Making a Case

HN

Washington State University

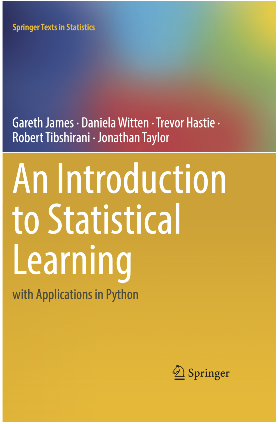
February 14, 2025

General

- Anything worth making needs patience and practice
- If you want mastery, you need to immerse yourself in it till it becomes your second nature, just like walking

- Top(?) two take aways from graduate school
  1. Try not to have a bias/prejudice. be playful 🔍
  2. When you are wrong, you are wrong ⚠

Source of This Notes



Notes from
An Introduction to Statistical Learning with Applications in Python

- It's an easy read and as the name suggests, it's just Introduction. Good for intuition building
- Its PDF is available for free from the Authors' website.
- Sign-up & receive coupons (30%-50% off)

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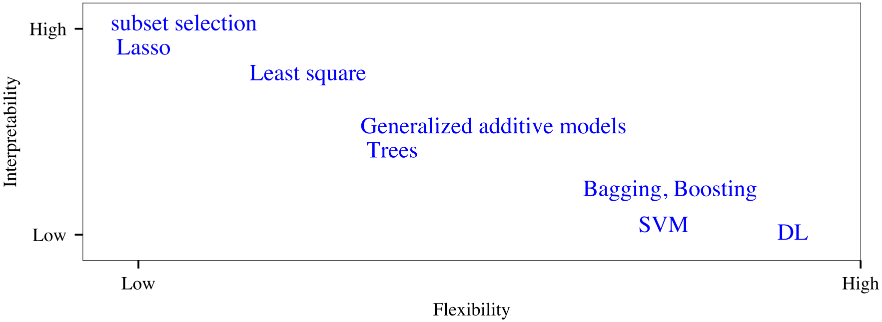
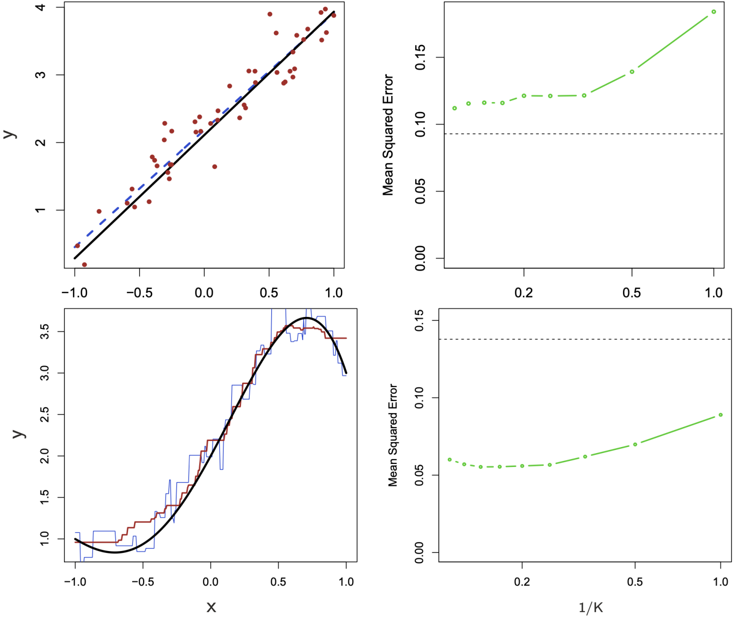


Comparison of Model Performances



Some Model Assumptions

- Logistic regression fits the data via likelihood maximization
- Linear Discriminant Analysis (LDA): distribution of X is normal in each class with identical covariance matrix.
- Quadratic Discriminant Analysis (QDA): distribution of X is normal in each class with class specific covariance matrix.

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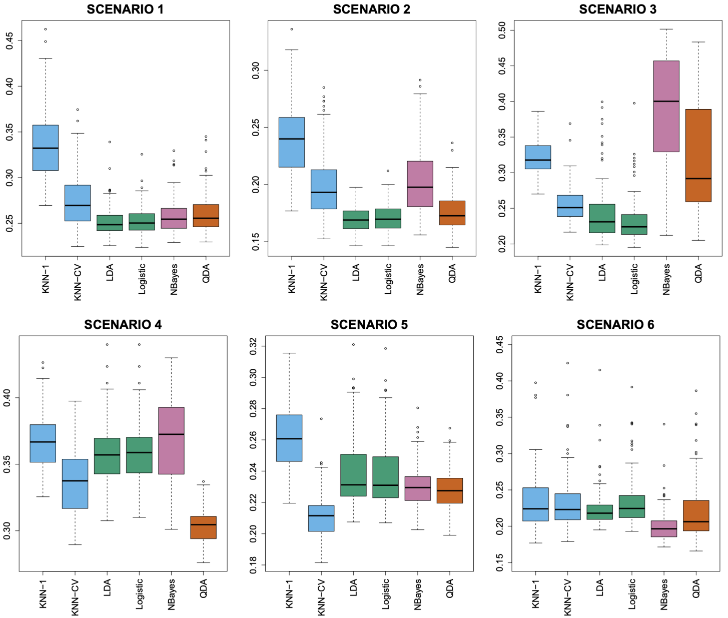

PCR vs. PLS

Two methods for reducing the dimensionality in regression

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Other uses of PCA

1. Missing value imputation
2. Recommender systems
3. EDA

a Note on p-value

"…, p-values have recently been the topic of extensive commentary in the social science research community, to the extent that some social science journals have gone so far as to ban the use of p-values altogether! We will simply comment that when properly understood and applied, p-values provide a powerful tool for drawing inferential conclusions from our data."

" …By contrast, if we fail to reject H_0, then our findings are more nebulous: we will not know whether we failed to reject H_0 because our sample size was too small (in which case testing H_0 again on a larger or higher-quality dataset might lead to rejection), or whether we failed to reject H_0 because H_0 really holds." P. 559 (and read page 564).

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- "…and an R^2 value well below 0.1 might be more realistic!" (page 79)

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More Resources

- Guesstimation: (Weinstein and Adam, 2008)
- First Course in Probability (Ross et al., 1976)
- Introduction to Linear Regression Analysis (Montgomery, Peck, and Vining, 2021)

Non-technical

- Excellent Sheep: The Miseducation of the American Elite and the Way to a Meaningful Life (Deresiewicz, 2014)
- The Culture Code: The Secrets of Highly Successful Groups (Coyle, 2018)

Tools

- Software Carpentry has lots of tutorials including GitHub!

Some Definition I

Definition (Variance of a method)

Variance refers to the amount by which $\hat{f}$ would change if we estimated it using a different training data set.

Bibliography I

- Coyle, D. (2018). *The Culture Code: The Secrets of Highly Successful Groups*. Bantam Books, an imprint of Random House, a division of Penguin Random House LLC New York.
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