Statistical Computing (36-350)
Lecture 11: Refactoring

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Agenda

- Abstraction adjusts programming to human strengths
- Refactoring adjusts code to bring out commonalities
- Ways of refactoring: names, objects, common operations, general operations
- Example: The jack-knife
The point of abstraction: program in ways which don’t use people as bad computers

Abstraction — hiding details and specifics, dealing in generalities and common patterns — is a way to do this

We have talked about lots of examples of this already

Data structures; Functions; Interfaces; Functions as objects
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Economics says: rely on *comparative* advantage

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144 &= 9 \times 16 = 3 \times 3 \times 4 \times 4 \\
360 &= 6 \times 60 = 3 \times 3 \times 4 \times 5 \times 2
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Once we have some code, and it (more or less) works, re-write it to emphasize commonalities:

- Parallel and transparent naming
- Grouping related values into objects
- Common or parallel sub-tasks become shared functions
- Common or parallel over-all tasks become general functions
R puts next to no limits on names of variables and functions.
∴ we should use names that make sense to humans

- Names should indicate purpose or meaning
  E.g., call something plot or predict when, but only when, it plots or predicts

- Similar objects should have similar names.
Example: conventions for functions related to random variables

- `dnorm` probability density of normal r.v.
- `rnorm` random value from normal r.v.
- `pnorm` cumulative probability of normal r.v.
- `qnorm` quantile of normal r.v.
- `dgamma` probability density of gamma r.v.
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ppois  ?
rt     ?
qchisq ?
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Your code is easier to understand
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  • it is more likely to be used (correctly)
  • it is easier to fix and improve
  • people (including you) waste time less puzzling over it
  • you are more easily replaced as a programmer
Notice that the same variables keep being used together
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Create a single data object (data frame, list, …) that includes them all as parts
Replace mentions of the individual variables with mentions of parts of the unified object
Advantages of Grouping

Clarity (especially if you give the object a good name)
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Makes sure that the right values are always present (pass the object as an argument to functions, rather than the components)
Memorization: if you know you are going to want to do the same calculation many times on these data values, do it once when you create the object, and store the result as a component
Notice that your code does the same thing, or nearly the same thing, in multiple places, as part doing something else
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Extract the common operation.

Write one function to do that operation, perhaps with additional arguments.
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Extract the common operation

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Call the new function in the old locations
Advantages of Extracting Common Operations

Main code focuses on \textit{what} is to be done, not \textit{how} (abstraction, human understanding)
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Improvements to the sub-task propagate everywhere
Drawback: bugs propagate everywhere too
**Notice** that you have several functions doing parallel, or nearly parallel, operations
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Extract the common pattern or general operation
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Write one function to do the general operation, with additional arguments (typically including functions)
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Extract the common pattern or general operation
Write one function to do the general operation, with additional arguments (typically including functions)
Call the new general function with appropriate arguments, rather than the old functions
Advantages of Extracting General Patterns

Clarifies the logic of what you are doing (abstraction, human understanding, use of statistical theory)
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Clarifies the logic of what you are doing (abstraction, human understanding, use of statistical theory)
Extending the same operation to new tasks is easy, not re-writing code from scratch
Old functions provide test cases to check if general function works
Re-factoring tends to make code look more like the result of top-down design
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*This is no accident*
Extended example: the jackknife

Have an estimator \( \hat{\theta} \) of parameter \( \theta \)
want the standard error of our estimate, \( se_{\hat{\theta}} \)
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Have an estimator \( \hat{\theta} \) of parameter \( \theta \)
want the standard error of our estimate, \( se_{\hat{\theta}} \)
The jackknife approximation:
omit case \( i \), get estimate \( \hat{\theta}_{(-i)} \)
Take the variance of all the \( \hat{\theta}_{(-i)} \)
multiply that variance by \( \frac{(n-1)^2}{n} \) to get \( \approx \) variance of \( \hat{\theta} \)
then \( se_{\hat{\theta}} = \) square root of that variance
(Why \( \frac{(n-1)^2}{n} \)? Think about just getting the standard error of the mean)
gamma.jackknife <- function(data) {
  n <- length(data)
  jackknife.ests <- matrix(NA,nrow=2,ncol=n)
  rownames(jackknife.ests) = c("a","s")
  for (omitted.point in 1:n) {
    fit <- gamma.est(data[-omitted.point])
    jackknife.ests["a",omitted.point] <- fit$a
    jackknife.ests["s",omitted.point] <- fit$s
  }
  variance.of.ests <- apply(jackknife.ests,1,var)
  jackknife-vars <- ((n-1)^2/n)*variance.of.ests
  jackknife.stderrs <- sqrt(jackknife.vars)
  return(jackknife.stderrs)
}
mean.jackknife <- function(data) {
  n <- length(data)
  jackknife.ests <- vector(length=n)
  for (omitted.point in 1:n) {
    new.mean <- mean(data[-omitted.point])
  }
  variance.of.ests <- var(new.mean)
  jackknife.var <- ((n-1)^2/n)*variance.of.ests
  jackknife.stderr <- sqrt(jackknife.var)
  return(jackknife.stderr)
}
Jackknife for linear regression coefficients

```
jackknife.lm <- function(data,p) {
  n <- nrow(data)
  jackknife.ests <- matrix(0,nrow=p,ncol=n)
  for (omit in 1:n) {
    new.coefs <- lm(YOUR.FORMULA.HERE,data=data[-omit,])$coefficients
    jackknife.ests[,omit] <- new.coefs
  }
  variance.of.ests <- apply(jackknife.ests,1,var)
  jackknife.var <- ((n-1)^2/n)*variance.of.ests
  jackknife.stderr <- sqrt(jackknife.var)
  return(jackknife.stderr)
}
```
Omitting one point or row is a common sub-task
Refactoring the Jackknife

Omitting one point or row is a common sub-task

The general pattern:

figure out the size of the data
for each case
  omit that case
  repeat some estimation and get a vector of numbers
take variances across cases
scale up variances
take the square roots
Omitting one point or row is a common sub-task
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Refactor by extracting the common “omit one” operation
Refactor by defining a general “jackknife” operation
The Common Operation

Works for vectors, lists, 1D and 2D arrays, matrices, data frames:

```
omit.case <- function(data, i) {
  d <- dim(data)
  if (is.null(d) || (length(d) == 1)) {
    return(data[-i])
  } else {
    return(data[-i,])
  }
}
```
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**EXERCISE:** Modify so it also handles higher-dimensional arrays
The General Operation

```r
jackknife <- function(estimator, data) {
  if (is.null(dim(data))) { n <- length(data) }
  else { n <- nrow(data) }
  jackknife.ests <- c()
  for (omit in 1:n) {
    reestimate <- estimator(omit.case(data, omit))
    jackknife.ests <- cbind(jackknife.ests, reestimate)
  }
  var.of.reestimates <- apply(jackknife.ests, 1, var)
  jackknife.var <- ((n-1)^2/n) * var.of.reestimates
  jackknife.stderr <- sqrt(jackknife.var)
  return(jackknife.stderr)
}
```

Could allow other arguments to `estimator`, spin off finding `n` as its own function, etc.
> jackknife(estimator=mean, data=rnorm(n=400, mean=7, sd=5))
[1] 0.2361081
> est.coefs <- function(data) {
  return(lm(Hwt~Bwt, data=data)$coefficients)
}
> est.coefs(cats)
(Intercept)   Bwt
-0.3566624   4.0340627
> jackknife(estimator=est.coefs, data=cats)
(Intercept)   Bwt
 0.8314142   0.3166847
Refactoring adjusts code to emphasize patterns
- Names are informative and systematic
- Objects keep related values together
- Common sub-tasks become specialized lower-level functions
- General patterns of operations become high-level general functions

Refactoring makes code look more like top-down design
Refactoring usually involves abstraction
Abstraction emphasizes human strengths