Functions: Part 3

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Week 7, Class 2

Agenda

- What makes functions "good"
- Building up functions
- Non–standard evaluation

Learning objectives

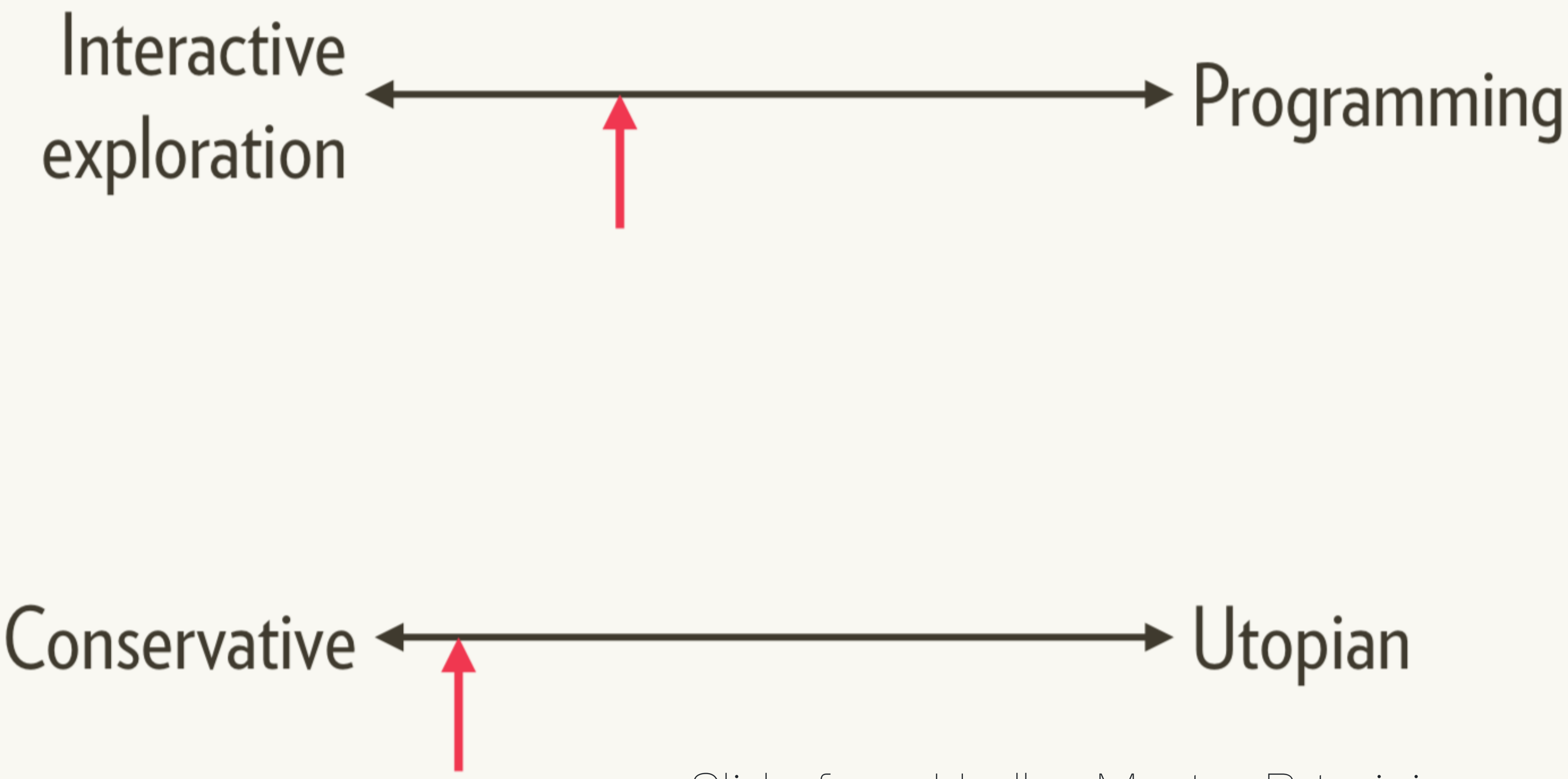
- Understand how functions build on top of each other and why "only do one thing" is a good mantra
- Understand non-standard evaluation is, even if you aren't able to fully work with it

Brainstorm

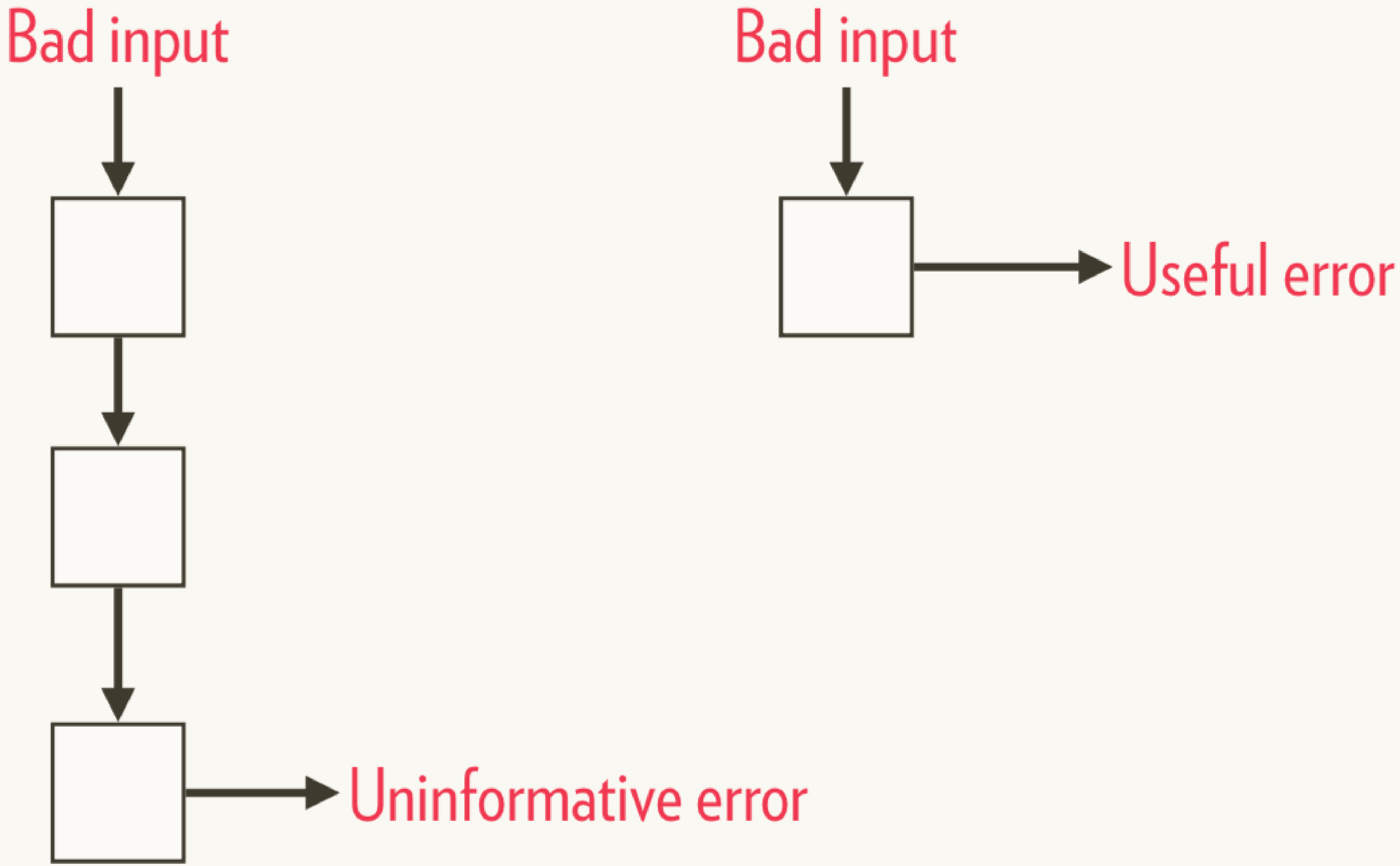
What makes a function "good" or "bad"

02:00

Two important tensions for understanding base R



Slide from Hadley Master R training



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Best

Right answer

Useful error

Not useful error

Worst

Wrong answer

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What does this mean operationally?

- Your function should do ONE thing (and do it well)
- Careful when naming functions – be as clear as possible
- Embed useful error messages and warnings
    - Particularly if you're working on a package or set of functions or others are using your functions
- Refactor your code to be more clear after initial drafts (it's okay to be messy on a first draft)

Example 1

- Anything we can do to clean this up?

```
both_na <- function(x, y) {
    if(length(x) != length(y)) {
        lx <- length(x)
        ly <- length(y)

        v_lngths <- paste0("x = ", lx, ", y = ", ly)

        if(lx %% ly == 0 | ly %% lx == 0) {
            warning("Vectors were recycled (", v_lngths, ")")
        }
        else {
            stop("Vectors are of different lengths and are not re
                 v_lngths)
        }
    }
    sum(is.na(x) & is.na(y))
}
```

Calculate if recyclable

```
recyclable <- function(x, y) {
    test1 <- length(x) %% length(y)
    test2 <- length(y) %% length(x)

    any(c(test1, test2) == 0)
}
```

Test it

```
a <- c(1, NA, NA, 3, 3, 9, NA)
b <- c(NA, 3, NA, 4, NA, NA, NA)

recyclable(a, b)
```

```
## [1] TRUE
```

```
recyclable(a, c(b, b))
```

```
## [1] TRUE
```

```
recyclable(a, c(b, b, b))
```

```
## [1] TRUE
```

```
recyclable(c(a, a), c(b, b, b))
```

```
## [1] FALSE
```

Revision

```
both_na <- function(x, y) {

    if(!recyclable(x, y)) {
        stop("Vectors are of different lengths and are not recyc
             "(x = ", length(x),
             ", y = ", length(y), ")")
    }

    if(length(x) == length(y)) {
        return(sum(is.na(x) & is.na(y)))
    }

    if(recyclable(x, y)) {
        warning("Vectors were recycled (",
                "x = ", length(x),
                ", y = ", length(y), ")")
        return(sum(is.na(x) & is.na(y)))
    }
}
```

Test it

```
both_na(a, b)
```

```
## [1] 2
```

```
both_na(a, c(b, b))
```

```
## Warning in both_na(a, c(b, b)): Vectors were recycled (x = 7, y = 14)
```

```
## [1] 4
```

```
both_na(c(a, b), c(b, b, b))
```

```
## Error in both_na(c(a, b), c(b, b, b)): Vectors are of different lengths
```

```
both_na(c(a, a), b)
```

```
## Warning in both_na(c(a, a), b): Vectors were recycled (x = 14, y = 7)
```

```
## [1] 4
```

Anything else?

Make errors/warnings a function

```
check_lengths <- function(x, y) {
    if(!length(x) == length(y)) {
        if(recyclable(x, y)) {
            warning("Vectors were recycled (",
                    "x = ", length(x),
                    ", y = ", length(y), ")")
        }
        else {
            stop("Vectors are of different lengths and are not re
             "(x = ", length(x),
             ", y = ", length(y), ")")
        }
    }
}
```

Revision 2

```r
both_na <- function(x, y) {
    check_lengths(x, y)
    sum(is.na(x) & is.na(y))
}
```

Test it

```
both_na(a, b)
```

```
## [1] 2
```

```
both_na(a, c(b, b))
```

```
## Warning in check_lengths(x, y): Vectors were recycled (x = 7, y = 14)
```

```
## [1] 4
```

```
both_na(c(a, b), c(b, b, b))
```

```
## Error in check_lengths(x, y): Vectors are of different lengths and are r
```

```
both_na(c(a, a), b)
```

```
## Warning in check_lengths(x, y): Vectors were recycled (x = 14, y = 7)
```

```
## [1] 4
```

Why would we do this?

- In this case – more readable code
- We might re-use the `recyclable` or `check_lengths` functions in other/new functions
- Helps make de-bugging easier

Quick de–bugging example

```r
f <- function(a) g(a)
g <- function(b) h(b)
h <- function(c) i(c)
i <- function(d) {
  if (!is.numeric(d)) {
    stop("`d` must be numeric", call. = FALSE)
  }
  d + 10
}
```

traceback

```
f("a")
traceback()
```

```
5: stop("`d` must be numeric", call. = FALSE) at #3
4: i(c) at #1
3: h(b) at #1
2: g(a) at #1
1: f("a")
```

Non–standard evaluation (NSE)

A high–level look

Note

- Were it not for the tidyverse, I would not even mention NSE
- Generally, it's not an incredibly important topic
- But, NSE is ubiquitous in the tidyverse – literally just about everything uses NSE, which makes programming with tidyverse functions more difficult

What is NSE

- Implementation of different scoping rules
- In dplyr and many others, arguments are evaluated inside the specified data frames, rather than the current or global environment.

How?

(a) Capture an expression (quote it) (b) Use the expression within the correct context (evaluate it)

So, `x` is evaluated as, e.g., `df$x` rather than `globalenv()$x`.

Example

Using the `percentile_df` function we created previously

- Here `base::substitute`

```
percentile_df <- function(x) {
    sorted <- sort(x)
    d <- data.frame(sorted, percentile = ecdf(sorted)(sorted))
    names(d)[1] <- paste0(substitute(x), collapse = "_")
    d
}
percentile_df(rnorm(100, 5, 0.2)) %>%
    head()
```

```
##   rnorm_100_5_0.2 percentile
## 1        4.384718       0.01
## 2        4.494705       0.02
## 3        4.500262       0.03
## 4        4.562786       0.04
## 5        4.564927       0.05
## 6        4.568238       0.06
```

Confusing

- Outside of a function, `substitute` operates just like `quote` – it quotes the input.
- Inside of a function, `substitute` does as its name implies – it substitutes the input for the name.

Example

```
quote(subset(df, select = var))
```

```
## subset(df, select = var)
```

```
substitute(subset(df, select = var))
```

```
## subset(df, select = var)
```

```
extract_var <- function(df, var) {
    substitute(df)
}
extract_var(mtcars)
```

```
## mtcars
```

Actually getting this thing to work

```r
extract_var <- function(df, var) {
    subset(eval(substitute(df)),
           select = var)
}
extract_var(mtcars, "mpg")
```

```
##                      mpg
## Mazda RX4           21.0
## Mazda RX4 Wag       21.0
## Datsun 710          22.8
## Hornet 4 Drive      21.4
## Hornet Sportabout   18.7
## Valiant             18.1
## Duster 360          14.3
## Merc 240D           24.4
## Merc 230            22.8
## Merc 280            19.2
## Merc 280C           17.8
## Merc 450SE          16.4
## Merc 450SL          17.3
## Merc 450SLC         15.2
```

Why `eval`

- `substitute` is quoting the input, but we then need to evaluate it.
- All of this is rather confusing
- The tidyverse uses it so frequently, they've decided to implement their own version, called `tidyeval`, which we'll get to in a minute.

Better

Use NSE for both arguments

```
extract_var <- function(df, var) {
    eval(substitute(var), envir = df)
}
extract_var(mtcars, mpg)
```

```
##  [1] 21.0 21.0 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 17.8 16.4 17.3 15
```

- The above is equivalent to `df$var` but where both `df` and `var` can be swapped programmatically.
- The `var` argument is being substituted in for whatever the user supplies, and is being evaluated within the `df` environment

Maybe more simply

```
extract_var <- function(df, var) {
    df[ ,as.character(substitute(var))]
}
extract_var(mtcars, mpg)
```

```
##  [1] 21.0 21.0 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 17.8 16.4 17.3 15
```

- Why `as.character`? Otherwise it is a symbol, which won't work.

- Note we could add `drop = FALSE` to this if we wanted to maintain the data frame structure

Taking this even further

```r
extract_vars <- function(df, ...) {
  vars <- substitute(alist(...))
    df[ ,as.character(vars)[-1]]
}
head(extract_vars(mtcars, mpg, cyl, disp))
```

```
##                    mpg cyl disp
## Mazda RX4         21.0   6  160
## Mazda RX4 Wag     21.0   6  160
## Datsun 710        22.8   4  108
## Hornet 4 Drive    21.4   6  258
## Hornet Sportabout 18.7   8  360
## Valiant           18.1   6  225
```

- We've now basically replicated `dplyr::select`
- Notice the use of `[-1]`, because calling `as.character` on `vars` always returns `alist` as the first element in the vector

Why is NSE used so frequently in the tidyverse?

```r
mpg %>%
  select(manufacturer, model, hwy)
```

```
## # A tibble: 234 x 3
##    manufacturer model        hwy
##    <chr>        <chr>      <int>
##  1 audi         a4            29
##  2 audi         a4            29
##  3 audi         a4            31
##  4 audi         a4            30
##  5 audi         a4            26
##  6 audi         a4            26
##  7 audi         a4            27
##  8 audi         a4 quattro    26
##  9 audi         a4 quattro    25
## 10 audi         a4 quattro    28
## # … with 224 more rows
```

Interactive work!

- It makes interactive work easier!
- But this make programming with these functions harder...
- Without NSE, `select` and similar functions would not know where `manufacturer`, `model`, or `hwy` "live". It would be looking for objects in the global environment with these names.

dplyr programming fail

- Let's say we wanted a function that returned means in a nice table-y format for a variable by two groups (e.g., cross-tab sort of format)
- Typically, we would start by solving this problem for a single situation, then we'd generalize it to a function.
- Let's do it!

```r
mtcars %>%
    group_by(cyl, gear) %>%
    summarize(mean = mean(mpg, na.rm = TRUE)) %>%
    pivot_wider(names_from = cyl, values_from = mean)
```

```
## # A tibble: 3 x 4
##    gear    `4`    `6`    `8`
##   <dbl>  <dbl> <dbl> <dbl>
## 1     3 21.5   19.75 15.05
## 2     4 26.925 19.75 NA
## 3     5 28.2   19.7  15.4
```

- Try generalizing the above code into a function

04:00

Generalize to a function

Typically, we would expect something like this to work

```
group_means <- function(data, outcome, group_1, group_2) {
    data %>%
        group_by(group_1, group_2) %>%
        summarize(mean = mean(outcome, na.rm = TRUE)) %>%
        pivot_wider(names_from = group_1, values_from = mean)
}
```

But it doesn't...

```
group_means(mtcars, mpg, cyl, gear)
```

```
## Error: Must group by variables found in `.data`.
## * Column `group_1` is not found.
## * Column `group_2` is not found.
```

```
group_means(diamonds, price, cut, clarity)
```

```
## Error: Must group by variables found in `.data`.
## * Column `group_1` is not found.
## * Column `group_2` is not found.
```

Why?

- It's looking for an object called `group_1` that doesn't exist inside the function or in the global workspace!

Solution

Quote it, and evaluate it in the correct place

The {rlang} version

```
group_means <- function(data, outcome, group_1, group_2) {
    out <- enquo(outcome) # Quote the inputs
    g1 <- enquo(group_1)
    g2 <- enquo(group_2)

    data %>%
        group_by(!!g1, !!g2) %>% # !! to evaluate (bang-bang)
        summarize(mean = mean(!!out, na.rm = TRUE)) %>%
        pivot_wider(names_from = !!g1, values_from = mean)
}
```

```r
group_means(mtcars, mpg, cyl, gear)
```

```
## # A tibble: 3 x 4
##    gear    `4`   `6`   `8`
##   <dbl>  <dbl> <dbl> <dbl>
## 1     3 21.5   19.75 15.05
## 2     4 26.925 19.75 NA
## 3     5 28.2   19.7  15.4
```

```r
group_means(diamonds, price, cut, clarity)
```

```
## # A tibble: 8 x 6
##   clarity     Fair     Good `Very Good`  Premium    Ideal
##   <ord>      <dbl>    <dbl>       <dbl>    <dbl>    <dbl>
## 1 I1      3703.533 3596.635    4078.226 3947.332 4335.726
## 2 SI2     5173.916 4580.261    4988.688 5545.937 4755.953
## 3 SI1     4208.279 3689.533    3932.391 4455.269 3752.118
## 4 VS2     4174.724 4262.236    4215.760 4550.331 3284.550
## 5 VS1     4165.141 3801.446    3805.353 4485.462 3489.744
## 6 VVS2    3349.768 3079.108    3037.765 3795.123 3250.290
## 7 VVS1    3871.353 2254.774    2459.441 2831.206 2468.129
## 8 IF      1912.333 4098.324    4396.216 3856.143 2272.913
```

Alternative: Pass the dots!

- Note, I've made the function a bit simpler here by removing the spread

```
group_means2 <- function(data, outcome, ...) {
    out <- enquo(outcome) # Still have to quote the outcome

    data %>%
        group_by(...) %>%
        summarize(mean = mean(!!out, na.rm = TRUE))
}

group_means2(mtcars, mpg, cyl, gear)
```

```
## # A tibble: 8 x 3
## # Groups:   cyl [3]
##     cyl  gear   mean
##   <dbl> <dbl>  <dbl>
## 1     4     3 21.5
## 2     4     4 26.925
## 3     4     5 28.2
## 4     6     3 19.75
## 5     6     4 19.75
## 6     6     5 19.7
```

Added benefit

I can now also pass as many columns as I want, and it will still work!

```
group_means2(diamonds, price, cut, clarity, color)
```

```
## # A tibble: 276 x 4
## # Groups:   cut, clarity [40]
##      cut   clarity color     mean
##      <ord> <ord>   <ord>    <dbl>
##   1 Fair  I1      D      7383
##   2 Fair  I1      E      2095.222
##   3 Fair  I1      F      2543.514
##   4 Fair  I1      G      3187.472
##   5 Fair  I1      H      4212.962
##   6 Fair  I1      I      3501
##   7 Fair  I1      J      5795.043
##   8 Fair  SI2     D      4355.143
##   9 Fair  SI2     E      4172.385
## 10 Fair  SI2     F      4520.112
## # … with 266 more rows
```

Wait a minute!

- This isn't the same thing

Correct

So in this case passing the dots won't fully fix our problem, but there is another alternative

Alternative syntax

Pipe-centric

- Because the `data` argument comes first, this function works just like any other in the tidyverse, e.g.,

```
diamonds %>%
  filter(color == "E") %>%
  select(carat, cut, clarity) %>%
  group_means3(carat, cut, clarity)
```

```
## # A tibble: 8 x 6
##   clarity      Fair      Good `Very Good`   Premium     Ideal
##   <ord>       <dbl>     <dbl>       <dbl>     <dbl>     <dbl>
## 1 I1      0.9688889 1.330870    1.069545  1.043     1.037778
## 2 SI2     1.015641  0.8825743   0.9304045 0.9576686 0.8744136
## 3 SI1     0.8670769 0.7238592   0.7230831 0.7262866 0.6706266
## 4 VS2     0.6902381 0.739375    0.6644135 0.6189348 0.5211356
## 5 VS1     0.6328571 0.6806742   0.6097952 0.6431507 0.5035919
## 6 VVS2    0.6007692 0.5601923   0.4267114 0.5115702 0.4839053
## 7 VVS1    0.64      0.4181395   0.4000588 0.4622857 0.4265075
## 8 IF     NA         0.3733333   0.5793023 0.5762963 0.4577215
```

Syntax note

- The `{{}}` syntax is obviously *much* easier to apply
- It gets you out of tidyeval complications maybe 80% of the time
- If you start doing a lot of programming w/the tidyverse, you'll probably want to read up more no tidyeval and get comfy with quoting/unquoting

Challenge

- Write a function that summarizes any numeric columns by returning the mean, standard deviation, min, and max values.

- For bonus points, embed a meaningful error message if the columns supplied are not numeric.

Example

```r
summarize_cols(diamonds, depth, table, price)
```

```
## # A tibble: 3 x 5
##   var          mean          sd   min   max
##   <chr>       <dbl>       <dbl> <dbl> <dbl>
## 1 depth    61.74940    1.432621    43    79
## 2 price  3932.800   3989.440      326 18823
## 3 table    57.45718    2.234491    43    95
```

07:00

Pass the dots!

```
summarize_cols <- function(data, ...) {
    data %>%
        select(...) %>%
        pivot_longer(everything(),
                     names_to = "var",
                     values_to = "val") %>%
        group_by(var) %>%
        summarize(mean = mean(val, na.rm = TRUE),
                  sd = sd(val, na.rm = TRUE),
                  min = min(val, na.rm = TRUE),
                  max = max(val, na.rm = TRUE))
}
```

Pipe–centric again

Just putting data as the first argument leads to a lot of benefits

```r
library(palmerpenguins)
penguins %>%
  select_if(is.numeric) %>%
  summarize_cols(everything())
```

```
## # A tibble: 5 x 5
##   var                    mean          sd   min    max
##   <chr>                 <dbl>       <dbl> <dbl>  <dbl>
## 1 bill_depth_mm      17.15117   1.974793   13.1   21.5
## 2 bill_length_mm     43.92193   5.459584   32.1   59.6
## 3 body_mass_g      4201.754   801.9545   2700   6300
## 4 flipper_length_mm  200.9152   14.06171    172    231
## 5 year             2008.029     0.8183559 2007   2009
```

Example with plotting

Linearity

- We want to check if an x/y relation is linear
- Function should produce linear and non–linear relations
- Optionally show the data

Maybe this?

```r
check_linear <- function(data, x, y, se = TRUE,
                                   points = FALSE) {
    p <- ggplot(data, aes(x, y))

    if(points) {
      p <- p + geom_point(color = "gray80")
    }
  if(se) {
      p <- p +
        geom_smooth(method = "lm") +
        geom_smooth()
  }
  else {
      p <- p +
        geom_smooth(method = "lm", se = FALSE) +
        geom_smooth(se = FALSE)
  }
  p
}
```

Nope

```
check_linear(penguins, bill_length_mm, bill_depth_mm)
```

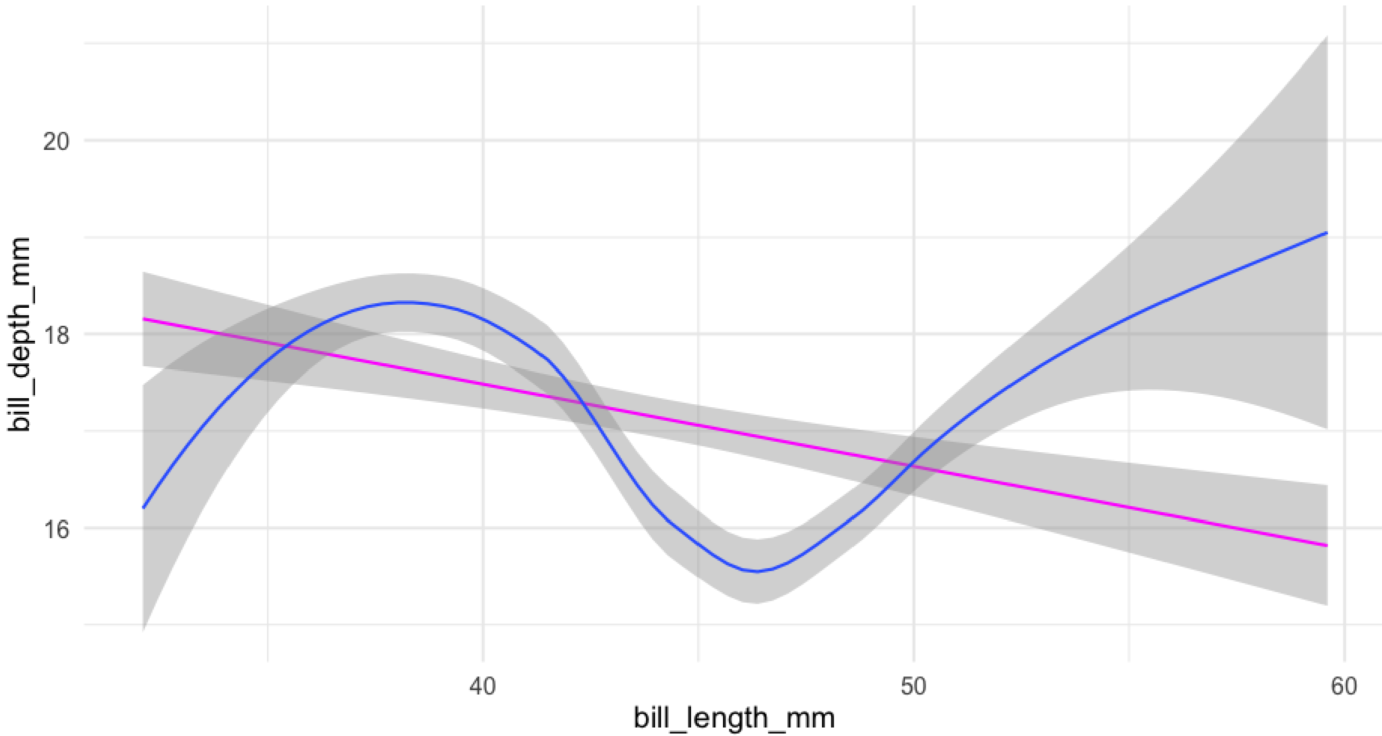
```
## Error in FUN(X[[i]], ...): object 'bill_length_mm' not found
```

Use tidyeval

Note – there are other approaches too, but they are soft deprecated

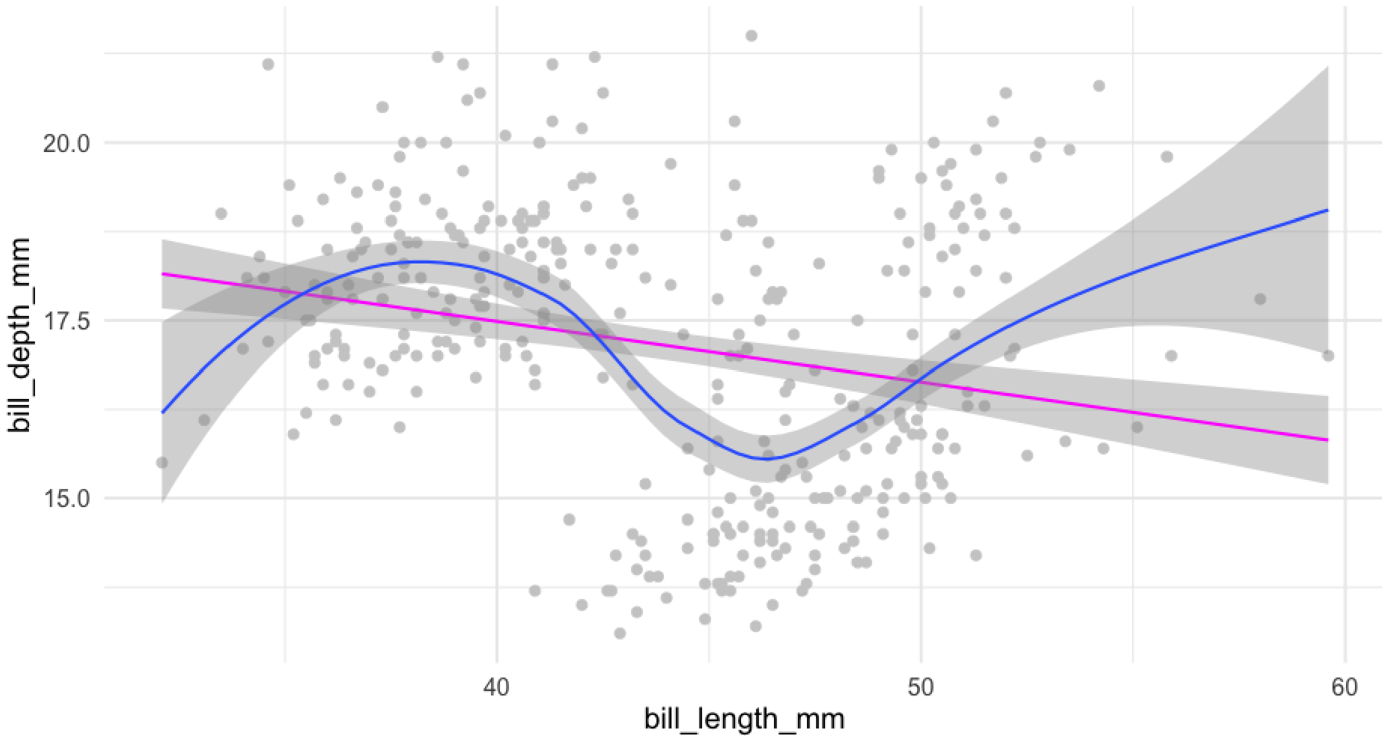
```
check_linear <- function(data, x, y, points = FALSE, ...) {
    p <- ggplot(data, aes({{x}}, {{y}}))
    if (points) {
      p <- p + geom_point(color = "gray80")
    }
    p +
      geom_smooth(method = "lm",
                  color = "magenta",
                    ...) +
      geom_smooth(...)
}
```

```r
check_linear(penguins, bill_length_mm, bill_depth_mm)
```



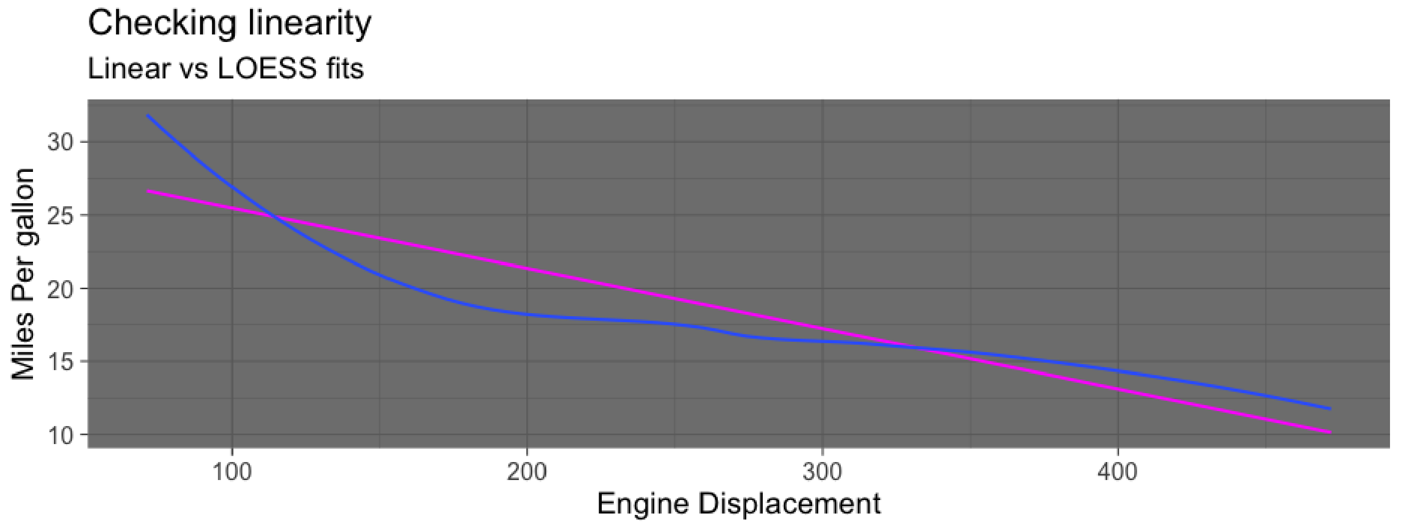
Add points

```
check_linear(penguins, bill_length_mm, bill_depth_mm,
             points = TRUE)
```



Add ggplot functions

```
check_linear(mtcars, disp, mpg, se = FALSE) +
    labs(title = "Checking linearity",
         subtitle = "Linear vs LOESS fits",
         x = "Engine Displacement",
         y = "Miles Per gallon") +
    theme_dark(20)
```



Building up plots

- Let's create a function that calculates means and standard errors for every numeric column in a data frame
- We'll then use this function to create a plotting function

Means/SE's

- First figure it out for a single example

- Note there's not built–in function for the standard error of the mean, which is $\frac{\sigma}{\sqrt{n}}$

```r
# SE function
se <- function(x) {
  x <- x[!is.na(x)]
  sd(x)/sqrt(length(x))
}
```

Full means/SEs

```r
penguins %>%
  select_if(is.numeric) %>%
  pivot_longer(everything(),
               names_to = "var",
               values_to = "val") %>%
  group_by(var) %>%
  summarize(mean = mean(val, na.rm = TRUE),
            se = se(val))
```

```
## # A tibble: 5 x 3
##   var                    mean         se
##   <chr>                 <dbl>      <dbl>
## 1 bill_depth_mm      17.15117  0.1067846
## 2 bill_length_mm     43.92193  0.2952205
## 3 body_mass_g      4201.754   43.36473
## 4 flipper_length_mm  200.9152   0.7603704
## 5 year             2008.029    0.04412279
```

Challenge

Try to generalize the code on the previous slide into a function. Test it on the `forcats::gss_cat` data.

03:00

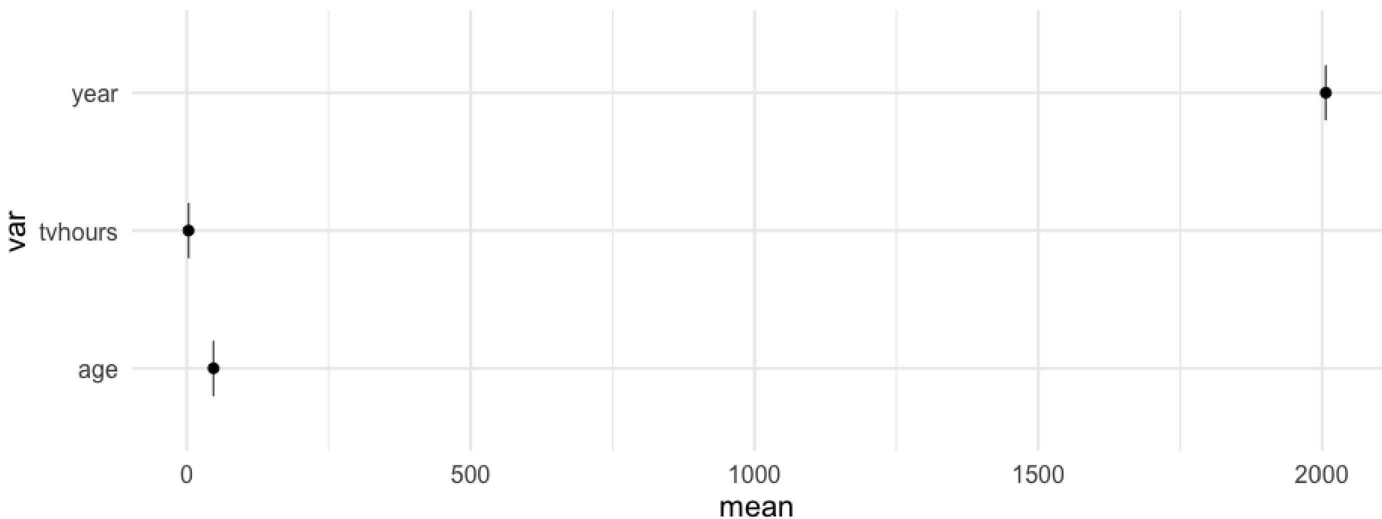
Translate to a function

```r
estimate_means <- function(df) {
  df %>%
    select_if(is.numeric) %>%
    pivot_longer(everything(),
                 names_to = "var",
                 values_to = "val") %>%
    group_by(var) %>%
    summarize(mean = mean(val, na.rm = TRUE),
              se = se(val))
}
estimate_means(forcats::gss_cat)
```

```
## # A tibble: 3 x 3
##   var            mean         se
##   <chr>         <dbl>      <dbl>
## 1 age        47.18008  0.1181556
## 2 tvhours     2.980771 0.02429812
## 3 year     2006.502    0.03037436
```

Plot

```
ggplot(estimate_means(forcats::gss_cat),
       aes(var, mean)) +
    geom_errorbar(aes(ymin = mean + qnorm(0.025)*se,
                      ymax = mean + qnorm(0.975)*se),
                  width = 0.4,
                  color = "gray40") +
    geom_point() +
    coord_flip()
```



Create plot function

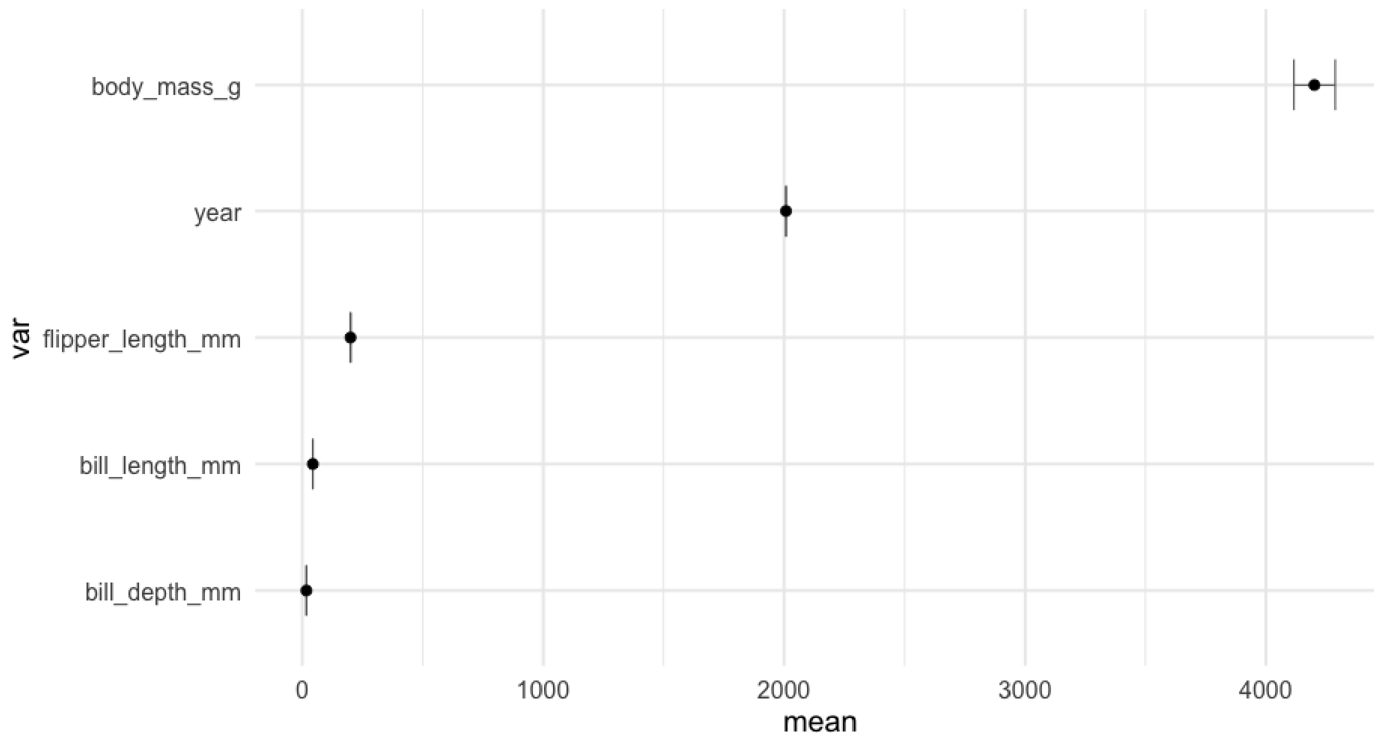
```
plot_means <- function(df) {
  means <- estimate_means(df) %>%
    mutate(var = reorder(factor(var), mean))

  ggplot(means, aes(var, mean)) +
    geom_errorbar(aes(ymin = mean + qnorm(0.025)*se,
                      ymax = mean + qnorm(0.975)*se),
                  width = 0.4,
                  color = "gray40") +
    geom_point() +
    coord_flip()
}
```

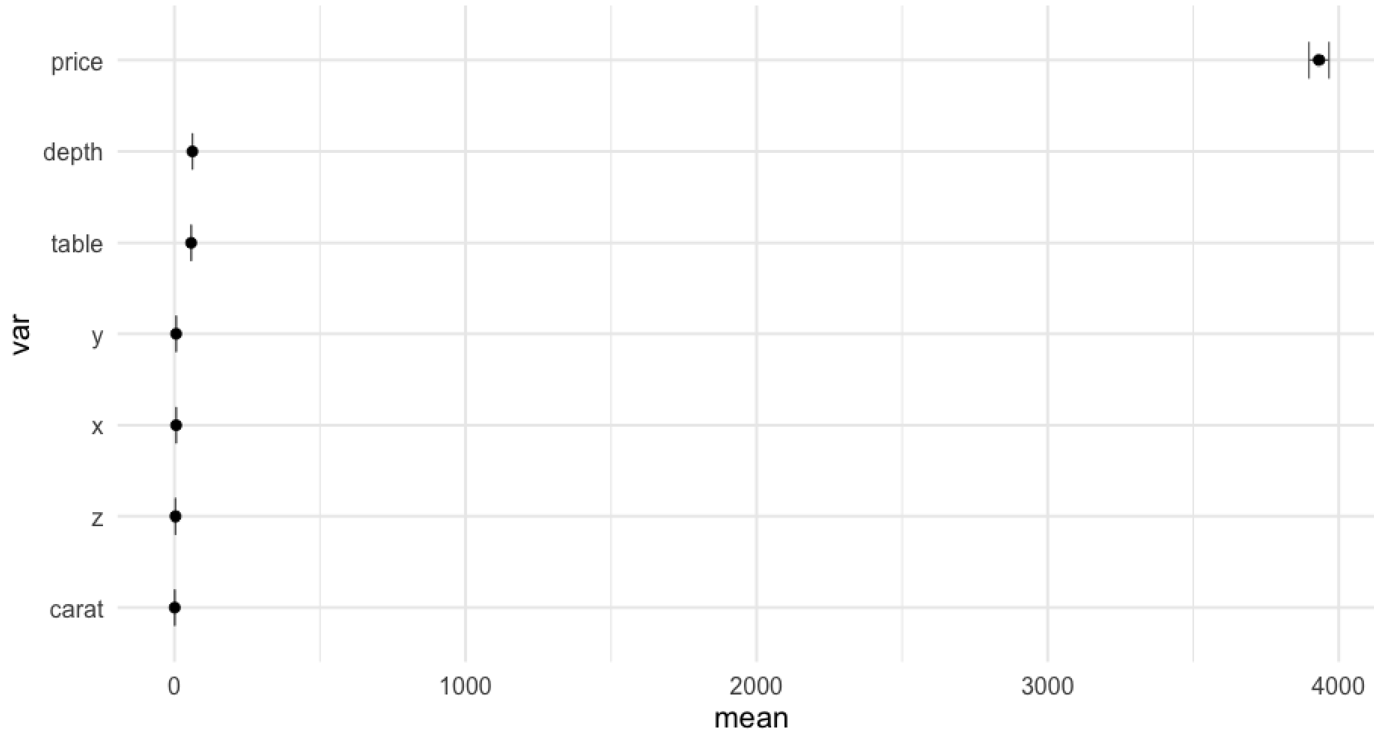
Notice we've successfully avoided tideval entirely in both examples!

Examples

```
plot_means(penguins)
```



```
plot_means(diamonds)
```



Overall takeaway

- Non-standard evaluation is confusing but kind of neat
- Programming with the tidyverse can be a bit more difficult, but not always
- Good to think about multiple ways to approach the same problem (and when programming, perhaps think outside the tidyverse at times)

Next time

Intro to shiny