

Lecture 4: Elements of Machine Learning Pt. 1

INFO 1998: Introduction to Machine Learning



CDS Education

Agenda

Today's Goal: build ML foundations

- **Define Machine Learning**
- **Start learning the language of ML**
- **Construct Linear Regression (via ScikitLearn)**
- **Introduce our Workflow**
- **Discuss Some Important Considerations**



Final Project Details

- **Posted to Website - Final Project Page**
- **Deadline 4/28/25 - Before Finals Week**
- **Read and get started!**
- **Use Ed Thread to find partners**
- **Mandatory Mid Semester Project Check-Ins starting Lecture 5-7**
 - **Not project midpoint, just mid-semester.**

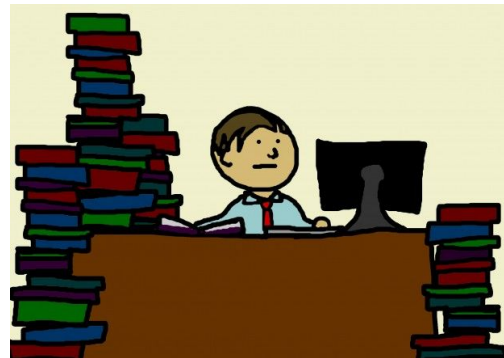


Constructing Machine Learning



Formalizing ML

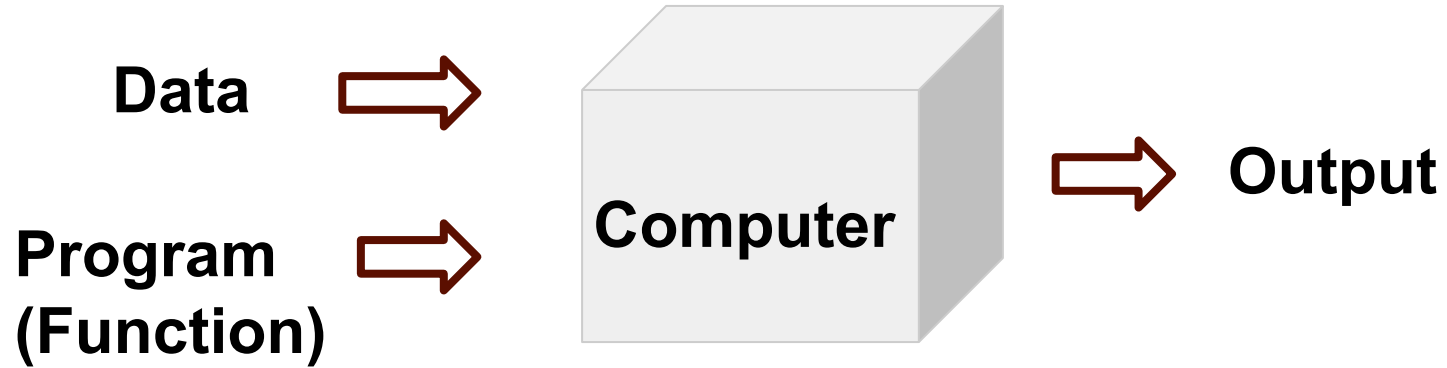
- We are constructing algorithms that:
 - Improve their performance **P**
 - At some task **T**
 - Based on experience **E**
- Example:
 - Email Spam Detection
 - **T**: Spam or not spam?
 - **P**: What percent of emails are classified correctly?
 - **E**: Dataset of labelled emails



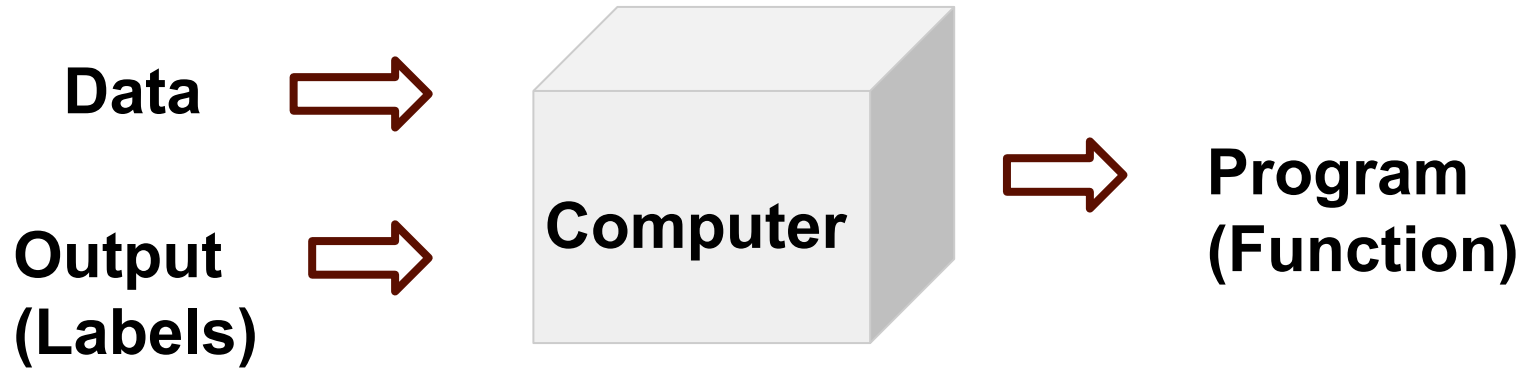
Credit: Ray Mooney



Writing Computer Programs

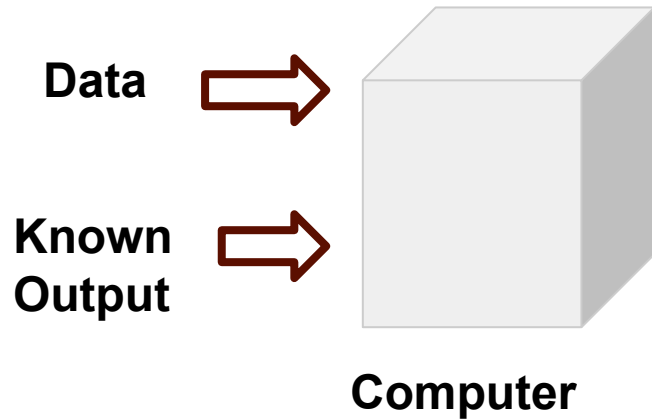


(Supervised) Machine Learning

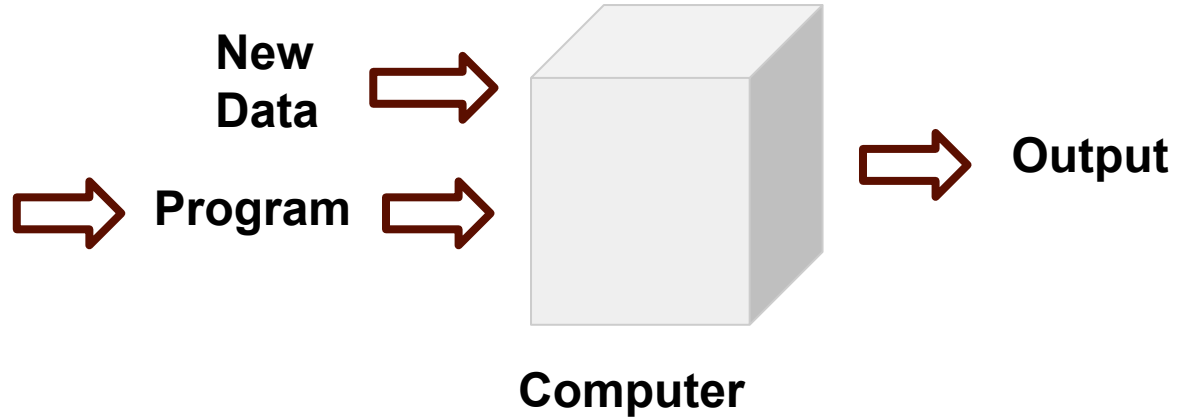


In Production

Machine Learning

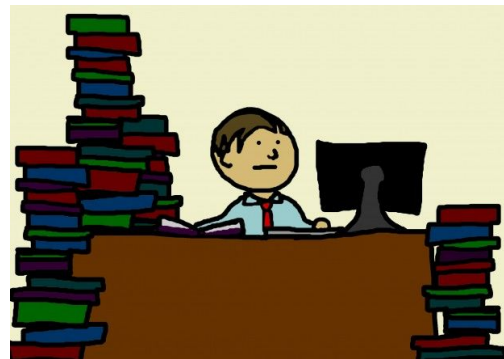


Traditional CS



Quick analogy: studying

- Setup
 - Goal: Be able to solve the test problems *well*
 - Resources: Practice problems + answers
- Method
 - You study those practice problems and answers. Given a problem, how do you get the answer?
- Result:
 - On the real test, the problems aren't the exact same as the practice problems. But they're similar!
 - Since you learned generally how to solve the practice problems, you can solve the similar test problems too.



*Note: this analogy describes supervised learning



Machine Learning can involve:

- Preprocessing data
- Splitting and selecting pieces of data
- Doing mathematical analysis on the data
- Deciding what data structures are needed to efficiently implement algorithms
- Implementing accuracy metrics
- ...and a lot more



What we're gonna do:

Our main tasks:

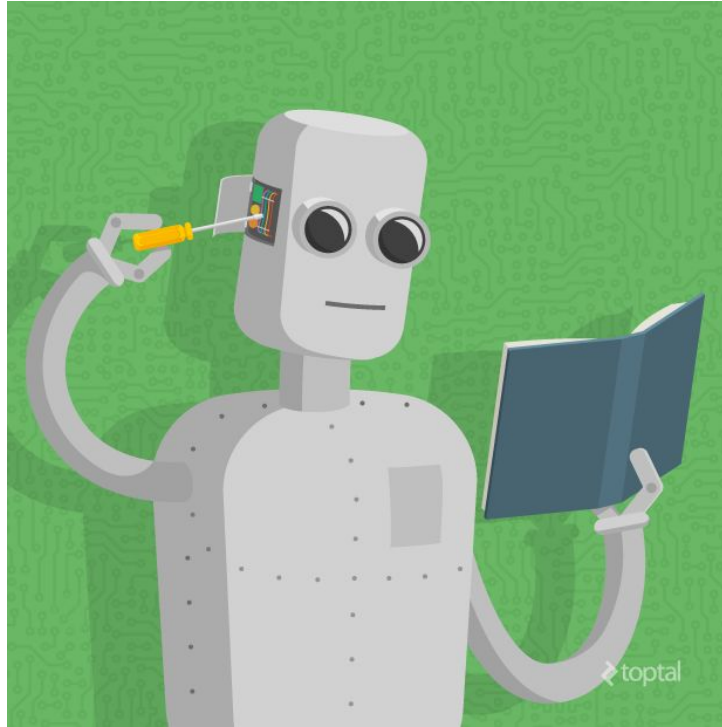
- **Formulate** a problem/question
- Find and **understand** data for that problem
- Choose a specific **algorithm class** to **solve** the problem
- Select features to **best** solve the problem
- Find which pandas, numpy, and scikit-learn functions do what we want
- Interpret the results and **fine-tune** our model

Write as little code as possible!

- Use pandas to deal with data
- Use numpy to do math
- Use scikit-learn (“sklearn”) to make & analyze ML models



Supervised Learning Models



Physics: A White-Box View of the World

- We have studied the world and crafted **models** *by ourselves* to represent it
- Our models are interpretable
- **White-box algorithms:** The inner workings of the algorithm are transparent

$$F=ma$$



Black Box Models

- Perhaps we can derive a process to solve the problem
 - Determine what a function would roughly look like
 - Think of relevant inputs
 - Allow the function to *build itself*
- **Black Box Model:** Results may not be interpretable!



Supervised Learning

- Models are procedures that maps input data to outputs
 - Resemble parametrized functions!
- Our job is to fill the parameters
- If we have training data and desired outputs, then we can do supervised learning.



No Free Lunch Theorem + Classification/Regression

- Every model makes assumptions!
- We cannot unilaterally apply any model to any problem.
- Classification
 - Group Data Into Distinct Classes
- Regression
 - Based on an input, provide a continuous-value output



Review: Dataset Structure

- Rows are data points
 - AKA samples
- Columns are features
 - A sample is made of lots of features, including our objective/label

	Name	Age	Major
0	Ann	19	Computer Science
1	Chris	20	Sociology
2	Dylan	19	Computer Science
3	Camilo	NaN	NaN
4	Tanmay	NaN	NaN



A Sample (Regression) Task

name	city	state	adm_rate	undergrads	cost	compl_4	median_hh_inc	median_earnings
Cornell University	Ithaca	NY	0.1507	14226	63596	0.8639	80346.48	73600
Washington University in St Louis	Saint Louis	MO	0.1674	7032	65887	0.8643	79298.58	66300
Lafayette College	Easton	PA	0.3025	2505	61905	0.8653	85923.51	67500
Johns Hopkins University	Baltimore	MD	0.1412	5862	63509	0.869	81539.46	69800
Vanderbilt University	Nashville	TN	0.1168	6857	62320	0.8697	76279.78	64500



What are some things we can do?

name	city	state	adm_rate	undergrads	cost	compl_4	median_hh_inc	median_earnings
Cornell University	Ithaca	NY	0.1507	14226	63596	0.8639	80346.48	73600
Washington University in St Louis	Saint Louis	MO	0.1674	7032	65887	0.8643	79298.58	66300
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Vanderbilt University	Nashville	TN	0.1168	6857	62320	0.8697	76279.78	64500



Predict Median Graduate Earnings

name	city	state	adm_rate	undergrads	cost	compl_4	median_hh_inc	median_earnings
Cornell University	Ithaca	NY	0.1507	14226	63596	0.8639	80346.48	73600
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Pick Some Features

name	city	state	adm_rate	undergrads	cost	compl_4	median_hh_inc	median_earnings
Cornell University	Ithaca	NY	0.1507	14226	63596	0.8639	80346.48	73600
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Our Goal?

name	city	state	adm_rate	undergrads	cost	compl_4	median_hh_in c	median_earnings
Cornell University	Ithaca	NY	0.1507	14226	63596	0.8639	80346.48	73600
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Vanderbilt University	Nashville	TN	0.1168	6857	62320	0.8697	76279.78	64500
Rutgers University	New Brunswick	NJ	0.5845	35102	29076	0.5838	82669.68	?
Case Western Reserve University	Cleveland	OH	0.3627	5039	59467	0.6311	69873.4	?



Lecture 4: Fundamentals of Machine Learning Pt. 1

INFO 1998: Introduction to Machine Learning



Attendance!



CDS Education

Linear Regression

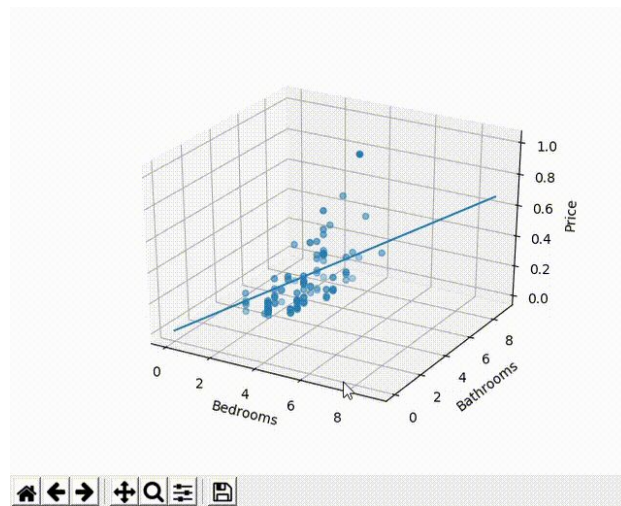
From an ML lens



Linear Regression

$$y = B_0 + B_1x_1 + \dots + B_px_p + \varepsilon$$

- x is an input; x_1, x_2, \dots, x_p are the features of x
- y is an output (usually a single value)
- B 's are “weights”
 - a linear regression equation is defined by its B 's
 - “program” produced by ML
- Given a set of x 's and y 's, find the “ B ”-s that “most closely” satisfies the equation above for training points
- Plug in *new* values to of x to predict respective y



$y = B_0 + B_I x_I + \dots$ is a model

- A relationship between inputs and outputs
 $y = B_0 + B_I x_I + \dots$ relates inputs to outputs
- A guess at how inputs and outputs are related

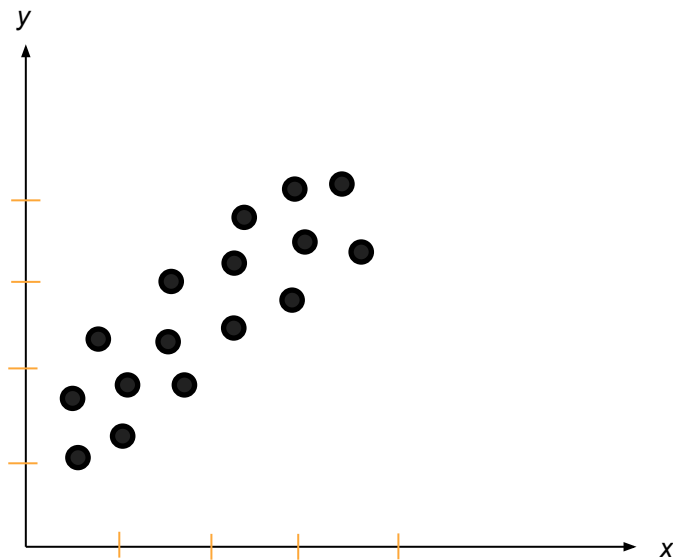
but $y = B_0 + B_I x_I + \dots$ is just a guess/estimate; it's not exactly true

- A set of assumptions we're imposing on the dataset

We're assuming output is linearly related to input features

- A configurable thing (hyperparameters)

Sorry, we don't cover very much linear regression configuration here 😊



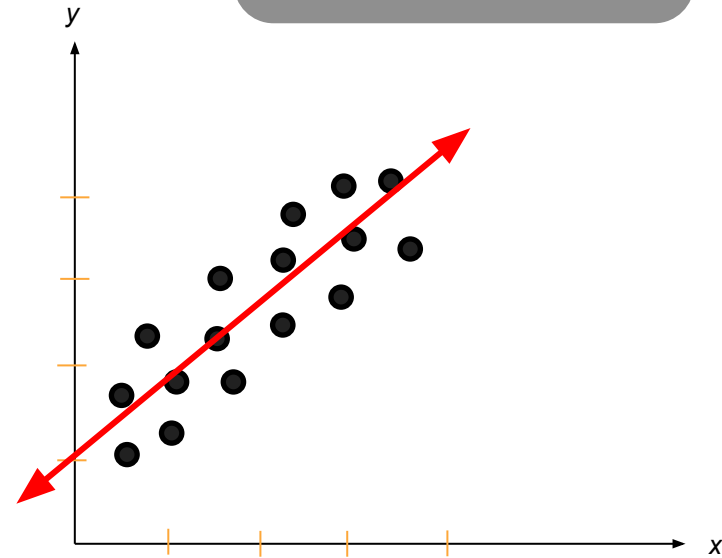
$$y = B_0 + B_I x$$



$y = B_0 + B_I x_I + \dots$ **is a model**

- **A relationship between inputs and outputs**
 $y = B_0 + B_I x_I + \dots$ relates inputs to outputs
- **Given some new set of inputs, we can guess y**

Use algorithm to “learn” parameters that give us this line of best fit

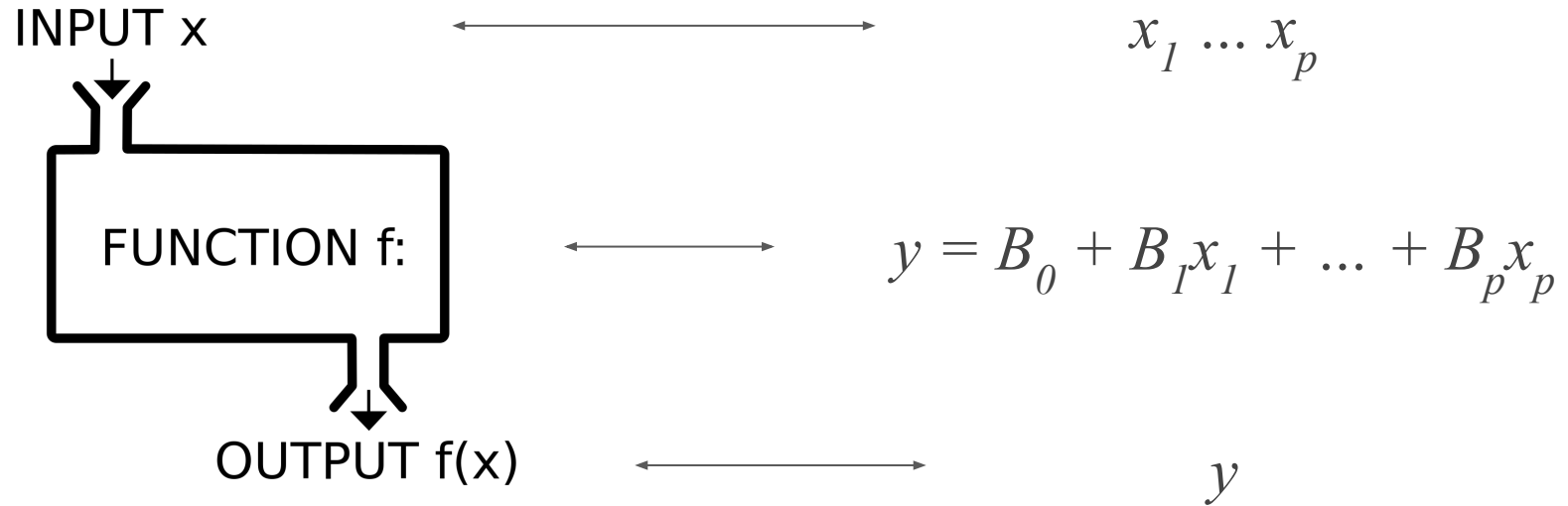


$$y = B_0 + B_I x$$



Linear Regression

Function



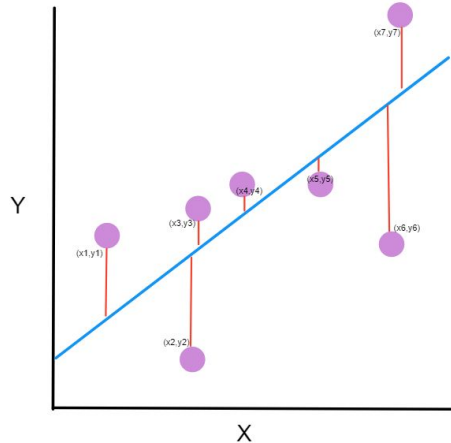
Our goal: Learn Weights

- We want to use our training data to figure out the best values for the “B” vector
- Intuition
 - There are infinitely many possible “lines” out there, we need the one that best fits our training data.
- How can this be done?



Linear Regression: Ordinary Least Squares

- *Ordinary least squares* method of linear regression calculates the weight vector B by minimizing the **mean-squared error** of the predicted y-values
- Other types of linear regression (i.e. ridge regression) use different *loss functions* to calculate the weights

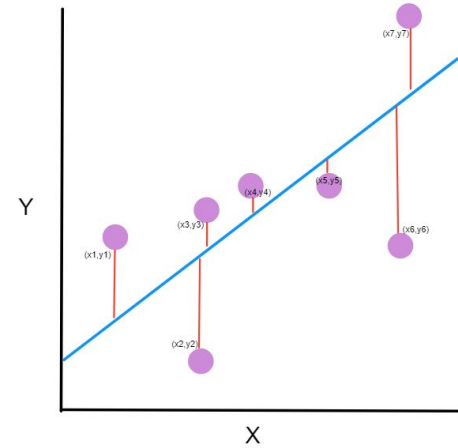


$$\text{MSE} = \overset{\text{Mean}}{\frac{1}{n}} \sum_{i=1}^n \left(\overset{\text{Error}}{Y_i - \hat{Y}_i} \right)^2 \quad \overset{\text{Squared}}{\quad}$$



"Training" a Model

- Dataset of n training points
- Datapoints: (X, Y_i) -> (input, output)
- Objective: Minimize MSE



1. Use the X values in our dataset to make a prediction

a. Note: X is a vector

$$\hat{Y}_i = B_0 + B_1 x_1 + \dots + B_p x_p + \varepsilon$$

2. Compare our prediction to the real Y_i

3. *Update B to get a better prediction*

a. Special Algorithm: Gradient Descent

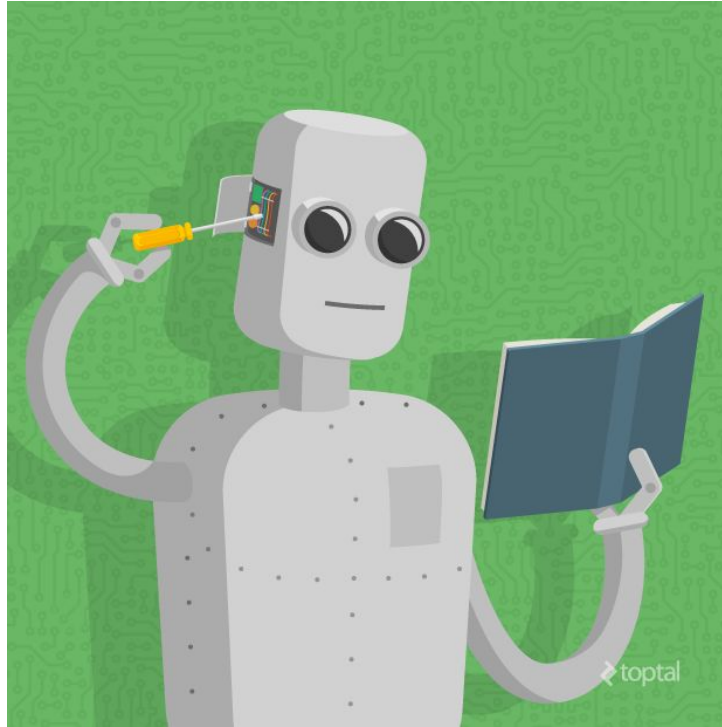
4. Repeat until MSE is as small as possible

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (\text{Error } Y_i - \hat{Y}_i)^2$$

The equation is annotated with boxes and labels: a blue box around $\frac{1}{n}$ is labeled "Mean", a blue box around $\sum_{i=1}^n$ is labeled "Error", and a blue box around $(Y_i - \hat{Y}_i)^2$ is labeled "Squared".



Making Good Models

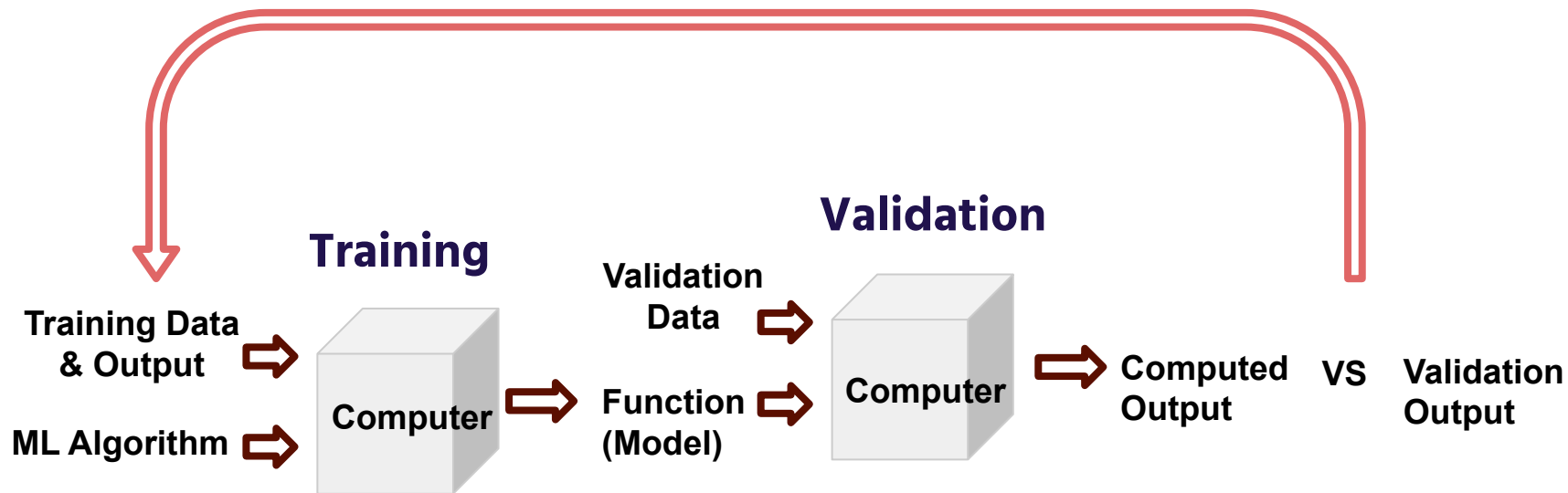


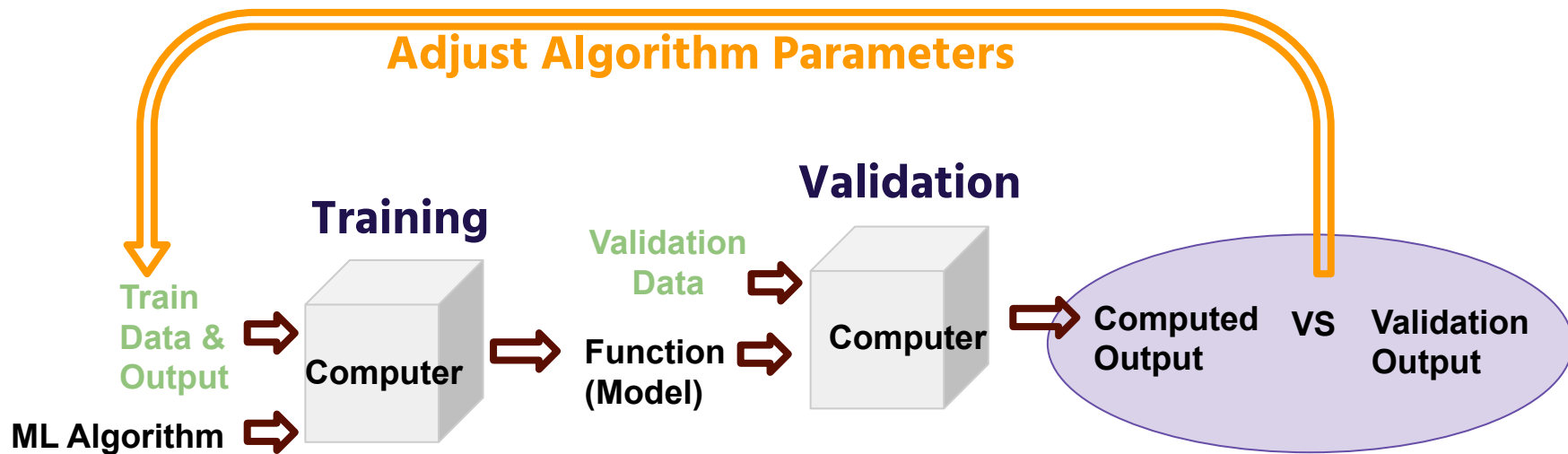
Terminology: Training and Validating

- Split data into two sets
- Train model on one, validate on the other
- “Model training” = learn a relationship/program
 - e.g. give the linear regression data so it can define the B 's
- “Model validation” = see if the learned relationship is accurate on other data



Our ML Workflow





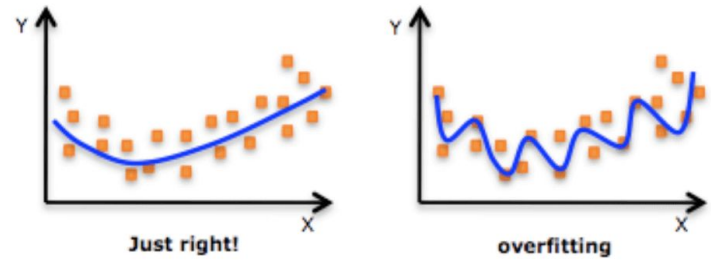
1. Select data

2. Assess model accuracy

3. Adjust Model



Pitfall of Training: Overfitting



Model is accurate for **train** data



Model can accurately predict **new** data

- We learned the specific mapping from **train input to train outputs...**
- But, we didn't learn the data's **general patterns** 😞😞😞😞😞😞

Solution: train on part of data, and check accuracy on a separate part of data (*validation* set)



Pitfall of Validation: Overfitting

Predicting well on validation set

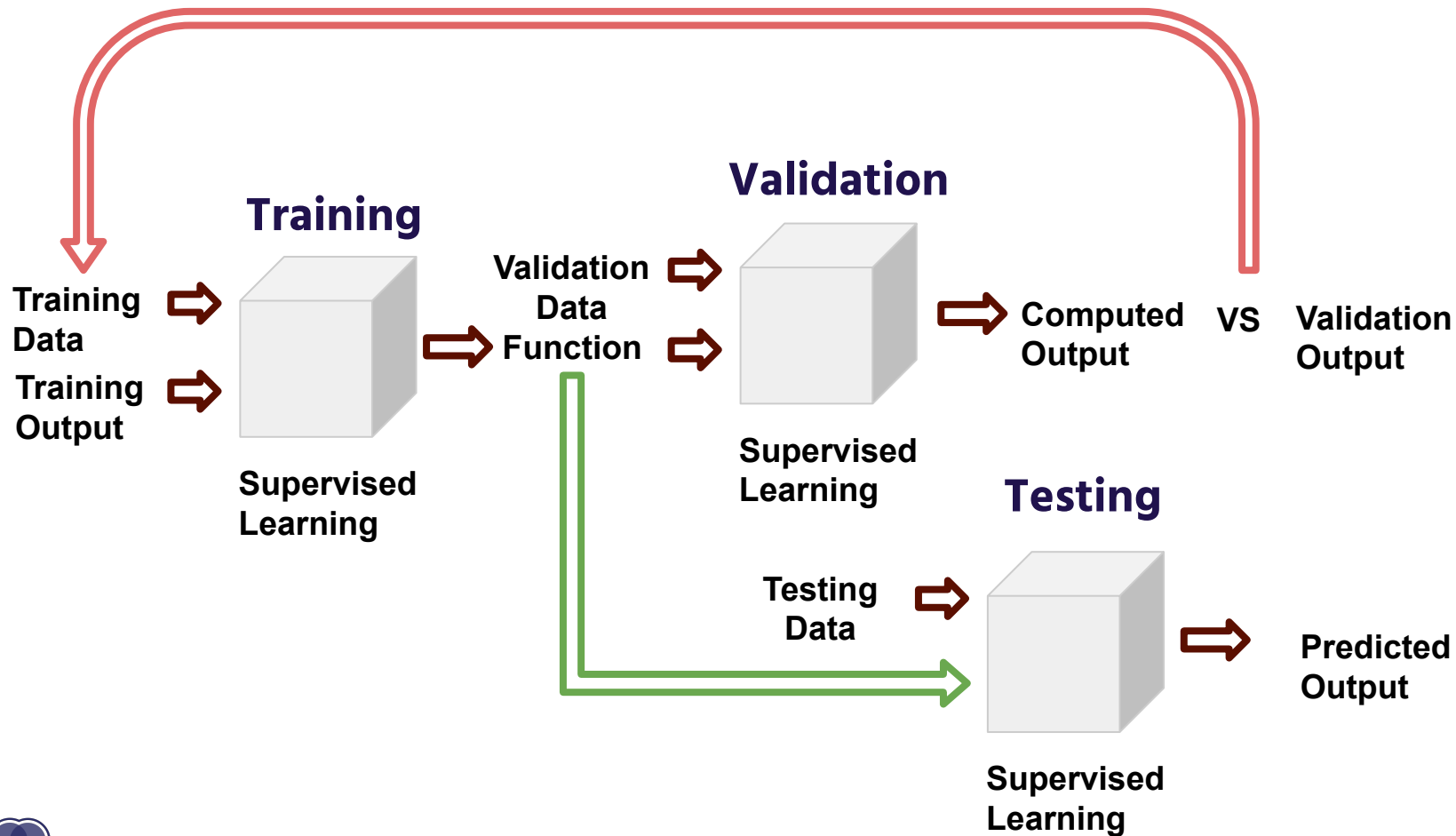


Predicting well on new data

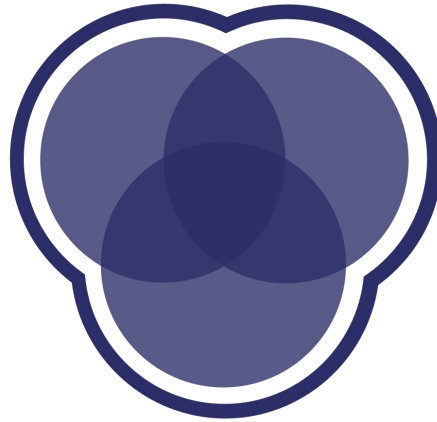
- We used the validation set to make our adjustments.
 - \Rightarrow Our model is **biased** to the validation set. 😊😓

Solution: keep a separate, rarely-used **test** set





Demo



Model Goals

When training a model we want our models to:

- Capture the trends of the training data
- Generalize well to other samples of the population
- Be moderately interpretable

The first two are especially difficult to do simultaneously!

The more sensitive the model, the less generalizable and vice versa.



Things to Keep In Mind

- Linear Regression is just one algorithm — we'll cover many more!
- The “model” produced by an algorithm is not always a simple equation like in linear regression.
- Validation is *really* important.
 - Overfitting is a huge problem!
 - We'll delve deeper in the next few lectures...



Coming Up

Assignment 3: Due tonight at 11:59pm EST

Assignment 4: Due at 11:59pm EST on **March 10**

Next Lecture: Assessing Model Accuracy + Fundamentals of ML

(What's Machine Learning? Part ∞)

