

Neural Network Architectures — Code-Focused Field Guide (PyTorch + Diagrams)

A practical, code-oriented overview of key architectures: what they are, when to use them, with minimal PyTorch examples.

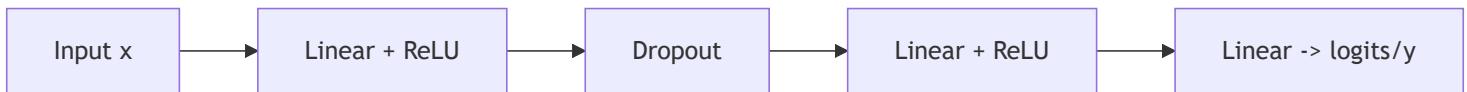
0) Quick “when to use what”

Modality / Task	First pick	Why	Alternatives
Tabular (CTR/ranking)	Wide & Deep / DLRM	sparse IDs + dense feats	Plain MLP
Images (classification)	ResNet / ViT (pretrained)	strong transfer	ConvNeXt, EfficientNet
Images (segmentation)	U-Net / DeepLab	multi-scale + skips	FPN, Mask R-CNN
Text understanding	Encoder Transformer (BERT)	contextual reps	BiLSTM+CRF (small)
Text/code generation	Decoder Transformer (GPT)	SOTA generation	RNN-LM (on-device)
Seq2Seq (translation)	Encoder–Decoder (T5/BART)	alignment via attention	CTC+attention hybrids
Time series	TCN / Transformer	long horizon receptive field	S4/SSM, classical
Speech (streaming ASR)	RNN-T / Conformer	streaming + accuracy	CTC + chunking
Graphs	GCN/GAT/GraphSAGE	exploits edges	Graph Transformers

Modality / Task	First pick	Why	Alternatives
Retrieval/verification	Siamese/contrastive	metric space	Triplet, ArcFace
Generative (images)	Diffusion (Latent)	fidelity + stability	GANs, autoreg.

1) MLP (Multi-Layer Perceptron)

Use: tabular, small dense features, heads on top of encoders.



```
import torch, torch.nn as nn
```

```
class MLP(nn.Module):
    def __init__(self, d_in, d_hidden=256, d_out=1, p=0.1):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(d_in, d_hidden),
            nn.ReLU(),
            nn.Dropout(p),
            nn.Linear(d_hidden, d_hidden),
            nn.ReLU(),
            nn.Linear(d_hidden, d_out)
        )
    def forward(self, x):
        return self.net(x)
```

Tip: standardize features, use weight decay, early stop for tabular.

When: lots of dense engineered features or embeddings; otherwise CNN/Transformer often wins.

2) CNNs (ResNet-style)

Use: images (and 2D/1D signals). Translation equivariance, local filters.



```

class BasicBlock(nn.Module):
    def __init__(self, c, stride=1):
        super().__init__()
        self.conv1 = nn.Conv2d(c, c, 3, stride, 1, bias=False)
        self.bn1 = nn.BatchNorm2d(c)
        self.conv2 = nn.Conv2d(c, c, 3, 1, 1, bias=False)
        self.bn2 = nn.BatchNorm2d(c)

    def forward(self, x):
        identity = x
        out = torch.relu(self.bn1(self.conv1(x)))
        out = self.bn2(self.conv2(out))
        out += identity
        return torch.relu(out)

class TinyResNet(nn.Module):
    def __init__(self, in_ch=3, num_classes=10):
        super().__init__()
        self.stem = nn.Sequential(
            nn.Conv2d(in_ch, 64, 7, 2, 3, bias=False),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.MaxPool2d(3, 2, 1))
        self.layer = nn.Sequential(*[BasicBlock(64) for _ in range(4)])
        self.head = nn.Linear(64, num_classes)

    def forward(self, x):
        x = self.stem(x)
        x = self.layer(x).mean(dim=(2,3)) # global avg pool
        return self.head(x)

```

Tips: transfer-learn from ResNet-50 (freeze most layers; train head), use augmentations (mixup, CutMix), cosine LR with warmup.

3) U-Net (Encoder–Decoder with skips)

Use: segmentation, denoising, image-to-image.

Encoder: conv ↓ ↓ ↓
 ↘ ↘
Skips ——————
Decoder: ↑ ↑ ↑ with concat

```

class ConvBlock(nn.Module):
    def __init__(self, c_in, c_out):
        super().__init__()
        self.block = nn.Sequential(
            nn.Conv2d(c_in, c_out, 3, padding=1), nn.ReLU(),
            nn.Conv2d(c_out, c_out, 3, padding=1), nn.ReLU())
    def forward(self, x): return self.block(x)

class UNet(nn.Module):
    def __init__(self, in_ch=1, out_ch=1, base=32):
        super().__init__()
        self.down1 = ConvBlock(in_ch, base)
        self.down2 = ConvBlock(base, base*2)
        self.down3 = ConvBlock(base*2, base*4)
        self.pool = nn.MaxPool2d(2)

        self.bottleneck = ConvBlock(base*4, base*8)

        self.up3 = nn.ConvTranspose2d(base*8, base*4, 2, 2)
        self.dec3 = ConvBlock(base*8, base*4)
        self.up2 = nn.ConvTranspose2d(base*4, base*2, 2, 2)
        self.dec2 = ConvBlock(base*4, base*2)
        self.up1 = nn.ConvTranspose2d(base*2, base, 2, 2)
        self.dec1 = ConvBlock(base*2, base)

        self.out = nn.Conv2d(base, out_ch, 1)

    def forward(self, x):
        s1 = self.down1(x); x = self.pool(s1)
        s2 = self.down2(x); x = self.pool(s2)
        s3 = self.down3(x); x = self.pool(s3)
        x = self.bottleneck(x)
        x = self.up3(x); x = torch.cat([x, s3], dim=1); x = self.dec3(x)
        x = self.up2(x); x = torch.cat([x, s2], dim=1); x = self.dec2(x)
        x = self.up1(x); x = torch.cat([x, s1], dim=1); x = self.dec1(x)
        return self.out(x)

```

Tips: use Dice/Focal loss with class imbalance; deep supervision helps.

4) RNNs (Vanilla / LSTM / GRU)

Use: streaming/online sequence modeling, low latency.

Diagram A

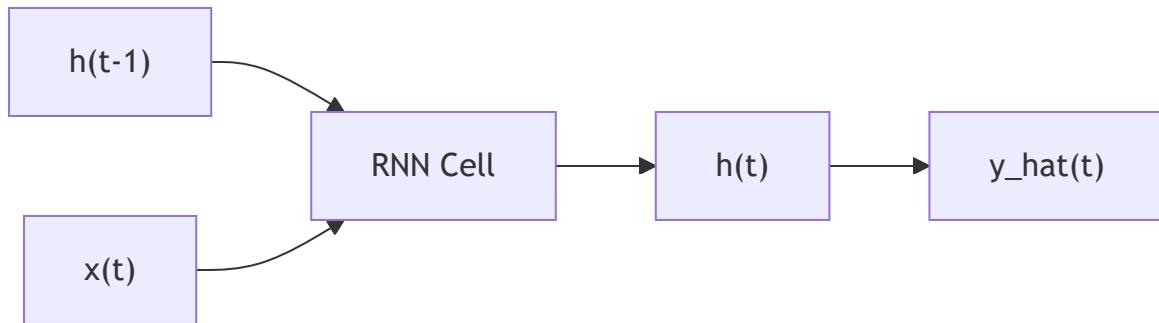
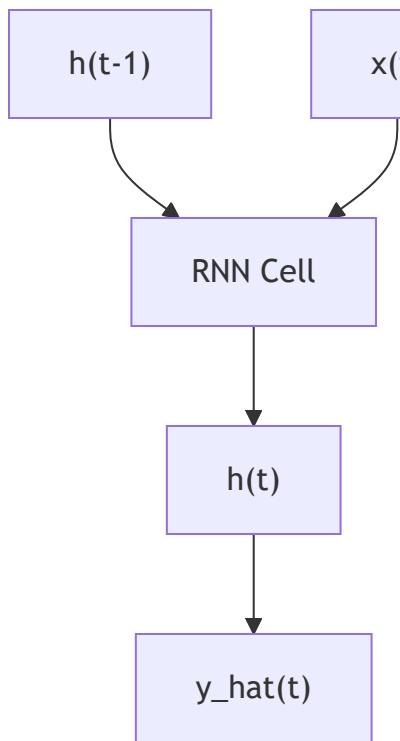


Diagram B



```

class TinyRNN(nn.Module):
    def __init__(self, d_in, d_hid, d_out):
        super().__init__()
        self.rnn = nn.GRU(d_in, d_hid, batch_first=True) # or nn.LSTM
        self.head = nn.Linear(d_hid, d_out)
    def forward(self, x, h0=None):
        # x: (B, T, d_in)
        h, _ = self.rnn(x, h0)
        logits = self.head(h)           # (B, T, d_out)
        return logits

```

Tips: orthogonal init for recurrent weights; gradient clipping; use LSTM/GRU over vanilla; RNN-T for streaming ASR.

5) Temporal Convolutional Networks (TCN)

Use: time series forecasting/classification with long receptive fields.

Diagram A

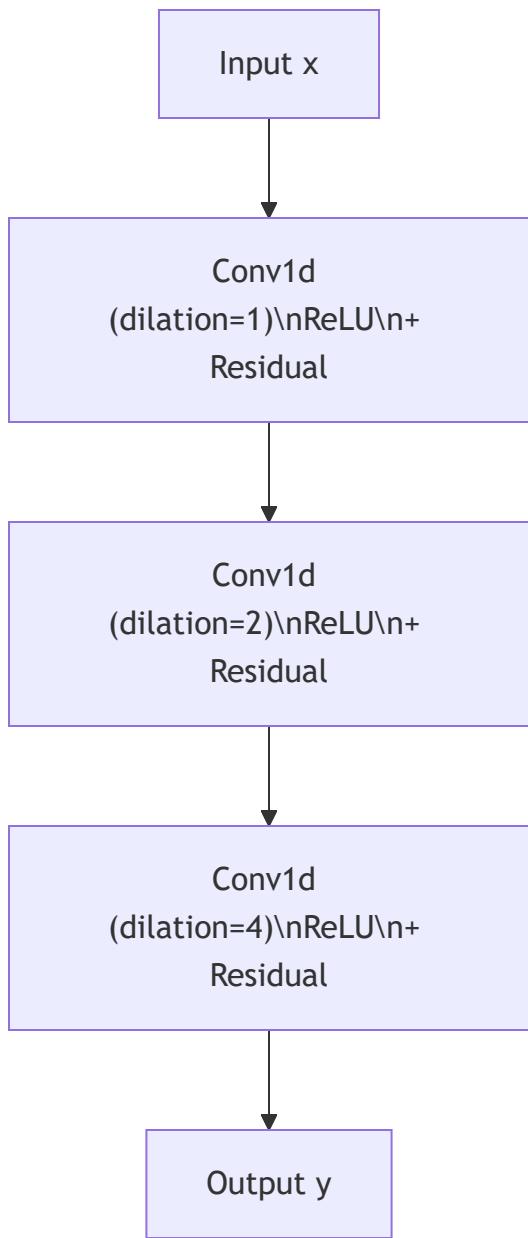


Diagram B

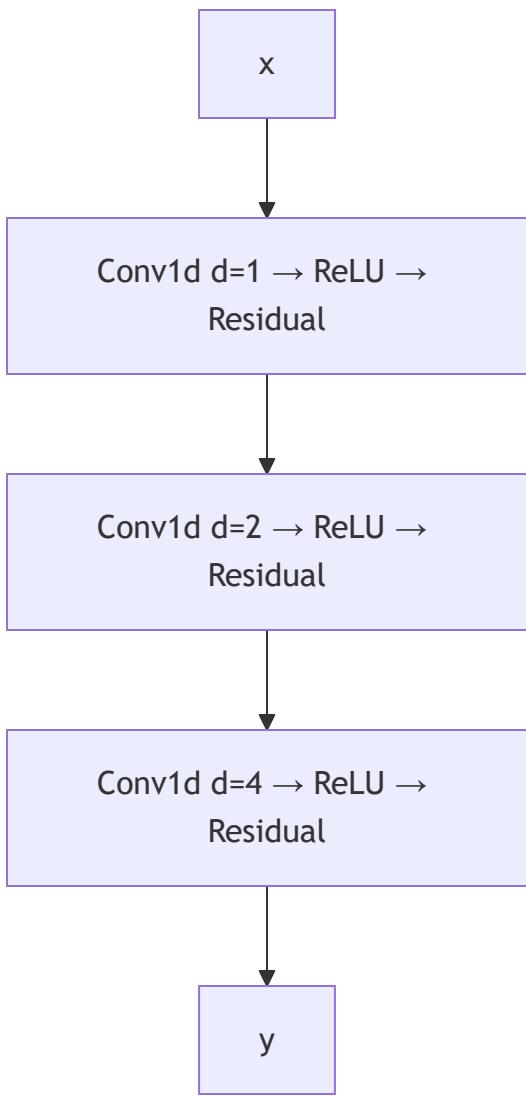
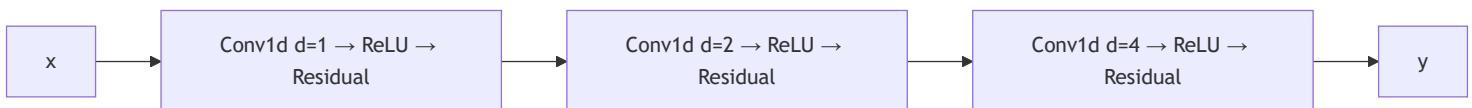


Diagram C



```

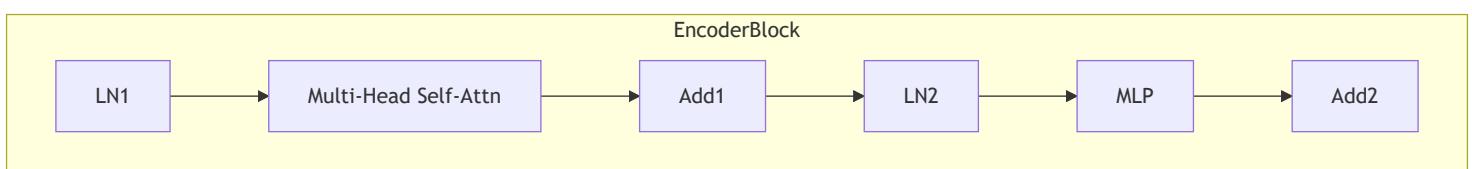
class TCNBlock(nn.Module):
    def __init__(self, c, k=3, dilation=1, p=0.1):
        super().__init__()
        self.net = nn.Sequential(
            nn.Conv1d(c, c, k, padding=dilation*(k-1)//2, dilation=dilation),
            nn.ReLU(),
            nn.Dropout(p),
            nn.Conv1d(c, c, k, padding=dilation*(k-1)//2, dilation=dilation))
    def forward(self, x):
        return torch.relu(self.net(x) + x)

class TinyTCN(nn.Module):
    def __init__(self, d_in, d_hid, d_out):
        super().__init__()
        self.proj = nn.Conv1d(d_in, d_hid, 1)
        self.blocks = nn.Sequential(
            TCNBlock(d_hid, dilation=1),
            TCNBlock(d_hid, dilation=2),
            TCNBlock(d_hid, dilation=4))
        self.head = nn.Conv1d(d_hid, d_out, 1)
    def forward(self, x): # x: (B, T, d_in)
        x = x.transpose(1,2)
        x = self.proj(x)
        x = self.blocks(x)
        return self.head(x).transpose(1,2) # (B,T,d_out)

```

6) Transformers (Encoder / Decoder / Enc-Dec)

Use: text/code, long-range dependencies, scalable transfer.



```

class MHSA(nn.Module):
    def __init__(self, d_model, n_heads):
        super().__init__()
        assert d_model % n_heads == 0
        self.nh = n_heads; self.dk = d_model // n_heads
        self.qkv = nn.Linear(d_model, 3*d_model)
        self.proj = nn.Linear(d_model, d_model)

    def forward(self, x, mask=None):
        B,T,D = x.shape
        q,k,v = self.qkv(x).chunk(3, dim=-1) # (B,T,D) each
        def split(t): return t.view(B,T,self.nh,self.dk).transpose(1,2) # (B,nh,
        q,k,v = map(split, (q,k,v))
        scores = (q @ k.transpose(-2,-1)) / (self.dk**0.5) # (B,nh,T,T)
        if mask is not None: scores = scores.masked_fill(mask==0, -1e9)
        w = scores.softmax(dim=-1)
        attn = w @ v # (B,nh,T,dk)
        attn = attn.transpose(1,2).contiguous().view(B,T,D)
        return self.proj(attn)

class TransformerBlock(nn.Module):
    def __init__(self, d_model=512, n_heads=8, d_ff=2048, p=0.1):
        super().__init__()
        self.ln1 = nn.LayerNorm(d_model)
        self.attn = MHSA(d_model, n_heads)
        self.ln2 = nn.LayerNorm(d_model)
        self.ff = nn.Sequential(
            nn.Linear(d_model, d_ff), nn.ReLU(), nn.Dropout(p),
            nn.Linear(d_ff, d_model))
    def forward(self, x, mask=None):
        x = x + self.attn(self.ln1(x), mask)
        x = x + self.ff(self.ln2(x))
        return x

```

Tips: use pretrained checkpoints; for long sequences consider efficient attention (Performer/Longformer) or SSMs; tune LR with warmup + cosine; apply weight decay to weights (exclude LayerNorm/bias).

7) Graph Neural Networks (GCN/GAT)

Use: data with nodes + edges (molecules, social nets, KGs).

Diagram A

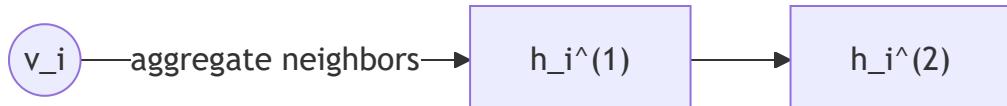


Diagram B



Diagram C



GCN layer (message passing): $(H^{(l+1)}) = \sigma(\hat{D}^{-1/2}\hat{A}\hat{D}^{-1/2} H^{(l)} W^{(l)})$

```
class GCNLayer(nn.Module):
    def __init__(self, d_in, d_out):
        super().__init__()
        self.lin = nn.Linear(d_in, d_out, bias=False)

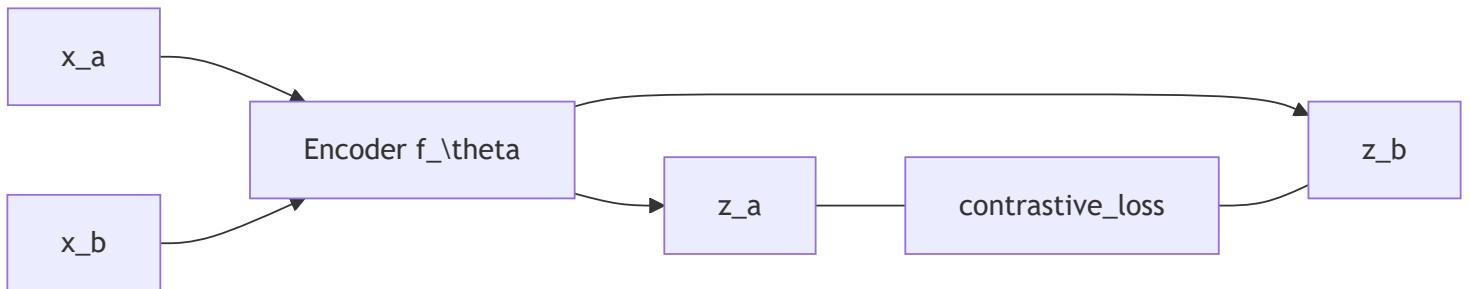
    def forward(self, X, A_hat): # X: (N,d), A_hat: normalized adj (N,N)
        return torch.relu(A_hat @ self.lin(X))

# Minimal forward:
# A_hat = add_self_loops_and_normalize(A) # precompute once
# X -> GCNLayer -> GCNLayer -> readout (mean/sum pooling) -> MLP
```

Tips: sample neighborhoods on large graphs; add residuals & norms; handle class imbalance with weighted loss.

8) Siamese / Contrastive (Metric Learning)

Use: retrieval, verification, deduplication (face/voice), CLIP-style.



```
class Encoder(nn.Module):
    def __init__(self, d_in, d_emb=128):
        super().__init__()
        self.net = nn.Sequential(nn.Linear(d_in, 256), nn.ReLU(), nn.Linear(256,
    def forward(self, x): return nn.functional.normalize(self.net(x), dim=-1)

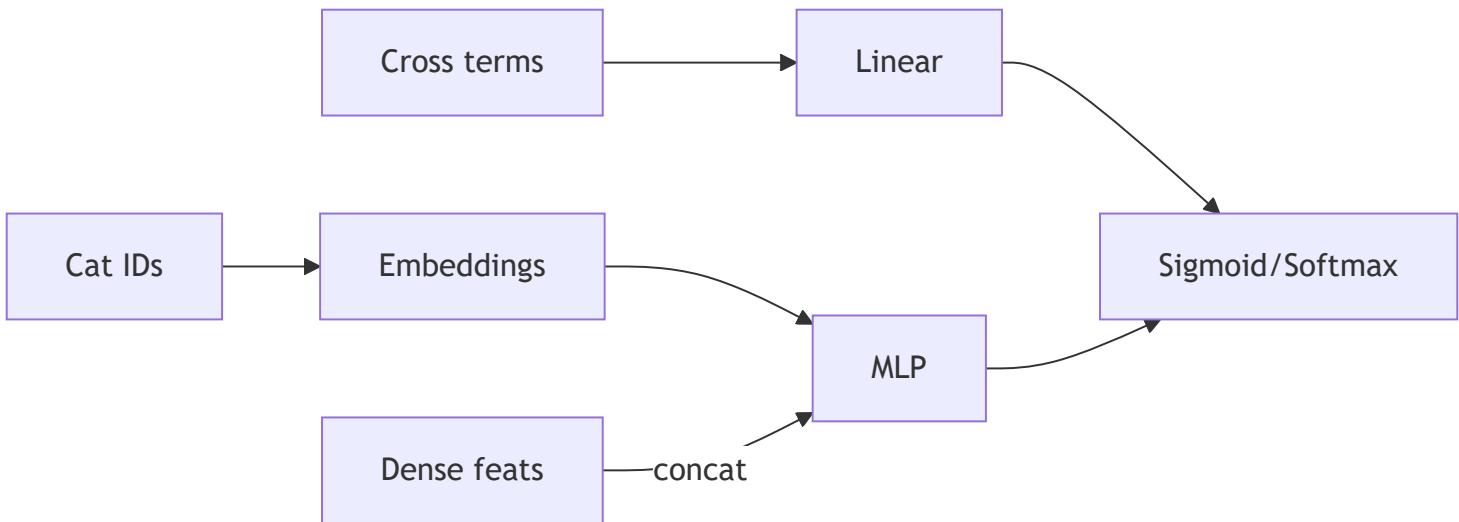
def contrastive_loss(z_a, z_b, tau=0.1):
    sim = z_a @ z_b.t() / tau # (B,B)
    target = torch.arange(z_a.size(0), device=z_a.device)
    return nn.CrossEntropyLoss()(sim, target) # InfoNCE (a->b); often add b->a
```



Tips: batch composition matters (hard negatives); use temperature; consider margin losses (ArcFace) for classification-as-metric.

9) Recruiters (Wide & Deep)

Use: sparse categorical IDs + dense numerical features.



```

class WideAndDeep(nn.Module):
    def __init__(self, num_ids, emb_dim, d_dense, d_hidden=256):
        super().__init__()
        self.emb = nn.Embedding(num_ids, emb_dim)
        self.deep = nn.Sequential(
            nn.Linear(emb_dim + d_dense, d_hidden), nn.ReLU(),
            nn.Linear(d_hidden, d_hidden), nn.ReLU())
        self.wide = nn.Linear(d_dense, 1) # example: linear over dense (add cr
        self.out = nn.Linear(d_hidden, 1)

    def forward(self, ids, dense):
        e = self.emb(ids).mean(dim=1) # bag multiple IDs: (B, M, emb) -> (B, 1, emb)
        deep_out = self.deep(torch.cat([e, dense], dim=-1))
        logit = self.wide(dense) + self.out(deep_out)
        return torch.sigmoid(logit).squeeze(-1)
  
```



Tips: embeddings dominate memory → consider quantization/sharding; calibrate outputs (Platt/temperature).

10) Diffusion (DDPM — toy skeleton)

Use: high-fidelity generation (images/audio). Below is a minimal 1D sketch.

```

class TinyUNet1D(nn.Module):
    def __init__(self, d=64):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(1, d), nn.SiLU(),
            nn.Linear(d, d), nn.SiLU(),
            nn.Linear(d, 1))
    def forward(self, x, t_emb): # t_emb ignored here; real models condition on t
        return self.net(x)

# Training loop idea (toy):
# sample t ~ Uniform({1..T}); add noise ε to x0 to get xt; predict ε
# loss = ||ε - ε_theta(xt, t)||^2

```

Tips: use sinusoidal time embeddings, U-Net backbones, cosine noise schedules; classifier-free guidance for conditional tasks; latent diffusion for speed.

11) Normalizing Flows (RealNVP-style affine coupling)

Use: exact likelihood + sampling.

```

class AffineCoupling(nn.Module):
    def __init__(self, d):
        super().__init__()
        self.s = nn.Sequential(nn.Linear(d//2, d), nn.ReLU(), nn.Linear(d, d//2))
        self.t = nn.Sequential(nn.Linear(d//2, d), nn.ReLU(), nn.Linear(d, d//2))
    def forward(self, x, reverse=False):
        x1, x2 = x.chunk(2, dim=-1)
        s, t = self.s(x1), self.t(x1)
        if not reverse:
            y2 = x2 * torch.exp(s) + t
            logdet = s.sum(dim=-1)
        else:
            y2 = (x2 - t) * torch.exp(-s)
            logdet = -s.sum(dim=-1)
        return torch.cat([x1, y2], dim=-1), logdet

```



Tips: stack many couplings + permutations; track log-det sums; careful init to stabilize training.

12) State-Space / Long-Sequence (S4-style intuition)

Use: very long sequences with sub-quadratic cost.

Idea: learn a linear time-invariant system ($x_{t+1} = Ax_t + Bu_t$, $y_t = Cx_t + Du_t$) discretized and convolved efficiently.

```

# Toy stand-in: depthwise 1D conv with long kernels (a crude SSM proxy)
class LongConv(nn.Module):
    def __init__(self, d_model, k=1024):
        super().__init__()
        self.dw = nn.Conv1d(d_model, d_model, k, groups=d_model, padding=k-1)
        self.ln = nn.LayerNorm(d_model)
    def forward(self, x):                      # x: (B,T,D)
        y = self.dw(x.transpose(1,2)).transpose(1,2)
        return self.ln(x + y)

```

Tips: if you need 10k+ context lengths with reasonable memory, try S4/Hyena; combine with attention for hybrid models.

13) Training patterns that generalize

```
def configure_optimizers(model, lr=3e-4, wd=0.01):
    # AdamW, exclude norms/bias from decay
    decay, no_decay = [], []
    for n, p in model.named_parameters():
        if not p.requires_grad: continue
        if p.ndim >= 2: decay.append(p)          # weights
        else: no_decay.append(p)                  # bias, LayerNorm, etc.
    return torch.optim.AdamW([
        {'params': decay, 'weight_decay': wd},
        {'params': no_decay, 'weight_decay': 0.0}], lr=lr)

def cosine_schedule(optimizer, warmup_steps, total_steps):
    def lr_lambda(step):
        if step < warmup_steps:
            return step / max(1, warmup_steps)
        progress = (step - warmup_steps) / max(1, total_steps - warmup_steps)
        return 0.5 * (1.0 + torch.cos(torch.pi * progress))
    return torch.optim.lr_scheduler.LambdaLR(optimizer, lr_lambda)
```

Other tips

- Initialize: Xavier for `tanh`, He/Kaiming for ReLU; orthogonal recurrent matrices.
- Regularize: dropout, data augmentation, label smoothing, early stopping.
- Stabilize: gradient clipping for RNN/Transformer; mixed precision (AMP); gradient accumulation.

14) Evaluation & selection checklist

1. **Data shape & scale:** images vs text vs graphs; label count; class imbalance.
2. **Context length / latency:** streaming? on-device? pick RNN/TCN/efficient attention when needed.
3. **Inductive bias:** do you have spatial/temporal/graph structure? choose CNN/TCN/GNN.

4. **Compute budget:** pretrained encoders and adapters (LoRA) save time & energy.
5. **Metrics:** accuracy vs F1 vs AUROC vs calibration; latency/throughput in deployment.

15) Minimal training loop template (classification)

```
def train_epoch(model, loader, optimizer, scheduler=None, clip=1.0, device="cuda"):  
    model.train(); total=correct=0  
    criterion = nn.CrossEntropyLoss()  
    for x, y in loader:  
        x, y = x.to(device), y.to(device)  
        optimizer.zero_grad(set_to_none=True)  
        logits = model(x)  
        loss = criterion(logits, y)  
        loss.backward()  
        nn.utils.clip_grad_norm_(model.parameters(), clip)  
        optimizer.step()  
        if scheduler: scheduler.step()  
        total += y.size(0); correct += (logits.argmax(1)==y).sum().item()  
    return correct/total
```

16) Common “gotchas”

- **Overfit on tabular:** trees often beat MLPs unless you have large data + embeddings.
- **BatchNorm with tiny batches:** switch to GroupNorm/LayerNorm for stability.
- **Weight decay on norms/biases:** usually exclude (see optimizer config above).
- **Class imbalance:** use weighted loss, focal loss, or resampling.
- **Sequence padding:** use masks in attention; avoid learning from padding tokens.

17) Where to go deeper (topics to search/study next)

- **Vision:** ResNet, ConvNeXt, ViT, Swin, UNet, DETR.
- **NLP:** BERT, T5, GPT; LoRA/adapters; instruction tuning; retrieval-augmented gen.
- **Audio/Speech:** Conformer, wav2vec 2.0, HuBERT, RNN-T.
- **Graphs:** GCN, GAT, GraphSAGE, Graph Transformer; positional encodings.
- **Generative:** VAE, GAN, Flows, Diffusion; classifier-free guidance; latent diffusion.
- **Long-context:** Performer, Longformer, S4/Hyena; memory modules.

Appendix: tiny “starter” datasets & shapes

- **Images:** $(B, 3, H, W) \rightarrow$ CNN/ViT; normalize to ImageNet stats for transfer.
- **Text:** token ids $(B, T) \rightarrow$ embedding + Transformer; pad + attention mask.
- **Time series:** $(B, T, \text{features}) \rightarrow$ TCN/RNN; z-score per feature.
- **Graphs:** node features (N, d) , edges $(E \times 2) \rightarrow$ GNN; build normalized adjacency.
- **Tabular:** dense (B, d) + sparse IDs $(B, M) \rightarrow$ embeddings + MLP head.