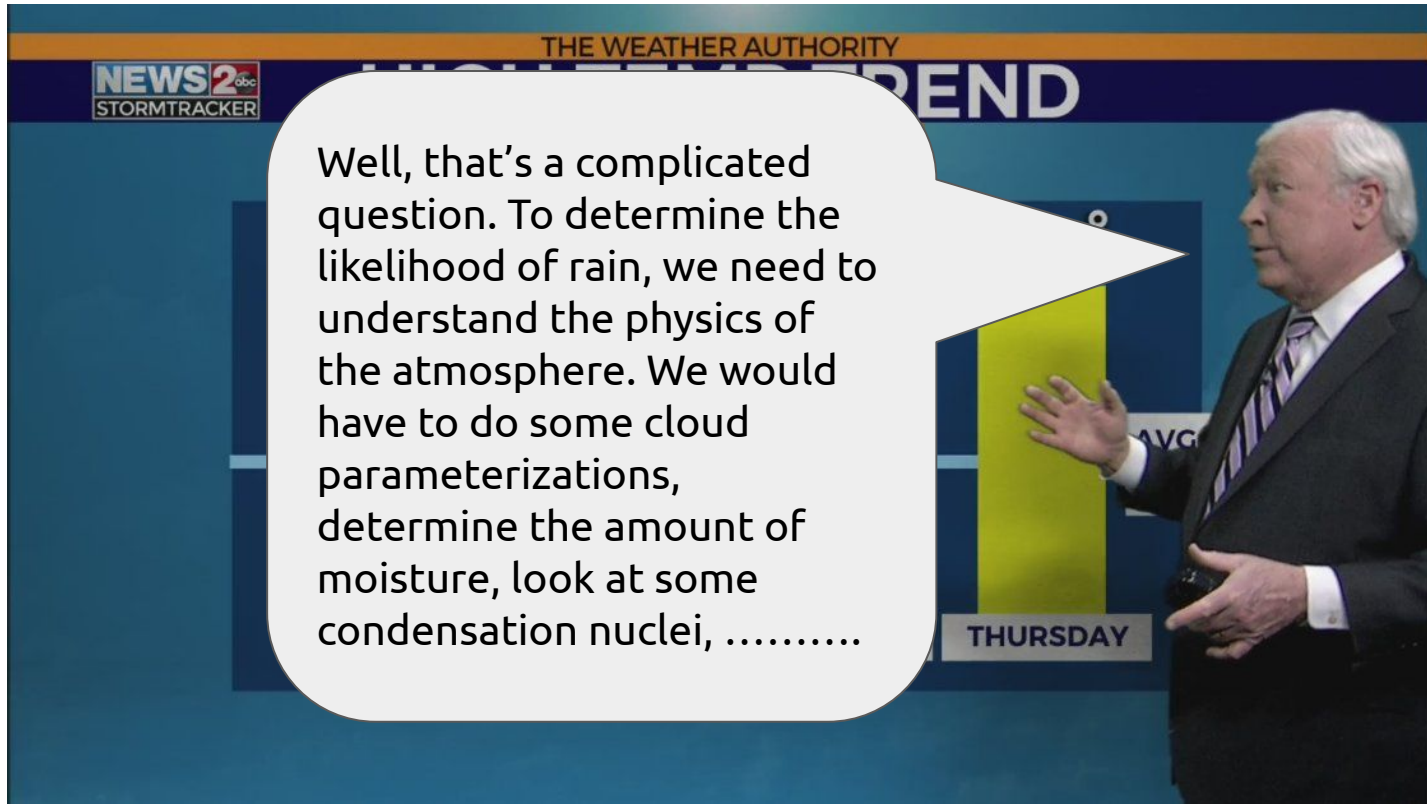


# Introduction to Supervised Learning

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

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



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

You look outside and it looks like this:

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

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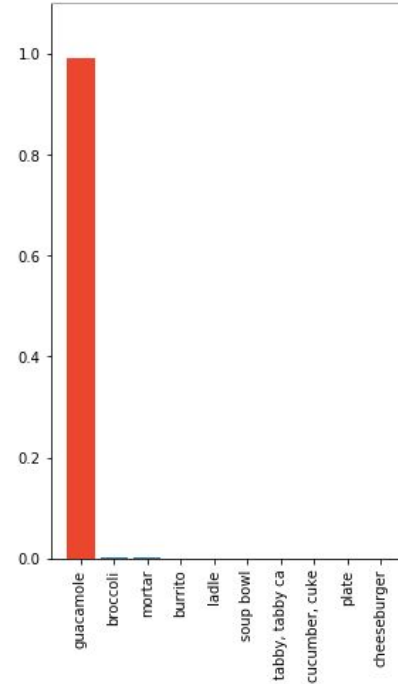


**Moral:** Given a good set of predictor variables and enough “experience” (training data), we can often make good predictions.

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.



50 100 150 200 250



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



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.

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.

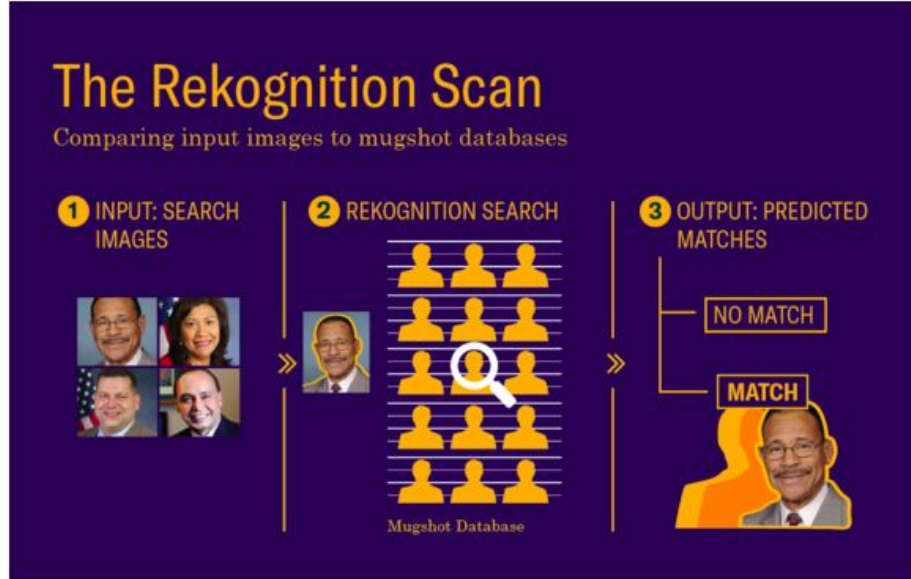
## Amazon ditched AI recruiting tool that favored men for technical jobs

**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>

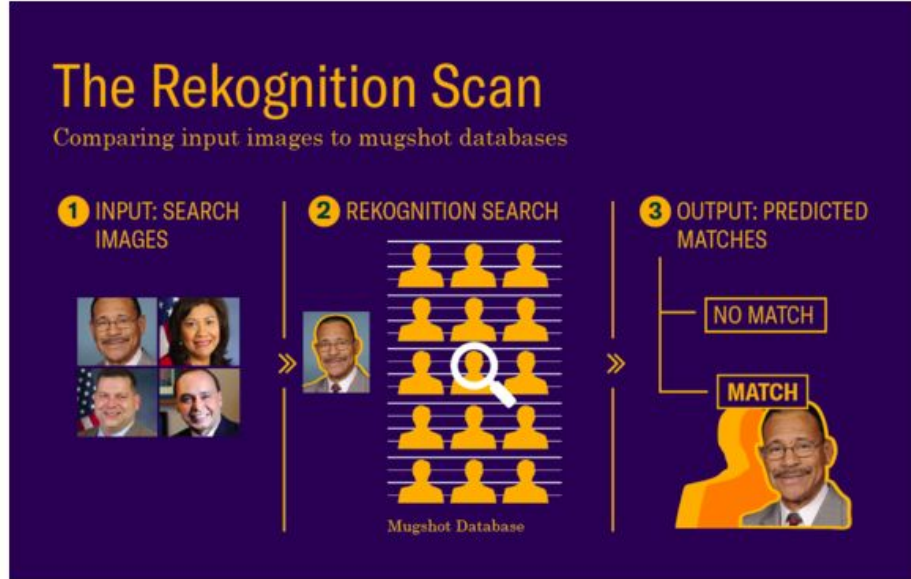
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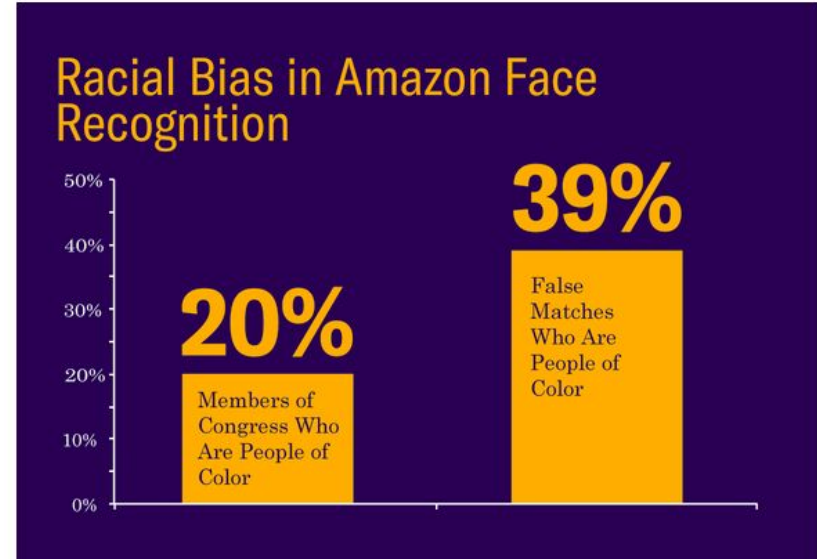
*Rep. Sanford Bishop (D-Ga.) was falsely identified by Amazon Rekognition as someone who had been arrested for a crime.*

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

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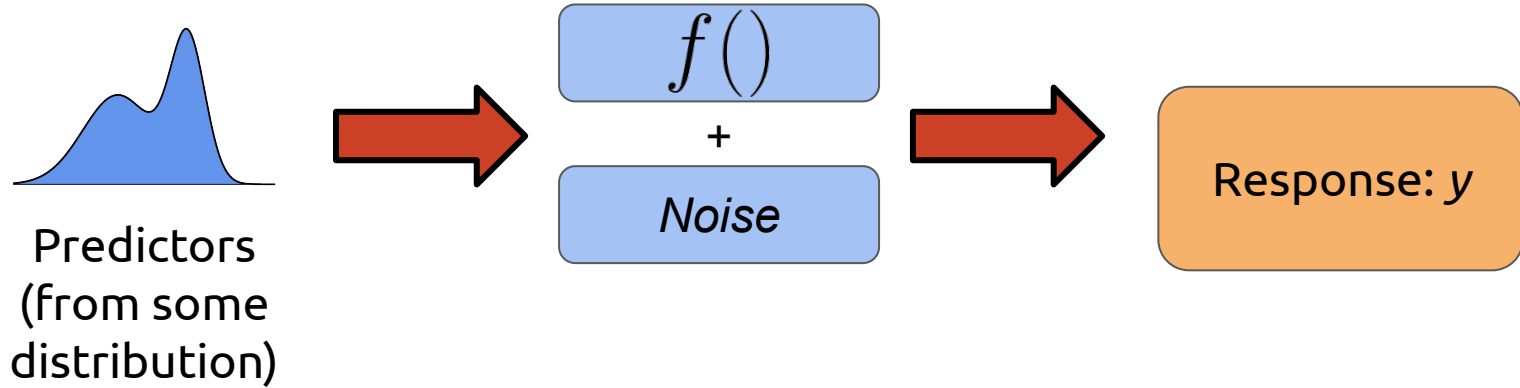
*Rep. Sanford Bishop (D-Ga.) was falsely identified by Amazon Rekognition as someone who had been arrested for a crime.*



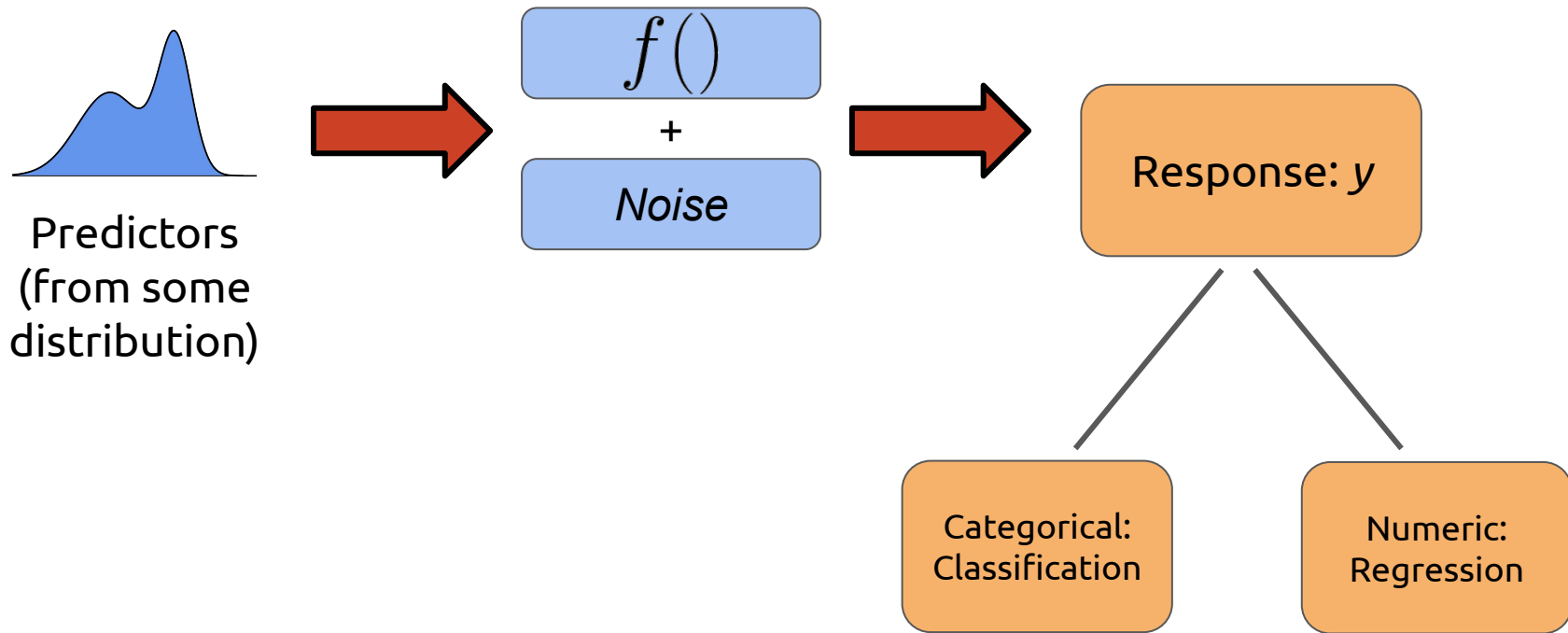
*People of color were disproportionately falsely matched in our test.*

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

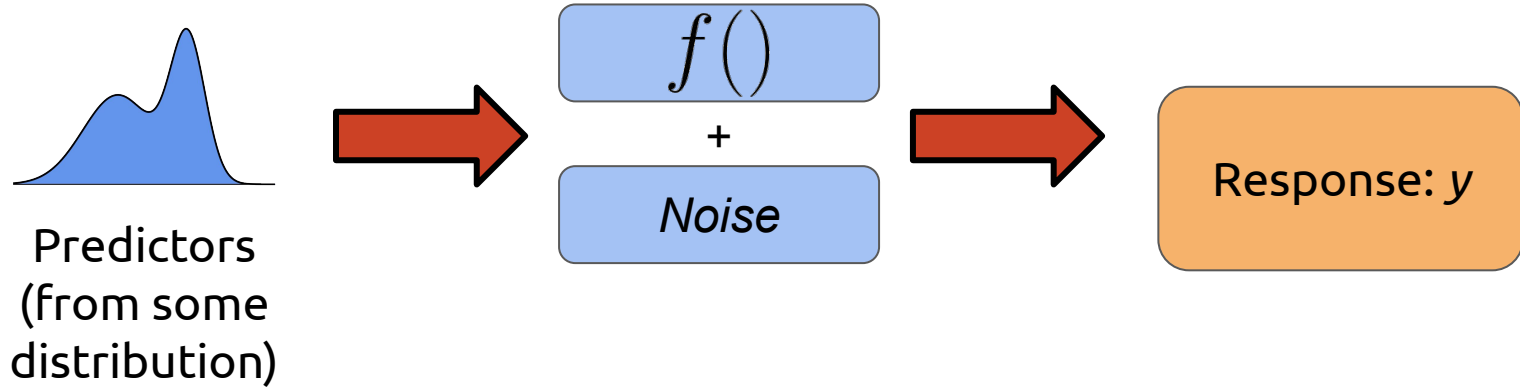
# Supervised Learning - Setup



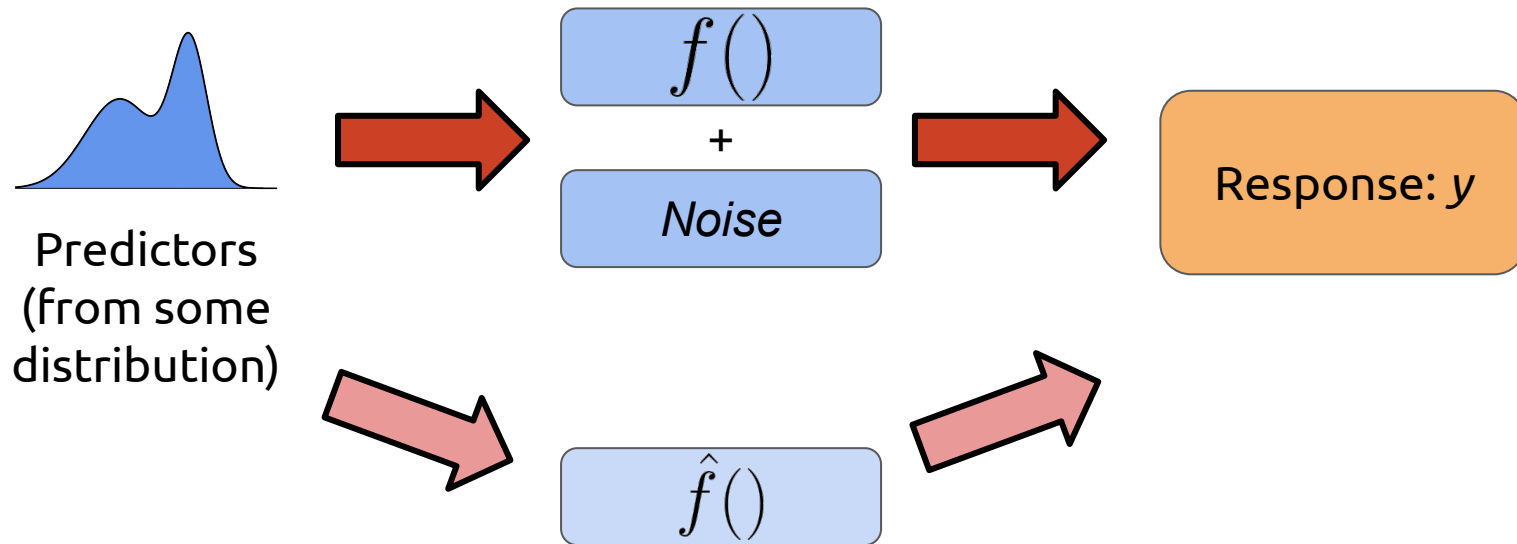
# Supervised Learning - Setup



# Supervised Learning - Setup

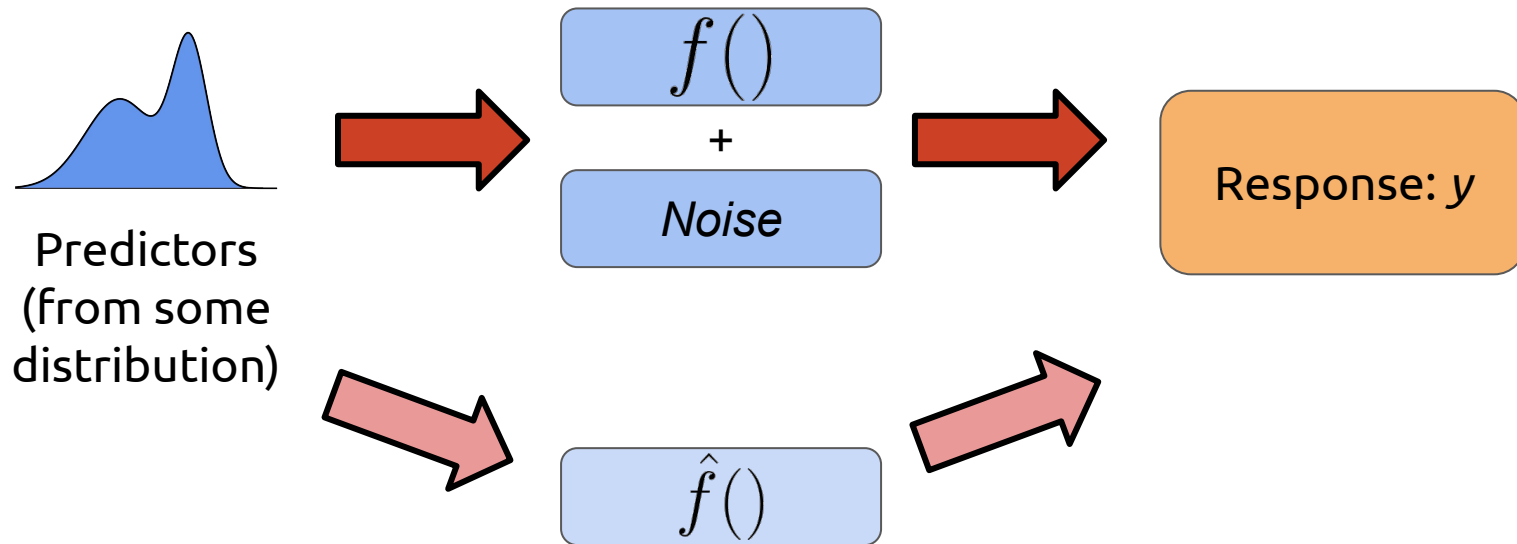


# Supervised Learning - Goals



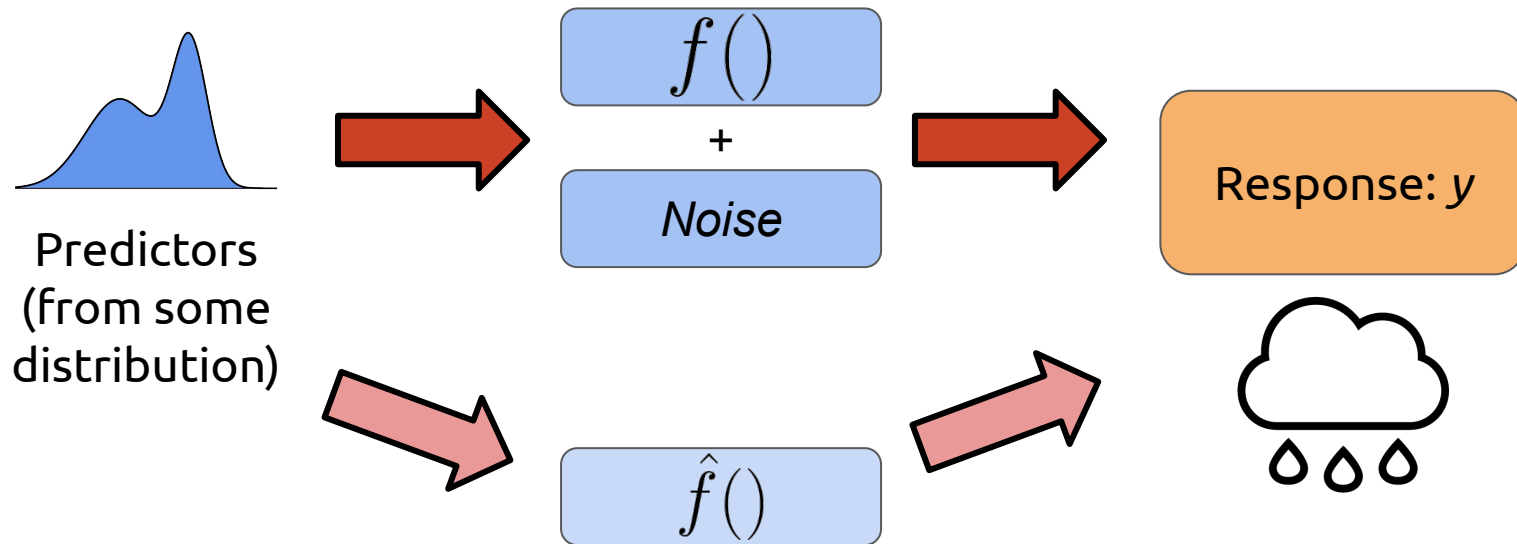


# Supervised Learning - Goals

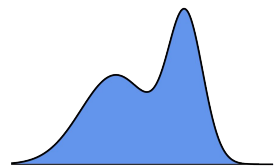


**Goal:** Choose a function so that the our predictions are close (on average) to the true values.

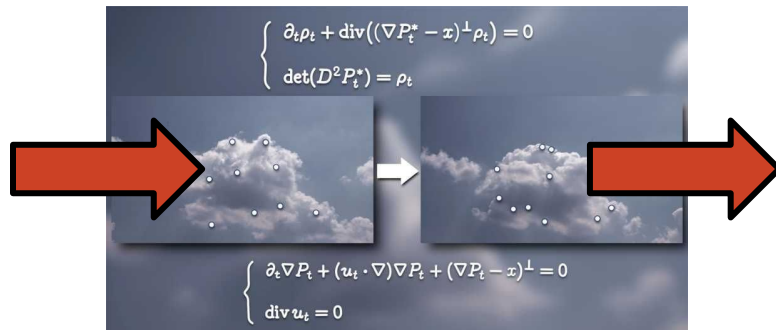
# Supervised Learning - Grossly Oversimplified



# Supervised Learning - Grossly Oversimplified



Predictors  
(from some  
distribution)

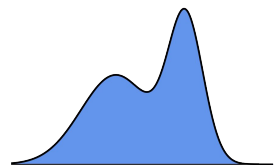


Response:  $y$

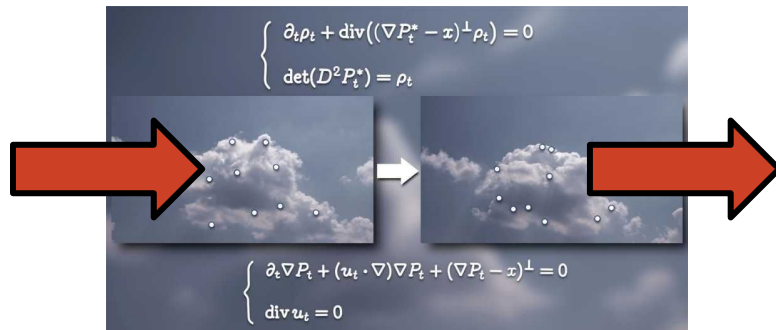


$\hat{f}()$

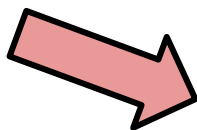
# Supervised Learning - Grossly Oversimplified



Predictors  
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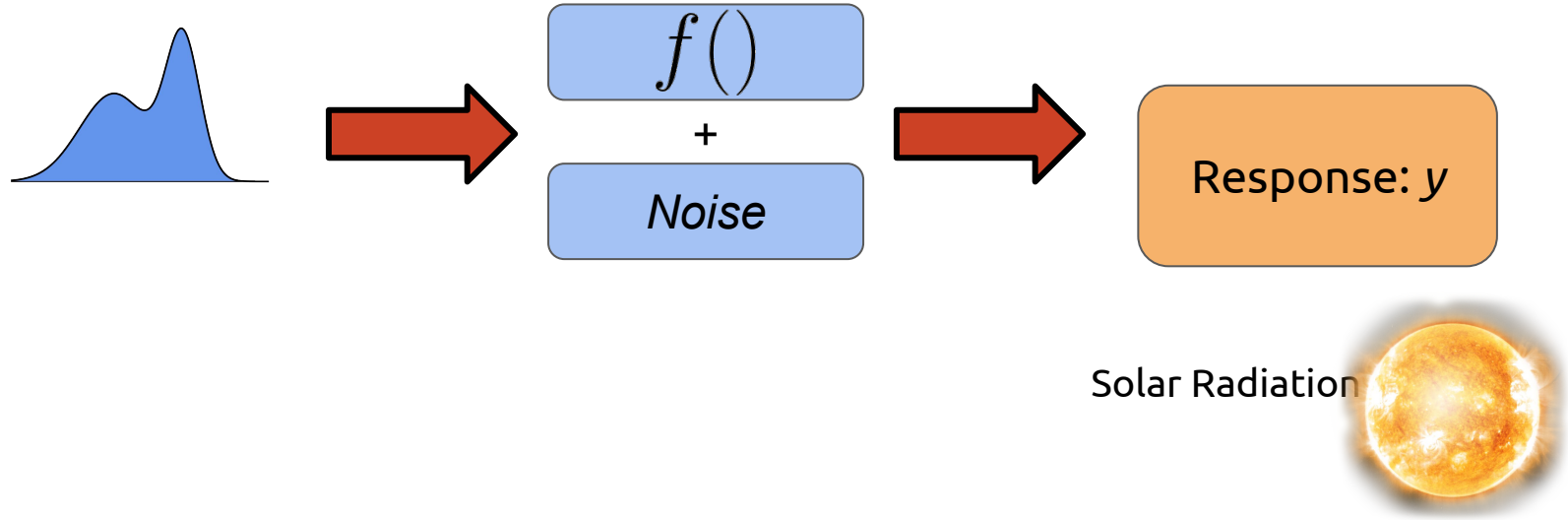
Response:  $y$



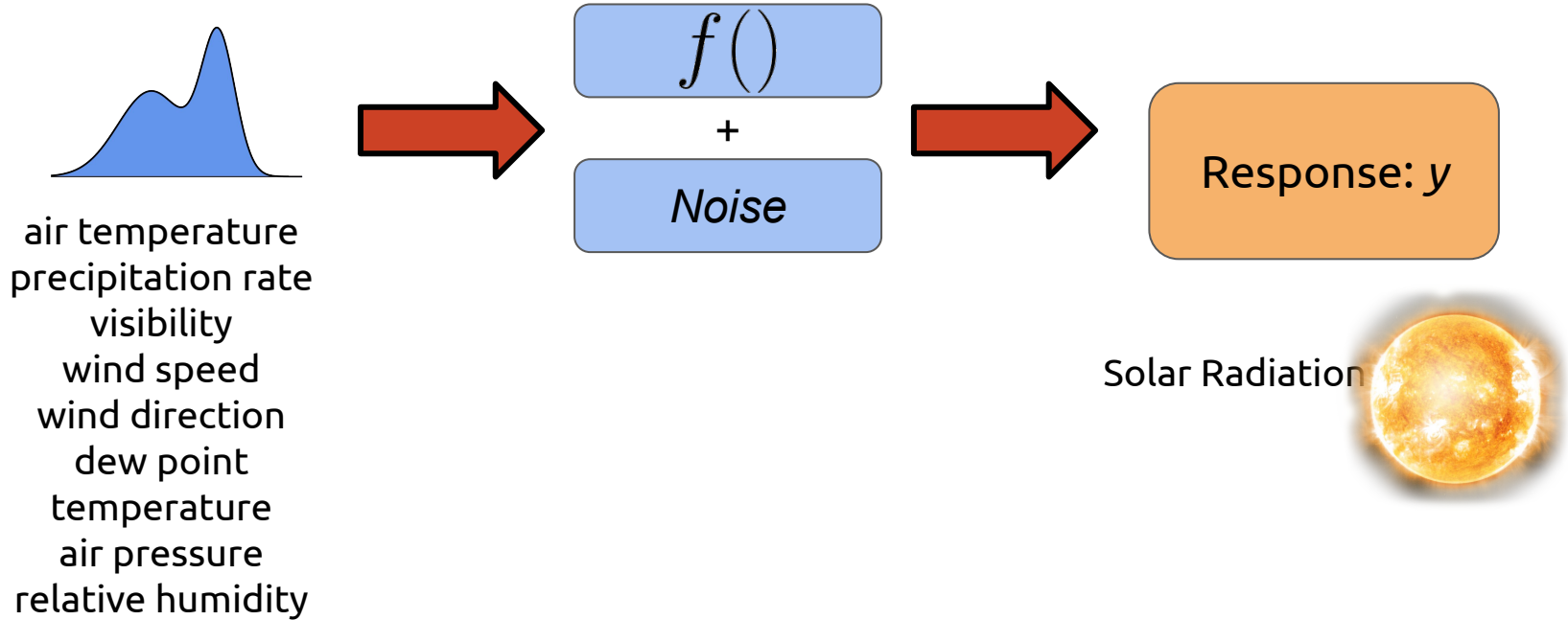
My knee is  
acting up. Must  
be rain coming.



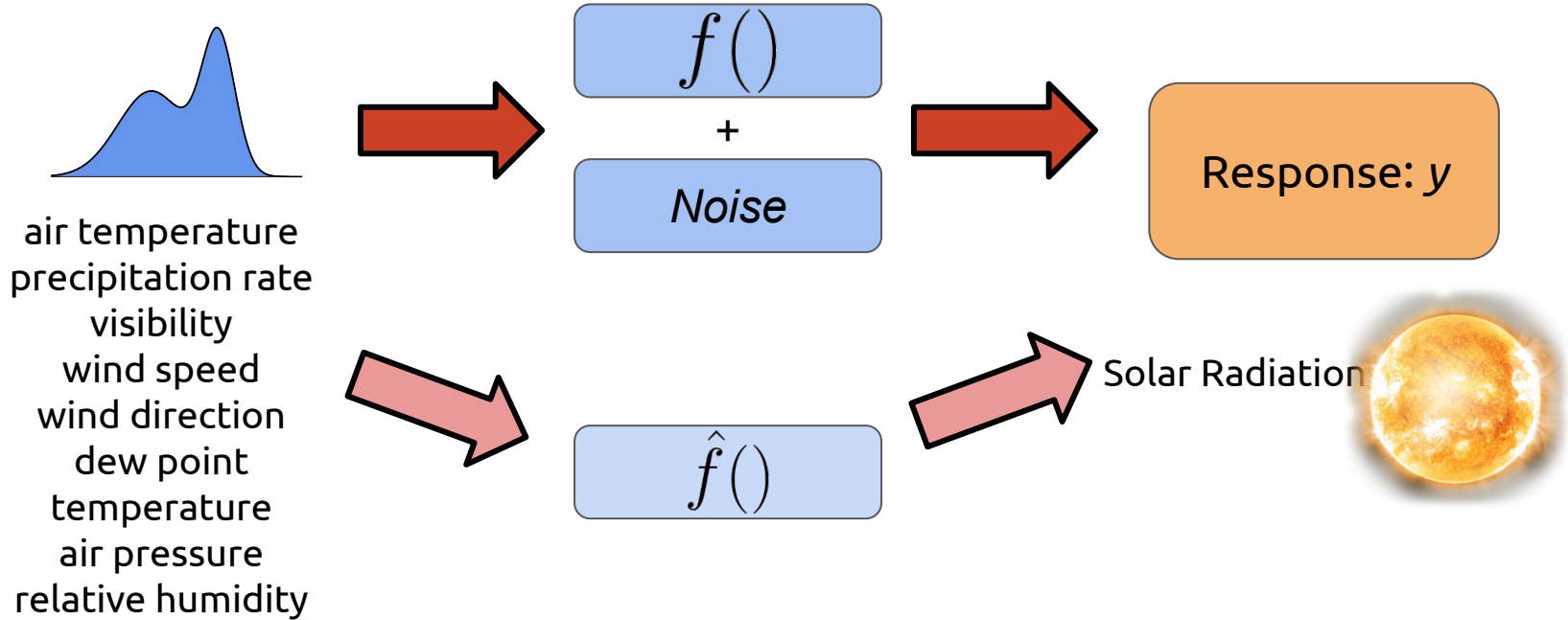
# Example - Weather Prediction



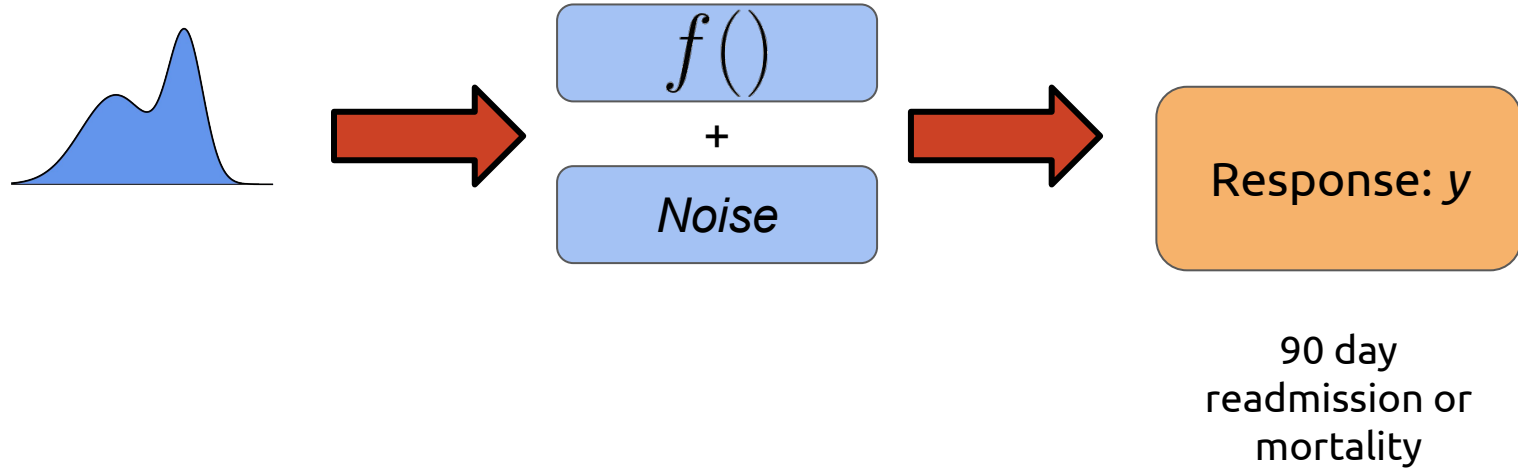
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# Example - Weather Prediction

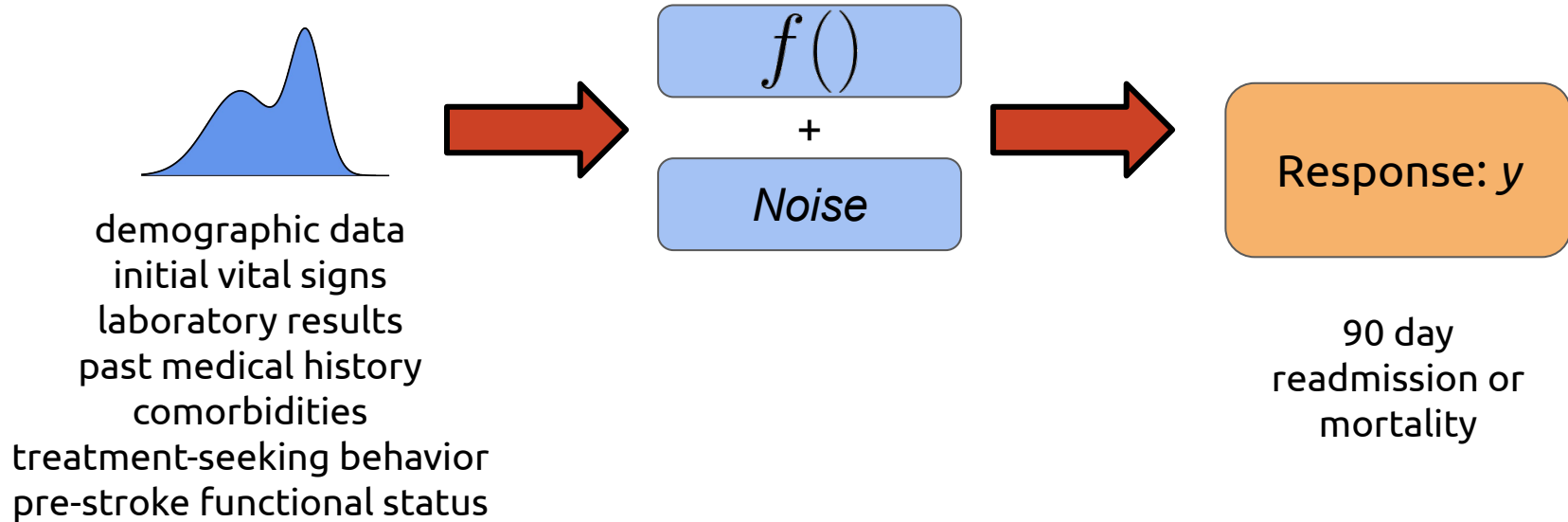


# Example - Readmission or Death of Stroke Patients

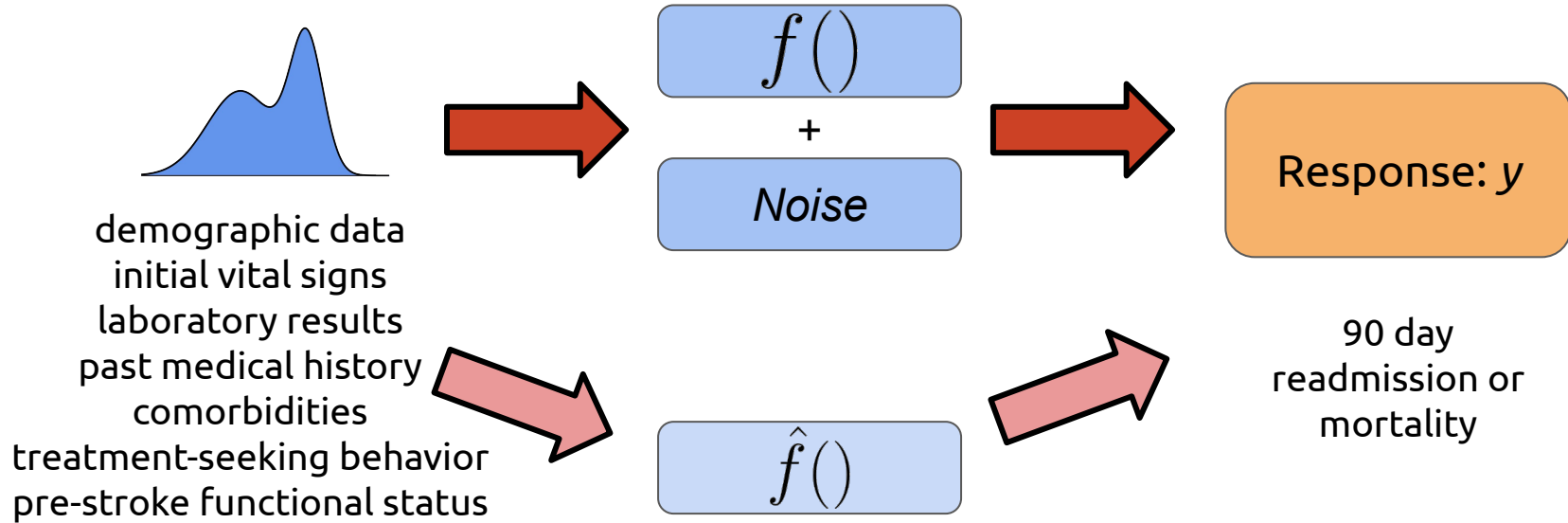




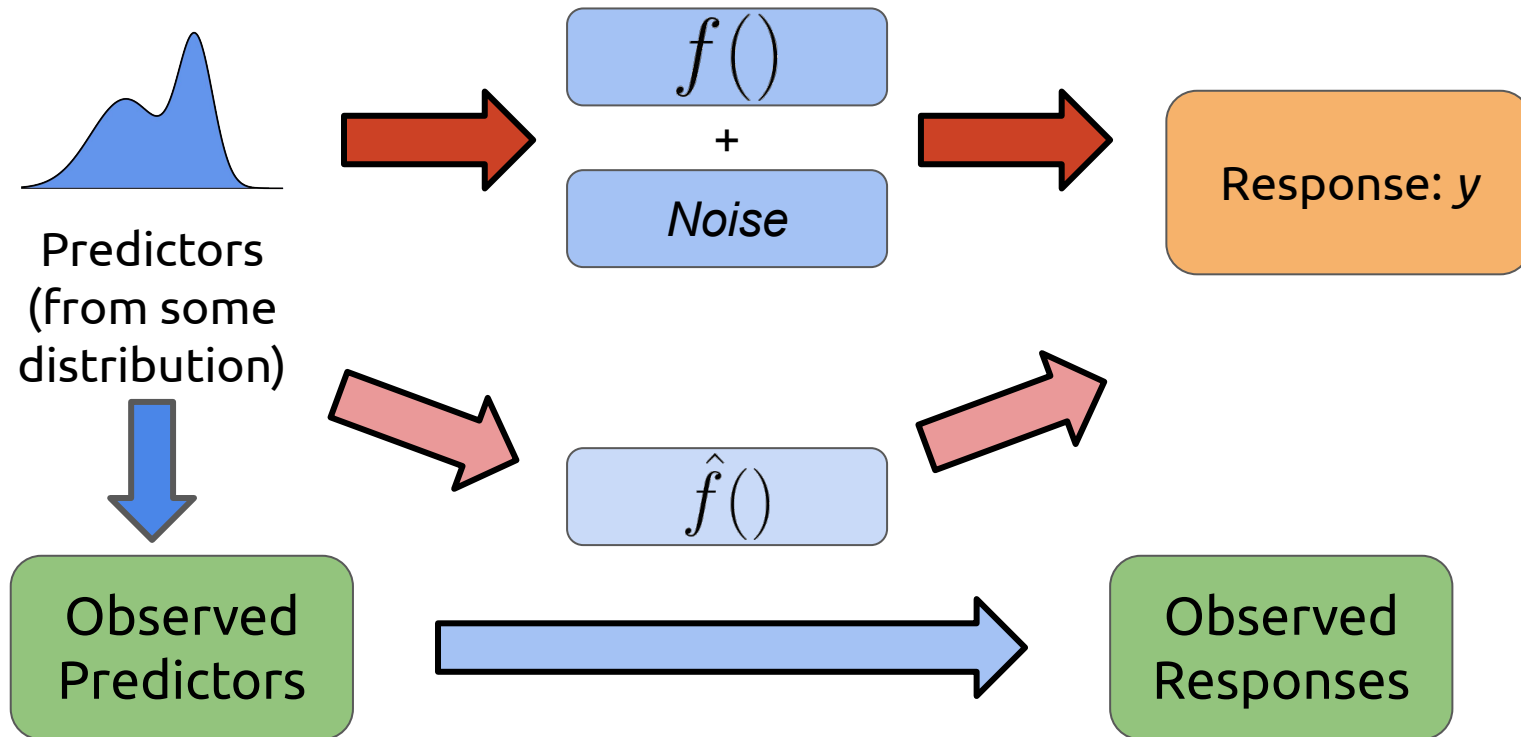
# Example - Readmission or Death of Stroke Patients



# Example - Readmission or Death of Stroke Patients



# 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.

# Measuring Generalization Data - How

If we only care about how well our model performs on unseen data, how do we measure that?

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We can't - it's unseen!

# Measuring Generalization Data - How

If we only care about how well our model performs on unseen data, how do we measure that?

We can't - it's unseen!

But, we can *estimate* it.

# Measuring Generalization Error - How

The most simple way to estimate generalization error is through employing a train/test split.



**Full Dataset**



# Measuring Generalization Error - How

The most simple way to estimate generalization error is through employing a train/test split.



**Training Data**

**Test Data**

# Measuring Generalization Error - How

The most simple way to estimate generalization error is through employing a train/test split.



Build a model on  
this

# Measuring Generalization Error - How

The most simple way to estimate generalization error is through employing a train/test split.

