Overview of Machine Learning

in particular, Supervised Learning

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Outline

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- "computer program," for us, means a function implemented on a computer that produces output from given input. The output is how the program achieves the task T.
- The procedures discussed in class – linear regression and the Perceptron algorithm for half-space model – fit into this paradigm...*kind of*.

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     <u>Closed form</u> for best choice of m, b, computing $(A^T A)^{-1} A^T \mathbf{y}$.
   - P: Mean squared error.

   Having closed form, result of simplicity of the form of $\hat{y}_i$.

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   - P: ??
     Whether its labels on all observed data are correct. But, only two results: *True* or *False*.
     If data is linearly separable, enough of experience E improves this measure (changing to *True*). Only happens if linearly separable.

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Examples.

- Market segmentation.
- News feed (grouping similar news articles).
- Separate audio sources in a mixed signal.
- Organize computing clusters.

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- Goal: to learn, from $\mathcal{S}$, a function $f^* : \mathbb{R}^d \to Y$ that "fits" (*approximates well*) the distribution $P_{X,Y}$.
- You might not be able to have points on the graph of f^* be typically "very close" to samples from $P_{X,Y}$. However, ideally, for an $\mathbf{x} \in \mathbb{R}^d$ corresponding y-value on graph is near the expected value given $\mathbf{x}$.

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Select a performance measure: **(empirical) loss function** $\mathcal{L}_\mathcal{S} : \Omega \to \mathbb{R}$.
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- Then, $\mathcal{L}_\mathcal{S}$ is used to determine how to make changes to parameters, ω, in order to decrease the value of $\mathcal{L}_\mathcal{S}$.
- In an ideal situation, you converge to some ω^*, a minimizer of $\mathcal{L}_\mathcal{S}$, and set $f^* = f_{\omega^*}$.

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For linear regression

Have sample data $\mathcal{S}$, with data points x_i in $\mathbb{R}$ (so, $d = 1$). The parameter space $\Omega = \mathbb{R}^2 = \{(m, b) \mid m \in \mathbb{R}, b \in \mathbb{R}\}$. For each $\omega = (m, b)$, we have

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Loss function: the MSE. That is, set

$$\mathcal{L}_{\mathcal{S}}(m, b) = \frac{1}{n}\sum_{i=1}^{n}(mx_i + b - y_i)^2.$$

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