A Neuron for Classification

Introduction to Neural Networks

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Høgskolen i Ålesund

February 2, 2015

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Outline

1. Subject overview
2. Classification Problems
3. Machine learning
4. The neuron as classifier
5. Training the Neuron
6. Summary

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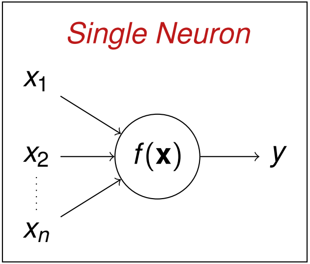
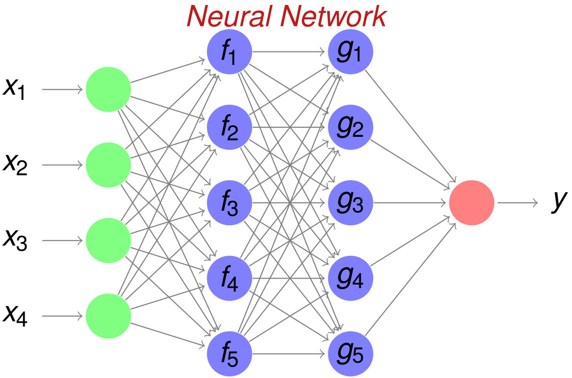
Imitating a Human Brain





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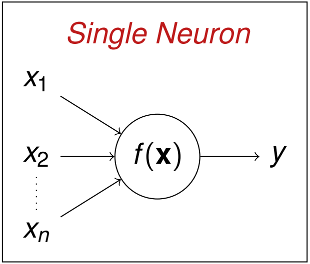
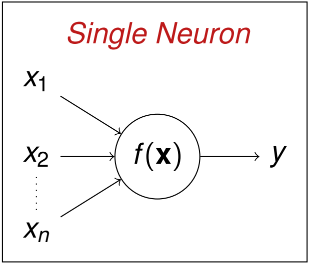
The Neuron as a Function



- Input observed features (data)
- Output decision

The Neuron as a Technological Discipline



- Classification problems
- Pattern recognition
- Machine learning
- Artificial Intelligence

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Classification problmes

Medicine	Is tumour benign or malign (cancer)?
Biology	Is this flower species A or species B?
Computing	Is the image synthetic (computer generated) or a real photo?
Technology	Is this bottle eligible for deposit return?

Database of test data:

`http://archive.ics.uci.edu/ml/`

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Data sets

Element	Purpose	Type
Feature vector	Input for the classifier (e.g. neural network)	Floating point vector (List of Double)
Class label	Correct output from the classifier	Discrete (String, Integer, Character)
Other data	Record ID, etc. (should be ignored)	Anything

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Iris Data Set

```
5.1,3.5,1.4,0.2,Iris-setosa
4.9,3.0,1.4,0.2,Iris-setosa
4.7,3.2,1.3,0.2,Iris-setosa (...)
7.0,3.2,4.7,1.4,Iris-versicolor
6.4,3.2,4.5,1.5,Iris-versicolor
6.9,3.1,4.9,1.5,Iris-versicolor
5.5,2.3,4.0,1.3,Iris-versicolor (...)
5.8,2.7,5.1,1.9,Iris-virginica
7.1,3.0,5.9,2.1,Iris-virginica
6.3,2.9,5.6,1.8,Iris-virginica
6.5,3.0,5.8,2.2,Iris-virginica
7.6,3.0,6.6,2.1,Iris-virginica
4.9,2.5,4.5,1.7,Iris-virginica (...)
```

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Objective

Iris classification

1. Input: feature vector $\mathbb{R}^4$
   - in Haskell: `[Double]` of length four
2. Output: species
   - Either Iris-setosa, Iris-versicolor, or Iris-virginica
3. String labels may be awkward

Iris-setosa	$+1$	$(1,0,0)$
Iris-versicolor	0	$(0,1,0)$
Iris-virginica	-1	$(0,0,1)$

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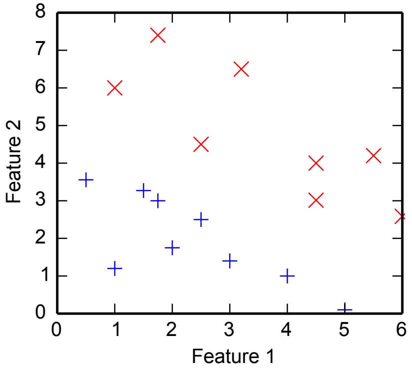
Classification in Graphics



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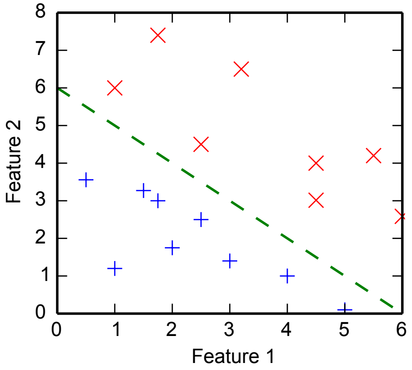
Classification in Graphics



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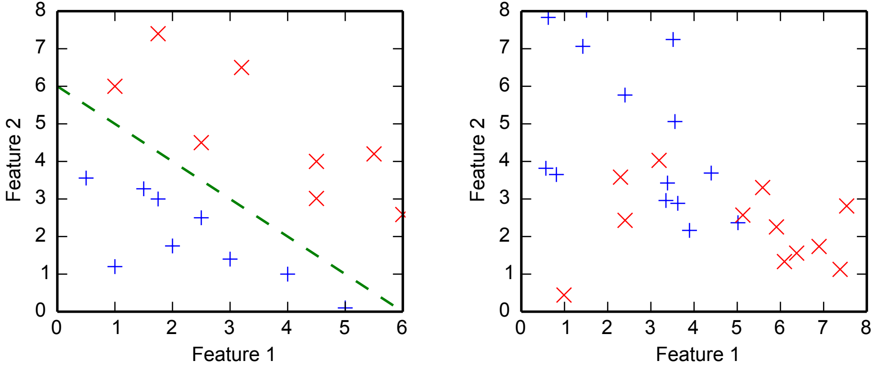
Classification in Graphics



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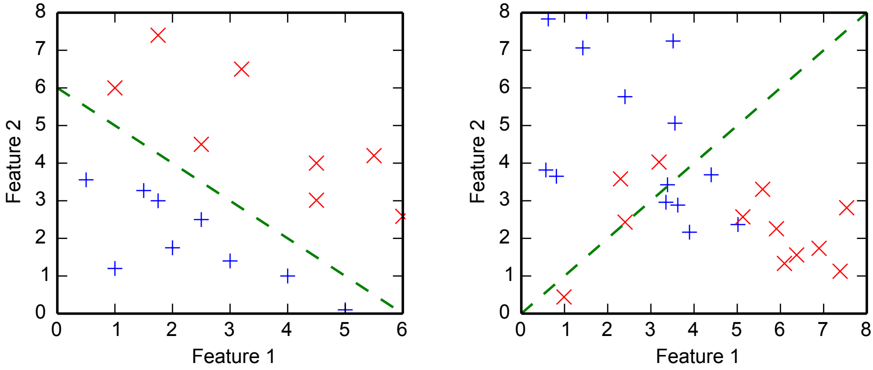
Classification in Graphics



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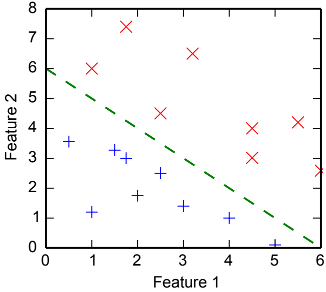
Approaches to classification

1. Analytic solutions
   1. known probability distribution
   2. pure theory
2. Statistics
   1. e.g. regression
   2. inference from observations
3. Machine learning
   1. huge data sets
   2. complex models



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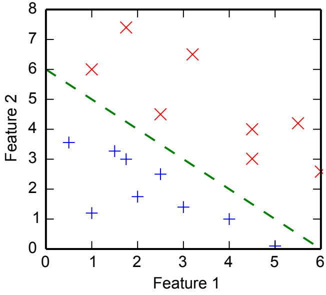
Machine learning

Phase 1 Training

1. data set with known class labels.
2. the algorithm learns the patterns.
3. output a model

Phase 2 Recall

1. data with unknown class label.
2. the algorithm predicts the class label.
3. uses the model from training



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Testing

1. You cannot trust a newly trained machine.
2. It must be tested
    1. data set with known class labels.
    2. the algorithm does recall (ignoring class labels).
    3. class predictions are compared to known labels
3. Estimate the error probabilities (statistics)
4. Independent data sets for training and testing

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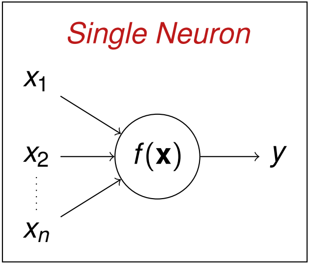
The neuron recall function



- Floating point in
- Floating point out

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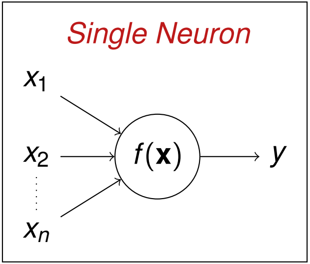

- Weights $\mathbf{w} = (w_1, w_2, \ldots, w_n)$
- Input $\mathbf{x}$
- $y = \mathbf{w} \cdot \mathbf{x}$
- Floating point in
- Floating point out

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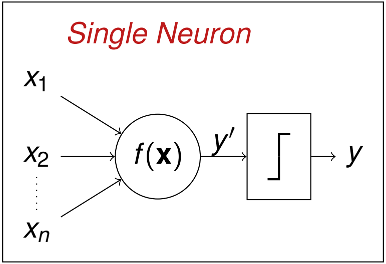
Discrete output



- $y' = \mathbf{w} \cdot \mathbf{x}$
- $y = \begin{cases} +1, & \text{when } y' > T \\ 0, & \text{otherwise.} \end{cases}$

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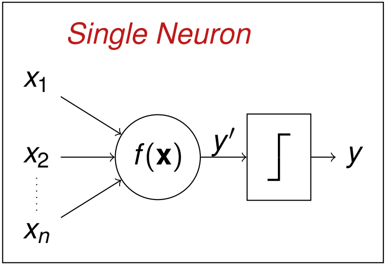
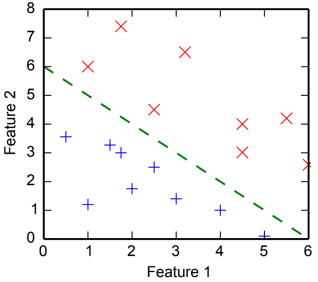
The Neuron as a Classifier





1. Equation $\mathbf{w} \cdot \mathbf{x} = T$
2. Draws a hyperplane
3. One class (+1) above the hyperplane
4. The other class (0) below the hyperplane

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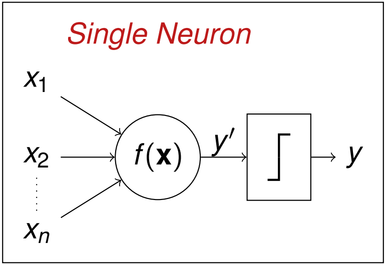
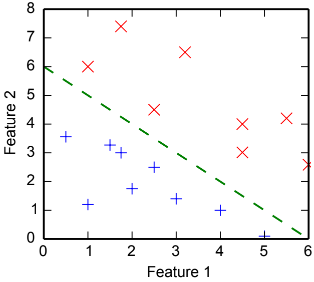
The Neuron as a Classifier





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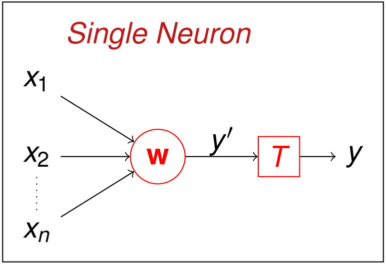
A Parameter too Many



1. $T = \mathbf{w} \cdot \mathbf{x} = \sum_{i=1}^{n} w_i x_i$
2. $0 = -T + \sum_{i=1}^{n} w_i x_i$
3. $0 = \sum_{i=0}^{n} w_i x_i$
   - where $x_0 = -1$ and $w_0 = T$

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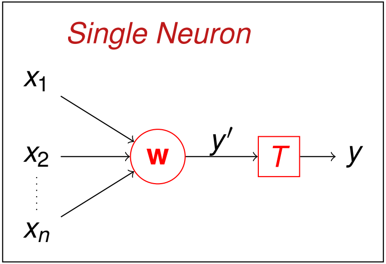

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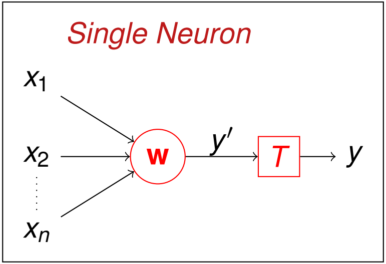

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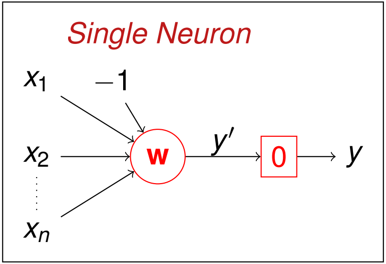

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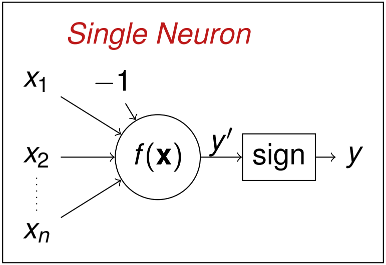
The neuron recall function



- Weights $\mathbf{w} = (w_0, w_1, w_2, \ldots, w_n)$
- Input $\mathbf{x} = (x_0, x_1, x_2, \ldots, x_n)$
  1. $x_0 = -1$
  2. $x_1, x_2, \ldots$ are feature values
- $y = \operatorname{sign} \mathbf{w} \cdot \mathbf{x}$
- Floating point in
- Binary value out

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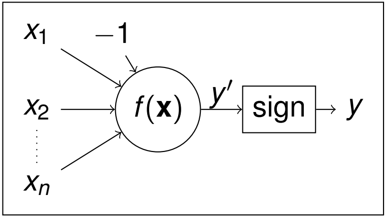

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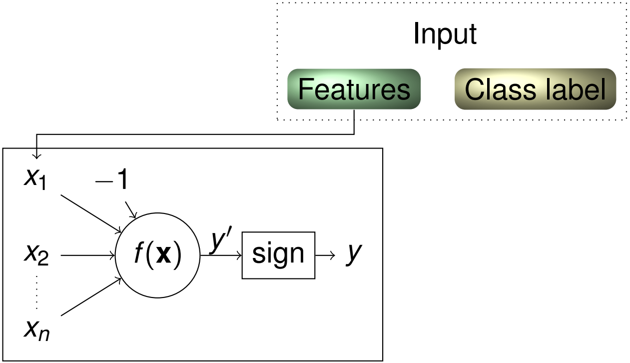

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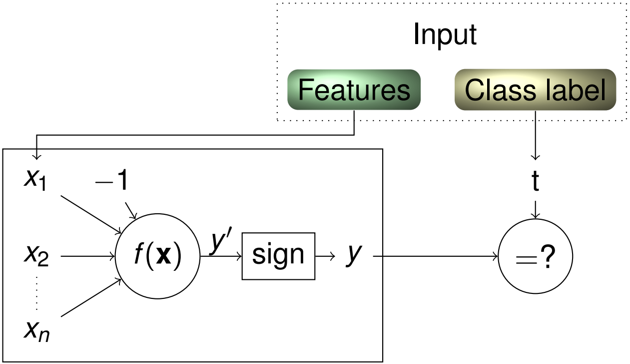

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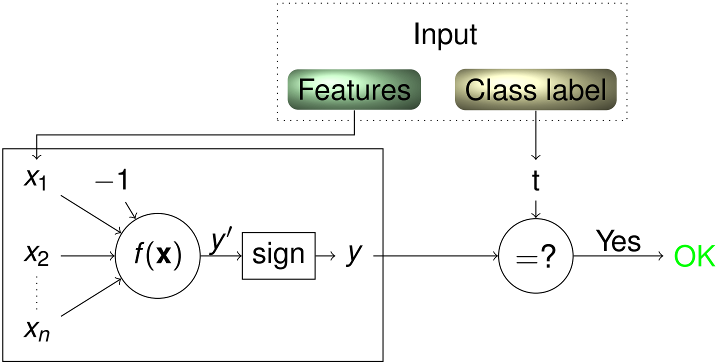

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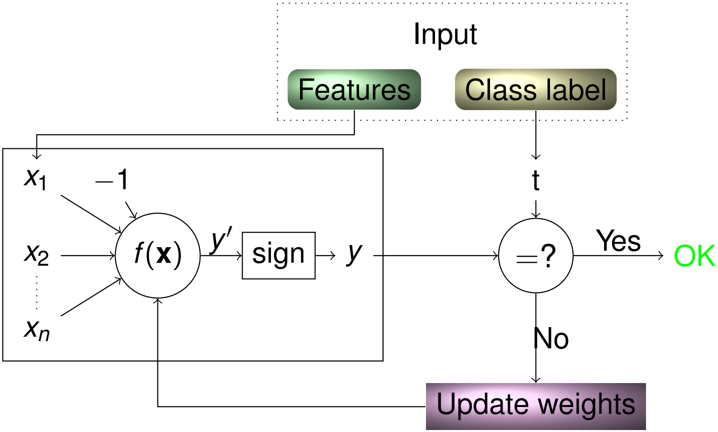

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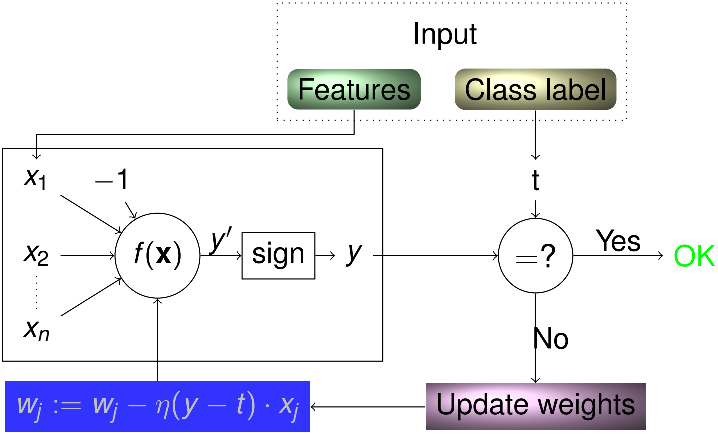

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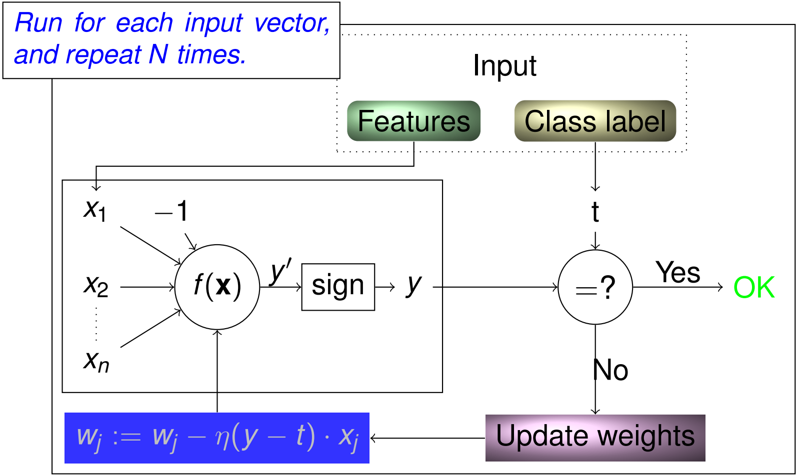

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Summary

- Classification determines if X is fowl or fish
- Selected features are used
- Models define plausible feature values for fowl and for fish
- Machine learning generate models too complex for human comprehension
- The single neuron is a linear classifier
- Return to details next week

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