

## ✓ WGAN-GP (Conv) on Fashion-MNIST (Portfolio Version)

This notebook adapts a class WGAN-GP implementation to a **more portfolio-friendly dataset** (Fashion-MNIST) and a **more standard image GAN architecture** (small Conv / DCGAN-style).

Included in notebook:

- WGAN-GP objective with gradient penalty
- Conv Generator + Conv Critic (no sigmoid)
- Fixed-noise sample grids saved each epoch
- Loss curves + brief observations

### ✓ 1) Setup

```
# !pip uninstall -y pillow
# !pip install -q --no-cache-dir "pillow==10.3.0"

import math, os, random
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
from torchvision import datasets, transforms, utils as vutils
from tqdm import tqdm
import PIL

seed = 42
random.seed(seed)
torch.manual_seed(seed)
torch.cuda.manual_seed_all(seed)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print("Device:", device)
print("torch:", torch.__version__)
print("torchvision:", __import__("torchvision").__version__)
print("pillow:", PIL.__version__)
```

```
Device: cuda
torch: 2.9.0+cu126
torchvision: 0.24.0+cu126
pillow: 11.3.0
```

### ✓ 2) Config

```

cfg = {
    # Data
    "dataset": "FashionMNIST",    # "MNIST" or "FashionMNIST"
    "image_size": 28,
    "channels": 1,

    # Model
    "latent_dim": 128,
    "g_base": 64,                # base channels for G
    "d_base": 64,                # base channels for D

    # Training
    "batch_size": 128,
    "lr": 2e-4,
    "betas": (0.0, 0.9),
    "n_critic": 5,
    "lambda_gp": 10.0,
    "epochs": 10,                # a bit longer for FashionMNIST
    "sample_every": 1,
    "num_samples": 64,

    # Outputs
    "save_dir": "./wgangp_fashion_conv"
}
cfg

```

```

{'dataset': 'FashionMNIST',
 'image_size': 28,
 'channels': 1,
 'latent_dim': 128,
 'g_base': 64,
 'd_base': 64,
 'batch_size': 128,
 'lr': 0.0002,
 'betas': (0.0, 0.9),
 'n_critic': 5,
 'lambda_gp': 10.0,
 'epochs': 10,
 'sample_every': 1,
 'num_samples': 64,
 'save_dir': './wgangp_fashion_conv'}

```

### 3) Data

```

transform = transforms.Compose([
    transforms.Resize(cfg["image_size"]),
    transforms.ToTensor(),
    transforms.Normalize([0.5], [0.5]) # map to [-1, 1]
])

ds_cls = getattr(datasets, cfg["dataset"])
train_ds = ds_cls(root="./data", train=True, transform=transform, download=True)
train_loader = DataLoader(train_ds, batch_size=cfg["batch_size"], shuffle=True, num_workers=2, pin_memory=True)

print("Dataset:", cfg["dataset"], "| N:", len(train_ds))

```

```

100%|██████████| 26.4M/26.4M [00:02<00:00, 11.3MB/s]
100%|██████████| 29.5k/29.5k [00:00<00:00, 201kB/s]
100%|██████████| 4.42M/4.42M [00:02<00:00, 2.15MB/s]
100%|██████████| 5.15k/5.15k [00:00<00:00, 13.6MB/s]Dataset: FashionMNIST | N: 60000

```

### 4) Models (Conv / DCGAN-lite)

```

# Notes:
# - Output size is 28x28. We'll upsample 7x7 -> 14x14 -> 28x28.
# - Critic outputs a scalar (no sigmoid).

class ConvGenerator(nn.Module):
    def __init__(self, z_dim, out_ch=1, base=64):
        super().__init__()
        self.net = nn.Sequential(
            # z -> (base*4) x 7 x 7
            nn.ConvTranspose2d(z_dim, base*4, kernel_size=7, stride=1, padding=0, bias=False),
            nn.BatchNorm2d(base*4),

```

```

nn.ReLU(True),

# 7x7 -> 14x14
nn.ConvTranspose2d(base*4, base*2, kernel_size=4, stride=2, padding=1, bias=False),
nn.BatchNorm2d(base*2),
nn.ReLU(True),

# 14x14 -> 28x28
nn.ConvTranspose2d(base*2, base, kernel_size=4, stride=2, padding=1, bias=False),
nn.BatchNorm2d(base),
nn.ReLU(True),

# final conv
nn.Conv2d(base, out_ch, kernel_size=3, stride=1, padding=1),
nn.Tanh()
)

def forward(self, z):
    z = z.view(z.size(0), z.size(1), 1, 1)
    return self.net(z)

class ConvCritic(nn.Module):
    def __init__(self, in_ch=1, base=64):
        super().__init__()
        self.features = nn.Sequential(
            nn.Conv2d(in_ch, base, kernel_size=4, stride=2, padding=1), # 28->14
            nn.LeakyReLU(0.2, inplace=True),

            nn.Conv2d(base, base*2, kernel_size=4, stride=2, padding=1), # 14->7
            nn.LeakyReLU(0.2, inplace=True),

            nn.Conv2d(base*2, base*4, kernel_size=3, stride=1, padding=1), # 7->7
            nn.LeakyReLU(0.2, inplace=True),
        )
        self.head = nn.Sequential(
            nn.Flatten(),
            nn.Linear((base*4) * 7 * 7, 1)
        )

    def forward(self, x):
        h = self.features(x)
        out = self.head(h)
        return out.view(-1)

G = ConvGenerator(cfg["latent_dim"], cfg["channels"], cfg["g_base"]).to(device)
D = ConvCritic(cfg["channels"], cfg["d_base"]).to(device)

print(sum(p.numel() for p in G.parameters()), "G params")
print(sum(p.numel() for p in D.parameters()), "D params")

```

```

2262465 G params
440001 D params

```

## ✓ 5) WGAN-GP utilities + optimizers

```

def gradient_penalty(D, real, fake):
    bsz = real.size(0)
    epsilon = torch.rand(bsz, 1, 1, 1, device=real.device, requires_grad=True)
    x_hat = epsilon * real + (1 - epsilon) * fake
    d_hat = D(x_hat)
    grads = torch.autograd.grad(
        outputs=d_hat, inputs=x_hat,
        grad_outputs=torch.ones_like(d_hat),
        create_graph=True, retain_graph=True, only_inputs=True
    )[0]
    grads = grads.view(bsz, -1)
    gp = ((grads.norm(2, dim=1) - 1.0) ** 2).mean()
    return gp

opt_D = optim.Adam(D.parameters(), lr=cfg["lr"], betas=cfg["betas"])
opt_G = optim.Adam(G.parameters(), lr=cfg["lr"], betas=cfg["betas"])

fixed_z = torch.randn(cfg["num_samples"], cfg["latent_dim"], device=device)
os.makedirs(cfg["save_dir"], exist_ok=True)

```

## 6) Training

```
log = {"g_loss": [], "d_loss": [], "gp": []}

for epoch in range(1, cfg["epochs"] + 1):
    G.train(); D.train()
    pbar = tqdm(train_loader, desc=f"Epoch {epoch}/{cfg['epochs']}")

    for real, _ in pbar:
        real = real.to(device)
        bsz = real.size(0)

        # ---- Train Critic ----
        for _ in range(cfg["n_critic"]):
            z = torch.randn(bsz, cfg["latent_dim"], device=device)
            fake = G(z).detach()

            d_real = D(real)
            d_fake = D(fake)

            gp = gradient_penalty(D, real, fake) * cfg["lambda_gp"]
            d_loss = -(d_real.mean() - d_fake.mean()) + gp

            opt_D.zero_grad(set_to_none=True)
            d_loss.backward()
            opt_D.step()

        # ---- Train Generator ----
        z = torch.randn(bsz, cfg["latent_dim"], device=device)
        fake = G(z)
        g_loss = -D(fake).mean()

        opt_G.zero_grad(set_to_none=True)
        g_loss.backward()
        opt_G.step()

        log["g_loss"].append(g_loss.item())
        log["d_loss"].append(d_loss.item())
        log["gp"].append(gp.item())
        pbar.set_postfix(g=float(g_loss.item()), d=float(d_loss.item()), gp=float(gp.item()))

    # ---- Save sample grid ----
    if epoch % cfg["sample_every"] == 0:
        G.eval()
        with torch.no_grad():
            samples = G(fixed_z).cpu()
            grid = vutils.make_grid(samples, nrow=int(math.sqrt(cfg["num_samples"])), normalize=True, value_range=(-1, 1))
            out_png = f"{cfg['save_dir']}/samples_epoch_{epoch:03d}.png"
            vutils.save_image(grid, out_png)
            print("Saved:", out_png)
```

```
Epoch 1/10:  0%|          | 0/469 [00:00<?, ?it/s]/usr/local/lib/python3.12/dist-packages/torch/autograd/graph.py:841: UserWarning: 
    return Variable._execution_engine.run_backward( # Calls into the C++ engine to run the backward pass
Epoch 1/10: 100%|██████████| 469/469 [01:37<00:00, 4.83it/s, d=-3.23, g=-13.5, gp=0.289]
Saved: ./wgangp_fashion_conv/samples_epoch_001.png
Epoch 2/10: 100%|██████████| 469/469 [01:35<00:00, 4.93it/s, d=-2.16, g=-10.3, gp=0.126]
Saved: ./wgangp_fashion_conv/samples_epoch_002.png
Epoch 3/10: 100%|██████████| 469/469 [01:35<00:00, 4.93it/s, d=-3.59, g=-10.2, gp=0.324]
Saved: ./wgangp_fashion_conv/samples_epoch_003.png
Epoch 4/10: 100%|██████████| 469/469 [01:35<00:00, 4.93it/s, d=-2.24, g=-8.12, gp=0.277]
Saved: ./wgangp_fashion_conv/samples_epoch_004.png
Epoch 5/10: 100%|██████████| 469/469 [01:35<00:00, 4.93it/s, d=-2.43, g=0.2, gp=0.295]
Saved: ./wgangp_fashion_conv/samples_epoch_005.png
Epoch 6/10: 100%|██████████| 469/469 [01:35<00:00, 4.93it/s, d=-2.45, g=-4.41, gp=0.144]
Saved: ./wgangp_fashion_conv/samples_epoch_006.png
Epoch 7/10: 100%|██████████| 469/469 [01:35<00:00, 4.93it/s, d=-1.84, g=-2.97, gp=0.183]
Saved: ./wgangp_fashion_conv/samples_epoch_007.png
Epoch 8/10: 100%|██████████| 469/469 [01:35<00:00, 4.93it/s, d=-2.38, g=0.498, gp=0.151]
Saved: ./wgangp_fashion_conv/samples_epoch_008.png
Epoch 9/10: 100%|██████████| 469/469 [01:35<00:00, 4.94it/s, d=-3.22, g=-0.405, gp=0.232]
Saved: ./wgangp_fashion_conv/samples_epoch_009.png
Epoch 10/10: 100%|██████████| 469/469 [01:35<00:00, 4.93it/s, d=-2.12, g=-6.45, gp=0.218]Saved: ./wgangp_fashion_conv/samples_epoch_
```

## 7) Sample grids (PDF-friendly)

```

import glob
import matplotlib.pyplot as plt
from PIL import Image
import os

paths = sorted(glob.glob(f"{cfg['save_dir']}/samples_epoch_*.png"))
want = ["_001", "_005", f"_{cfg['epochs']:03d}"]
show = [p for p in paths if any(w in p for w in want)] or paths[:3]

for p in show:
    img = Image.open(p)
    epoch_label = os.path.basename(p).replace("samples_epoch_", "").replace(".png", "")
    plt.figure(figsize=(4,4))
    plt.imshow(img)
    plt.axis("off")
    plt.title(f"Fixed-z Samples — Epoch {epoch_label}")
    plt.show()

```

Fixed-z Samples — Epoch 001



Fixed-z Samples — Epoch 005



Fixed-z Samples — Epoch 010



```
import matplotlib.pyplot as plt
```

```
def plot_curve(vals, title):  
    plt.figure(figsize=(6,4))  
    plt.plot(vals)  
    plt.title(title)  
    plt.xlabel("Step")  
    plt.ylabel(title)  
    plt.show()
```

```
plot_curve(log["d_loss"], "Critic loss (WGAN-GP)")  
plot_curve(log["g_loss"], "Generator loss")  
plot_curve(log["gp"], "Gradient penalty term")
```

