Artificial Intelligence

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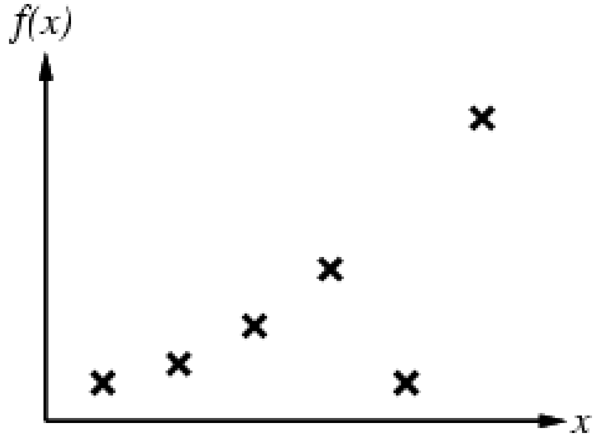
Machine Learning

- Learning is essential for unknown environments
  - Learning modifies the agent's decision mechanisms to improve performance
- Design of a learning element is affected by
  - Which components of the performance element are to be learned
  - What feedback is available to learn these components
  - What representation is used for the components
- Type of feedback:
  - Supervised learning
    - Correct answers for each example
  - Unsupervised learning
    - Correct answers are not given

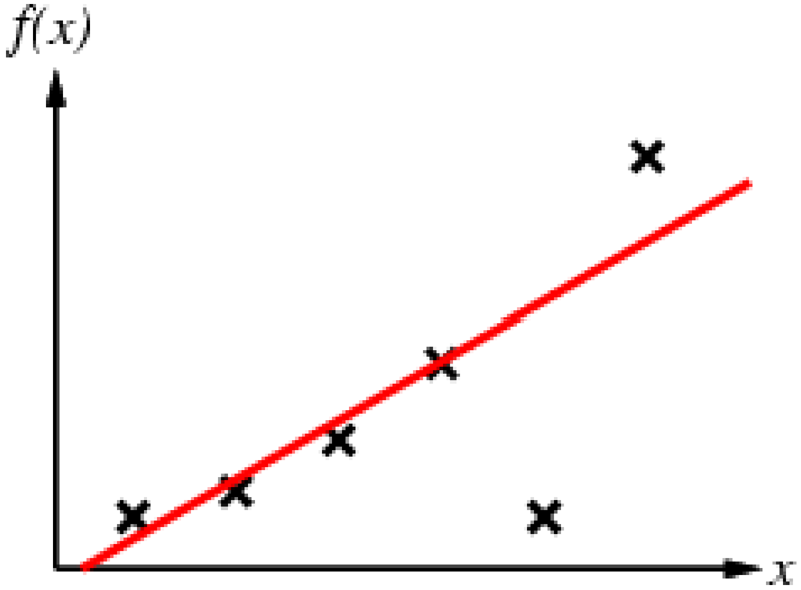
Inductive Learning

- Simplest form
  - learn a function f from examples pair $(x, f(x))$
- Problem
  - Given a training set of examples
  - Find a hypothesis h such that $h \approx f$
- This is a highly simplified model of real learning
  - Ignores prior knowledge
  - Assumes examples are given



Example of Inductive Learning

- Construct/adjust *h* to agree with *f* on training set
  - *h* is consistent if it agrees with *f* on all example



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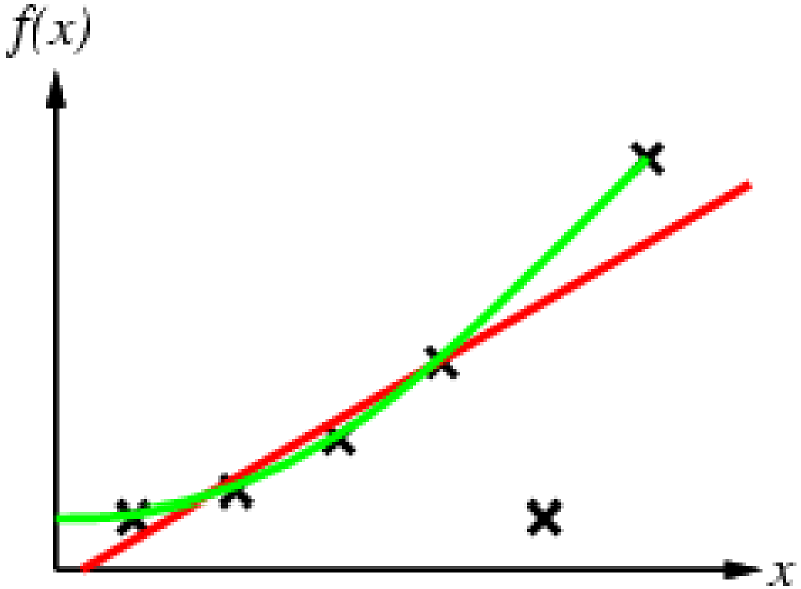

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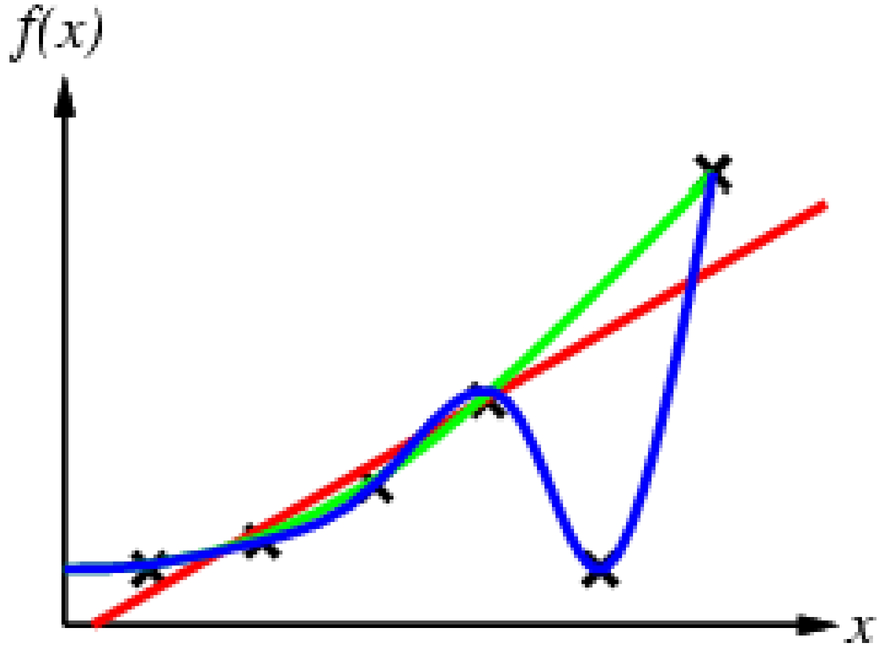

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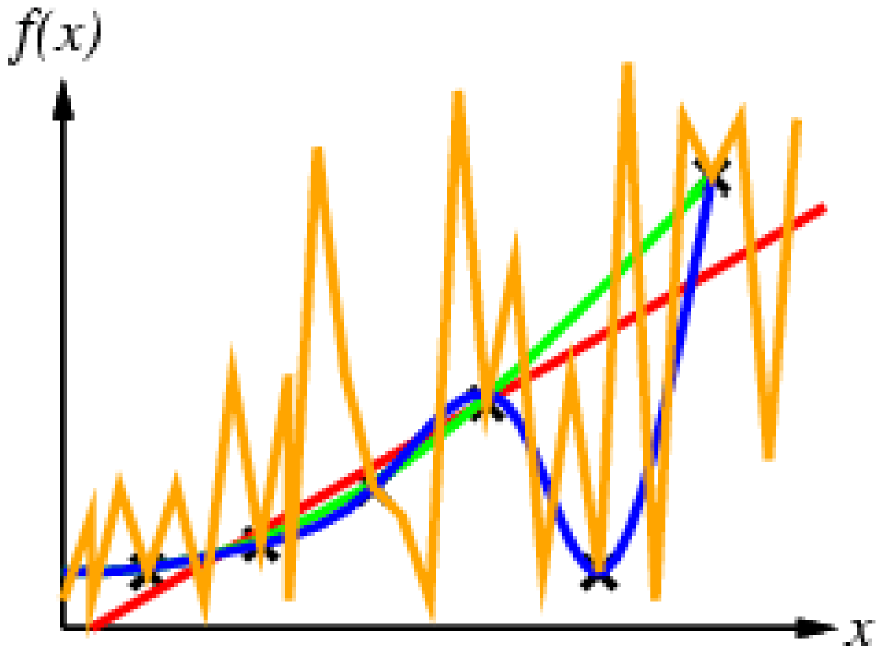
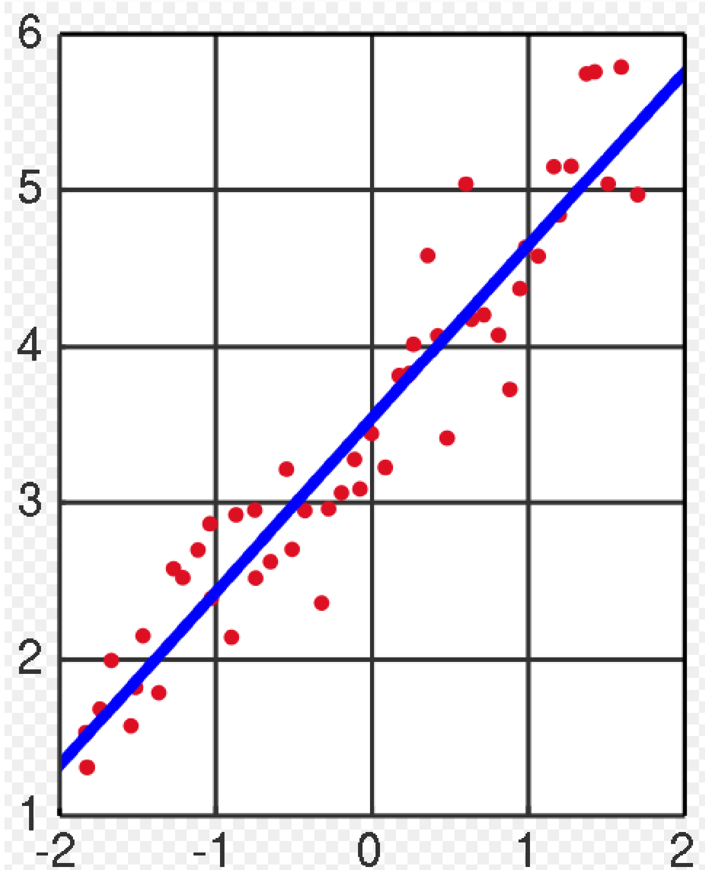


Univariate Linear Regression

- Regression with a univariate linear function is also known as "fitting a straight line".
- A univariate linear function (a straight line) with input x and output y has the form $y = w_1 x + w_0$
- Loss function: $Loss(h_w) = \sum_j (y_j - (w_1 x_j + w_0))^2$

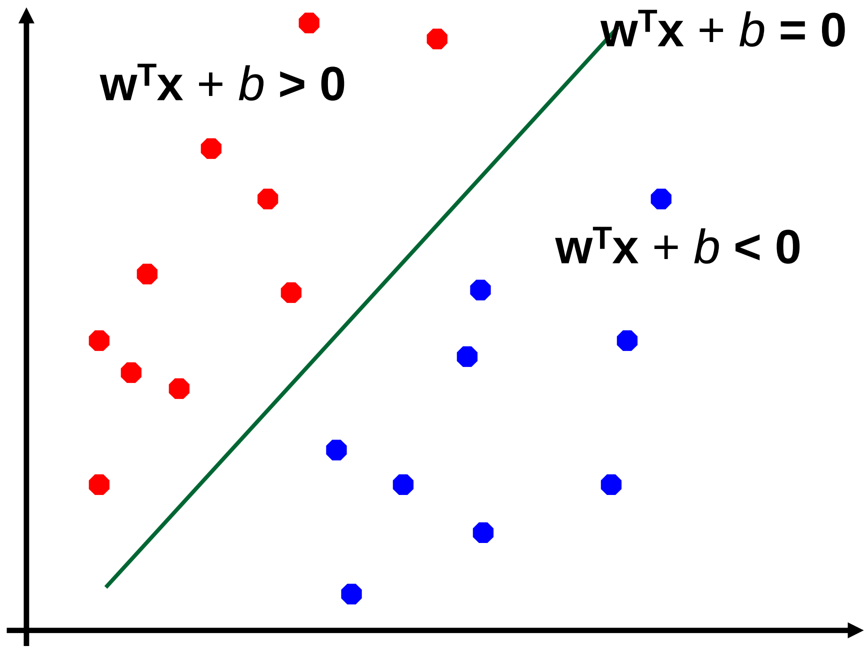


Solutions to Univariate Linear Regression

- The partial derivatives of $Loss(h_w)$ with respect to w_0 and w_1 are zero:
  - $\partial \sum_j (y_j - (w_1 x_j + w_0))^2 / \partial w_0 = 0$
  - $\partial \sum_j (y_j - (w_1 x_j + w_0))^2 / \partial w_1 = 0$
- These equations has unique solutions
  - $w_1 = (N(\sum x_j y_j) - (\sum x_j)(\sum y_j)) / (N(\sum x_j^2) - (\sum x_j)^2)$
  - $w_0 = (\sum y_j - w_1 (\sum x_j)) / N$

Linear Classification

- Linear classification can be viewed as the task of finding the linear separator that can separate different classes in the feature space:



$$f(\mathbf{x}) = \text{sign}(\mathbf{w}^T\mathbf{x} + b)$$

Linear Classification with Hard Threshold

- Linear functions can be used to do classification as well as regression:
- $h_{\mathbf{w}}(\mathbf{x}) = \text{Threshold}(\mathbf{w}^T\mathbf{x})$
- where Threshold(z)= 1 if $z > 0$ and 0 otherwise.
- Since the loss function is undifferentiable, we cannot obtain the solution as in the regression problem.
- $w_i \leftarrow w_i + \alpha(y\text{-}h_w(\mathbf{x}))x_i$