Neural Networks in Python (PA6 Lab)

CS114 Lab 13

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May 1, 2020

Python Deep Learning Libraries

- CNTK
- Keras
- MXNet
- PyTorch
- TensorFlow
- Theano
- etc.

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- Numpy

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    - Seriously, everyone should code a neural network from scratch at least once...

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  - $\mathbf{x} = [\mathbf{E}_{w_1}, ..., \mathbf{E}_{w_m}] \in \mathbb{R}^{dm}$

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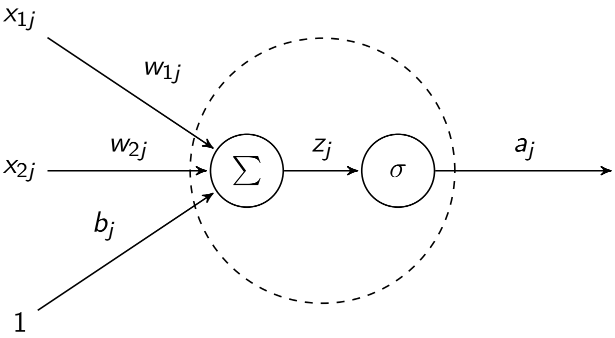
  - Recommended intervals very roughly correspond to this

Graphical Representation of a Neuron



Forward Propagation

- $\mathbf{h}_1 = \mathrm{ReLU}(\mathbf{x}\mathbf{W_1} + \mathbf{b}_1)$
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  - In the end, you don't need as many transposes

Rectified Linear Unit

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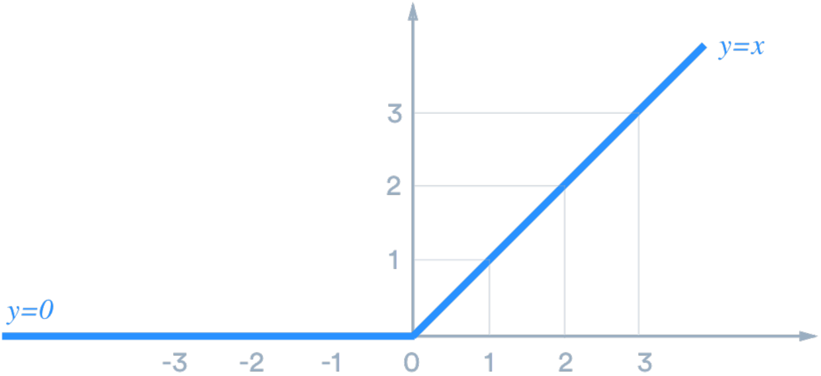

Source

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- All layer outputs should have shape `[batch_size, ...]`

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- To compute the loss for the training set, we average this $J(\theta)$ across all training examples

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  - Broadcasting will turn one Hadamard product into a matrix (dot) product

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- $\theta_{t+1} = \theta_t - \eta \nabla L$

General Advice

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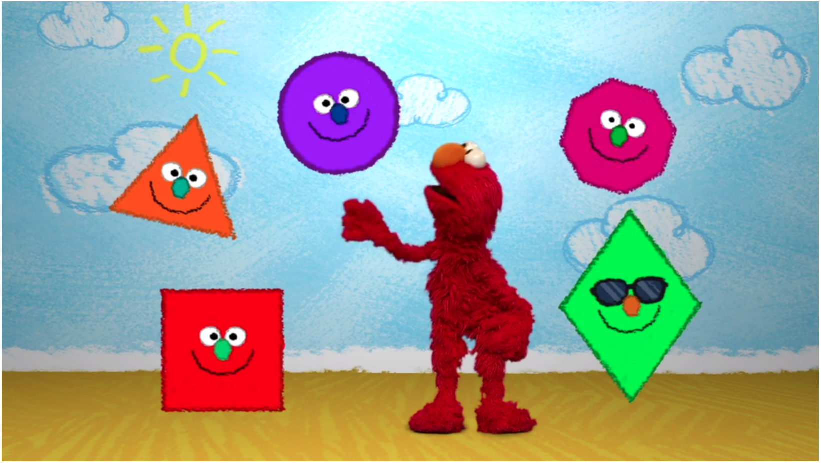

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