Artificial Neural Networks and Deep Learning

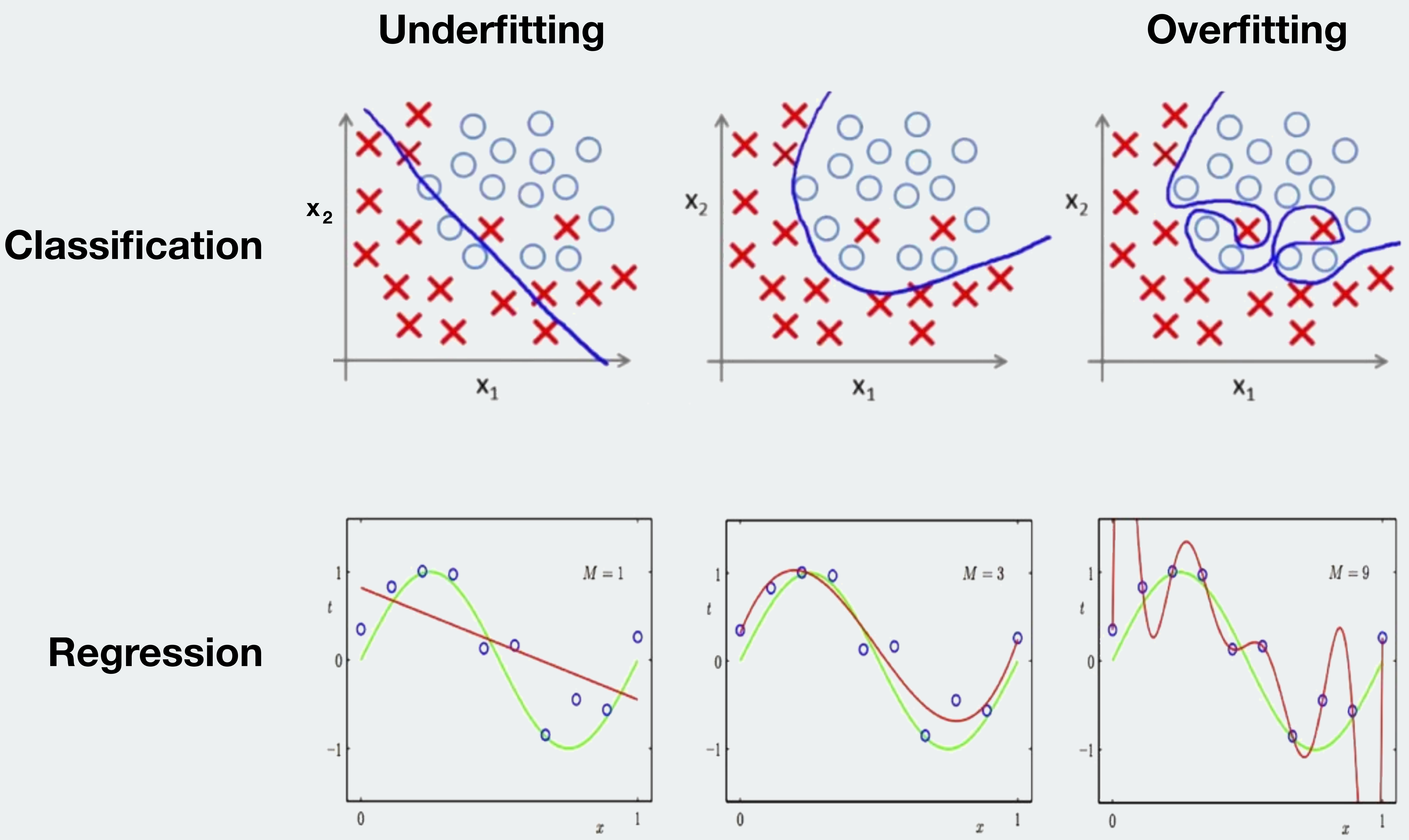
Week 3

Keras, overfitting and regularization

Regularization

Tricks to avoid overfitting

Regularization – underfitting and overfitting



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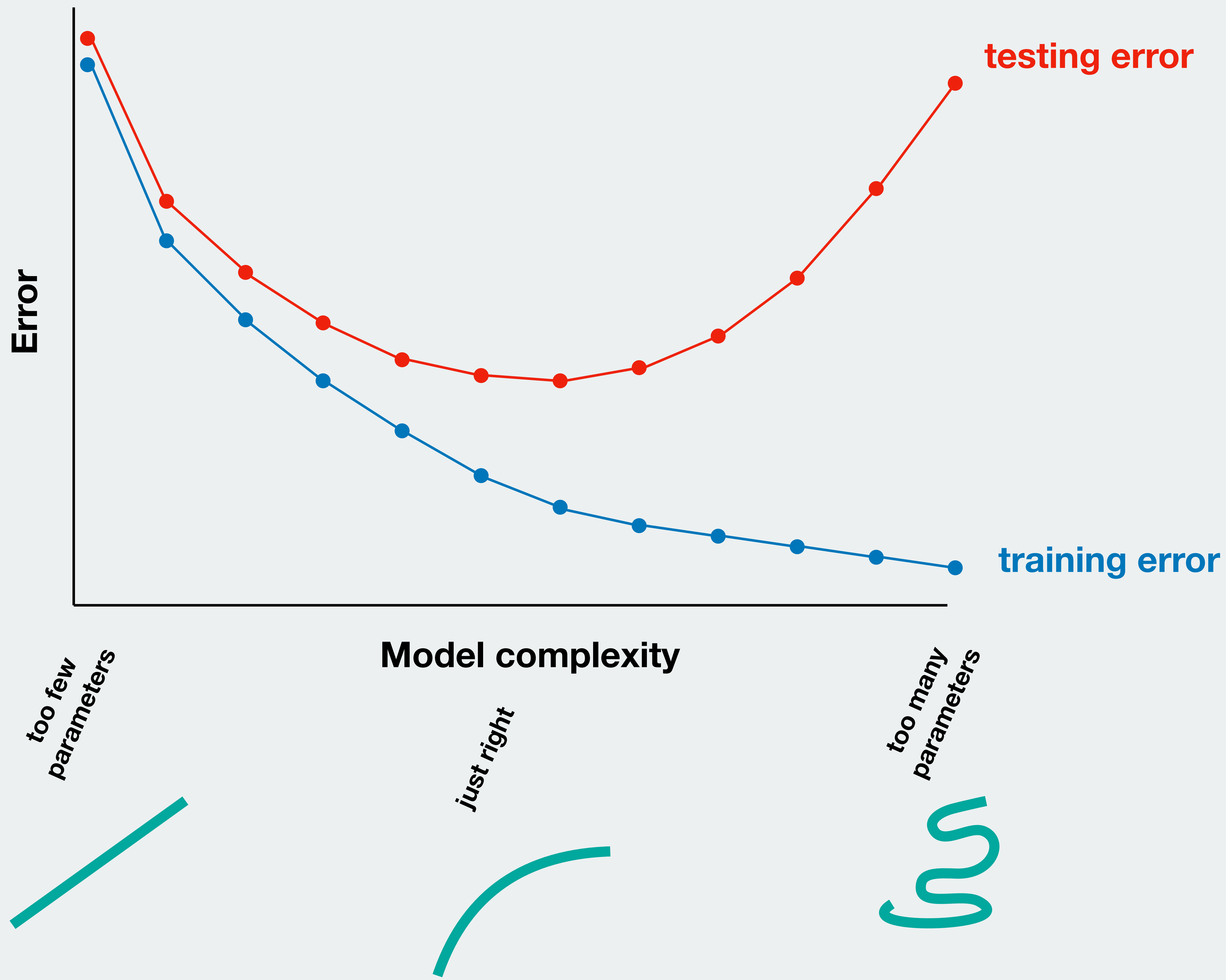
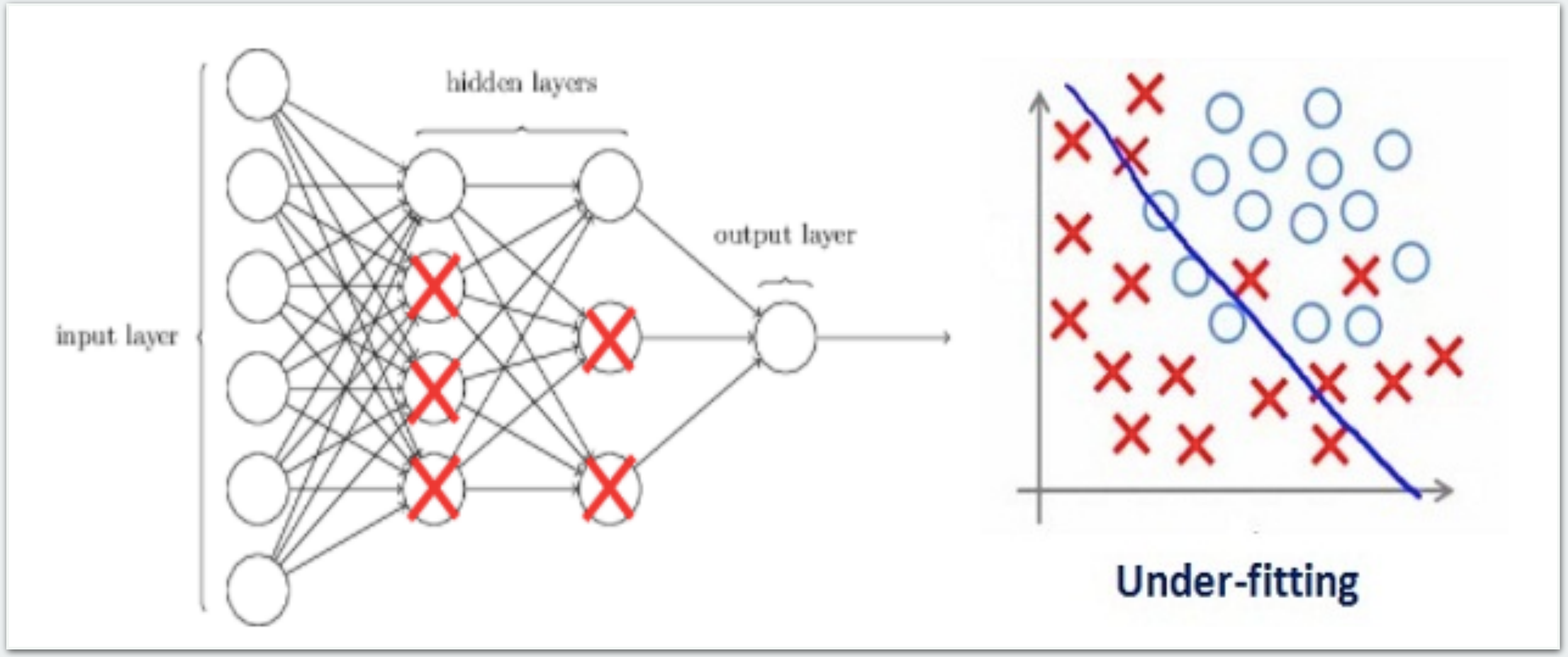


Regularization – *how* does regularization reduce overfitting?



https://www.analyticsvidhya.com/blog/2018/04/fundamentals-deep-learning-regularization-techniques/

Regularization – Different techniques

L-norm regularization: "Introduce a cost for large weights"

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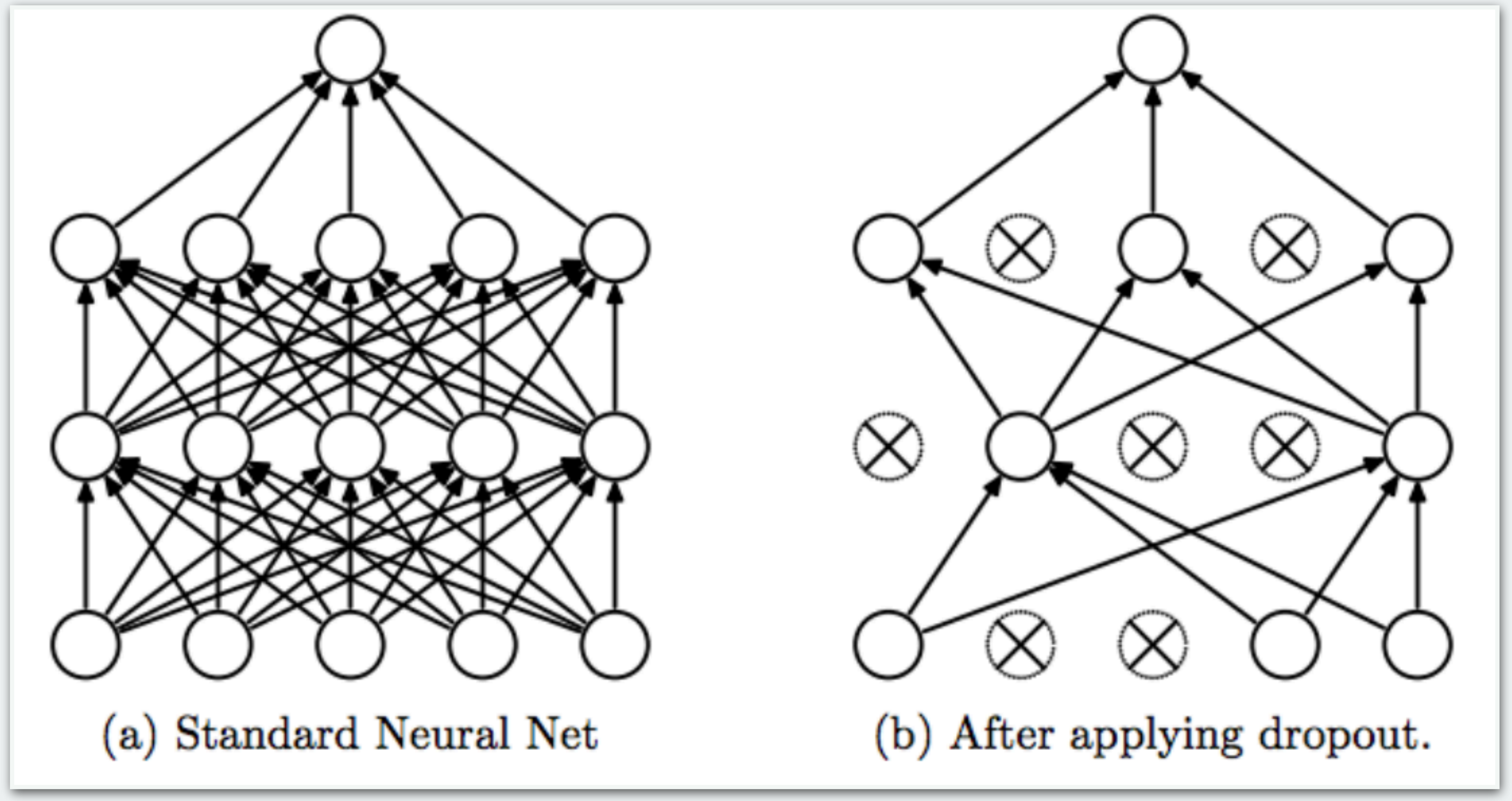
Dropout:

“In each SGD step, randomly ignore a fraction p of neurons”



Srivastava, Nitish, et al. ”Dropout: a simple way to prevent neural networks from overfitting”, JMLR 2014

- Can select p in wide range. Typical is 0.2 – 0.8, dependent on size of ANN
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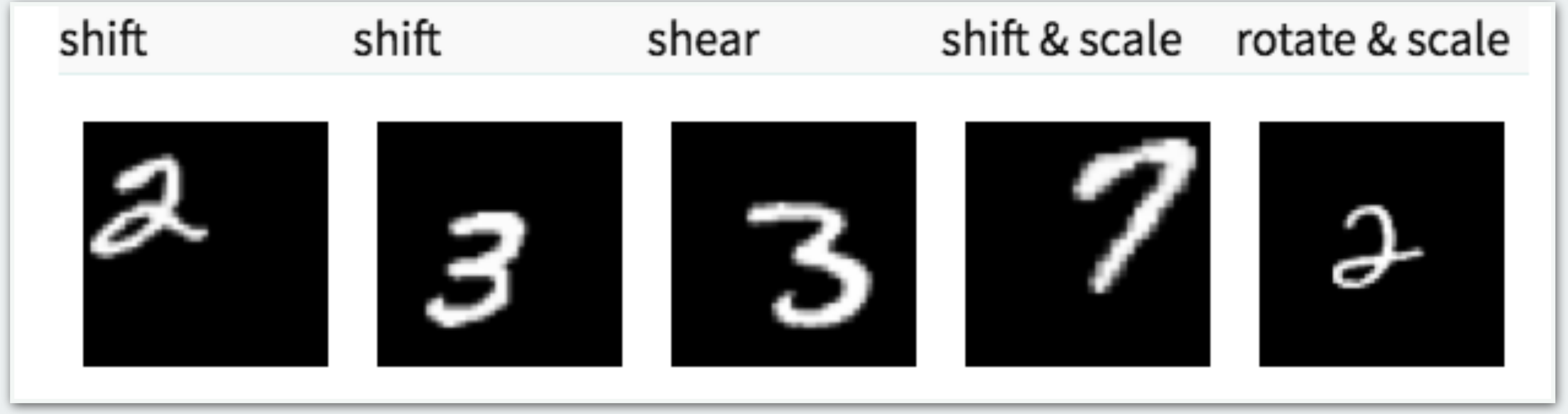
Data augmentation

“Shear, shift, scale and/or rotate input data”



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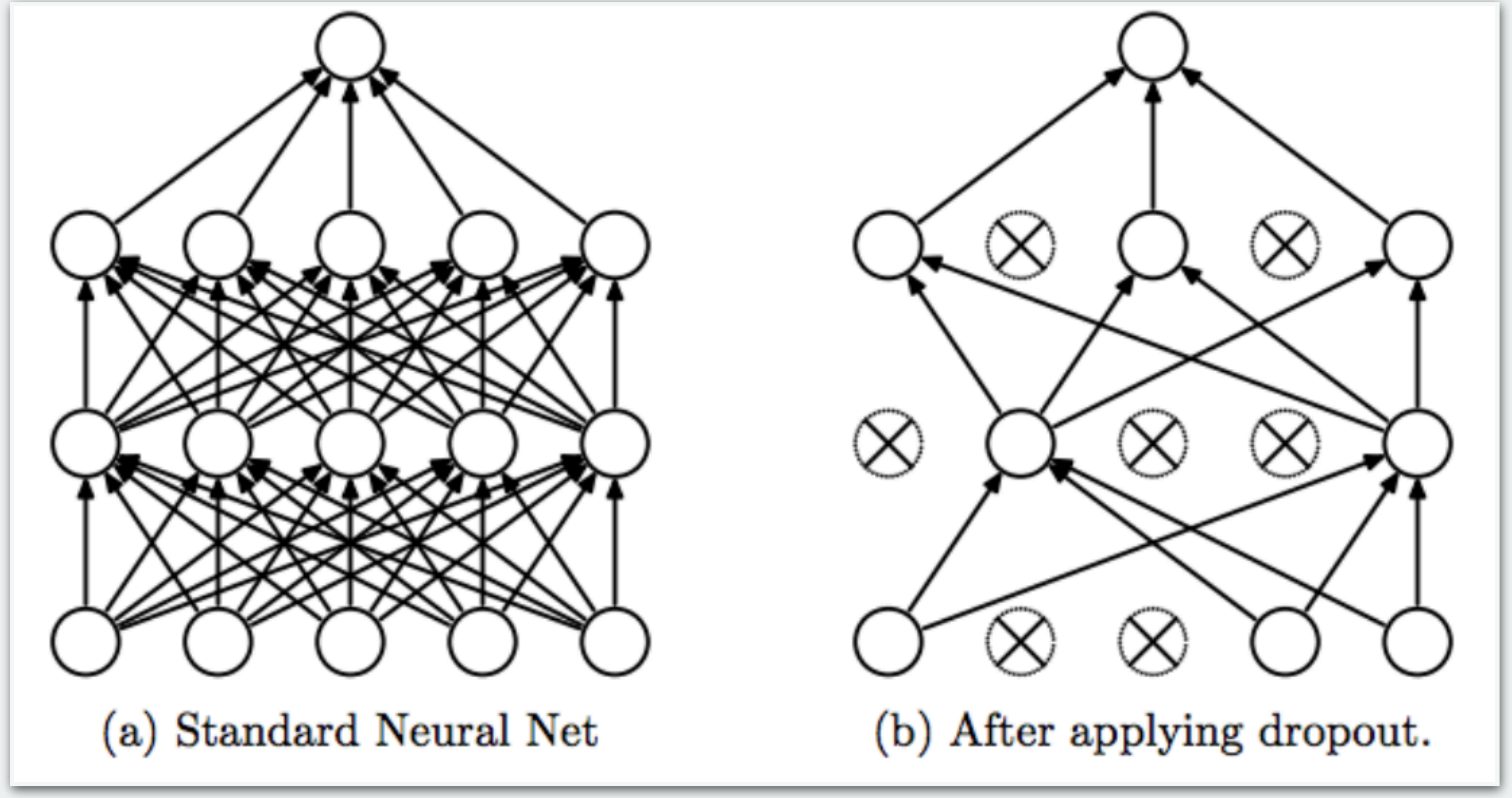

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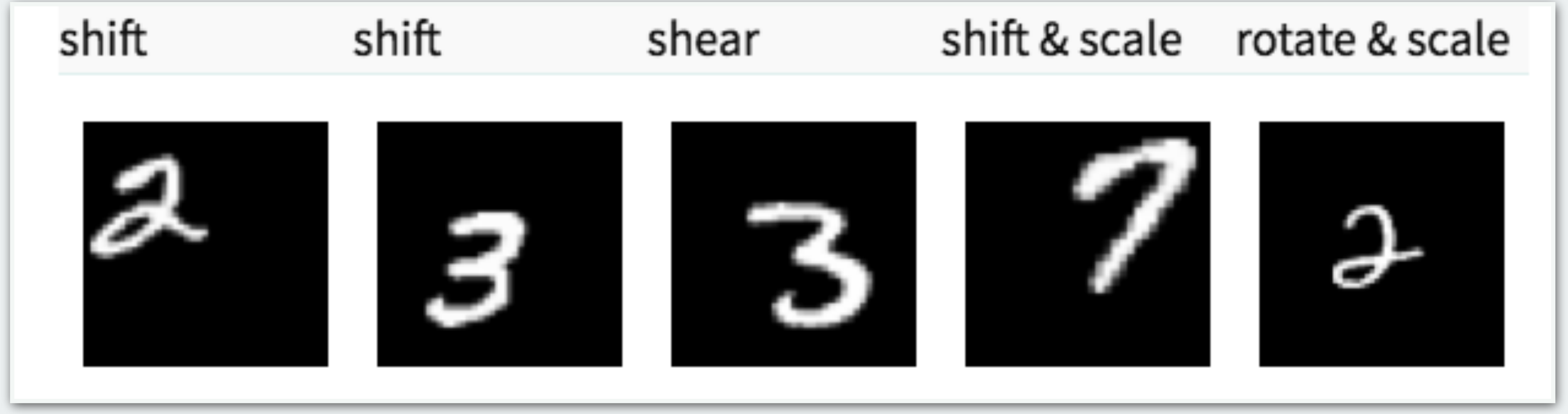
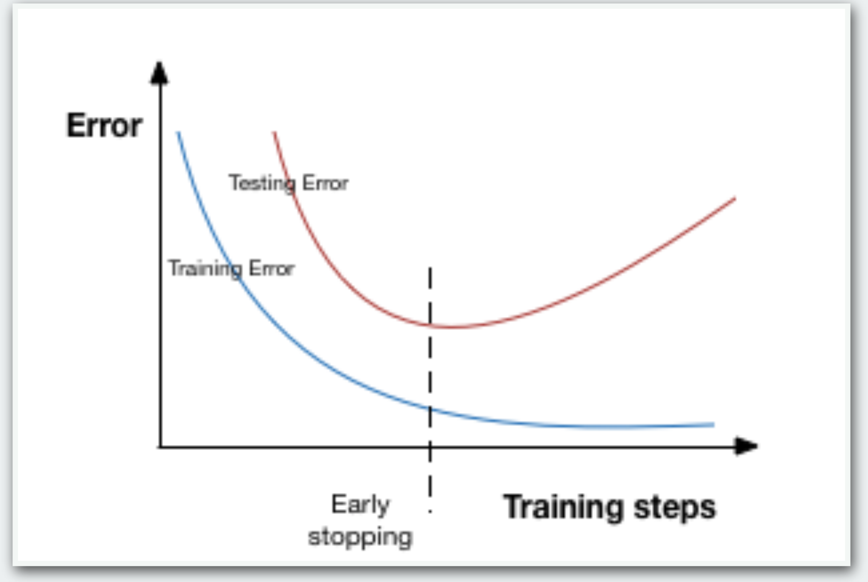


Early stopping

“Stop training when performance on validation dataset starts worsening”



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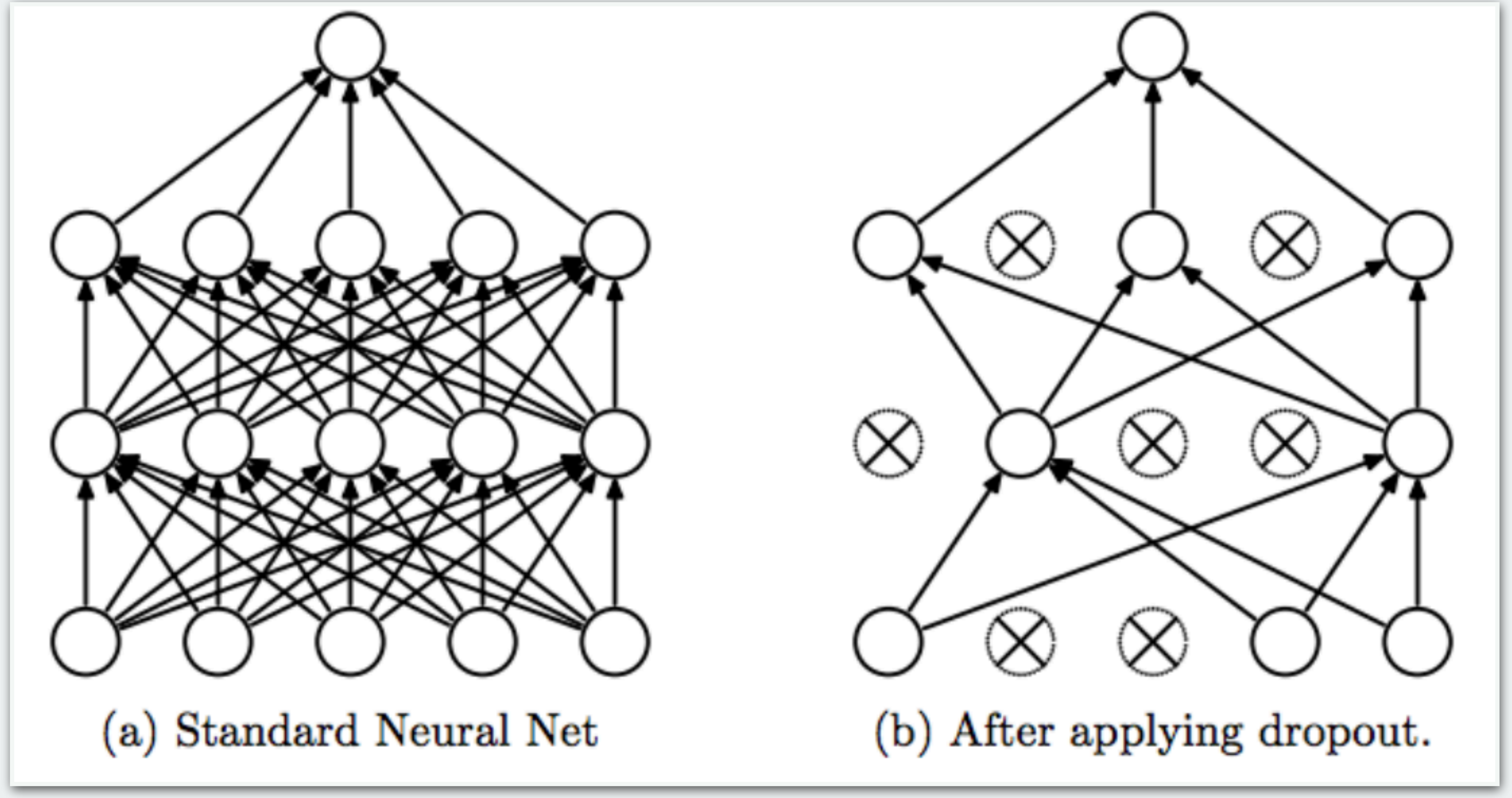

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A quick word on:

The Vanishing Gradient Problem

Vanishing gradients – A problem in *deep* neural nets

Problem:

- Gradients closer and closer to the input tend to get smaller and smaller
- Leads to smaller weight updates near input and larger weight updates near output
- Bad because layers near input take part in recognizing “simple” patterns, which are important to learning

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \times w_2 \times \sigma'(z_2) \times w_3 \times \sigma'(z_3) \times w_4 \times \sigma'(z_4) \times \frac{\partial C}{\partial a_4}$$

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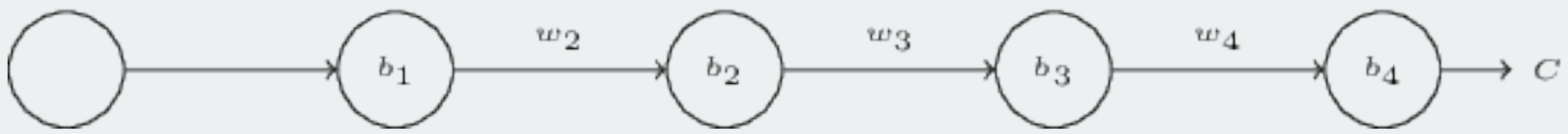

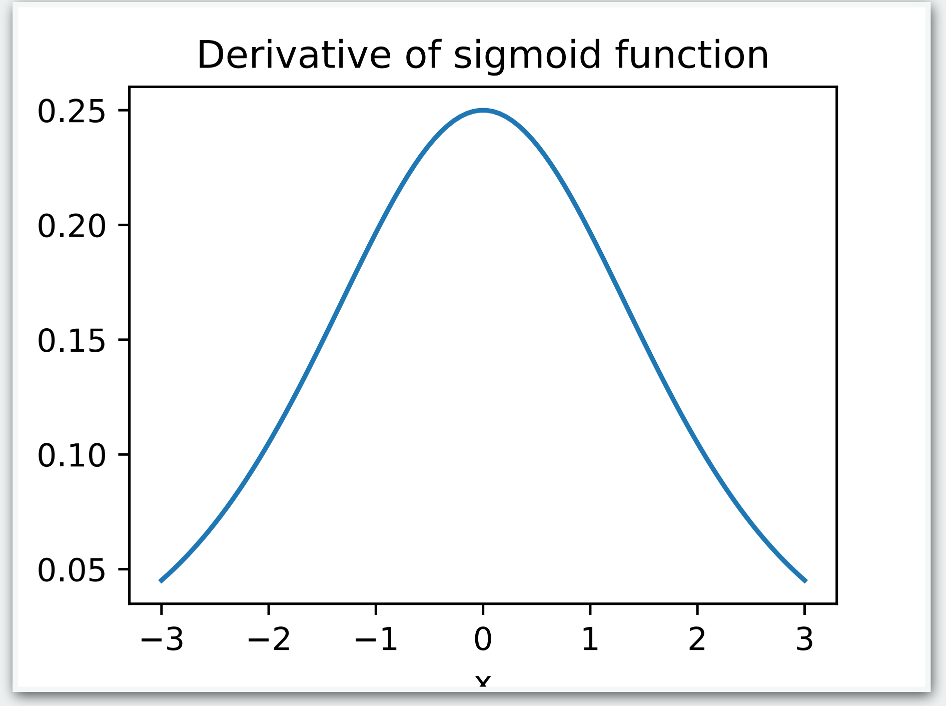

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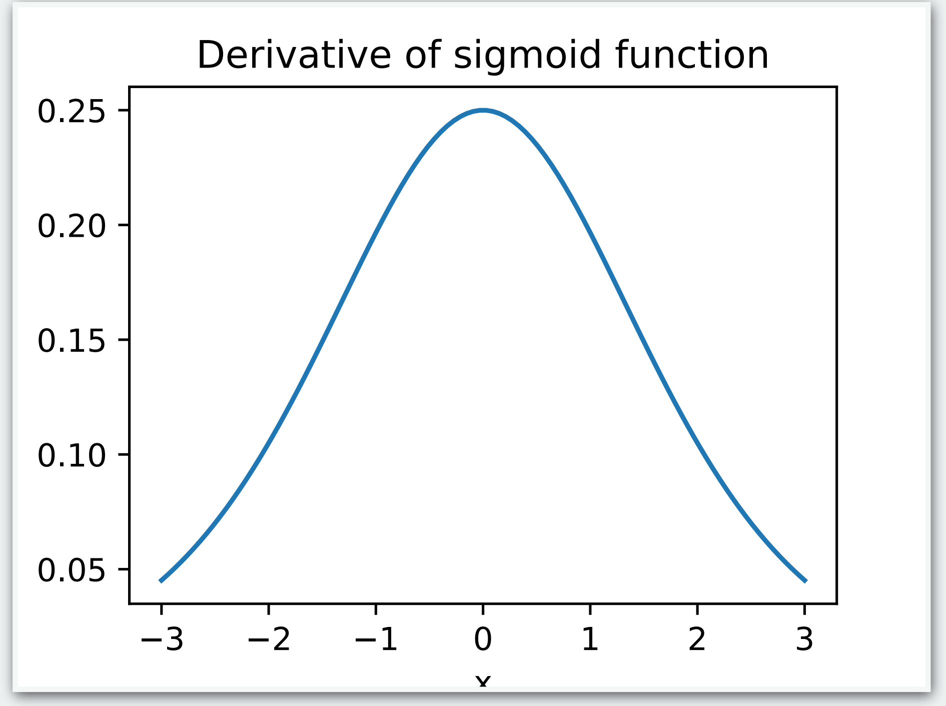
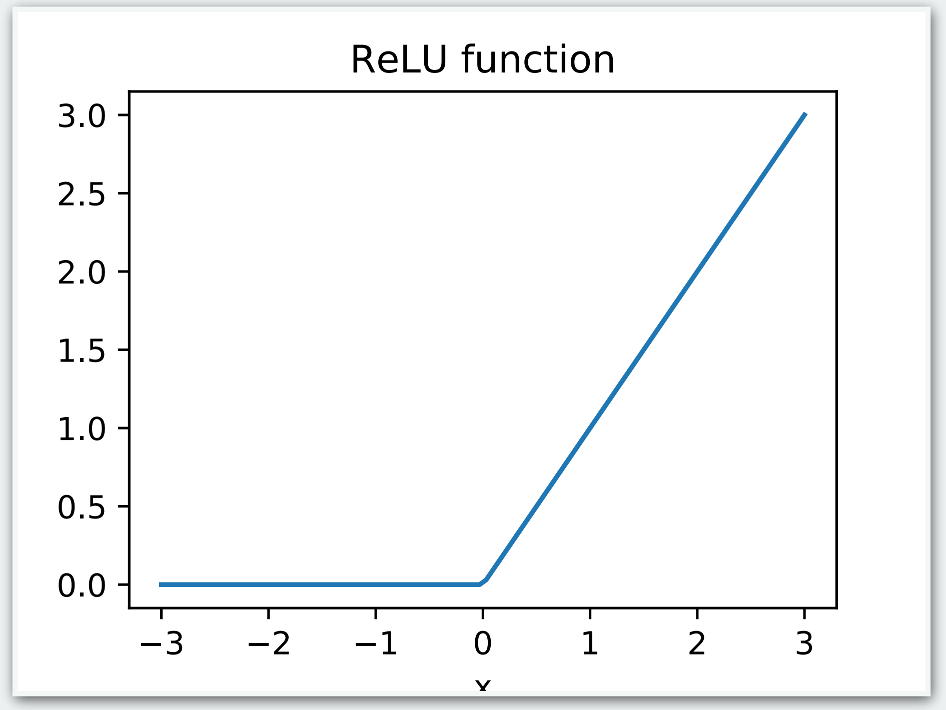
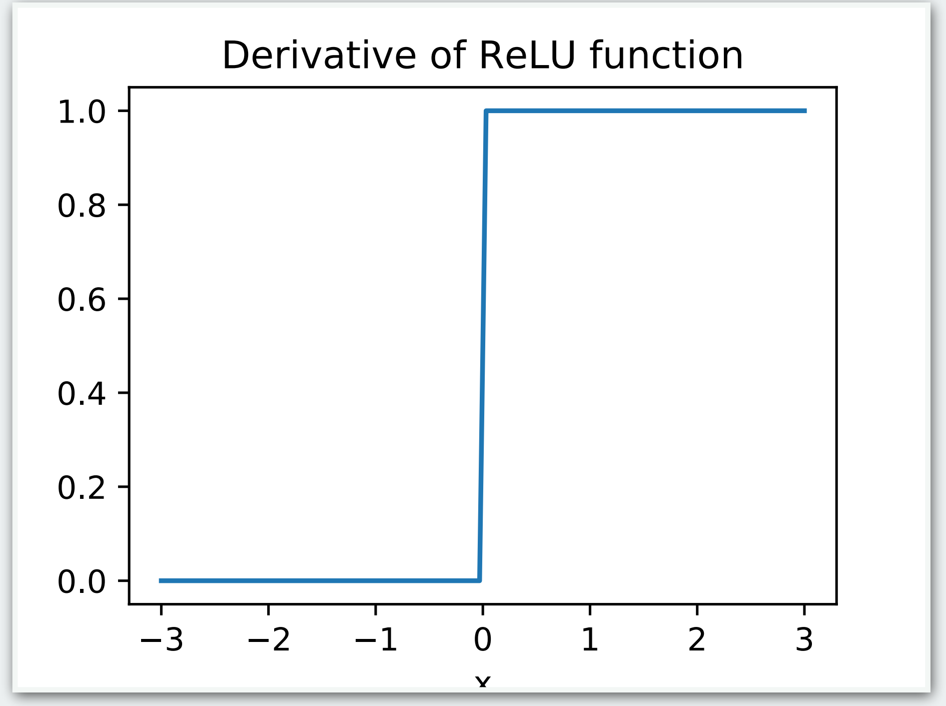


Solution:

- Use an activation function without small gradient for high values
- Candidate activation function: ReLU





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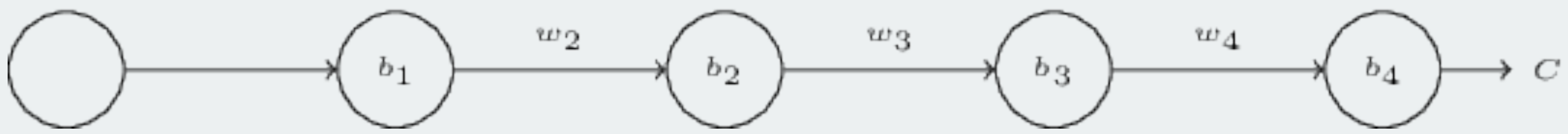

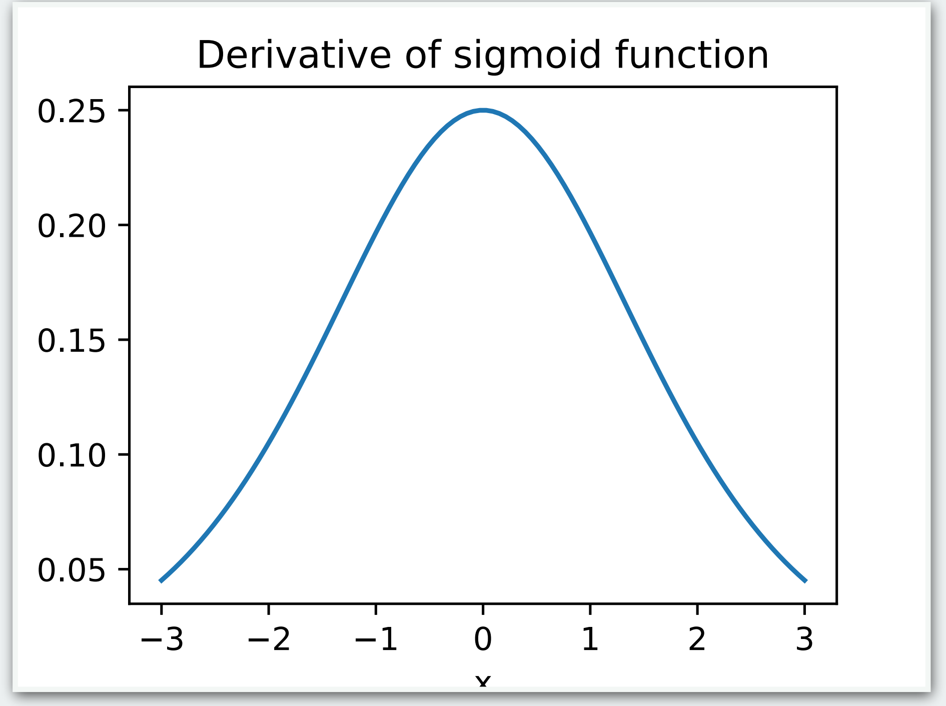

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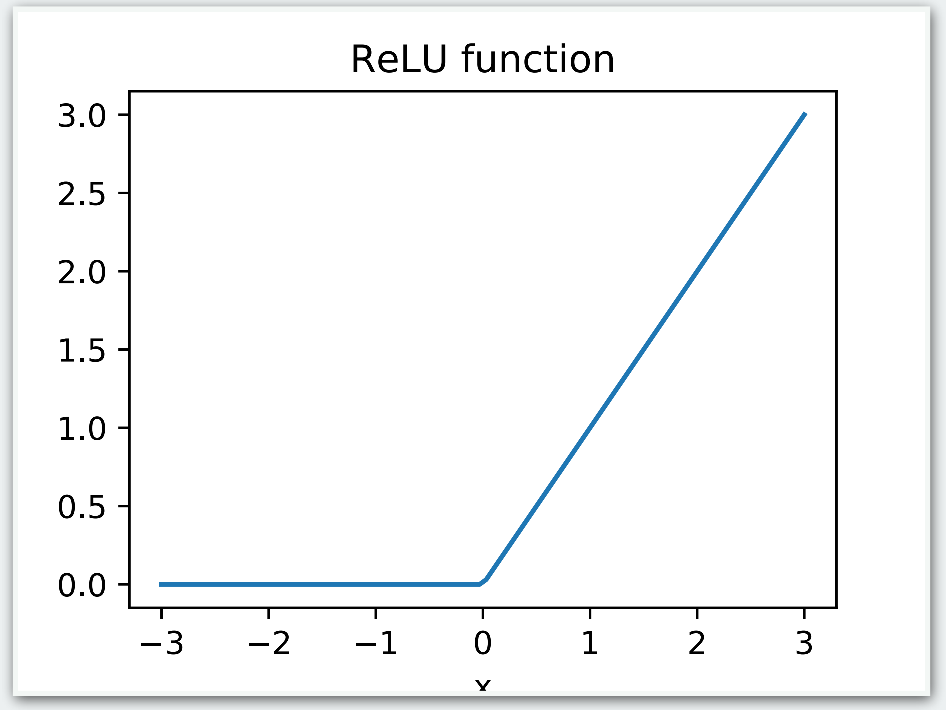

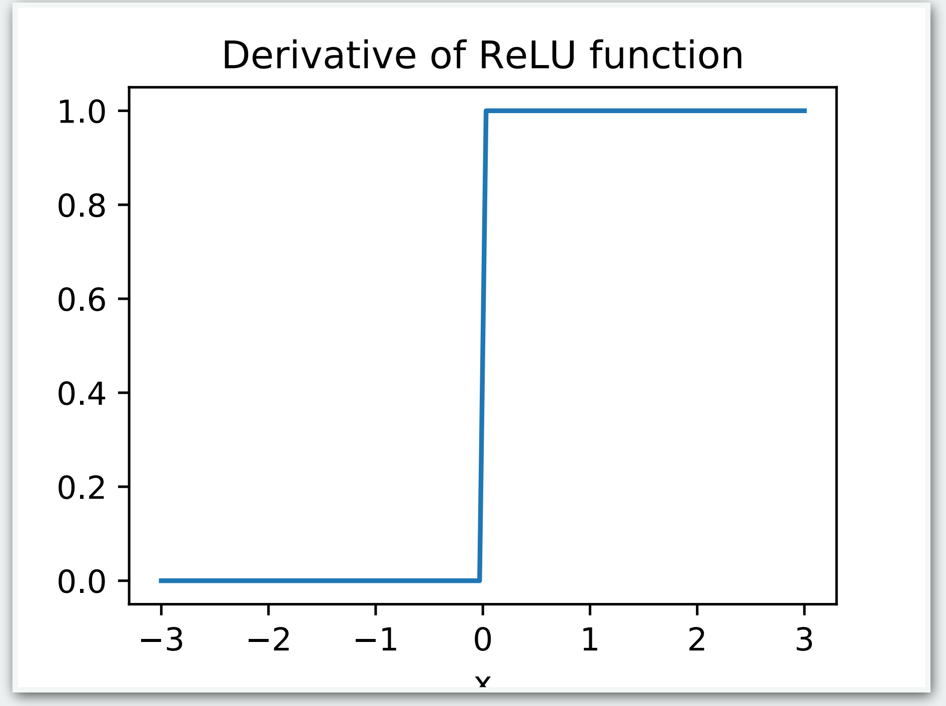

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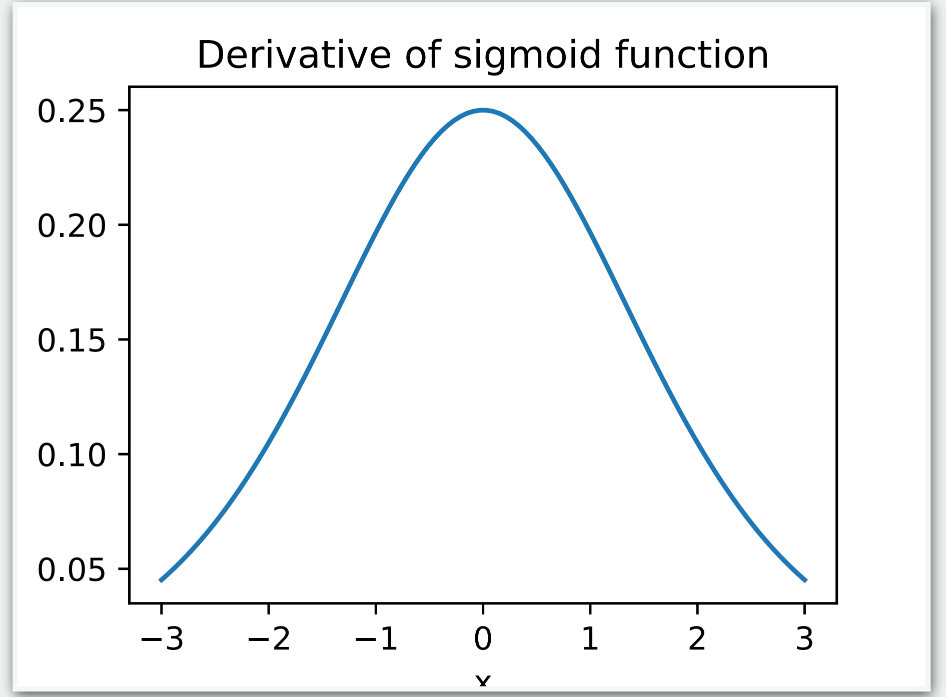

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