Introduction to Supervised Learning

Question - Is it going to rain today? Do I need my umbrella?

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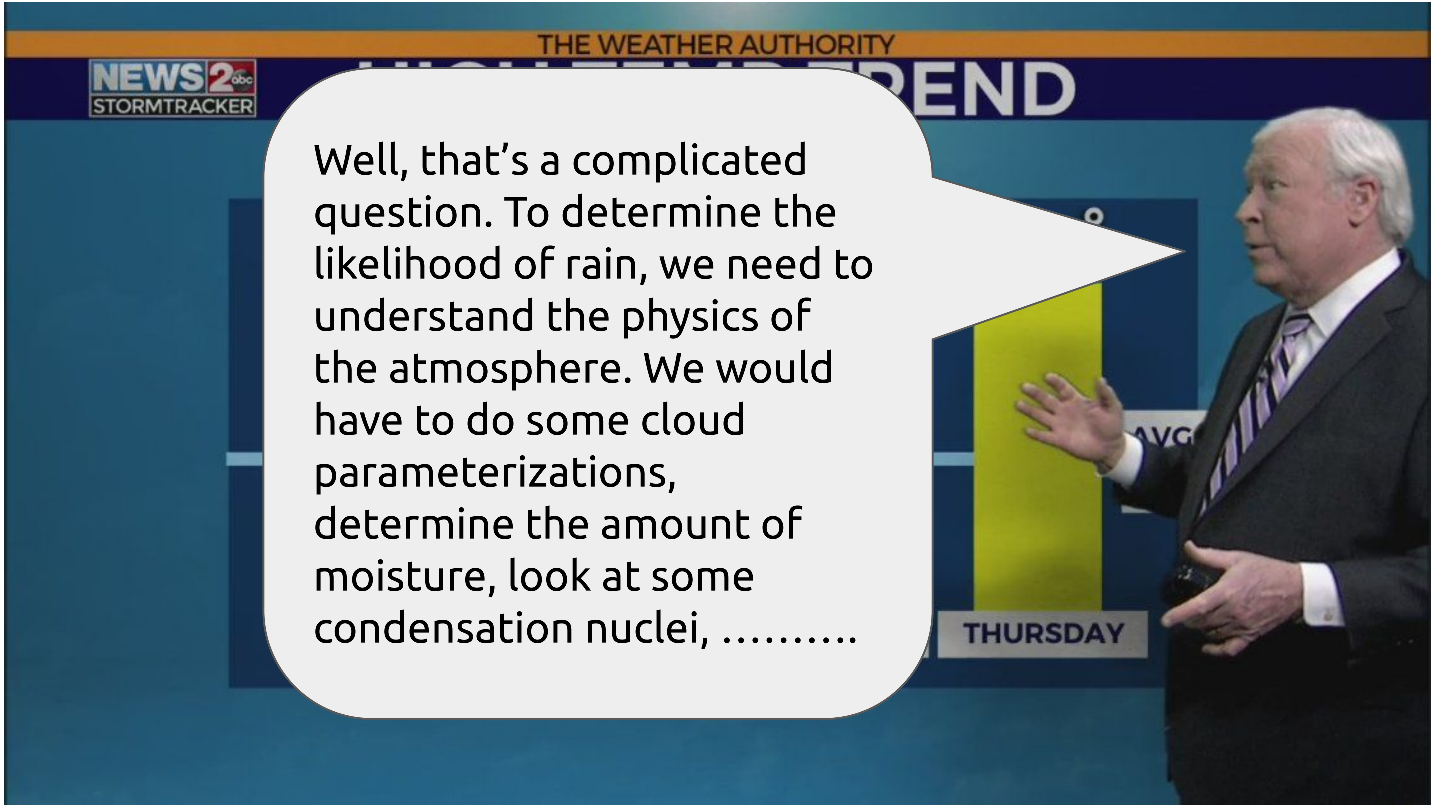

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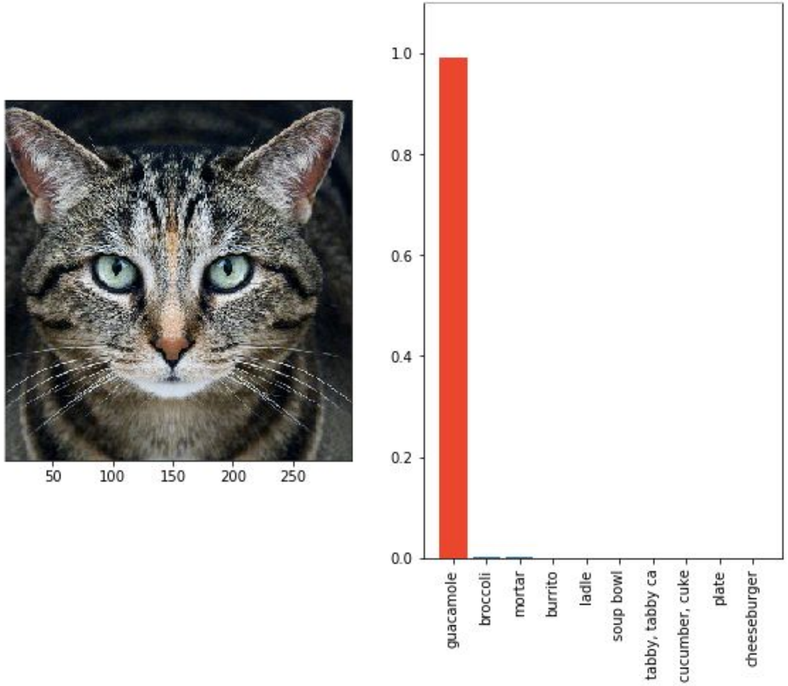
Moral: Given a good set of predictor variables and enough “experience” (training data), we can often make good predictions.

Before we get started, a word of caution: machine learning is more than just dumping a lot of data into a magic black box to make predictions.



https://www.theverge.com/2017/11/2/16597276/google-ai-image-attacks-adversarial-turtle-rifle-3d-printed

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EXCLUSIVE

STAT+

IBM's Watson supercomputer recommended 'unsafe and incorrect' cancer treatments, internal documents show

By Casey Ross and Ike Swetlitz July 25, 2018

Reprints

https://www.statnews.com/2018/07/25/ibm-watson-recommended-unsafe-incorrect-treatments/

Before we get started, a word of caution: machine learning is more than just dumping a lot of data into a magic black box to make predictions.

Amazon ditched AI recruiting tool that favored men for technical jobs

Specialists had been building computer programs since 2014 to review résumés in an effort to automate the search process

https://www.theguardian.com/technology/2018/oct/10/amazon-hiring-ai-gender-bias-recruiting-engine

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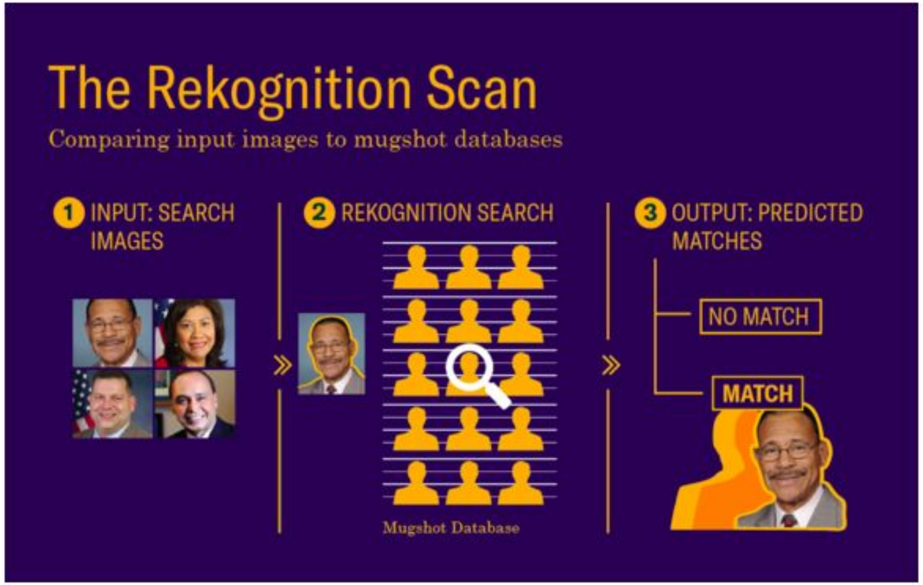

Rep. Sanford Bishop (D-Ga.) was falsely identified by Amazon Rekognition as someone who had been arrested for a crime.

https://www.aclu.org/blog/privacy-technology/surveillance-technologies/amazons-face-recognition-falsely-matched-28

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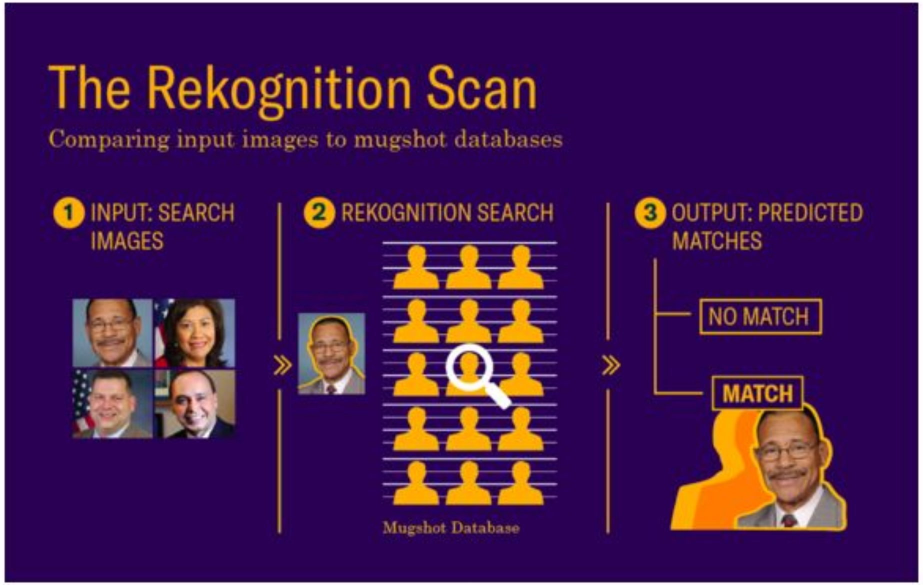

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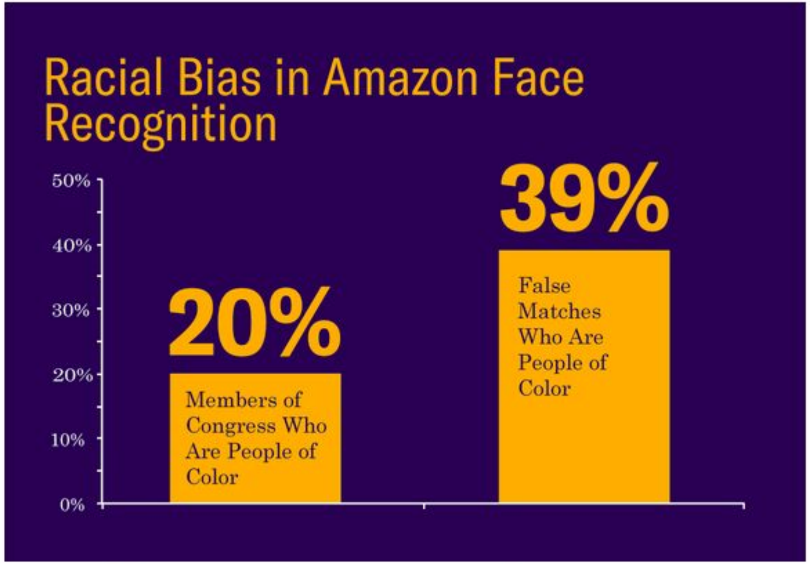

People of color were disproportionately falsely matched in our test.

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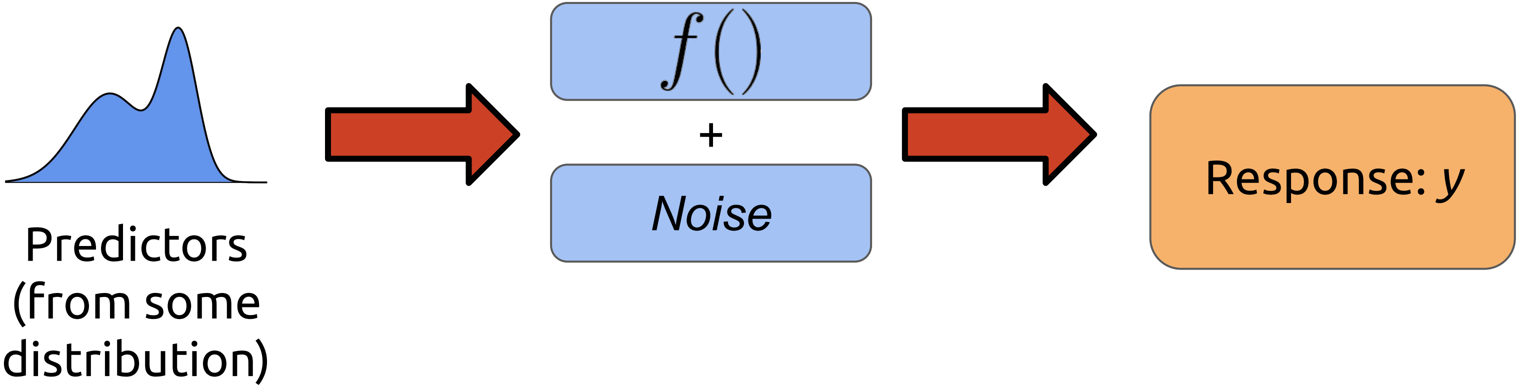
Supervised Learning - Setup



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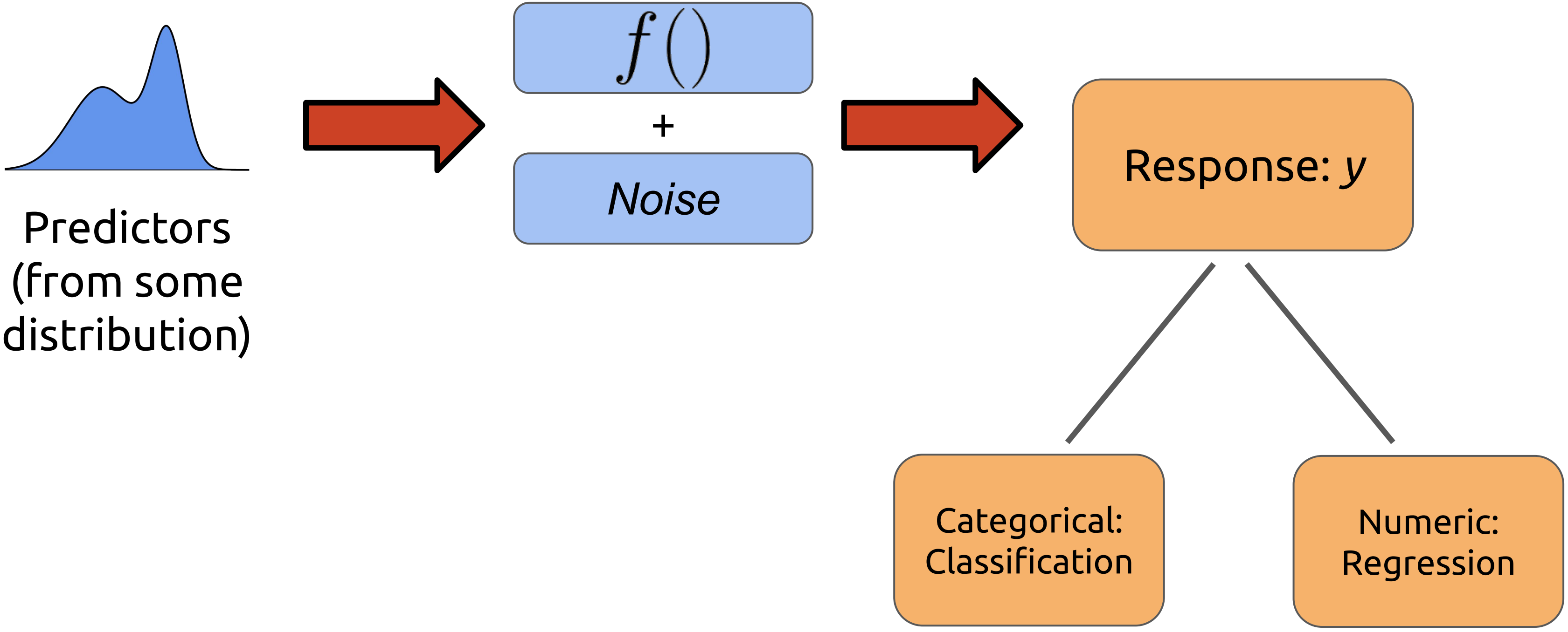

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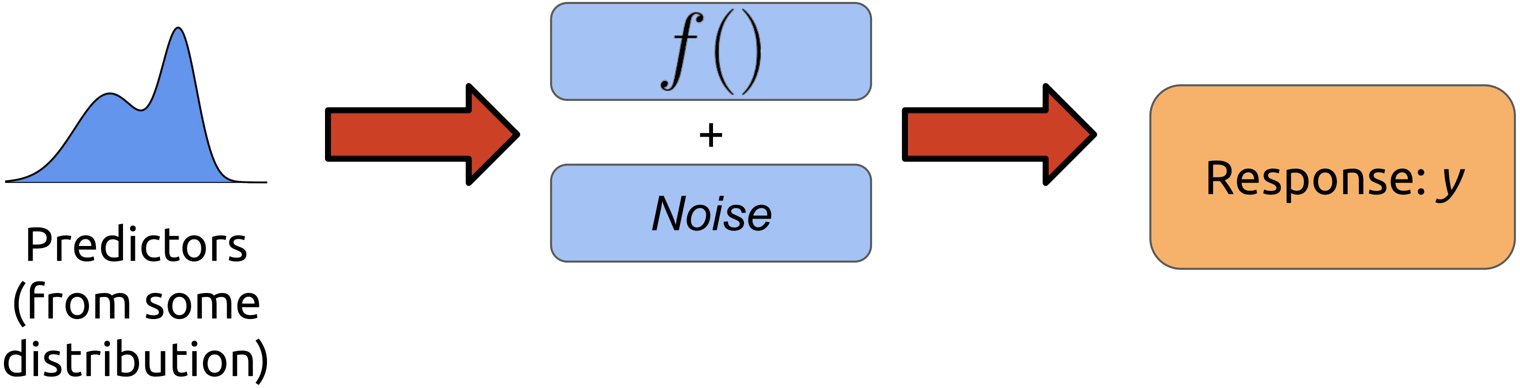
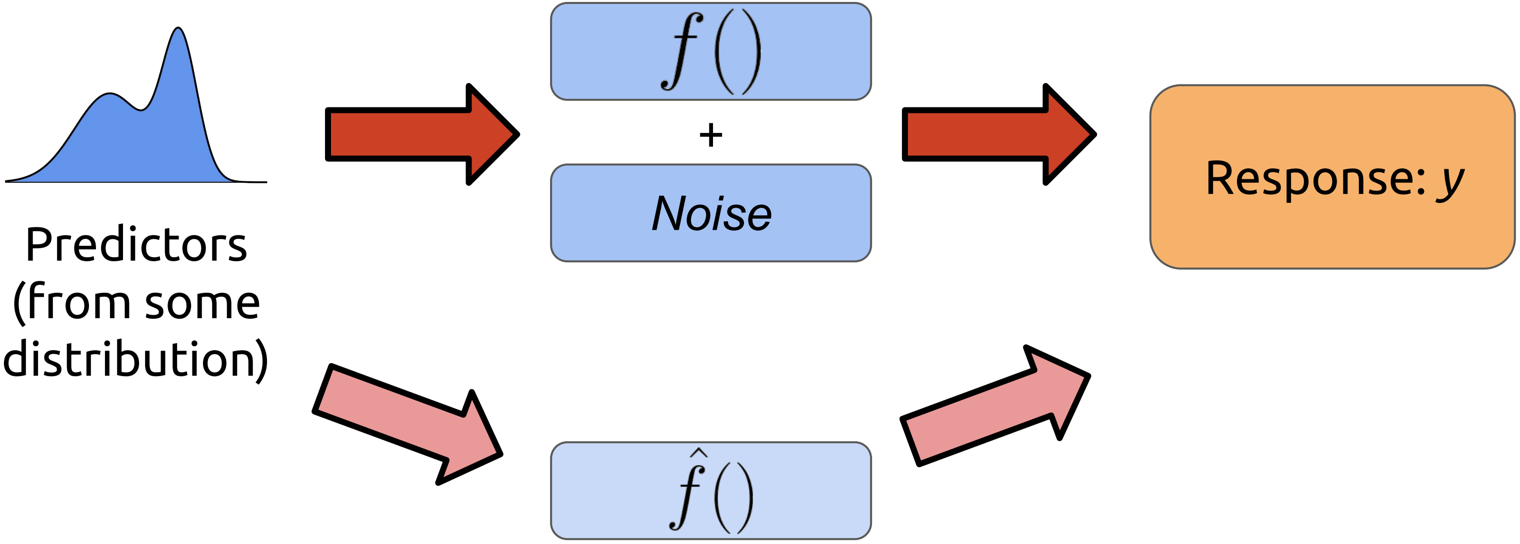


Supervised Learning - Goals



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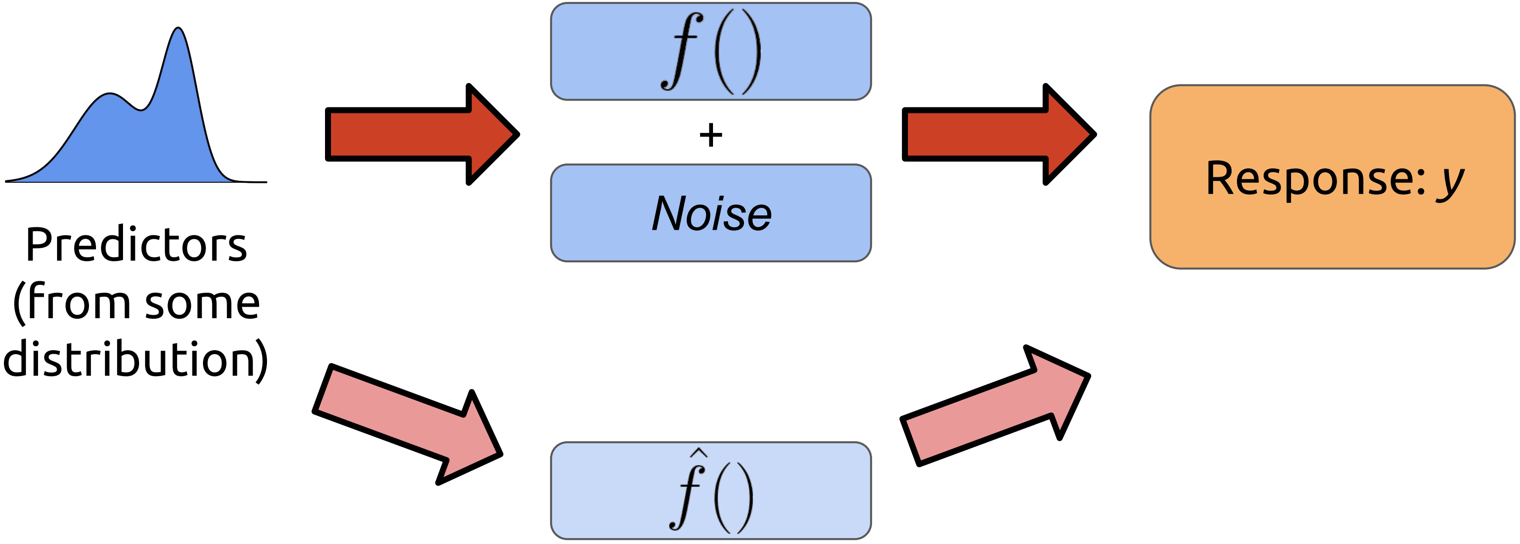
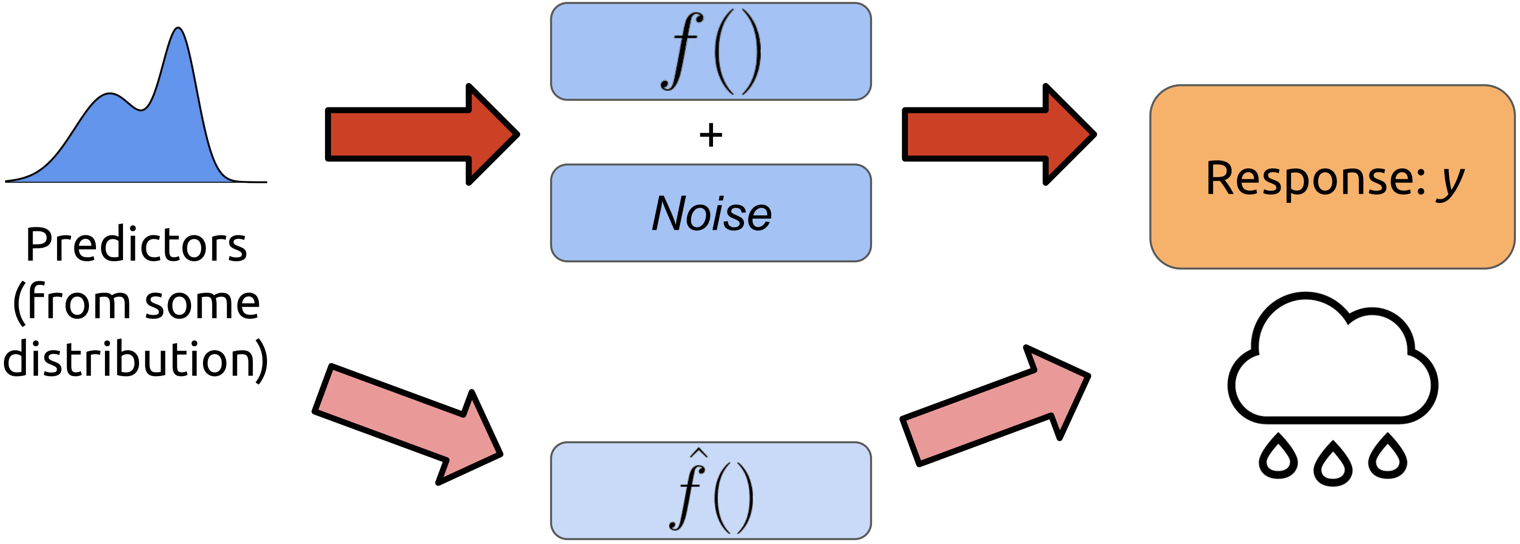


Goal: Choose a function so that the our predictions are close (on average) to the true values.

Supervised Learning - Grossly Oversimplified



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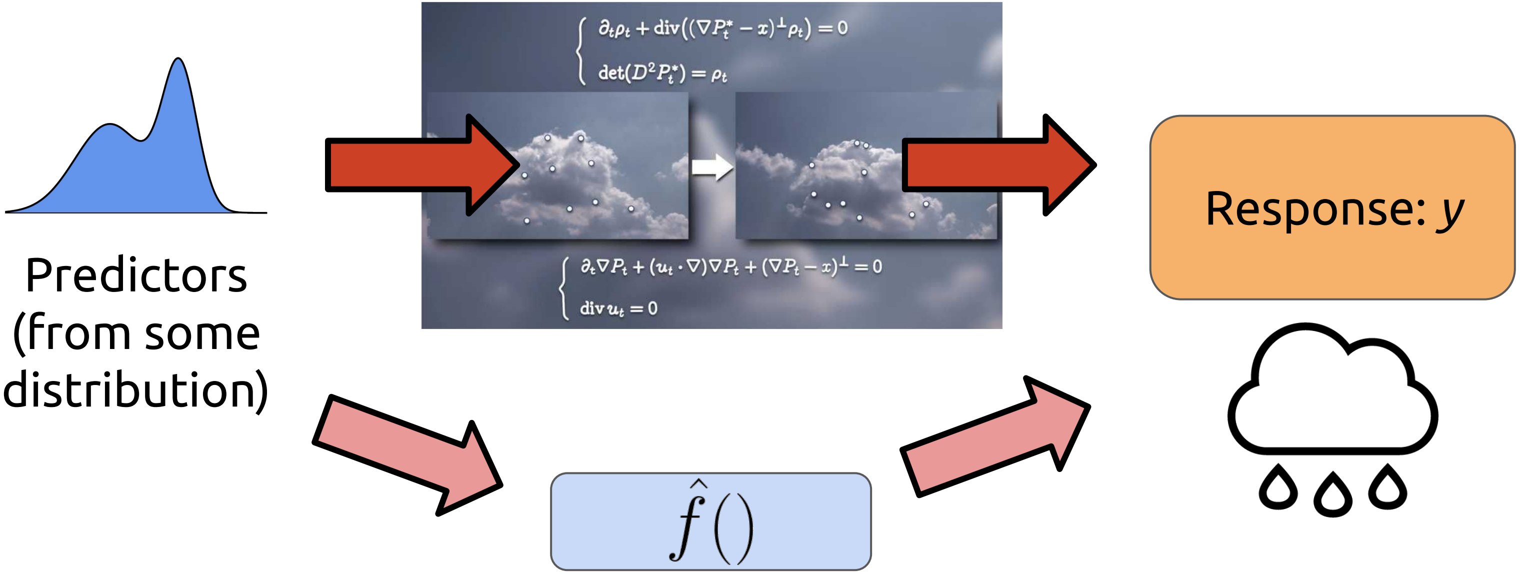

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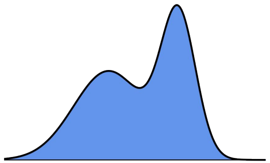
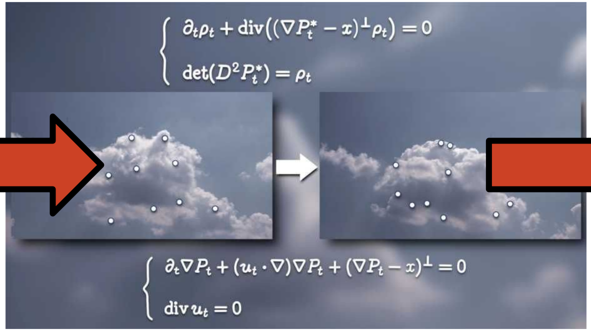
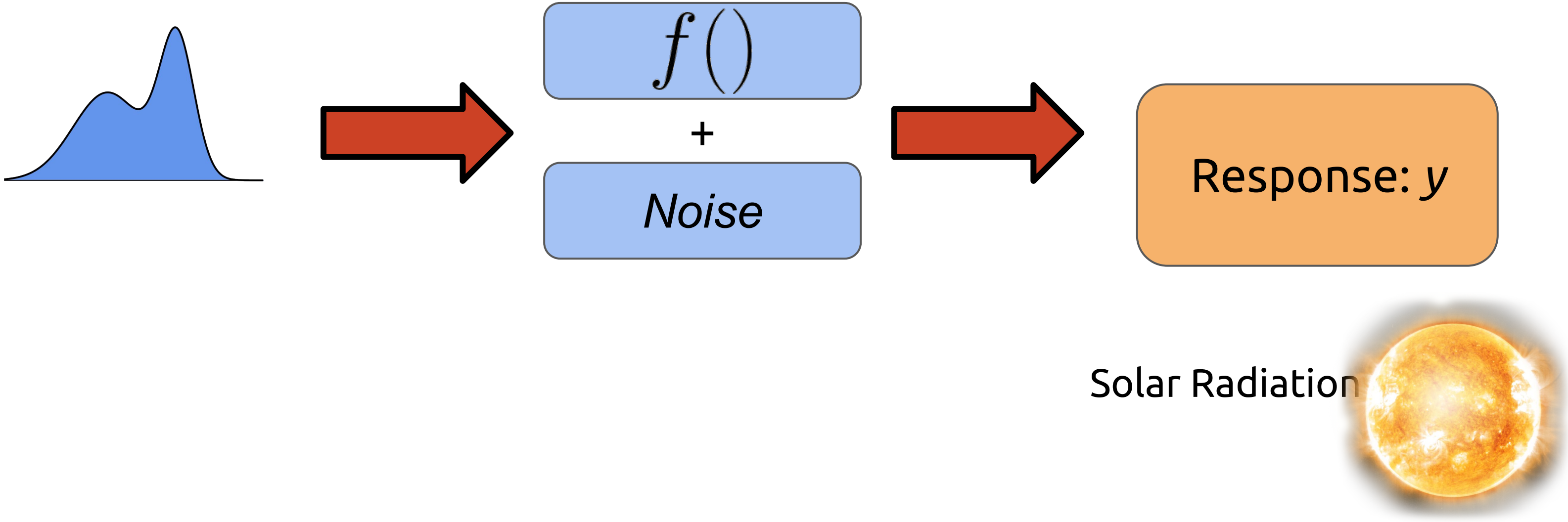


Predictors (from some distribution)



Response: y

Example - Weather Prediction



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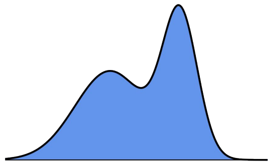

air temperature
precipitation rate
visibility
wind speed
wind direction
dew point
temperature
air pressure
relative humidity

$f()$

+

Noise

Response: y

Solar Radiation

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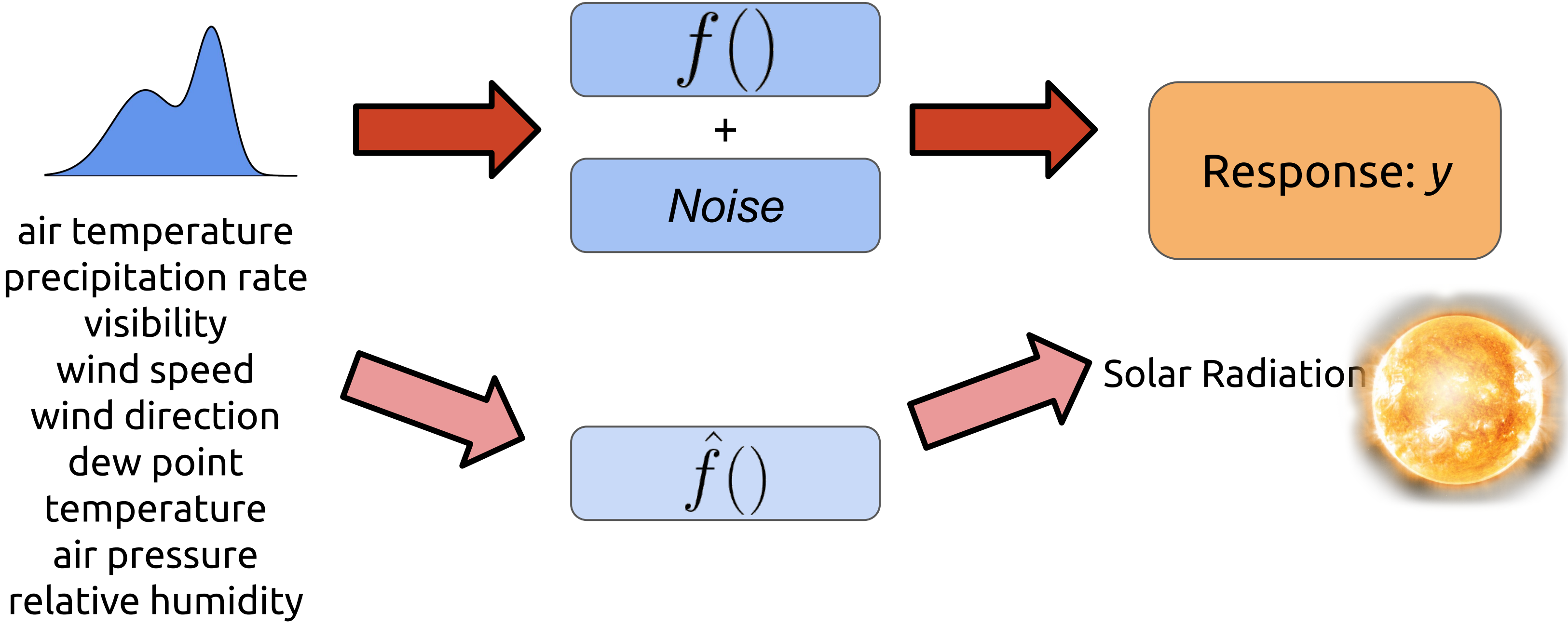

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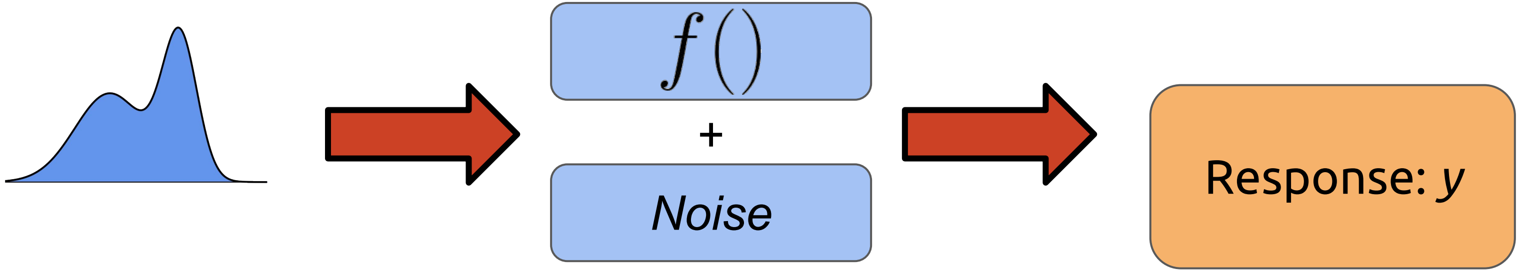
Example - Readmission or Death of Stroke Patients



90 day
readmission or
mortality

https://www.mdpi.com/2076-3417/10/18/6337/pdf

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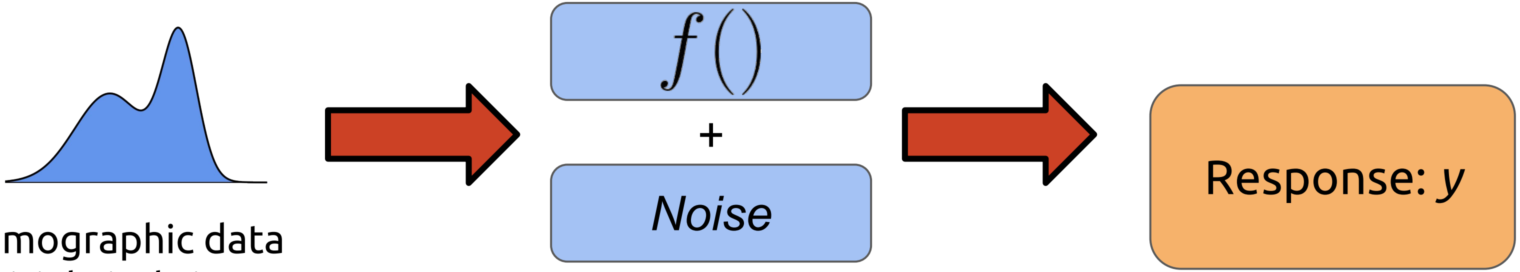

demographic data
initial vital signs
laboratory results
past medical history
comorbidities
treatment-seeking behavior
pre-stroke functional status

90 day
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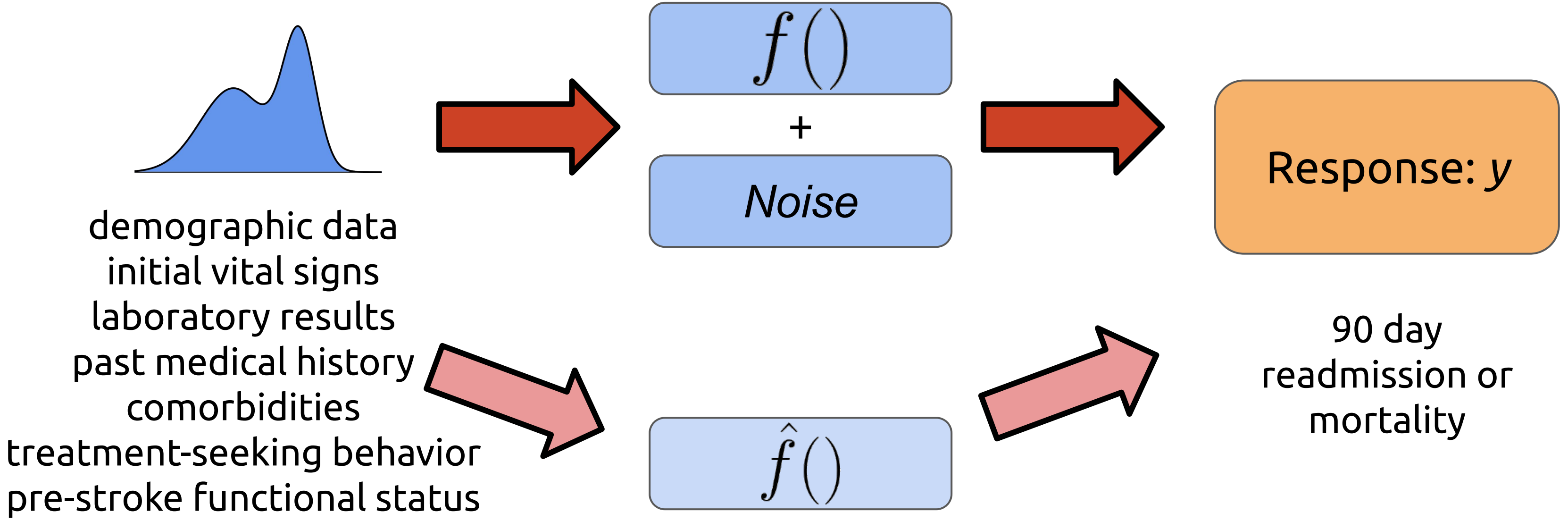

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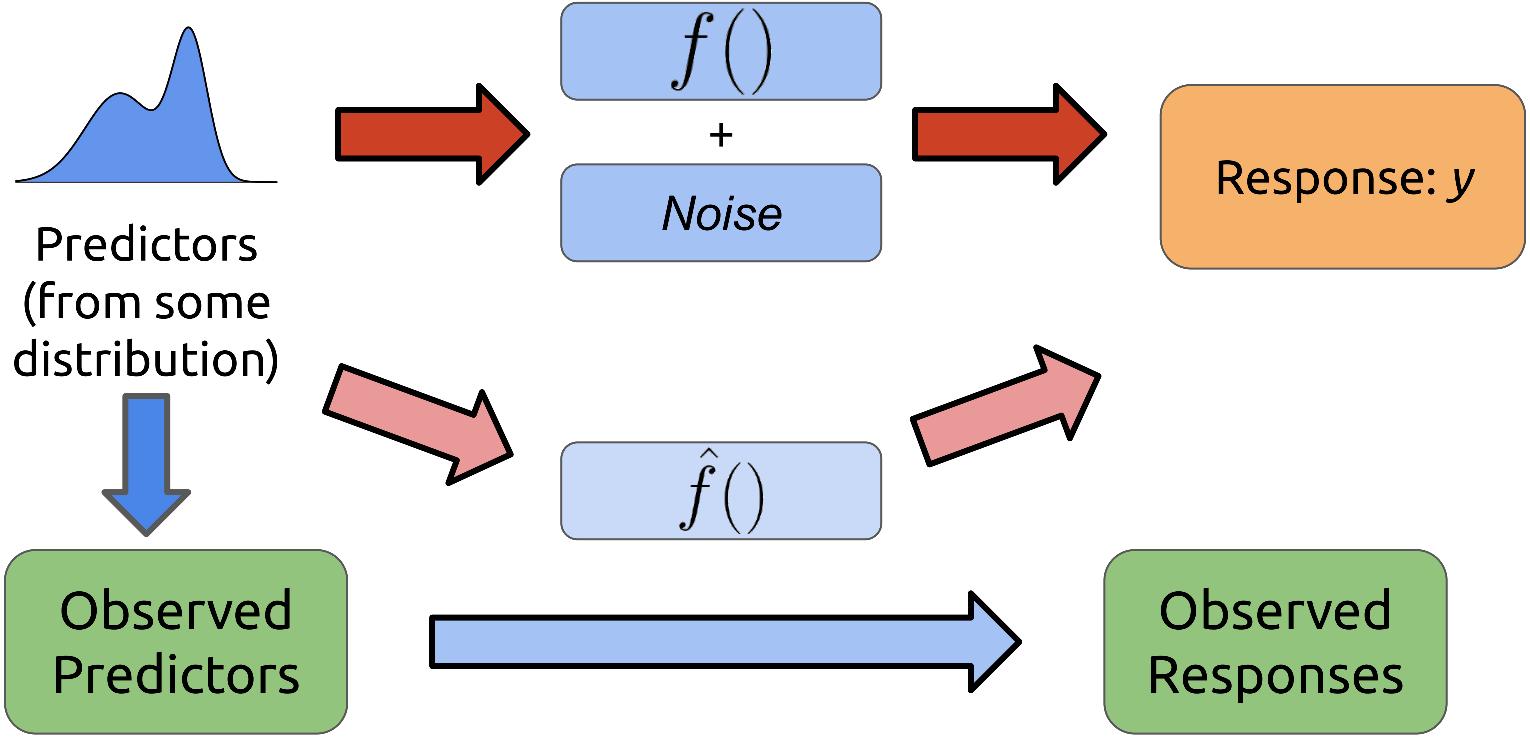
Supervised Learning - How



Supervised Learning - Goals

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.

Supervised Learning - How?

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Linear regression use a particularly simple functional form to make predictions - a weighted sum of the predictor variables.

Linear Regression

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

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

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

Linear Regression

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:

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

Linear Regression

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:

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

Linear Regression

How do we find the values for the coefficients?

Linear Regression

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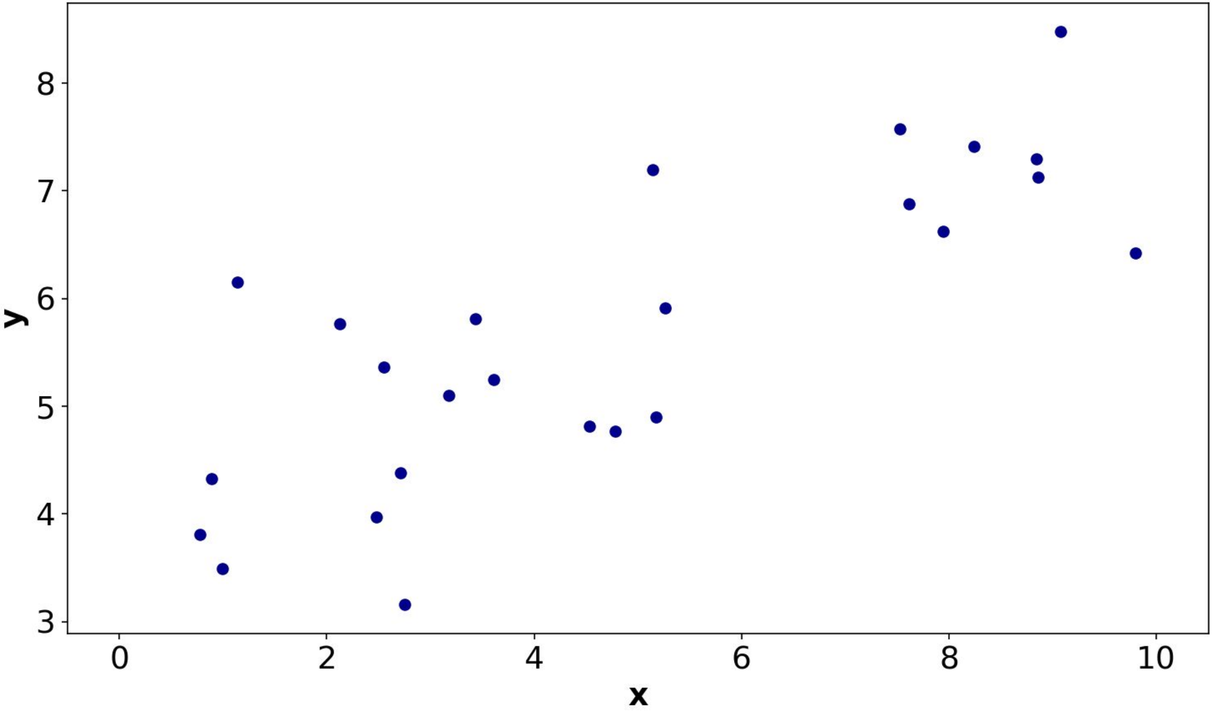
The usual way to do it is to minimize the total squared residuals between the predicted and actual values for the data used to fit/train the model.

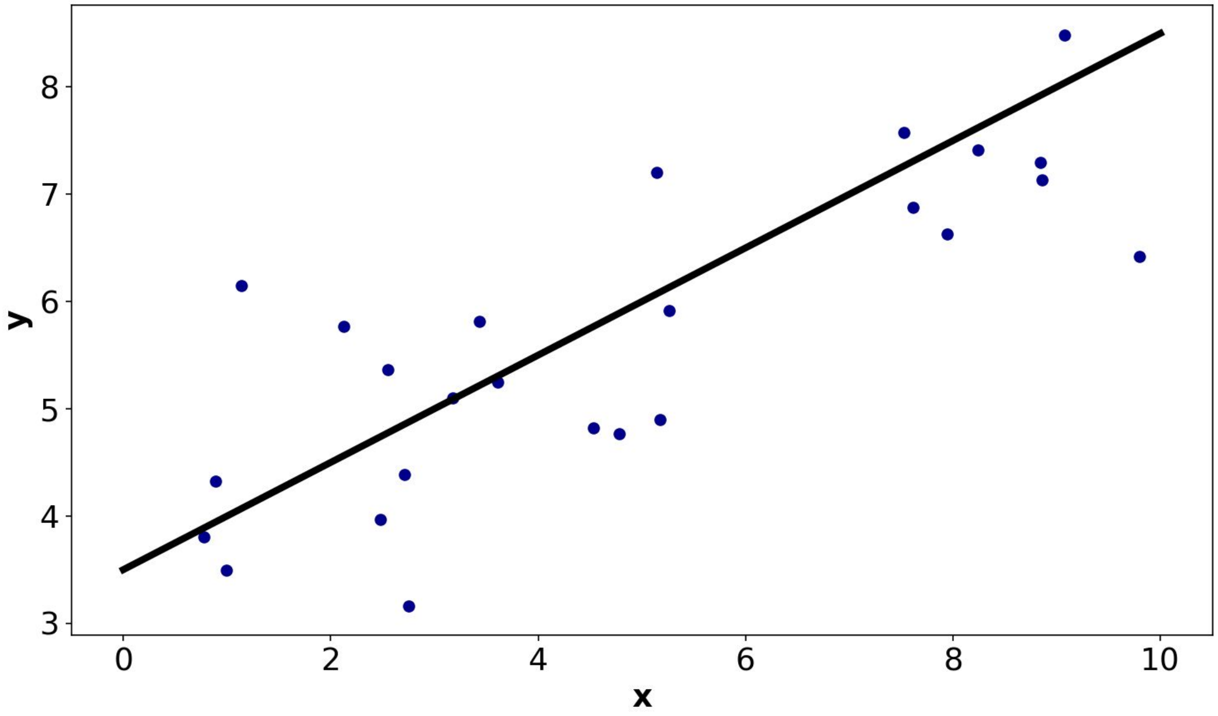
$$RSS = \sum_{i=1}^{n} (y_i - \hat{f}(\vec{x}_i))^2$$

Linear Regression



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

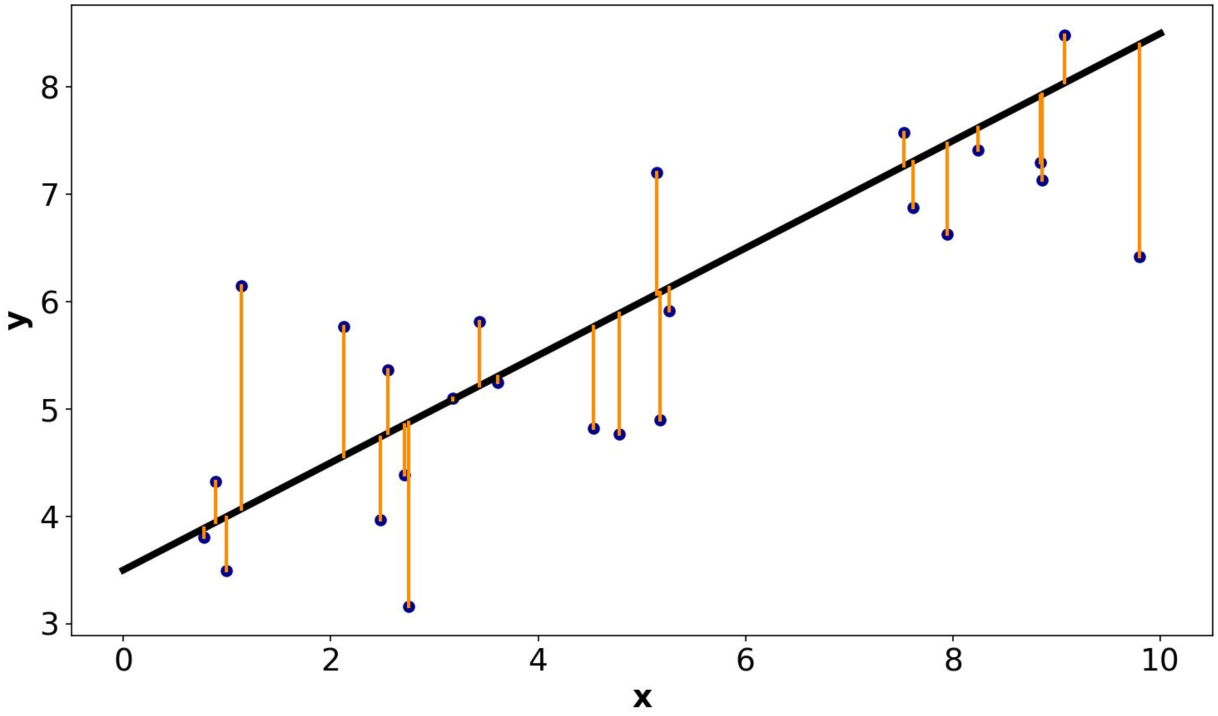
Linear Regression



One possible line:

y = 3.5 + 0.5x

Linear Regression



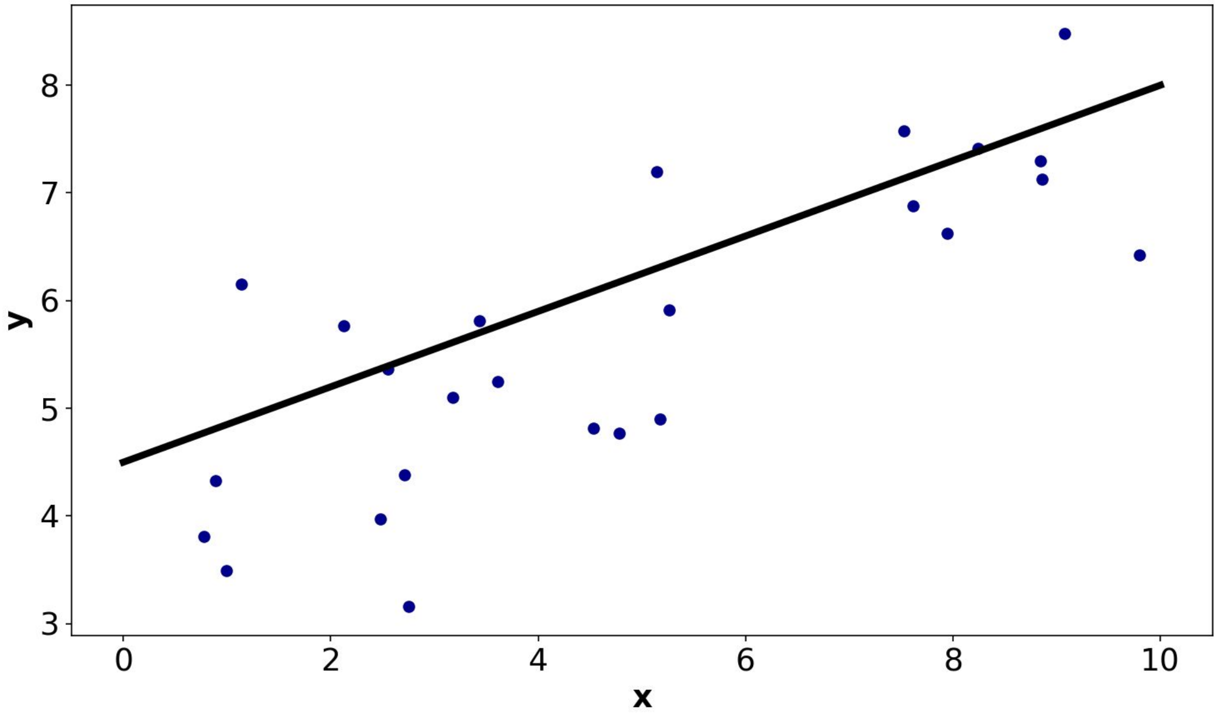
One possible line:

y = 3.5 + 0.5x

For this line,

RSS = 20.36

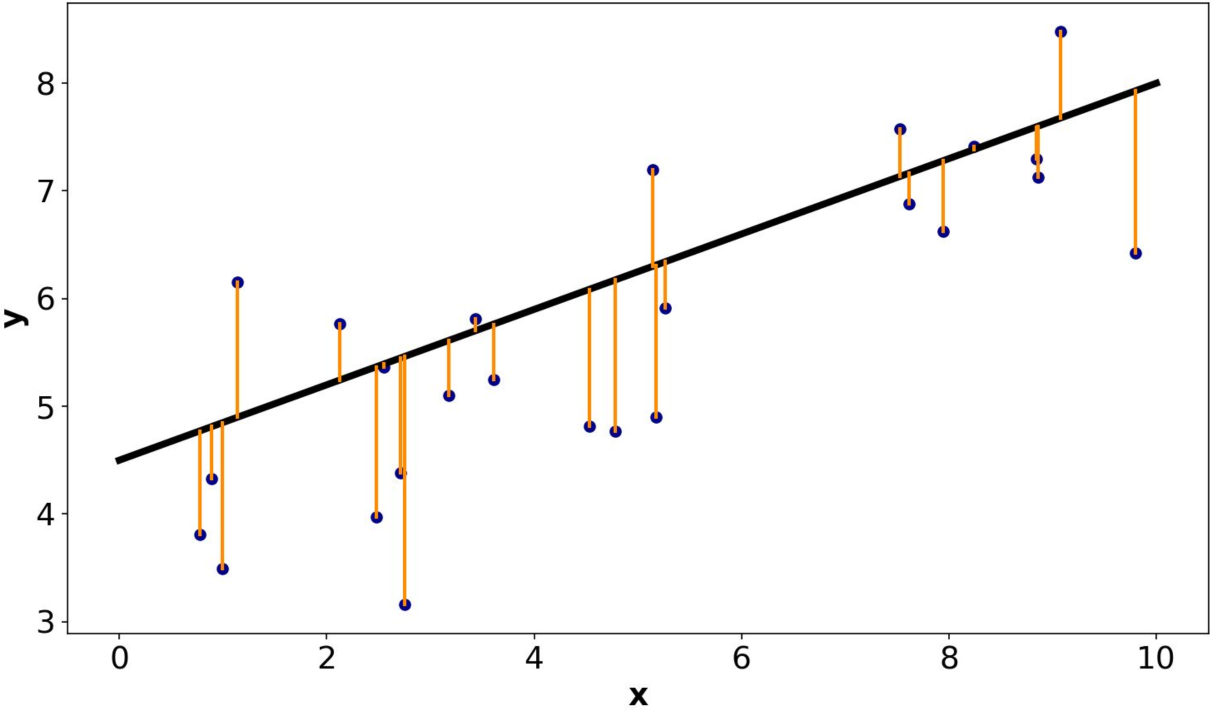
Linear Regression



Another possibility:

$$y = 4.5 + 0.35x$$

Linear Regression



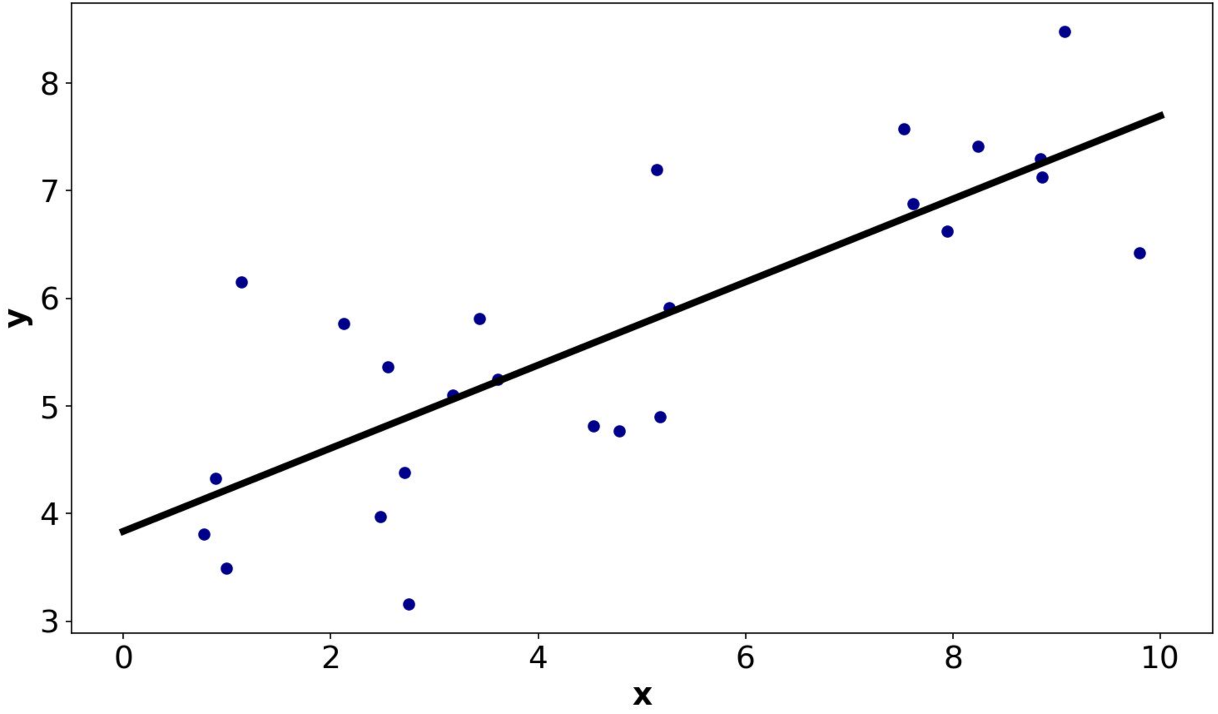
Another possibility:

$y = 4.5 + 0.35x$

Here,

RSS = 24.28

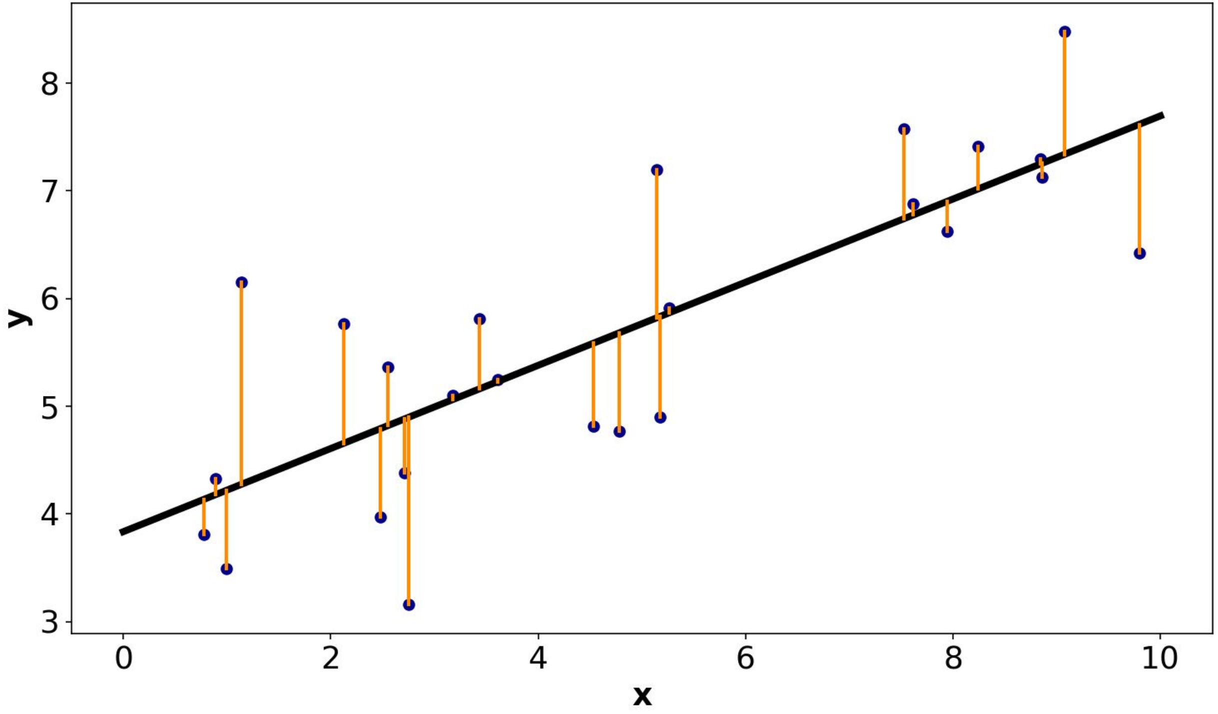
Linear Regression



The best possible:

$y = 3.84 + 0.386x$

Linear Regression



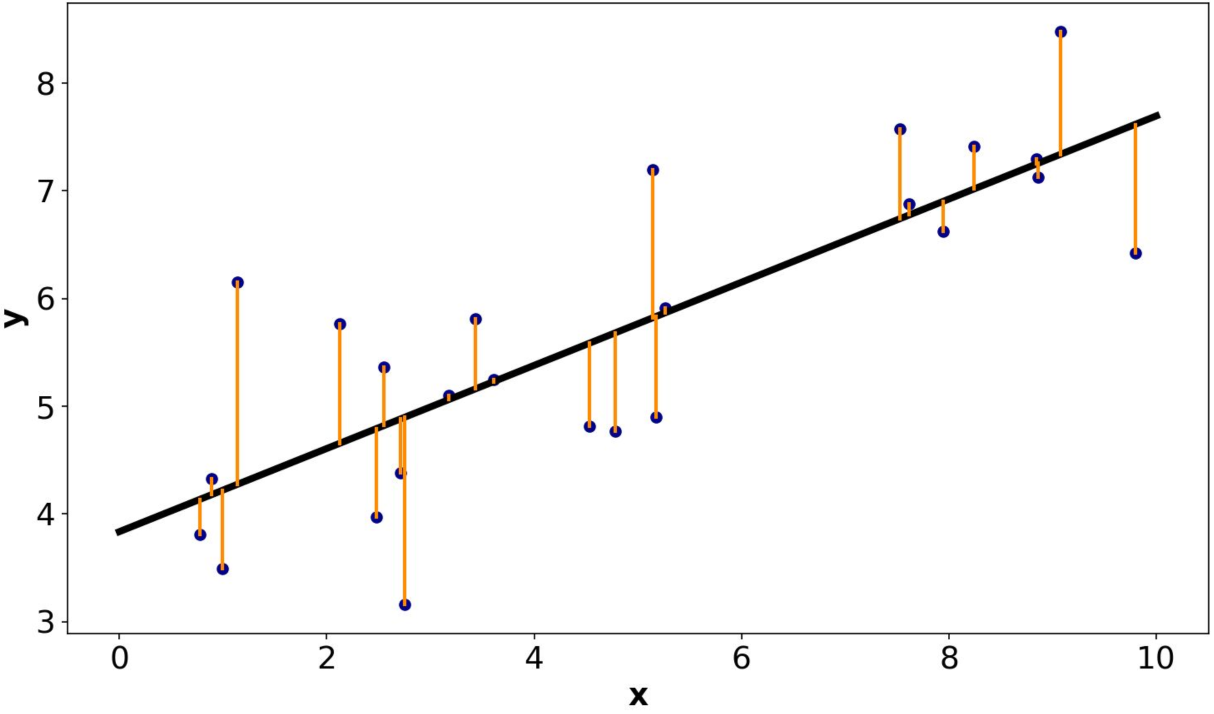
The best possible:

y = 3.84 + 0.386x

Here,

RSS = 17.97

Linear Regression



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?