

6ELEN018W - Applied Robotics  
Lecture 8: Robot Control - Intelligent Control  
Algorithms

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# What is Control and Why it is Needed

- ▶ A robot needs to move its joints to achieve tasks
- ▶ A mobile robot moves to different locations

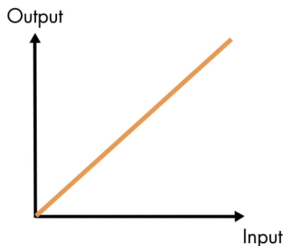
The movement of a robot (joints) is done using actuators.

In general, everything can be considered as **control**:

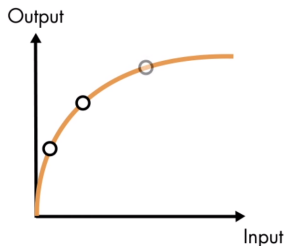
- ▶ Decisions we make affect (control) our future
- ▶ Decision while driving affect (control) the next position and the final location
- ▶ Control theory is a big area used not only in engineering and robotics, but in computer science
- ▶ Can be seen as what is the best next action to take (given a specific state) so as to achieve (optimise) specific objectives!

# Linear vs Nonlinear Systems

Linear System



Nonlinear System



- In real life all systems are nonlinear, however many of them can be linearised about their operation point.

Linear systems are easier to analyse and prove mathematically their behaviour and properties.

# Classical (Traditional) Robot Control

- ▶ Manipulators and fixed robots are very good in their operation!
- ▶ Kinematics, inverse kinematics and dynamics are well understood for fixed mechanics and robots working in the same environment.
- ▶ Their actuators are very well controlled.
- ▶ Linearity assumptions (or operation near points where their dynamics is linearised) makes it possible to analyse their behaviour and stability.

**BUT**

# Complex Systems

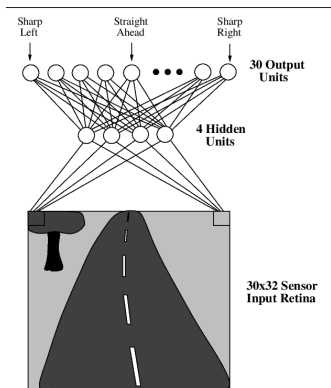
Real Life systems are complex.

- ▶ Robots which do complex work are non-linear (and their behaviour/response cannot be linearised). Impossible to control using classical methods.
- ▶ Robots need to be adaptive and be able to cope with unknown environments and unseen situations similarly to how humans do.
  - ▶ Robots have to be adaptive knowing what that they are going to do if encountering a partially unknown environment, a completely unknown environment or unknown difficulties.
  - ▶ We send robots to space.
- ▶ Reconfigurable Robots
  - ▶ What happens if damage happens in one of the actuators with the robot or one of their thumbs might hit an obstacle and it might lose part of it?

⇒ A new challenge: **Intelligent Control** based on intelligent algorithms.

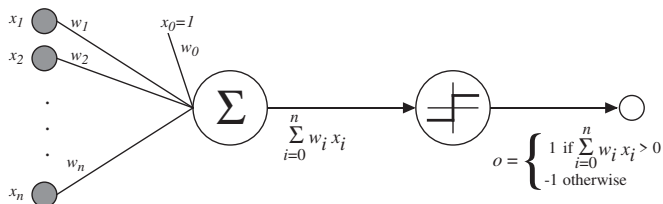
# Robot Driving a Car - Autonomous Driving

**ALVINN [Pomerleau 1989] drives 70 mph on highways**



<https://www.youtube.com/watch?v=IaoIqVMd6tc&t=71s>

# Perceptron

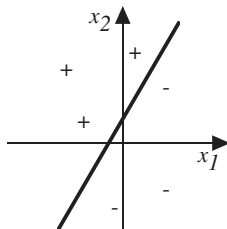


$$o(x_1, \dots, x_n) = \begin{cases} 1 & \text{if } w_0 + w_1 x_1 + \dots + w_n x_n > 0 \\ -1 & \text{otherwise.} \end{cases}$$

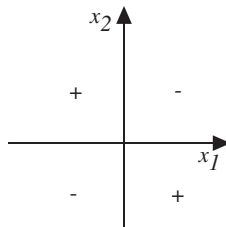
A simpler vector notation can be used:

$$o(\vec{x}) = \begin{cases} 1 & \text{if } \vec{w} \cdot \vec{x} > 0 \\ -1 & \text{otherwise.} \end{cases}$$

## Perceptron (cont'd)



(a)



(b)

Represents some useful functions

- ▶ What weights represent  $g(x_1, x_2) = AND(x_1, x_2)$ ?

But some functions are not representable with a single layer of neurons.

- ▶ e.g., not linearly separable (such as the XOR function)



# Perceptron training rule

$$w_i \leftarrow w_i + \Delta w_i$$

where

$$\Delta w_i = \eta(t - o)x_i$$

Where:

- ▶  $t = c(\vec{x})$  is target value
- ▶  $o$  is perceptron output
- ▶  $\eta$  is small constant (e.g., .1) called *learning rate*

Can prove it will converge:

- ▶ If training data is linearly separable
- ▶ and  $\eta$  sufficiently small

# Gradient Descent

To understand, consider simpler *linear unit*, where

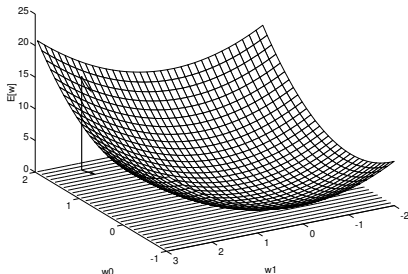
$$o = w_0 + w_1x_1 + \cdots + w_nx_n$$

Let's learn  $w_i$ 's that minimise the squared error

$$E[\vec{w}] \equiv \frac{1}{2} \sum_{d \in D} (t_d - o_d)^2$$

where  $D$  is set of training examples

## Gradient Descent (cont'd)



Gradient

$$\nabla E[\vec{w}] \equiv \left[ \frac{\partial E}{\partial w_0}, \frac{\partial E}{\partial w_1}, \dots, \frac{\partial E}{\partial w_n} \right]$$

Training rule:

$$\Delta \vec{w} = -\eta \nabla E[\vec{w}]$$

i.e.,

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i}$$

## Calculating the Derivative

$$\begin{aligned}\frac{\partial E}{\partial w_i} &= \frac{\partial}{\partial w_i} \frac{1}{2} \sum_d (t_d - o_d)^2 \\&= \frac{1}{2} \sum_d \frac{\partial}{\partial w_i} (t_d - o_d)^2 \\&= \frac{1}{2} \sum_d 2(t_d - o_d) \frac{\partial}{\partial w_i} (t_d - o_d) \\&= \sum_d (t_d - o_d) \frac{\partial}{\partial w_i} (t_d - \vec{w} \cdot \vec{x}_d) \\ \frac{\partial E}{\partial w_i} &= \sum_d (t_d - o_d) (-x_{i,d})\end{aligned}$$

# Application of Gradient Descent

Each training example is a pair of the form  $\langle \vec{x}, t \rangle$ , where  $\vec{x}$  is the vector of input values, and  $t$  is the target output value.  $\eta$  is the learning rate (e.g., .05).

- ▶ Initialise each  $w_i$  to some small random value
- ▶ Until the termination condition is met, Do
  - ▶ Initialise each  $\Delta w_i$  to zero.
  - ▶ For each  $\langle \vec{x}, t \rangle$  in *training\_examples*, Do
    - ▶ Input the instance  $\vec{x}$  to the unit and compute the output  $o$
    - ▶ For each linear unit weight  $w_i$ , Do

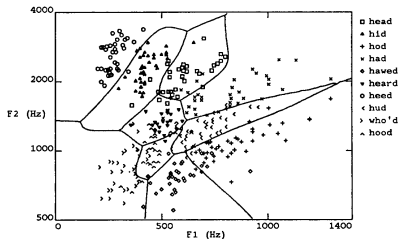
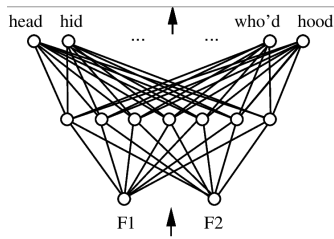
$$\Delta w_i \leftarrow \Delta w_i + \eta(t - o)x_i$$

- ▶ For each linear unit weight  $w_i$ , Do

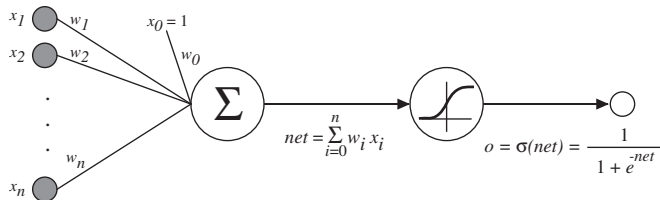
$$w_i \leftarrow w_i + \Delta w_i$$

# Multilayer Perceptrons with Hidden Layers and Sigmoid Units

To overcome the limitations of the single layer Perceptron (linear separability):



# Sigmoid Unit



$\sigma(x)$  is the sigmoid function

$$\frac{1}{1 + e^{-x}}$$

Nice property:  $\frac{d\sigma(x)}{dx} = \sigma(x)(1 - \sigma(x))$

We can derive gradient descent rules to train:

- ▶ One sigmoid unit
- ▶ *Multilayer networks* of sigmoid units  $\rightarrow$  Backpropagation

# Backpropagation Algorithm

Initialise all weights to small random numbers.

Until satisfied, Do:

- ▶ For each training example, Do
  1. Input the training example to the network and compute the network outputs
  2. For each output unit  $k$

$$\delta_k \leftarrow o_k(1 - o_k)(t_k - o_k)$$

3. For each hidden unit  $h$

$$\delta_h \leftarrow o_h(1 - o_h) \sum_{k \in \text{outputs}} w_{k,h} \delta_k$$

4. Update each network weight  $w_{i,j}$

$$w_{i,j} \leftarrow w_{i,j} + \Delta w_{i,j}$$

where

$$\Delta w_{i,j} = \eta \delta_j x_i$$



# More on Backpropagation

- ▶ Gradient descent over entire *network* weight vector
- ▶ Will find a local, not necessarily global error minimum
  - ▶ In practice, often works well (can run multiple times)
- ▶ Often include weight *momentum*  $\alpha$

$$\Delta w_{i,j}(n) = \eta \delta_j x_i + \alpha \Delta w_{i,j}(n-1)$$

- ▶ Minimises error over *training* examples
  - ▶ Will it generalise well to subsequent examples?
- ▶ Training can take thousands of iterations  $\rightarrow$  slow!
- ▶ Using network after training is very fast

# Convergence of Backpropagation

Gradient descent to some local minimum

- ▶ Perhaps not global minimum...
- ▶ Add momentum
- ▶ Stochastic gradient descent
- ▶ Train multiple nets with different initial weights

# Expressive Capabilities of ANNs

Boolean functions:

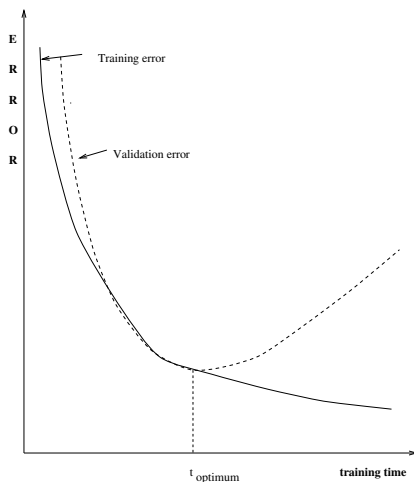
- ▶ Every boolean function can be represented by network with single hidden layer
- ▶ but might require exponential (in number of inputs) hidden units

Continuous functions:

- ▶ Every bounded continuous function can be approximated with arbitrarily small error, by network with one hidden layer [Cybenko 1989; Hornik et al. 1989]
- ▶ Any function can be approximated to arbitrary accuracy by a network with two hidden layers [Cybenko 1988].

# How to Avoid Overfitting and Improve Generalisation

Split the data into 3 sets, *training*, *testing* and *validation* and stop the training according to the following diagram.



# Tips for Using Backpropagation

- ▶ When a sigmoid is used in the output layer, use 0.9 and 0.1 instead of 1 and 0 as the targets, to avoid the saturated parts of the sigmoid function.
- ▶ Experiment with different learning rates and number of hidden nodes and layers. Do not use more than 3 hidden layers.
- ▶ Preprocess your data by scaling them in the same range. If some features (columns) are not relevant you can discard them completely.

# Using the sklearn Python module

To install:

- ▶ On your own computer (ideally in a virtual environment but this is not compulsory):  

```
pip install -U scikit-learn
```
- ▶ In the university labs the sklearn module is already installed inside Anaconda. Start the Jupyter lab application from inside Anaconda and start using it.

# An Example Using `sklearn` - The Diabetes Dataset

A well-known dataset is the diabetes dataset, used to create a neural network which can predict whether someone has diabetes.

- ▶ 442 diabetes patients
- ▶ Input variables (features): age, sex, body mass index, average blood pressure, and six blood serum measurements.

# An Example Using sklearn - The Diabetes Dataset (cont'd)

```
from sklearn.neural_network import MLPRegressor
from sklearn import datasets
from sklearn.model_selection import train_test_split

import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import mean_squared_error

# load all the data from the dataset
diabetes = datasets.load_diabetes()

# check the matrix shape (number of features and data for the inputs)
print(diabetes.data.shape)

# check the shape (number of data for targets)
print(diabetes.target.shape)

# feature (column) names
print(diabetes.feature_names)

X = diabetes.data
y = diabetes.target
```



# An Example Using sklearn - The Diabetes Dataset (cont'd)

```
# Create training/ test data split
X_train, X_test, y_train, \
    y_test = train_test_split(X, y, test_size=0.2, random_state=1)

# Instantiate MLPRegressor
nn = MLPRegressor(
    activation='relu',
    hidden_layer_sizes=(10, 10),
    alpha=0.001,
    max_iter = 10000,
    random_state=20,
    early_stopping=False
)

# Train the model
nn.fit(X_train, y_train)

# Make prediction
pred = nn.predict(X_test)

# Calculate accuracy and error metrics
test_set_rsquared = nn.score(X_test, y_test)
test_set_rmse = np.sqrt(mean_squared_error(y_test, pred))
```

# An Example Using sklearn - The Diabetes Dataset (cont'd)

```
# Print R_squared and RMSE value
print('R_squared value: ', test_set_rsquared)
print('RMSE: ', test_set_rmse)

# Predict unknown data
y_pred = nn.predict(X_test)

# plot prediction and actual data
plt.plot(y_test, y_pred, '.')

# plot a line, a perfit predict would all fall on this line
x = np.linspace(0, 330, 2)
y = x
plt.plot(x, y)
plt.show()
```

## Further Material

For other details and related material see:

Dimitris C. Dracopoulos, *Evolutionary Learning Algorithms for Neural Adaptive Control*, Springer Verlag, London, August 1997, ISBN: 3-540-76161-6.