Announcements

- 1. Will give feedback on everyone's workflow critiques before next class
- 2. Final workflow project change
 - a. Week 10: Presentation -> "in-class hackathon"
 - b. Come prepared with a few changes you're stuck on, advice you want to ask
 - c. Due date for project -> 3/17 (Week 11)
 - d. Project guidelines will be posted shortly

Today

- 1. Workflow self-critique presentations
- 2. Break
- 3. Refactoring and technical debt
- 4. Advanced functions tutorial

PSYC 259: Principles of Data Science

Week 6: Technical debt

Technical debt, design smells, and refactoring

(Suryanarayana et al. 2015)

"Technical debt"

- Debt that we incur by writing code
 - "Interest" accrues the longer we fail to pay off the debt
- "...debt that accrues when you knowingly or unknowingly make wrong or non-optimal design decisions"
 - For a software company, that debt can be time/money
 - For a lab, that debt is more likely time/fidelity

"Design smells"

 "...certain structures in the design that indicate violation of fundamental design principles and negatively impact design quality"

 Hard coding, duplicated code, poor documentation, inflexibility, etc.

Example

- A grad student writes code to clean/analyze Exp 1
 - The details of the study are "hard-coded"
 - Cleaning/analysis in one long script
 - Variable names are hard to understand and the script is poorly documented
 - Used packages/functions that are now deprecated
- The code works...but now there's an Exp 2 that adds IVs and additional measurements
 - The technical debt of those original design decisions must be repaid by re-coding Exp 2

Software always needs to be maintained

- Is the structure of the original code making it hard to write features?
- What are the effects of small changes/ extensions on other parts of the code base?
- Are inputs changing in quality/format?
- How does old code run on new software/ hardware?

How to pay off technical debt

Refactoring

- Rewriting code to change its design, style, or structure without changing its function
- The opposite of "if it ain't broke, don't fix it"!
- Just like revising is a part of writing, refactoring is a part of coding
 - We rephrase/refactor as we write code
 - We make larger changes to structure when needed

Design qualities to strive towards

- Understandability = able to reread your code in a week/ month/year/decade, share it with others
- Reusability = general enough to be used again
- Changeability = can modify code easily without changing its function
- Reliability = code is resistant to breaking in the future

Examples using the built-in diamonds dataset

```
> head(diamonds)
# A tibble: 6 x 10
 carat cut color clarity depth table price
 <dbl> <ord> <ord> <ord> <dbl> <dbl> <int>
1 0.23 Ideal E SI2 61.5 55 326
2 0.21 Premium E SI1 59.8 61 326
3 0.23 Good E VS1 56.9 65 327
4 0.290 Premium I VS2 62.4 58 334
             J SI2 63.3 58
5 0.31 Good
                                  335
6 0.24 Very Good J
              VVS2
                      62.8
                               57
                                  336
```

Goal: Filter data by cut and calculate the average price

Understandability & Reusability

```
> csmp
    Ideal Premium Good Very Good Fair
3457.542 4584.258 3928.864 3981.760 4358.758
```

Understandability & Reusability

```
#BETTER
library("tidyverse")
df <- diamonds

price_summary <- df %>% group_by(cut) %>% summarize(mean_price = mean(price))
cut_prices <- price_summary %>% pull(mean_price) %>% set_names(price_summary$cut)
```

Understandability & Reusability

```
#BETTER
library("tidyverse")
df <- diamonds
price by cut <- function(data, cut name) {</pre>
  data %>%
    filter(cut == cut name) %>%
    summarize(mean price = mean(price)) %>%
    as.double
cut levels <- fct unique(df$cut)</pre>
map_dbl(cut_levels, ~ price_by_cut(df, .x)) %>% set_names(cut_levels)
```

Non-standard evaluation can help with reusability

```
library("tidyverse")
df <- diamonds
dv by iv <- function(data, iv var, iv level, dv) {</pre>
  data %>%
    filter({{iv var}} == iv level) %>%
    summarize(mean dv = mean({dv}))) %>%
    as.double
cut levels <- fct unique(df$cut)</pre>
map(cut_levels, ~ dv_by_iv(df, cut, .x, price)) %>% set_names(cut_levels)
map(cut levels, ~ dv by iv(df, cut, .x, depth)) %>% set names(cut levels)
```

Default arguments can help make functions more reusable

```
price_by_cut <- function(data, cut_name, na.rm = T) {
   data %>%
     filter(cut == cut_name) %>%
        summarize(mean_price = mean(price, na.rm = na.rm)) %>%
        as.double
}
```

if() statements can also help with reusability

 In functions, you can use them to handle different options

```
if (condition == T) {
    #Do the stuff here
} else {
    #Do the stuff here
}
```

if() statements can also help with reusability

 In functions, you can use them to handle different options

```
price_by_cut <- function(data, cut_name = "Overall", na.rm = T) {
   if (cut_name != "Overall") {
     data <- filter(data, cut == cut_name)
   }
   data %>%
     summarize(mean_price = mean(price, na.rm = na.rm)) %>%
     as.double
}
```

Changeability & reliability

- Avoiding hard-coding filenames and working directories
- Avoiding repetitive code (easier to change if it needs to be changed in fewer places)
- Refactoring to avoid deprecated functions (or track package dates to recreate environment)

What leads to technical debt?

- Lack of awareness
- Schedule pressure
 - Priority is to get results, not to write good code
- When should you refactor?
 - After rushing to meet a deadline
 - Before starting an experiment 2 or adding a large analysis component
 - Preserve pre-refactored versions if published