

# Deep Learning 101

How to train a neural network

# Schedule

week	Date	Topic
9	10.27	Environment setup, python, Jupyter, PyCharm, TensorFlow, & regression
10	11.03	Training and testing
11	11.11	CNN
12	11.18	RNN
13	11.24	Autoencoder & GAN

# Today's Class

- Recap
- How to train a neural network
  - Feature
  - Hypothesis
  - Activation functions
  - Cost functions
  - Gradient descent and Backpropagation
- Lab time

# Recap

- Neural network as a function
  - $y = f(x)$
- Perceptron
  - $Y = WX + b$
  - Two inputs:  $x_1, x_2$
  - One output:  $y$
  - Linear regression
- XOR problem
  - Linear regression can't solve the XOR problem
  - Require multivariate regression

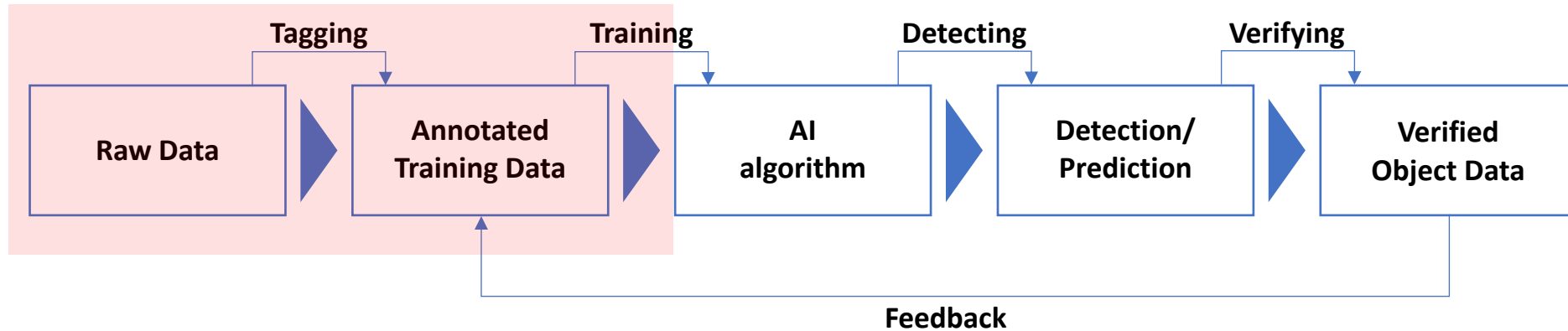
# What

- Dataset: data for training and testing
  - Requires preprocessing
- Model: What the network learns
  - Training, validation, and testing
- Inference: Model in action
  - Predicting based on the learned model

# The Challenge



## The Time-Consuming Part for AI development



Training data is the most important part of AI development, but it is also the most difficult and time-consuming part

# How to train a model

- Define input and output
- Decide on the input features
- Build layers of the network: hyperparameters
  - Number of layers
  - Learning rate
  - Number of epochs
  - Etc.
- Train the model: parameters
  - Weights and biases
  - Variables in TensorFlow
- Verify the model:
  - Using verification data

# Models and Functions

- Hypothesis:

$$H(x_1, x_2, x_3) = w_1x_1 + w_2x_2 + w_3x_3 + b$$

- Activation:
  - Sigmoid, ReLU, LeakyReLU, etc.

- Cost:
$$cost(W, b) = \frac{1}{m} \sum_{I=1}^m (H(x_1^{(i)}, x_2^{(i)}, x_3^{(i)}) - y^{(i)})^2$$



# Matrix multiplication

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 7 & 8 \\ 9 & 10 \\ 11 & 12 \end{bmatrix} = \begin{bmatrix} 58 & \\ & \end{bmatrix}$$

The "Dot Product" is where we **multiply matching members**, then sum up:

$$(1, 2, 3) \bullet (7, 9, 11) = 1 \times 7 + 2 \times 9 + 3 \times 11 \\ = 58$$

<https://www.mathsisfun.com/algebra/matrix-multiplying.html>

# Functions using matrix

- Hypothesis

- $Y = WX + b$   
$$\begin{pmatrix} x_1 & x_2 & x_3 \end{pmatrix} \cdot \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} = (x_1 w_1 + x_2 w_2 + x_3 w_3)$$

- Activation function

- Cost function

$$cost(W, b) = \frac{1}{m} \sum_{I=1}^m (H(x_1^{(i)}, x_2^{(i)}, x_3^{(i)}) - y^{(i)})^2$$

# Activation functions

- Introduces non-linearity
- Normalizes the output: activation functions are also called Normalization functions
- Different kinds
  - Step function:  $f(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{w} \cdot \mathbf{x} + b > 0, \\ 0 & \text{otherwise} \end{cases}$
  - Sigmoid:

$$S(x) = \frac{1}{1 + e^{-x}}$$

$S(x)$  = sigmoid function

$e$  = Euler's number

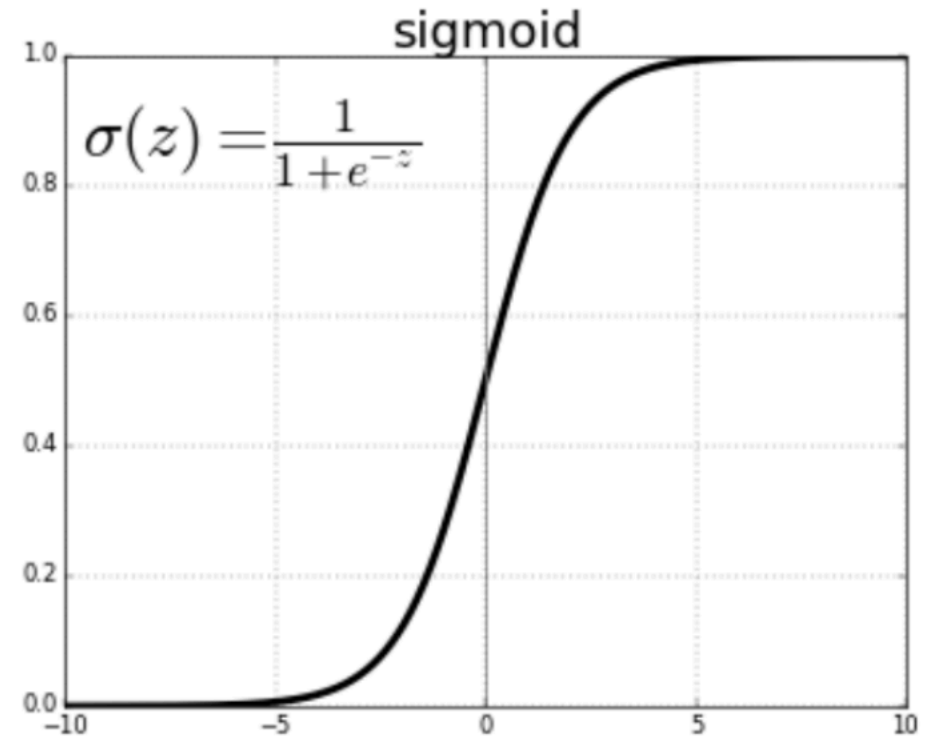
# Activation function: Sigmoid

- Sigmoid:

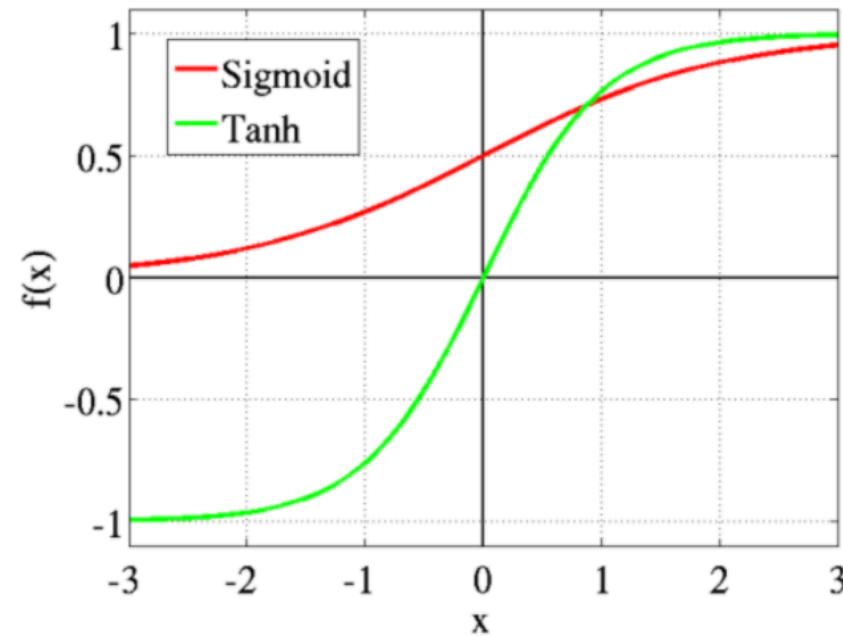
$$S(x) = \frac{1}{1 + e^{-x}}$$

$S(x)$  = sigmoid function

$e$  = Euler's number



# Activation functions: Sigmoid and Tanh



<https://www.neuronactivator.com/blog/what-even-is-activation-function>

# Activation Functions: ReLU and Leaky ReLU

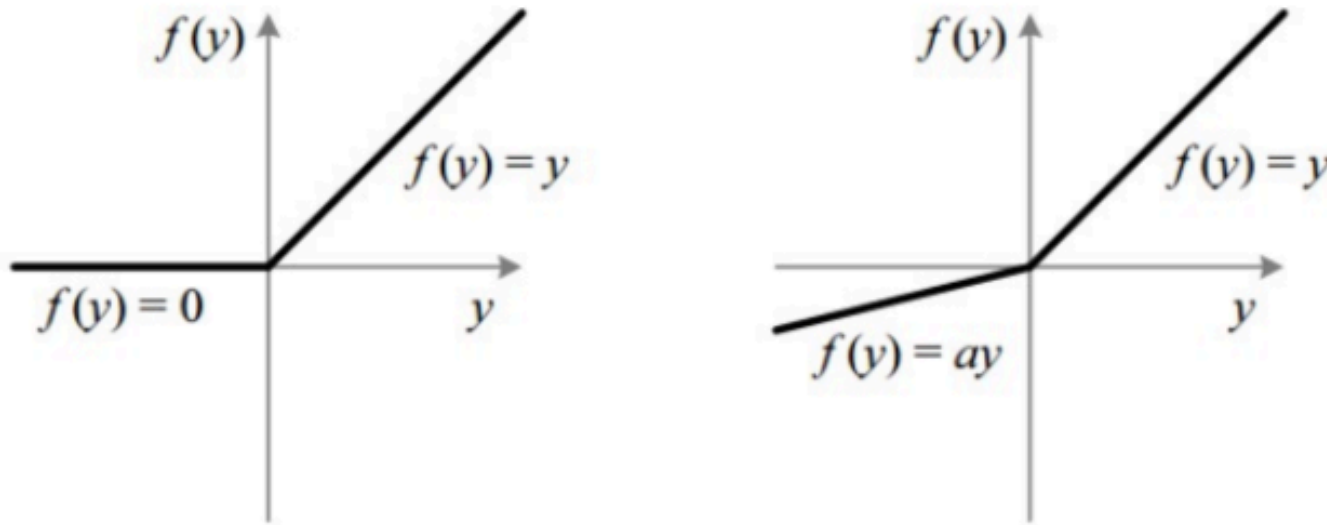


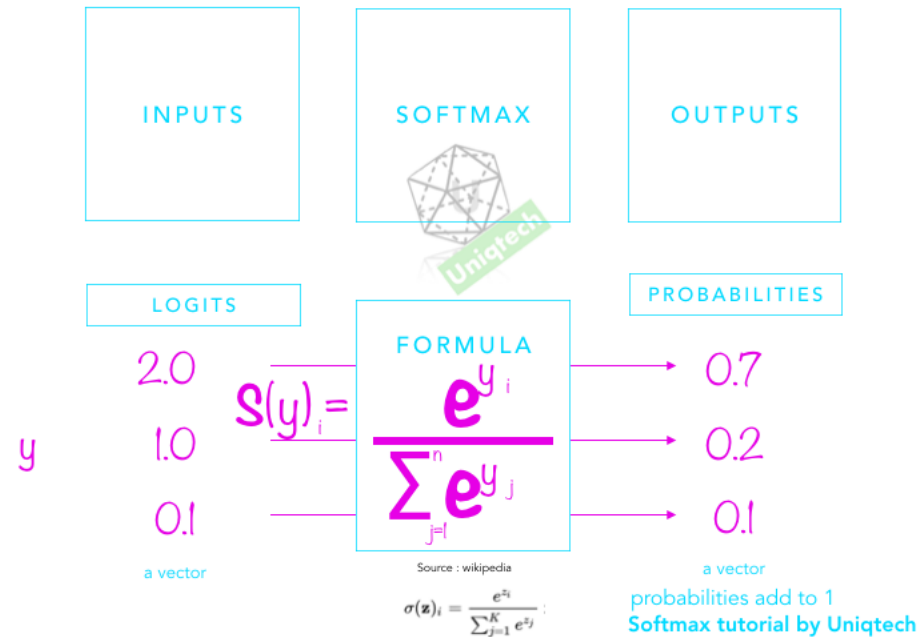
Fig : ReLU v/s Leaky ReLU

<https://www.neuronactivator.com/blog/what-even-is-activation-function>

# Activation Function: Softmax

- The softmax function is often used in the final layer of a neural network-based classifier.
- All probabilities sum to one
- Often used with a [log loss](#) (or [cross-entropy](#)) cost function
- To solve a non-linear variant of multinomial logistic regression.

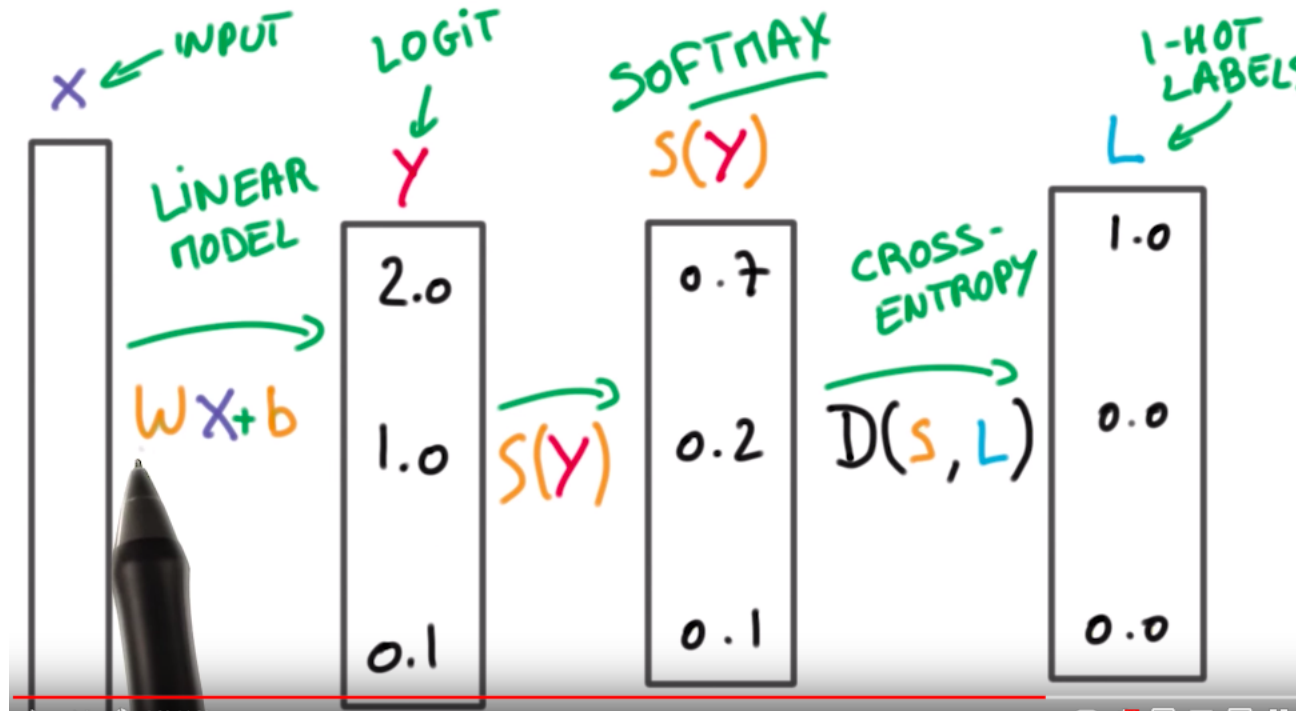
# Activation Function: Softmax



<https://medium.com/data-science-bootcamp/understand-the-softmax-function-in-minutes-f3a59641e86d>



# Loss Function: Cross Entropy

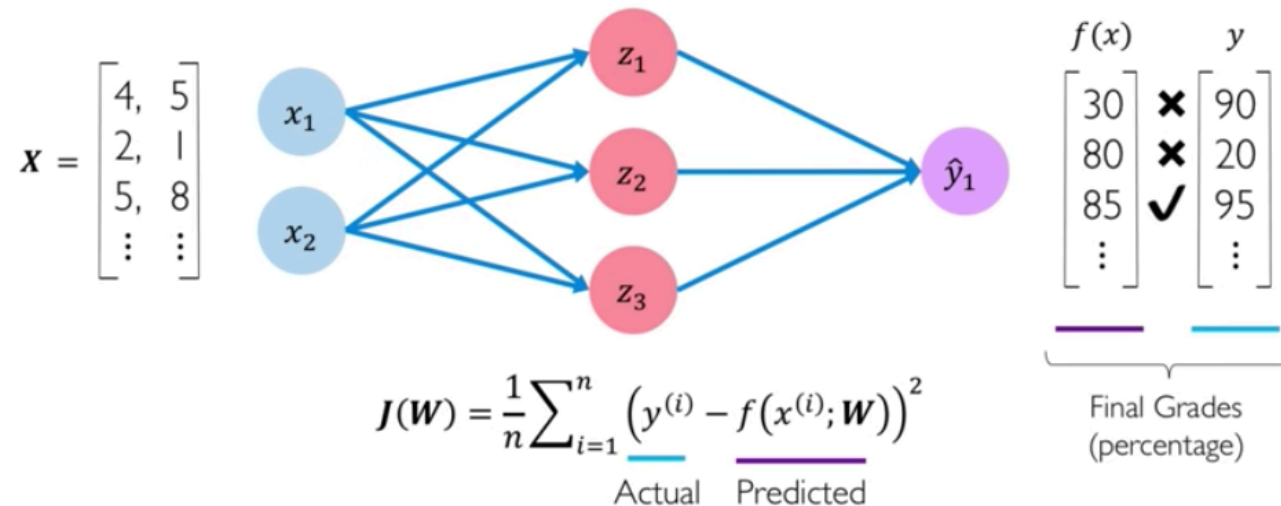


<https://medium.com/data-science-bootcamp/understand-cross-entropy-loss-in-minutes-9fb263caee9a>

# Loss Function: Mean Squared Error

## Mean Squared Error Loss

*Mean squared error loss can be used with regression models that output continuous real numbers*



```
loss = tf.reduce_mean( tf.square(tf.subtract(y, predicted)) )
```

# Training is minimizing the cost

- Training a neural network is basically the problem of minimizing the cost function.
- Gradient descent is the most popular approach.
- For a given cost function, minimize  $\text{cost}(W, b)$

# Backpropagation

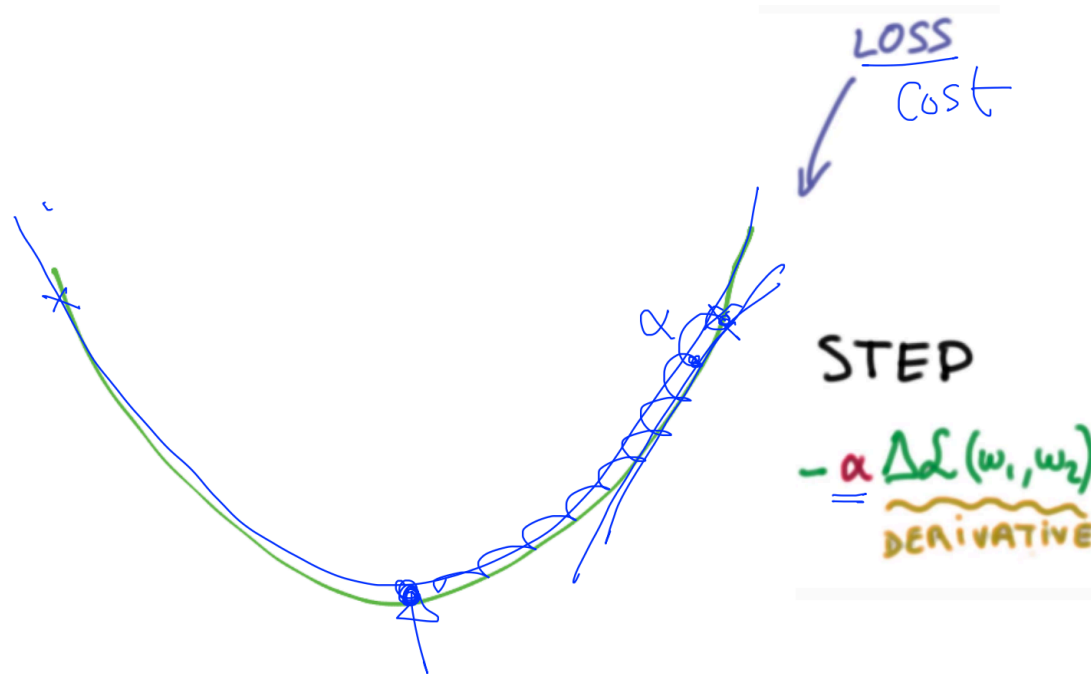
1. Use Calculus: the study of change
2. Batches, mini-batches, and stochastic batches

## Steps:

1. Take the derivative: the slope of a tangent line at a specific point in time
  2. Partial derivative
  3. The chain rule: composite functions
- 
- Backpropagation of errors: Updating weights using gradient descent

# Backpropagation using gradient descent

## Gradient descent

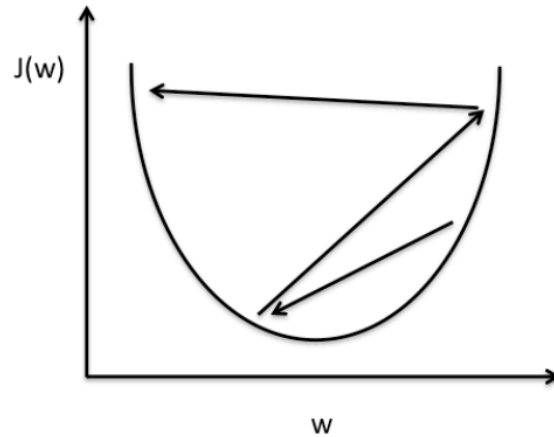


# Problems with training

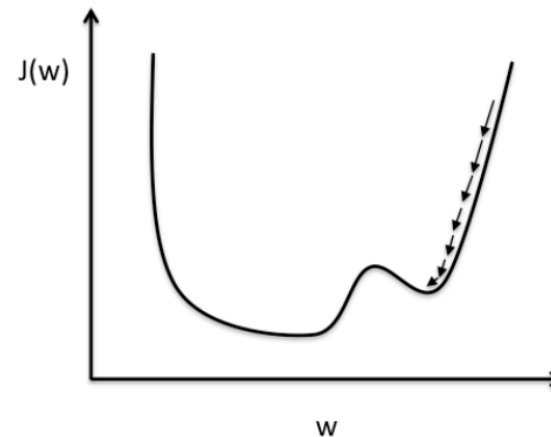
- Initial weights: random means you can't predict
- Vanishing/exploding gradients
- Local minima
- Overfitting & underfitting
- Hyperparameters: learning rate, number of layers, etc. require human intelligence!

# Learning rate

Learning rate: NaN!

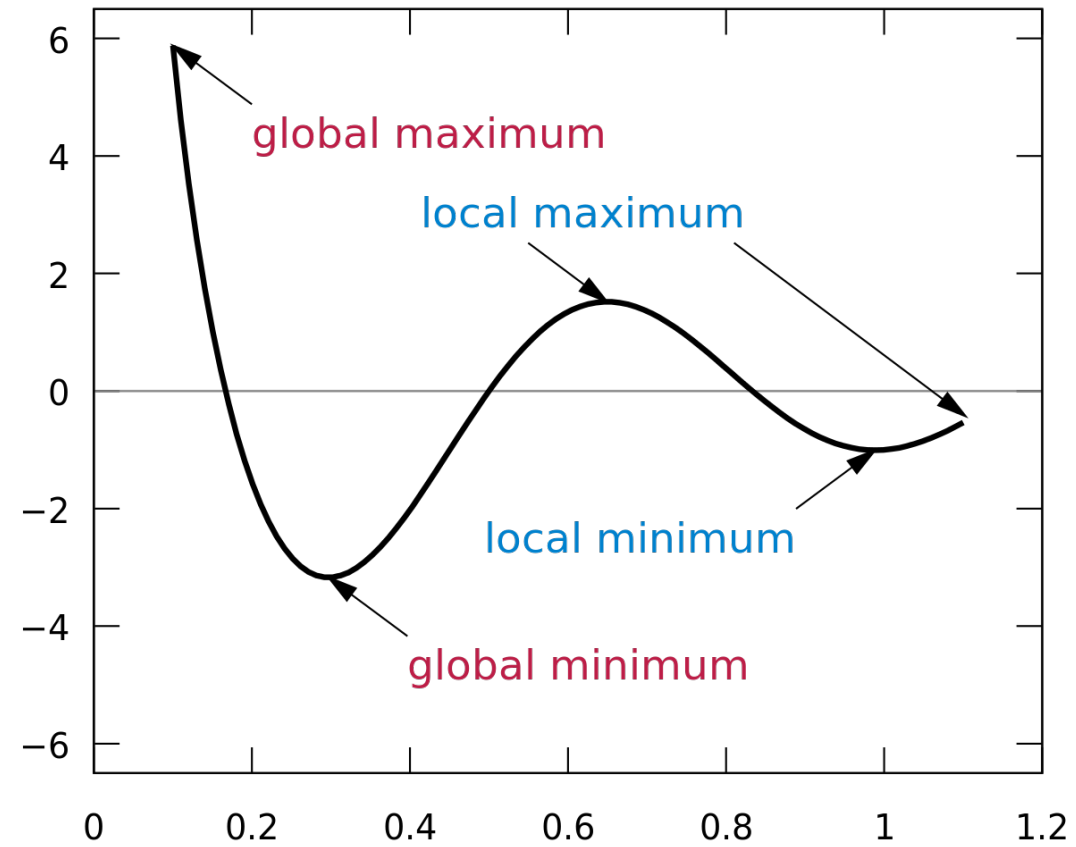


Large learning rate: Overshooting.



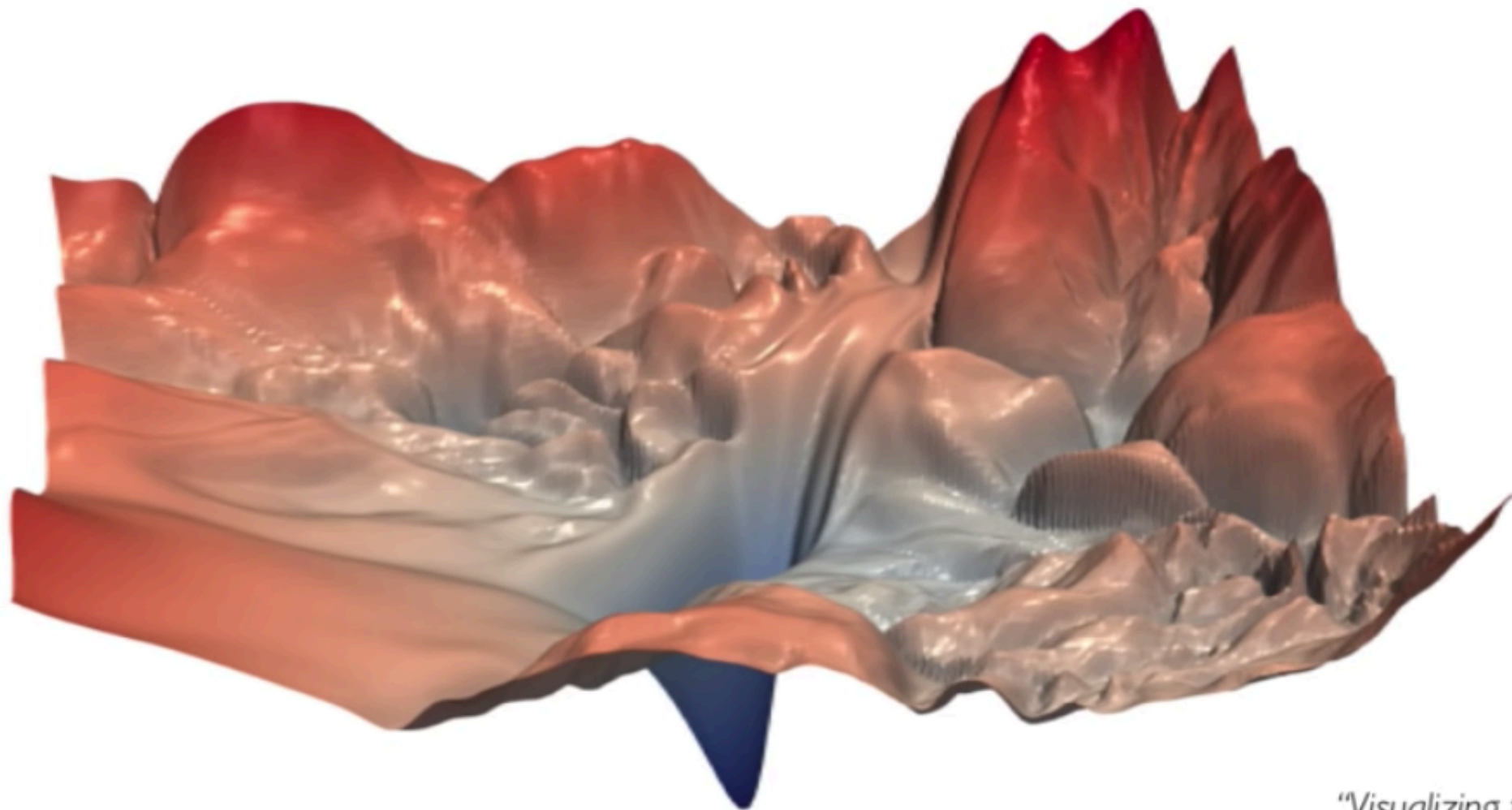
Small learning rate: Many iterations until convergence and trapping in local minima.

# Local minima





# Training Neural Networks is Difficult



*"Visualizing the loss landscape of neural nets". Dec 2017.*

# Lab time

- To clone: from your terminal
  - >git clone <https://github.com/changsin/DeepLearning-101.git>
- Or use google colab to point to the git hub repository
- Git is an open source version control system
  - Github is a host service using git.