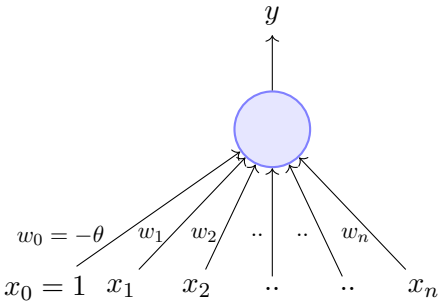
Module 3.2: A typical Supervised Machine Learning Setup

- What next ?

Sigmoid (logistic) Neuron



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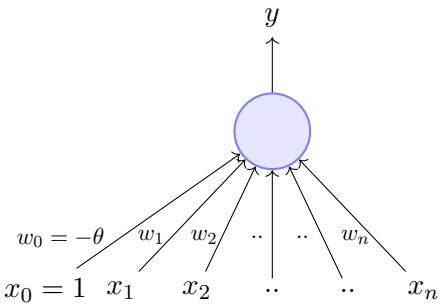

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- Well, just as we had an algorithm for learning the weights of a perceptron, we also need a way of learning the weights of a sigmoid neuron

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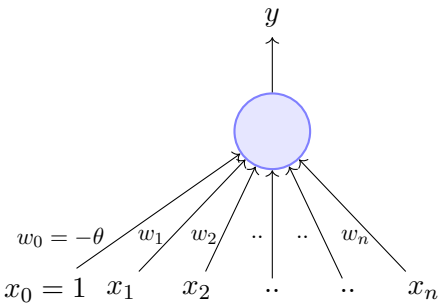

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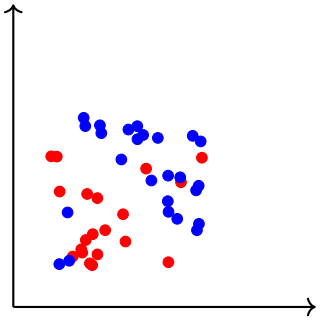
- Well, just as we had an algorithm for learning the weights of a perceptron, we also need a way of learning the weights of a sigmoid neuron
- Before we see such an algorithm we will revisit the concept of **error**



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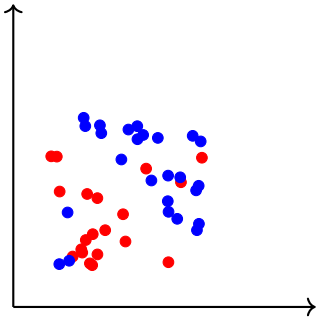

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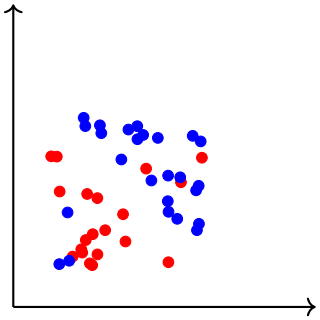

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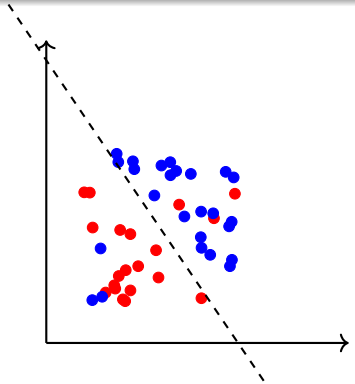

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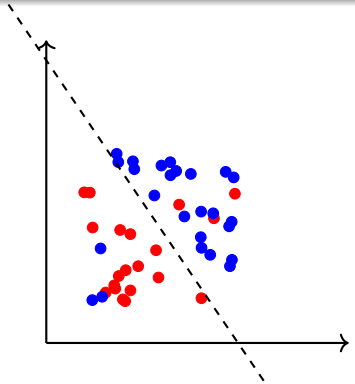

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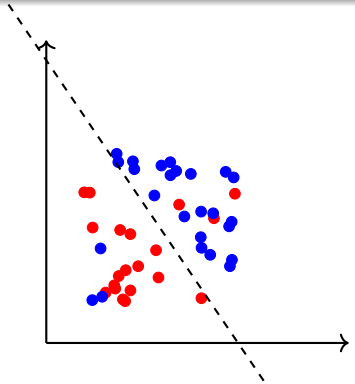

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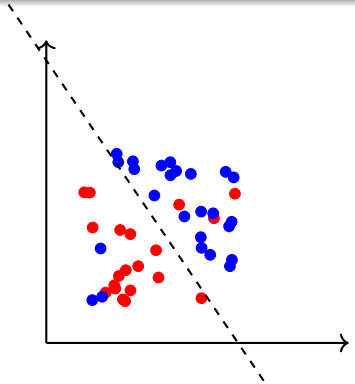

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- From now on, we will accept that it is hard to drive the error to 0 in most cases and will instead aim to reach the minimum possible error

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