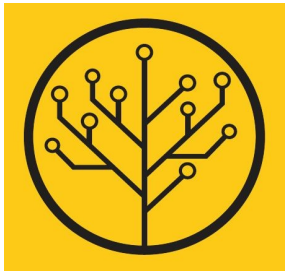
Practical Deep Learning

Episode 0

ML recap. Intro to deep learning



Linear Regression

Model:

$$X \longrightarrow Wx + b \longrightarrow Y^{pred}$$

Objective function:

$$L = \sum_i \left(y_i - y_i^{pred} \right)^2$$

Optimization (exact):

$$w = \left(X^T X \right)^{-1} X^T y$$

Linear Regression

Model:

$$X \longrightarrow Wx + b \longrightarrow Y^{pred}$$

Objective function:

$$L = \sum_i \left(y_i - y_i^{pred} \right)^2$$

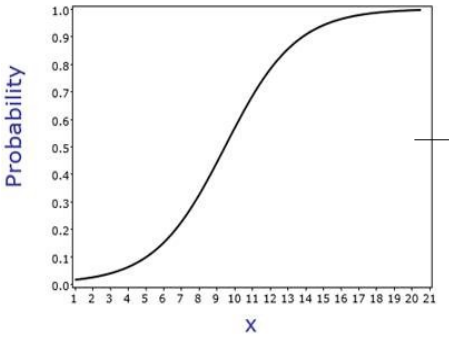
Optimization (iterative):

$$w_0 \leftarrow 0$$

$$w_{i+1} \leftarrow w_i - \alpha \frac{\partial L}{\partial W}$$

$$\frac{\partial L}{\partial W} = \sum_i -2x\left(y_i - \left(wx_i + b\right)\right)$$

Logistic Regression

X → Wx +b → 

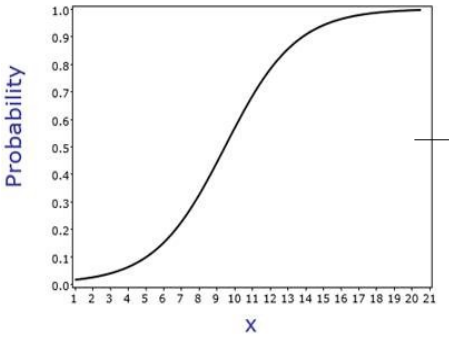
→ P(y)

$$P(y) = \sigma(Wx + b)$$

Objective function ?

Logistic Regression

Model:

X → Wx +b → 

→ P(y|x)

Objective function:

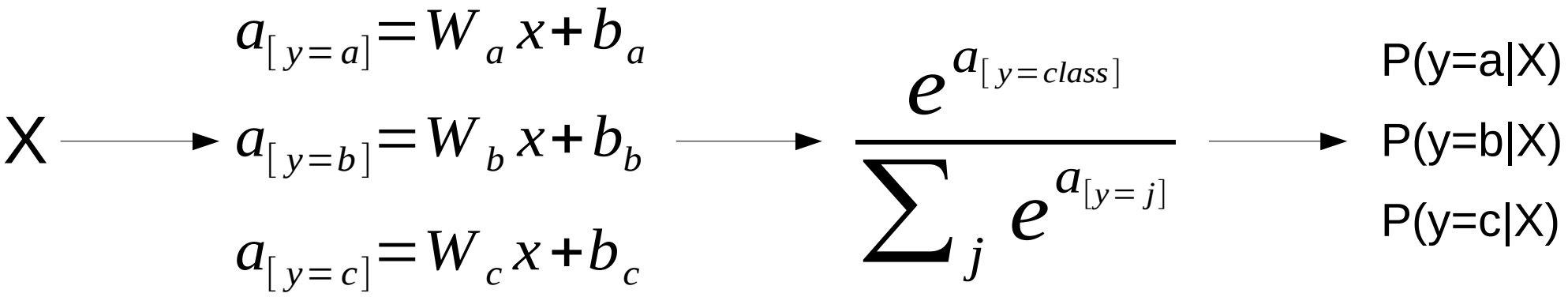
$$L = -\sum_i y_i \log P(y|x_i) + (1-y_i) \log (1 - P(y|x_i))$$

Optimization (iterative):

You guessed it!

Logistic Regression

Model:



Objective function:

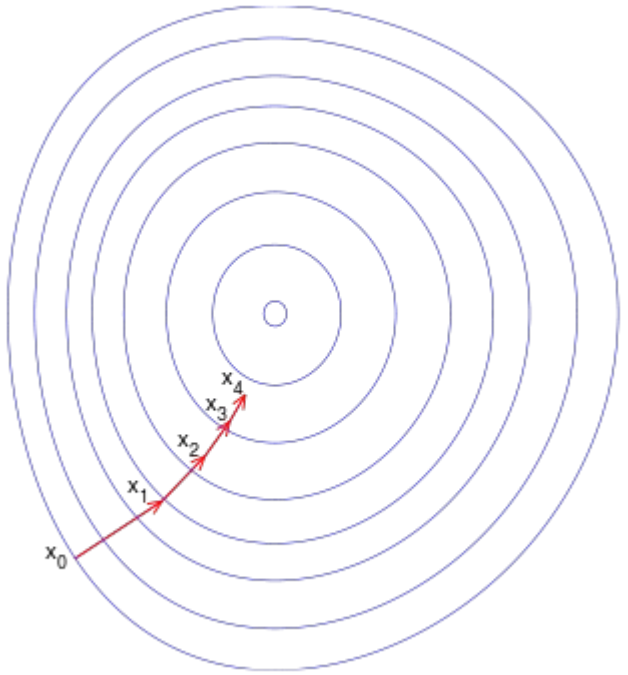
$$L = -\sum_i \sum_{class} [y_i = class] \log P\left(y = class | x_i\right)$$

Gradient descent

Update:

$$w_{i+1} \leftarrow w_i - \alpha \frac{\partial L}{\partial w}$$

- a – learning rate a<<1
- L – loss function



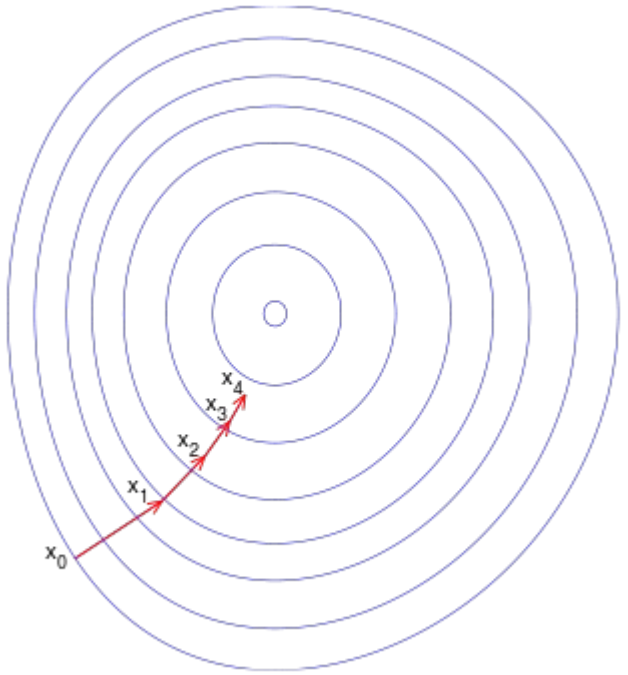
Can we do better?

Gradient descent

Update:

$$w_{i+1} \leftarrow w_i - \alpha \frac{\partial L}{\partial w}$$

- a – learning rate a<<1
- L – loss function



Can we do better?

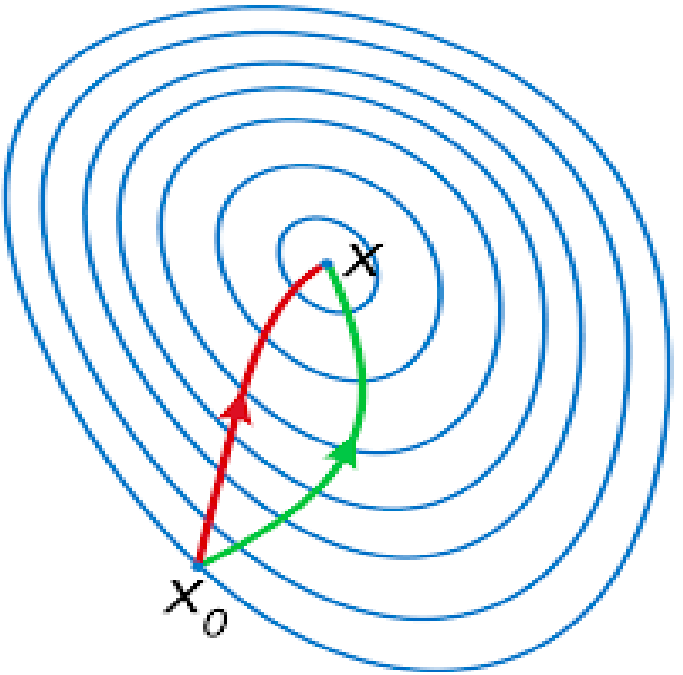
Newton-Raphson

Parameter update

$$w_{i+1} \leftarrow w_i - \alpha H_L^{-1} \frac{\partial L}{\partial w}$$

Hessian:

$$\mathbf{H} = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1\, \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_1\, \partial x_n} \\ \frac{\partial^2 f}{\partial x_2\, \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \cdots & \frac{\partial^2 f}{\partial x_2\, \partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n\, \partial x_1} & \frac{\partial^2 f}{\partial x_n\, \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}.$$



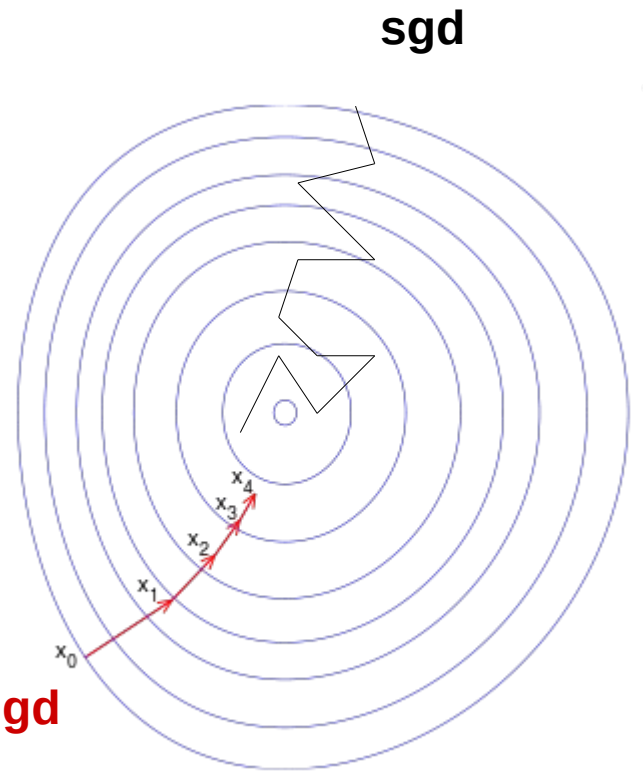
Red: Newton-Raphson
Green: gradient descent

Any drawbacks?

Stochastic gradient descent

Loss function is mean over all data samples.

Approximate with 1 or few random samples.



Update:

$$w_{i+1} \leftarrow w_i - \alpha E \frac{\partial L}{\partial w}$$

- E – expectation
- Learning rate should decrease

SGD with momentum

Idea: move towards “overall gradient direction”,
Not just current gradient.

$$w_0 \leftarrow 0 \,;\, v_0 \leftarrow 0$$

$$\nu_{i+1} \leftarrow \alpha \frac{\partial L}{\partial w} + \mu \nu_i$$

$$w_{i+1} \leftarrow w_i - \nu_{i+1}$$

Helps for noisy gradient / canyon problem

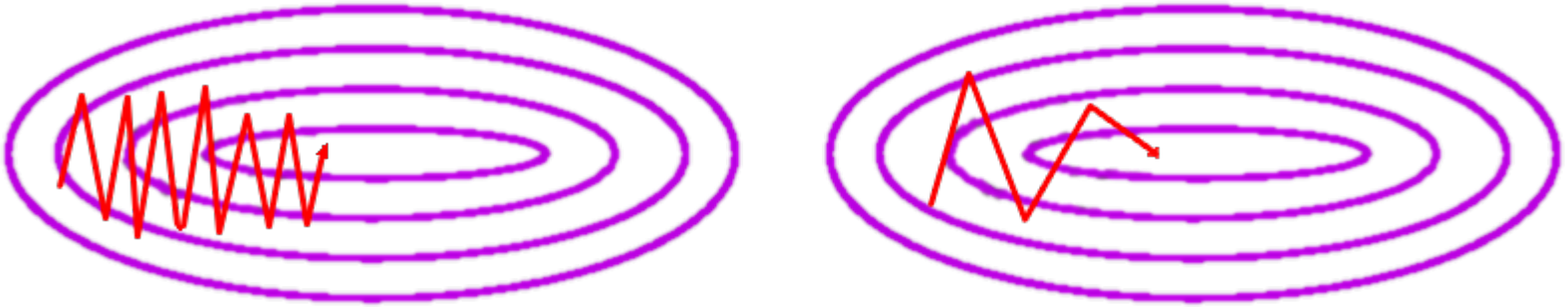
SGD with momentum

Idea: move towards “overall gradient direction”, Not just current gradient.

$$w_0 \leftarrow 0 \,;\, v_0 \leftarrow 0$$

$$\nu_{i+1} \leftarrow \alpha \frac{\partial L}{\partial w} + \mu \nu_i$$

$$w_{i+1} \leftarrow w_i - \nu_{i+1}$$



AdaGrad

Idea: decrease learning rate individually for each parameter in proportion to sum of it's gradients so far.

$$G_t = \sum_{\tau=1}^{t} \left[\frac{\partial L}{\partial w} \right]^2$$

"Total update path length" (for each parameter)

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{G_t + \epsilon}} \frac{\partial L}{\partial w}$$

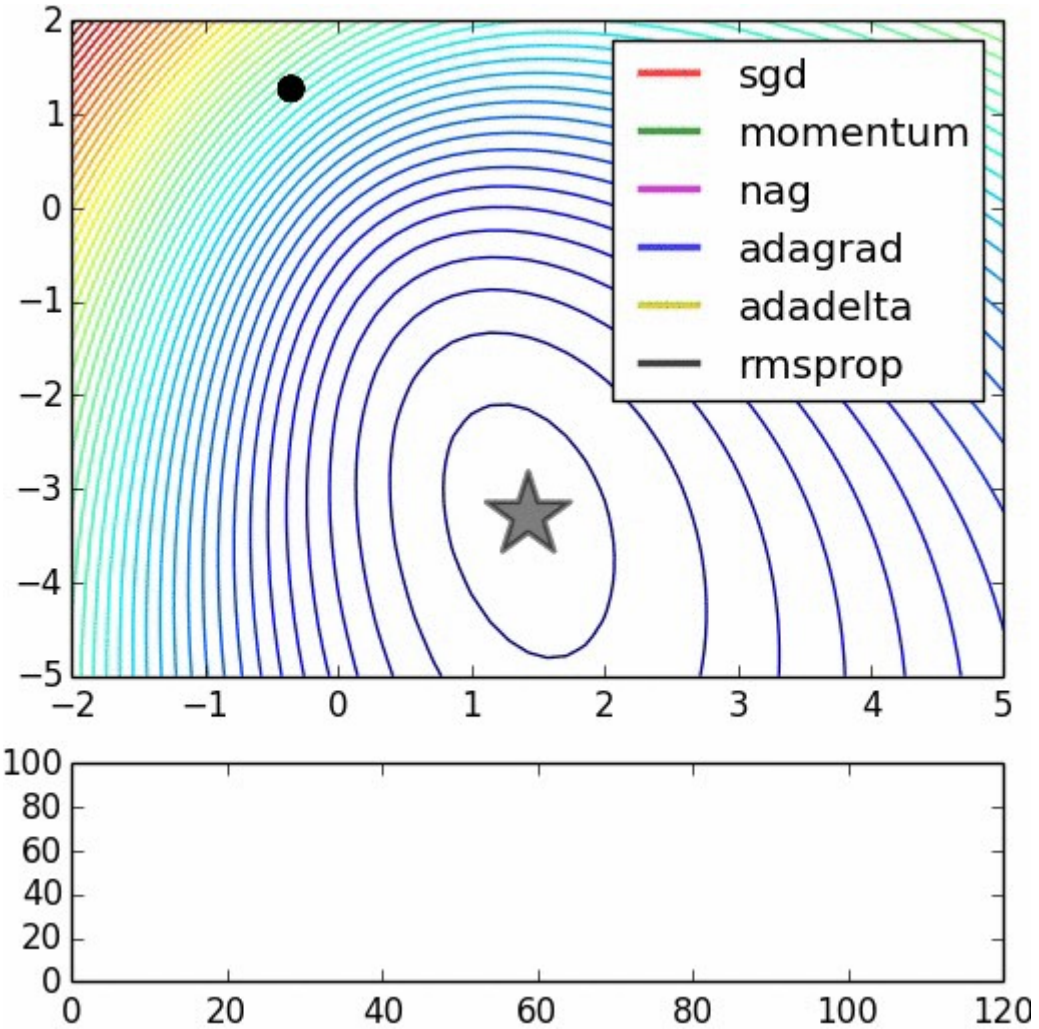
RMSProp

Idea: make sure all gradient steps have approximately same magnitude (by keeping moving average of magnitude)

$$ms_{t+1} = \gamma \cdot ms_t + (1-\gamma)\left\|\frac{\partial L}{\partial w}\right\|^2$$

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{ms+\epsilon}}\frac{\partial L}{\partial w}$$

Alltogether



Moar stuff

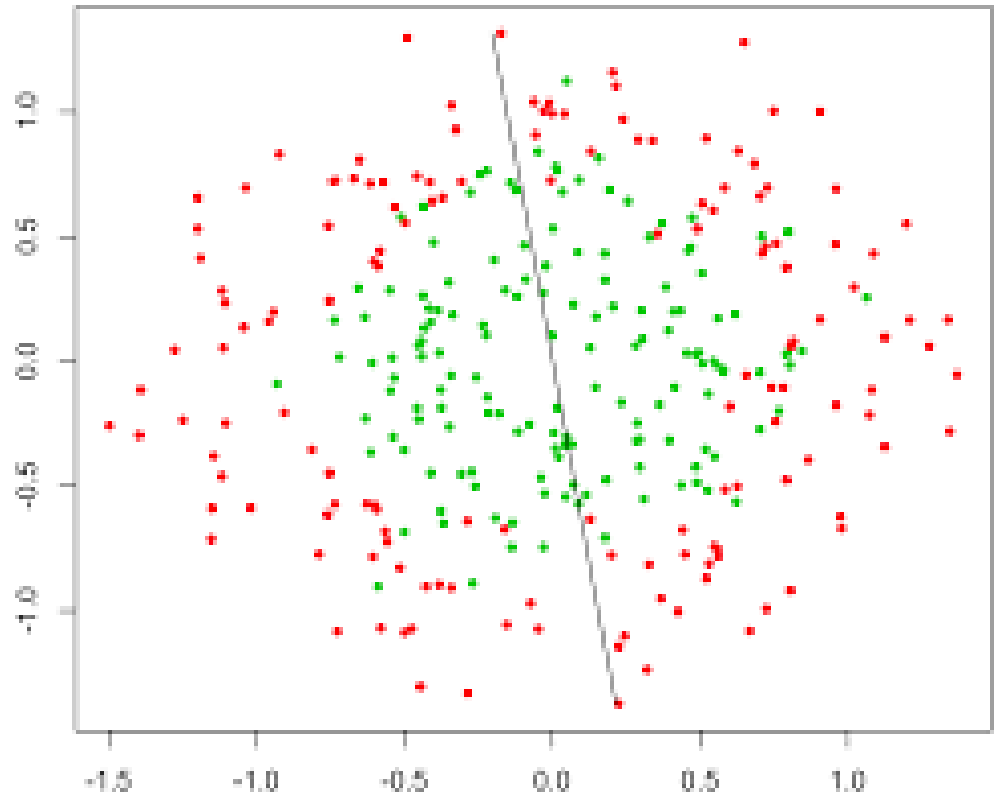
Without Hessian

- Adadelta ~ adagrad with window
- Adam ~ rmsprop + momentum
- Nesterov-momentum
- Hessian-free (narrow)
- Conjugate gradients

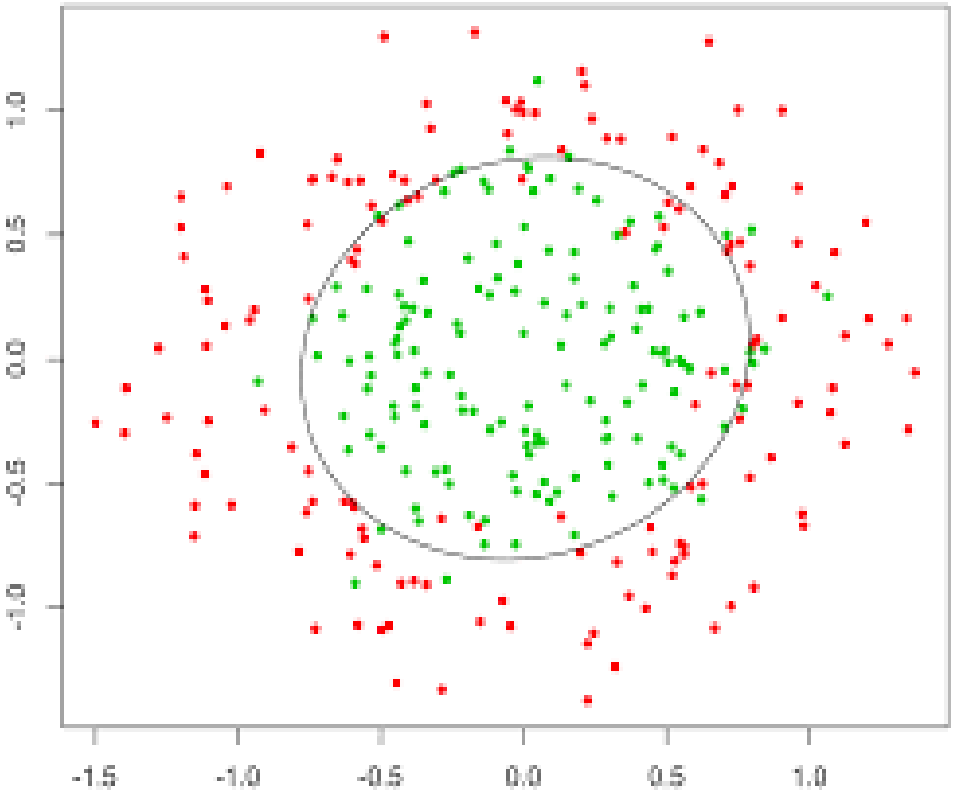
Estimate inverse Hessian

- BFGS
- L-BFGS
- ****-BFGS

Nonlinear dependencies



What we have



What we want

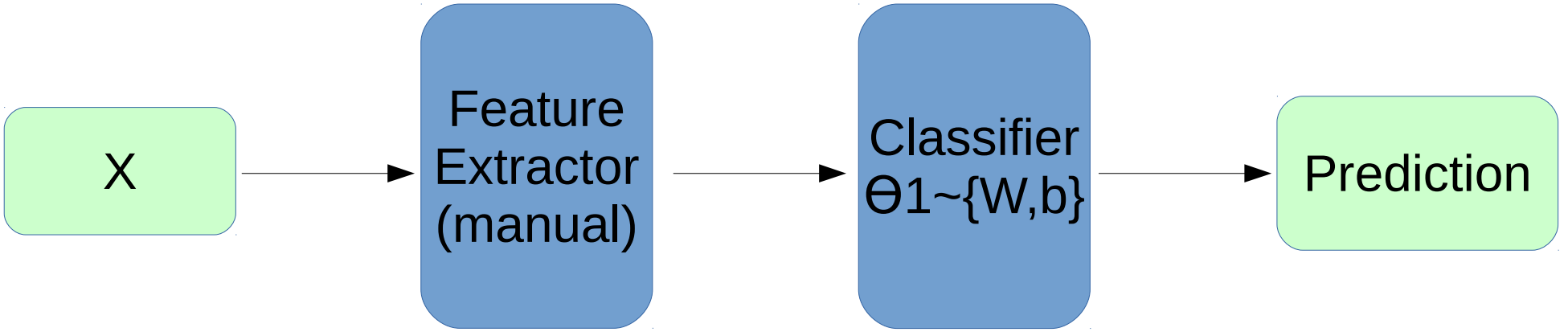
- How to get that?

Feature extraction

Loss, for example:

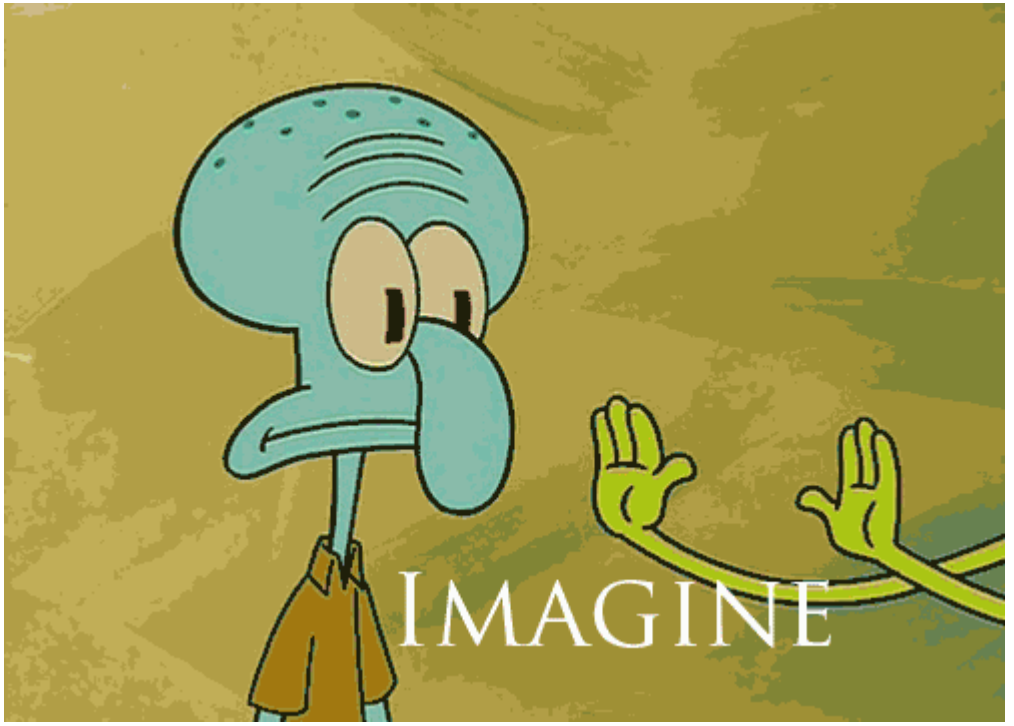
$$L = -\sum_i y_i \log P(y|x_i) + (1 - y_i) \log (1 - P(y|x_i))$$

Model:



Training:

$$\underset{\theta_1}{argmin}\, L(y, P(y|x))$$



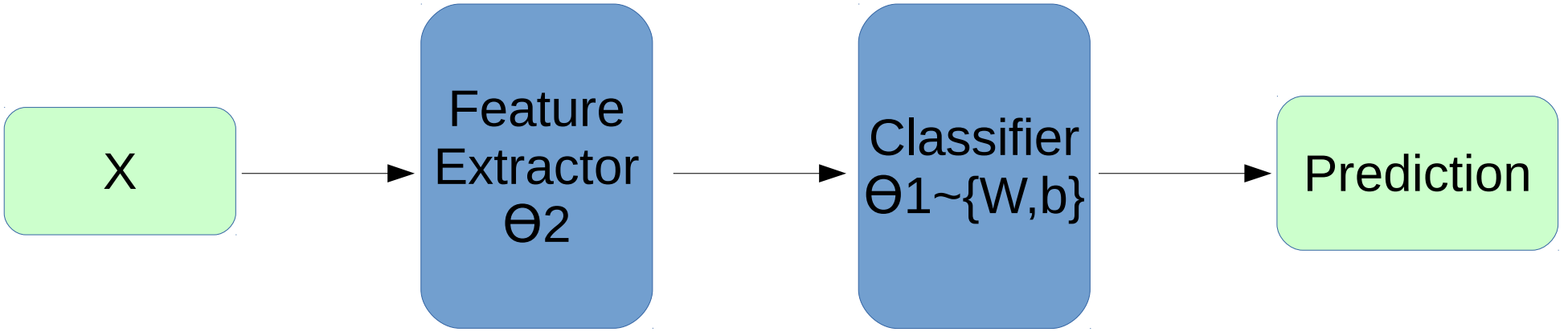
Features would tune to your problem automatically!

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:



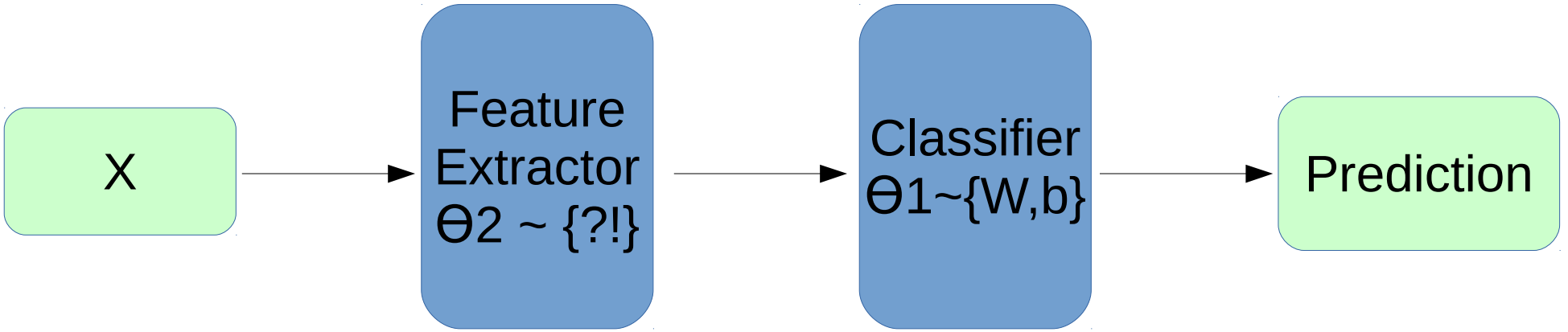
Training: ? $\underset{\theta_1}{argmin}\, L(y, P(y|x))$

What do we want, exactly?

Loss, for example:

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

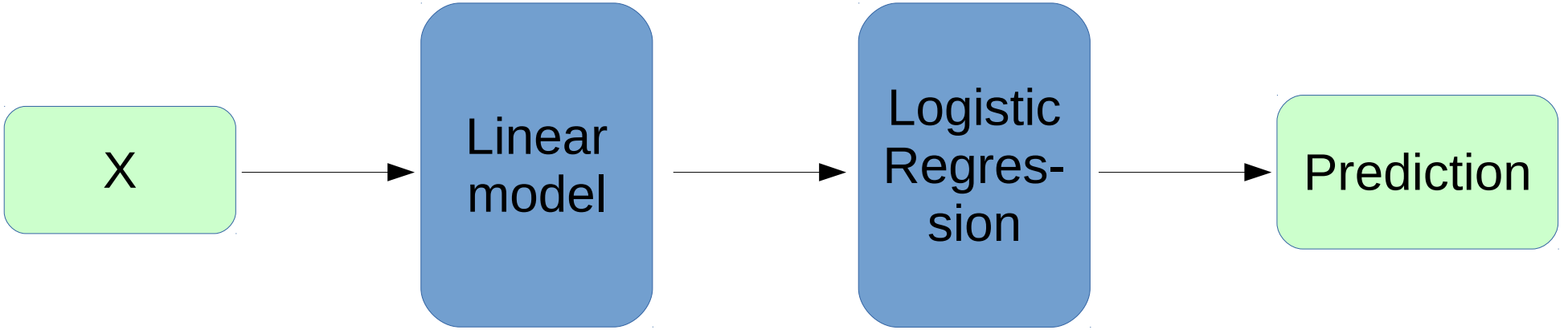
Model:



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

Try linear

Model:

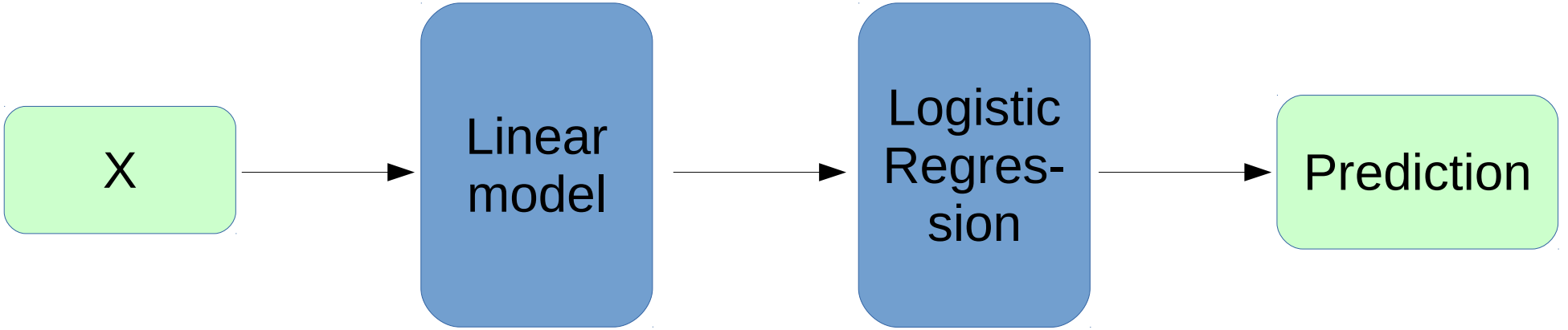


$$h_j = \sum_{\substack{i \\ j \in \{1,2,\ldots,n\}}} w_{ij}^{h} x_i + b_j^{h}$$

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

Try linear

Model:



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

Output:

$$P(y|x) = \sigma\left(\sum_j w_j^o \left(\sum_i w_{ij}^h x_i + b_j^h\right) + b^o\right)$$

Is it any better than logistic regression?

Try linear

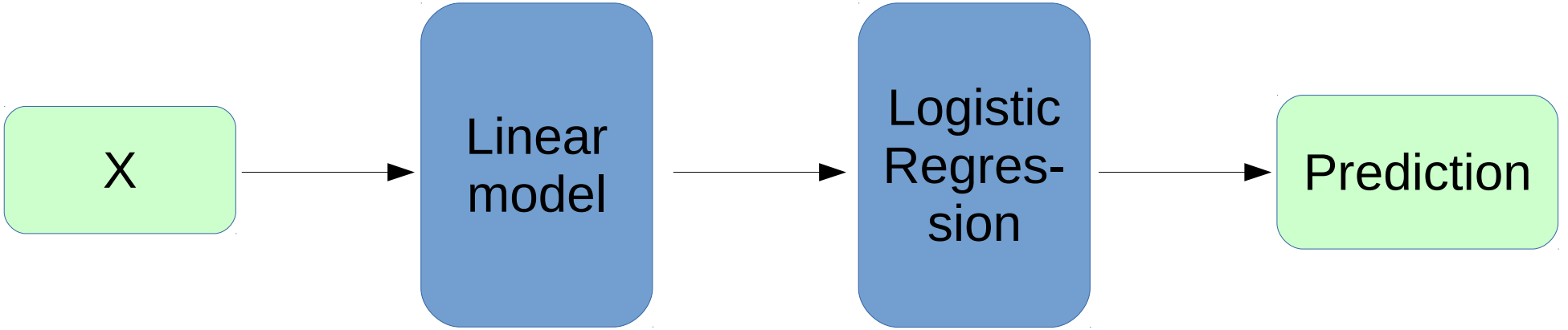
$$P(y|x) = \sigma\left(\sum_j w^o_j \left(\sum_i w^h_{ij} x_i + b^h_j\right) + b^o\right)$$

$$w'_i = \sum_j w^o_j w^h_{ij} \qquad b' = \sum_j w^o_j b^h_j + b^o$$

$$P(y|x) = \sigma\left(\sum_i w'_i x_i + b'\right)$$

Try linear

Model:



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

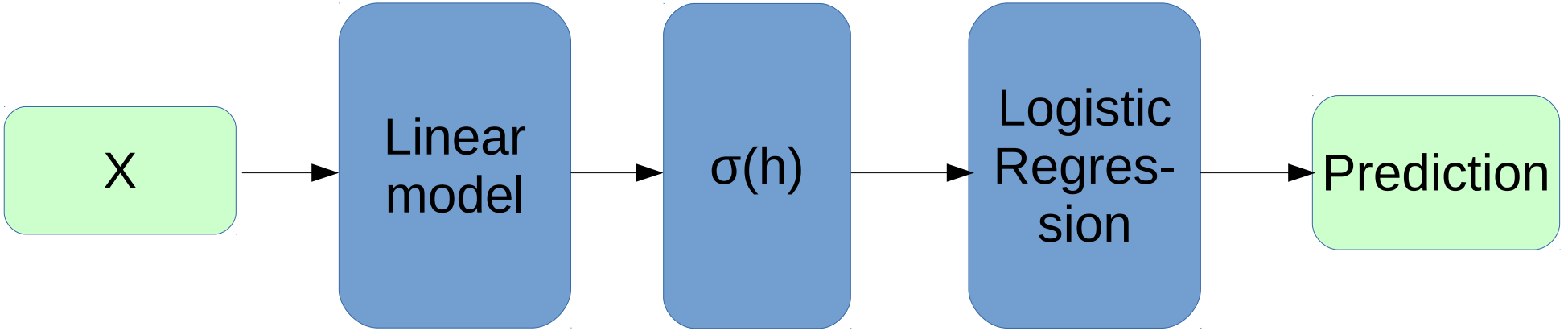
Output:

$$P(y|x) = \sigma\left(\sum_j w_j^o \left(\sum_i w_{ij}^h x_i + b_j^h\right) + b^o\right)$$

Is it any better than logistic regression?

Nonlinearity

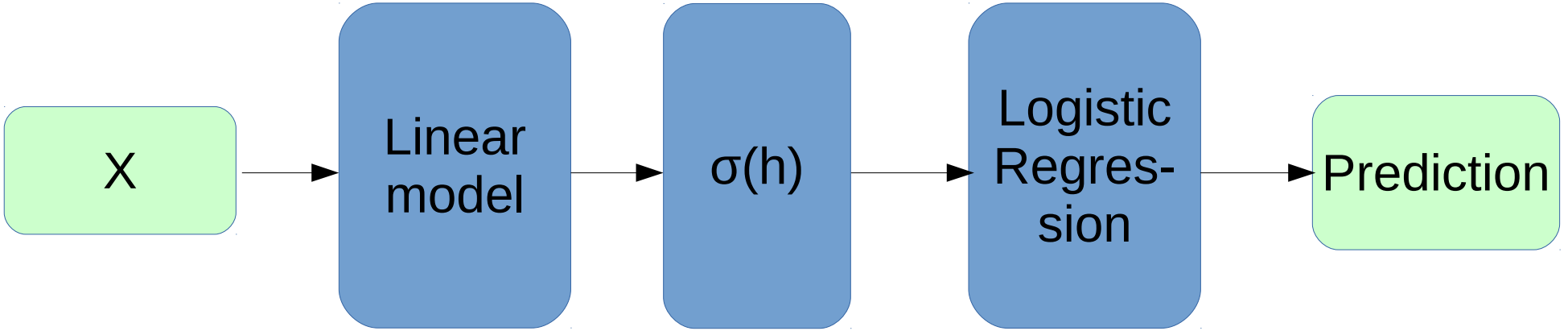
Model:



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

Nonlinearity

Model:



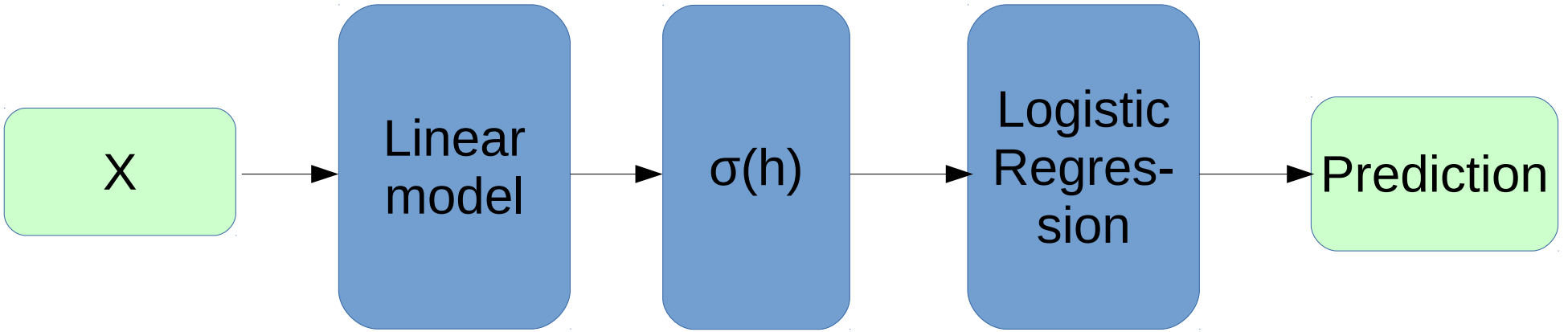
$$h_j = \sigma\left(\sum_{\substack{i \\ j \in \{1,2,\ldots,n\}}} w_{ij}^h x_i + b_j^h\right) \qquad y_{pred} = \sigma\left(\sum_j w_j^o h_j + b^o\right)$$

Output:

$$P(y|x) = \sigma\left(\sum_j w_j^o \sigma\left(\sum_i w_{ij}^h x_i + b_j^h\right) + b^o\right)$$

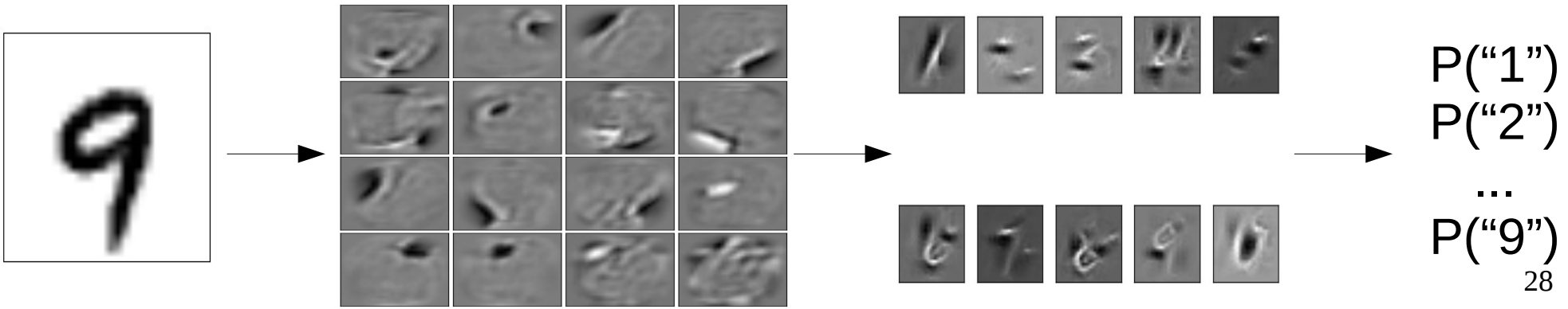
Nonlinearity

Model:



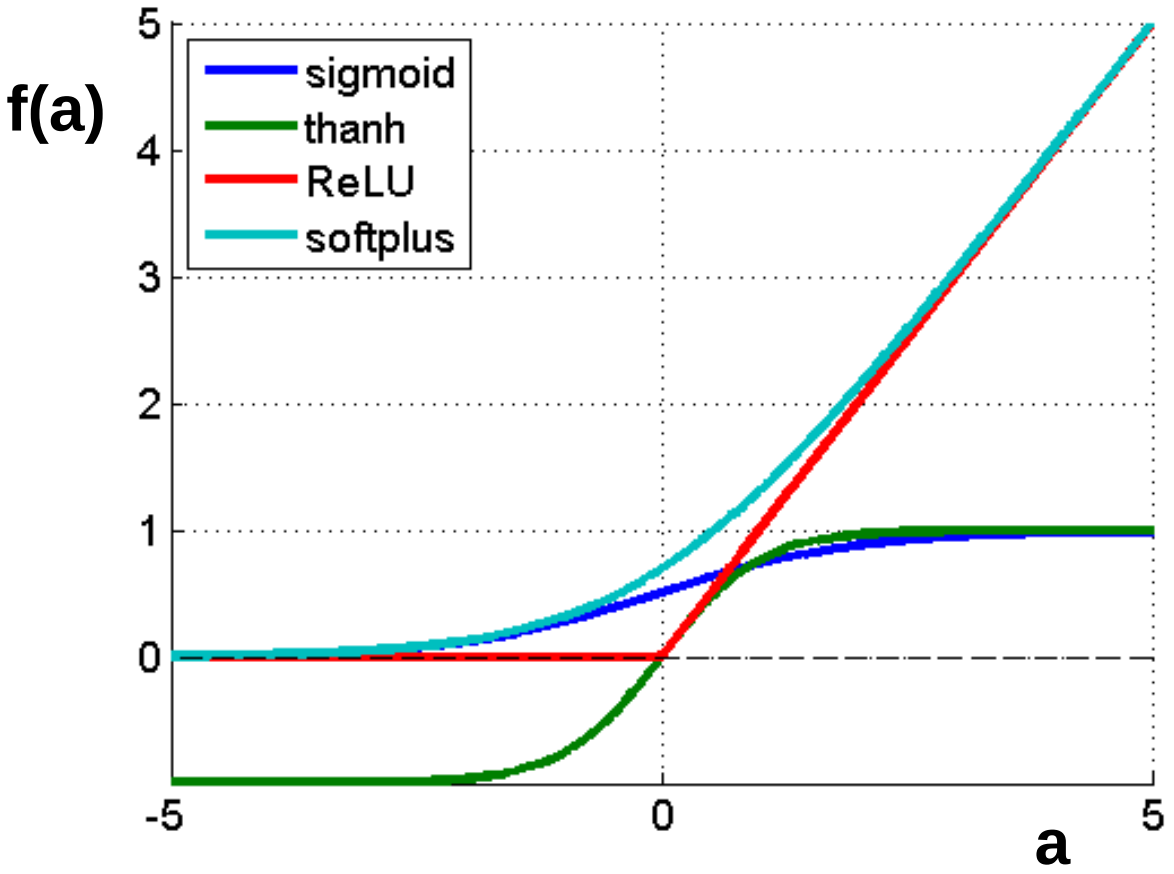
$$h_j = \sigma\left(\sum_{i \in \{1.2.....n\}} w_{ij}^h x_i + b_j^h\right)$$

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

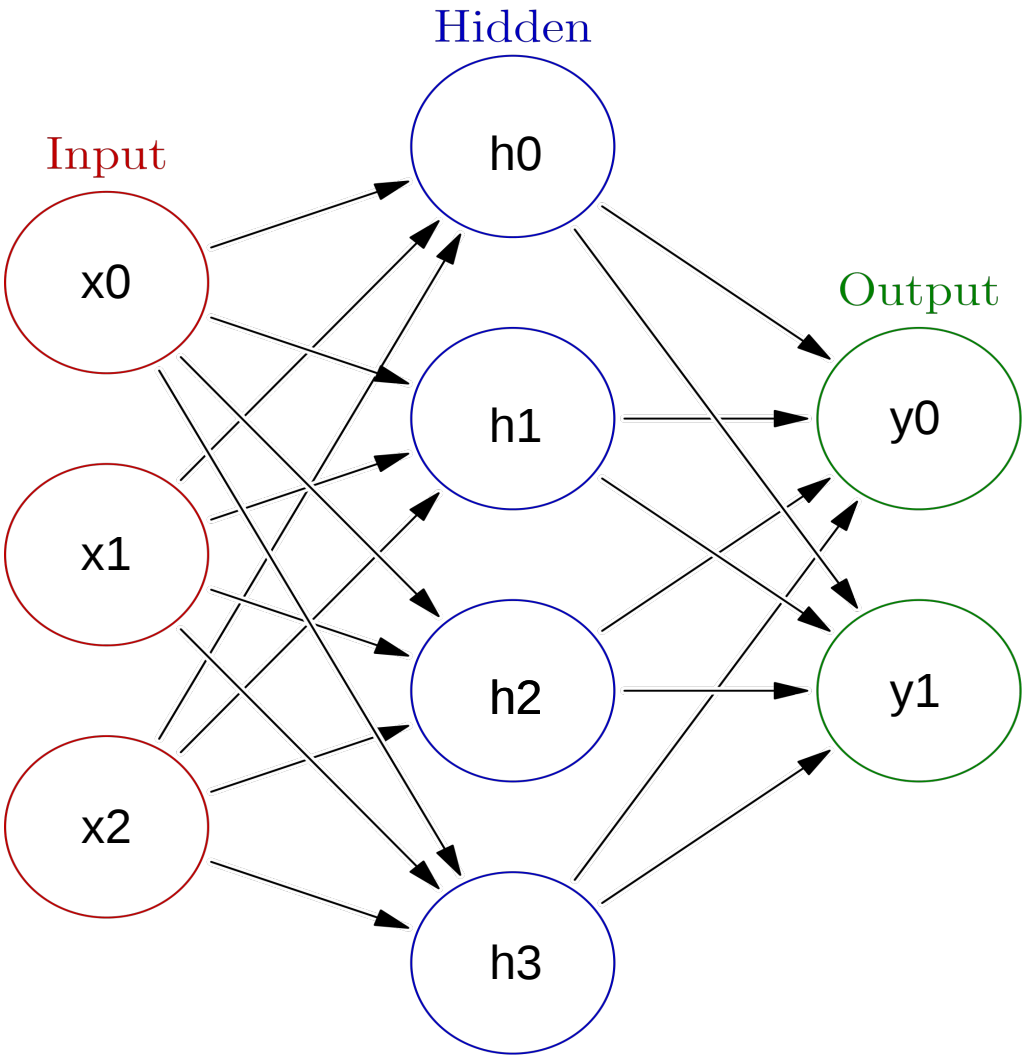


Nonlinearity

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

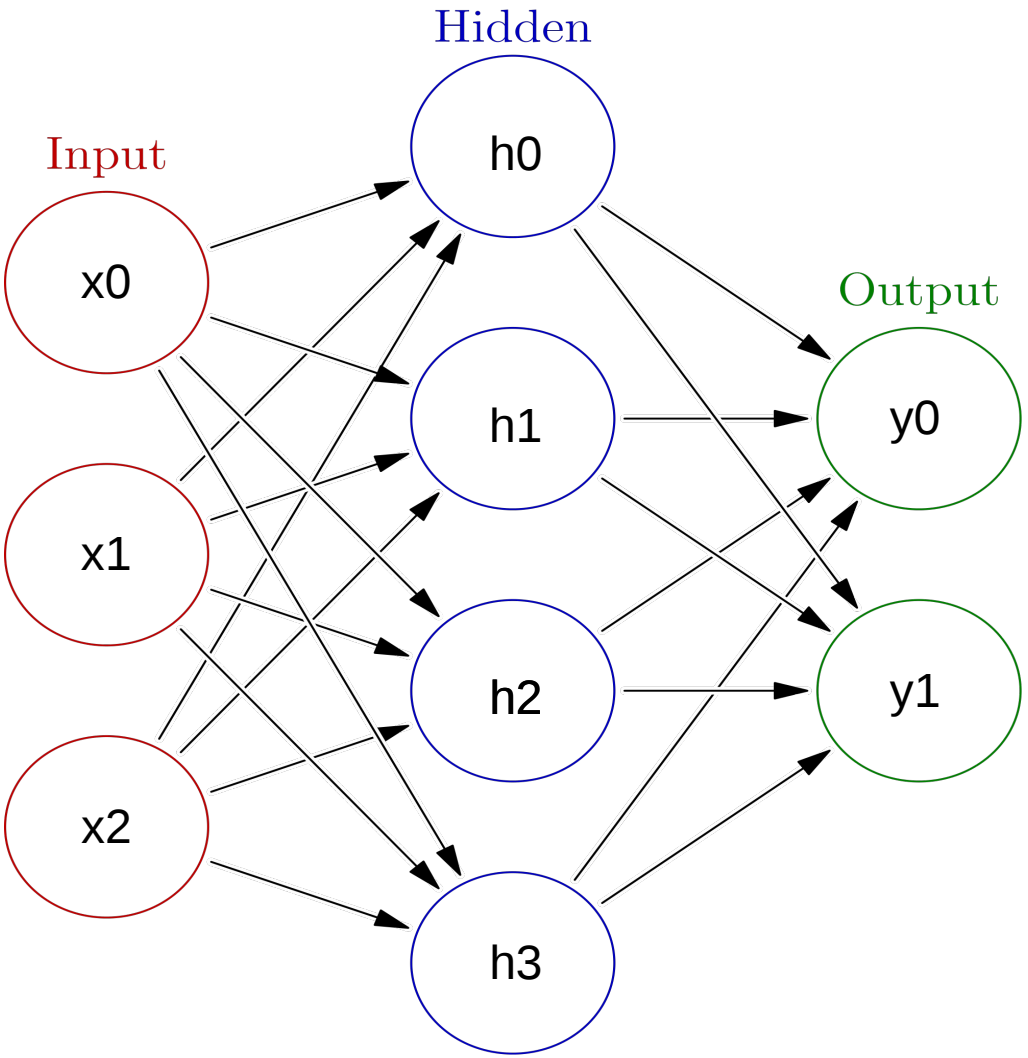


Initialization, symmetry problem



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

Initialization, symmetry problem

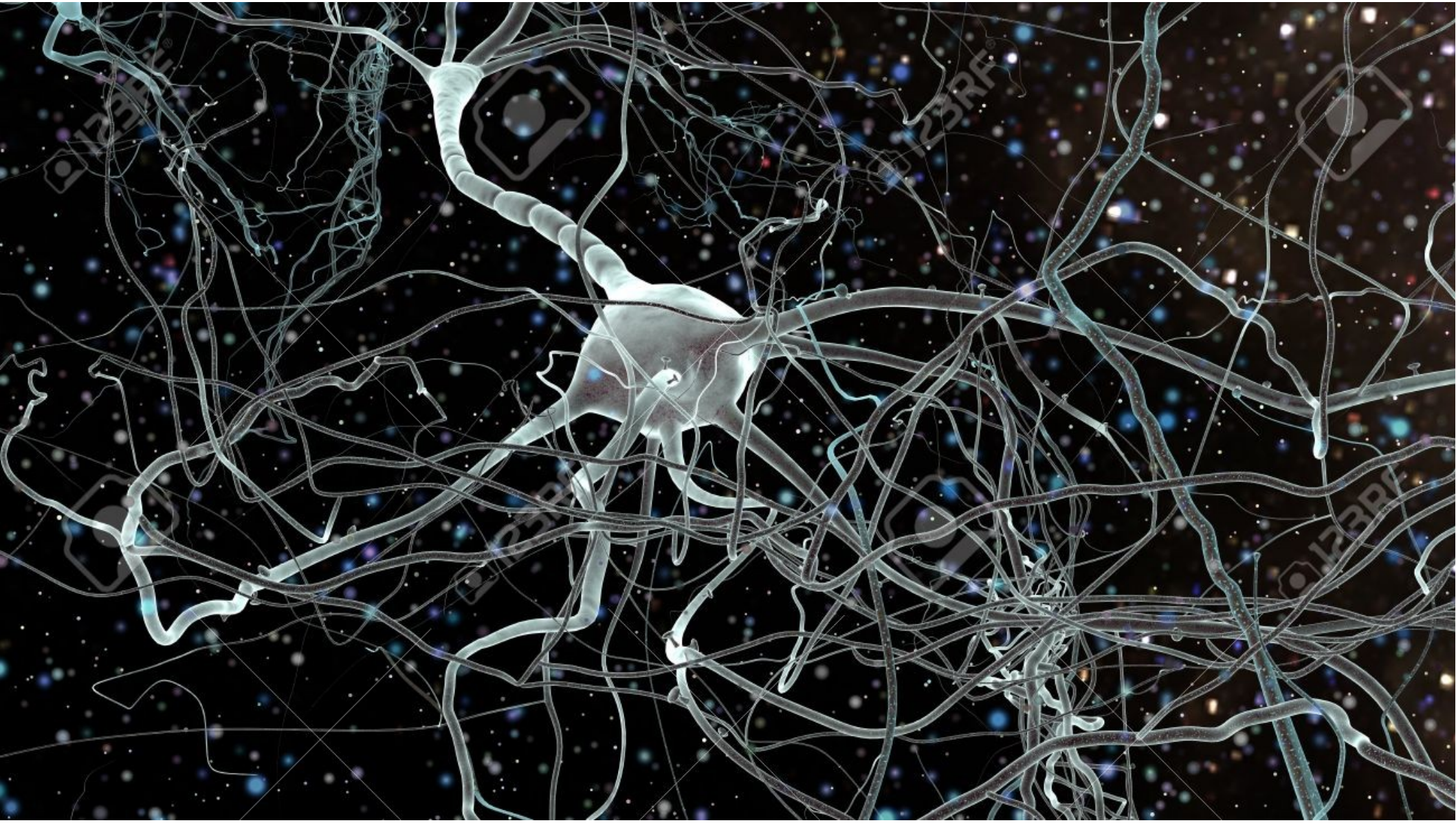


- Break the symmetry!
- Initialize with random numbers!

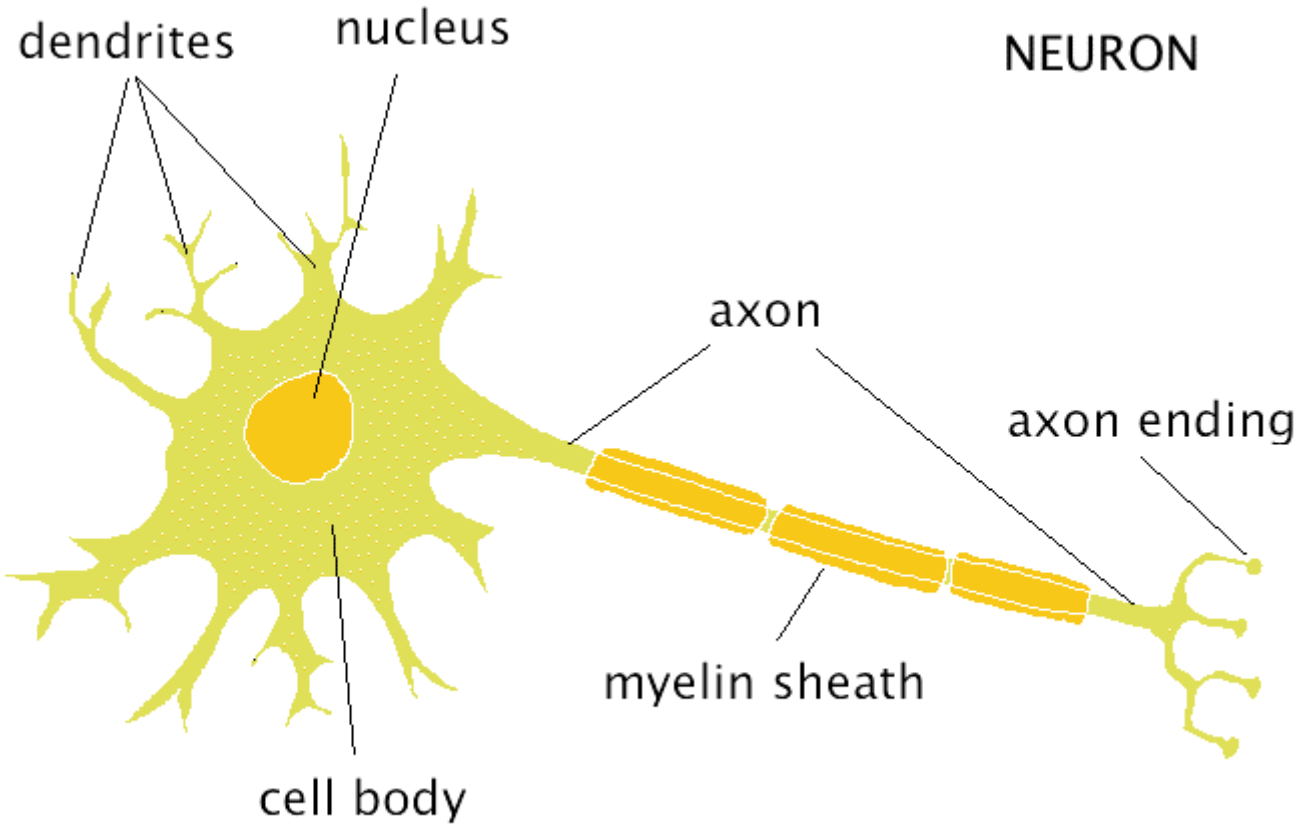
  $W \leftarrow N(0,0.01)$?

  $W \leftarrow U(0,0.1)$?
- Can get a bit better for deep NNs

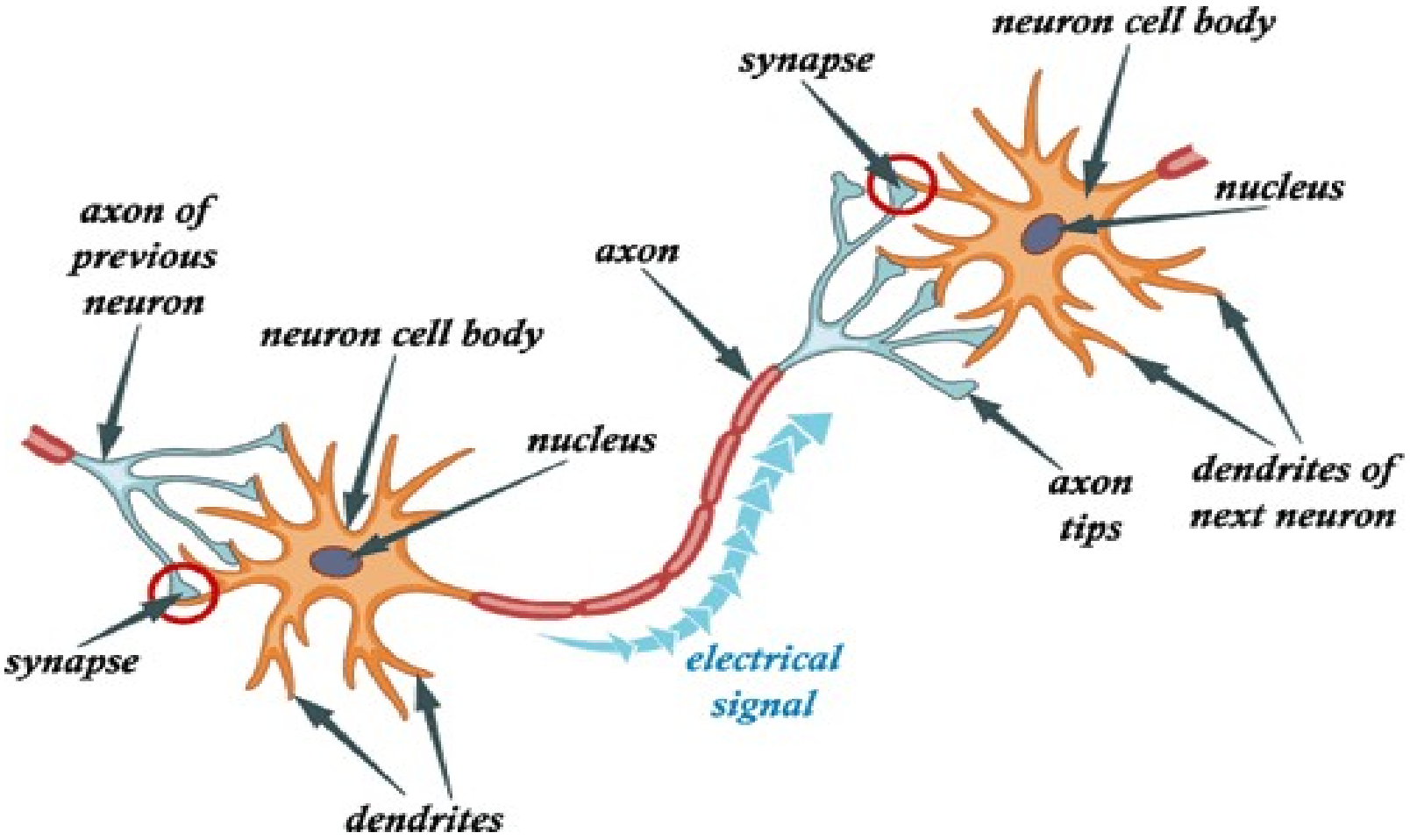
Biological inspiration



Biological inspiration

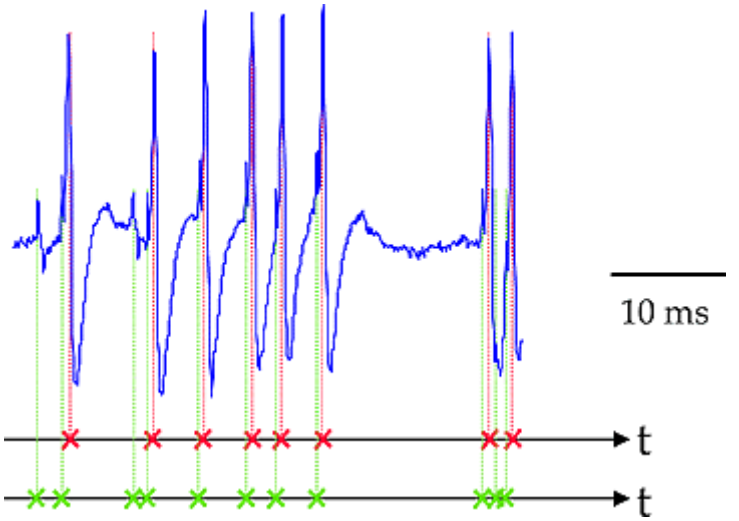


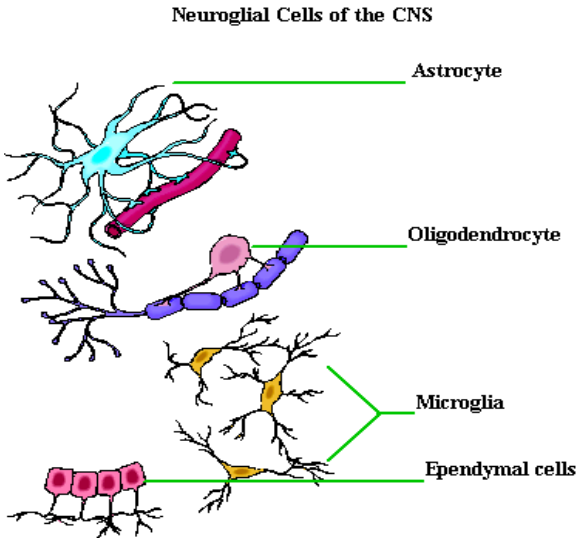
Biological inspiration



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

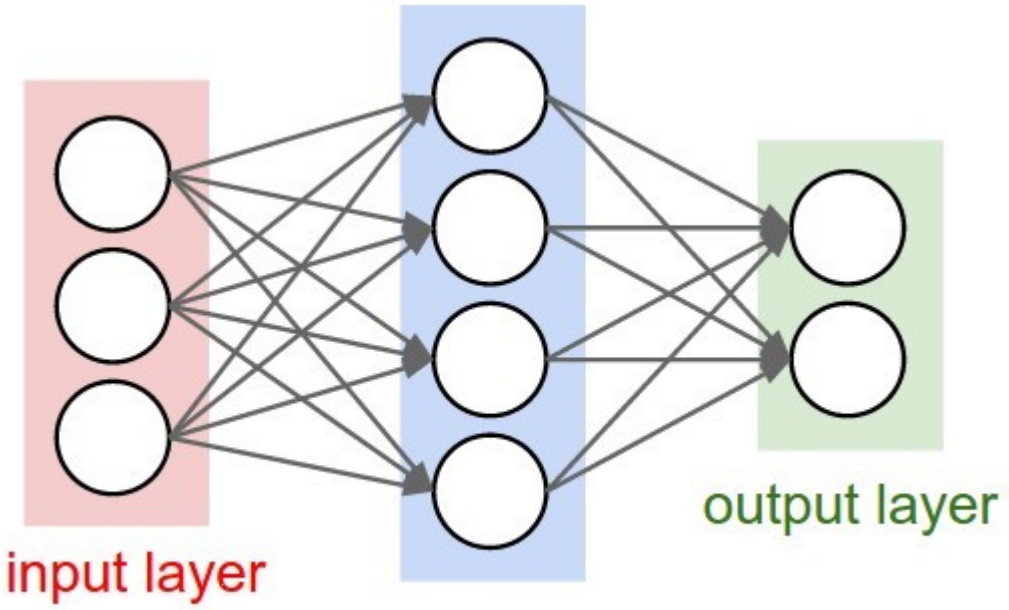




Connectionist phrasebook

- 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”

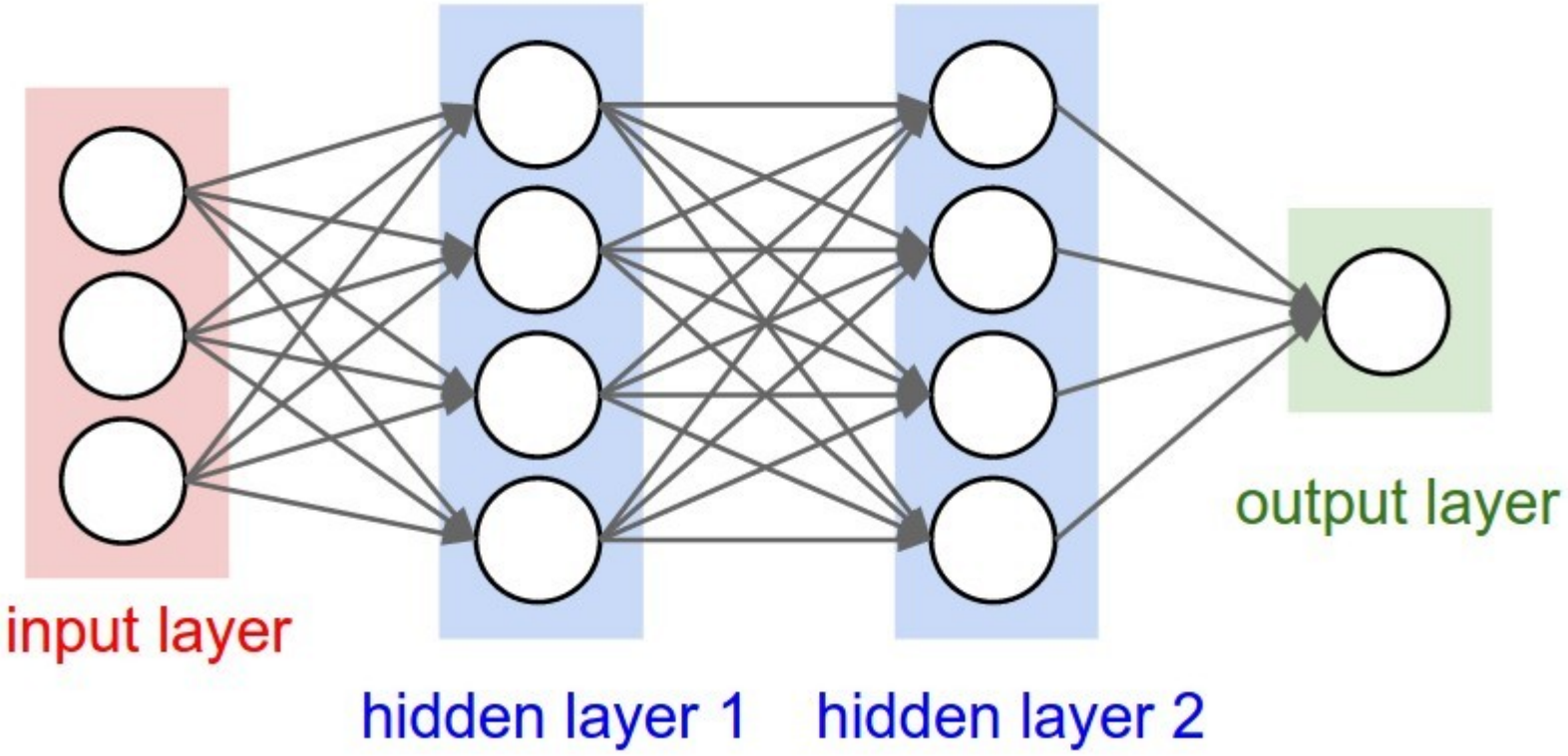
Connectionist phrasebook



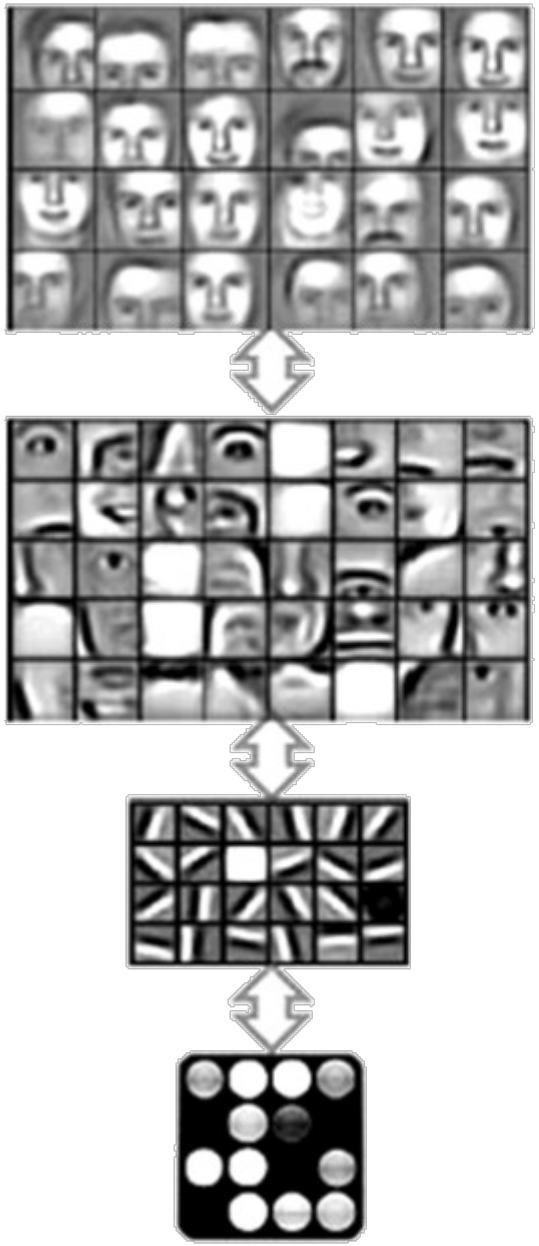
Dense layer
with a nonlinearity

- “Train it via backprop!”

Connectionist phrasebook



How do we train it?



Discrete Choices

⋮

Layer 2 Features

Layer 1 Features

Original Data

Potential caveats?

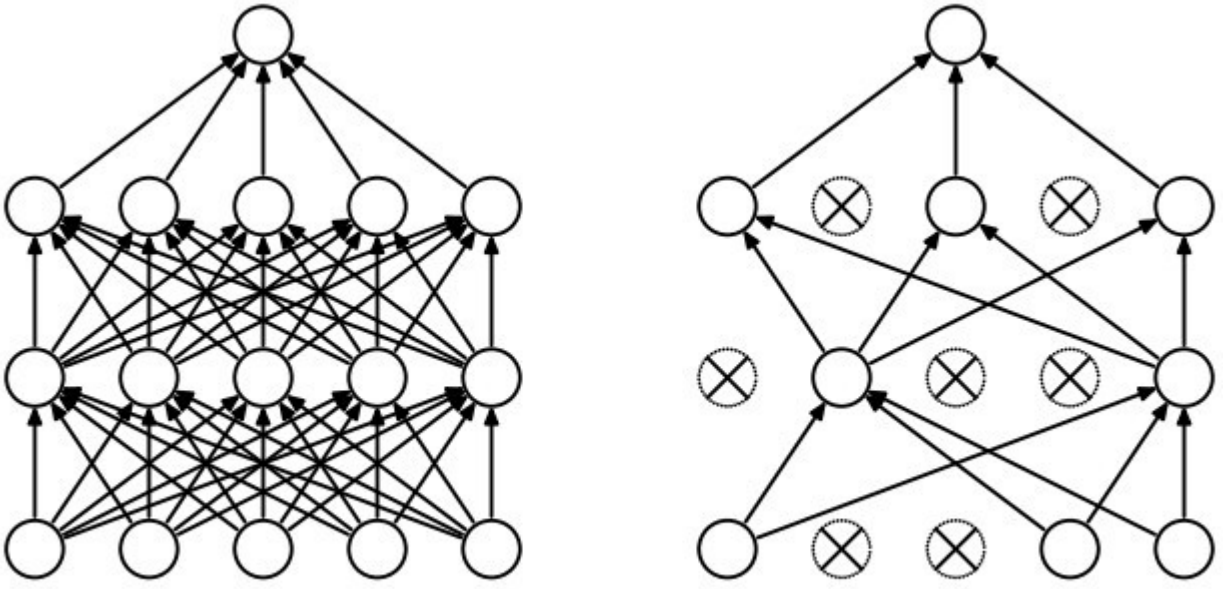
Potential caveats?

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

Regularization

- L1, L2, as usual

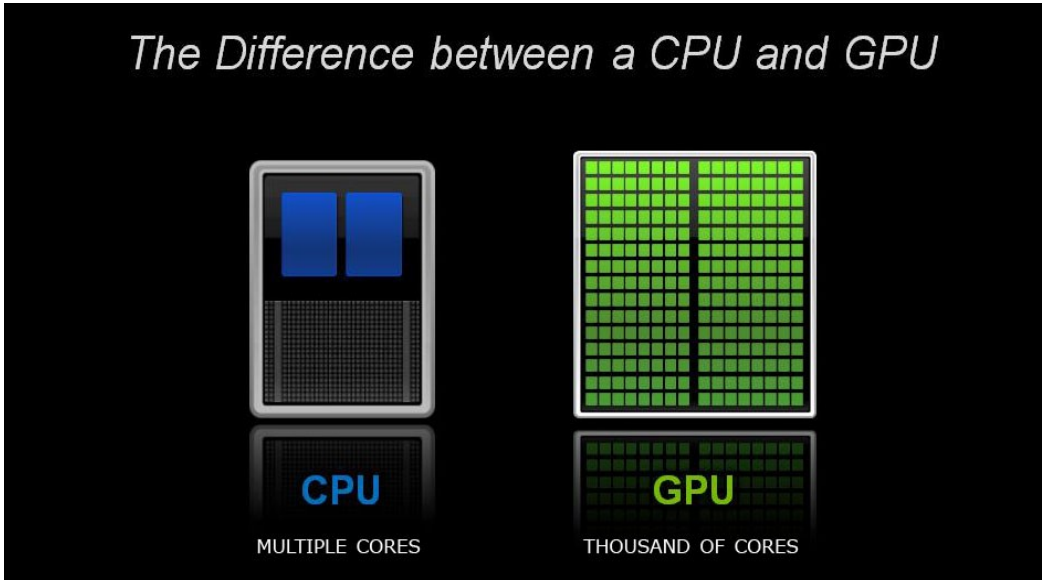
- Dropout



(a) Standard Neural Net

(b) After applying dropout.

Computation



Nuff

Let's go implement that!