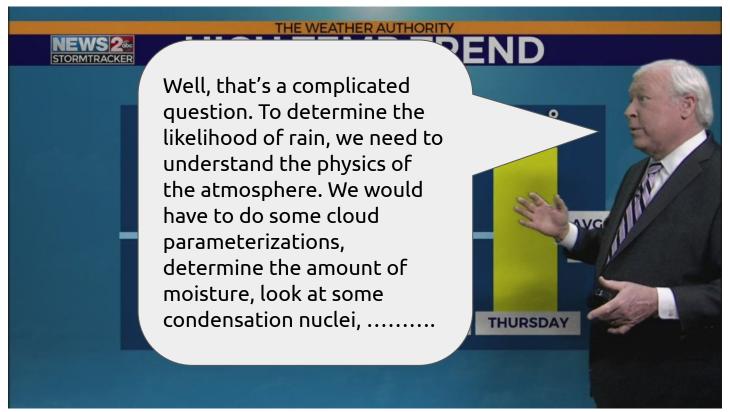
Introduction to Supervised Learning



You look outside and it looks like this:

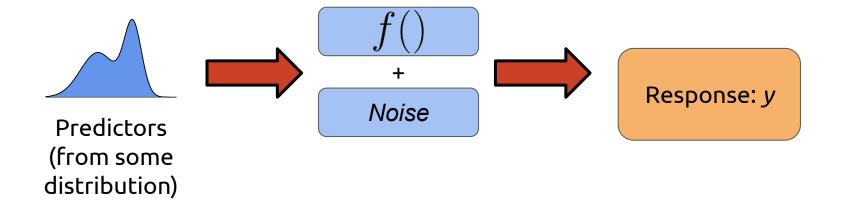
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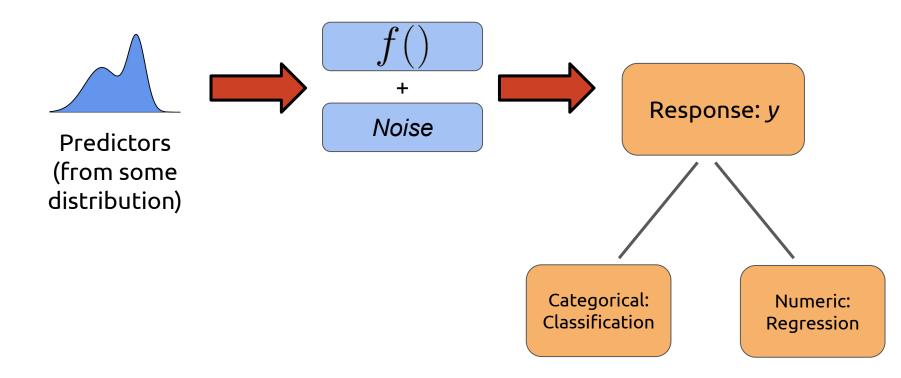
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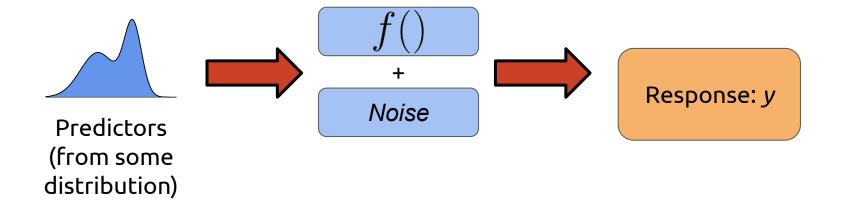
Supervised Learning - Setup

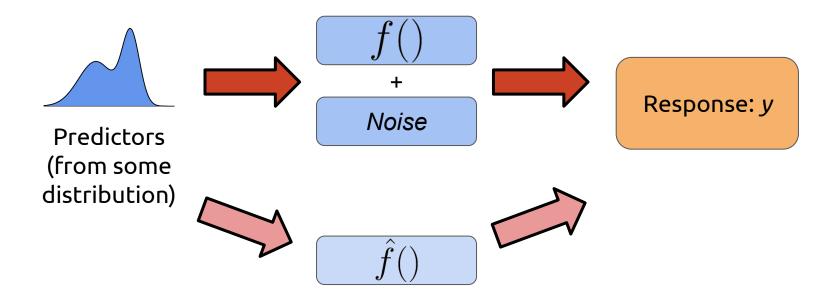


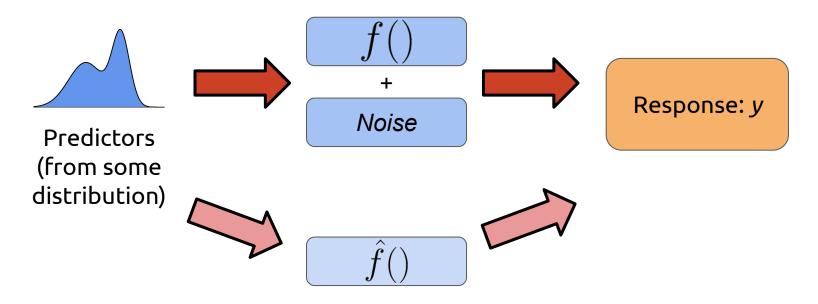
Supervised Learning - Setup



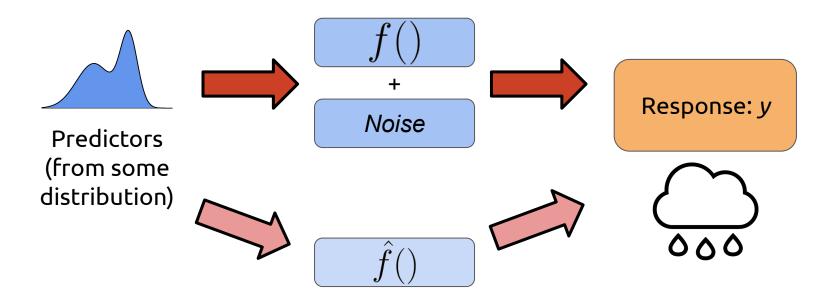
Supervised Learning - Setup



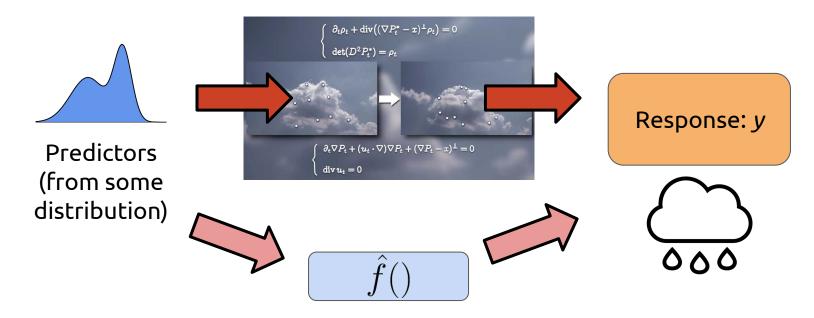




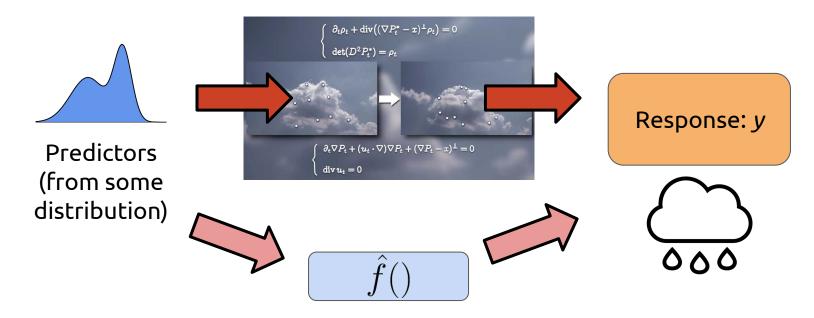
Goal: Choose a function so that the our predictions are close (on average) to the true values.



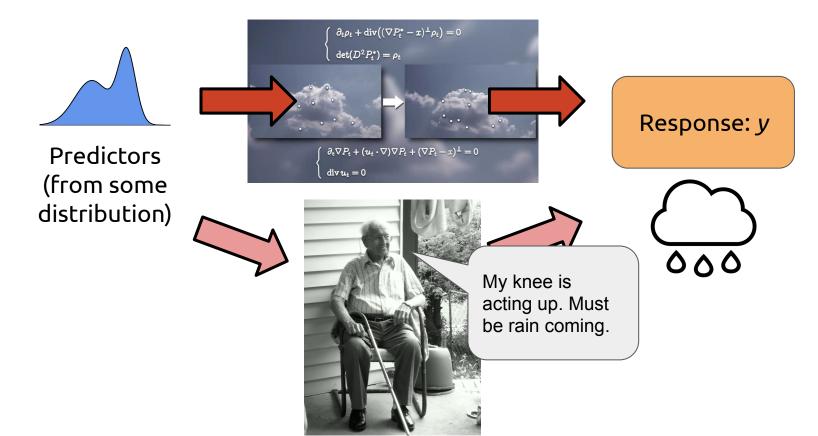
Supervised Learning - Grossly Simplified



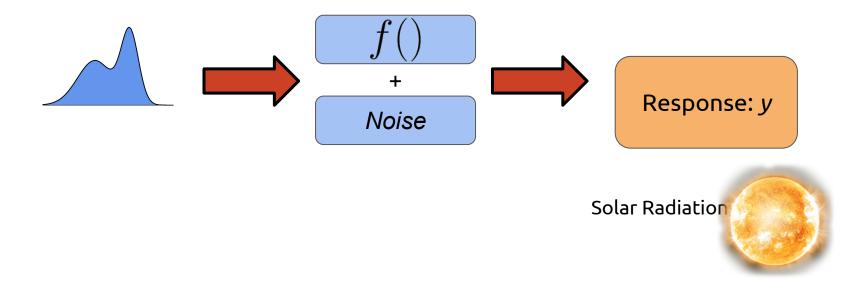
Supervised Learning - Grossly Simplified



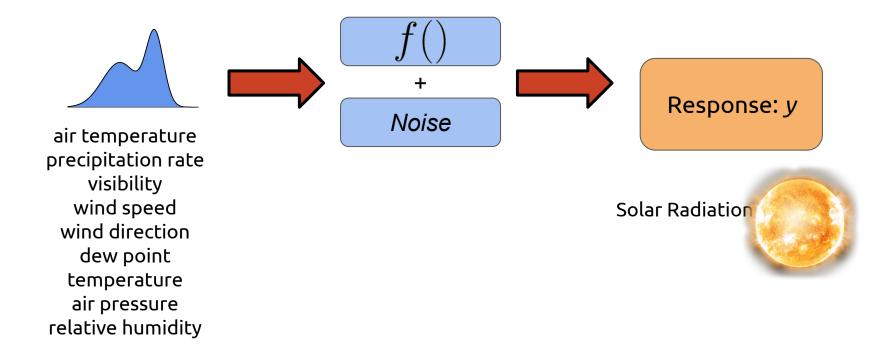
Supervised Learning - Grossly Simplified



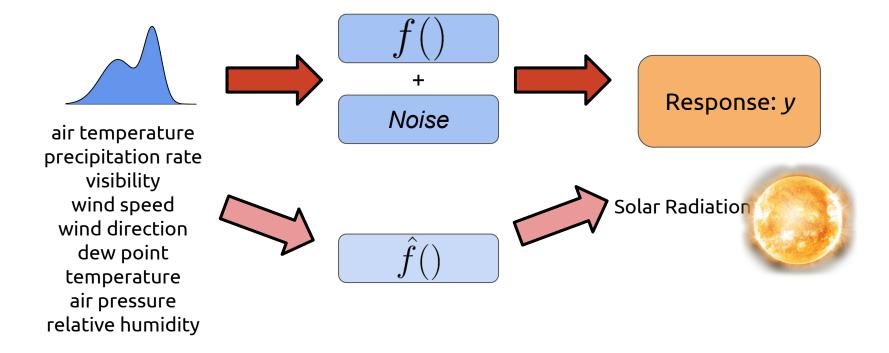
Example - Weather Prediction



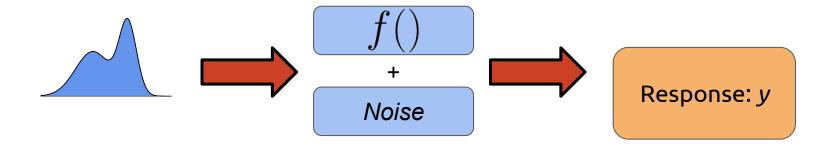
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Example - Weather Prediction

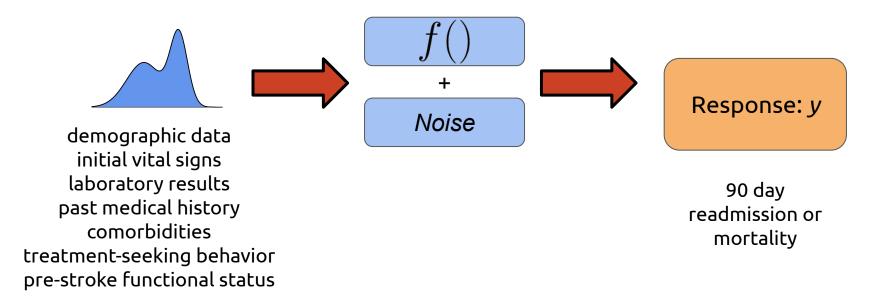


Example - Readmission or Death of Stroke Patients

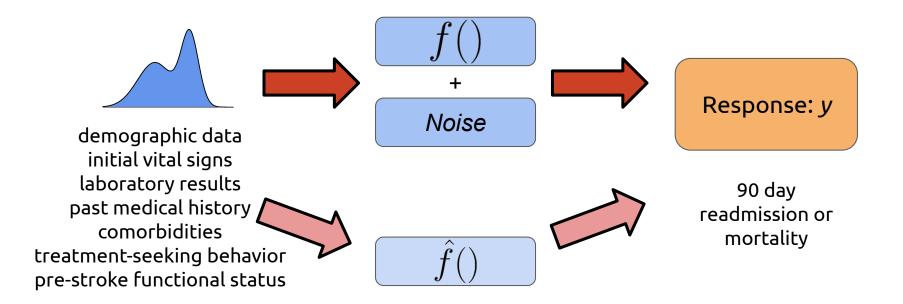


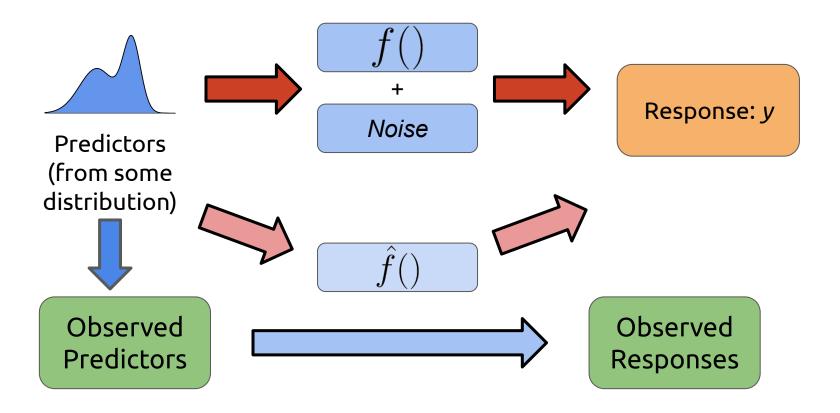
90 day readmission or mortality

Example - Readmission or Death of Stroke Patients



Example - Readmission or Death of Stroke Patients





To measure how "good" our model is, we need some way to measure "error" (eg. mean squared error).

Our goal is to minimize the expected loss over *new* data.

Important: We are not trying to minimize loss over the observed data (which is often very easy to do), but to minimize the *generalization error* - the performance on unseen data.

We need to pick a way to make predictions from our available training data.

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For example, we can pick a functional form for $\hat{f}()$

Linear regression is a way to make predictions where we pick a particular functional form for our predictor function.

Given k predictors $x^{(1)}$, $x^{(2)}$,..., $x^{(k)}$, linear regression uses the following equation to predict the target variable:

$$\hat{f}(\vec{x}) = \beta_0 + \beta_1 x^{(1)} + \beta_2 x^{(2)} + \dots + \beta_k x^{(k)}$$

Here, β_0 , β_1 ,..., β_k are constants that are determined by using the available training data.

Example: We might want to try and predict home price (our target) based on square footage (sqft), number of bedrooms (br), and number of floors (floors).

The model we will use to make predictions will look like:

$$\hat{f}(\vec{x}) = \beta_0 + \beta_1 \cdot (\text{sqft}) + \beta_2 \cdot (\text{br}) + \beta_3 \cdot (\text{floors})$$

Example: We might want to try and predict home price (our target) based on square footage (sqft), number of bedrooms (br), and number of floors (floors).

The model we will use to make predictions will look like:

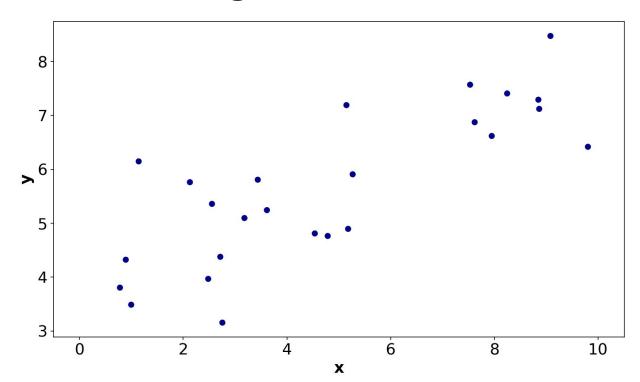
$$\hat{f}(x) = 40000 + 180 \cdot (\text{sqft}) + 15000 \cdot (\text{br}) + 30000 \cdot (\text{floors})$$

How do we find the values for the coefficients?

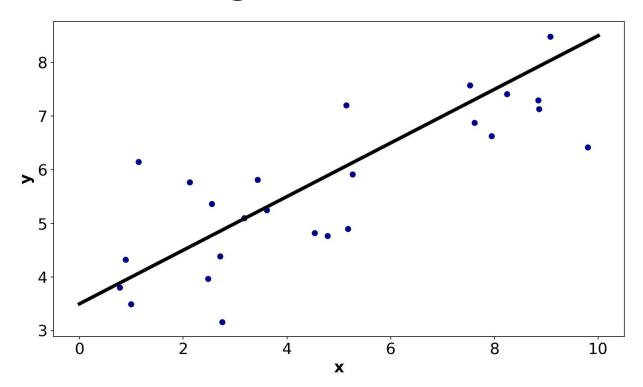
How do we find the values for the coefficients?

The usual way to do it is to minimize the total squared residuals between the predicted and actual values for the data used to fit/train the model.

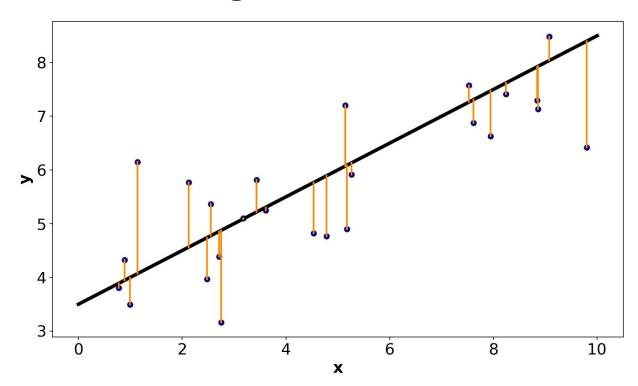
$$RSS = \sum_{i=1}^{n} (y_i - \hat{f}(\vec{x}_i))^2$$



Example: Let's say we have this data available. We want to predict *y* based on our one predictor, *x*.



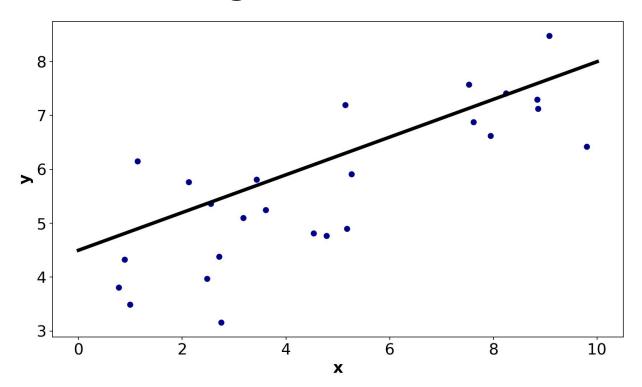
One possible line: y = 3.5 + 0.5x



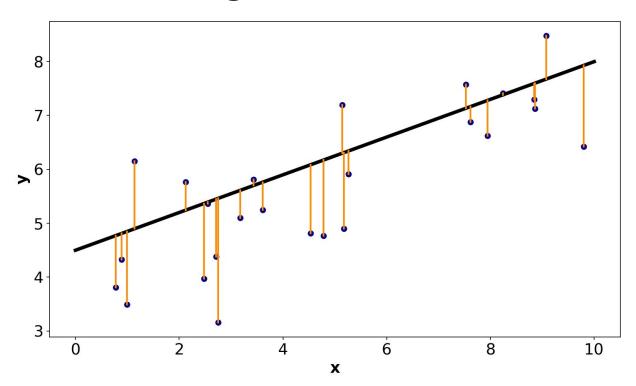
One possible line:

$$y = 3.5 + 0.5x$$

For this line, RSS = 20.36

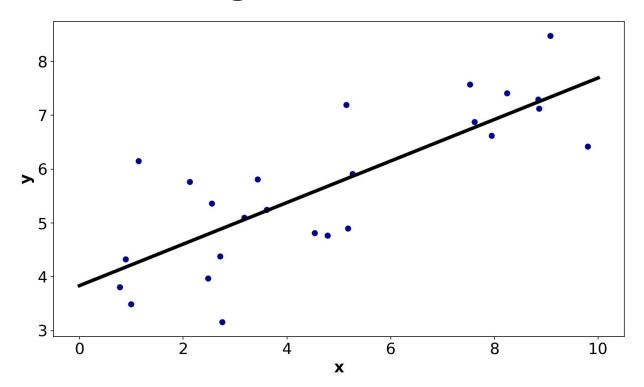


Another possibility: y = 4.5 + 0.35x

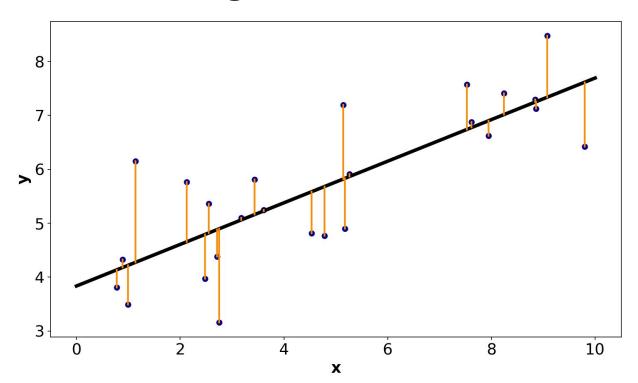


Another possibility: y = 4.5 + 0.35x

Here, RSS = 24.28

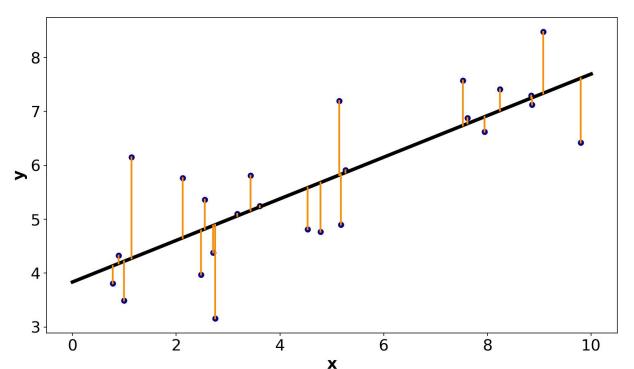


The best possible: y = 3.84 + 0.386x



The best possible: y = 3.84 + 0.386x

Here, RSS = 17.97



For the best-fitting line, the average (absolute) residual is equal to 0.67.

Can we expect that on new data generated by the same process, we will be off on average by 0.67 still?