Test Study Guide

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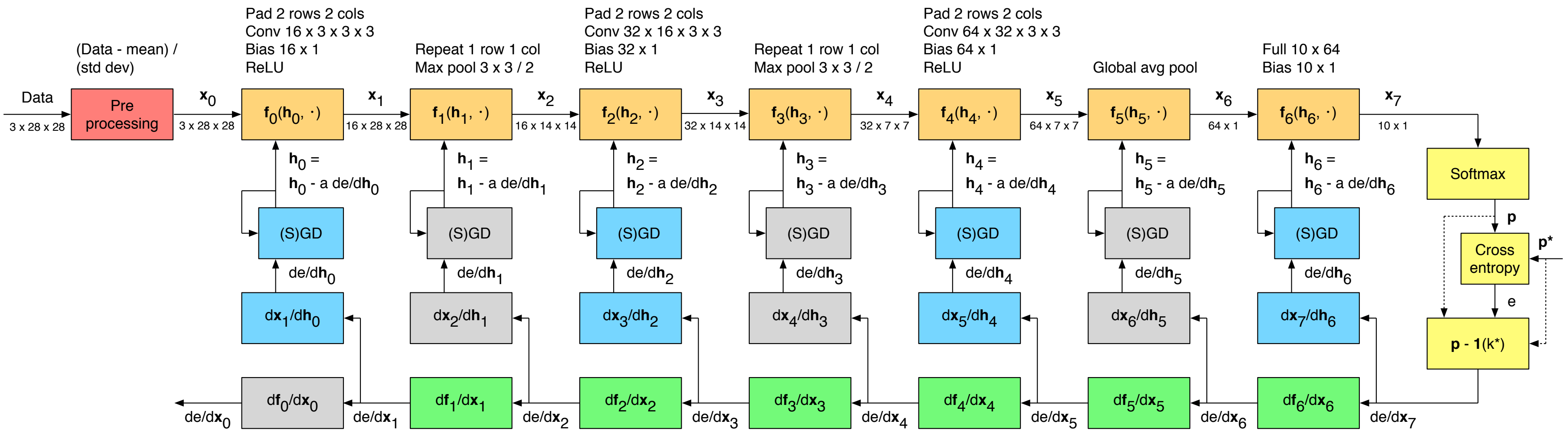
Example Network



Introduction

- Information extraction framework (data to information)
    - Pre processing
    - Feature extraction
    - Prediction
    - Post processing

- Pre and post processing
    - Tend to be application dependent

- Feature extraction and prediction
    - Can use CNNs for feature extraction and prediction for many applications
    - Use machine learning to learn CNN parameters from data

Linear Algebra

- CNN style 2D convolution
  - With an input size of N_i x L_r x L_c
  - With an input 0 pad of (F_r – 1) rows and (F_c – 1) cols
  - With a filter size of N_o x N_i x F_r x F_c
  - What is the output size (note zero padding of F – 1)? N_o x L_r x L_c
  - What is the equivalent matrix problem size? $M_{BLAS} = N_o$, $N_{BLAS} = L_r L_c$, $K_{BLAS} = N_i F_r F_c$
  - How many MACs not taking advantage of 0s in pad? $N_o N_i F_r F_c L_r L_c$

- Matrix vector multiplication
  - With an input size of N_i x 1
  - With a filter size of N_o x N_i
  - What is the output size? N_o x 1
  - Can you use an inner product to write output m? $\langle \mathbf{H}(m, :)^T, \mathbf{x} \rangle$, strength $||\mathbf{H}(m, :)||_2$, alignment θ
  - How many weights? $N_o N_i$

Calculus

- Gradient
  - Scalar function of multiple variables
  - Partial derivative with respect to each variable
  - Points in direction of maximum change of function
  - $\nabla f(\mathbf{x}) = [(\partial f/\partial x_0)\ (\partial f/\partial x_1)\ \ldots\ (\partial f/\partial x_{K-1})]^T$
  - Compute the gradient of the error with respect to the final output

- Error gradient propagation
  - How do we propagate? Reverse mode automatic differentiation / chain rule from calculus
  - What does it do? Constructs a graph that propagates the error gradient from the end to the beginning
  - How does it work? $\partial e/\partial \mathbf{x}_d = (\partial \mathbf{x}_{d+1}/\partial \mathbf{x}_d)\ (\partial e/\partial \mathbf{x}_{d+1}) = (\partial \mathbf{f}_d/\partial \mathbf{x}_d)\ (\partial e/\partial \mathbf{x}_{d+1})$

- Parameter update
  - How do we update? Gradient descent (later, many variants)
  - What does it do? Update the parameters in a small step in the opposite direction of the error gradient
  - How does it work? $\partial e/\partial \mathbf{h}_d = (\partial \mathbf{x}_{d+1}/\partial \mathbf{h}_d)\ (\partial e/\partial \mathbf{x}_{d+1})$, $\mathbf{h}_d \leftarrow \mathbf{h}_d - \alpha\ \partial e/\partial \mathbf{h}_d$

Probability

- Input normalization
  - Assume the input **X** has mean μ and std dev σ
  - How can you normalize to 0 mean unit variance? — $\mathbf{X} \leftarrow (\mathbf{X} - \mu) / \sigma$
- Soft max cross entropy error
  - What does soft max do? — Converts network output to a ~ PMF
    $\mathbf{p} = f(\mathbf{x}) = (1/(\Sigma_k e^{x(k)})) [e^{x(0)}\ e^{x(1)} \ldots e^{x(K-1)}]^T$
  - What does cross entropy do for a 1 hot input? — Divergence between network PMF and true PMF $\mathbf{p}^*$
    $e = f(\mathbf{p}^*, \mathbf{p}) = -\Sigma_k p^*(k) \log(p(k))$
  - What is the soft max cross entropy error gradient? — $\mathbf{p} - \mathbf{1}(k^*)$ where $\mathbf{p}$ is the network PMF and k^* is the correct class
- Feature map compression
  - Assume feature map elements are independent
  - And all have the same PMF and 8 bit quantization
  - $p_X(0) = 0.5$, $p_X(!= 0) = 0.5 / 255$
  - What is the entropy bound for compression? — $H(X) = -(0.5 \log_2(0.5)) - ((255)(0.5/255) \log_2(0.5/255))$
    ~ 5 bits per element

Algorithms

- Pooling
  - What does it do? Reduces the spatial resolution of the feature maps
  - What else? Increases the receptive field size

- Sequential comparison sort
  - For unknown input require O(N log2(N)) comparisons
  - Can you outline a short proof of this bound?
  - Proof outline
    - There are N! possible arrangements of a sequence of length N
    - View the arrangements as a random variable X(s)
      - The probability of each arrangement is 1/N!
      - Uniform probability mass function with support of size N!
    - The entropy (information) of a realization of this random variable
      - $H(X(s)) = -\Sigma\ (1/N!) \log_2(1/N!) = \log_2(N!)$
    - Each comparison in a comparison sort gives at most 1 bit of information
    - To reduce the entropy to 0 with C comparisons need $\log_2(N!) - C \leq 0$
      - $C \geq \log_2(N!) \approx O(N \log_2(N))$ via Stirling's approximation

Design

- Tail
  - What is a common tail design? 64 x 3 x 7 x 7 / 2 conv, 3 x 3 / 2 max pool
- Body
  - How is CNN convolution commonly split? Standard convolution (spatial), 1x1 CNN convolution (channel)
  - Why? Save computation and memory, still get spatial and channel mixing
  - How does a residual building block work? $x_{d+1} = f_d(x_d) = x_d + h_d(x_d)$
  - Why? Error gradient propagates as identity + perturbation, allows deeper nets
- Head
  - What is a common head design? Global avg pool, matrix vector mult, bias add, soft max or arg max
  - What is assumed in this? Output classes are linearly (affine) separable from features
- Receptive field size
  - What is the receptive field size at $\mathbf{x}_5$? ((1 + 2)*2 + 2 + 2)*2 + 2 + 2 = 24 pixels in the original input
  - How was that calculated? Start at end with 1, filter adds F – 1 and down sampling multiplies