AE 16: Exam 02 Review

Add your name here

> **Important**
>
> The AE is due on GitHub by Thursday, December 08, 11:59pm.
>
> Note: This in-class review is not exhaustive. Use lecture notes notes, application exercises, labs, homework, and readings for a comprehensive exam review.

Packages

```
library(tidyverse)
library(tidymodels)
library(knitr)
```

Part 1: Multiple linear regression

The goal of this analysis is to use characteristics of loan applications to predict the interest rate on the loan. We will use a random sample of loans given by Lending Club, a peer-to-peer lending service. The random sample was drawn from `loans_full_schema` in the **openintro** R package. Click here for the codebook.

```
loans <- read_csv("data/loans-sample.csv")
```

Exercise 1

Split the data into training (75%) and testing (25%) sets. Use seed `1205`.

```
# add code here
```

Exercise 2

Write the equation of the statistical model for predicting interest rate (`interest_rate`) from debt to income ratio (`debt_to_income`), the term of loan (`term`), the number of inquiries (credit checks) into the applicant's credit during the last 12 months (`inquiries_last_12m`), whether there are any bankruptcies listed in the public record for this applicant (`bankrupt`), and the type of application (`application_type`). The model should allow for the effect of to income ratio on interest rate to vary by application type.

[Add model here]

Exercise 3

Specify a linear regression model. Call it `loans_spec`.

```
# add code here
```

Exercise 4

Use the training data to build the following recipe:

- Predict `interest_rate` from `debt_to_income`, `term`, `inquiries_last_12m`, `public_record_bankrupt`, and `application_type`.
- Mean center `debt_to_income`.
- Make `term` a factor.
- Create a new variable: `bankrupt` that takes on the value "no" if `public_record_bankrupt` is 0 and the value "yes" if `public_record_bankrupt` is 1 or higher. Then, remove `public_record_bankrupt`.
- Interact `application_type` with `debt_to_income`.
- Create dummy variables where needed and drop any zero variance variables.

```
# add code here
```

Exercise 5

Create the workflow that brings together the model specification and recipe.

```
# add code here
```

Exercise 6

Conduct 10-fold cross validation. Use the seed `1205`. You will only collect the default metrics, R^2 and RMSE. You do not need to collect AIC, BIC or Adj. R^2.

```
# add code here
```

Exercise 7

Collect and summarize R^2 and RMSE metrics from your CV resamples.

```
# add code here
```

Why are we focusing on $R^{2}and RMSE instead of adjusted} R^2, AIC, BIC?

[Add response here]

Exercise 8

Refit the model on the entire training data.

```
# add code here
```

Then, interpret the following in the context of the data:

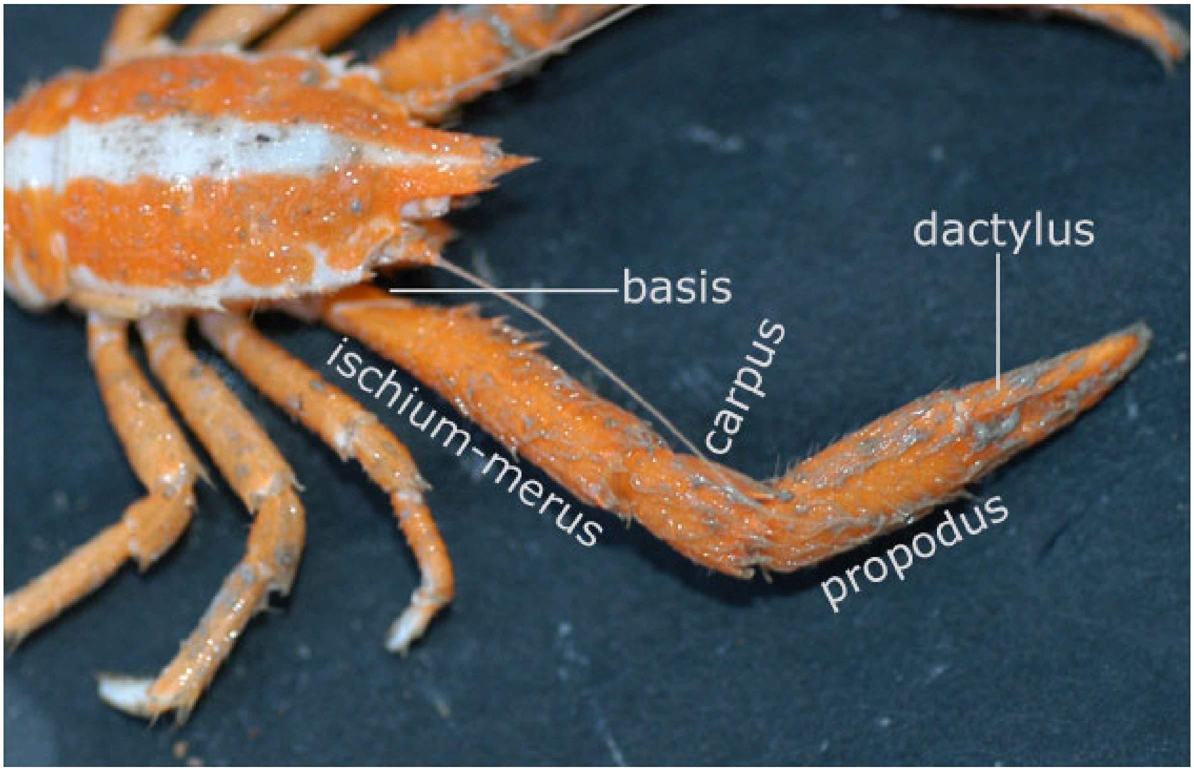
- Intercept
- `debt_to_income` for joint applications
- `term`

Part 2: Logistic regression

Data

As part of a study of the effects of predatory invasive crab species on snail populations, researchers measured the mean closing forces and the propodus heights of the claws on several crabs of three species.

```
claws <- read_csv("data/claws.csv") |>
  mutate(lb = as_factor(lb))
```



The data set contains following variables:

- `force`: Closing force of claw (newtons)
- `height`: Propodus height (mm)
- `species`: Crab species - Cp(Cancer productus), Hn (Hemigrapsus nudus), Lb(Lophopanopeus bellus)
- `lb`: 1 if Lophopanopeus bellus species, 0 otherwise
- `hn`: 1 if Hemigrapsus nudus species, 0 otherwise
- `cp`: 1 if Cancer productus species, 0 otherwise
- `force_cent`: mean centered force
- `height_cent`: mean centered height

Getting started

- Why do we use the log-odds as the response variable?

[Add response here]

- Fill in the blanks:

    - Use log-odds to …

  - Use odds to …
  - Use probabilities to …

- Suppose we want to use force to determine whether or not a crab is from the Lophopanopeus bellus (Lb) species. Why should we use a logistic regression model for this analysis?

Exercise 9

We will use `force_cent`, the mean-centered variable for force in the model. The model output is below. Write the equation of the model produced by R. Don't forget to fill in the blanks for ….

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-0.798	0.358	-2.233	0.026	-1.542	-0.123
force_cent	0.043	0.039	1.090	0.276	-0.034	0.123

Let π be…

$$\log\left(\frac{\hat{\pi}}{1-\hat{\pi}}\right) =$$

Exercise 10

Interpret the intercept in the context of the data.

Exercise 11

Interpret the effect of force in the context of the data.

Exercise 12

Now let's consider adding height to the model. Fit the model that includes `height_cent`. Then use AIC to choose the model that best fits the data.

```
lb_fit_2 <- logistic_reg() |>
  set_engine("glm") |>
  fit(lb ~ force_cent + height_cent, data = claws)
```

```r
tidy(lb_fit_2, conf.int = TRUE) |>
  kable(digits = 3)
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	-1.130	0.463	-2.443	0.015	-2.167	-0.306
force_cent	0.211	0.092	2.279	0.023	0.056	0.424
height_cent	-0.895	0.398	-2.249	0.025	-1.815	-0.234

Exercise 13

What do the following mean in the context of this data. Explain and calculate them.

- Sensitivity: …
- Specificity: …
- Negative predictive power: …

> **! Important**
>
> To submit the AE:
>
> - Render the document to produce the PDF with all of your work from today's class.
> - Push all your work to your `ae-16-` repo on GitHub. (You do not submit AEs on Gradescope).