Module 3.2: A typical Supervised Machine Learning Setup
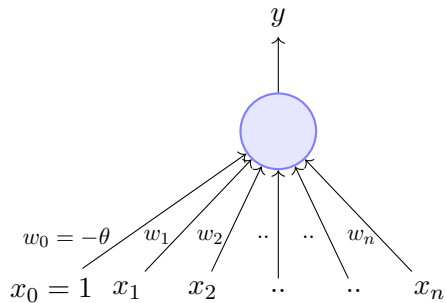
- What next ?

Sigmoid (logistic) Neuron
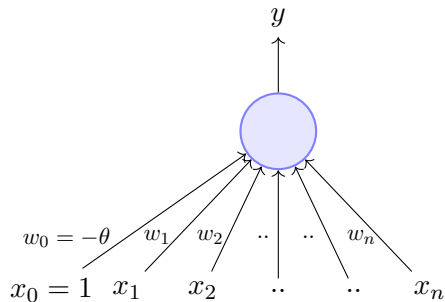
y

$w_0 = -\theta$ w_1 w_2 $..$ $..$ w_n

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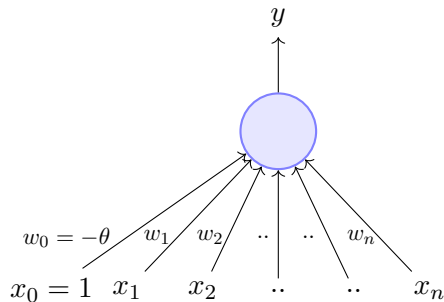
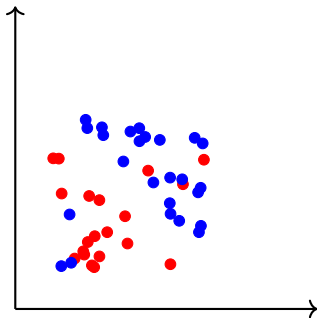**Sigmoid (logistic) Neuron**

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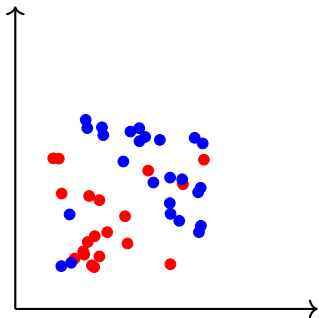- Before we see such an algorithm we will revisit the concept of **error**

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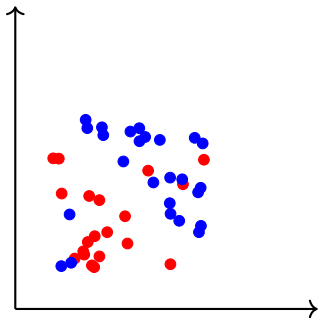
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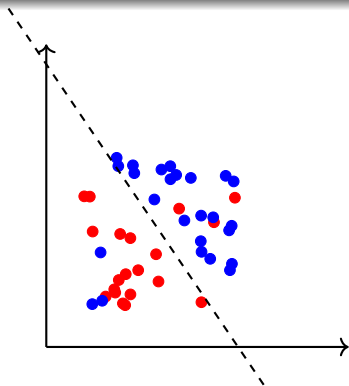- We would probably end up with a line like this ...

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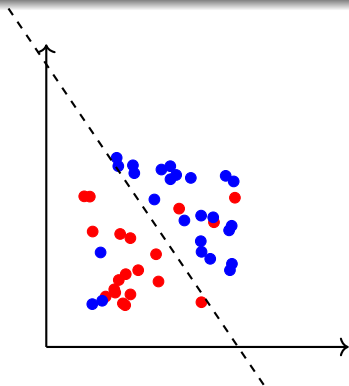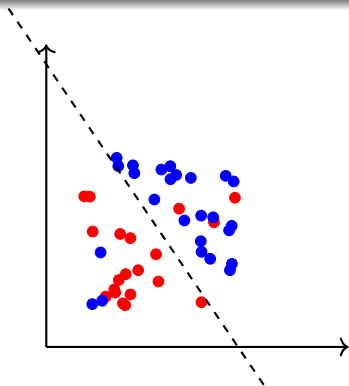- This line doesn't seem to be too bad

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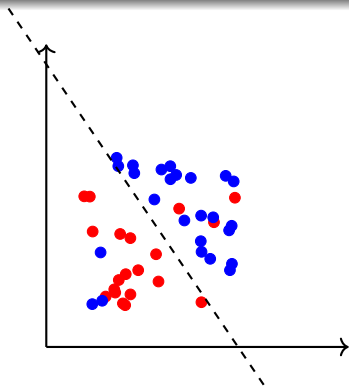
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- From now on, we will accept that it is hard to drive the error to 0 in most cases and will instead aim to reach the minimum possible error

Mitesh M. Khapra   CS7015 (Deep Learning) : Lecture 3

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The learning algorithm should aim to find a w which minimizes the above function (squared error between y and $\hat{y}$)