ISEA Week 5 – Machine Learning Fundamentals

Lovenoor (Lavi) Aulck

IES Institute of Education Sciences

AmplifyLearn.AI

UNIVERSITY of WASHINGTON eScience Institute
ADVANCING DATA-INTENSIVE DISCOVERY IN ALL FIELDS

UNIVERSITY OF OREGON

Outline

- Level-setting
- Model Selection
- Warm Up Exercise
- Machine Learning Overview
- Basics
- Programming Exercise

Who Am I?

IES Institute of Education Sciences

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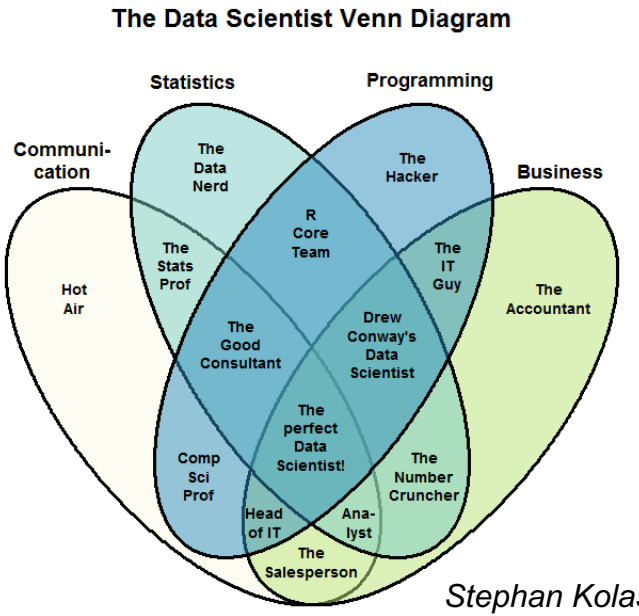
You Will Need...

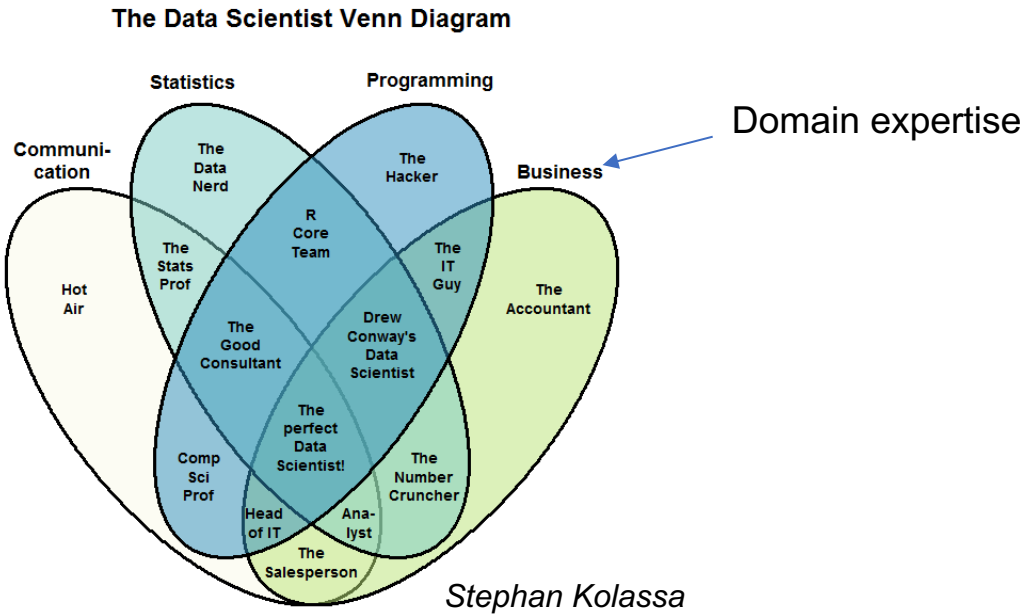
- You will need to have the following python packages installed and working for the demos:
  - pandas
  - numpy
  - seaborn (and/or matplotlib)
  - sklearn
  - statsmodels
  - random

A Data Scientist



Stephan Kolassa

A Data Scientist



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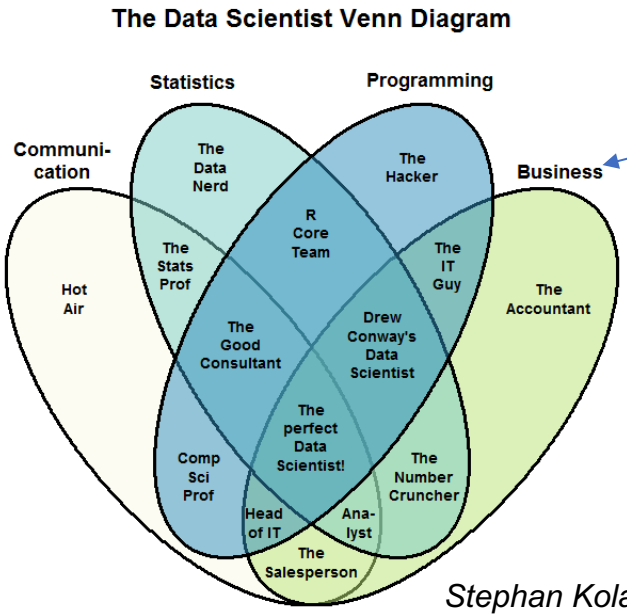

Domain expertise

Critical thinking, creativity, and experimental design?

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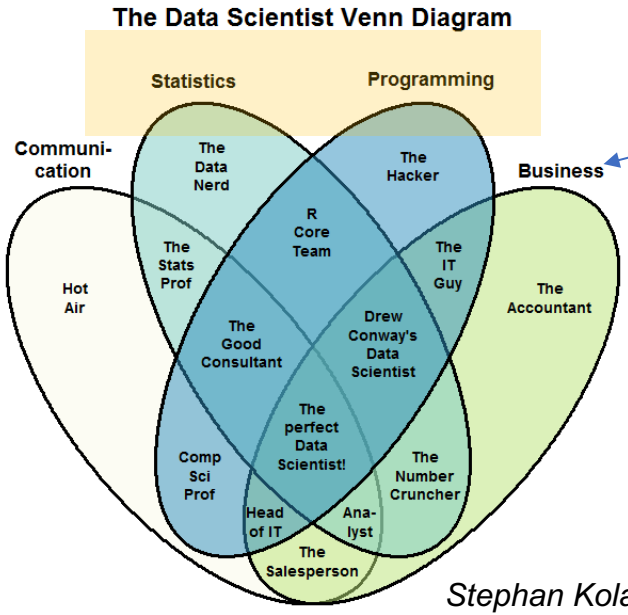

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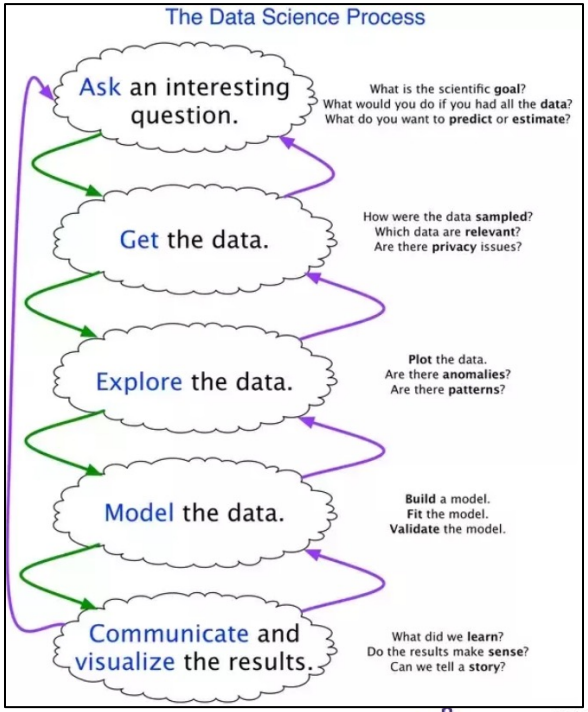

Joe Blitzstein

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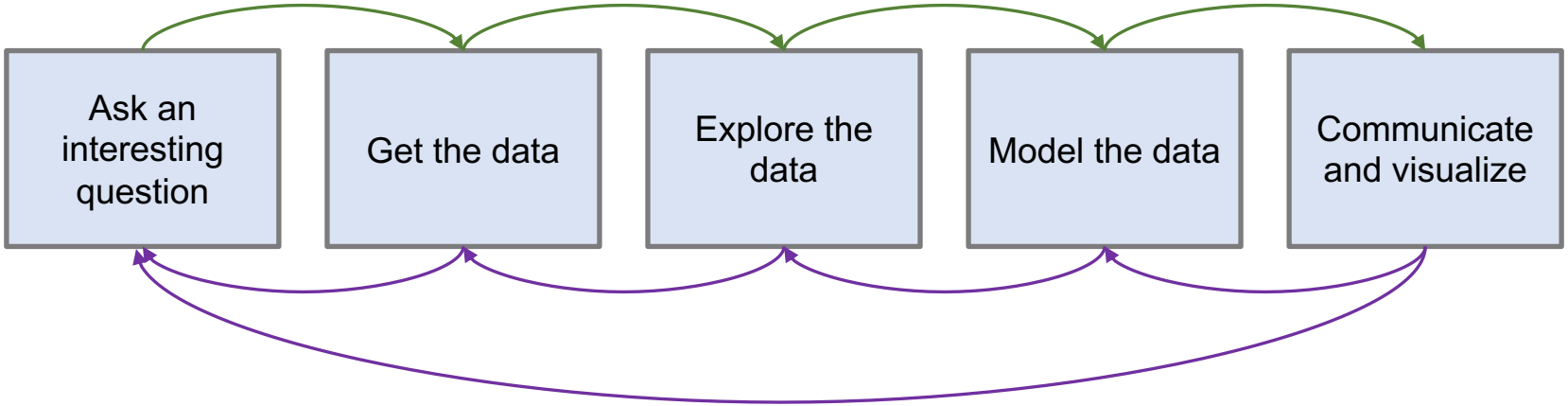

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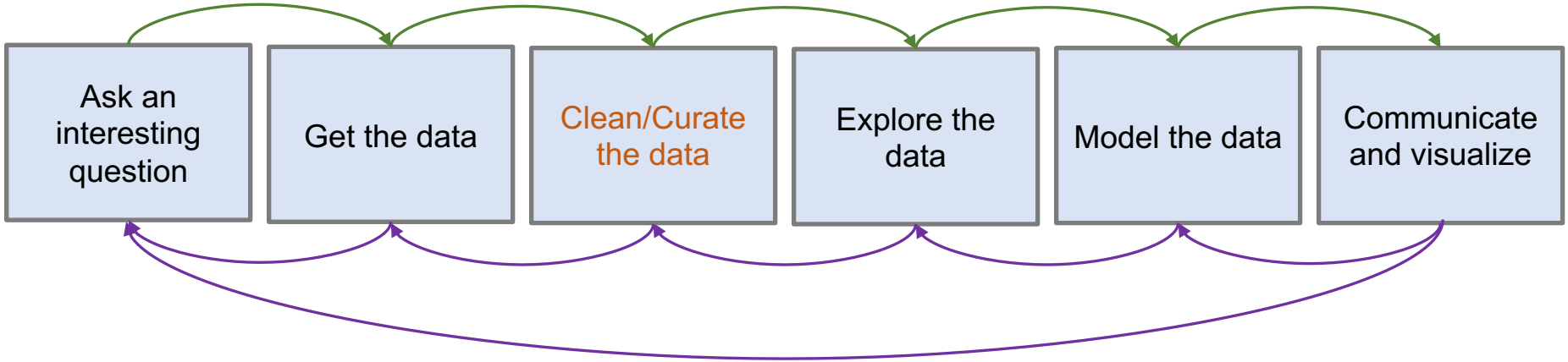

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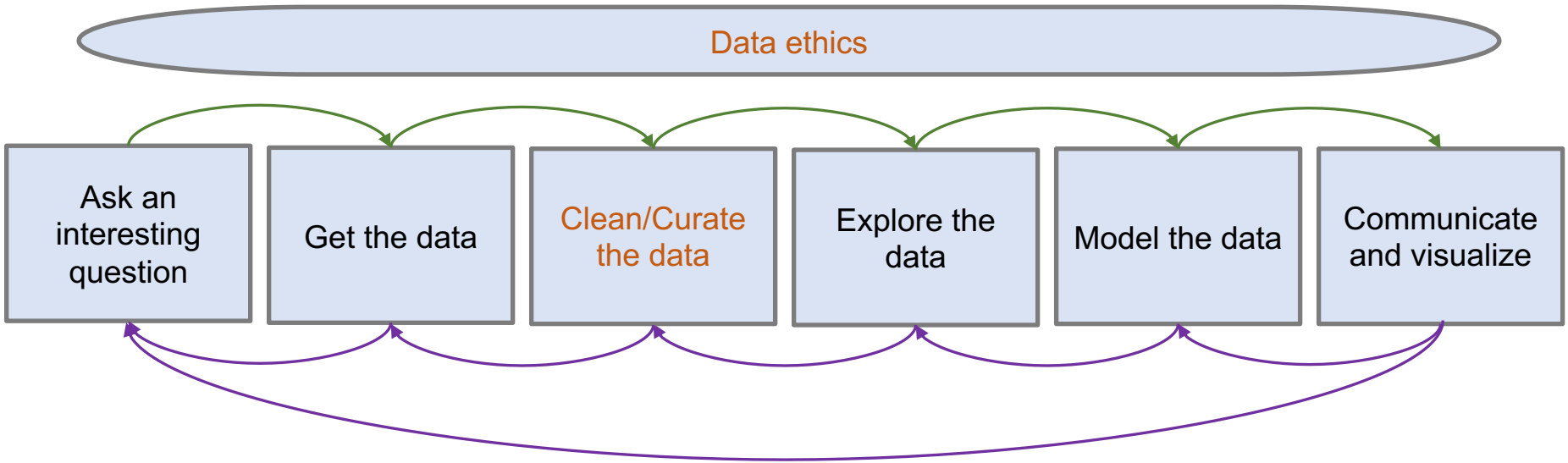

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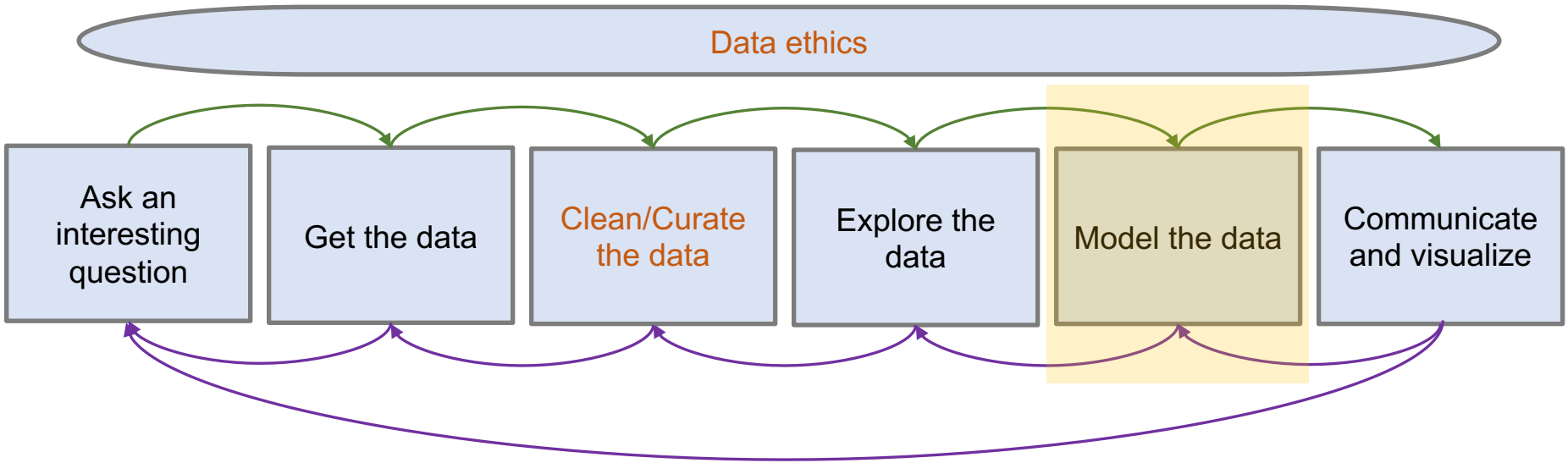

How To Build A Model (A Game)

Examine outputs from regression model

Build a regression model using explanatory variables of interest

Expand and iterate on model

Clean/curate the data

Explore the data and calculate descriptive statistics of the variables in the dataset

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We specify a question and ensure we have the data to answer the question

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- Statistics/economics: explain a relationship
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- Machine learning: predict the future
  - Ties in with the idea of prediction

Example: Earnings

- Inference
  - What are the determinants of income?
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- Prediction
  - What is the predicted income for person X?
  - What are the descriptors of a person with income Y?

Example: Earnings

Data on Swiss labor force outcomes:

	working	income	age	educ	kids	oldkids	foreign	welfare
1	No	48411.71	30	8	1	1	no	FALSE
2	Yes	37206.96	45	8	0	1	no	TRUE
3	no	58022.03	46	9	0	0	no	FALSE
4	no	66502.78	31	11	2	0	no	FALSE
5	no	66734.01	44	12	0	2	no	FALSE
6	yes	61589.95	42	12	0	1	no	FALSE
7	no	94344.38	51	8	0	0	no	FALSE
8	yes	35987.18	32	8	0	2	no	TRUE
9	no	41140.16	39	12	0	0	no	FALSE
10	no	35825.67	43	11	0	2	no	TRUE
11	no	42642.98	45	11	0	2	no	FALSE
12	no	35157.35	60	12	0	0	no	TRUE
13	no	75326.86	33	11	2	0	no	FALSE
14	no	148221.3	56	14	0	0	no	FALSE
15	no	98870.09	56	11	0	0	no	FALSE
16	no	80297.36	47	11	0	1	no	FALSE
17	no	52117.34	50	8	0	0	no	FALSE

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- Have we measured the causal effect of an additional year of education on wages?
  - With another year of education, will I definitely earn $2,518 more?

The Model Is Right...?

> “All models are wrong but some are useful”

- George Box

> “... all models are limited by the validity of the assumptions on which they ride”

- Collier, Sekhon, and Stark

> “Assumptions behind models are rarely articulated, let alone defended.”

- David Freedman

Models for Predictions

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  - Miss features, omit dependencies, make assumptions, etc

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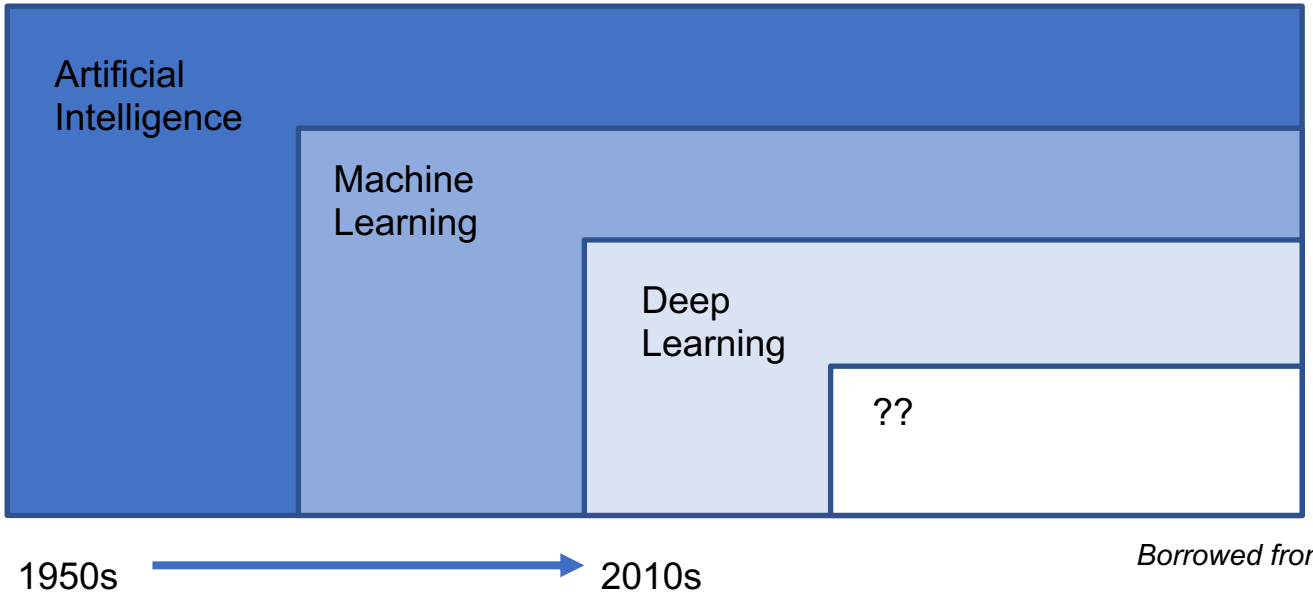
- A critical concern of machine learning is the ability to build models that accurately generalize while a critical concern of econometrics is the ability to build models that capture relationships

What is Machine Learning?

- Machine learning is the science of getting computers to act without being explicitly programmed
- Machine learning is a scientific discipline that explores the construction and study of algorithms that learn from data
- Machine learning is a natural outgrowth at the intersection of computer science and statistics

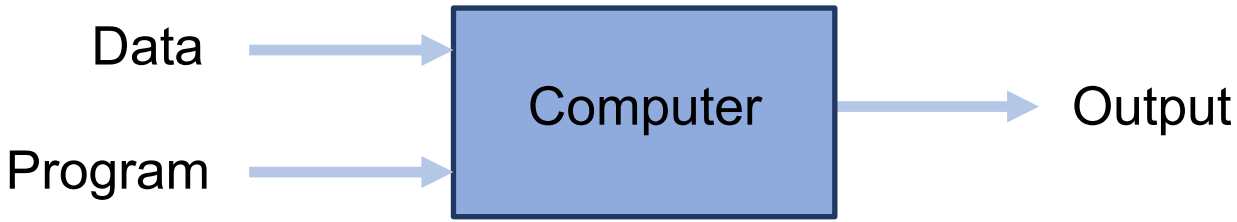
What is Machine Learning?



Borrowed from Nvidia

What is Machine Learning?

Traditional Programming



Machine Learning

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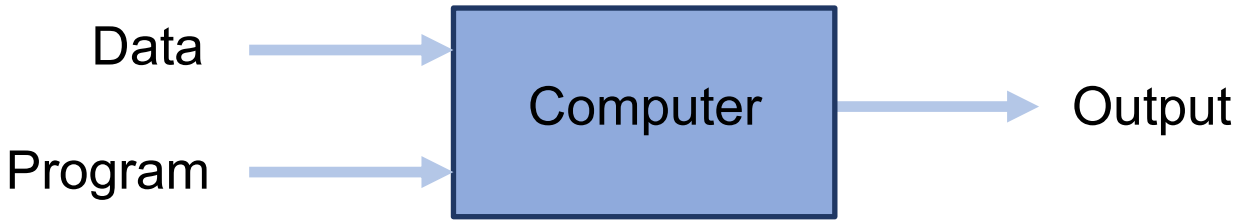
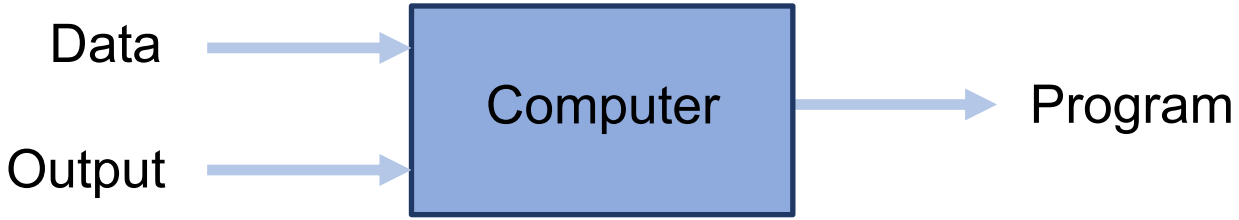


Machine Learning



What is Machine Learning?

"Learning is (like) farming, which lets nature do most of the work. Farmers combine seeds and nutrients to grow crops. Learners combine knowledge with data to grow programs."

- Pedro Domingos

“Flavors” of Machine Learning

- Supervised learning
- Unsupervised learning
- Semi-supervised learning
- Reinforcement learning

Supervised Learning

- We know the “correct” answer for values
  - We’re trying to model the input (independent) variables as they relate to the output (dependent) variables
- Examples
  - Predicting whether a student will graduate from a university
  - Predicting salary upon graduation
  - Other examples?

Unsupervised Learning

- We don't know the "correct" answer for values
  - We're trying to discover underlying structure
- Examples
  - Extracting topics/themes from textual surveys of students
  - Understanding the relationships between different departments/programs
  - Finding bottlenecks in student course offerings

“Pop” Quiz

Would you address each of the below with a supervised or unsupervised learning algorithm?

- Given email labelled spam or not, build a spam detector
- Given news articles on the web, group them into sets based on topic
- Given a database of customer data, find market segments/customer groups
- Given patients with a disease, determine if new patients have the disease
- Given phone records of individuals, determine which are the wealthiest
- Given phone records of individuals and survey data about their income, predict the incomes of new subscribers

Semi-supervised Learning

- We know the “correct” answer for some values
  - The input data contains both labelled and unlabeled instances
- Examples?

Reinforcement Learning

- We develop “agents” that seek to maximize “reward”
  - We’re trying to build models that will seek to maximize some gain
- Examples
  - Creating personalized curricula for students
  - Creating educational content for students

ML Basics

- Thousands of ML algorithms
  - No one knows them all
  - Often tweaks or small improvements to existing approaches

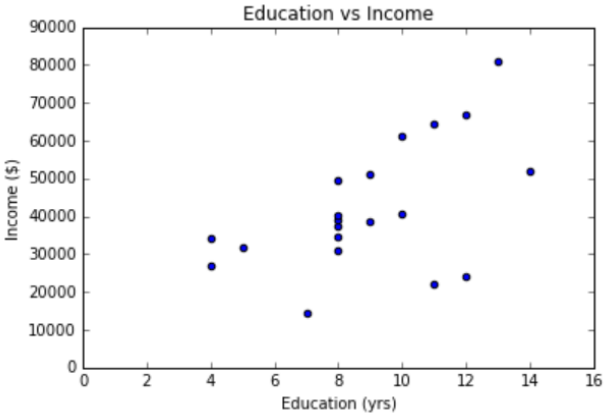
ML Basics

- Thousands of ML algorithms
  - No one knows them all
  - Often tweaks or small improvements to existing approaches
- Every ML algorithm has three components
  - The representation (the model)
  - The evaluation (the cost/objective function)
  - The optimization (the search)

Designing for Prediction: Key Ideas

- Generalization and overfitting
- Training, validation, and test data
- Evaluation metrics
- Baselines
- Error analysis

Modeling Education and Income



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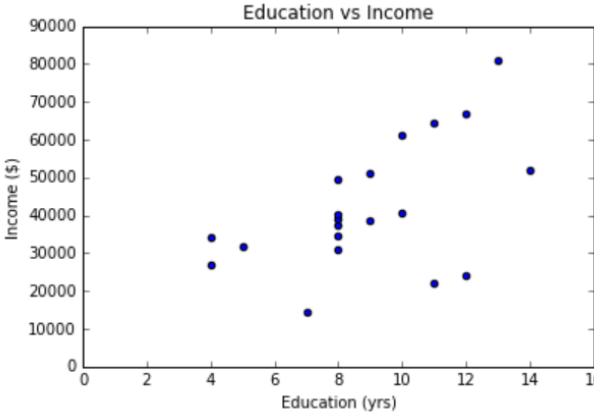

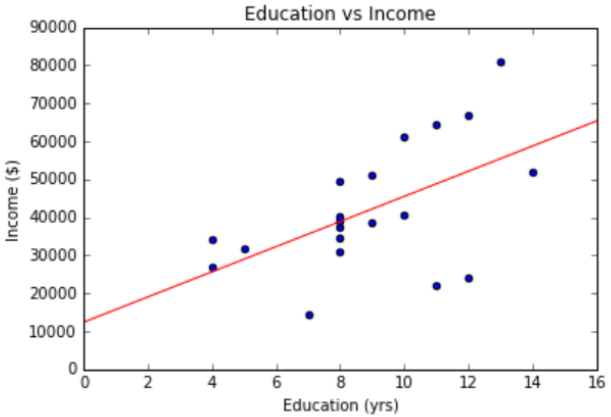

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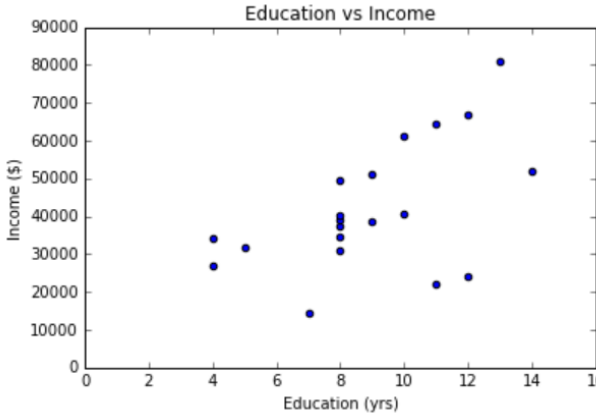

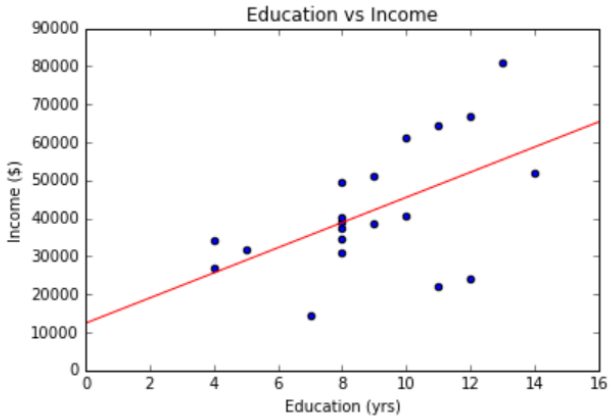

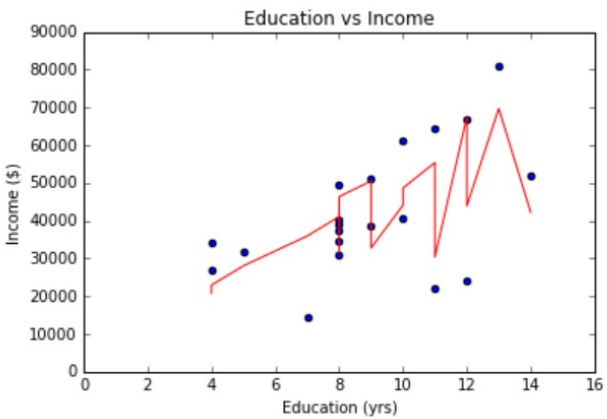

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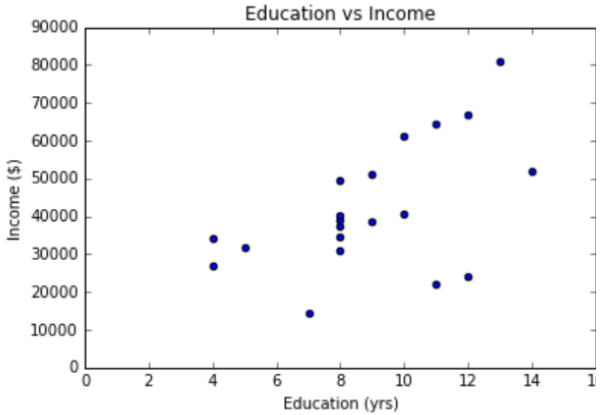
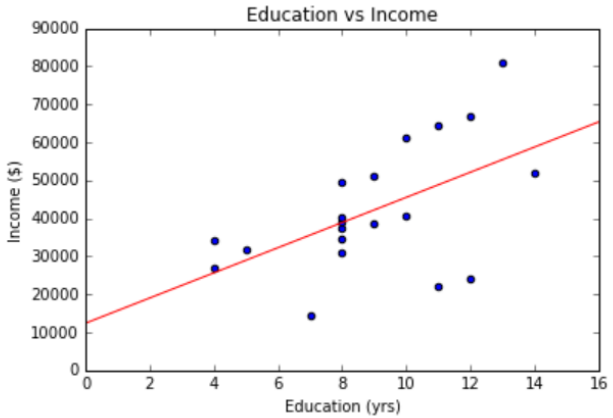
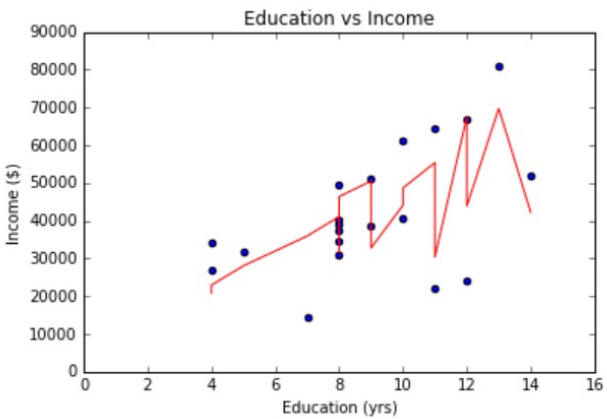


Plotting

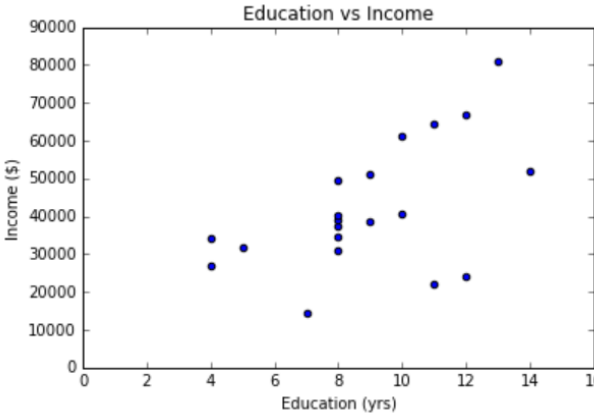


One Variable



“Kitchen Sink”

Modeling Education and Income



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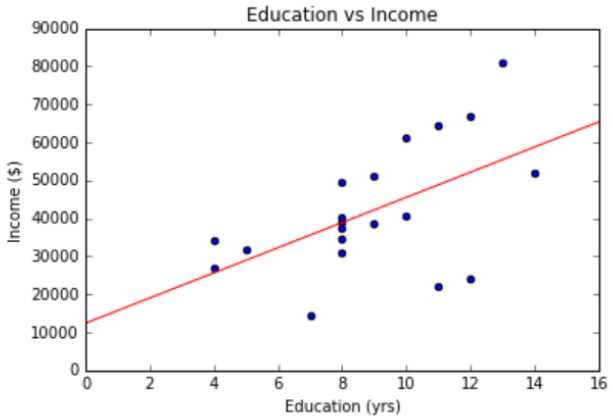

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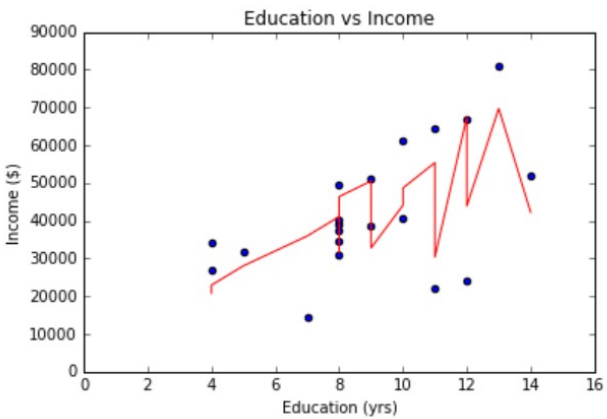

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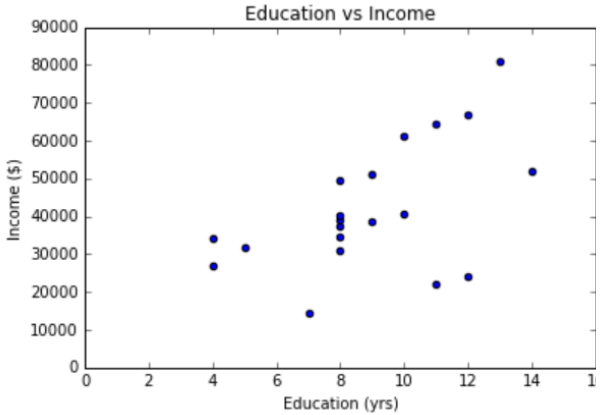

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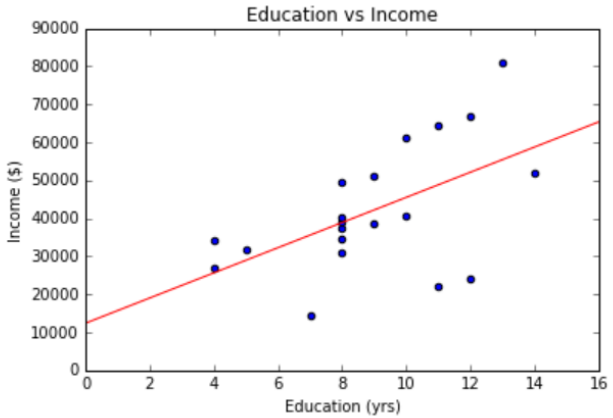

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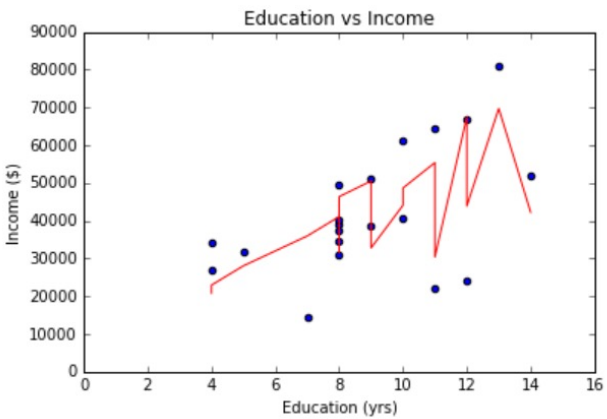

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Notebook #1

Determining Model Fit

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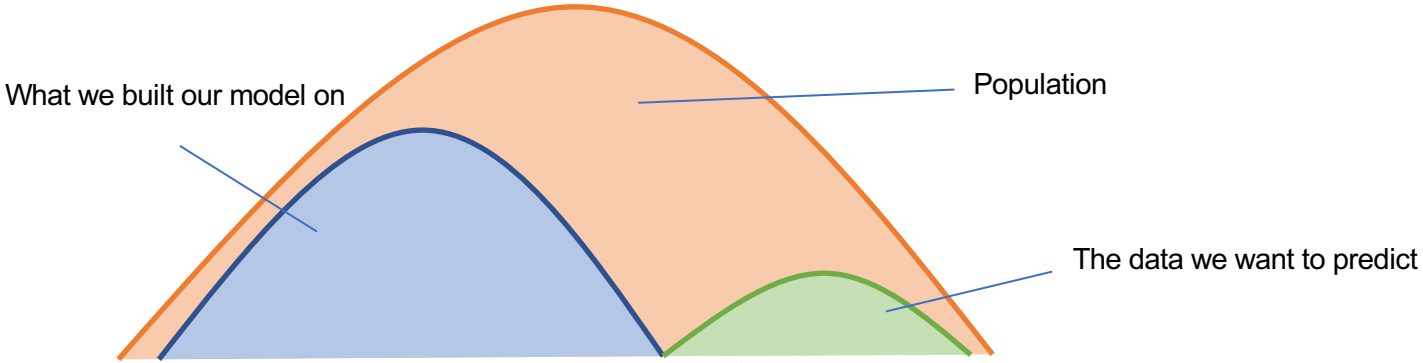
- Should we keep adding features? Is this what we want?

The ML Dilemma

> We want to find a balance between modeling the data we have while also being able to generalize to unseen data



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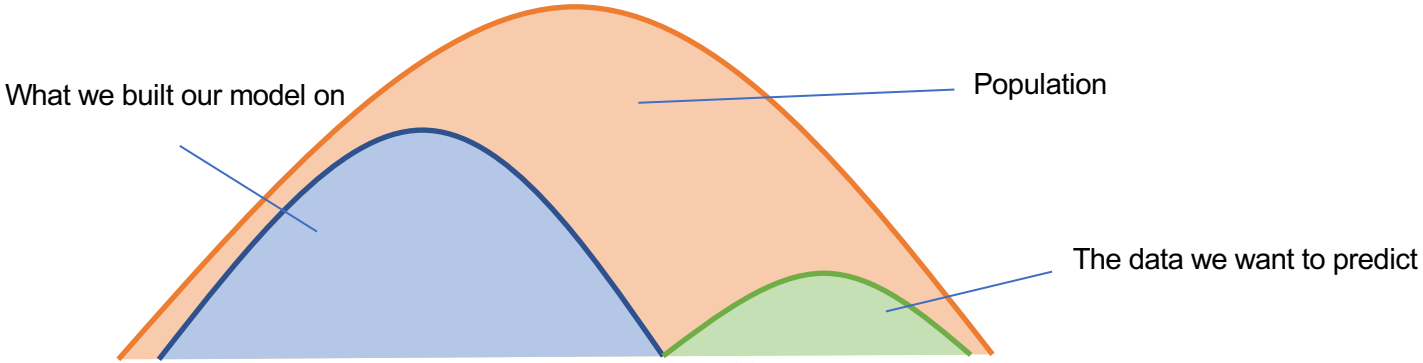

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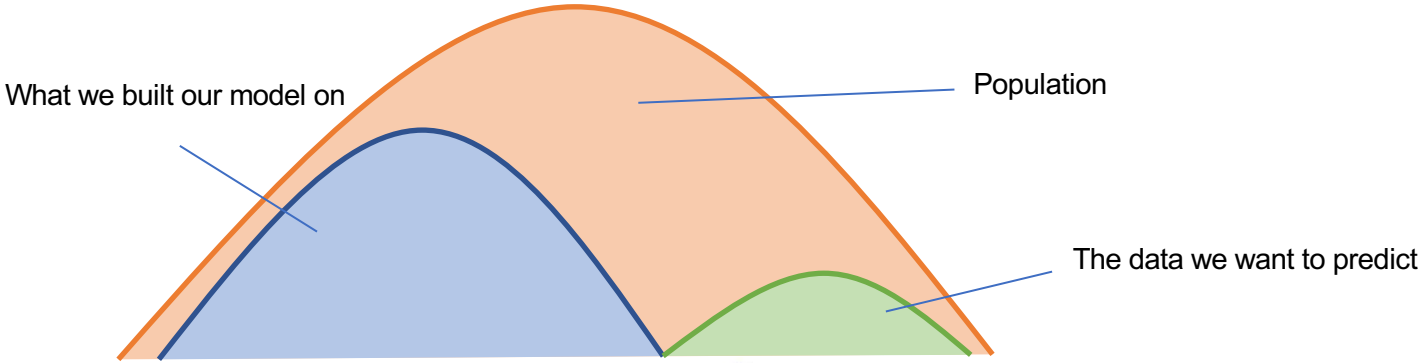
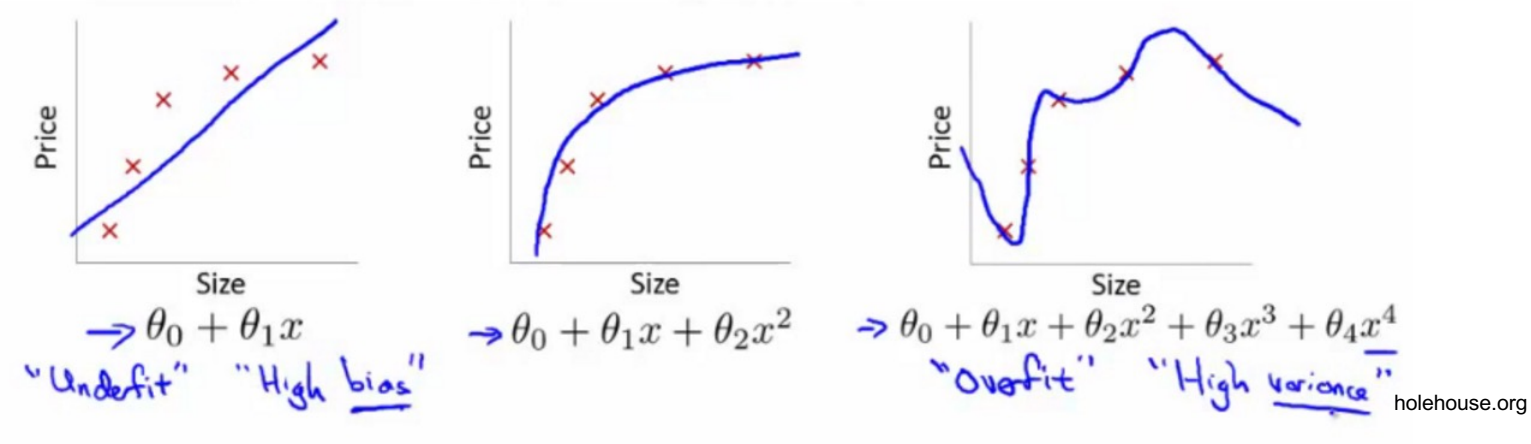
bias



Bias-Variance Tradeoff



Bias-Variance Tradeoff: the problem of simultaneously minimizing two sources of error that prevent generalization

Overfitting and Underfitting

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Test Data

Until you're ready to report final results...

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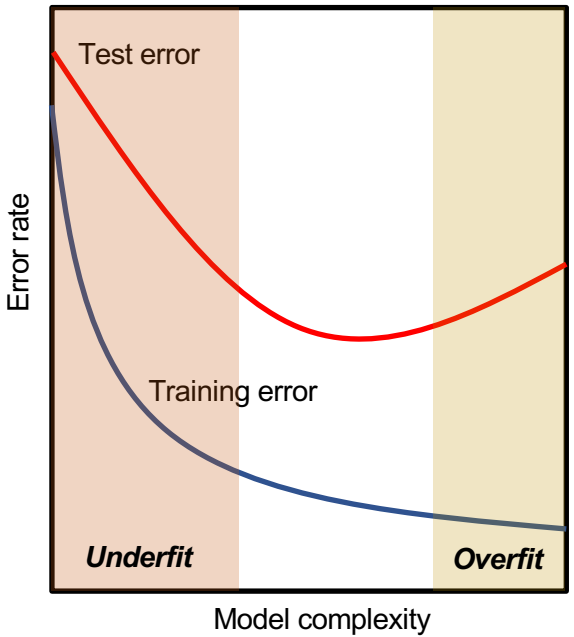
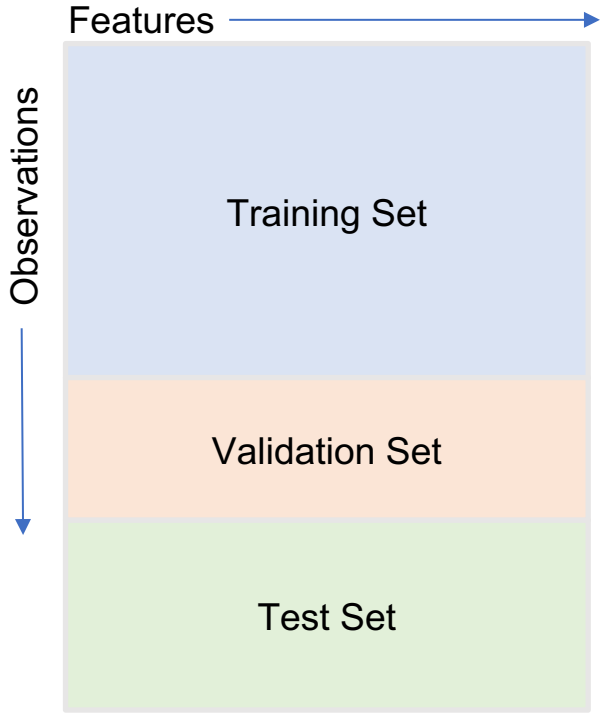
How Prediction Experiments Work

- ML experiments typically separate data into a training/test set
- Model is fit on training set
  - Validation set is often used to fine tune
- Performance is measured on the test set
  - This gives something of a "real-world" approximation of how well the model performs



A Typical (Supervised) ML Experiment

- Data with labelled instances
  - Split into training, validation, and test sets



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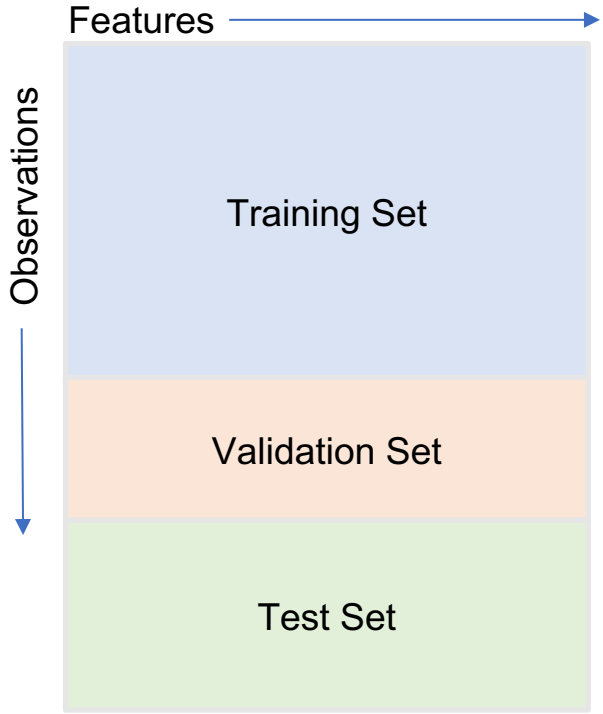

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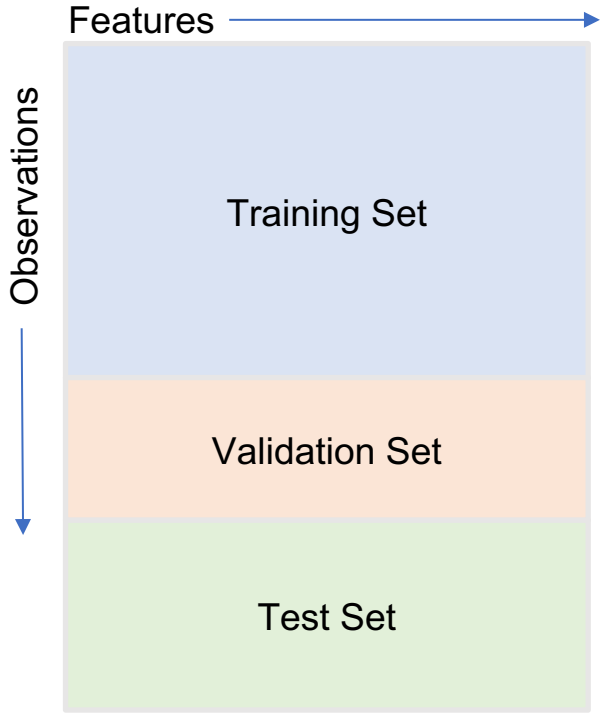
- Evaluation
  - Many metrics and context-dependent
  - Ideally, what we use to train should be our final evaluation criteria



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  - Example: beta coefficients in regression
- Hyperparameter:
  - A value that is set before the learning process
  - External to the data
  - Often tuned with a particular end result in mind
  - Example: regularization strength in regression

Bootstrapping

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- Bootstrapping can help us recycle and maximize data usage
  - It also allows us an easy avenue to tune hyperparameters

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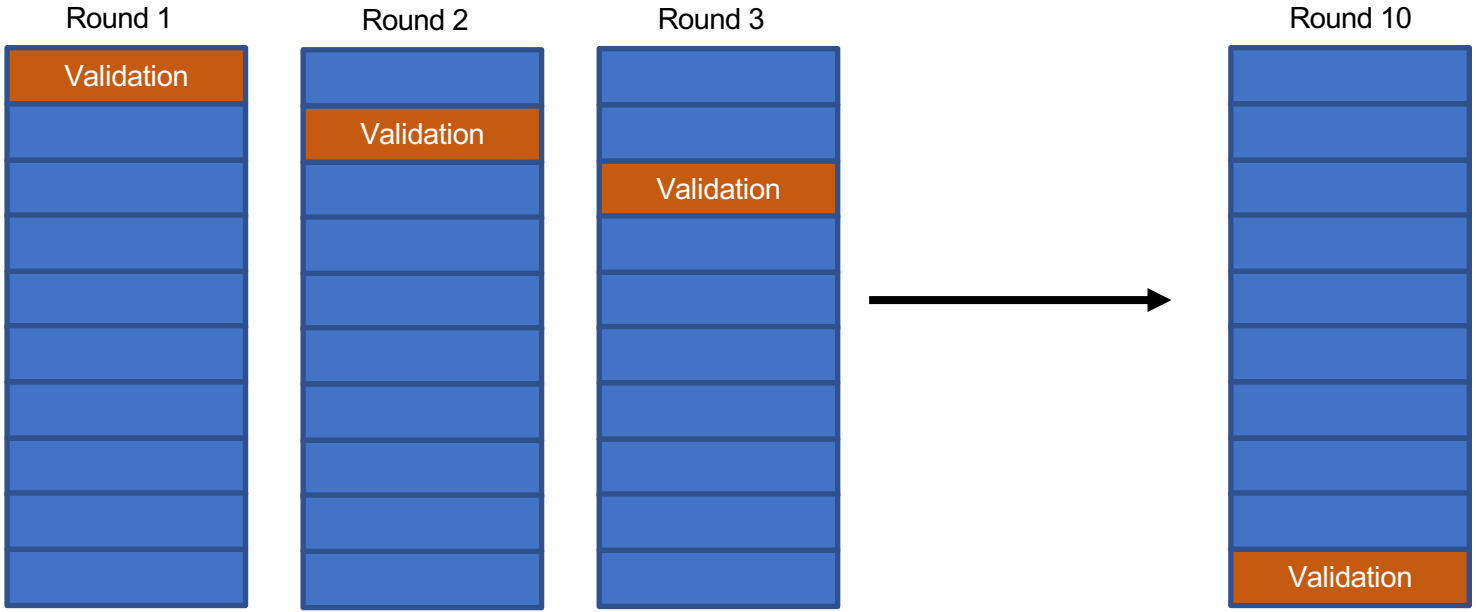
- Involves fitting and re-fitting the model K times!
  - Can be computationally cumbersome

K-Fold Cross Validation



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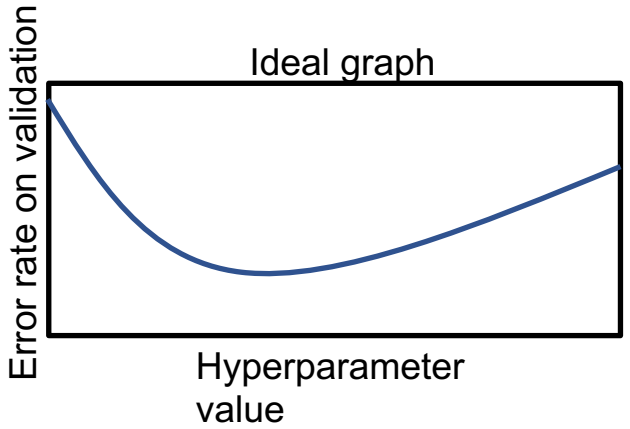
- KFCV can be used to identify which hyperparameter settings work best
- Process:
  - Start at a value of interest for hyperparameter(s) of interest
  - Use KFCV to evaluate
  - Adjust hyperparameters
  - Repeat
- Use optimized hyperparameters to train the final model



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- Log loss for either
- Many, many more

Baselines

- We also often need to quantify progress (accuracy, correctness) relative to something meaningful. The following are often used:
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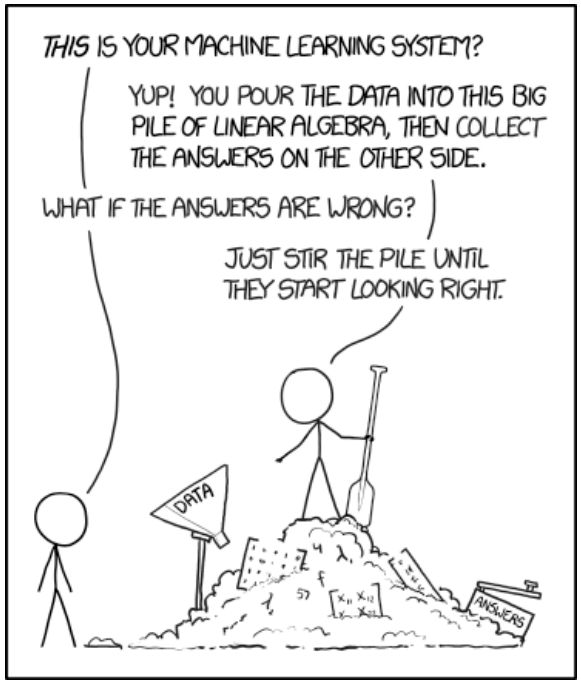
- Example: if our dataset has 90% of students retained, is an accuracy of 90% when predicting retention really all that great?

Error Analysis

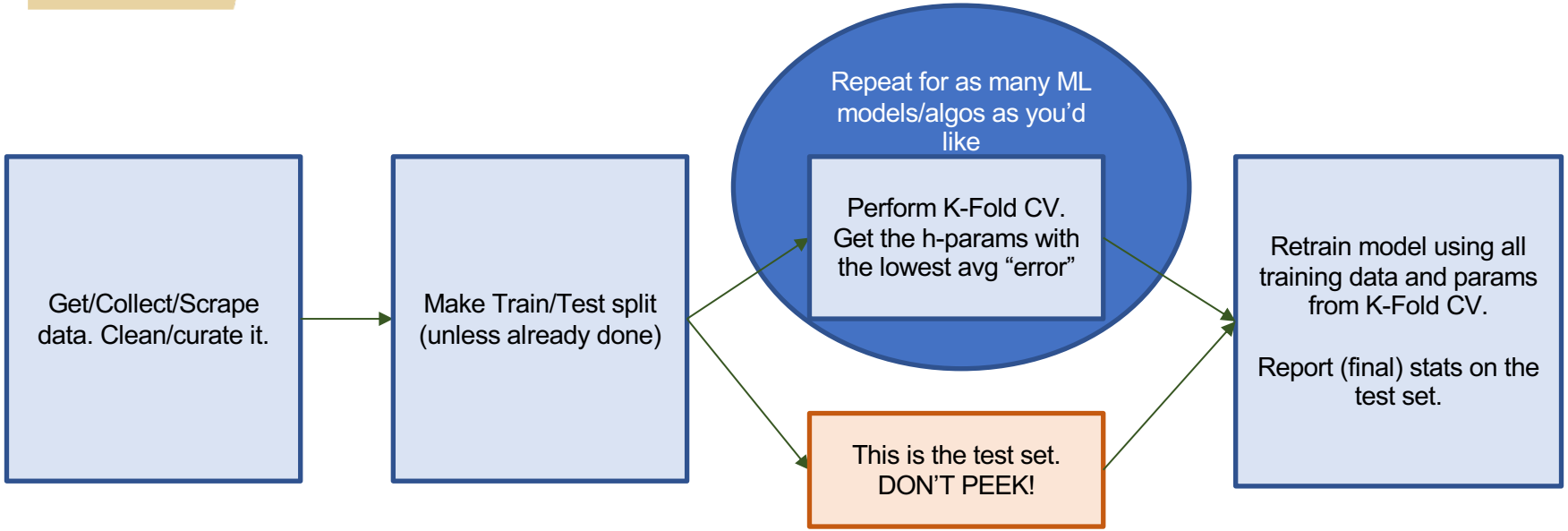
- Error analysis tries to explain the gap between current and perfect performance
  - Why is the model incorrect?
  - Where is it incorrect?
  - What types of observations does it need more leverage for?

- Things rarely work out of the box
  - Be ready to tune/tweak and re-tweak

Error Analysis



The Workflow*



*not always the workflow

Notebook #2

Ethics

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- Beware of black boxes
- Pay attention to “explainable” ML
  - Just because something predicts well, doesn’t mean we can’t understand it
- Pay attention to biases in your data!
  - Your models will always reflect the biases they inherit
  - This can also relate to blindspots in your data

Homework

Your homework for next week:

- On the back end of the second notebook
- Do the readings/watch the videos

Wrapping Up

- Level-setting
- Model Selection
- Warm Up Exercise
- Machine Learning Overview
- Basics
- Programming Exercise