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

Dr Dimitris C. Dracopoulos

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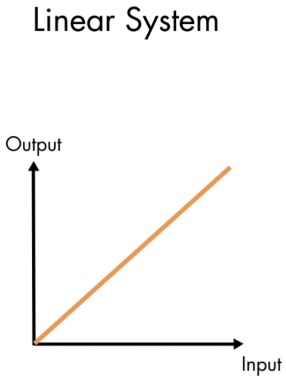
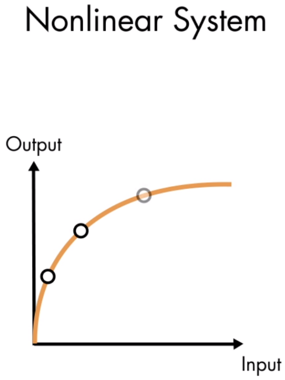
- Decision while driving affect (control) the next position and the final location
- Control theory is a big area used not only in engineering and robotics, but in computer science
- Can be seen as what is <u>the best next action to take</u> (given a specific state) so as to <u>achieve (optimise) specific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

Linear vs Nonlinear Systems

Linear vs Nonlinear Systems





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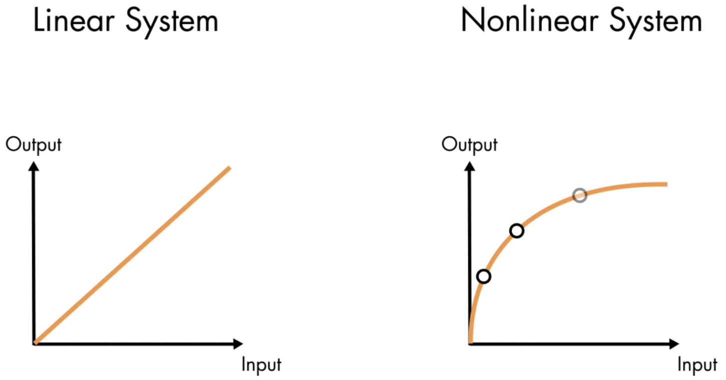

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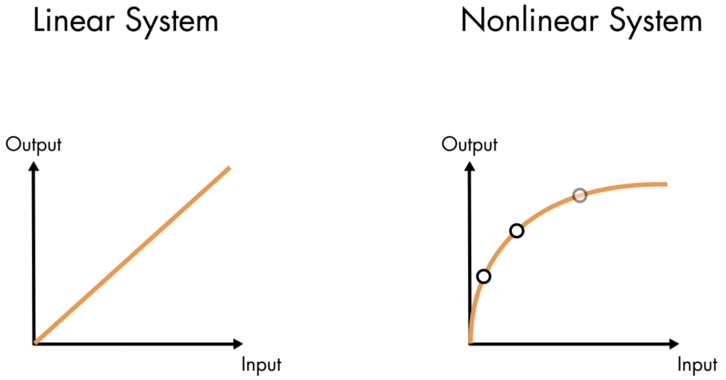

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Linear systems are easier to analyse and prove mathematically their behaviour and properties.

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$\Longrightarrow$ A new challenge: **Intelligent Control**

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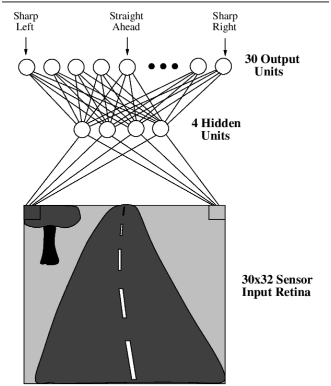
$\Longrightarrow$ A new challenge: **Intelligent Control** based on intelligent algorithms.

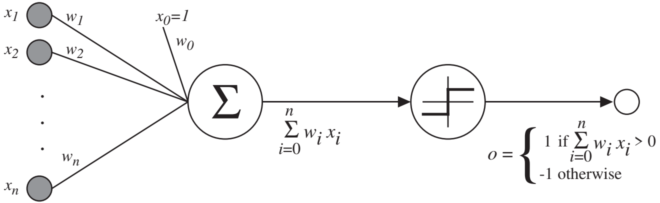
Robot Driving a Car - Autonomous Driving

ALVINN [Pomerleau 1989] drives 70 mph on highways



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

Perceptron



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

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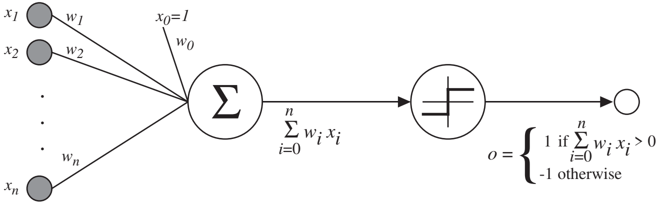

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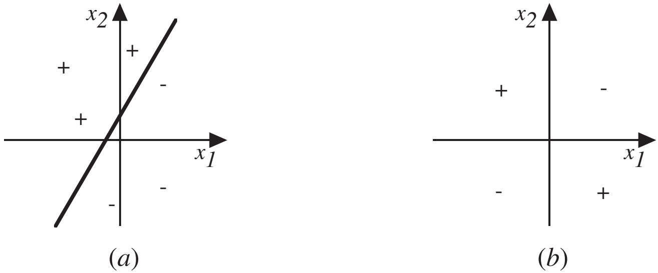
A simpler vector notation can be used:

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

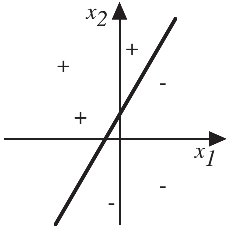
Perceptron (cont'd)



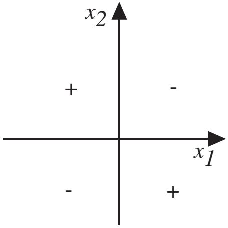
Represents some useful functions

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

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
- η is small constant (e.g., .1) called *learning rate*

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Can prove it will converge:

- If training data is linearly separable
- and η sufficiently small

Gradient Descent

To understand, consider simpler *linear unit*, where

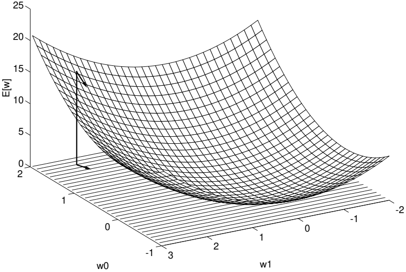
$$o = w_0 + w_1 x_1 + \cdots + w_n x_n$$

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

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

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. η is the learning rate (e.g., .05).

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- Initialise each w_i to some small random value
- Until the termination condition is met, Do
  - Initialise each Δw_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

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

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Multilayer Perceptrons with Hidden Layers and Sigmoid Units

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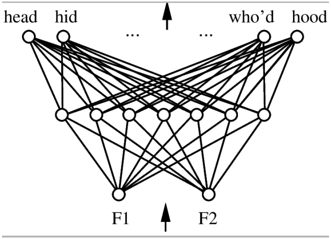
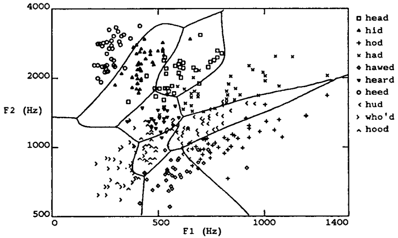
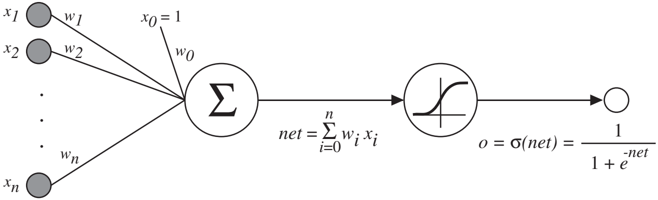




Sigmoid Unit



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

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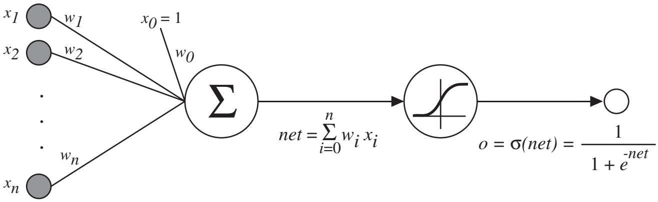

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Nice property: $\frac{d\sigma(x)}{dx} = \sigma(x)(1 - \sigma(x))$

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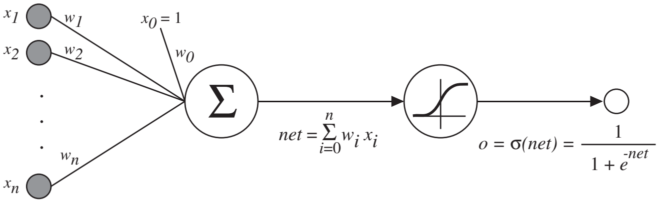

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Nice property: $\frac{d\sigma(x)}{dx} = \sigma(x)(1 - \sigma(x))$
We can derive gradient descent rules to train:

- 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

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

  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* α

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

- 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

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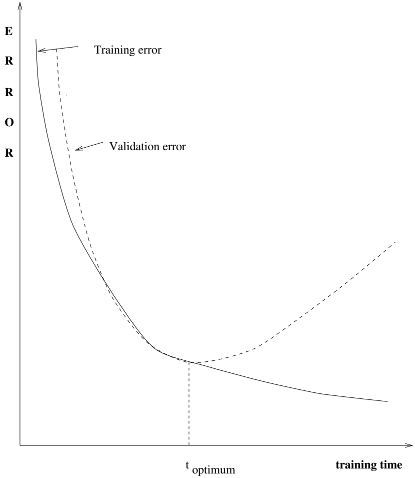
Continuous functions:

- 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.

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- 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.pylab 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.