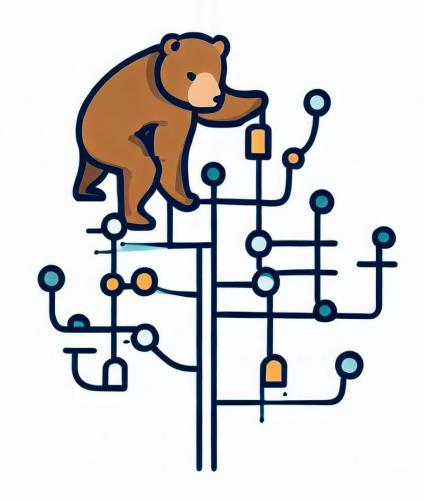
Advanced Techniques

UCSB SUMMER STATS WORKSHOP 2023

WEEK 6



Plan for Today

- 1. Dan: decision trees
 - Decision tree exercise
- 2. Ashley: cluster analysis
 - Cluster analysis exercise
- 3. Final project help

Springer Texts in Statistics

Gareth James Daniela Witten Trevor Hastie Robert Tibshirani

An Introduction to Statistical Learning

with Applications in R

Second Edition



Supervised machine learning technique

Attempts to predict an outcome variable using some set of predictor variables

Normally do this with some kind of linear model:

• outcome = B_1^* predictor1 + B_2^* predictor2 + B_3^* (predictor1*predictor2) + B_0^*

Main effects

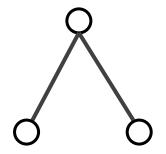
Interaction

Intercept

Recursive binary partitioning

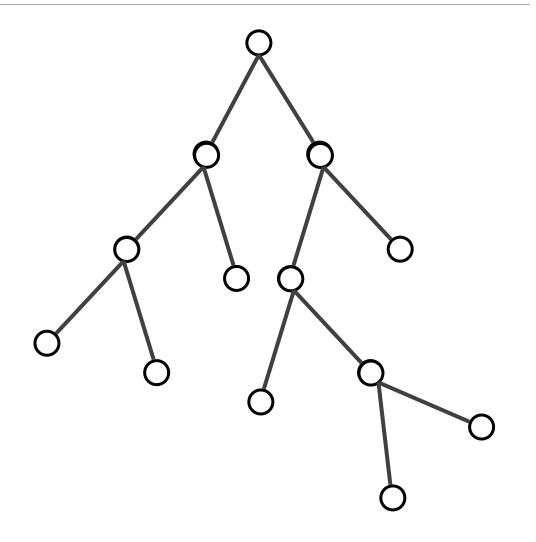
Recursive binary partitioning

- Split the data into two parts...
- ...according to one of the predictor variables...
- ...usually so as to:
 - Maximize differences between partitions and/or
 - Minimize differences within partitions



Recursive binary partitioning

Split the splits



Suppose you're going on vacation...

Need to decide what clothes to pack

Two possible cities:

- New York City
- Santa Barbara

Two times of year:

- Winter
- Summer

Collect weather data from Wikipedia

City	Season	Av. Temp (F)
Santa Barbara	Summer (June)	65.1
Santa Barbara	Summer (July)	68.3
Santa Barbara	Winter (Jan.)	56.6
Santa Barbara	Winter (Feb.)	57.1
New York City	Summer (June)	72
New York City	Summer (July)	77.5
New York City	Winter (Jan.)	33.7
New York City	Winter (Feb.)	35.9

Suppose you're going on vacation...

ANOVA approach:

vacayAnova <- Im(temp ~ season * city)</pre>

Probably a significant interaction between city and season in predicting temperature

But how does that help you pack?

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M = 61.78, SD = 5.84

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M = 54.78, SD = 23.19

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M = 70.73, SD = 5.32

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M = 45.83, SD = 12.76

City partition:



Season partition:



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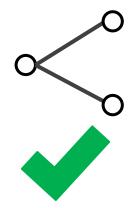
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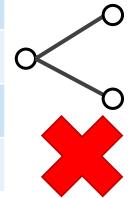
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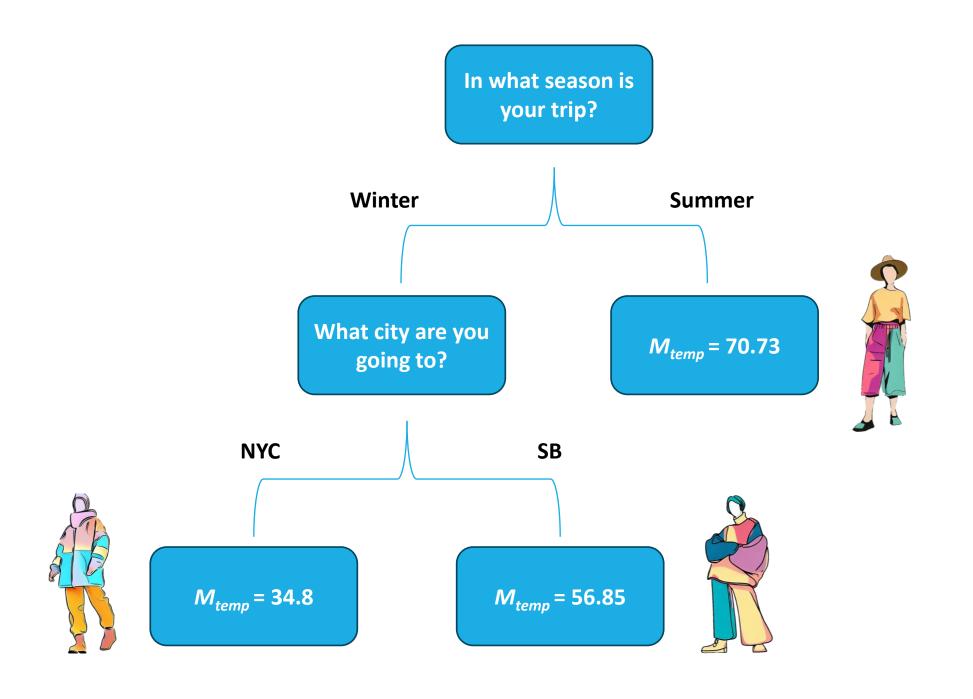


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Straightforward to interpret

Immediately lend themselves to decision making

Especially useful in industry contexts

But also good for science

Zoe Liberman



Social cognitive development, food, language

https://liberman.psych.ucsb. edu/research

Example Data

n = 400 children

Ages 3-12

Children watched a video of two dolls interacting

One doll (the sharer) shared food with a second doll (the recipient)

Sharer either shared:

- A liked food (cookies)
- A disliked food (broccoli)

Also shared either:

- 1 piece of food
- 5 pieces of food

Afterwards, children were given the choice to play with either doll

Recorded which doll the children chose

Additionally, parents rated children using a 7-point Likert scale on:

- Pickiness about vegetables (1 = not picky at all, 7 = extremely picky)
- Pickiness about fruits (1 = not picky at all, 7 = extremely picky)

Example Data: Decision Trees

RQ1: Do children prefer a doll who shares a liked food over a disliked food?

RQ2: Do children prefer a doll who shares more over a doll who shares less?

RQ3: Do attitudes about sharing differ with age?