Statistical Computing (36-350) Lecture 6: Top-Down Design

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- Top-down design of programs
- Example: Linear regression in R

ESSENTIAL READING FOR FRIDAY: Sec. 7.6 and 7.9 of the textbook

- Start with the big-picture view of the problem
- Break the problem into a few big parts
- Figure out how to fit the parts together
- Go do this for each part

Resources: what information is available as part of the problem? (Usually arguments) Requirements: what information do we want as part of the solution? (Usually return values) What do we have to do to transform the problem statement into a solution? Try to break the calculation into a *few* (say \leq 5) parts

- Bad: write 500 lines of code, chop it into five 100-line blocks
- Good: each part is an independent calculation, using separate data

Advantages of the good way:

- More comprehensible to human beings
- Easier to improve and extend (respect interfaces)

Assume that you can solve each part, and their solutions are functions Write top-level code for the function which puts those steps together:

```
# Not actual code
big.job <- function(lots.of.arguments) {
    intermediate.result <- first.step(some.of.the.args)
    final.result <- second.step(intermediate.result,rest.of.the.args)
    return(final.result)
}</pre>
```

The sub-functions don't have to be written when you *declare* the main function, just when you *run* it

Recursion: Because each sub-function solves a single well-defined problem, we can solve it by top-down design

The step above tells you what the arguments are, and what the return value must be (interface)

The step above doesn't care how you turn inputs to output (internals)

Stop when we hit a sub-problem we can solve in a few steps with *built-in* functions





 Top-down design only works if you understand

- the problem, and
- a systematic method for solving the problem
- \therefore it forces you to think **algorithmically**

First guesses about how to break down the problem are often wrong

but functional approach contains effects of changes

 \therefore don't be afraid to change the design

Basic form of the model:

$$Y = X^T \beta + \text{noise}$$

Least-squares estimation: find $\hat{\beta}$ such that the mean squared error $n^{-1}\sum_{i=1}^{n} (y_i - x_i^T \beta)^2$ is minimized Solution:

$$\hat{\beta} = (\mathbf{x}^T \mathbf{x})^{-1} \mathbf{x}^T \mathbf{y}$$

where **x** is $n \times p$ matrix of inputs, **y** is $n \times 1$ matrix of responses $n^{-1}(\mathbf{x}^T \mathbf{x})$ is covariance matrix of *X* $n^{-1}\mathbf{x}^T\mathbf{y}$ is vector of covariances of *X* and *Y*

The lm (linear model) function:

lm(formula,data, [[many other options]])

formula: something like Hwt ~ 1 + Sex + Bwt + Bwt:Sex data: Data frame to look for the variables in the formula in Return value is an 1m object, with coefficients, standard errors, residuals, ... How would we write this?

- Prepare design matrix **x** from formula and data
- Prepare response vector y from formula and data
- Solution Calculate coefficients from x and y
- Prepare extra information (residuals, standard errors, etc.) from x, y and coefficients
- Seturn everything

Now go do each of the top-level steps (in any order)

Remember the OLS estimator:

$$\hat{\beta} = (\mathbf{x}^T \mathbf{x})^{-1} \mathbf{x}^T \mathbf{y}$$

This is a one-liner in R:

beta.hat = solve(t(X) %*% X) %*% t(X) %*% Y

(remember solve(A) returns A^{-1}) but what if $\mathbf{x}^T \mathbf{x}$ is singular? Roughly, each term on the RHS of the formula leads to a column in **X**

- Plain variables (like Bwt) need a column each
- An intercept needs a column of 1s
- Dummy or indicator variables need binary columns (like Sex)
- Interactions need a column of products (like Bwt:Sex)
- Transformations (say log)

. . .

Use names on these columns to match formula terms, so these carry through to the coefficients Making Y is similar \therefore lots of common sub-sub-functions

- Top-down design is a recursive heuristic for coding
 - Split your problem into a few sub-problems; write code tying their solutions together
 - 9 If any sub-problems still need solving, go write their functions
- Leads to many short functions, each solving one well-defined problem
- Disciplines you to think algorithmically