Introduction(week 1, part 1)

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## Logistics

* (almost) everything at course web page, https://bbolker.github.io/stat790
* Zoom link: https://tinyurl.com/stat790-zoom-2023
* communication/forums (TBD)
* assignment marks (TBD)

## Integrity

* [notes on honesty](../honesty.html)
* why copying code is good
* Stack Overflow, ChatGPT, and all that
* group work

## Materials

* Two books:
  + Hastie, Tibshirani, and Friedman (2009) (approx ch. 1-10, 14-15)
  + Shalizi (2022) (approx. ch. 1-4, 7-9, 14-15, 23?)
* Primary literature TBD
* Why both?

## Prerequisites

From the course outline:

* linear algebra (pref. numeric: MATH 3NA)
* probability & statistics (at least up to regression: STATS 3A03)
* computation (pref. R, possibly Python/Julia/Matlab/etc.)
* ML/data science (STATS 780)

See also ADA p. 15.

## Goals

* understand theory behind (novel) SL/ML methods
* read papers
* (choose methods)
* implement methods
* read/understand/improve existing methods

## Technical skills & tools

These are not focal to the course, but are unavoidable and useful

* reproducibility: version control (Git/GitHub)
* machinery
  + R, Julia
  + VSCode
  + Unix shell?
  + reproducibility: Quarto/Sweave/Jupyter notebooks
* *command line bullshittery* (“bullshit (read: diagnosing and debugging weird things) is a part of life in the world of computers”) (Adar 2015)

## About me

* weird background (physics u/g, Zoology PhD, epidemiological modeling)
* biases/interests:
  + scientific inference pure prediction (but see Navarro (2019))
  + generative models
  + data visualization
  + solving problems in context, practical issues
  + rants (p-values, snooping, dichotomization, unbalanced categorical responses …)

# Overview of material/themes

## what is ``statistical learning’’ anyway?

* statistics computational statistics machine learning AI
  + inference vs. prediction
  + parametric vs. nonparametric
  + pure analysis vs. pure computation
  + small/medium vs. big data

## (aside) what is “big data”?

* enough data that you need to worry about computational efficiency
* enough data that you need to worry about moving data around  
  (e.g. currently $\grtsim 2$ Tb?)

## big picture

* make connections between methods
  + analogy: t-test/ANOVA/regression vs “the general linear model” (Lindeløv 2019)
* building blocks/themes

## basis construction/feature engineering

* SL typically uses **nonparametric** methods
  + families of curves/distributions that can be expanded/made arbitrarily complex
* basis construction
  + splines, Gaussian processes, tree splits, wavelets, Fourier bases, neural network architecture …

## choice of loss function

e.g.

* L2 (least-squares): convenient, traditional (selects mean)
* L1 (minimum absolute deviation): more robust (selects median)
* categorical responses: accuracy?
  + continuous measures almost better than discretized ones
* negative log-likelihood/deviance
* **depends on context**

## optimization

* (stochastic) gradient descent
* iterative methods, e.g.:
  + IRLS (iteratively reweighted least squares), expectation-maximization
  + quasi-Newton (Broyden-Fletcher-Goldfarb-Shanno)
  + expectation-maximization
* map/reduce

## bias/variance tradeoff

* under/overfitting, Goldilocks
  + shrinkage, regularization, penalization, dropout (neural networks), tree depth, learning rate (boosting), early stopping, priors …

## quantifying accuracy and uncertainty

* raw point estimates are problematic
* accuracy measures
* uncertainty measures
* methods:
  + parametric methods
  + train/validate/test (cross-validation etc.); out-of-bag error
  + bootstrap?
  + high-dimensional inference (Dezeure et al. 2015)
  + conformal prediction (Shafer and Vovk 2008)

## sparsity

* dimension reduction
  + structural zeros within vectors or matrices  
    e.g. adjacency matrices
  + reduced-rank matrices
* computational efficiency
* a means to an end

## references

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Shalizi, Cosma Rohilla. 2022. *Advanced Data Analysis from an Elementary Point of View*. <https://www.stat.cmu.edu/~cshalizi/ADAfaEPoV/>.