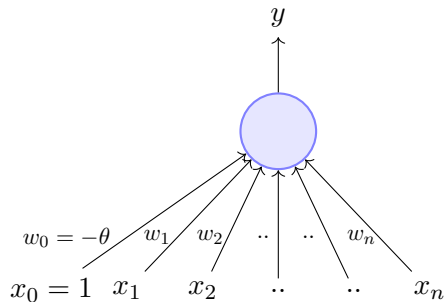


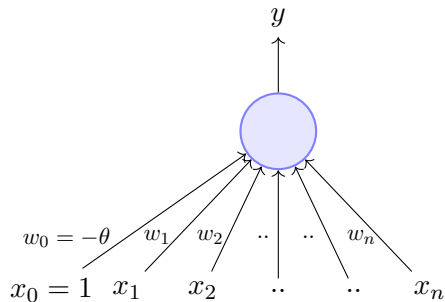
Module 3.2: A typical Supervised Machine Learning Setup

- What next ?

Sigmoid (logistic) Neuron

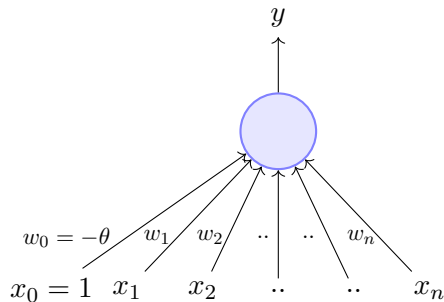


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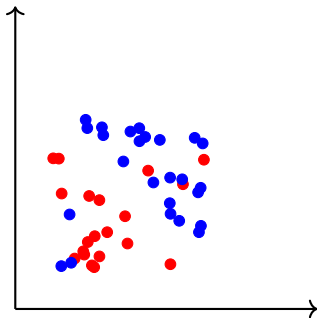
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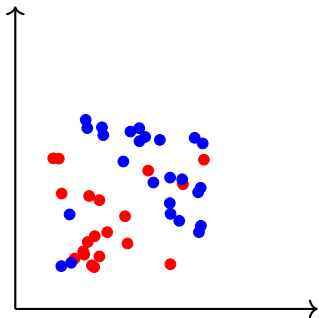
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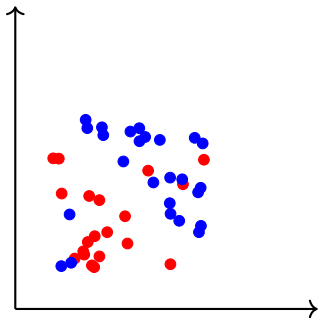
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- Before we see such an algorithm we will revisit the concept of **error**

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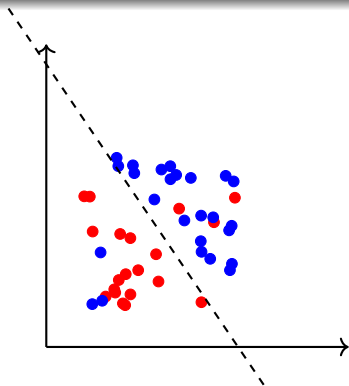




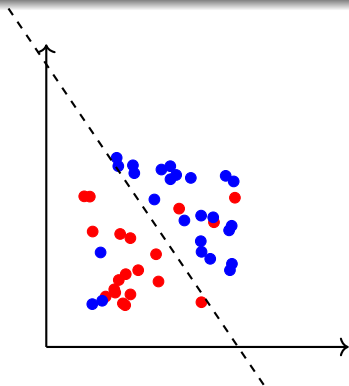
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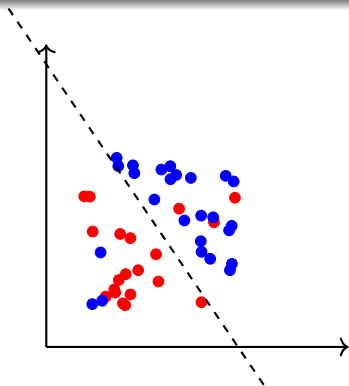
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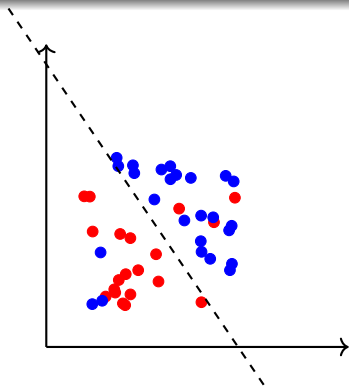
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- From now on, we will accept that it is hard to drive the error to 0 in most cases and will instead aim to reach the minimum possible error

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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})