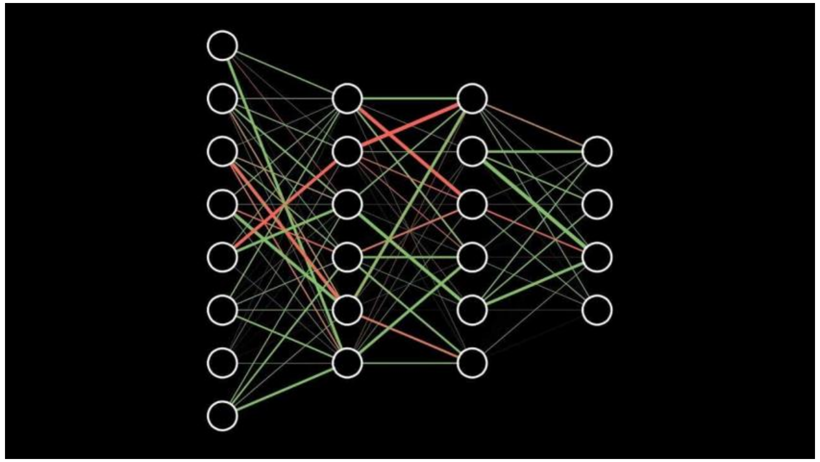
Deep Learning Workshop

Neural Networks and Friends



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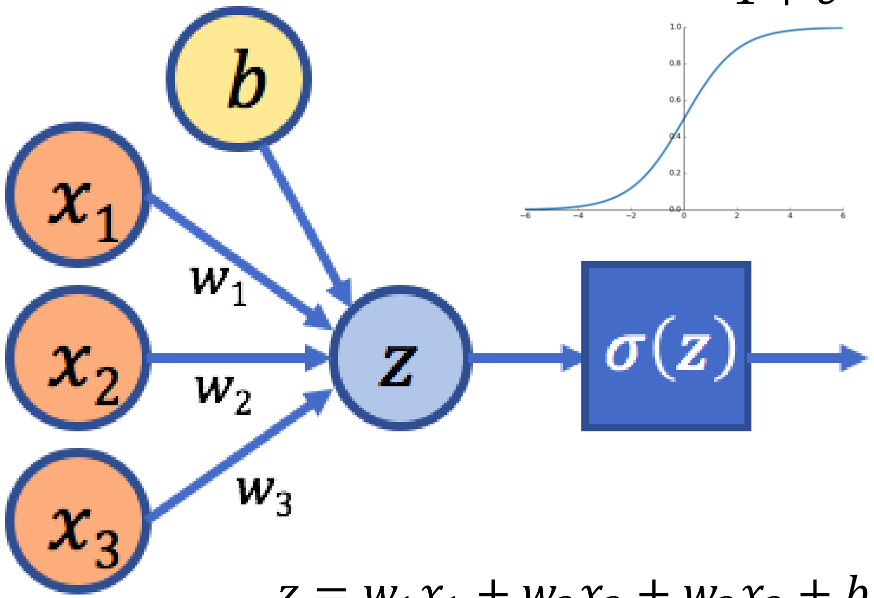
HELP University, Faculty of Computing and Digital Technology

Logistic Regression

$$\sigma(z) = \frac{1}{1+e^{-z}}$$



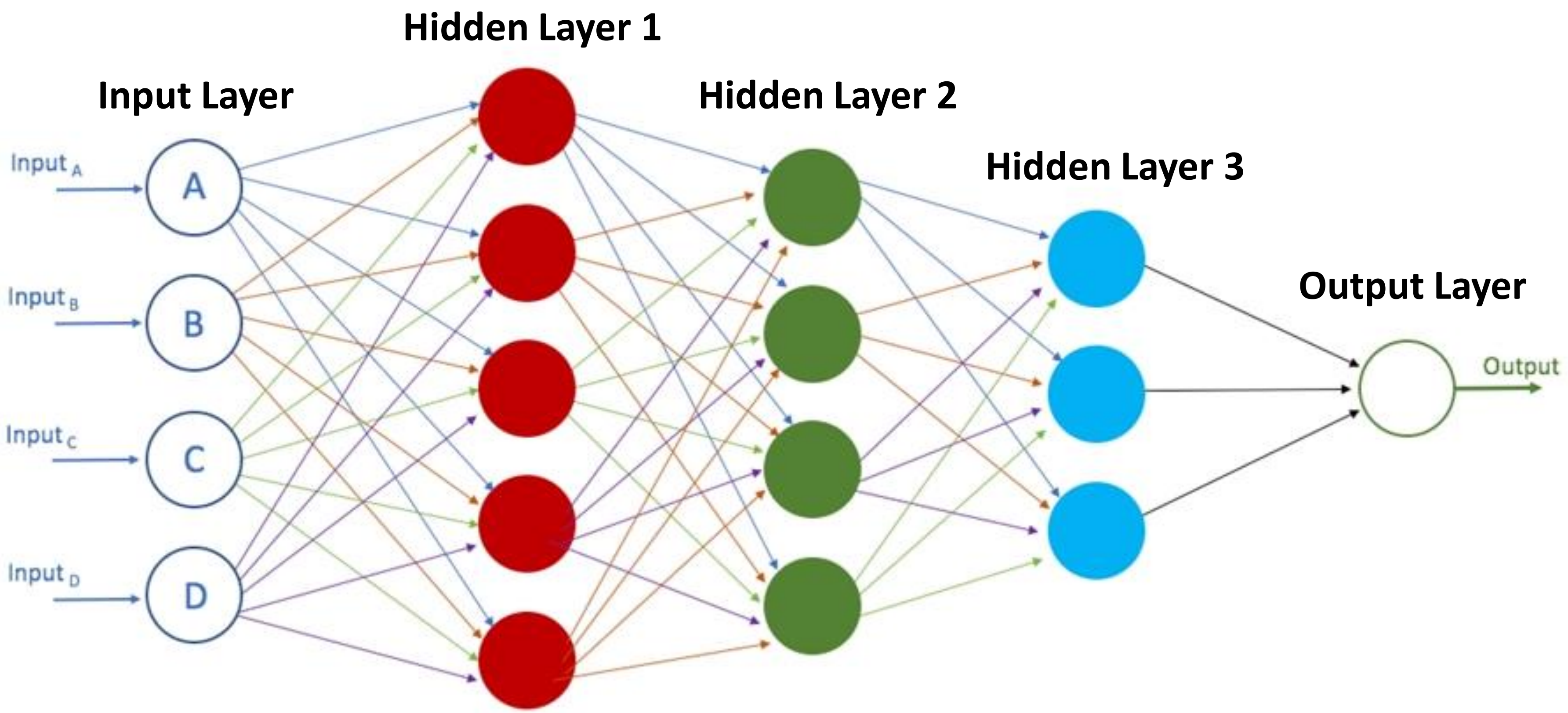
$$P(y = 1|x)$$

$$z = w_1x_1 + w_2x_2 + w_3x_3 + b$$

x: input data
b: bias
w: weights
σ: activation function

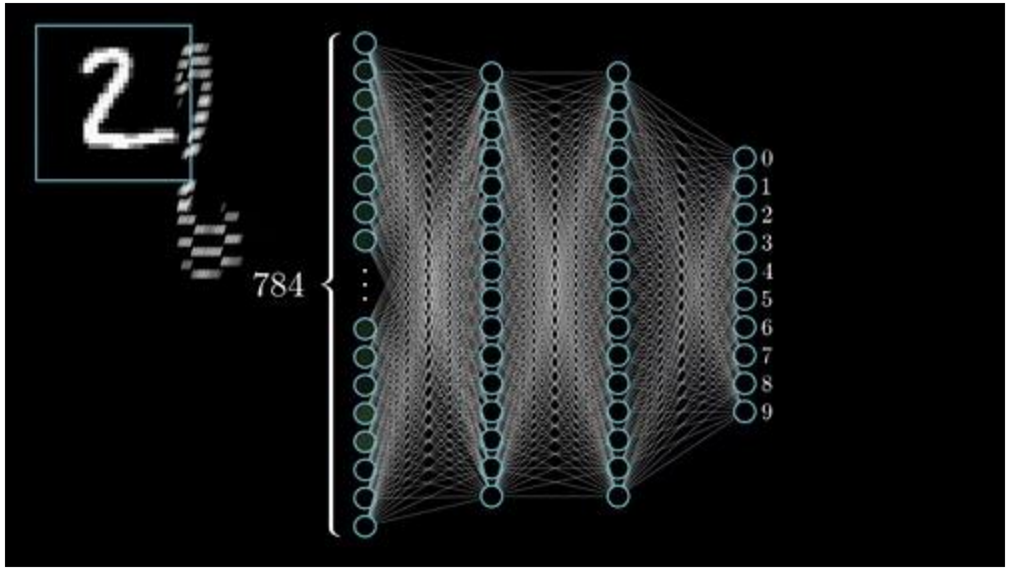
Logistic Regression from https://medium.com/@melodious/understanding-deep-neural-networks-from-first-principles-logistic-regression-bd2f01c9e263

Neural Network



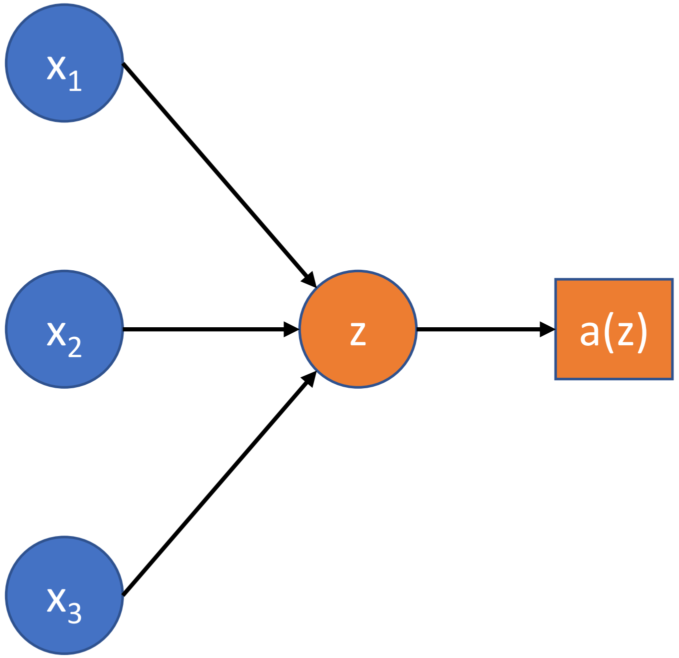
Deep Neural Network from https://developer.oracle.com/databases/neural-network-machine-learning.html

Neural Network

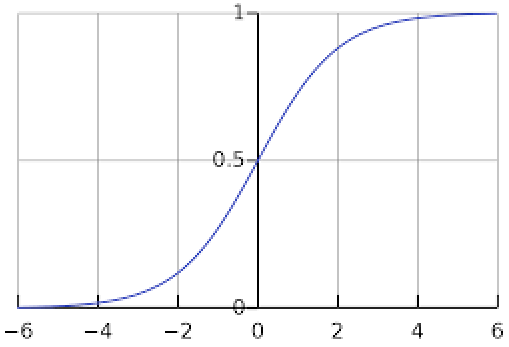


Neural Network GIF from https://www.youtube.com/channel/UCYO_jab_esuFRV4b17AJtAw

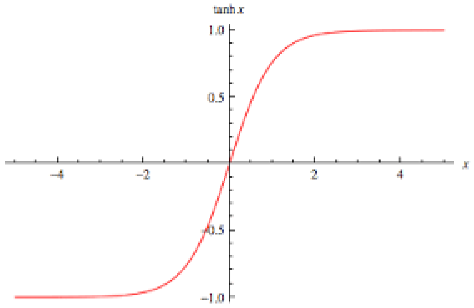
Activation Functions



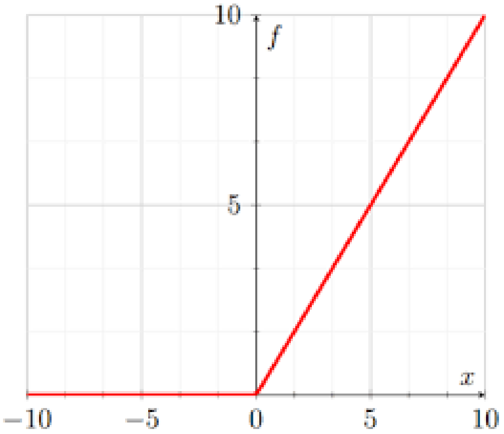
Sigmoid(z) = $\frac{1}{1+e^{-z}}$



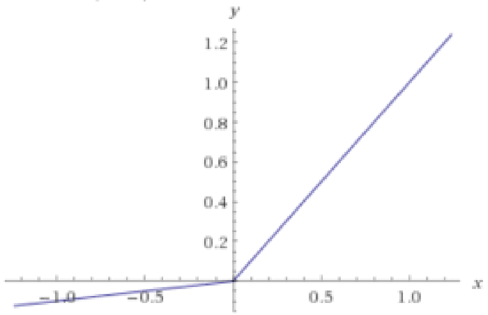
Tanh(z) = $\frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$



ReLU(z) = max(0, z)

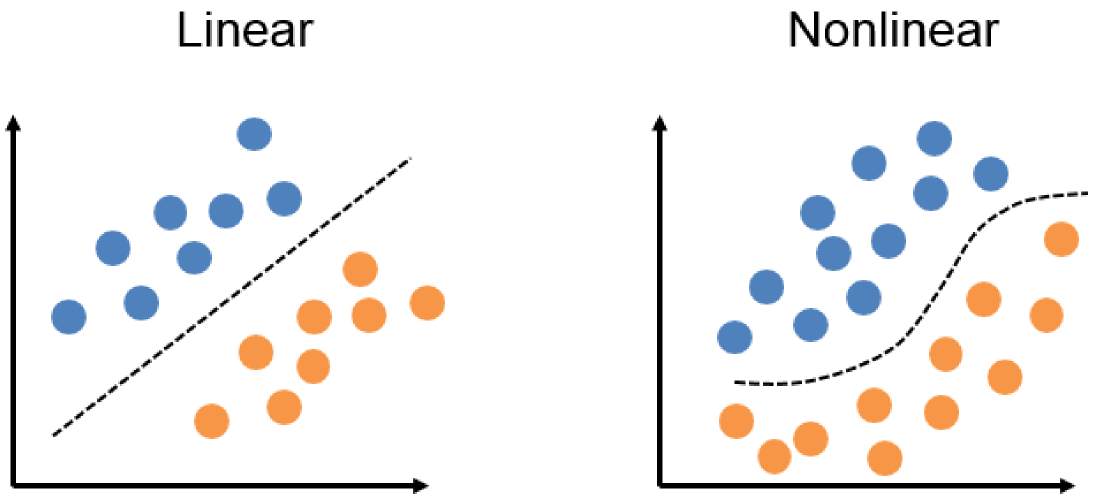


Leaky_ReLU(z) = max(0.1z, z)



Why Activation Functions?

- Specifically we want **non-linear** activation functions
- To allow our model to learn **non-linear** mappings
- Most input-output mappings we would like to learn are **non-linear**



* The activation function should also be **differentiable**

How do we train the model?

1. Forward pass to obtain prediction

$$\mathbf{x} \longrightarrow \overset{\mathbf{w}^{(1)}}{\boxed{\text{Model}}} \longrightarrow \hat{y}$$

2. Calculate error using cost function, J

$$e = J(\boldsymbol{w})$$

3. Use backpropagation to calculate gradient

$$\frac{\partial e}{\partial \boldsymbol{w}^{(1)}}$$

4. Update weights using an optimization algorithm (typically a variant of gradient descent)

$$\mathbf{w}^{(2)} = \mathbf{w}^{(1)} - \alpha \frac{\partial e}{\partial \boldsymbol{w}^{(1)}}$$

Types of Cost Function

- **Mean Absolute Error / L1 Loss**
  - $J = \frac{1}{N}\sum_i^N |y_i - \hat{\mathrm{y}}_{\mathrm{i}}|$
- **Mean Squared Error / L2 Loss / Euclidean distance**
  - $J = \frac{1}{N}\sum_i^N (y_i - \hat{\mathrm{y}}_{\mathrm{i}})^2$

Typically used in regression

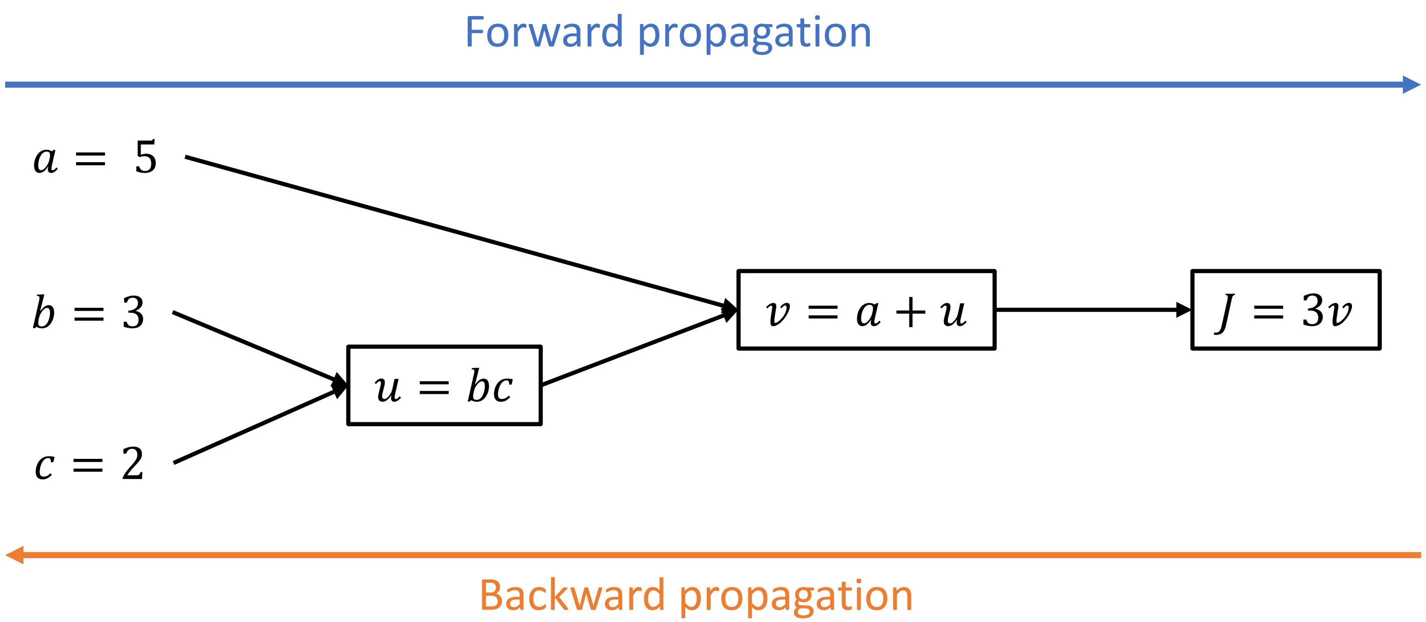
- **Binary cross-entropy Loss (C = 2)**
  - $J = \frac{1}{N}\sum_i^N (-y_i \log \hat{\mathrm{y}}_{\mathrm{i}} - (1 - y_i) \log(1 - \hat{\mathrm{y}}_{\mathrm{i}}))$
- **Cross-entropy Loss**
  - $J = \frac{1}{N}\sum_i^N \left[-\sum_j^C y_j \log \hat{\mathrm{y}}_{\mathrm{j}}\right]$

Typically used in classification

* There are many types of cost functions that are possible depending on what you want your model to learn

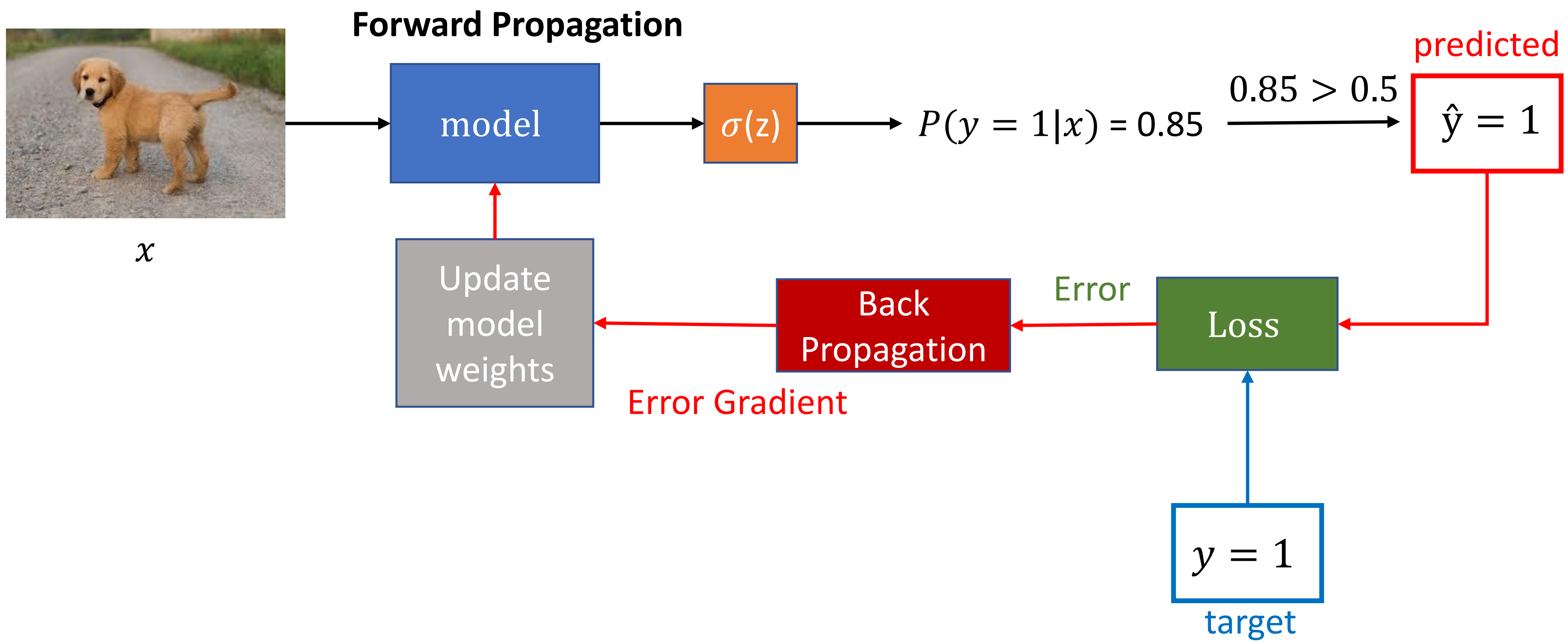
Backpropagation

- Used to calculate error gradient with respect to the model weights
- Calculate using chain rule



Computation graph as shown in by [Andrew Ng in his deeplearning.ai course]

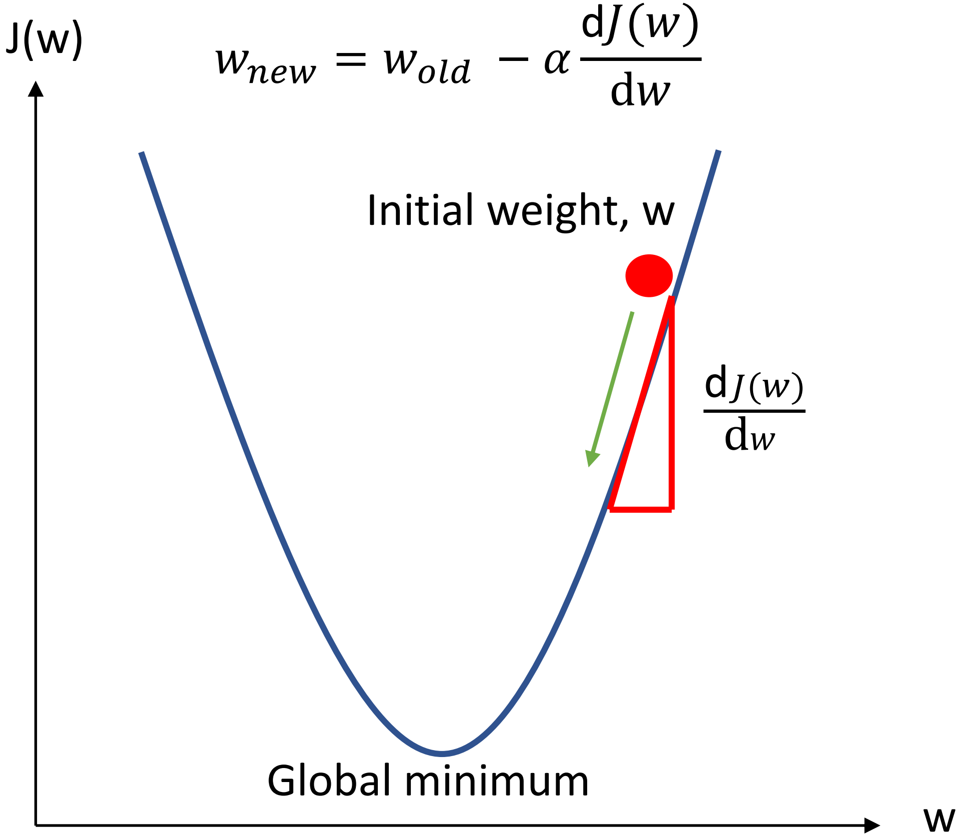
Loss Calculation and Back Propagation



Gradient Descent

- Method to optimize our model and find our optimal weights
- We want to find the weights, w that minimize our cost function, J(w)
- Currently, there are many variants to improve standard gradient descent

$$w_{new} = w_{old} - \alpha \frac{\mathrm{d}J(w)}{\mathrm{d}w}$$



Batch Gradient Descent

- Training is normally carried out in **batches** of training data
- **Stochastic Gradient Descent**
  - Update weights for each training data example
  - More generalization
- **Batch Gradient Descent**
  - Update weights after going through **every** training data example
  - Faster computation (vectorization)
- **Mini-batch Gradient Descent**
  - Update weights after going through **N** training data examples

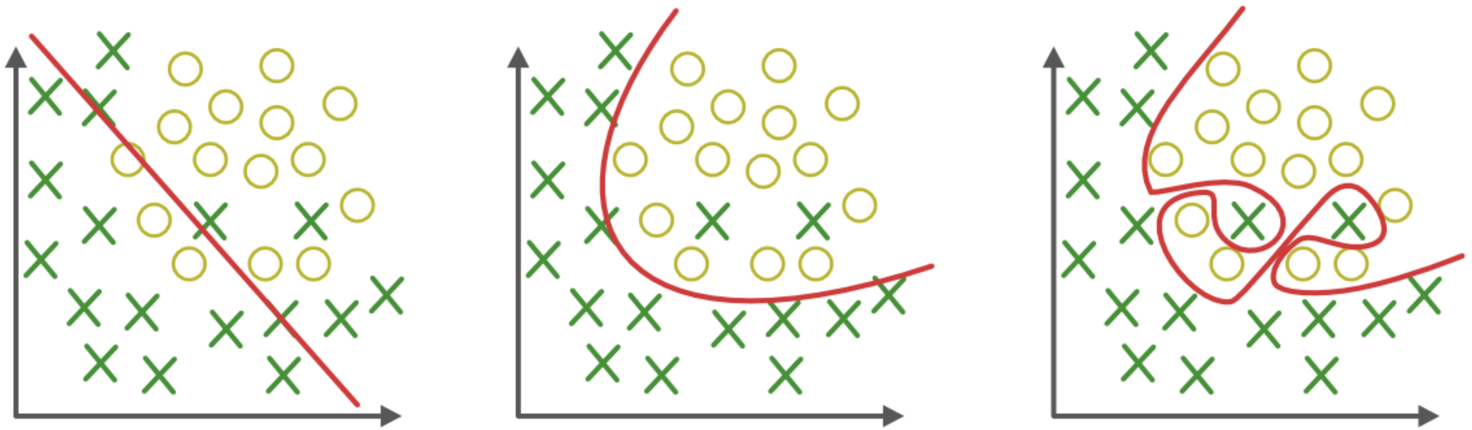
Evaluating your Model

- **Identify how well the model performs**
- **Identify how well the model generalizes to unseen data samples**
- **Quantitative analysis**
  - Use performance metrics
- **Qualitative analysis**
  - Useful for visual based output

Underfitting and Overfitting

Understanding the model's ability to **generalize** to unseen data

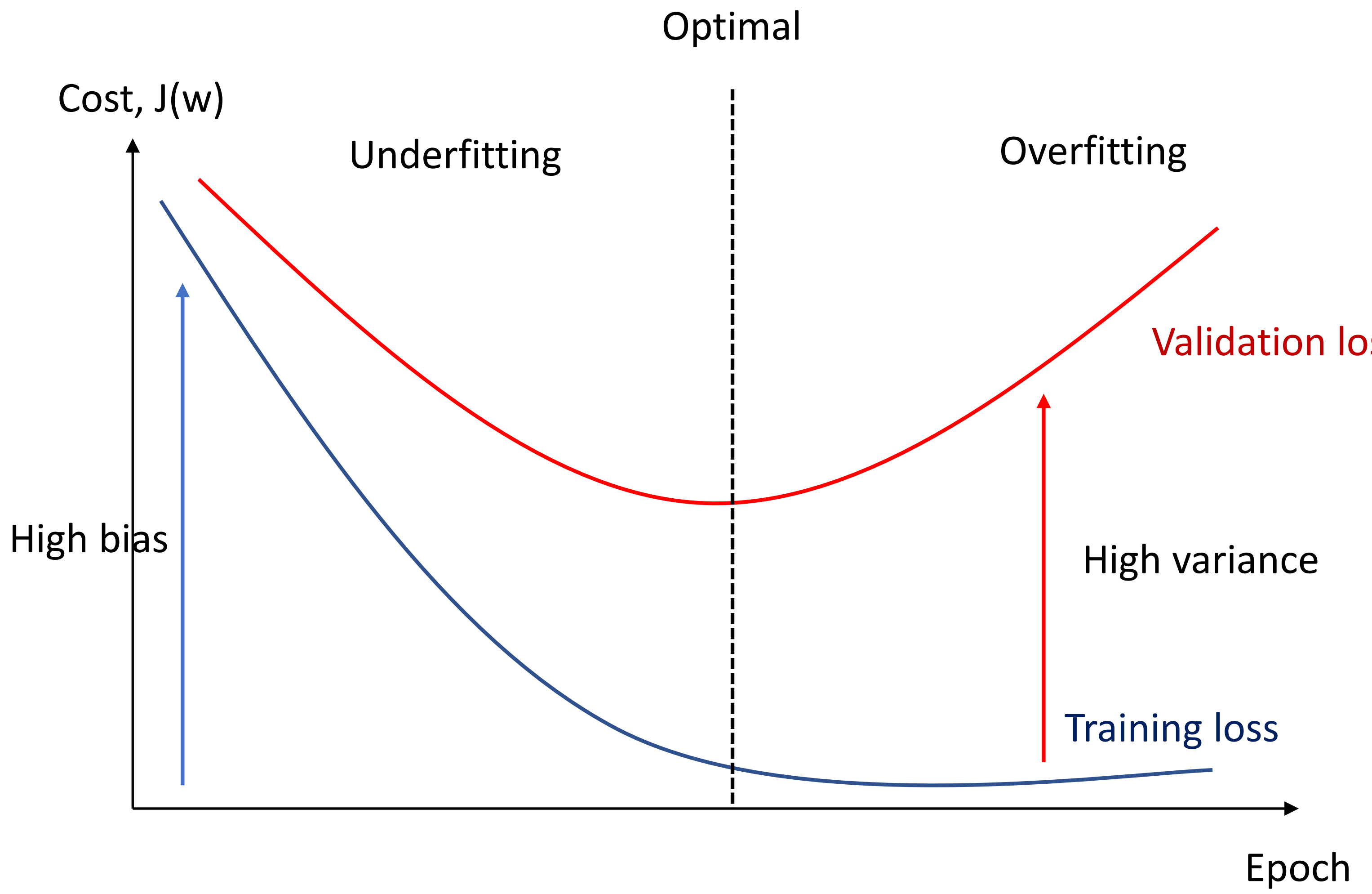
High bias | High variance



Underfitting | Good fit | Overfitting

Graphs from https://towardsdatascience.com/underfitting-and-overfitting-in-machine-learning-and-how-to-deal-with-it-6fe4a8a49dbf

Underfitting and Overfitting



How do we deal with this? - **Regularization**

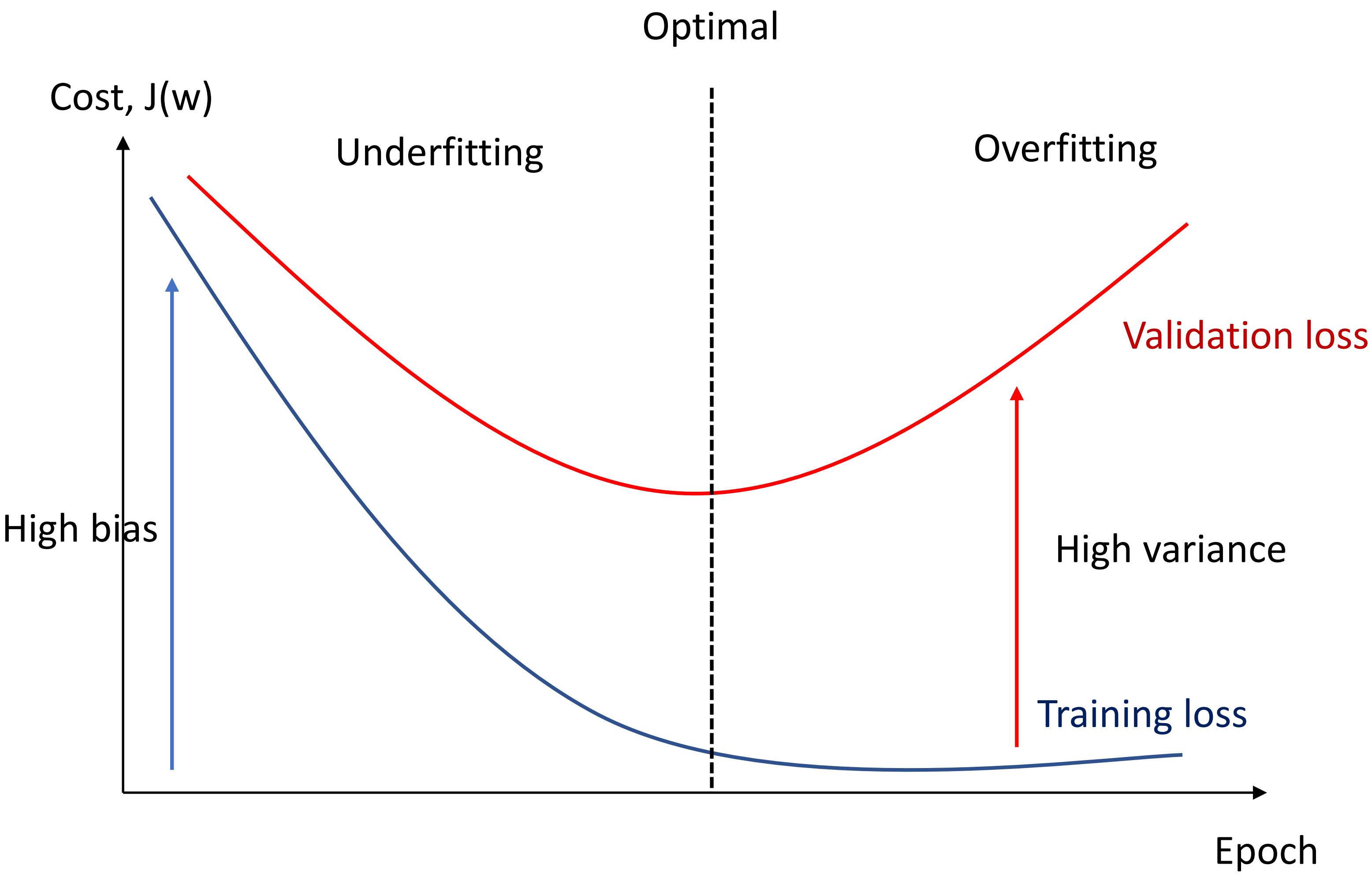
Underfitting and Overfitting

- **We would like to reduce bias and variance**
- **Reducing bias (Prevent underfitting)**
    - Increase size of network
    - Train longer
- **Reducing variance (Prevent overfitting)**
    - Add more training data
    - Regularization

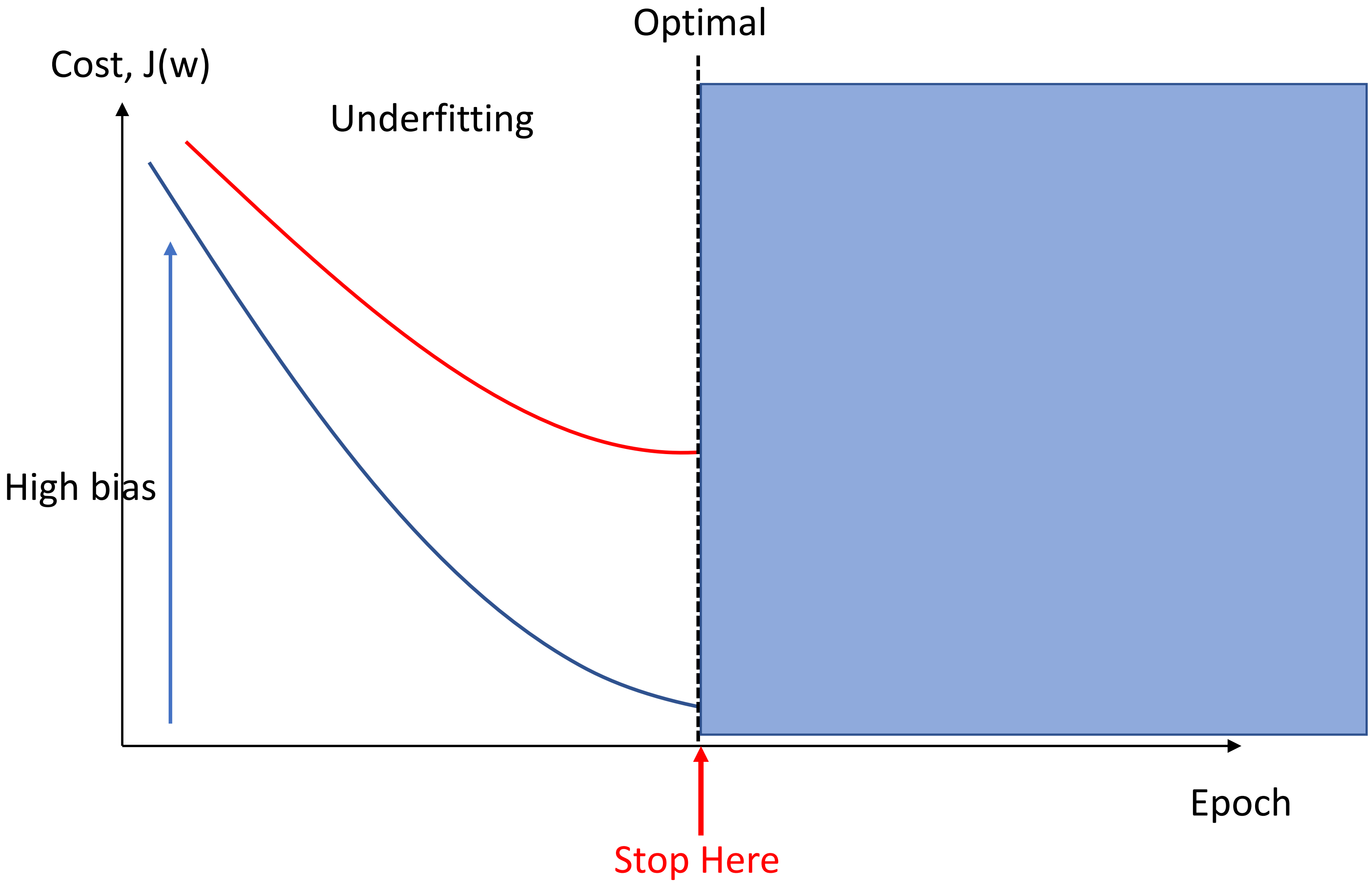
Regularization

- **Process of adding or constraining information in order to prevent overfitting**
- **Prevent our network from "memorizing" the correct output when training**
- **Types of regularization methods**
  - L1 regularization ⟵ add to cost function
    - $\lambda \sum_{i=1}^{N} |w_i|$
  - L2 regularization ⟵ add to cost function
    - $\lambda \sum_{i=1}^{N} w_i^2$
  - Dropout layer
  - Early stopping
  - Data augmentation
  - Batch Normalization

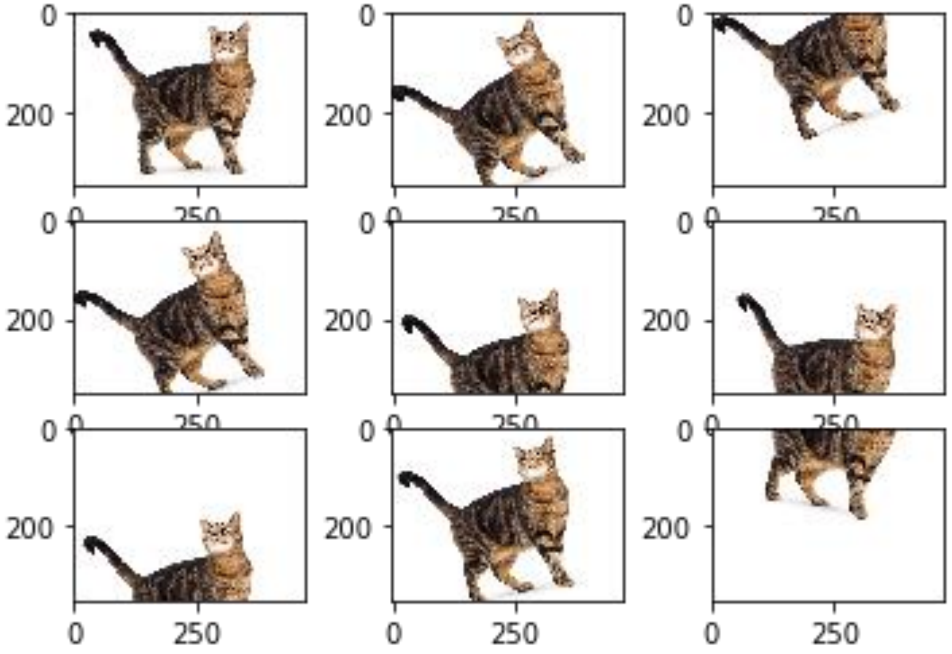
Regularization: Early Stopping



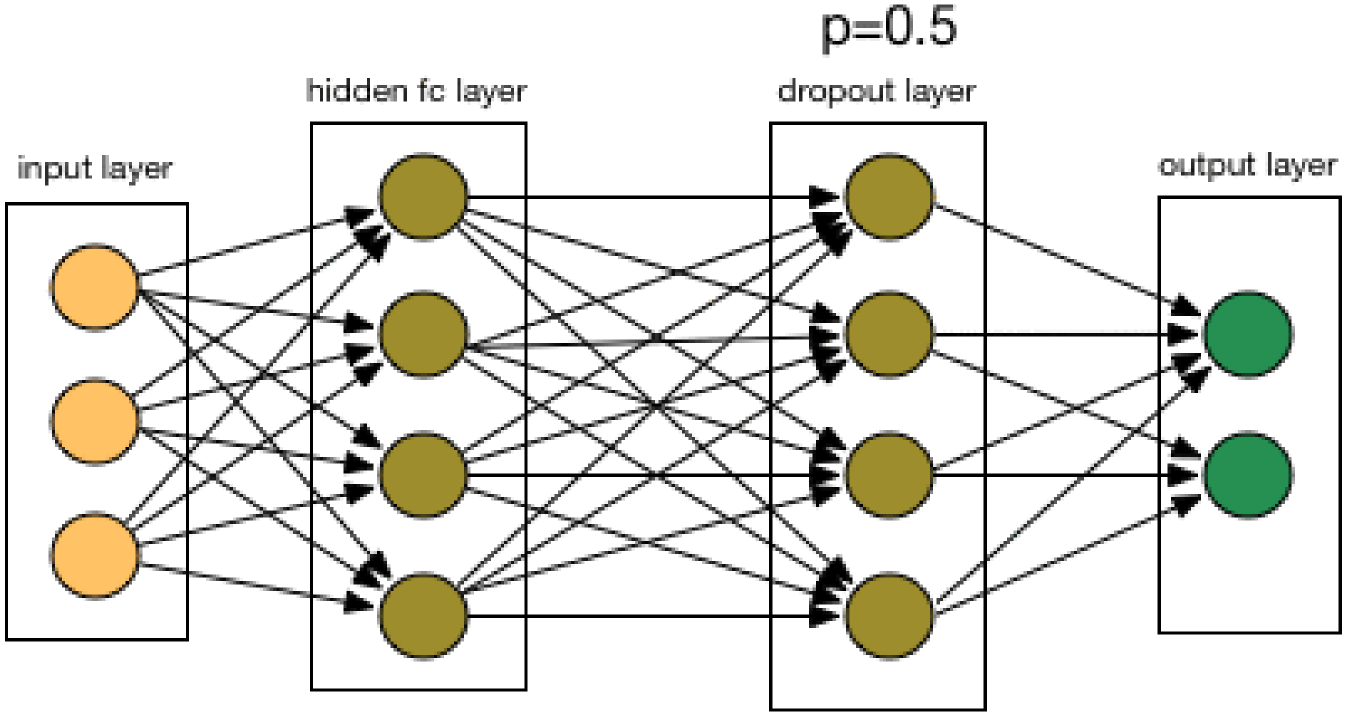
Regularization: Early Stopping



Regularization: Data Augmentation



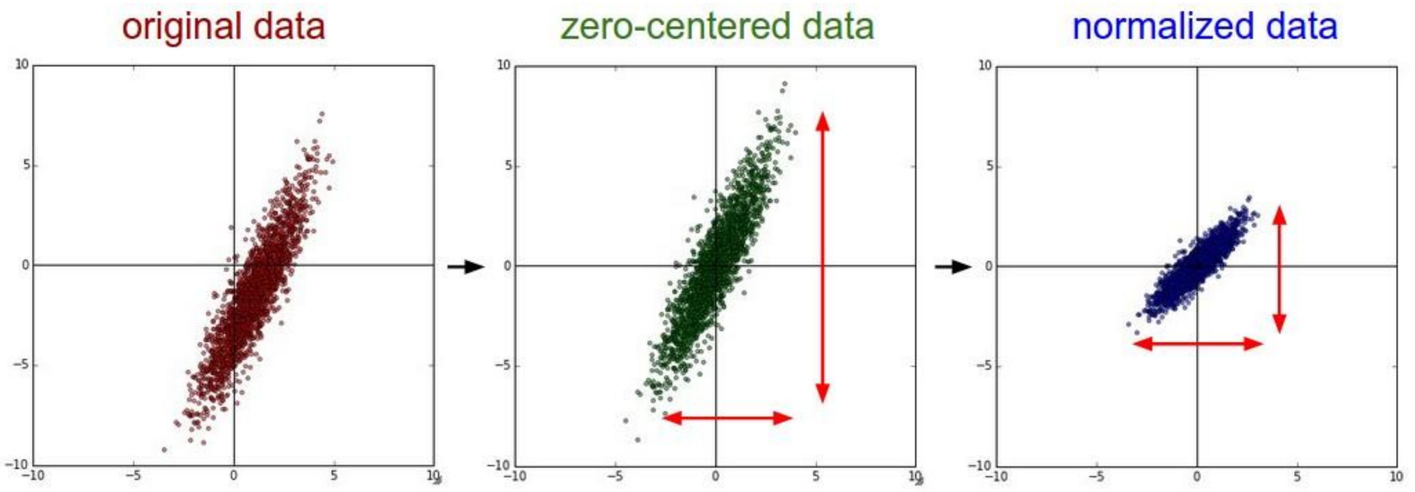
Regularization: Dropout



Training time

Normalization

- **Input normalization**
  - Scale input data to [0, 1] or [-1, 1] or according to mean and std
- **Batch normalization**
  - Normalization activations at hidden layer inputs

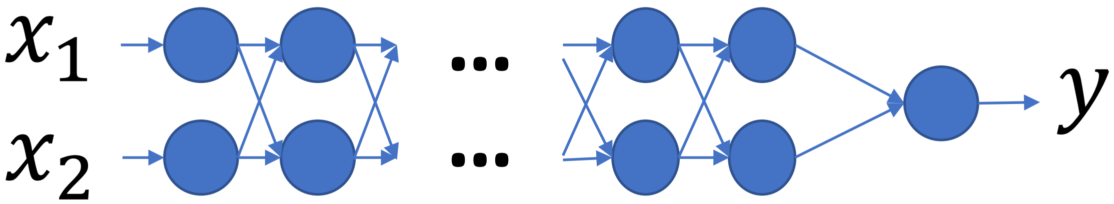


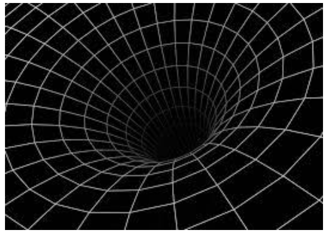
Why Normalization?

- **Input normalization**
  - Set features to similar scales *(imagine one set of features range [0…1] and another [0…1,000])*
  - Reduce outlier
  - Speed up training
- **Batch normalization**
  - Make weights deeper in networks more robust to changes in weights in earlier layers

Vanishing/Exploding Gradients

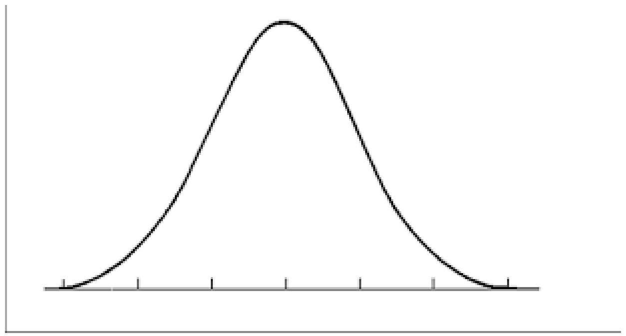
- **As neural network becomes deeper, gradient propagation can result in gradients becoming vanishing-ly small or exploding-ly large**
- **How to deal with this?**
  - Gradient Clipping
  - Weight Initialization
  - Weight Regularization
  - Increase capacity of network
    - Change number of hidden layers





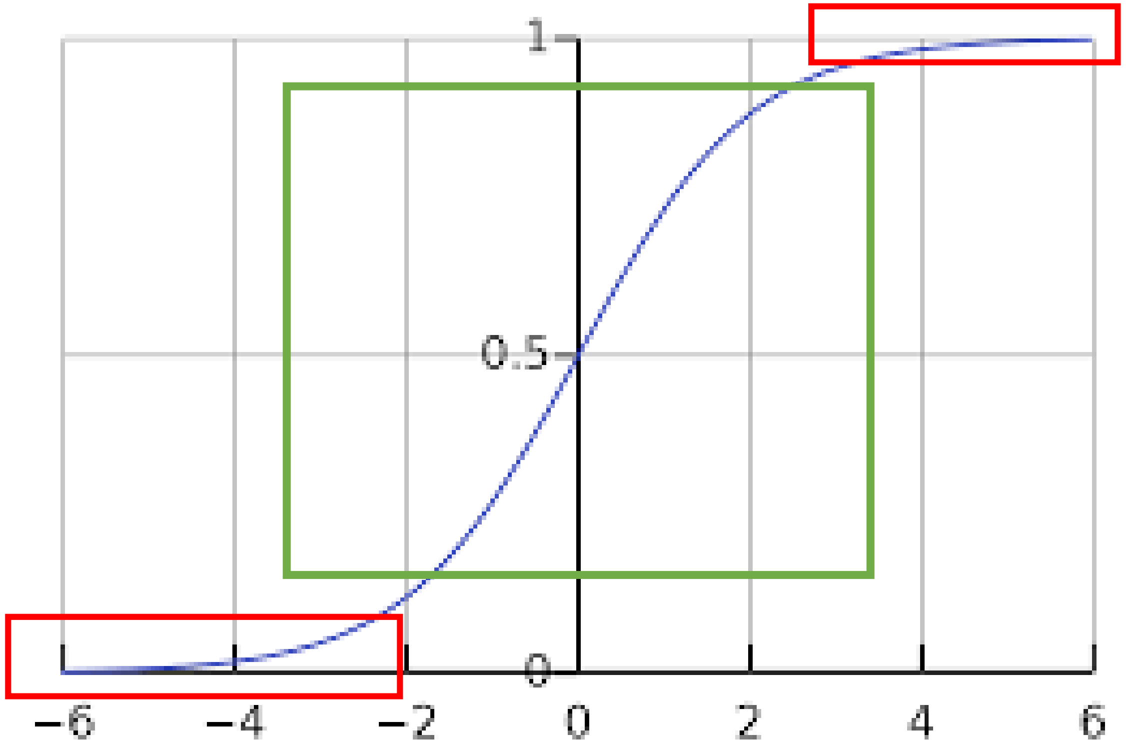
Weight Initialization

- **Weight initialization helps prevent the network from converging too slowly or "exploding"**
- **Zero initialization**
  - No matter how long you train, hidden unit weights will all be the same
  - **Not helpful**
- **Random initialization**
  - Typically Gaussian distribution
- **Xavier initialization**
  - Multiply randomly initialized weights with $\sqrt{\frac{1}{n}}$ where n is the number of features for the given layer

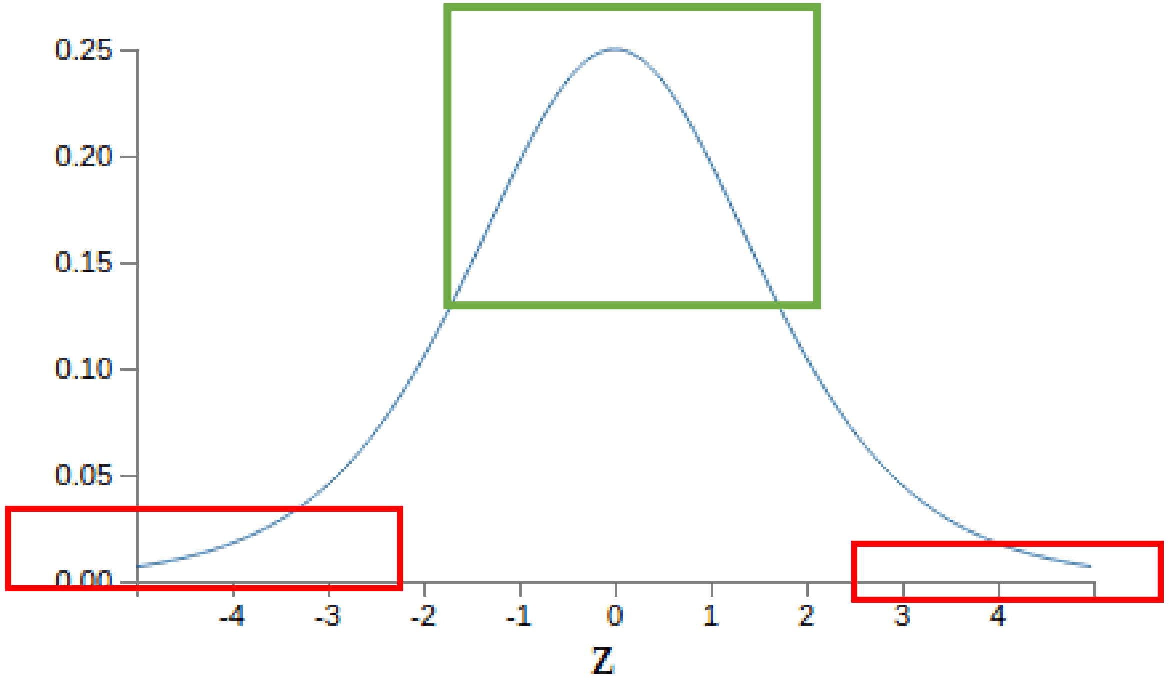


Weight Initialization

Sigmoid

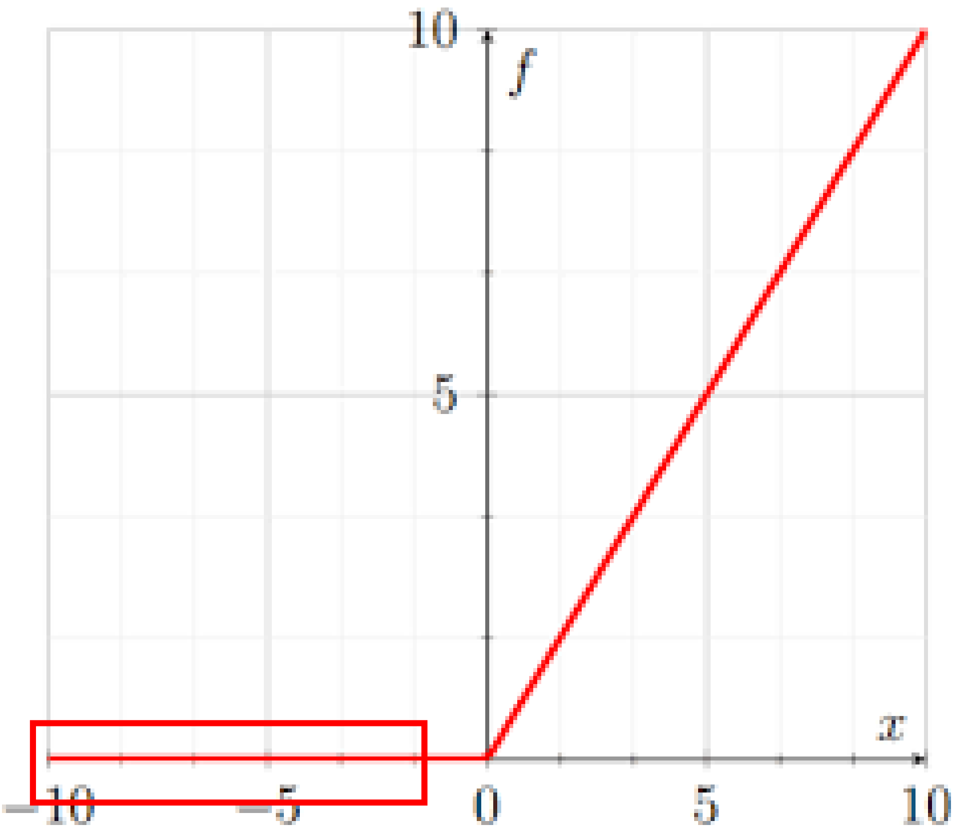


Derivative

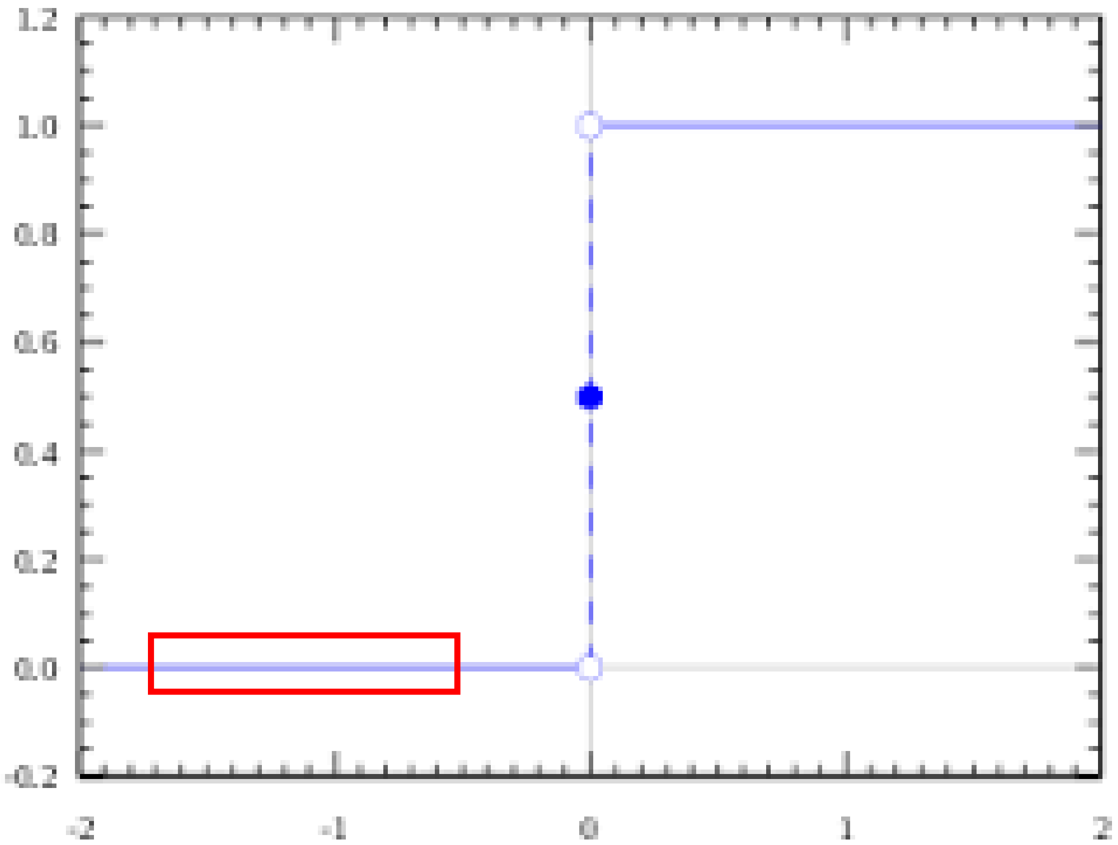


Weight Initialization

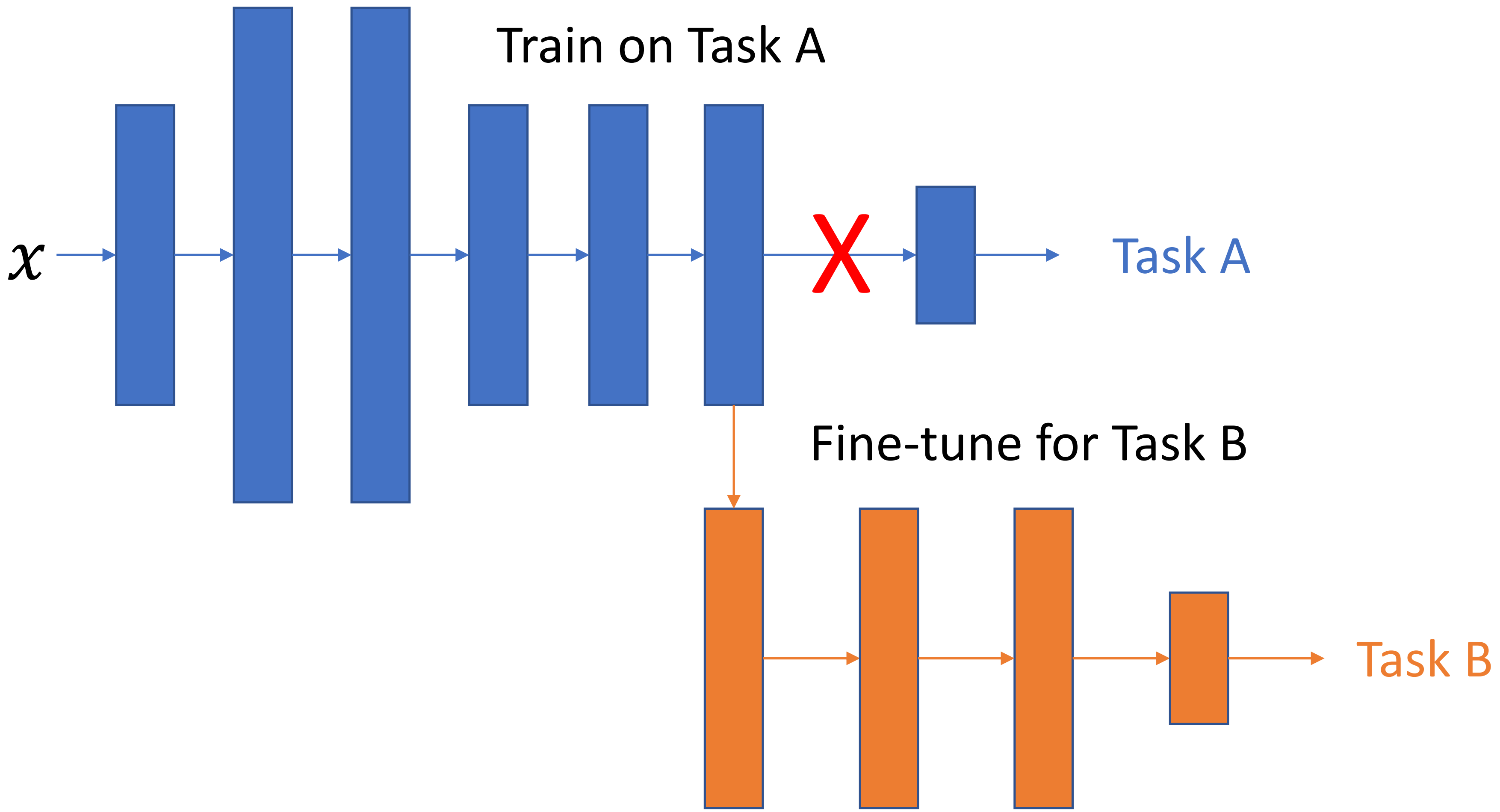
ReLU



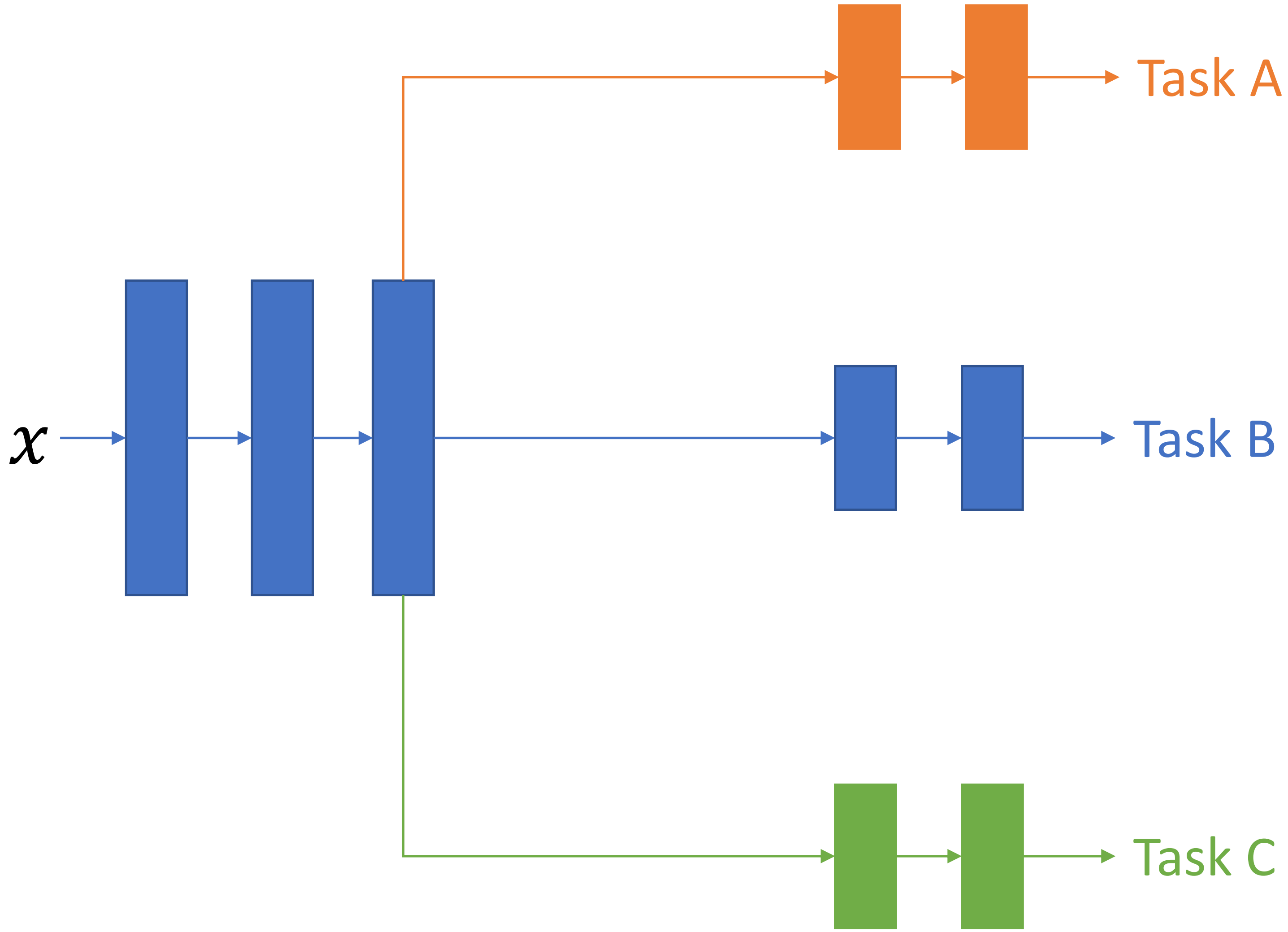
Derivative



Transfer Learning



Multitask Learning



Questions?