Introducing {workboots}

Generate prediction intervals from tidymodel workflows

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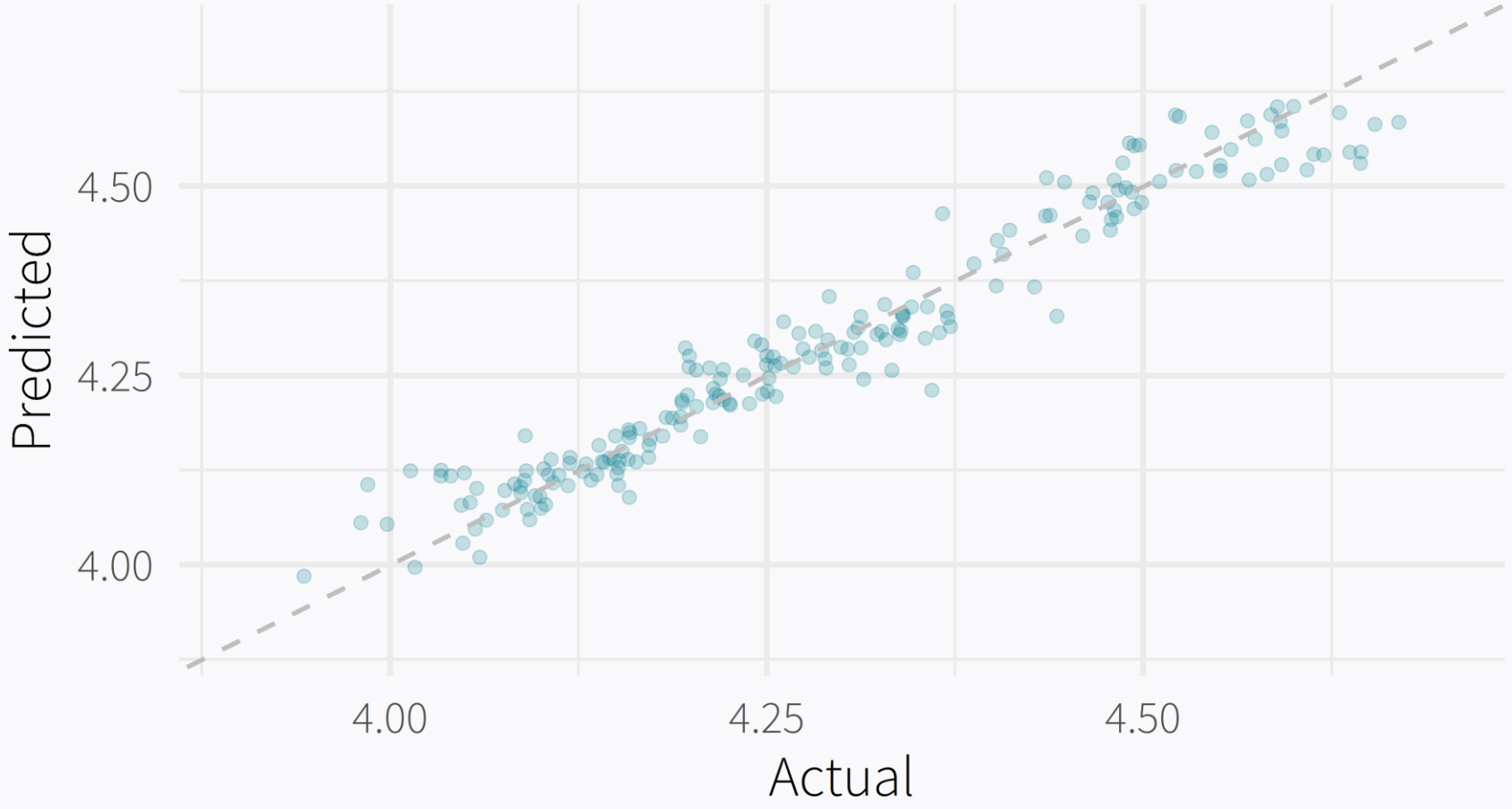
2022-07-27


BURNDY
PATRIOT® PAT750XT-18V
HIGH PERFORMANCE


AUTOMAXX

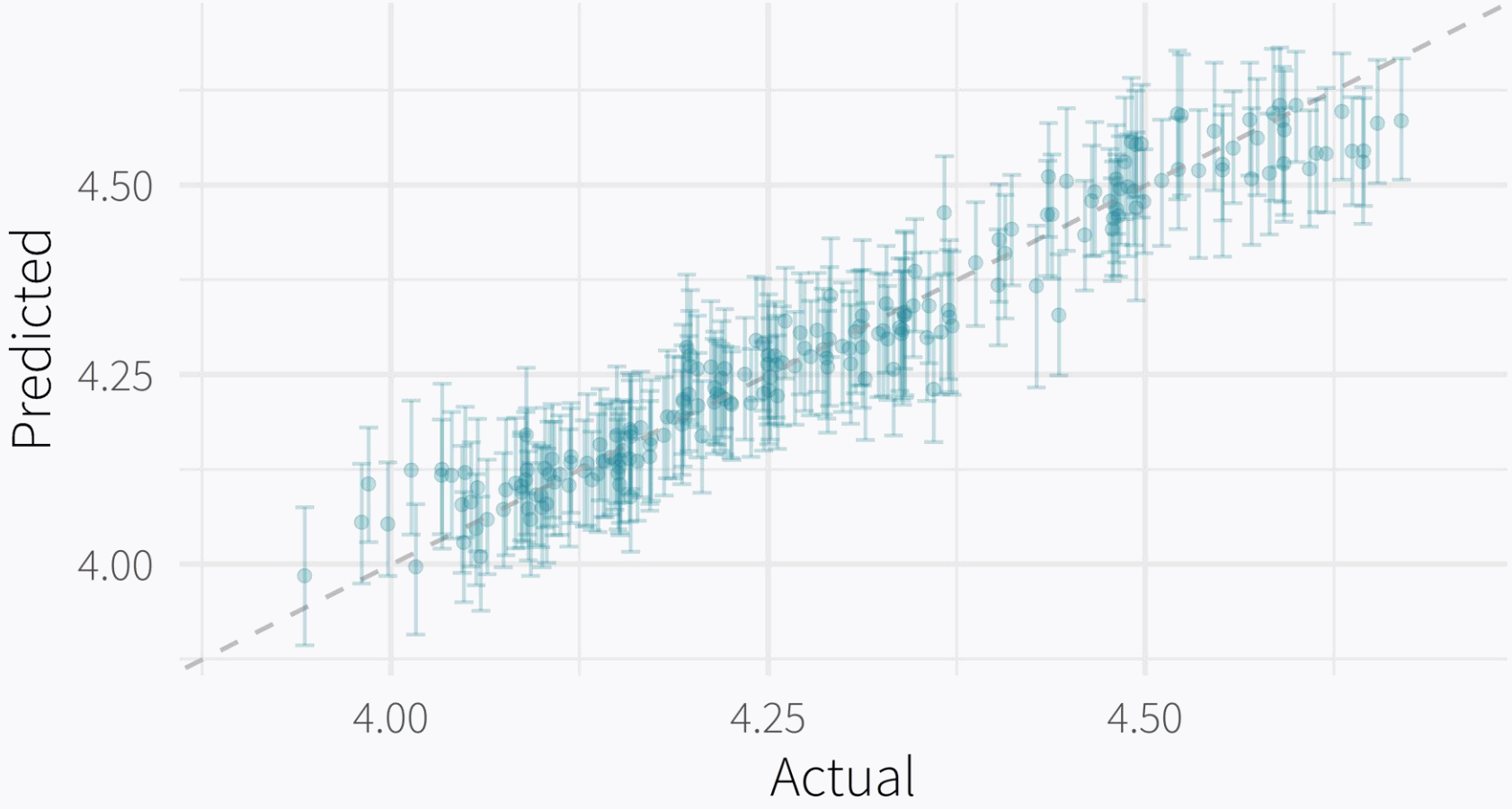
A model without {workboots}

On its own, XGBoost can only generate point predictions



A model with {workboots}

With workboots, we can generate prediction intervals!



Motivation/Background

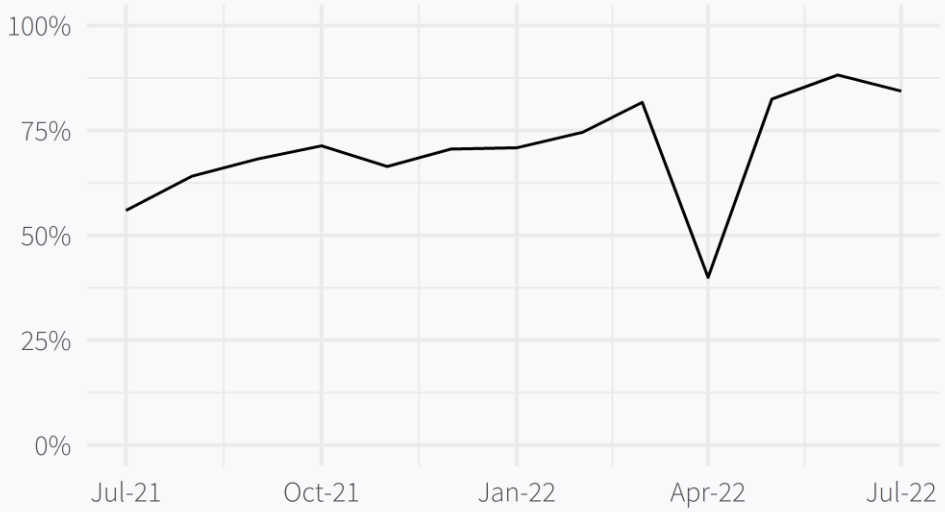
about me

MEMORIAL HERMANN

- Sr. CX Analyst, MHHS
- Patient satisfaction survey data
- Administer, understand, improve
- Answering questions

Monthly Patient Satisfaction Scores

Why the large drop in April?



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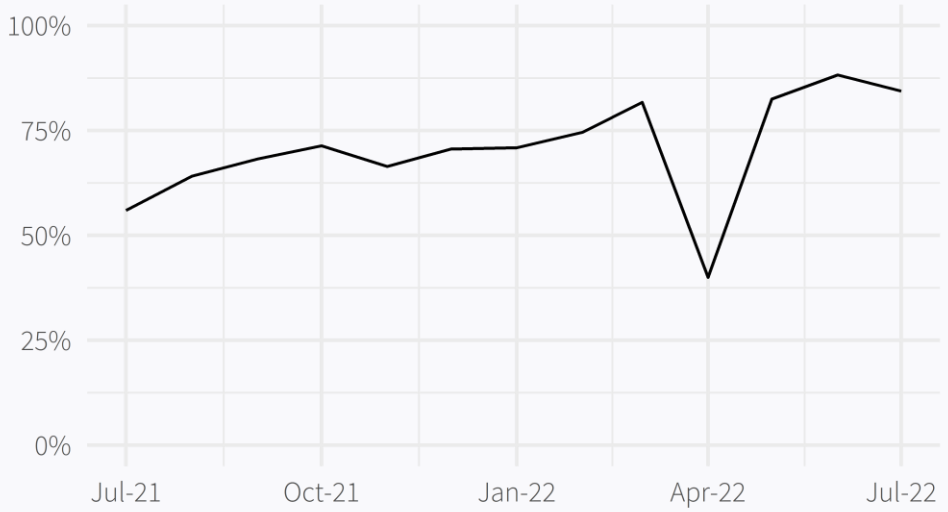
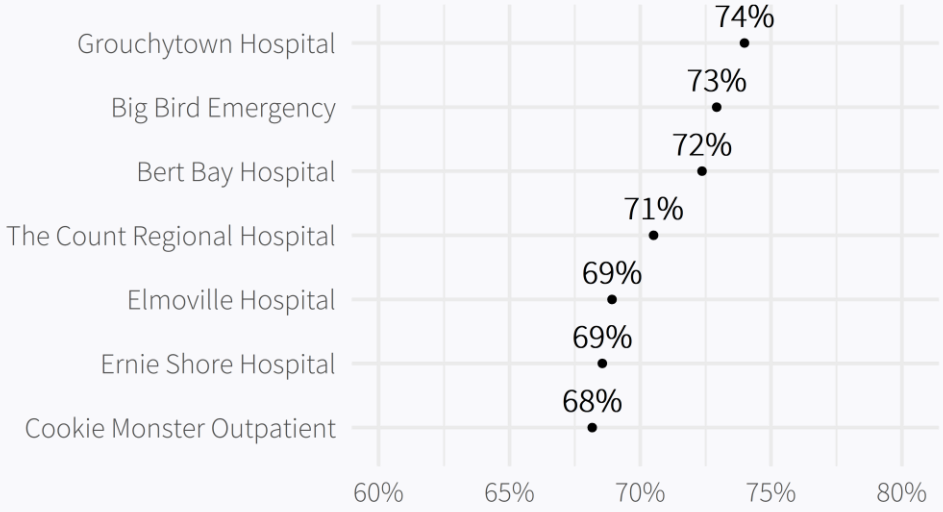


Patient Satisfaction Scores by Hosptial

Are these real differences across the hospitals?



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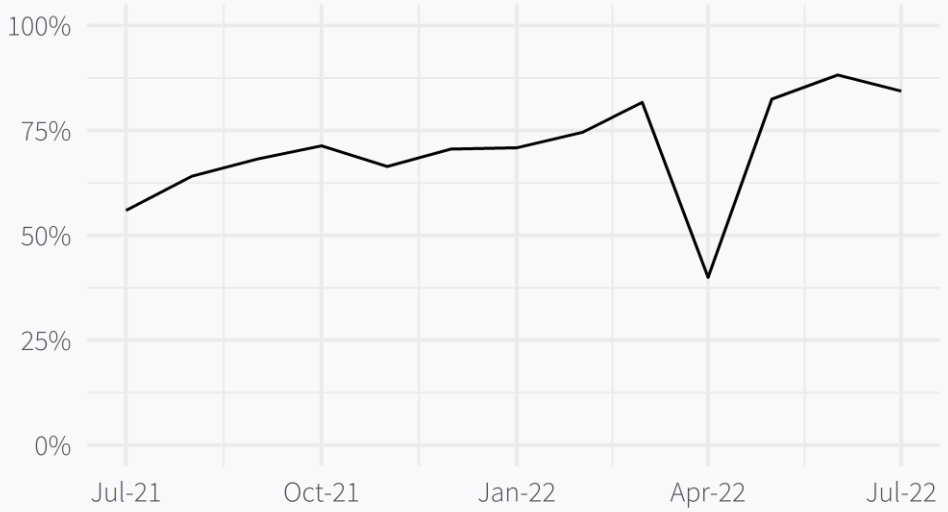

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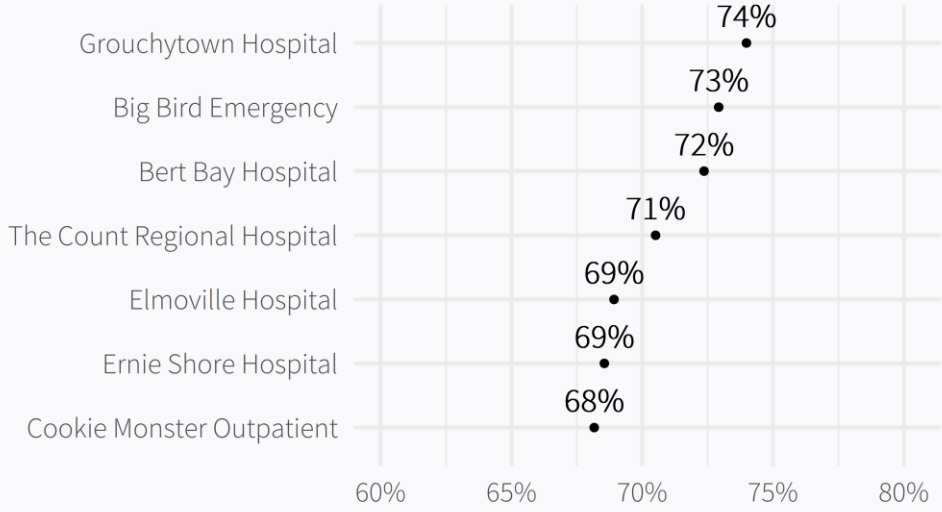
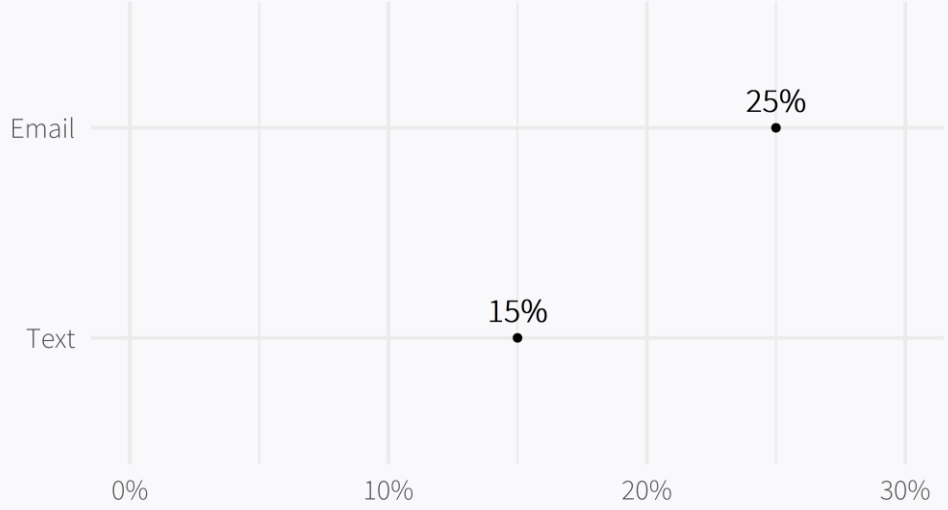


Response Rates by Distribution Method

Which method gets more responses?



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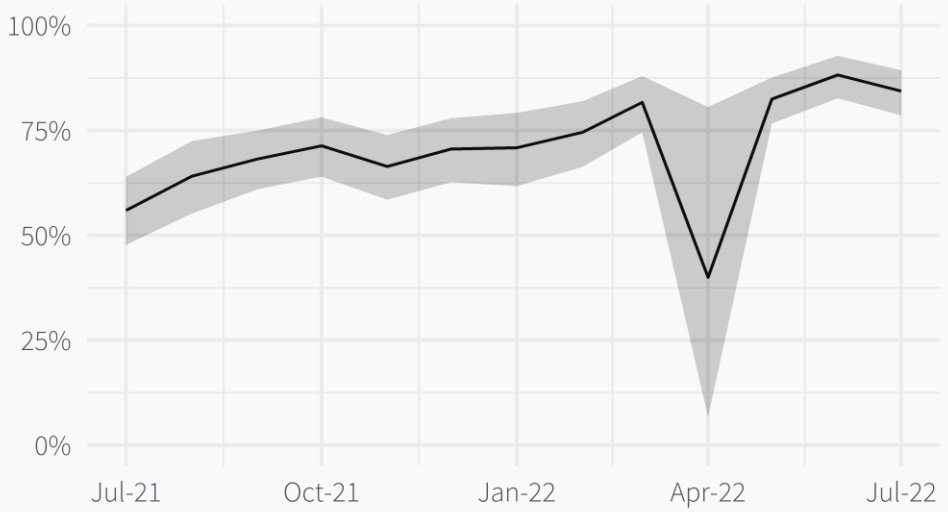

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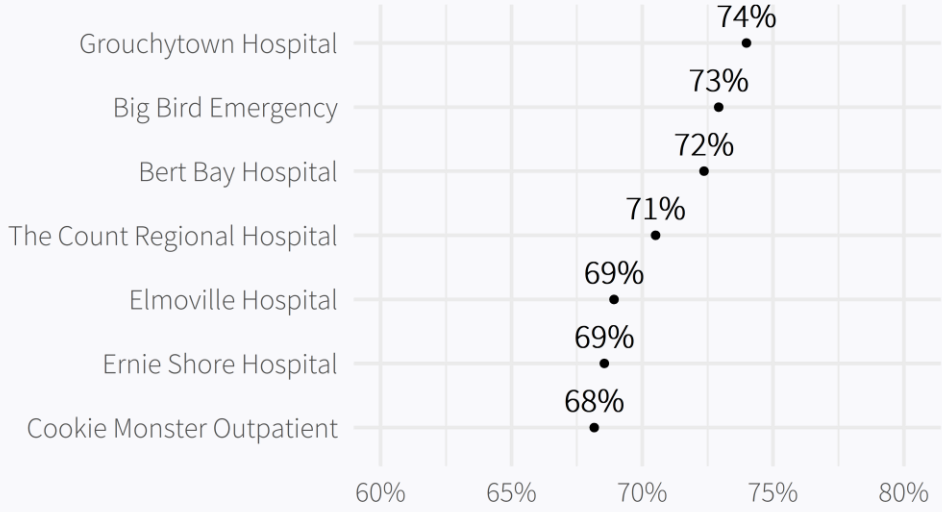

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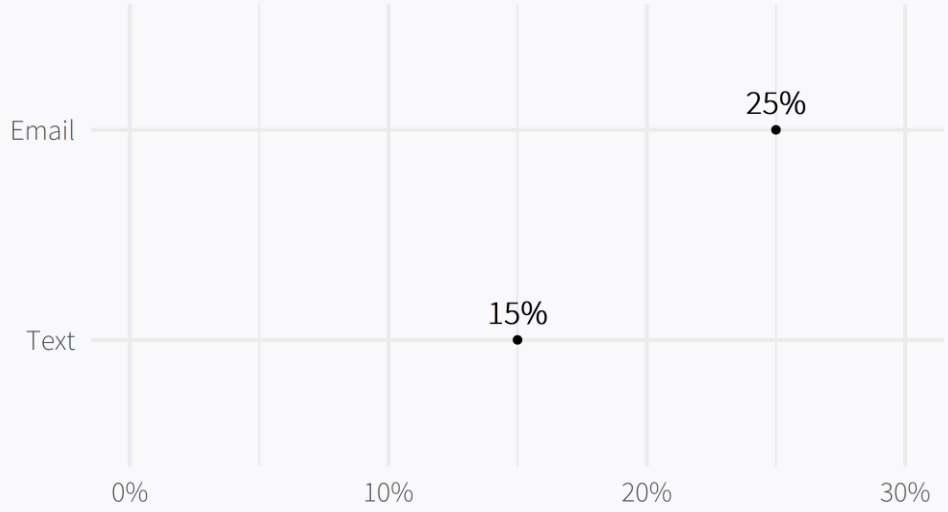

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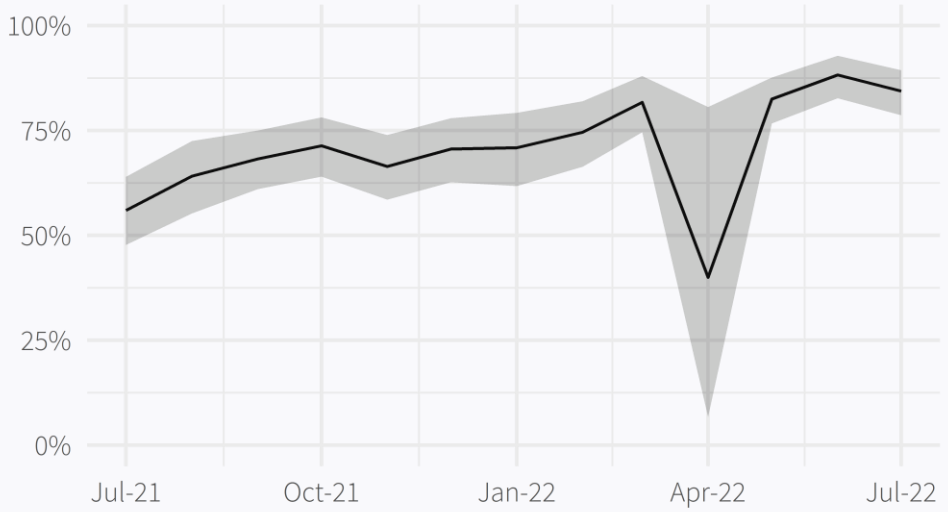

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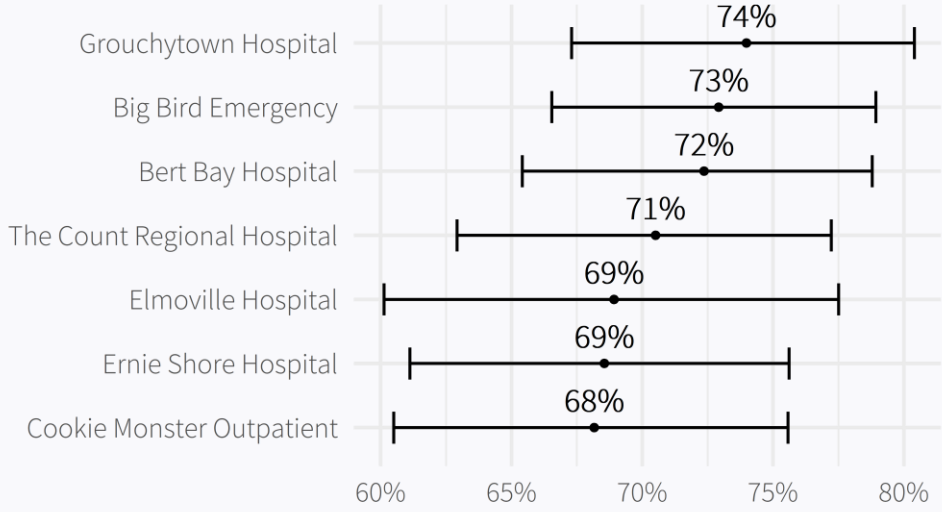

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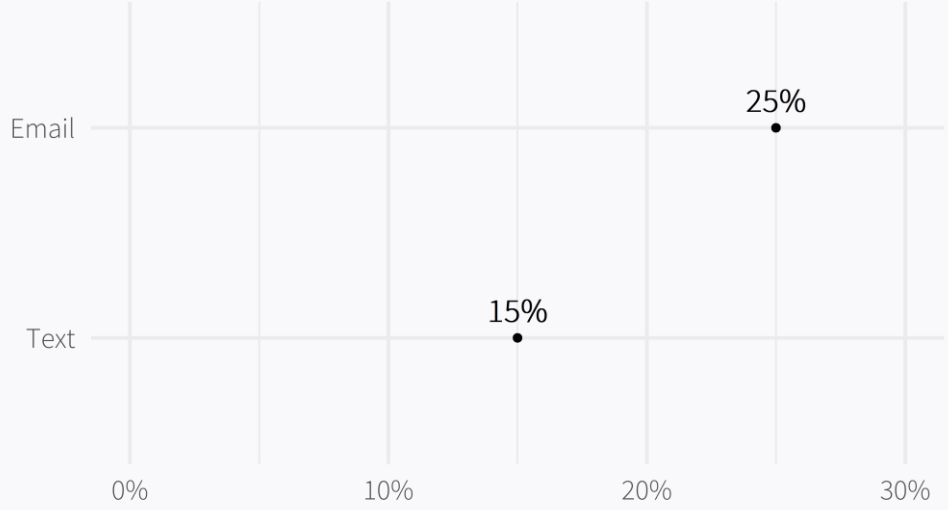

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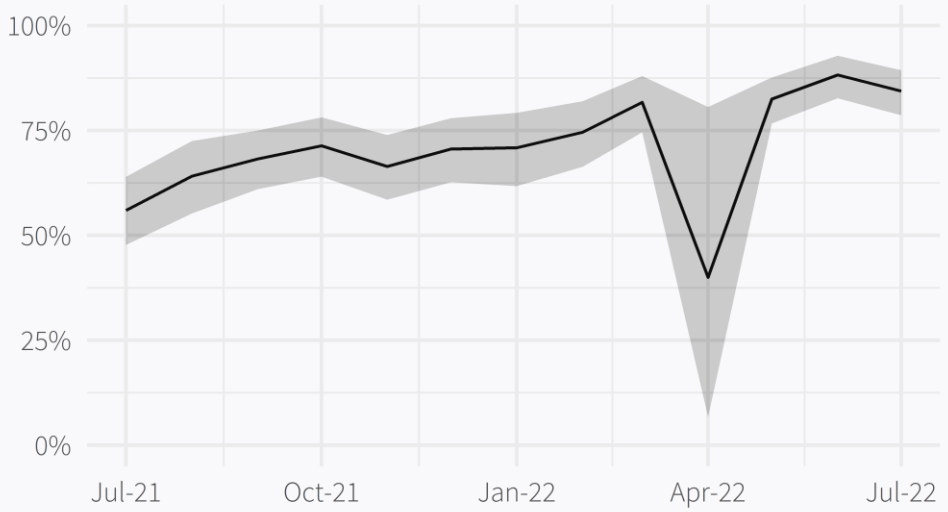

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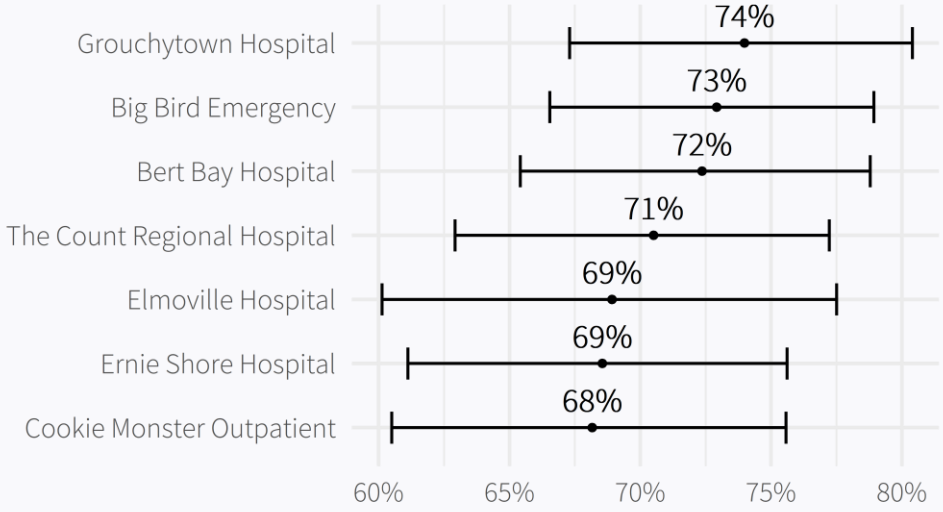

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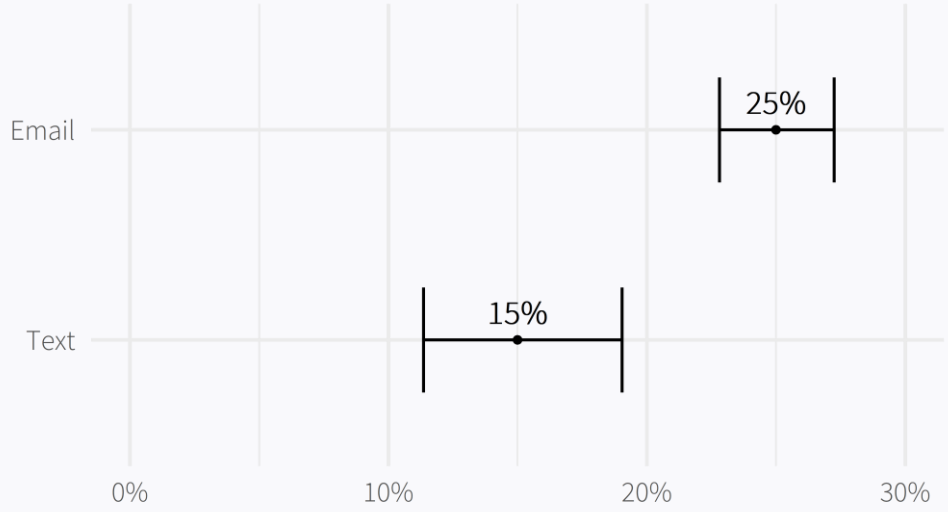


5.0 (19)

★★★★★

4.6 (2,280)

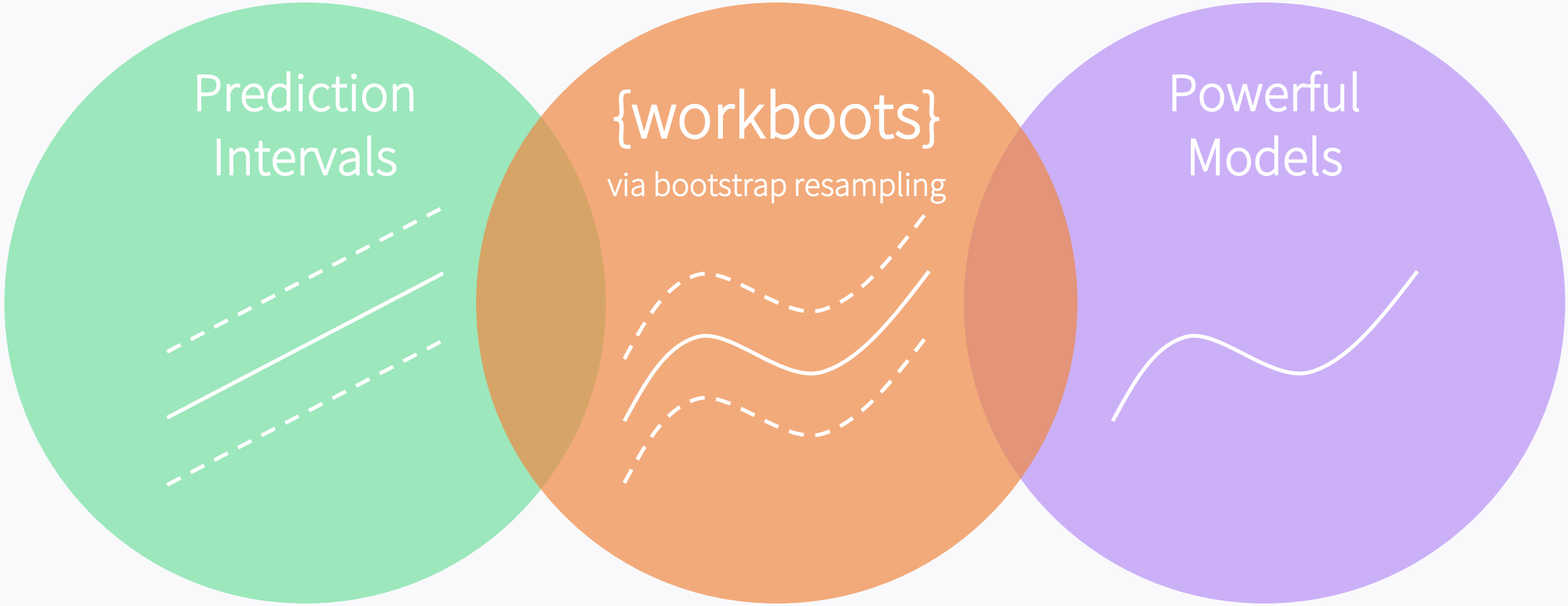
★★★★½

What are the drivers of patient satisfaction?

What will our score be?

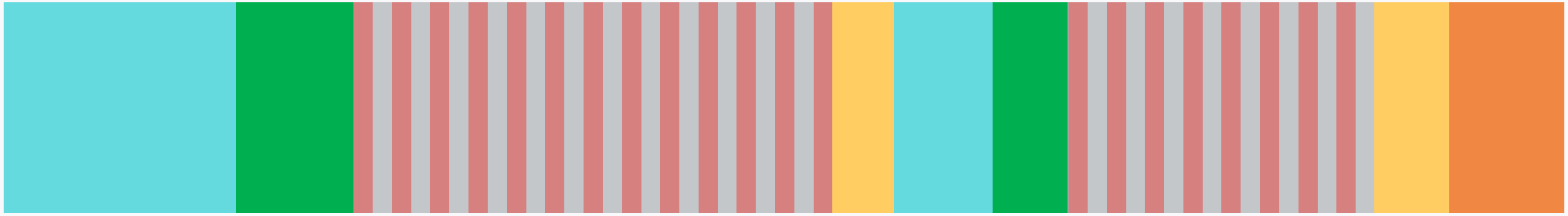
How many responses are we expecting?


XGBoost
me
lm()


Prediction Intervals
{workboots}
via bootstrap resampling
Powerful Models

Package Overview

model building timeline



Exploratory Data Analysis

Model Fit

Model Evaluation

Feature Engineering

Model Tuning

Model Finalization

model building timeline

workboots

Exploratory Data Analysis

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Model Finalization

how this works

1. Generate resamples
2. Fit many models to resamples
3. Predict on new data
4. Summarize prediction range

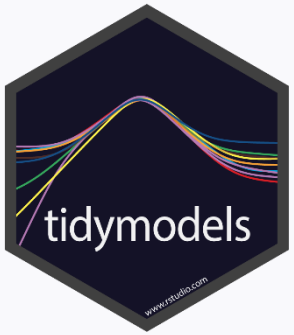
workboots checklist

- ✓ Normally distributed residuals
- ✓ Time to run
- ✓ Actually need powerful model

using workboots

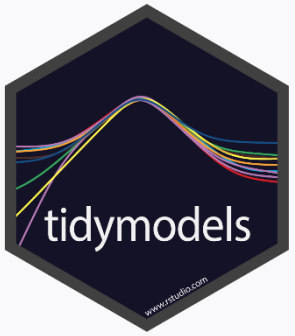
1. Set up a workflow
2. Generate predictions
3. Summarise results

set up a workflow




```
library(tidymodels)
```

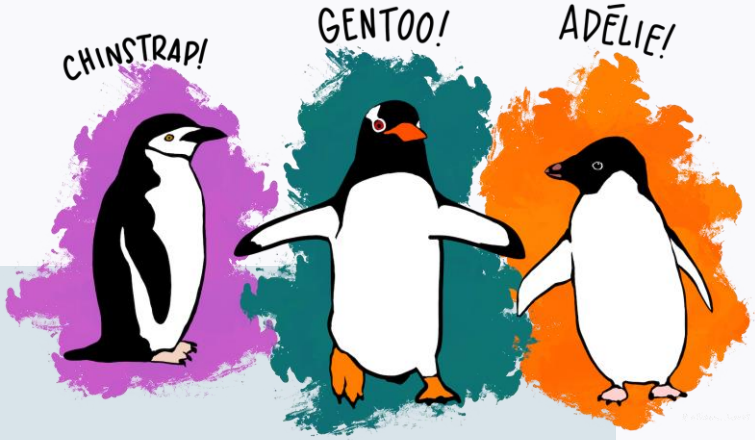
set up a workflow




```
library(tidymodels)

# setup our data
data("penguins")
penguins <- penguins %>% drop_na()
```

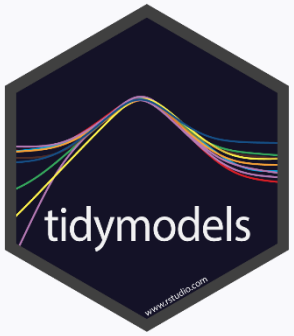
set up a workflow




```
penguins %>% glimpse()

#> Rows: 333
#> Columns: 7
#> $ species           <fct> Adelie, Adelie, Adelie, ...
#> $ island            <fct> Torgersen, Torgersen, To...
#> $ bill_length_mm    <dbl> 39.1, 39.5, 40.3, 36.7, ...
#> $ bill_depth_mm     <dbl> 18.7, 17.4, 18.0, 19.3, ...
#> $ flipper_length_mm <int> 181, 186, 195, 193, 190,...
#> $ body_mass_g       <int> 3750, 3800, 3250, 3625, ...
#> $ sex               <fct> male, female, female, fe...
```

set up a workflow

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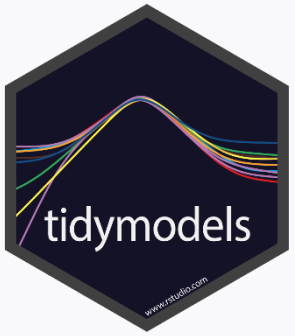
library(tidymodels)

# setup our data
data("penguins")
penguins <- penguins %>% drop_na()

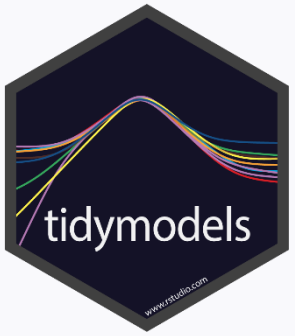
set.seed(123)
penguins_split <- initial_split(penguins)
penguins_test <- testing(penguins_split)
penguins_train <- training(penguins_split)
```

set up a workflow




```
# setup a basic preprocessing recipe
penguins_rec <-
  recipe(body_mass_g ~ ., data = penguins_train) %>%
  step_dummy(all_nominal())
```

set up a workflow

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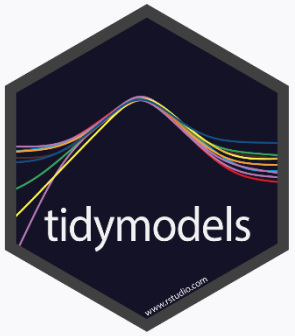


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# put together a workflow
penguins_wf <-
  workflow() %>%
  add_recipe(penguins_rec) %>%
  add_model(boost_tree("regression"))
```

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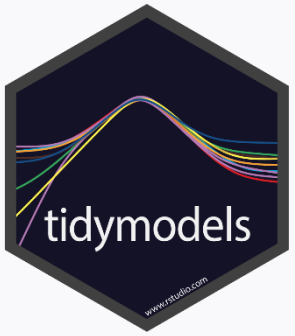


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time for workboots!

generate predictions


```
library(workboots)
```

generate predictions


```
library(workboots)

# generate a bootstrap prediction interval
set.seed(345)
penguins_preds <-
  penguins_wf %>%
  predict_boots(
    n = 2000,
    training_data = penguins_train,
    new_data = penguins_test,
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generate predictions


```
penguins_preds
```

```
#> # A tibble: 84 x 5
#>     rowid .preds
#>     <int> <list>
#> 1       1 <tibble [2,000 x 2]>
#> 2       2 <tibble [2,000 x 2]>
#> 3       3 <tibble [2,000 x 2]>
#> 4       4 <tibble [2,000 x 2]>
#> 5       5 <tibble [2,000 x 2]>
#> # ... with 79 more rows
```

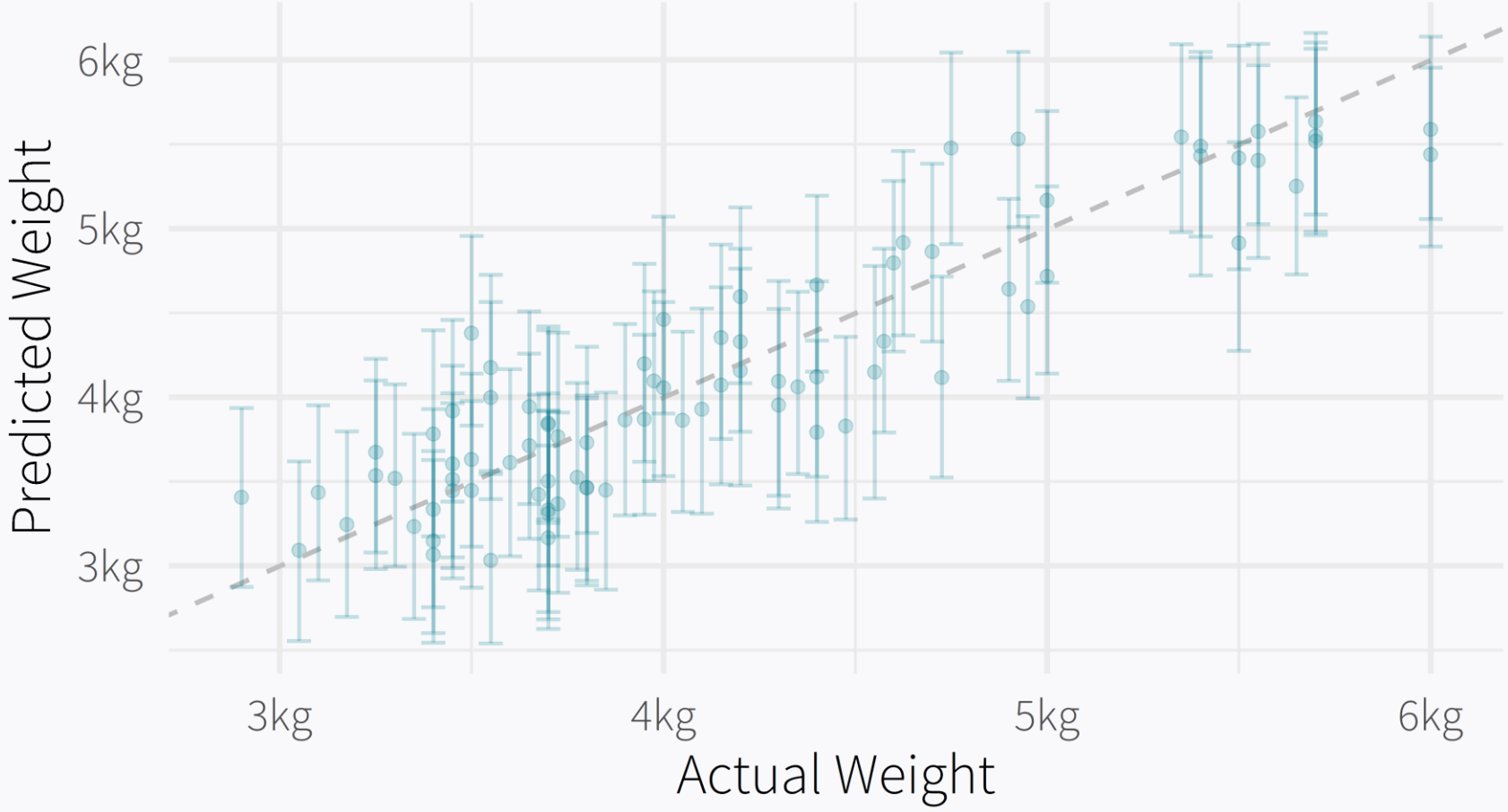
summarise results


```
penguins_preds %>%
  summarise_predictions() %>% select(-.preds)

#> # A tibble: 84 x 5
#>     rowid .pred .pred_lower .pred_upper
#>     <int> <dbl>       <dbl>       <dbl>
#> 1       1 3465.       2913.       3994.
#> 2       2 3535.       2982.       4100.
#> 3       3 3604.       3050.       4187.
#> 4       4 4157.       3477.       4764.
#> 5       5 3868.       3305.       4372.
#> # ... with 79 more rows
```

Predicting Palmer Penguin Pounds

workboots allows us to generate prediction intervals



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    interval = "confidence"
  )
```
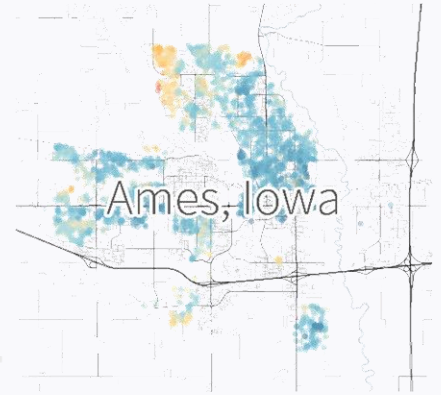
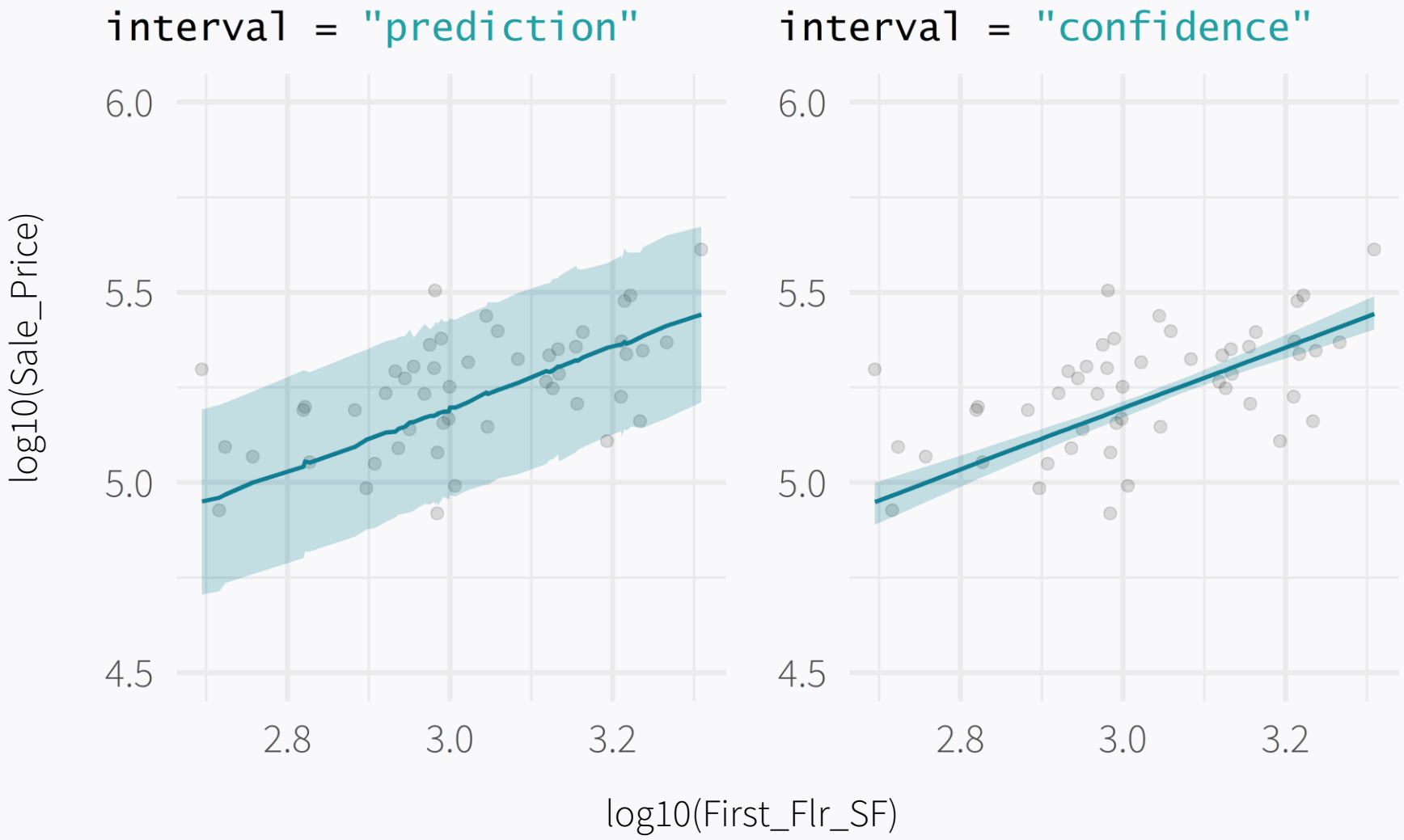

{workboots} can generate multiple interval types





generate importances


```
# generate a bootstrap variable importances
set.seed(345)
penguins_vi <-
  penguins_wf %>%
  vi_boots(
    n = 2000,
    training_data = penguins_train
  )
```

generate importances

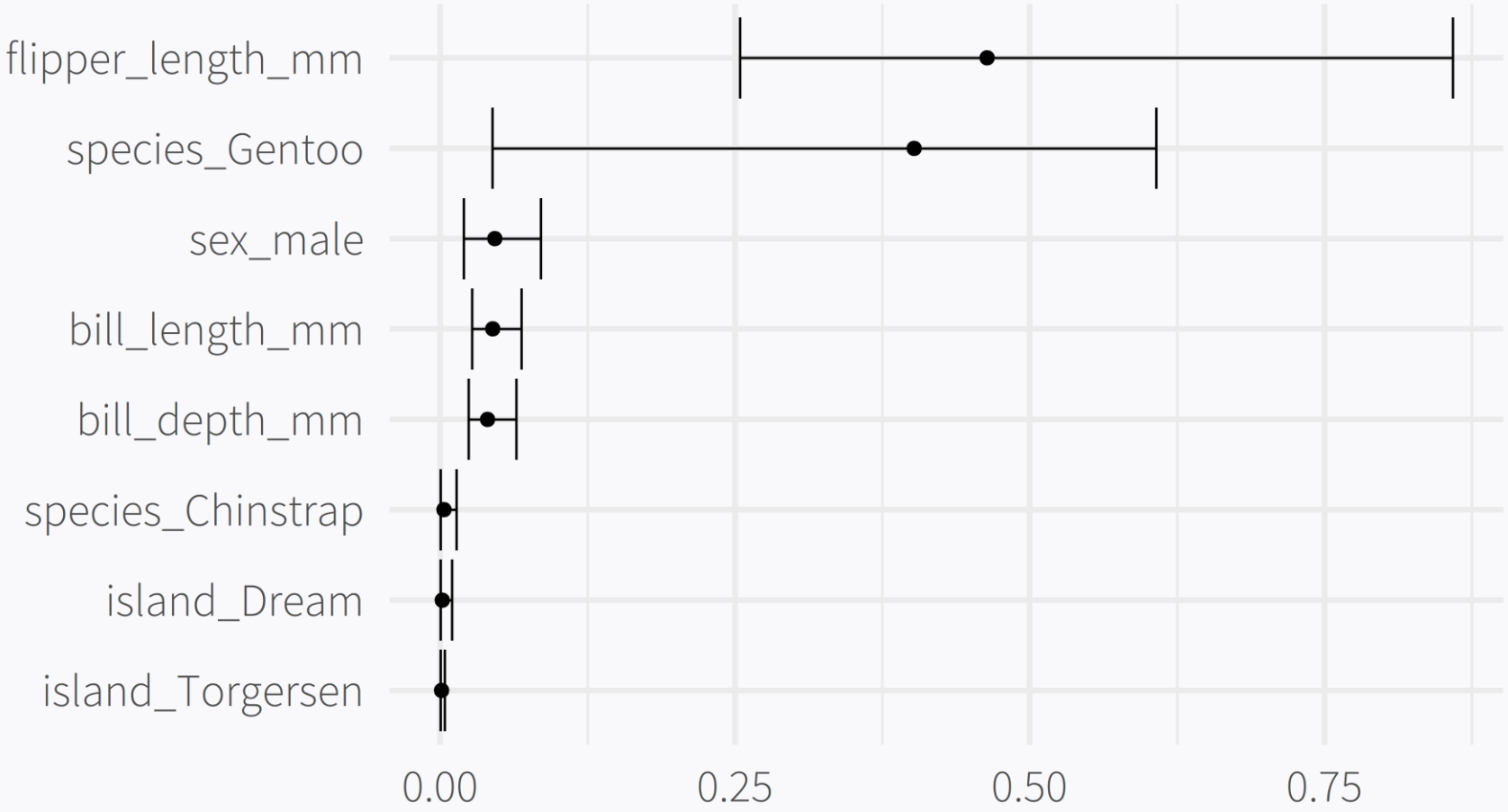

```
penguins_vi

#> # A tibble: 8 x 2
#>   variable           .importances
#>   <int>              <list>
#> 1 flipper_length_mm <vi [2,000 x 2]>
#> 2 species_Gentoo    <vi [1,928 x 2]>
#> 3 bill_length_mm    <vi [2,000 x 2]>
#> 4 bill_depth_mm     <vi [2,000 x 2]>
#> 5 sex_male          <vi [2,000 x 2]>
#> # ... With 3 more rows
```

summarise importances


```
penguins_vi %>%
  summarise_importance() %>% select(-.importances)

#> # A tibble: 8 x 2
#>   variable           .importance .importance_lower
#>   <int>                    <dbl>               <dbl>
#> 1 flipper_length_mm        0.464               0.254
#> 2 species_Gentoo           0.402               0.044
#> 3 bill_length_mm           0.045               0.027
#> 4 bill_depth_mm            0.040               0.024
#> 5 sex_male                 0.046               0.020
#> # ... with 3 more rows, and 1 more variable:
#> #     .importance_upper <dbl>
```

Bootstrap estimations of variable importance

Uses vip::vi() under the hood



give it a shot!

- Specific tool, specific job
- Generate prediction intervals
- Use any model type

thank you!

connect with me!

Social

- twitter: @markjrieke
- github: github.com/markjrieke
- Linkedin: linkedin.com/in/mark-j-rieke-ab4b0ab4

additional resources

Packages

- ngboostForecast : Probabilistic forecasting with Python's ngboost [CRAN/github]
- ggdist : Visualizations of distributions and uncertainty [CRAN/github]
- spin : Functions for simulating prediction intervals [github]
- ungeviz : Tools for visualizing uncertainty with ggplot2 [github]

Reading

- Bootstrap Methods and their Application, (Davison and Hinkley)
- Improvements on Cross Validation – the .632+ Bootstrap Method, (Efron and Tibshirani)
- Tidy Modeling with R (Kuhn and Silge)
- Applied Predictive Modeling (Kuhn and Johnson)

Backup