

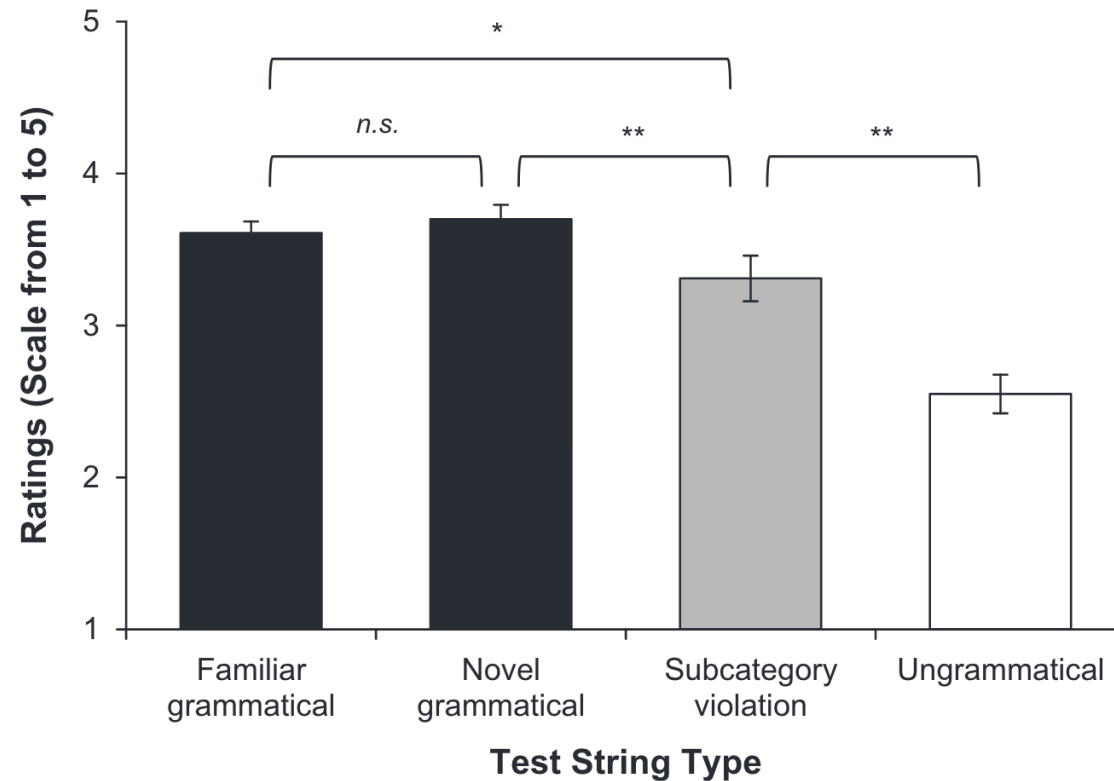
Three common mistakes in statistics and how to avoid them

Elizabeth Pankratz

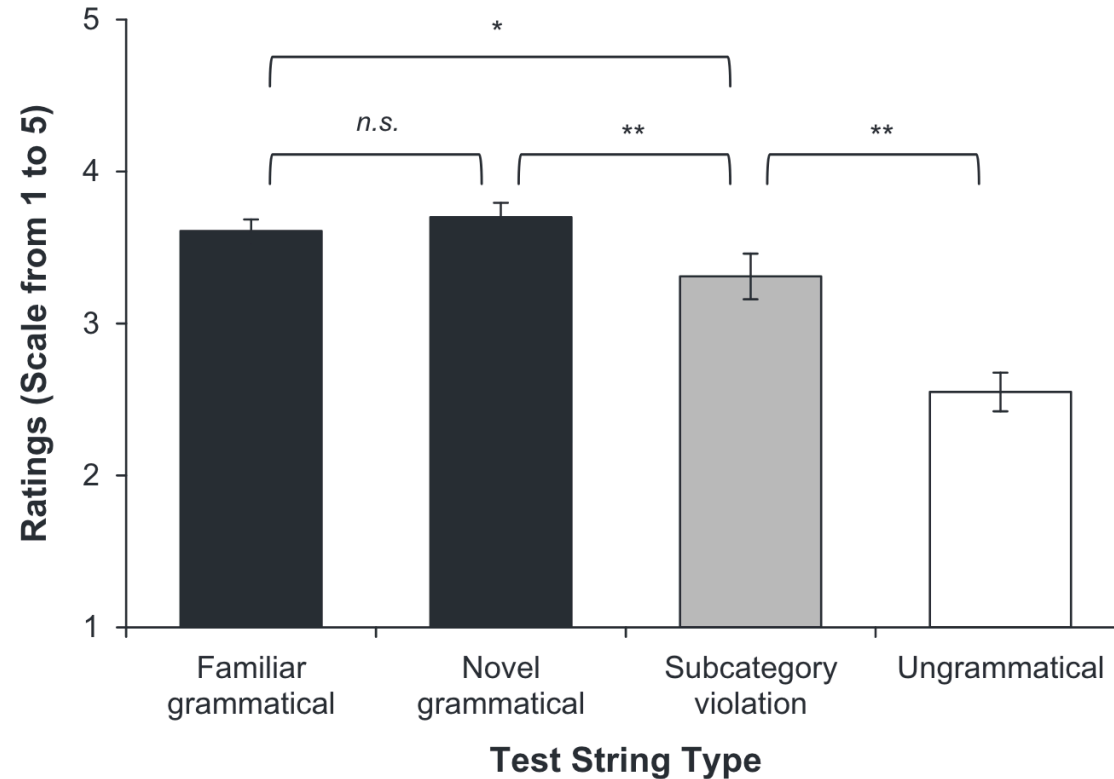
Department of Psychology
The University of Edinburgh

Something you won't be able to unsee

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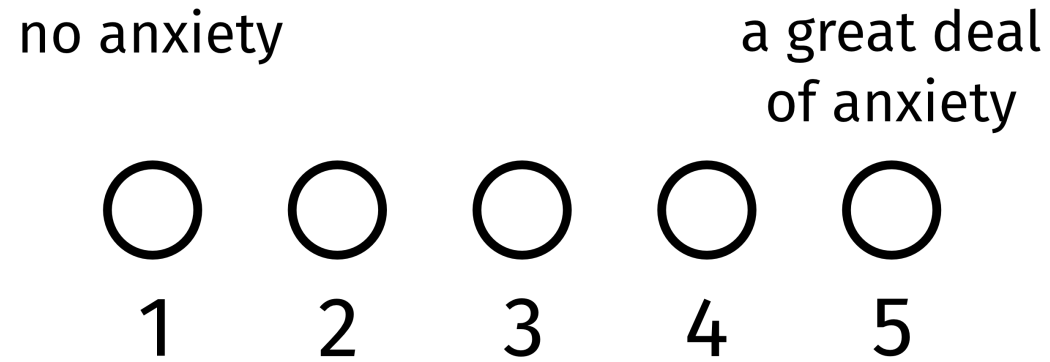
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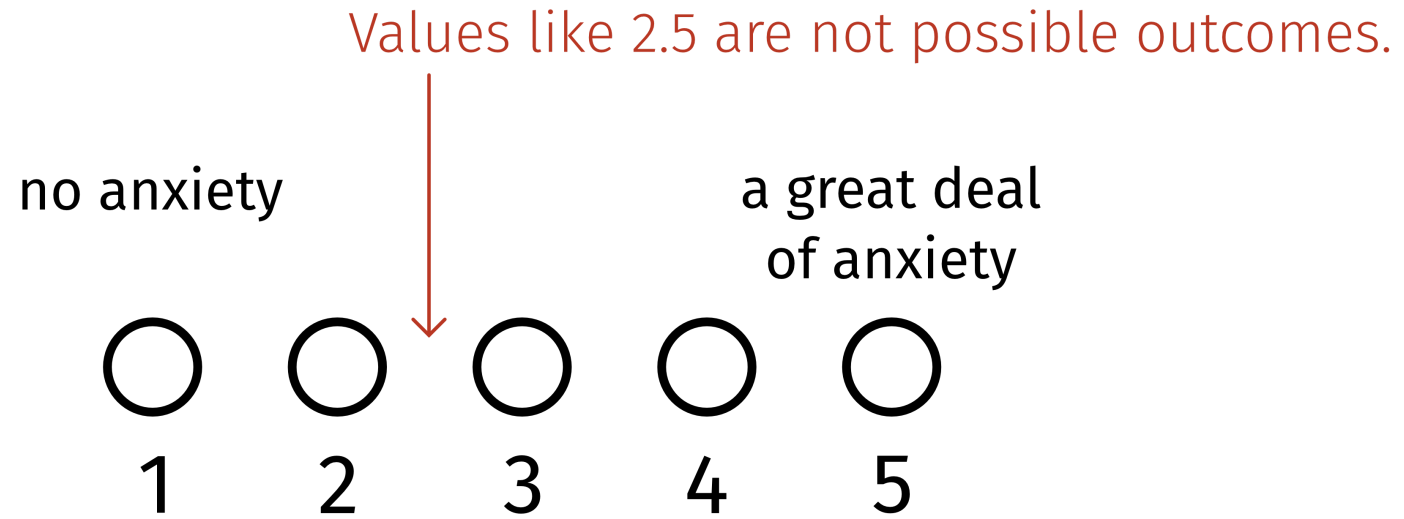
Taking the means of discrete ratings is very common—but a little strange!

Why Likert scale ratings aren't continuous numeric

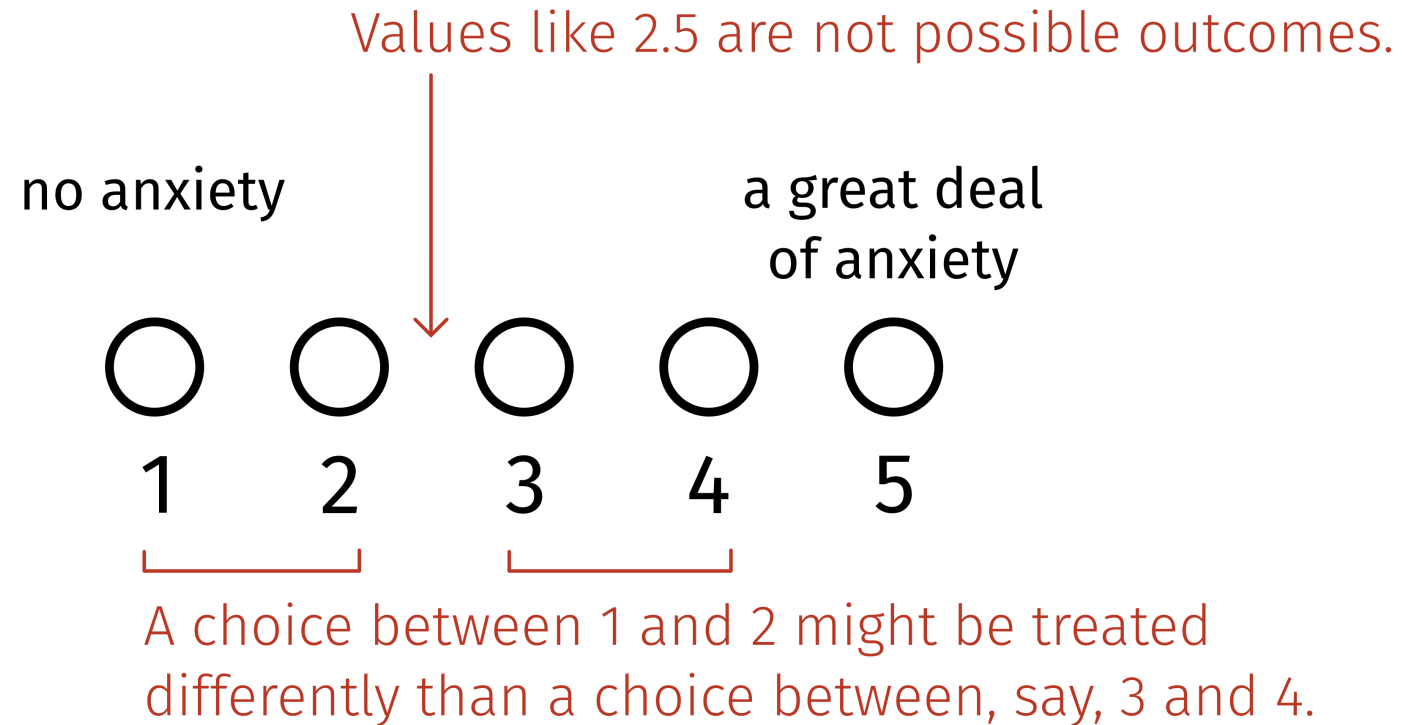
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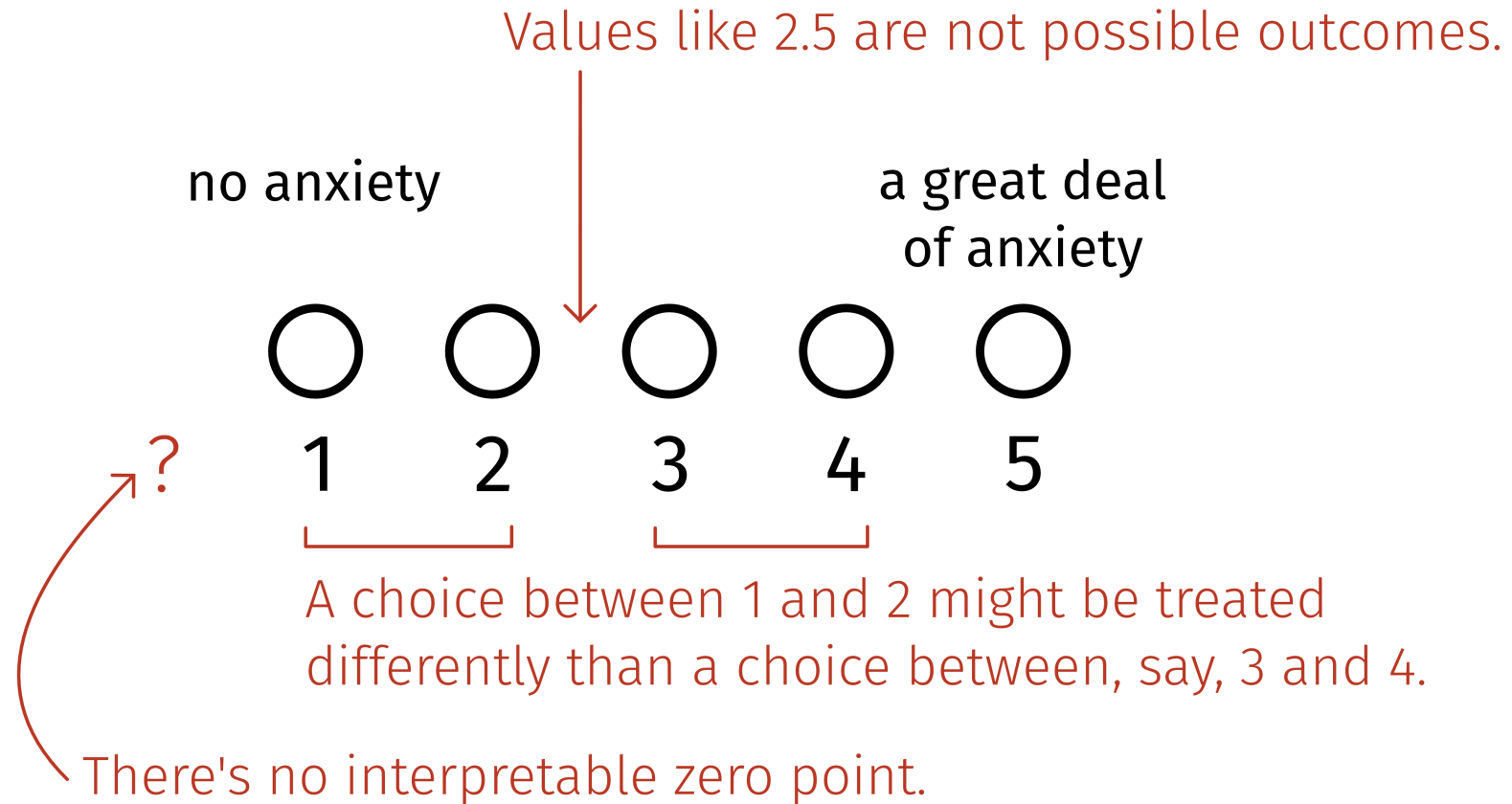
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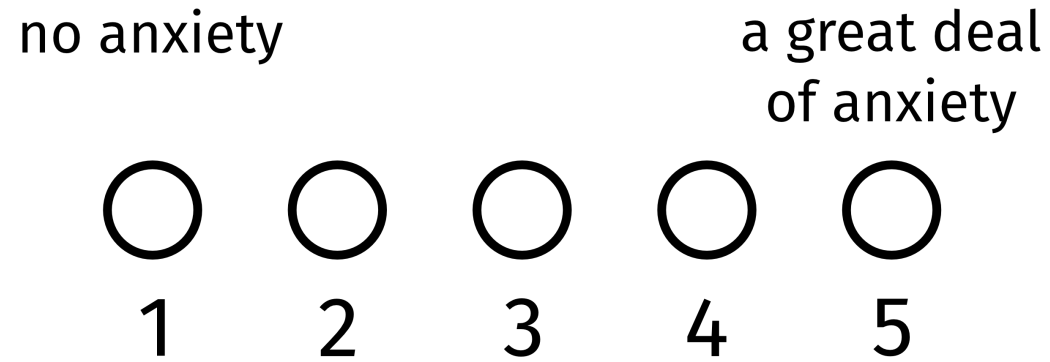
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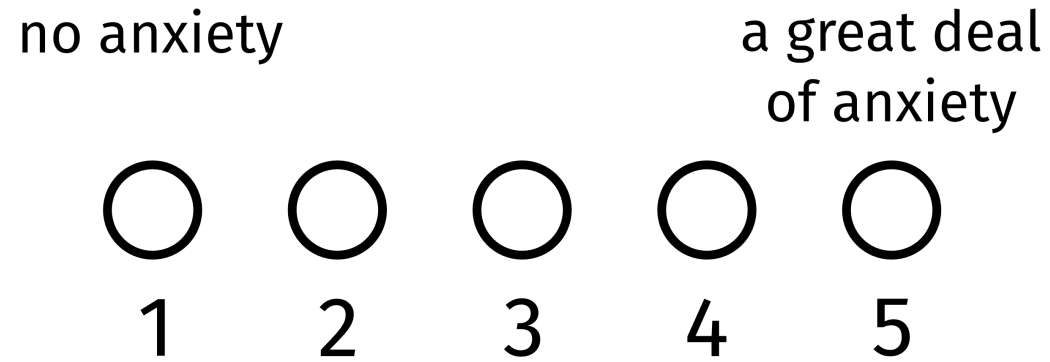
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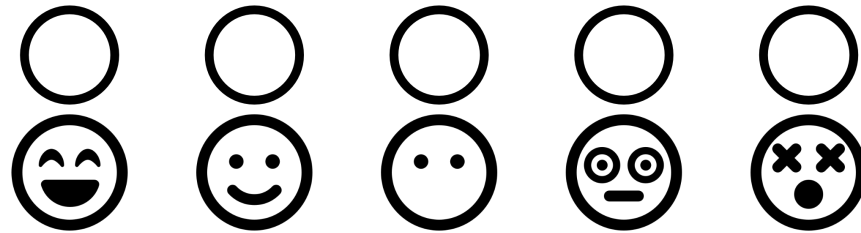


Numbers on a Likert scale are just labels.

Why Likert scale ratings aren't continuous numeric

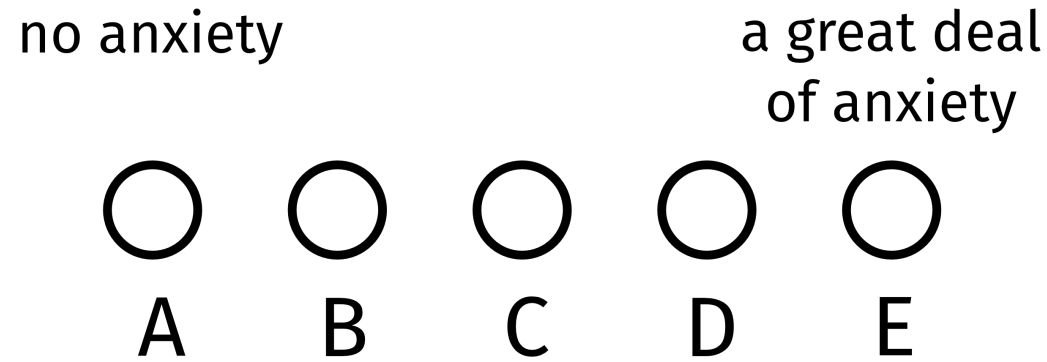
no anxiety

a great deal
of anxiety



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Numbers on a Likert scale are just labels.

The mistake

How you'll avoid it

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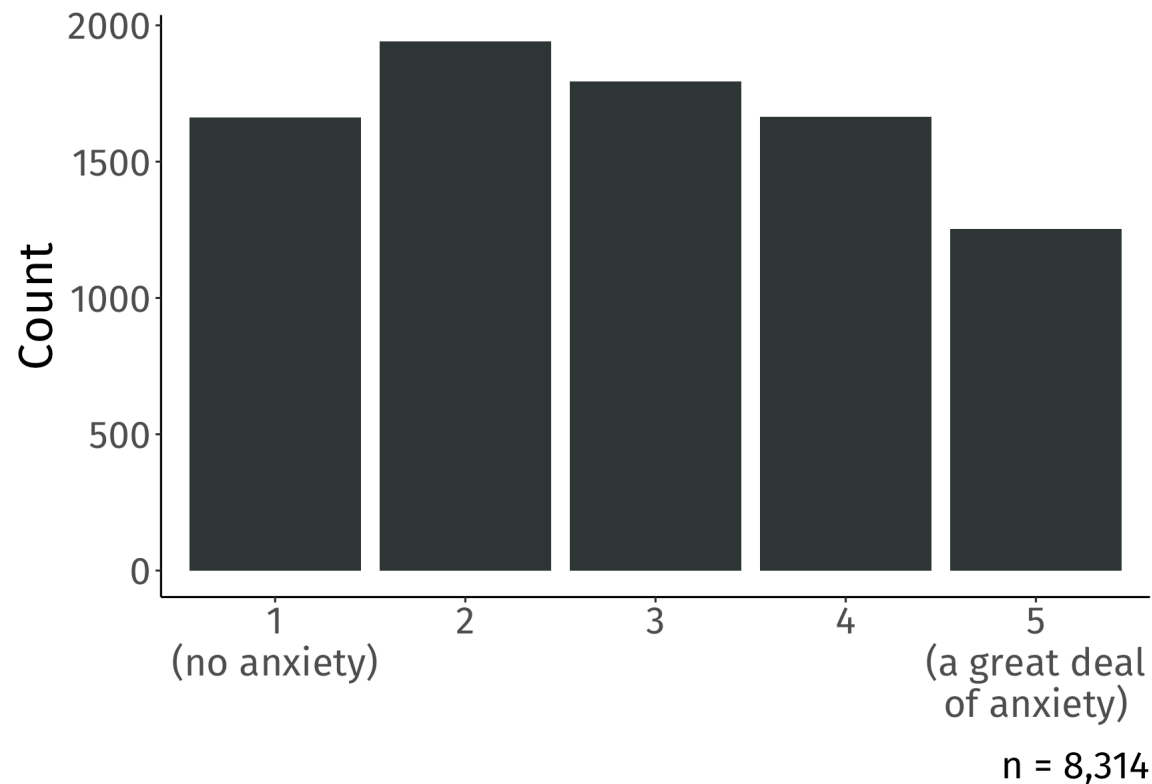
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The data: Students' anxiety ratings for “Going to ask my statistics teacher for individual help with material I am having difficulty understanding”.

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```
slice(anx, 45:50)
```

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

`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

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Store categorical variables as factors.

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

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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
```


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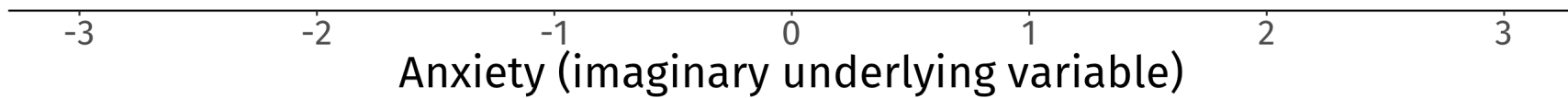
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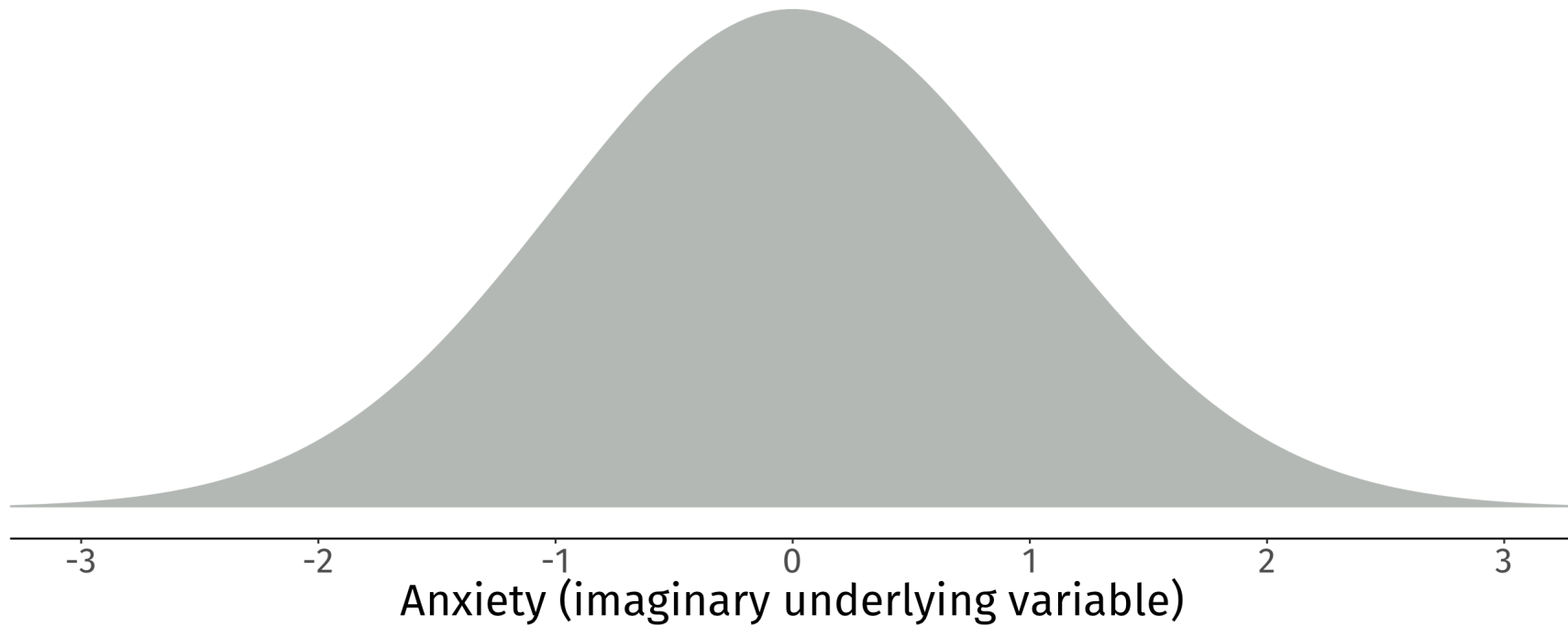
When a variable comes from a Likert scale, tell R it's categorical using **factor()**.

What ordinal regression models do

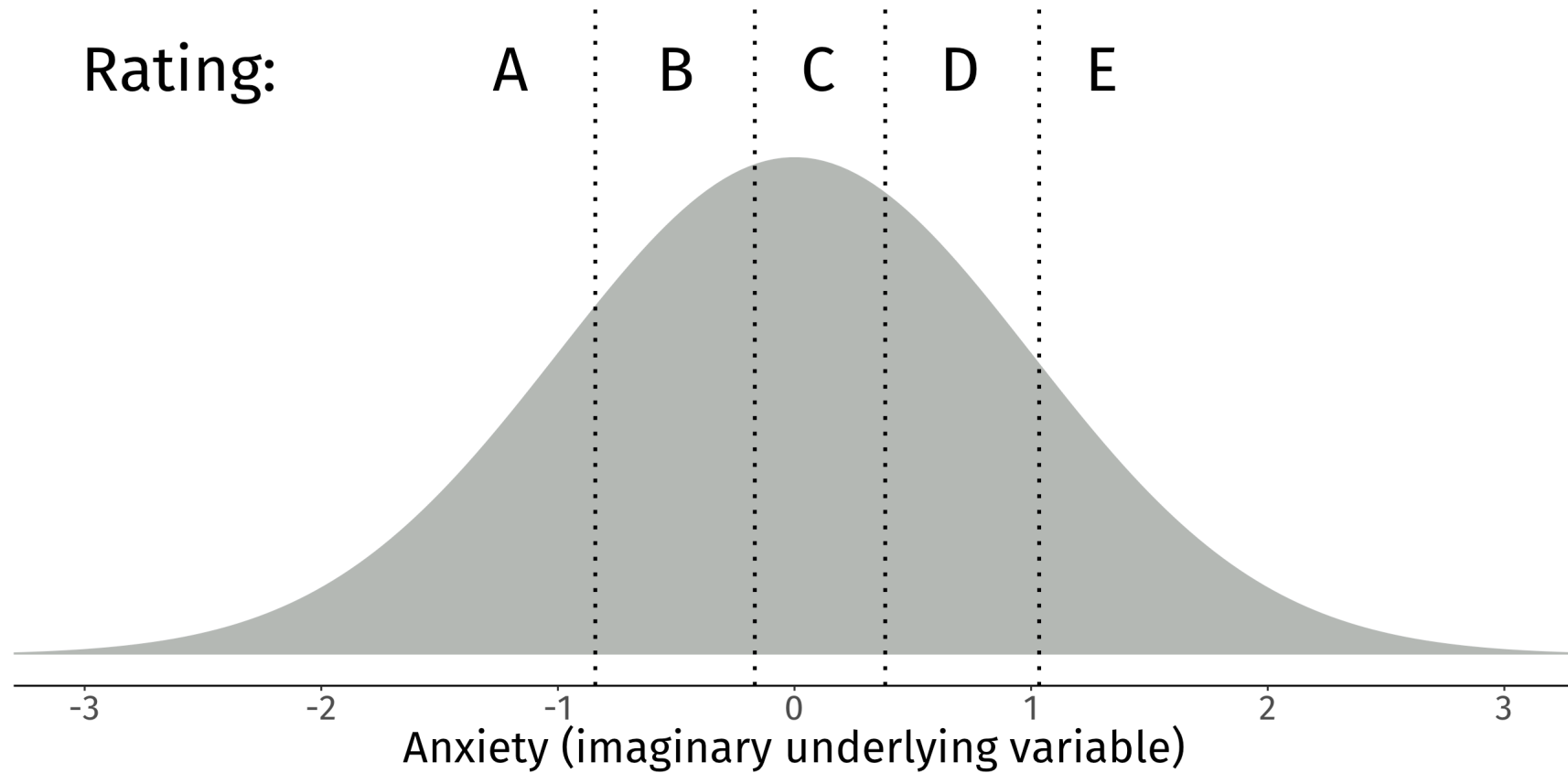
What ordinal regression models do



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What ordinal regression models do



Fit ordinal regression models with `polr()`

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```
library(MASS)           # MASS contains the polr() function

anx_fit1 <- polr(
  rating ~ 1,           # intercept-only model, to start
  data = anx,
  Hess = TRUE, method = 'probit' # ask me in the Q+A!
)
```


Fit ordinal regression models with `polr()`

```
summary(anx_fit1)
```

Intercepts:

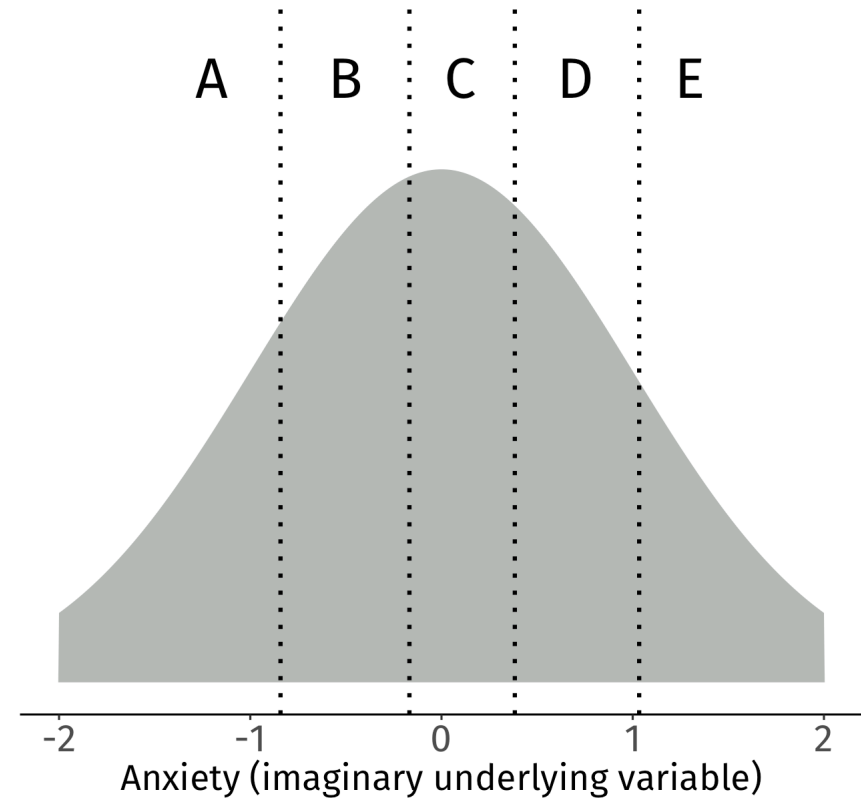
##	Value	Std. Error	t value
## A B	-0.8420	0.0157	-53.7268
## B C	-0.1678	0.0138	-12.1462
## C D	0.3833	0.0141	27.1512
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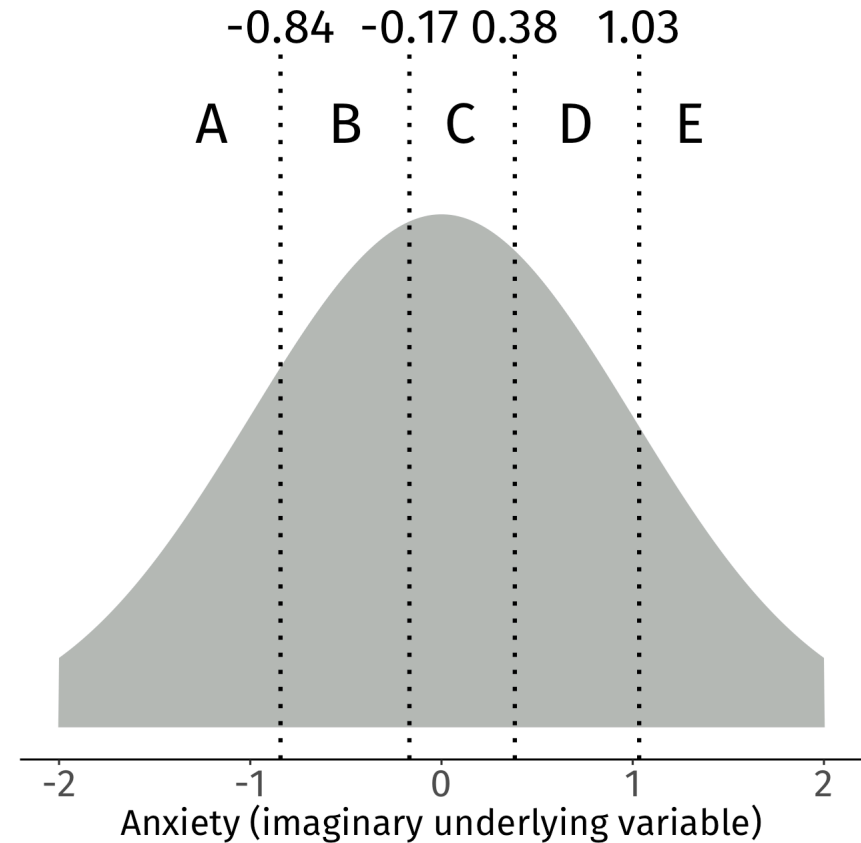


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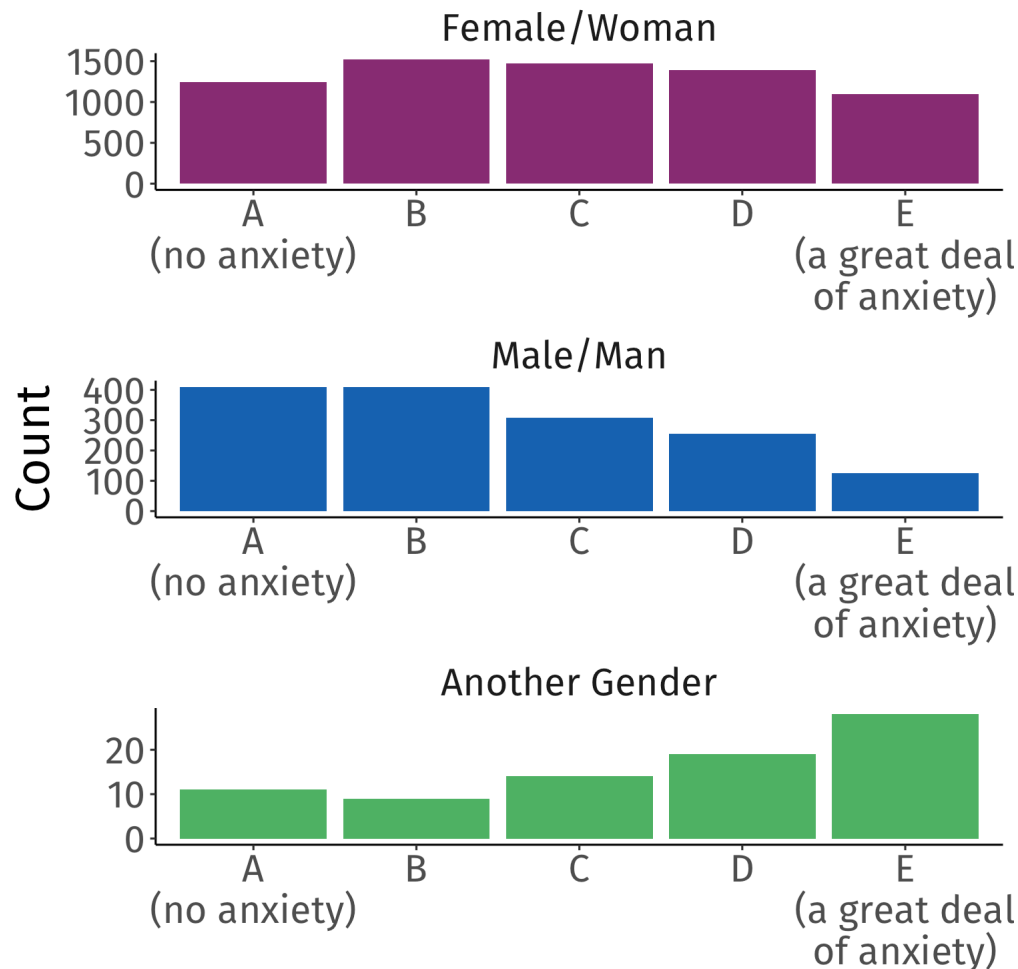
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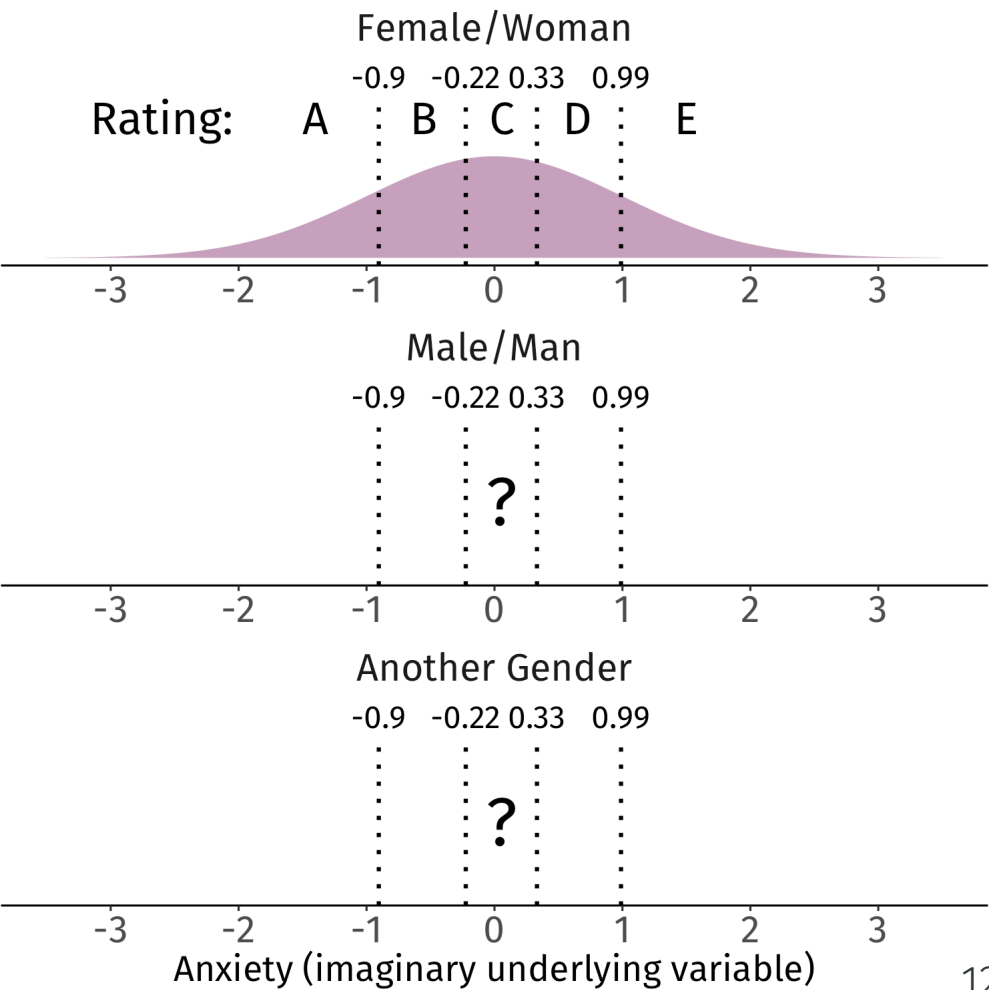
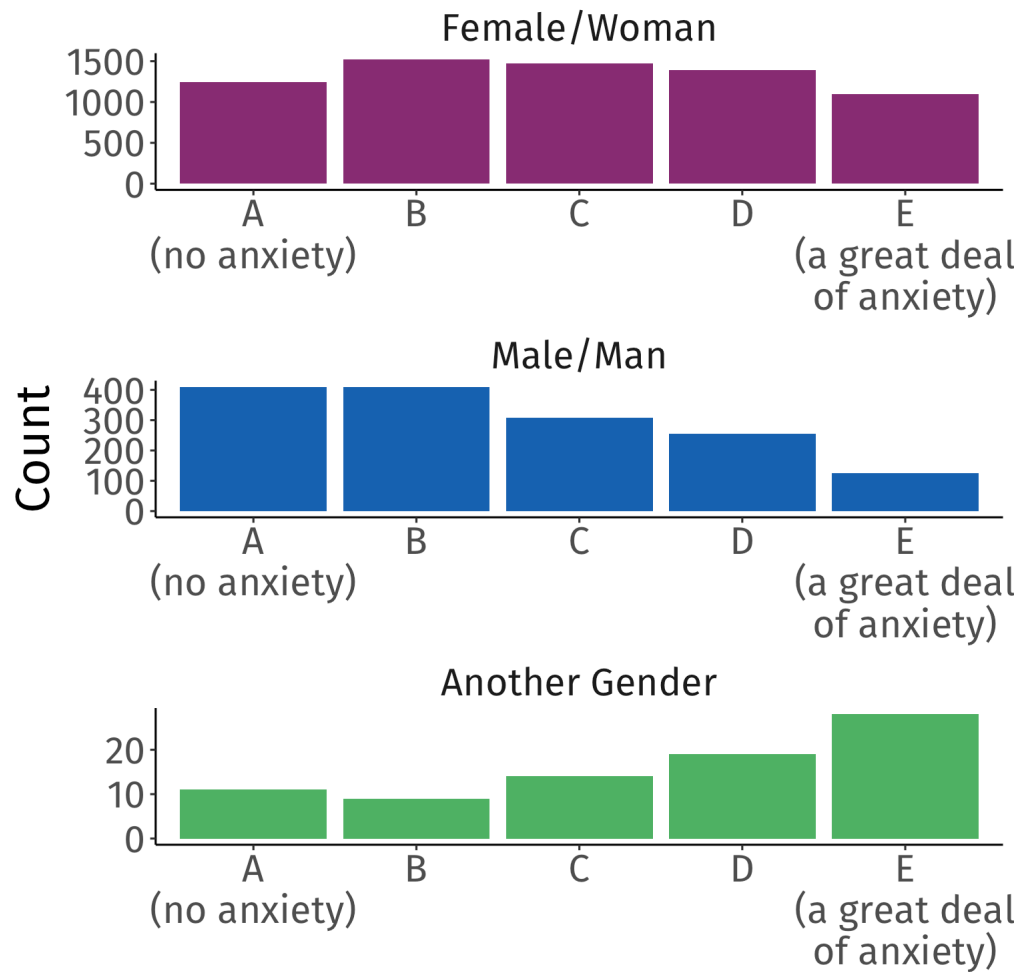


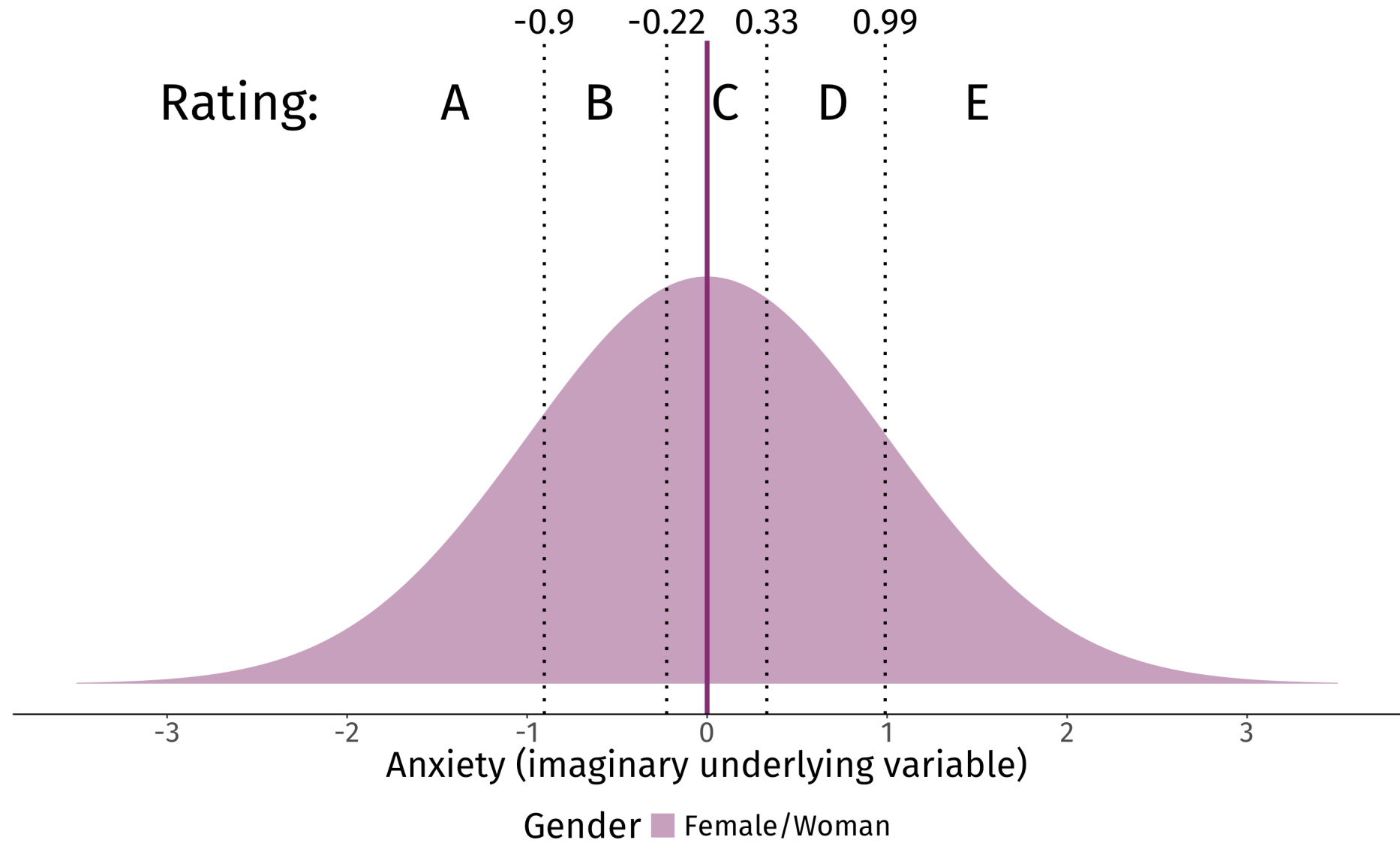
How does a student's gender affect ratings for "Going to ask my statistics teacher for individual help with material I am having difficulty understanding"?

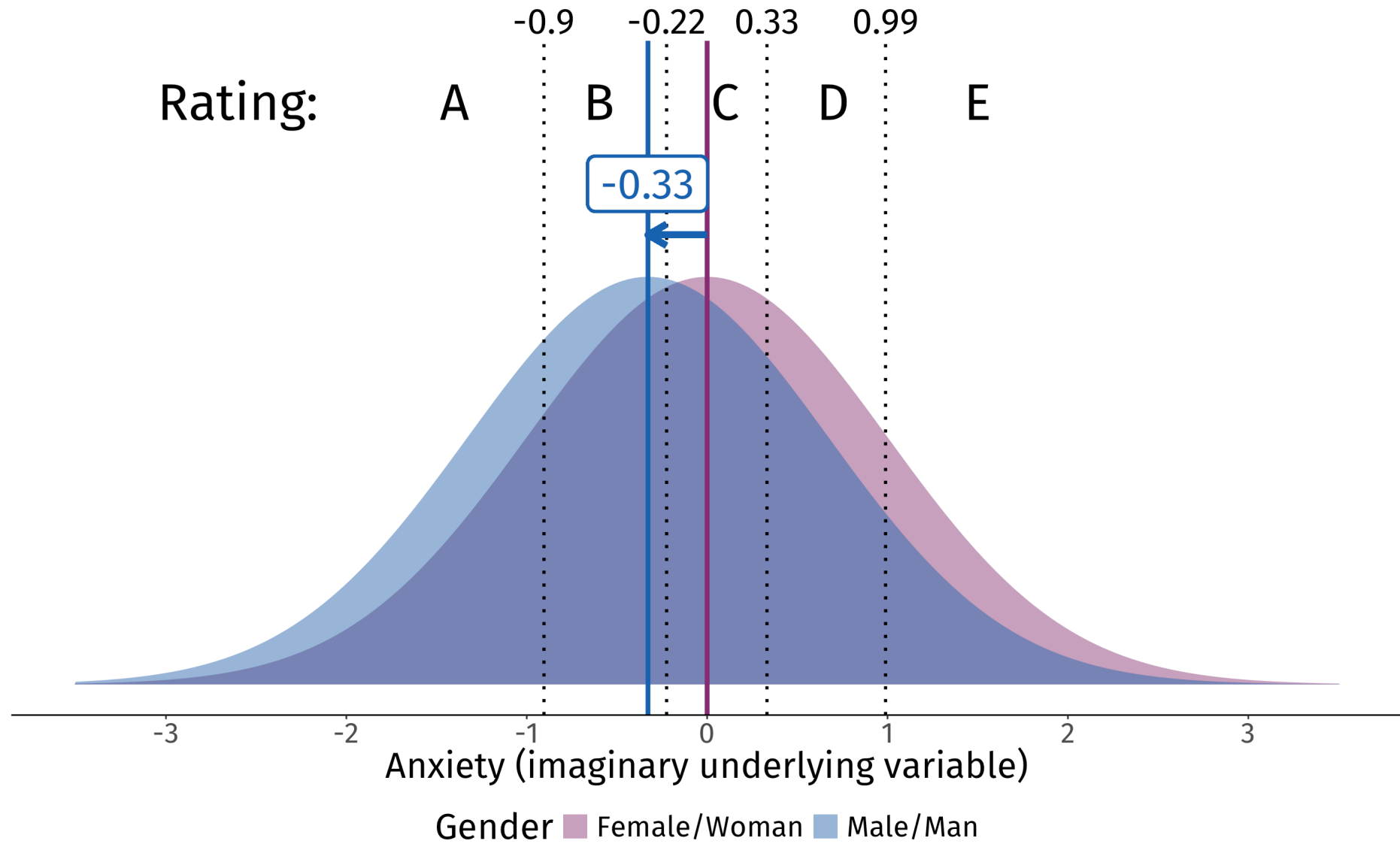
How does a student’s gender affect ratings for “Going to ask my statistics teacher for individual help with material I am having difficulty understanding”?

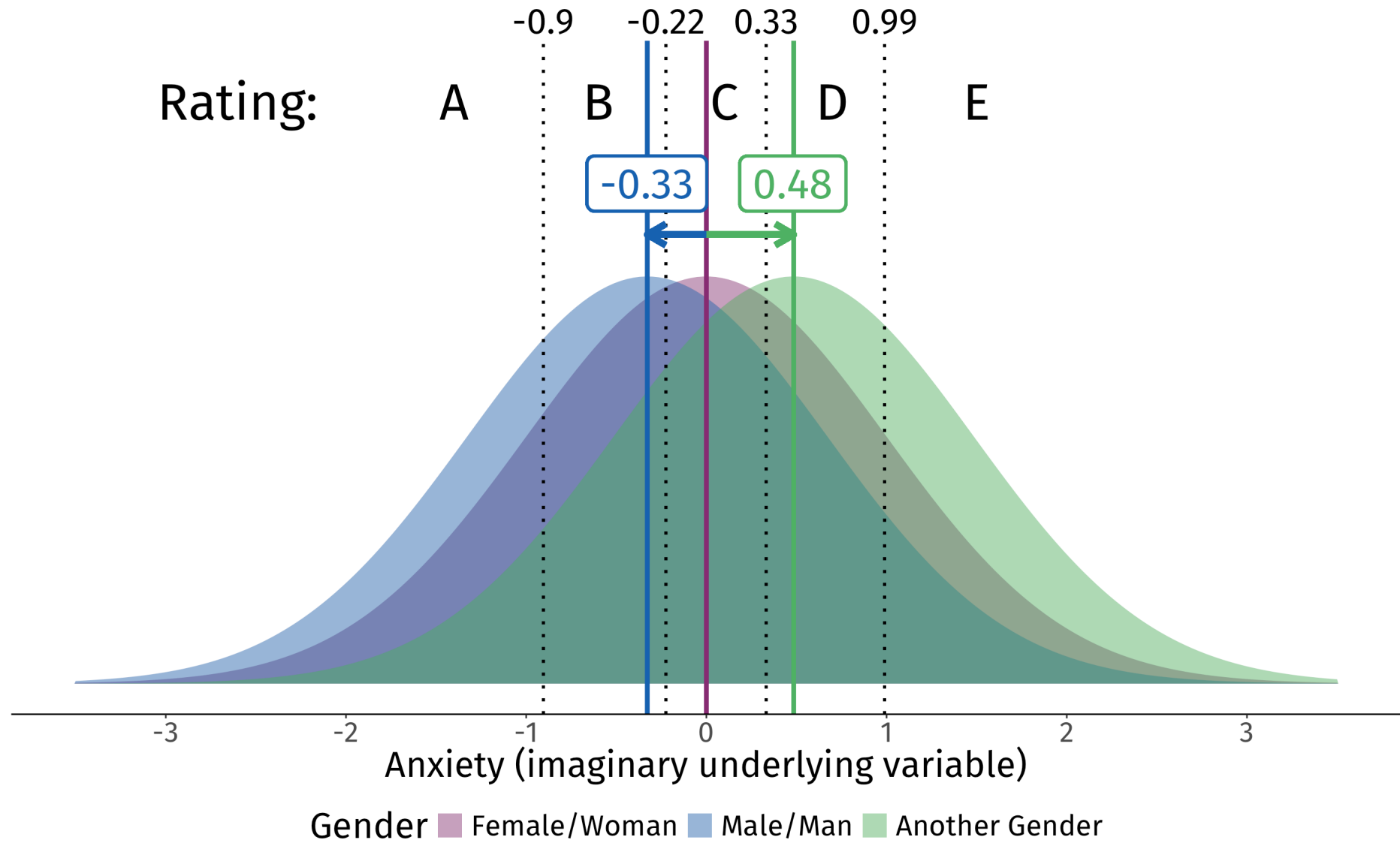


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Are the effects of **gender** significant?

Coefficients:

##		Value	Std. Error	t value
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##	genderAnother Gender	0.4846	0.11992	4.041

No p -values in the model summary.

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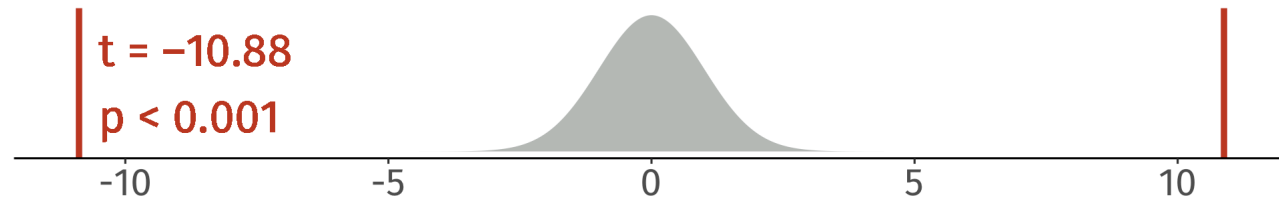
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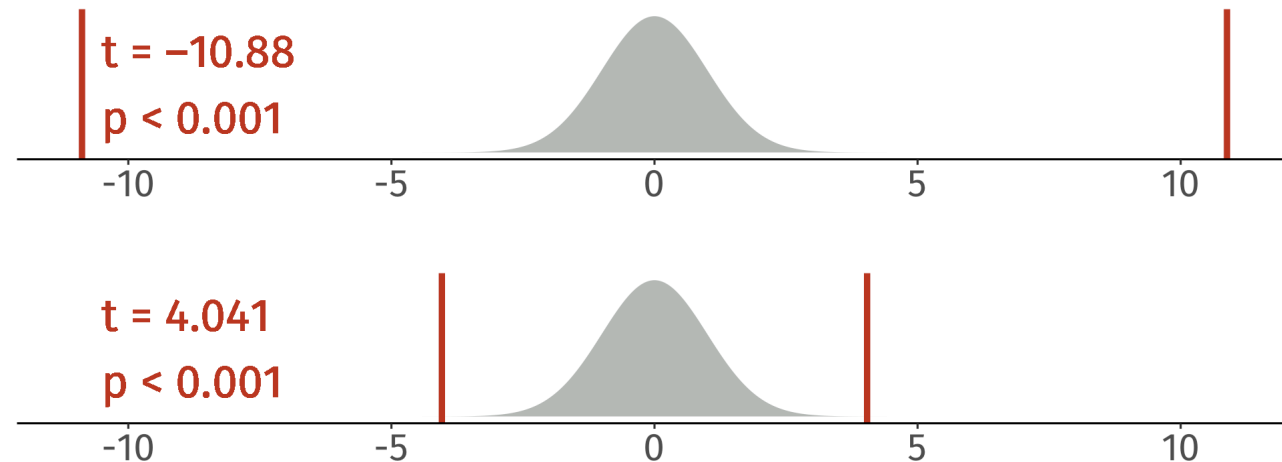
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Why don't significant p -values mean an effect exists?

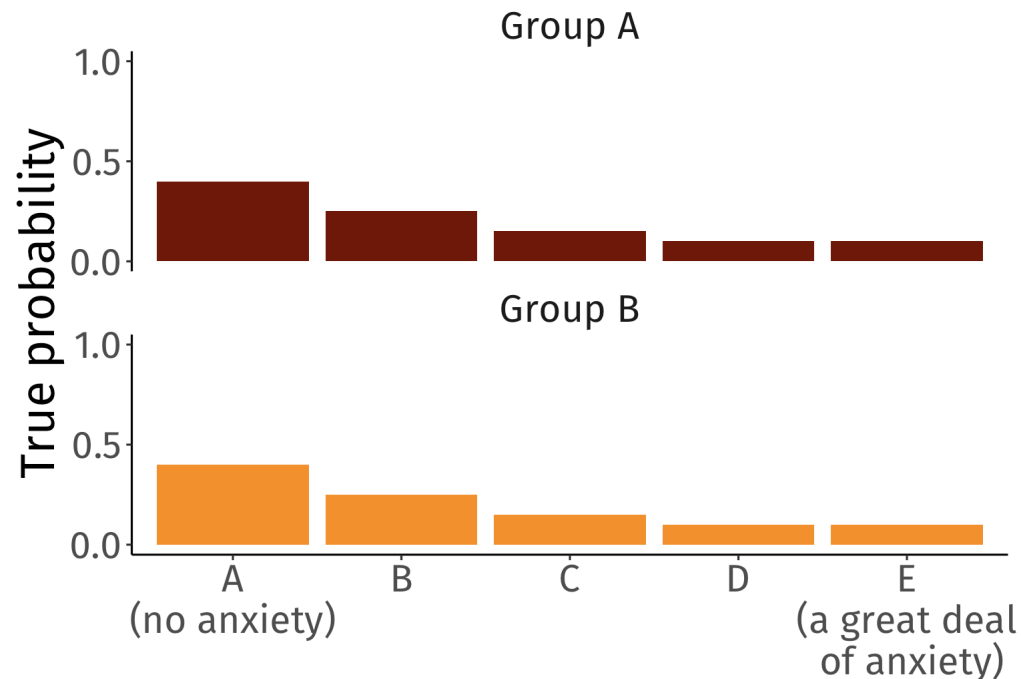
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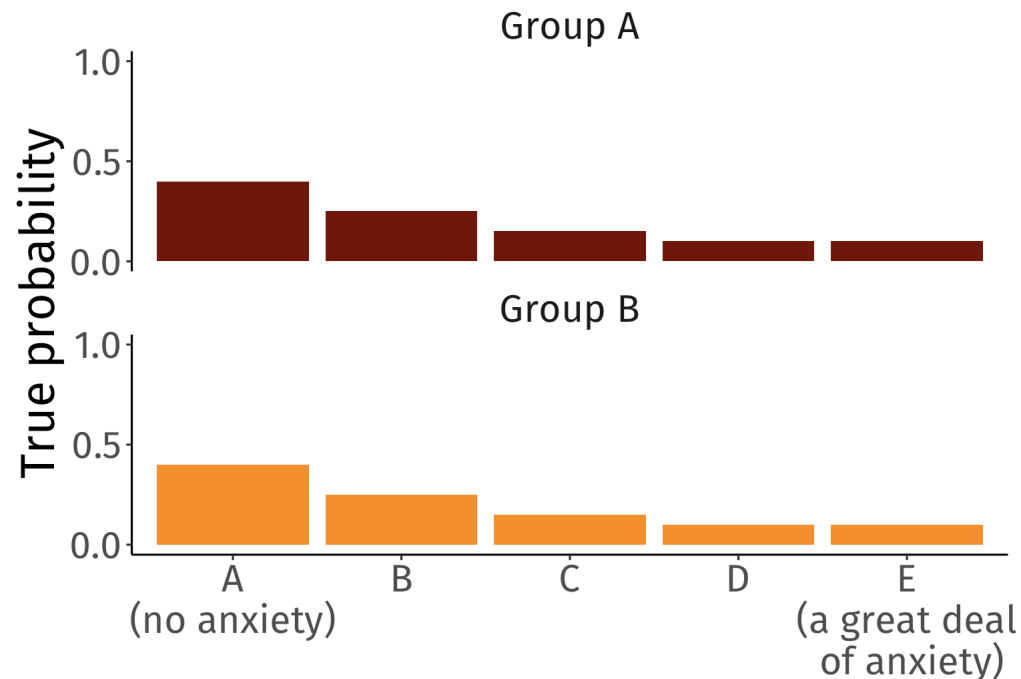
No difference in the true population:



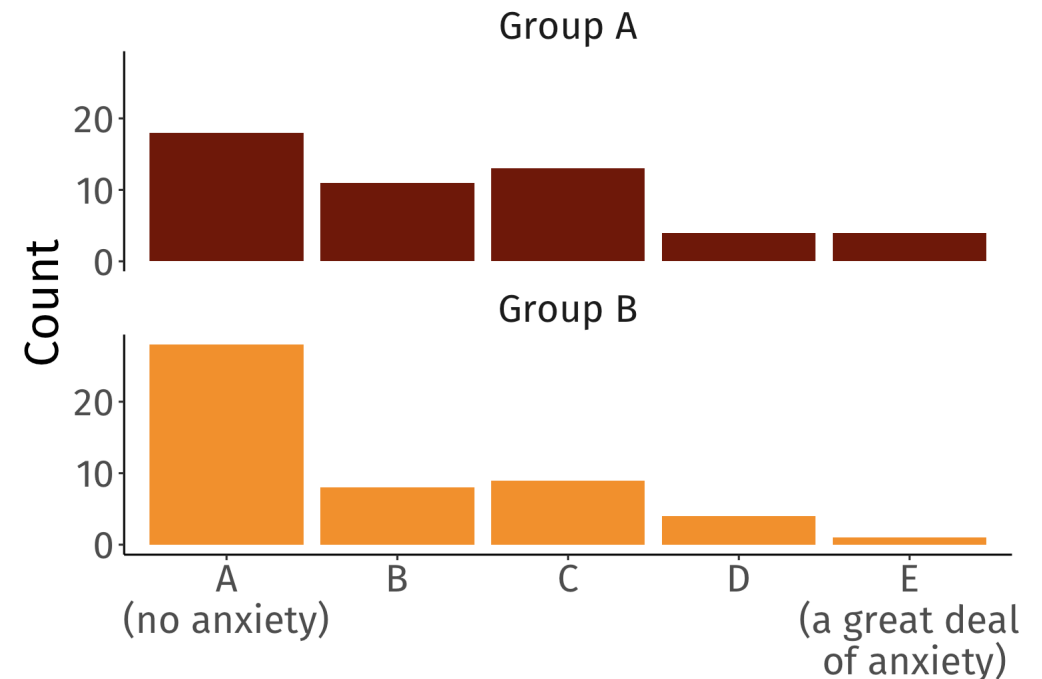
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Because we can also get significant p -values when there really is *no* effect.

No difference in the true population:



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



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

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sim_fit <- polr(rating ~ group, data = simdat, method = 'probit', Hess = TRUE)  
summary(sim_fit)
```

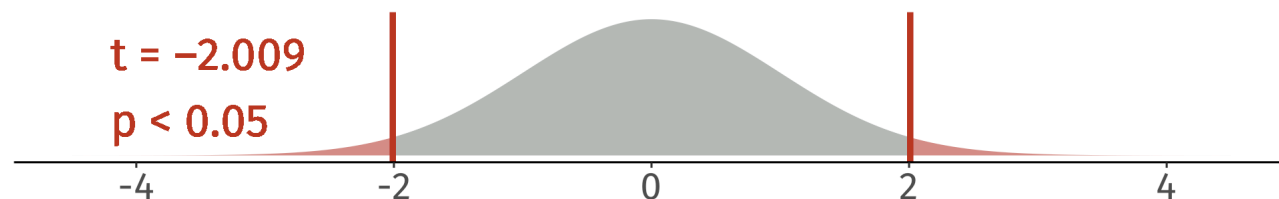
```
## Coefficients:  
##              Value Std. Error t value  
## groupGroup B -0.4479      0.2229  -2.009
```

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

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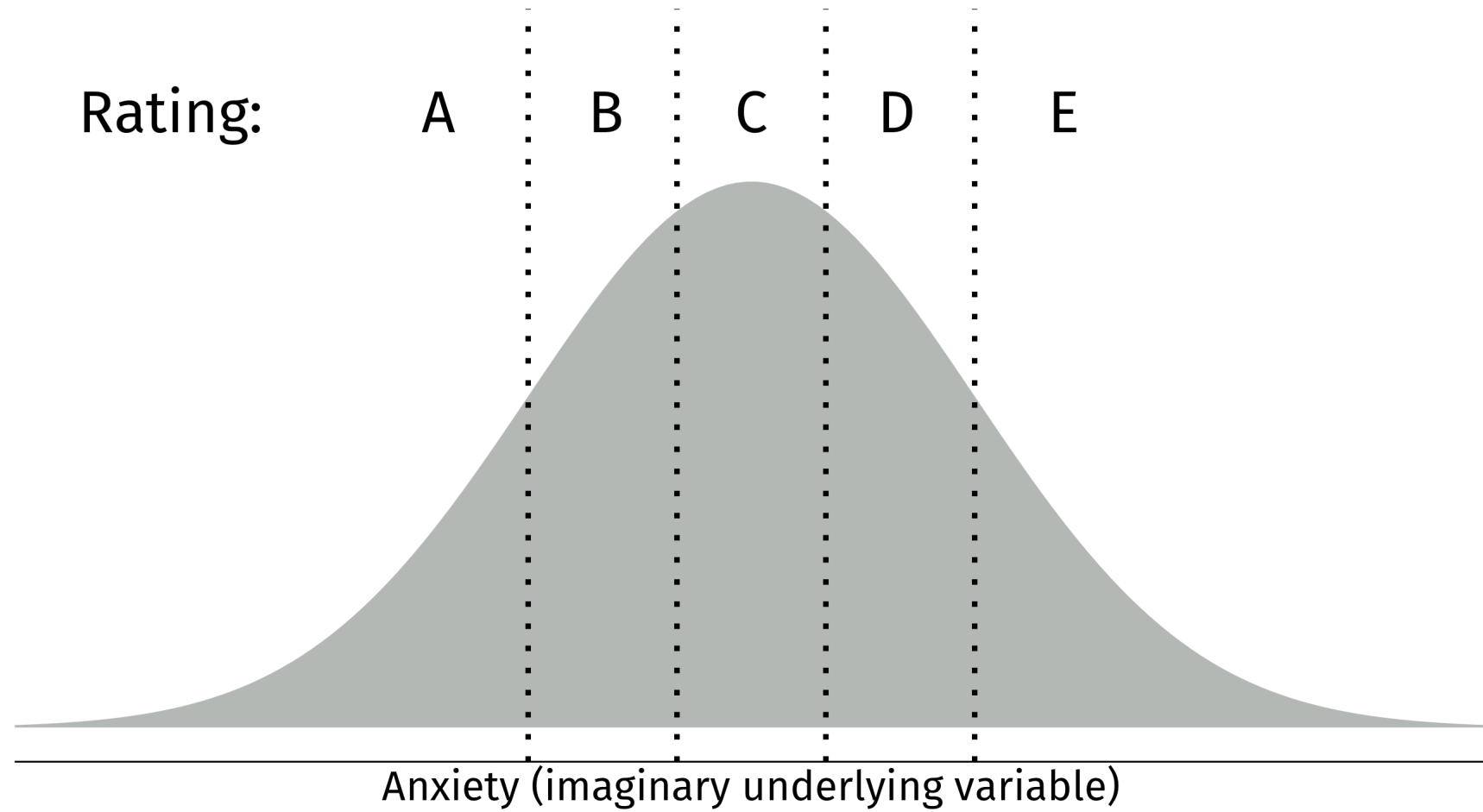
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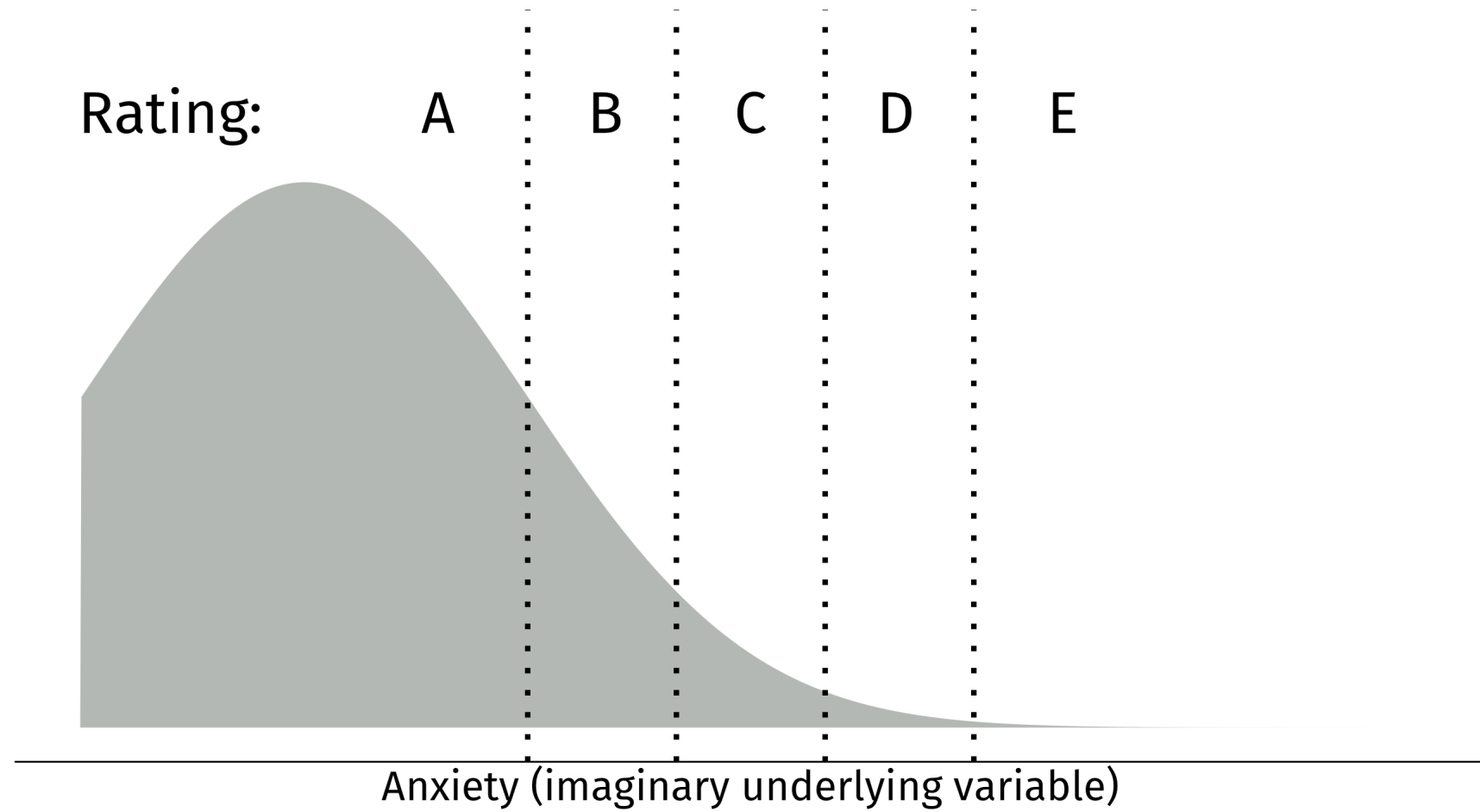
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Thank you! 😊 Time for questions!

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.