

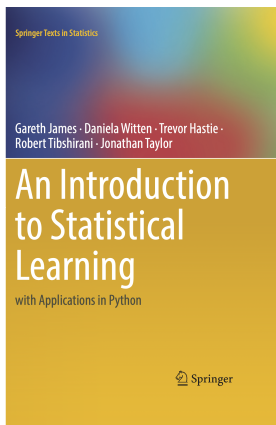
# Making a Case

HN

February 18, 2025



# Source of These 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)

# Last thing first (There is no magic wand)

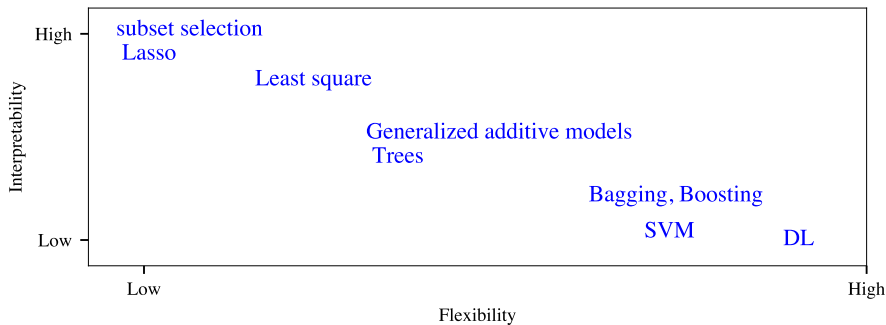
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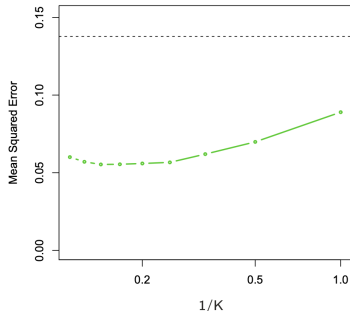
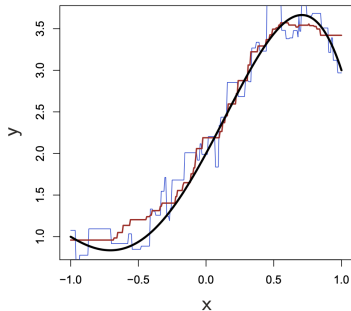
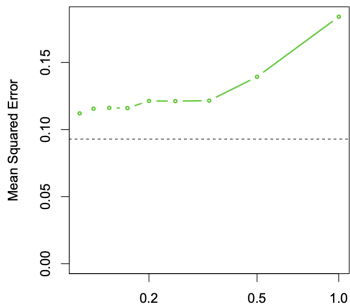
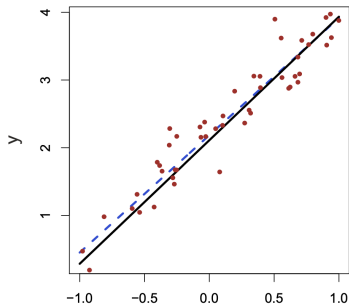
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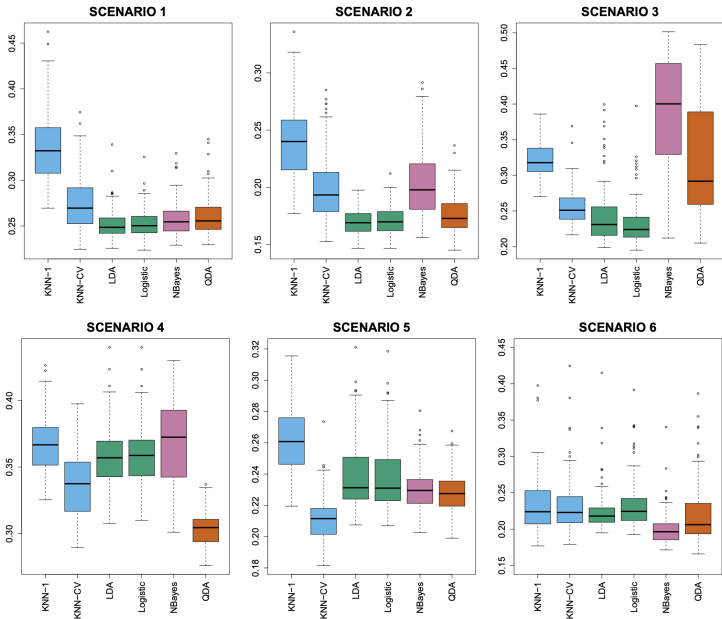
# Comparison of Model Performances



# 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.

# Comparison of Model Performances





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

# Some Notes 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.”

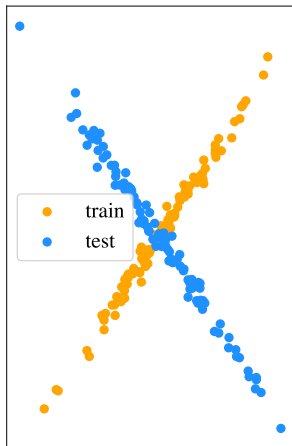
“ ...By contrast, if we fail to reject  $H_0$ , then our findings are more nebulous: we will not know whether we failed to reject  $H_0$  because our sample size was too small (in which case testing  $H_0$  again on a larger or higher-quality dataset might lead to rejection), or whether we failed to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

# Some Notes on p-value

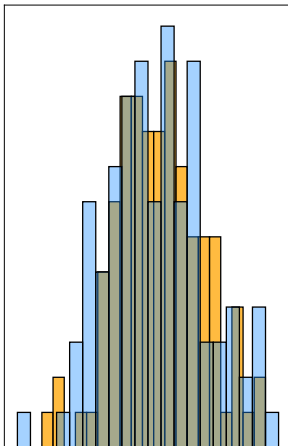
## Remark

**Hierarchical principle:** *if we include an interaction in a model, we should also include the main effects, even if the p-values associated with their coefficients are not significant.*

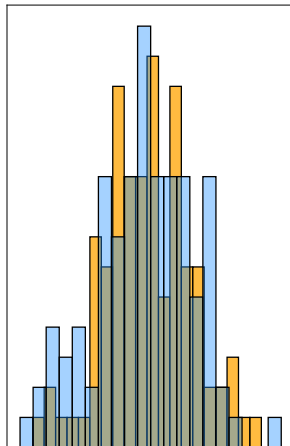
# Train Set v. Test Set



x distribution

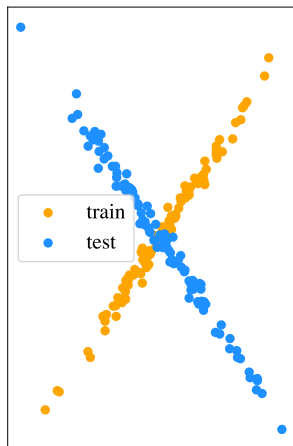


y distribution

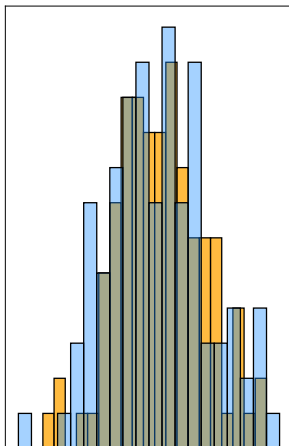




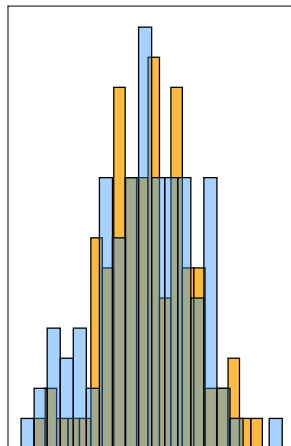
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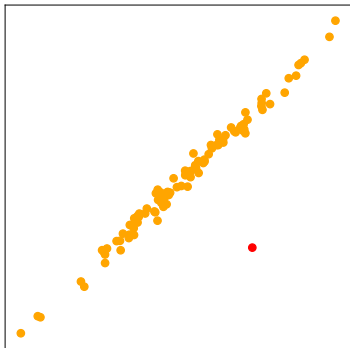
y distribution



■ Earth Mover's Distance: 13

■ Kullback Divergence:  $\infty$

# High-Leverage Points



We cannot look only at one dimension to detect unusual points.

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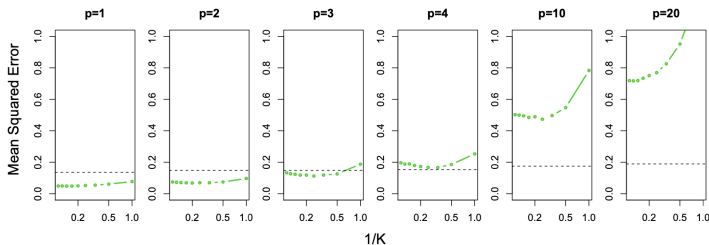
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- “...and an  $R^2$  value well below 0.1 might be more realistic!”  
(page 79)

# Do I have enough data?

Do I have enough data? It depends. That question is ill imposed. Depends on the dimension (number of variables). So, it is about the ratio  $n/p$ . See figure below and page 22 of **hastie2017elements** which is freely available too on [Authors' website](#).



**Figure:** Test MSE for linear regression (black dashed lines) and KNN (green curves) as the number of variables  $p$  increases. The true function is non-linear in the first variable, as in the lower panel in Figure 3.19, and does not depend on the additional variables. The performance of linear regression deteriorates slowly in the presence of these additional noise variables, whereas KNN's performance degrades much more quickly as  $p$  increases.

- 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 Q
  - 2 When you are wrong, you are wrong ⚠

# More Resources

- First Course in Probability (Ross et al., [1976](#))
- Introduction to Linear Regression Analysis (Montgomery, Peck, and Vining, [2021](#))

## Non-technical

- Guesstimation: (Weinstein and Adam, [2008](#))
- 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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