## **Chapter 5 Deep Learning**

# **Deep Learning**

### Machine Learning





## **Problem: Vanishing Gradient**



# Why Vanishing Gradients

- Gradients of the loss function approach to zero, making the network hard to train.
- Sigmoid function squishes a large input space into a small input space between 0 and 1.
- Therefore, a large change in the input of the sigmoid function will cause a small change in the output.
- Hence, the derivative becomes small.



## **ReLU and Derivatives**





### How Does ReLU Solve Vanishing Gradient?

• **RELU** activation **solves** this by having a gradient slope of 1, so during backpropagation, there isn't gradients passed back that are progressively getting smaller and smaller, but instead they are staying the same, which is how RELU solves the vanishing gradient problem

# SiLU (Sigmoid Linear Unit)

#### 1. SiLU (Sigmoid Linear Unit)

여기서  $\sigma(x)$  는 Sigmoid 함수를 의미합니다.

SiLU(Sigmoid Linear Unit, 또는 Swish로도 알려졌습니다)는 인공 신경망의 활성화 함수 중 하나 로 아래와 같이 정의 됩니다.

### $SiLU(x) = x \cdot \sigma(x)$









### How Does Dropout Reduce Overfitting?

 Dropout prevents overfitting due to a layer's "over-reliance" on a few of its inputs. Because these inputs aren't always present during training (i.e. they are dropped at random), the layer learns to use all of its inputs, improving generalization

# Dropout

Dropout: A Simple Way to Prevent Neural Networks from Overfitting [Srivastava et al. 2014]



# Dropout

Waaaait a second...

How could this possibly be a good idea?



# **Computational Load**

- Multidimensional Optimization
- GPU Computation (GIE, GPU Inference Engine)



# Optimization

#### ADAM: a method for stochastic optimization [Kingma et al. 2015]



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https://arxiv.org/pdf/1412.6980.pdf

### Data vs. Neural Nets

