432 Class 05 Slides

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Moving Forward

- Predicting a Binary outcome
  - using a linear probability model
  - using logistic regression and `glm`
- Creating the `smart3` and `smart3_sh` data
  - A "shadow" to track what is imputed

Setup

```r
library(conflicted)                  # a new idea
library(here); library(magrittr)
library(janitor); library(knitr)
library(patchwork); library(broom)
library(equatiomatic)
library(simputation); library(naniar)
library(faraway)                     # for orings data
library(rms)
library(tidyverse)

theme_set(theme_bw())
conflict_prefer("summarize", "dplyr") # choose over Hmisc
conflict_prefer("filter", "dplyr") # choose over stats
options(dplyr.summarise.inform = FALSE)
```

A First Example: Space Shuttle O-Rings

Challenger Space Shuttle Data

The US space shuttle Challenger exploded on 1986-01-28. An investigation ensued into the reliability of the shuttle's propulsion system. The explosion was eventually traced to the failure of one of the three field joints on one of the two solid booster rockets. Each of these six field joints includes two O-rings which can fail.

The discussion among engineers and managers raised concern that the probability of failure of the O-rings depended on the temperature at launch, which was forecast to be 31 degrees F. There are strong engineering reasons based on the composition of O-rings to support the judgment that failure probability may rise monotonically as temperature drops.

We have data on 23 space shuttle flights that preceded *Challenger* on primary o-ring erosion and/or blowby and on the temperature in degrees Fahrenheit. No previous liftoff temperature was under 53 degrees F.

The "O-rings" data

```
orings1 <- faraway::orings %>%
    tibble() %>%
    mutate(burst = case_when( damage > 0 ~ 1,
                              TRUE ~ 0))

orings1 %>% summary()
```

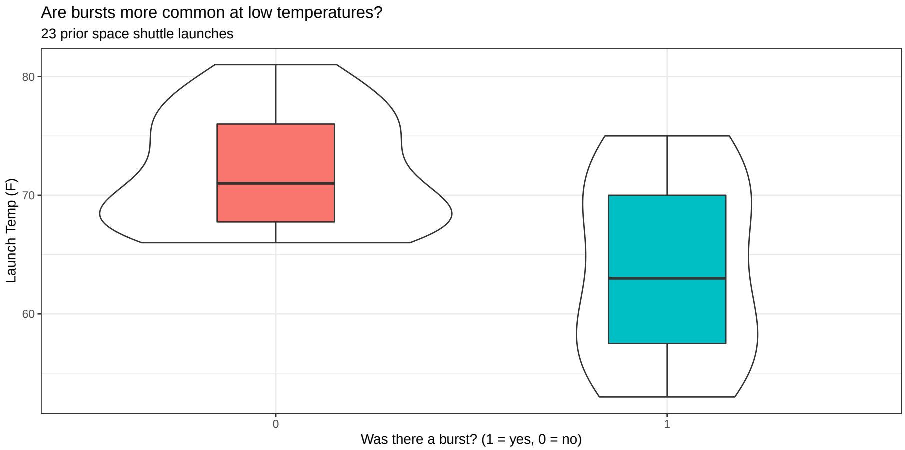
```
      temp            damage           burst       
 Min.   :53.00   Min.   :0.0000   Min.   :0.0000  
 1st Qu.:67.00   1st Qu.:0.0000   1st Qu.:0.0000  
 Median :70.00   Median :0.0000   Median :0.0000  
 Mean   :69.57   Mean   :0.4783   Mean   :0.3043  
 3rd Qu.:75.00   3rd Qu.:1.0000   3rd Qu.:1.0000  
 Max.   :81.00   Max.   :5.0000   Max.   :1.0000  
```

- damage = number of damage incidents out of 6 possible
- we set burst = 1 if damage > 0

Code to plot `burst` and `temp` in our usual way...

```
ggplot(orings1, aes(x = factor(burst), y = temp)) +
    geom_violin() +
    geom_boxplot(aes(fill = factor(burst)), width = 0.3) +
    guides(fill = "none") +
    labs(title = "Are bursts more common at low temperatures?'
         subtitle = "23 prior space shuttle launches",
         x = "Was there a burst? (1 = yes, 0 = no)",
         y = "Launch Temp (F)")
```

Plotted Association of `burst` and `temp`

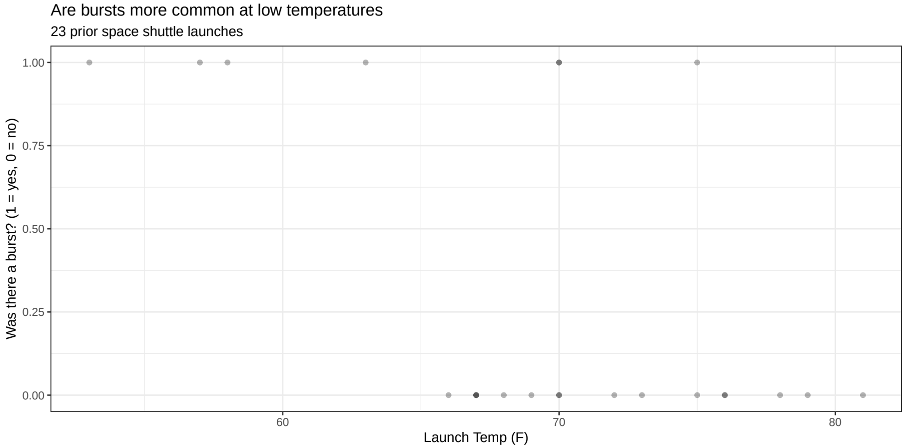


What if we want to predict Prob(burst) using temp?

We want to treat the binary variable `burst` as the outcome, and `temp` as the predictor...

```
ggplot(orings1, aes(x = temp, y = burst)) +
    geom_point(alpha = 0.3) +
    labs(title = "Are bursts more common at low temperatures",
         subtitle = "23 prior space shuttle launches",
         y = "Was there a burst? (1 = yes, 0 = no)",
         x = "Launch Temp (F)")
```

Plot of Prob(burst) by temperature at launch



Fit a linear model to predict Prob(burst)?

```
mod1 <- lm(burst ~ temp, data = orings1)

tidy(mod1, conf.int = T) %>% kable(digits = 3)
```

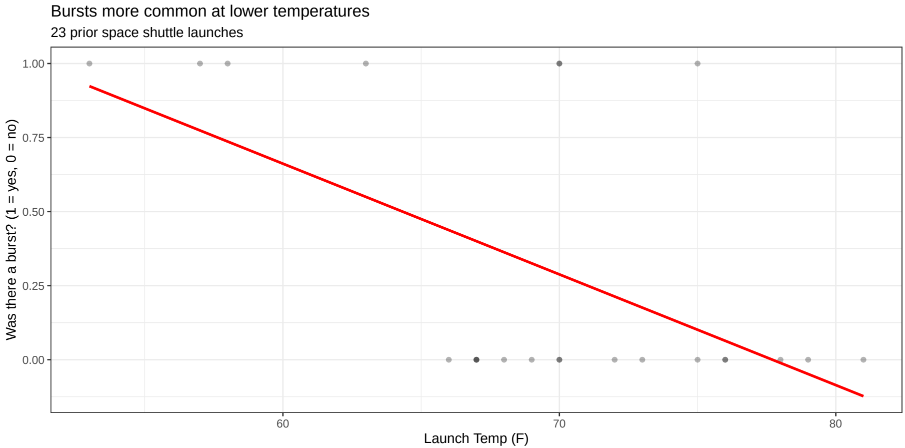
term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	2.905	0.842	3.450	0.002	1.154	4.656
temp	-0.037	0.012	-3.103	0.005	-0.062	-0.012

- This is a **linear probability model**.

```
extract_eq(mod1, use_coefs = TRUE, coef_digits = 3)
```

$$\widehat{\text{burst}} = 2.905 - 0.037(\text{temp}) \tag{1}$$

Add linear probability model to our plot?

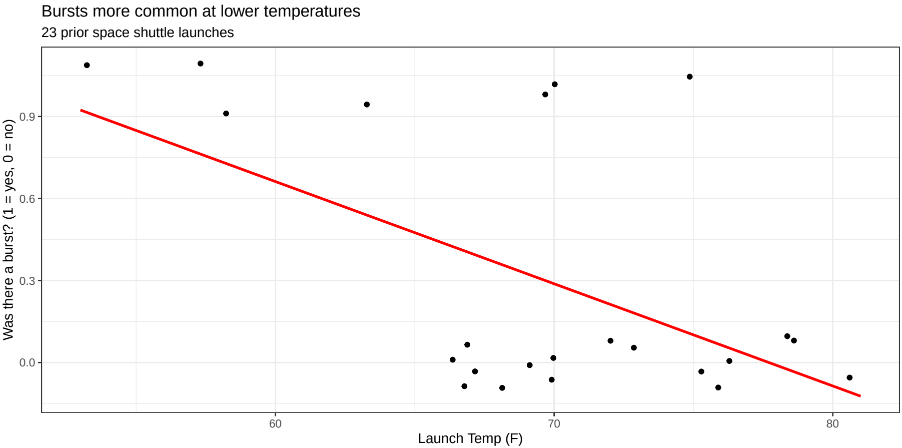


- It would help if we could see the individual launches...

Add vertical jitter and our mod1 model?

```
ggplot(orings1, aes(x = temp, y = burst)) +
    geom_jitter(height = 0.1) +
    geom_smooth(method = "lm", se = F, col = "red",
                formula = y ~ x) +
    labs(title = "Bursts more common at lower temperatures",
         subtitle = "23 prior space shuttle launches",
         y = "Was there a burst? (1 = yes, 0 = no)",
         x = "Launch Temp (F)")
```

Resulting plot with points jittered and linear model



- What's wrong with this picture?

Making Predictions with `mod1`

```
tidy(mod1, conf.int = T) %>%
    kable(digits = c(0,5,3,3,3,3,3))
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	2.90476	0.842	3.450	0.002	1.154	4.656
temp	-0.03738	0.012	-3.103	0.005	-0.062	-0.012

- What does `mod1` predict for the probability of a burst if the temperature at launch is 70 degrees F?

$$Prob(burst) = 2.90476 - 0.03738(70) = 0.288$$

- What if the temperature was actually 60 degrees F?

Making Several Predictions with mod1

Let's use our linear probability model mod1 to predict the probability of a burst at some other temperatures...

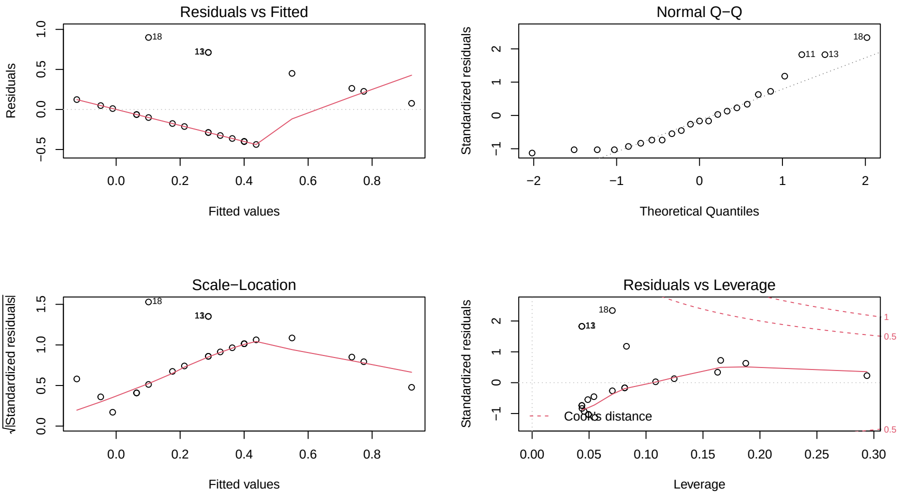
```
newtemps <- tibble(temp = c(80, 70, 60, 50, 31))

augment(mod1, newdata = newtemps)
```

```
# A tibble: 5 x 2
   temp .fitted
  <dbl>   <dbl>
1    80 -0.0857
2    70  0.288
3    60  0.662
4    50  1.04
5    31  1.75
```

- Uh, oh.

Residual Plots for `mod1`?



- Uh, oh.

Models to predict a Binary Outcome

Our outcome takes on two values (zero or one) and we then model the probability of a "one" response given a linear function of predictors.

Idea 1: Use a *linear probability model*

- Main problem: predicted probabilities that are less than 0 and/or greater than 1
- Also, how can we assume Normally distributed residuals when outcomes are 1 or 0?

Idea 2: Build a *non-linear* regression approach

- Most common approach: logistic regression, part of the class of *generalized* linear models

The Logit Link and Logistic Function

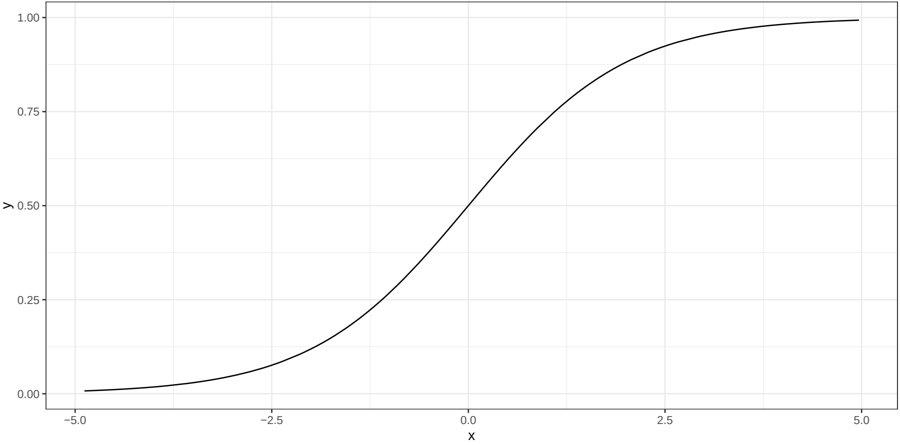
The function we use in logistic regression is called the **logit link**.

$$logit(\pi) = log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k$$

The inverse of the logit function is called the **logistic function**. If logit(π) $= \eta$, then $\pi = \frac{exp(\eta)}{1+exp(\eta)}$.

- The logistic function $\frac{e^x}{1+e^x}$ takes any value x in the real numbers and returns a value between 0 and 1.

The Logistic Function $y = \frac{e^x}{1+e^x}$



The logit or log odds

We usually focus on the **logit** in statistical work, which is the inverse of the logistic function.

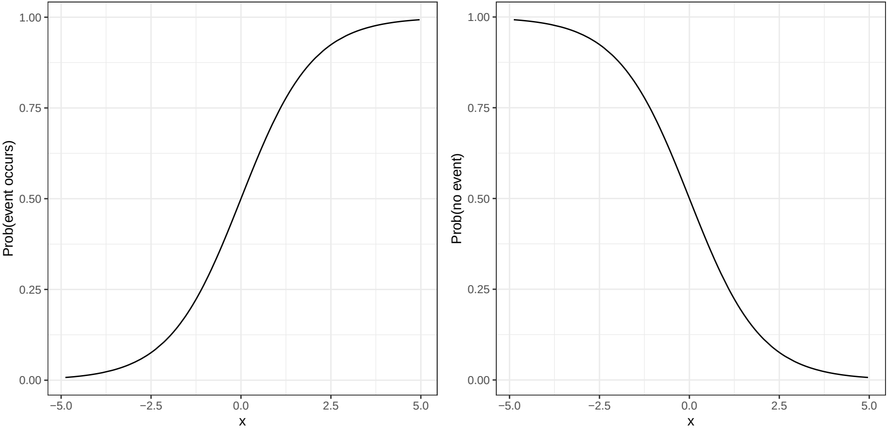
- If we have a probability $\pi < 0.5$, then $logit(\pi) < 0$.
- If our probability $\pi > 0.5$, then $logit(\pi) > 0$.
- Finally, if $\pi = 0.5$, then $logit(\pi) = 0$.

Why is this helpful?

- log(odds(Y = 1)) or logit(Y = 1) covers all real numbers.
- Prob(Y = 1) is restricted to [0, 1].

Predicting Pr(event) or Pr(no event)

- Can we flip the story?



Returning to the prediction of Prob(burst)

We'll use the `glm` function in R, specifying a logistic regression model.

- Instead of predicting $Pr(burst)$, we're predicting $log(odds(burst))$ or $logit(burst)$.

```
mod2 <- glm(burst ~ temp, data = orings1,
            family = binomial(link = "logit"))

tidy(mod2, conf.int = TRUE) %>%
  select(term, estimate, std.error, conf.low, conf.high) %>%
  kable(digits = c(0,4,3,3,3))
```

term	estimate	std.error	conf.low	conf.high
(Intercept)	15.0429	7.379	3.331	34.342
temp	-0.2322	0.108	-0.515	-0.061

Our model `mod2`

```
extract_eq(mod2, use_coefs = TRUE, coef_digits = 4)
```

$$\log\left[\frac{\widehat{P(\mathrm{burst} = 1)}}{1 - \widehat{P(\mathrm{burst} = 1)}}\right] = 15.0429 - 0.2322(\mathrm{temp}) \tag{2}$$

$$logit(burst) = log(odds(burst)) = 15.0429 - 0.2322 temp$$

- For a temperature of 70 F at launch, what is the prediction?

Let's look at the results

- For a temperature of 70 F at launch, what is the prediction?

log(odds(burst)) = 15.0429 - 0.2322 (70) = -1.211

- Exponentiate to get the odds, on our way to estimating the probability.

odds(burst) = exp(-1.211) = 0.2979

- so, we can estimate the probability by

$$Pr(burst) = \frac{0.2979}{(0.2979 + 1)} = 0.230.$$

Prediction from `mod2` for temp = 60

What is the predicted probability of a burst if the temperature is 60 degrees?

- log(odds(burst)) = 15.0429 - 0.2322 (60) = 1.1109
- odds(burst) = exp(1.1109) = 3.0371
- Pr(burst) = 3.0371 / (3.0371 + 1) = 0.752

Will `augment` do this, as well?

```
temps <- tibble(temp = c(60,70))

augment(mod2, newdata = temps, type.predict = "link")
```

```
# A tibble: 2 x 2
   temp .fitted
  <dbl>   <dbl>
1    60    1.11
2    70   -1.21
```

```
augment(mod2, newdata = temps, type.predict = "response")
```

```
# A tibble: 2 x 2
   temp .fitted
  <dbl>   <dbl>
1    60   0.753
2    70   0.230
```

Plotting the Logistic Regression Model

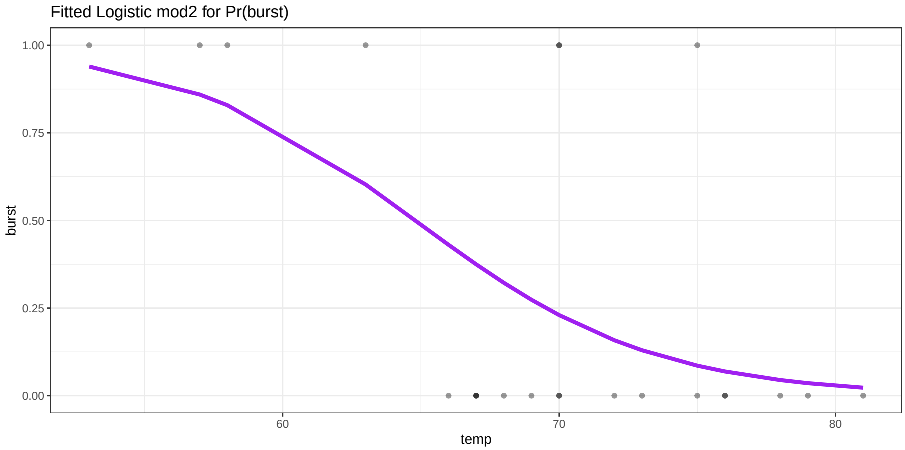
Use the augment function to get the fitted probabilities into the original data, then plot.

```
mod2_aug <- augment(mod2, type.predict = "response")

ggplot(mod2_aug, aes(x = temp, y = burst)) +
  geom_point(alpha = 0.4) +
  geom_line(aes(x = temp, y = .fitted),
            col = "purple", size = 1.5) +
  labs(title = "Fitted Logistic mod2 for Pr(burst)")
```

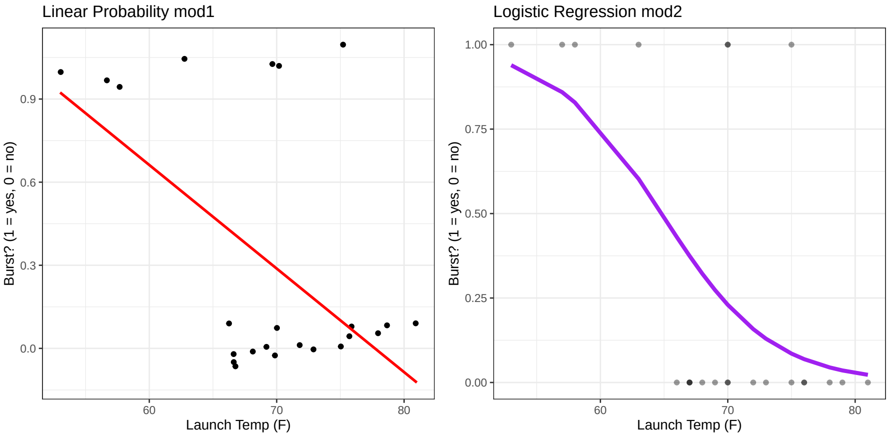
- Results on next slide

Plotting Model `m2`



Note that we're just connecting the predictions made for observed `temp` values with `geom_line`, so the appearance of the function isn't as smooth as the actual logistic regression model.

Comparing the fits of `mod1` and `mod2`...



Could we try exponentiating the `mod2` coefficients?

How can we interpret the coefficients of the model?

$$logit(burst) = log(odds(burst)) = 15.043 - 0.232 temp$$

Exponentiating the coefficients is helpful...

```
exp(-0.232)
```

```
[1] 0.7929461
```

Suppose Launch A's temperature was one degree higher than Launch B's.

- The **odds** of Launch A having a burst are 0.793 times as large as they are for Launch B.
- Odds Ratio estimate comparing two launches whose `temp` differs by 1 degree is 0.793

Exponentiated and tidied slope of `temp` (`mod2`)

```
tidy(mod2, exponentiate = TRUE, conf.int = TRUE) %>%
    filter(term == "temp") %>%
    select(term, estimate, std.error, conf.low, conf.high) %>%
    kable(digits = 3)
```

term	estimate	std.error	conf.low	conf.high
temp	0.793	0.108	0.597	0.941

- What would it mean if the Odds Ratio for `temp` was 1?
- How about an odds ratio that was greater than 1?

Regression on a Binary Outcome

Linear Probability Model (a linear model)

```
lm(event ~ predictor1 + predictor2 + ..., data = tibblename)
```

- Pr(event) is linear in the predictors

Logistic Regression Model (generalized linear model)

```
glm(event ~ pred1 + pred2 + ..., data = tibblename,
             family = binomial(link = "logit"))
```

- Logistic Regression forces a prediction in (0, 1)
- log(odds(event)) is linear in the predictors

The logistic regression model

$$logit(event) = log\left(\frac{Pr(event)}{1 - Pr(event)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k$$

$$odds(event) = \frac{Pr(event)}{1 - Pr(event)}$$

$$Pr(event) = \frac{odds(event)}{odds(event) + 1}$$

$$Pr(event) = \frac{exp(logit(event))}{1 + exp(logit(event))}$$

Building a `smart3` tibble

BRFSS and SMART (Creating smart3)

```
smart3 <- read_csv(here("data/smart_ohio.csv")) %>%
    mutate(SEQNO = as.character(SEQNO)) %>%
    select(SEQNO, mmsa, mmsa_wt, landline,
           age_imp, healthplan, dm_status,
           fruit_day, drinks_wk, activity,
           smoker, physhealth, bmi, genhealth)
```

`smart3` Variables, by Type

Variable	Type	Description
`landline`	Binary (1/0)	survey conducted by landline? (vs. cell)
`healthplan`	Binary (1/0)	subject has health insurance?
`age_imp`	Quantitative	age (imputed from groups - see Notes)
`fruit_day`	Quantitative	mean servings of fruit / day
`drinks_wk`	Quantitative	mean alcoholic drinks / week
`bmi`	Quantitative	body-mass index (in kg/m^2)
`physhealth`	Count (0-30)	of last 30 days, # in poor physical health
`dm_status`	Categorical	diabetes status (4 levels, *we'll collapse to 2*)
`activity`	Categorical	physical activity level (4 levels, *we'll re-level*)
`smoker`	Categorical	smoking status (4 levels, *we'll collapse to 3*)
`genhealth`	Categorical	self-reported overall health (5 levels)

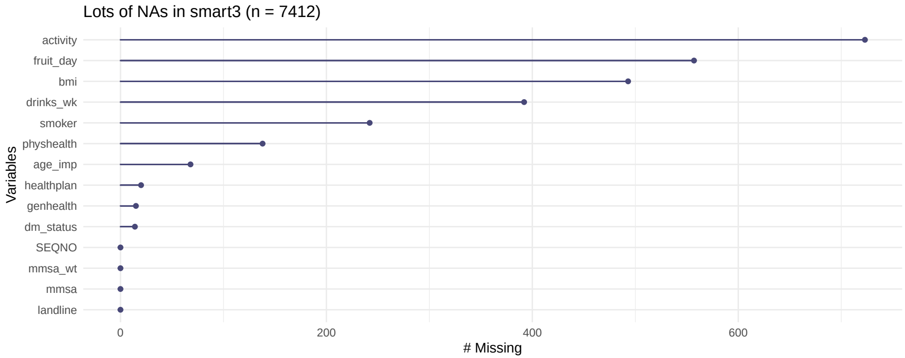
Collapsing Two Factors, Re-leveling another

```
smart3 <- smart3 %>% type.convert() %>%
    mutate(SEQNO = as.character(SEQNO)) %>%
    mutate(dm_status =
           fct_collapse(factor(dm_status),
                        Yes = "Diabetes",
                        No = c("No-Diabetes",
                               "Pre-Diabetes",
                               "Pregnancy-Induced"))) %>%
    mutate(smoker =
           fct_collapse(factor(smoker),
                        Current = c("Current_not_daily",
                                    "Current_daily"))) %>%
    mutate(activity =
             fct_relevel(factor(activity),
                         "Highly_Active", "Active",
                         "Insufficiently_Active",
                         "Inactive"))
```

Visualizing Missingness in Variables

```r
gg_miss_var(smart3) +
  labs(title = "Lots of NAs in smart3 (n = 7412)")
```

```
Warning: It is deprecated to specify `guide = FALSE` to
remove a guide. Please use `guide = "none"` instead.
```



Creating a "Shadow" to track what is imputed

```
smart3_sh <- smart3 %>% bind_shadow()
```

smart3_sh creates new variables, ending in _NA

```
names(smart3_sh)
```

```
 [1] "SEQNO"          "mmsa"           "mmsa_wt"
 [4] "landline"       "age_imp"        "healthplan"
 [7] "dm_status"      "fruit_day"      "drinks_wk"
[10] "activity"       "smoker"         "physhealth"
[13] "bmi"            "genhealth"      "SEQNO_NA"
[16] "mmsa_NA"        "mmsa_wt_NA"     "landline_NA"
[19] "age_imp_NA"     "healthplan_NA" "dm_status_NA"
[22] "fruit_day_NA"   "drinks_wk_NA"   "activity_NA"
[25] "smoker_NA"      "physhealth_NA" "bmi_NA"
[28] "genhealth_NA"
```

What are the new variables tracking?

```
smart3_sh %>% count(smoker, smoker_NA)
```

```
# A tibble: 4 x 3
  smoker  smoker_NA     n
  <fct>   <fct>     <int>
1 Current !NA        1290
2 Former  !NA        1999
3 Never   !NA        3881
4 <NA>    NA          242
```

The `fct_explicit_na` warning: A pain point

My general preference is to not use `fct_explicit_na`, and if I see a warning about that, I typically suppress it from printing.

"Simple" Imputation Strategy

```
set.seed(2022432)
smart3_sh <- smart3_sh %>%
    data.frame() %>%
        impute_rhd(dm_status + smoker ~ 1) %>%
        impute_rhd(healthplan + activity ~ 1) %>%
        impute_rlm(age_imp + fruit_day + drinks_wk + bmi ~
                     mmsa + landline + healthplan) %>%
        impute_knn(physhealth ~ bmi) %>%
        impute_cart(genhealth ~ activity + physhealth +
                      mmsa + healthplan) %>%
    tibble()
```

Check to see that imputation worked...

Before imputation, what fraction of our cases are complete?

```
pct_complete_case(smart3)
```

```
[1] 81.08473
```

After imputation, do any of our cases have missing values?

```
pct_miss_case(smart3_sh)
```

```
[1] 0
```

Saving the `smart3` and `smart3_sh` tibbles to `.Rds`

```
saveRDS(smart3, "data/smart3.Rds")
saveRDS(smart3_sh, "data/smart3_sh.Rds")
```

Using diabetes status (yes/no) to predict whether BMI > 30

Create binary outcome variable

```
smart3_sh <- readRDS("data/smart3_sh.Rds") %>%
  mutate(bmigt30 = as.numeric(bmi > 30),
         dm_status = fct_relevel(dm_status, "No"))

smart3_sh %>%
  group_by(bmigt30) %>%
  summarize(n = n(), mean(bmi), min(bmi), max(bmi)) %>%
  kable(digits = 2)
```

bmigt30	n	mean(bmi)	min(bmi)	max(bmi)
0	5074	25.26	13.30	30.00
1	2338	35.85	30.01	75.52

Predicting `BMI > 30` using diabetes status (a factor)

```
mod_DM <- smart3_sh %$%
  glm(bmigt30 ~ dm_status,
      family = binomial(link = logit))

tidy(mod_DM) %>% select(term, estimate) %>%
  kable(digits = 3)
```

term	estimate
(Intercept)	-0.949
dm_statusYes	1.048

Equation: `logit(BMI > 30) = -0.949 + 1.048 (dm_statusYes)`

How can we interpret this result?

Interpreting the `mod_DM` Equation

`logit(BMI > 30) = -0.949 + 1.048 (dm_statusYes)`

- Harry has diabetes.
  - His predicted `logit(BMI > 30)` is -0.949 + 1.048 (1) = 0.099
- Sally does not have diabetes.
  - Her predicted `logit(BMI > 30)` is -0.949 + 1.048 (0) = -0.949

Now, `logit(BMI > 30)` = `log(odds(BMI > 30))`, so exponentiate to get the odds...

- Harry has predicted `odds(BMI > 30)` = exp(0.099) = 1.104
- Sally has predicted `odds(BMI > 30)` = exp(-0.949) = 0.387

Can we convert these odds into something more intuitive?

Converting Odds to Probabilities

- Harry has predicted `odds(BMI > 30)` $=$ exp(0.099) $= 1.104$
- Sally has predicted `odds(BMI > 30)` $=$ exp(-0.949) $= 0.387$

$$odds(BMI > 30) = \frac{Pr(BMI > 30)}{1 - Pr(BMI > 30)}$$

and

$$Pr(BMI > 30) = \frac{odds(BMI > 30)}{odds(BMI > 30) + 1}$$

- So Harry's predicted `Pr(BMI > 30)` $= 1.104 \,/\, 2.104 = 0.52$
- Sally's predicted `Pr(BMI > 30)` $= 0.387 \,/\, 1.387 = 0.28$
- odds range from 0 to ∞, and log(odds) range from $-\infty$ to ∞.
- odds > 1 if probability > 0.5. If odds $= 1$, then probability $= 0.5$.

What about the odds ratio?

```
logit(BMI > 30) = -0.949 + 1.048 (dm_statusYes)
```

- Harry, with diabetes, has odds(BMI $> 30) = 1.104$
- Sally, without diabetes, has odds(BMI $> 30) = 0.387$

Odds Ratio for BMI > 30 associated with having diabetes (vs. not) $=$

$$\frac{1.104}{0.387} = 2.85$$

- Our model estimates that a subject with diabetes has 2.85 times the odds (285% of the odds) of a subject without diabetes of having BMI > 30.

Can we calculate the odds ratio from the equation's coefficients?

- Yes, `exp(1.048)` $= 2.85$.

Tidy with exponentiation

```
tidy(mod_DM, exponentiate = TRUE,
     conf.int = TRUE, conf.level = 0.9) %>%
  select(term, estimate, conf.low, conf.high) %>%
  kable(digits = 3)
```

term	estimate	conf.low	conf.high
(Intercept)	0.387	0.369	0.405
dm_statusYes	2.851	2.556	3.181

- The odds ratio for BMI > 30 among subjects with diabetes as compared to those without diabetes is 2.851
- The odds of BMI > 30 are 285.1% as large (2.851 times as large) for subjects with diabetes as they are for subjects without diabetes, according to this model.
- A 90% uncertainty interval for the odds ratio estimate includes (2.556, 3.181).

Interpreting these summaries

Connecting the Odds Ratio and Log Odds Ratio to probability statements...

- If the probabilities were the same (for diabetes and non-diabetes subjects) of having BMI > 30, then the odds would also be the same, and so the odds ratio would be 1.
- If the probabilities of BMI > 30 were the same and thus the odds were the same, then the log odds ratio would be `log(1)` $= 0$.

```
logit(BMI > 30) = -0.949 + 1.048 (dm_statusYes)
```

1. If the log odds of a coefficient (like `diabetes = Yes`) are negative, then what does that imply?

2. What if we flipped the order of the levels for diabetes so our model was about `diabetes = No`?

Flipping the model changes slope and intercept!

```
mod_DM_no <- smart3_sh %$%
  glm(bmigt30 ~ (dm_status == "No"),
      family = binomial(link = logit))

tidy(mod_DM_no) %>% select(term, estimate) %>%
  kable(digits = 3)
```

term	estimate
(Intercept)	0.098
dm_status == "No"TRUE	-1.048

Old: `logit(BMI > 30) = -0.949 + 1.048 (dm_statusYes)`

New: `logit(BMI > 30) = 0.098 - 1.048 (dm_status = No)`

Predictions from the two models?

DMYes: `logit(BMI > 30) = -0.949 + 1.048 (dm_status = Yes)`
DMNo: `logit(BMI > 30) = 0.098 - 1.048 (dm_status = No)`

Harry lives with diabetes. Sally does not.

Using the DMYes model:

- logit(Harry's BMI $>$ 30) $=$ -0.949 $+$ 1.048 $=$ 0.098
- logit(Sally's BMI $>$ 30) $=$ -0.949

Using the DMNo model:

- logit(Harry's BMI $>$ 30) $=$ 0.098
- logit(Sally's BMI $>$ 30) $=$ 0.098 - 1.048 $=$ -0.949

Comparison to the 2x2 Table Results?

```
smart3_sh %>% tabyl(bmigt30, dm_status)
```

```
 bmigt30   No Yes
       0 4551 523
       1 1761 577
```

That's not quite the 2x2 table we want.

We want to switch the order of both variables

```
temp1 <- smart3_sh %>%
    select(bmigt30, dm_status, SEQNO)

temp1 <- temp1 %>%
    mutate(bmigt30 = fct_relevel(factor(bmigt30), "1"),
           dm_status = fct_relevel(dm_status, "Yes"))

temp1 %>% tabyl(bmigt30, dm_status)
```

```
 bmigt30 Yes   No
       1 577 1761
       0 523 4551
```

Resulting 2x2 Table Result

```
temp1 %$% Epi::twoby2(bmigt30, dm_status)
```

```
2 by 2 table analysis:
------------------------------------------------------
Outcome   : Yes
Comparing : 1 vs. 0

  Yes   No    P(Yes) 95% conf. interval
1 577 1761    0.2468    0.2297   0.2647
0 523 4551    0.1031    0.0950   0.1117

                                   95% conf. interval
             Relative Risk: 2.3943    2.1498   2.6666
         Sample Odds Ratio: 2.8512    2.5024   3.2486
Conditional MLE Odds Ratio: 2.8506    2.4969   3.2554
    Probability difference: 0.1437    0.1246   0.1633
```

Using smoking status (multi-categorical) to predict diabetes (yes/no)

Can we use smoker to predict dm_status?

```
smart3_sh %>% tabyl(smoker, dm_status) %>%
    adorn_totals() %>%
    adorn_percentages(den = "row") %>%
    adorn_pct_formatting() %>%
    adorn_ns(position = "front")
```

```
  smoker            No          Yes
 Current 1170 (87.8%)  163 (12.2%)
  Former 1689 (81.9%)  373 (18.1%)
   Never 3453 (86.0%)  564 (14.0%)
   Total 6312 (85.2%) 1100 (14.8%)
```

Logistic Regression for dm_status by smoker

```
mod_SM <- glm(dm_status ~ smoker,
             family = binomial(link = "logit"),
             data = smart3_sh)

tidy(mod_SM) %>% select(term, estimate) %>% kable(dig = 3)
```

term	estimate
(Intercept)	-1.971
smokerFormer	0.461
smokerNever	0.159

What is being fit, exactly?

```
extract_eq(mod_SM, use_coefs = TRUE, coef_digits = 3,
           wrap = TRUE, terms_per_line = 2, label = NA)
```

$$
\begin{aligned}
\log\left[\frac { P(\widehat{\operatorname{dm\_status}} = \operatorname{Yes}) }{ 1 - P(\widehat{\operatorname{dm\_status}} = \operatorname{Yes}) } \right] &= -1.971 + 0.461(\operatorname{smoker}_{\operatorname{Former}}) + \\
&\quad 0.159(\operatorname{smoker}_{\operatorname{Never}})
\end{aligned} \tag{3}
$$

Resulting Predictions from `mod_SM`

```
logit(dm = Yes) = -1.971 + 0.461 Former + 0.159 Never
```

- from logit to odds via exponentiation

Smoking Status	logit(DM = Yes)	odds(DM = Yes)
Current	-1.971	exp(-1.971) = 0.139
Former	-1.971 + 0.461 = -1.510	exp(-1.510) = 0.221
Never	-1.971 + 0.159 = -1.812	exp(-1.812) = 0.163

- convert from odds to probabilities (do these match our table?)

Smoking Status	odds(DM = Yes)	Pr(DM = Yes)
Current	0.139	.139/1.139 = 0.122
Former	0.221	.221/1.221 = 0.181
Never	0.163	.163/1.163 = 0.140

Next Time

- Binary regression models with multiple predictors
- Assessing the quality of fit for a logistic model