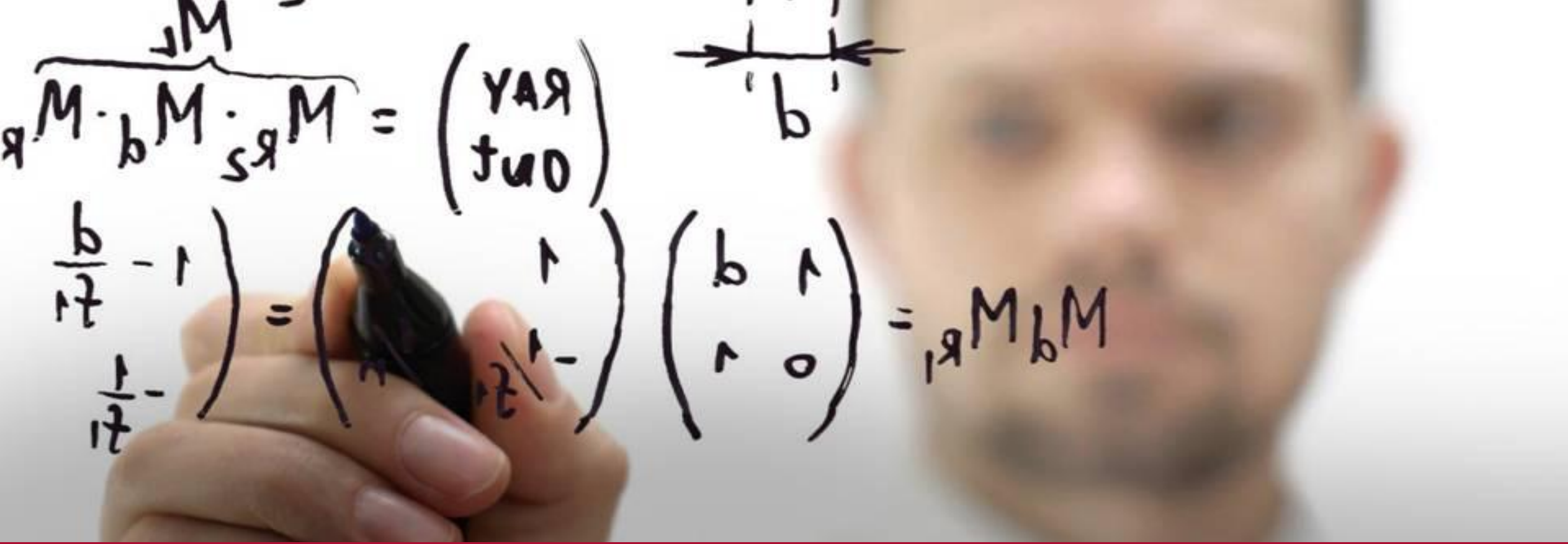
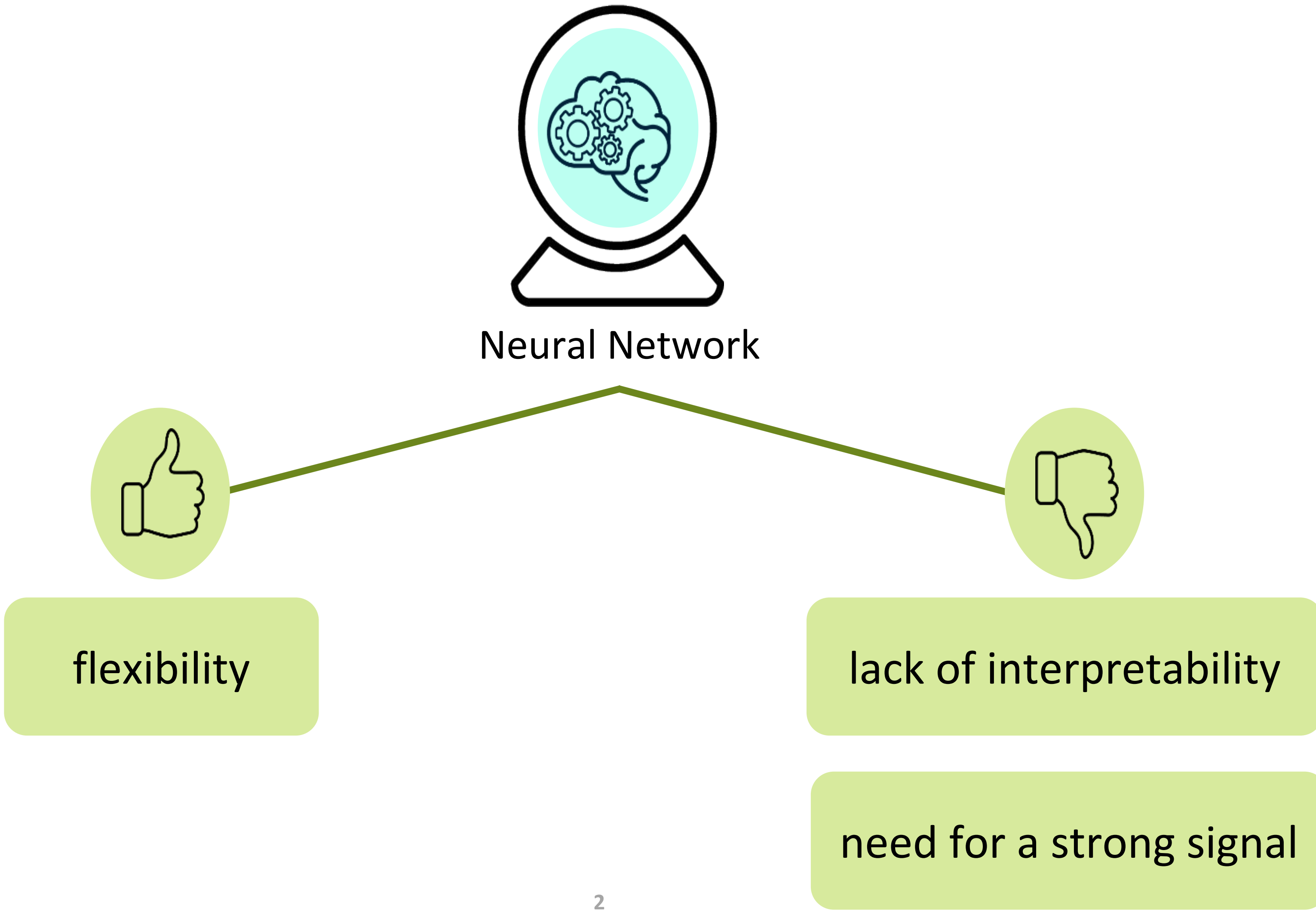


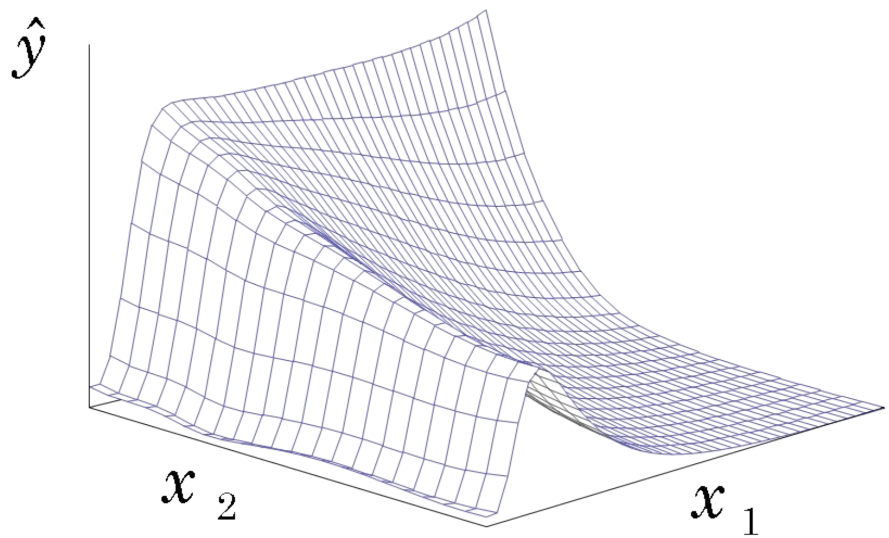
Lesson XII : Neural Network

Advantages and Disadvantages of Neural Networks



Universal Approximator

Given enough neurons and time, a neural network can model any input/output relationship, to any degree of precision.



Neural Network Prediction Formula

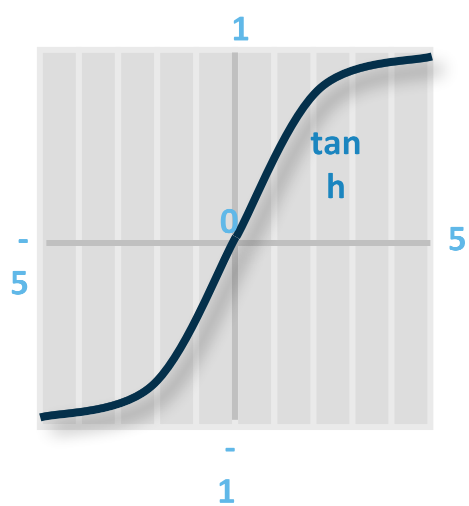
hidden unit

prediction estimate

$$\hat{y} = \hat{w}_{00} + \hat{w}_{01} \cdot H_1 + \hat{w}_{02} \cdot H_2 + \hat{w}_{03} \cdot H_3$$

bias estimate

weight estimate



$$H_1 = \tanh(\hat{w}_{10} + \hat{w}_{11} x_1 + \hat{w}_{12} x_2)$$

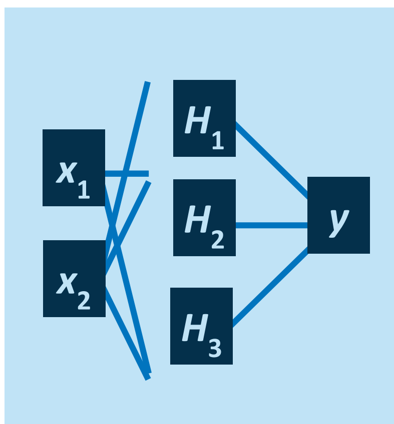
$$H_2 = \tanh(\hat{w}_{20} + \hat{w}_{21} x_1 + \hat{w}_{22} x_2)$$

$$H_3 = \tanh(\hat{w}_{30} + \hat{w}_{31} x_1 + \hat{w}_{32} x_2)$$

activation function

Neural Network Diagram

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \hat{w}_{00} + \hat{w}_{01} \cdot H_1 + \hat{w}_{02} \cdot H_2 + \hat{w}_{03} \cdot H_3$$



$$H_1 = \tanh(\hat{w}_{10} + \hat{w}_{11}\, x_1 + \hat{w}_{12}\, x_2)$$

$$H_2 = \tanh(\hat{w}_{20} + \hat{w}_{21}\, x_1 + \hat{w}_{22}\, x_2)$$

$$H_3 = \tanh(\hat{w}_{30} + \hat{w}_{31}\, x_1 + \hat{w}_{32}\, x_2)$$

input layer | hidden layer | target layer

Prediction Illustration: Neural Networks

1. Standardize (scale) the input variables.

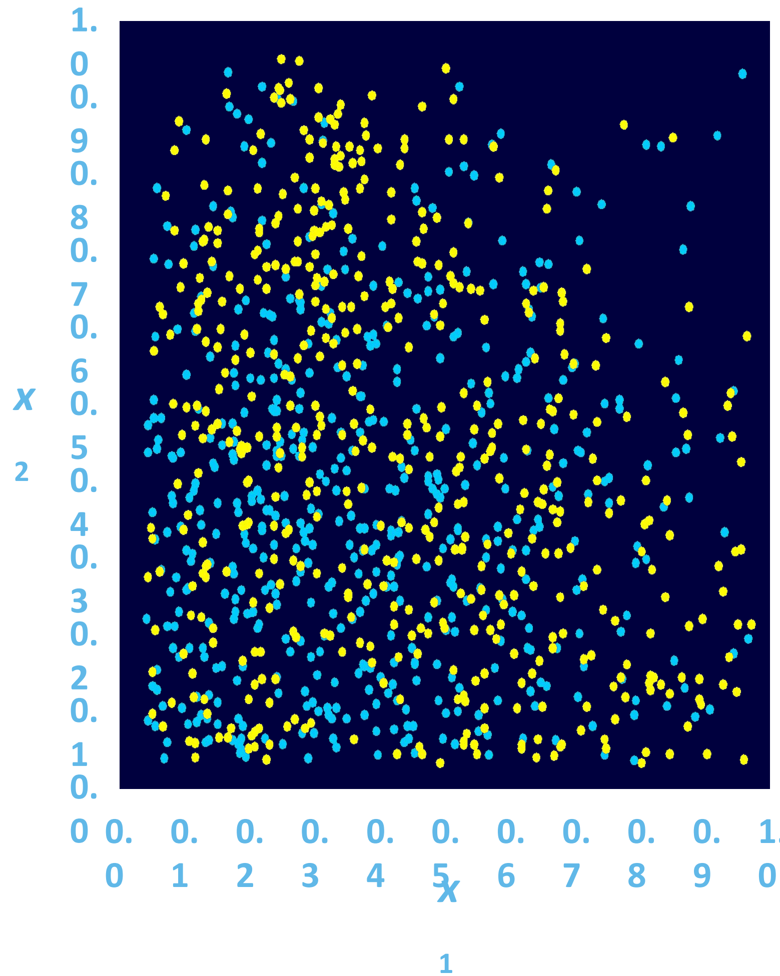
logit

$$\mathrm{logit}(\hat{p}) = \hat{w}_{00} + \hat{w}_{01} \cdot H_1 + \hat{w}_{02} \cdot H_2 + \hat{w}_{03} \cdot H_3$$

$$H_1 = \tanh(\hat{w}_{10} + \hat{w}_{11}\, x_1 + \hat{w}_{12}\, x_2)$$

$$H_2 = \tanh(\hat{w}_{20} + \hat{w}_{21}\, x_1 + \hat{w}_{22}\, x_2)$$

$$H_3 = \tanh(\hat{w}_{30} + \hat{w}_{31}\, x_1 + \hat{w}_{32}\, x_2)$$



Standardization Methods

Midrange

- $midrange = \frac{(Max+Min)}{2}$
- $x_{midrange} = \frac{(x-midrange)}{range/2}$
- Midrange is 0. Half range is 1.

Z-Score

- $\mu = 0$ and $\sigma = 1$
- $x_{std} = z = \frac{x-\mu}{\sigma}$

Standardization can be defined for hidden and target layers.

Prediction Illustration: Neural Networks

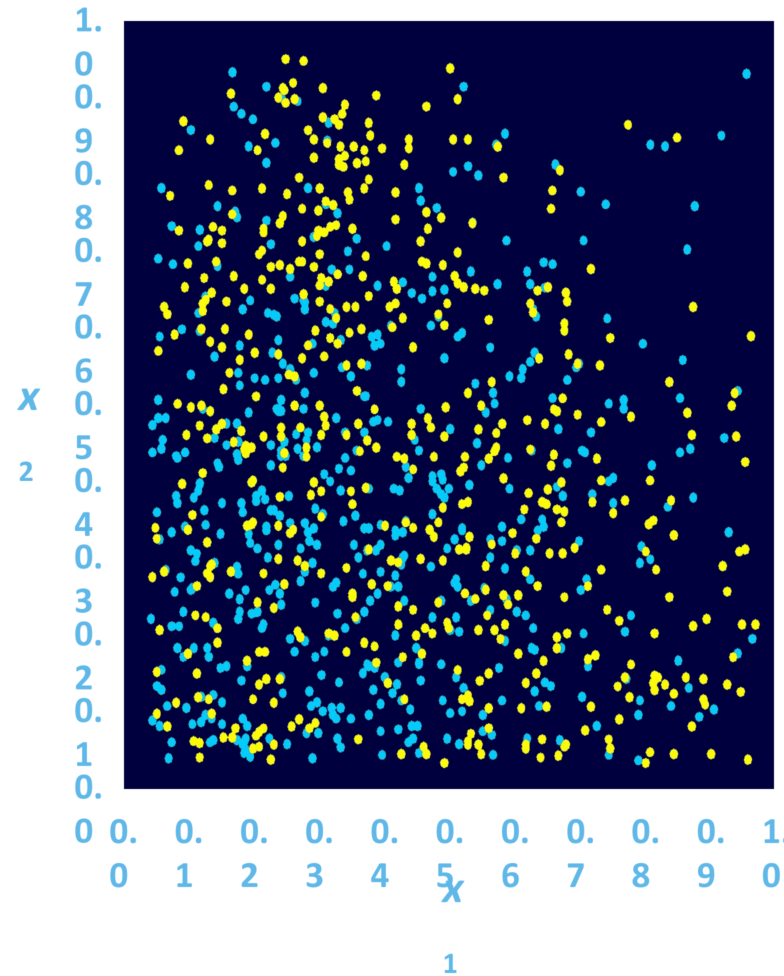
2. Find the weight estimates.

$$\text{logit}(\hat{p}) = \boxed{\hat{w}_{00}} + \boxed{\hat{w}_{01}} H_1 + \boxed{\hat{w}_{02}} H_2 + \boxed{\hat{w}_{03}} H_3$$

$$H_1 = \tanh(\boxed{\hat{w}_{10}} + \boxed{\hat{w}_{11}} x_1 + \boxed{\hat{w}_{12}} x_2)$$

$$H_2 = \tanh(\boxed{\hat{w}_{20}} + \boxed{\hat{w}_{21}} x_1 + \boxed{\hat{w}_{22}} x_2)$$

$$H_3 = \tanh(\boxed{\hat{w}_{30}} + \boxed{\hat{w}_{31}} x_1 + \boxed{\hat{w}_{32}} x_2)$$



Prediction Illustration: Neural Networks

2. Find the weight estimates.

$$\text{logit}(\hat{p}) = \hat{w}_{00} + \hat{w}_{01} H_1 + \hat{w}_{02} H_2 + \hat{w}_{03} H_3$$

$$H_1 = \tanh(\hat{w}_{10} + \hat{w}_{11} x_1 + \hat{w}_{12} x_2)$$

$$H_2 = \tanh(\hat{w}_{20} + \hat{w}_{21} x_1 + \hat{w}_{22} x_2)$$

$$H_3 = \tanh(\hat{w}_{30} + \hat{w}_{31} x_1 + \hat{w}_{32} x_2)$$

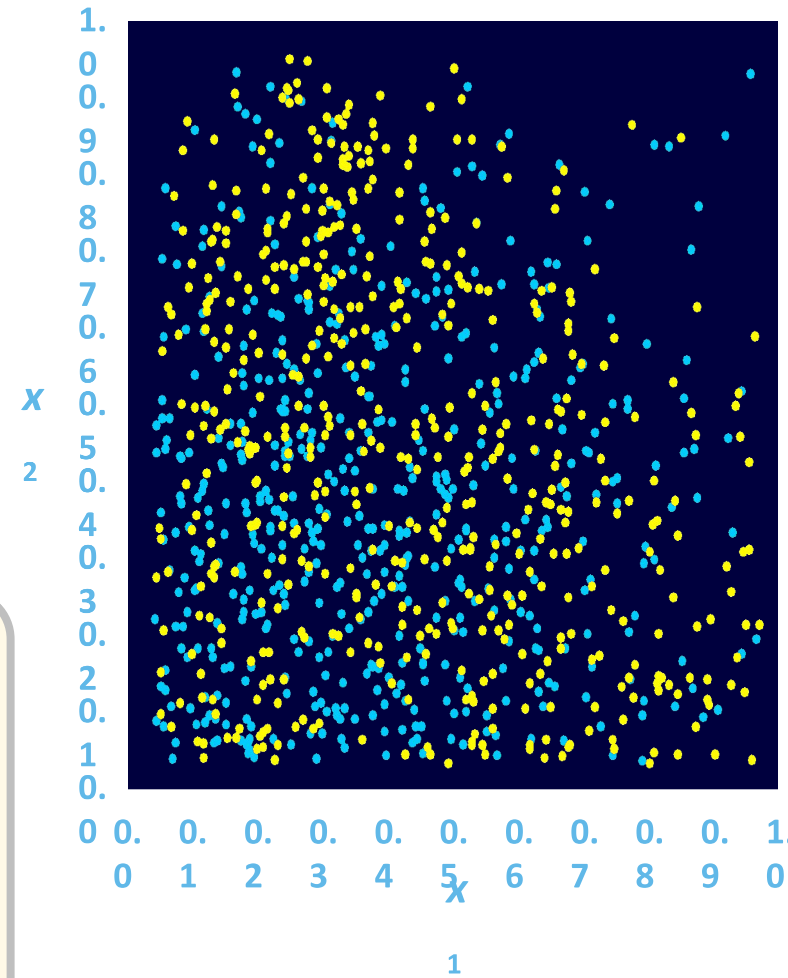
Binary Target

minimize

$$-2 \cdot \Big[\overbrace{\sum \log(\hat{p}_i) + \sum \log(1 - \hat{p}_i)}^{\text{log-likelihood function}} \Big]$$

primary outcome training cases

secondary outcome training cases



Prediction Illustration: Neural Networks

3. Obtain a prediction.

$$\text{logit}(\hat{p}) = -0.5 + -2.6\ H_1 + -1.9\ H_2 + -0.63\ H_3$$

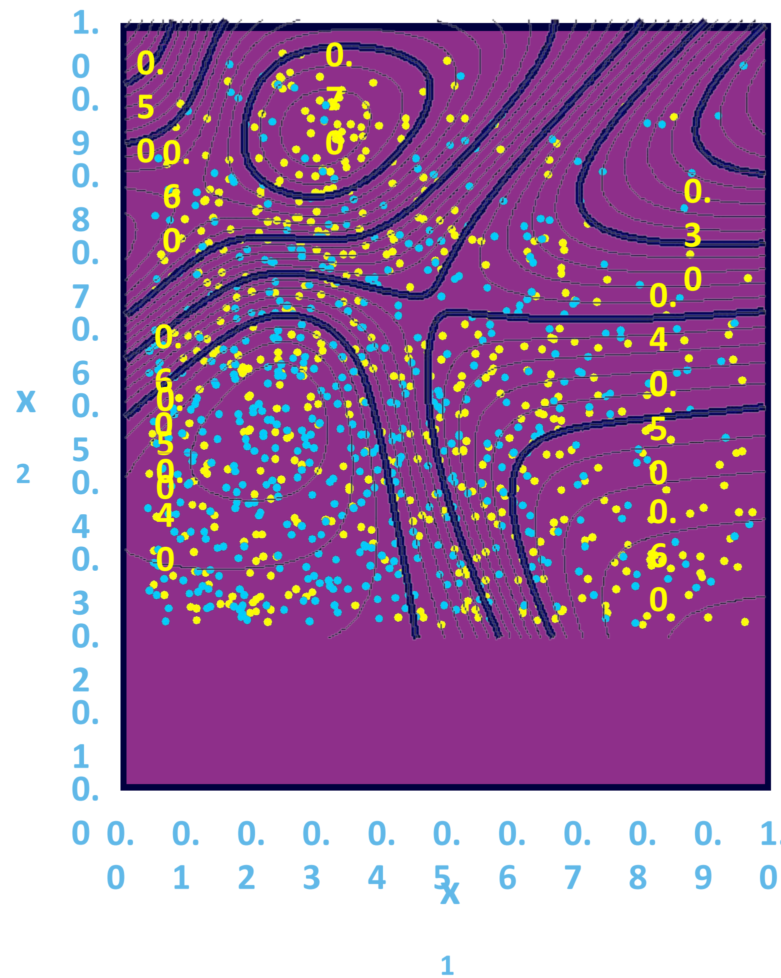
$$H_1 = \tanh(-1.8 + 0.25\ x_1 + -1.8\ x_2)$$

$$H_2 = \tanh(\ 2.7 + 2.7\ x_1 + -5.3\ x_2)$$

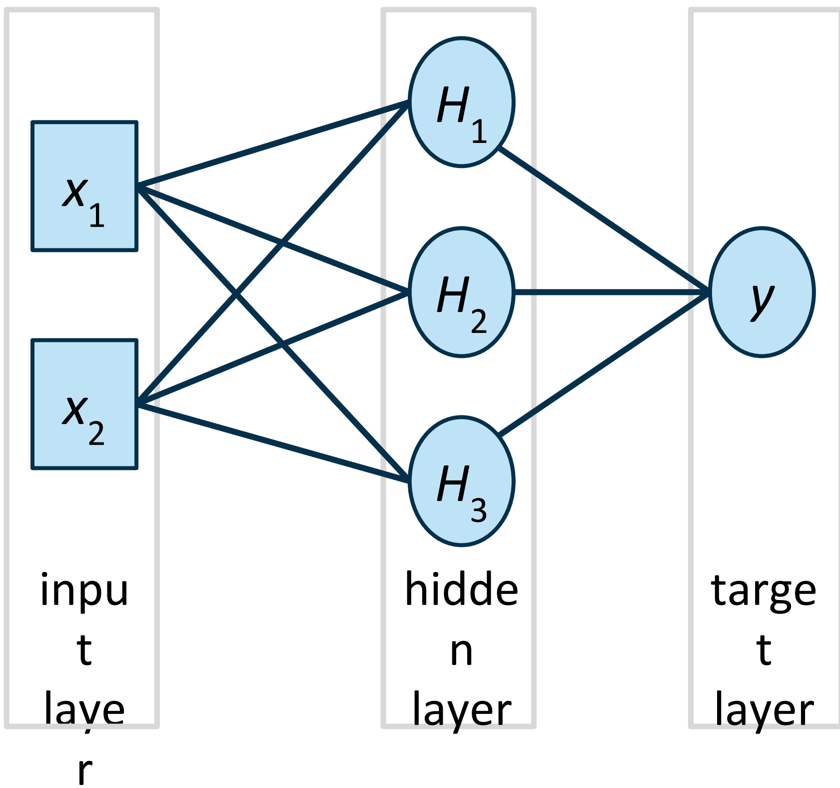
$$H_3 = \tanh(-5.0 + 8.1\ x_1 + 4.3\ x_2)$$

Logistic Function

$$\hat{p} = \frac{1}{1 + e^{-\text{logit}(\hat{p})}}$$



Network Architecture



different connection types

number of layers

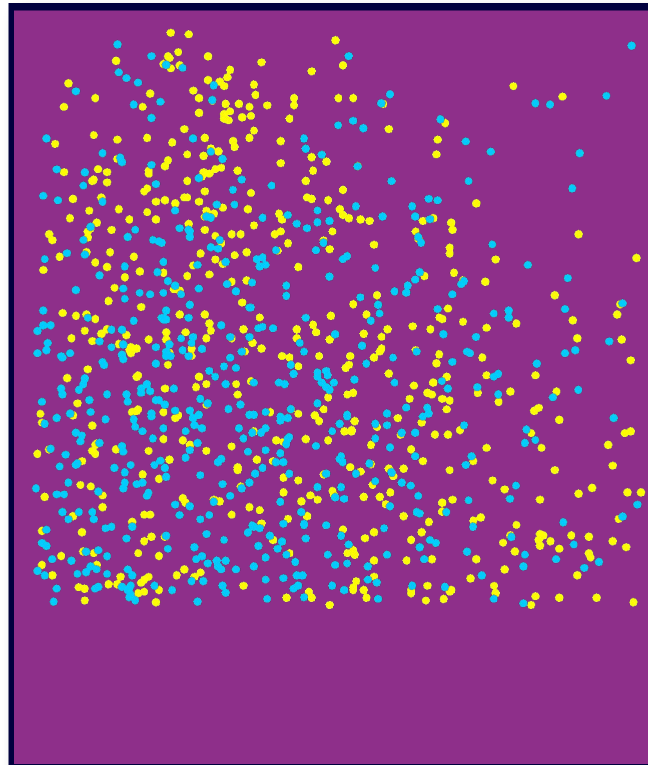
activation functions

number of neurons in each layer

Early Stopping

Initial hidden unit weights

$$\text{logit}(\hat{p}) = 0 + 0 \cdot H_1 + 0 \cdot H_2 + 0 \cdot H_3$$



Early Stopping

Initial hidden unit weights

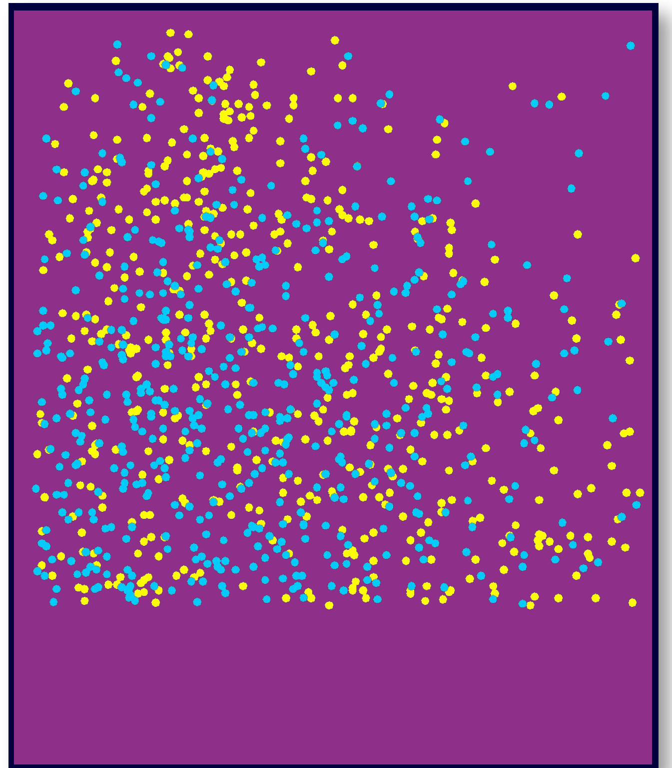
logit($\hat{p}$) = $0 + 0 \cdot H_1 + 0 \cdot H_2 + 0 \cdot H_3$

$H_1 = \tanh(-1.5 - .03x_1 - .07x_2)$

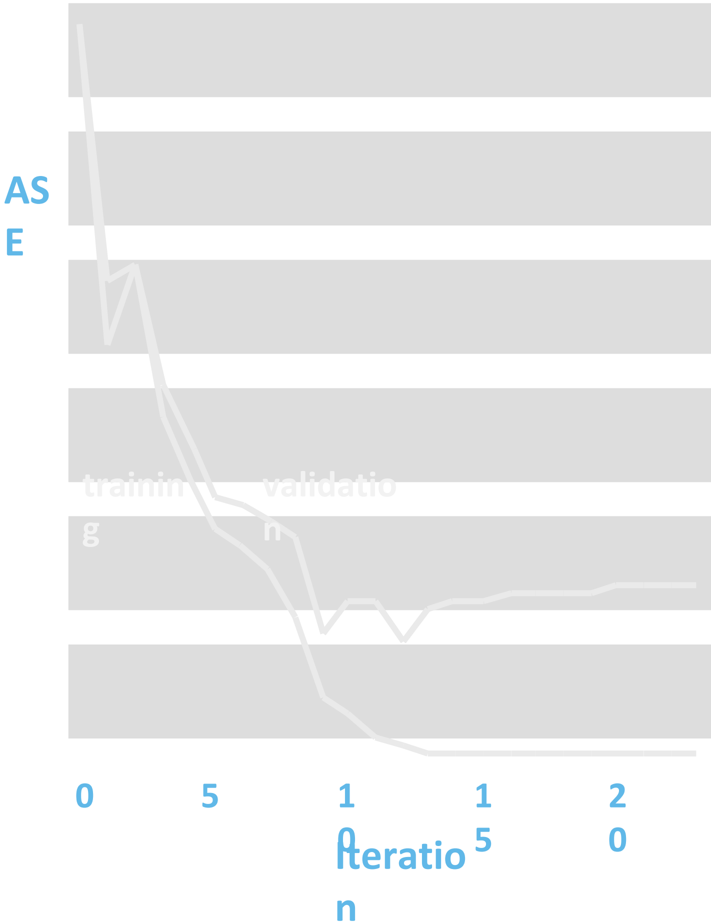
$H_2 = \tanh(.79 - .17x_1 - .16x_2)$

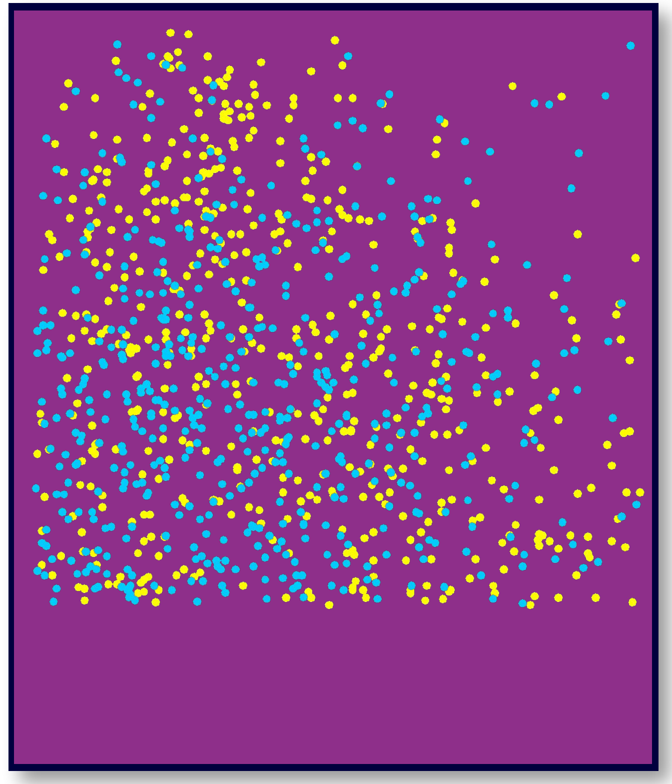
$H_3 = \tanh(.57 + .05x_1 +.35x_2)$

Random initial input weights and biases

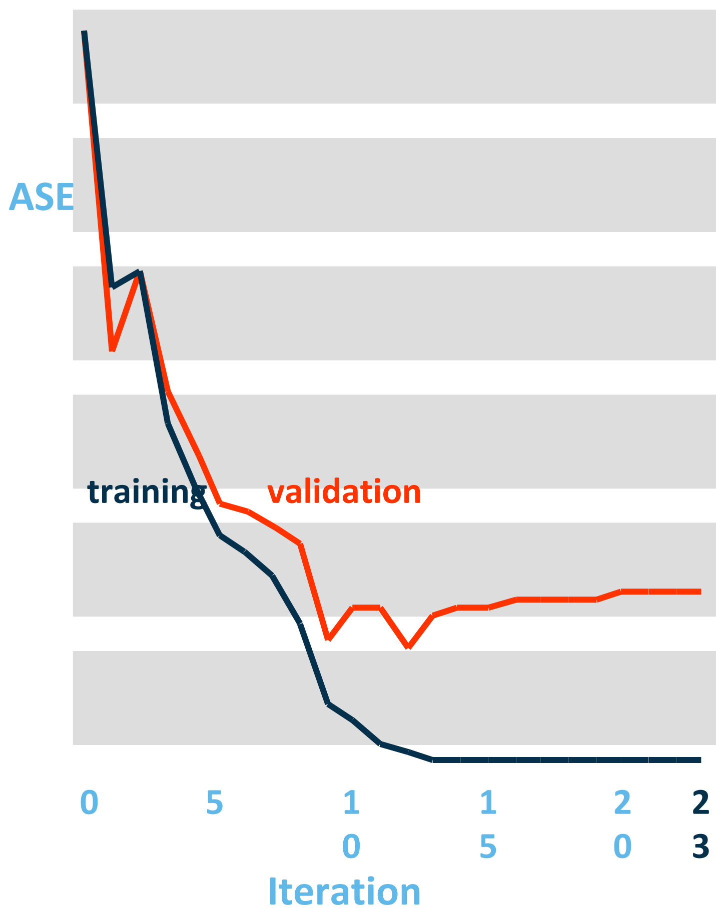


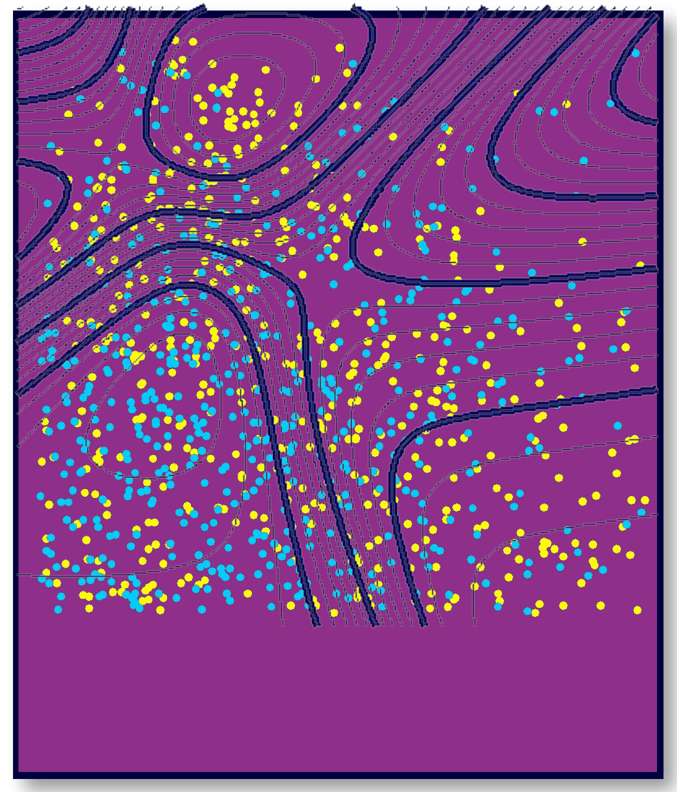
Early Stopping



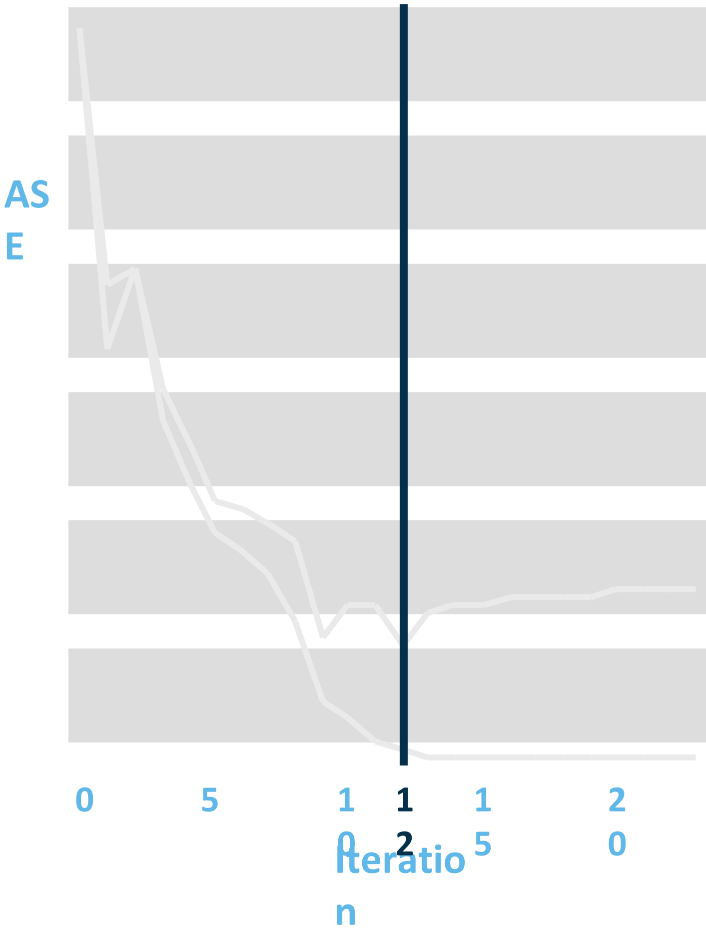


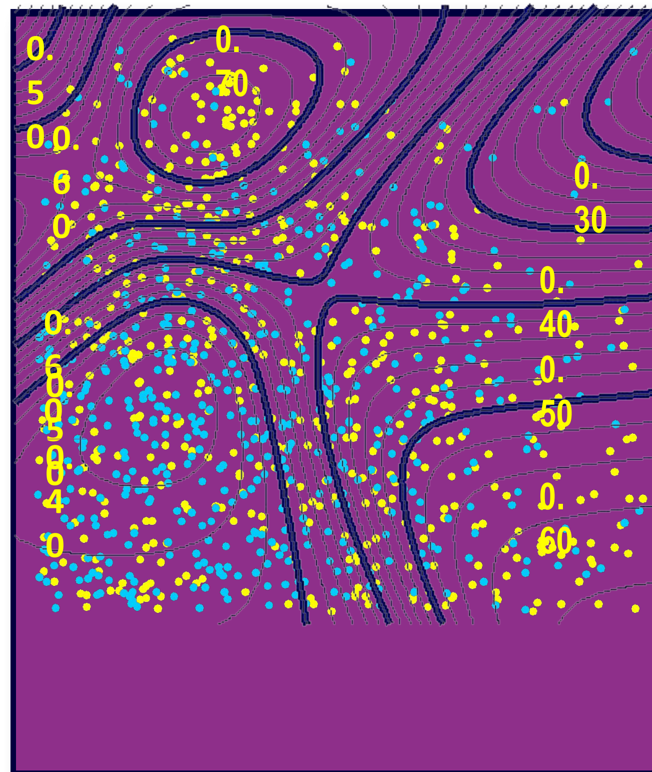
Early Stopping





Early Stopping





Parameter Estimation: Example

$$\text{logit}(\hat{p}) = \hat{w}_{00} + \hat{w}_{01} H_1 + \hat{w}_{02} H_2 + \hat{w}_{03} H_3$$

$$H_1 = \tanh(\hat{w}_{10} + \hat{w}_{11} x_1 + \hat{w}_{12} x_2)$$

$$H_2 = \tanh(\hat{w}_{20} + \hat{w}_{21} x_1 + \hat{w}_{22} x_2)$$

$$H_3 = \tanh(\hat{w}_{30} + \hat{w}_{31} x_1 + \hat{w}_{32} x_2)$$

The error function is always a deviance function.

Binary Target

minimize

$$-2 \cdot \left[\overbrace{\sum \log(\hat{p}_i) + \sum \log(1 - \hat{p}_i)}^{\text{log-likelihood function}} \right]$$

primary outcome training cases

secondary outcome training cases

Bernoulli function

Construct a NN using SKlearn

ADSUP Lesson 11 SVM

1- Construct a NN model for Organics Dataset

Practice

This practice reinforces the concepts in relation to neural network modeling. You use Model Studio to build a neural network model based on hyperparameter autotune.

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