

19) CNN

CNN Architecture

- Made of 3 layers:

- ① Convolution - learn kernels (filters) to create feature maps of data
- ② Pooling - Downsample feature maps
- ③ Fully Connected - Categorical/Continuous Prediction

- Typical structure: $2D \times N \rightarrow \text{Convolution} \rightarrow \text{actFun} \rightarrow \text{Pooling} \rightarrow 1D \rightarrow \text{Fully Connected} \rightarrow \hat{y}$
+ RF of each pixel by: add wider (+ # feature maps) layers for - pixel size

CNN Autoencoder

- Used to process noisy & occluded images

• Structure: $2D \times \text{block} \rightarrow \text{input} \rightarrow \text{encoder} \rightarrow \text{Latent} \rightarrow \text{Decoder} \rightarrow \text{output}$
The diagram shows a sequence of blocks: input (2D) goes into an encoder (two 'conv' blocks), then a 'pool' block, then a 'Latent' space (represented by a stack of blocks), then a 'Decoder' (two 'convT' blocks), and finally an 'output' (2D).

• Train workflow: Feed model noisy data \rightarrow Backprop it on clean data

Custom Loss Function

- Exceeds the boundary of implementing PyTorch loss functions

• Code: class myLossFunc(nn.Module):

def __init__(self): super().__init__()

def forward(self, yhat, y):

return formula result

① L1 loss: $L(\hat{y}, y) = m^{-1} \sum_{i=1}^m |\hat{y}_i - y_i|$

② L2 avg loss: $MSE + m^{-1} \left| \sum_{i=1}^m \hat{y}_i \right|$

③ Correlation: $\frac{\sum_{i=1}^m (\hat{y}_i - \mu_{\hat{y}})(y_i - \mu_y)}{(m-1) \sigma_{\hat{y}} \sigma_y}$

• ① is useful for image processing as it promotes sparse weights

② classification/LLMs

distributed weights + small output

DL vs. Stats

- Model workflow: $\Theta \xrightarrow{\text{generates}} X \xrightarrow{\text{predict}} \hat{y}$
params distributed data $\hat{\Theta}$ - mostly stats job

Dropout in Convolution Layers

- Introduces noises to feature maps to help generalization

• Apply small dropout rate (.1 ~ .25) so it won't break spatial dependence in weights