

COMP219: Artificial Intelligence

Lecture 26: Linear Models and Non-parametric Models

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Class Test 2 Reminder

- Class test 2 will take place **next week**
 - 15th December, 15:00
 - Again, based on first letter of last name:
 - A-G → CHAD-ROTB
 - H-Z → CTH-LTA
- Procedure will be the same as last time
- The format is a mix of MCQ and written answers
- The test covers **all** context except Prolog
- Some sample questions will be discussed on Monday

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Overview

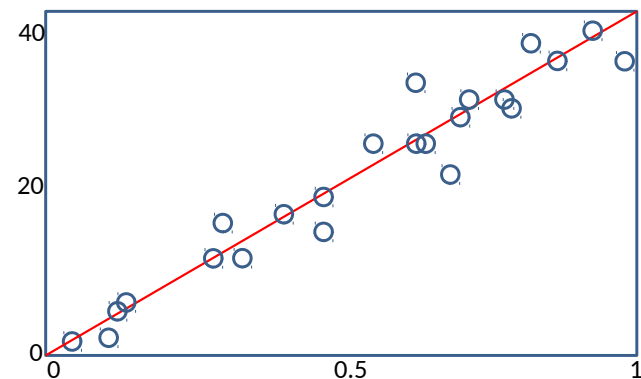
- **Last time**
 - Types of learning; supervised learning; decision trees
- **Today**
 - More supervised learning methods
 - Regression and classification with linear models
 - Non-parametric models
 - K -nearest neighbours
 - A brief look at unsupervised learning
- Learning outcomes covered today:

Identify or describe the major approaches to learning in AI and apply these to simple examples.

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Linear Models

- Linear functions of continuous valued inputs have been used for hundreds of years
- Fitting a line to a function



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Univariate Linear Regression

- The task of “fitting a straight line”
- A univariate linear function with input x and output y has the form

$$y = w_1 x + w_0$$

where w_0 and w_1 are real valued coefficients (weights) to be learned

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Fitting a Straight Line

- To fit a line to the data we have to find the values of the weights $[w_0, w_1]$ that **minimise the empirical loss**
- Typically: squared loss function summed over all the training examples

$$Loss(h_w) = \sum_{j=1}^N (y_j - (w_1 x_j + w_0))^2$$

which finds a value for the distance of each training example from the line drawn using $[w_0, w_1]$

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Linear Regression

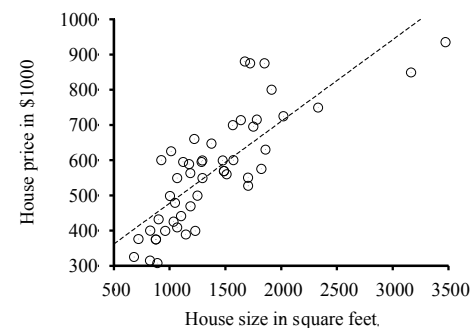
- We define \mathbf{w} to be the vector $[w_0, w_1]$ and define

$$h_{\mathbf{w}}(x) = w_1 x + w_0$$

- The task of finding the $h_{\mathbf{w}}$ that best fits the data is called **linear regression**

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Example: Houses for Sale



- Data points plot price vs floor space of houses for sale in Berkeley in July 2009
- Linear function hypothesis that minimises squared error loss:
 $y = 0.232x + 246$

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Linear Classification

- Linear functions can be used for **classification** as well as regression
- A **decision boundary** is a line that separates two classes
- A **linear** decision boundary is called a **linear separator** and data that admit such a separator are called **linearly separable**

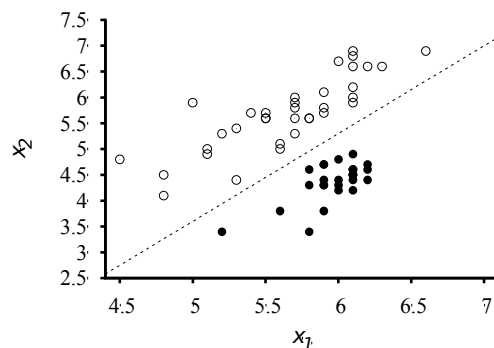
Example: Earthquake or Explosion?

- We have a training data set with information about 2 classes:
 - earthquakes (interesting to seismologists)
 - underground explosions (interesting for arms control)
- Each data point has 2 inputs (x_1, x_2) which describe body (x_1) and surface (x_2) wave magnitudes computed from a seismic signal
- The task of classification is to learn a hypothesis h that will take new data points (x_1, x_2) and return either 0 for earthquakes or 1 for explosions

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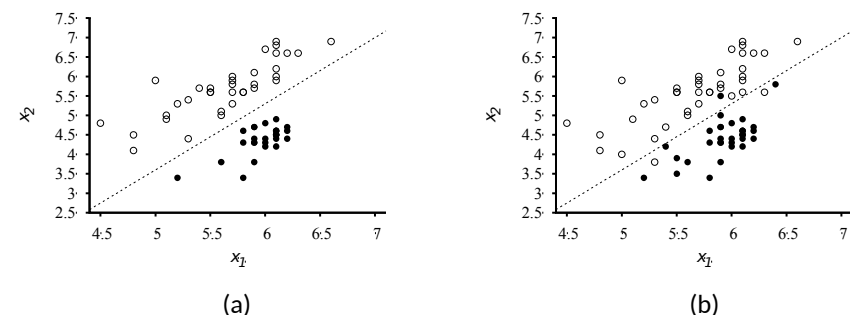
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Seismic Example continued



- Plot of two seismic data parameters for earthquakes (white circles) and explosions (black circles) and a decision boundary (**linear separator**)
- Explosions (class 1) are to the right of the line (higher x_1 and lower x_2) – the line can be thought of as a **threshold function**

Seismic Example continued



- Including more/different training data can affect the decision boundary
- In (b) above, including more data points into the same domain has meant that the earthquakes and explosions are no longer linearly separable

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Parametric Models

- Linear regression uses the training data to estimate a fixed set of parameters \mathbf{w} that defines our hypothesis $h_{\mathbf{w}}(x)$ and at that point we no longer need the training data
- A learning model that summarises data with a set of parameters of fixed size is called a **parametric model**
- No matter how much data you give a parametric model, it always needs the same number of parameters
- However, if there are a large number of examples available and the correct function is wiggly not linear, the model shouldn't be restricted to linear functions...

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Nearest Neighbour Models



Improve on table lookup with a small variation:

- **k-nearest neighbours** lookup: given x_q find the k examples that are nearest to x_q
- First **find** $\text{NN}(k, x_q)$ then...
- ...to **classify**, take the **plurality vote** of the neighbours
 - In binary classification, majority vote
 - To avoid ties, k is always odd
- ...for **regression**, take the **mean** or **median** of k neighbours

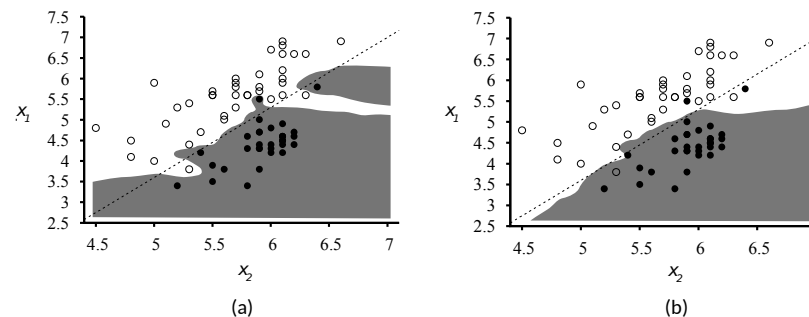
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Non-parametric Models

- **Non-parametric models** cannot be characterised by a bounded set of parameters
 - e.g.: allow to vary, then use more complex model if we have more data
- e.g. Suppose our hypothesis retains all of the training examples and uses them to predict the next example; this is non-parametric as the number of parameters is unbounded
 - This approach is called **instance-based learning**
 - Simplest method is **table lookup** – but this method does not generalise well (if x not in table, return a default value)

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Seismic Example Revisited



- (a) k -nearest-neighbour model showing the explosion class decision boundary with $k=1$ (note the **overfitting**, i.e. when a model describes noise instead of the underlying relationship)
- (b) with $k=5$ the overfitting problem is removed for this dataset

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Exercise

- Suppose a 7-nearest-neighbours regression search returns {4,2,8,4,9,11,100} as the 7 nearest y values for a given x value.
- What is the value of y ?

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Measuring Distance



- To find the nearest neighbours, we need to measure the distance between examples
- For Boolean attribute values, we measure the **Hamming distance**, i.e. number of attributes on which the two points differ
- NB: if we use the raw numbers for each attribute then the total distance is affected by a difference in scale in any dimension
 - e.g. if we change measurements from cm to miles in dimension i but keep all others the same, we will get different nearest neighbours
- Therefore we need to apply **normalisation** to the measurements in each dimension, i.e. rescale them
 - e.g. to numbers between 0 and 1

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Exercise

- Suppose a 7-nearest-neighbours regression search returns {4,2,8,4,9,11,100} as the 7 nearest y values for a given x value.
- What is the value of y ?
- Using *median*: $y=8$
- Using *mean*: $y=138/7$ i.e. 19.7

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Example: Normalisation

- To normalise height data of a group one method is to rescale the data to values between 0 and 1 using

$$x' = \frac{x - \min}{\max - \min}$$

where x is the original value and x' is the normalised value

- Example:
[155, 158, 160, 162, 164, 166, 169, 171, 172, 175]

$$\min = 155; \max = 175 \text{ so } x' = \frac{x - 155}{20}$$

Normalised data:

[0, 0.15, 0.25, 0.35, 0.45, 0.55, 0.7, 0.8, 0.85, 1]

Exercise

- Calculate the Hamming distance between the following two input points:

[T, T, T, F, F, T, T, F, T, F]

[T, F, T, F, T, F, F, F, T, T]

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Exercise

- Calculate the Hamming distance between the following two input points:

[T, T, T, F, F, T, T, F, T, F]

[T, F, T, F, T, F, F, F, T, T]

- **Solution: 5**

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Supervised Learning - Summary

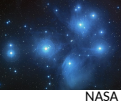
- We have looked at:
 - Decision trees
 - Linear regression
 - Linear classification
 - Non-parametric models
 - *k*-nearest neighbours

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Unsupervised Learning

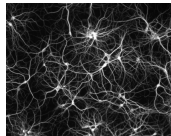
- It is not always possible to acquire example data to use to train a learning algorithm
- In unsupervised learning the agent learns patterns in the input even though no explicit feedback is supplied
- There are two complementary perspectives:
 - *Self-organisation*, which tries to understand the principles of organisation of natural systems and use them to create efficient algorithms (e.g. Kohonen self-organising maps)
 - *Statistical approach*, which tries to extract the most relevant information from the distribution of unlabelled data (**clustering**)

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Self-Organisation

- Self-organisation is observed in a wide range of natural processes
 - *Physics*: formation of crystals, star formation, chemical reactions,...
 - *Biology*: folding of proteins, social insects, flocking behaviour, brain functioning,...
 - *Social science*: critical mass, group thinking, herd behaviour,...
 - *Computer science*: cellular automata, multi-agent systems, random graphs,...



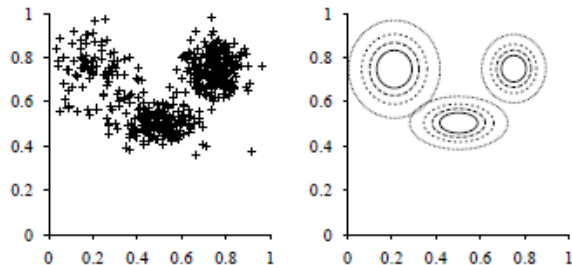
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Clustering and its applications

- **Clustering** is the problem of detecting potentially useful and *distinct* clusters/categories in a collection of unlabelled objects
 - e.g. suppose we record the spectra of 100,000 stars. Astronomers have to perform unsupervised clustering to identify categories of stars (e.g. “red giant”, “white dwarf”)
- Example applications:
 - *Marketing*: group customers on properties and buying records
 - *Finance*: fraud detection
 - *Counter-terrorism*: identifying groups from Internet usage
 - *Insurance*: identifying high cost and fraudulent policy holders
 - *City planning*: group houses according to their type, value and location
 - *Earthquake studies*: identify dangerous zones
 - *WWW*: document classification, weblog data of access patterns

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Clustering



- Shows 500 data points each with 2 continuous attributes (e.g. stars with spectral intensities at 2 different frequencies)
- Model shows 3 clusters

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Summary

- More on supervised learning
 - Regression and classification with linear models
 - Non-parametric models
 - *k*-nearest neighbours
- Unsupervised learning
 - Clustering
- **Next time**
 - Reinforcement models

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