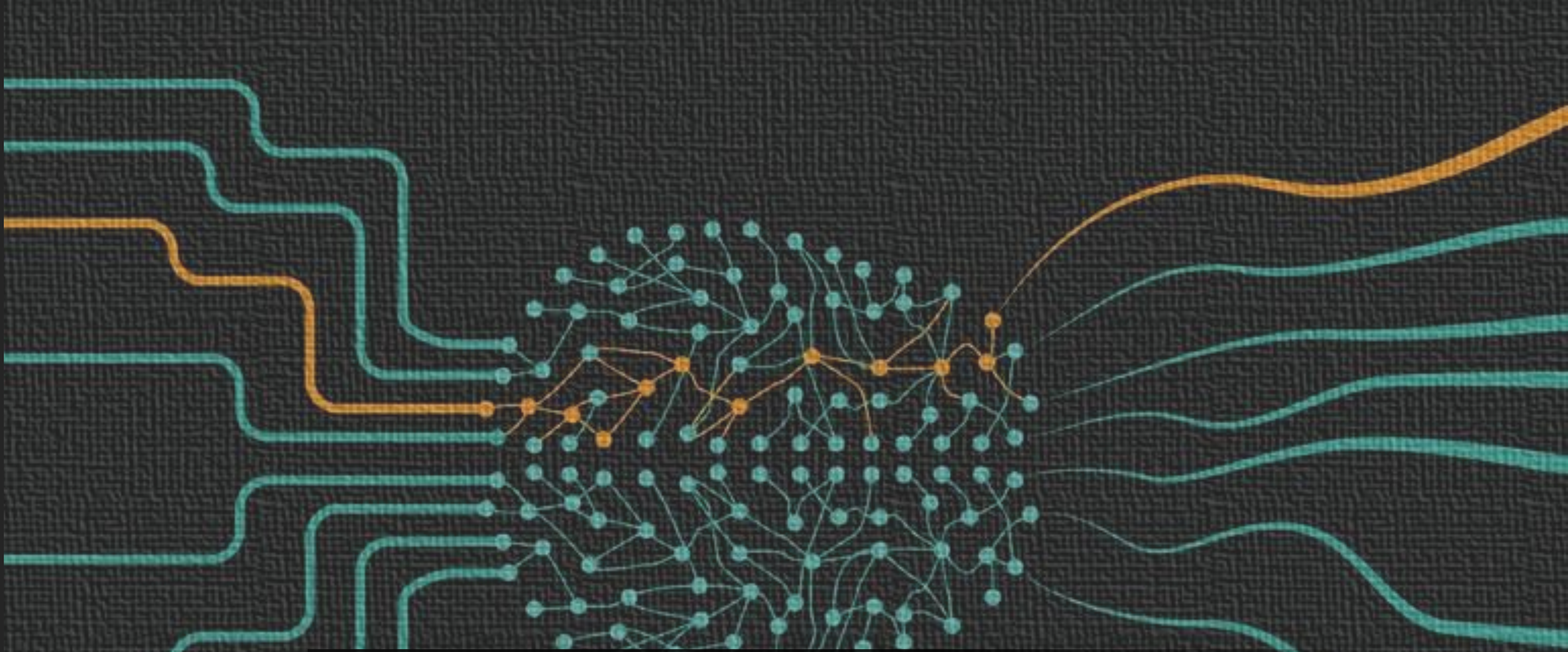


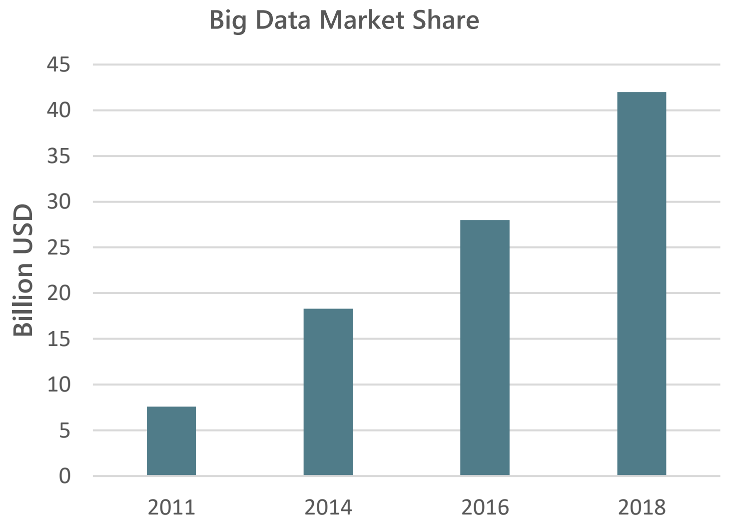
Introduction to Machine Learning

Özgür Martin

Why Now?

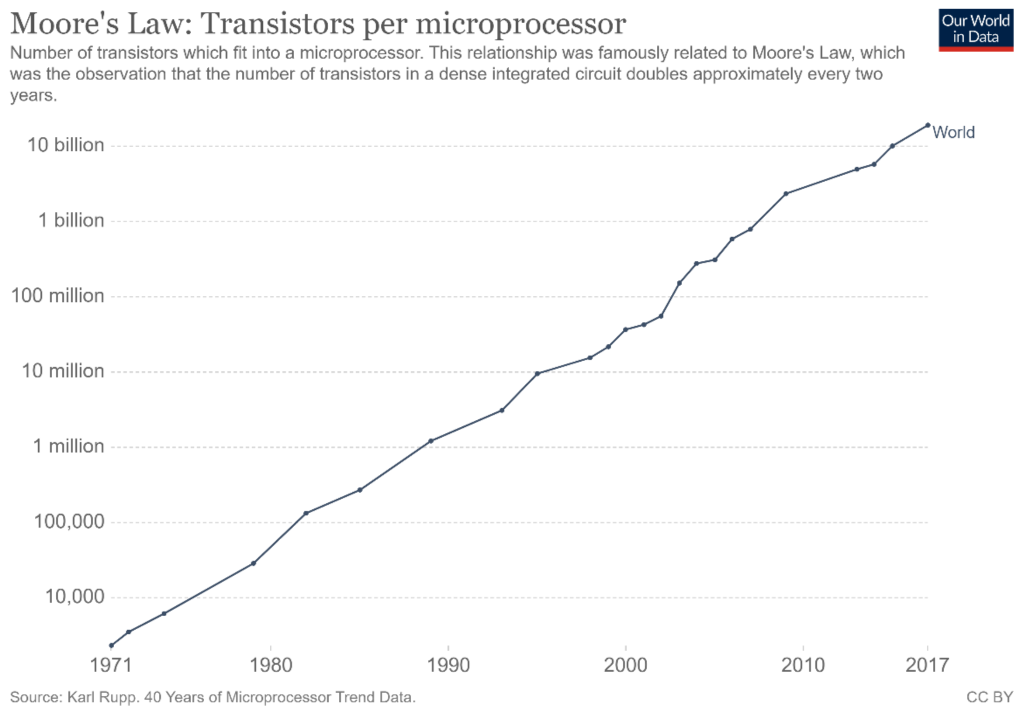
Big Data

- Data is learning material for AI algorithms.
- More data means more learning material for AI models.
- Big data thus enables more consistent and accurate AI models.



Processing Power

Despite speculations, processing power has been steadily increasing exponentially.



Processing Power

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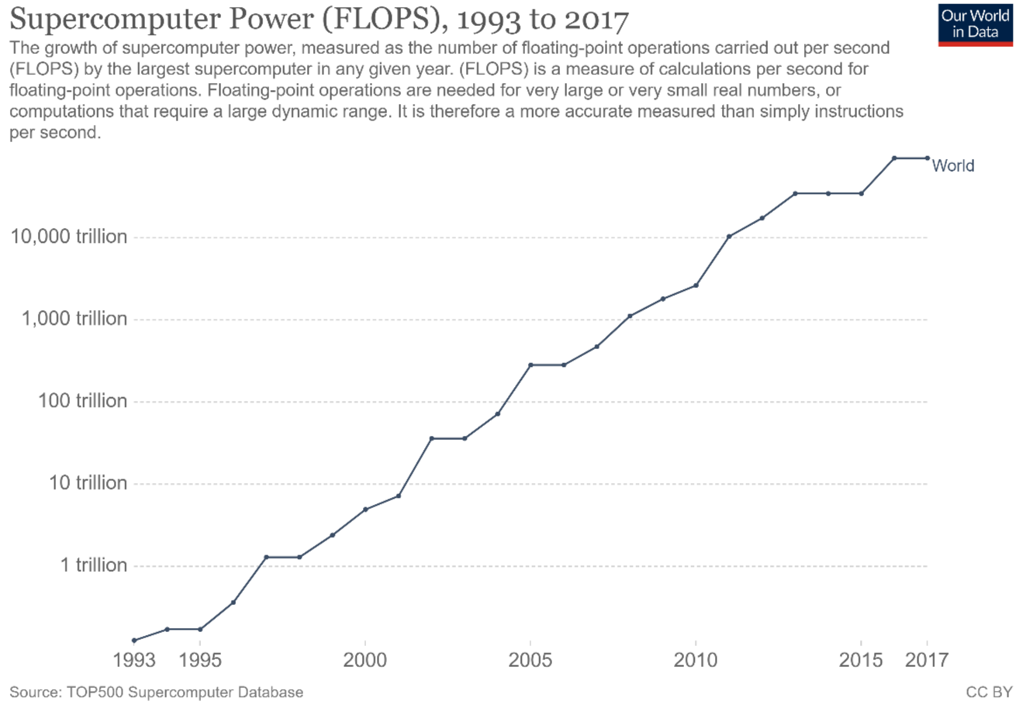


Theoretical Paradigm Shift

In the earlier days of AI, one needed a deep understanding of the problem in mathematical terms in order to reach useful conclusions using AI models.

Deep Blue vs Kasparov - 1997

Deep Blue (and its successors) ran on an algorithm which uses a precise measure of «how good» a given position is in a game of chess.

Once you can measure how good positions are then it is not very difficult to select moves which lead toward better positions.

Theoretical Paradigm Shift

Modern AI algorithms rely on «statistical learning» which, at least in certain instances, can overcome the lack of mathematical understanding of a problem.

Go

Go has long been known to be notoriously difficult for mathematical analysis.

In 1970's AI researchers thought computers could not possibly beat the best human players.

Theoretical Paradigm Shift

Statistical learning, expressed through a specific class of models «deep neural networks», has proven to be extremely powerful by defeating Lee Sedol decisively.

AlphaGo vs Lee Sedol - 2017

Lee Sedol, acknowledged that winning one game against AlphaGo was a big accomplishment.

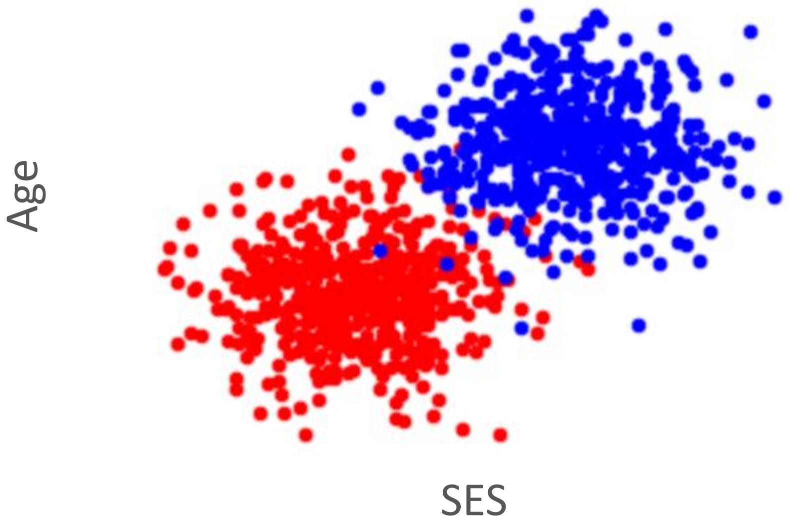
It is know deemed impossible for humans to win a matchup against AlphaGo.

Typical Statistical Learning Setup *

- We have two measurements on our subjects, say socioeconomic status and age. These are called ***features***.

- We also observe a certain outcome variable for each subject, say using a certain product. This is called the ***target variable***.

- The set of these observations (features and target) is called the ***learning data***.

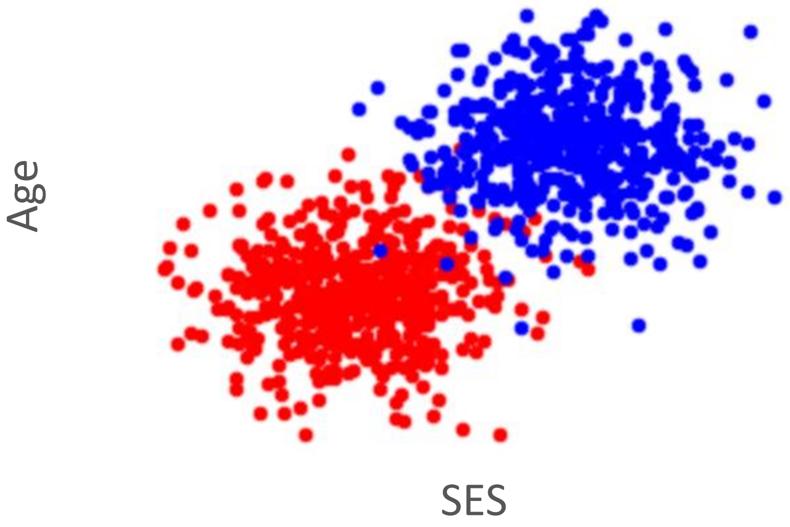


* Also called ***Supervised Learning***

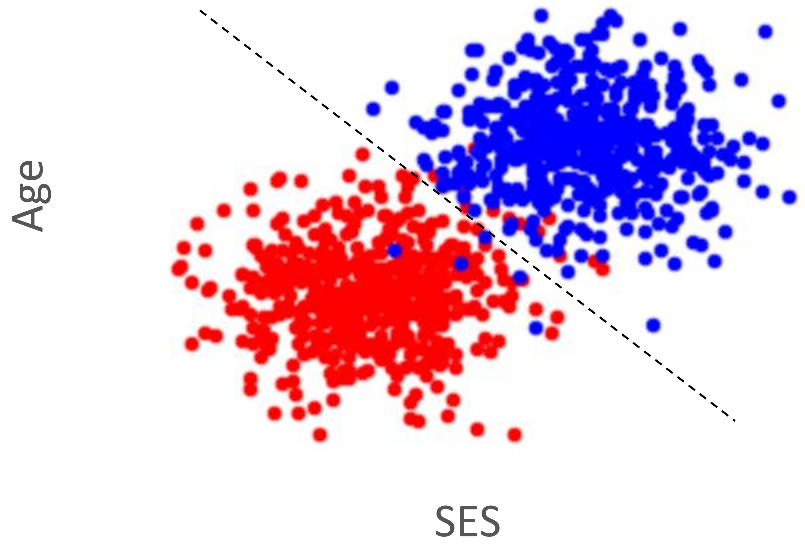
Typical Statistical Learning Setup

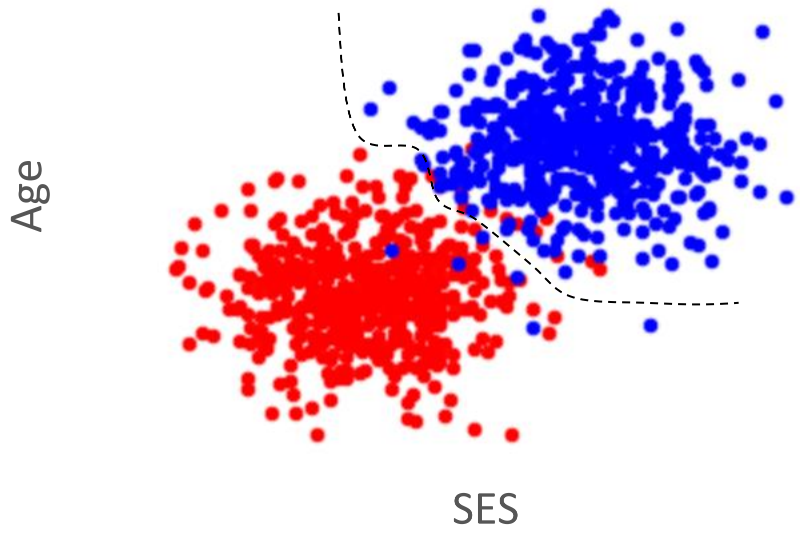
- An algorithm which gives a procedure to distinguish blue and red points looking at SES and Age variables is called an AI model.

- Such an algorithm «learns» from our observed data and then we use it to make predictions about new cases.



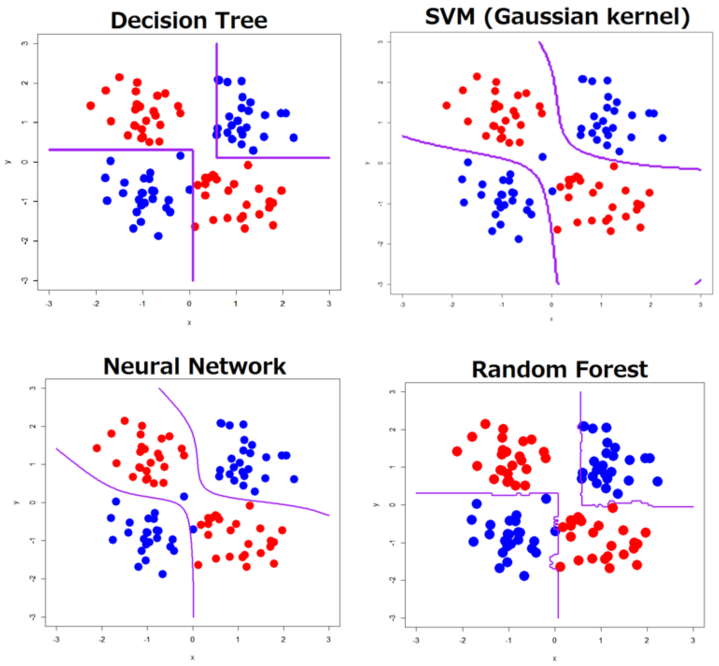
Issue 1: Too Many Options





Solve Issue 1: Restrict

In order to be able to find a solution our algorithms need to be restricted to a certain class of possible solutions.

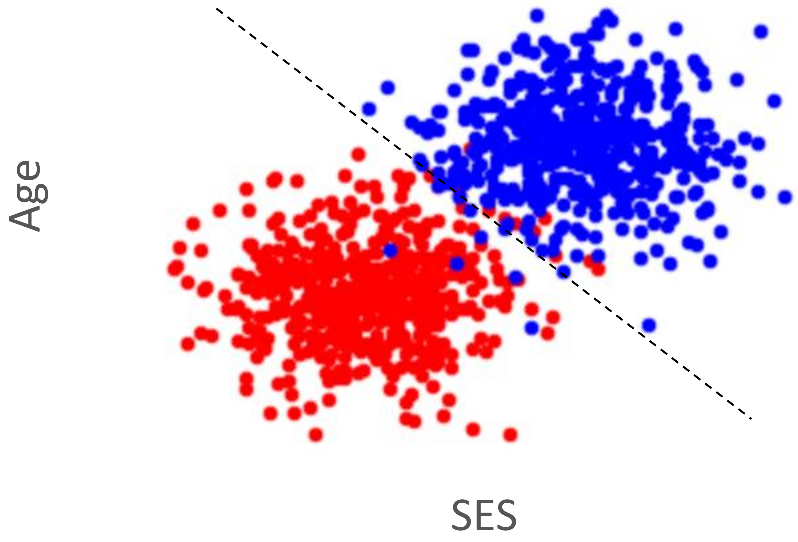


Issue 2: The Best Solution

After we decide on the method (random forests and neural networks are the primary choices in modern applications) we need to find an ***optimal*** solution.

For example, if we decide to solve this problem with a line we want to find the line which gives minimum classification error.

Gradient boosting and ***gradient descent*** are examples of optimization techniques used in modern AI applications.



Issue 3: Data Availability

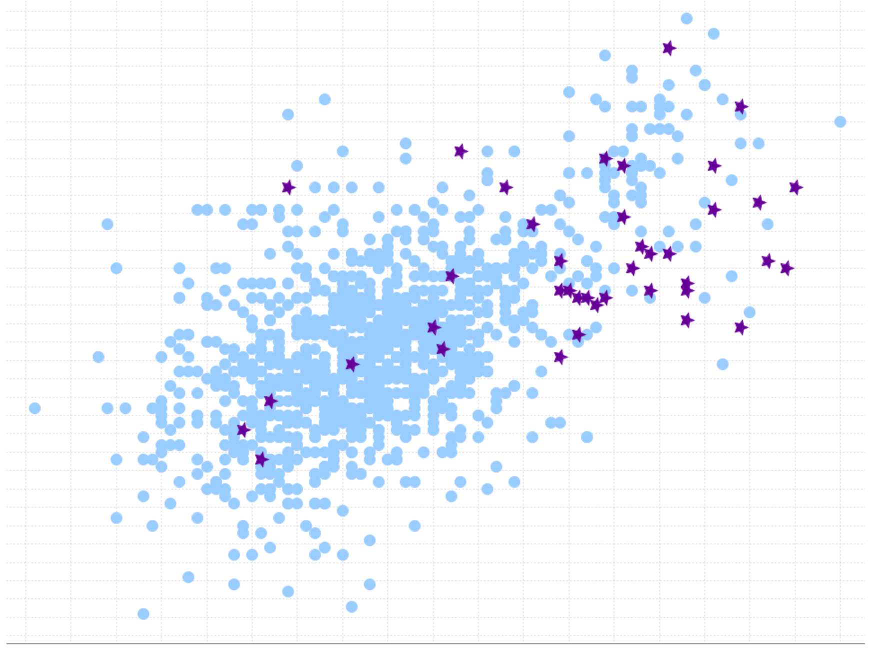
«If we have data let’s look at data. If all we have are opinions, let’s go with mine.»

Jim Barksdale

Statistical learning is based on the assumption that we do have actual data collected from real samples. No data often means no AI.

Issue 4: The Problem Itself

We simply can not expect to obtain a reliable solution to every problem by collecting data.



A Machine Learning Example

The CIFAR-10* dataset consists of 60000 32x32 color images in 10 classes, with 6000 images per class.

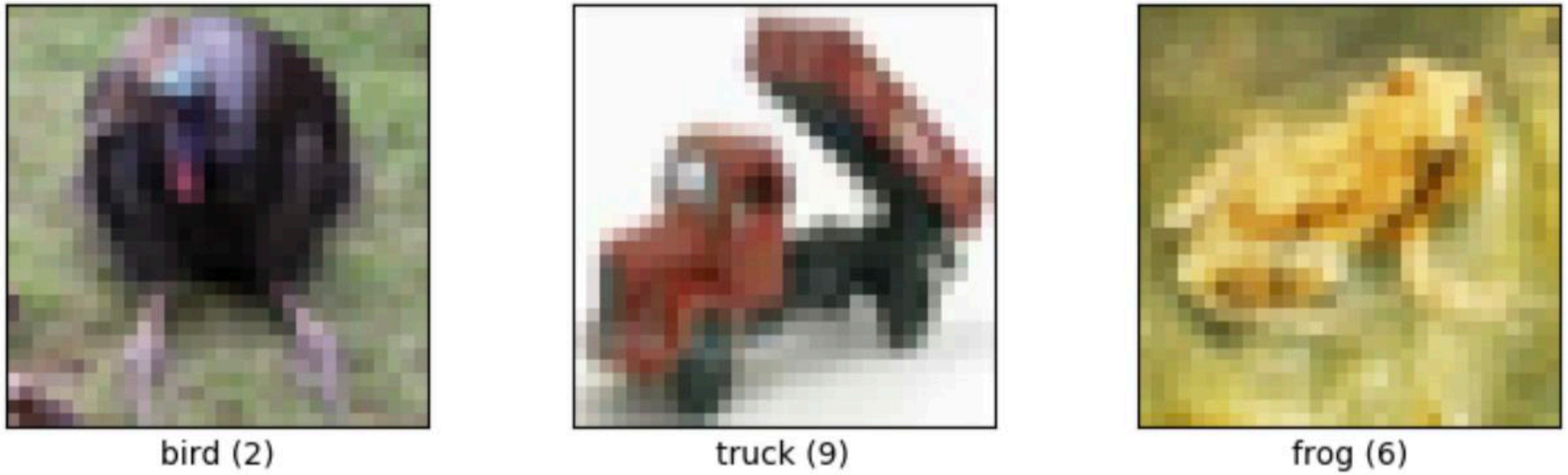


Image from www.tensorflow.org

*Alex Krizhevsky, Learning multiple layers of features from tiny images, Tech. report, 2009.

A Machine Learning Example

Denote the images in the dataset by

$$\{x_i\}_{i=1}^n \text{ with } x_i = (\underbrace{x_{i,1}, \ldots, x_{i,d_x}}_{\text{pixels in the image}}) \in \mathbb{R}^{d_x}$$

Denote the labels by

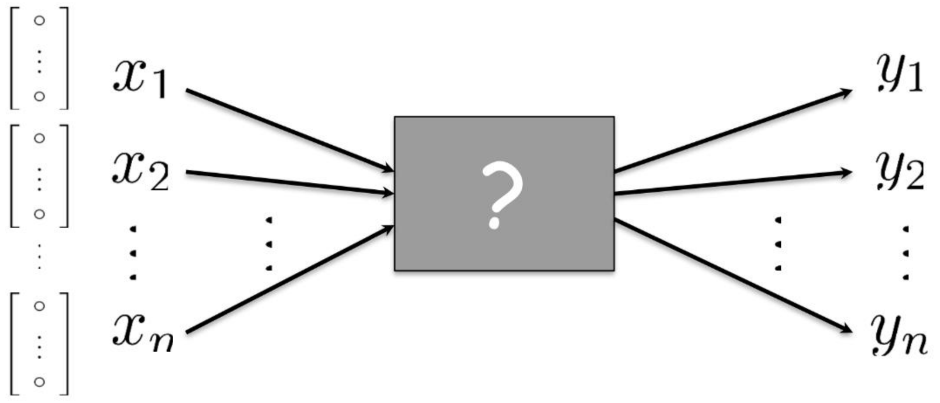
$$\{y_i\}_{i=1}^n \text{ with } y_i \in \{1, \ldots, 10\} \subset \mathbb{R}$$

We call the set $\{(x_1, y_1), \ldots, (x_n, y_n)\} \subset \mathbb{R}^{d_x} \times \mathbb{R}$ as the **training points**.

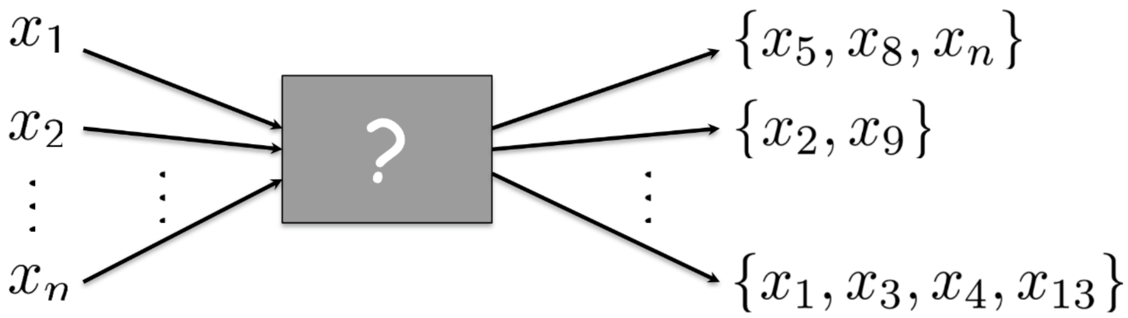
n=60000 and $d_x = 32 \times 32 \times 3 = 3072$ since every pixel has 3 values for RGB colors.

Machine Learning

Supervised Learning



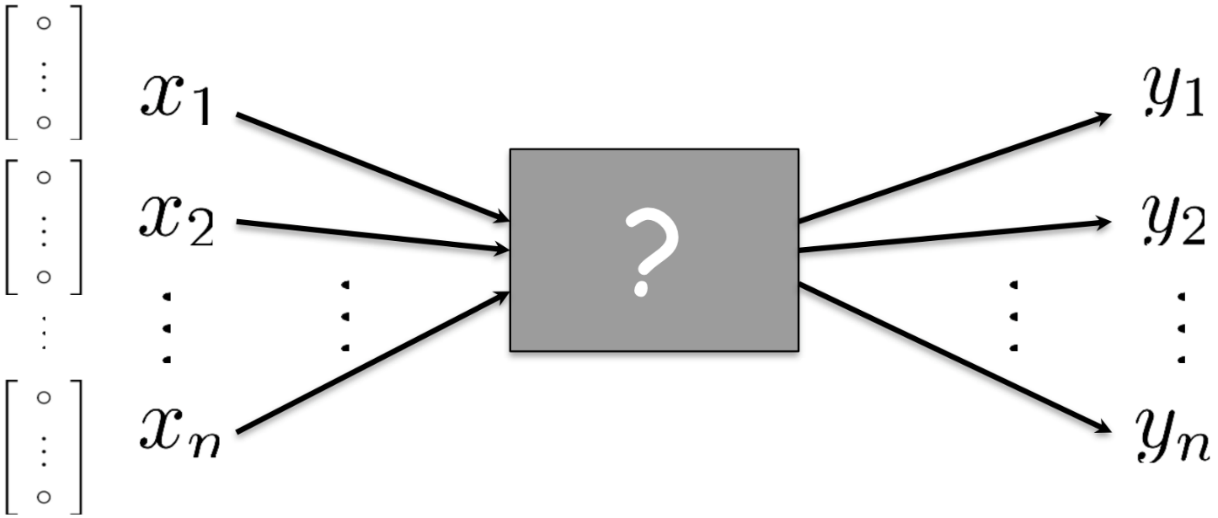
Unsupervised Learning



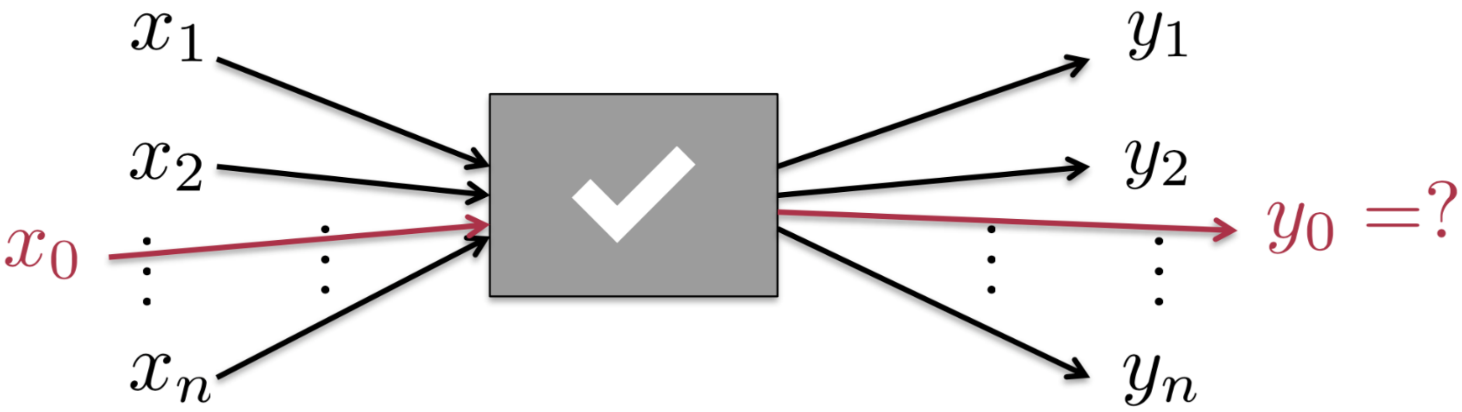
* independent variable; predictor; feature
# dependent variable; target value

Supervised Learning

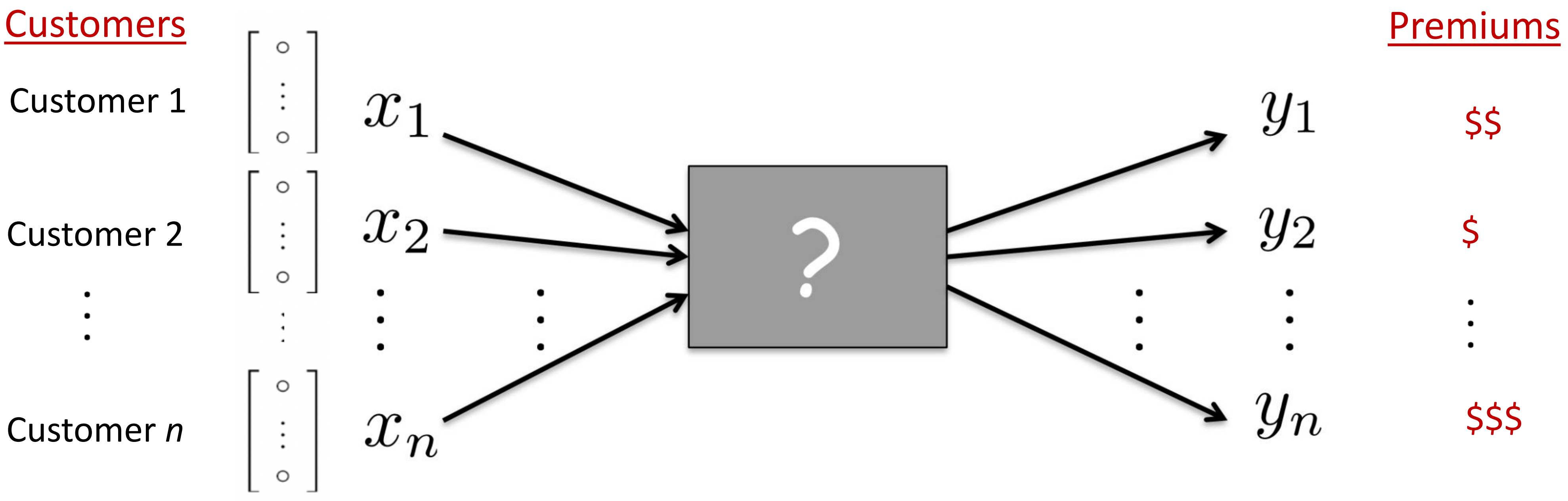
Training data
$\{(x_i, y_i): i = 1, \ldots, n\}$



Test data
(x_0, y_0)



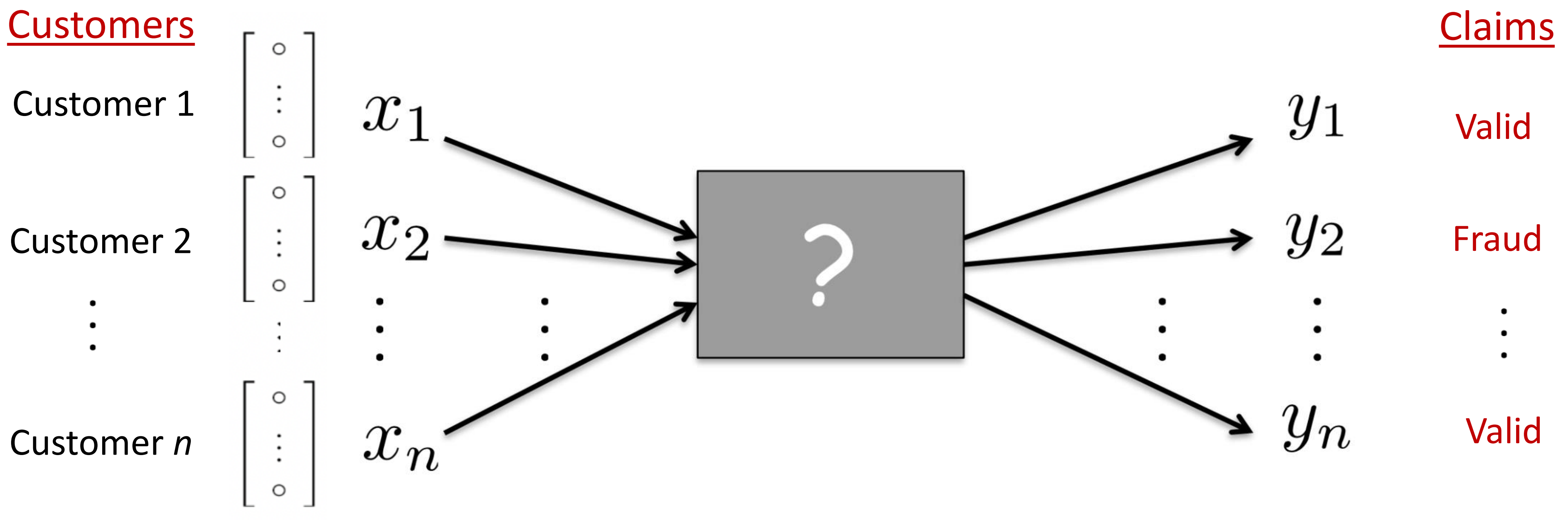
Supervised Learning



Regression

Training data
$\{(x_i, y_i): i = 1, \ldots, n\}$

Supervised Learning

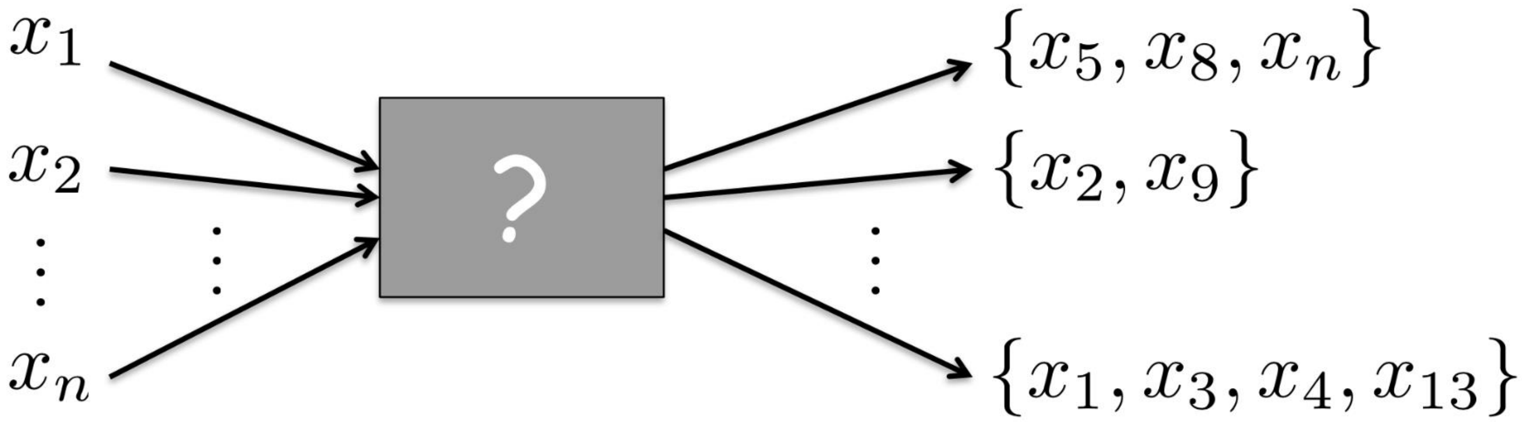


Classification

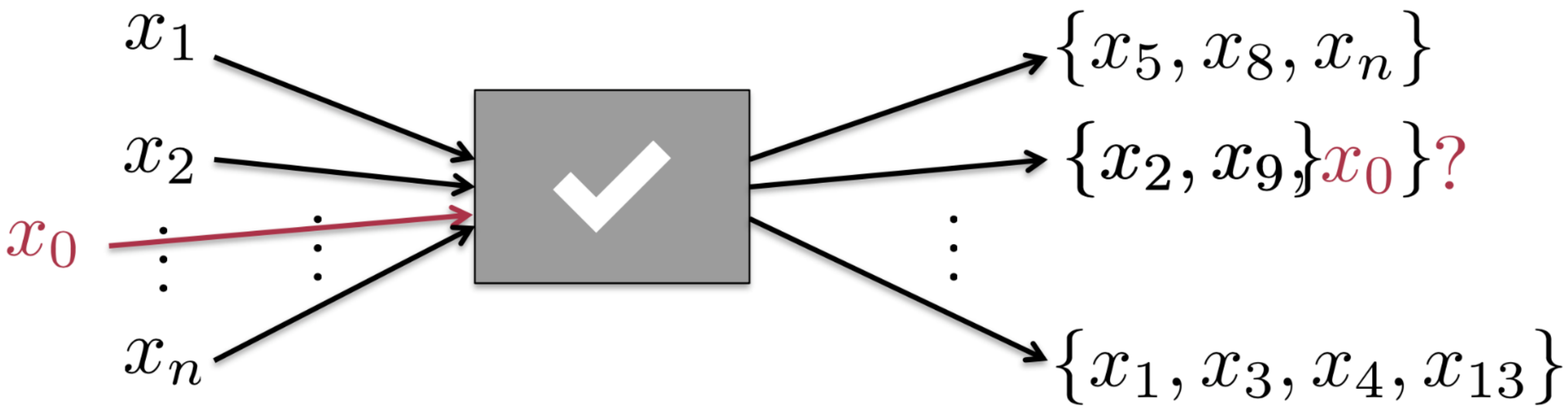
Training data
$\{(x_i, y_i): i = 1, \ldots, n\}$

Unsupervised Learning

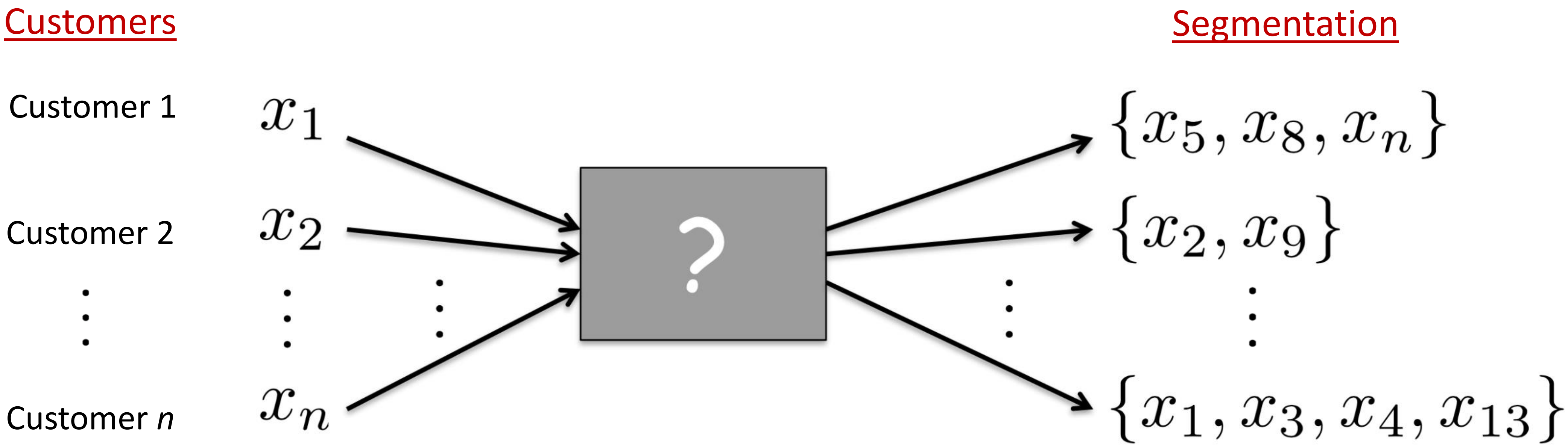
Training data
$\{x_i : i = 1, \ldots, n\}$



Test data
x_0



Unsupervised Learning



Clustering

Training data
$\{x_i: i = 1,\ldots, n\}$

Expectation from Learning

Prediction

$$x_0 = \begin{bmatrix} \circ \\ \vdots \\ \circ \end{bmatrix} \longrightarrow y_0 = ?$$

What?

Inference

$$x_0 = \begin{bmatrix} \bullet \\ \vdots \\ \bullet \end{bmatrix} \xrightarrow{?} y_0$$

How?

The Problem of Learning

$X = (X_1, X_2, \ldots, X_p)$

Unknown Function

$$Y = f(X) + \epsilon \quad \xrightarrow{\text{Approximate?}} \quad \hat{Y} = \hat{f}(X)$$

Random Error Term

(Independent of Input)

The Problem of Learning

Target Function

$f : X \to Y$ $\qquad$ $y = f(x) + \epsilon$

$x \mapsto f(x)$

Training Data

$(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)$

Learning Algorithm

Result

$\hat{f} : X \to Y$ $\qquad$ $\hat{f}(x) \sim f(x)$

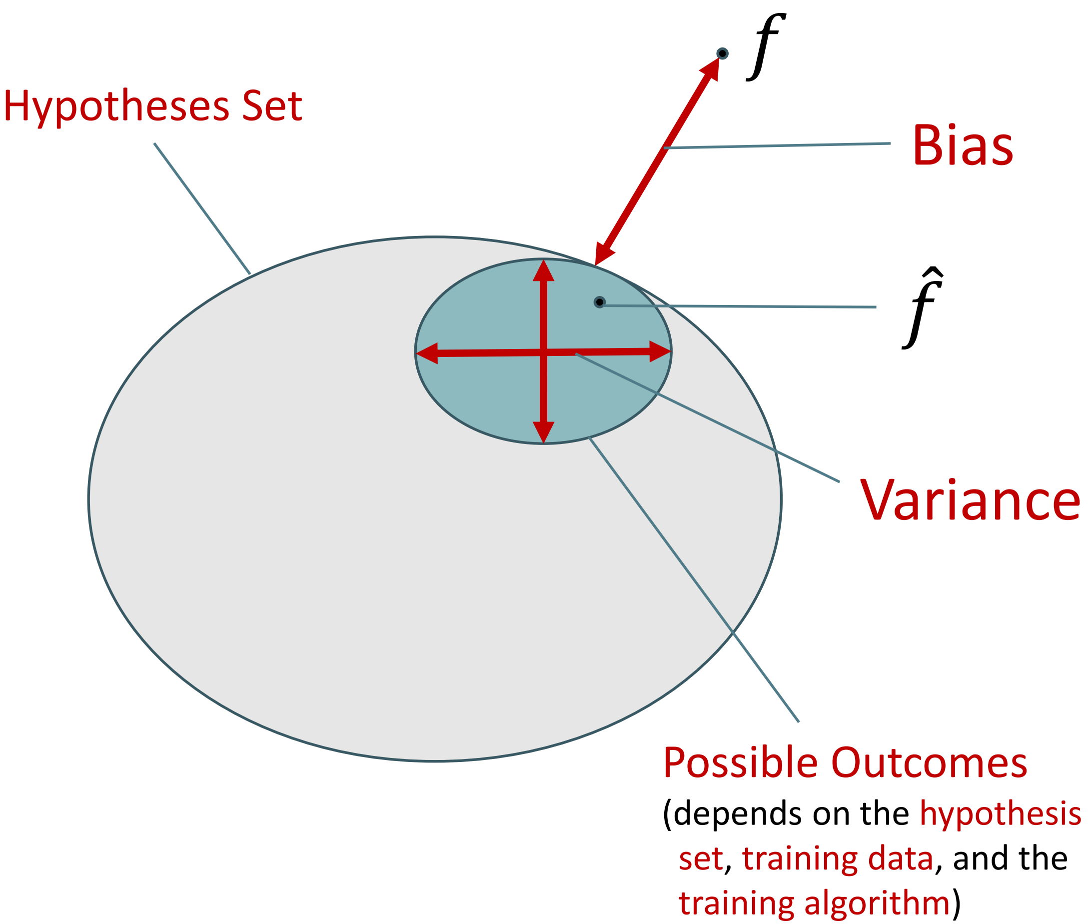
$x \longmapsto \hat{f}(x)$

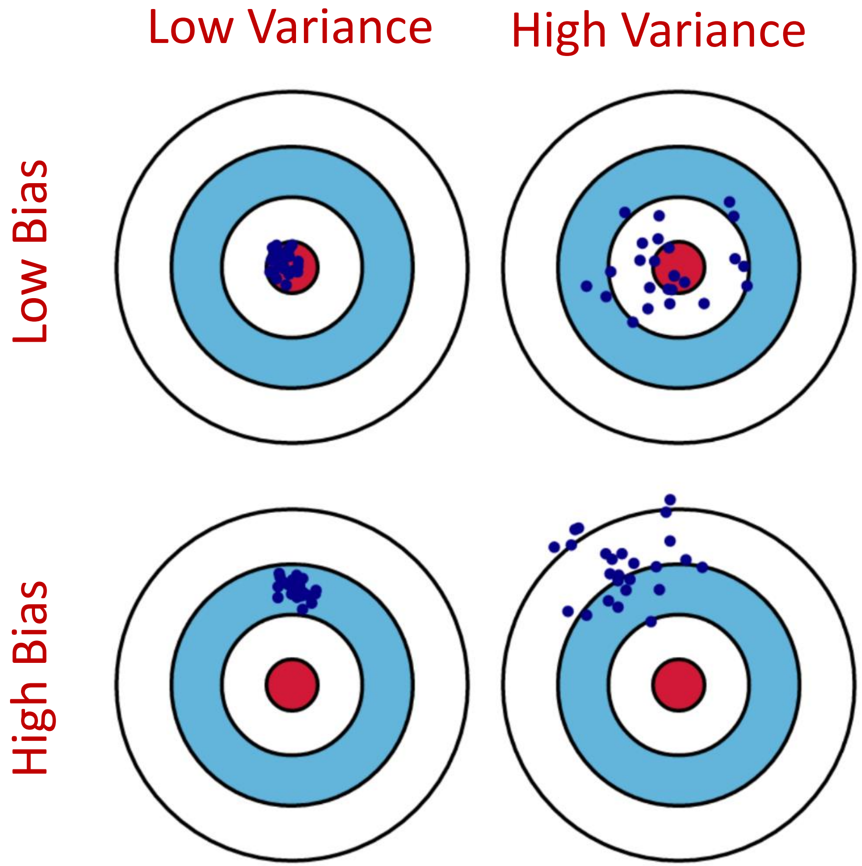
Hypotheses Set:

- Impossible to consider all possible functions
- Considering all possible functions may not give the best result
- Therefore, we will chose a restricted set ($\mathcal{H}$)

Yaser Abu-Mostafa, Caltech Course
https://www.youtube.com/watch?v=mbyG85GZ0PI&list=PLD63A284B7615313A

The Problem of Learning





How flexible should the model be?

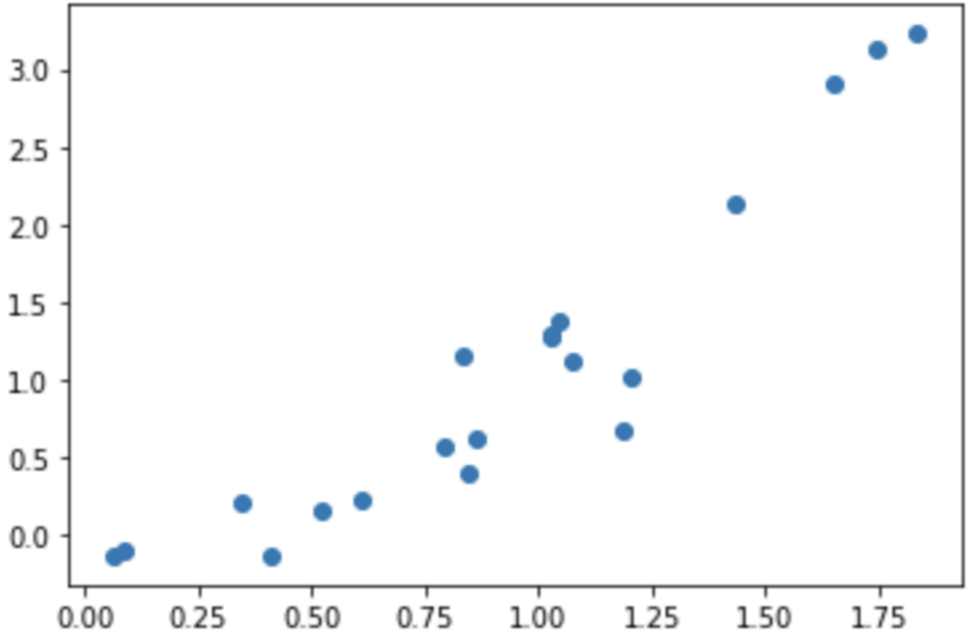
Aim: To find a function which

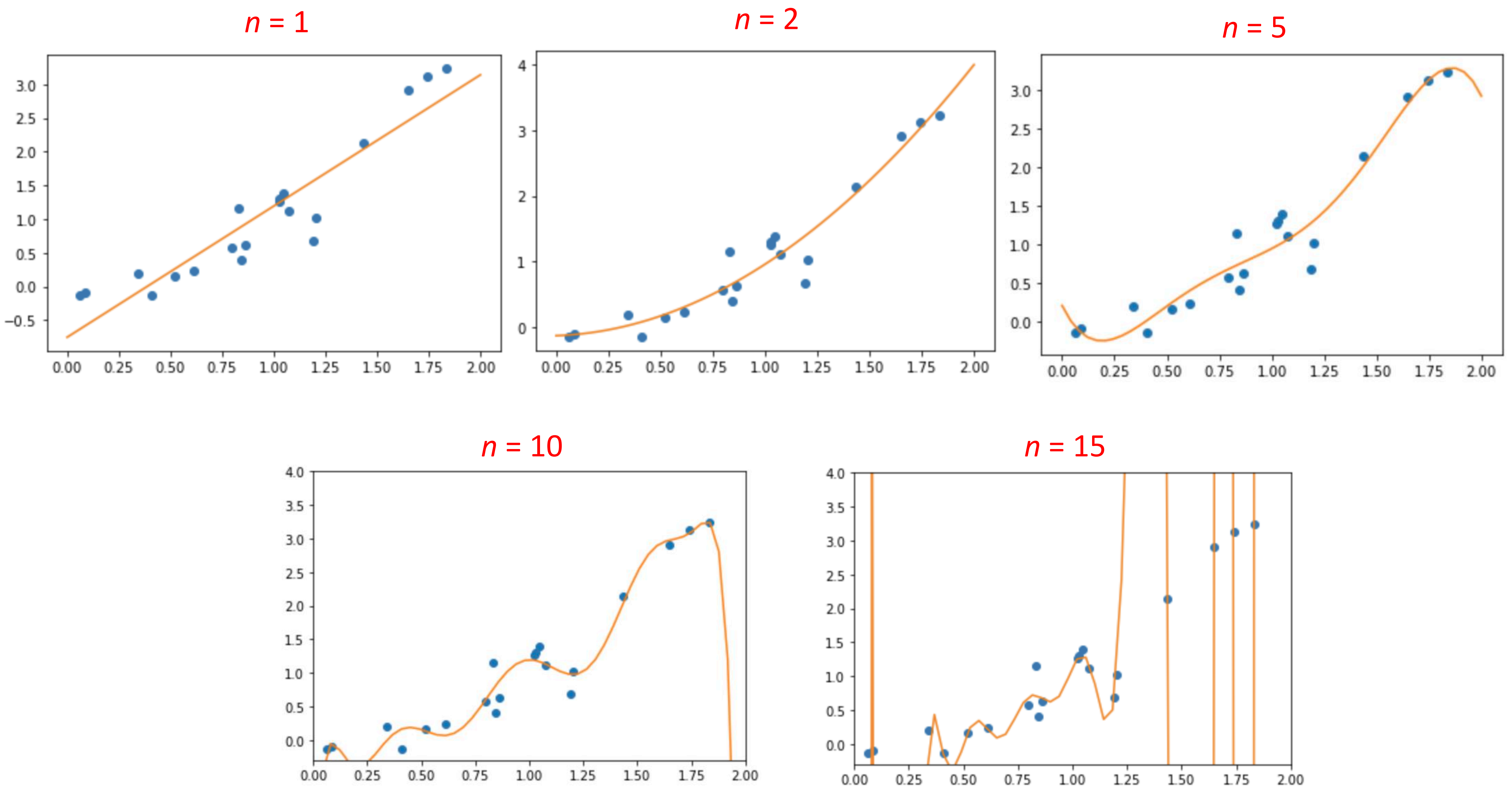
- Models the data best
- Performs well in the new data

Let's try a polynomial:

$$P(x) = c_n x^n + \cdots + c_1 x + c_0$$

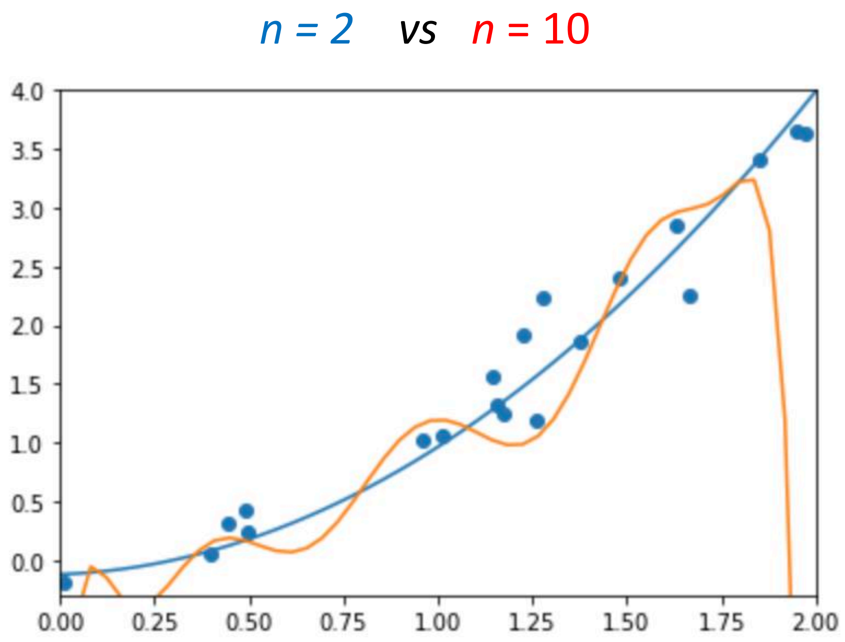
What should n be? Big-Small?

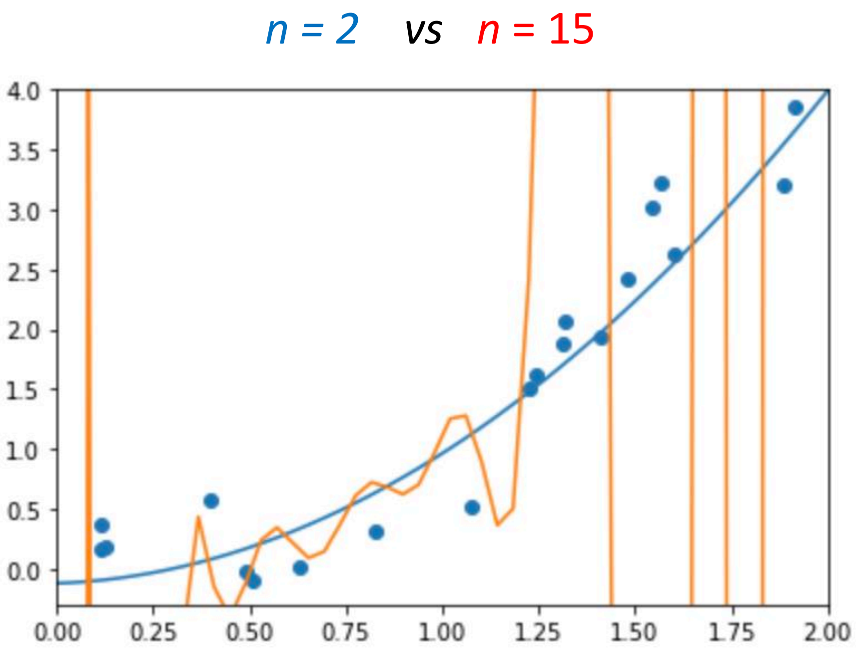



$n = 1$
$n = 2$
$n = 5$
$n = 10$
$n = 15$

This data came from a function of the form: $Y = X^2 + \epsilon$

With new data, compare the performance of $n = 2$ vs $n = 10$ or $n = 15$





Overfitting for n = 10, 15!

$n \uparrow$ *Variance* $\uparrow$ *Bias* $\downarrow$