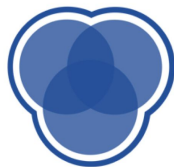


INFO 1998: Introduction to Machine Learning

Download `Lecture5Homework.ipynb`, `lecture5dataA.csv`, and `lecture5dataB.csv`

(also pull up `Lecture4Homework.ipynb` — you'll find it helpful)



CDS Education

We explore, learn, and educate big minds.

Lecture 5: Fundamentals of Machine Learning Pt. 2

INFO 1998: Introduction to Machine Learning

Tuning Models



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Announcements

Mid-Semester Check-in

Where you should be right now:

- Have an idea of what your problem statement/hypothesis is
- Have your group chosen
- Have your data set chosen and some progress



What We'll Cover

Last Time's Goal: identify what ML is and write ML code (to some extent)

This Time's Goal: how to tell if your ML model is *useful*



Agenda

1. Review
2. Measuring Accuracy
3. Bias-Variance trade-off
4. Feature Selection
5. Other Types of machine learning



Review: Defining ML

We want to predict the future

- Take some known input and output
- Learn the data's pattern and come up with a way to, given a future input, predict the corresponding output

Now: *how* do we learn the data's pattern?



Review: Model

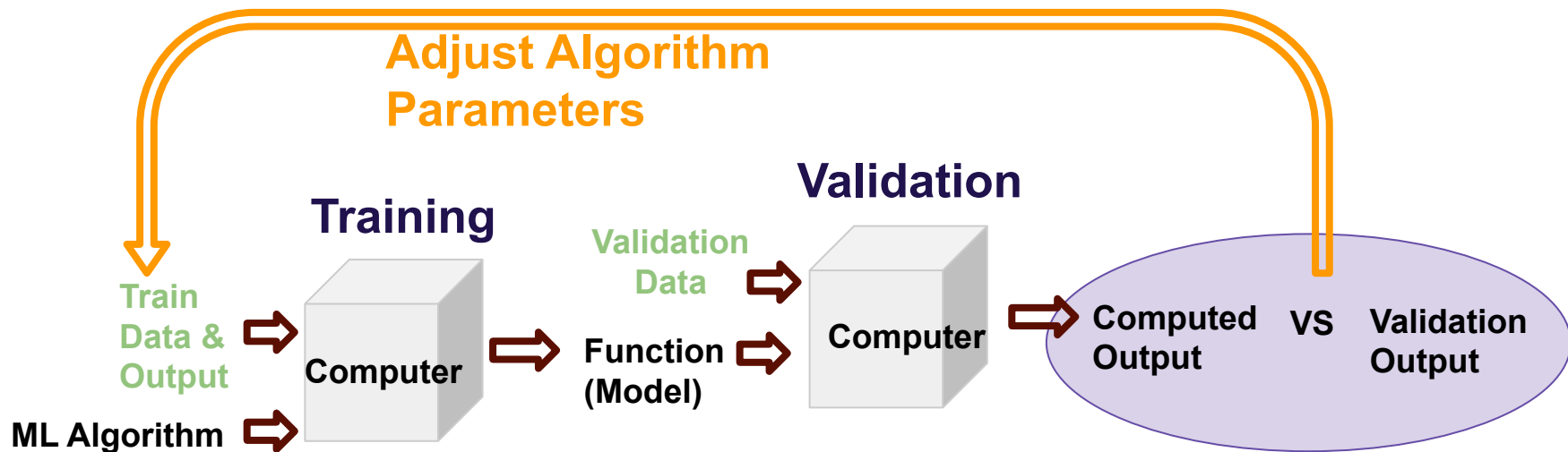
- Something you use to predict outputs
- The Linear Regression Algorithm produces Linear Regression Models
- “Model training” = learn a relationship/program
- “Model validation” = see if the learned relationship is accurate on other data
- “Model testing” = final model performance



Measuring Bias / Loss

(training accuracy)



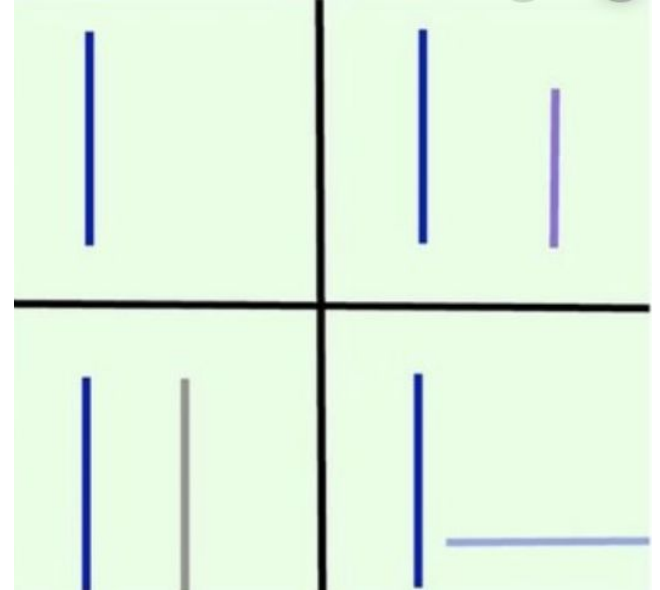


1. Split data (lecture 7)
2. Assess model accuracy (today)
3. Adjust Model (a bit today)



Loss, Cost, and Score Functions

- **Loss Function**
 - Penalty for missing a single data point
- **Cost Function**
 - Indicates how bad the whole model is
 - Applies loss function to each point, then combines that into a single number
 - ex: average of (loss from each point)
- **Score Function**
 - A more interpretable version of the cost function (how well we did)
 - Loss/Cost used in training to help a model learn, Score is just what we use for interpretability



Linear Regression Loss Formula: Euclidean Distance

$$\text{loss}(x, y^*) = (h(x) - y^*)^2$$

Two things to note about this loss function:

- Positives and negatives won't cancel
- Large errors are penalized to a power of 2 more
- Cost Function - average of the loss function over all the points

In what situations might you want a high penalty loss function as opposed to a lower penalty function?



Solution: Compare to Baseline

- When determining accuracy, usually want to compare our model to a **baseline**
 - For regression, one baseline model is the model that predicts the **average** of the target value for every point
 - For our purposes: don't worry about the baseline *model*, just have a set of baseline *predictions*



Cost -> Accuracy Score

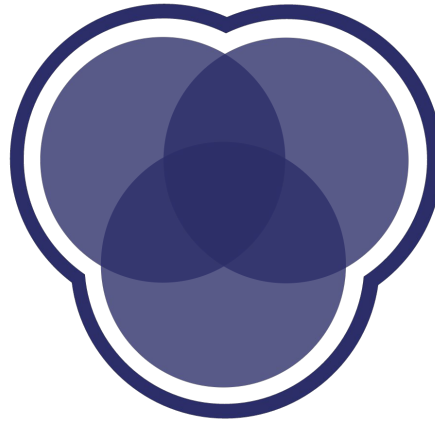
- sklearn's score function is:

$$1 - ([\text{Cost of model}] / [\text{Cost of baseline}])$$

- 1 is very, very good
- 0 means you were as bad as the baseline
- <0 means either your baseline predictions were accurate, or you really, really messed up



Demo



Overfitting and Underfitting

(what makes a model good?)



Model Goals

When training a model, we want our model to:

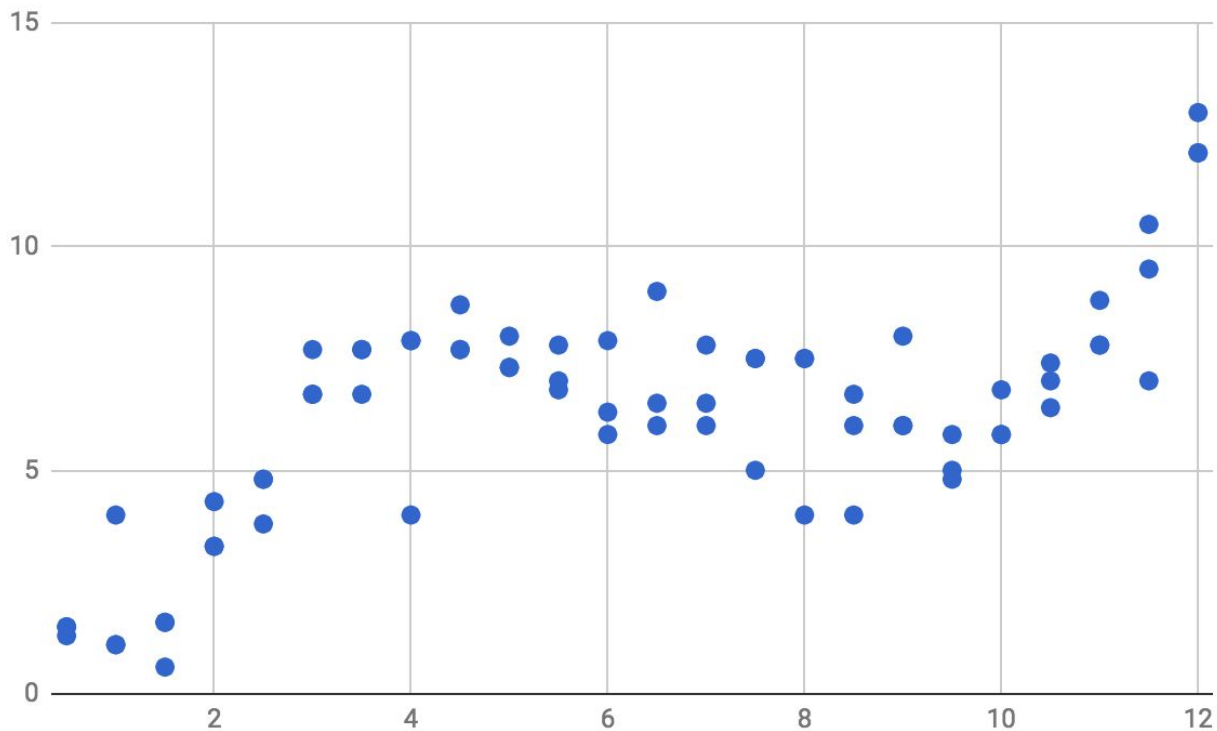
- Capture the trends of the training data
- Generalize well to other samples of the population
- Be moderately interpretable

The first two are especially difficult to do simultaneously!

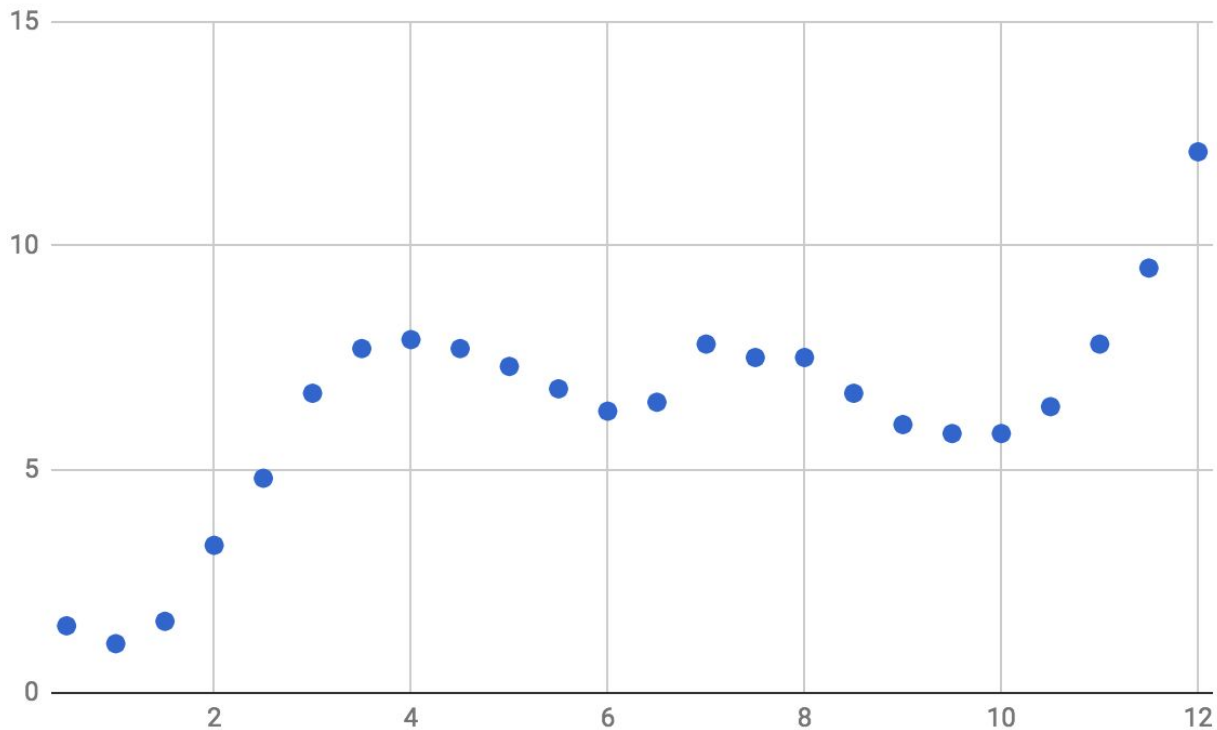
The more sensitive the model, the less generalizable and vice versa.



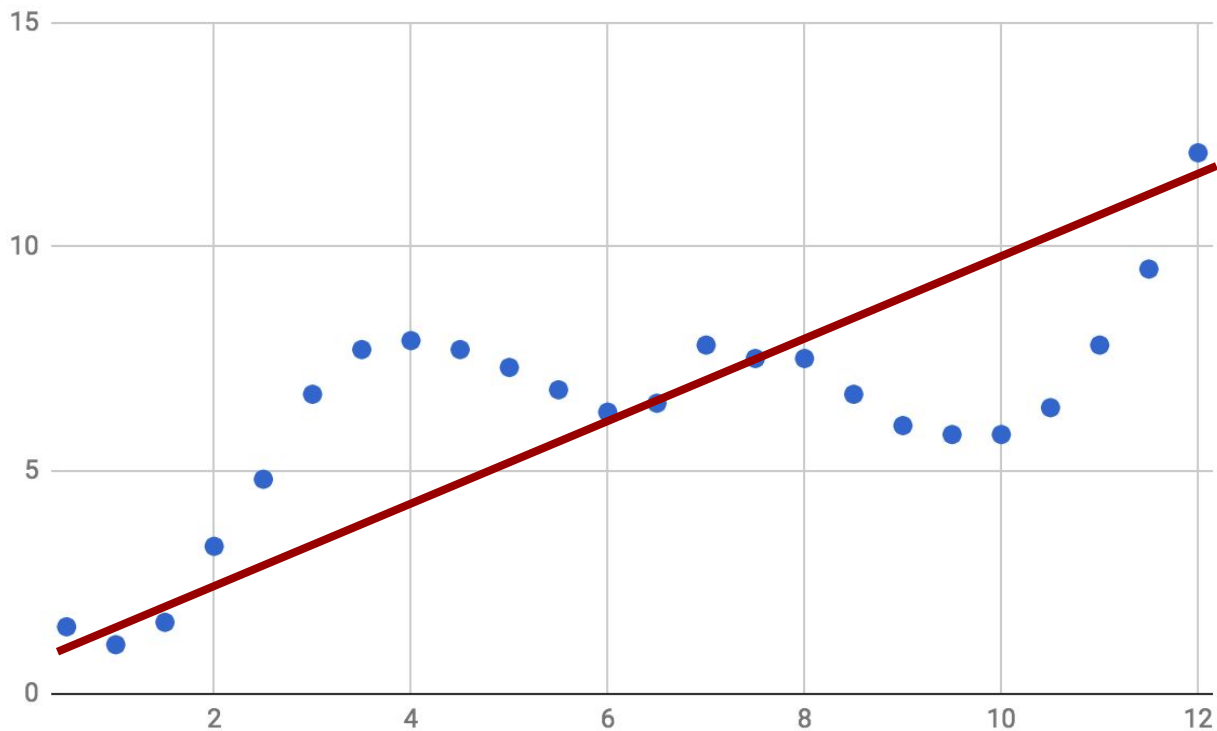
Underfitting



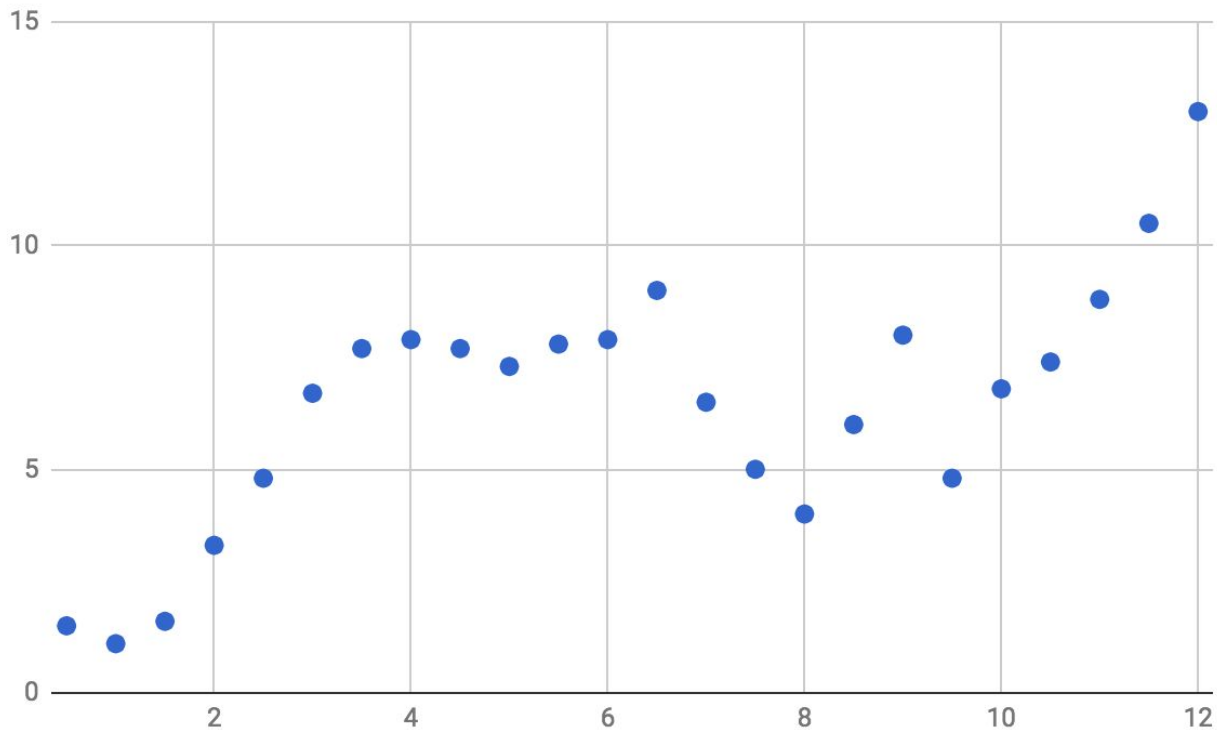
Underfitting



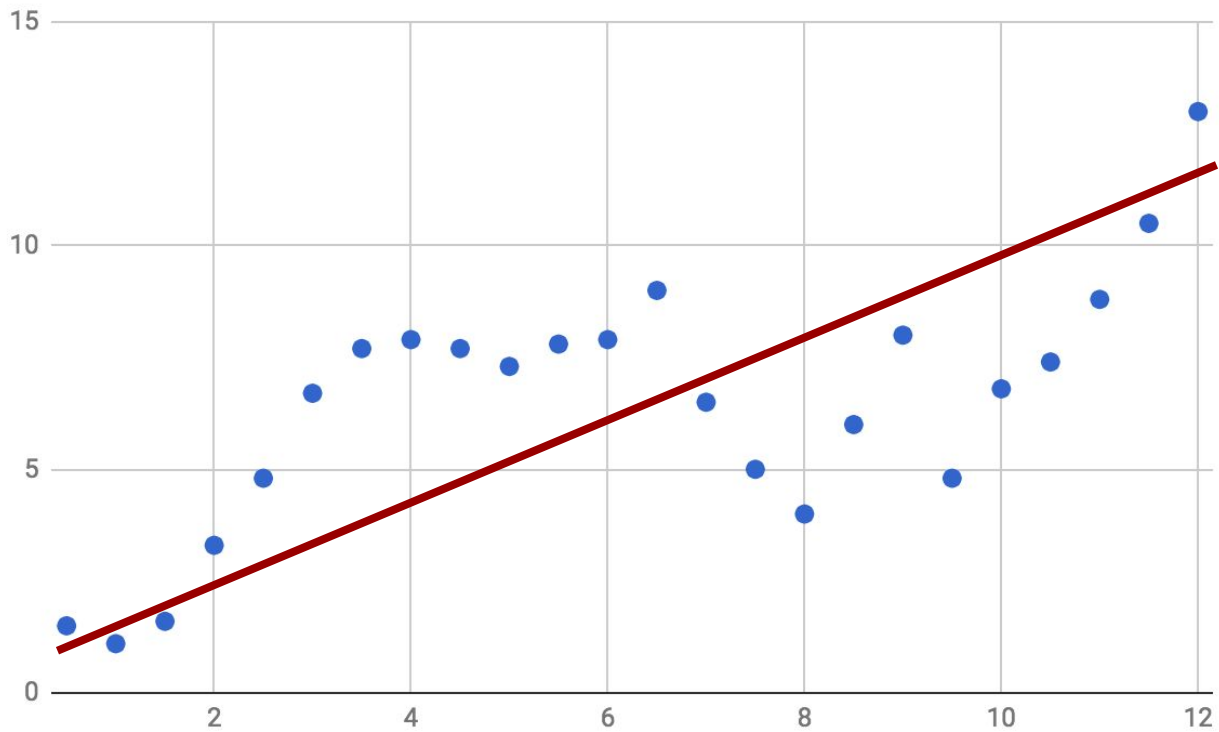
Underfitting



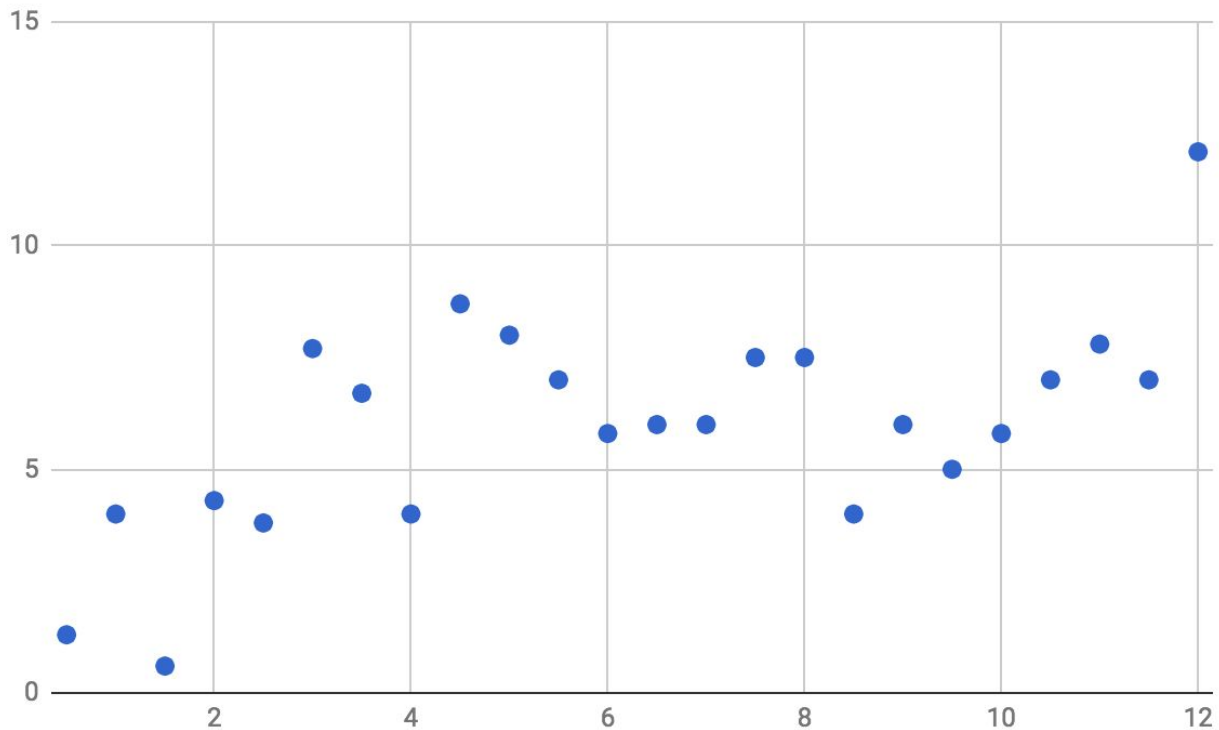
Underfitting



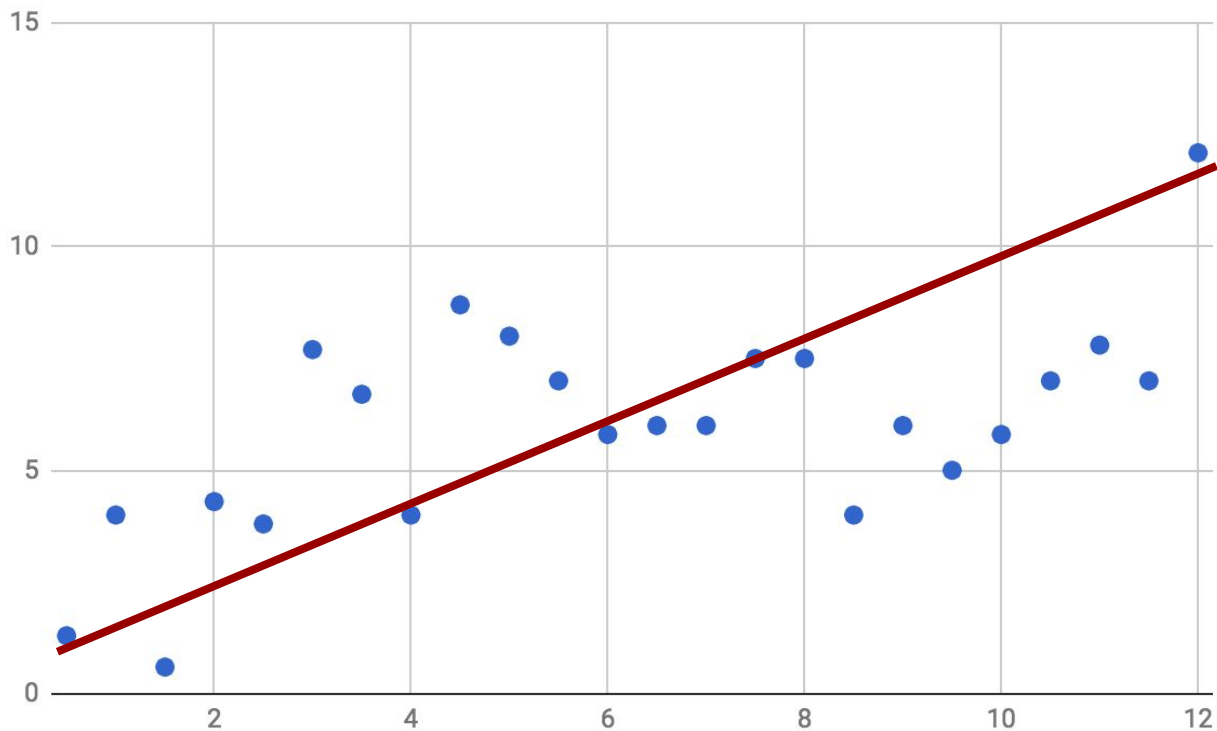
Underfitting



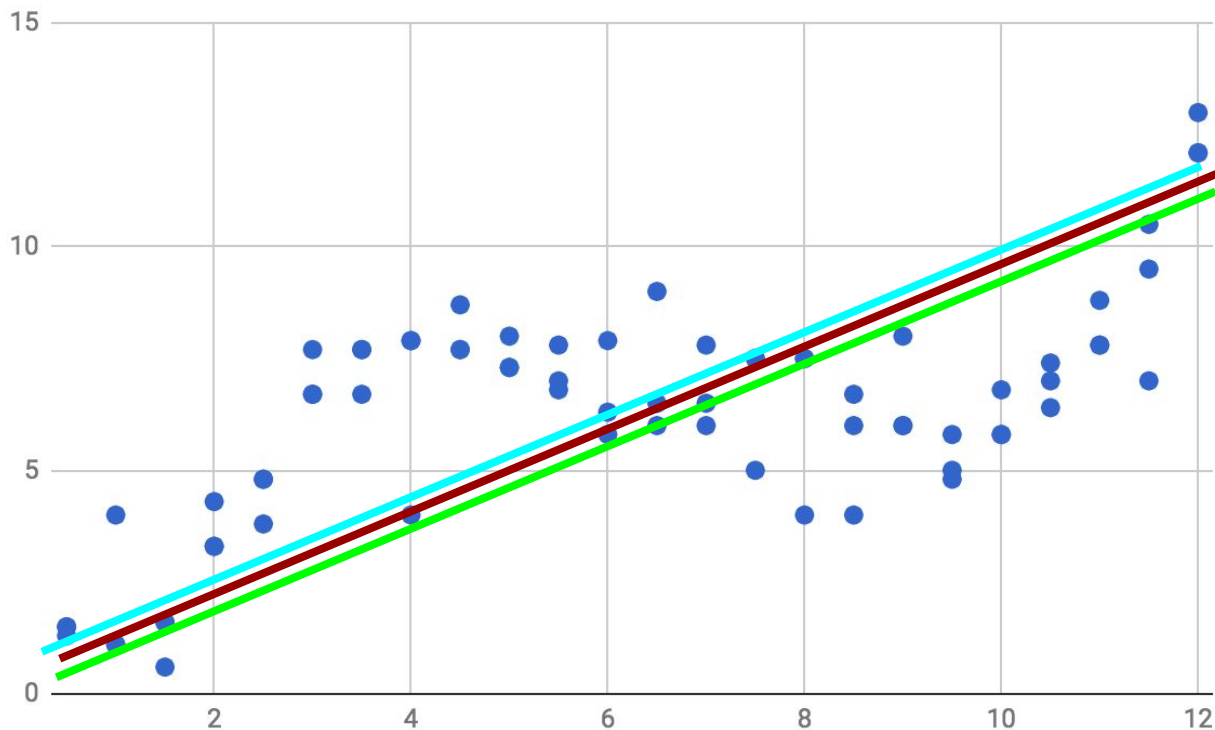
Underfitting



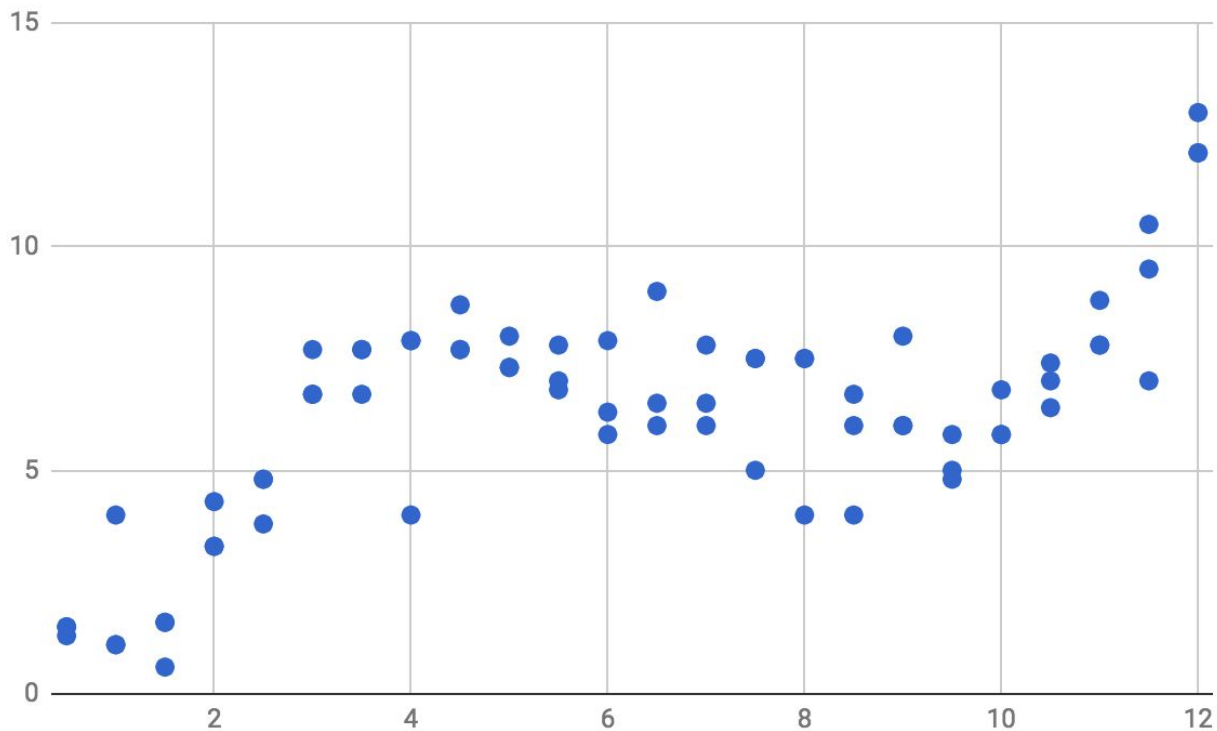
Underfitting



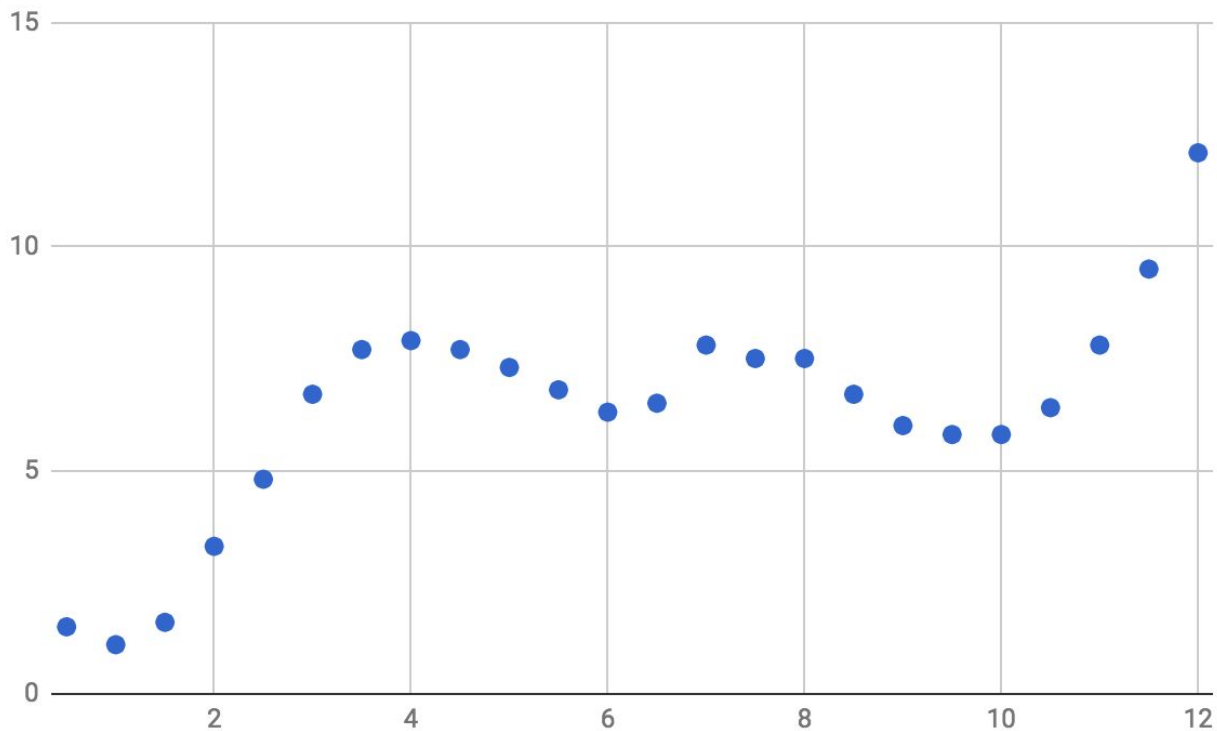
Underfitting: at least the models are consistent...



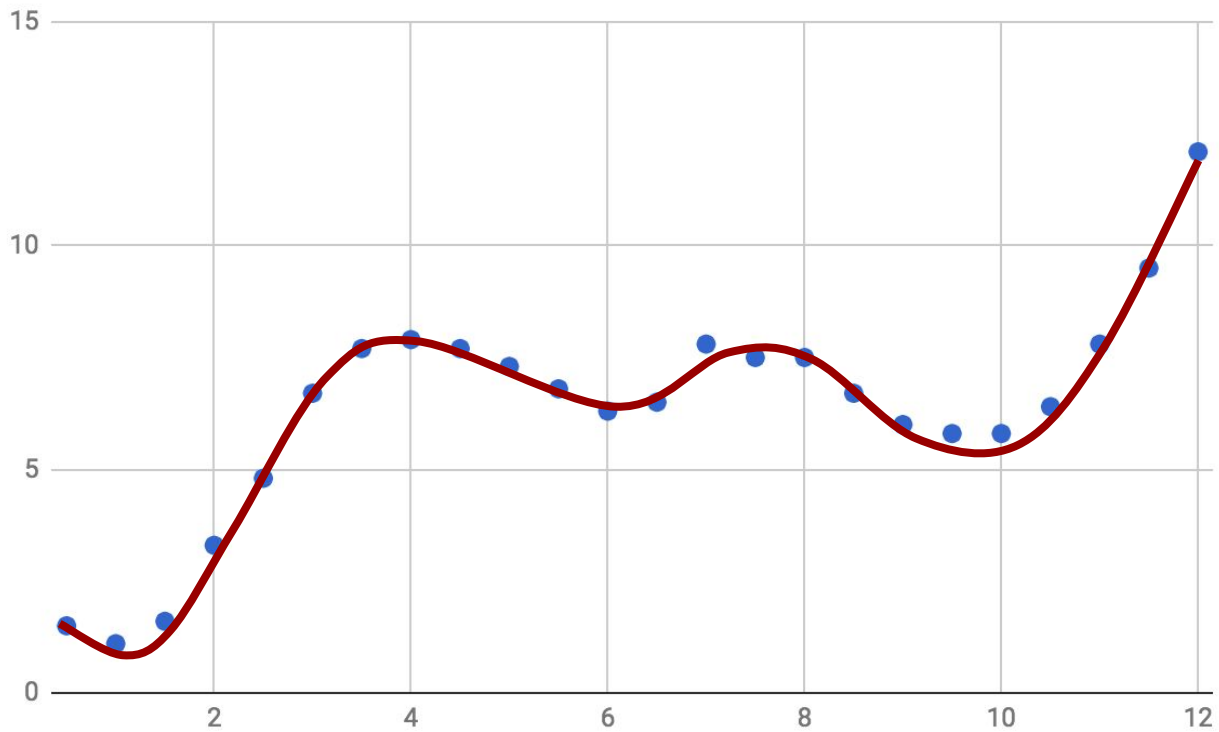
Overfitting



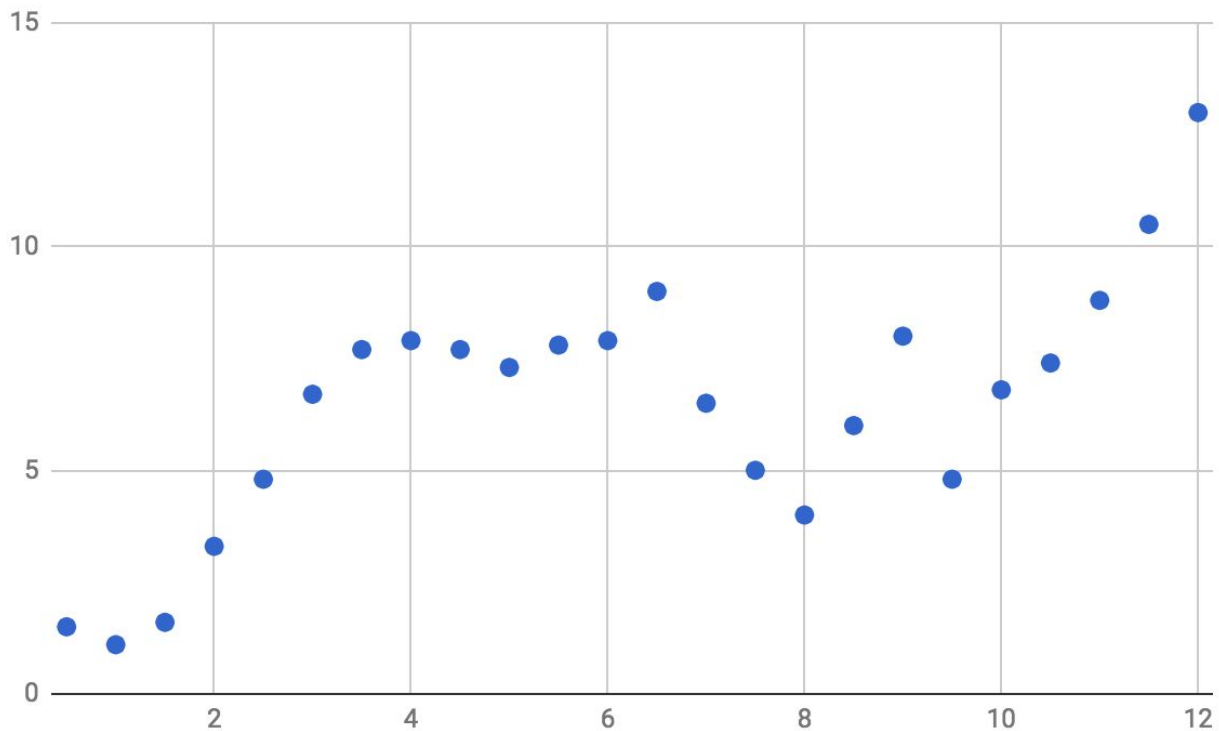
Overfitting



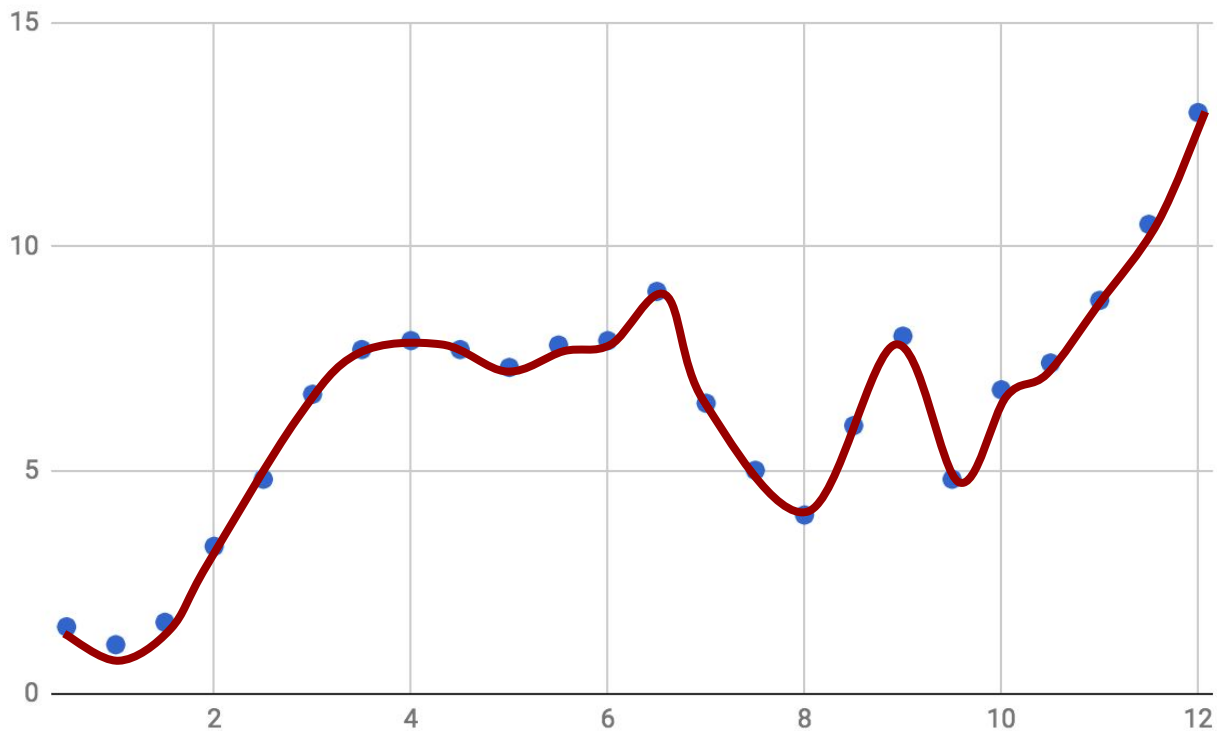
Overfitting



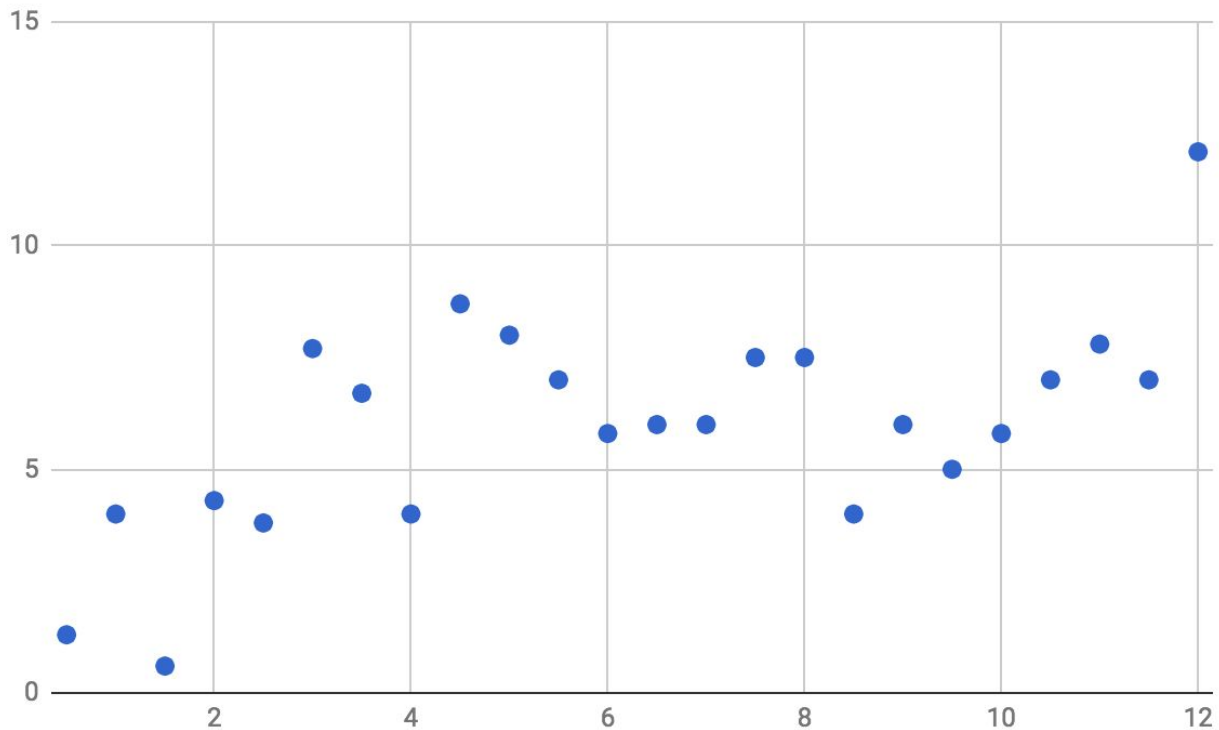
Overfitting



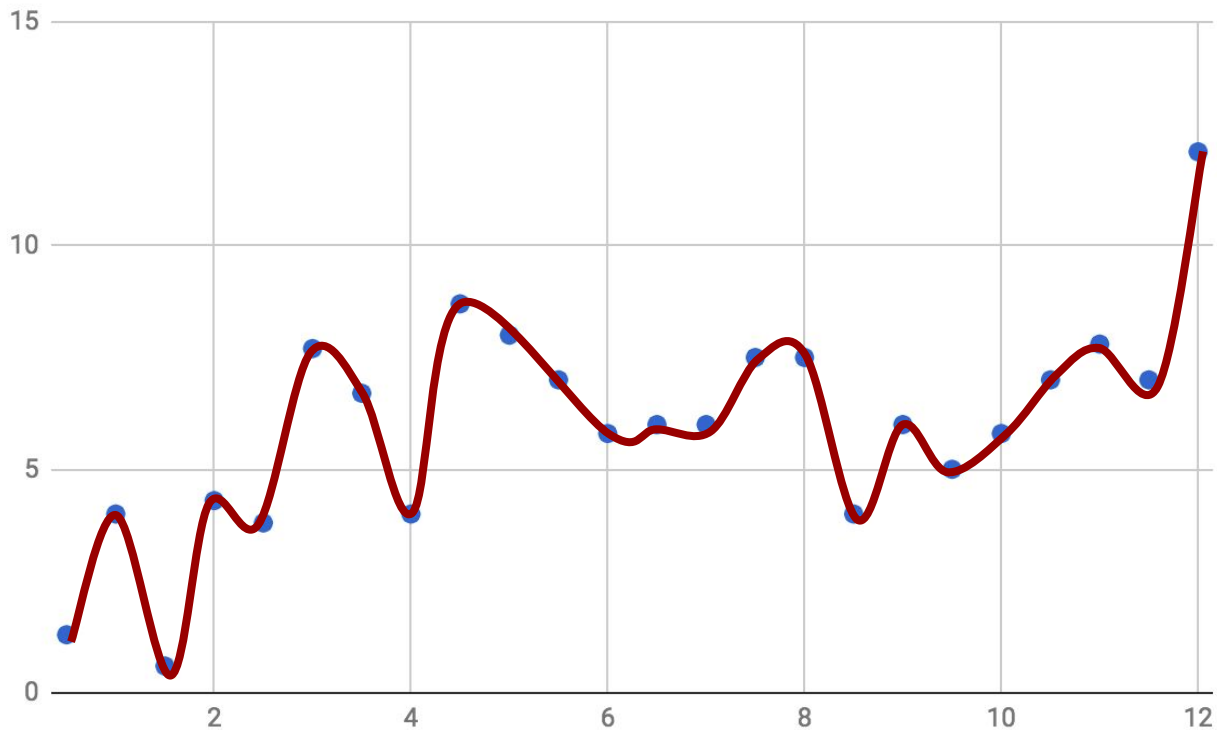
Overfitting



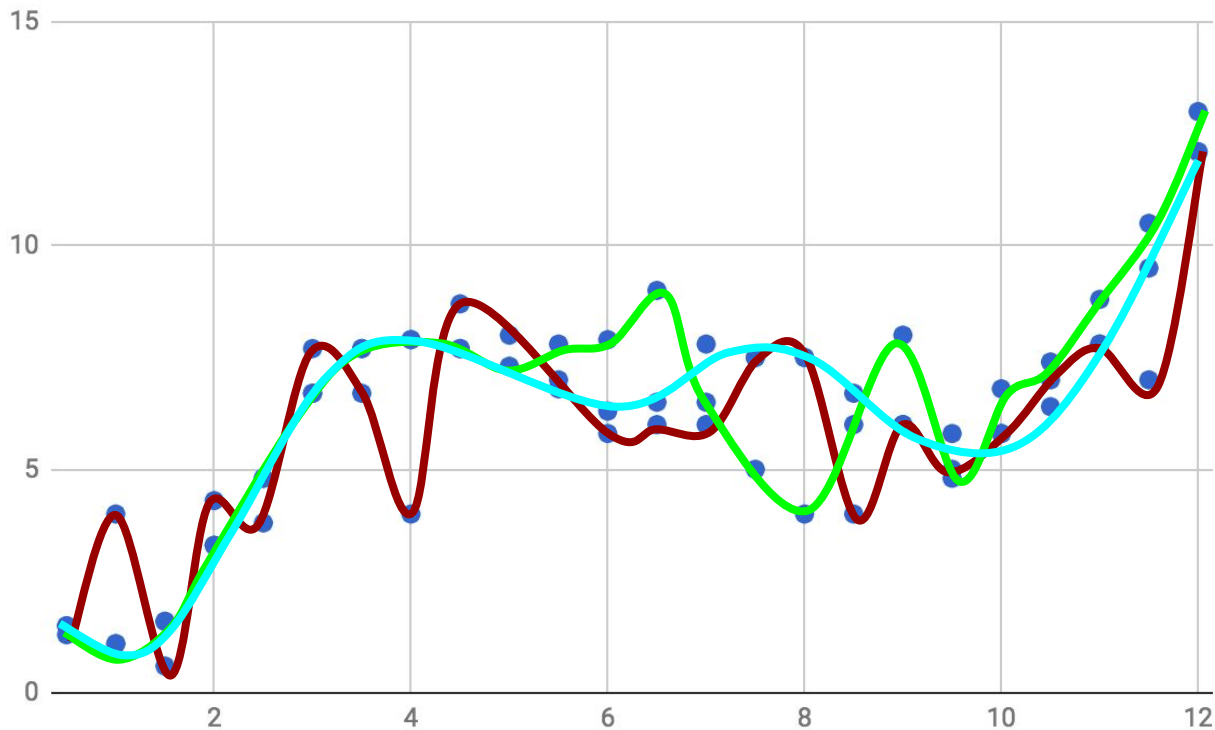
Overfitting



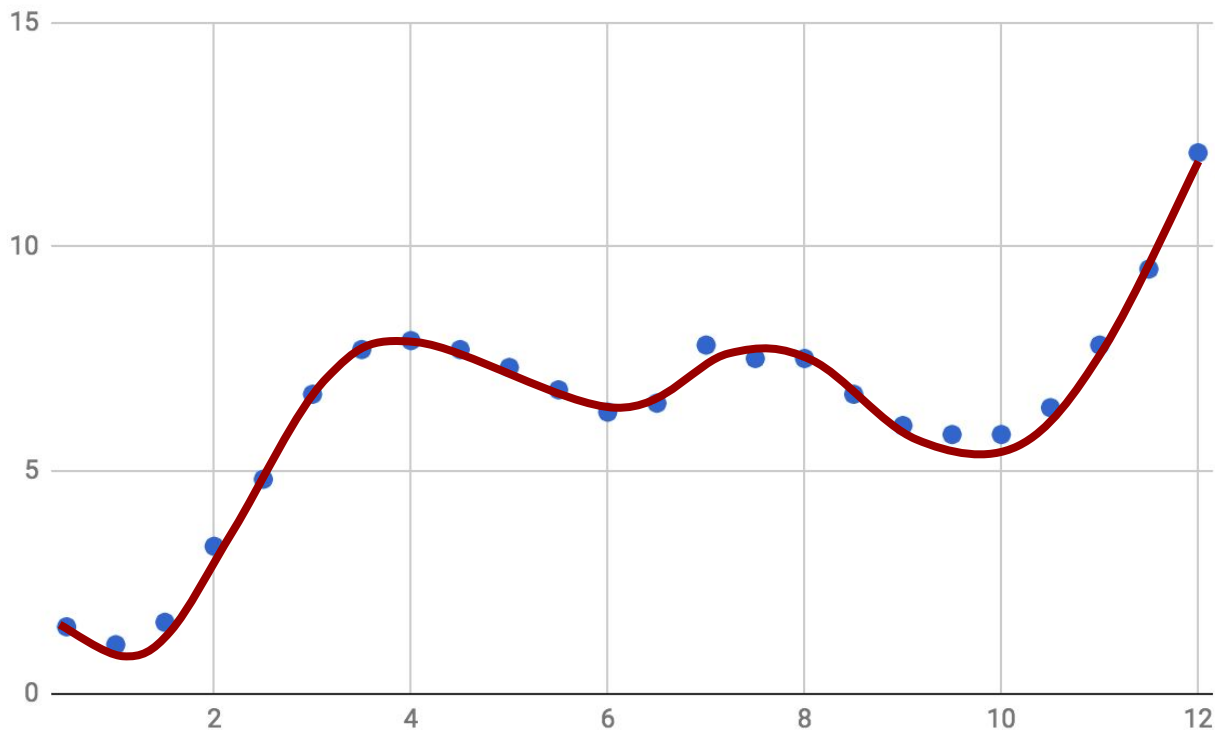
Overfitting



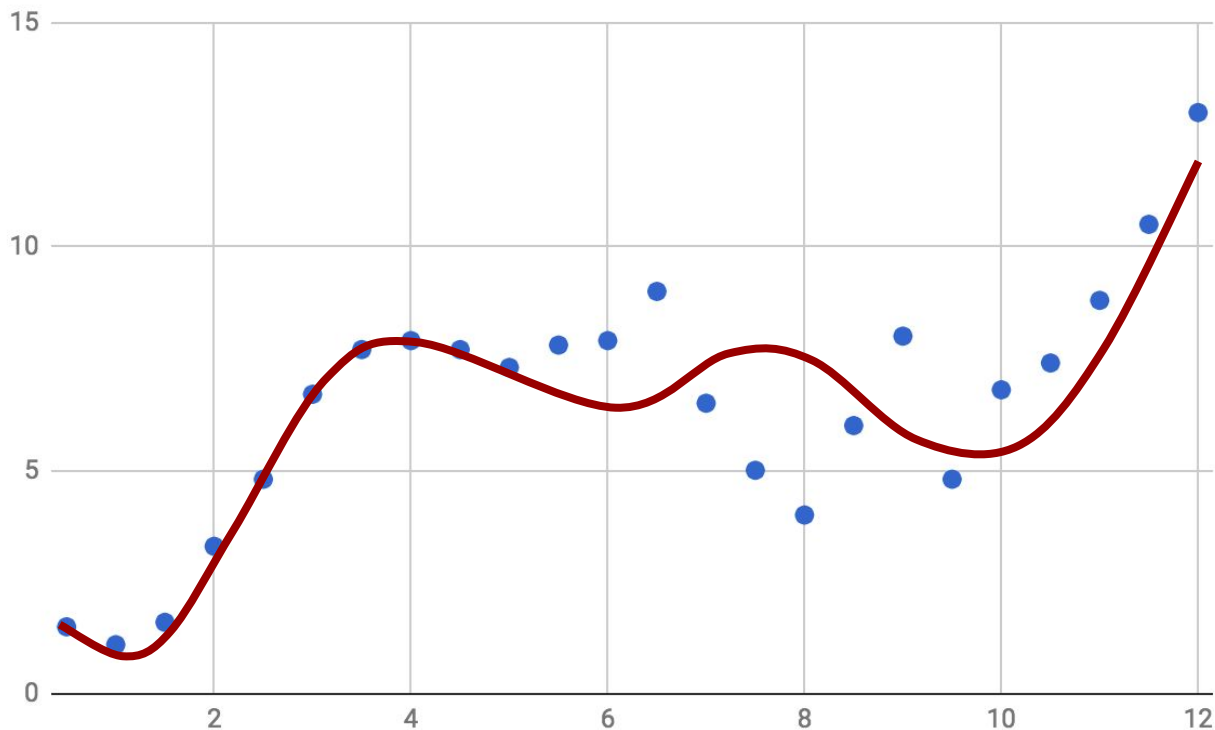
Overfitting: Inconsistent Models!



Overfitting: Results from training with high sensitivity



Overfitting: doesn't generalize well!



Definitions

Bias

- A measure of underfitting

Variance

- A measure of overfitting

Either alone is hard to interpret, but together they are helpful

<http://www.r2d3.us/visual-intro-to-machine-learning-part-2/>



Balancing Bias and Variance

$$\mathbb{E}\left[(y - \hat{f}(x))^2\right] = \text{Bias}[\hat{f}(x)]^2 + \text{Var}[\hat{f}(x)] + \sigma^2$$

$$\text{Bias}[\hat{f}(x)] = \mathbb{E}[\hat{f}(x) - f(x)]$$

$$\text{Var}[\hat{f}(x)] = \mathbb{E}[\hat{f}(x)^2] - \mathbb{E}[\hat{f}(x)]^2$$

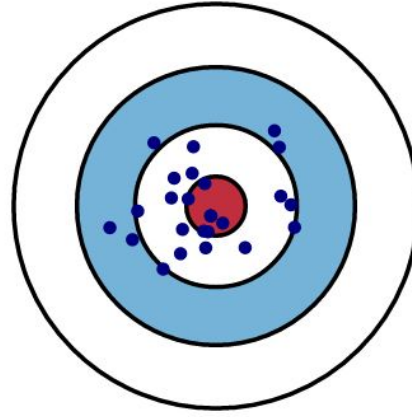
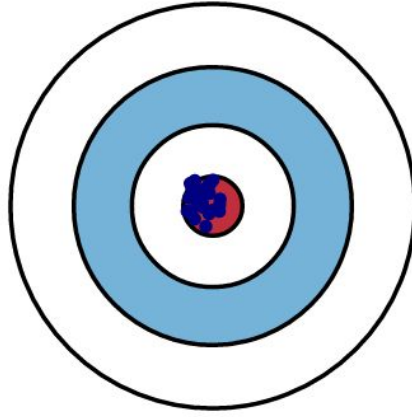
Error = (expected loss of accuracy)² + inconsistency of model + irreducible error



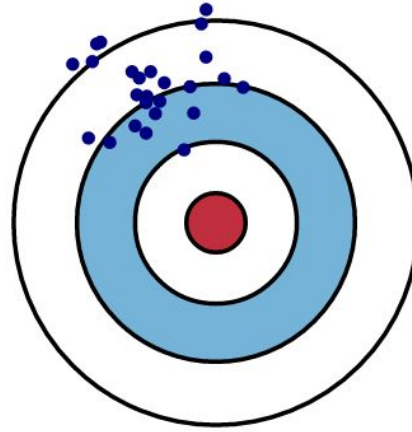
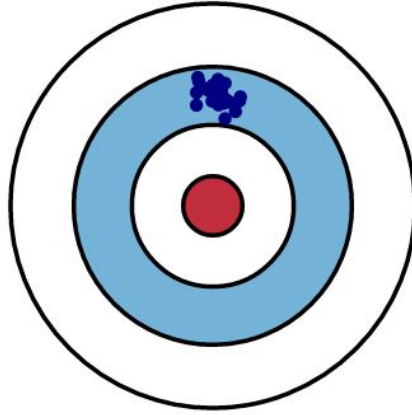
Low Variance

High Variance

Low Bias



High Bias



What does this mean intuitively?

Bias

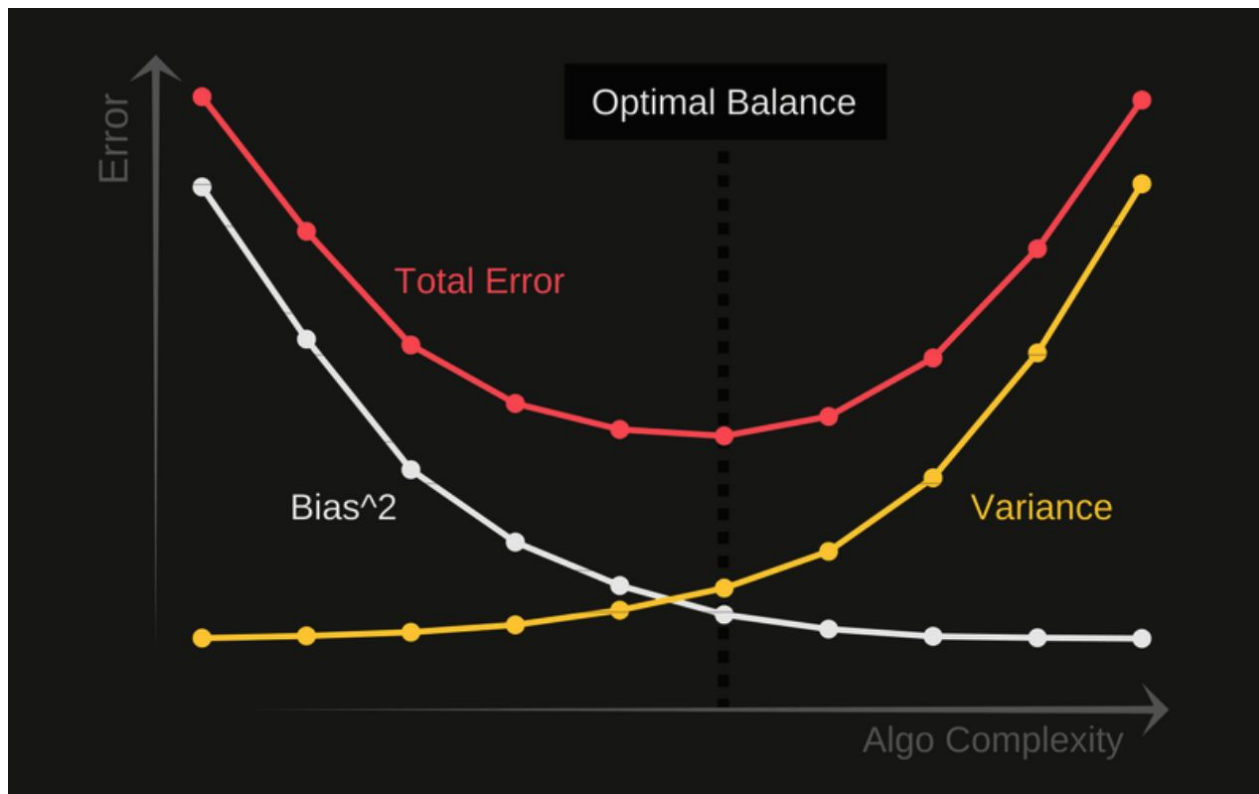
- Bad
- Results from incorrect assumptions in the learning algorithm

Variance

- Bad
- Results from sensitivity to fluctuations in the data



Balancing Bias and Variance



Feature Selection

(adjusting models)



Methods

- **Goal:** Find subset of features that gives a good enough model, in a reasonable amount of time.



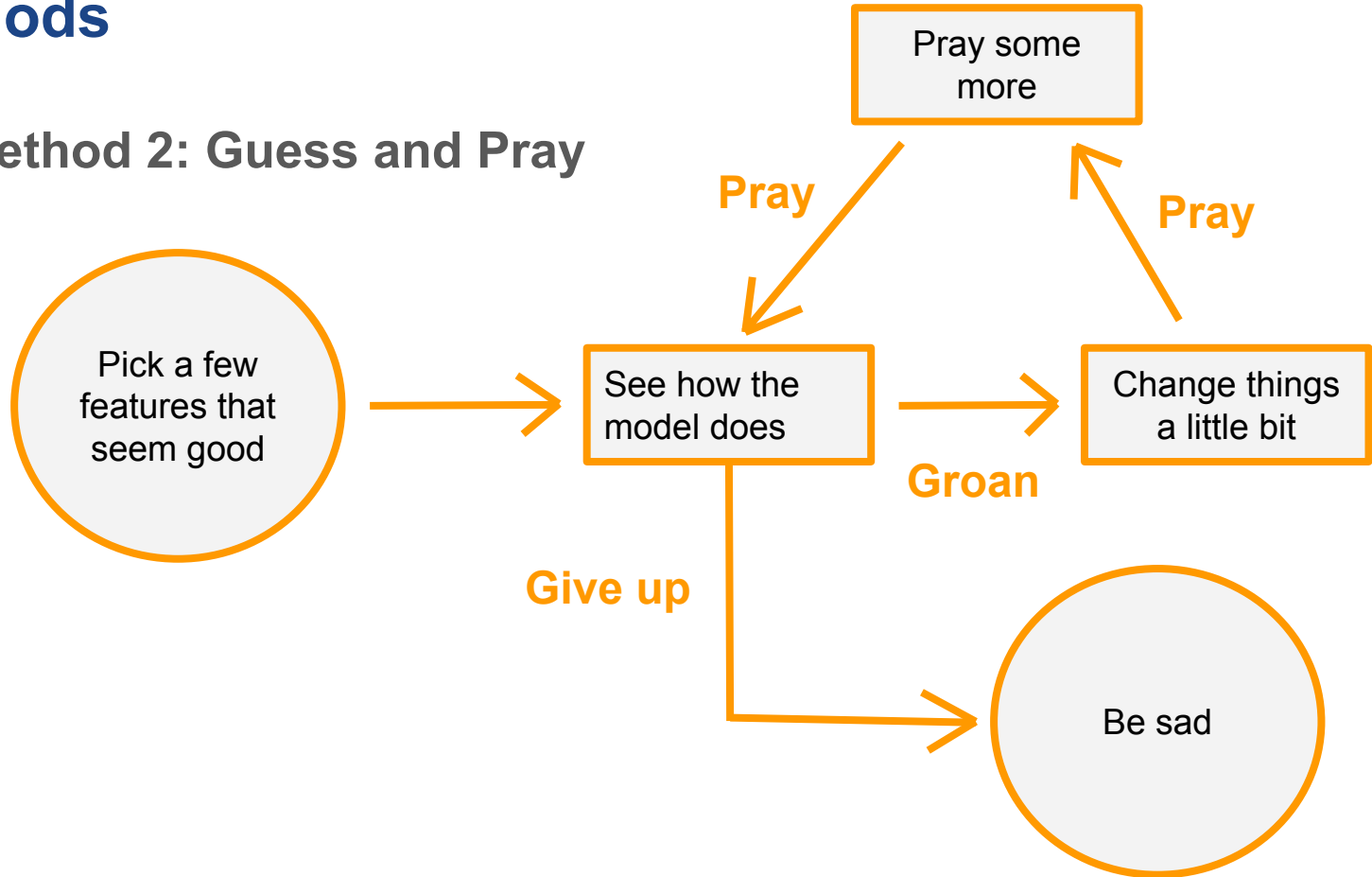
Methods

- **Goal:** Find subset of features that gives a good enough model, in a reasonable amount of time.
- **Method 1: Best Subset**
 - Test **all** subsets for best one
 - Benefits:
 - **Best** subset out of current features
 - Drawbacks:
 - Slow
 - Even slower with feature engineering



Methods

- Method 2: Guess and Pray



Methods

- **Goal:** Find subset of features that gives a good enough model, in a reasonable amount of time.
- **Method 2: Guess and Pray**
 - Guess
 - Benefits:
 - ??
 - Drawbacks:
 - Time consuming for data scientist
 - Unreliable



Methods

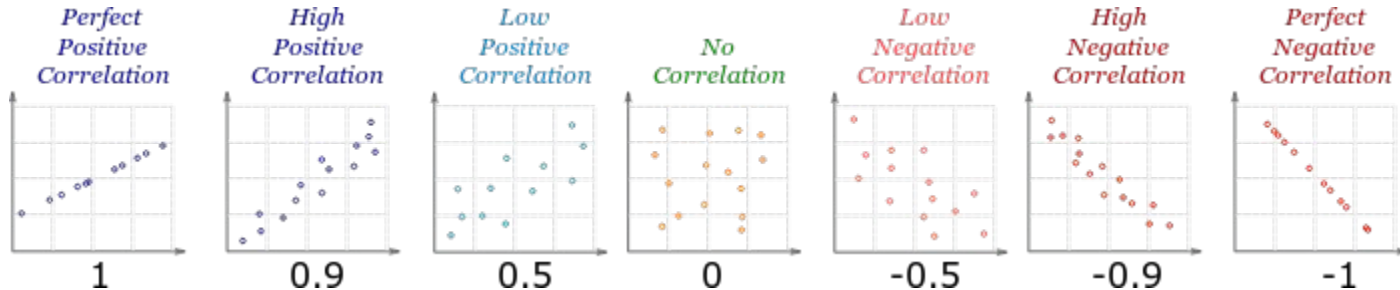
- **Goal:** Find subset of features that gives a good enough model, in a reasonable amount of time.
- **Method 3: Stepwise**
 - Pick a few features, then programmatically add/remove features using statistics
 - Benefits:
 - Complexity and runtime are adjustable
 - Drawbacks:
 - Can do very badly if you're not careful
 - Requires more thinking



Correlation, r

The correlation between two variables describes to what extent changing one would change the other.

- Real-valued in $[-1,1]$
- A variable is always perfectly correlated with itself (correlation=1)



Important Case: Collinearity

Collinear: when two features have a correlation near -1 or 1

- If a feature is collinear with the target, then it's a good choice for linear regression
- If two features are collinear, they're *redundant*
 - Might as well not use one of them
 - Some models *require/assume* that no features used are collinear



Side Note: Scaling and Normalizing

- Some models require data to be centered
- Some models need features to be on the same scale
 - A few ways of doing it
 - Divide by max, minus min divide by max minus min, minus mean divide by standard deviation.

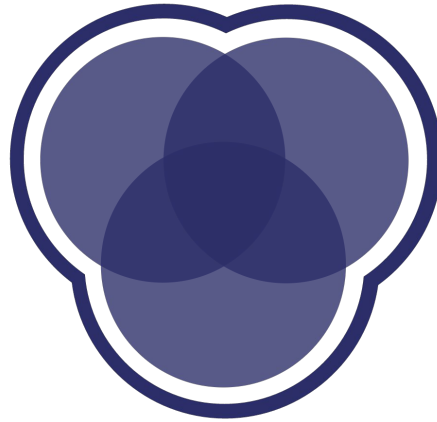


Other Ways to Adjust your Model

- HyperParameters
- Feature engineering
- Just changing to a different algorithm



Demo



Different Types of ML

(supervised & unsupervised)
(classification & regression)



Supervised vs. Unsupervised

Supervised learning...

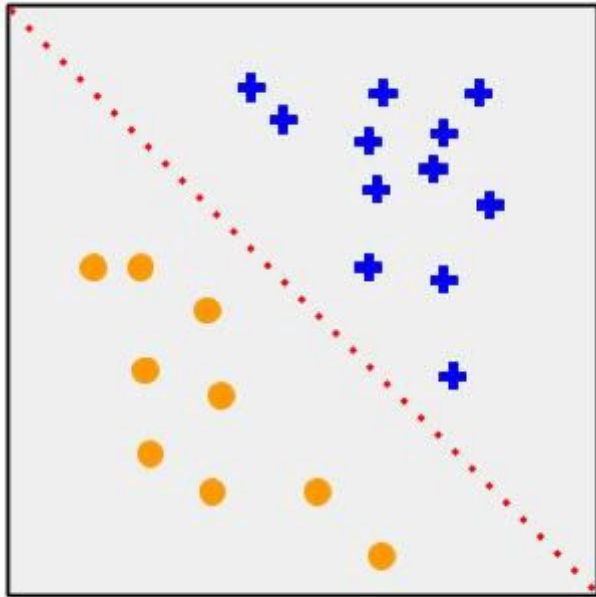
- Known target variable info
- Validation examples

Unsupervised learning...

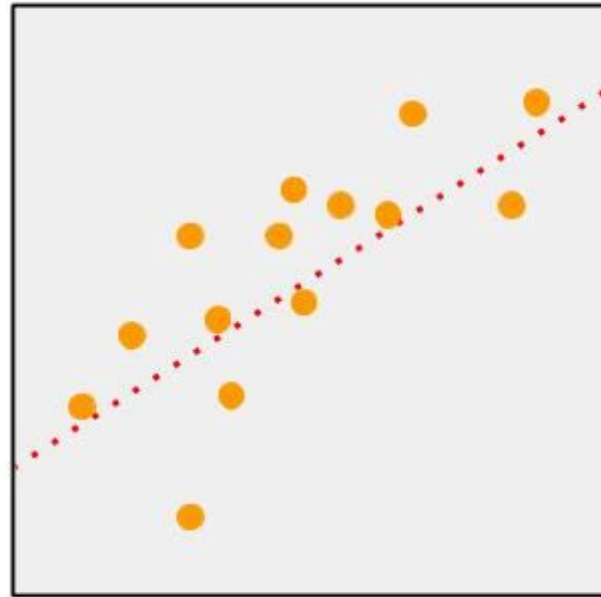
- Unknown target variables
- Difficult to validate



Classification vs. Regression



Classification



Regression



Other Classes of ML Algorithms (which we won't cover)

- What if you can't / don't want to see all your data at once?
- Maybe you only want to use a few pieces of your data (but don't have the time to manually select each piece of data...)
- A different approach, Trial & Error: The algorithm tries one thing, sees how that works, makes adjustments, tries again, etc.



Final Notes



Always remember both bias and variance!

Coming Up

- **Assignment 5:** Due at 4:30pm on October 27, 2021
- **Next Lecture:** Intro to Classification
- Last day to drop: October 21st (tomorrow)



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