

# The Math Behind Neural Networks

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# Overview

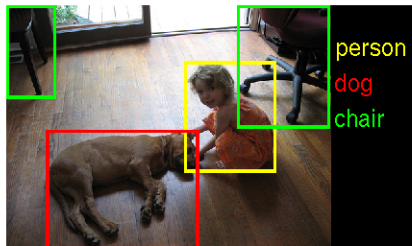
- 1 Background
- 2 Connection to research

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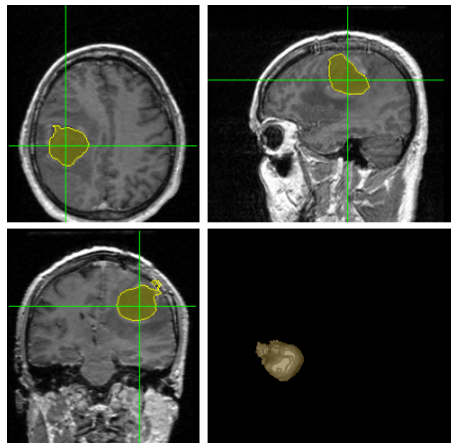
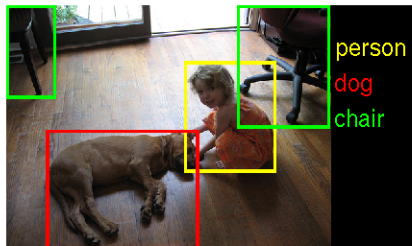
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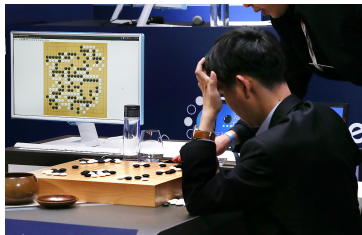
# Motivation



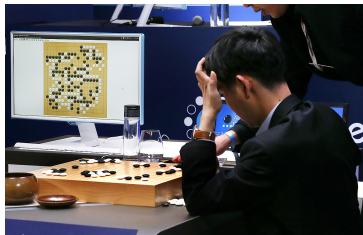
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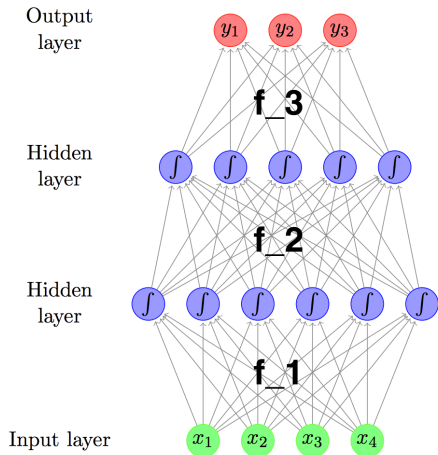


# Motivation





# Model



- $X$  inputs,  $Y$  outputs
- $f_N : X \rightarrow Y$
- $f_N(\vec{x}) = f_3(f_2(f_1(\vec{x})))$

# Model (cont.)

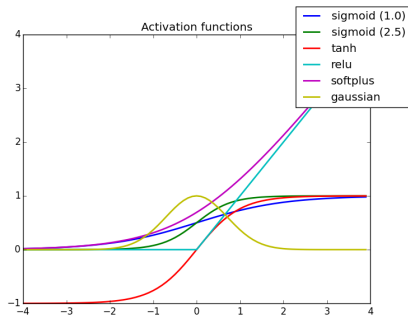
- $f_i : \mathbb{R}^d \rightarrow \mathbb{R}^k$

# Model (cont.)

- $f_i : \mathbb{R}^d \rightarrow \mathbb{R}^k$
- $W_i \in \mathbb{R}^{d \times k}$

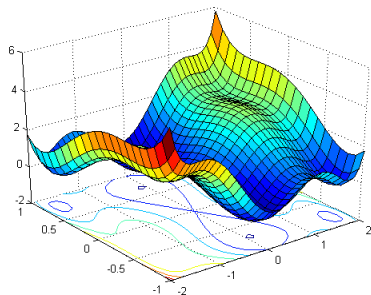
# Model (cont.)

- $f_i : \mathbb{R}^d \rightarrow \mathbb{R}^k$
- $W_i \in \mathbb{R}^{d \times k}$
- $\sigma$  activation function
- $f_i(\vec{x}) = \sigma(W_i \cdot \vec{x})$



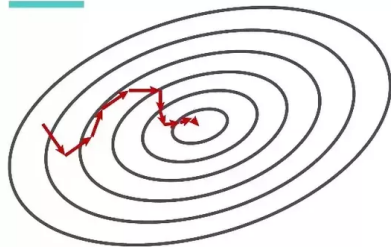
# Loss Function

- $X, Y$  dataset containing  $x_i, y_i$
- $W$  set of all  $W_i$
- $L(W) = \sum_i (y_i - f_N(x_i))^2$



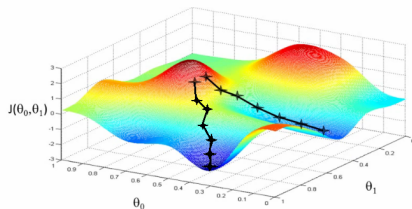
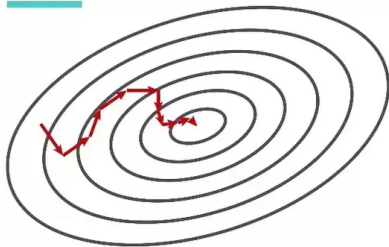
# Stochastic Gradient Descent

Stochastic Gradient Descent



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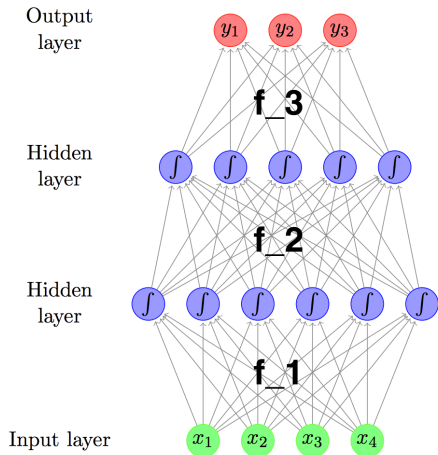
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# Terminology



- *Depth*: number of layers
- *Width*: Number of units (neurons) per layer

# Approximation Results

## Universal Approximation

Any function can be approximated to arbitrary precision by a neural network with one hidden layer (depth 2).

# Approximation Results

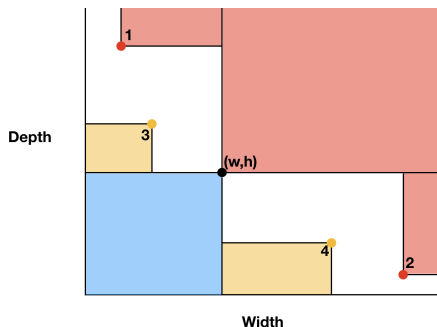
## Universal Approximation

Any function can be approximated to arbitrary precision by a neural network with one hidden layer (depth 2).

## Exponential Depth Efficiency

There exists a deep network (width 2, depth  $k$ ) that cannot be well approximated by a shallow network with width  $2^k$ .

# Approximation Questions



- How do width and depth impact approximation capabilities?
- Is a deeper network necessarily more powerful?

# Thank You!