Activation Functions

ELU

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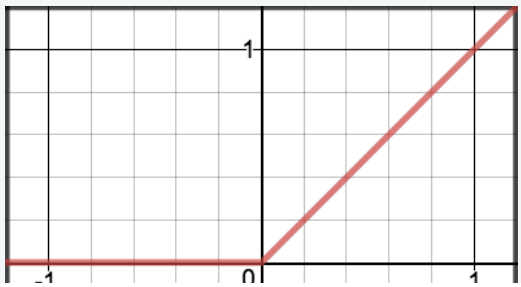
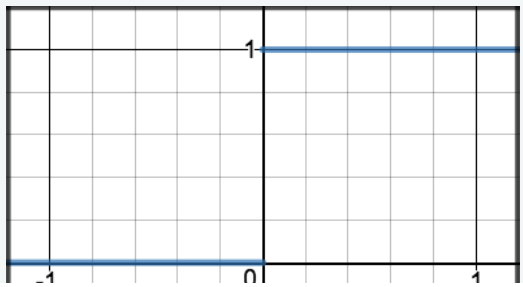
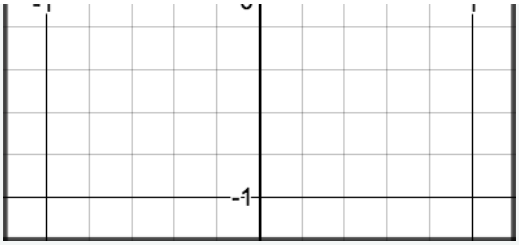
ReLU

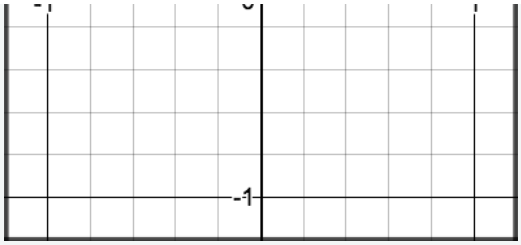
A recent invention which stands for Rectified Linear Units. The formula is deceptively simple: $max(0, z)$. Despite its name and appearance, it's not linear and provides the same benefits as Sigmoid but with better performance.

Function	Derivative
$R(z) = \left\{ \begin{array}{ll} z & z > 0 \\ 0 & z <= 0 \end{array} \right\}$	$R'(z) = \left\{ \begin{array}{ll} 1 & z > 0 \\ 0 & z < 0 \end{array} \right\}$










```
def relu(z):
  return max(0, z)
```

```
def relu_prime(z):
  return 1 if z > 0 else 0
```

Pros

- Pro 1

Cons

- Con 1

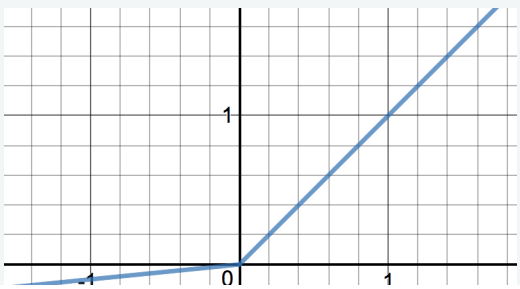
Further reading

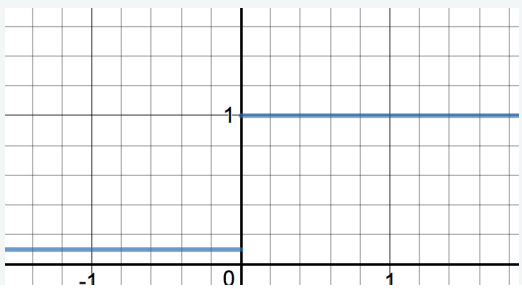
- Deep Sparse Rectifier Neural Networks Glorot et al., (2011)
- Yes You Should Understand Backprop, Karpathy (2016)

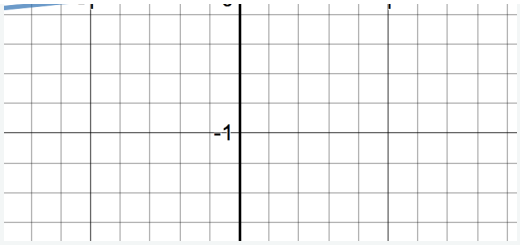
LeakyReLU

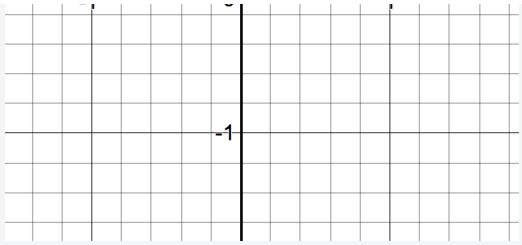
LeakyRelu is a variant of ReLU. Instead of being 0 when $z < 0$, a leaky ReLU allows a small, non-zero, constant gradient α (Normally, $\alpha = 0.01$). However, the consistency of the benefit across tasks is presently unclear. [1]

Function	Derivative
$R(z) = \left\{ \begin{array}{ll} z & z > 0 \\ \alpha z & z <= 0 \end{array} \right\}$	$R'(z) = \left\{ \begin{array}{ll} 1 & z > 0 \\ \alpha & z < 0 \end{array} \right\}$










```
def leakyrelu(z, alpha):
        return max(alpha * z, z)
```

```
def leakyrelu_prime(z, alpha):
        return 1 if z > 0 else alpha
```

Pros

- Pro 1

Cons

- Con 1

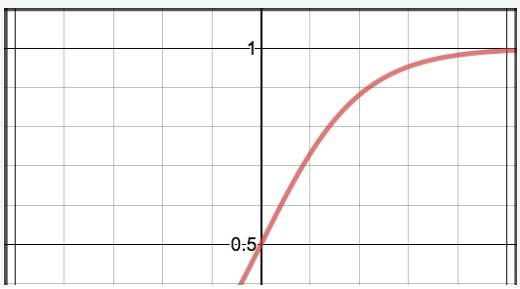
Further reading

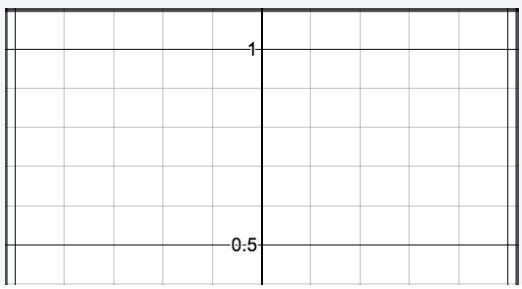
- Delving Deep into Rectifiers: Surpassing Human-Level Performance on ImageNet Classification, Kaiming He et al. (2015)

Sigmoid

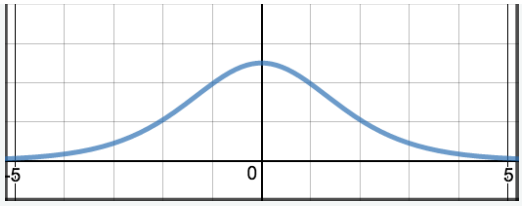
Sigmoid takes a real value as input and outputs another value between 0 and 1. It's easy to work with and has all the nice properties of activation functions: it's non-linear, continuously differentiable, monotonic, and has a fixed output range.

Function	Derivative
$S(z) = \frac{1}{1 + e^{-z}}$	$S'(z) = S(z) \cdot (1 - S(z))$






```
def sigmoid(z):
  return 1.0 / (1 + np.exp(-z))
```




```
def sigmoid_prime(z):
  return sigmoid(z) * (1-sigmoid(z))
```

Pros

- Pro 1

Cons

- Con 1

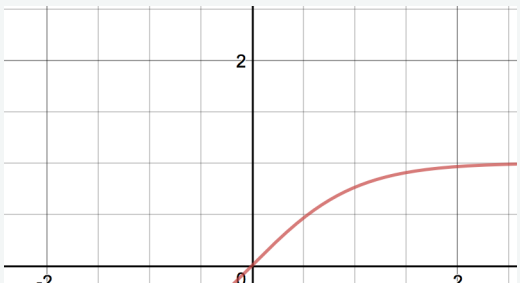
Further reading

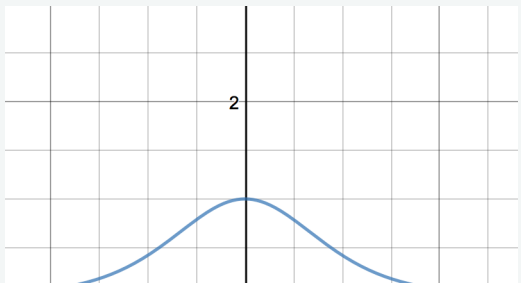
- Yes You Should Understand Backprop, Karpathy (2016)

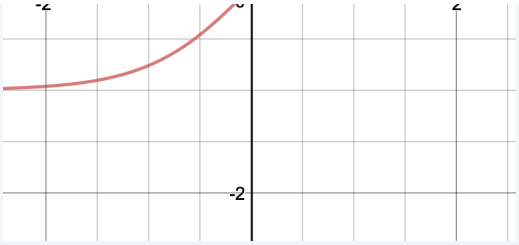
Tanh

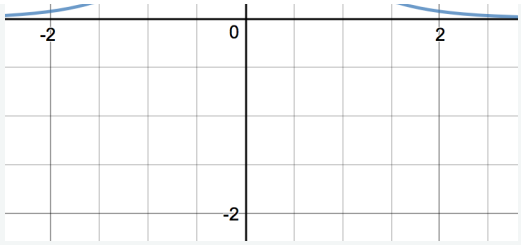
Tanh squashes a real-valued number to the range [-1, 1]. It's non-linear. But unlike Sigmoid, its output is zero-centered. Therefore, in practice the tanh non-linearity is always preferred to the sigmoid nonlinearity. [1]

Function	Derivative
$tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	$tanh'(z) = 1 - tanh(z)^2$










```
def tanh(z):
        return (np.exp(z) - np.exp(-z))
        / (np.exp(z) + np.exp(-z))
```

```
def tanh_prime(z):
        return 1 - np.power(tanh(z), 2)
```

Pros

- Pro 1

Cons

- Con 1

Softmax

Be the first to contribute!

References

[1] (1, 2) http://cs231n.github.io/neural-networks-1/