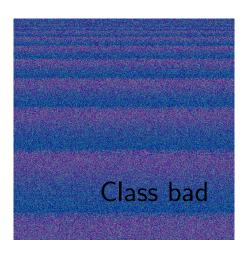
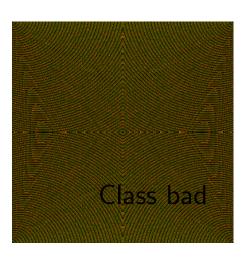
EXAMPLE OF ATTRIBUTE SELECTION 1









- Which attributes (features) are important in telling the difference between bad and good?
 - 1. Compute a set of potentially useful features for each image
 - 2. Perform feature selection using all weka methods
 - 3. The most frequently occurring features can be associated with aesthetic value.

EXAMPLE OF ATTRIBUTE SELECTION 2

| Feature | Description | | | | | |
|----------------|--|--|--|--|--|--|
| F02 | Earth Mover Distance from unsaturated grey | | | | | |
| | (Colourfulness) | | | | | |
| F01, F03 - F07 | Average hue, saturation, brightness on all pixels and | | | | | |
| | the pixels in the centre of the image | | | | | |
| F08 - F19 | Various wavelet functions used to compute levels of | | | | | |
| | smoothness on different scales | | | | | |
| F20 - F21 | Image dimensions (width+height, width/height) | | | | | |
| F22 | The number of contiguous regions based on colour | | | | | |
| | similarity larger than $1/100$ th of the total number of | | | | | |
| | pixels in the image | | | | | |
| F23 - F37 | Average hue, saturation and brightness for each of the | | | | | |
| | 5 largest contiguous regions of similar colours | | | | | |
| F38 - F42 | Size in pixels of each of the 5 largest regions of similar | | | | | |
| | contiguous colours divided by the total number of pixels | | | | | |
| | in the image | | | | | |
| F43 - F44 | Two variations on the measure of complimentary | | | | | |
| | colours | | | | | |
| F45 - F49 | The location in the image of the centre of each of the | | | | | |
| | 5 largest contiguous regions of similar colours | | | | | |
| F50 - F52 | Depth of field effect (emulating telephoto lens zoom) | | | | | |
| | on each of the hue, saturation and brightness channels | | | | | |

MOST IMPORTANT ATTRIBUTES

| CFS | Gain | Info | OneR | Relief | Symmetric | Wrapper |
|-----|-------|------|------|--------|-----------|---------|
| | Ratio | Gain | | | Uncert | |
| F01 | F30 | F25 | F25 | F04 | F30 | F04 |
| F04 | F29 | F41 | F41 | F07 | F45 | F18 |
| F07 | F27 | F40 | F26 | F41 | F39 | F21 |
| F13 | F34 | F39 | F39 | F25 | F29 | F31 |
| F16 | F28 | F42 | F40 | F24 | F35 | F36 |
| F25 | F45 | F44 | F38 | F03 | F42 | F41 |
| F30 | F33 | F37 | F31 | F06 | F27 | |
| F37 | F12 | F43 | F01 | F01 | F34 | |
| F39 | F39 | F45 | F04 | F13 | F37 | |
| F40 | | F38 | F07 | F16 | F25 | |
| F42 | | | | | | |
| F45 | | | | | | |

Number of occurrences

5 F39 5 F25 4 F41 4 F04 3 F45 3 F42 3 F40 3 F37 3 F30 3 F07 3 F01

• Golden Nugget. Only colour features are being used, no texture features.

EXAMPLE OF ATTRIBUTE SELEC

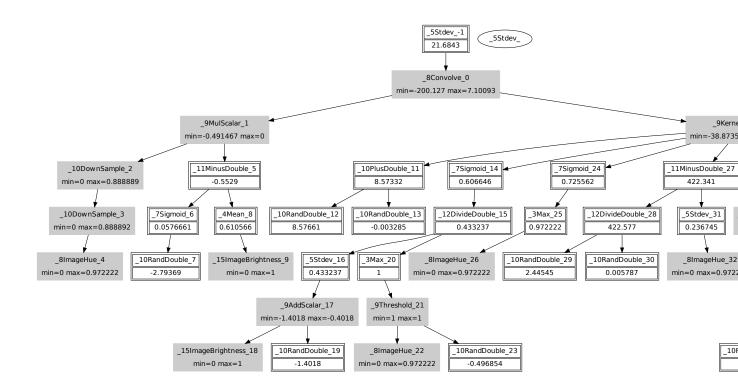
Classification accuracy of selected feature

| Classifier | Full | CFS | GainRatio | InfoGain | OneR | Re |
|---------------|------|-----|-----------|----------|------|----|
| OneR | 72 | 71 | 71 | 72 | 72 | 7: |
| J48 | 87 | 88 | 75 | 88 | 87 | 8 |
| Random Forest | 91 | 92 | 77 | 88 | 88 | 9 |
| SMO | 89 | 83 | 55 | 79 | 79 | 8 |

Classification accuracy of EVOLVED featu

| Classifier | Accuracy |
|---------------|----------|
| OneR | 80.3% |
| J48 | 89.7% |
| Random Forest | 91.8% |
| SMO | 89.9% |

AN EVOLVED FEATURE



PREPARATION OF DATA FOR DATA MINING

- This lecture will be based on the files in: /KDrive/SEH/SCSIT/Students/Courses /COSC2111/DataMining/
 - data/parking_duration_of_parking_event_vs_street_ID.csv
 This is a file of 12,208,179 parking events in the city of Melbourne.
 - data/parking-small.csv
 This is a random subset of 10,000 events
 - code-and-scripts/parking-time.sh
 This is a script for taking the arrival date-time and generating useful features for data mining.
- Some typical data Arrival Time 24/08/2012 11:34 17/03/2012 13:07 7/12/2011 19:50 3/03/2012 14:36 29/1/2012 12:26

PREPARATION OF DATA FOR DATA MINING

Very bad

- EXCEL or other spreadsheet
- Your favourite editor
- Interactive manual steps

• Why?

- The procedure always needs to be done several times
- Repeated manual steps introduce error
- Little value in learning from erroneous data

Very good

- Data preparation script that can be executed repeatedly and independently verified for correctness
- Uses mature utility programs

UNIX TOOLS FOR DATA MINERS

- Minimum requirement
 - cat, head, tail, cut, grep, pr, paste, sort, uniq,
 tr
 - Substitution with sed
 - Basic shell scripting
- To be an expert
 - Regular expressions
 - Advanced sed
 - Advanced shell scripting
 - awk or perl or python
- On a windows PC, install CYGWIN or equivalent
 Windows 10 has Ubuntu
 Mac has terminal

UNIX AND XWINDOWS ON UNIX SERVERS

- 1. Read the basic unix guide (Canvas week 6)
- 2. Use putty with X connection
- 3. On RMIT servers run xeyes to verify X connection
- 4. On RMIT servers start xclock to avoid timeout
- 5. putty demo

Important Unix tools

```
cat file1 file2 file3
Concatenate files to standard output
head -n 100 file
Send the first 100 lines to stdout
tail -n 10 file
Send the last 10 lines to stdout
cut -d',' -f7 file
Send col 7 to stdout
sed -e's/from/to/'|
Stream editor: replace first occurrence in
a line from with to
sed -e's+from+to+g'
replace all occurrences from with to
paste -d, col1 col2 col3
merge lines of files col1 col2 col3
fgrep str file
Get regular [fixed] expression
Send only lines that contain str to stdout
egrep -e'RE' file
Send only lines that contain the regular expression
RE to stdout
```

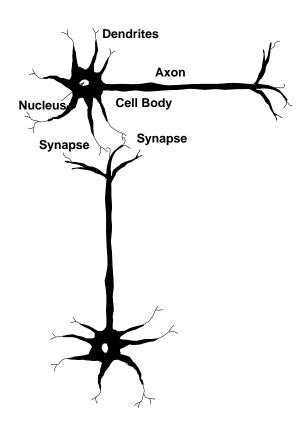
tr ' ',' file
Translate characters
Change all occurrences of space to comma

tr -d'\r' file
Delete all occurrences of the return character
sort file
Sort
uniq file
Omit or count repeated lines
wc -l file
Word count, count lines (-l)

NEURAL NETWORKS SUMMARY

- 1. Introduction
- 2. Biological origins
- 3. Computational neuron
- 4. Overview of architectures
- 5. Feed forward networks
- 6. Training of networks (JavaNNS Package)
- 7. Data encoding/preparation

BIOLOGICAL NEURON



- The neuron receives impulses (signals) from other neurons via dendrites
- The neuron sends impulses to other neurons via the axon
- Input at dendrite, output from axon
- Synapse: dendrite of one neuron and axon of another
- Impulses cause neurotransmitters (chemicals) to diffuse across the synapse
- Enhance (excite) or inhibit
- Action adjusted (by learning?)

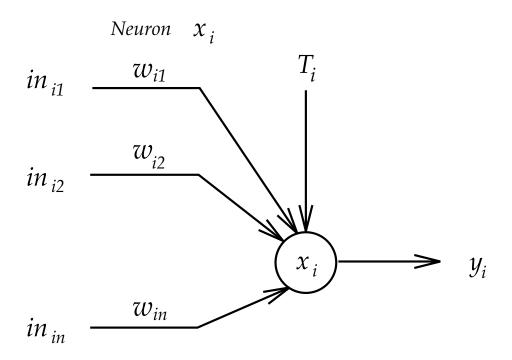
CEREBRAL CORTEX

- ullet Contains 10^{11} neurons = no. stars in Milky Way
- Neurons massively connected
- ullet Each neuron is connected to 10^3 to 10^4 other neurons
- Much more complex and dense than telephone network
- ullet Brain contains 10^{14} to 10^{15} connections
- Brain message passing is 1,000,000 times slower than modern electronic circuits
- A complex decision like recognizing a face takes a few hundred milliseconds
- Operational speed of neurons is a few millisecon
- Thus computations cannot take more than 100 serial stages
- One hundred step rule

KINDS OF ARTIFICIAL NEURAL NETWORKS

- There are a very large number of network types
 - Hopfield
 - Hebbian
 - Recurrent
 - Radial Basis Functions
 - Kohonen self organizing map
 - **–** . . .
- We look only at the most frequently used types
 - Feed forward multi-layer perceptron with
 - with logistic OR linear threshold units
 - trained by backward error propagation

ARTIFICIAL NEURON



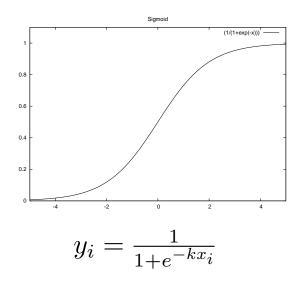
• Computation carried out by the neuron

$$x_{i} = \sum_{j=1}^{n} w_{ij} i n_{ij} + T_{i}$$
$$y_{i} = transfer function(x_{i})$$

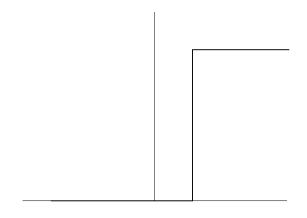
- Transfer function is usually non-linear
- \bullet T_i
 - Threshold
 - also called the bias
 - sometimes written w_0

COMMON TRANSFER FUNCTIONS

Sigmoid/Logistic

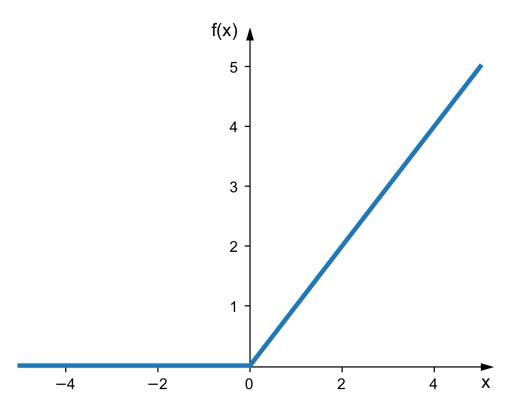


Threshold



 $if \ x < t \ then \ 0 \ else \ 1$

DEEP NETWORK ACTIVATION FUNCTION



ReLU (Rectified linear Unit)

$$y_i = 0 \text{ for } x \leq 0$$

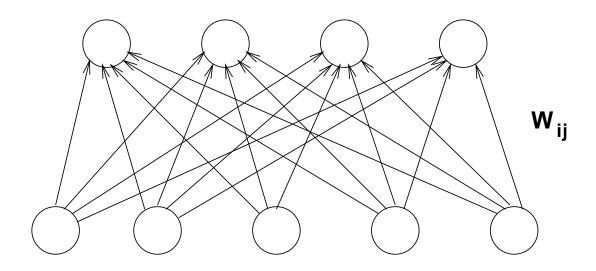
$$y_i = x \text{ for } x < 0$$

https://sebastianraschka.com/faq/docs/relu-derivative.html

ANN ARCHITECTURE 1

(Non data mining application)

Output Pattern



Input Pattern

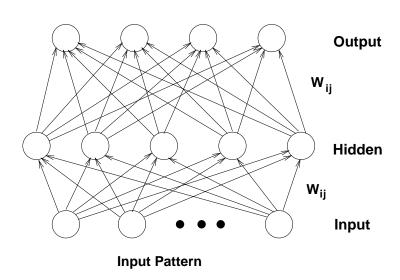
- Two layer network [One layer of weights]
- Could be used for associative memory
- Encodes $((A_1, B_1), (A_2, B_2), ...(A_k, B_k))$
 - Put in a picture of a person, get out a name
 - Put in a partial/smudged picture, get out the full, clean picture
 - Put in a noisy audio signal, get out the clean sound
- Neural networks are particulary good at dealing with noisy, erroneous or incomplete patterns.

ANN ARCHITECTURE 2

- Feed Forward Network
- Can operate as a pattern classifier

Digits in Ascii Underwater Weather
Postcode Text Object Predicition

Output Pattern



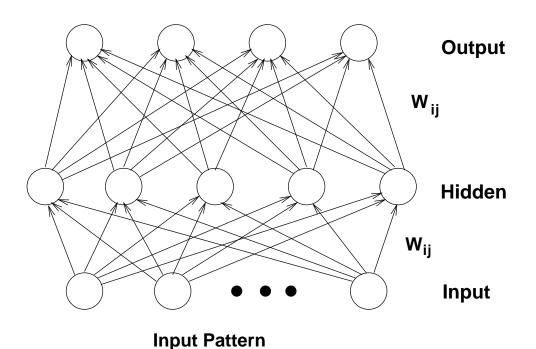
Picture of an Speech Sonar Weather Envelope Waveform Signal Data

ANN ARCHITECTURE 3

- Feed Forward Network
- Function Approximator/Time series predictor

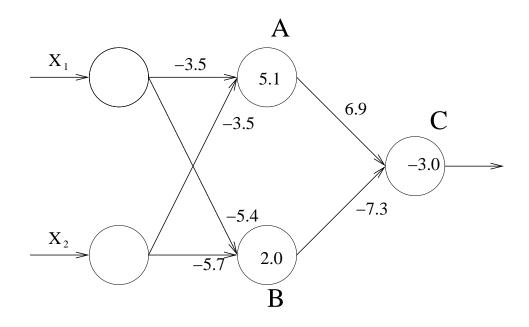
Prediction of Prediction of Survival Amount activity stock price months Rain

Output Pattern



Sunspot Stockmarket Heart attack Weather Time Series Time Series Data Data

NETWORK EXAMPLE



- ullet Suppose the input is $X_1=0, X_2=0$
 - Output from node A: $0 \times (-3.5) + 0 \times (-3.5) + 5.1 = 5.1$ logistic(5.1) = 0.99
 - Output from node B: $0\times (-5.4) + 0\times (-5.7) + 2.0 = 2.0 \\ logistic(2.0) = 0.88$
 - Output from node C: $0.99 \times 6.9 + 0.88 \times (-7.3) + (-3.0) = \\ 6.83 6.42 3.0 = -2.59 \\ logistic(-2.59) = 0.06$
- Output of network is 0.06

ANN FOR XOR

• Truth table for Exclusive OR (XOR)

| $\overline{X_1}$ | X_2 | Output |
|------------------|-------|--------|
| 0 | 0 | 0 |
| 0 | 1 | 1 |
| 1 | 0 | 1 |
| 1 | 1 | 0 |

• If each of these examples/patterns is input to the network

| $\overline{X_1}$ | X_2 | Desired | Actual | Error | Squared |
|------------------|-------|---------|--------|-------|---------|
| | | Output | Output | | Error |
| 0 | 0 | 0 | 0.06 | 0.06 | 0.0036 |
| 0 | 1 | 1 | 0.92 | 0.08 | 0.0064 |
| 1 | 0 | 1 | 0.92 | 0.08 | 0.0064 |
| 1 | 1 | 0 | 0.10 | 0.10 | 0.01 |

• Total sum squared error (TSS) for n patterns $\sum_{i=1}^{n} (Desired_i - Actual_i)^2$ = 0.0264

Mean squared error (MSE) TSS/n = 0.0264/4 = 0.066

• TSS or MSE is plotted during training