0.1 Output Dimensions in CNNs

Derive the formula for calculating the output dimensions of a convolutional layer given:

- Input volume dimensions $H \times W \times D$
- Number of filters K
- Filter dimensions $F \times F$
- Stride S
- Padding P

0.2 Calculating Parameters in a CNN Layer

Mathematically express the total number of parameters in a convolutional layer including:

- K filters of size $F \times F \times D$
- Bias terms for each filter

0.3 Loss Function in Autoencoders

Derive the mean squared error (MSE) loss function for an autoencoder, discussing how it impacts the training process by minimizing the reconstruction error between the input and the output.

0.4 Improvement in SNR for Denoising Autoencoders

Derive the expected improvement in signal-to-noise ratio (SNR) when using a denoising autoencoder that reduces the noise power by a certain percentage.

0.5 Layer Normalization

Derive the equations for layer normalization applied to a vector $X = [x_1, x_2, \ldots, x_n]$, including the calculation of the normalized scores and the incorporation of learnable parameters γ and β.

0.6 Dropout Effect on Network Activation

Derive the mathematical expectation of the output of a neuron when dropout is applied during training and explain how to adjust this output during test time.

0.7 Weight Decay in Backpropagation

Include weight decay in the derivation of the weight update rule for a neural network, explaining how this affects the gradient during backpropagation.

0.8 Transposed Convolution Output Dimensions

Derive the formula for the output dimensions of a transposed convolution layer given:

- Input volume dimensions $H \times W \times D$
- Number of filters K
- Filter dimensions $F \times F$
- Stride S
- Padding P

0.9 Gradient Clipping Technique

Mathematically derive the procedure for gradient clipping in neural network training, explaining how it affects the gradient magnitudes and the implications for training stability.

0.10 Batch Normalization's Impact on Learning Rate

Discuss the relationship between batch normalization and learning rate adjustments in a neural network. Derive how batch normalization can stabilize the learning process, thus allowing for higher learning rates without causing divergence.