In [1]:
```python
# Core
import os, re, math, random, json
from pathlib import Path

import numpy as np
import pandas as pd

# Torch
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import TensorDataset, DataLoader, random_split

# Utils
from IPython.display import display
import matplotlib.pyplot as plt

DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
DEVICE
```
Out[1]:
```
'cuda'
```

In [2]:
```python
import torch
print("Torch version:", torch.__version__)
print("Built with CUDA:", torch.version.cuda)
print("CUDA available:", torch.cuda.is_available())
print("Device count:", torch.cuda.device_count())
if torch.cuda.is_available():
    print("GPU name:", torch.cuda.get_device_name(0))
```
```
Torch version: 2.8.0+cu129
Built with CUDA: 12.9
CUDA available: True
Device count: 1
GPU name: NVIDIA GeForce RTX 3060 Laptop GPU
```

In [4]:
```python
ROOT = Path.cwd()  # current working directory (your notebook dir)
DATA_RAW = "C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/data/raw
DATA_PROC = "C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/data/pr
MODELS = "C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/models"
RESULTS = "/C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/results"


# CHANGE THIS if your file lives elsewhere:
DATA_PATH = DATA_RAW + "/promoters.data"

DATA_PATH, DATA_RAW, DATA_PROC, MODELS, RESULTS
```
Out[4]:
```
('C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/data/raw/promoter
s.data',
 'C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/data/raw',
 'C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/data/processed',
 'C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/models',
 '/C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/results')
```

In [5]:
```python
# Peek at the first 20 lines of the dataset
with open(DATA_PATH) as f:
    for i in range(20):
        line = f.readline()
        if not line:
            break
        print(repr(line))
```
```
'+,S10,\t\ttactagcaatacgcttgcgttcggtggttaagtatgtataatgcgcgggcttgtcgt\n'
'+,AMPC,\t\ttgctatcctgacagttgtcacgctgattggtgtcgttacaatctaacgcatcgccaa\n'
'+,AROH,\t\tgtactagagaactagtgcattagcttatttttttgttatcatgctaaccacccggcg\n'
'+,DEOP2,\taattgtgatgtgtatcgaagtgtgttgcggagtagatgttagaatactaacaaactc\n'
'+,LEU1_TRNA,\ttcgataattaactattgacgaaaagctgaaaaccactagaatgcgcctccgtggtag\n'
'+,MALEFG,\taggggcaaggaggatggaaagaggttgccgtataaagaaactagagtccgtttaggt\n'
'+,MALK,\t\tcaggggtggaggatttaagccatctcctgatgacgcatagtcagcccatcatgaat\n'
'+,RECA,\t\ttttctacaaaacacttgatactgtatgagcatacagtataattgcttcaacagaaca\n'
'+,RPOB,\t\tcgacttaatatactgcgacaggacgtccgttctgtgtaaatcgcaatgaaatggttt\n'
'+,RRNAB_P1,\tttttaaatttcctcttgtcaggccggaataactccctataatgcgccaccactgaca\n'
'+,RRNAB_P2,\tgcaaaaataaatgcttgactctgtagcgggaaggcgtattatgcacaccccgcgccg\n'
'+,RRNDEX_P2,\tcctgaaattcagggttgactctgaaagaggaaagcgtaatatacgccacctcgcgac\n'
'+,RRND_P1,\tgatcaaaaaaatacttgtgcaaaaaattgggatccctataatgcgcctccgttgaga\n'
'+,RRNE_P1,\tctgcaatttttctattgcggcctgcggagaactccctataatgcgcctccatcgaca\n'
'+,RRNG_P1,\tttttatatttttcgcttgtcaggccggaataactccctataatgcgccaccactgaca\n'
'+,RRNG_P2,\taagcaaagaaatgcttgactctgtagcgggaaggcgtattatgcacaccgccgcgcc\n'
'+,RRNX_P1,\tatgcatttttccgcttgtcttcctgagccgactccctataatgcgcctccatcgaca\n'
'+,TNAA,\t\taaacaatttcagaatagacaaaaactctgagtgtaataatgtagcctcgtgtcttgc\n'
'+,TYRT,\t\tctcaacgtaacactttacagcggcgcgtcatttgatatgatgcgccccgcttcccg\n'
'+,ARAC,\t\tgcaaataatcaatgtggacttttctgccgtgattatagacacttttgttacgcgttt\n'
```

In [6]:
```python
def parse_uci_lines(lines):
    """
    Parses promoter data formatted as:
      +,GENENAME,sequence
      -,GENENAME,sequence
    Returns list of (label:int, sequence:str)
    """
    out = []
    for ln in lines:
        ln = ln.strip()
        if not ln or ln.startswith("#"):
            continue
        # Format like '+,GENE,sequence'
        m = re.match(r'^([+\-]),\s*([^,]+),\s*([ACGTacgt]+)', ln)
        if m:
            label = 1 if m.group(1) == '+' else 0
            gene = m.group(2).strip()
            seq = m.group(3).upper()
            out.append((label, seq))
    return out

# re-run parser
with open(DATA_PATH) as f:
    pairs = parse_uci_lines(f.readlines())
print(f"Parsed {len(pairs)} sequences from {DATA_PATH}")

# preview first 3
for i in range(3):
    print(pairs[i])
```

```
Parsed 106 sequences from C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Gene
ration/data/raw/promoters.data
(1, 'TACTAGCAATACGCTTGCGTTCGGTGGTTAAGTATGTATAATGCGCGGGCTTGTCGT')
(1, 'TGCTATCCTGACAGTTGTCACGCTGATTGGTGTCGTTACAATCTAACGCATCGCCAA')
(1, 'GTACTAGAGAACTAGTGCATTAGCTTATTTTTTTGTTATCATGCTAACCACCCGGCG')
```

In [7]:
```
import re, numpy as np

L = 200  # fixed sequence length
base2idx = {'A':0, 'C':1, 'G':2, 'T':3}

def one_hot(seq, L=200):
    s = re.sub(r'[^ACGTacgt]', 'A', seq).upper()
    s = s[:L].ljust(L, 'A')  # pad to fixed length
    x = np.zeros((L,4), dtype=np.float32)
    for i,ch in enumerate(s):
        x[i, base2idx.get(ch, 0)] = 1.0
    return x

X = np.stack([one_hot(seq, L=L) for _, seq in pairs])
y = np.array([lab for lab,_ in pairs], dtype=np.int64)

print("Shape:", X.shape, "Promoters:", (y==1).sum(), "Non-promoters:", (y==0).sum())
```

```
Shape: (106, 200, 4) Promoters: 53 Non-promoters: 53
```

In [8]:
```
from torch.utils.data import TensorDataset, DataLoader, random_split
import torch

PROC_PATH = Path("data/processed/uci_promoters_l200.npz")
np.savez_compressed(PROC_PATH, X=X, y=y)
print("Saved", PROC_PATH)

Xt = torch.from_numpy(X)
ds = TensorDataset(Xt)
n_total = len(ds)
n_val = int(0.15 * n_total)
n_train = n_total - n_val

train_ds, val_ds = random_split(ds, [n_train, n_val], generator=torch.Generator().manual_seed(42))
train_dl = DataLoader(train_ds, batch_size=32, shuffle=True)
val_dl = DataLoader(val_ds, batch_size=32, shuffle=False)

print(f"Train: {n_train}, Val: {n_val}")
```

```
Saved data\processed\uci_promoters_l200.npz
Train: 91, Val: 15
```

In [9]:
```
import torch.nn as nn
import torch.nn.functional as F

class ConvVAE(nn.Module):
    def __init__(self, L=200, z_dim=128, base_c=64, tau_start=1.0):
        super().__init__()
        self.L = L
        self.z_dim = z_dim
        self.tau = tau_start

        # Encoder
        self.enc = nn.Sequential(
            nn.Conv1d(4, base_c, 7, padding=3), nn.ReLU(),
            nn.Conv1d(base_c, base_c*2, 5, padding=2), nn.ReLU(),
            nn.AdaptiveAvgPool1d(1)
        )
        self.mu = nn.Linear(base_c*2, z_dim)
        self.logvar = nn.Linear(base_c*2, z_dim)

        # Decoder
        self.fc = nn.Linear(z_dim, base_c*2)
        self.dec = nn.Sequential(
            nn.Conv1d(base_c*2, base_c, 5, padding=2), nn.ReLU(),
            nn.Conv1d(base_c, 4, 1)
        )

    def encode(self, x):
        h = self.enc(x.transpose(1,2)).squeeze(-1)
        return self.mu(h), self.logvar(h)

    def reparam(self, mu, logvar):
        std = (0.5 * logvar).exp()
        eps = torch.randn_like(std)
        return mu + eps * std

    def decode_logits(self, z):
        h = self.fc(z).unsqueeze(-1).repeat(1,1,self.L)
        logits = self.dec(h).transpose(1,2)
        return logits

    def forward(self, x, tau=None):
        tau = self.tau if tau is None else tau
        mu, logvar = self.encode(x)
        z = self.reparam(mu, logvar)
        logits = self.decode_logits(z)
        g = F.gumbel_softmax(logits, tau=tau, hard=False, dim=-1)
        return logits, g, mu, logvar
```

In [10]:
```
def kl_anneal(epoch, total=30, beta_max=0.1):
    return min(beta_max, beta_max * (epoch / total))

def tau_schedule(epoch, total=100, tau_start=1.0, tau_end=0.5):
    import math
    t = 0.5 * (1 + math.cos(math.pi * epoch / total))
    return tau_end + (tau_start - tau_end) * t
```

In [11]:
```
DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
model = ConvVAE(L=L, z_dim=128, base_c=64).to(DEVICE)
opt = torch.optim.AdamW(model.parameters(), lr=3e-4)

EPOCHS = 300
best_val = float("inf")
history = {"train": [], "val": []}

for epoch in range(1, EPOCHS+1):
    model.train()
    beta = kl_anneal(epoch)
    model.tau = tau_schedule(epoch)
    tr_loss = 0

    for (xb,) in train_dl:
        xb = xb.to(DEVICE)
        logits, g, mu, logvar = model(xb)
        target = xb.argmax(-1)
        recon = F.cross_entropy(logits.reshape(-1, 4), target.reshape(-1))
        kl = -0.5 * torch.mean(1 + logvar - mu.pow(2) - logvar.exp())
        loss = recon + beta * kl

        opt.zero_grad()
        loss.backward()
        opt.step()
        tr_loss += loss.item() * xb.size(0)

    tr_loss /= len(train_dl.dataset)

    # Validation
    model.eval()
    va_loss = 0
    with torch.no_grad():
        for (xb,) in val_dl:
            xb = xb.to(DEVICE)
            logits, g, mu, logvar = model(xb)
            target = xb.argmax(-1)
            recon = F.cross_entropy(logits.reshape(-1, 4), target.reshape(-1))
            kl = -0.5 * torch.mean(1 + logvar - mu.pow(2) - logvar.exp())
            loss = recon + beta * kl
            va_loss += loss.item() * xb.size(0)
    va_loss /= len(val_dl.dataset)

    print(f"Epoch {epoch:03d}: Train={tr_loss:.4f} Val={va_loss:.4f} Beta={beta:.3f} Tau={model.tau:.3f}")
    history["train"].append(tr_loss)
    history["val"].append(va_loss)

    if va_loss < best_val:
        best_val = va_loss
        torch.save(model.state_dict(), "models/vae_uci.pt")
```

```
Epoch 001: Train=1.3523 Val=1.3289 Beta=0.003 Tau=1.000
Epoch 002: Train=1.3261 Val=1.2734 Beta=0.007 Tau=1.000
Epoch 003: Train=1.2646 Val=1.1879 Beta=0.010 Tau=0.999
Epoch 004: Train=1.1980 Val=1.1596 Beta=0.013 Tau=0.998
Epoch 005: Train=1.1306 Val=1.0899 Beta=0.017 Tau=0.997
Epoch 006: Train=1.0481 Val=0.9408 Beta=0.020 Tau=0.996
Epoch 007: Train=0.9456 Val=0.8503 Beta=0.023 Tau=0.994
Epoch 008: Train=0.8360 Val=0.7666 Beta=0.027 Tau=0.992
Epoch 009: Train=0.8096 Val=0.7930 Beta=0.030 Tau=0.990
Epoch 010: Train=0.8206 Val=0.8141 Beta=0.033 Tau=0.988
Epoch 011: Train=0.8260 Val=0.7861 Beta=0.037 Tau=0.985
Epoch 012: Train=0.7825 Val=0.7513 Beta=0.040 Tau=0.982
Epoch 013: Train=0.7785 Val=0.7522 Beta=0.043 Tau=0.979
Epoch 014: Train=0.7968 Val=0.7700 Beta=0.047 Tau=0.976
Epoch 015: Train=0.7826 Val=0.7679 Beta=0.050 Tau=0.973
Epoch 016: Train=0.7849 Val=0.7555 Beta=0.053 Tau=0.969
Epoch 017: Train=0.7753 Val=0.7414 Beta=0.057 Tau=0.965
Epoch 018: Train=0.7726 Val=0.7436 Beta=0.060 Tau=0.961
Epoch 019: Train=0.7815 Val=0.7506 Beta=0.063 Tau=0.957
Epoch 020: Train=0.7752 Val=0.7419 Beta=0.067 Tau=0.952
Epoch 021: Train=0.7693 Val=0.7403 Beta=0.070 Tau=0.948
Epoch 022: Train=0.7728 Val=0.7417 Beta=0.073 Tau=0.943
Epoch 023: Train=0.7689 Val=0.7451 Beta=0.077 Tau=0.938
Epoch 024: Train=0.7690 Val=0.7457 Beta=0.080 Tau=0.932
Epoch 025: Train=0.7718 Val=0.7409 Beta=0.083 Tau=0.927
Epoch 026: Train=0.7658 Val=0.7596 Beta=0.087 Tau=0.921
Epoch 027: Train=0.7669 Val=0.7437 Beta=0.090 Tau=0.915
Epoch 028: Train=0.7722 Val=0.7398 Beta=0.093 Tau=0.909
Epoch 029: Train=0.7706 Val=0.7582 Beta=0.097 Tau=0.903
Epoch 030: Train=0.7699 Val=0.7523 Beta=0.100 Tau=0.897
Epoch 031: Train=0.7674 Val=0.7419 Beta=0.100 Tau=0.891
Epoch 032: Train=0.7710 Val=0.7509 Beta=0.100 Tau=0.884
Epoch 033: Train=0.7663 Val=0.7385 Beta=0.100 Tau=0.877
Epoch 034: Train=0.7687 Val=0.7479 Beta=0.100 Tau=0.870
Epoch 035: Train=0.7690 Val=0.7457 Beta=0.100 Tau=0.863
Epoch 036: Train=0.7675 Val=0.7553 Beta=0.100 Tau=0.856
Epoch 037: Train=0.7666 Val=0.7421 Beta=0.100 Tau=0.849
Epoch 038: Train=0.7686 Val=0.7420 Beta=0.100 Tau=0.842
Epoch 039: Train=0.7681 Val=0.7438 Beta=0.100 Tau=0.835
Epoch 040: Train=0.7669 Val=0.7421 Beta=0.100 Tau=0.827
Epoch 041: Train=0.7681 Val=0.7475 Beta=0.100 Tau=0.820
Epoch 042: Train=0.7679 Val=0.7499 Beta=0.100 Tau=0.812
Epoch 043: Train=0.7652 Val=0.7358 Beta=0.100 Tau=0.805
Epoch 044: Train=0.7644 Val=0.7397 Beta=0.100 Tau=0.797
Epoch 045: Train=0.7709 Val=0.7451 Beta=0.100 Tau=0.789
Epoch 046: Train=0.7651 Val=0.7396 Beta=0.100 Tau=0.781
Epoch 047: Train=0.7647 Val=0.7423 Beta=0.100 Tau=0.774
Epoch 048: Train=0.7651 Val=0.7491 Beta=0.100 Tau=0.766
Epoch 049: Train=0.7651 Val=0.7431 Beta=0.100 Tau=0.758
Epoch 050: Train=0.7690 Val=0.7419 Beta=0.100 Tau=0.750
Epoch 051: Train=0.7649 Val=0.7416 Beta=0.100 Tau=0.742
Epoch 052: Train=0.7653 Val=0.7400 Beta=0.100 Tau=0.734
Epoch 053: Train=0.7641 Val=0.7376 Beta=0.100 Tau=0.726
Epoch 054: Train=0.7667 Val=0.7497 Beta=0.100 Tau=0.719
Epoch 055: Train=0.7640 Val=0.7421 Beta=0.100 Tau=0.711
Epoch 056: Train=0.7648 Val=0.7413 Beta=0.100 Tau=0.703
Epoch 057: Train=0.7659 Val=0.7403 Beta=0.100 Tau=0.695
Epoch 058: Train=0.7642 Val=0.7384 Beta=0.100 Tau=0.688
Epoch 059: Train=0.7659 Val=0.7416 Beta=0.100 Tau=0.680
Epoch 060: Train=0.7627 Val=0.7441 Beta=0.100 Tau=0.673
Epoch 061: Train=0.7669 Val=0.7430 Beta=0.100 Tau=0.665
Epoch 062: Train=0.7656 Val=0.7422 Beta=0.100 Tau=0.658
Epoch 063: Train=0.7672 Val=0.7376 Beta=0.100 Tau=0.651
Epoch 064: Train=0.7644 Val=0.7404 Beta=0.100 Tau=0.644
Epoch 065: Train=0.7653 Val=0.7347 Beta=0.100 Tau=0.637
Epoch 066: Train=0.7640 Val=0.7378 Beta=0.100 Tau=0.630
Epoch 067: Train=0.7627 Val=0.7406 Beta=0.100 Tau=0.623
Epoch 068: Train=0.7633 Val=0.7395 Beta=0.100 Tau=0.616
Epoch 069: Train=0.7654 Val=0.7441 Beta=0.100 Tau=0.609
Epoch 070: Train=0.7644 Val=0.7394 Beta=0.100 Tau=0.603
Epoch 071: Train=0.7625 Val=0.7397 Beta=0.100 Tau=0.597
Epoch 072: Train=0.7647 Val=0.7394 Beta=0.100 Tau=0.591
Epoch 073: Train=0.7670 Val=0.7392 Beta=0.100 Tau=0.585
Epoch 074: Train=0.7623 Val=0.7352 Beta=0.100 Tau=0.579
Epoch 075: Train=0.7641 Val=0.7351 Beta=0.100 Tau=0.573
Epoch 076: Train=0.7617 Val=0.7342 Beta=0.100 Tau=0.568
Epoch 077: Train=0.7640 Val=0.7411 Beta=0.100 Tau=0.562
Epoch 078: Train=0.7615 Val=0.7389 Beta=0.100 Tau=0.557
Epoch 079: Train=0.7627 Val=0.7421 Beta=0.100 Tau=0.552
Epoch 080: Train=0.7658 Val=0.7400 Beta=0.100 Tau=0.548
Epoch 081: Train=0.7620 Val=0.7352 Beta=0.100 Tau=0.543
Epoch 082: Train=0.7639 Val=0.7371 Beta=0.100 Tau=0.539
Epoch 083: Train=0.7613 Val=0.7416 Beta=0.100 Tau=0.535
Epoch 084: Train=0.7635 Val=0.7431 Beta=0.100 Tau=0.531
Epoch 085: Train=0.7618 Val=0.7409 Beta=0.100 Tau=0.527
Epoch 086: Train=0.7623 Val=0.7368 Beta=0.100 Tau=0.524
Epoch 087: Train=0.7621 Val=0.7383 Beta=0.100 Tau=0.521
Epoch 088: Train=0.7625 Val=0.7421 Beta=0.100 Tau=0.518
Epoch 089: Train=0.7622 Val=0.7442 Beta=0.100 Tau=0.515
Epoch 090: Train=0.7614 Val=0.7353 Beta=0.100 Tau=0.512
Epoch 091: Train=0.7615 Val=0.7344 Beta=0.100 Tau=0.510
Epoch 092: Train=0.7621 Val=0.7374 Beta=0.100 Tau=0.508
Epoch 093: Train=0.7623 Val=0.7323 Beta=0.100 Tau=0.506
Epoch 094: Train=0.7608 Val=0.7374 Beta=0.100 Tau=0.504
Epoch 095: Train=0.7620 Val=0.7423 Beta=0.100 Tau=0.503
Epoch 096: Train=0.7624 Val=0.7387 Beta=0.100 Tau=0.502
Epoch 097: Train=0.7600 Val=0.7351 Beta=0.100 Tau=0.501
Epoch 098: Train=0.7630 Val=0.7331 Beta=0.100 Tau=0.500
Epoch 099: Train=0.7614 Val=0.7352 Beta=0.100 Tau=0.500
Epoch 100: Train=0.7622 Val=0.7344 Beta=0.100 Tau=0.500
Epoch 101: Train=0.7639 Val=0.7403 Beta=0.100 Tau=0.500
Epoch 102: Train=0.7610 Val=0.7366 Beta=0.100 Tau=0.500
Epoch 103: Train=0.7631 Val=0.7403 Beta=0.100 Tau=0.501
Epoch 104: Train=0.7595 Val=0.7446 Beta=0.100 Tau=0.502
Epoch 105: Train=0.7590 Val=0.7383 Beta=0.100 Tau=0.503
Epoch 106: Train=0.7616 Val=0.7379 Beta=0.100 Tau=0.504
Epoch 107: Train=0.7594 Val=0.7347 Beta=0.100 Tau=0.506
Epoch 108: Train=0.7597 Val=0.7396 Beta=0.100 Tau=0.508
Epoch 109: Train=0.7616 Val=0.7378 Beta=0.100 Tau=0.510
Epoch 110: Train=0.7593 Val=0.7350 Beta=0.100 Tau=0.512
Epoch 111: Train=0.7592 Val=0.7397 Beta=0.100 Tau=0.515
Epoch 112: Train=0.7598 Val=0.7345 Beta=0.100 Tau=0.518
Epoch 113: Train=0.7586 Val=0.7350 Beta=0.100 Tau=0.521
Epoch 114: Train=0.7616 Val=0.7417 Beta=0.100 Tau=0.524
Epoch 115: Train=0.7596 Val=0.7359 Beta=0.100 Tau=0.527
Epoch 116: Train=0.7601 Val=0.7364 Beta=0.100 Tau=0.531
Epoch 117: Train=0.7591 Val=0.7323 Beta=0.100 Tau=0.535
Epoch 118: Train=0.7603 Val=0.7348 Beta=0.100 Tau=0.539
Epoch 119: Train=0.7599 Val=0.7330 Beta=0.100 Tau=0.543
Epoch 120: Train=0.7596 Val=0.7424 Beta=0.100 Tau=0.548
Epoch 121: Train=0.7606 Val=0.7306 Beta=0.100 Tau=0.552
Epoch 122: Train=0.7585 Val=0.7351 Beta=0.100 Tau=0.557
Epoch 123: Train=0.7583 Val=0.7340 Beta=0.100 Tau=0.562
Epoch 124: Train=0.7593 Val=0.7330 Beta=0.100 Tau=0.568
Epoch 125: Train=0.7598 Val=0.7328 Beta=0.100 Tau=0.573
Epoch 126: Train=0.7597 Val=0.7310 Beta=0.100 Tau=0.579
Epoch 127: Train=0.7577 Val=0.7357 Beta=0.100 Tau=0.585
Epoch 128: Train=0.7607 Val=0.7294 Beta=0.100 Tau=0.591
Epoch 129: Train=0.7580 Val=0.7377 Beta=0.100 Tau=0.597
Epoch 130: Train=0.7580 Val=0.7301 Beta=0.100 Tau=0.603
Epoch 131: Train=0.7588 Val=0.7335 Beta=0.100 Tau=0.609
Epoch 132: Train=0.7582 Val=0.7319 Beta=0.100 Tau=0.616
Epoch 133: Train=0.7565 Val=0.7326 Beta=0.100 Tau=0.623
Epoch 134: Train=0.7582 Val=0.7338 Beta=0.100 Tau=0.630
Epoch 135: Train=0.7583 Val=0.7301 Beta=0.100 Tau=0.637
Epoch 136: Train=0.7560 Val=0.7323 Beta=0.100 Tau=0.644
Epoch 137: Train=0.7571 Val=0.7374 Beta=0.100 Tau=0.651
Epoch 138: Train=0.7579 Val=0.7330 Beta=0.100 Tau=0.658
Epoch 139: Train=0.7565 Val=0.7294 Beta=0.100 Tau=0.665
Epoch 140: Train=0.7567 Val=0.7352 Beta=0.100 Tau=0.673
Epoch 141: Train=0.7584 Val=0.7343 Beta=0.100 Tau=0.680
Epoch 142: Train=0.7576 Val=0.7321 Beta=0.100 Tau=0.688
Epoch 143: Train=0.7589 Val=0.7325 Beta=0.100 Tau=0.695
Epoch 144: Train=0.7598 Val=0.7292 Beta=0.100 Tau=0.703
Epoch 145: Train=0.7572 Val=0.7305 Beta=0.100 Tau=0.711
Epoch 146: Train=0.7582 Val=0.7292 Beta=0.100 Tau=0.719
Epoch 147: Train=0.7561 Val=0.7290 Beta=0.100 Tau=0.726
Epoch 148: Train=0.7565 Val=0.7326 Beta=0.100 Tau=0.734
Epoch 149: Train=0.7576 Val=0.7380 Beta=0.100 Tau=0.742
Epoch 150: Train=0.7556 Val=0.7289 Beta=0.100 Tau=0.750
Epoch 151: Train=0.7564 Val=0.7284 Beta=0.100 Tau=0.758
Epoch 152: Train=0.7565 Val=0.7343 Beta=0.100 Tau=0.766
Epoch 153: Train=0.7552 Val=0.7350 Beta=0.100 Tau=0.774
Epoch 154: Train=0.7562 Val=0.7295 Beta=0.100 Tau=0.781
Epoch 155: Train=0.7539 Val=0.7344 Beta=0.100 Tau=0.789
Epoch 156: Train=0.7552 Val=0.7301 Beta=0.100 Tau=0.797
Epoch 157: Train=0.7552 Val=0.7288 Beta=0.100 Tau=0.805
Epoch 158: Train=0.7557 Val=0.7330 Beta=0.100 Tau=0.812
Epoch 159: Train=0.7564 Val=0.7277 Beta=0.100 Tau=0.820
Epoch 160: Train=0.7548 Val=0.7300 Beta=0.100 Tau=0.827
Epoch 161: Train=0.7529 Val=0.7309 Beta=0.100 Tau=0.835
Epoch 162: Train=0.7554 Val=0.7285 Beta=0.100 Tau=0.842
Epoch 163: Train=0.7532 Val=0.7285 Beta=0.100 Tau=0.849
Epoch 164: Train=0.7541 Val=0.7300 Beta=0.100 Tau=0.856
Epoch 165: Train=0.7550 Val=0.7264 Beta=0.100 Tau=0.863
Epoch 166: Train=0.7532 Val=0.7287 Beta=0.100 Tau=0.870
Epoch 167: Train=0.7525 Val=0.7293 Beta=0.100 Tau=0.877
Epoch 168: Train=0.7542 Val=0.7269 Beta=0.100 Tau=0.884
Epoch 169: Train=0.7541 Val=0.7302 Beta=0.100 Tau=0.891
Epoch 170: Train=0.7536 Val=0.7271 Beta=0.100 Tau=0.897
Epoch 171: Train=0.7526 Val=0.7319 Beta=0.100 Tau=0.903
Epoch 172: Train=0.7541 Val=0.7363 Beta=0.100 Tau=0.909
Epoch 173: Train=0.7533 Val=0.7302 Beta=0.100 Tau=0.915
Epoch 174: Train=0.7523 Val=0.7277 Beta=0.100 Tau=0.921
Epoch 175: Train=0.7526 Val=0.7281 Beta=0.100 Tau=0.927
Epoch 176: Train=0.7526 Val=0.7334 Beta=0.100 Tau=0.932
Epoch 177: Train=0.7518 Val=0.7275 Beta=0.100 Tau=0.938
Epoch 178: Train=0.7526 Val=0.7291 Beta=0.100 Tau=0.943
Epoch 179: Train=0.7520 Val=0.7241 Beta=0.100 Tau=0.948
Epoch 180: Train=0.7533 Val=0.7260 Beta=0.100 Tau=0.952
Epoch 181: Train=0.7525 Val=0.7258 Beta=0.100 Tau=0.957
Epoch 182: Train=0.7526 Val=0.7272 Beta=0.100 Tau=0.961
Epoch 183: Train=0.7528 Val=0.7318 Beta=0.100 Tau=0.965
Epoch 184: Train=0.7514 Val=0.7270 Beta=0.100 Tau=0.969
Epoch 185: Train=0.7515 Val=0.7276 Beta=0.100 Tau=0.973
Epoch 186: Train=0.7519 Val=0.7328 Beta=0.100 Tau=0.976
Epoch 187: Train=0.7515 Val=0.7278 Beta=0.100 Tau=0.979
Epoch 188: Train=0.7511 Val=0.7299 Beta=0.100 Tau=0.982
Epoch 189: Train=0.7519 Val=0.7248 Beta=0.100 Tau=0.985
Epoch 190: Train=0.7519 Val=0.7265 Beta=0.100 Tau=0.988
Epoch 191: Train=0.7514 Val=0.7281 Beta=0.100 Tau=0.990
Epoch 192: Train=0.7512 Val=0.7272 Beta=0.100 Tau=0.992
Epoch 193: Train=0.7507 Val=0.7249 Beta=0.100 Tau=0.994
Epoch 194: Train=0.7510 Val=0.7271 Beta=0.100 Tau=0.996
Epoch 195: Train=0.7516 Val=0.7281 Beta=0.100 Tau=0.997
Epoch 196: Train=0.7508 Val=0.7307 Beta=0.100 Tau=0.998
Epoch 197: Train=0.7505 Val=0.7290 Beta=0.100 Tau=0.999
Epoch 198: Train=0.7515 Val=0.7269 Beta=0.100 Tau=1.000
Epoch 199: Train=0.7503 Val=0.7244 Beta=0.100 Tau=1.000
Epoch 200: Train=0.7501 Val=0.7262 Beta=0.100 Tau=1.000
Epoch 201: Train=0.7509 Val=0.7254 Beta=0.100 Tau=1.000
Epoch 202: Train=0.7503 Val=0.7273 Beta=0.100 Tau=1.000
Epoch 203: Train=0.7508 Val=0.7240 Beta=0.100 Tau=0.999
Epoch 204: Train=0.7499 Val=0.7289 Beta=0.100 Tau=0.998
Epoch 205: Train=0.7508 Val=0.7301 Beta=0.100 Tau=0.997
Epoch 206: Train=0.7508 Val=0.7288 Beta=0.100 Tau=0.996
Epoch 207: Train=0.7503 Val=0.7240 Beta=0.100 Tau=0.994
Epoch 208: Train=0.7508 Val=0.7283 Beta=0.100 Tau=0.992
Epoch 209: Train=0.7503 Val=0.7276 Beta=0.100 Tau=0.990
Epoch 210: Train=0.7501 Val=0.7233 Beta=0.100 Tau=0.988
Epoch 211: Train=0.7500 Val=0.7282 Beta=0.100 Tau=0.985
Epoch 212: Train=0.7500 Val=0.7270 Beta=0.100 Tau=0.982
Epoch 213: Train=0.7496 Val=0.7261 Beta=0.100 Tau=0.979
Epoch 214: Train=0.7501 Val=0.7222 Beta=0.100 Tau=0.976
Epoch 215: Train=0.7495 Val=0.7247 Beta=0.100 Tau=0.973
Epoch 216: Train=0.7503 Val=0.7255 Beta=0.100 Tau=0.969
Epoch 217: Train=0.7496 Val=0.7244 Beta=0.100 Tau=0.965
Epoch 218: Train=0.7496 Val=0.7246 Beta=0.100 Tau=0.961
Epoch 219: Train=0.7499 Val=0.7259 Beta=0.100 Tau=0.957
Epoch 220: Train=0.7507 Val=0.7265 Beta=0.100 Tau=0.952
Epoch 221: Train=0.7495 Val=0.7250 Beta=0.100 Tau=0.948
Epoch 222: Train=0.7488 Val=0.7240 Beta=0.100 Tau=0.943
Epoch 223: Train=0.7494 Val=0.7230 Beta=0.100 Tau=0.938
Epoch 224: Train=0.7494 Val=0.7245 Beta=0.100 Tau=0.932
Epoch 225: Train=0.7491 Val=0.7240 Beta=0.100 Tau=0.927
Epoch 226: Train=0.7485 Val=0.7264 Beta=0.100 Tau=0.921
Epoch 227: Train=0.7504 Val=0.7244 Beta=0.100 Tau=0.915
Epoch 228: Train=0.7499 Val=0.7232 Beta=0.100 Tau=0.909
Epoch 229: Train=0.7507 Val=0.7263 Beta=0.100 Tau=0.903
Epoch 230: Train=0.7486 Val=0.7237 Beta=0.100 Tau=0.897
Epoch 231: Train=0.7489 Val=0.7268 Beta=0.100 Tau=0.891
Epoch 232: Train=0.7490 Val=0.7249 Beta=0.100 Tau=0.884
Epoch 233: Train=0.7490 Val=0.7236 Beta=0.100 Tau=0.877
Epoch 234: Train=0.7489 Val=0.7231 Beta=0.100 Tau=0.870
Epoch 235: Train=0.7498 Val=0.7251 Beta=0.100 Tau=0.863
Epoch 236: Train=0.7495 Val=0.7293 Beta=0.100 Tau=0.856
Epoch 237: Train=0.7494 Val=0.7239 Beta=0.100 Tau=0.849
Epoch 238: Train=0.7490 Val=0.7237 Beta=0.100 Tau=0.842
Epoch 239: Train=0.7484 Val=0.7248 Beta=0.100 Tau=0.835
Epoch 240: Train=0.7481 Val=0.7255 Beta=0.100 Tau=0.827
Epoch 241: Train=0.7491 Val=0.7256 Beta=0.100 Tau=0.820
Epoch 242: Train=0.7485 Val=0.7271 Beta=0.100 Tau=0.812
Epoch 243: Train=0.7497 Val=0.7274 Beta=0.100 Tau=0.805
Epoch 244: Train=0.7479 Val=0.7241 Beta=0.100 Tau=0.797
Epoch 245: Train=0.7481 Val=0.7238 Beta=0.100 Tau=0.789
Epoch 246: Train=0.7491 Val=0.7264 Beta=0.100 Tau=0.781
Epoch 247: Train=0.7481 Val=0.7233 Beta=0.100 Tau=0.774
Epoch 248: Train=0.7494 Val=0.7235 Beta=0.100 Tau=0.766
Epoch 249: Train=0.7484 Val=0.7240 Beta=0.100 Tau=0.758
Epoch 250: Train=0.7477 Val=0.7253 Beta=0.100 Tau=0.750
Epoch 251: Train=0.7484 Val=0.7237 Beta=0.100 Tau=0.742
Epoch 252: Train=0.7480 Val=0.7222 Beta=0.100 Tau=0.734
Epoch 253: Train=0.7482 Val=0.7238 Beta=0.100 Tau=0.726
Epoch 254: Train=0.7480 Val=0.7224 Beta=0.100 Tau=0.719
Epoch 255: Train=0.7480 Val=0.7240 Beta=0.100 Tau=0.711
Epoch 256: Train=0.7479 Val=0.7243 Beta=0.100 Tau=0.703
Epoch 257: Train=0.7486 Val=0.7211 Beta=0.100 Tau=0.695
Epoch 258: Train=0.7478 Val=0.7236 Beta=0.100 Tau=0.688
Epoch 259: Train=0.7477 Val=0.7217 Beta=0.100 Tau=0.680
Epoch 260: Train=0.7484 Val=0.7222 Beta=0.100 Tau=0.673
Epoch 261: Train=0.7473 Val=0.7229 Beta=0.100 Tau=0.665
Epoch 262: Train=0.7477 Val=0.7237 Beta=0.100 Tau=0.658
Epoch 263: Train=0.7478 Val=0.7222 Beta=0.100 Tau=0.651
Epoch 264: Train=0.7477 Val=0.7224 Beta=0.100 Tau=0.644
Epoch 265: Train=0.7471 Val=0.7240 Beta=0.100 Tau=0.637
Epoch 266: Train=0.7485 Val=0.7238 Beta=0.100 Tau=0.630
Epoch 267: Train=0.7474 Val=0.7221 Beta=0.100 Tau=0.623
Epoch 268: Train=0.7477 Val=0.7226 Beta=0.100 Tau=0.616
Epoch 269: Train=0.7476 Val=0.7245 Beta=0.100 Tau=0.609
Epoch 270: Train=0.7474 Val=0.7280 Beta=0.100 Tau=0.603
Epoch 271: Train=0.7471 Val=0.7231 Beta=0.100 Tau=0.597
Epoch 272: Train=0.7477 Val=0.7213 Beta=0.100 Tau=0.591
Epoch 273: Train=0.7474 Val=0.7233 Beta=0.100 Tau=0.585
Epoch 274: Train=0.7472 Val=0.7253 Beta=0.100 Tau=0.579
Epoch 275: Train=0.7479 Val=0.7214 Beta=0.100 Tau=0.573
Epoch 276: Train=0.7479 Val=0.7233 Beta=0.100 Tau=0.568
Epoch 277: Train=0.7469 Val=0.7234 Beta=0.100 Tau=0.562
Epoch 278: Train=0.7477 Val=0.7208 Beta=0.100 Tau=0.557
Epoch 279: Train=0.7468 Val=0.7255 Beta=0.100 Tau=0.552
Epoch 280: Train=0.7463 Val=0.7218 Beta=0.100 Tau=0.548
Epoch 281: Train=0.7468 Val=0.7224 Beta=0.100 Tau=0.543
Epoch 282: Train=0.7473 Val=0.7226 Beta=0.100 Tau=0.539
Epoch 283: Train=0.7477 Val=0.7229 Beta=0.100 Tau=0.535
Epoch 284: Train=0.7472 Val=0.7217 Beta=0.100 Tau=0.531
Epoch 285: Train=0.7474 Val=0.7244 Beta=0.100 Tau=0.527
Epoch 286: Train=0.7471 Val=0.7232 Beta=0.100 Tau=0.524
Epoch 287: Train=0.7471 Val=0.7226 Beta=0.100 Tau=0.521
Epoch 288: Train=0.7471 Val=0.7218 Beta=0.100 Tau=0.518
Epoch 289: Train=0.7464 Val=0.7228 Beta=0.100 Tau=0.515
Epoch 290: Train=0.7471 Val=0.7226 Beta=0.100 Tau=0.512
Epoch 291: Train=0.7471 Val=0.7233 Beta=0.100 Tau=0.510
Epoch 292: Train=0.7459 Val=0.7240 Beta=0.100 Tau=0.508
Epoch 293: Train=0.7463 Val=0.7217 Beta=0.100 Tau=0.506
Epoch 294: Train=0.7465 Val=0.7223 Beta=0.100 Tau=0.504
Epoch 295: Train=0.7471 Val=0.7231 Beta=0.100 Tau=0.503
Epoch 296: Train=0.7472 Val=0.7194 Beta=0.100 Tau=0.502
Epoch 297: Train=0.7465 Val=0.7236 Beta=0.100 Tau=0.501
Epoch 298: Train=0.7464 Val=0.7226 Beta=0.100 Tau=0.500
Epoch 299: Train=0.7463 Val=0.7218 Beta=0.100 Tau=0.500
Epoch 300: Train=0.7467 Val=0.7237 Beta=0.100 Tau=0.500
```

In [13]:

```python
import torch
import torch.nn.functional as F
from tqdm import tqdm

DEVICE = "cuda" if torch.cuda.is_available() else "cpu"

# ----------------------------- Hyperparameters -----------------------------
EPOCHS_PRETRAIN = 30      # phase 1: reconstruction only
EPOCHS_VAE = 150          # phase 2: full VAE training
LR = 0.01                 # learning rate
BETA_MAX = 0.2            # smaller KL weight = better recon
TAU_START, TAU_END = 1.0, 0.5
CLIP_NORM = 1.0
BATCH_SIZE = 32
MODEL_PATH = Path("models/vae_uci_tuned.pt")

# ----------------------------- Utility Functions -----------------------------
def kl_anneal(epoch, total=30, beta_max=0.2):
    """Linearly ramp up the KL term"""
    return min(beta_max, beta_max * (epoch / max(1, total)))

def tau_schedule(epoch, total=100, tau_start=1.0, tau_end=0.5):
    """Cosine temperature decay for Gumbel-softmax"""
    import math
    t = 0.5 * (1 + math.cos(math.pi * epoch / total))
    return tau_end + (tau_start - tau_end) * t

# ----------------------------- Setup -----------------------------
model = ConvVAE(L=L, z_dim=128, base_c=64).to(DEVICE)
opt = torch.optim.AdamW(model.parameters(), lr=LR)

# DataLoaders
train_dl = DataLoader(train_ds, batch_size=BATCH_SIZE, shuffle=True)
val_dl = DataLoader(val_ds, batch_size=BATCH_SIZE, shuffle=False)

history = {"train": [], "val": []}
best_val = float("inf")

# ----------------------------- Phase 1: Autoencoder pretraining -----------------------------
print("\n===== Phase 1: Autoencoder pretraining (no KL term) =====")

for epoch in range(1, EPOCHS_PRETRAIN + 1):
    model.train()
    tr_loss = 0.0
    for (xb,) in tqdm(train_dl, desc=f"Pretrain {epoch}/{EPOCHS_PRETRAIN}"):
        xb = xb.to(DEVICE)
        logits, g, mu, logvar = model(xb)
        target = xb.argmax(-1)
        recon = F.cross_entropy(logits.reshape(-1, 4), target.reshape(-1))

        opt.zero_grad(set_to_none=True)
        recon.backward()
        torch.nn.utils.clip_grad_norm_(model.parameters(), CLIP_NORM)
        opt.step()

        tr_loss += recon.item() * xb.size(0)
    tr_loss /= len(train_dl.dataset)

    # validation
    model.eval()
    va_loss = 0
    with torch.no_grad():
        for (xb,) in val_dl:
            xb = xb.to(DEVICE)
            logits, g, mu, logvar = model(xb)
            target = xb.argmax(-1)
            recon = F.cross_entropy(logits.reshape(-1, 4), target.reshape(-1))
            va_loss += recon.item() * xb.size(0)
    va_loss /= len(val_dl.dataset)

    print(f"Epoch {epoch:03d}: TrainRecon={tr_loss:.4f}  ValRecon={va_loss:.4f}")

# ----------------------------- Phase 2: Full VAE training -----------------------------
print("\n===== Phase 2: Variational fine-tuning =====")

for epoch in range(1, EPOCHS_VAE + 1):
    model.train()
    beta = kl_anneal(epoch, total=50, beta_max=BETA_MAX)
    model.tau = tau_schedule(epoch, total=EPOCHS_VAE, tau_start=TAU_START, tau_end=TAU_END)

    tr_loss = 0.0
    for (xb,) in tqdm(train_dl, desc=f"VAE {epoch}/{EPOCHS_VAE}"):
        xb = xb.to(DEVICE)
        logits, g, mu, logvar = model(xb)
        target = xb.argmax(-1)
        recon = F.cross_entropy(logits.reshape(-1, 4), target.reshape(-1))
        kl = -0.5 * torch.mean(1 + logvar - mu.pow(2) - logvar.exp())
        loss = recon + beta * kl

        opt.zero_grad(set_to_none=True)
        loss.backward()
        torch.nn.utils.clip_grad_norm_(model.parameters(), CLIP_NORM)
        opt.step()
        tr_loss += loss.item() * xb.size(0)
    tr_loss /= len(train_dl.dataset)

    # Validation
    model.eval()
    va_loss = 0.0
    with torch.no_grad():
        for (xb,) in val_dl:
            xb = xb.to(DEVICE)
            logits, g, mu, logvar = model(xb)
            target = xb.argmax(-1)
            recon = F.cross_entropy(logits.reshape(-1, 4), target.reshape(-1))
            kl = -0.5 * torch.mean(1 + logvar - mu.pow(2) - logvar.exp())
            loss = recon + beta * kl
            va_loss += loss.item() * xb.size(0)
    va_loss /= len(val_dl.dataset)

    history["train"].append(tr_loss)
    history["val"].append(va_loss)

    print(f"Epoch {epoch:03d}: Train={tr_loss:.4f}  Val={va_loss:.4f}  β={beta:.3f}  τ={model.tau:.3f}")

    if va_loss < best_val:
        best_val = va_loss
        torch.save(model.state_dict(), MODEL_PATH)
        print(f"✅ Saved best model to {MODEL_PATH} (val={best_val:.4f})")
```

```
===== Phase 1: Autoencoder pretraining (no KL term) =====
Pretrain 1/30: 100%|██████████| 3/3 [00:00<00:00, 46.48it/s]
Epoch 001: TrainRecon=2.0489  ValRecon=2.0973
Pretrain 2/30: 100%|██████████| 3/3 [00:00<00:00, 41.16it/s]
Epoch 002: TrainRecon=1.3841  ValRecon=0.7799
Pretrain 3/30: 100%|██████████| 3/3 [00:00<00:00, 73.84it/s]
Epoch 003: TrainRecon=0.8418  ValRecon=0.7894
Pretrain 4/30: 100%|██████████| 3/3 [00:00<00:00, 233.94it/s]
Epoch 004: TrainRecon=0.8416  ValRecon=0.7902
Pretrain 5/30: 100%|██████████| 3/3 [00:00<00:00, 170.42it/s]
Epoch 005: TrainRecon=0.8051  ValRecon=0.7659
Pretrain 6/30: 100%|██████████| 3/3 [00:00<00:00, 147.74it/s]
Epoch 006: TrainRecon=0.7858  ValRecon=0.7490
Pretrain 7/30: 100%|██████████| 3/3 [00:00<00:00, 156.40it/s]
Epoch 007: TrainRecon=0.7722  ValRecon=0.7479
Pretrain 8/30: 100%|██████████| 3/3 [00:00<00:00, 169.12it/s]
Epoch 008: TrainRecon=0.7701  ValRecon=0.7404
Pretrain 9/30: 100%|██████████| 3/3 [00:00<00:00, 211.79it/s]
Epoch 009: TrainRecon=0.7596  ValRecon=0.7433
Pretrain 10/30: 100%|██████████| 3/3 [00:00<00:00, 212.92it/s]
Epoch 010: TrainRecon=0.7625  ValRecon=0.7427
Pretrain 11/30: 100%|██████████| 3/3 [00:00<00:00, 216.22it/s]
Epoch 011: TrainRecon=0.7600  ValRecon=0.7448
Pretrain 12/30: 100%|██████████| 3/3 [00:00<00:00, 236.28it/s]
Epoch 012: TrainRecon=0.7597  ValRecon=0.7373
Pretrain 13/30: 100%|██████████| 3/3 [00:00<00:00, 233.98it/s]
Epoch 013: TrainRecon=0.7619  ValRecon=0.7551
Pretrain 14/30: 100%|██████████| 3/3 [00:00<00:00, 170.32it/s]
Epoch 014: TrainRecon=0.7594  ValRecon=0.7325
Pretrain 15/30: 100%|██████████| 3/3 [00:00<00:00, 188.49it/s]
Epoch 015: TrainRecon=0.7529  ValRecon=0.7345
Pretrain 16/30: 100%|██████████| 3/3 [00:00<00:00, 191.35it/s]
Epoch 016: TrainRecon=0.7506  ValRecon=0.7253
Pretrain 17/30: 100%|██████████| 3/3 [00:00<00:00, 189.01it/s]
```

```
Epoch 017: TrainRecon=0.7493  ValRecon=0.7233
Pretrain 18/30: 100%|██████████| 3/3 [00:00<00:00, 142.22it/s]
Epoch 018: TrainRecon=0.7463  ValRecon=0.7179
Pretrain 19/30: 100%|██████████| 3/3 [00:00<00:00, 190.33it/s]
Epoch 019: TrainRecon=0.7453  ValRecon=0.7187
Pretrain 20/30: 100%|██████████| 3/3 [00:00<00:00, 242.61it/s]
Epoch 020: TrainRecon=0.7441  ValRecon=0.7209
Pretrain 21/30: 100%|██████████| 3/3 [00:00<00:00, 227.82it/s]
Epoch 021: TrainRecon=0.7441  ValRecon=0.7176
Pretrain 22/30: 100%|██████████| 3/3 [00:00<00:00, 177.09it/s]
Epoch 022: TrainRecon=0.7434  ValRecon=0.7182
Pretrain 23/30: 100%|██████████| 3/3 [00:00<00:00, 182.09it/s]
Epoch 023: TrainRecon=0.7430  ValRecon=0.7171
Pretrain 24/30: 100%|██████████| 3/3 [00:00<00:00, 197.84it/s]
Epoch 024: TrainRecon=0.7424  ValRecon=0.7179
Pretrain 25/30: 100%|██████████| 3/3 [00:00<00:00, 208.31it/s]
Epoch 025: TrainRecon=0.7423  ValRecon=0.7173
Pretrain 26/30: 100%|██████████| 3/3 [00:00<00:00, 207.13it/s]
Epoch 026: TrainRecon=0.7420  ValRecon=0.7168
Pretrain 27/30: 100%|██████████| 3/3 [00:00<00:00, 179.58it/s]
Epoch 027: TrainRecon=0.7417  ValRecon=0.7169
Pretrain 28/30: 100%|██████████| 3/3 [00:00<00:00, 175.42it/s]
Epoch 028: TrainRecon=0.7420  ValRecon=0.7179
Pretrain 29/30: 100%|██████████| 3/3 [00:00<00:00, 239.42it/s]
Epoch 029: TrainRecon=0.7413  ValRecon=0.7171
Pretrain 30/30: 100%|██████████| 3/3 [00:00<00:00, 178.31it/s]
Epoch 030: TrainRecon=0.7415  ValRecon=0.7162

===== Phase 2: Variational fine-tuning =====
VAE 1/150: 100%|██████████| 3/3 [00:00<00:00, 166.11it/s]
Epoch 001: Train=0.7492  Val=0.7246  β=0.004  τ=1.000
✅ Saved best model to models\vae_uci_tuned.pt (val=0.7246)
VAE 2/150: 100%|██████████| 3/3 [00:00<00:00, 189.69it/s]
Epoch 002: Train=0.7563  Val=0.7302  β=0.008  τ=1.000
VAE 3/150: 100%|██████████| 3/3 [00:00<00:00, 173.93it/s]
Epoch 003: Train=0.7603  Val=0.7316  β=0.012  τ=1.000
VAE 4/150: 100%|██████████| 3/3 [00:00<00:00, 160.28it/s]
Epoch 004: Train=0.7603  Val=0.7309  β=0.016  τ=0.999
VAE 5/150: 100%|██████████| 3/3 [00:00<00:00, 154.87it/s]
Epoch 005: Train=0.7562  Val=0.7297  β=0.020  τ=0.999
VAE 6/150: 100%|██████████| 3/3 [00:00<00:00, 157.39it/s]
Epoch 006: Train=0.7530  Val=0.7250  β=0.024  τ=0.998
VAE 7/150: 100%|██████████| 3/3 [00:00<00:00, 148.46it/s]
Epoch 007: Train=0.7532  Val=0.7313  β=0.028  τ=0.997
VAE 8/150: 100%|██████████| 3/3 [00:00<00:00, 154.52it/s]
Epoch 008: Train=0.7554  Val=0.7338  β=0.032  τ=0.996
VAE 9/150: 100%|██████████| 3/3 [00:00<00:00, 170.78it/s]
Epoch 009: Train=0.7565  Val=0.7310  β=0.036  τ=0.996
VAE 10/150: 100%|██████████| 3/3 [00:00<00:00, 207.99it/s]
Epoch 010: Train=0.7623  Val=0.7292  β=0.040  τ=0.995


VAE 11/150: 100%|██████████| 3/3 [00:00<00:00, 175.58it/s]
Epoch 011: Train=0.7609  Val=0.7375  β=0.044  τ=0.993
VAE 12/150: 100%|██████████| 3/3 [00:00<00:00, 187.10it/s]
Epoch 012: Train=0.7667  Val=0.7398  β=0.048  τ=0.992
VAE 13/150: 100%|██████████| 3/3 [00:00<00:00, 171.39it/s]
Epoch 013: Train=0.7615  Val=0.7333  β=0.052  τ=0.991
VAE 14/150: 100%|██████████| 3/3 [00:00<00:00, 210.08it/s]
Epoch 014: Train=0.7598  Val=0.7332  β=0.056  τ=0.989
VAE 15/150: 100%|██████████| 3/3 [00:00<00:00, 191.93it/s]
Epoch 015: Train=0.7604  Val=0.7545  β=0.060  τ=0.988
VAE 16/150: 100%|██████████| 3/3 [00:00<00:00, 164.19it/s]
Epoch 016: Train=0.7625  Val=0.7393  β=0.064  τ=0.986
VAE 17/150: 100%|██████████| 3/3 [00:00<00:00, 174.05it/s]
Epoch 017: Train=0.7624  Val=0.7336  β=0.068  τ=0.984
VAE 18/150: 100%|██████████| 3/3 [00:00<00:00, 214.59it/s]
Epoch 018: Train=0.7612  Val=0.7343  β=0.072  τ=0.982
VAE 19/150: 100%|██████████| 3/3 [00:00<00:00, 152.94it/s]
Epoch 019: Train=0.7600  Val=0.7332  β=0.076  τ=0.980
VAE 20/150: 100%|██████████| 3/3 [00:00<00:00, 194.23it/s]
Epoch 020: Train=0.7615  Val=0.7323  β=0.080  τ=0.978
VAE 21/150: 100%|██████████| 3/3 [00:00<00:00, 183.19it/s]
Epoch 021: Train=0.7592  Val=0.7325  β=0.084  τ=0.976
VAE 22/150: 100%|██████████| 3/3 [00:00<00:00, 146.40it/s]
Epoch 022: Train=0.7600  Val=0.7348  β=0.088  τ=0.974
VAE 23/150: 100%|██████████| 3/3 [00:00<00:00, 159.19it/s]
Epoch 023: Train=0.7636  Val=0.7374  β=0.092  τ=0.972
VAE 24/150: 100%|██████████| 3/3 [00:00<00:00, 178.39it/s]
Epoch 024: Train=0.7645  Val=0.7316  β=0.096  τ=0.969
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VAE 25/150: 100%|██████████| 3/3 [00:00<00:00, 184.89it/s]
Epoch 025: Train=0.7609  Val=0.7330  β=0.100  τ=0.967
VAE 26/150: 100%|██████████| 3/3 [00:00<00:00, 131.27it/s]
Epoch 026: Train=0.7627  Val=0.7380  β=0.104  τ=0.964
VAE 27/150: 100%|██████████| 3/3 [00:00<00:00, 146.88it/s]
Epoch 027: Train=0.7613  Val=0.7415  β=0.108  τ=0.961
VAE 28/150: 100%|██████████| 3/3 [00:00<00:00, 164.99it/s]
Epoch 028: Train=0.7631  Val=0.7430  β=0.112  τ=0.958
VAE 29/150: 100%|██████████| 3/3 [00:00<00:00, 159.03it/s]
Epoch 029: Train=0.7649  Val=0.7463  β=0.116  τ=0.955
VAE 30/150: 100%|██████████| 3/3 [00:00<00:00, 159.38it/s]
Epoch 030: Train=0.7681  Val=0.7357  β=0.120  τ=0.952
VAE 31/150: 100%|██████████| 3/3 [00:00<00:00, 174.10it/s]
Epoch 031: Train=0.7627  Val=0.7327  β=0.124  τ=0.949
VAE 32/150: 100%|██████████| 3/3 [00:00<00:00, 158.57it/s]
Epoch 032: Train=0.7597  Val=0.7320  β=0.128  τ=0.946
VAE 33/150: 100%|██████████| 3/3 [00:00<00:00, 175.05it/s]
Epoch 033: Train=0.7632  Val=0.7371  β=0.132  τ=0.943
VAE 34/150: 100%|██████████| 3/3 [00:00<00:00, 184.97it/s]
Epoch 034: Train=0.7642  Val=0.7358  β=0.136  τ=0.939
VAE 35/150: 100%|██████████| 3/3 [00:00<00:00, 186.41it/s]
Epoch 035: Train=0.7616  Val=0.7294  β=0.140  τ=0.936
VAE 36/150: 100%|██████████| 3/3 [00:00<00:00, 159.15it/s]
Epoch 036: Train=0.7628  Val=0.7356  β=0.144  τ=0.932
VAE 37/150: 100%|██████████| 3/3 [00:00<00:00, 220.82it/s]
Epoch 037: Train=0.7629  Val=0.7334  β=0.148  τ=0.929
VAE 38/150: 100%|██████████| 3/3 [00:00<00:00, 120.27it/s]
Epoch 038: Train=0.7601  Val=0.7385  β=0.152  τ=0.925
VAE 39/150: 100%|██████████| 3/3 [00:00<00:00, 124.85it/s]
Epoch 039: Train=0.7635  Val=0.7349  β=0.156  τ=0.921
VAE 40/150: 100%|██████████| 3/3 [00:00<00:00, 161.81it/s]
Epoch 040: Train=0.7575  Val=0.7324  β=0.160  τ=0.917
VAE 41/150: 100%|██████████| 3/3 [00:00<00:00, 152.42it/s]
Epoch 041: Train=0.7600  Val=0.7377  β=0.164  τ=0.913
VAE 42/150: 100%|██████████| 3/3 [00:00<00:00, 173.24it/s]
Epoch 042: Train=0.7590  Val=0.7432  β=0.168  τ=0.909
VAE 43/150: 100%|██████████| 3/3 [00:00<00:00, 165.50it/s]
Epoch 043: Train=0.7608  Val=0.7343  β=0.172  τ=0.905
VAE 44/150: 100%|██████████| 3/3 [00:00<00:00, 173.40it/s]
Epoch 044: Train=0.7586  Val=0.7359  β=0.176  τ=0.901
VAE 45/150: 100%|██████████| 3/3 [00:00<00:00, 177.55it/s]
Epoch 045: Train=0.7602  Val=0.7426  β=0.180  τ=0.897
VAE 46/150: 100%|██████████| 3/3 [00:00<00:00, 146.03it/s]
Epoch 046: Train=0.7586  Val=0.7316  β=0.184  τ=0.893
VAE 47/150: 100%|██████████| 3/3 [00:00<00:00, 204.45it/s]
Epoch 047: Train=0.7591  Val=0.7350  β=0.188  τ=0.888
VAE 48/150: 100%|██████████| 3/3 [00:00<00:00, 160.65it/s]
Epoch 048: Train=0.7607  Val=0.7326  β=0.192  τ=0.884
VAE 49/150: 100%|██████████| 3/3 [00:00<00:00, 183.39it/s]
Epoch 049: Train=0.7601  Val=0.7337  β=0.196  τ=0.880
VAE 50/150: 100%|██████████| 3/3 [00:00<00:00, 166.96it/s]
Epoch 050: Train=0.7605  Val=0.7336  β=0.200  τ=0.875


VAE 51/150: 100%|██████████| 3/3 [00:00<00:00, 156.73it/s]
Epoch 051: Train=0.7583  Val=0.7389  β=0.200  τ=0.870
VAE 52/150: 100%|██████████| 3/3 [00:00<00:00, 167.91it/s]
Epoch 052: Train=0.7580  Val=0.7336  β=0.200  τ=0.866
VAE 53/150: 100%|██████████| 3/3 [00:00<00:00, 162.14it/s]
Epoch 053: Train=0.7569  Val=0.7285  β=0.200  τ=0.861
VAE 54/150: 100%|██████████| 3/3 [00:00<00:00, 154.58it/s]
Epoch 054: Train=0.7589  Val=0.7304  β=0.200  τ=0.856
VAE 55/150: 100%|██████████| 3/3 [00:00<00:00, 187.53it/s]
Epoch 055: Train=0.7541  Val=0.7290  β=0.200  τ=0.852
VAE 56/150: 100%|██████████| 3/3 [00:00<00:00, 161.89it/s]
Epoch 056: Train=0.7569  Val=0.7283  β=0.200  τ=0.847
VAE 57/150: 100%|██████████| 3/3 [00:00<00:00, 208.80it/s]
Epoch 057: Train=0.7561  Val=0.7272  β=0.200  τ=0.842
VAE 58/150: 100%|██████████| 3/3 [00:00<00:00, 155.66it/s]
Epoch 058: Train=0.7570  Val=0.7344  β=0.200  τ=0.837
VAE 59/150: 100%|██████████| 3/3 [00:00<00:00, 155.94it/s]
Epoch 059: Train=0.7561  Val=0.7295  β=0.200  τ=0.832
VAE 60/150: 100%|██████████| 3/3 [00:00<00:00, 170.05it/s]
Epoch 060: Train=0.7561  Val=0.7332  β=0.200  τ=0.827
VAE 61/150: 100%|██████████| 3/3 [00:00<00:00, 180.20it/s]
Epoch 061: Train=0.7649  Val=0.7360  β=0.200  τ=0.822
VAE 62/150: 100%|██████████| 3/3 [00:00<00:00, 162.77it/s]
Epoch 062: Train=0.7610  Val=0.7428  β=0.200  τ=0.817
VAE 63/150: 100%|██████████| 3/3 [00:00<00:00, 166.55it/s]
Epoch 063: Train=0.7628  Val=0.7449  β=0.200  τ=0.812
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VAE 64/150: 100%|██████████| 3/3 [00:00<00:00, 195.26it/s]
Epoch 064: Train=0.7608  Val=0.7314  β=0.200  τ=0.807
VAE 65/150: 100%|██████████| 3/3 [00:00<00:00, 173.06it/s]
Epoch 065: Train=0.7630  Val=0.7357  β=0.200  τ=0.802

VAE 66/150: 100%|██████████| 3/3 [00:00<00:00, 178.52it/s]
Epoch 066: Train=0.7589  Val=0.7804  β=0.200  τ=0.797
VAE 67/150: 100%|██████████| 3/3 [00:00<00:00, 183.78it/s]
Epoch 067: Train=0.7574  Val=0.7299  β=0.200  τ=0.792
VAE 68/150: 100%|██████████| 3/3 [00:00<00:00, 168.42it/s]
Epoch 068: Train=0.7566  Val=0.7285  β=0.200  τ=0.787
VAE 69/150: 100%|██████████| 3/3 [00:00<00:00, 198.20it/s]
Epoch 069: Train=0.7651  Val=0.7386  β=0.200  τ=0.781
VAE 70/150: 100%|██████████| 3/3 [00:00<00:00, 168.73it/s]
Epoch 070: Train=0.7607  Val=0.7396  β=0.200  τ=0.776
VAE 71/150: 100%|██████████| 3/3 [00:00<00:00, 214.73it/s]
Epoch 071: Train=0.7676  Val=0.7452  β=0.200  τ=0.771
VAE 72/150: 100%|██████████| 3/3 [00:00<00:00, 162.08it/s]
Epoch 072: Train=0.7741  Val=0.7402  β=0.200  τ=0.766
VAE 73/150: 100%|██████████| 3/3 [00:00<00:00, 157.99it/s]
Epoch 073: Train=0.7635  Val=0.7279  β=0.200  τ=0.760
VAE 74/150: 100%|██████████| 3/3 [00:00<00:00, 159.45it/s]
Epoch 074: Train=0.7808  Val=0.7336  β=0.200  τ=0.755
VAE 75/150: 100%|██████████| 3/3 [00:00<00:00, 136.64it/s]
Epoch 075: Train=0.7713  Val=0.7454  β=0.200  τ=0.750
VAE 76/150: 100%|██████████| 3/3 [00:00<00:00, 185.91it/s]
Epoch 076: Train=0.7714  Val=0.7497  β=0.200  τ=0.745
VAE 77/150: 100%|██████████| 3/3 [00:00<00:00, 143.93it/s]
Epoch 077: Train=0.7738  Val=0.7425  β=0.200  τ=0.740
VAE 78/150: 100%|██████████| 3/3 [00:00<00:00, 159.48it/s]
Epoch 078: Train=0.7680  Val=0.7490  β=0.200  τ=0.734
VAE 79/150: 100%|██████████| 3/3 [00:00<00:00, 146.97it/s]
Epoch 079: Train=0.7819  Val=0.7373  β=0.200  τ=0.729
VAE 80/150: 100%|██████████| 3/3 [00:00<00:00, 136.16it/s]
Epoch 080: Train=0.7624  Val=0.7394  β=0.200  τ=0.724

VAE 81/150: 100%|██████████| 3/3 [00:00<00:00, 142.85it/s]
Epoch 081: Train=0.7635  Val=0.7388  β=0.200  τ=0.719
VAE 82/150: 100%|██████████| 3/3 [00:00<00:00, 141.99it/s]
Epoch 082: Train=0.7631  Val=0.7357  β=0.200  τ=0.713
VAE 83/150: 100%|██████████| 3/3 [00:00<00:00, 146.81it/s]
Epoch 083: Train=0.7598  Val=0.7401  β=0.200  τ=0.708
VAE 84/150: 100%|██████████| 3/3 [00:00<00:00, 123.53it/s]
Epoch 084: Train=0.7572  Val=0.7351  β=0.200  τ=0.703
VAE 85/150: 100%|██████████| 3/3 [00:00<00:00, 115.50it/s]
Epoch 085: Train=0.7599  Val=0.7355  β=0.200  τ=0.698
VAE 86/150: 100%|██████████| 3/3 [00:00<00:00, 132.76it/s]
Epoch 086: Train=0.7606  Val=0.7310  β=0.200  τ=0.693
VAE 87/150: 100%|██████████| 3/3 [00:00<00:00, 170.56it/s]
Epoch 087: Train=0.7576  Val=0.7307  β=0.200  τ=0.688
VAE 88/150: 100%|██████████| 3/3 [00:00<00:00, 156.70it/s]
Epoch 088: Train=0.7606  Val=0.7324  β=0.200  τ=0.683
VAE 89/150: 100%|██████████| 3/3 [00:00<00:00, 160.52it/s]
Epoch 089: Train=0.7672  Val=0.7328  β=0.200  τ=0.678
VAE 90/150: 100%|██████████| 3/3 [00:00<00:00, 144.19it/s]
Epoch 090: Train=0.7569  Val=0.7313  β=0.200  τ=0.673
VAE 91/150: 100%|██████████| 3/3 [00:00<00:00, 135.47it/s]
Epoch 091: Train=0.7587  Val=0.7356  β=0.200  τ=0.668
VAE 92/150: 100%|██████████| 3/3 [00:00<00:00, 151.19it/s]
Epoch 092: Train=0.7583  Val=0.7352  β=0.200  τ=0.663
VAE 93/150: 100%|██████████| 3/3 [00:00<00:00, 126.31it/s]
Epoch 093: Train=0.7573  Val=0.7348  β=0.200  τ=0.658
VAE 94/150: 100%|██████████| 3/3 [00:00<00:00, 147.79it/s]
Epoch 094: Train=0.7550  Val=0.7344  β=0.200  τ=0.653
VAE 95/150: 100%|██████████| 3/3 [00:00<00:00, 126.45it/s]
Epoch 095: Train=0.7562  Val=0.7335  β=0.200  τ=0.648
VAE 96/150: 100%|██████████| 3/3 [00:00<00:00, 103.29it/s]
Epoch 096: Train=0.7572  Val=0.7288  β=0.200  τ=0.644
VAE 97/150: 100%|██████████| 3/3 [00:00<00:00, 141.44it/s]
Epoch 097: Train=0.7562  Val=0.7318  β=0.200  τ=0.639
VAE 98/150: 100%|██████████| 3/3 [00:00<00:00, 140.70it/s]
Epoch 098: Train=0.7542  Val=0.7340  β=0.200  τ=0.634

VAE 99/150: 100%|██████████| 3/3 [00:00<00:00, 169.38it/s]
Epoch 099: Train=0.7561  Val=0.7305  β=0.200  τ=0.630
VAE 100/150: 100%|██████████| 3/3 [00:00<00:00, 140.12it/s]
Epoch 100: Train=0.7564  Val=0.7319  β=0.200  τ=0.625
VAE 101/150: 100%|██████████| 3/3 [00:00<00:00, 143.71it/s]
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Epoch 101: Train=0.7577  Val=0.7356  β=0.200  τ=0.620
VAE 102/150: 100%|██████████| 3/3 [00:00<00:00, 166.68it/s]
Epoch 102: Train=0.7558  Val=0.7348  β=0.200  τ=0.616
VAE 103/150: 100%|██████████| 3/3 [00:00<00:00, 156.57it/s]
Epoch 103: Train=0.7552  Val=0.7316  β=0.200  τ=0.612
VAE 104/150: 100%|██████████| 3/3 [00:00<00:00, 156.41it/s]
Epoch 104: Train=0.7522  Val=0.7284  β=0.200  τ=0.607


VAE 105/150: 100%|██████████| 3/3 [00:00<00:00, 170.06it/s]
Epoch 105: Train=0.7517  Val=0.7290  β=0.200  τ=0.603
VAE 106/150: 100%|██████████| 3/3 [00:00<00:00, 173.25it/s]
Epoch 106: Train=0.7619  Val=0.7318  β=0.200  τ=0.599
VAE 107/150: 100%|██████████| 3/3 [00:00<00:00, 169.92it/s]
Epoch 107: Train=0.7527  Val=0.7292  β=0.200  τ=0.595
VAE 108/150: 100%|██████████| 3/3 [00:00<00:00, 153.74it/s]
Epoch 108: Train=0.7544  Val=0.7290  β=0.200  τ=0.591
VAE 109/150: 100%|██████████| 3/3 [00:00<00:00, 148.21it/s]
Epoch 109: Train=0.7535  Val=0.7300  β=0.200  τ=0.587
VAE 110/150: 100%|██████████| 3/3 [00:00<00:00, 143.82it/s]
Epoch 110: Train=0.7534  Val=0.7305  β=0.200  τ=0.583
VAE 111/150: 100%|██████████| 3/3 [00:00<00:00, 194.37it/s]
Epoch 111: Train=0.7541  Val=0.7262  β=0.200  τ=0.579
VAE 112/150: 100%|██████████| 3/3 [00:00<00:00, 163.72it/s]
Epoch 112: Train=0.7997  Val=0.7337  β=0.200  τ=0.575
VAE 113/150: 100%|██████████| 3/3 [00:00<00:00, 167.78it/s]
Epoch 113: Train=0.7594  Val=0.7366  β=0.200  τ=0.571
VAE 114/150: 100%|██████████| 3/3 [00:00<00:00, 164.61it/s]
Epoch 114: Train=0.7645  Val=0.7413  β=0.200  τ=0.568
VAE 115/150: 100%|██████████| 3/3 [00:00<00:00, 154.44it/s]
Epoch 115: Train=0.7666  Val=0.7397  β=0.200  τ=0.564
VAE 116/150: 100%|██████████| 3/3 [00:00<00:00, 145.98it/s]
Epoch 116: Train=0.7633  Val=1.0197  β=0.200  τ=0.561
VAE 117/150: 100%|██████████| 3/3 [00:00<00:00, 172.74it/s]
Epoch 117: Train=0.7632  Val=0.7497  β=0.200  τ=0.557
VAE 118/150: 100%|██████████| 3/3 [00:00<00:00, 151.86it/s]
Epoch 118: Train=0.7801  Val=0.7433  β=0.200  τ=0.554
VAE 119/150: 100%|██████████| 3/3 [00:00<00:00, 144.93it/s]
Epoch 119: Train=0.7691  Val=0.7442  β=0.200  τ=0.551
VAE 120/150: 100%|██████████| 3/3 [00:00<00:00, 126.02it/s]
Epoch 120: Train=0.7635  Val=0.7357  β=0.200  τ=0.548
VAE 121/150: 100%|██████████| 3/3 [00:00<00:00, 150.11it/s]
Epoch 121: Train=0.7653  Val=0.7381  β=0.200  τ=0.545


VAE 122/150: 100%|██████████| 3/3 [00:00<00:00, 137.79it/s]
Epoch 122: Train=0.7625  Val=0.7358  β=0.200  τ=0.542
VAE 123/150: 100%|██████████| 3/3 [00:00<00:00, 171.99it/s]
Epoch 123: Train=0.7612  Val=0.7398  β=0.200  τ=0.539


VAE 124/150: 100%|██████████| 3/3 [00:00<00:00, 168.21it/s]
Epoch 124: Train=0.7625  Val=0.7357  β=0.200  τ=0.536
VAE 125/150: 100%|██████████| 3/3 [00:00<00:00, 183.30it/s]
Epoch 125: Train=0.7609  Val=0.7375  β=0.200  τ=0.533
VAE 126/150: 100%|██████████| 3/3 [00:00<00:00, 152.18it/s]
Epoch 126: Train=0.7593  Val=0.7353  β=0.200  τ=0.531
VAE 127/150: 100%|██████████| 3/3 [00:00<00:00, 157.96it/s]
Epoch 127: Train=0.7582  Val=0.7327  β=0.200  τ=0.528
VAE 128/150: 100%|██████████| 3/3 [00:00<00:00, 132.45it/s]
Epoch 128: Train=0.7566  Val=0.7335  β=0.200  τ=0.526
VAE 129/150: 100%|██████████| 3/3 [00:00<00:00, 175.09it/s]
Epoch 129: Train=0.7561  Val=0.7338  β=0.200  τ=0.524
VAE 130/150: 100%|██████████| 3/3 [00:00<00:00, 158.23it/s]
Epoch 130: Train=0.7546  Val=0.7322  β=0.200  τ=0.522
VAE 131/150: 100%|██████████| 3/3 [00:00<00:00, 158.59it/s]
Epoch 131: Train=0.7549  Val=0.7307  β=0.200  τ=0.520
VAE 132/150: 100%|██████████| 3/3 [00:00<00:00, 180.22it/s]
Epoch 132: Train=0.7554  Val=0.7305  β=0.200  τ=0.518
VAE 133/150: 100%|██████████| 3/3 [00:00<00:00, 203.78it/s]
Epoch 133: Train=0.7533  Val=0.7291  β=0.200  τ=0.516
VAE 134/150: 100%|██████████| 3/3 [00:00<00:00, 197.53it/s]
Epoch 134: Train=0.7534  Val=0.7282  β=0.200  τ=0.514
VAE 135/150: 100%|██████████| 3/3 [00:00<00:00, 204.33it/s]
Epoch 135: Train=0.7533  Val=0.7287  β=0.200  τ=0.512
VAE 136/150: 100%|██████████| 3/3 [00:00<00:00, 167.62it/s]
Epoch 136: Train=0.7526  Val=0.7268  β=0.200  τ=0.511
VAE 137/150: 100%|██████████| 3/3 [00:00<00:00, 158.12it/s]
Epoch 137: Train=0.7519  Val=0.7273  β=0.200  τ=0.509
VAE 138/150: 100%|██████████| 3/3 [00:00<00:00, 135.43it/s]
Epoch 138: Train=0.7503  Val=0.7244  β=0.200  τ=0.508
✅ Saved best model to models\vae_uci_tuned.pt (val=0.7244)
```
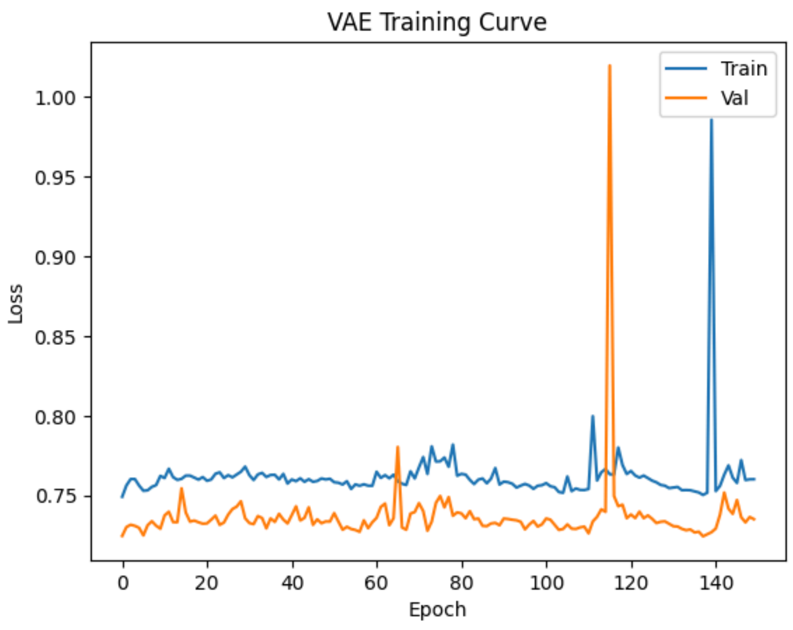

```
VAE 139/150: 100%|██████████| 3/3 [00:00<00:00, 124.59it/s]
Epoch 139: Train=0.7518  Val=0.7257  β=0.200  τ=0.507
VAE 140/150: 100%|██████████| 3/3 [00:00<00:00, 127.18it/s]
Epoch 140: Train=0.9857  Val=0.7270  β=0.200  τ=0.505
VAE 141/150: 100%|██████████| 3/3 [00:00<00:00, 156.98it/s]
Epoch 141: Train=0.7528  Val=0.7293  β=0.200  τ=0.504
VAE 142/150: 100%|██████████| 3/3 [00:00<00:00, 206.00it/s]
Epoch 142: Train=0.7560  Val=0.7379  β=0.200  τ=0.504
VAE 143/150: 100%|██████████| 3/3 [00:00<00:00, 191.95it/s]
Epoch 143: Train=0.7631  Val=0.7518  β=0.200  τ=0.503
VAE 144/150: 100%|██████████| 3/3 [00:00<00:00, 182.48it/s]
Epoch 144: Train=0.7688  Val=0.7417  β=0.200  τ=0.502
VAE 145/150: 100%|██████████| 3/3 [00:00<00:00, 188.91it/s]
Epoch 145: Train=0.7612  Val=0.7384  β=0.200  τ=0.501
VAE 146/150: 100%|██████████| 3/3 [00:00<00:00, 187.78it/s]
Epoch 146: Train=0.7578  Val=0.7472  β=0.200  τ=0.501
VAE 147/150: 100%|██████████| 3/3 [00:00<00:00, 183.80it/s]
Epoch 147: Train=0.7722  Val=0.7363  β=0.200  τ=0.500

VAE 148/150: 100%|██████████| 3/3 [00:00<00:00, 179.15it/s]
Epoch 148: Train=0.7597  Val=0.7331  β=0.200  τ=0.500
VAE 149/150: 100%|██████████| 3/3 [00:00<00:00, 151.19it/s]
Epoch 149: Train=0.7601  Val=0.7365  β=0.200  τ=0.500
VAE 150/150: 100%|██████████| 3/3 [00:00<00:00, 138.42it/s]
Epoch 150: Train=0.7602  Val=0.7351  β=0.200  τ=0.500
```

In [14]:
```
import matplotlib.pyplot as plt

plt.plot(history["train"], label="Train")
plt.plot(history["val"], label="Val")
plt.legend()
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("VAE Training Curve")
plt.show()
```



In [15]:
```
model.load_state_dict(torch.load("models/vae_uci.pt"))
model.eval()

with torch.no_grad():
    z = torch.randn(100, 128, device=DEVICE)
    logits = model.decode_logits(z)
    probs = torch.softmax(logits, dim=-1)
    idx = probs.argmax(dim=-1).cpu().numpy()

bases = np.array(list("ACGT"))
seqs = ["".join(bases[i]) for i in idx]

print("Example generated sequence:")
print(seqs[0][:100], "...")
```

```
Example generated sequence:
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA ...
```

In [16]:
```
def gc_content(seq):
    return (seq.count('G') + seq.count('C')) / len(seq)

def homopolymer(seq):
    longest, curr = 1, 1
    for i in range(1, len(seq)):
        if seq[i] == seq[i-1]:
            curr += 1
            longest = max(longest, curr)
        else:
            curr = 1
    return longest

gc_vals = [gc_content(s) for s in seqs]
runs = [homopolymer(s) for s in seqs]

print(f"Avg GC%: {np.mean(gc_vals):.3f}")
print(f"Avg longest homopolymer: {np.mean(runs):.2f}")
```

```
Avg GC%: 0.000
Avg longest homopolymer: 199.94
```

In [31]:
```
bases = np.array(list("ACGT"))

xb = next(iter(val_dl))[0][:5].to(DEVICE)
model.eval()
with torch.no_grad():
    logits, _, _, _ = model(xb)
pred_idx = logits.argmax(-1).cpu().numpy()
true_idx = xb.argmax(-1).cpu().numpy()

for i in range(5):
    print(f"\nSample {i+1}")
    print("True :", "".join(bases[true_idx[i]]))
    print("Recon:", "".join(bases[pred_idx[i]]))
```

```
Sample 1
True : TGTTGATTTTCCATGCGGTGTTTTGCGCAATGTTAATCGCTTTGTACACCTCAGGCAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
Recon: AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA

Sample 2
True : ATTACAAAAAGTGCTTTCTGAACTGAACAAAAAAGAGTAAAGTTAGTCGCGTAGGGTAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
Recon: AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA

Sample 3
True : TTACGTTGGCGACCGCTAGGACTTTCTTGTTGATTTTCCATGCGGTGTTTTGCGCAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
Recon: AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA

Sample 4
True : CTGCAATTTTTCTATTGCGGCCTGCGGAGAACTCCCTATAATGCGCCTCCATCGACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
Recon: AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA

Sample 5
True : AGGAGGAACTACGCAAGGTTGGAACATCGGAGAGATGCCAGCCAGCGCACCTGCACGAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
Recon: AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA
```

TRY 2

In [17]:
```
import os, re, numpy as np, torch, torch.nn as nn, torch.nn.functional as F
from torch.utils.data import TensorDataset, DataLoader, random_split
from pathlib import Path
from tqdm import tqdm
import math

# set device
DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
print("Using device:", DEVICE)
```

```
Using device: cuda
```

In [20]:
```
DATA_PATH = Path("C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/da

def parse_uci_lines(lines):
    pairs = []
    for line in lines:
        line = line.strip()
        if not line or line.startswith("#"):
            continue
        try:
            lab, name, seq = line.split(",", 2)
        except:
            continue
        seq = seq.replace("\t", "").strip().upper()
        seq = re.sub(r"[^ACGT]", "A", seq)
        label = 1 if lab == "+" else 0
        pairs.append((label, seq))
```

```python
    return pairs

if DATA_PATH.exists():
    pairs = parse_uci_lines(DATA_PATH.read_text().splitlines())
    print(f"Parsed {len(pairs)} sequences from {DATA_PATH}")
    print("Example:", pairs[0])
else:
    raise FileNotFoundError("promoters.data file not found.")
```

```
Parsed 106 sequences from C:\Users\Akshat\Desktop\Hopkins\Fall_2025\Computational_genomics\Project\Cancer-Tumor-promoter-Gene
ration\data\raw\promoters.data
Example: (1, 'TACTAGCAATACGCTTGCGTTCGGTGGTTAAGTATGTATAATGCGCGGGCTTGTCGT')
```

In [21]:
```python
import re, numpy as np
from pathlib import Path

L = 57  # window length for Phase 1
base2idx = {"A":0, "C":1, "G":2, "T":3}

def one_hot_and_mask(seq, L=200):
    s = re.sub(r"[^ACGTacgt]", "A", seq).upper()[:L]  # truncate, don't pad with A
    x = np.zeros((L,4), dtype=np.float32)
    m = np.zeros((L,),   dtype=np.float32)
    for i,ch in enumerate(s):
        x[i, base2idx[ch]] = 1.0
        m[i] = 1.0
    return x, m

X_list, M_list, y_list = [], [], []
for lab, seq in pairs:
    x, m = one_hot_and_mask(seq, L=L)
    X_list.append(x); M_list.append(m); y_list.append(lab)

X = np.stack(X_list).astype("float32")  # [N,L,4]
M = np.stack(M_list).astype("float32")  # [N,L]
y = np.array(y_list)

Path("data/processed").mkdir(parents=True, exist_ok=True)
np.savez_compressed("data/processed/uci_promoters_masked.npz", X=X, M=M, y=y)
X.shape, M.shape, y.shape, M.sum(axis=1).mean()
```

Out[21]:
```
((106, 57, 4), (106, 57), (106,), np.float32(57.0))
```

In [22]:
```python
PROC_PATH = Path("data/processed")
PROC_PATH.mkdir(parents=True, exist_ok=True)
np.savez_compressed(PROC_PATH / "uci_promoters_masked.npz", X=X, M=M, y=y)
print("Saved dataset →", PROC_PATH / "uci_promoters_masked.npz")
```

```
Saved dataset → data\processed\uci_promoters_masked.npz
```

In [23]:
```python
import torch
from torch.utils.data import TensorDataset, DataLoader, random_split

dat = np.load("data/processed/uci_promoters_masked.npz")
Xt = torch.from_numpy(dat["X"])   # [N,L,4] float32 (0/1 only at real positions)
Mt = torch.from_numpy(dat["M"])   # [N,L]   float32 (1=real, 0=pad)

ds = TensorDataset(Xt, Mt)
n_val = max(1, int(0.15 * len(ds)))
n_train = len(ds) - n_val
train_ds, val_ds = random_split(ds, [n_train, n_val], generator=torch.Generator().manual_seed(42))

BATCH = 32
train_dl = DataLoader(train_ds, batch_size=BATCH, shuffle=True, drop_last=False)
val_dl   = DataLoader(val_ds,   batch_size=BATCH, shuffle=False, drop_last=False)

DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
DEVICE, len(train_ds), len(val_ds)
```

Out[23]:
```
('cuda', 91, 15)
```

In [24]:
```python
import torch.nn as nn
import torch.nn.functional as F

class ConvVAE(nn.Module):
    def __init__(self, L=57, z_dim=64, base_c=32):
        super().__init__()
        self.L = L
        self.z_dim = z_dim

        # Encoder
        self.enc = nn.Sequential(
            nn.Conv1d(4, base_c, 7, padding=3), nn.ReLU(),
            nn.Conv1d(base_c, base_c*2, 5, padding=2), nn.ReLU(),
            nn.AdaptiveAvgPool1d(1)
        )
        self.mu     = nn.Linear(base_c*2, z_dim)
        self.logvar = nn.Linear(base_c*2, z_dim)

        # Decoder (a bit deeper)
        self.fc  = nn.Linear(z_dim, base_c*2)
        self.dec = nn.Sequential(
            nn.Conv1d(base_c*2, base_c, 7, padding=3), nn.ReLU(),
            nn.Conv1d(base_c, base_c, 5, padding=2),   nn.ReLU(),
            nn.Conv1d(base_c, 4, 1)                    # logits per base
        )

    def encode(self, x):                         # x: [B,L,4]
        h = self.enc(x.transpose(1,2)).squeeze(-1)  # [B,2c]
        return self.mu(h), self.logvar(h)

    def reparam(self, mu, logvar, sample=True):
        if not sample:
            return mu
        std = (0.5*logvar).exp()
        eps = torch.randn_like(std)
        return mu + eps*std

    def decode_logits(self, z):                  # z: [B,z]
        h = self.fc(z).unsqueeze(-1).repeat(1,1,self.L)  # [B,2c,L]
        return self.dec(h).transpose(1,2)                # [B,L,4]

    def forward(self, x, sample=True):
        mu, logvar = self.encode(x)
        z = self.reparam(mu, logvar, sample=sample)
        logits = self.decode_logits(z)
        return logits, z, mu, logvar
```

In [25]:
```
import math, torch

# Reverse-complement augmentation on one-hot [B,L,4]
def reverse_complement_onehot(x):  # x in {0,1}, float ok
    # swap channels A<->T (0<->3), C<->G (1<->2), and reverse along length
    x_rc = x.flip(dims=[1]).clone()  # reverse length
    x_rc = x_rc[..., [3,2,1,0]]      # swap channels
    return x_rc

# Masked cross-entropy (only real bases contribute)
def masked_ce_recon(logits, x, mask):
    # logits: [B,L,4], x: [B,L,4] one-hot, mask: [B,L]
    target_idx = x.argmax(dim=-1)        # [B,L]
    ce = F.cross_entropy(
        logits.reshape(-1,4),
        target_idx.reshape(-1),
        reduction='none'
    ).reshape(target_idx.shape)          # [B,L]
    denom = mask.sum() + 1e-8
    return (ce * mask).sum() / denom

# Small entropy bonus to avoid single-base collapse
def entropy_bonus(logits, mask, weight=1e-3):
    # encourage per-position entropy (discourage peaky all-one-base)
    p = F.softmax(logits, dim=-1)                     # [B,L,4]
    ent = -(p * (p.clamp_min(1e-8)).log()).sum(-1)  # [B,L]
    denom = mask.sum() + 1e-8
    return -weight * (ent * mask).sum() / denom     # negative: we SUBTRACT entropy

def kl_gaussian(mu, logvar):
    return -0.5 * torch.mean(1 + logvar - mu.pow(2) - logvar.exp())

def kl_anneal(epoch, total=80, beta_max=0.1):
    return min(beta_max, beta_max * (epoch / max(1,total)))
```

In [26]:
```
# Adjust model + optimizer for 57 bp data
model = ConvVAE(L=57, z_dim=64, base_c=32).to(DEVICE)

# slightly slower learning rate for stability
opt = torch.optim.AdamW(model.parameters(), lr=3e-3, weight_decay=1e-4)
CLIP = 1.0

EPOCHS_PRE = 120   # longer AE warm-up since dataset is tiny
EPOCHS_VAE = 150   # same fine-tune length

best_val = float("inf")
Path("models").mkdir(parents=True, exist_ok=True)

print("\n== Phase 1: Autoencoder warm-up (deterministic z, masked CE + entropy bonus) ==")
for epoch in range(1, EPOCHS_PRE + 1):
    model.train()
    tr = 0.0
    for xb, mb in train_dl:
        xb, mb = xb.to(DEVICE), mb.to(DEVICE)

        # --- reverse complement + light noise augmentation ---
        if torch.rand(1).item() < 0.5:
            xb = reverse_complement_onehot(xb)
        xb = (xb + 0.05 * torch.randn_like(xb)).clamp(0, 1)

        # deterministic forward pass
        logits, z, mu, logvar = model(xb, sample=False)
        recon = masked_ce_recon(logits, xb, mb)
        entro = entropy_bonus(logits, mb, weight=1e-3)
```

```python
        loss = recon + entro

        opt.zero_grad(set_to_none=True)
        loss.backward()
        torch.nn.utils.clip_grad_norm_(model.parameters(), CLIP)
        opt.step()
        tr += loss.item() * xb.size(0)
    tr /= len(train_dl.dataset)

    # ---- validation ----
    model.eval()
    va = 0.0
    with torch.no_grad():
        for xb, mb in val_dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            logits, z, mu, logvar = model(xb, sample=False)
            recon = masked_ce_recon(logits, xb, mb)
            entro = entropy_bonus(logits, mb, weight=1e-3)
            va += (recon + entro).item() * xb.size(0)
    va /= len(val_dl.dataset)

    print(f"Pre {epoch:03d} | train={tr:.4f} | val={va:.4f}")

print("\n== Phase 2: VAE fine-tune (masked CE + β·KL + entropy bonus) ==")
for epoch in range(1, EPOCHS_VAE + 1):
    beta = kl_anneal(epoch, total=80, beta_max=0.05)  # gentler KL schedule
    model.train()
    tr = 0.0

    for xb, mb in train_dl:
        xb, mb = xb.to(DEVICE), mb.to(DEVICE)
        if torch.rand(1).item() < 0.5:
            xb = reverse_complement_onehot(xb)
        xb = (xb + 0.05 * torch.randn_like(xb)).clamp(0, 1)

        logits, z, mu, logvar = model(xb, sample=True)
        recon = masked_ce_recon(logits, xb, mb)
        kl = kl_gaussian(mu, logvar)
        entro = entropy_bonus(logits, mb, weight=1e-3)
        loss = recon + beta * kl + entro

        opt.zero_grad(set_to_none=True)
        loss.backward()
        torch.nn.utils.clip_grad_norm_(model.parameters(), CLIP)
        opt.step()
        tr += loss.item() * xb.size(0)
    tr /= len(train_dl.dataset)

    # ---- validation ----
    model.eval()
    va = 0.0
    with torch.no_grad():
        for xb, mb in val_dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            logits, z, mu, logvar = model(xb, sample=True)
            recon = masked_ce_recon(logits, xb, mb)
            kl = kl_gaussian(mu, logvar)
            entro = entropy_bonus(logits, mb, weight=1e-3)
            va += (recon + beta * kl + entro).item() * xb.size(0)
    va /= len(val_dl.dataset)

    print(f"VAE {epoch:03d} | train={tr:.4f} | val={va:.4f} | β={beta:.3f}")

    if va < best_val:
        best_val = va
        torch.save(model.state_dict(), "models/vae_promoter_57bp.pt")
        print(f"✅ Saved best (val={best_val:.4f})")
```

```
== Phase 1: Autoencoder warm-up (deterministic z, masked CE + entropy bonus) ==
Pre 001 | train=1.3889 | val=1.3805
Pre 002 | train=1.3820 | val=1.3809
Pre 003 | train=1.3827 | val=1.3821
Pre 004 | train=1.3804 | val=1.3826
Pre 005 | train=1.3835 | val=1.3810
Pre 006 | train=1.3813 | val=1.3787
Pre 007 | train=1.3792 | val=1.3757
Pre 008 | train=1.3775 | val=1.3725
Pre 009 | train=1.3754 | val=1.3680
Pre 010 | train=1.3742 | val=1.3720
Pre 011 | train=1.3777 | val=1.3681
Pre 012 | train=1.3720 | val=1.3690
Pre 013 | train=1.3716 | val=1.3716
Pre 014 | train=1.3726 | val=1.3684
Pre 015 | train=1.3715 | val=1.3678
Pre 016 | train=1.3696 | val=1.3679
Pre 017 | train=1.3707 | val=1.3680
Pre 018 | train=1.3710 | val=1.3672
Pre 019 | train=1.3689 | val=1.3670
Pre 020 | train=1.3693 | val=1.3679
Pre 021 | train=1.3700 | val=1.3683
Pre 022 | train=1.3686 | val=1.3690
Pre 023 | train=1.3704 | val=1.3689
Pre 024 | train=1.3692 | val=1.3683
Pre 025 | train=1.3688 | val=1.3680
Pre 026 | train=1.3691 | val=1.3688
Pre 027 | train=1.3687 | val=1.3693
Pre 028 | train=1.3685 | val=1.3693
Pre 029 | train=1.3684 | val=1.3693
Pre 030 | train=1.3680 | val=1.3691
Pre 031 | train=1.3684 | val=1.3685
Pre 032 | train=1.3689 | val=1.3684
Pre 033 | train=1.3674 | val=1.3688
Pre 034 | train=1.3670 | val=1.3684
Pre 035 | train=1.3670 | val=1.3686
Pre 036 | train=1.3681 | val=1.3686
Pre 037 | train=1.3684 | val=1.3693
Pre 038 | train=1.3685 | val=1.3712
Pre 039 | train=1.3678 | val=1.3717
Pre 040 | train=1.3672 | val=1.3707
Pre 041 | train=1.3692 | val=1.3693
Pre 042 | train=1.3667 | val=1.3678
Pre 043 | train=1.3676 | val=1.3671
Pre 044 | train=1.3661 | val=1.3687
Pre 045 | train=1.3654 | val=1.3659
Pre 046 | train=1.3641 | val=1.3648
Pre 047 | train=1.3601 | val=1.3686
Pre 048 | train=1.3623 | val=1.3670
Pre 049 | train=1.3604 | val=1.3635
Pre 050 | train=1.3608 | val=1.3626
Pre 051 | train=1.3587 | val=1.3601
Pre 052 | train=1.3588 | val=1.3600
Pre 053 | train=1.3575 | val=1.3604
Pre 054 | train=1.3576 | val=1.3611
Pre 055 | train=1.3568 | val=1.3602
Pre 056 | train=1.3570 | val=1.3598
Pre 057 | train=1.3575 | val=1.3605
Pre 058 | train=1.3560 | val=1.3599
Pre 059 | train=1.3560 | val=1.3597
Pre 060 | train=1.3565 | val=1.3593
Pre 061 | train=1.3563 | val=1.3596
Pre 062 | train=1.3550 | val=1.3598
Pre 063 | train=1.3561 | val=1.3603
Pre 064 | train=1.3544 | val=1.3598
Pre 065 | train=1.3550 | val=1.3598
Pre 066 | train=1.3541 | val=1.3600
Pre 067 | train=1.3541 | val=1.3616
Pre 068 | train=1.3555 | val=1.3601
Pre 069 | train=1.3559 | val=1.3587
Pre 070 | train=1.3551 | val=1.3584
Pre 071 | train=1.3546 | val=1.3588
Pre 072 | train=1.3536 | val=1.3588
Pre 073 | train=1.3541 | val=1.3589
Pre 074 | train=1.3538 | val=1.3593
Pre 075 | train=1.3531 | val=1.3597
Pre 076 | train=1.3529 | val=1.3608
Pre 077 | train=1.3525 | val=1.3601
Pre 078 | train=1.3547 | val=1.3599
Pre 079 | train=1.3535 | val=1.3597
Pre 080 | train=1.3533 | val=1.3599
Pre 081 | train=1.3547 | val=1.3596
Pre 082 | train=1.3541 | val=1.3595
Pre 083 | train=1.3542 | val=1.3611
Pre 084 | train=1.3530 | val=1.3611
Pre 085 | train=1.3526 | val=1.3621
Pre 086 | train=1.3528 | val=1.3588
Pre 087 | train=1.3531 | val=1.3579
Pre 088 | train=1.3521 | val=1.3578
Pre 089 | train=1.3530 | val=1.3587
Pre 090 | train=1.3527 | val=1.3586
Pre 091 | train=1.3516 | val=1.3604
Pre 092 | train=1.3521 | val=1.3604
Pre 093 | train=1.3514 | val=1.3608
Pre 094 | train=1.3534 | val=1.3610
Pre 095 | train=1.3536 | val=1.3605
Pre 096 | train=1.3535 | val=1.3605
Pre 097 | train=1.3522 | val=1.3598
Pre 098 | train=1.3518 | val=1.3612
Pre 099 | train=1.3514 | val=1.3608
Pre 100 | train=1.3517 | val=1.3596
Pre 101 | train=1.3512 | val=1.3585
Pre 102 | train=1.3510 | val=1.3614
Pre 103 | train=1.3536 | val=1.3585
Pre 104 | train=1.3512 | val=1.3585
Pre 105 | train=1.3512 | val=1.3584
Pre 106 | train=1.3510 | val=1.3622
Pre 107 | train=1.3523 | val=1.3603
Pre 108 | train=1.3509 | val=1.3602
Pre 109 | train=1.3502 | val=1.3589
Pre 110 | train=1.3508 | val=1.3611
Pre 111 | train=1.3487 | val=1.3597
Pre 112 | train=1.3493 | val=1.3633
Pre 113 | train=1.3528 | val=1.3570
Pre 114 | train=1.3510 | val=1.3628
Pre 115 | train=1.3524 | val=1.3575
Pre 116 | train=1.3514 | val=1.3561
Pre 117 | train=1.3501 | val=1.3600
Pre 118 | train=1.3492 | val=1.3568
Pre 119 | train=1.3468 | val=1.3556
Pre 120 | train=1.3470 | val=1.3561

== Phase 2: VAE fine-tune (masked CE + β·KL + entropy bonus) ==
VAE 001 | train=1.5720 | val=1.4159 | β=0.001
✅ Saved best (val=1.4159)
VAE 002 | train=1.4028 | val=1.3947 | β=0.001
✅ Saved best (val=1.3947)
VAE 003 | train=1.3925 | val=1.3882 | β=0.002
✅ Saved best (val=1.3882)
VAE 004 | train=1.3848 | val=1.3859 | β=0.003
✅ Saved best (val=1.3859)
VAE 005 | train=1.3840 | val=1.3822 | β=0.003
✅ Saved best (val=1.3822)
VAE 006 | train=1.3868 | val=1.3807 | β=0.004
✅ Saved best (val=1.3807)
VAE 007 | train=1.3871 | val=1.3852 | β=0.004
VAE 008 | train=1.3858 | val=1.3790 | β=0.005
✅ Saved best (val=1.3790)
VAE 009 | train=1.3850 | val=1.3811 | β=0.006
VAE 010 | train=1.3836 | val=1.3856 | β=0.006
VAE 011 | train=1.3856 | val=1.3913 | β=0.007
VAE 012 | train=1.3831 | val=1.3780 | β=0.007
✅ Saved best (val=1.3780)
VAE 013 | train=1.3844 | val=1.3885 | β=0.008
VAE 014 | train=1.3830 | val=1.3780 | β=0.009
✅ Saved best (val=1.3780)
VAE 015 | train=1.3810 | val=1.3775 | β=0.009
✅ Saved best (val=1.3775)
VAE 016 | train=1.3811 | val=1.3784 | β=0.010
VAE 017 | train=1.3802 | val=1.3787 | β=0.011
VAE 018 | train=1.3798 | val=1.3804 | β=0.011
VAE 019 | train=1.3784 | val=1.3817 | β=0.012
VAE 020 | train=1.3776 | val=1.3784 | β=0.013
VAE 021 | train=1.3805 | val=1.3791 | β=0.013
VAE 022 | train=1.3789 | val=1.4674 | β=0.014
VAE 023 | train=1.3870 | val=1.3782 | β=0.014
VAE 024 | train=1.3808 | val=1.3777 | β=0.015
VAE 025 | train=1.3800 | val=1.3899 | β=0.016
VAE 026 | train=1.3839 | val=1.3893 | β=0.016
VAE 027 | train=1.3853 | val=1.3879 | β=0.017
VAE 028 | train=1.3857 | val=1.3832 | β=0.017
VAE 029 | train=1.3823 | val=1.3819 | β=0.018
VAE 030 | train=1.3814 | val=1.3809 | β=0.019
VAE 031 | train=1.3798 | val=1.3750 | β=0.019
✅ Saved best (val=1.3750)
VAE 032 | train=1.3786 | val=1.4029 | β=0.020
VAE 033 | train=1.3811 | val=1.3753 | β=0.021
VAE 034 | train=1.3854 | val=1.3755 | β=0.021
VAE 035 | train=1.3775 | val=1.3787 | β=0.022
VAE 036 | train=1.3778 | val=1.3787 | β=0.023
VAE 037 | train=1.3768 | val=1.3779 | β=0.023
VAE 038 | train=1.3759 | val=1.3782 | β=0.024
VAE 039 | train=1.3775 | val=1.3768 | β=0.024
VAE 040 | train=1.3764 | val=1.3768 | β=0.025
VAE 041 | train=1.3770 | val=1.3756 | β=0.026
VAE 042 | train=1.3761 | val=1.3770 | β=0.026
VAE 043 | train=1.3744 | val=1.3763 | β=0.027
VAE 044 | train=1.3754 | val=1.3758 | β=0.028
VAE 045 | train=1.3742 | val=1.3734 | β=0.028
✅ Saved best (val=1.3734)
VAE 046 | train=1.3741 | val=1.3752 | β=0.029
VAE 047 | train=1.3745 | val=1.3753 | β=0.029
VAE 048 | train=1.3740 | val=1.3752 | β=0.030
VAE 049 | train=1.3737 | val=1.3762 | β=0.031
VAE 050 | train=1.3737 | val=1.3740 | β=0.031
VAE 051 | train=1.3735 | val=1.3746 | β=0.032
VAE 052 | train=1.3737 | val=1.4058 | β=0.033
VAE 053 | train=1.3822 | val=1.3742 | β=0.033
VAE 054 | train=1.3726 | val=1.3742 | β=0.034
VAE 055 | train=1.3749 | val=1.3737 | β=0.034
VAE 056 | train=1.3735 | val=1.3744 | β=0.035
VAE 057 | train=1.3730 | val=1.3757 | β=0.036
VAE 058 | train=1.3752 | val=1.3742 | β=0.036
VAE 059 | train=1.3730 | val=1.3759 | β=0.037
VAE 060 | train=1.3738 | val=1.3737 | β=0.038
VAE 061 | train=1.3731 | val=1.3753 | β=0.038
VAE 062 | train=1.3750 | val=1.3791 | β=0.039
VAE 063 | train=1.3738 | val=1.3752 | β=0.039
VAE 064 | train=1.3726 | val=1.3738 | β=0.040
VAE 065 | train=1.3739 | val=1.3758 | β=0.041
VAE 066 | train=1.3714 | val=1.3759 | β=0.041
VAE 067 | train=1.3709 | val=1.3737 | β=0.042
VAE 068 | train=1.3725 | val=1.3715 | β=0.043
✅ Saved best (val=1.3715)
VAE 069 | train=1.3707 | val=1.3725 | β=0.043
VAE 070 | train=1.3708 | val=1.3733 | β=0.044
VAE 071 | train=1.3725 | val=1.3720 | β=0.044
VAE 072 | train=1.3714 | val=1.3719 | β=0.045
VAE 073 | train=1.3706 | val=1.3707 | β=0.046
✅ Saved best (val=1.3707)
VAE 074 | train=1.3712 | val=1.3729 | β=0.046
VAE 075 | train=1.3682 | val=1.3707 | β=0.047
✅ Saved best (val=1.3707)
VAE 076 | train=1.3681 | val=1.3710 | β=0.048
VAE 077 | train=1.3675 | val=1.3722 | β=0.048
VAE 078 | train=1.3687 | val=1.3706 | β=0.049
✅ Saved best (val=1.3706)
VAE 079 | train=1.3653 | val=1.3688 | β=0.049
✅ Saved best (val=1.3688)
VAE 080 | train=1.3690 | val=1.3738 | β=0.050
VAE 081 | train=1.3689 | val=1.3683 | β=0.050
✅ Saved best (val=1.3683)
VAE 082 | train=1.3677 | val=1.3712 | β=0.050
VAE 083 | train=1.3691 | val=1.3714 | β=0.050
VAE 084 | train=1.3660 | val=1.3727 | β=0.050
VAE 085 | train=1.3661 | val=1.3674 | β=0.050
✅ Saved best (val=1.3674)
VAE 086 | train=1.3688 | val=1.3727 | β=0.050
VAE 087 | train=1.3678 | val=1.3685 | β=0.050
VAE 088 | train=1.3671 | val=1.3690 | β=0.050
VAE 089 | train=1.3657 | val=1.3666 | β=0.050
✅ Saved best (val=1.3666)
VAE 090 | train=1.3672 | val=1.3684 | β=0.050
VAE 091 | train=1.3667 | val=1.3658 | β=0.050
✅ Saved best (val=1.3658)
VAE 092 | train=1.3664 | val=1.3685 | β=0.050
VAE 093 | train=1.3668 | val=1.3696 | β=0.050
VAE 094 | train=1.3663 | val=1.3643 | β=0.050
✅ Saved best (val=1.3643)
VAE 095 | train=1.3670 | val=1.3659 | β=0.050
VAE 096 | train=1.3668 | val=1.3662 | β=0.050
VAE 097 | train=1.3669 | val=1.3668 | β=0.050
VAE 098 | train=1.3643 | val=1.3637 | β=0.050
✅ Saved best (val=1.3637)
VAE 099 | train=1.3660 | val=1.3691 | β=0.050
VAE 100 | train=1.3664 | val=1.3681 | β=0.050
VAE 101 | train=1.3662 | val=1.3689 | β=0.050
VAE 102 | train=1.3659 | val=1.3665 | β=0.050
VAE 103 | train=1.3674 | val=1.3674 | β=0.050
VAE 104 | train=1.3665 | val=1.3669 | β=0.050
VAE 105 | train=1.3668 | val=1.3709 | β=0.050
VAE 106 | train=1.3666 | val=1.3666 | β=0.050
VAE 107 | train=1.3669 | val=1.3720 | β=0.050
VAE 108 | train=1.3658 | val=1.3673 | β=0.050
VAE 109 | train=1.3658 | val=1.3635 | β=0.050
✅ Saved best (val=1.3635)
VAE 110 | train=1.3651 | val=1.3641 | β=0.050
VAE 111 | train=1.3638 | val=1.3650 | β=0.050
VAE 112 | train=1.3658 | val=1.3632 | β=0.050
✅ Saved best (val=1.3632)
VAE 113 | train=1.3646 | val=1.3670 | β=0.050
VAE 114 | train=1.3630 | val=1.3673 | β=0.050
VAE 115 | train=1.3652 | val=1.3666 | β=0.050
VAE 116 | train=1.3657 | val=1.3651 | β=0.050
VAE 117 | train=1.3671 | val=1.3638 | β=0.050
VAE 118 | train=1.3664 | val=1.3674 | β=0.050
VAE 119 | train=1.3654 | val=1.3662 | β=0.050
VAE 120 | train=1.3645 | val=1.3692 | β=0.050
VAE 121 | train=1.3647 | val=1.3646 | β=0.050
VAE 122 | train=1.3643 | val=1.3671 | β=0.050
VAE 123 | train=1.3651 | val=1.3680 | β=0.050
VAE 124 | train=1.3641 | val=1.3640 | β=0.050
VAE 125 | train=1.3634 | val=1.3668 | β=0.050
VAE 126 | train=1.3643 | val=1.3677 | β=0.050
VAE 127 | train=1.3644 | val=1.3633 | β=0.050
VAE 128 | train=1.3631 | val=1.3671 | β=0.050
VAE 129 | train=1.3650 | val=1.3646 | β=0.050
VAE 130 | train=1.3643 | val=1.3658 | β=0.050
VAE 131 | train=1.3659 | val=1.3673 | β=0.050
VAE 132 | train=1.3639 | val=1.3664 | β=0.050
VAE 133 | train=1.3638 | val=1.3699 | β=0.050
VAE 134 | train=1.3633 | val=1.3671 | β=0.050
VAE 135 | train=1.3655 | val=1.3640 | β=0.050
VAE 136 | train=1.3643 | val=1.3654 | β=0.050
VAE 137 | train=1.3651 | val=1.3691 | β=0.050
VAE 138 | train=1.3638 | val=1.3648 | β=0.050
VAE 139 | train=1.3634 | val=1.3647 | β=0.050
VAE 140 | train=1.3630 | val=1.3632 | β=0.050
✅ Saved best (val=1.3632)
VAE 141 | train=1.3652 | val=1.3667 | β=0.050
VAE 142 | train=1.3636 | val=1.3667 | β=0.050
VAE 143 | train=1.3643 | val=1.3643 | β=0.050
VAE 144 | train=1.3624 | val=1.3651 | β=0.050
VAE 145 | train=1.3659 | val=1.3674 | β=0.050
VAE 146 | train=1.3639 | val=1.3676 | β=0.050
VAE 147 | train=1.3635 | val=1.3674 | β=0.050
VAE 148 | train=1.3642 | val=1.3642 | β=0.050
VAE 149 | train=1.3644 | val=1.3652 | β=0.050
VAE 150 | train=1.3641 | val=1.3676 | β=0.050
```

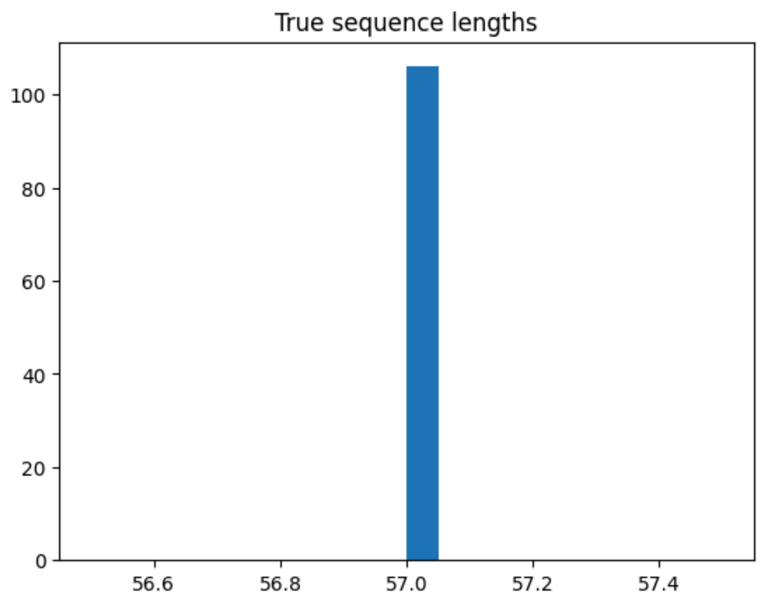
In [27]:
```python
bases = np.array(list("ACGT"))
xb, mb = next(iter(val_dl))
xb = xb.to(DEVICE)
model.load_state_dict(torch.load("models/vae_promoter_57bp.pt", map_location=DEVICE))
model.eval()

with torch.no_grad():
    logits, _, _, _ = model(xb)
pred_idx = logits.argmax(-1).cpu().numpy()
true_idx = xb.argmax(-1).cpu().numpy()

for i in range(3):
    print(f"\nSample {i+1}")
    print("True :", "".join(bases[true_idx[i]][:120]))
    print("Recon:", "".join(bases[pred_idx[i]][:120]))
```

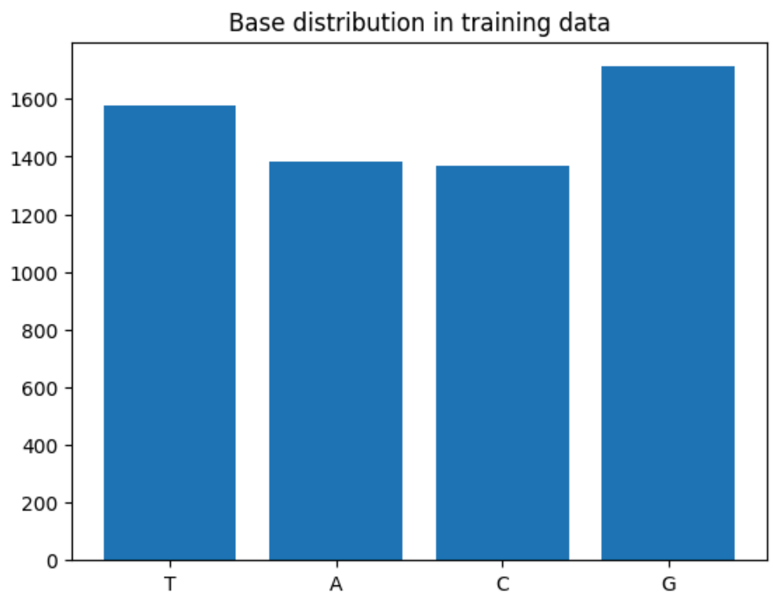
```
Sample 1
True : TGTTGATTTTCCATGCGGTGTTTTGCGCAATGTTAATCGCTTTGTACACCTCAGGCA
Recon: TTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTTCCCTT

Sample 2
True : ATTACAAAAAGTGCTTTCTGAACTGAACAAAAAAGAGTAAAGTTAGTCGCGTAGGGT
Recon: AAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA

Sample 3
True : TTACGTTGGCGACCGCTAGGACTTTCTTGTTGATTTTCCATGCGGTGTTTTGCGCAA
Recon: CCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCCTT
```

In [28]:
```python
from collections import Counter
counts = Counter("".join(seq for _, seq in pairs))
{b: counts[b]/sum(counts.values()) for b in "ACGT"}
```

Out[28]:
```
{'A': 0.260675273088381 34,
 'C': 0.22922873220787818,
 'G': 0.2267461105594174,
 'T': 0.28334988414432305}
```

In [29]:
```python
import matplotlib.pyplot as plt

lengths = [m.sum() for m in M]
plt.hist(lengths, bins=20); plt.title("True sequence lengths"); plt.show()

counts = Counter("".join(seq for _, seq in pairs))
plt.bar(counts.keys(), [counts[k] for k in "ACGT"])
plt.title("Base distribution in training data"); plt.show()
```





Try 3

In [30]:
```
# === Cell 1: Setup & Imports ===
import os, re, math, random, numpy as np
from pathlib import Path

import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import TensorDataset, DataLoader, random_split

from tqdm import tqdm

# Reproducibility
SEED = 42
random.seed(SEED); np.random.seed(SEED); torch.manual_seed(SEED)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
print("Device:", DEVICE)
```

```
Device: cuda
```

In [32]:
```
# === Cell 2: Parse UCI promoters and re-encode to 57 bp ===
DATA_PATH = Path("C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/da
assert DATA_PATH.exists(), f"Missing file: {DATA_PATH}"

def parse_uci_lines(lines):
    pairs = []
    for line in lines:
        line = line.strip()
        if not line or line.startswith("#"):
            continue
        # Format: "+,GENE,sequence" or "-,GENE,sequence"
        try:
            lab, gene, seq = line.split(",", 2)
        except:
            continue
        seq = seq.replace("\t", "").strip().upper()
        seq = re.sub(r"[^ACGT]", "A", seq)
        label = 1 if lab == "+" else 0
        pairs.append((label, seq))
    return pairs

pairs = parse_uci_lines(DATA_PATH.read_text().splitlines())
print(f"Parsed {len(pairs)} sequences")
print("Example:", pairs[0])
```

```
Parsed 106 sequences
Example: (1, 'TACTAGCAATACGCTTGCGTTCGGTGGTTAAGTATGTATAATGCGCGGGCTTGTCGT')
```

In [33]:
```
# === Cell 3: One-hot encode to L=57 with mask ===
L = 57  # actual observed length in this dataset

base2idx = {"A":0, "C":1, "G":2, "T":3}

def one_hot_and_mask(seq, L=57):
    s = seq[:L]                       # truncate to 57
    x = np.zeros((L,4), dtype=np.float32)
    m = np.zeros((L,),  dtype=np.float32)
    for i,ch in enumerate(s):
        x[i, base2idx[ch]] = 1.0
        m[i] = 1.0
    return x, m

X_list, M_list, y_list = [], [], []
for lab, seq in pairs:
    x, m = one_hot_and_mask(seq, L=L)
    X_list.append(x); M_list.append(m); y_list.append(lab)

X = np.stack(X_list).astype("float32")  # [N,57,4]
M = np.stack(M_list).astype("float32")  # [N,57]
y = np.array(y_list)

print("Shapes:", X.shape, M.shape, y.shape)
print("All mask rows sum to:", M.sum(axis=1)[:5], "(should be 57s)")
```

```
Shapes: (106, 57, 4) (106, 57) (106,)
All mask rows sum to: [57. 57. 57. 57. 57.] (should be 57s)
```

In [35]:
```
# === Cell 4: Save/Load processed arrays & DataLoaders ===
Path("data/processed").mkdir(parents=True, exist_ok=True)
np.savez_compressed("data/processed/uci_57bp.npz", X=X, M=M, y=y)
print("Saved → data/processed/uci_57bp.npz")

dat = np.load("data/processed/uci_57bp.npz")
Xt = torch.from_numpy(dat["X"])  # [N,57,4] float32
Mt = torch.from_numpy(dat["M"])  # [N,57]   float32

ds = TensorDataset(Xt, Mt)
n_val = max(1, int(0.15 * len(ds)))
n_train = len(ds) - n_val
train_ds, val_ds = random_split(ds, [n_train, n_val], generator=torch.Generator().manual_seed(42))

BATCH = 16
train_dl = DataLoader(train_ds, batch_size=BATCH, shuffle=True,  drop_last=False)
val_dl   = DataLoader(val_ds,   batch_size=BATCH, shuffle=False, drop_last=False)

print(f"Train={len(train_ds)}  Val={len(val_ds)}  Batch={BATCH}  L={Xt.shape[1]}")
```

```
Saved → data/processed/uci_57bp.npz
Train=91  Val=15  Batch=16  L=57
```

In [36]:
```
# === Cell 5: Tiny Transformer Autoencoder ===
class TinyTransformerAE(nn.Module):
    def __init__(self, L=57, emb_dim=32, nhead=4, depth=2, ff_dim=64, p_drop=0.1):
        super().__init__()
        self.L = L
        self.embed = nn.Linear(4, emb_dim)
        self.pos   = nn.Parameter(torch.randn(1, L, emb_dim))
        enc_layer  = nn.TransformerEncoderLayer(
            d_model=emb_dim, nhead=nhead, dim_feedforward=ff_dim,
            dropout=p_drop, batch_first=True, norm_first=True
        )
        self.encoder = nn.TransformerEncoder(enc_layer, num_layers=depth)
        self.dec = nn.Sequential(
            nn.Linear(emb_dim, ff_dim),
            nn.ReLU(),
            nn.Dropout(p_drop),
            nn.Linear(ff_dim, 4)          # logits per base
        )

        # zero-init final layer helps avoid constant-base bias at start
        nn.init.zeros_(self.dec[-1].weight)
        nn.init.zeros_(self.dec[-1].bias)

    def forward(self, x):  # x: [B,L,4] one-hot
        h = self.embed(x) + self.pos     # [B,L,emb]
        h = self.encoder(h)              # [B,L,emb]
        logits = self.dec(h)             # [B,L,4]
        return logits

model = TinyTransformerAE(L=L, emb_dim=32, nhead=4, depth=2, ff_dim=64, p_drop=0.2).to(DEVICE)
n_params = sum(p.numel() for p in model.parameters())
print(f"Model params: {n_params/1e3:.1f}K")
```

```
Model params: 21.4K
C:\Users\Akshat\AppData\Roaming\Python\Python313\site-packages\torch\nn\modules\transformer.py:392: UserWarning: enable_neste
d_tensor is True, but self.use_nested_tensor is False because encoder_layer.norm_first was True
  warnings.warn(
```

In [37]:

```
# === Cell 6: Train Loop (masked cross-entropy) ===
def masked_ce(logits, x, mask):
    # logits: [B,L,4], x one-hot [B,L,4], mask [B,L]
    target = x.argmax(-1)                                  # [B,L]
    loss = F.cross_entropy(logits.reshape(-1,4),
                           target.reshape(-1),
                           reduction='none').reshape(target.shape)  # [B,L]
    return (loss * mask).sum() / (mask.sum() + 1e-8)

opt = torch.optim.AdamW(model.parameters(), lr=1e-2, weight_decay=1e-3)
EPOCHS = 300
best = float('inf')
Path("models").mkdir(parents=True, exist_ok=True)

MASK_PROB = 0.1  # mask 20% of bases each batch

def apply_mask(x, m, mask_prob=MASK_PROB):
    x = x.clone()
    mask = torch.rand_like(m) < mask_prob
    for i in range(x.size(0)):
        x[i][mask[i]] = torch.tensor([0.25, 0.25, 0.25, 0.25], device=x.device)
    return x, mask

for epoch in range(1, EPOCHS+1):
    model.train(); tr = 0.0
    for xb, mb in train_dl:
        xb, mb = xb.to(DEVICE), mb.to(DEVICE)

        # randomly mask 20% of bases
        xb_masked, mask_idx = apply_mask(xb, mb)
        logits = model(xb_masked)

        loss = masked_ce(logits, xb, mb * mask_idx.float())  # only predict masked sites

        opt.zero_grad()
        loss.backward()
        opt.step()
        tr += loss.item() * xb.size(0)
    tr /= len(train_dl.dataset)

    # val (same logic)
    model.eval(); va = 0.0
    with torch.no_grad():
        for xb, mb in val_dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            xb_masked, mask_idx = apply_mask(xb, mb)
            logits = model(xb_masked)
            va += masked_ce(logits, xb, mb * mask_idx.float()).item() * xb.size(0)
    va /= len(val_dl.dataset)

    if va < best:
        best = va
        torch.save(model.state_dict(), "models/transformer_promoter_masked.pt")

    if epoch % 20 == 0 or epoch == 1:
        print(f"Epoch {epoch:03d} | train={tr:.4f} | val={va:.4f} | best={best:.4f}")
```

```
Epoch 001 | train=1.3948 | val=1.4038 | best=1.4038
Epoch 020 | train=1.3762 | val=1.4006 | best=1.3664
Epoch 040 | train=1.3867 | val=1.3747 | best=1.3504
Epoch 060 | train=1.3634 | val=1.3790 | best=1.3476
Epoch 080 | train=1.3725 | val=1.3941 | best=1.3324
Epoch 100 | train=1.3597 | val=1.3733 | best=1.3324
Epoch 120 | train=1.3821 | val=1.4247 | best=1.3105
Epoch 140 | train=1.3826 | val=1.3724 | best=1.3105
Epoch 160 | train=1.3652 | val=1.3755 | best=1.3105
Epoch 180 | train=1.3745 | val=1.3888 | best=1.3105
Epoch 200 | train=1.3774 | val=1.3798 | best=1.3105
Epoch 220 | train=1.3785 | val=1.4829 | best=1.3105
Epoch 240 | train=1.3853 | val=1.3877 | best=1.3105
Epoch 260 | train=1.3808 | val=1.3942 | best=1.3105
Epoch 280 | train=1.3827 | val=1.3897 | best=1.3105
Epoch 300 | train=1.3797 | val=1.3884 | best=1.3105
```

In [42]:

```
# === Cell 7: Reconstructions ===
bases = np.array(list("ACGT"))
model.load_state_dict(torch.load("models/transformer_promoter_masked.pt", map_location=DEVICE))
model.eval()
```

```python
xb, mb = next(iter(val_dl))
xb = xb.to(DEVICE)
with torch.no_grad():
    logits = model(xb)
pred_idx = logits.argmax(-1).cpu().numpy()
true_idx = xb.argmax(-1).cpu().numpy()

for i in range(min(5, xb.size(0))):
    print(f"\nSample {i+1}")
    print("True :", "".join(bases[true_idx[i]]))
    print("Recon:", "".join(bases[pred_idx[i]]))
```

```
Sample 1
True : TGTTGATTTTCCATGCGGTGTTTTGCGCAATGTTAATCGCTTTGTACACCTCAGGCA
Recon: ATTTAAATCTCGTTTTGCCATTCGTGTTGTATTTTTTTTAATTTTCTTCCACATTTT

Sample 2
True : ATTACAAAAAGTGCTTTCTGAACTGAACAAAAAAGAGTAAAGTTAGTCGCGTAGGGT
Recon: ATTTAAATAAAGTTTTGCCATTGGTGTTGTATTTTTTTTTATTTTTCTTCCCCTTATT

Sample 3
True : TTACGTTGGCGACCGCTAGGACTTTCTTGTTGATTTTCCATGCGGTGTTTTGCGCAA
Recon: ATTTAAATAACGTTTTGCCATTCGTGTTGTATTTTTTTTAATTTACTTTCACATTTT

Sample 4
True : CTGCAATTTTTCTATTGCGGCCTGCGGAGAACTCCCTATAATGCGCCTCCATCGACA
Recon: CTTTAAATAACGTTTTGCCAGTCTTGTTGTATTTTTTTTATTATACTTCCACATTTT

Sample 5
True : AGGAGGAACTACGCAAGGTTGGAACATCGGAGAGATGCCAGCCAGCGCACCTGCACG
Recon: ATTTAAATAACGTTTTGCCATTTTTGTTGTATTTTTTTTTAATTTTCTTTCATATTTA
```

In [43]:
```python
# === Cell 8 (Optional): Denoising variants ===
model.eval()
xb, mb = next(iter(train_dl))
xb = xb.to(DEVICE)
with torch.no_grad():
    noisy = (xb + 0.10*torch.randn_like(xb)).clamp(0,1)
    logits = model(noisy)
    idx = logits.argmax(-1).cpu().numpy()

gen = ["".join(bases[i]) for i in idx]
print("\nGenerated (denoised) variants from a mini-batch:")
for s in gen[:3]:
    print(s)
```

```
Generated (denoised) variants from a mini-batch:
ATTTAAATAACGTTTTGCCATTGTTGTTGTATTTTTTTTTATTTTTCTTTCACATTTT
ATTTAAATAACGTTTTGCCATTTATGTTGTATTTTTTTATATTATTCTTTCCCATTTT
ATTTAATTAAAGTTTTGCCATTGTTGTTGTATTTTTTTTTAATTTTCTTTCCCTTTTT
```

In [44]:
```python
MASK_PROB = 0.2

def apply_mask(x, m, mask_prob=MASK_PROB):
    x = x.clone()
    mask = torch.rand_like(m) < mask_prob
    for i in range(x.size(0)):
        x[i][mask[i]] = torch.tensor([0.25,0.25,0.25,0.25], device=x.device)
    return x, mask

model.eval()
xb, mb = next(iter(val_dl))
xb, mb = xb.to(DEVICE), mb.to(DEVICE)
xb_masked, mask_idx = apply_mask(xb, mb)

with torch.no_grad():
    logits = model(xb_masked)
pred_idx = logits.argmax(-1).cpu().numpy()
true_idx = xb.argmax(-1).cpu().numpy()
masked = mask_idx.cpu().numpy()

bases = np.array(list("ACGT"))
for i in range(3):
    true = "".join(bases[true_idx[i]])
    recon = "".join(bases[pred_idx[i]])
    mask_visual = "".join(["░" if masked[i,j] else true[j] for j in range(L)])
    print(f"\nSample {i+1}\nMasked: {mask_visual}\nRecon : {recon}\nTrue  : {true}")
```

```
Sample 1
Masked: T░░TGATTTTCCATG░GGTGT░T░GCGC░ATGTTAATCGCTTTGTA░A░░░CA░GCA
Recon : ATTTAAATCTCGTTTTGCCATTCTTGTTGTATTTTTTTTTAATTTTCTTTCACATTTT
True  : TGTTGATTTTCCATGCGGTGTTTTGCGCAATGTTAATCGCTTTGTACACCTCAGGCA

Sample 2
Masked: ATTACAAA░░GTG░TTTCTG░ACTGAAC░░AAAAGAGTAAAGTTAGTCGCGTA░GGT
Recon : ATTTAAATAAAGTTTTGCCATTGGTGTTGTATTTTTTTTTATTTTTCTTTCCCTTATT
True  : ATTACAAAAAGTGCTTTCTGAACTGAACAAAAAAGAGTAAAGTTAGTCGCGTAGGGT

Sample 3
Masked: TT░░GTT░GCGACCG░TAG░AC░TTCTT░TT░ATTTTCC░TGCG░TG░░TTG░GCAA
Recon : ATTTAAATAACGTTTTGCCATTGTTGTTGTATTTTTTATATTTTTCTTTCACATTTT
True  : TTACGTTGGCGACCGCTAGGACTTTCTTGTTGATTTTCCATGCGGTGTTTTGCGCAA
```

In [46]:
```python
def base_accuracy(model, dataloader):
    model.eval()
    total, correct = 0, 0
    with torch.no_grad():
        for xb, mb in dataloader:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            logits = model(xb)
            pred = logits.argmax(-1)
            true = xb.argmax(-1)
            mask = mb.bool()
            correct += (pred[mask] == true[mask]).sum().item()
            total += mask.sum().item()
    return correct / total

acc = base_accuracy(model, val_dl)
print(f"Base Accuracy on Validation: {acc:.3f}")
```
```
Base Accuracy on Validation: 0.292
```

In [48]:
```python
import math
def perplexity(model, dataloader):
    model.eval()
    nll, n_bases = 0.0, 0
    with torch.no_grad():
        for xb, mb in dataloader:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            logits = model(xb)
            target = xb.argmax(-1)
            loss = F.cross_entropy(
                logits.reshape(-1,4),
                target.reshape(-1),
                reduction='none'
            ).reshape(target.shape)
            nll += (loss * mb).sum().item()
            n_bases += mb.sum().item()
    ppl = math.exp(nll / n_bases)
    return ppl

ppl = perplexity(model, val_dl)
print(f"Perplexity: {ppl:.2f}")
```
```
Perplexity: 4.03
```

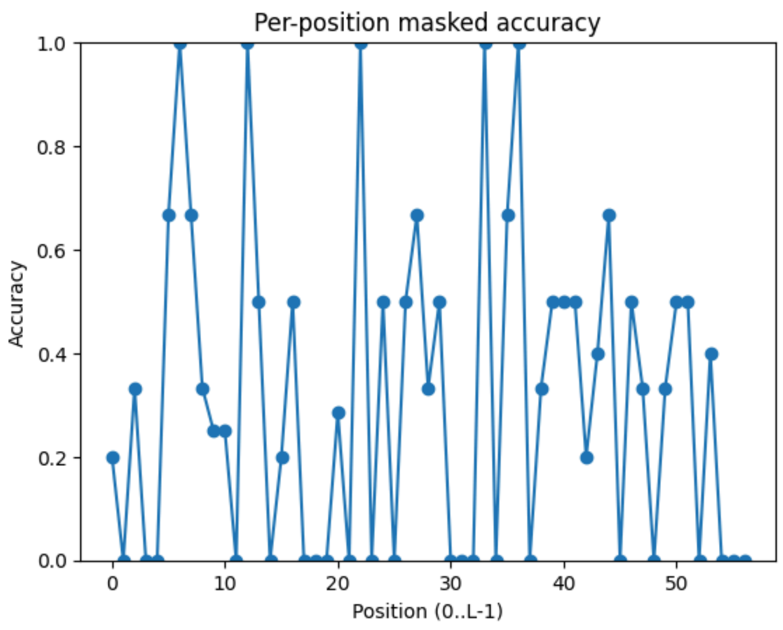
In [49]:
```python
from collections import Counter

def gc_content(seq): return (seq.count("G")+seq.count("C"))/len(seq)

def kmer_freqs(seqs, k=3):
    counts = Counter()
    for s in seqs:
        for i in range(len(s)-k+1):
            counts[s[i:i+k]] += 1
    total = sum(counts.values())
    for kmer in counts: counts[kmer] /= total
    return counts

# True vs reconstructed
bases = np.array(list("ACGT"))
true_seqs = ["".join(bases[x.argmax(-1).cpu().numpy()]) for x,_ in val_dl.dataset]
model.eval()
with torch.no_grad():
    recon_logits = model(torch.stack([x for x,_ in val_dl.dataset]).to(DEVICE))
recon_seqs = ["".join(bases[p]) for p in recon_logits.argmax(-1).cpu().numpy()]

true_gc = np.mean([gc_content(s) for s in true_seqs])
recon_gc = np.mean([gc_content(s) for s in recon_seqs])
print(f"GC% True={true_gc:.3f}, Recon={recon_gc:.3f}")

# k-mer correlation
from scipy.stats import pearsonr
t3 = kmer_freqs(true_seqs, 3); r3 = kmer_freqs(recon_seqs, 3)
shared = sorted(set(t3) & set(r3))
corr = pearsonr([t3[k] for k in shared],[r3[k] for k in shared])[0]
print(f"3-mer distribution correlation: {corr:.3f}")
```
```
GC% True=0.449, Recon=0.218
3-mer distribution correlation: 0.288
```

In [50]:
```python
import torch, torch.nn.functional as F, numpy as np
from collections import defaultdict

MASK_PROB = 0.2
bases = np.array(list("ACGT"))

def apply_mask(x, m, mask_prob=MASK_PROB):
    x = x.clone()
    mask = torch.rand_like(m) < mask_prob
    # replace masked positions with uniform distribution (no info)
    x[mask] = torch.tensor([0.25,0.25,0.25,0.25], device=x.device)
    return x, mask

def eval_masked_metrics(model, dl, topk=(1,2,3)):
    model.eval()
    total_masked = 0
    correct_at_k = defaultdict(int)
    nll_sum = 0.0

    with torch.no_grad():
        for xb, mb in dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            xb_masked, mask_idx = apply_mask(xb, mb)
            logits = model(xb_masked)                       # [B,L,4]
            logp = F.log_softmax(logits, dim=-1)
            target = xb.argmax(-1)                          # [B,L]

            # only consider masked positions
            mask_flat = mask_idx.reshape(-1)
            target_flat = target.reshape(-1)
            logp_flat = logp.reshape(-1, 4)

            if mask_flat.sum() == 0:
                continue

            # NLL
            nll = -logp_flat[mask_flat, :].gather(1, target_flat[mask_flat].unsqueeze(1)).mean()
            nll_sum += nll.item() * mask_flat.sum().item()

            # top-k
            probs = torch.exp(logp_flat[mask_flat, :])      # [M,4]
            topk_idx = torch.topk(probs, k=max(topk), dim=-1).indices  # [M,K]
            for k in topk:
                correct_at_k[k] += (topk_idx[:, :k] == target_flat[mask_flat].unsqueeze(1)).any(dim=1).sum().item()

            total_masked += mask_flat.sum().item()

    out = {f"top{k}_acc": correct_at_k[k] / total_masked for k in topk}
    out["nll"] = nll_sum / total_masked
    out["ppl"] = float(np.exp(out["nll"]))
    out["masked_frac"] = MASK_PROB
    return out

masked_scores = eval_masked_metrics(model, val_dl, topk=(1,2,3))
print(masked_scores)
```

```
{'top1_acc': 0.2710843373493976, 'top2_acc': 0.5240963855421686, 'top3_acc': 0.7710843373493976, 'nll': 1.408839464187622, 'p
pl': 4.091204658377315, 'masked_frac': 0.2}
```

In [51]:
```
import numpy as np

def per_position_accuracy(model, dl):
    model.eval()
    L = next(iter(dl))[0].shape[1]
    correct = np.zeros(L, dtype=np.int64)
    total   = np.zeros(L, dtype=np.int64)
    with torch.no_grad():
        for xb, mb in dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            xb_masked, mask_idx = apply_mask(xb, mb)
            logits = model(xb_masked)
            pred = logits.argmax(-1)        # [B,L]
            true = xb.argmax(-1)
            mask = mask_idx.bool()

            for pos in range(L):
                mpos = mask[:, pos]
                correct[pos] += (pred[mpos, pos] == true[mpos, pos]).sum().item()
                total[pos]   += mpos.sum().item()
    acc = np.divide(correct, np.maximum(total, 1))
    return acc

acc_pos = per_position_accuracy(model, val_dl)
print("Position-wise masked accuracy (first 20):", np.round(acc_pos[:20], 3))

# Quick plot (optional)
import matplotlib.pyplot as plt
plt.plot(acc_pos, marker='o'); plt.ylim(0,1)
plt.title("Per-position masked accuracy"); plt.xlabel("Position (0..L-1)"); plt.ylabel("Accuracy")
plt.show()
```

```
Position-wise masked accuracy (first 20): [0.2   0.    0.333 0.    0.    0.667 1.    0.667 0.333 0.25  0.25  0.
 1.    0.5   0.    0.2   0.5   0.    0.    0.   ]
```



In [52]:
```python
import numpy as np

def masked_confusion(model, dl):
    cm = np.zeros((4,4), dtype=np.int64)  # rows=true, cols=pred
    with torch.no_grad():
        for xb, mb in dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            xb_masked, mask_idx = apply_mask(xb, mb)
            logits = model(xb_masked)
            pred = logits.argmax(-1)
            true = xb.argmax(-1)
            mask = mask_idx.bool()

            t = true[mask].cpu().numpy().ravel()
            p = pred[mask].cpu().numpy().ravel()
            for ti, pi in zip(t, p): cm[ti, pi] += 1
    return cm

cm = masked_confusion(model, val_dl)
print("Confusion matrix (rows=true A C G T, cols=pred):\n", cm)
```

```
Confusion matrix (rows=true A C G T, cols=pred):
 [[11  7  5 30]
 [ 5  3  3 18]
 [ 9  7  5 21]
 [ 4  5  2 32]]
```

In [53]:
```python
import re

def eval_motif_recall(model, dl, motif="TATAAT", mask_prob=0.2):
    hits_true = hits_recon = 0
    with torch.no_grad():
        for xb, mb in dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            xb_masked, mask_idx = apply_mask(xb, mb)
            logits = model(xb_masked)
            pred = logits.argmax(-1).cpu().numpy()
            true = xb.argmax(-1).cpu().numpy()
            for i in range(true.shape[0]):
                t = "".join(bases[true[i]])
                r = "".join(bases[pred[i]])
                hits_true += len(re.findall(motif, t))
                hits_recon += len(re.findall(motif, r))
    return hits_true, hits_recon

for m in ["TATAAT", "TTGACA"]:
    ht, hr = eval_motif_recall(model, val_dl, motif=m, mask_prob=0.2)
    print(f"{m}: true_hits={ht}  recon_hits={hr}  recall≈{hr/max(ht,1):.2f}")
```

```
TATAAT: true_hits=2  recon_hits=2  recall≈1.00
TTGACA: true_hits=0  recon_hits=0  recall≈0.00
```

In [54]:
```python
def calibration_buckets(model, dl, bins=10):
    model.eval()
    bucket_correct = np.zeros(bins)
    bucket_count   = np.zeros(bins)
    with torch.no_grad():
        for xb, mb in dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            xb_masked, mask_idx = apply_mask(xb, mb)
            logits = model(xb_masked)
            probs  = torch.softmax(logits, dim=-1)
            top_p, top_i = probs.max(-1)
            true = xb.argmax(-1)
            mask = mask_idx.bool()

            conf = top_p[mask].cpu().numpy().ravel()
            corr = (top_i[mask] == true[mask]).cpu().numpy().ravel()
            idx = np.minimum((conf * bins).astype(int), bins-1)
            for k, c in zip(idx, corr):
                bucket_correct[k] += c
                bucket_count[k]   += 1
    return bucket_correct / np.maximum(bucket_count, 1), bucket_count

acc_b, cnt_b = calibration_buckets(model, val_dl, bins=10)
print("Bucket accuracies:", np.round(acc_b,3))
print("Bucket counts    :", cnt_b.astype(int))
```

```
Bucket accuracies: [0.    0.    0.33  0.271 0.583 0.6   0.    0.    0.    0.   ]
Bucket counts    : [  0   0 106  48  12   5   0   0   0   0]
```

TRY 4

In [55]:
```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader
from pathlib import Path
import numpy as np
import random
from tqdm import tqdm
```

In [56]:
```
L = 50        # target sequence length (truncate/pad)
Z_DIM = 64    # latent dimension
BATCH_SIZE = 32
LR = 1e-3
EPOCHS = 150
```

In [58]:
```
DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
DATA_PATH = Path("C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/da
```

In [59]:
```
base2idx = {'A':0, 'C':1, 'G':2, 'T':3}

def one_hot_encode(seq, L=57):
    x = np.zeros((L, 4), dtype=np.float32)
    m = np.zeros(L, dtype=np.float32)
    for i, ch in enumerate(seq[:L]):
        if ch in base2idx:
            x[i, base2idx[ch]] = 1.0
            m[i] = 1.0
    return x, m

# Load and encode sequences
def load_sequences(path, L=57):
    seqs = [line.strip().upper() for line in open(path) if line.strip()]
    X, M = zip(*(one_hot_encode(s, L) for s in seqs))
    X, M = np.stack(X), np.stack(M)
    print(f"Loaded {len(X)} sequences, shape={X.shape}")
    return X, M

X, M = load_sequences(DATA_PATH, L=L)

# Dataset class
class PromoterDataset(torch.utils.data.Dataset):
    def __init__(self, X, M):
        self.X = torch.tensor(X)
        self.M = torch.tensor(M)
    def __len__(self): return len(self.X)
    def __getitem__(self, idx):
        return self.X[idx], self.M[idx]

# --- Create full dataset ---
full_ds = PromoterDataset(X, M)
n_total = len(full_ds)
n_train = int(0.7 * n_total)
n_val   = int(0.15 * n_total)
n_test  = n_total - n_train - n_val

train_ds, val_ds, test_ds = random_split(
    full_ds, [n_train, n_val, n_test],
    generator=torch.Generator().manual_seed(42)  # reproducibility
)

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

# --- DataLoaders ---
BATCH_SIZE = 32
train_dl = DataLoader(train_ds, batch_size=BATCH_SIZE, shuffle=True)
val_dl   = DataLoader(val_ds, batch_size=BATCH_SIZE, shuffle=False)
test_dl  = DataLoader(test_ds, batch_size=BATCH_SIZE, shuffle=False)
```

```
Loaded 14098 sequences, shape=(14098, 50, 4)
Dataset split -> Train: 9868, Val: 2114, Test: 2116
```

In [60]:
```
class ConvVAE(nn.Module):
    def __init__(self, L=57, z_dim=64, base_c=32):
        super().__init__()
        self.enc = nn.Sequential(
            nn.Conv1d(4, base_c, 5, padding=2), nn.ReLU(),
            nn.Conv1d(base_c, base_c*2, 5, padding=2), nn.ReLU(),
            nn.AdaptiveAvgPool1d(1)
        )
        self.fc_mu = nn.Linear(base_c*2, z_dim)
        self.fc_logvar = nn.Linear(base_c*2, z_dim)

        self.fc_dec = nn.Linear(z_dim, base_c*2*L)
        self.dec = nn.Sequential(
            nn.Conv1d(base_c*2, base_c, 3, padding=1), nn.ReLU(),
            nn.Conv1d(base_c, 4, 1)
        )

    def encode(self, x):
        h = self.enc(x.permute(0,2,1))
        h = h.squeeze(-1)
        return self.fc_mu(h), self.fc_logvar(h)

    def reparam(self, mu, logvar):
        std = torch.exp(0.5 * logvar)
        eps = torch.randn_like(std)
        return mu + eps * std

    def decode(self, z):
        h = self.fc_dec(z)
        h = h.view(z.size(0), -1, L)
        out = self.dec(h).permute(0,2,1)
        return out

    def forward(self, x):
        mu, logvar = self.encode(x)
        z = self.reparam(mu, logvar)
        logits = self.decode(z)
        return logits, mu, logvar
```

In [61]:
```
def vae_loss(logits, target, mu, logvar, mask, beta=0.1):
    """
    logits: predicted base logits (B, L, 4)
    target: one-hot encoded true sequence (B, L, 4)
    mu, logvar: latent parameters (B, z_dim)
    mask: binary mask of valid positions (B, L)
    beta: weight for KL term
    """
    B = target.size(0)

    # Cross entropy reconstruction loss
    recon = F.cross_entropy(
        logits.reshape(-1, 4),
        target.argmax(-1).reshape(-1),
        reduction='none'
    )
    recon = (recon * mask.reshape(-1)).sum() / mask.sum()

    # KL divergence between q(z|x) and N(0,1)
    kl = -0.5 * torch.sum(1 + logvar - mu.pow(2) - logvar.exp()) / B

    loss = recon + beta * kl
    return loss, recon, kl
```

In [62]:
```
model = ConvVAE(L=L, z_dim=Z_DIM).to(DEVICE)
opt = torch.optim.AdamW(model.parameters(), lr=LR)
best_val = float("inf")
Path("models").mkdir(exist_ok=True)

for epoch in range(1, EPOCHS+1):
    model.train()
    total_train = 0
    for xb, mb in train_dl:
        xb, mb = xb.to(DEVICE), mb.to(DEVICE)
        logits, mu, logvar = model(xb)
        loss, recon, kl = vae_loss(logits, xb, mu, logvar, mb)
        opt.zero_grad()
        loss.backward()
        opt.step()
        total_train += loss.item() * xb.size(0)
    train_loss = total_train / len(train_dl.dataset)

    # Validation
    model.eval()
    total_val = 0
    with torch.no_grad():
        for xb, mb in val_dl:
            xb, mb = xb.to(DEVICE), mb.to(DEVICE)
            logits, mu, logvar = model(xb)
            loss, _, _ = vae_loss(logits, xb, mu, logvar, mb)
            total_val += loss.item() * xb.size(0)
    val_loss = total_val / len(val_dl.dataset)

    if val_loss < best_val:
        best_val = val_loss
        torch.save(model.state_dict(), "models/vae_promoter.pt")

    print(f"Epoch {epoch:03d} | train={train_loss:.4f} | val={val_loss:.4f} | best={best_val:.4f}")
```

```
Epoch 001 | train=1.3681 | val=1.3567 | best=1.3567
Epoch 002 | train=1.3545 | val=1.3526 | best=1.3526
Epoch 003 | train=1.3519 | val=1.3511 | best=1.3511
Epoch 004 | train=1.3509 | val=1.3506 | best=1.3506
Epoch 005 | train=1.3505 | val=1.3498 | best=1.3498
Epoch 006 | train=1.3500 | val=1.3496 | best=1.3496
Epoch 007 | train=1.3498 | val=1.3494 | best=1.3494
Epoch 008 | train=1.3495 | val=1.3490 | best=1.3490
Epoch 009 | train=1.3496 | val=1.3489 | best=1.3489
Epoch 010 | train=1.3493 | val=1.3491 | best=1.3489
Epoch 011 | train=1.3494 | val=1.3489 | best=1.3489
Epoch 012 | train=1.3490 | val=1.3491 | best=1.3489
Epoch 013 | train=1.3491 | val=1.3491 | best=1.3489
Epoch 014 | train=1.3490 | val=1.3487 | best=1.3487
Epoch 015 | train=1.3490 | val=1.3486 | best=1.3486
Epoch 016 | train=1.3489 | val=1.3479 | best=1.3479
Epoch 017 | train=1.3487 | val=1.3483 | best=1.3479
Epoch 018 | train=1.3489 | val=1.3486 | best=1.3479
Epoch 019 | train=1.3487 | val=1.3485 | best=1.3479
Epoch 020 | train=1.3487 | val=1.3487 | best=1.3479
Epoch 021 | train=1.3487 | val=1.3486 | best=1.3479
Epoch 022 | train=1.3487 | val=1.3484 | best=1.3479
Epoch 023 | train=1.3486 | val=1.3482 | best=1.3479
Epoch 024 | train=1.3486 | val=1.3483 | best=1.3479
Epoch 025 | train=1.3486 | val=1.3482 | best=1.3479
Epoch 026 | train=1.3485 | val=1.3481 | best=1.3479
Epoch 027 | train=1.3486 | val=1.3483 | best=1.3479
Epoch 028 | train=1.3485 | val=1.3483 | best=1.3479
Epoch 029 | train=1.3484 | val=1.3482 | best=1.3479
Epoch 030 | train=1.3485 | val=1.3483 | best=1.3479
Epoch 031 | train=1.3485 | val=1.3479 | best=1.3479
Epoch 032 | train=1.3484 | val=1.3484 | best=1.3479
Epoch 033 | train=1.3485 | val=1.3481 | best=1.3479
Epoch 034 | train=1.3484 | val=1.3481 | best=1.3479
Epoch 035 | train=1.3484 | val=1.3480 | best=1.3479
Epoch 036 | train=1.3485 | val=1.3476 | best=1.3476
Epoch 037 | train=1.3484 | val=1.3481 | best=1.3476
Epoch 038 | train=1.3484 | val=1.3480 | best=1.3476
Epoch 039 | train=1.3483 | val=1.3483 | best=1.3476
Epoch 040 | train=1.3484 | val=1.3479 | best=1.3476
Epoch 041 | train=1.3484 | val=1.3480 | best=1.3476
Epoch 042 | train=1.3483 | val=1.3479 | best=1.3476
Epoch 043 | train=1.3484 | val=1.3480 | best=1.3476
Epoch 044 | train=1.3482 | val=1.3483 | best=1.3476
Epoch 045 | train=1.3484 | val=1.3478 | best=1.3476
Epoch 046 | train=1.3483 | val=1.3478 | best=1.3476
Epoch 047 | train=1.3484 | val=1.3479 | best=1.3476
Epoch 048 | train=1.3482 | val=1.3477 | best=1.3476
Epoch 049 | train=1.3483 | val=1.3482 | best=1.3476
Epoch 050 | train=1.3484 | val=1.3478 | best=1.3476
Epoch 051 | train=1.3482 | val=1.3478 | best=1.3476
Epoch 052 | train=1.3482 | val=1.3476 | best=1.3476
Epoch 053 | train=1.3483 | val=1.3479 | best=1.3476
Epoch 054 | train=1.3483 | val=1.3479 | best=1.3476
Epoch 055 | train=1.3482 | val=1.3476 | best=1.3476
Epoch 056 | train=1.3482 | val=1.3477 | best=1.3476
Epoch 057 | train=1.3483 | val=1.3476 | best=1.3476
Epoch 058 | train=1.3482 | val=1.3483 | best=1.3476
Epoch 059 | train=1.3482 | val=1.3481 | best=1.3476
Epoch 060 | train=1.3483 | val=1.3477 | best=1.3476
Epoch 061 | train=1.3482 | val=1.3480 | best=1.3476
Epoch 062 | train=1.3482 | val=1.3476 | best=1.3476
Epoch 063 | train=1.3481 | val=1.3478 | best=1.3476
Epoch 064 | train=1.3482 | val=1.3477 | best=1.3476
Epoch 065 | train=1.3482 | val=1.3478 | best=1.3476
Epoch 066 | train=1.3483 | val=1.3477 | best=1.3476
Epoch 067 | train=1.3481 | val=1.3479 | best=1.3476
Epoch 068 | train=1.3481 | val=1.3478 | best=1.3476
Epoch 069 | train=1.3481 | val=1.3477 | best=1.3476
Epoch 070 | train=1.3481 | val=1.3478 | best=1.3476
Epoch 071 | train=1.3482 | val=1.3476 | best=1.3476
Epoch 072 | train=1.3481 | val=1.3480 | best=1.3476
Epoch 073 | train=1.3482 | val=1.3476 | best=1.3476
Epoch 074 | train=1.3480 | val=1.3476 | best=1.3476
Epoch 075 | train=1.3482 | val=1.3478 | best=1.3476
Epoch 076 | train=1.3481 | val=1.3480 | best=1.3476
Epoch 077 | train=1.3481 | val=1.3476 | best=1.3476
Epoch 078 | train=1.3481 | val=1.3477 | best=1.3476
Epoch 079 | train=1.3481 | val=1.3476 | best=1.3476
Epoch 080 | train=1.3481 | val=1.3475 | best=1.3475
Epoch 081 | train=1.3481 | val=1.3477 | best=1.3475
Epoch 082 | train=1.3480 | val=1.3479 | best=1.3475
Epoch 083 | train=1.3482 | val=1.3475 | best=1.3475
Epoch 084 | train=1.3481 | val=1.3476 | best=1.3475
Epoch 085 | train=1.3481 | val=1.3477 | best=1.3475
Epoch 086 | train=1.3481 | val=1.3476 | best=1.3475
Epoch 087 | train=1.3481 | val=1.3479 | best=1.3475
Epoch 088 | train=1.3480 | val=1.3477 | best=1.3475
Epoch 089 | train=1.3482 | val=1.3479 | best=1.3475
Epoch 090 | train=1.3481 | val=1.3475 | best=1.3475
Epoch 091 | train=1.3482 | val=1.3478 | best=1.3475
Epoch 092 | train=1.3481 | val=1.3478 | best=1.3475
Epoch 093 | train=1.3481 | val=1.3475 | best=1.3475
Epoch 094 | train=1.3481 | val=1.3477 | best=1.3475
Epoch 095 | train=1.3480 | val=1.3475 | best=1.3475
Epoch 096 | train=1.3481 | val=1.3476 | best=1.3475
Epoch 097 | train=1.3481 | val=1.3475 | best=1.3475
Epoch 098 | train=1.3481 | val=1.3475 | best=1.3475
Epoch 099 | train=1.3481 | val=1.3477 | best=1.3475
Epoch 100 | train=1.3481 | val=1.3479 | best=1.3475
Epoch 101 | train=1.3481 | val=1.3474 | best=1.3474
Epoch 102 | train=1.3482 | val=1.3477 | best=1.3474
Epoch 103 | train=1.3481 | val=1.3477 | best=1.3474
Epoch 104 | train=1.3481 | val=1.3476 | best=1.3474
Epoch 105 | train=1.3480 | val=1.3476 | best=1.3474
Epoch 106 | train=1.3481 | val=1.3477 | best=1.3474
Epoch 107 | train=1.3480 | val=1.3480 | best=1.3474
Epoch 108 | train=1.3481 | val=1.3476 | best=1.3474
Epoch 109 | train=1.3481 | val=1.3476 | best=1.3474
Epoch 110 | train=1.3481 | val=1.3476 | best=1.3474
Epoch 111 | train=1.3481 | val=1.3478 | best=1.3474
Epoch 112 | train=1.3480 | val=1.3474 | best=1.3474
Epoch 113 | train=1.3480 | val=1.3475 | best=1.3474
Epoch 114 | train=1.3480 | val=1.3476 | best=1.3474
Epoch 115 | train=1.3481 | val=1.3477 | best=1.3474
Epoch 116 | train=1.3481 | val=1.3476 | best=1.3474
Epoch 117 | train=1.3481 | val=1.3478 | best=1.3474
Epoch 118 | train=1.3480 | val=1.3475 | best=1.3474
Epoch 119 | train=1.3481 | val=1.3475 | best=1.3474
Epoch 120 | train=1.3480 | val=1.3477 | best=1.3474
Epoch 121 | train=1.3480 | val=1.3474 | best=1.3474
Epoch 122 | train=1.3481 | val=1.3474 | best=1.3474
Epoch 123 | train=1.3480 | val=1.3475 | best=1.3474
Epoch 124 | train=1.3481 | val=1.3478 | best=1.3474
Epoch 125 | train=1.3481 | val=1.3474 | best=1.3474
Epoch 126 | train=1.3481 | val=1.3475 | best=1.3474
Epoch 127 | train=1.3480 | val=1.3476 | best=1.3474
Epoch 128 | train=1.3480 | val=1.3476 | best=1.3474
Epoch 129 | train=1.3481 | val=1.3476 | best=1.3474
Epoch 130 | train=1.3480 | val=1.3474 | best=1.3474
Epoch 131 | train=1.3480 | val=1.3476 | best=1.3474
Epoch 132 | train=1.3480 | val=1.3473 | best=1.3473
Epoch 133 | train=1.3480 | val=1.3477 | best=1.3473
Epoch 134 | train=1.3480 | val=1.3473 | best=1.3473
Epoch 135 | train=1.3480 | val=1.3475 | best=1.3473
Epoch 136 | train=1.3480 | val=1.3477 | best=1.3473
Epoch 137 | train=1.3480 | val=1.3474 | best=1.3473
Epoch 138 | train=1.3481 | val=1.3474 | best=1.3473
Epoch 139 | train=1.3480 | val=1.3475 | best=1.3473
Epoch 140 | train=1.3480 | val=1.3475 | best=1.3473
Epoch 141 | train=1.3480 | val=1.3474 | best=1.3473
Epoch 142 | train=1.3480 | val=1.3478 | best=1.3473
Epoch 143 | train=1.3480 | val=1.3476 | best=1.3473
Epoch 144 | train=1.3481 | val=1.3475 | best=1.3473
Epoch 145 | train=1.3480 | val=1.3479 | best=1.3473
Epoch 146 | train=1.3479 | val=1.3476 | best=1.3473
Epoch 147 | train=1.3479 | val=1.3475 | best=1.3473
Epoch 148 | train=1.3480 | val=1.3478 | best=1.3473
Epoch 149 | train=1.3480 | val=1.3478 | best=1.3473
Epoch 150 | train=1.3481 | val=1.3475 | best=1.3473
```

In [126…

```
len("ATAGCAGCTTCTGAACTGGTTACCTGCCGTGAGTAAATTAAAATTTTATT")
```

Out[126]:

```
50
```

In [64]:

```
import numpy as np
import torch

# --- Load best model checkpoint ---
model.load_state_dict(torch.load("models/vae_promoter.pt", map_location=DEVICE))
model.eval()

# --- generate new promoter-like sequences ---
N_SAMPLES = 10          # number of synthetic sequences to generate
with torch.no_grad():
    z = torch.randn(N_SAMPLES, Z_DIM).to(DEVICE)      # random latent vectors
    logits = model.decode(z)                          # decode into DNA logits
    probs = torch.softmax(logits, dim=-1)
    seqs = torch.argmax(probs, dim=-1).cpu().numpy()  # choose most likely base

# --- convert to readable DNA strings ---
idx2base = np.array(['A','C','G','T'])
generated_seqs = ["".join(idx2base[s]) for s in seqs]

print("✅ Example synthetic promoter sequences:\n")
for i, s in enumerate(generated_seqs, 1):
    print(f"{i:02d}. {s}")
```

```
✅ Example synthetic promoter sequences:

01. TTTTTAATAATGTTTTTGAAATTTTTGTTAATTTGGGTTAAATTTATATT
02. TTTTTATTAATTTTTTTGCAAATTTTGTTAATTTGGGTTAAATTTATAAT
03. TTGTTAATAATTTTTTTGCAATTATTGTTAATTTGGGTTATATTTATATT
04. TTTTTAATAATTTTTTTGAAATTTTTGTTAATTTGGGTTAAATTTATAAT
05. TTGTTGATAAATTTTTTGAAAATTTGGGTAATTTGGGTTAAATTTATAAT
06. TTTTTAATAAATTTTTTGACAATTTGGTTAATTTGGGTTAAATTTAAAAT
07. TTGTTAAAAATTTTTTTGCAATTTTTGTTAATTTGGGTTAAATTTATAAT
08. TTGTTAATAATTTTTTTGCAATTTTTGTAAATTTGGGTTAAATTTAAATT
09. TTTTTGATAATGTTTTTGATATTTTTGGTAATTTGGGTTAAATTTATATT
10. TTTTTAAAAAAATTTTTGCAAATTTTGTAAATTTGGGTTAAATTTAAAAT
```

In [65]:
```python
from pathlib import Path
Path("results").mkdir(exist_ok=True)

with open("results/generated_promoters.fa", "w") as f:
    for i, seq in enumerate(generated_seqs, 1):
        f.write(f">synthetic_{i}\n{seq}\n")

print(f"Saved {len(generated_seqs)} synthetic sequences → results/generated_promoters.fa")
```

```
Saved 10 synthetic sequences → results/generated_promoters.fa
```

In [66]:
```python
def gc_content(seq):
    return (seq.count('G') + seq.count('C')) / len(seq)

def homopolymer(seq):
    longest = curr = 1
    for i in range(1, len(seq)):
        if seq[i] == seq[i-1]:
            curr += 1
            longest = max(longest, curr)
        else:
            curr = 1
    return longest

gc_vals = [gc_content(s) for s in generated_seqs]
homopolymers = [homopolymer(s) for s in generated_seqs]

print(f"Average GC% = {np.mean(gc_vals):.3f}")
print(f"Average longest homopolymer run = {np.mean(homopolymers):.2f}")
```

```
Average GC% = 0.136
Average longest homopolymer run = 6.40
```

In [67]:
```python
# reconstruct real sequences (if X available as one-hot)
idx2base = np.array(['A','C','G','T'])
real_strs = ["".join(idx2base[np.argmax(x, axis=1)]) for x in X[:len(generated_seqs)]]

gc_real = [gc_content(s) for s in real_strs]
gc_gen  = [gc_content(s) for s in generated_seqs]
print(f"Real GC% = {np.mean(gc_real):.3f}, Generated GC% = {np.mean(gc_gen):.3f}")
```

```
Real GC% = 0.422, Generated GC% = 0.136
```

In [68]:
```python
motifs = ["TATAAA", "GGGCGG", "CCAAT", "CACGTG"]

def motif_count(seq, motif):
    return seq.count(motif)

for motif in motifs:
    real_hits = sum(motif_count(s, motif) for s in real_strs)
    gen_hits  = sum(motif_count(s, motif) for s in generated_seqs)
    recall = gen_hits / max(real_hits, 1)
    print(f"{motif}: real={real_hits}, generated={gen_hits}, recall≈{recall:.2f}")
```

```
TATAAA: real=0, generated=0, recall≈0.00
GGGCGG: real=0, generated=0, recall≈0.00
CCAAT: real=2, generated=0, recall≈0.00
CACGTG: real=0, generated=0, recall≈0.00
```

In [69]:
```python
from collections import Counter
from itertools import product
from scipy.stats import pearsonr

def kmer_freqs(seq, k=3):
    kmers = [seq[i:i+k] for i in range(len(seq)-k+1)]
    c = Counter(kmers)
    total = sum(c.values())
    return {kmer: c[kmer]/total for kmer in c}

k = 3
alphabet = ['A','C','G','T']
all_kmers = ["".join(p) for p in product(alphabet, repeat=k)]

real_freqs = np.array([np.mean([kmer_freqs(s, k).get(km, 0) for s in real_strs]) for km in all_kmers])
gen_freqs  = np.array([np.mean([kmer_freqs(s, k).get(km, 0) for s in generated_seqs]) for km in all_kmers])

pcc, _ = pearsonr(real_freqs, gen_freqs)
print(f"{k}-mer distribution correlation (PCC): {pcc:.3f}")
```

```
3-mer distribution correlation (PCC): 0.661
```

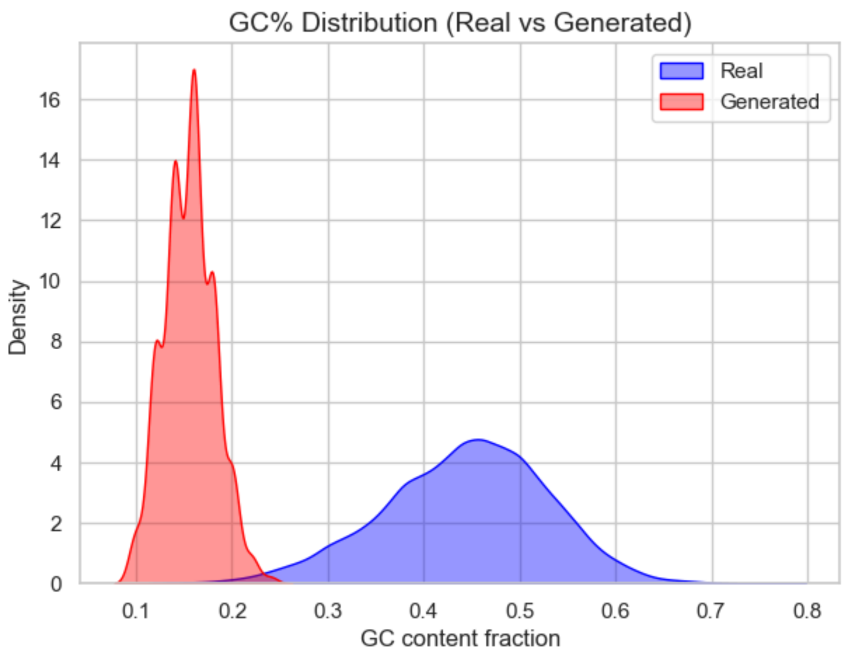
In [70]:
```python
import torch
import numpy as np

model.eval()

# number of new sequences to generate
N = 500

# generate latent codes from normal distribution
z = torch.randn(N, model.fc_mu.out_features).to(DEVICE)

with torch.no_grad():
    logits = model.decode(z)                     # shape: [N, L, 4]
    probs = torch.softmax(logits, dim=-1)
    sampled = torch.argmax(probs, dim=-1).cpu().numpy()

# decode one-hot indices to A/C/G/T strings
idx2nt = np.array(["A", "C", "G", "T"])
gen_sequences = ["".join(idx2nt[s]) for s in sampled]

print(f"Generated {len(gen_sequences)} synthetic promoter sequences.")
print(f"Example generated: {gen_sequences[0][:80]}...")
```

```
Generated 500 synthetic promoter sequences.
Example generated: TTTTTATTAATTTTTTTGAAATTTTTGTTAATTTGGGTTAAATTTATAAT...
```

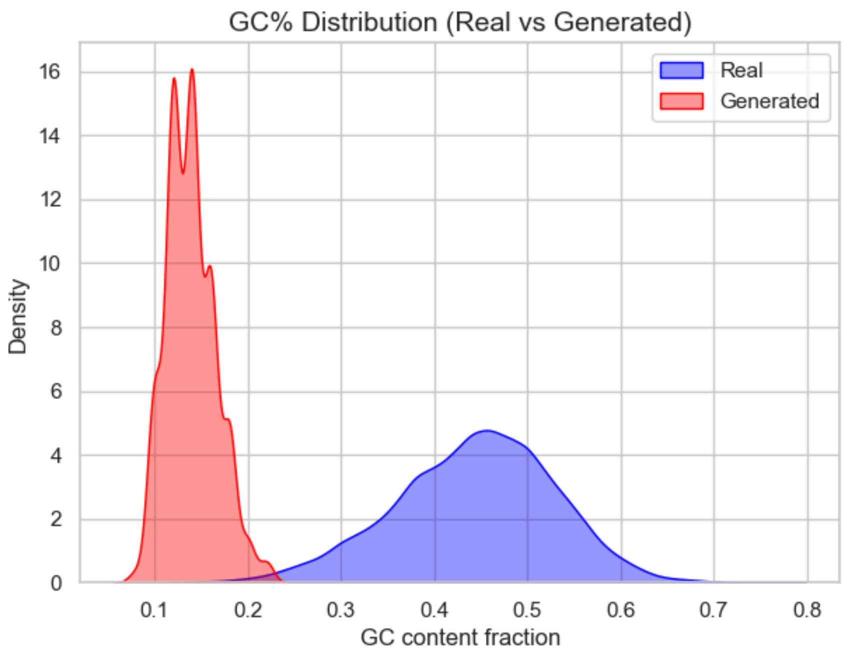
In [71]:
```python
with open(DATA_PATH) as f:
    real_sequences = [line.strip().upper() for line in f if len(line.strip()) > 0]

# Generated sequences: from your trained VAE
# (replace this with your generated list variable if you already have one)
generated_sequences = gen_sequences  # or whatever variable holds your generated promoters

print(f"Loaded {len(real_sequences)} real and {len(generated_sequences)} generated sequences.")
print(f"Example real: {real_sequences[0][:50]}...")
print(f"Example generated: {generated_sequences[0][:50]}...")
```

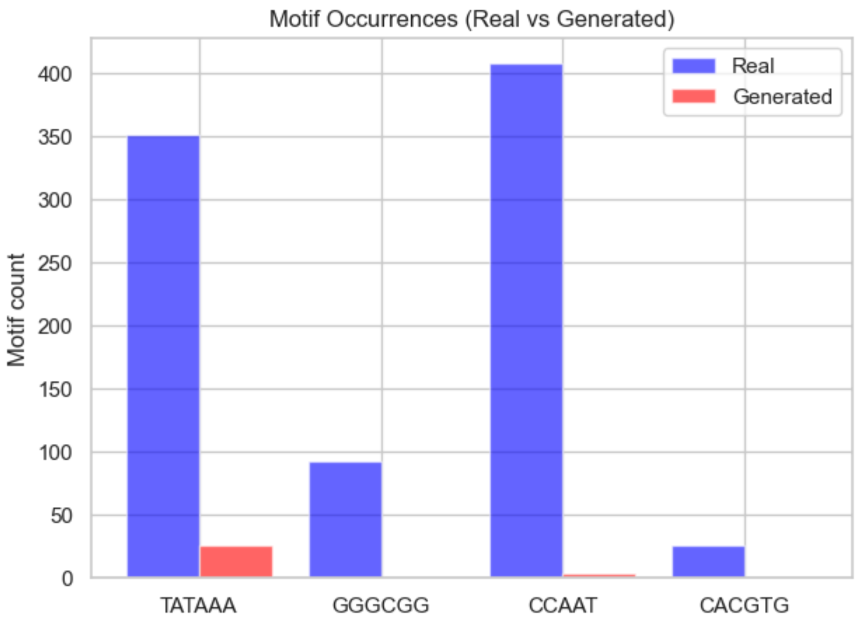
```
Loaded 14098 real and 500 generated sequences.
Example real: ATAGCAGCTTCTGAACTGGTTACCTGCCGTGAGTAAATTAAAATTTTATT...
Example generated: TTTTTATTAATTTTTTTGAAATTTTTGTTAATTTGGGTTAAATTTATAAT...
```

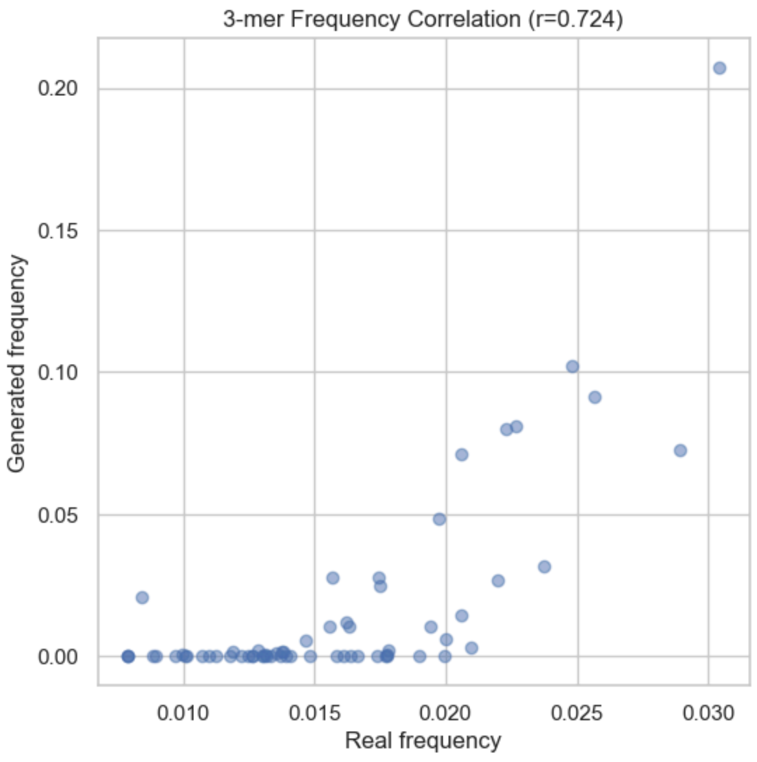
In [155…
```python
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid")

def gc_content(seq):
    seq = seq.upper()
    return (seq.count("G") + seq.count("C")) / len(seq)

# compute GC%
gc_real = [gc_content(s) for s in real_sequences]
gc_gen = [gc_content(s) for s in generated_sequences]

plt.figure(figsize=(7,5))
sns.kdeplot(gc_real, fill=True, color='blue', label='Real', alpha=0.4)
sns.kdeplot(gc_gen, fill=True, color='red', label='Generated', alpha=0.4)
plt.title("GC% Distribution (Real vs Generated)", fontsize=14)
plt.xlabel("GC content fraction")
plt.ylabel("Density")
plt.legend()
plt.show()
```



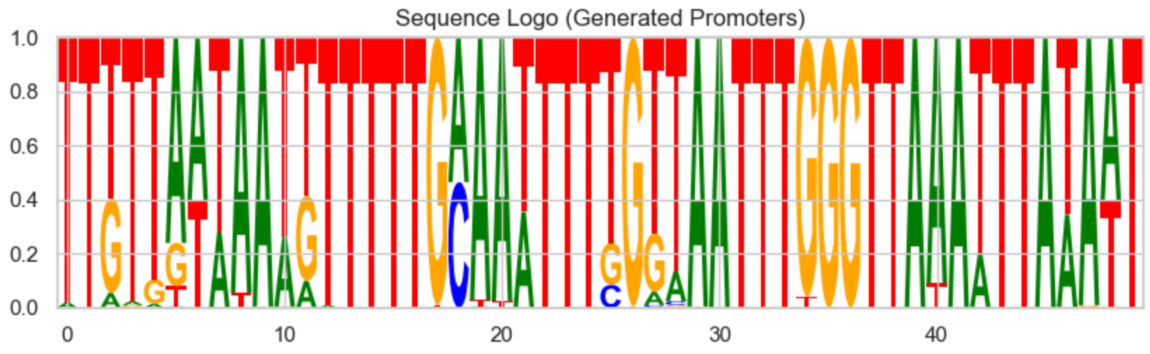
In [73]:
```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
from itertools import product
import pandas as pd
import logomaker

sns.set(style="whitegrid")

# --- Helper functions ---
def gc_content(seq):
    seq = seq.upper()
    return (seq.count("G") + seq.count("C")) / len(seq)

def kmer_freqs(seqs, k=3):
    all_kmers = [''.join(p) for p in product('ACGT', repeat=k)]
    counts = Counter()
    for seq in seqs:
        for i in range(len(seq)-k+1):
            counts[seq[i:i+k]] += 1
    total = sum(counts.values())
    return np.array([counts[km]/total for km in all_kmers]), all_kmers

def onehot_to_df(seqs):
    L = len(seqs[0])
    df = pd.DataFrame(0, index=list("ACGT"), columns=range(L))
    for seq in seqs:
        for i, base in enumerate(seq):
            if base in "ACGT":
                df.loc[base, i] += 1
    df = df.div(df.sum(axis=0), axis=1)
    return df.T

# --- GC content comparison ---
gc_real = [gc_content(s) for s in real_sequences]
gc_gen = [gc_content(s) for s in generated_sequences]

plt.figure(figsize=(7,5))
sns.kdeplot(gc_real, fill=True, color='blue', label='Real', alpha=0.4)
sns.kdeplot(gc_gen, fill=True, color='red', label='Generated', alpha=0.4)
plt.title("GC% Distribution (Real vs Generated)", fontsize=14)
plt.xlabel("GC content fraction")
plt.ylabel("Density")
plt.legend()
plt.show()

# --- Motif frequency comparison ---
motifs = ["TATAAA", "GGGCGG", "CCAAT", "CACGTG"]
motif_counts_real = [sum(m in s for s in real_sequences) for m in motifs]
motif_counts_gen = [sum(m in s for s in generated_sequences) for m in motifs]

x = np.arange(len(motifs))
plt.figure(figsize=(7,5))
plt.bar(x - 0.2, motif_counts_real, 0.4, label='Real', color='blue', alpha=0.6)
plt.bar(x + 0.2, motif_counts_gen, 0.4, label='Generated', color='red', alpha=0.6)
plt.xticks(x, motifs)
plt.ylabel("Motif count")
plt.title("Motif Occurrences (Real vs Generated)")
plt.legend()
plt.show()

# --- 3-mer correlation ---
real_kmers, kmers = kmer_freqs(real_sequences, k=3)
gen_kmers, _ = kmer_freqs(generated_sequences, k=3)
corr = np.corrcoef(real_kmers, gen_kmers)[0,1]

plt.figure(figsize=(6,6))
plt.scatter(real_kmers, gen_kmers, alpha=0.5)
plt.title(f"3-mer Frequency Correlation (r={corr:.3f})")
plt.xlabel("Real frequency")
plt.ylabel("Generated frequency")
plt.show()

# --- Sequence logo of generated sequences ---
df_gen = onehot_to_df(generated_sequences[:200])  # take 200 for clarity
plt.figure(figsize=(12,3))
logomaker.Logo(df_gen)
plt.title("Sequence Logo (Generated Promoters)")
plt.show()

print(f"\nGC% Mean (real): {np.mean(gc_real):.3f} | (gen): {np.mean(gc_gen):.3f}")
print(f"3-mer correlation: {corr:.3f}")
```


GC% Distribution (Real vs Generated)
Real
Generated
Density
GC content fraction
0
2
4
6
8
10
12
14
16
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8


Motif Occurrences (Real vs Generated)
Real
Generated
Motif count
0
50
100
150
200
250
300
350
400
TATAAA
GGGCGG
CCAAT
CACGTG


3-mer Frequency Correlation (r=0.724)
Generated frequency
Real frequency
0.00
0.05
0.10
0.15
0.20
0.010
0.015
0.020
0.025
0.030

```
<Figure size 1200x300 with 0 Axes>
```



```
GC% Mean (real): 0.443 | (gen): 0.139
3-mer correlation: 0.724
```

TRY 5

In [75]:
```python
import torch, torch.nn as nn, torch.nn.functional as F
from torch.utils.data import DataLoader, TensorDataset, random_split
import numpy as np, matplotlib.pyplot as plt, seaborn as sns
from pathlib import Path
from itertools import product
from collections import Counter
import pandas as pd, logomaker, random

DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
print("Running on:", DEVICE)

# --- Helper functions ---
def onehot_encode(seq):
    mapping = {"A":0, "C":1, "G":2, "T":3}
    arr = np.zeros((len(seq), 4))
    for i, b in enumerate(seq):
        if b in mapping:
            arr[i, mapping[b]] = 1
    return arr

def reverse_complement(seq):
    return seq[::-1].translate(str.maketrans("ACGT", "TGCA"))

# --- Load data ---
DATA_PATH = Path("C:/Users/Akshat/Desktop/Hopkins/Fall_2025/Computational_genomics/Project/Cancer-Tumor-promoter-Generation/da
with open(DATA_PATH) as f:
    real_sequences = [line.strip().upper() for line in f if len(line.strip()) > 0]

# augment with reverse-complements
aug_sequences = real_sequences + [reverse_complement(s) for s in real_sequences]
print(f"Loaded {len(aug_sequences)} sequences after augmentation.")

L = len(aug_sequences[0])
X = np.stack([onehot_encode(s) for s in aug_sequences])
X = torch.tensor(X, dtype=torch.float32)

# --- Train/Val/Test split (70/15/15) ---
n = len(X)
n_train = int(0.7*n)
n_val = int(0.15*n)
n_test = n - n_train - n_val
train_ds, val_ds, test_ds = random_split(X, [n_train, n_val, n_test])

train_dl = DataLoader(train_ds, batch_size=128, shuffle=True)
val_dl   = DataLoader(val_ds, batch_size=128)
test_dl  = DataLoader(test_ds, batch_size=128)

print(f"Split: {n_train} train | {n_val} val | {n_test} test | Seq len = {L}")
```

```
Running on: cuda
Loaded 28196 sequences after augmentation.
Split: 19737 train | 4229 val | 4230 test | Seq len = 50
```

In [76]:
```python
class DeepConvVAE(nn.Module):
    def __init__(self, L=57, z_dim=128, base_c=64):
        super().__init__()
        self.L = L
        self.base_c = base_c

        # --- Encoder ---
        self.enc = nn.Sequential(
            nn.Conv1d(4, base_c, 5, padding=2),
            nn.ReLU(),
            nn.Conv1d(base_c, base_c*2, 5, padding=2),
            nn.ReLU(),
            nn.Conv1d(base_c*2, base_c*4, 5, padding=2),
            nn.ReLU(),
            nn.Conv1d(base_c*4, base_c*4, 3, padding=1),
            nn.ReLU(),
            nn.Conv1d(base_c*4, base_c*4, 3, padding=1),
            nn.LayerNorm([base_c*4, L]),
            nn.ReLU(),
            nn.Flatten()
        )

        enc_out = base_c*4*L
        self.fc_mu = nn.Linear(enc_out, z_dim)
        self.fc_logvar = nn.Linear(enc_out, z_dim)

        # --- Decoder ---
        self.fc_dec = nn.Linear(z_dim, enc_out)
        self.dec = nn.Sequential(
            nn.Conv1d(base_c*4, base_c*4, 3, padding=1),
            nn.ReLU(),
            nn.Conv1d(base_c*4, base_c*2, 5, padding=2),
            nn.ReLU(),
            nn.Conv1d(base_c*2, base_c, 5, padding=2),
            nn.ReLU(),
            nn.Conv1d(base_c, base_c, 5, padding=2),
            nn.ReLU(),
            nn.Conv1d(base_c, 4, 1)
        )

    def encode(self, x):
        x = x.permute(0,2,1)
        h = self.enc(x)
        mu = self.fc_mu(h)
        logvar = self.fc_logvar(h)
        return mu, logvar

    def reparam(self, mu, logvar):
        std = torch.exp(0.5*logvar)
        eps = torch.randn_like(std)
        return mu + eps * std

    def decode(self, z):
        h = self.fc_dec(z)
        h = h.view(-1, self.base_c*4, self.L)
        return self.dec(h).permute(0,2,1)

    def forward(self, x):
        mu, logvar = self.encode(x)
        z = self.reparam(mu, logvar)
        logits = self.decode(z)
        return logits, mu, logvar
```

In [77]:
```
def vae_loss(logits, target, mu, logvar, beta=0.05):
    recon = F.cross_entropy(logits.reshape(-1,4), target.argmax(-1).reshape(-1))
    kl = -0.5 * torch.mean(1 + logvar - mu.pow(2) - logvar.exp())
    return recon + beta * kl, recon, kl

model = ConvVAE(L=L, z_dim=64, base_c=64).to(DEVICE)
opt = torch.optim.AdamW(model.parameters(), lr=1e-3, weight_decay=1e-4)

EPOCHS = 200
best_val = 1e9

for epoch in range(1, EPOCHS+1):
    model.train(); tr_loss = 0
    for xb in train_dl:
        xb = xb.to(DEVICE)
        logits, mu, logvar = model(xb)
        loss, rec, kl = vae_loss(logits, xb, mu, logvar, beta=0.05)
        opt.zero_grad()
        loss.backward()
        opt.step()
        tr_loss += loss.item() * xb.size(0)
    tr_loss /= len(train_dl.dataset)

    model.eval(); val_loss = 0
    with torch.no_grad():
        for xb in val_dl:
            xb = xb.to(DEVICE)
            logits, mu, logvar = model(xb)
            loss, _, _ = vae_loss(logits, xb, mu, logvar, beta=0.05)
            val_loss += loss.item() * xb.size(0)
    val_loss /= len(val_dl.dataset)
    print(f"Epoch {epoch:03d} | train={tr_loss:.4f} | val={val_loss:.4f}")

    if val_loss < best_val:
        best_val = val_loss
        torch.save(model.state_dict(), "models/vae_promoter_balanced.pt")
        print(f"✅ Saved best model (val={best_val:.4f})")
```

```
Epoch 001 | train=1.3684 | val=1.3528
✅ Saved best model (val=1.3528)
Epoch 002 | train=1.3488 | val=1.3478
✅ Saved best model (val=1.3478)
Epoch 003 | train=1.3469 | val=1.3468
✅ Saved best model (val=1.3468)
Epoch 004 | train=1.3426 | val=1.3396
✅ Saved best model (val=1.3396)
Epoch 005 | train=1.3385 | val=1.3386
✅ Saved best model (val=1.3386)
Epoch 006 | train=1.3369 | val=1.3360
✅ Saved best model (val=1.3360)
Epoch 007 | train=1.3302 | val=1.3267
✅ Saved best model (val=1.3267)
Epoch 008 | train=1.3208 | val=1.3184
✅ Saved best model (val=1.3184)
Epoch 009 | train=1.3158 | val=1.3160
✅ Saved best model (val=1.3160)
Epoch 010 | train=1.3125 | val=1.3110
✅ Saved best model (val=1.3110)
Epoch 011 | train=1.3046 | val=1.3034
✅ Saved best model (val=1.3034)
Epoch 012 | train=1.2956 | val=1.2911
✅ Saved best model (val=1.2911)
Epoch 013 | train=1.2829 | val=1.2800
✅ Saved best model (val=1.2800)
Epoch 014 | train=1.2748 | val=1.2732
✅ Saved best model (val=1.2732)
Epoch 015 | train=1.2660 | val=1.2639
✅ Saved best model (val=1.2639)
Epoch 016 | train=1.2488 | val=1.2384
✅ Saved best model (val=1.2384)
Epoch 017 | train=1.2233 | val=1.2147
✅ Saved best model (val=1.2147)
Epoch 018 | train=1.2026 | val=1.1977
✅ Saved best model (val=1.1977)
Epoch 019 | train=1.1874 | val=1.1856
✅ Saved best model (val=1.1856)
Epoch 020 | train=1.1752 | val=1.1754
✅ Saved best model (val=1.1754)
Epoch 021 | train=1.1664 | val=1.1669
✅ Saved best model (val=1.1669)
Epoch 022 | train=1.1581 | val=1.1589
✅ Saved best model (val=1.1589)
Epoch 023 | train=1.1497 | val=1.1516
✅ Saved best model (val=1.1516)
Epoch 024 | train=1.1433 | val=1.1470
✅ Saved best model (val=1.1470)
Epoch 025 | train=1.1371 | val=1.1413
✅ Saved best model (val=1.1413)
Epoch 026 | train=1.1309 | val=1.1359
✅ Saved best model (val=1.1359)
Epoch 027 | train=1.1257 | val=1.1294
✅ Saved best model (val=1.1294)
Epoch 028 | train=1.1209 | val=1.1272
✅ Saved best model (val=1.1272)
Epoch 029 | train=1.1172 | val=1.1235
✅ Saved best model (val=1.1235)
Epoch 030 | train=1.1132 | val=1.1207
✅ Saved best model (val=1.1207)
Epoch 031 | train=1.1094 | val=1.1177
✅ Saved best model (val=1.1177)
Epoch 032 | train=1.1054 | val=1.1110
✅ Saved best model (val=1.1110)
Epoch 033 | train=1.1010 | val=1.1091
✅ Saved best model (val=1.1091)
Epoch 034 | train=1.0973 | val=1.1052
✅ Saved best model (val=1.1052)
Epoch 035 | train=1.0926 | val=1.1010
✅ Saved best model (val=1.1010)
Epoch 036 | train=1.0891 | val=1.1001
✅ Saved best model (val=1.1001)
Epoch 037 | train=1.0846 | val=1.0959
✅ Saved best model (val=1.0959)
Epoch 038 | train=1.0815 | val=1.0946
✅ Saved best model (val=1.0946)
Epoch 039 | train=1.0779 | val=1.0880
✅ Saved best model (val=1.0880)
Epoch 040 | train=1.0745 | val=1.0899
Epoch 041 | train=1.0712 | val=1.0835
✅ Saved best model (val=1.0835)
Epoch 042 | train=1.0681 | val=1.0821
✅ Saved best model (val=1.0821)
Epoch 043 | train=1.0657 | val=1.0836
Epoch 044 | train=1.0644 | val=1.0778
✅ Saved best model (val=1.0778)
Epoch 045 | train=1.0609 | val=1.0754
✅ Saved best model (val=1.0754)
Epoch 046 | train=1.0585 | val=1.0768
Epoch 047 | train=1.0562 | val=1.0740
✅ Saved best model (val=1.0740)
Epoch 048 | train=1.0546 | val=1.0714
```

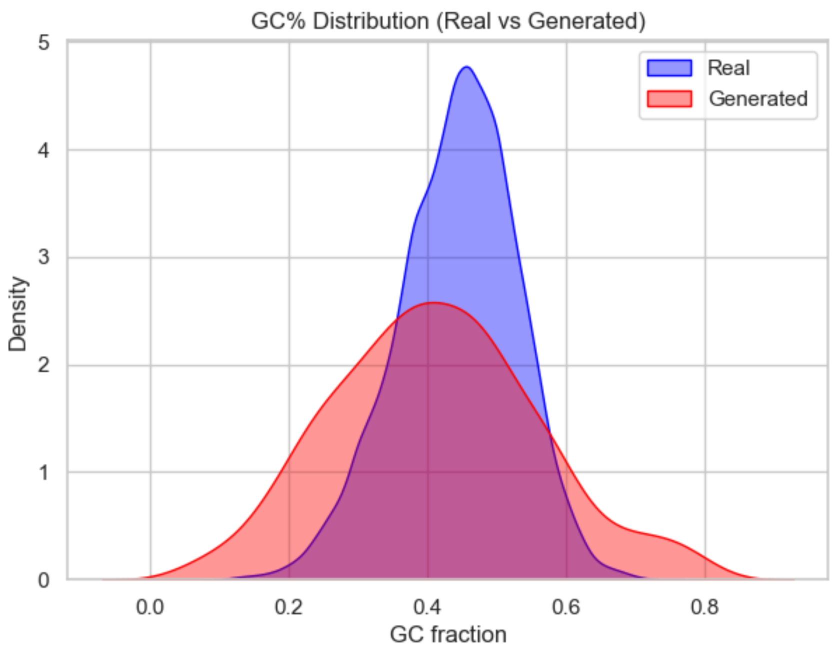
```
✅ Saved best model (val=1.0714)
Epoch 049 | train=1.0522 | val=1.0711
✅ Saved best model (val=1.0711)
Epoch 050 | train=1.0511 | val=1.0686
✅ Saved best model (val=1.0686)
Epoch 051 | train=1.0485 | val=1.0666
✅ Saved best model (val=1.0666)
Epoch 052 | train=1.0466 | val=1.0676
Epoch 053 | train=1.0455 | val=1.0664
✅ Saved best model (val=1.0664)
Epoch 054 | train=1.0437 | val=1.0654
✅ Saved best model (val=1.0654)
Epoch 055 | train=1.0422 | val=1.0620
✅ Saved best model (val=1.0620)
Epoch 056 | train=1.0396 | val=1.0628
Epoch 057 | train=1.0386 | val=1.0607
✅ Saved best model (val=1.0607)
Epoch 058 | train=1.0361 | val=1.0608
Epoch 059 | train=1.0341 | val=1.0585
✅ Saved best model (val=1.0585)
Epoch 060 | train=1.0319 | val=1.0571
✅ Saved best model (val=1.0571)
Epoch 061 | train=1.0307 | val=1.0562
✅ Saved best model (val=1.0562)
Epoch 062 | train=1.0284 | val=1.0545
✅ Saved best model (val=1.0545)
Epoch 063 | train=1.0262 | val=1.0547
Epoch 064 | train=1.0242 | val=1.0510
✅ Saved best model (val=1.0510)
Epoch 065 | train=1.0216 | val=1.0488
✅ Saved best model (val=1.0488)
Epoch 066 | train=1.0184 | val=1.0487
✅ Saved best model (val=1.0487)
Epoch 067 | train=1.0155 | val=1.0447
✅ Saved best model (val=1.0447)
Epoch 068 | train=1.0127 | val=1.0443
✅ Saved best model (val=1.0443)
Epoch 069 | train=1.0099 | val=1.0392
✅ Saved best model (val=1.0392)
Epoch 070 | train=1.0068 | val=1.0401
Epoch 071 | train=1.0051 | val=1.0356
✅ Saved best model (val=1.0356)
Epoch 072 | train=1.0026 | val=1.0353
✅ Saved best model (val=1.0353)
Epoch 073 | train=0.9990 | val=1.0337
✅ Saved best model (val=1.0337)
Epoch 074 | train=0.9964 | val=1.0348
Epoch 075 | train=0.9944 | val=1.0306
✅ Saved best model (val=1.0306)
Epoch 076 | train=0.9912 | val=1.0287
✅ Saved best model (val=1.0287)
Epoch 077 | train=0.9881 | val=1.0236
✅ Saved best model (val=1.0236)
Epoch 078 | train=0.9854 | val=1.0203
✅ Saved best model (val=1.0203)
Epoch 079 | train=0.9828 | val=1.0219
Epoch 080 | train=0.9803 | val=1.0187
✅ Saved best model (val=1.0187)
Epoch 081 | train=0.9773 | val=1.0172
✅ Saved best model (val=1.0172)
Epoch 082 | train=0.9756 | val=1.0167
✅ Saved best model (val=1.0167)
Epoch 083 | train=0.9739 | val=1.0150
✅ Saved best model (val=1.0150)
Epoch 084 | train=0.9707 | val=1.0126
✅ Saved best model (val=1.0126)
Epoch 085 | train=0.9687 | val=1.0118
✅ Saved best model (val=1.0118)
Epoch 086 | train=0.9674 | val=1.0113
✅ Saved best model (val=1.0113)
Epoch 087 | train=0.9655 | val=1.0086
✅ Saved best model (val=1.0086)
Epoch 088 | train=0.9634 | val=1.0129
Epoch 089 | train=0.9617 | val=1.0077
✅ Saved best model (val=1.0077)
Epoch 090 | train=0.9602 | val=1.0039
✅ Saved best model (val=1.0039)
Epoch 091 | train=0.9594 | val=1.0053
Epoch 092 | train=0.9570 | val=1.0050
Epoch 093 | train=0.9554 | val=1.0014
✅ Saved best model (val=1.0014)
Epoch 094 | train=0.9536 | val=1.0017
Epoch 095 | train=0.9527 | val=1.0032
Epoch 096 | train=0.9515 | val=0.9985
✅ Saved best model (val=0.9985)
Epoch 097 | train=0.9486 | val=0.9975
✅ Saved best model (val=0.9975)
Epoch 098 | train=0.9479 | val=1.0006
Epoch 099 | train=0.9464 | val=0.9946
✅ Saved best model (val=0.9946)
Epoch 100 | train=0.9450 | val=0.9985
Epoch 101 | train=0.9435 | val=0.9958
Epoch 102 | train=0.9425 | val=1.0029
Epoch 103 | train=0.9407 | val=0.9934
✅ Saved best model (val=0.9934)
Epoch 104 | train=0.9398 | val=0.9911
✅ Saved best model (val=0.9911)
Epoch 105 | train=0.9373 | val=0.9912
Epoch 106 | train=0.9362 | val=0.9921
Epoch 107 | train=0.9347 | val=0.9910
✅ Saved best model (val=0.9910)
Epoch 108 | train=0.9332 | val=0.9881
✅ Saved best model (val=0.9881)
Epoch 109 | train=0.9314 | val=0.9909
Epoch 110 | train=0.9304 | val=0.9929
Epoch 111 | train=0.9288 | val=0.9908
Epoch 112 | train=0.9275 | val=0.9857
✅ Saved best model (val=0.9857)
Epoch 113 | train=0.9269 | val=0.9888
Epoch 114 | train=0.9244 | val=0.9874
Epoch 115 | train=0.9232 | val=0.9855
✅ Saved best model (val=0.9855)
Epoch 116 | train=0.9218 | val=0.9845
✅ Saved best model (val=0.9845)
Epoch 117 | train=0.9211 | val=0.9856
Epoch 118 | train=0.9190 | val=0.9843
✅ Saved best model (val=0.9843)
Epoch 119 | train=0.9178 | val=0.9805
✅ Saved best model (val=0.9805)
Epoch 120 | train=0.9169 | val=0.9816
Epoch 121 | train=0.9154 | val=0.9833
Epoch 122 | train=0.9147 | val=0.9777
✅ Saved best model (val=0.9777)
Epoch 123 | train=0.9133 | val=0.9793
Epoch 124 | train=0.9120 | val=0.9791
Epoch 125 | train=0.9113 | val=0.9845
Epoch 126 | train=0.9101 | val=0.9797
Epoch 127 | train=0.9092 | val=0.9810
Epoch 128 | train=0.9088 | val=0.9798
Epoch 129 | train=0.9071 | val=0.9763
✅ Saved best model (val=0.9763)
Epoch 130 | train=0.9068 | val=0.9752
✅ Saved best model (val=0.9752)
Epoch 131 | train=0.9067 | val=0.9778
Epoch 132 | train=0.9056 | val=0.9792
Epoch 133 | train=0.9046 | val=0.9781
Epoch 134 | train=0.9036 | val=0.9742
✅ Saved best model (val=0.9742)
Epoch 135 | train=0.9029 | val=0.9775
Epoch 136 | train=0.9023 | val=0.9770
Epoch 137 | train=0.9017 | val=0.9795
Epoch 138 | train=0.9011 | val=0.9764
Epoch 139 | train=0.9008 | val=0.9757
Epoch 140 | train=0.9004 | val=0.9786
Epoch 141 | train=0.8990 | val=0.9797
Epoch 142 | train=0.8990 | val=0.9727
✅ Saved best model (val=0.9727)
Epoch 143 | train=0.8983 | val=0.9756
Epoch 144 | train=0.8976 | val=0.9747
Epoch 145 | train=0.8968 | val=0.9749
Epoch 146 | train=0.8968 | val=0.9813
Epoch 147 | train=0.8958 | val=0.9765
Epoch 148 | train=0.8950 | val=0.9781
Epoch 149 | train=0.8951 | val=0.9790
Epoch 150 | train=0.8944 | val=0.9775
Epoch 151 | train=0.8936 | val=0.9760
Epoch 152 | train=0.8929 | val=0.9804
Epoch 153 | train=0.8922 | val=0.9797
Epoch 154 | train=0.8920 | val=0.9754
Epoch 155 | train=0.8917 | val=0.9756
Epoch 156 | train=0.8912 | val=0.9878
Epoch 157 | train=0.8915 | val=0.9755
Epoch 158 | train=0.8901 | val=0.9787
Epoch 159 | train=0.8892 | val=0.9827
Epoch 160 | train=0.8889 | val=0.9816
Epoch 161 | train=0.8891 | val=0.9744
Epoch 162 | train=0.8884 | val=0.9788
Epoch 163 | train=0.8886 | val=0.9750
Epoch 164 | train=0.8878 | val=0.9737
Epoch 165 | train=0.8877 | val=0.9842
Epoch 166 | train=0.8867 | val=0.9814
Epoch 167 | train=0.8859 | val=0.9762
Epoch 168 | train=0.8863 | val=0.9789
Epoch 169 | train=0.8854 | val=0.9817
Epoch 170 | train=0.8851 | val=0.9795
Epoch 171 | train=0.8849 | val=0.9840
Epoch 172 | train=0.8838 | val=0.9885
Epoch 173 | train=0.8842 | val=0.9831
Epoch 174 | train=0.8831 | val=0.9803
Epoch 175 | train=0.8834 | val=0.9786
Epoch 176 | train=0.8827 | val=0.9746
Epoch 177 | train=0.8822 | val=0.9784
Epoch 178 | train=0.8815 | val=0.9909
Epoch 179 | train=0.8816 | val=0.9800
Epoch 180 | train=0.8808 | val=0.9778
Epoch 181 | train=0.8807 | val=0.9880
Epoch 182 | train=0.8802 | val=0.9793
Epoch 183 | train=0.8802 | val=0.9797
Epoch 184 | train=0.8792 | val=0.9828
Epoch 185 | train=0.8788 | val=0.9810
Epoch 186 | train=0.8789 | val=0.9845
Epoch 187 | train=0.8784 | val=0.9867
Epoch 188 | train=0.8782 | val=0.9847
Epoch 189 | train=0.8781 | val=0.9819
Epoch 190 | train=0.8776 | val=0.9846
Epoch 191 | train=0.8765 | val=0.9828
Epoch 192 | train=0.8764 | val=0.9830
Epoch 193 | train=0.8761 | val=0.9840
Epoch 194 | train=0.8758 | val=0.9909
Epoch 195 | train=0.8757 | val=0.9813
Epoch 196 | train=0.8752 | val=0.9846
Epoch 197 | train=0.8748 | val=0.9888
Epoch 198 | train=0.8743 | val=0.9825
Epoch 199 | train=0.8745 | val=0.9859
Epoch 200 | train=0.8736 | val=0.9876
```

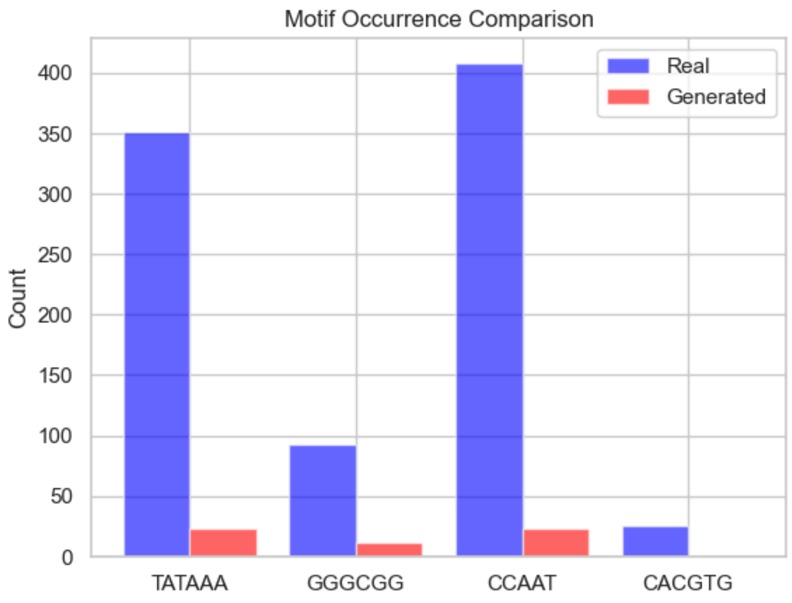
In [78]:
```python
model.load_state_dict(torch.load("models/vae_promoter_balanced.pt", map_location=DEVICE))
model.eval()

N = 500
z = torch.randn(N, 64).to(DEVICE) * 1.5  # larger variance for diversity
with torch.no_grad():
    logits = model.decode(z)
    probs = torch.softmax(logits, dim=-1)
    sampled = torch.argmax(probs, dim=-1).cpu().numpy()

idx2nt = np.array(["A","C","G","T"])
gen_sequences = ["".join(idx2nt[s]) for s in sampled]
print(f"Generated {len(gen_sequences)} new promoter sequences.")
print(gen_sequences[0][:80])
```

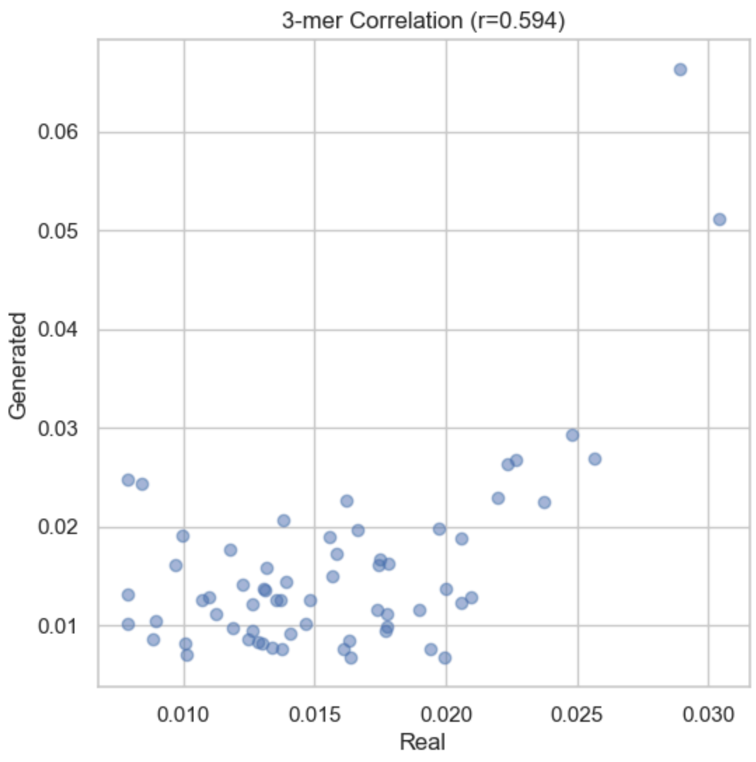
```
Generated 500 new promoter sequences.
TGAAGGGCTTTATGCTAATAATTGACAAAAAAAGGTATTTAATCCCAATT
```

In [79]:
```python
# ---------- helpers ----------
def gc_content(seq): return (seq.count("G")+seq.count("C"))/len(seq)
def kmer_freqs(seqs, k=3):
    all_kmers = [''.join(p) for p in product('ACGT', repeat=k)]
    counts = Counter()
    for seq in seqs:
        for i in range(len(seq)-k+1):
            counts[seq[i:i+k]] += 1
    total = sum(counts.values())
    return np.array([counts[km]/total for km in all_kmers]), all_kmers
def onehot_to_df(seqs):
    L = len(seqs[0])
    df = pd.DataFrame(0, index=list("ACGT"), columns=range(L))
    for seq in seqs:
        for i,b in enumerate(seq):
            if b in "ACGT":
                df.loc[b,i]+=1
    return (df/df.sum()).T

# ---------- GC content ----------
gc_real = [gc_content(s) for s in real_sequences]
gc_gen = [gc_content(s) for s in gen_sequences]
plt.figure(figsize=(7,5))
sns.kdeplot(gc_real, fill=True, color='blue', label='Real', alpha=0.4)
sns.kdeplot(gc_gen, fill=True, color='red', label='Generated', alpha=0.4)
plt.title("GC% Distribution (Real vs Generated)")
plt.xlabel("GC fraction"); plt.legend(); plt.show()

# ---------- Motif counts ----------
motifs = ["TATAAA", "GGGCGG", "CCAAT", "CACGTG"]
motif_counts_real = [sum(m in s for s in real_sequences) for m in motifs]
motif_counts_gen = [sum(m in s for s in gen_sequences) for m in motifs]
x = np.arange(len(motifs))
plt.bar(x-0.2, motif_counts_real, 0.4, label='Real', color='blue', alpha=0.6)
plt.bar(x+0.2, motif_counts_gen, 0.4, label='Generated', color='red', alpha=0.6)
plt.xticks(x, motifs); plt.ylabel("Count"); plt.legend()
plt.title("Motif Occurrence Comparison"); plt.show()

# ---------- 3-mer correlation ----------
real_k, _ = kmer_freqs(real_sequences)
gen_k, _ = kmer_freqs(gen_sequences)
corr = np.corrcoef(real_k, gen_k)[0,1]
plt.figure(figsize=(6,6))
plt.scatter(real_k, gen_k, alpha=0.5)
plt.title(f"3-mer Correlation (r={corr:.3f})")
plt.xlabel("Real"); plt.ylabel("Generated"); plt.show()

# ---------- Sequence logo ----------
df_gen = onehot_to_df(gen_sequences[:200])
plt.figure(figsize=(12,3))
logomaker.Logo(df_gen)
plt.title("Sequence Logo (Generated Promoters)"); plt.show()
```

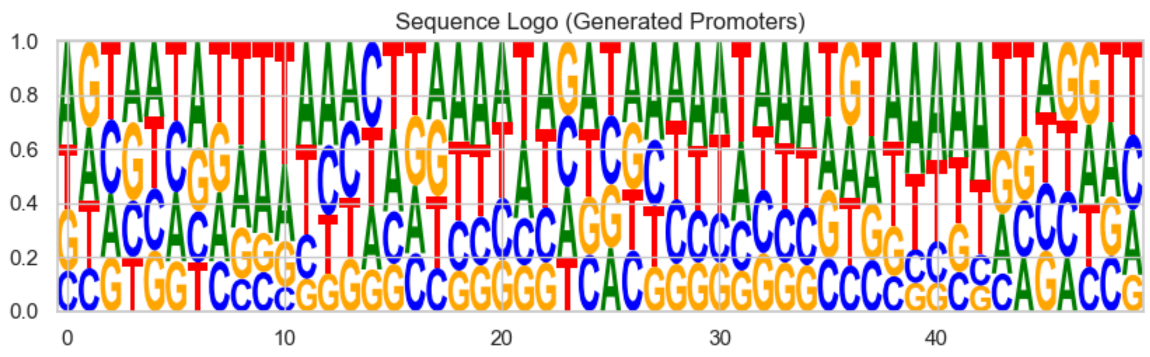
```
print(f"GC mean (real)={np.mean(gc_real):.3f}, (gen)={np.mean(gc_gen):.3f}")
print(f"3-mer correlation = {corr:.3f}")
```







```
<Figure size 1200x300 with 0 Axes>
```



```
GC mean (real)=0.443, (gen)=0.412
3-mer correlation = 0.594
```

Deeper model with residual connections

In [80]:
```python
import torch
import torch.nn as nn
import torch.nn.functional as F

# ----------------------------
# Basic Residual Block (1D)
# ----------------------------
class ResBlock(nn.Module):
    def __init__(self, in_ch, out_ch, kernel_size=5, dropout=0.1, seq_len=57):
        super().__init__()
        self.conv1 = nn.Conv1d(in_ch, out_ch, kernel_size, padding=kernel_size//2)
        self.conv2 = nn.Conv1d(out_ch, out_ch, kernel_size, padding=kernel_size//2)
        self.ln1 = nn.LayerNorm([out_ch, seq_len])
        self.ln2 = nn.LayerNorm([out_ch, seq_len])
        self.dropout = nn.Dropout(dropout)
        self.shortcut = (
            nn.Conv1d(in_ch, out_ch, 1) if in_ch != out_ch else nn.Identity()
        )

    def forward(self, x):
        residual = self.shortcut(x)
        out = F.relu(self.ln1(self.conv1(x)))
        out = self.dropout(F.relu(self.ln2(self.conv2(out))))
        return out + residual  # skip connection


# ----------------------------
# Residual Deep Convolutional VAE
# ----------------------------
class ResidualDeepConvVAE(nn.Module):
    def __init__(self, L=57, z_dim=256, base_c=64, dropout=0.1):
        super().__init__()
        self.L = L
        self.base_c = base_c
        # ----- Encoder -----
        self.enc_blocks = nn.Sequential(
            ResBlock(4, base_c, dropout=dropout, seq_len=L),
            ResBlock(base_c, base_c, dropout=dropout, seq_len=L),
            ResBlock(base_c, base_c*2, dropout=dropout, seq_len=L),
            ResBlock(base_c*2, base_c*2, dropout=dropout, seq_len=L),
            ResBlock(base_c*2, base_c*4, dropout=dropout, seq_len=L),
            ResBlock(base_c*4, base_c*4, dropout=dropout, seq_len=L),
        )

        enc_out_dim = base_c*4*L
        self.fc_mu = nn.Linear(enc_out_dim, z_dim)
        self.fc_logvar = nn.Linear(enc_out_dim, z_dim)

        # ----- Decoder -----
        self.fc_dec = nn.Linear(z_dim, enc_out_dim)
        self.dec_blocks = nn.Sequential(
            ResBlock(base_c*4, base_c*4, dropout=dropout, seq_len=L),
            ResBlock(base_c*4, base_c*2, dropout=dropout, seq_len=L),
            ResBlock(base_c*2, base_c*2, dropout=dropout, seq_len=L),
            ResBlock(base_c*2, base_c, dropout=dropout, seq_len=L),
            ResBlock(base_c, base_c, dropout=dropout, seq_len=L),
            nn.Conv1d(base_c, 4, 1)  # output logits
        )

    def encode(self, x):
        x = x.permute(0, 2, 1)  # (B,4,L)
        h = self.enc_blocks(x)
        h = h.flatten(start_dim=1)
        mu = self.fc_mu(h)
        logvar = self.fc_logvar(h)
        return mu, logvar

    def reparam(self, mu, logvar):
        std = torch.exp(0.5 * logvar)
        eps = torch.randn_like(std)
        return mu + eps * std

    def decode(self, z):
        h = self.fc_dec(z)
        h = h.view(-1, self.base_c*4, self.L)
        out = self.dec_blocks(h)
        return out.permute(0, 2, 1)  # (B,L,4)

    def forward(self, x):
        mu, logvar = self.encode(x)
        z = self.reparam(mu, logvar)
        logits = self.decode(z)
        return logits, mu, logvar
```

In [92]:
```
def vae_loss(logits, target, mu, logvar, beta=0.05):
    recon = F.cross_entropy(logits.reshape(-1,4), target.argmax(-1).reshape(-1))
    kl = -0.5 * torch.mean(1 + logvar - mu.pow(2) - logvar.exp())
    return recon + beta * kl, recon, kl

model = ResidualDeepConvVAE(L=L, z_dim=256, base_c=64, dropout=0.1).to(DEVICE)
opt = torch.optim.AdamW(model.parameters(), lr=5e-4, weight_decay=1e-4)
EPOCHS = 200
best_val = 1e9

for epoch in range(1, EPOCHS+1):
    model.train(); tr_loss = 0
    for xb in train_dl:
        xb = xb.to(DEVICE)
        logits, mu, logvar = model(xb)
        loss, rec, kl = vae_loss(logits, xb, mu, logvar, beta=0.05)
        opt.zero_grad()
        loss.backward()
        opt.step()
        tr_loss += loss.item() * xb.size(0)
    tr_loss /= len(train_dl.dataset)

    model.eval(); val_loss = 0
    with torch.no_grad():
        for xb in val_dl:
            xb = xb.to(DEVICE)
            logits, mu, logvar = model(xb)
            loss, _, _ = vae_loss(logits, xb, mu, logvar, beta=0.05)
            val_loss += loss.item() * xb.size(0)
    val_loss /= len(val_dl.dataset)
    print(f"Epoch {epoch:03d} | train={tr_loss:.4f} | val={val_loss:.4f}")

    if val_loss < best_val:
        best_val = val_loss
        torch.save(model.state_dict(), "models/vae_promoter_residual.pt")
        print(f"✅ Saved best model (val={best_val:.4f})")
```

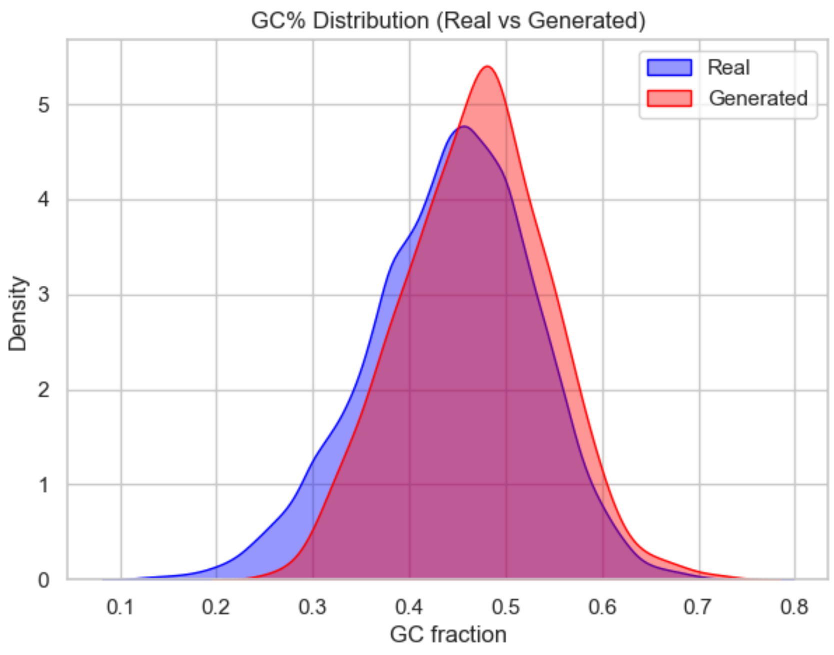
```
Epoch 001 | train=0.8083 | val=0.0840
✅ Saved best model (val=0.0840)
Epoch 002 | train=0.0876 | val=0.0705
✅ Saved best model (val=0.0705)
Epoch 003 | train=0.0751 | val=0.0668
✅ Saved best model (val=0.0668)
Epoch 004 | train=0.0691 | val=0.0623
✅ Saved best model (val=0.0623)
Epoch 005 | train=0.0655 | val=0.0607
✅ Saved best model (val=0.0607)
Epoch 006 | train=0.0634 | val=0.0600
✅ Saved best model (val=0.0600)
Epoch 007 | train=0.0619 | val=0.0569
✅ Saved best model (val=0.0569)
Epoch 008 | train=0.0603 | val=0.0561
✅ Saved best model (val=0.0561)
Epoch 009 | train=0.0598 | val=0.0555
✅ Saved best model (val=0.0555)
Epoch 010 | train=0.0584 | val=0.0553
✅ Saved best model (val=0.0553)
Epoch 011 | train=0.0576 | val=0.0541
✅ Saved best model (val=0.0541)
Epoch 012 | train=0.0566 | val=0.0531
✅ Saved best model (val=0.0531)
Epoch 013 | train=0.0560 | val=0.0531
Epoch 014 | train=0.0552 | val=0.0529
✅ Saved best model (val=0.0529)
Epoch 015 | train=0.0539 | val=0.0508
✅ Saved best model (val=0.0508)
Epoch 016 | train=0.0531 | val=0.0503
✅ Saved best model (val=0.0503)
Epoch 017 | train=0.0531 | val=0.0502
✅ Saved best model (val=0.0502)
Epoch 018 | train=0.0522 | val=0.0486
✅ Saved best model (val=0.0486)
Epoch 019 | train=0.0515 | val=0.0480
✅ Saved best model (val=0.0480)
Epoch 020 | train=0.0510 | val=0.0483
Epoch 021 | train=0.0500 | val=0.0476
✅ Saved best model (val=0.0476)
Epoch 022 | train=0.0494 | val=0.0489
Epoch 023 | train=0.0486 | val=0.0471
✅ Saved best model (val=0.0471)
Epoch 024 | train=0.0481 | val=0.0478
Epoch 025 | train=0.0475 | val=0.0452
✅ Saved best model (val=0.0452)
Epoch 026 | train=0.0474 | val=0.0450
✅ Saved best model (val=0.0450)
Epoch 027 | train=0.0464 | val=0.0450
✅ Saved best model (val=0.0450)
Epoch 028 | train=0.0457 | val=0.0437
✅ Saved best model (val=0.0437)
Epoch 029 | train=0.0456 | val=0.0435
✅ Saved best model (val=0.0435)
Epoch 030 | train=0.0451 | val=0.0432
✅ Saved best model (val=0.0432)
Epoch 031 | train=0.0440 | val=0.0425
✅ Saved best model (val=0.0425)
Epoch 032 | train=0.0443 | val=0.0431
Epoch 033 | train=0.0435 | val=0.0420
✅ Saved best model (val=0.0420)
Epoch 034 | train=0.0431 | val=0.0409
✅ Saved best model (val=0.0409)
Epoch 035 | train=0.0423 | val=0.0409
Epoch 036 | train=0.0423 | val=0.0408
✅ Saved best model (val=0.0408)
Epoch 037 | train=0.0416 | val=0.0404
✅ Saved best model (val=0.0404)
Epoch 038 | train=0.0414 | val=0.0406
Epoch 039 | train=0.0410 | val=0.0402
✅ Saved best model (val=0.0402)
Epoch 040 | train=0.0400 | val=0.0391
✅ Saved best model (val=0.0391)
Epoch 041 | train=0.0401 | val=0.0388
✅ Saved best model (val=0.0388)
Epoch 042 | train=0.0399 | val=0.0386
✅ Saved best model (val=0.0386)
Epoch 043 | train=0.0397 | val=0.0389
Epoch 044 | train=0.0392 | val=0.0383
✅ Saved best model (val=0.0383)
Epoch 045 | train=0.0388 | val=0.0376
✅ Saved best model (val=0.0376)
Epoch 046 | train=0.0384 | val=0.0381
Epoch 047 | train=0.0382 | val=0.0377
Epoch 048 | train=0.0379 | val=0.0371
✅ Saved best model (val=0.0371)
Epoch 049 | train=0.0378 | val=0.0381
Epoch 050 | train=0.0380 | val=0.0362
✅ Saved best model (val=0.0362)
Epoch 051 | train=0.0373 | val=0.0366
Epoch 052 | train=0.0368 | val=0.0368
Epoch 053 | train=0.0370 | val=0.0368
Epoch 054 | train=0.0368 | val=0.0362
Epoch 055 | train=0.0364 | val=0.0363
Epoch 056 | train=0.0362 | val=0.0363
Epoch 057 | train=0.0362 | val=0.0359
✅ Saved best model (val=0.0359)
Epoch 058 | train=0.0357 | val=0.0353
✅ Saved best model (val=0.0353)
Epoch 059 | train=0.0356 | val=0.0352
✅ Saved best model (val=0.0352)
Epoch 060 | train=0.0354 | val=0.0347
✅ Saved best model (val=0.0347)
Epoch 061 | train=0.0354 | val=0.0353
Epoch 062 | train=0.0350 | val=0.0347
Epoch 063 | train=0.0349 | val=0.0345
✅ Saved best model (val=0.0345)
Epoch 064 | train=0.0349 | val=0.0351
Epoch 065 | train=0.0348 | val=0.0348
Epoch 066 | train=0.0346 | val=0.0340
✅ Saved best model (val=0.0340)
Epoch 067 | train=0.0345 | val=0.0345
Epoch 068 | train=0.0345 | val=0.0344
Epoch 069 | train=0.0346 | val=0.0345
Epoch 070 | train=0.0343 | val=0.0342
Epoch 071 | train=0.0341 | val=0.0339
✅ Saved best model (val=0.0339)
Epoch 072 | train=0.0341 | val=0.0339
✅ Saved best model (val=0.0339)
Epoch 073 | train=0.0338 | val=0.0335
✅ Saved best model (val=0.0335)
Epoch 074 | train=0.0337 | val=0.0336
Epoch 075 | train=0.0338 | val=0.0344
Epoch 076 | train=0.0340 | val=0.0340
Epoch 077 | train=0.0337 | val=0.0331
✅ Saved best model (val=0.0331)
Epoch 078 | train=0.0336 | val=0.0332
Epoch 079 | train=0.0335 | val=0.0333
Epoch 080 | train=0.0333 | val=0.0331
Epoch 081 | train=0.0332 | val=0.0329
✅ Saved best model (val=0.0329)
Epoch 082 | train=0.0332 | val=0.0332
Epoch 083 | train=0.0331 | val=0.0333
Epoch 084 | train=0.0332 | val=0.0333
Epoch 085 | train=0.0331 | val=0.0325
✅ Saved best model (val=0.0325)
Epoch 086 | train=0.0331 | val=0.0321
✅ Saved best model (val=0.0321)
Epoch 087 | train=0.0328 | val=0.0325
Epoch 088 | train=0.0328 | val=0.0327
Epoch 089 | train=0.0328 | val=0.0324
Epoch 090 | train=0.0327 | val=0.0331
Epoch 091 | train=0.0327 | val=0.0330
Epoch 092 | train=0.0328 | val=0.0323
Epoch 093 | train=0.0325 | val=0.0324
Epoch 094 | train=0.0325 | val=0.0320
✅ Saved best model (val=0.0320)
Epoch 095 | train=0.0325 | val=0.0321
Epoch 096 | train=0.0327 | val=0.0323
Epoch 097 | train=0.0323 | val=0.0325
Epoch 098 | train=0.0325 | val=0.0321
Epoch 099 | train=0.0323 | val=0.0327
Epoch 100 | train=0.0322 | val=0.0321
Epoch 101 | train=0.0320 | val=0.0321
Epoch 102 | train=0.0324 | val=0.0318
✅ Saved best model (val=0.0318)
Epoch 103 | train=0.0320 | val=0.0316
✅ Saved best model (val=0.0316)
Epoch 104 | train=0.0320 | val=0.0320
Epoch 105 | train=0.0320 | val=0.0323
Epoch 106 | train=0.0321 | val=0.0324
Epoch 107 | train=0.0321 | val=0.0317
Epoch 108 | train=0.0319 | val=0.0323
Epoch 109 | train=0.0317 | val=0.0317
Epoch 110 | train=0.0319 | val=0.0319
Epoch 111 | train=0.0318 | val=0.0317
Epoch 112 | train=0.0320 | val=0.0315
✅ Saved best model (val=0.0315)
Epoch 113 | train=0.0318 | val=0.0315
Epoch 114 | train=0.0319 | val=0.0315
✅ Saved best model (val=0.0315)
Epoch 115 | train=0.0316 | val=0.0316
Epoch 116 | train=0.0318 | val=0.0316
Epoch 117 | train=0.0315 | val=0.0316
Epoch 118 | train=0.0317 | val=0.0318
Epoch 119 | train=0.0317 | val=0.0314
✅ Saved best model (val=0.0314)
Epoch 120 | train=0.0315 | val=0.0318
Epoch 121 | train=0.0314 | val=0.0315
Epoch 122 | train=0.0315 | val=0.0313
✅ Saved best model (val=0.0313)
Epoch 123 | train=0.0315 | val=0.0315
Epoch 124 | train=0.0313 | val=0.0316
Epoch 125 | train=0.0315 | val=0.0313
```

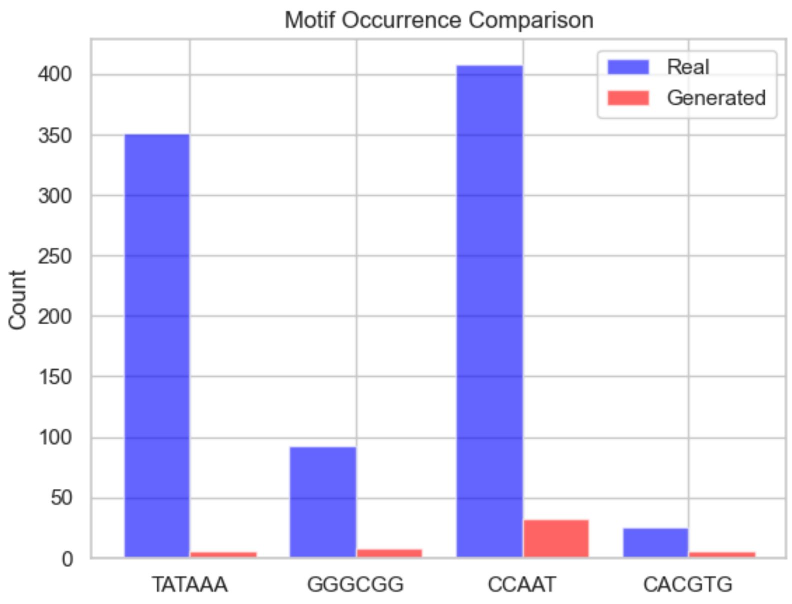
```
✅ Saved best model (val=0.0313)
Epoch 126 | train=0.0313 | val=0.0312
✅ Saved best model (val=0.0312)
Epoch 127 | train=0.0311 | val=0.0312
Epoch 128 | train=0.0313 | val=0.0310
✅ Saved best model (val=0.0310)
Epoch 129 | train=0.0313 | val=0.0310
Epoch 130 | train=0.0314 | val=0.0315
Epoch 131 | train=0.0311 | val=0.0310
Epoch 132 | train=0.0312 | val=0.0310
Epoch 133 | train=0.0311 | val=0.0310
Epoch 134 | train=0.0311 | val=0.0311
Epoch 135 | train=0.0310 | val=0.0311
Epoch 136 | train=0.0310 | val=0.0311
Epoch 137 | train=0.0310 | val=0.0310
Epoch 138 | train=0.0308 | val=0.0307
✅ Saved best model (val=0.0307)
Epoch 139 | train=0.0310 | val=0.0310
Epoch 140 | train=0.0310 | val=0.0309
Epoch 141 | train=0.0309 | val=0.0307
Epoch 142 | train=0.0308 | val=0.0305
✅ Saved best model (val=0.0305)
Epoch 143 | train=0.0309 | val=0.0310
Epoch 144 | train=0.0308 | val=0.0309
Epoch 145 | train=0.0307 | val=0.0308
Epoch 146 | train=0.0307 | val=0.0306
Epoch 147 | train=0.0308 | val=0.0308
Epoch 148 | train=0.0308 | val=0.0305
Epoch 149 | train=0.0308 | val=0.0305
✅ Saved best model (val=0.0305)
Epoch 150 | train=0.0306 | val=0.0304
✅ Saved best model (val=0.0304)
Epoch 151 | train=0.0305 | val=0.0304
✅ Saved best model (val=0.0304)
Epoch 152 | train=0.0309 | val=0.0308
Epoch 153 | train=0.0306 | val=0.0306
Epoch 154 | train=0.0305 | val=0.0304
✅ Saved best model (val=0.0304)
Epoch 155 | train=0.0305 | val=0.0302
✅ Saved best model (val=0.0302)
Epoch 156 | train=0.0307 | val=0.0304
Epoch 157 | train=0.0303 | val=0.0304
Epoch 158 | train=0.0307 | val=0.0304
Epoch 159 | train=0.0304 | val=0.0304
Epoch 160 | train=0.0305 | val=0.0301
✅ Saved best model (val=0.0301)
Epoch 161 | train=0.0303 | val=0.0305
Epoch 162 | train=0.0304 | val=0.0306
Epoch 163 | train=0.0304 | val=0.0303
Epoch 164 | train=0.0304 | val=0.0304
Epoch 165 | train=0.0303 | val=0.0300
✅ Saved best model (val=0.0300)
Epoch 166 | train=0.0302 | val=0.0300
Epoch 167 | train=0.0304 | val=0.0303
Epoch 168 | train=0.0305 | val=0.0305
Epoch 169 | train=0.0301 | val=0.0299
✅ Saved best model (val=0.0299)
Epoch 170 | train=0.0302 | val=0.0303
Epoch 171 | train=0.0302 | val=0.0302
Epoch 172 | train=0.0302 | val=0.0300
Epoch 173 | train=0.0302 | val=0.0303
Epoch 174 | train=0.0302 | val=0.0300
Epoch 175 | train=0.0302 | val=0.0298
✅ Saved best model (val=0.0298)
Epoch 176 | train=0.0301 | val=0.0298
Epoch 177 | train=0.0302 | val=0.0299
Epoch 178 | train=0.0301 | val=0.0302
Epoch 179 | train=0.0301 | val=0.0300
Epoch 180 | train=0.0299 | val=0.0301
Epoch 181 | train=0.0301 | val=0.0304
Epoch 182 | train=0.0301 | val=0.0301
Epoch 183 | train=0.0300 | val=0.0298
✅ Saved best model (val=0.0298)
Epoch 184 | train=0.0300 | val=0.0300
Epoch 185 | train=0.0299 | val=0.0301
Epoch 186 | train=0.0300 | val=0.0300
Epoch 187 | train=0.0300 | val=0.0301
Epoch 188 | train=0.0298 | val=0.0300
Epoch 189 | train=0.0299 | val=0.0297
✅ Saved best model (val=0.0297)
Epoch 190 | train=0.0299 | val=0.0297
✅ Saved best model (val=0.0297)
Epoch 191 | train=0.0298 | val=0.0300
Epoch 192 | train=0.0299 | val=0.0298
Epoch 193 | train=0.0299 | val=0.0297
Epoch 194 | train=0.0297 | val=0.0295
✅ Saved best model (val=0.0295)
Epoch 195 | train=0.0296 | val=0.0297
Epoch 196 | train=0.0296 | val=0.0296
Epoch 197 | train=0.0298 | val=0.0297
Epoch 198 | train=0.0296 | val=0.0296
Epoch 199 | train=0.0297 | val=0.0296
Epoch 200 | train=0.0296 | val=0.0296
```

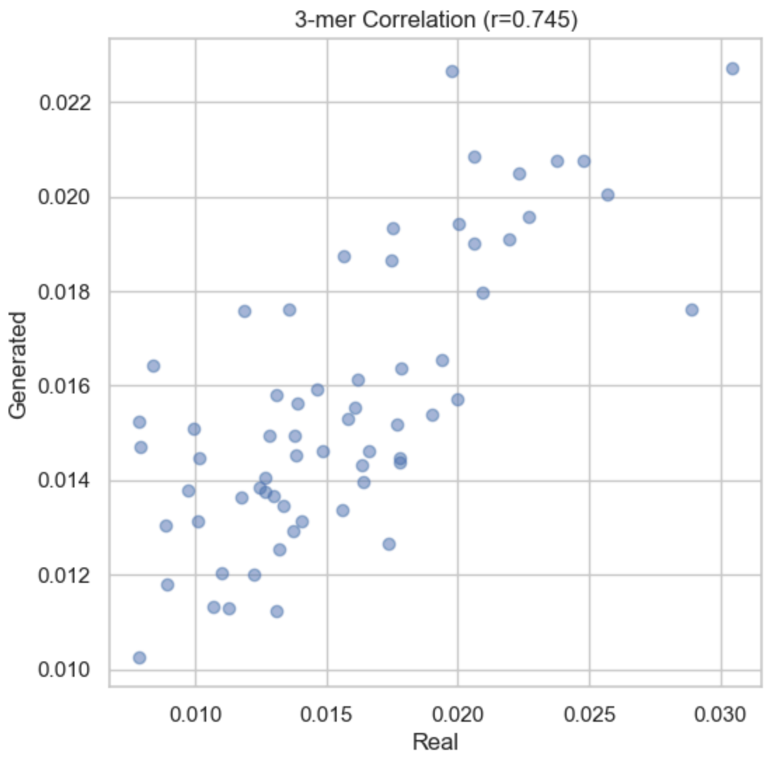
In [93]:
```
model.load_state_dict(torch.load("models/vae_promoter_residual.pt", map_location=DEVICE))
model.eval()

N = 500
z = torch.randn(N, 256).to(DEVICE) * 1.5  # larger variance for diversity
with torch.no_grad():
    logits = model.decode(z)
    probs = torch.softmax(logits, dim=-1)
    sampled = torch.argmax(probs, dim=-1).cpu().numpy()

idx2nt = np.array(["A","C","G","T"])
gen_sequences = ["".join(idx2nt[s]) for s in sampled]
print(f"Generated {len(gen_sequences)} new promoter sequences.")
print(gen_sequences[0][:80])
```

```
Generated 500 new promoter sequences.
GGCGTTAGGGCAGAGTCCGCCGACTTGGGAATTTGACTCCAGGTTCCTAC
```

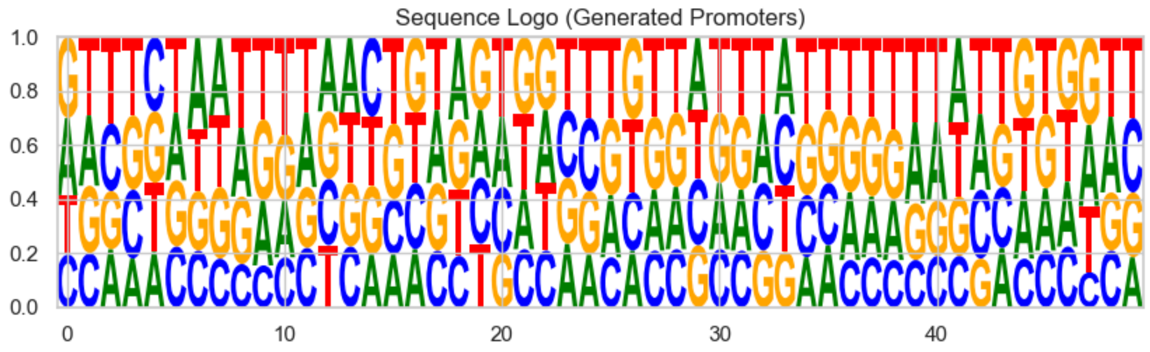
In [94]:
```
# ---------- helpers ----------
def gc_content(seq): return (seq.count("G")+seq.count("C"))/len(seq)
def kmer_freqs(seqs, k=3):
    all_kmers = [''.join(p) for p in product('ACGT', repeat=k)]
    counts = Counter()
    for seq in seqs:
        for i in range(len(seq)-k+1):
            counts[seq[i:i+k]] += 1
    total = sum(counts.values())
    return np.array([counts[km]/total for km in all_kmers]), all_kmers
def onehot_to_df(seqs):
    L = len(seqs[0])
    df = pd.DataFrame(0, index=list("ACGT"), columns=range(L))
    for seq in seqs:
        for i,b in enumerate(seq):
            if b in "ACGT":
                df.loc[b,i]+=1
    return (df/df.sum()).T

# ---------- GC content ----------
gc_real = [gc_content(s) for s in real_sequences]
gc_gen = [gc_content(s) for s in gen_sequences]
plt.figure(figsize=(7,5))
sns.kdeplot(gc_real, fill=True, color='blue', label='Real', alpha=0.4)
sns.kdeplot(gc_gen, fill=True, color='red', label='Generated', alpha=0.4)
plt.title("GC% Distribution (Real vs Generated)")
plt.xlabel("GC fraction"); plt.legend(); plt.show()

# ---------- Motif counts ----------
motifs = ["TATAAA", "GGGCGG", "CCAAT", "CACGTG"]
motif_counts_real = [sum(m in s for s in real_sequences) for m in motifs]
motif_counts_gen = [sum(m in s for s in gen_sequences) for m in motifs]
x = np.arange(len(motifs))
plt.bar(x-0.2, motif_counts_real, 0.4, label='Real', color='blue', alpha=0.6)
plt.bar(x+0.2, motif_counts_gen, 0.4, label='Generated', color='red', alpha=0.6)
plt.xticks(x, motifs); plt.ylabel("Count"); plt.legend()
plt.title("Motif Occurrence Comparison"); plt.show()

# ---------- 3-mer correlation ----------
real_k, _ = kmer_freqs(real_sequences)
gen_k, _ = kmer_freqs(gen_sequences)
corr = np.corrcoef(real_k, gen_k)[0,1]
plt.figure(figsize=(6,6))
plt.scatter(real_k, gen_k, alpha=0.5)
plt.title(f"3-mer Correlation (r={corr:.3f})")
plt.xlabel("Real"); plt.ylabel("Generated"); plt.show()

# ---------- Sequence logo ----------
df_gen = onehot_to_df(gen_sequences[:200])
plt.figure(figsize=(12,3))
logomaker.Logo(df_gen)
plt.title("Sequence Logo (Generated Promoters)"); plt.show()

print(f"GC mean (real)={np.mean(gc_real):.3f}, (gen)={np.mean(gc_gen):.3f}")
print(f"3-mer correlation = {corr:.3f}")
```


GC% Distribution (Real vs Generated)
Real
Generated
Density
GC fraction
0
1
2
3
4
5
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8


Motif Occurrence Comparison
Real
Generated
Count
0
50
100
150
200
250
300
350
400
TATAAA
GGGCGG
CCAAT
CACGTG


3-mer Correlation (r=0.745)
Generated
Real
0.010
0.012
0.014
0.016
0.018
0.020
0.022
0.010
0.015
0.020
0.025
0.030

```
<Figure size 1200x300 with 0 Axes>
```



```
GC mean (real)=0.443, (gen)=0.469
3-mer correlation = 0.745
```