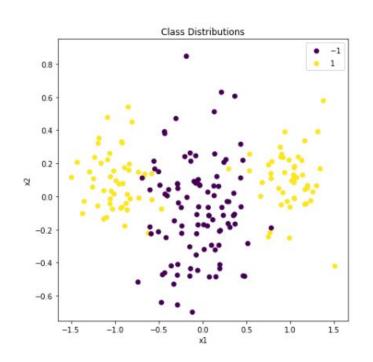
# Lab 1b Artificial Neural Networks and Deep Architectures

2 February 2023

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## Classification with a two-layer perceptron

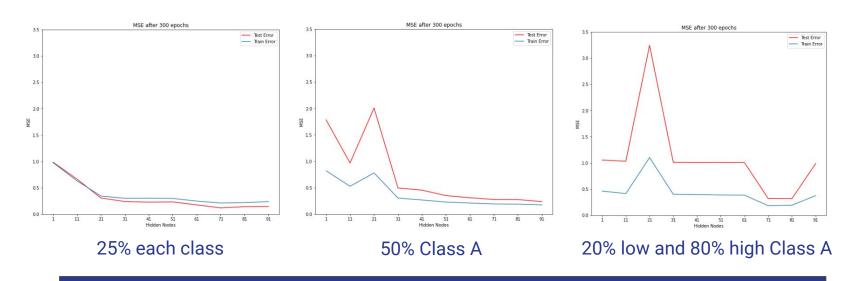


#### Non-Linearly Separable Data

2 classes drawn from three different Gaussian distributions.

|                    | Class A (1)                    | Class B (-1) |
|--------------------|--------------------------------|--------------|
| Mean               | 50% (1, 0.1),<br>50% (-1, 0.1) | (0, -0.1)    |
| Standard Deviation | 0.2                            | 0.3          |

## Train - Validation Error vs Hidden Nodes

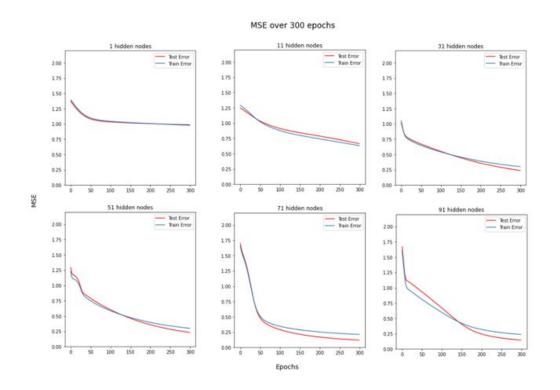


| Learning Rate | 0.001 |
|---------------|-------|
| Alpha         | 0.25  |
| Epochs        | 300   |

Error decreases as number of hidden neurons increases

For higher numbers the error starts increasing again

# Learning Curve over 300 Epochs



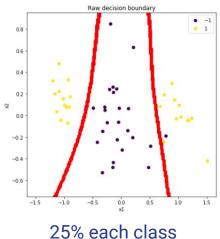
#### 25% from each class

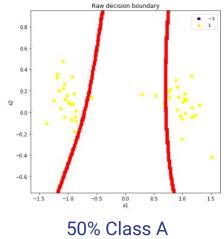
Error decreases as number of hidden neurons increases

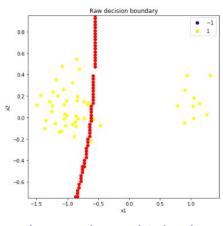
For higher numbers the error starts increasing again

MSE for 71 hidden nodes: 0.12

## Raw Decision Boundaries







5% each class 50% Class

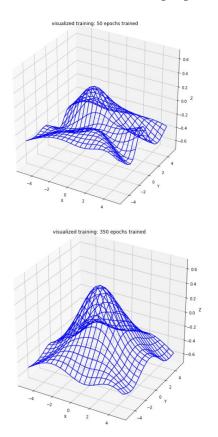
20% low and 80% high Class A

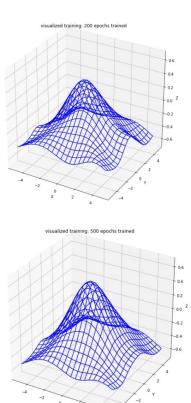
| Learning Rate | 0.001 |
|---------------|-------|
| Alpha         | 0.25  |
| Epochs        | 300   |

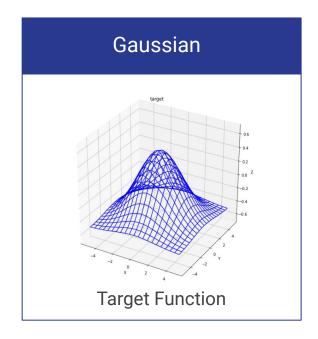
Almost perfectly classified in the test set with both classes

More errors in the unbalanced sets, especially in the last

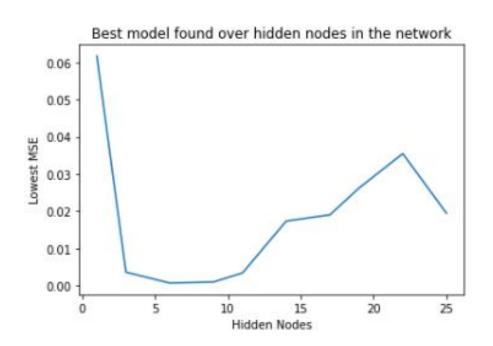
# **Function Approximation**







## Training with Different Hidden Nodes

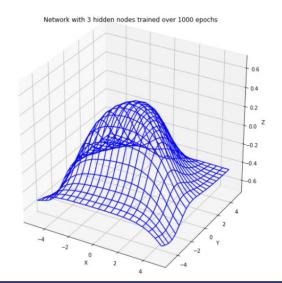


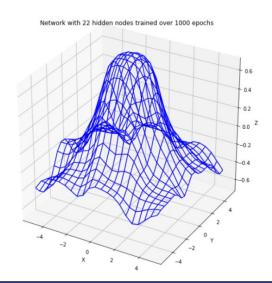
#### MSE vs Hidden Nodes

Lowest error for 6 hidden nodes

The error seems decreasing after 20 hidden nodes, but mostly due to a good initialization of weights

# Training with Different Hidden Nodes



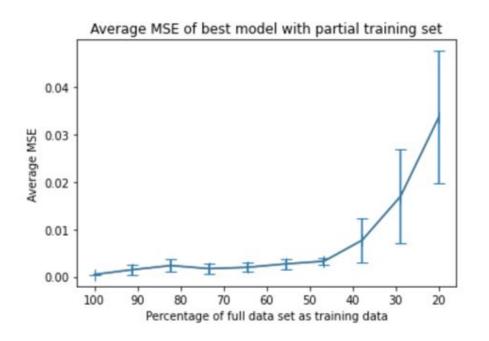


| Learning Rate | 0.01 |
|---------------|------|
| Alpha         | 0.1  |
| Epochs        | 1000 |

Too few hidden nodes don't capture the function

Too many hidden nodes bring the model to get stuck in many local minima

### **Model Generalization**



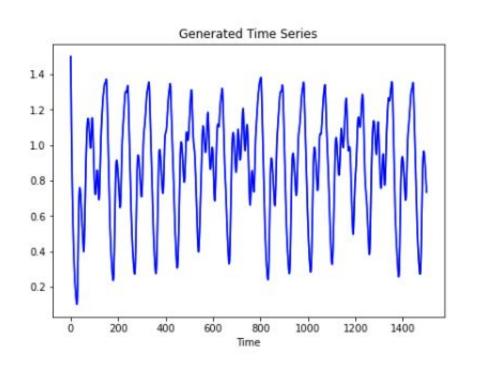
#### Best model

| Hidden Nodes | 6   |
|--------------|-----|
| Epochs       | 500 |

Consistent performance until at least 40% of the data is used for training

Less than 40% of data there are not enough to approximate the function

## **Time Series Prediction**

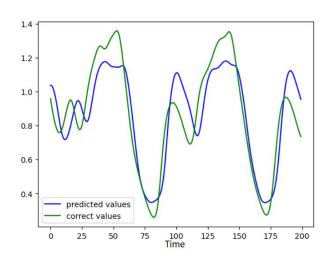


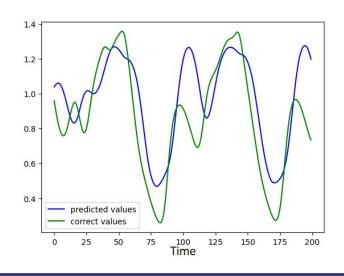
#### Time Series

Generated 1500 data points

Only 1200 will be used [301:1500]

## **Best and Worst Architectures**

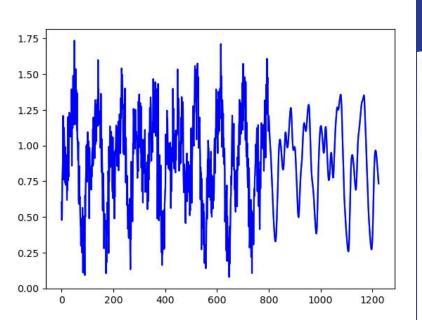




|       | Hidden Nodes | MSE   | Variance  |
|-------|--------------|-------|-----------|
| Best  | (4,2)        | 0.018 | 1.6*10e-5 |
| Worst | (3,6)        | 0.042 | 3.6*10e-4 |

Even worst architecture can still capture the overall shape of the data

# Time Series Prediction with Noisy Training Data



#### **Noisy Data**

| Hidden Nodes | $\lambda = 10^{-6}$ |                 | $\lambda = 10^{-4}$ |                 |
|--------------|---------------------|-----------------|---------------------|-----------------|
|              | $\sigma = 0.05$     | $\sigma = 0.15$ | $\sigma = 0.05$     | $\sigma = 0.15$ |
| 3            | 0.010               | 0.022           | 0.016               | 0.026           |
| 6            | 0.014               | 0.018           | 0.017               | 0.020           |
| 9            | 0.020               | 0.030           | 0.018               | 0.022           |

Increasing the regularization parameter increases the performance of complex models

It also seems better to improve it when there is more noise

## Final remarks

- Models very susceptible to randomization if few data points
- Few hidden nodes don't capture complexity, too many hidden nodes get stuck in local minima
- Increasing the regularisation parameter can be a solution to deal with more complex model or more noisy data.

# Thank you!