

# Introduction to Neural Networks Continued

Hunter Glanz

# OUTLINE

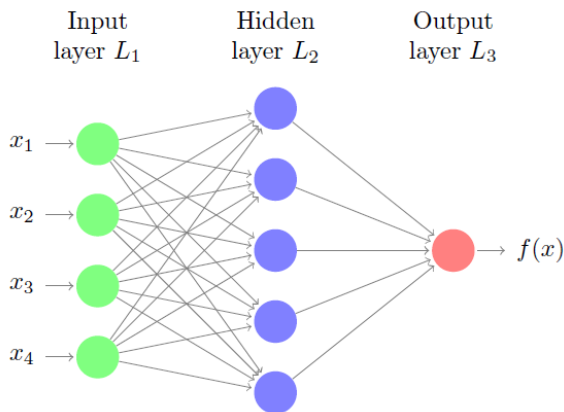
## The Method

# Overview

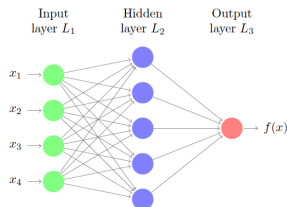
- ▶ Neural networks are highly parameterized models inspired by the human brain

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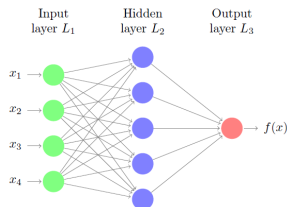
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# More Detail

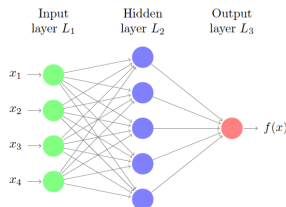


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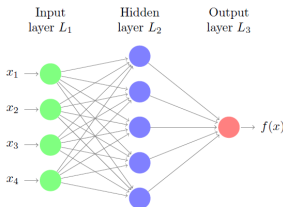
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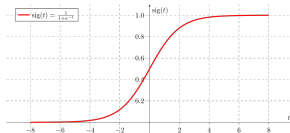
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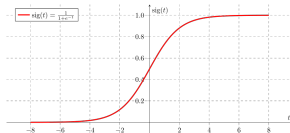
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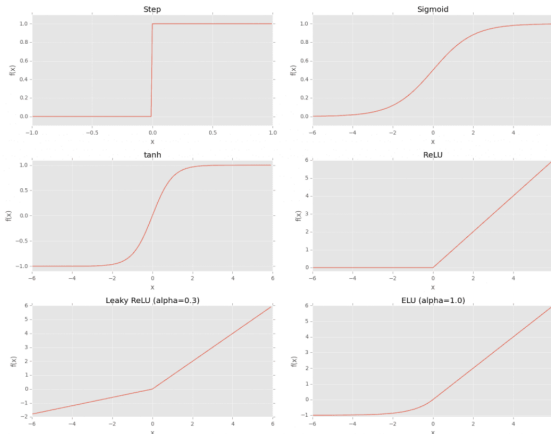
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- ▶ For quantitative regression,  $h$  is typically the identity
- ▶ For classification,  $h$  is once again the sigmoid

# Some Updates on Activation Functions

- Some other popular choices:



**Figure 4:** Top-left: Step function. Top-right: Sigmoid activation function. Mid-left: Hyperbolic tangent. Mid-right: ReLU activation (most used activation function for deep neural networks). Bottom-left: Leaky ReLU, variant of the ReLU that allows for negative values. Bottom-right: ELU, another variant of ReLU that can often perform better than Leaky ReLU.

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  - ▶ Additionally, saturated models are often overfitted
- ▶ **A solution:**
  - ▶ Use other activation functions like ReLU (Rectified Linear Unit) defined as  $f(x) = \max(0, x)$ .