Deep learning
Episode 1

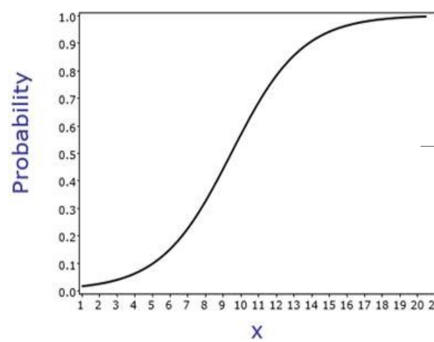
Neural networks 101

Yandex
Data Factory

LAMBDA

British Hedgehog
Preservation Society

Recap: logistic regression

X ⟶ Wx +b ⟶ 

⟶ P(y)

Gradient descent

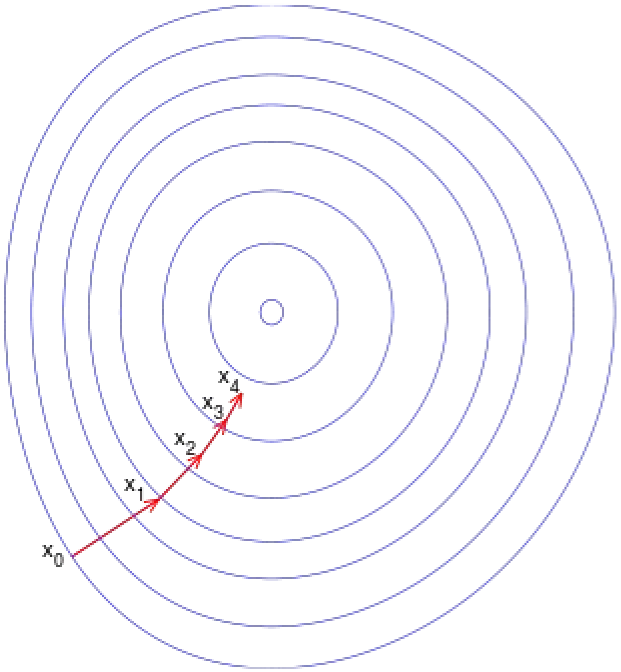
$$y_{pred}(\bar{x}) = \sigma(\bar{w} \cdot \bar{x} + b)$$

$$L = -\sum_i y_i \log P(y|x_i) + (1 - y_i) \log(1 - P(y|x_i))$$

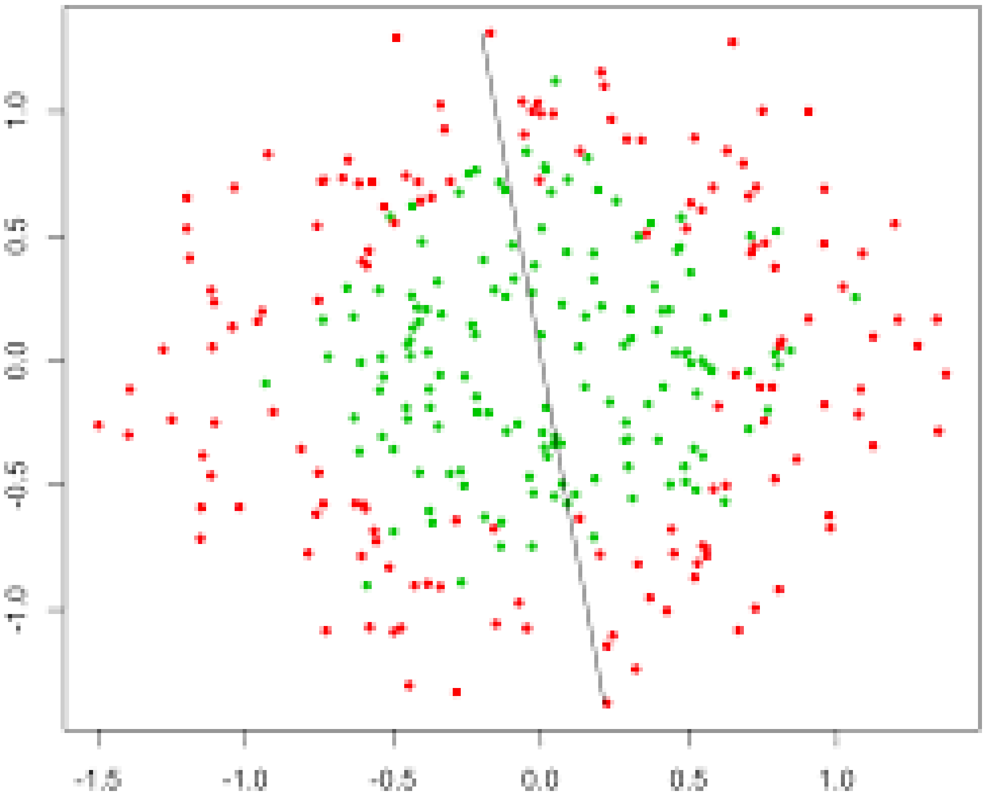
Repeat until convergence

$$\theta_j := \theta_j - \alpha \cdot \frac{\partial L(y, y_{pred})}{\partial \theta_j}$$

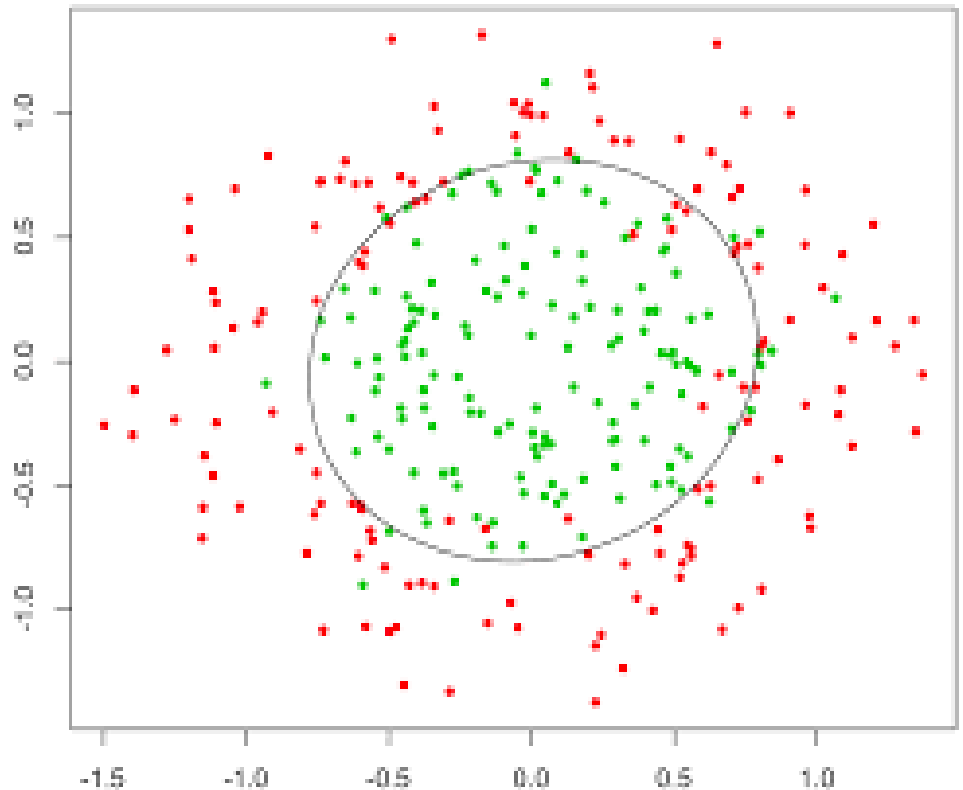
ϴ~{W,b}



Nonlinear dependencies



What we have



What we want

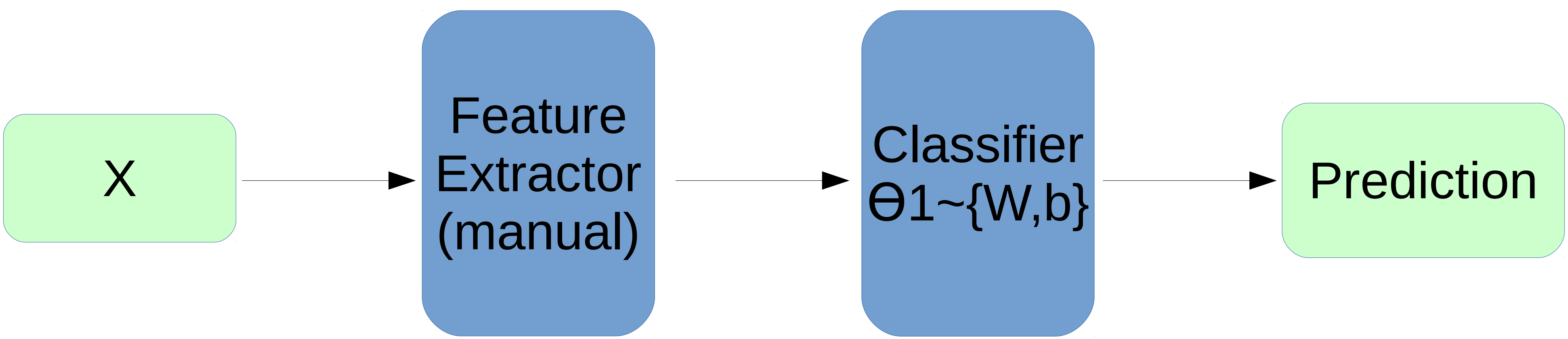
- How to get that?

Feature extraction

Loss, for example:

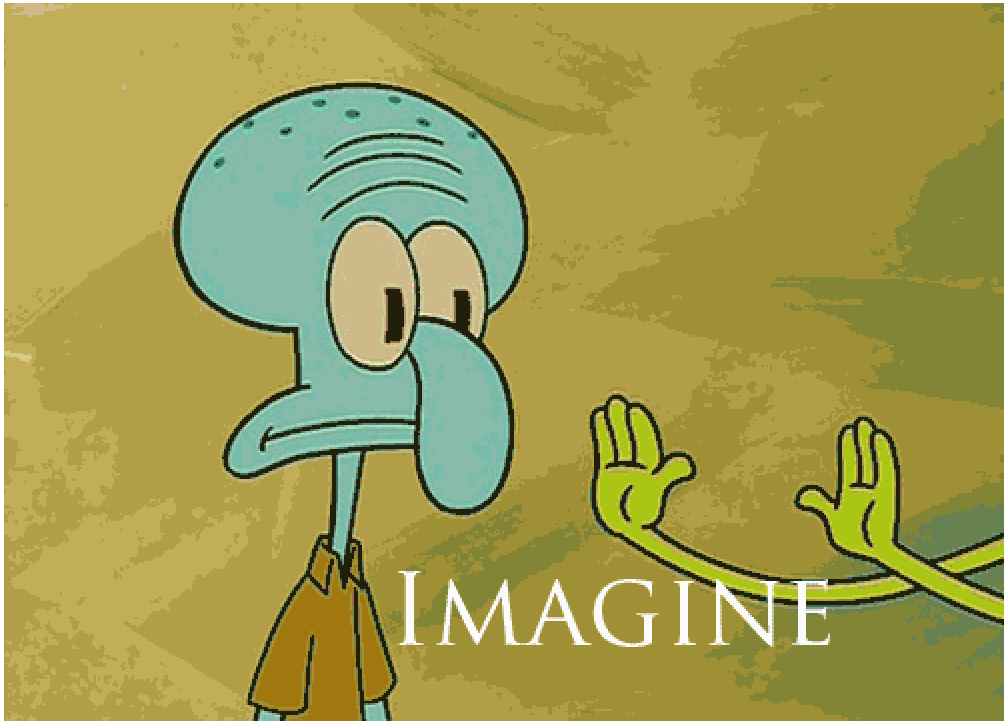
$$L = -\sum_i y_i \log P(y|x_i) + (1 - y_i) \log(1 - P(y|x_i))$$

Model:



Training:

$$\underset{\theta_1}{argmin}\, L(y, y_{pred}(x))$$



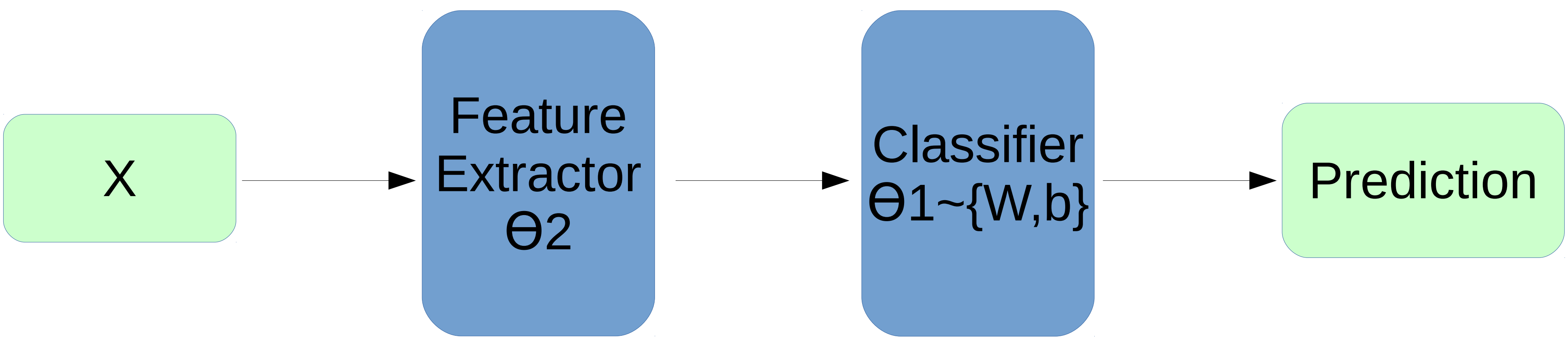
Features would tune to your problem automatically!

What do we want, exactly?

Loss, for example:

$$L = -\sum_i y_i \log P(y|x_i) + (1 - y_i)\log(1 - P(y|x_i))$$

Model:



Training: ?

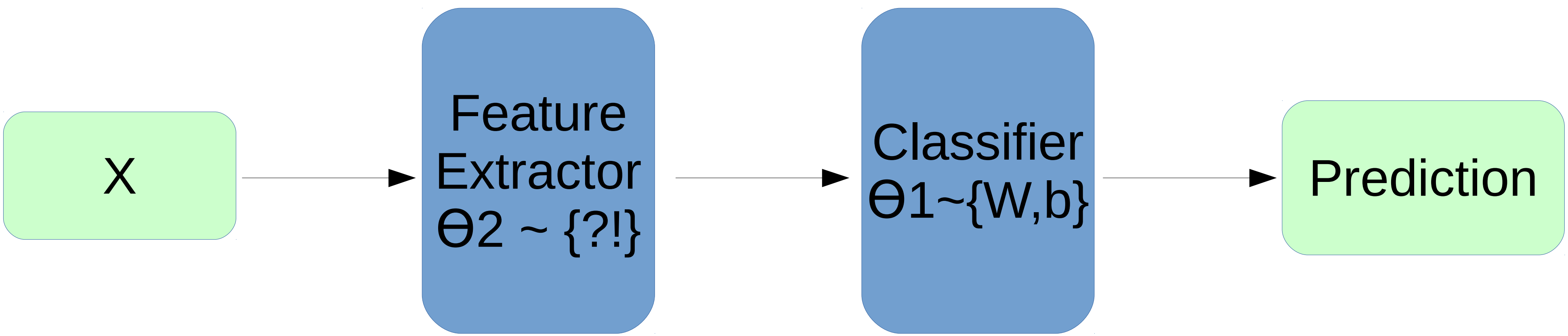
$$\underset{\theta_1}{argmin}\, L(y, y_{pred}(x))$$

What do we want, exactly?

Loss, for example:

$$L = -\sum_i y_i \log P(y|x_i) + (1 - y_i) \log(1 - P(y|x_i))$$

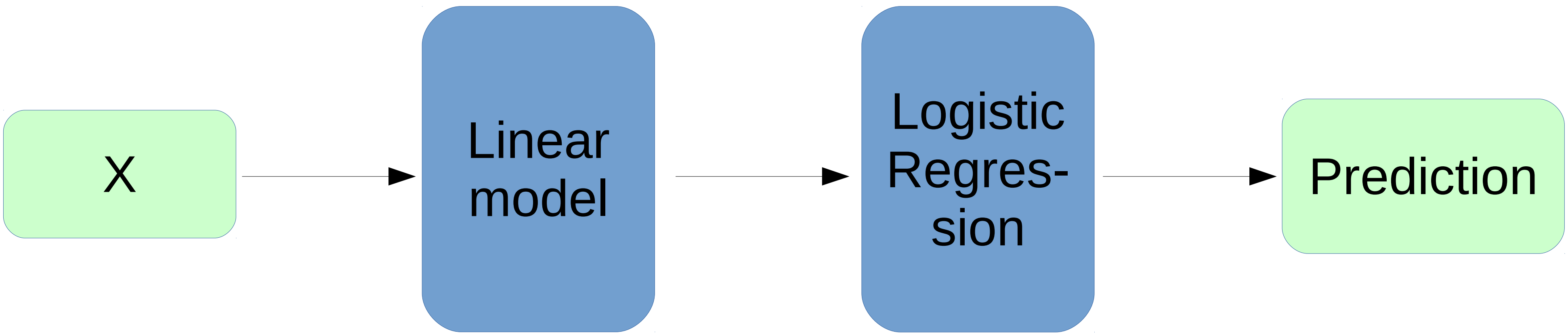
Model:



Gradients: $\underset{\theta_2}{argmin}\, L(y, y_{pred}(x))$ $\underset{\theta_1}{argmin}\, L(y, y_{pred}(x))$

Try linear

Model:

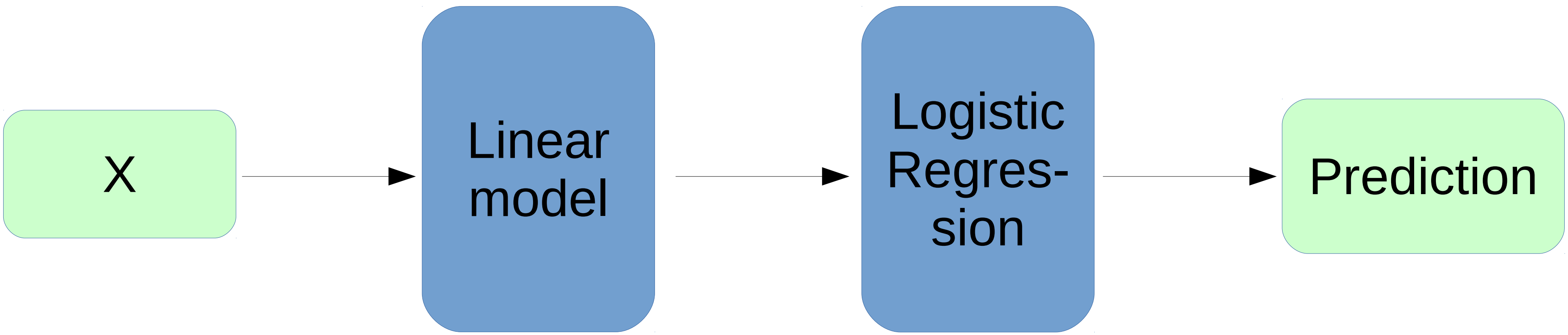


$$h_j=\sum_i w_{ij}^h x_i+b_j^h \quad j\in\{1,2,\ldots,n\}$$

$$y_{pred}=\sigma\left(\sum_j w_j^o h_j+b^o\right)$$

Try linear

Model:



$$h_j = \sum_i w_{ij}^h x_i + b_j^h \qquad y_{pred} = \sigma\left(\sum_j w_j^o h_j + b^o\right)$$

$$j \in \{1,2,\ldots,n\}$$

Output:

$$y_{pred} = \sigma\left(\sum_j w_j^o \left(\sum_i w_{ij}^h x_i + b_j^h\right) + b^o\right)$$

Is it any better than logistic regression?

Try linear

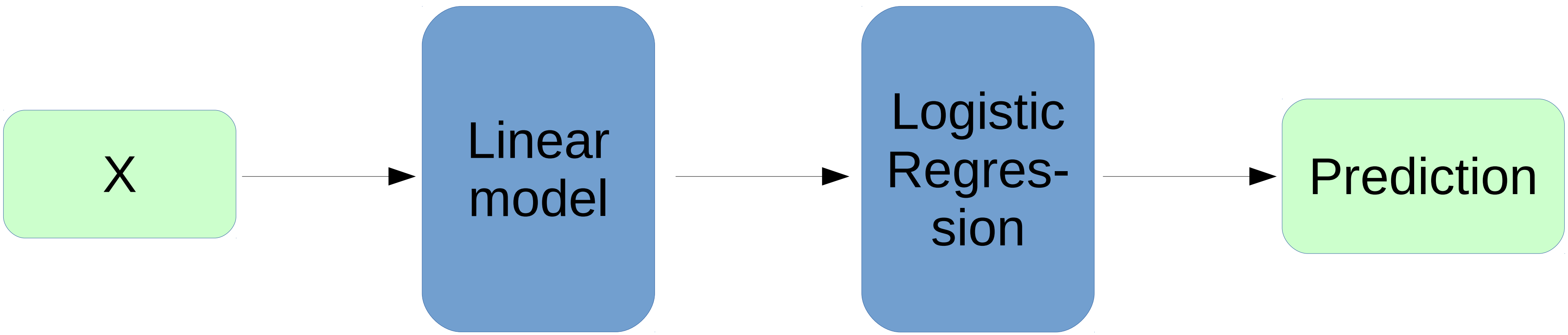
$$y_{pred} = \sigma\Big(\sum_j w_j^o \Big(\sum_i w_{ij}^h x_i + b_j^h\Big) + b^o\Big)$$

$$w'_i = \sum_j w_j^o w_{ij}^h \qquad b' = \sum_j w_j^o b_j^h + b^o$$

$$y_{pred} = \sigma\Big(\sum_i w'_i x_i + b'\Big)$$

Try linear

Model:



$$h_j = \sum_i w_{ij}^h x_i + b_j^h \qquad y_{pred} = \sigma\left(\sum_j w_j^o h_j + b^o\right)$$

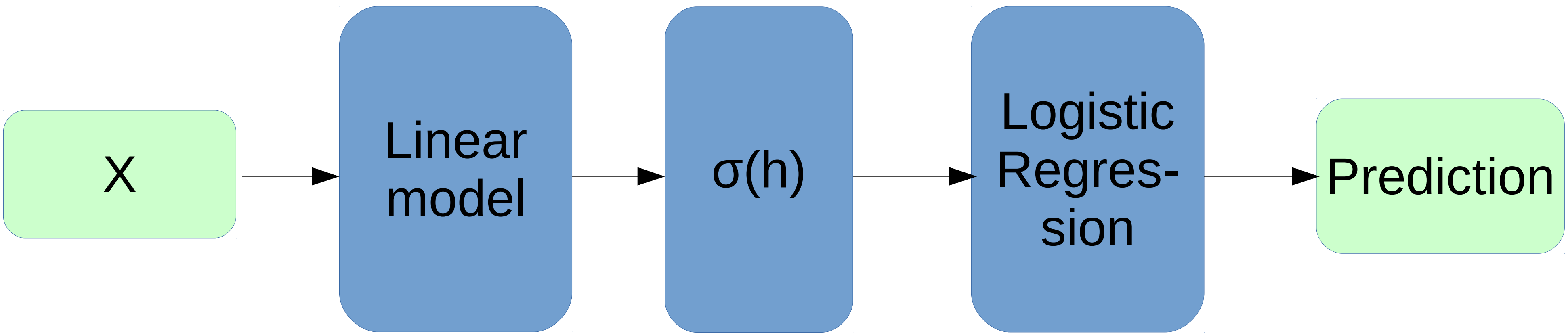
$$j \in \{1,2,\ldots,n\}$$

Output: $$y_{pred} = \sigma\left(\sum_j w_j^o \left(\sum_i w_{ij}^h x_i + b_j^h\right) + b^o\right)$$

Is it any better than logistic regression?

Nonlinearity

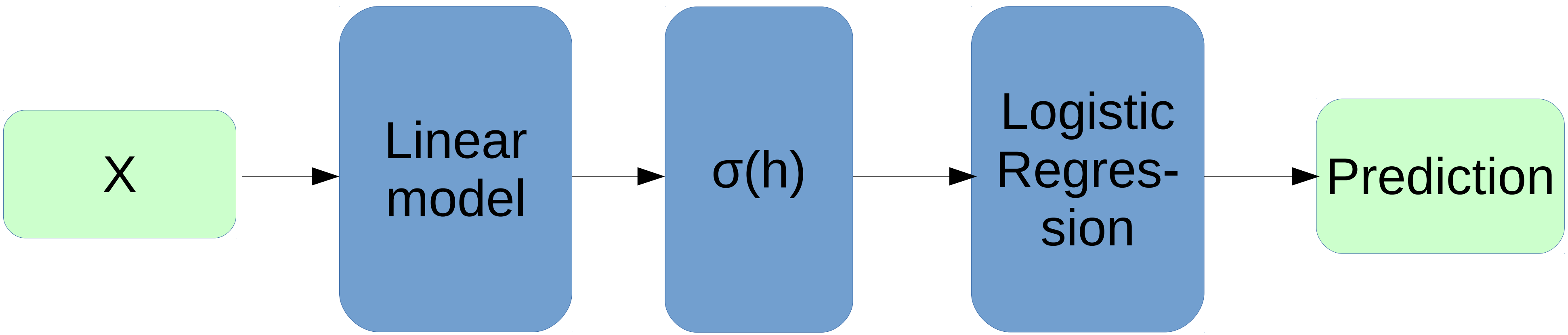
Model:



$$h_j = \sigma\left(\sum_{\substack{i \\ j \in \{1,2,\ldots,n\}}} w_{ij}^h x_i + b_j^h\right) \qquad y_{pred} = \sigma\left(\sum_j w_j^o h_j + b^o\right)$$

Nonlinearity

Model:



$$h_j = \sigma\left(\sum_i w_{ij}^h x_i + b_j^h\right) \qquad y_{pred} = \sigma\left(\sum_j w_j^o h_j + b^o\right)$$

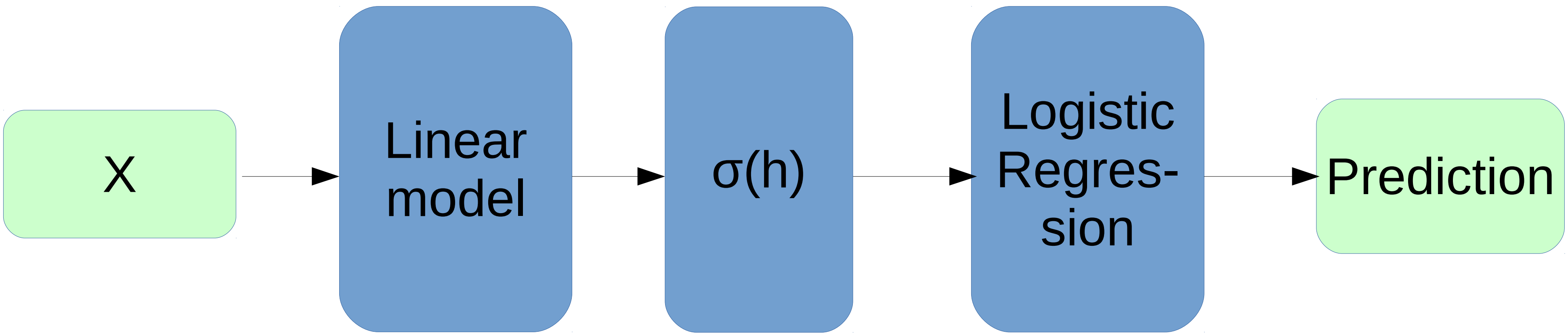
$$j \in \{1, 2, \dots, n\}$$

Output:

$$y_{pred} = \sigma\left(\sum_j w_j^o \sigma\left(\sum_i w_{ij}^h x_i + b_j^h\right) + b^o\right)$$

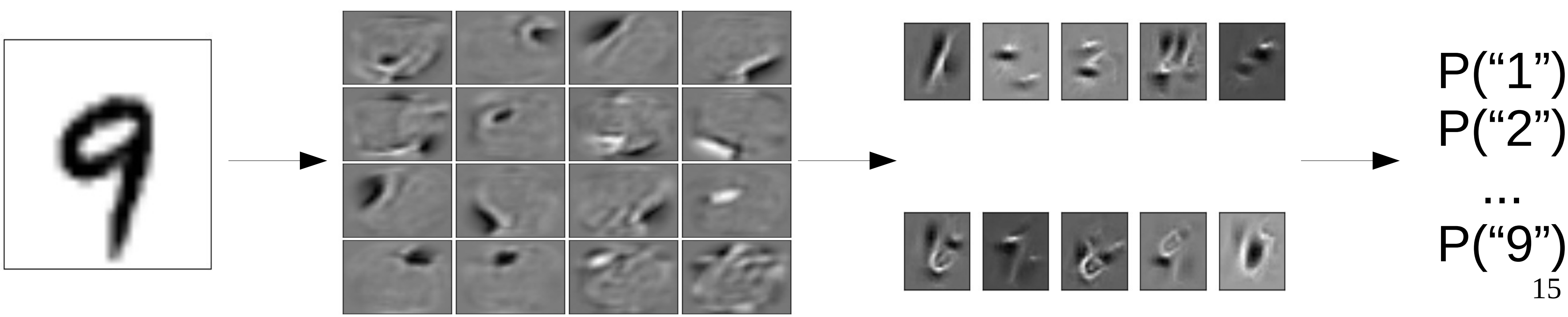
Nonlinearity

Model:



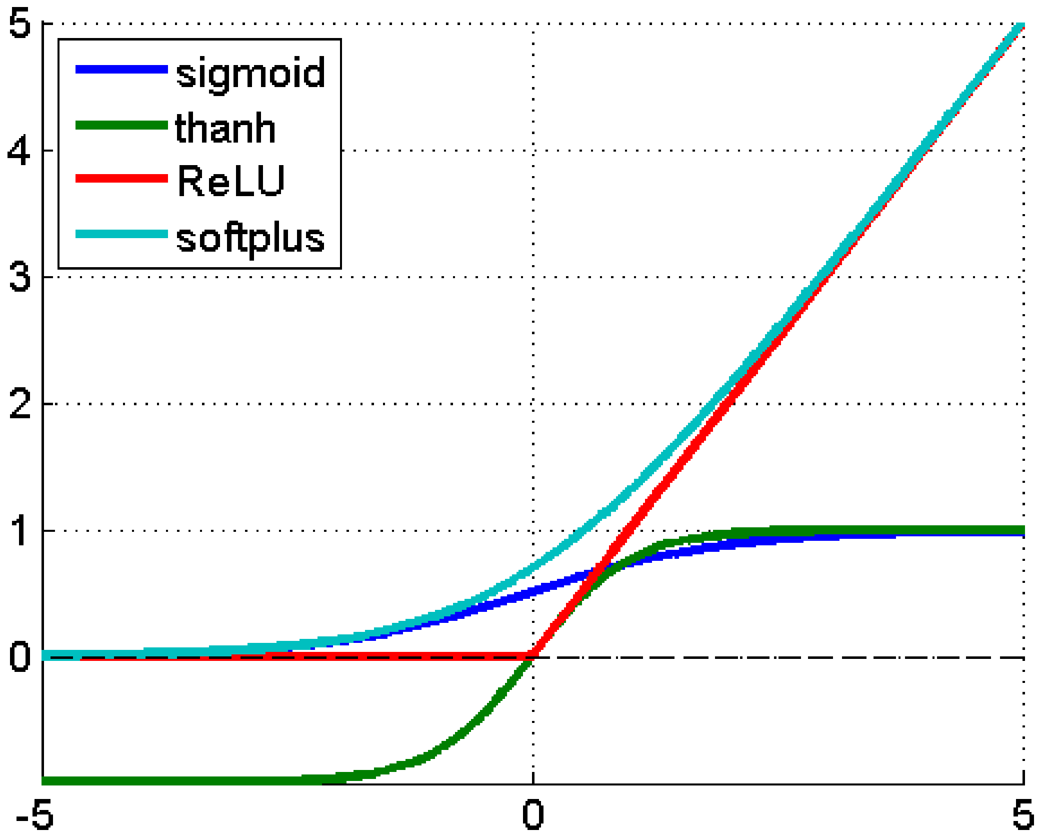
$$h_j=\sigma\left(\sum_{i\in\{1,2,\dots,n\}} w_{ij}^h x_i+b_j^h\right)$$

$$y_{pred}=\sigma\left(\sum_j w_j^o h_j+b^o\right)$$

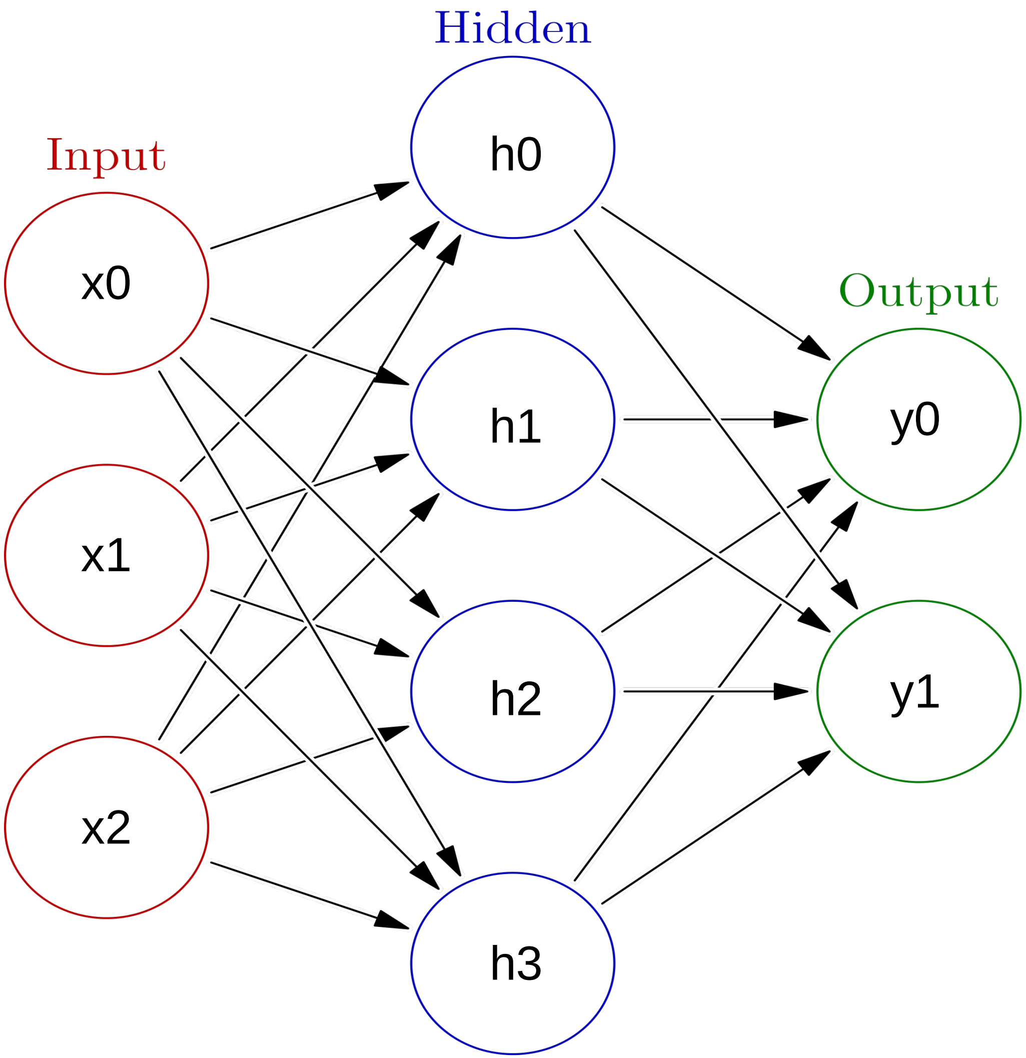


Nonlinearity

- f(a) = 1/(1+e^a)
- f(a) = tanh(a)
- f(a) = max(0,a)
- f(a) = log(1+e^x)

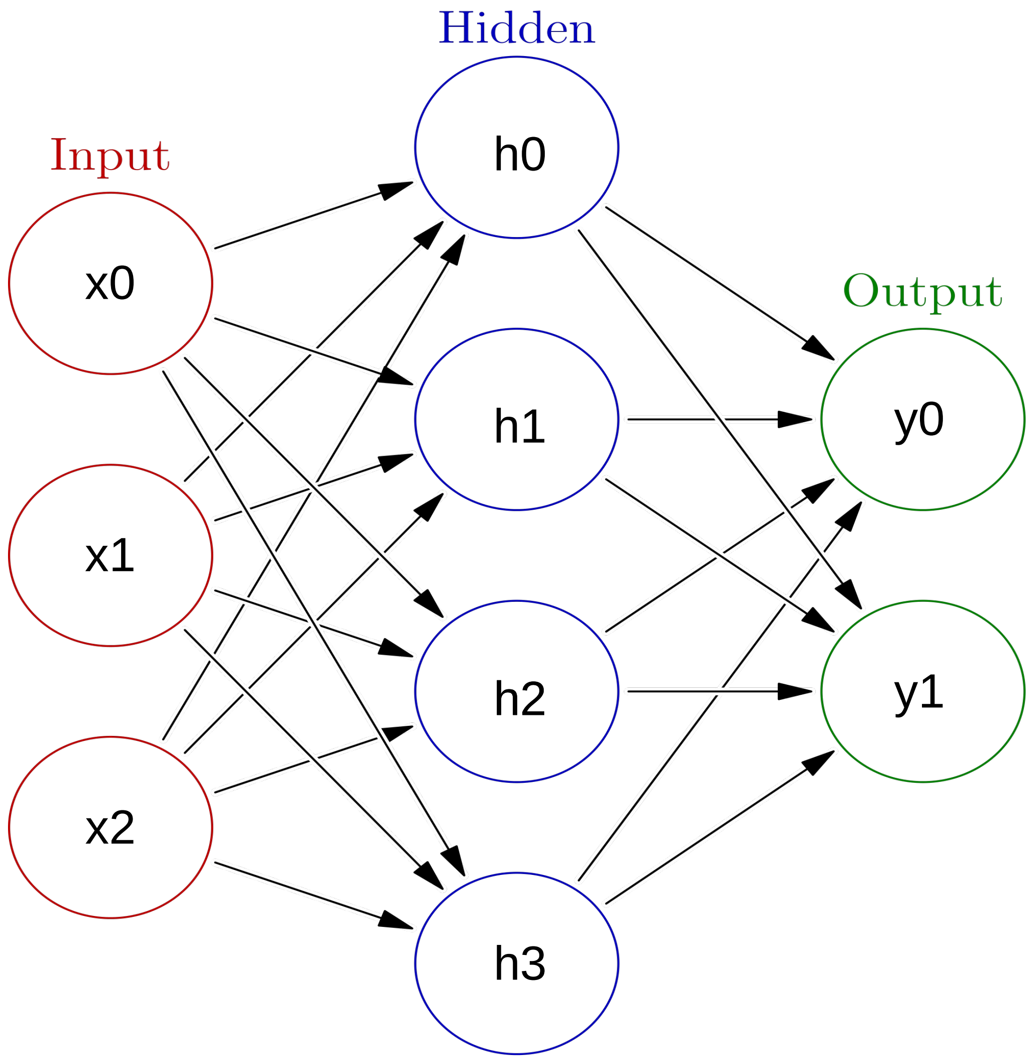


Initialization, symmetry problem



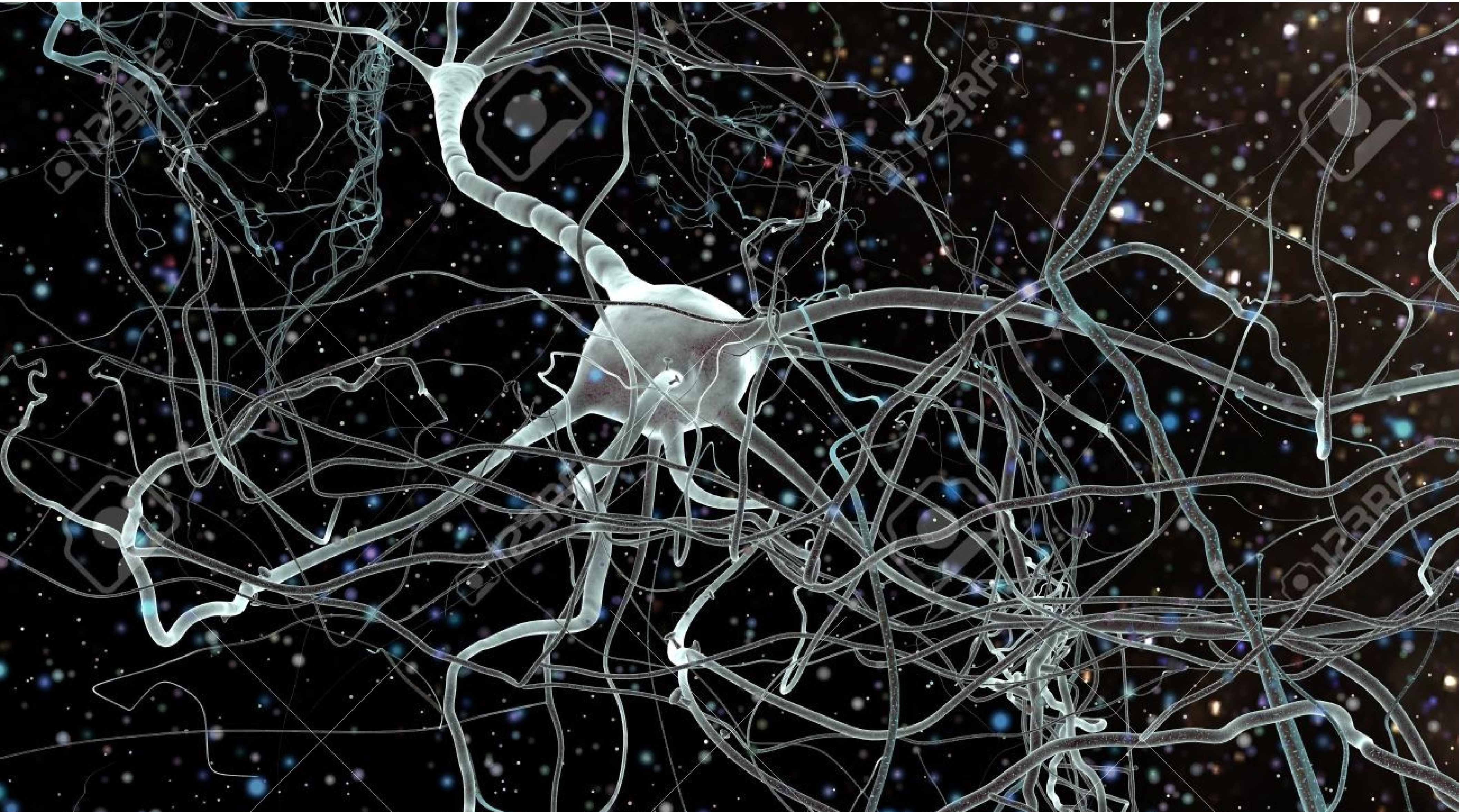
- Initialize with zeros
  $W \leftarrow 0$
- What will the first step look like?

Initialization, symmetry problem

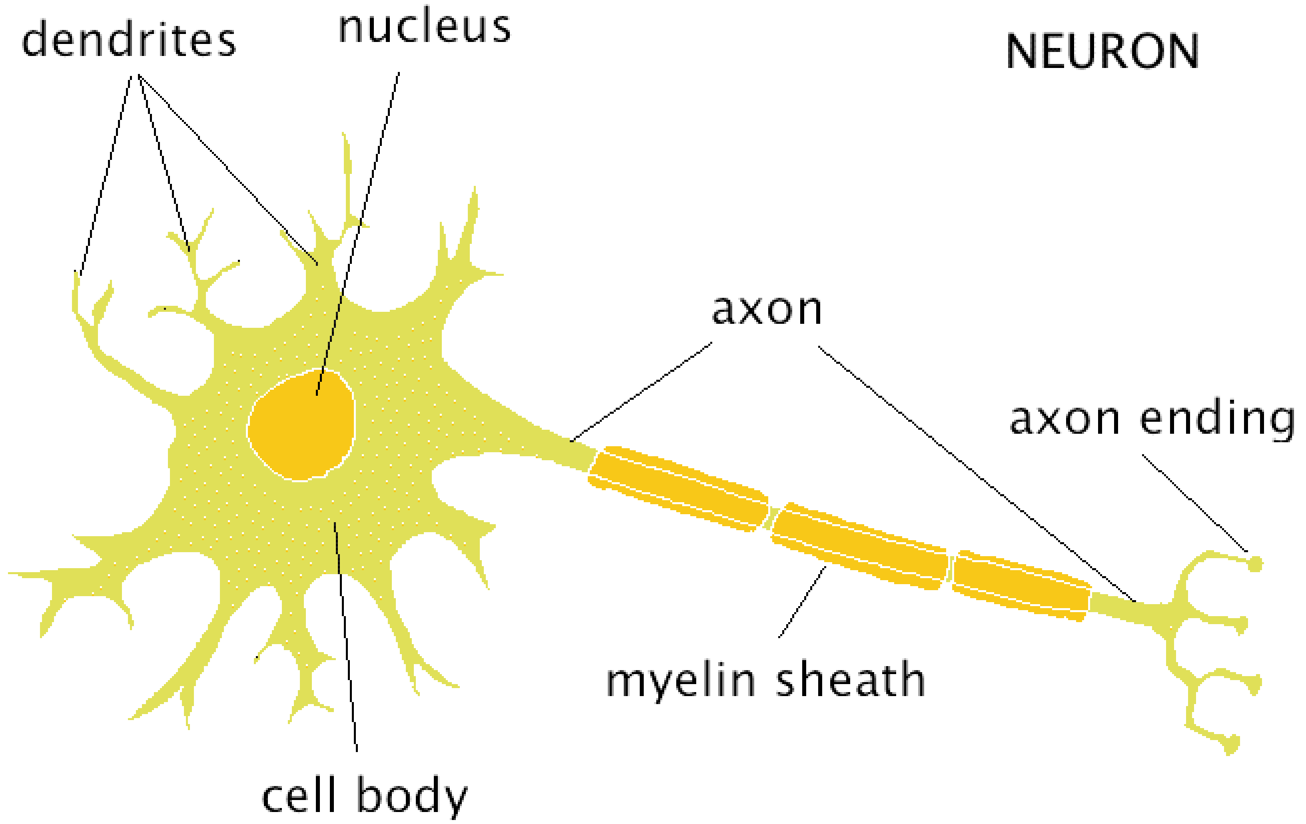


- Break the symmetry!
- Initialize with random numbers!
  $W \leftarrow N(0,0.01)$?
  $W \leftarrow U(0,0.1)$?
- Can get a bit better for deep NNs

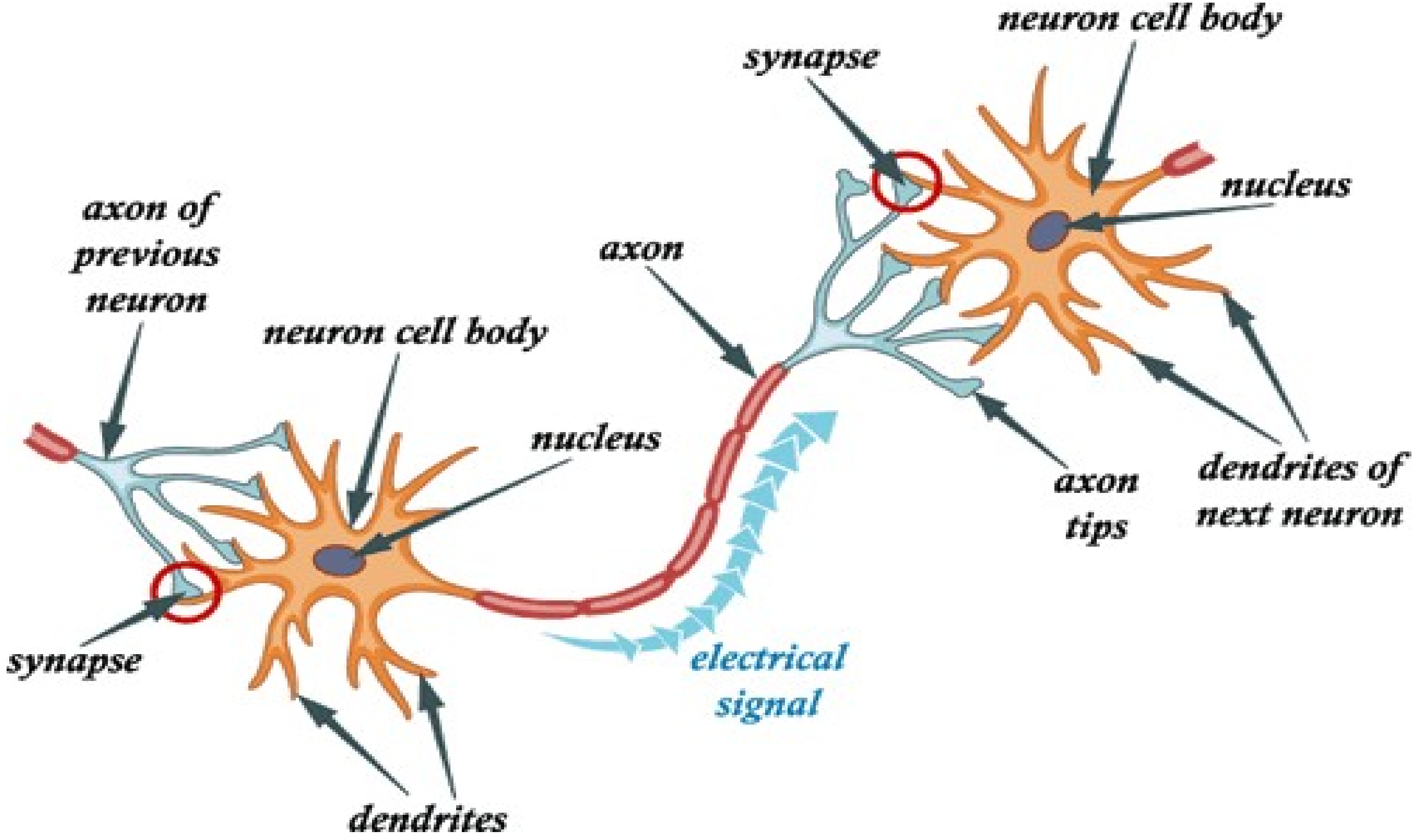
Biological inspiration



Biological inspiration

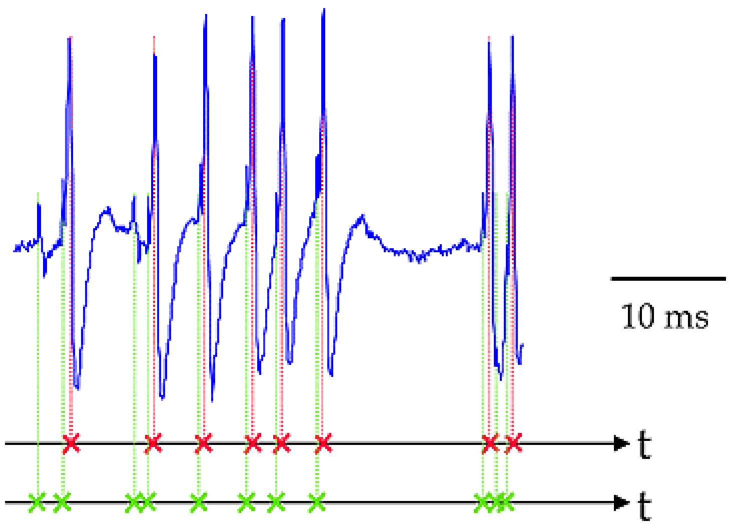


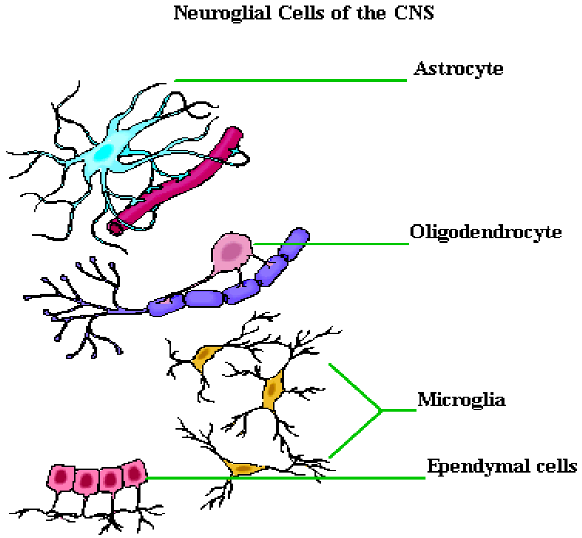
Biological inspiration



Not actual neurons :)

- Neurons react in “spikes”, not real numbers
- Neurons maintain/change their states over time
- No one knows for sure how they “train”
- Neuroglial cells are important But noone knows, why

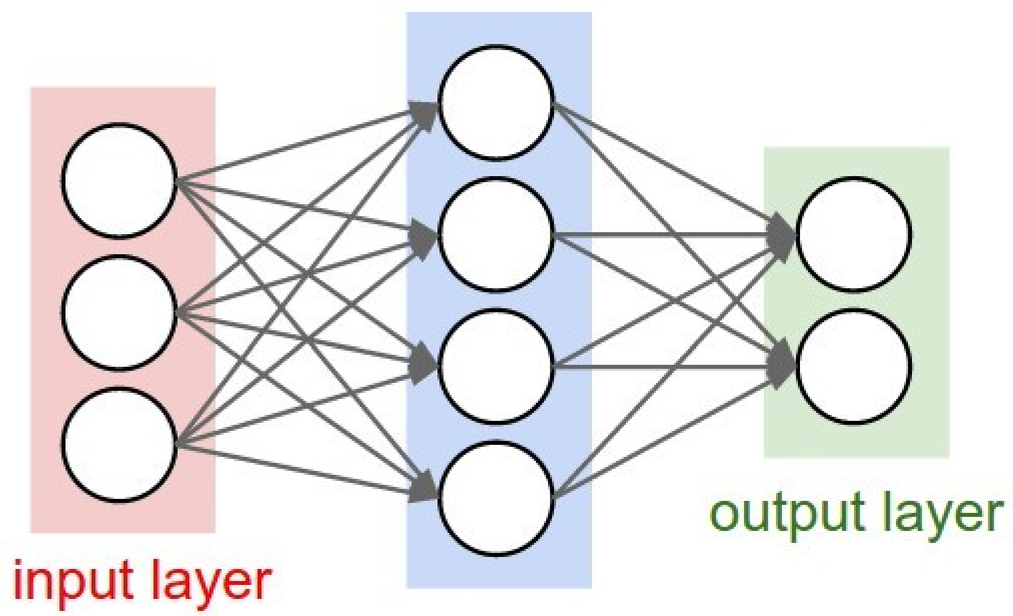




Connectionist phrasebook

- Layer – a building block for NNs :
  - “Dense layer”: $f(x) = Wx+b$
  - “Nonlinearity layer”: $f(x) = \sigma(x)$
  - Input layer, output layer
  - A few more we gonna cover later
- Activation – layer output
  - i.e. some intermediate signal in the NN
- Backpropagation – a fancy word for “chain rule”

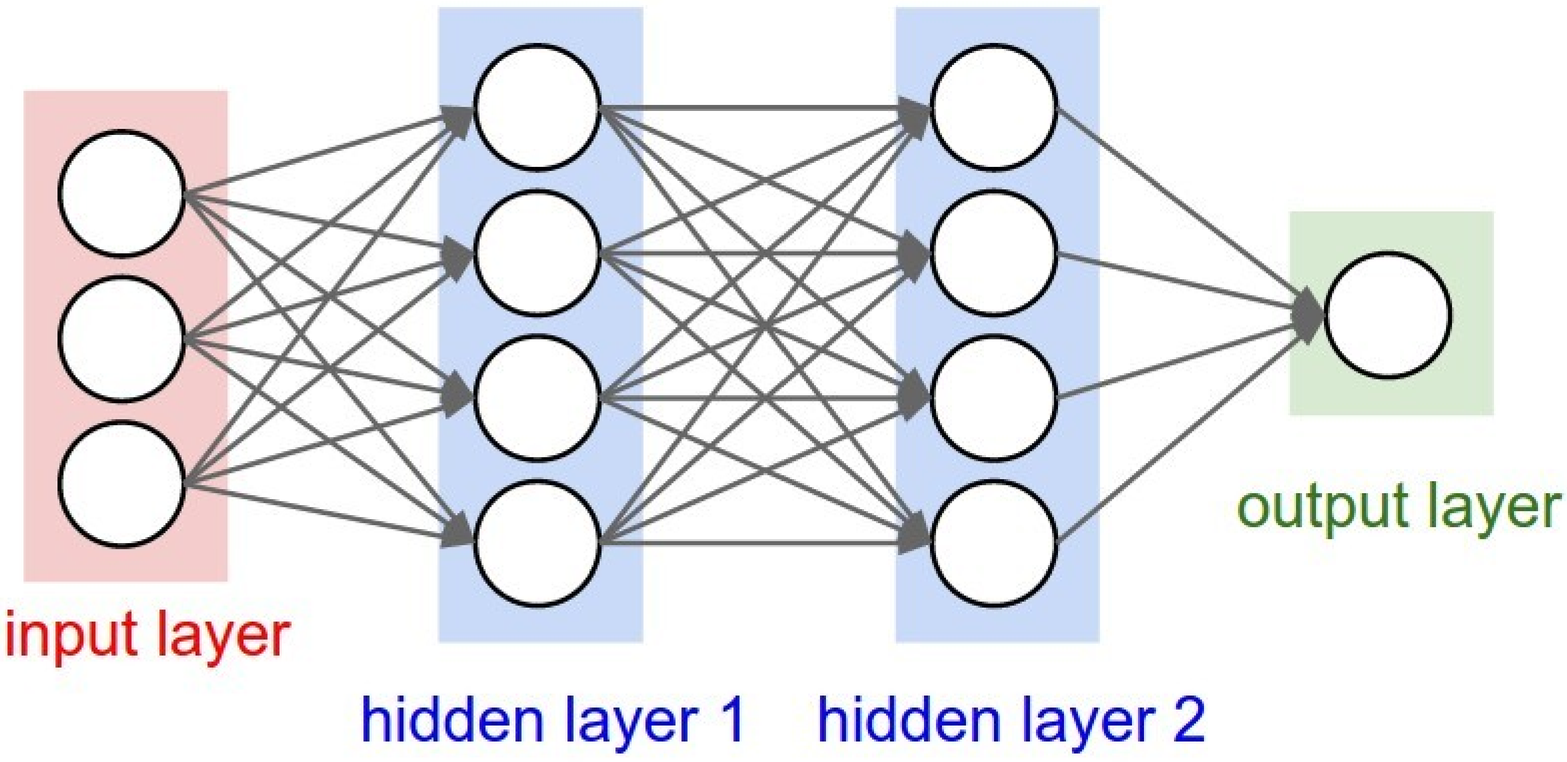
Connectionist phrasebook



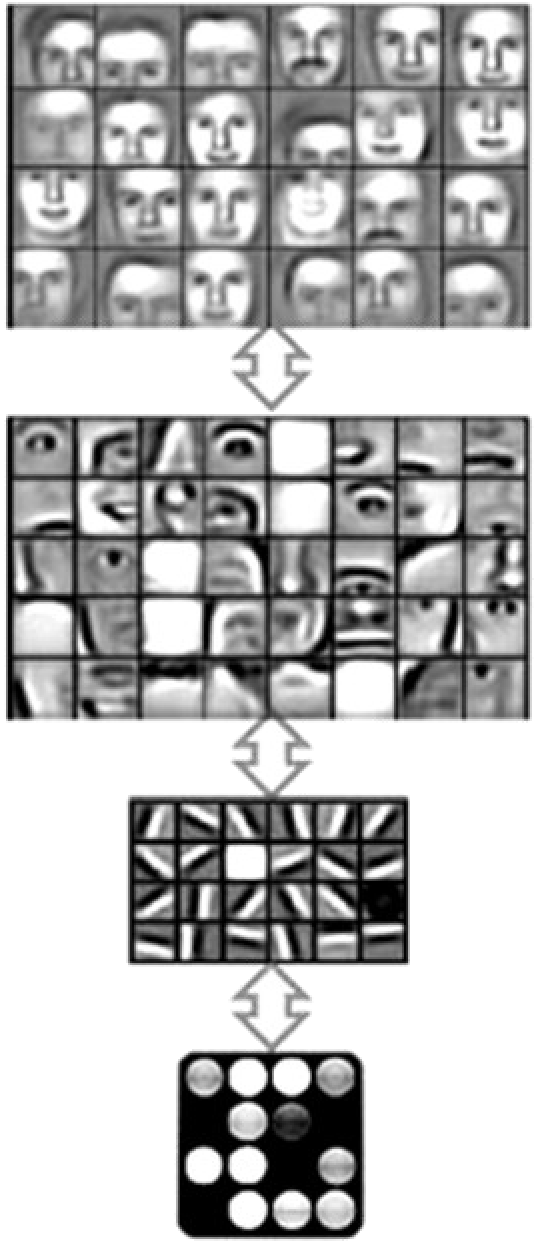
Dense layer
with a nonlinearity

- “Train it via backprop!”

Connectionist phrasebook



How do we train it?



Discrete Choices

⋮

Layer 2 Features

Layer 1 Features

Original Data

Potential caveats?

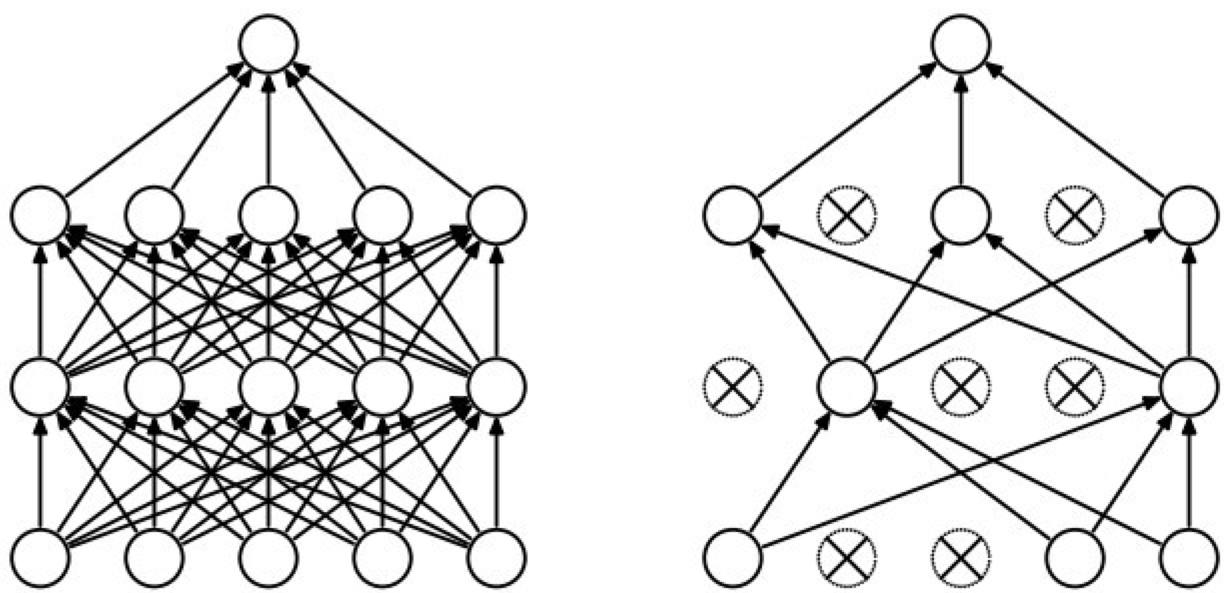
Potential caveats?

- Hardcore overfitting
- No “golden standard” for architecture
- Computationally heavy

Regularization

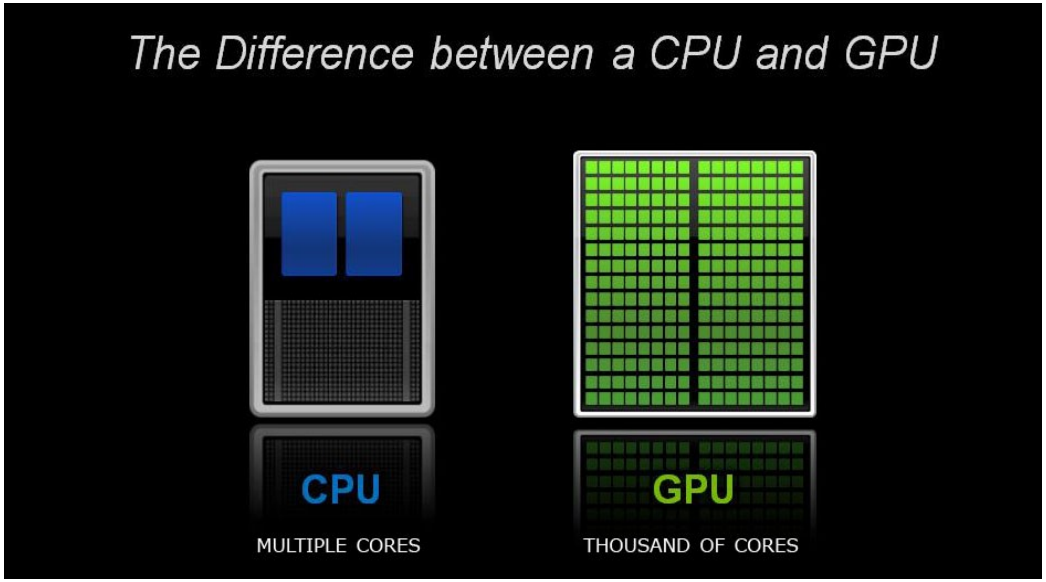
- L1, L2, as usual

- Dropout

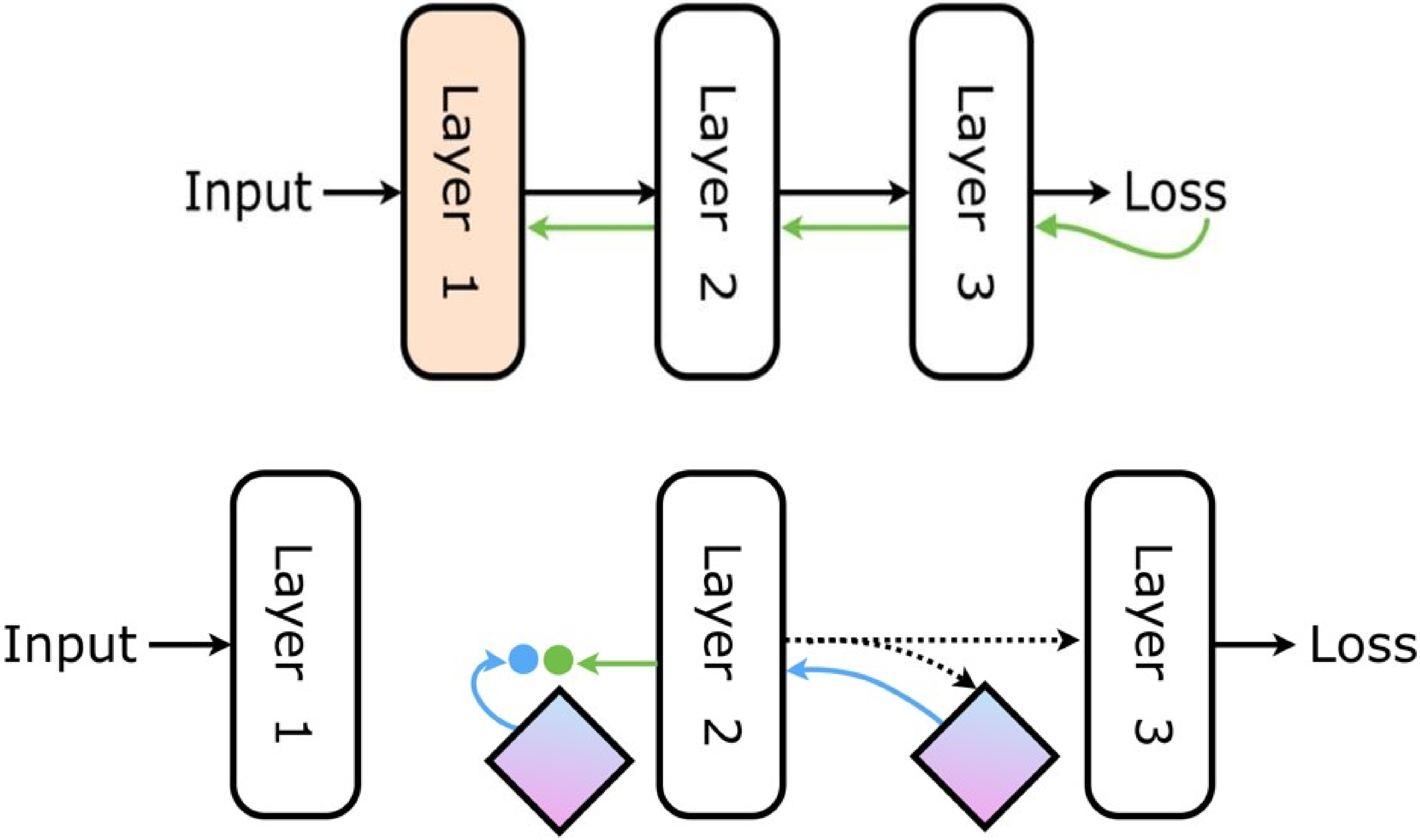


(a) Standard Neural Net (b) After applying dropout.

Computation



Is backprop the only choice?



Nuff

Let's code some neural networks!