Machine Learning with Python: A Hands-On Introduction

https://github.com/cbrownley/2023MLWEEK_MLWITHPYTHON

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Agenda (too much...we'll take our time:)

8:30-8:45 – Setup and Overview

8:45-9:30 – Data preprocessing	1:00-1:30 – Regression (california housing)	
9:30-10:00 - Hands-on: Data preprocessing	1:30-2:00 – Hands-on: Regression	

12:30-1:00 – Hands-on: Decision Trees

10:00-10:30 - Cross-validation	2:00-2:30 – Hands-on: Shrinkage methods
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12:00-12:30 – Hands-on: Classification 4:00-4:30 – Hands-on: **Explainable ML**

Prediction vs Causal Inference

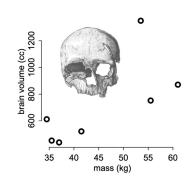
Problems of Prediction

What function describes these points? (fitting, compression)

What function explains these points? (causal inference)

What would happen if we changed a point's mass? (intervention)

What is the next observation from the same process? (prediction)



Good & Bad Controls

"Control" variable: Variable introduced to an analysis so that a causal estimate is possible

Common wrong heuristics for choosing control variables

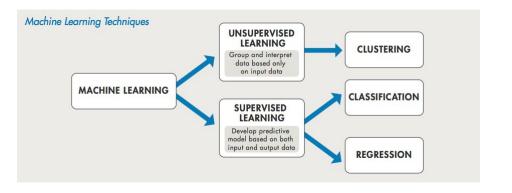
Anything in the spreadsheet **YOLO**!

Any variables not highly collinear

Any pre-treatment measurement (baseline)



Supervised vs Unsupervised

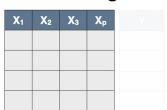


Supervised Learning

X ₁	X ₂	Х3	Хр	Υ

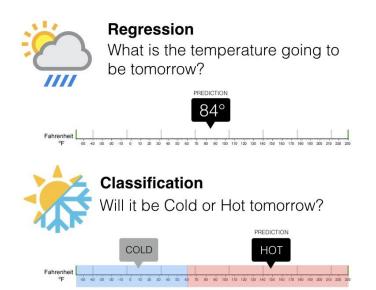
Target

Un-Supervised Learning



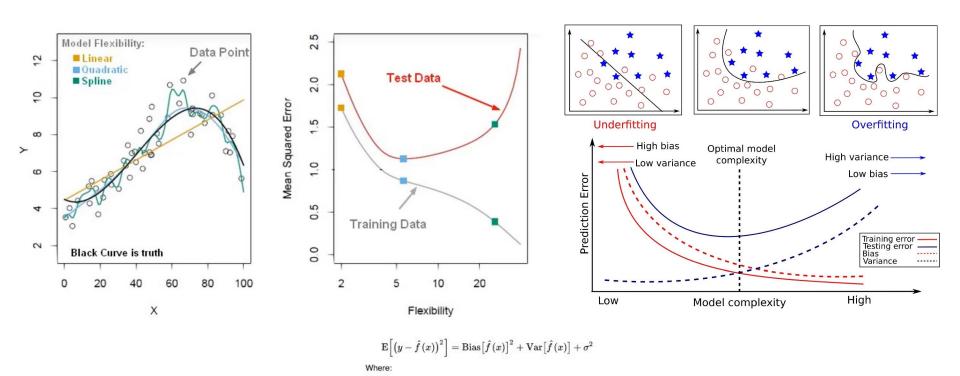
No Target

Regression vs Classification





The Bias-Variance Trade-off



 $\operatorname{Bias}\big[\hat{f}\left(x\right)\big] = \operatorname{E}\big[\hat{f}\left(x\right) - f(x)\big]$

 $\operatorname{Var} \left[\hat{f}(x) \right] = \operatorname{E} [\hat{f}(x)^2] - \operatorname{E} [\hat{f}(x)]^2$

Flexibility vs Interpretability

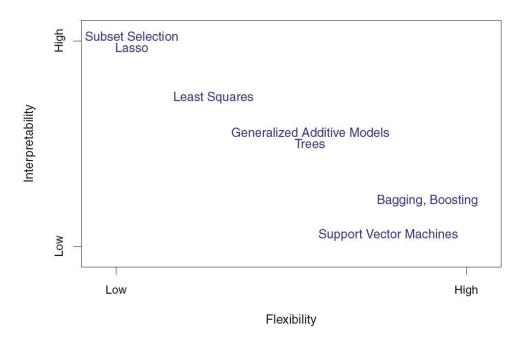


FIGURE 2.7. A representation of the tradeoff between flexibility and interpretability, using different statistical learning methods. In general, as the flexibility of a method increases, its interpretability decreases.