Overview of Machine Learning

with focus on Supervised Learning

Chris Cornwell

Aug 26, 2025

Outline

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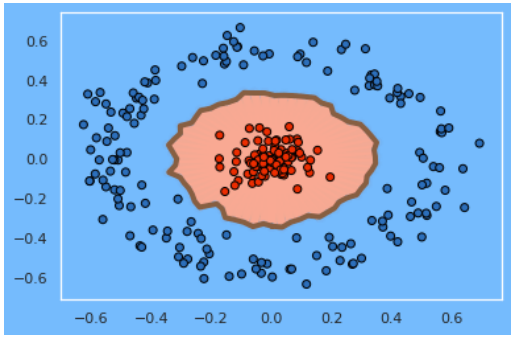
- Concerned with designing, understanding algorithms which allow computer program to “learn.”



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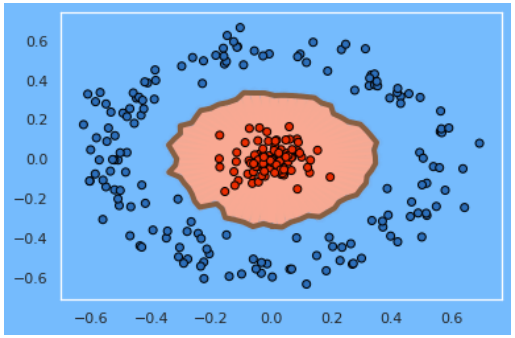

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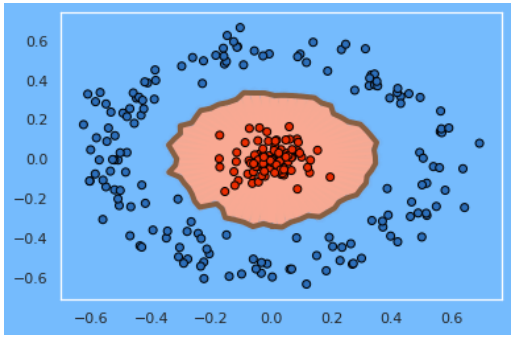

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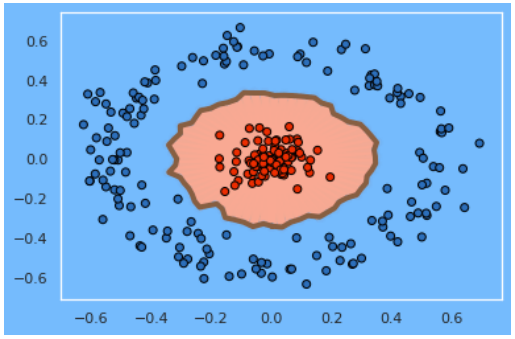
- Can be single ML model performing task (e.g., finding person in an image, speech-to-text, sentiment analysis)
- Or, many separate models combined together ⟵ what makes AI work (e.g., self-driving cars, LLM’s or chatbots).



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- Performance measure *M*: for us, called a *cost function* or *loss function*.

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- Separate audio sources in a mixed signal.

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- The labeled sample data is called **training data**. The goal is to “learn” a function from the training data that will do well labeling new data, not seen during learning process.
- “Doing well” is measured by a loss function (*M* from Mitchell’s description).
- The learning algorithm starts with some function; it doesn’t do labeling well, but the algorithm uses the loss function to alter that function to something better. ($\leftarrow$ “learning”)

Example Images

Example 1 - Supervised learning, Section 1.1 of textbook

Cat or Dog?

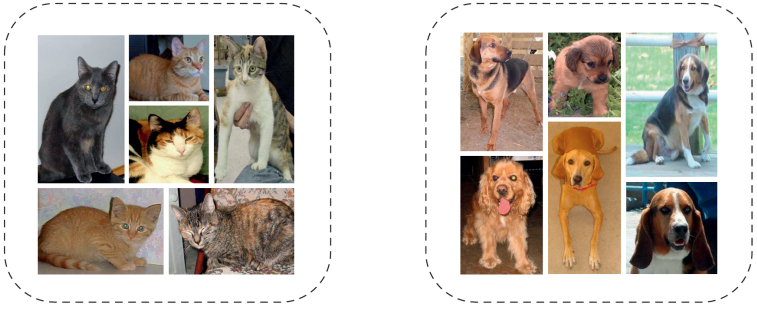

Figure 1.1 from textbook

- Training data. The images, each with label `'cat'` or `'dog'`.

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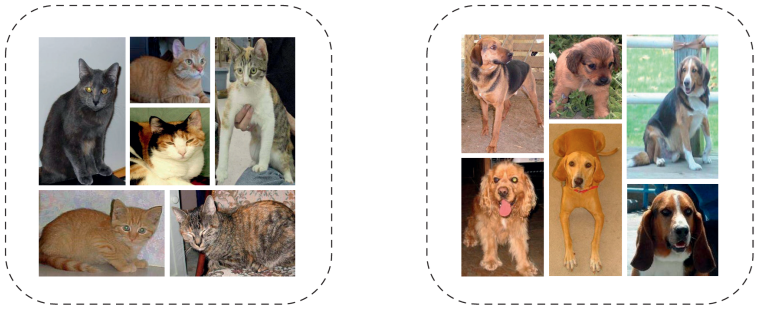

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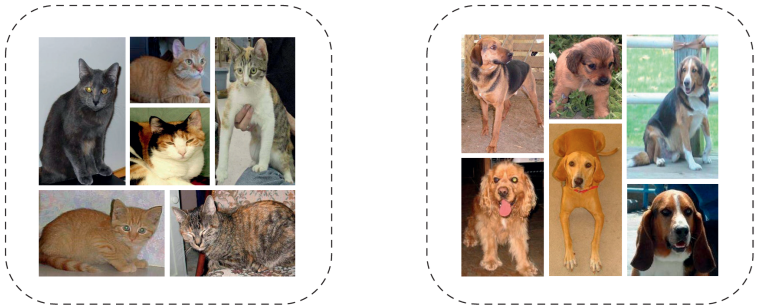

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- **Designing features.** "Cartoon image" of ML model's function: computes N **features** from each image $\rightsquigarrow$ vectors (points) in $\mathbb{R}^N$ $\rightsquigarrow$ points with one label separated from those with other label (by graph of linear function).

Designing features, to easily separate data

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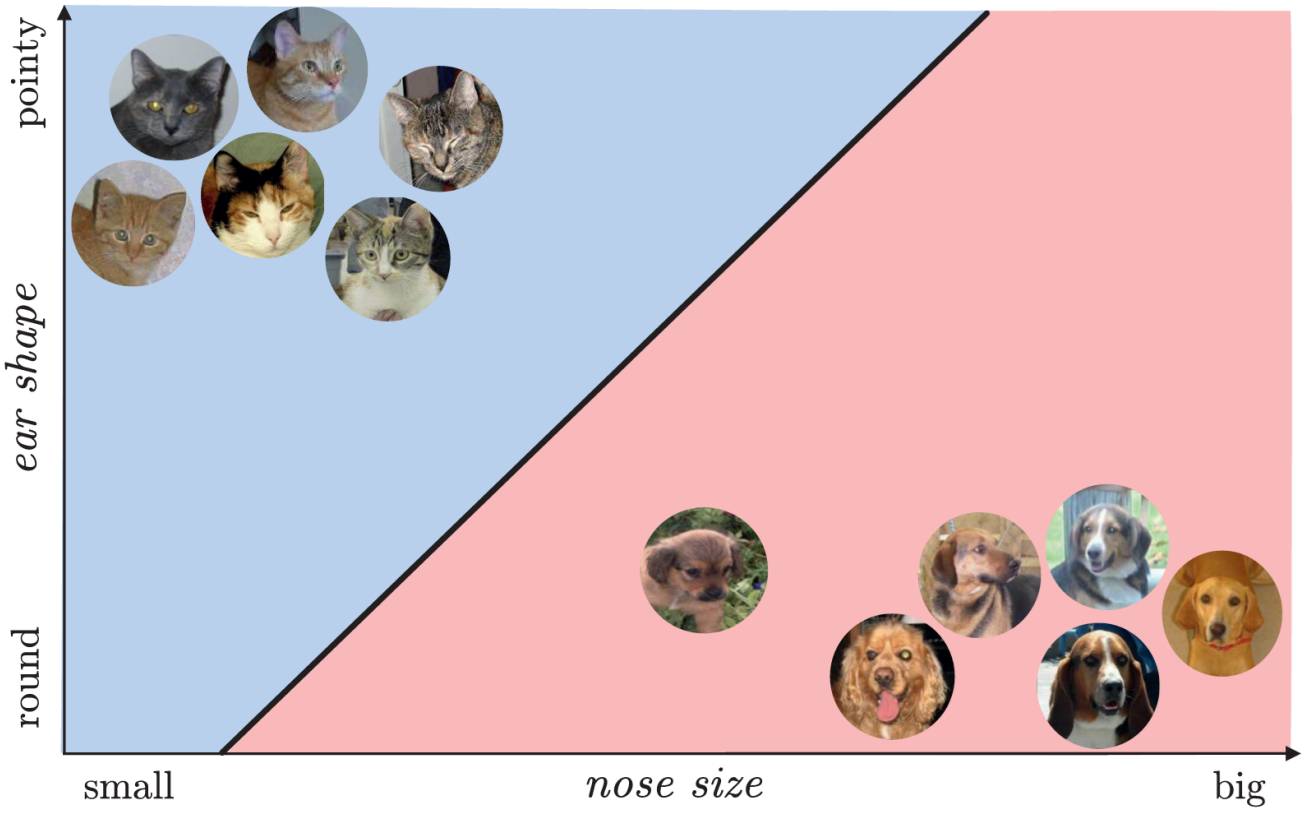
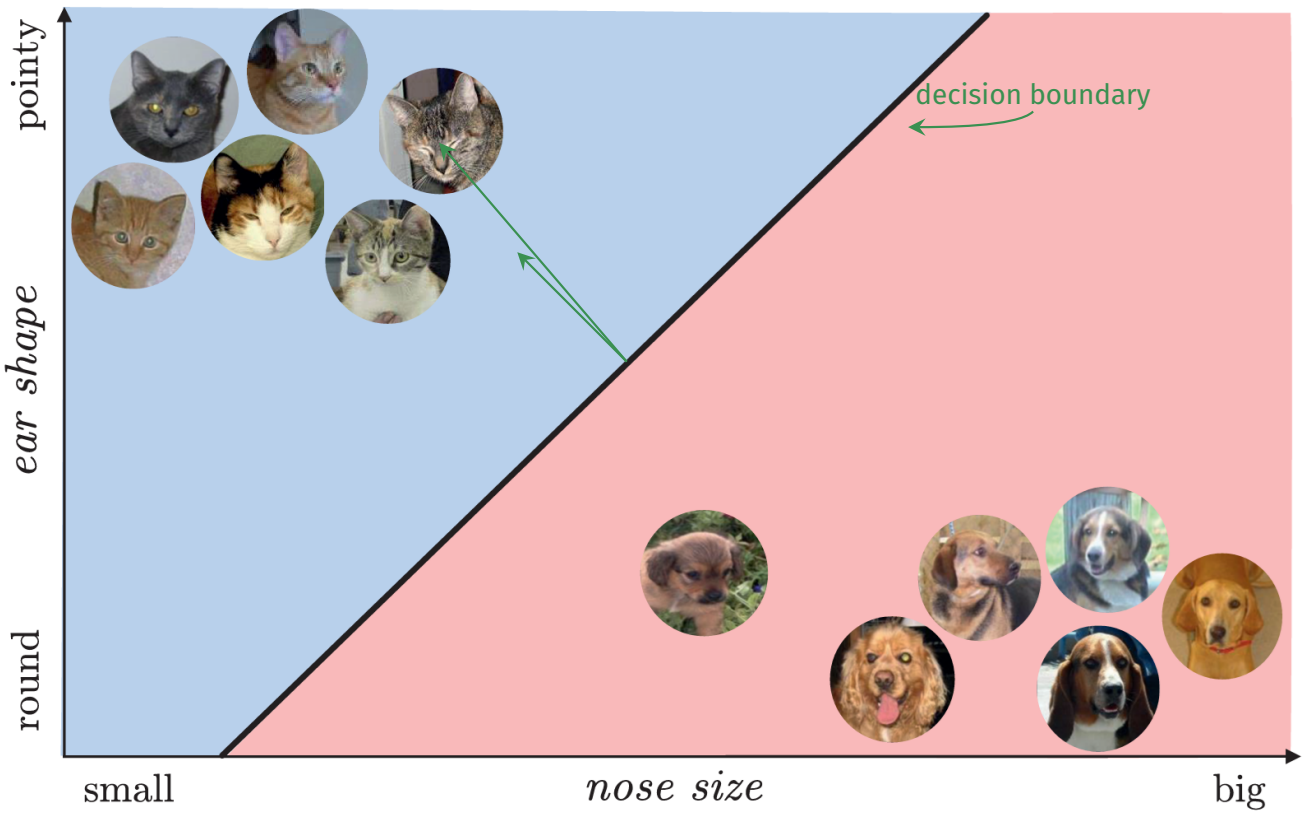


Figure 1.3 from textbook

“Doing well” once features are chosen

A way to assign positive or negative number to each, based on **decision boundary**’s side it is on; farther from 0 when distance is farther from decision boundary.



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Example 2 - Supervised learning, Section 1.2 of textbook

Predict share price

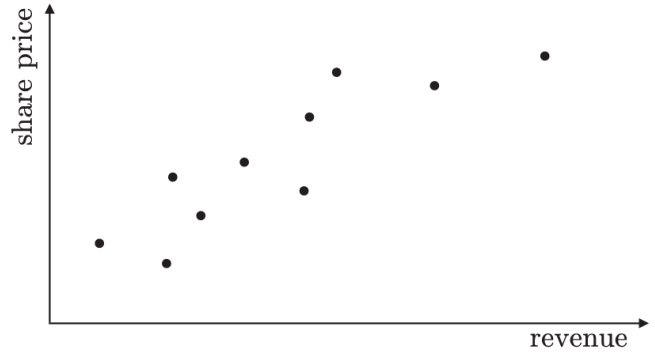
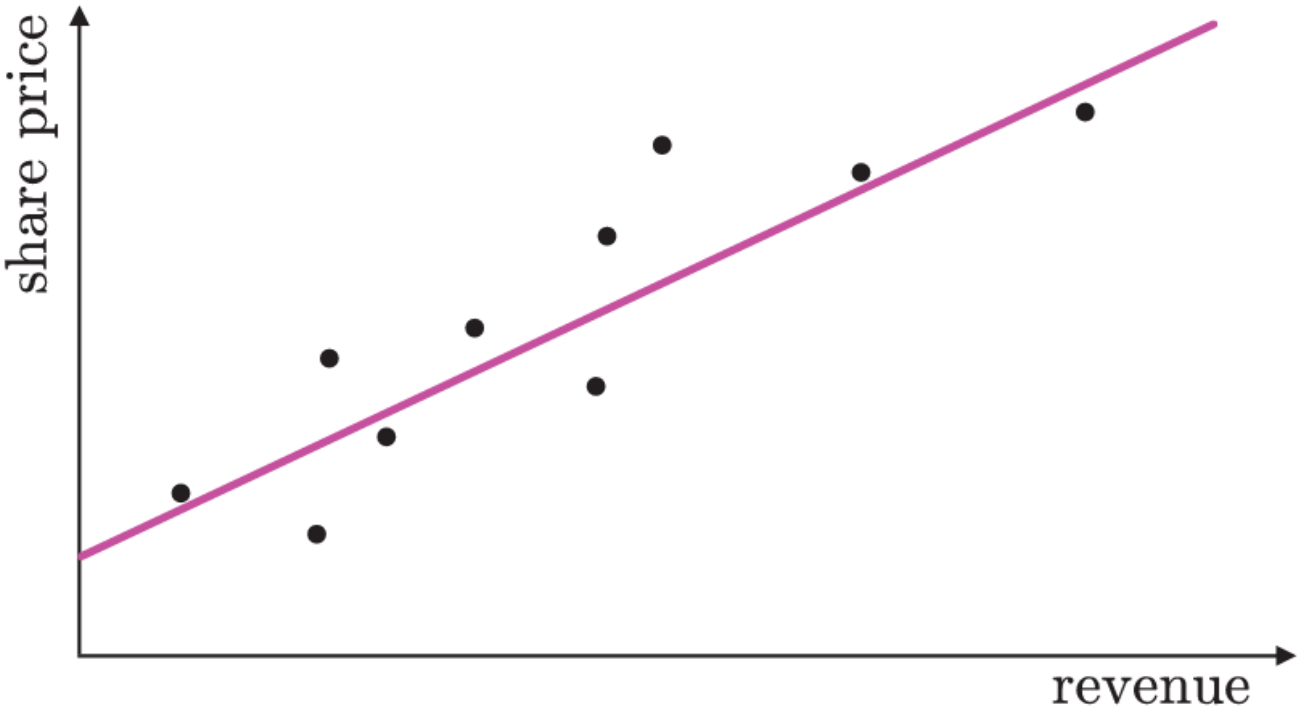


Figure 1.7, upper-left from textbook

- From training data, pick one feature: revenue. Label: the share price.
- Each revenue, a number in $\mathbb{R}$. One "independent variable," call it x.
- **Designing features.** Here, have used a feature already at hand. Not always best idea when there are multiple independent variables (we'll see examples later, where you design features).

Example 2 - Predict response variable, share price

Revenue value: x. Find a function $f(x) = \hat{m}x + \hat{b}$, so that if y is share price for x and we set $\hat{y} = f(x)$ then y and $\hat{y}$ are close, on average. (Linear Regression)



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Supervised learning, very generally

Have an "input space" (often is $\mathbb{R}^N$, for some N, or subset of it[1]). Have an output space, or label space, Y. (Y is a finite list of labels for classification; it is $\mathbb{R}$ or an interval in $\mathbb{R}$ for regression.)

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- Given a sample $\mathcal{S} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{P}$, with $\mathbf{x}_i \in \mathbb{R}^N$ and $y_i \in Y$, drawn from an (unknown) joint probability distribution $\rho_{X,Y} : \mathbb{R}^N \times Y \longrightarrow [0, \infty)$.

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- Might not be possible for points on graph of f^* to be typically "close" to samples from $\rho_{X,Y}$. However, for an $\mathbf{x} \in \mathbb{R}^N$, the corresponding $f^*(\mathbf{x})$ should be near expected value of y, given $\mathbf{x}$.

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- Ideally, converge to some ω^*, a minimizer of $\mathcal{L}_\mathcal{S}$, and set $f^* = f_{\omega^*}$.

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Questions?