

# Machine Learning

## Activation Functions

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# Objectives

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## Objectives:

- ▶ Review - Activation Functions in Neural Networks
- ▶ Review - Back-propagation
- ▶ Understand - Vanishing and Exploding Gradients
- ▶ Identify - Common Activation Functions
- ▶ Initialize - Best Practices per Activation Function

# Review

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# Activation Functions

$$\phi_w(x) = \sum_{i=0}^n w_i x_i$$

# Loss and Gradient

Loss function

$$J(\boldsymbol{\theta})$$

Gradient w.r.t  $\boldsymbol{\theta}$

$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta})$$

# Back-propagation

- ▶ Forward pass (compute)
- ▶ Backward pass (error propagation)
- ▶ Vanishing gradients
- ▶ Exploding gradients

# Common Activation Functions

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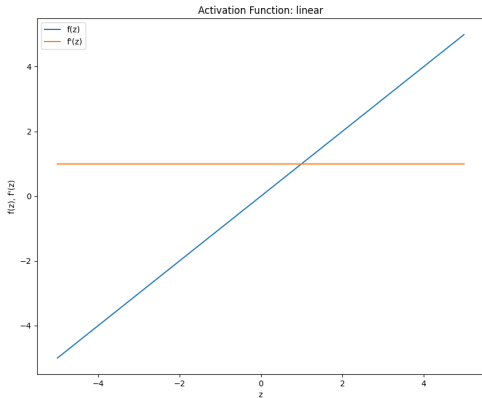


# Linear

$$f(x) = x$$

## Notes:

- ▶ Smooth
- ▶ Fast
- ▶ linear

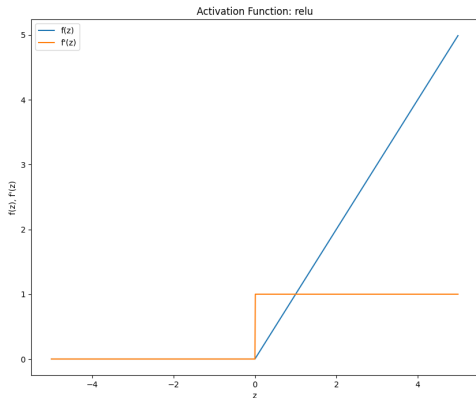


# Rectified Linear

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

## Notes:

- ▶ Not smooth
- ▶ Fast
- ▶ No gradient on left side (neurons “die”)
- ▶ `relu`

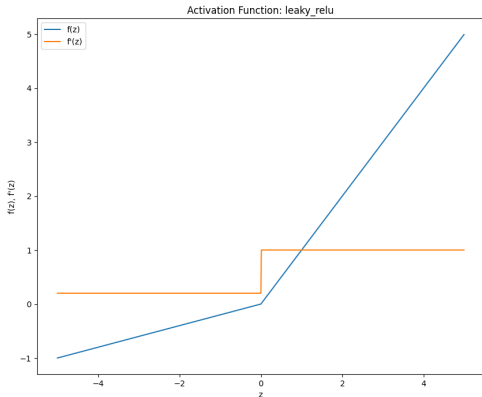


# Leaky ReLU

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha x & \text{if } x \leq 0 \end{cases}$$

## Notes:

- ▶ Not smooth
- ▶ Fast
- ▶ Small gradient on left side (neurons don't "die")
- ▶ `leaky_relu`

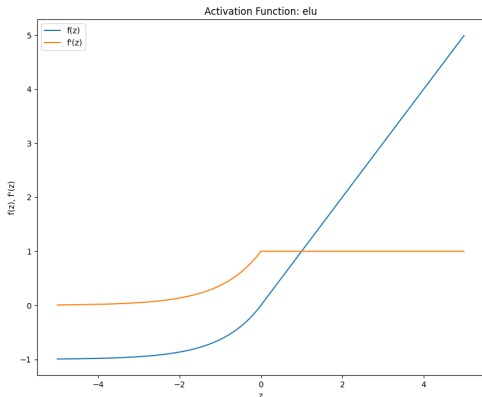


# Exponential Linear Unit

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha(e^x - 1) & \text{if } x \leq 0 \end{cases}$$

## Notes:

- ▶ Smooth if  $\alpha = 1$
- ▶ Slower to compute
- ▶ Gradient descent may converge faster
- ▶ Small gradient on left side (neurons don't "die")
- ▶ elu

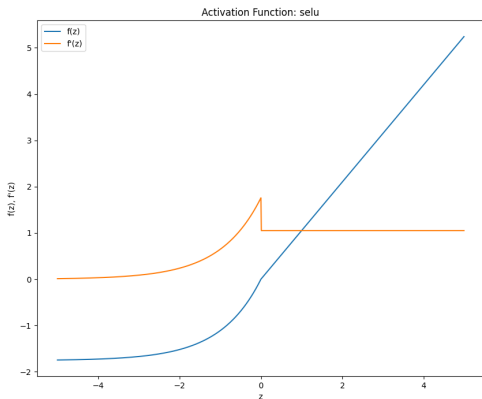


# Scaled ELU

$$f(x) = \begin{cases} sx & \text{if } x > 0 \\ s\alpha(e^x - 1) & \text{if } x \leq 0 \end{cases}$$

## Notes:

- ▶ Only useful on stacks of dense layers
- ▶ selu

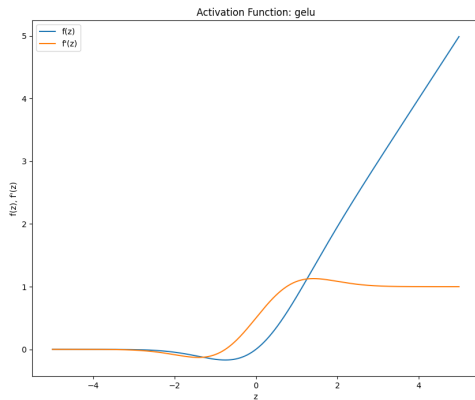


# Gaussian ELU

$$f(x) = x\Phi(x)$$

## Notes:

- ▶  $\Phi(x)$  is the Gaussian cumulative distribution function
- ▶ More computationally expensive
- ▶ Maybe faster convergence
- ▶ `gelu`

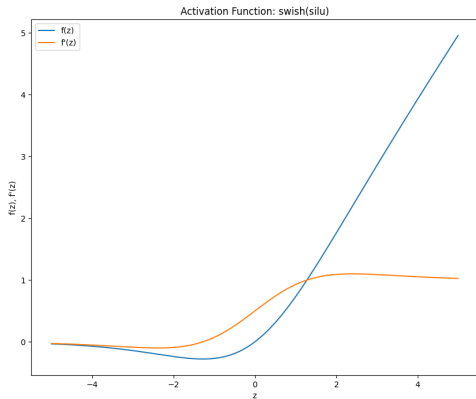


# Sigmoid Linear Unit (Swish)

$$f(x) = x\sigma(x)$$

## Notes:

- ▶  $\sigma(x)$  is the sigmoid function
- ▶ Sometimes better than GELU
- ▶ silu, swish

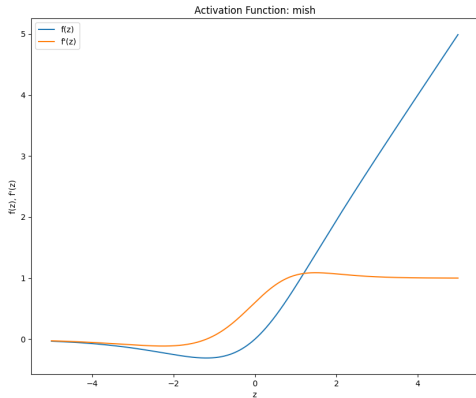


# MISH

$$f(x) = x \tanh(\log(1 + e^x))$$

## Notes:

- ▶ Sometimes better than GELU, Swish
- ▶ mish



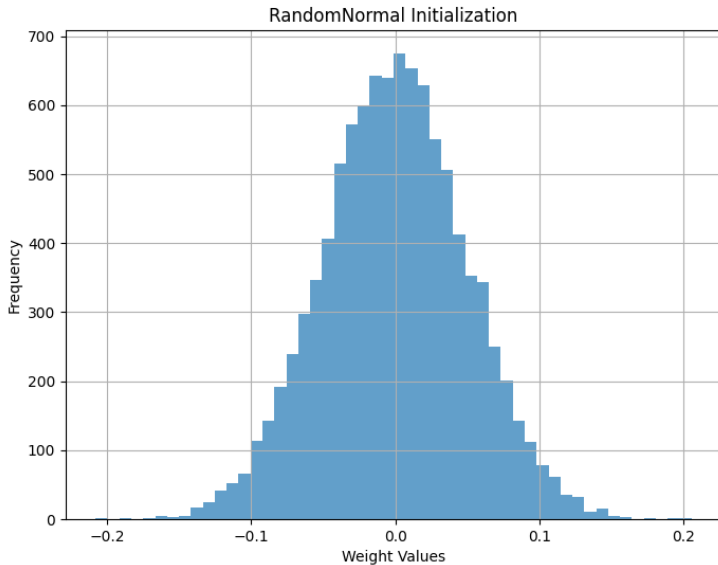


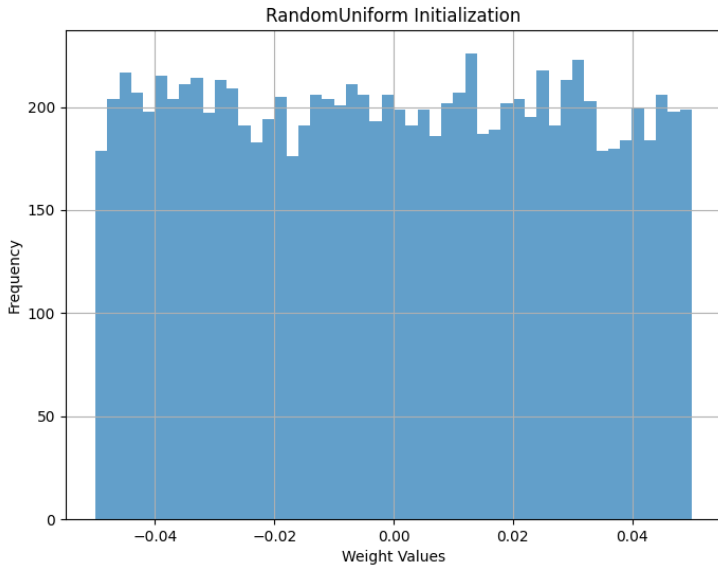
# Implementation

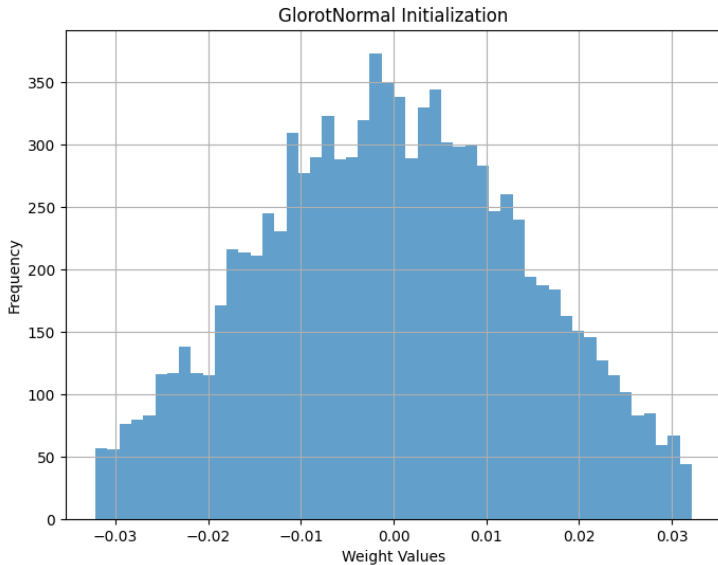
```
model.add(keras.layers.Dense(units, activation="leaky_relu"))
```

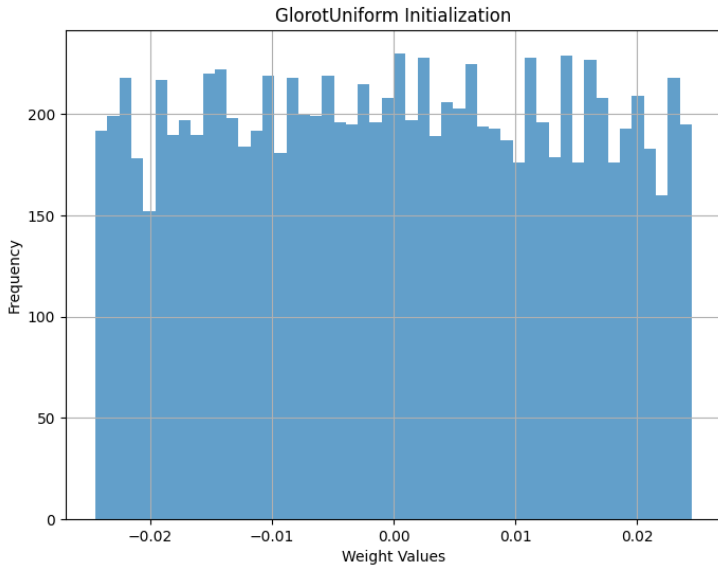
# Weight Initialization

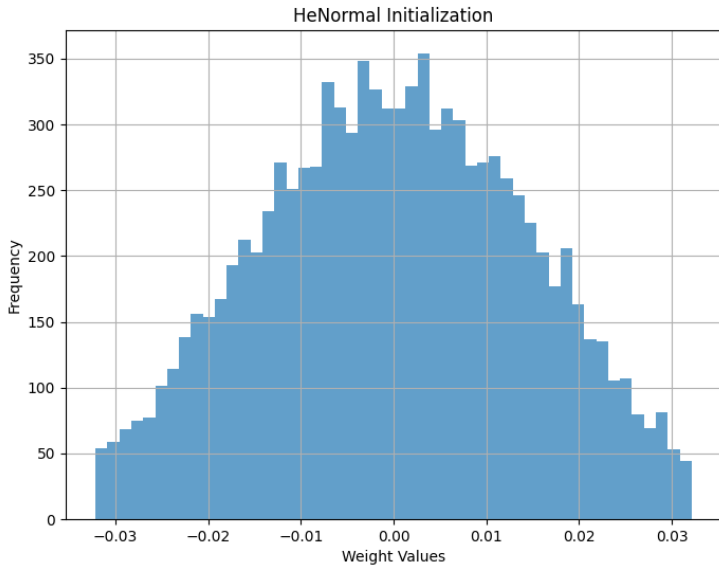
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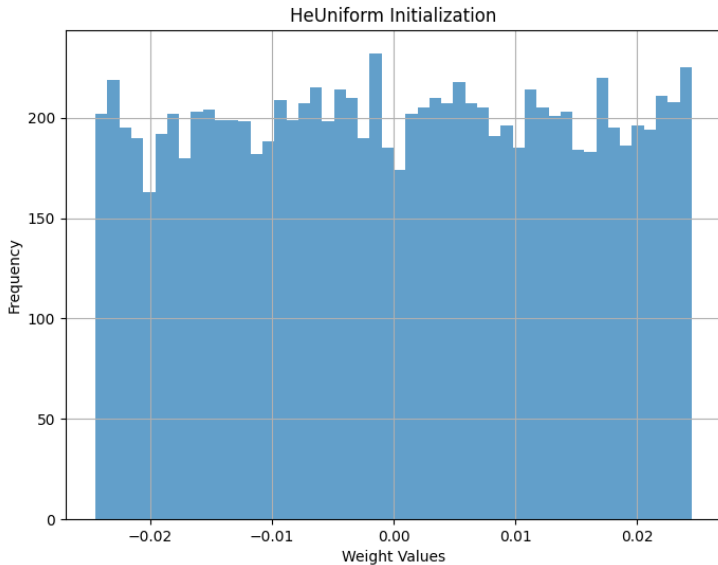




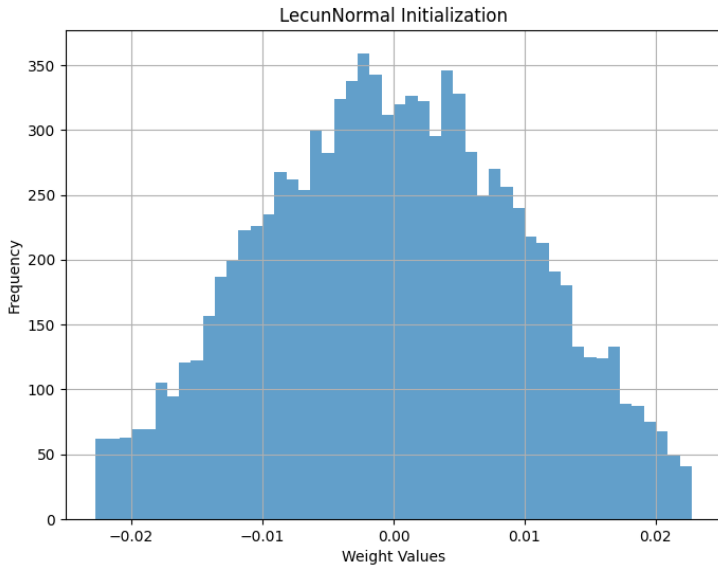


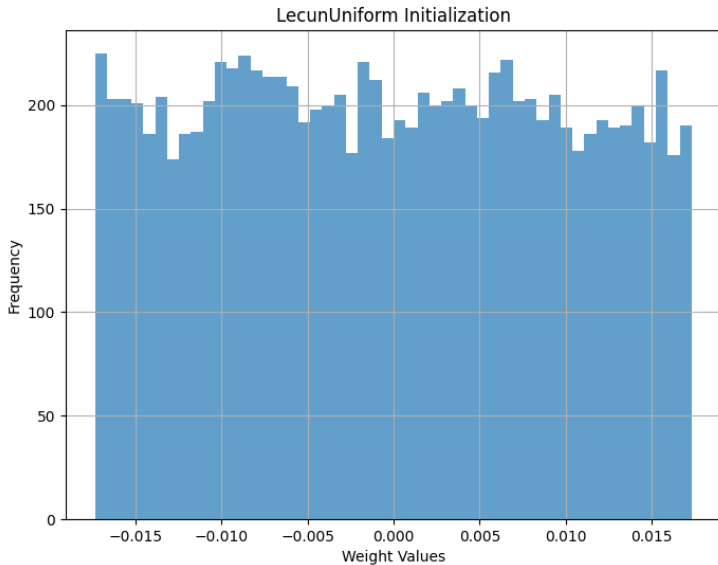












<b>Activation</b>	<b>Recommended Initialization</b>
Linear	Glorot
Sigmoid	Glorot
Hyperbolic Tangent	Glorot
Rectified Linear Unit	He
Leaky ReLU	He
Exponential Linear Unit	He
Scaled Exponential Linear Unit	LeCun
Gaussian Error Linear Unit	He
Sigmoid Linear Unit, Swish	He
Mish	He

# Implementation

```
model.add(keras.layers.Dense(units, activation="leaky_relu",  
                             kernel_initializer="he_normal"))
```

# Summary

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# Topics

- ▶ Activation Functions
- ▶ Initializations

# Activation Functions

Function	Keras Name
Linear	linear
Sigmoid	sigmoid
Hyperbolic Tangent	tanh
Rectified Linear Unit	relu
Leaky ReLU	leak_relu
Exponential Linear Unit	elu
Scaled Exponential Linear Unit	selu
Gaussian Error Linear Unit	gelu
Sigmoid Linear Unit, Swish	swish,silu
Mish	mish

# Initializations

Function	Keras Name
Zeros	zeros
Ones	ones
Random Normal	random_normal
Random Uniform	random_uniform
Glorot (Xavier) Normal	glorot_normal
Glorot (Xavier) Uniform	glorot_uniform
He Normal	he_normal
He Uniform	he_uniform
Lecun Normal	lecun_normal
Lecun Uniform	lecun_uniform