Introduction to Neural Networks

Hunter Glanz

1 / 9

The Method

OUTLINE

The Method

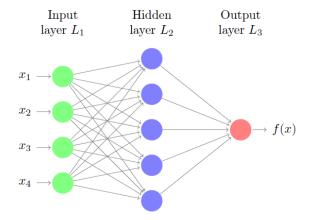
Assessing Neural Networks

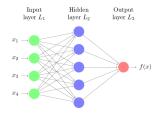
Overview

► Neural networks are highly parameterized models inspired by the human brain

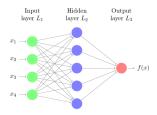
Overview

► Neural networks are highly parameterized models inspired by the human brain



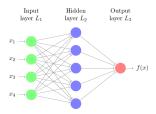


4 / 9

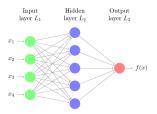


Four predictors or inputs x_j

4 / 9



- \triangleright Four predictors or inputs x_i
- ► Five hidden units $a_{\ell} = g(w_{\ell 0}^{(1)} + \sum_{j=1}^{4} w_{\ell j}^{(1)} x_j)$



- ► Four predictors or inputs *x_j*
- ► Five hidden units $a_{\ell} = g(w_{\ell 0}^{(1)} + \sum_{j=1}^{4} w_{\ell j}^{(1)} x_j)$
- Single output unit $o = h(w_0^{(2)} + \sum_{\ell=1}^5 w_\ell^{(2)} a_\ell)$

4□ > 4□ > 4 = > 4 = > = 90

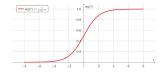
ightharpoonup Four predictors or inputs x_j

- \triangleright Four predictors or inputs x_j
- Five hidden units $a_\ell = g(w_{\ell 0}^{(1)} + \sum_{j=1}^4 w_{\ell j}^{(1)} x_j)$

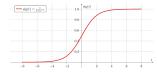
- ightharpoonup Four predictors or inputs x_j
- ► Five hidden units $a_{\ell} = g(w_{\ell 0}^{(1)} + \sum_{j=1}^{4} w_{\ell j}^{(1)} x_j)$
- Single output unit $o = h(w_0^{(2)} + \sum_{\ell=1}^5 w_\ell^{(2)} a_\ell)$

- Four predictors or inputs x_j
- ► Five hidden units $a_{\ell} = g(w_{\ell 0}^{(1)} + \sum_{j=1}^{4} w_{\ell j}^{(1)} x_j)$
- Single output unit $o = h(w_0^{(2)} + \sum_{\ell=1}^5 w_\ell^{(2)} a_\ell)$
- ▶ Typically $g(t) = 1/(1 + e^{-t})$ a sigmoid

- \triangleright Four predictors or inputs x_j
- ► Five hidden units $a_{\ell} = g(w_{\ell 0}^{(1)} + \sum_{j=1}^{4} w_{\ell j}^{(1)} x_j)$
- ► Single output unit $o = h(w_0^{(2)} + \sum_{\ell=1}^5 w_\ell^{(2)} a_\ell)$
- ▶ Typically $g(t) = 1/(1 + e^{-t})$ a sigmoid

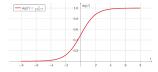


- \triangleright Four predictors or inputs x_j
- ► Five hidden units $a_{\ell} = g(w_{\ell 0}^{(1)} + \sum_{j=1}^{4} w_{\ell j}^{(1)} x_j)$
- ► Single output unit $o = h(w_0^{(2)} + \sum_{\ell=1}^5 w_\ell^{(2)} a_\ell)$
- ▶ Typically $g(t) = 1/(1 + e^{-t})$ a sigmoid



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

- \triangleright Four predictors or inputs x_j
- ► Five hidden units $a_{\ell} = g(w_{\ell 0}^{(1)} + \sum_{j=1}^{4} w_{\ell j}^{(1)} x_j)$
- ► Single output unit $o = h(w_0^{(2)} + \sum_{\ell=1}^5 w_\ell^{(2)} a_\ell)$
- ▶ Typically $g(t) = 1/(1 + e^{-t})$ a sigmoid



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

How are neural networks different from the ensemble methods we've discussed this term?

4 D > 4 B > 4 B > 4 B > 9 9 0

Fitting a Neural Network

- ▶ **Iteratively fit the weights** to minimize some loss function, *L*
 - ▶ *L* depends on your problem, but think of RSS or classification error

Fitting a Neural Network

- ▶ **Iteratively fit the weights** to minimize some loss function, *L*
 - L depends on your problem, but think of RSS or classification error
- In fact...we want to minimize:

minimize_W
$$\frac{1}{n} \sum_{i=1}^{n} L[y_i, f(x_i; \mathcal{W})] + \lambda J(\mathcal{W})$$
 (1.1)

where \mathcal{W} is the collection of weights, J is a nonnegative regularization term, and $\lambda \geq 0$ is a tuning parameter

Tuning Parameters

- Number of hidden layers
- Number of units in each hidden layer
- Starting values for the weights
- Choice of non-linearities (the form of the g function)
- Choice of regularization
- Choice of stopping time

Tuning Parameters

- Number of hidden layers
- Number of units in each hidden layer
- Starting values for the weights
- Choice of non-linearities (the form of the g function)
- Choice of regularization
- Choice of stopping time
- ▶ How do we determine these?!

Tuning Parameters

- Number of hidden layers
- Number of units in each hidden layer
- Starting values for the weights
- Choice of non-linearities (the form of the g function)
- Choice of regularization
- Choice of stopping time
- How do we determine these?!

A little bit of cross-validation

► Too many weights can lead to overfitting and a global minimum of the loss

8 / 9

- ► Too many weights can lead to overfitting and a global minimum of the loss
- Current wisdom:

- ► Too many weights can lead to overfitting and a global minimum of the loss
- Current wisdom:
 - ▶ Better to have large number of hidden units (5 to 100)

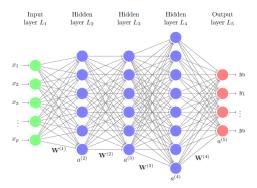
- ► Too many weights can lead to overfitting and a global minimum of the loss
- Current wisdom:
 - Better to have large number of hidden units (5 to 100)
 - Control model complexity with regularization (cross-validation)
 - Regularization slows the rate of overfitting

- Too many weights can lead to overfitting and a global minimum of the loss
- Current wisdom:
 - ▶ Better to have large number of hidden units (5 to 100)
 - Control model complexity with regularization (cross-validation)
 - Regularization slows the rate of overfitting
 - More hidden layers increases complexity, but tends to be task specific

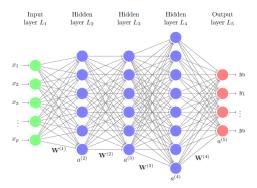
- ► Too many weights can lead to overfitting and a global minimum of the loss
- Current wisdom:
 - Better to have large number of hidden units (5 to 100)
 - Control model complexity with regularization (cross-validation)
 - Regularization slows the rate of overfitting
 - More hidden layers increases complexity, but tends to be task specific
 - Stopping time can also be determined with cross-validation, but is less of a problem with regularization

- ► Too many weights can lead to overfitting and a global minimum of the loss
- Current wisdom:
 - Better to have large number of hidden units (5 to 100)
 - Control model complexity with regularization (cross-validation)
 - Regularization slows the rate of overfitting
 - More hidden layers increases complexity, but tends to be task specific
 - Stopping time can also be determined with cross-validation, but is less of a problem with regularization
 - Choice of starting weight values can affect movement of the algorithm and where it ends up
 - Shouldn't be zero
 - ► Shouldn't be large
 - ► Try multiple sets

More Complex

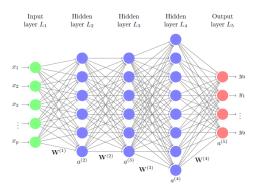


More Complex



▶ Non-linear extension of traditional linear models

More Complex



- ▶ Non-linear extension of traditional linear models
- From very regularized and constrained, to very flexible