer = pipe.tokenizer
text_encoder = pipe.text_encoder
noise_scheduler = pipe.scheduler
device = "cuda"

for param in unet.parameters():
    param.requires_grad = False

for name, param in unet.named_parameters():
      should_unfreeze = False

      if "attn2" in name and ("to_k" in name or "to_v" in name or "to_out" in name):
          should_unfreeze = True

      if "attn1" in name and ("to_k" in name or "to_v" in name or "to_q" in name):
          should_unfreeze = True

      if "mid_block" in name:
          should_unfreeze = True

      if "up_blocks.2" in name or "up_blocks.3" in name:
          if "resnets" in name and "conv" in name:
              should_unfreeze = True

      if should_unfreeze:
          param.requires_grad = True

trainable_params = [p for p in unet.parameters() if p.requires_grad]

optimizer = AdamW(trainable_params, lr=1e-5, eps=1e-4, weight_decay=0.01)

print(f"Trainable params: {sum(p.numel() for p in trainable_params):,}")
print(f"Total params: {sum(p.numel() for p in unet.parameters()):,}")
print(f"Trainable %: {100 * sum(p.numel() for p in trainable_params) / sum(p.numel() for p in unet
print("\nUnfrozen layers:")
for name, param in unet.named_parameters():
    if param.requires_grad:
        print(f"  {name}: {param.numel():,}")
```

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4.1 Training Loops (Edited to include Bounding boxes and zoning from Fashionpedia)

```
from torch.optim.lr_scheduler import CosineAnnealingLR
from torchvision.transforms.functional import to_pil_image

def encode_prompt(texts):
    tokens = tokenizer(
        list(texts),
        padding="max_length",
        max_length=tokenizer.model_max_length,
        truncation=True,
        return_tensors="pt",
    ).input_ids.to(device)
    with torch.no_grad():
        text_embeds = text_encoder(tokens)[0]
    return text_embeds

def encode_vae_images(images):
    images = images.to(device, dtype=torch.float16)
    with torch.no_grad():
        latents = vae.encode(images).latent_dist.sample()
    return latents * vae.config.scaling_factor

def create_bbox_mask(bboxes, image_size, expansion_factor=1.15):
    """
    Author: Disclaimer! I Used ChatGPT to help me generate this function. The
    source idea and inspiration came from Bayesian Approach to Digital Matting
```

```
    (Chuang Et. al 2001)

    Create soft masks from bounding boxes with slight expansion for context.

    Args:
        bboxes: List of [x1, y1, x2, y2] bounding boxes (normalized 0-1 or pixel coords)
        image_size: (height, width) of the image
        expansion_factor: Factor to expand bbox (1.15 = 15% larger)
    """
    h, w = image_size
    batch_size = len(bboxes)
    masks = torch.zeros(batch_size, 1, h, w, device=device, dtype=torch.float16)

    for i, bbox in enumerate(bboxes):
        if bbox is None or len(bbox) != 4:
            continue

        x1, y1, x2, y2 = bbox
        # If normalized coordinates, convert to pixels
        if x2 <= 1.0:
            x1, x2 = x1 * w, x2 * w
            y1, y2 = y1 * h, y2 * h
        # Expand bbox slightly
        cx, cy = (x1 + x2) / 2, (y1 + y2) / 2
        bw, bh = (x2 - x1) * expansion_factor, (y2 - y1) * expansion_factor
        x1_new = max(0, int(cx - bw/2))
        y1_new = max(0, int(cy - bh/2))
        x2_new = min(w, int(cx + bw/2))
        y2_new = min(h, int(cy + bh/2))
        masks[i, 0, y1_new:y2_new, x1_new:x2_new] = 1.0

    return masks

def compute_hierarchical_loss(noise_pred, noise, mask_latent, bbox_latent,
                              lambda_context=0.3, lambda_preserve=0.5):
    """
    Author: Disclaimer! I Used ChatGPT to help me generate this function. The
    source idea and inspiration came from Bayesian Approach to Digital Matting
    (Chuang Et. al 2001)

    Three-zone hierarchical loss:
    - Tight clothing region (from segmentation): full editing loss
    - Context region: moderate preservation (allows smooth transitions)
    - Background: strong preservation
    """
    # Zone 1: Tight clothing mask (primary edit region)
    M_tight = mask_latent

    # Zone 2: Transition Zone
    M_context = bbox_latent * (1.0 - mask_latent)

    # Zone 3: Background
    M_bg = 1.0 - bbox_latent

    # Compute losses for each zone
    L_tight = F.mse_loss((noise_pred * M_tight).float(), (noise * M_tight).float())
    L_context = F.mse_loss((noise_pred * M_context).float(), (noise * M_context).float())
    L_bg = F.mse_loss((noise_pred * M_bg).float(), (noise * M_bg).float())

    # Weighted combination
    total_loss = L_tight + lambda_context * L_context + lambda_preserve * L_bg

    return total_loss, {
        'L_tight': L_tight.item(),
        'L_context': L_context.item(),
        'L_bg': L_bg.item()
    }

@torch.no_grad()
def validate(val_loader, num_samples=50):
```

```
"""Calculate validation metrics.
    Disclaimer: I used ChatGPT to help me generate part of this function
"""
unet.eval()

val_losses = []
clip_scores = []
dir_sims = []

samples_processed = 0
for batch in val_loader:
    if samples_processed >= num_samples: #no samples
        break
    pixel_values = batch["pixel_values"].to(device, dtype=torch.float16)
    cond_images = batch["conditioning_image"].to(device, dtype=torch.float16)
    masks = batch["mask"].to(device, dtype=torch.float16)
    prompts = batch["prompt"]
    bboxes = batch.get("bbox", None)

    # Compute validation loss
    target_latents = encode_vae_images(pixel_values)
    cond_latents = encode_vae_images(cond_images)
    mask_latent = F.interpolate(masks, size=target_latents.shape[-2:], mode="nearest")
    mask_latent = mask_latent.expand(-1, 4, -1, -1)

    # Create bounding boxes if available
    if bboxes is not None:
        bbox_masks = create_bbox_mask(bboxes, (masks.shape[2], masks.shape[3]))
        bbox_latent = F.interpolate(bbox_masks, size=target_latents.shape[-2:], mode="nearest")
        bbox_latent = bbox_latent.expand(-1, 4, -1, -1)
    else:
        # I used CHATGPT to help me design this fallback
        bbox_latent = F.max_pool2d(mask_latent, kernel_size=5, stride=1, padding=2)

    noise = torch.randn_like(target_latents)
    timesteps = torch.randint(0, noise_scheduler.config.num_train_timesteps,
                              (target_latents.shape[0],), device=device, dtype=torch.long)
    noisy_latents = noise_scheduler.add_noise(target_latents, noise, timesteps)
    model_input = torch.cat([noisy_latents, cond_latents], dim=1)
    text_embeds = encode_prompt(prompts)

    with torch.autocast(device_type="cuda", dtype=torch.float16):

    #calculate the loss
    noise_pred = unet(model_input, timesteps, encoder_hidden_states=text_embeds, return_dict=Fa
    loss, _ = compute_hierarchical_loss(noise_pred, noise, mask_latent, bbox_latent,
                                        lambda_context=LAMBDA_CONTEXT,
                                        lambda_preserve=LAMBDA_PRESERVE)
    val_losses.append(loss.item())
    if samples_processed % 5 == 0: #skip every 5 to save compute time
        cond_img_pil = to_pil_image(cond_images[0].cpu().float() * 0.5 + 0.5)

        with torch.autocast("cuda"):
            edited = pipe(
                prompt=prompts[0],
                image=cond_img_pil,
                num_inference_steps=20,
                guidance_scale=7.5,
                image_guidance_scale=1.5,
            ).images[0]

        clip_score = calculate_clip_score(edited, prompts[0], clip_model, clip_processor)
        dir_sim = calculate_clip_directional_similarity(cond_img_pil, edited, prompts[0], clip_

        clip_scores.append(clip_score)
        dir_sims.append(dir_sim)

    samples_processed += 1

unet.train()
```

```
  return {
      "val_loss": sum(val_losses) / len(val_losses),
      "clip_score": sum(clip_scores) / len(clip_scores) if clip_scores else 0,
      "dir_sim": sum(dir_sims) / len(dir_sims) if dir_sims else 0,
  }


# Hyperparameters
EPOCHS = 4
MAX_GRAD_NORM = 1.0
LAMBDA_CONTEXT = 0.5  # Weight for context region
LAMBDA_PRESERVE = 0.7  # Weight for background preservation
PATIENCE = 2

num_training_steps = EPOCHS * len(train_loader)
scheduler = CosineAnnealingLR(optimizer, T_max=num_training_steps)

unet.train()
train_losses = []
val_metrics_history = []
best_val_dirsim = float("-inf")
epochs_no_improve = 0

for epoch in range(EPOCHS):
  epoch_losses = []
  loss_components = {'tight': [], 'context': [], 'bg': []}
  pbar = tqdm(train_loader, desc=f"Epoch {epoch+1}/{EPOCHS}")

  for step, batch in enumerate(pbar):
      pixel_values = batch["pixel_values"].to(device, dtype=torch.float16)
      cond_images = batch["conditioning_image"].to(device, dtype=torch.float16)
      masks = batch["mask"].to(device, dtype=torch.float16)
      prompts = batch["prompt"]

      bboxes = batch.get("bbox", None)

      with torch.no_grad():
          target_latents = encode_vae_images(pixel_values)
          cond_latents = encode_vae_images(cond_images)
          mask_latent = F.interpolate(masks, size=target_latents.shape[-2:], mode="nearest")
          mask_latent = mask_latent.expand(-1, 4, -1, -1)
          if bboxes is not None:
              bbox_masks = create_bbox_mask(bboxes, (masks.shape[2], masks.shape[3]))
              bbox_latent = F.interpolate(bbox_masks, size=target_latents.shape[-2:], mode="neare
              bbox_latent = bbox_latent.expand(-1, 4, -1, -1)
          else:
              # Fallback: use dilated segmentation mask as approximation from chatGPT
              bbox_latent = F.max_pool2d(mask_latent, kernel_size=5, stride=1, padding=2)

      noise = torch.randn_like(target_latents)
      bsz = target_latents.shape[0]
      timesteps = torch.randint(
          0, noise_scheduler.config.num_train_timesteps,
          (bsz,), device=device, dtype=torch.long
      )

      noisy_latents = noise_scheduler.add_noise(target_latents, noise, timesteps)
      model_input = torch.cat([noisy_latents, cond_latents], dim=1)
      text_embeds = encode_prompt(prompts)

      optimizer.zero_grad()
      with torch.autocast(device_type="cuda", dtype=torch.float16):
          noise_pred = unet(
              model_input,
              timesteps,
              encoder_hidden_states=text_embeds,
              return_dict=False
          )[0]
      loss, loss_dict = compute_hierarchical_loss(
```

```
            noise_pred, noise, mask_latent, bbox_latent,
            lambda_context=LAMBDA_CONTEXT,
            lambda_preserve=LAMBDA_PRESERVE
        )


        loss_components['tight'].append(loss_dict['L_tight'])
        loss_components['context'].append(loss_dict['L_context'])
        loss_components['bg'].append(loss_dict['L_bg'])
        if not torch.isfinite(loss):
            print(f"Non-finite loss at step {step}, skipping...")
            continue

        loss.backward()
        torch.nn.utils.clip_grad_norm_(trainable_params, MAX_GRAD_NORM)

        # Check for NaN gradients
        has_nan_grad = False
        for p in trainable_params:
            if p.grad is not None and not torch.isfinite(p.grad).all():
                has_nan_grad = True
                break

        if has_nan_grad:
            print(f"Non-finite gradient at step {step}, skipping...")
            optimizer.zero_grad()
            continue

        optimizer.step()
        scheduler.step()

        epoch_losses.append(loss.item())
        pbar.set_postfix({
            "loss": f"{loss.item():.4f}",
            "L_tight": f"{loss_dict['L_tight']:.3f}",
            "L_ctx": f"{loss_dict['L_context']:.3f}",
            "lr": f"{scheduler.get_last_lr()[0]:.2e}"
        })

    avg_loss = sum(epoch_losses) / len(epoch_losses) if epoch_losses else float('nan')
    train_losses.append(avg_loss)

    # ChatGPT generated these print statements for me
    print(f"Epoch {epoch+1} average loss: {avg_loss:.4f}")
    print(f"  Loss breakdown - Tight: {sum(loss_components['tight'])/len(loss_components['tight'])
          f"Context: {sum(loss_components['context'])/len(loss_components['context']):.4f}, "
          f"Background: {sum(loss_components['bg'])/len(loss_components['bg']):.4f}")

    print(f"Running validation...")
    val_metrics = validate(val_loader, num_samples=50)
    val_metrics_history.append(val_metrics)

    print(f"  Val Loss: {val_metrics['val_loss']:.4f}")
    print(f"  CLIP Score: {val_metrics['clip_score']:.2f}")
    print(f"  Directional Sim: {val_metrics['dir_sim']:.2f}")


#Early stopping if no improvement
    if val_metrics['dir_sim'] > best_val_dirsim:
        best_val_dirsim = val_metrics['dir_sim']
        epochs_no_improve = 0
        torch.save(unet.state_dict(), "unet_best.pt")
        print(f"  New best model saved! (dir_sim: {best_val_dirsim:.2f})")
    else:
        epochs_no_improve += 1
        print(f"  No improvement for {epochs_no_improve} epoch(s)")

        if epochs_no_improve >= PATIENCE:
            print(f"Early stopping triggered at epoch {epoch+1}")
            break
```

```
#save at this checkpoint
  torch.save({
      'epoch': epoch,
      'unet_state_dict': unet.state_dict(),
      'optimizer_state_dict': optimizer.state_dict(),
      'scheduler_state_dict': scheduler.state_dict(),
      'train_losses': train_losses,
      'val_metrics': val_metrics_history,
  }, f"checkpoint_epoch{epoch+1}.pt")

print("Training complete!")
print(f"Best directional similarity: {best_val_dirsim:.2f}")
```

Show hidden output

```
# plot training loss

plt.figure(figsize=(10, 5))
plt.plot(range(1, len(train_losses) + 1), train_losses, marker='o')
plt.xlabel("Epoch")
plt.ylabel("Average Loss")
plt.title("Training Loss - Bounding Box Fine-tuning")
plt.grid(True)
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
/tmp/ipython-input-2932974737.py in <cell line: 0>()
      1 # plot training loss
      2
----> 3 plt.figure(figsize=(10, 5))
      4 plt.plot(range(1, len(train_losses) + 1), train_losses, marker='o')
      5 plt.xlabel("Epoch")

NameError: name 'plt' is not defined
```

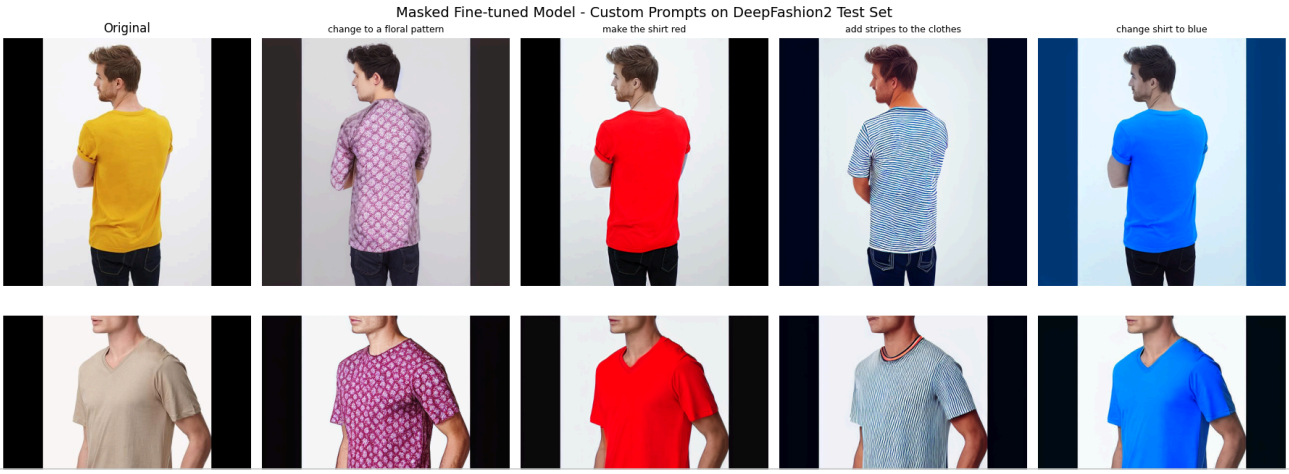
```
# Load fine-tuned model for eval

state_dict = torch.load("unet_best.pt", map_location=device)
unet.load_state_dict(state_dict, strict=False)

pipe.unet = unet
pipe.to("cuda")
pipe.unet.eval()

print("Fine-tuned model loaded!")
```

```
Fine-tuned model loaded!
```

```
custom_prompts = [
    "change to a floral pattern",
    "make the shirt red",
    "add stripes to the clothes",
    "change shirt to blue",
]

NUM_TEST_IMAGES = 5

fig, axes = plt.subplots(NUM_TEST_IMAGES, len(custom_prompts) + 1, figsize=(18, 4 * NUM_TEST_IMAGI

custom_results = []

for row in range(NUM_TEST_IMAGES):
    actual_idx = test_ds.indices[row]
    t = triplets[actual_idx]
    src = dataset["train"][t["src_idx"]]
    original_image = src["images"]

    if max(original_image.size) > 512:
```

```
        original_image = original_image.copy()
        original_image.thumbnail((512, 512), Image.Resampling.LANCZOS)

    axes[row, 0].imshow(original_image)
    axes[row, 0].set_title("Original" if row == 0 else "")
    axes[row, 0].axis("off")

    for col, prompt in enumerate(custom_prompts):
        with torch.autocast("cuda"):
            edited = pipe(
                prompt=prompt,
                image=original_image,
                num_inference_steps=50,
                guidance_scale=7.5,
                image_guidance_scale=1.5,
            ).images[0]

        clip_score = calculate_clip_score(edited, prompt, clip_model, clip_processor)
        clip_directional = calculate_clip_directional_similarity(
            original_image, edited, prompt, clip_model, clip_processor
        )
        lpips_val = calculate_lpips(original_image, edited)

        custom_results.append({
            'image': row,
            'prompt': prompt,
            'clip_score': clip_score,
            'directional_similarity': clip_directional,
            'lpips': lpips_val,
        })

        axes[row, col + 1].imshow(edited)
        axes[row, col + 1].set_title(prompt if row == 0 else "", fontsize=9)
        axes[row, col + 1].axis("off")

plt.tight_layout()
plt.savefig("custom_prompts_deepfashion2.png", dpi=150, bbox_inches='tight')
plt.show()

# Summary
df_custom = pd.DataFrame(custom_results)
print("\n Custom Prompts Evaluation ===")
print(f"mean CLIP Score: {df_custom['clip_score'].mean():.2f}")
print(f"mean Directional Similarity: {df_custom['directional_similarity'].mean():.2f}")
print(f"mean LPIPS: {df_custom['lpips'].mean():.4f}")
print("\nPer-prompt averages:")
print(df_custom.groupby('prompt')[['clip_score', 'directional_similarity']].mean())
```

```
100%  50/50 [00:11<00:00,  4.33it/s]
100%  50/50 [00:11<00:00,  4.24it/s]
100%  50/50 [00:11<00:00,  4.24it/s]
100%  50/50 [00:11<00:00,  4.30it/s]
100%  50/50 [00:11<00:00,  4.36it/s]
100%  50/50 [00:11<00:00,  4.38it/s]
100%  50/50 [00:11<00:00,  4.40it/s]
100%  50/50 [00:11<00:00,  4.36it/s]
100%  50/50 [00:11<00:00,  4.35it/s]
100%  50/50 [00:11<00:00,  4.34it/s]
100%  50/50 [00:11<00:00,  4.32it/s]
100%  50/50 [00:11<00:00,  4.33it/s]
100%  50/50 [00:11<00:00,  4.34it/s]
100%  50/50 [00:11<00:00,  4.36it/s]
100%  50/50 [00:11<00:00,  4.36it/s]
100%  50/50 [00:11<00:00,  4.37it/s]
100%  50/50 [00:11<00:00,  4.34it/s]
100%  50/50 [00:11<00:00,  4.36it/s]
100%  50/50 [00:11<00:00,  4.35it/s]
100%  50/50 [00:11<00:00,  4.33it/s]
```




```
# compare baseline vs fine tuned
print(f"Baseline Mean CLIP Score: {pd.DataFrame(results)['clip_score_edited'].mean():.2f}")
print(f"Fine-tuned Mean CLIP Score: {df_custom['clip_score'].mean():.2f}")
print(f"\nBaseline Mean Directional Sim: {pd.DataFrame(results)['clip_directional_similarity'].mea
print(f"Fine-tuned Mean Directional Sim: {df_custom['directional_similarity'].mean():.2f}")
```

```
=== Comparison ===
Baseline Mean CLIP Score: 23.03
Fine-tuned Mean CLIP Score: 22.14

Baseline Mean Directional Sim: 7.82
Fine-tuned Mean Directional Sim: 11.91
```

```
# evaluating on fashion pedia dataset

test_prompts = [
    "change to a floral pattern",
    "make the shirt red",
    "add stripes to the clothes",
    "change shirt to blue",
]

```

```
NUM_SAMPLES = 5

finetuned_fashionpedia_results = []

for idx in range(NUM_SAMPLES):
    sample = fashionpedia_samples[idx]
    original_image = sample['image']

    if max(original_image.size) > 512:
        original_image = original_image.copy()
        original_image.thumbnail((512, 512), Image.Resampling.LANCZOS)

    for prompt in test_prompts:
        # Generate with fine-tuned model
        with torch.autocast("cuda"):
            edited = pipe(
                prompt=prompt,
                image=original_image,
                num_inference_steps=50,
                guidance_scale=7.5,
                image_guidance_scale=1.5,
            ).images[0]

        # Calculate metrics
        clip_score = calculate_clip_score(edited, prompt, clip_model, clip_processor)
        clip_directional = calculate_clip_directional_similarity(
            original_image, edited, prompt, clip_model, clip_processor
        )

        finetuned_fashionpedia_results.append({
            'sample': idx,
            'prompt': prompt,
            'clip_score': clip_score,
            'directional_similarity': clip_directional,
        })

df_finetuned_fp = pd.DataFrame(finetuned_fashionpedia_results)

print(f"Mean CLIP Score: {df_finetuned_fp['clip_score'].mean():.2f}")
print(f"Mean Directional Similarity: {df_finetuned_fp['directional_similarity'].mean():.2f}")

# Compare with baseline on FashionPedia
print(f"Baseline Mean CLIP Score: {pd.DataFrame(results)['clip_score_edited'].mean():.2f}")
print(f"Fine-tuned Mean CLIP Score: {df_finetuned_fp['clip_score'].mean():.2f}")
print(f"\nBaseline Mean Directional Sim: {pd.DataFrame(results)['clip_directional_similarity'].mea
print(f"Fine-tuned Mean Directional Sim: {df_finetuned_fp['directional_similarity'].mean():.2f}")
```

```
100%                                      50/50 [00:08<00:00,  6.30it/s]
100%                                      50/50 [00:08<00:00,  6.24it/s]
100%                                      50/50 [00:08<00:00,  6.23it/s]
100%                                      50/50 [00:08<00:00,  6.24it/s]
100%                                      50/50 [00:08<00:00,  6.29it/s]
100%                                      50/50 [00:08<00:00,  6.29it/s]
100%                                      50/50 [00:08<00:00,  6.28it/s]
100%                                      50/50 [00:08<00:00,  6.27it/s]
100%                                      50/50 [00:08<00:00,  6.28it/s]
100%                                      50/50 [00:08<00:00,  6.29it/s]
100%                                      50/50 [00:08<00:00,  6.29it/s]
100%                                      50/50 [00:08<00:00,  6.29it/s]
100%                                      50/50 [00:08<00:00,  6.26it/s]
100%                                      50/50 [00:08<00:00,  6.25it/s]
100%                                      50/50 [00:08<00:00,  6.32it/s]
100%                                      50/50 [00:08<00:00,  6.28it/s]
100%                                      50/50 [00:09<00:00,  5.04it/s]
100%                                      50/50 [00:10<00:00,  5.04it/s]
100%                                      50/50 [00:10<00:00,  5.03it/s]
100%                                      50/50 [00:10<00:00,  5.03it/s]
=== Fine-tuned Model on FashionPedia ===
Mean CLIP Score: 19.16
Mean Directional Similarity: 10.61

=== Comparison on FashionPedia ===
Baseline Mean CLIP Score: 23.03
Fine-tuned Mean CLIP Score: 19.16

Baseline Mean Directional Sim: 7.82
Fine-tuned Mean Directional Sim: 10.61
```

```python
# plotting for fine tuned model on fashionpedia

fig, axes = plt.subplots(NUM_SAMPLES, len(test_prompts) + 1, figsize=(18, 4 * NUM_SAMPLES))

for row in range(NUM_SAMPLES):
    sample = fashionpedia_samples[row]
    original_image = sample['image']

    if max(original_image.size) > 512:
        original_image = original_image.copy()
        original_image.thumbnail((512, 512), Image.Resampling.LANCZOS)

    axes[row, 0].imshow(original_image)
    axes[row, 0].set_title("Original" if row == 0 else "")
    axes[row, 0].axis("off")

    for col, prompt in enumerate(test_prompts):
        with torch.autocast("cuda"):
            edited = pipe(
                prompt=prompt,
                image=original_image,
                num_inference_steps=50,
                guidance_scale=7.5,
                image_guidance_scale=1.5,
            ).images[0]

        axes[row, col + 1].imshow(edited)
        axes[row, col + 1].set_title(prompt if row == 0 else "", fontsize=9)
        axes[row, col + 1].axis("off")
```

```
plt.suptitle("Fine-tuned Model on FashionPedia (unseen data)", fontsize=14)
plt.tight_layout()
plt.savefig("finetuned_on_fashionpedia.png", dpi=150, bbox_inches='tight')
plt.show()
```

```
100%  50/50 [00:08<00:00,  6.28it/s]
100%  50/50 [00:08<00:00,  6.24it/s]
100%  50/50 [00:08<00:00,  6.27it/s]
100%  50/50 [00:08<00:00,  6.30it/s]
100%  50/50 [00:08<00:00,  6.28it/s]
100%  50/50 [00:08<00:00,  6.25it/s]
100%  50/50 [00:08<00:00,  6.23it/s]
100%  50/50 [00:08<00:00,  6.25it/s]
100%  50/50 [00:08<00:00,  6.25it/s]
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100%  50/50 [00:08<00:00,  6.25it/s]
100%  50/50 [00:08<00:00,  6.25it/s]
100%  50/50 [00:08<00:00,  6.28it/s]
100%  50/50 [00:08<00:00,  6.25it/s]
100%  50/50 [00:08<00:00,  6.26it/s]
100%  50/50 [00:10<00:00,  5.03it/s]
100%  50/50 [00:10<00:00,  5.05it/s]
100%  50/50 [00:10<00:00,  5.02it/s]
100%  50/50 [00:10<00:00,  5.04it/s]
```
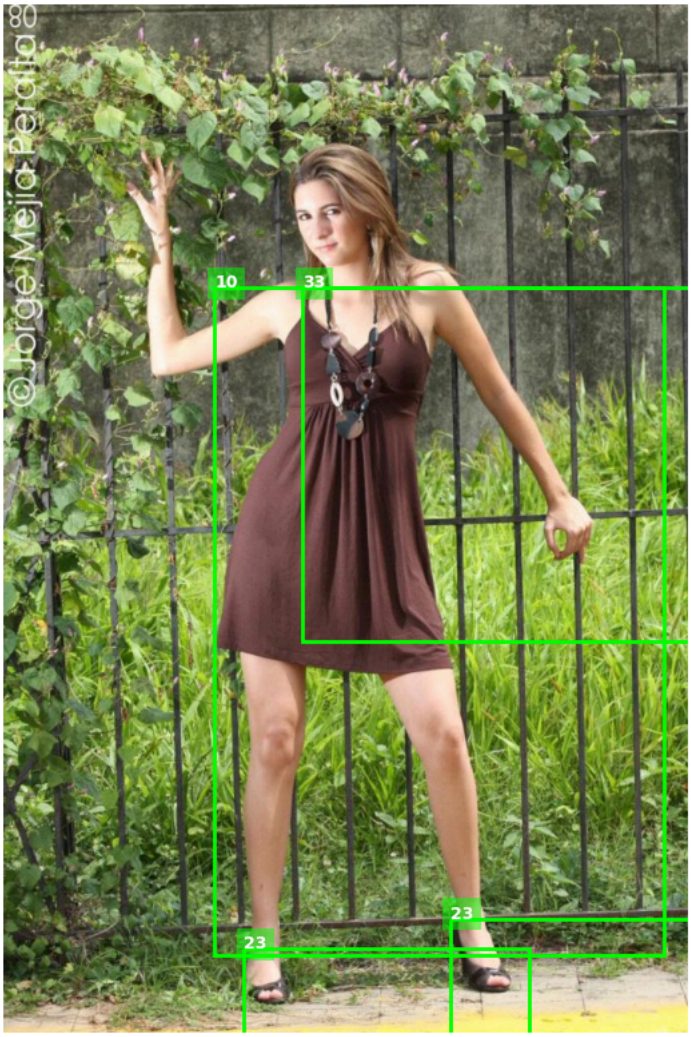

5. The following code is used to generate some visualizations for our paper given the datasets we were using (FashionPedia). It is mostly generated using AI and not use in our actual experimentation.

```
import matplotlib.pyplot as plt
import matplotlib.patches as patches
from datasets import load_dataset

# 1. Load dataset
print("Loading FashionPedia stream...")
dataset_fashionpedia = load_dataset("detection-datasets/fashionpedia", split="train", streaming=T
```

```
# 2. Grab just 5 samples
print("Fetching samples...")
fashionpedia_samples = list(dataset_fashionpedia.take(5))

# 3. Robust Helper to get Class Names
# We check if 'objects' is a dict or an object to avoid the AttributeError
def get_category_names(dataset):
    try:
        # Try standard Hugging Face object access
        return dataset.features['objects'].feature['category'].names
    except AttributeError:
        try:
            # Fallback: Try dictionary access (common in some Colab envs)
            return dataset.features['objects']['feature']['category']['names']
        except (KeyError, TypeError):
            # If all else fails, return None and we will just print IDs
            print("Warning: Could not extract class names. Displaying IDs only.")
            return None

class_names = get_category_names(dataset_fashionpedia)

def get_label_name(cat_id):
    if class_names and cat_id < len(class_names):
        return class_names[cat_id]
    return str(cat_id) # Return ID if names failed to load

# 4. Visualization Function
def visualize_sample(sample):
    image = sample['image']
    objects = sample['objects']

    # Create a figure
    fig, ax = plt.subplots(figsize=(10, 10))
    ax.imshow(image)

    # Loop through all objects detected in the image
    # Note: Some datasets use 'categories' instead of 'category', we handle both
    cat_keys = objects.get('category', objects.get('categories', []))

    for bbox, cat_id in zip(objects['bbox'], cat_keys):
        # Format is [x_min, y_min, width, height]
        x, y, w, h = bbox

        # Create a Rectangle patch
        rect = patches.Rectangle((x, y), w, h, linewidth=2, edgecolor='#00FF00', facecolor='none')
        ax.add_patch(rect)

        # Add the label text above the box
        label_text = get_label_name(cat_id)
        ax.text(x, y, label_text, color='white', fontsize=9, weight='bold',
                bbox=dict(facecolor='#00FF00', edgecolor='none', alpha=0.5))

    plt.axis('off')
    plt.show()

# 5. Show the first image
print(f"Visualizing Sample 0...")
visualize_sample(fashionpedia_samples[0])
```

```
Loading FashionPedia stream...
Fetching samples...
Warning: Could not extract class names. Displaying IDs only.
Visualizing Sample 0...
```




```
import matplotlib.pyplot as plt
import matplotlib.patches as patches
import numpy as np
from datasets import load_dataset

# 1. Load Dataset
print("Loading FashionPedia stream...")
dataset = load_dataset("detection-datasets/fashionpedia", split="train", streaming=True)
sample = next(iter(dataset))

image_pil = sample['image']
image = np.array(image_pil)
h, w, _ = image.shape
objects = sample['objects']

# get the dress (target_idx 3)
max_area = 0
target_idx = 3
bx, by, bw, bh = [int(v) for v in objects['bbox'][target_idx]]

# 3. Create Zone Masks

# Zone 1: Tight Edit Region (the actual bounding box)
mask_tight = np.zeros((h, w), dtype=np.uint8)
mask_tight[by:by+bh, bx:bx+bw] = 1

# Zone 2: Context Region (expanded box minus tight box)
```

```
EXPANSION_FACTOR = 1.3
cx, cy = bx + bw/2, by + bh/2
new_w, new_h = bw * EXPANSION_FACTOR, bh * EXPANSION_FACTOR

nx1 = int(max(0, cx - new_w/2))
ny1 = int(max(0, cy - new_h/2))
nx2 = int(min(w, cx + new_w/2))
ny2 = int(min(h, cy + new_h/2))

mask_expanded = np.zeros((h, w), dtype=np.uint8)
mask_expanded[ny1:ny2, nx1:nx2] = 1

mask_context = mask_expanded - mask_tight
mask_context = np.clip(mask_context, 0, 1)

# Zone 3: Background (everything outside expanded box)
mask_bg = 1 - mask_expanded

# 4. Visualization
fig, axes = plt.subplots(1, 4, figsize=(20, 5))

# Plot A: Original Image with bounding boxes
axes[0].imshow(image)
# Original bbox (yellow)
rect_tight = patches.Rectangle((bx, by), bw, bh, linewidth=2,
                               edgecolor='yellow', facecolor='none', label='Tight')
# Expanded bbox (cyan)
rect_expanded = patches.Rectangle((nx1, ny1), nx2-nx1, ny2-ny1, linewidth=2,
                                  edgecolor='cyan', facecolor='none', label='Expanded')
axes[0].add_patch(rect_expanded)
axes[0].add_patch(rect_tight)
axes[0].set_title(f"Original Image\nObject {target_idx}: {objects['category'][target_idx]}")
axes[0].legend()
axes[0].axis('off')

# Plot B: Zone 1 (Tight Edit Region)
overlay_tight = np.zeros_like(image)
overlay_tight[mask_tight == 1] = [255, 100, 100]  # Red tint
blended = np.where(mask_tight[..., None] == 1,
                   image * 0.5 + overlay_tight * 0.5,
                   image * 0.3).astype(np.uint8)
axes[1].imshow(blended)
axes[1].set_title("Zone 1: Tight Edit Region\n(High penalty for changes)")
axes[1].axis('off')

# Plot C: Zone 2 (Context Region)
overlay_context = np.zeros_like(image)
overlay_context[mask_context == 1] = [100, 255, 100]  # Green tint
blended = np.where(mask_context[..., None] == 1,
                   image * 0.5 + overlay_context * 0.5,
                   image * 0.3).astype(np.uint8)
axes[2].imshow(blended)
axes[2].set_title("Zone 2: Context Region\n(Medium penalty for changes)")
axes[2].axis('off')

# Plot D: Zone 3 (Background - Should be Preserved)
overlay_bg = np.zeros_like(image)
overlay_bg[mask_bg == 1] = [100, 100, 255]  # Blue tint
blended = np.where(mask_bg[..., None] == 1,
                   image * 0.5 + overlay_bg * 0.5,
                   image * 0.3).astype(np.uint8)
axes[3].imshow(blended)
axes[3].set_title("Zone 3: Background\n(Strongest penalty - preserve)")
axes[3].axis('off')

plt.tight_layout()
plt.show()

# Print zone statistics
print(f"\nZone Statistics:")
```

```
print(f"Zone 1 (Tight): {mask_tight.sum()} pixels ({100*mask_tight.sum()/(h*w):.1f}%)")
print(f"Zone 2 (Context): {mask_context.sum()} pixels ({100*mask_context.sum()/(h*w):.1f}%)")
print(f"Zone 3 (Background): {mask_bg.sum()} pixels ({100*mask_bg.sum()/(h*w):.1f}%)")
```

```
Loading FashionPedia stream...
```


```
Zone Statistics:
Zone 1 (Tight): 297920 pixels (42.7%)
Zone 2 (Context): 156760 pixels (22.4%)
Zone 3 (Background): 243688 pixels (34.9%)
```

```
# --- Load InstructPix2Pix ---
from diffusers import StableDiffusionInstructPix2PixPipeline, DPMSolverMultistepScheduler
from datasets import load_dataset
import torch
import PIL
import matplotlib.pyplot as plt

# Load model
model_id = "timbrooks/instruct-pix2pix"
pipe = StableDiffusionInstructPix2PixPipeline.from_pretrained(
    model_id,
    torch_dtype=torch.float16,
    safety_checker=None,
)
pipe.to("cuda")

pipe.scheduler = DPMSolverMultistepScheduler.from_config(pipe.scheduler.config)

# --- Load ONE example from FashionPedia ---
dataset = load_dataset("detection-datasets/fashionpedia", split="train", streaming=True)
first_item = next(iter(dataset))     # get only the FIRST sample

original_image = first_item["image"].convert("RGB")

print("Loaded first FashionPedia image")
display(original_image)

# --- Apply edit ---
prompt = "Give her clothes a floral pattern"

edited = pipe(
    prompt=prompt,
    image=original_image,
    num_inference_steps=100,
    guidance_scale=12,
    image_guidance_scale=2.0,
```

```
).images[0]

# --- Show side-by-side ---
plt.figure(figsize=(12,6))
plt.subplot(1,2,1)
plt.title("Original")
plt.imshow(original_image)
plt.axis("off")

plt.subplot(1,2,2)
plt.title("Edited: Floral Pattern")
plt.imshow(edited)
plt.axis("off")

plt.show()


```