432 Class 11 Slides

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Today's Agenda

Fitting logistic regressions using `tidymodels` packages

- Pre-processing activities
- Model building (with multiple fitting engines)
- Measuring model effectiveness
- Creating a model workflow

Setup

```r
library(here); library(knitr)
library(magrittr); library(janitor)
library(naniar); library(equatiomatic)

library(tidymodels)
library(tidyverse)

theme_set(theme_bw())
```

Today's Data (from Class 09)

```
fram_raw <- read_csv(here("data/framingham.csv")) %>%
    type.convert() %>%
    clean_names()
```

Again, the variables describe n = 4238 adults examined at baseline, then followed for 10 years to see if they developed incident coronary heart disease. Our outcome (below) has no missing values.

```
fram_raw %>% tabyl(ten_year_chd)
```

```
 ten_year_chd    n   percent
            0 3594 0.8480415
            1  644 0.1519585
```

Data Cleanup

```
fram_new <- fram_raw %>%
    rename(cigs = "cigs_per_day",
           stroke = "prevalent_stroke",
           hrate = "heart_rate",
           sbp = "sys_bp",
           chd10_n = "ten_year_chd") %>%
    mutate(educ = fct_recode(factor(education),
                     "Some HS" = "1",
                     "HS grad" = "2",
                     "Some Coll" = "3",
                     "Coll grad" = "4")) %>%
    mutate(chd10_f = fct_recode(factor(chd10_n),
                     "chd" = "1", "chd_no" = "0")) %>%
    select(subj_id, chd10_n, chd10_f, age,
           cigs, educ, hrate, sbp, stroke)
```

Data Descriptions (Main Variables Today)

The variables we'll use today are:

Variable	Description
`subj_id`	identifying code added by Dr. Love
`chd10_n`	(numeric) 1 = coronary heart disease in next 10 years
`chd10_f`	(factor) "chd_yes" or "chd_no" in next ten years
`age`	in years (range is 32 to 70)
`cigs`	number of cigarettes smoked per day
`educ`	4-level factor: educational attainment
`hrate`	heart rate in beats per minute
`sbp`	systolic blood pressure in mm Hg
`stroke`	1 = history of stroke, else 0

Steps we'll describe today

1. Prepare our (binary) outcome.
2. Split the data into training and testing samples.
3. Build a recipe for our model.
    - Specify roles for outcome and predictors.
    - Deal with missing data in a reasonable way.
    - Complete all necessary pre-processing so we can fit models.
4. Specify a modeling engine for each fit we will create.
    - There are five available engines just for linear regression!
5. Create a workflow for each engine and fit model to the training data.
6. Compare coefficients graphically from two modeling approaches.
7. Assess performance in the models we create in the training data.
8. Compare multiple models based on their performance in test data.

Key Reference: Kuhn and Silge, *Tidy Modeling with R* or TMWR

Stage 1. Prepare our outcome.

To do logistic regression using `tidymodels`, we'll want our binary outcome to be a factor variable.

```
fram_new %$% str(chd10_f)
```

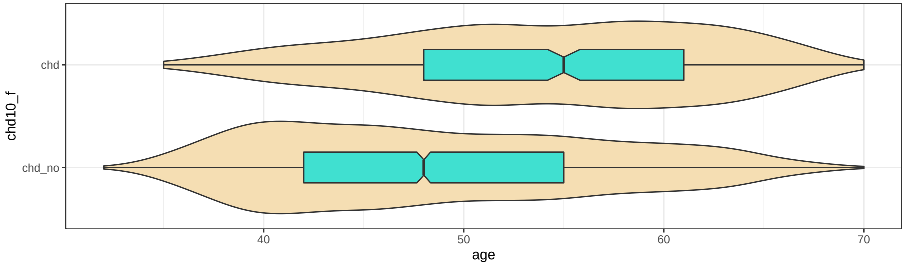
```
 Factor w/ 2 levels "chd_no","chd": 1 1 1 2 1 1 2 1 1 1 ...
```

```
fram_new %>% tabyl(chd10_f, chd10_n)
```

```
 chd10_f    0   1
  chd_no 3594   0
     chd    0 644
```

Working with Binary Outcome Models

Does Pr(CHD in next ten years) look higher for *older* or *younger* people?



chd10_f	n	mean(age)	sd(age)	median(age)
chd_no	3594	48.77	8.41	48
chd	644	54.15	8.01	55

So what do we expect in this model?

Pr(CHD in next ten years) looks higher for *older* people?

If we predict log(odds(CHD in next ten years)), we want to ensure that value will be **rising** with increased age.

So, for the mage_1 model below, what sign do we expect for the slope of age?

```
mage_1 <- glm(chd10_f ~ age, family = binomial,
              data = fram_new)
```

Results for `mage_1`

```
tidy(mage_1) %>% kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	-5.558	0.284	-19.585	0
age	0.075	0.005	14.166	0

```
tidy(mage_1, exponentiate = TRUE) %>% kable(digits = 3)
```

term	estimate	std.error	statistic	p.value
(Intercept)	0.004	0.284	-19.585	0
age	1.077	0.005	14.166	0

Six ways to specify the outcome for this model

```
x1 <- glm(chd10_f ~ age,
          family = binomial, data = fram_new)
x2 <- glm(chd10_n ~ age,
          family = binomial, data = fram_new)
x3 <- glm((chd10_n == "1") ~ age,
          family = binomial, data = fram_new)
x4 <- glm((chd10_n == "0") ~ age,
          family = binomial, data = fram_new)
x5 <- glm((chd10_f == "chd") ~ age,
          family = binomial, data = fram_new)
x6 <- glm((chd10_f == "chd_no") ~ age,
          family = binomial, data = fram_new)
```

What will happen to the age coefficient in these models?

Age Models x1 and x2

```
x1 <- glm(chd10_f ~ age,
          family = binomial, data = fram_new)
extract_eq(x1, use_coefs = TRUE)
```

$$\log\left[\frac { P(\widehat{\operatorname{chd10\_f} = \operatorname{chd}}) }{ 1 - P(\widehat{\operatorname{chd10\_f} = \operatorname{chd}}) } \right] = -5.56 + 0.07(\operatorname{age})$$

```
x2 <- glm(chd10_n ~ age,
          family = binomial, data = fram_new)
extract_eq(x2, use_coefs = TRUE)
```

$$\log\left[\frac { P(\widehat{\operatorname{chd10\_n} = \operatorname{1}}) }{ 1 - P(\widehat{\operatorname{chd10\_n} = \operatorname{1}}) } \right] = -5.56 + 0.07(\operatorname{age})$$

Age Models x3 and x4

```
x3 <- glm((chd10_n == "1") ~ age,
          family = binomial, data = fram_new)
extract_eq(x3, use_coefs = TRUE)
```

$$\log\left[\frac{\widehat{P(\mathrm{chd10\_n} = 1)}}{1 - \widehat{P(\mathrm{chd10\_n} = 1)}}\right] = -5.56 + 0.07(\mathrm{age})$$

```
x4 <- glm((chd10_n == "0") ~ age,
          family = binomial, data = fram_new)
extract_eq(x4, use_coefs = TRUE)
```

$$\log\left[\frac{\widehat{P(\mathrm{chd10\_n} = 0)}}{1 - \widehat{P(\mathrm{chd10\_n} = 0)}}\right] = 5.56 - 0.07(\mathrm{age})$$

Age Models x5 and x6

```
x5 <- glm((chd10_f == "chd") ~ age,
          family = binomial, data = fram_new)
extract_eq(x5, use_coefs = TRUE)
```

$$\log\left[\frac { P(\widehat{\operatorname{chd10\_f} = \operatorname{chd}}) }{ 1 - P(\widehat{\operatorname{chd10\_f} = \operatorname{chd}}) } \right] = -5.56 + 0.07(\operatorname{age})$$

```
x6 <- glm((chd10_f == "chd_no") ~ age,
          family = binomial, data = fram_new)
extract_eq(x6, use_coefs = TRUE)
```

$$\log\left[\frac { P(\widehat{\operatorname{chd10\_f} = \operatorname{chd\_no}}) }{ 1 - P(\widehat{\operatorname{chd10\_f} = \operatorname{chd\_no}}) } \right] = 5.56 - 0.07(\operatorname{age})$$

Stage 2. Split the data into training/test samples.

```
set.seed(20210311)

fram_splits <-
    initial_split(fram_new, prop = 3/4, strata = chd10_f)

fram_train <- training(fram_splits)
fram_test <- testing(fram_splits)
```

Did the stratification work?

```
fram_train %>% tabyl(chd10_f)
```

```
 chd10_f    n   percent
  chd_no 2696 0.8480654
     chd  483 0.1519346
```

```
fram_test %>% tabyl(chd10_f)
```

```
 chd10_f   n   percent
  chd_no 898 0.8479698
     chd 161 0.1520302
```

Stage 3. Build a recipe for our model.

```
fram_rec <-
    recipe(chd10_f ~ age + cigs + educ + hrate +
               sbp + stroke, data = fram_new) %>%
    step_bagimpute(all_predictors()) %>%
    step_dummy(all_nominal(), -all_outcomes()) %>%
    step_normalize(all_predictors())
```

1. Specify the roles for the outcome and the predictors.
2. Use bagged trees to impute missing values in predictors.
3. Form dummy variables to represent all categorical variables.
    - Forgetting the `-all_outcomes()` wasted a half hour of my life, so learn from my mistake.
4. Normalize (subtract mean and divide by SD) all quantitative predictors.

Stage 4. Specify engines for our fit(s).

```
fram_glm_model <-
    logistic_reg() %>%
    set_engine("glm")

prior_dist <- rstanarm::normal(0, 3)

fram_stan_model <- logistic_reg() %>%
    set_engine("stan",
               prior_intercept = prior_dist,
               prior = prior_dist)
```

Stage 5. Create a workflow and fit model(s).

```
fram_glm_wf <- workflow() %>%
    add_model(fram_glm_model) %>%
    add_recipe(fram_rec)

fram_stan_wf <- workflow() %>%
    add_model(fram_stan_model) %>%
    add_recipe(fram_rec)
```

Ready to fit the models?

Fit the `glm` and `stan` models

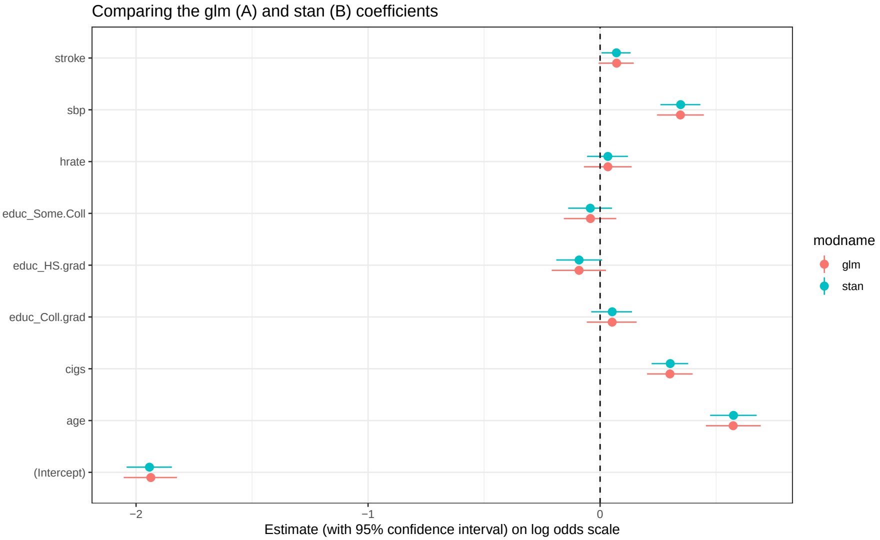
```
fit_A <- fit(fram_glm_wf, fram_train)

set.seed(432)
fit_B <- fit(fram_stan_wf, fram_train)
```

Produce tidied coefficients (log odds scale)

```
A_tidy <- tidy(fit_A, conf.int = T) %>%
    mutate(modname = "glm")

B_tidy <- broom.mixed::tidy(fit_B, conf.int = T) %>%
    mutate(modname = "stan")

coefs_comp <- bind_rows(A_tidy, B_tidy)
```

That's set us up for some plotting.

Stage 6. Compare coefficients of the fits.



Can we compare coefficients as odds ratios?

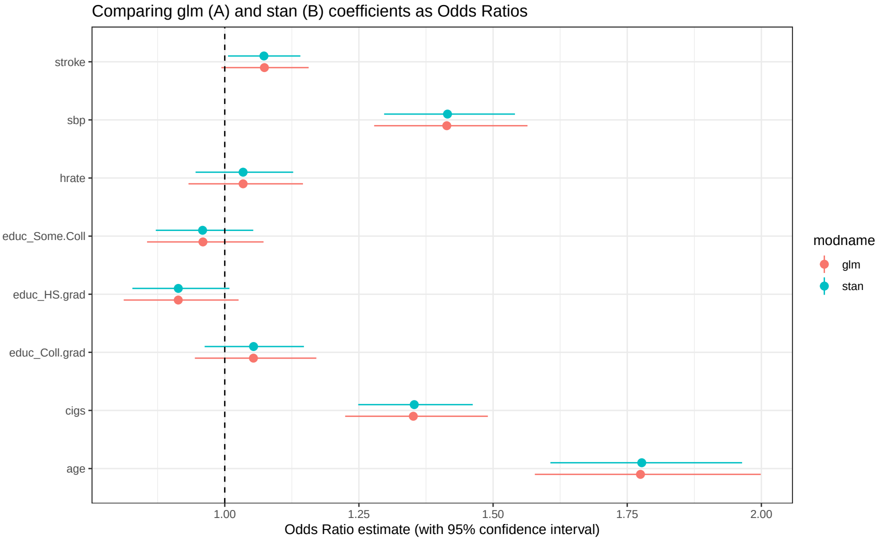
```
A_odds <- A_tidy %>%
    mutate(odds = exp(estimate),
           odds_low = exp(conf.low),
           odds_high = exp(conf.high)) %>%
    filter(term != "(Intercept)") %>%
    select(modname, term, odds, odds_low, odds_high)

head(A_odds, 2)
```

```
# A tibble: 2 x 5
  modname term   odds odds_low odds_high
  <chr>   <chr> <dbl>    <dbl>     <dbl>
1 glm     age    1.77     1.58      2.00
2 glm     cigs   1.35     1.22      1.49
```

Then repeat to create B_odds (hidden in the slides)

```
B_odds <- B_tidy %>%
    mutate(odds = exp(estimate),
```

Combined Results and Graph (OR scale)



Stage 7. Assess training sample performance.

1. We'll make predictions for the training sample using each model, and use them to find the C statistic and plot the ROC curve.
2. We'll show some other summaries of performance in the training sample.

Make Predictions with `fit_A`

We'll start by using the `glm` model `fit_A` to make predictions.

```
glm_probs <-
    predict(fit_A, fram_train, type = "prob") %>%
    bind_cols(fram_train %>% select(chd10_f))

head(glm_probs, 4)
```

```
# A tibble: 4 x 3
  .pred_chd_no .pred_chd chd10_f
         <dbl>     <dbl> <fct>
1        0.955    0.0448 chd_no
2        0.857    0.143  chd_no
3        0.612    0.388  chd
4        0.881    0.119  chd_no
```

Obtain C statistic for fit_A

Next, we'll use `roc_auc` from `yardstick`. This assumes that the first level of `chd10_f` is the thing we're trying to predict. Is that true in our case?

```
fram_train %>% tabyl(chd10_f)
```

```
 chd10_f    n   percent
  chd_no 2696 0.8480654
     chd  483 0.1519346
```

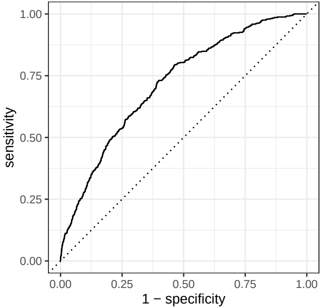
No. We want to predict the second level: `chd`. So we need to switch the `event_level` to "second", like this.

```
glm_probs %>% roc_auc(chd10_f, .pred_chd,
                      event_level = "second") %>%
    kable(dig = 5)
```

.metric	.estimator	.estimate
roc_auc	binary	0.71735

Can we plot the ROC curve for `fit_A`?

```
glm_roc <- glm_probs %>%
    roc_curve(chd10_f, .pred_chd, event_level = "second")
autoplot(glm_roc)
```



- Again, our C statistic for the `glm` fit is 0.717.

Make Predictions with `fit_B`

We'll use the `stan` model `fit_B` to make predictions.

```
stan_probs <-
    predict(fit_B, fram_train, type = "prob") %>%
    bind_cols(fram_train %>% select(chd10_f))
```

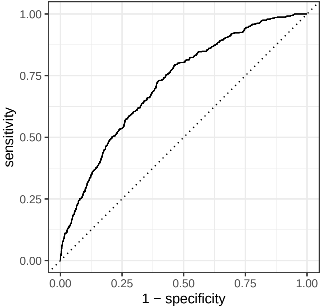
Now, we'll obtain the C statistic for `fit_B`

```
stan_probs %>%
    roc_auc(chd10_f, .pred_chd,
                     event_level = "second") %>%
    kable(dig = 5)
```

.metric	.estimator	.estimate
roc_auc	binary	0.71736

Plotting the ROC curve for `fit_B`?

```
stan_roc <- stan_probs %>%
    roc_curve(chd10_f, .pred_chd, event_level = "second")
autoplot(stan_roc)
```



- Again, our C statistic for the `stan` fit is also 0.717.

Other available summaries from `yardstick`

For a logistic regression where we're willing to specify a decision rule, we can consider:

- `Conf_mat` which produces a confusion matrix if we specify a decision rule.
    - There is a way to tidy a confusion matrix, summarize it with `summary()` and autoplot it with either a mosaic or a heatmap.
- `accuracy` = proportion of the data that are predicted correctly
- `kap` is very similar to `accuracy` but is normalized by the accuracy that would be expected by chance alone and is most useful when one or more classes dominate the distribution - attributed to Cohen (1960)
- `sens` = sensitivity and `spec` specificity
- `ppv` positive predictive value and `npv` negative predictive value

Establishing a decision rule for the `glm` fit

Let's use `.pred_chd > 0.2` for now to indicate a prediction of `chd`.

```
glm_probs <-
    predict(fit_A, fram_train, type = "prob") %>%
    bind_cols(fram_train %>% select(chd10_f)) %>%
    mutate(chd10_pre =
               ifelse(.pred_chd > 0.2, "chd", "chd_no")) %>%
    mutate(chd10_pre = fct_relevel(factor(chd10_pre),
                                   "chd_no"))
```

What can we run now?

```
conf_mat(glm_probs, truth = chd10_f, estimate = chd10_pre)
```

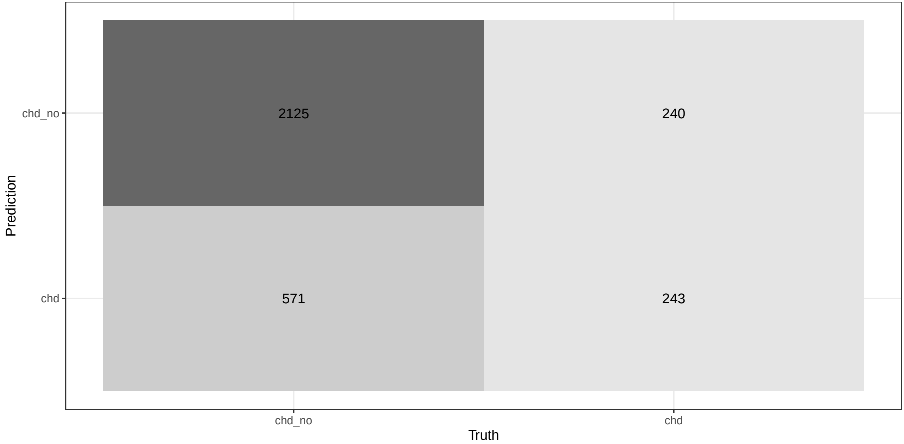
```
          Truth
Prediction chd_no  chd
    chd_no   2125  240
    chd       571  243
```

```
metrics(glm_probs, truth = chd10_f, estimate = chd10_pre)
```

```
# A tibble: 2 x 3
  .metric  .estimator .estimate
  <chr>    <chr>          <dbl>
1 accuracy binary         0.745
2 kap      binary         0.227
```

Plot a confusion matrix for the `glm` fit?

```
conf_mat(glm_probs,
         truth = chd10_f, estimate = chd10_pre) %>%
    autoplot(type = "heatmap")
```



More Confusion Matrix Summaries?

Other available metrics include:

- sensitivity, specificity, positive predictive value, negative predictive value, and the statistics below.

```
conf_mat(glm_probs, truth = chd10_f, estimate = chd10_pre) %>%
    summary() %>% slice(7:13)
```

```
# A tibble: 7 x 3
  .metric              .estimator .estimate
  <chr>                <chr>          <dbl>
1 mcc                  binary         0.240
2 j_index              binary         0.291
3 bal_accuracy         binary         0.646
4 detection_prevalence binary         0.744
5 precision            binary         0.899
6 recall               binary         0.788
7 f_meas               binary         0.840
```

Establishing a decision rule for the stan fit

Let's also use .pred_chd > 0.2 to indicate a prediction of chd.

```
stan_probs <-
    predict(fit_B, fram_train, type = "prob") %>%
    bind_cols(fram_train %>% select(chd10_f)) %>%
    mutate(chd10_pre =
               ifelse(.pred_chd > 0.2, "chd", "chd_no")) %>%
    mutate(chd10_pre = fct_relevel(factor(chd10_pre),
                                   "chd_no"))
```

Confusion Matrix and Basic Metrics

```
conf_mat(stan_probs, truth = chd10_f, estimate = chd10_pre)
```

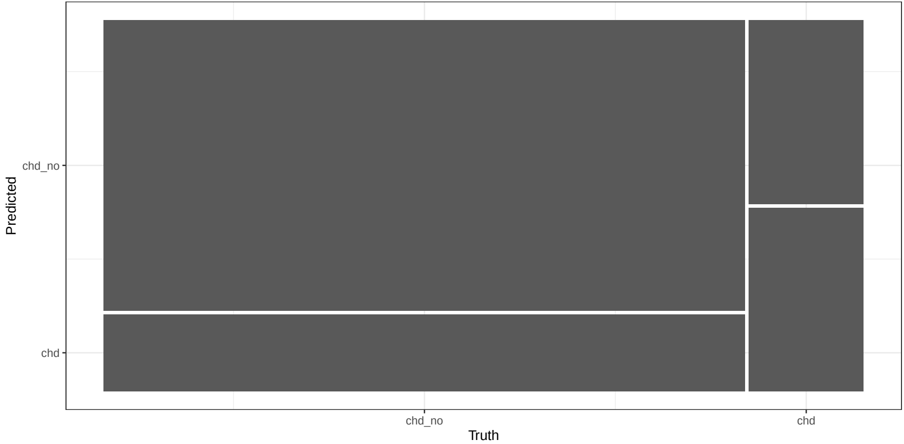
```
          Truth
Prediction chd_no  chd
    chd_no   2131  242
    chd       565  241
```

```
metrics(stan_probs, truth = chd10_f, estimate = chd10_pre)
```

```
# A tibble: 2 x 3
  .metric  .estimator .estimate
  <chr>    <chr>          <dbl>
1 accuracy binary         0.746
2 kap      binary         0.227
```

Plot a confusion matrix?

```
conf_mat(stan_probs,
         truth = chd10_f, estimate = chd10_pre) %>%
    autoplot(type = "mosaic")
```



More Confusion Matrix Summaries?

```
conf_mat(stan_probs,
         truth = chd10_f, estimate = chd10_pre) %>%
    summary()
```

```
# A tibble: 13 x 3
   .metric              .estimator .estimate
   <chr>                <chr>          <dbl>
 1 accuracy             binary         0.746
 2 kap                  binary         0.227
 3 sens                 binary         0.790
 4 spec                 binary         0.499
 5 ppv                  binary         0.898
 6 npv                  binary         0.299
 7 mcc                  binary         0.239
 8 j_index              binary         0.289
 9 bal_accuracy         binary         0.645
10 detection_prevalence binary         0.746
```

Stage 8. Assess test sample performance.

```
glm_test <-
    predict(fit_A, fram_test, type = "prob") %>%
    bind_cols(fram_test %>% select(chd10_f))

stan_test <-
    predict(fit_B, fram_test, type = "prob") %>%
    bind_cols(fram_test %>% select(chd10_f))
```

Test Sample C statistic comparison?

```
glm_test %>% roc_auc(chd10_f, .pred_chd,
                     event_level = "second") %>%
    kable(dig = 4)
```

.metric	.estimator	.estimate
roc_auc	binary	0.7253

```
stan_test %>% roc_auc(chd10_f, .pred_chd,
                     event_level = "second") %>%
    kable(dig = 4)
```

.metric	.estimator	.estimate
roc_auc	binary	0.7254

Coming Up

1. Quiz A will be available tomorrow, due 2021-03-22.
2. Project 1 portfolio and presentation are due 2021-03-29.
3. Remember, we don't have class on Tuesday. Enjoy the "break".
4. Next class is Class 12 on 2021-03-18.
    - We'll discuss p values, the replication crisis, and some related matters.

Thank you!