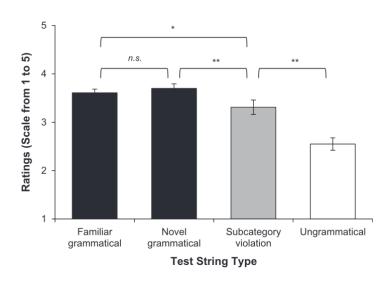
# Three common mistakes in statistics and how to avoid them

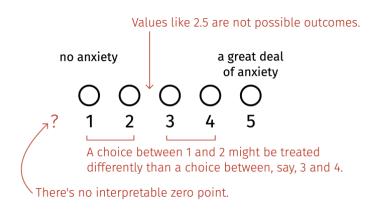
Elizabeth Pankratz, 26 March 2025

### Something you won't be able to unsee

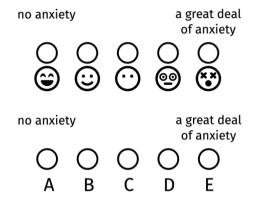


Taking the means of discrete ratings is very common—but a little strange!

## Why Likert scale ratings aren't continuous numeric



Numbers on a Likert scale are just labels.



### The mistake and how you'll avoid it

#### The mistake

#### How you'll avoid it

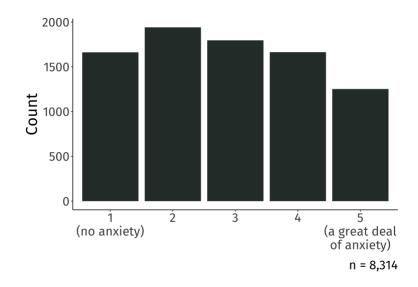
A common R mistake: Letting R treat all variables that look like numbers as continuous numeric.

**An advanced stats mistake:** Modelling categorical, ordinal data as if it were numeric.

#### A foundational stats mistake:

Interpreting a significant *p*-value as evidence that an effect exists in the real world.

The data: Students' anxiety ratings for "Going to ask my statistics teacher for individual help with material I am having difficulty understanding".



```
slice(anx, 45:50)
## # A tibble: 6 × 3
##
     unique_id gender
                              rating
##
     <chr>
               <chr>
                               <dbl>
## 1 7d28c303 Female/Woman
## 2 7d55383a Another Gender
                                   4
## 3 8116550a Female/Woman
                                   1
## 4 83491ff9 Female/Woman
## 5 8450f8ad Male/Man
                                   2
## 6 876547d6 Female/Woman
```

rating looks like numbers, and R treats it like numbers, as dbl.

So it's tempting to manipulate it like numbers.

```
mean(anx$rating)
## [1] 2.868054
```

#### Remember: We are smarter than R is

Store categorical variables as factors.

```
anx <- anx |>
mutate(rating = factor(rating))
```

Now it's impossible to incorrectly treat them as if they're numeric!

```
mean(anx$rating)
## [1] NA
```

### The mistake and how you'll avoid it

#### The mistake

#### How you'll avoid it

A common R mistake: Letting R treat all variables that look like numbers as continuous numeric.

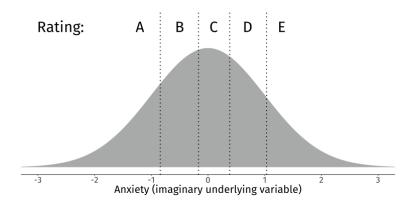
When a variable comes from a Likert scale, tell R it's categorical using factor().

**An advanced stats mistake:** Modelling categorical, ordinal data as if it were numeric.

#### A foundational stats mistake:

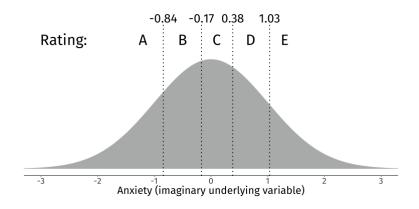
Interpreting a significant *p*-value as evidence that an effect exists in the real world.

### What ordinal regression models do

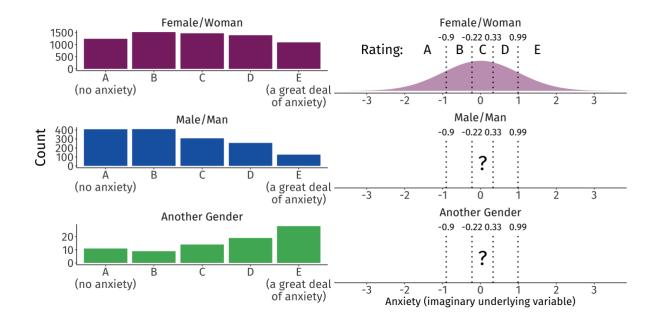


### Fit ordinal regression models with polr()

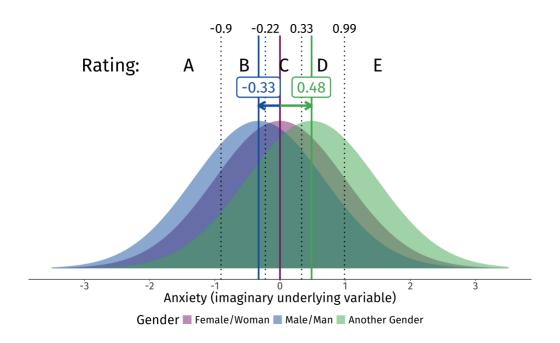
```
library(MASS)
                    # MASS contains the polr() function
anx_fit1 <- polr(</pre>
  rating ~ 1,
                     # intercept-only model, to start
  data = anx,
 Hess = TRUE, method = 'probit' # ask me in the Q+A!
summary(anx_fit1)
## Intercepts:
##
       Value
                Std. Error t value
        -0.8420
## 1|2
                  0.0157
                           -53.7268
## 2|3
      -0.1678
                  0.0138
                            -12.1462
                            27.1512
## 3|4
         0.3833
                  0.0141
## 4|5
         1.0339
                  0.0168
                            61.6193
```



How does a student's gender affect ratings for "Going to ask my statistics teacher for individual help with material I am having difficulty understanding"?



### [don't turn the page until after the activity!]



### The mistake and how you'll avoid it

#### The mistake

A common R mistake: Letting R treat all variables that look like numbers as continuous numeric.

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#### A foundational stats mistake:

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#### How you'll avoid it

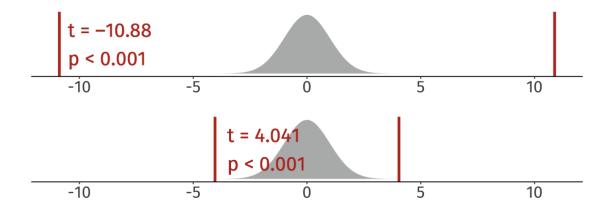
When a variable comes from a Likert scale, tell R it's categorical using factor().

Apply and interpret ordinal regression models (e.g., polr() from MASS).

### Are the effects of gender significant?

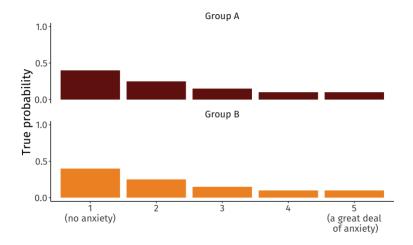
No *p*-values in the model summary.

But it's common practice to compare these *t*-values to a standard normal distribution.

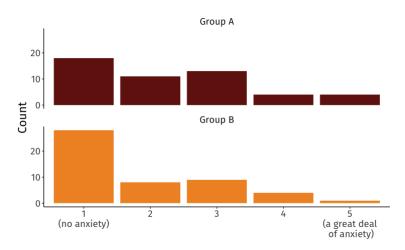


## Why don't significant *p*-values mean an effect exists?

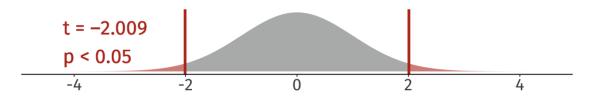
Because we can also get significant *p*-values when there really is *no* effect. No difference in the true population:



A possible random sample (n = 50 per group):



```
sim_fit <- polr(rating ~ group, data = simdat, method = 'probit',</pre>
Hess = TRUE)
summary(sim_fit)
## Coefficients:
                  Value Std. Error t value
## groupGroup B -0.4479 0.2229 -2.009
```



So p is significant, but in the true population, Group A and Group B were identical!

### The mistake and how you'll avoid it

### The mistake

A common R mistake: Letting R treat all variables that look like numbers as continuous numeric.

An advanced stats mistake: Modelling categorical, ordinal data as if it were numeric.

#### A foundational stats mistake: Interpreting a significant p-value as

evidence that an effect exists in the real world.

#### How you'll avoid it

When a variable comes from a Likert scale, tell R it's categorical using factor().

Apply and interpret ordinal regression models (e.g., polr() from MASS).

Understand that significant p-values can arise even if no effect exists in the real world.

### Some really nice resources

- Jamieson's (2004) paper Likert scales: How to (ab)use them.
- UCLA Statistical Methods and Data Analytics's web page Ordinal Logistic Regression.
- Kurz' (2021) blog post Notes on the Bayesian cumulative probit.
- Vasishth and Nicenboim's (2016) paper Statistical Methods for Linguistic Research: Foundational Ideas Part I.
- Gelman and Hill's (2007) book Data Analysis Using Regression and Multilevel/Hierarchical Models.

#### Plot on Slide 2 from

Reeder, P. A., Newport, E. L., & Aslin, R. N. (2017). Distributional learning of subcategories in an artificial grammar: Category generalization and subcategory restrictions. *Journal of Memory and Language*, 97, 17–29.

#### Data from

Terry, J., Ross, R. M., Nagy, T., Salgado, M., Garrido-Vásquez, P., Sarfo, J. O., Cooper, S., Buttner, A. C., Lima, T. J. S., Öztürk, İ., Akay, N., Santos, F. H., Artemenko, C., Copping, L. T., Elsherif, M. M., Milovanović, I., Cribbie, R. A., Drushlyak, M. G., Swainston, K., ... Field, A. P. (2023). Data from an International Multi-Centre Study of Statistics and Mathematics Anxieties and Related Variables in University Students (the SMARVUS Dataset). *Journal of Open Psychology Data*, 11(1), 8.