Ablation Study for Domain-Specific InstructPix2Pix

This standalone notebook reuses the *Final_Project* pipeline (data prep, etc), but runs the ablation study.

```
# install packages required
%pip install -q lpips pytorch-msssim
```

```
import os
import gc
import math
import json
import copy
import random
import re
from dataclasses import dataclass, asdict
from typing import Dict, List, Any

import numpy as np
import pandas as pd
import torch
import torch.nn.functional as F
from torch import nn
from torch.utils.data import Dataset, DataLoader
from torchvision import transforms
import torchvision.transforms.functional as TF
from torchvision.transforms.functional import to_pil_image

from PIL import Image
import matplotlib.pyplot as plt
from tqdm.auto import tqdm
from collections import defaultdict

from datasets import load_dataset
from diffusers import StableDiffusionInstructPix2PixPipeline, DDPMScheduler
from transformers import CLIPProcessor, CLIPModel
from torch.optim import AdamW
from torch.optim.lr_scheduler import CosineAnnealingLR

import lpips
from pytorch_msssim import ssim as ssim_torch

# for replication can remove
SEED = 42
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed_all(SEED)

device = "cuda" if torch.cuda.is_available() else "cpu"
assert device == "cuda", "This ablation requires a CUDA-enabled runtime."
print(f"Using device: {device}")

```

```
Using device: cuda
```

```
clip_model = CLIPModel.from_pretrained("openai/clip-vit-large-patch14").to(device)
clip_processor = CLIPProcessor.from_pretrained("openai/clip-vit-large-patch14")

lpips_model = lpips.LPIPS(net='vgg').to(device)
lpips_model.eval()

_to_tensor = transforms.ToTensor()

def pil_to_tensor(image: Image.Image) -> torch.Tensor:
    return _to_tensor(image).unsqueeze(0).to(device)
```

```
def _match_image_size(candidate: Image.Image, reference: Image.Image) -> Image.Image:
    if candidate.size != reference.size:
        return candidate.resize(reference.size, Image.Resampling.LANCZOS)
    return candidate

def calculate_lpips(img1: Image.Image, img2: Image.Image) -> float:
    img2_aligned = _match_image_size(img2, img1)
    x = 2 * pil_to_tensor(img1) - 1.0
    y = 2 * pil_to_tensor(img2_aligned) - 1.0
    with torch.no_grad():
        return lpips_model(x, y).item()

def calculate_ssim(img1: Image.Image, img2: Image.Image) -> float:
    img2_aligned = _match_image_size(img2, img1)
    x = pil_to_tensor(img1)
    y = pil_to_tensor(img2_aligned)
    return ssim_torch(x, y, data_range=1.0, size_average=True).item()

def calculate_clip_score(image: Image.Image, text: str) -> float:
    inputs = clip_processor(text=[text], images=image, return_tensors="pt", padding=True).to(devi
    with torch.no_grad():
        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

def calculate_clip_directional_similarity(original_img, edited_img, text):
    with torch.no_grad():
        inputs_orig = clip_processor(images=original_img, return_tensors="pt").to(device)
        orig_embeds = clip_model.get_image_features(**inputs_orig)
        orig_embeds = orig_embeds / orig_embeds.norm(dim=-1, keepdim=True)

        inputs_edit = clip_processor(images=edited_img, return_tensors="pt").to(device)
        edit_embeds = clip_model.get_image_features(**inputs_edit)
        edit_embeds = edit_embeds / edit_embeds.norm(dim=-1, keepdim=True)

        inputs_text = clip_processor(text=[text], return_tensors="pt", padding=True).to(device)
        text_embeds = clip_model.get_text_features(**inputs_text)
        text_embeds = text_embeds / text_embeds.norm(dim=-1, keepdim=True)

        img_direction = edit_embeds - orig_embeds
        img_direction = img_direction / (img_direction.norm(dim=-1, keepdim=True) + 1e-8)

        null_text = clip_processor(text=[""], return_tensors="pt", padding=True).to(device)
        null_embeds = clip_model.get_text_features(**null_text)
        null_embeds = null_embeds / null_embeds.norm(dim=-1, keepdim=True)

        text_direction = text_embeds - null_embeds
        text_direction = text_direction / (text_direction.norm(dim=-1, keepdim=True) + 1e-8)

        directional_sim = (img_direction @ text_direction.T).item()
    return directional_sim * 100

print("metric stack ready.")
```

```
/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py:104: UserWarning:
Error while fetching `HF_TOKEN` secret value from your vault: 'Requesting secret HF_TOKEN timed out. Secrets can only
You are not authenticated with the Hugging Face Hub in this notebook.
If the error persists, please let us know by opening an issue on GitHub (https://github.com/huggingface/huggingface_h
  warnings.warn(
Using a slow image processor as `use_fast` is unset and a slow processor was saved with this model. `use_fast=True` w
Setting up [LPIPS] perceptual loss: trunk [vgg], v[0.1], spatial [off]
/usr/local/lib/python3.12/dist-packages/torchvision/models/_utils.py:208: UserWarning: The parameter 'pretrained' is
  warnings.warn(
/usr/local/lib/python3.12/dist-packages/torchvision/models/_utils.py:223: UserWarning: Arguments other than a weight
  warnings.warn(msg)
Loading model from: /usr/local/lib/python3.12/dist-packages/lpips/weights/v0.1/vgg.pth
Metric stack ready.
```

```
FASHIONPEDIA_STREAM_LIMIT = 100
MAX_TRIPLETS = 1500
IMAGE_SIZE = 512
BATCH_SIZE = 1
CHECKPOINT_DIR = "ablation_checkpoints"
os.makedirs(CHECKPOINT_DIR, exist_ok=True)

print("Loading FashionPedia stream (for qualitative eval)...")
dataset_fashionpedia = load_dataset("detection-datasets/fashionpedia", split="train", streaming=
fashionpedia_samples = list(dataset_fashionpedia.take(FASHIONPEDIA_STREAM_LIMIT))
print(f"Loaded {len(fashionpedia_samples)} FashionPedia samples for eval.")

print("Loading DeepFashion2 (with masks) ...")
deepfashion_dataset = load_dataset("SaffalPoosh/deepFashion-with-masks")
print(deepfashion_dataset)


def generate_instruction(caption1: str, caption2: str) -> str:
    part2 = caption2.lower().split("in ")[-1] if "in " in caption2.lower() else caption2.lower()
    return f"change to {part2}"


def build_triplets(hf_dataset, max_triplets: int):
    by_pid = defaultdict(list)
    for i in range(len(hf_dataset["train"])):
        by_pid[hf_dataset["train"][i]["pid"]].append(i)

    triplets = []
    for pid, indices in tqdm(by_pid.items(), desc="Building triplets"):
        if len(indices) < 2:
            continue
        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:
                    return triplets
    return triplets

triplets = build_triplets(deepfashion_dataset, max_triplets=MAX_TRIPLETS)
print(f"Total triplets for ablation: {len(triplets)}")


class TripletDataset(Dataset):
    def __init__(self, triplet_list, hf_data, size=IMAGE_SIZE):
        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(),
        ])
        self.color_jitter = transforms.ColorJitter(0.1, 0.1, 0.1, 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"].convert("RGB")
```

```
        edit_img = tgt["images"].convert("RGB")
        src_mask = src["mask"].convert("L")
        instruction = generate_instruction(src["caption"], tgt["caption"])

        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)

        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)
        mask_tensor = (mask_tensor > 0.5).float()

        return {
            "conditioning_image": conditioning_image,
            "pixel_values": pixel_values,
            "prompt": instruction,
            "mask": mask_tensor,
        }

full_ds = TripletDataset(triplets, deepfashion_dataset, size=IMAGE_SIZE)
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(SEED)
)

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)}")

peek = next(iter(train_loader))
print(f"Conditioning shape: {peek['conditioning_image'].shape}")
print(f"Sample prompt: {peek['prompt'][0]}")

```

```
Loading FashionPedia stream (for qualitative eval)...
Loaded 100 FashionPedia samples for eval.
Loading DeepFashion2 (with masks) ...
data/train-00002-of-00004-f11f7b29a225c1(…):   0%|          | 0.00/361M [00:00<?, ?B/s]
data/train-00003-of-00004-e6de6e7287b28c(…):   0%|          | 0.00/361M [00:00<?, ?B/s]
Generating train split:   0%|          | 0/40658 [00:00<?, ? examples/s]
DatasetDict({
    train: Dataset({
        features: ['images', 'gender', 'pose', 'cloth_type', 'pid', 'caption', 'mask', 'mask_overlay'],
        num_rows: 40658
    })
})
Building triplets:   0%|          | 0/7557 [00:00<?, ?it/s]
Total triplets for ablation: 1500
Train: 1200, Val: 150, Test: 150
Conditioning shape: torch.Size([1, 3, 512, 512])
Sample prompt: change to a white shirt and jeans
```

```
ABLATION_EPOCHS = 2
EVAL_PROMPTS = [
    "change to a floral pattern",
    "make the shirt red",
    "add stripes to the clothes",
    "change shirt to blue",
]
NUM_EVAL_IMAGES = 2
```

```
FASHIONPEDIA_EVAL_IMAGES = 2

@dataclass
class AblationConfig:
    name: str
    learning_rate: float
    lambda_preserve: float
    guidance_scale: float
    image_guidance_scale: float
    num_inference_steps: int
    unfreeze_strategy: str
    weight_decay: float = 0.01
    max_grad_norm: float = 1.0


def config_slug(name: str) -> str:
    base = name.lower().replace(" ", "_")
    return re.sub(r"[^a-z0-9_]+", "", base) or "config"


def apply_unfreeze_strategy(unet, strategy: str):
    for param in unet.parameters():
        param.requires_grad = False

    trainable_names = []

    def is_attn_proj(name):
        targets = ["to_q", "to_k", "to_v", "to_out"]
        return any(t in name for t in targets)

    for name, param in unet.named_parameters():
        should_train = False
        if "attn" in name and is_attn_proj(name):
            should_train = True
        if "mid_block" in name and strategy in {"attn_mid", "attn_mid_up", "attn_mid_resnet"}:
            should_train = True
        if strategy in {"attn_mid_up", "attn_mid_resnet"} and "up_blocks" in name:
            if "resnets" in name and "conv" in name:
                should_train = True
        if strategy == "attn_mid_resnet" and "down_blocks" in name and "resnets" in name and "co
            should_train = True

        if should_train:
            param.requires_grad = True
            trainable_names.append(name)

    return trainable_names


def prepare_components(config: AblationConfig):
    pipe = StableDiffusionInstructPix2PixPipeline.from_pretrained(
        "timbrooks/instruct-pix2pix",
        torch_dtype=torch.float16,
        safety_checker=None,
    ).to(device)
    pipe.scheduler = DDPMScheduler.from_config(pipe.scheduler.config)

    unet = pipe.unet
    tokenizer = pipe.tokenizer
    text_encoder = pipe.text_encoder
    vae = pipe.vae
    noise_scheduler = pipe.scheduler

    trainable_names = apply_unfreeze_strategy(unet, config.unfreeze_strategy)
    trainable_params = [p for p in unet.parameters() if p.requires_grad]
    optimizer = AdamW(trainable_params, lr=config.learning_rate, eps=1e-4, weight_decay=config.we
    scheduler = CosineAnnealingLR(optimizer, T_max=ABLATION_EPOCHS * len(train_loader))

    return {
        "pipe": pipe,
```

```
        "unet": unet,
        "tokenizer": tokenizer,
        "text_encoder": text_encoder,
        "vae": vae,
        "noise_scheduler": noise_scheduler,
        "optimizer": optimizer,
        "scheduler": scheduler,
        "trainable_params": trainable_params,
        "trainable_names": trainable_names,
    }


def encode_prompt(tokenizer, text_encoder, 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(vae, 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 train_one_epoch(config, components):
    unet = components["unet"]
    vae = components["vae"]
    tokenizer = components["tokenizer"]
    text_encoder = components["text_encoder"]
    noise_scheduler = components["noise_scheduler"]
    optimizer = components["optimizer"]
    scheduler = components["scheduler"]
    trainable_params = components["trainable_params"]

    unet.train()
    epoch_losses = []
    progress = tqdm(train_loader, desc=f"{config.name} — train", leave=False)
    for batch in progress:
        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"]

        with torch.no_grad():
            target_latents = encode_vae_images(vae, pixel_values)
            cond_latents = encode_vae_images(vae, cond_images)
            mask_latent = F.interpolate(masks, size=target_latents.shape[-2:], mode="nearest")
            mask_latent = mask_latent.expand(-1, 4, -1, -1)

        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(tokenizer, text_encoder, 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_(

        M_cloth = mask_latent
        M_bg = 1.0 - mask_latent
```

```
        L_denoise = F.mse_loss((noise_pred * M_cloth).float(), (noise * M_cloth).float())
        L_preserve = F.mse_loss((noise_pred * M_bg).float(), (noise * M_bg).float())
        loss = L_denoise + config.lambda_preserve * L_preserve

        if not torch.isfinite(loss):
            continue

        loss.backward()
        torch.nn.utils.clip_grad_norm_(trainable_params, config.max_grad_norm)
        optimizer.step()
        scheduler.step()

        epoch_losses.append(loss.item())
        progress.set_postfix({"loss": f"{loss.item():.4f}", "lr": f"{scheduler.get_last_lr()[0]:

    avg_loss = float(np.mean(epoch_losses)) if epoch_losses else float("nan")
    return avg_loss


def validate_one_epoch(config, components, max_batches=50):
    unet = components["unet"]
    vae = components["vae"]
    tokenizer = components["tokenizer"]
    text_encoder = components["text_encoder"]
    noise_scheduler = components["noise_scheduler"]

    unet.eval()
    val_losses = []
    with torch.no_grad():
        for batch_idx, batch in enumerate(val_loader):
            if batch_idx >= max_batches:
                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"]

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

            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(tokenizer, text_encoder, prompts)

            with torch.autocast(device_type="cuda", dtype=torch.float16):
                noise_pred = unet(model_input, timesteps, encoder_hidden_states=text_embeds, retu

            M_cloth = mask_latent
            M_bg = 1.0 - mask_latent
            L_denoise = F.mse_loss((noise_pred * M_cloth).float(), (noise * M_cloth).float())
            L_preserve = F.mse_loss((noise_pred * M_bg).float(), (noise * M_bg).float())
            loss = L_denoise + config.lambda_preserve * L_preserve
            val_losses.append(loss.item())

    avg_val = float(np.mean(val_losses)) if val_losses else float("nan")
    unet.train()
    return avg_val


def evaluate_config(pipe, config: AblationConfig):
    pipe.unet.eval()
    deepfashion_rows = []
    fashionpedia_rows = []
    deepfashion_visuals = []
    fashionpedia_visuals = []
```

```
219
220     for row in range(NUM_EVAL_IMAGES):
221         actual_idx = test_ds.indices[row % len(test_ds)]
222         triplet = triplets[actual_idx]
223         src = deepfashion_dataset["train"][triplet["src_idx"]]
224         original_image = src["images"]
225         if max(original_image.size) > 512:
226             original_image = original_image.copy()
227             original_image.thumbnail((512, 512), Image.Resampling.LANCZOS)
228
229         row_visual = {"original": original_image.copy(), "edits": []}
230         for prompt in EVAL_PROMPTS:
231             with torch.autocast("cuda"):
232                 edited = pipe(
233                     prompt=prompt,
234                     image=original_image,
235                     num_inference_steps=config.num_inference_steps,
236                     guidance_scale=config.guidance_scale,
237                     image_guidance_scale=config.image_guidance_scale,
238                 ).images[0]
239             clip_score = calculate_clip_score(edited, prompt)
240             dir_sim = calculate_clip_directional_similarity(original_image, edited, prompt)
241             lpips_val = calculate_lpips(original_image, edited)
242             ssim_val = calculate_ssim(original_image, edited)
243             deepfashion_rows.append({
244                 "config": config.name,
245                 "dataset": "DeepFashion2",
246                 "row": row,
247                 "prompt": prompt,
248                 "clip_score": clip_score,
249                 "directional_similarity": dir_sim,
250                 "lpips": lpips_val,
251                 "ssim": ssim_val,
252             })
253             row_visual["edits"].append({"prompt": prompt, "image": edited.copy(), "clip": clip_s
254         deepfashion_visuals.append(row_visual)
255
256     for row in range(FASHIONPEDIA_EVAL_IMAGES):
257         sample = fashionpedia_samples[row]
258         original_image = sample['image']
259         if max(original_image.size) > 512:
260             original_image = original_image.copy()
261             original_image.thumbnail((512, 512), Image.Resampling.LANCZOS)
262
263         row_visual = {"original": original_image.copy(), "edits": []}
264         for prompt in EVAL_PROMPTS:
265             with torch.autocast("cuda"):
266                 edited = pipe(
267                     prompt=prompt,
268                     image=original_image,
269                     num_inference_steps=config.num_inference_steps,
270                     guidance_scale=config.guidance_scale,
271                     image_guidance_scale=config.image_guidance_scale,
272                 ).images[0]
273             clip_score = calculate_clip_score(edited, prompt)
274             dir_sim = calculate_clip_directional_similarity(original_image, edited, prompt)
275             lpips_val = calculate_lpips(original_image, edited)
276             ssim_val = calculate_ssim(original_image, edited)
277             fashionpedia_rows.append({
278                 "config": config.name,
279                 "dataset": "FashionPedia",
280                 "row": row,
281                 "prompt": prompt,
282                 "clip_score": clip_score,
283                 "directional_similarity": dir_sim,
284                 "lpips": lpips_val,
285                 "ssim": ssim_val,
286             })
287             row_visual["edits"].append({"prompt": prompt, "image": edited.copy(), "clip": clip_s
288         fashionpedia_visuals.append(row_visual)
```

```
    return {
        "deepfashion_metrics": pd.DataFrame(deepfashion_rows),
        "fashionpedia_metrics": pd.DataFrame(fashionpedia_rows),
        "deepfashion_visuals": deepfashion_visuals,
        "fashionpedia_visuals": fashionpedia_visuals,
    }
```

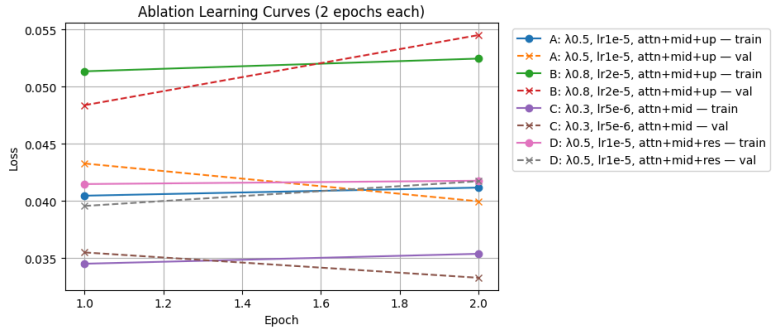
```
ABLATION_CONFIGS = [
    AblationConfig(
        name="A: λ0.5, lr1e-5, attn+mid+up",
        learning_rate=1e-5,
        lambda_preserve=0.5,
        guidance_scale=7.5,
        image_guidance_scale=1.5,
        num_inference_steps=40,
        unfreeze_strategy="attn_mid_up",
    ),
    AblationConfig(
        name="B: λ0.8, lr2e-5, attn+mid+up",
        learning_rate=2e-5,
        lambda_preserve=0.8,
        guidance_scale=8.0,
        image_guidance_scale=1.7,
        num_inference_steps=50,
        unfreeze_strategy="attn_mid_up",
    ),
    AblationConfig(
        name="C: λ0.3, lr5e-6, attn+mid",
        learning_rate=5e-6,
        lambda_preserve=0.3,
        guidance_scale=6.5,
        image_guidance_scale=1.3,
        num_inference_steps=35,
        unfreeze_strategy="attn_mid",
    ),
    AblationConfig(
        name="D: λ0.5, lr1e-5, attn+mid+res",
        learning_rate=1e-5,
        lambda_preserve=0.5,
        guidance_scale=7.0,
        image_guidance_scale=1.4,
        num_inference_steps=40,
        unfreeze_strategy="attn_mid_resnet",
    ),
]

ablation_runs: List[Dict[str, Any]] = []

for cfg in ABLATION_CONFIGS:
    print(f"\n===== Running ablation: {cfg.name} =====")
    components = prepare_components(cfg)
    trainable_count = sum(p.numel() for p in components["trainable_params"])

    history = []
    for epoch in range(ABLATION_EPOCHS):
        train_loss = train_one_epoch(cfg, components)
        val_loss = validate_one_epoch(cfg, components, max_batches=len(val_loader))
        history.append({"epoch": epoch + 1, "train_loss": train_loss, "val_loss": val_loss})
        print(f"Epoch {epoch+1}/{ABLATION_EPOCHS} — train: {train_loss:.4f}, val: {val_loss:.4f}")

        ckpt_path = os.path.join(CHECKPOINT_DIR, f"{config_slug(cfg.name)}_epoch{epoch+1}.pt")
        torch.save({
            "config": asdict(cfg),
            "epoch": epoch + 1,
            "unet_state_dict": components["unet"].state_dict(),
            "optimizer_state_dict": components["optimizer"].state_dict(),
```

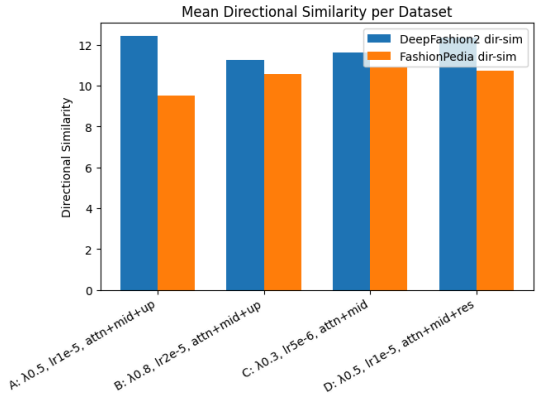
```
            "scheduler_state_dict": components["scheduler"].state_dict(),
        }, ckpt_path)
        print(f"  ↳ checkpoint saved to {ckpt_path}")

    eval_artifacts = evaluate_config(components["pipe"], cfg)

    run_summary = {
        "config": asdict(cfg),
        "history": history,
        "trainable_params": trainable_count,
        "deepfashion_metrics": eval_artifacts["deepfashion_metrics"],
        "fashionpedia_metrics": eval_artifacts["fashionpedia_metrics"],
        "deepfashion_visuals": eval_artifacts["deepfashion_visuals"],
        "fashionpedia_visuals": eval_artifacts["fashionpedia_visuals"],
    }
    ablation_runs.append(run_summary)

    del components["pipe"]
    del components
    torch.cuda.empty_cache()
    gc.collect()

```

```
===== Running ablation: A: λ0.5, lr1e-5, attn+mid+up =====
model_index.json:   0%|          | 0.00/616 [00:00<?, ?B/s]
Fetching 13 files:   0%|          | 0/13 [00:00<?, ?it/s]
config.json:   0%|          | 0.00/617 [00:00<?, ?B/s]
merges.txt: 0.00B [00:00, ?B/s]
scheduler_config.json:   0%|          | 0.00/569 [00:00<?, ?B/s]
preprocessor_config.json:   0%|          | 0.00/518 [00:00<?, ?B/s]
special_tokens_map.json:   0%|          | 0.00/472 [00:00<?, ?B/s]
tokenizer_config.json:   0%|          | 0.00/806 [00:00<?, ?B/s]
vocab.json: 0.00B [00:00, ?B/s]
text_encoder/model.safetensors:   0%|          | 0.00/492M [00:00<?, ?B/s]
config.json: 0.00B [00:00, ?B/s]
config.json:   0%|          | 0.00/553 [00:00<?, ?B/s]
vae/diffusion_pytorch_model.safetensors:   0%|          | 0.00/335M [00:00<?, ?B/s]
unet/diffusion_pytorch_model.safetensors:   0%|          | 0.00/3.44G [00:00<?, ?B/s]
Loading pipeline components...:   0%|          | 0/6 [00:00<?, ?it/s]
`torch_dtype` is deprecated! Use `dtype` instead!
A: λ0.5, lr1e-5, attn+mid+up — train:   0%|          | 0/1200 [00:00<?, ?it/s]
Epoch 1/2 — train: 0.0405, val: 0.0433
  ↳ checkpoint saved to ablation_checkpoints/a_05_lr1e5_attnmidup_epoch1.pt
A: λ0.5, lr1e-5, attn+mid+up — train:   0%|          | 0/1200 [00:00<?, ?it/s]
Epoch 2/2 — train: 0.0412, val: 0.0400
  ↳ checkpoint saved to ablation_checkpoints/a_05_lr1e5_attnmidup_epoch2.pt
  0%|          | 0/40 [00:00<?, ?it/s]
  0%|          | 0/40 [00:00<?, ?it/s]
  0%|          | 0/40 [00:00<?, ?it/s]
  0%|          | 0/40 [00:00<?, ?it/s]
  0%|          | 0/40 [00:00<?, ?it/s]
  0%|          | 0/40 [00:00<?, ?it/s]
  0%|          | 0/40 [00:00<?, ?it/s]
  0%|          | 0/40 [00:00<?, ?it/s]
  0%|          | 0/40 [00:00<?, ?it/s]
```

```python
history_rows = []
all_metrics_rows = []
for run in ablation_runs:
    cfg_name = run["config"]["name"]
    for entry in run["history"]:
        history_rows.append({"config": cfg_name, **entry})
    all_metrics_rows.append(run["deepfashion_metrics"])
    all_metrics_rows.append(run["fashionpedia_metrics"])

history_df = pd.DataFrame(history_rows)
metrics_df = pd.concat(all_metrics_rows, ignore_index=True)
metric_cols = ["clip_score", "directional_similarity", "lpips", "ssim"]
numeric_metrics = metrics_df[["config", "dataset"] + metric_cols].copy()

fig, axes = plt.subplots(1, 2, figsize=(16, 5))
for cfg_name, group in history_df.groupby("config"):
    axes[0].plot(group["epoch"], group["train_loss"], marker='o', label=f"{cfg_name} — train")
    axes[0].plot(group["epoch"], group["val_loss"], marker='x', linestyle='--', label=f"{cfg_name
axes[0].set_title("Ablation Learning Curves (2 epochs each)")
axes[0].set_xlabel("Epoch")
axes[0].set_ylabel("Loss")
axes[0].grid(True)
axes[0].legend(bbox_to_anchor=(1.02, 1), loc='upper left')

agg = numeric_metrics.groupby(["config", "dataset"], as_index=False)[metric_cols].mean()
configs = [run["config"]["name"] for run in ablation_runs]
x = np.arange(len(configs))
width = 0.35

for idx, dataset in enumerate(["DeepFashion2", "FashionPedia"]):
    subset = agg[agg["dataset"] == dataset].set_index("config")
    scores = [subset.loc[cfg, "directional_similarity"] for cfg in configs]
    axes[1].bar(x + (idx - 0.5) * width, scores, width=width, label=f"{dataset} dir-sim")

axes[1].set_title("mean Directional Similarity per Dataset")
axes[1].set_xticks(x)
axes[1].set_xticklabels(configs, rotation=30, ha='right')
axes[1].set_ylabel("Directional Similarity")
axes[1].legend()
plt.tight_layout()
plt.show()

```

```
print("Metric summary (CLIP / DirSim / LPIPS / SSIM):")
display(agg[["config", "dataset"] + metric_cols])
```






```
Metric summary (CLIP / DirSim / LPIPS / SSIM):
```

	config	dataset	clip_score	directional_similarity	lpips	ssim
0	A: λ0.5, lr1e-5, attn+mid+up	DeepFashion2	20.509795	12.442044	0.355809	0.495023
1	A: λ0.5, lr1e-5, attn+mid+up	FashionPedia	19.427384	9.522973	0.408848	0.487818
2	B: λ0.8, lr2e-5, attn+mid+up	DeepFashion2	20.870804	11.254064	0.270278	0.554784
3	B: λ0.8, lr2e-5, attn+mid+up	FashionPedia	19.699326	10.573883	0.364491	0.528399
4	C: λ0.3, lr5e-6, attn+mid	DeepFashion2	21.855139	11.615444	0.331672	0.483953
5	C: λ0.3, lr5e-6, attn+mid	FashionPedia	20.084592	10.888882	0.399855	0.485995
6	D: λ0.5, lr1e-5, attn+mid+res	DeepFashion2	21.722468	12.338617	0.296990	0.492303
7	D: λ0.5, lr1e-5, attn+mid+res	FashionPedia	20.142740	10.744428	0.377625	0.515408

```
All four ablation runs completed.
```

```
# === Visualization Set 2: qualitative grids for both datasets ===
def plot_dataset_grid(runs, key, title):
    rows = len(runs)
    cols = len(EVAL_PROMPTS) + 1
    fig, axes = plt.subplots(rows, cols, figsize=(3.8 * cols, 3.2 * rows))
    if rows == 1:
        axes = np.expand_dims(axes, axis=0)

    for r, run in enumerate(runs):
        cfg_name = run["config"]["name"]
        sample_row = run[key][0]
        axes[r, 0].imshow(sample_row["original"])
        axes[r, 0].set_title(f"{cfg_name}\nOriginal", fontsize=10)
        axes[r, 0].axis('off')
        for c, edit in enumerate(sample_row["edits"], start=1):
            axes[r, c].imshow(edit["image"])
            axes[r, c].set_title(f"{edit['prompt']}\nCLIP {edit['clip']:.1f} / Dir {edit['dir']:.1
            axes[r, c].axis('off')
    plt.suptitle(title, fontsize=14)
    plt.tight_layout()
    plt.show()

plot_dataset_grid(ablation_runs, "deepfashion_visuals", "Ablation Outputs — DeepFashion2 test set"
plot_dataset_grid(ablation_runs, "fashionpedia_visuals", "Ablation Outputs — FashionPedia validat
```