

17-803 Empirical Methods

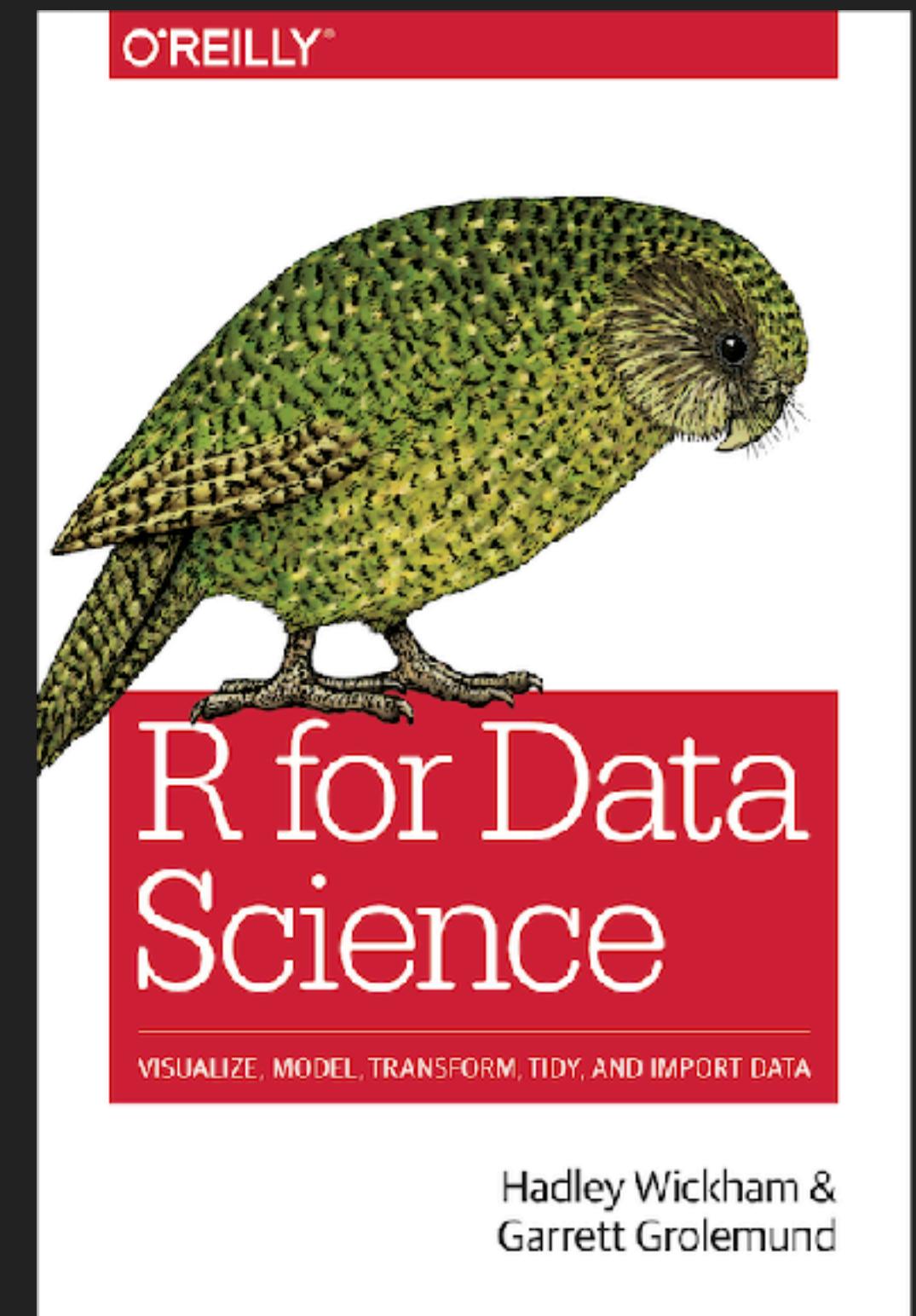
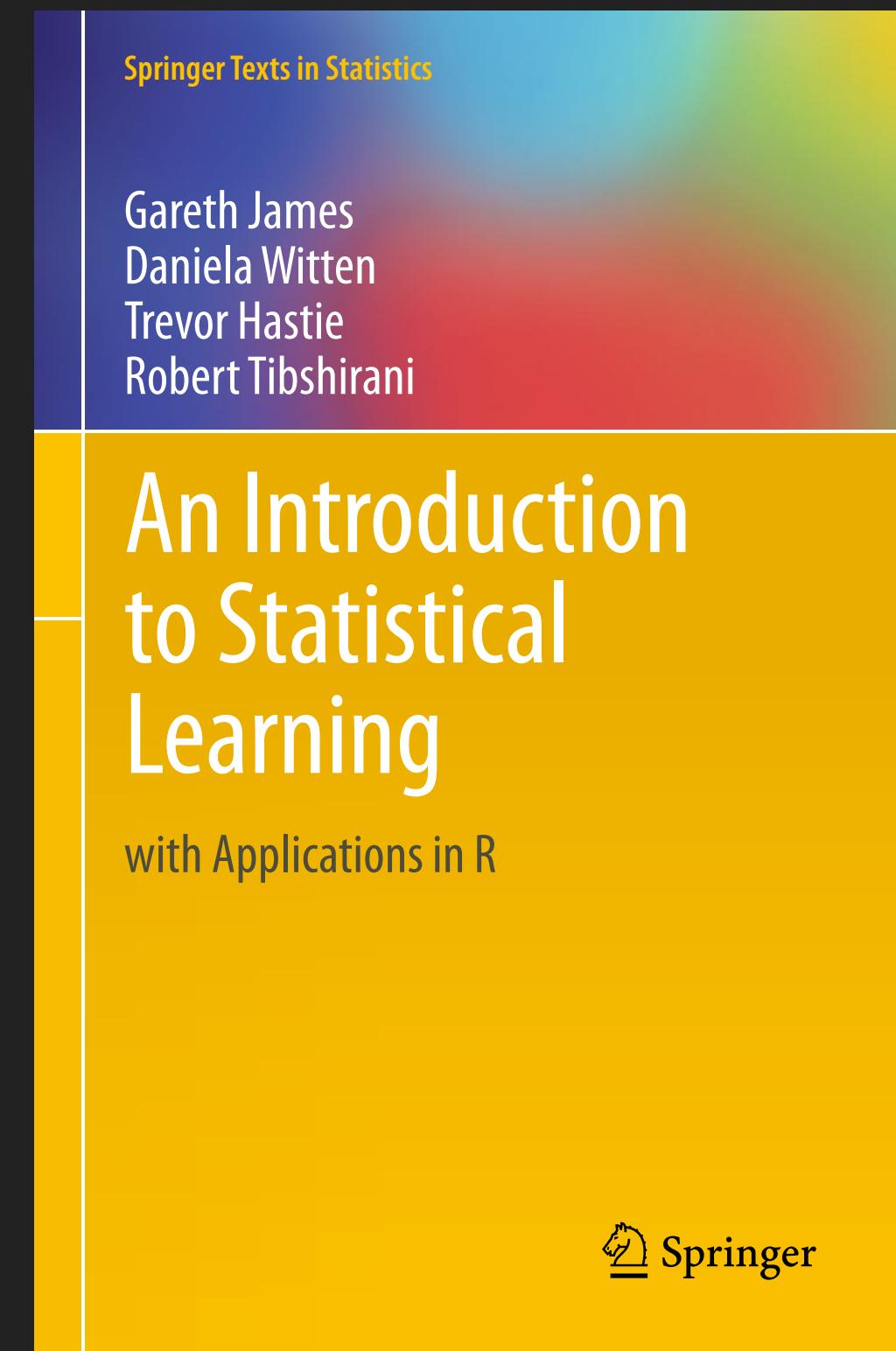
Bogdan Vasilescu, S3D

# Regression Modeling (Part 2)

Thursday, March 21, 2024

# Outline for Today

- ▶ More linear regression (Rmd + only limited slides)



## ✓ regression

- Chapter 2 - Wooldridge - Simple Regression.pdf
- Chapter 3 from "An Introduction to Statistical Learning".pdf
- Chapter 4 from "Practical Statistics for Data Scientists" - O'Reilly Media (2020).pdf
- Chapters 22-24 from "R for Data Science".pdf
- Harrell - Chapter 4 - Modeling Strategies.pdf
- Harrell - Chapters 1&2 - Regression General Aspects.pdf

Ch 3 (Linear regression)

Ch 22-24 (Modeling)

# More To Read

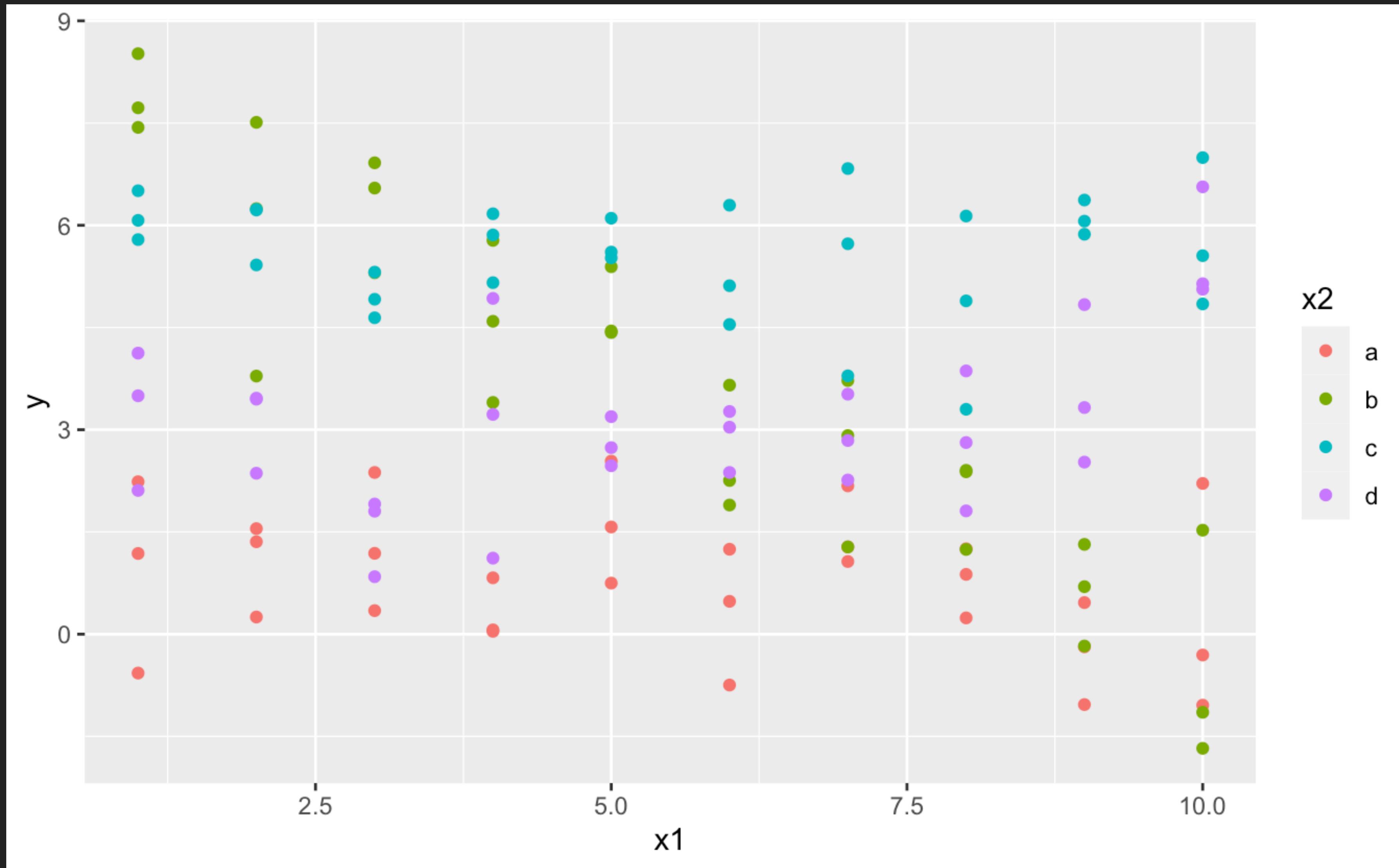
- ▶ Dealing with outliers: <https://andrewpbray.github.io/reg/week6B-outliers.html>
- ▶ Assumptions: <https://blog.msbstats.info/posts/2018-08-30-linear-regression-assumptions/>
- ▶ Diagnostics:
  - ▶ Anscombe: <https://andrewpbray.github.io/reg/week6A-diagnostics.html>
  - ▶ [https://www.andrew.cmu.edu/user/achoulde/94842/homework/regression\\_diagnostics.html](https://www.andrew.cmu.edu/user/achoulde/94842/homework/regression_diagnostics.html)
  - ▶ <https://data.library.virginia.edu/diagnostic-plots/>
- ▶ Q-Q plots: <http://seankross.com/2016/02/29/A-Q-Q-Plot-Dissection-Kit.html>
- ▶ Interactive visualization: [https://gallery.shinyapps.io/slr\\_diag/](https://gallery.shinyapps.io/slr_diag/)
- ▶ How to code categorical variables in a regression: <https://stats.idre.ucla.edu/r/library/r-library-contrast-coding-systems-for-categorical-variables/>
- ▶ Understanding model outputs: <https://www.andrew.cmu.edu/user/achoulde/94842/>
- ▶ Alpha vs p-value: [https://rationalwiki.org/wiki/Statistical\\_significance#Alpha\\_value\\_versus\\_p-value](https://rationalwiki.org/wiki/Statistical_significance#Alpha_value_versus_p-value)

# See Also

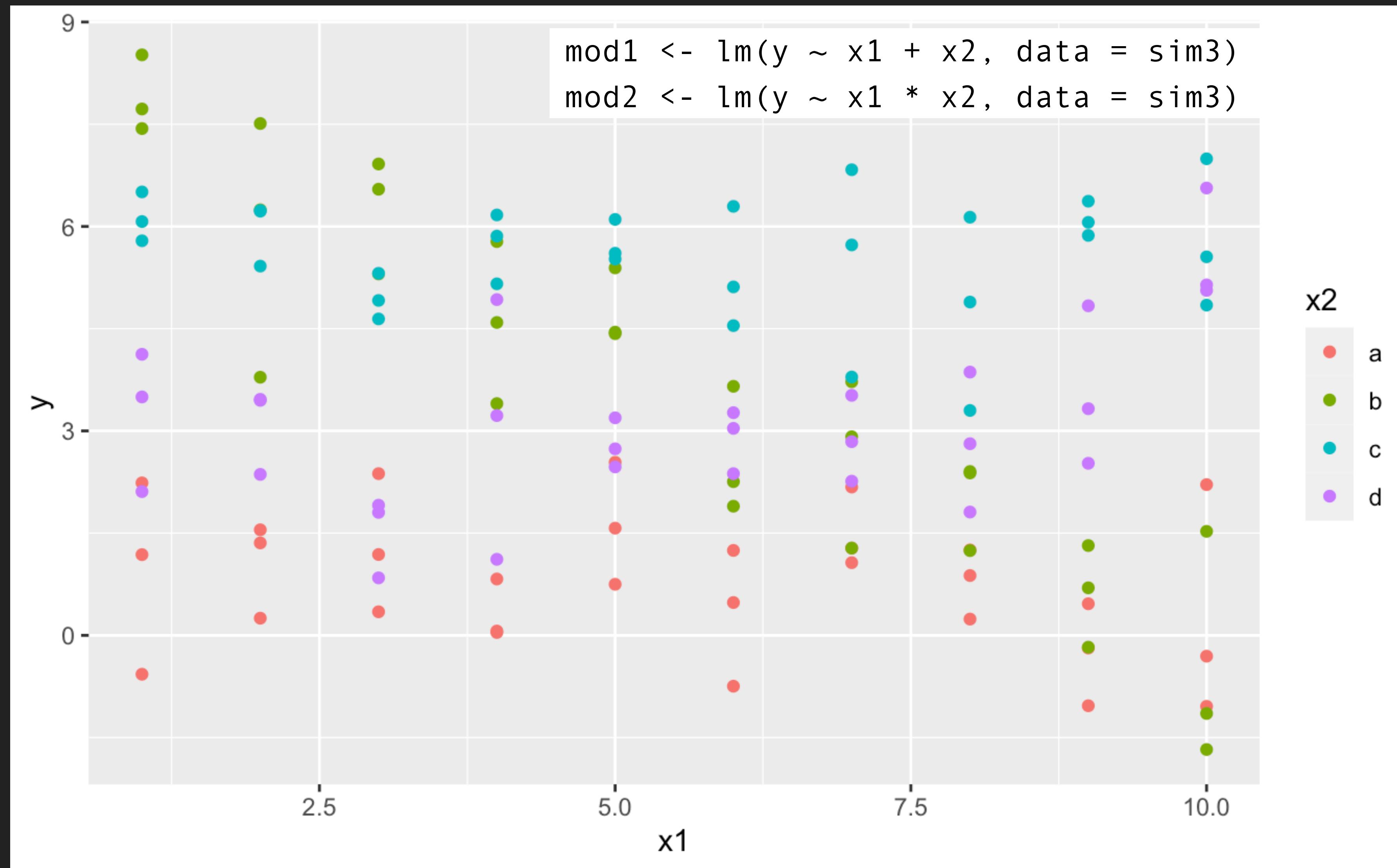
- ▶ CMU 94-842: Programming in R for Analytics:
- ▶ <https://www.andrew.cmu.edu/user/achoulde/94842/>

# Another interaction example

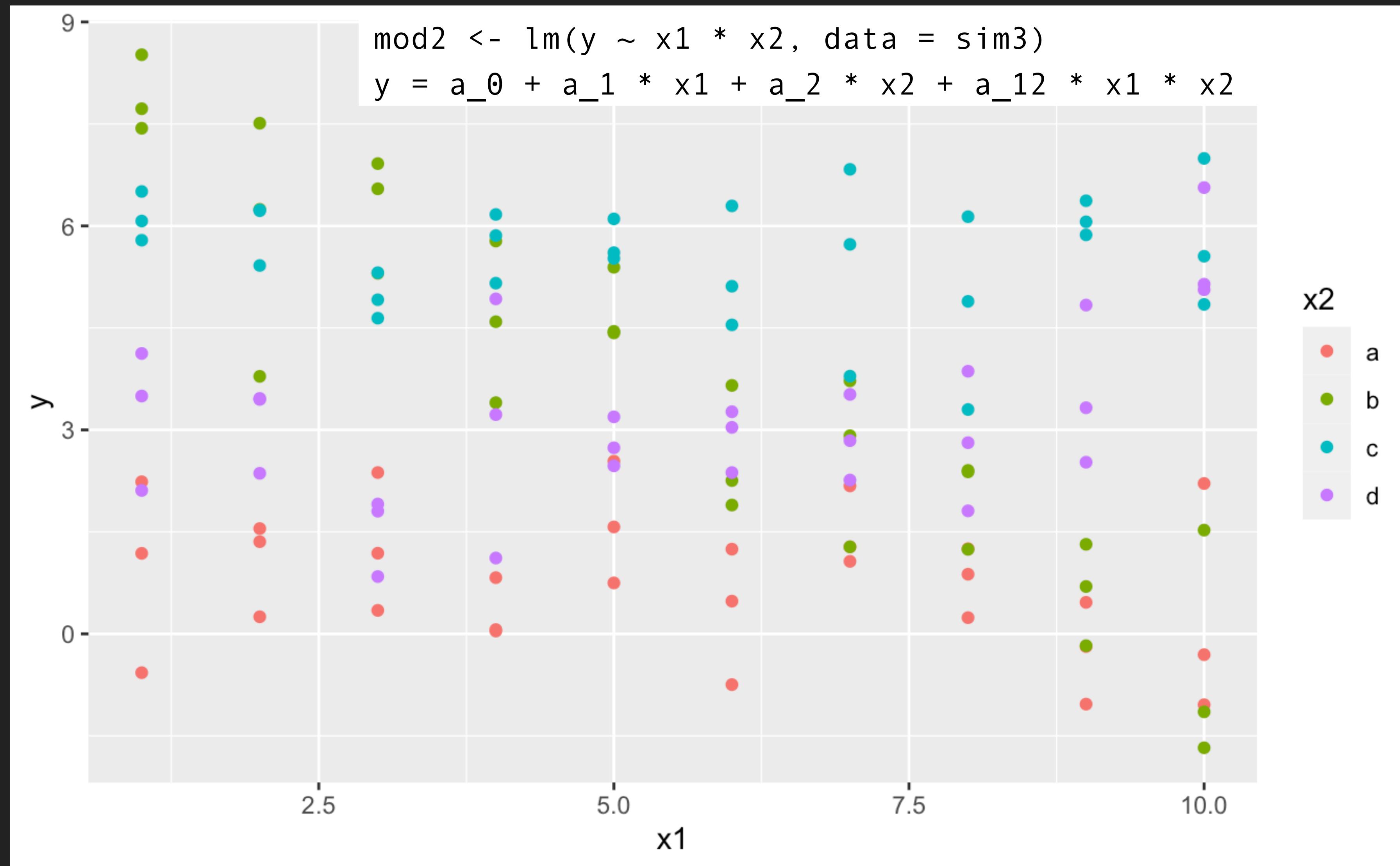
# What happens when you combine a continuous and a categorical variable?



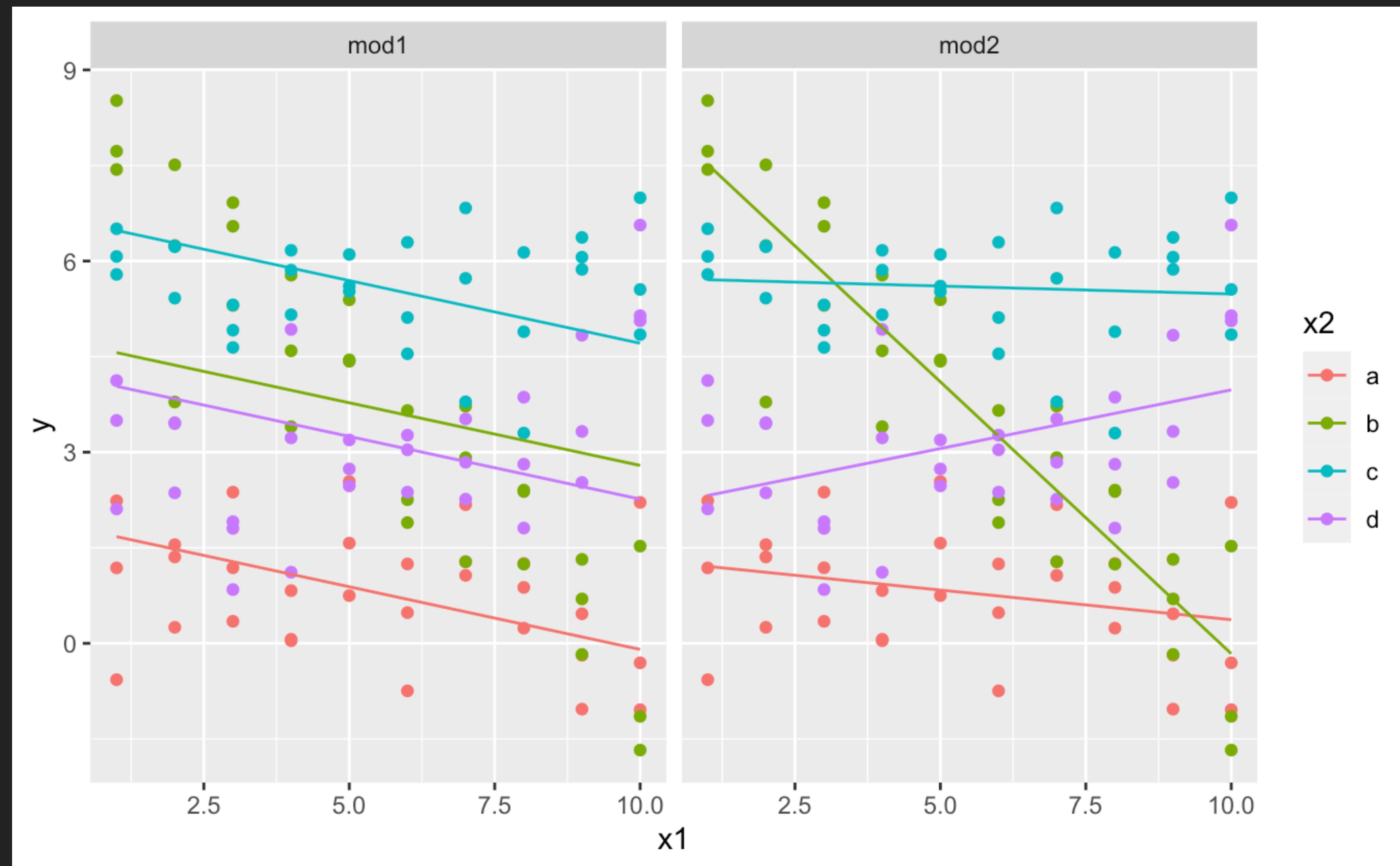
# There are two possible models you could fit to this data



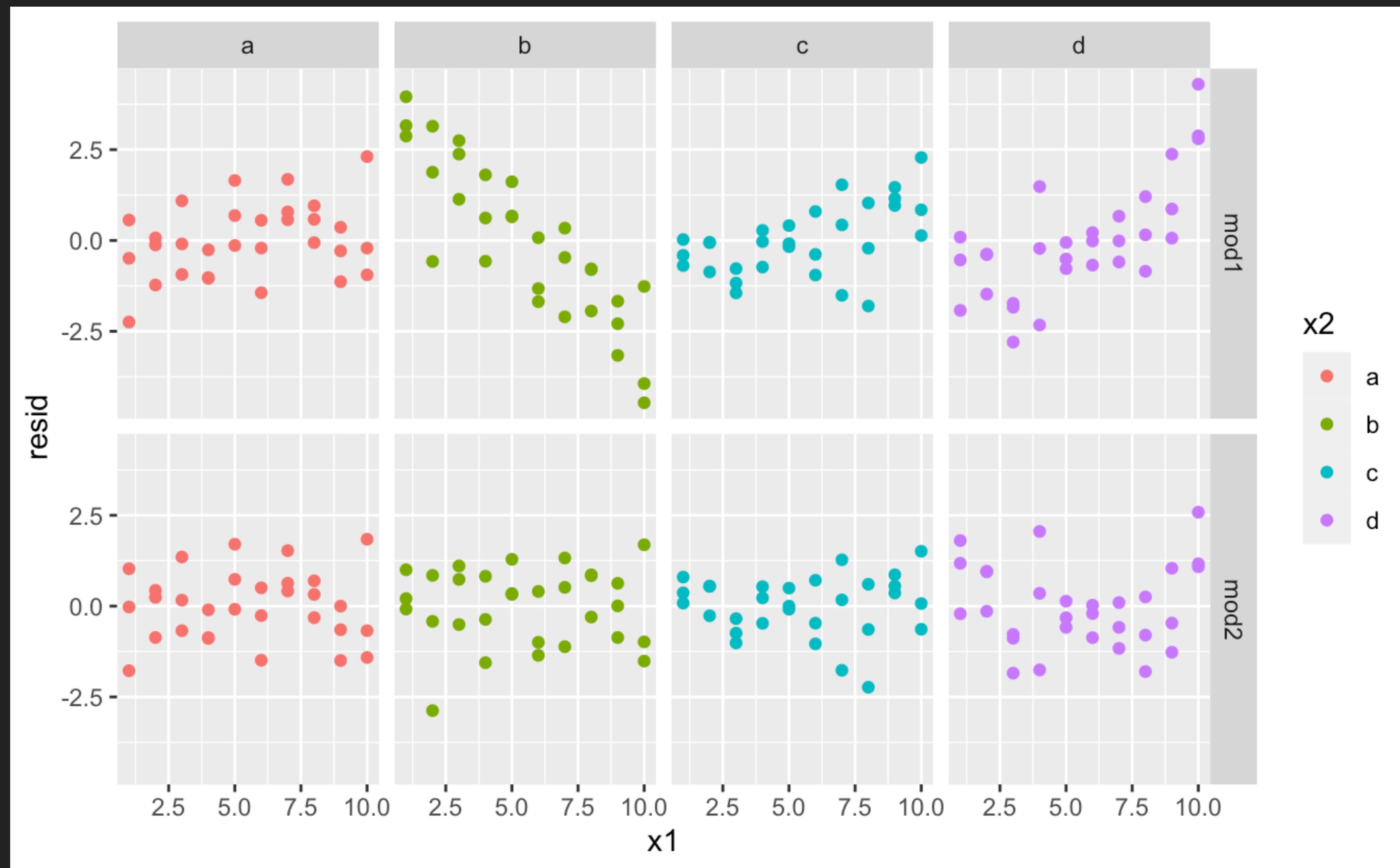
**\*: Both the interaction and the individual components are included in the model**



# The model using \* has a different slope and intercept for each line

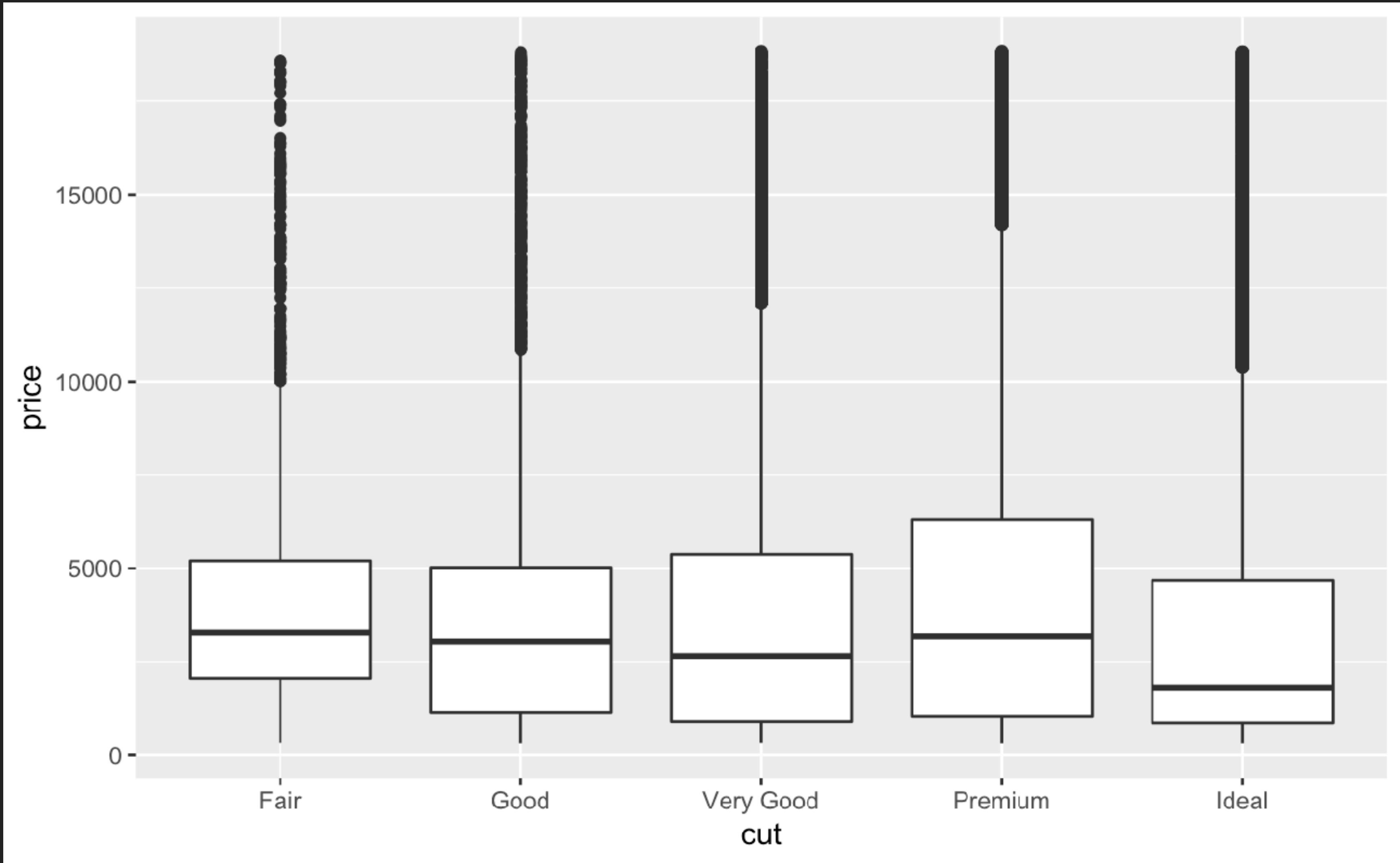


# Which model is better for this data?



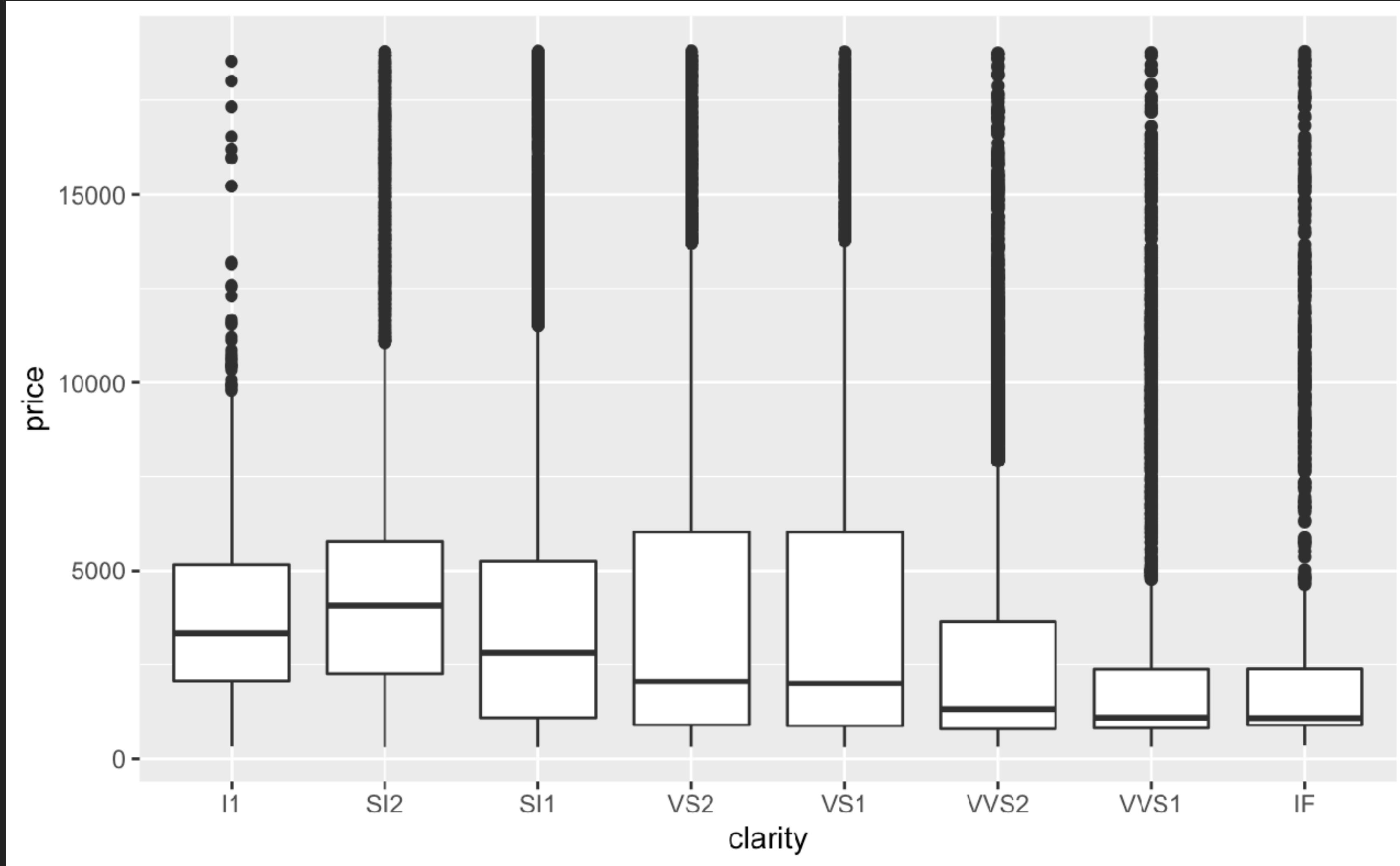
# Another example

# Why are low quality diamonds more expensive?



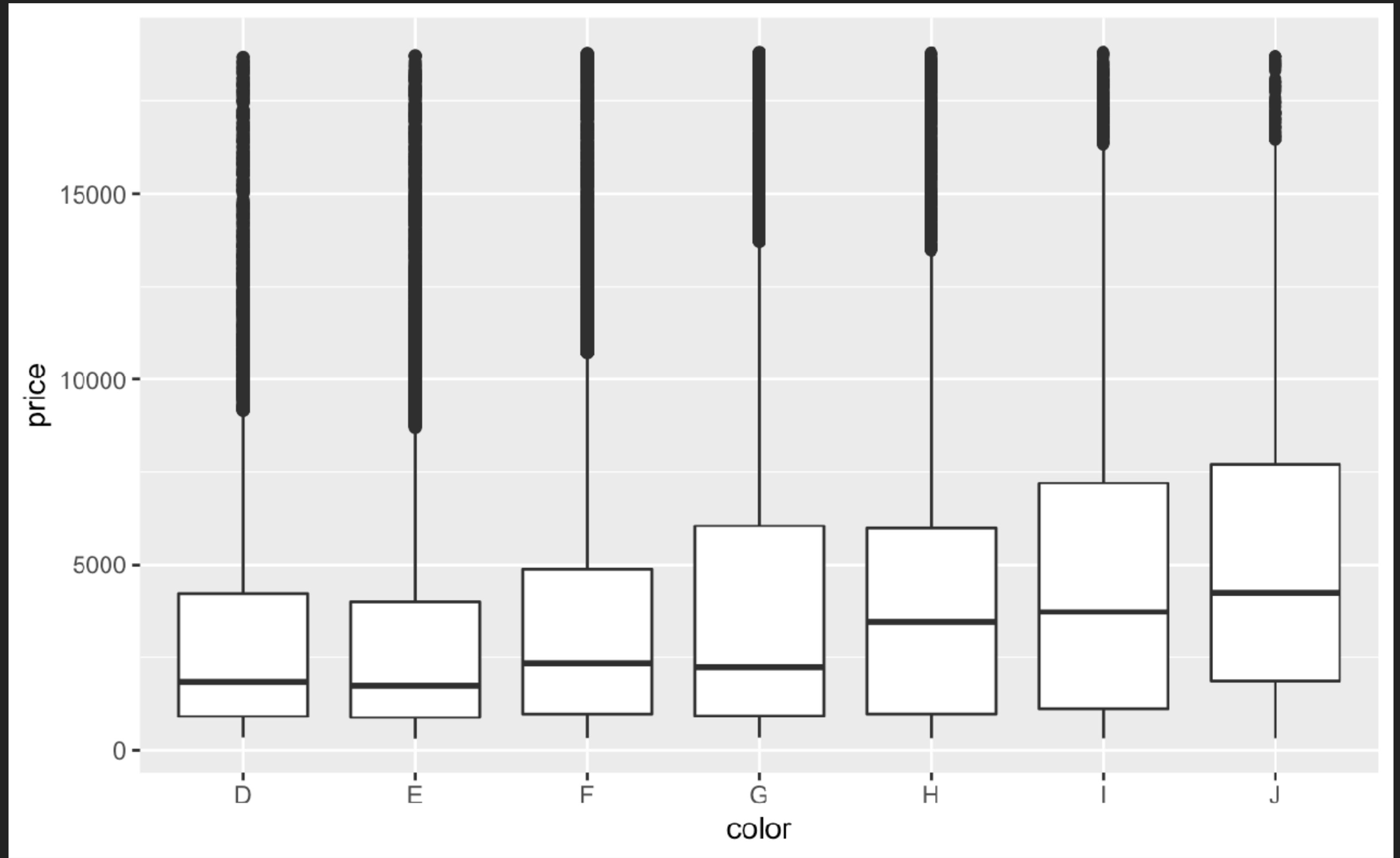
► Fair: worst cut

# Why are low quality diamonds more expensive?



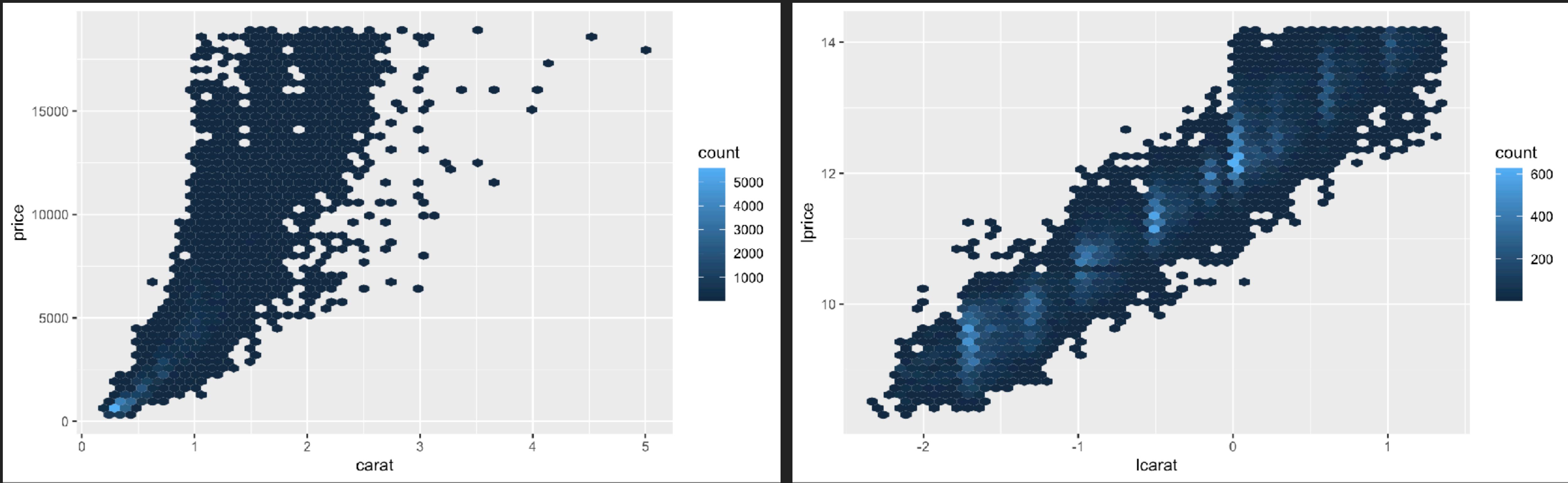
- ▶ I1: inclusions visible to the naked eye (worst clarity)

# Why are low quality diamonds more expensive?



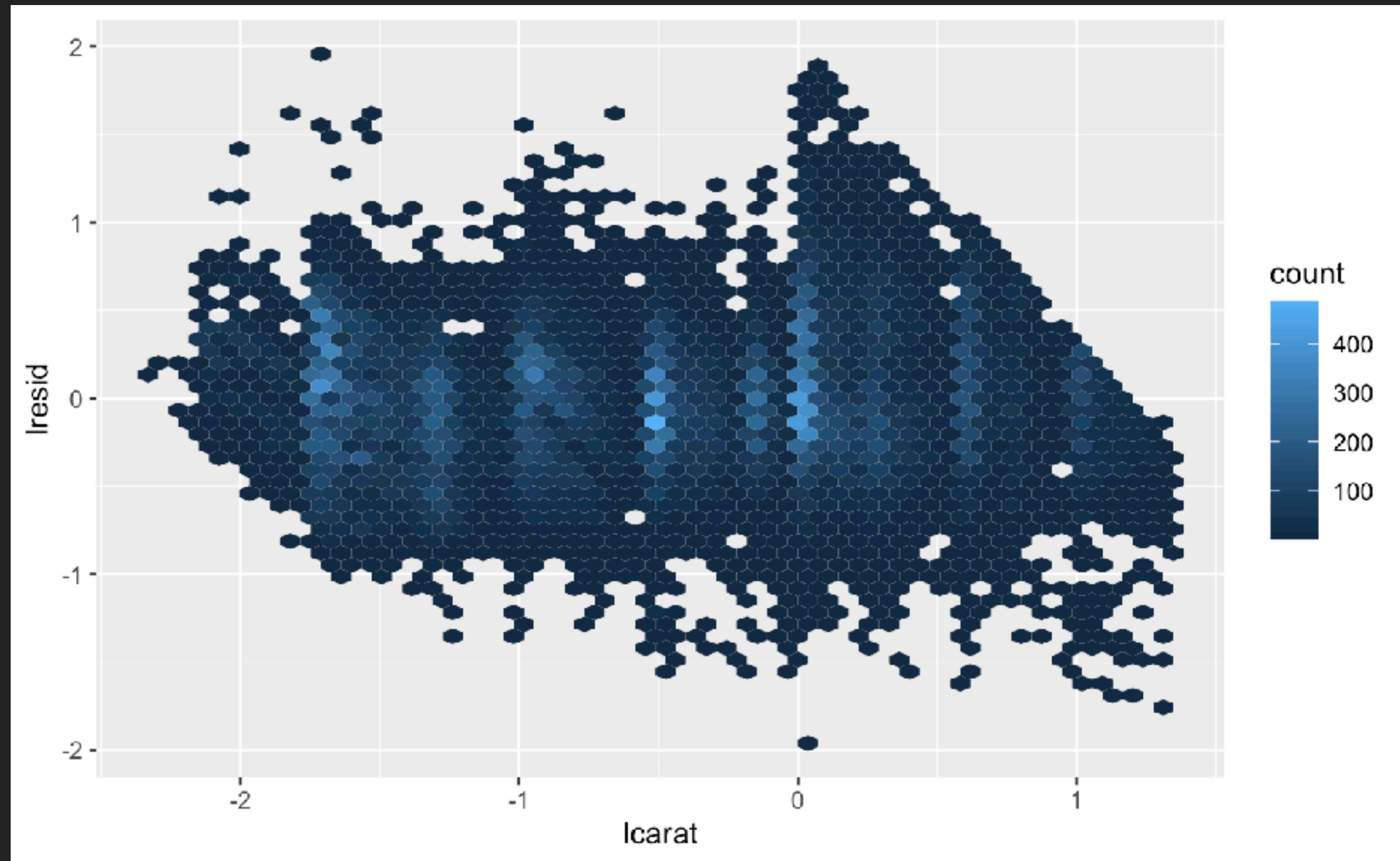
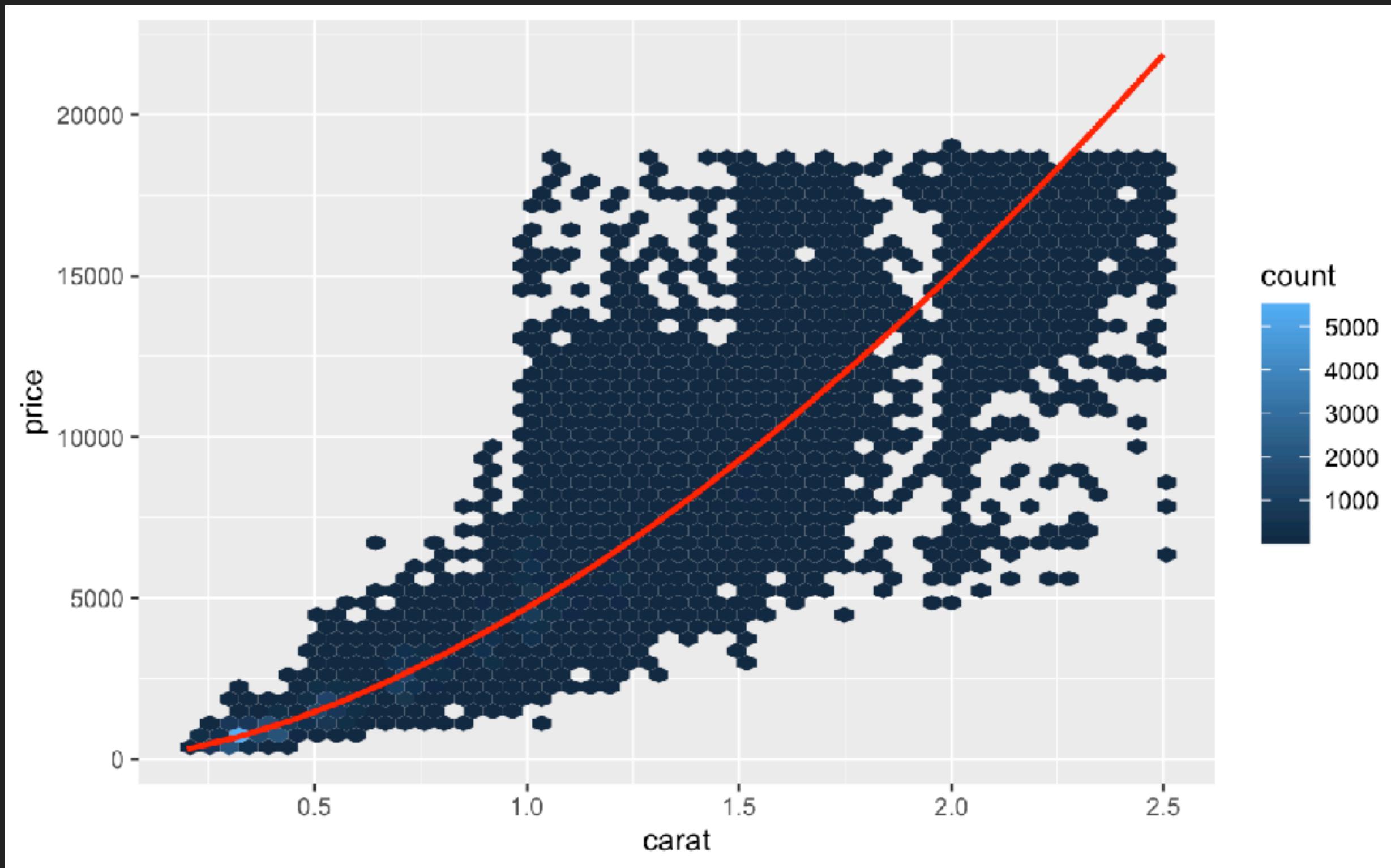
- ▶ J: slightly yellow (worst color)

# Because lower quality diamonds tend to be larger



- ▶ The weight of the diamond is the single most important factor for determining the price of the diamond.
  - ▶ Left: raw
  - ▶ Right: log-transformed

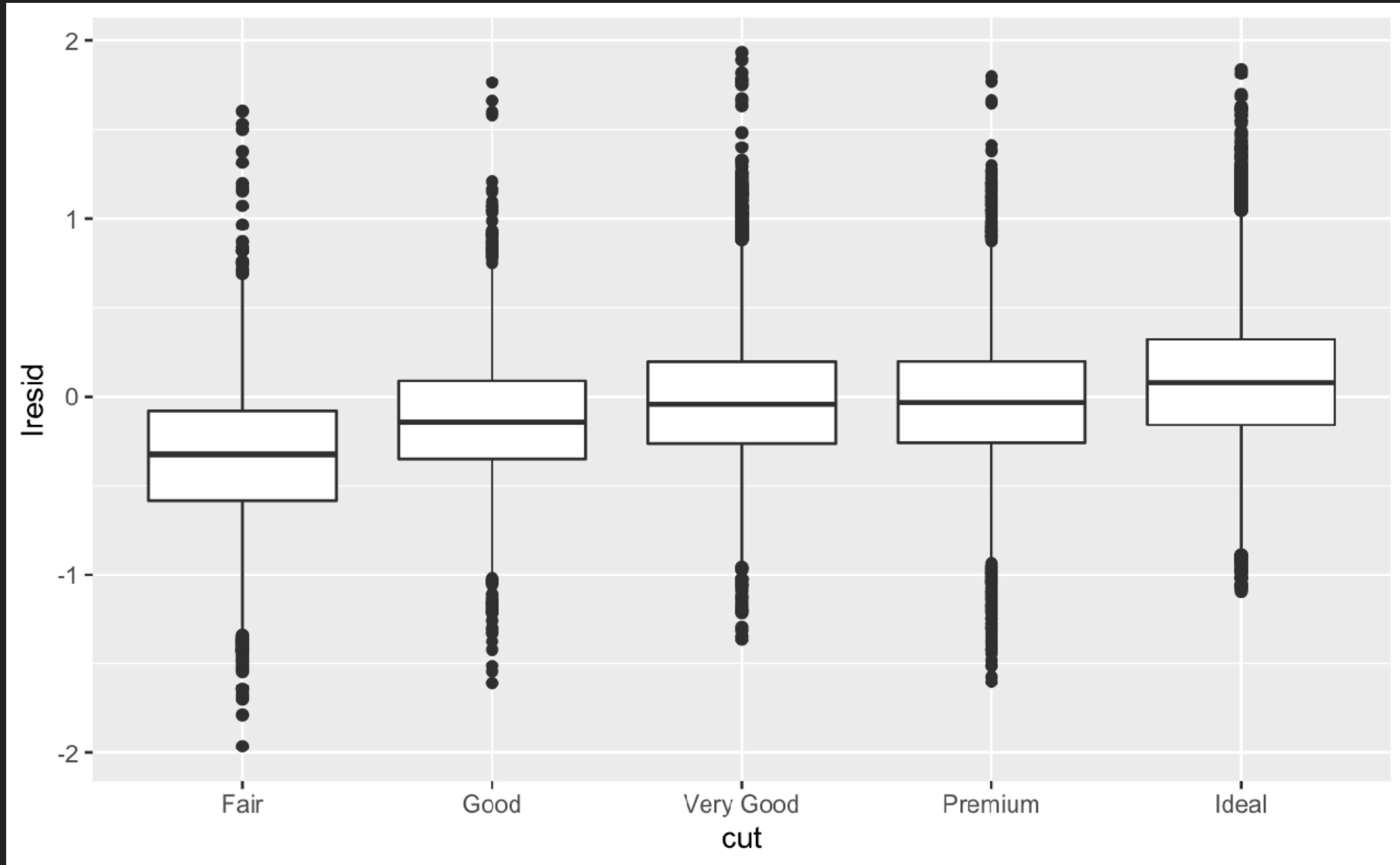
# Let's remove that strong linear pattern



```
mod_diamond <- lm(lprice ~ lcarat, data = diamonds2)
```

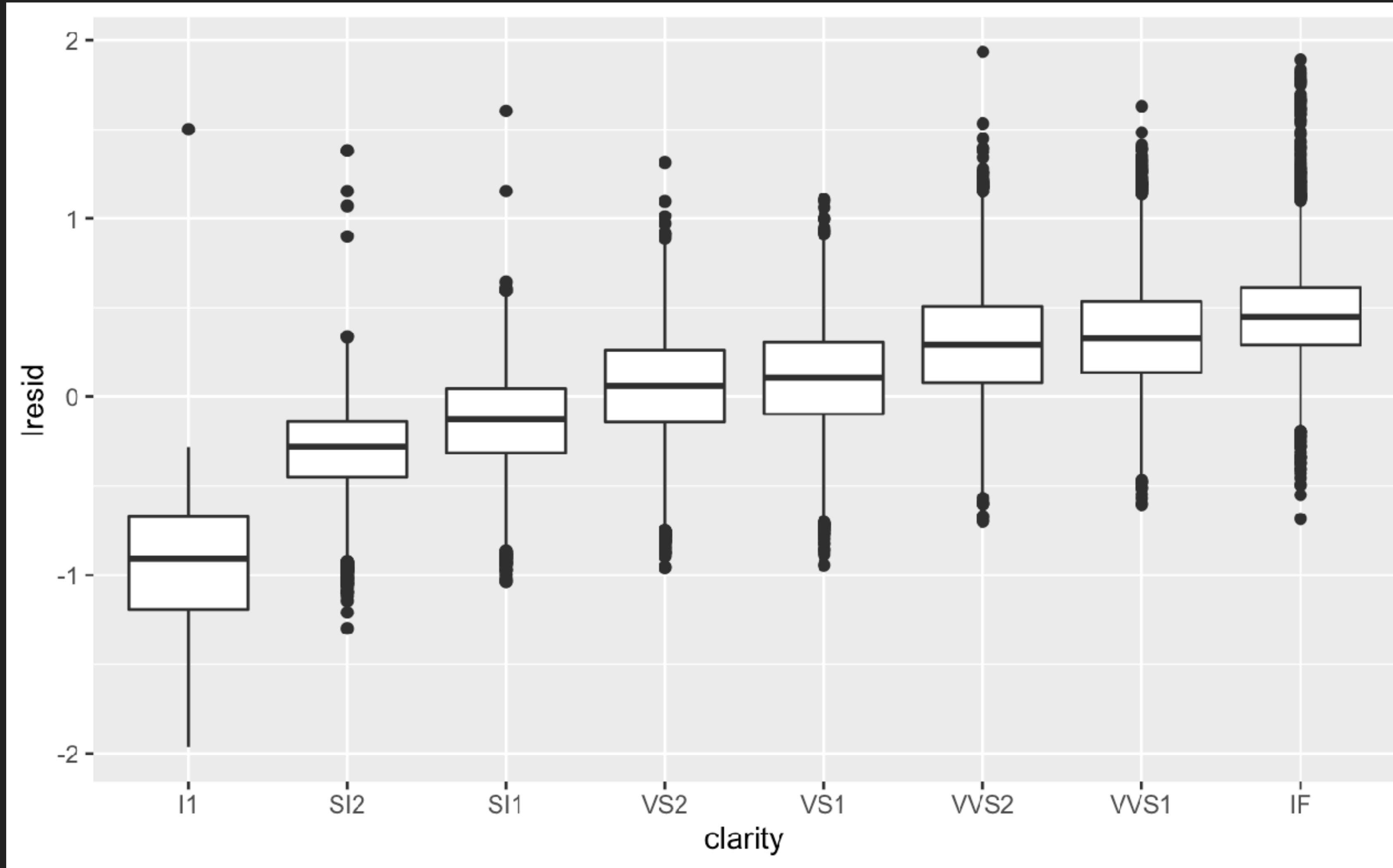
- Residuals confirm that we've successfully removed the strong linear pattern.

# Now we see the relationship we expect



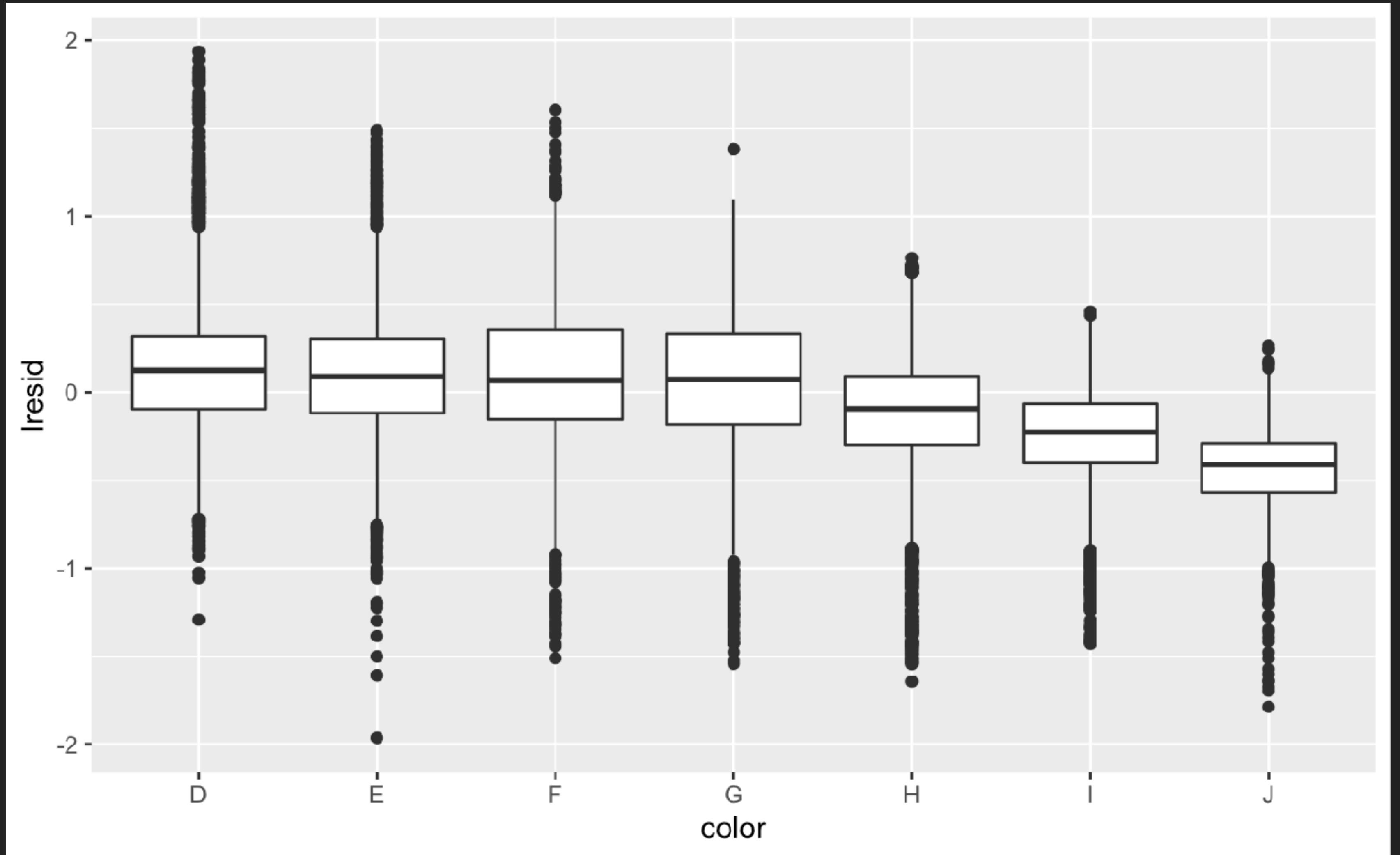
- ▶ Re-did our motivating plots using those residuals instead of price.
- ▶ Fair: worst cut

# Now we see the relationship we expect



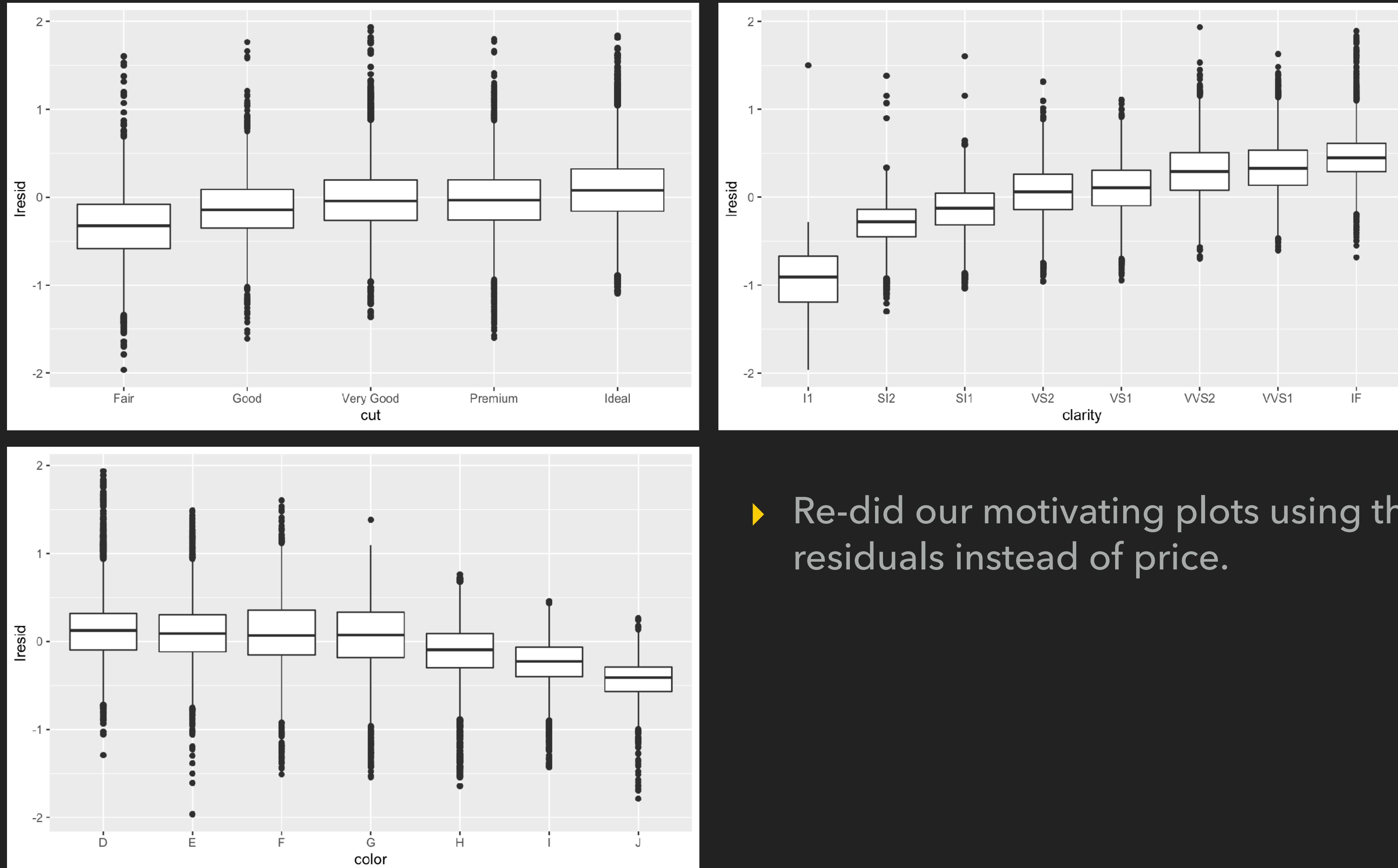
- ▶ I1: inclusions visible to the naked eye (worst clarity)

# Now we see the relationship we expect



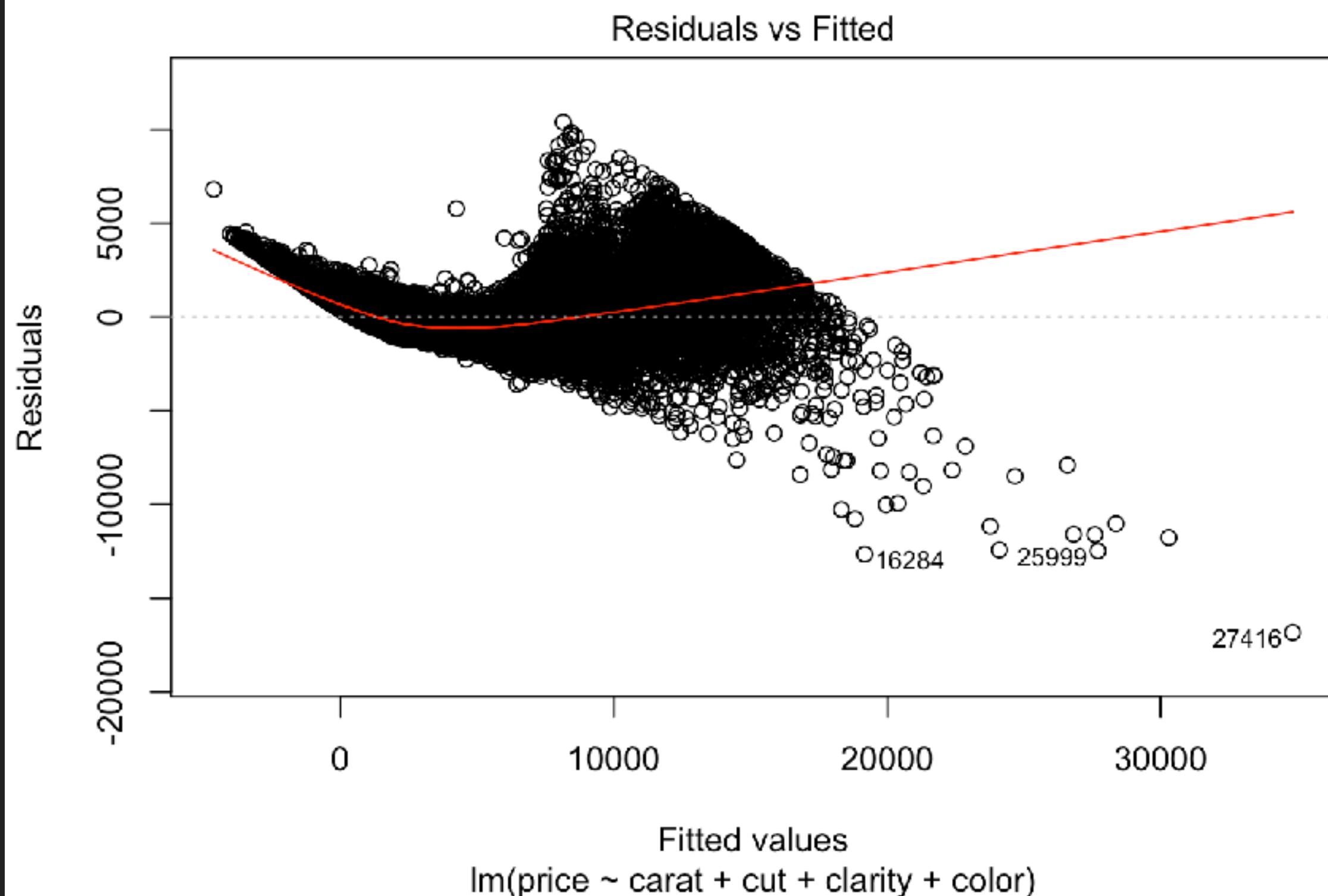
- ▶ J: slightly yellow (worst color)

# Now we see the relationship we expect

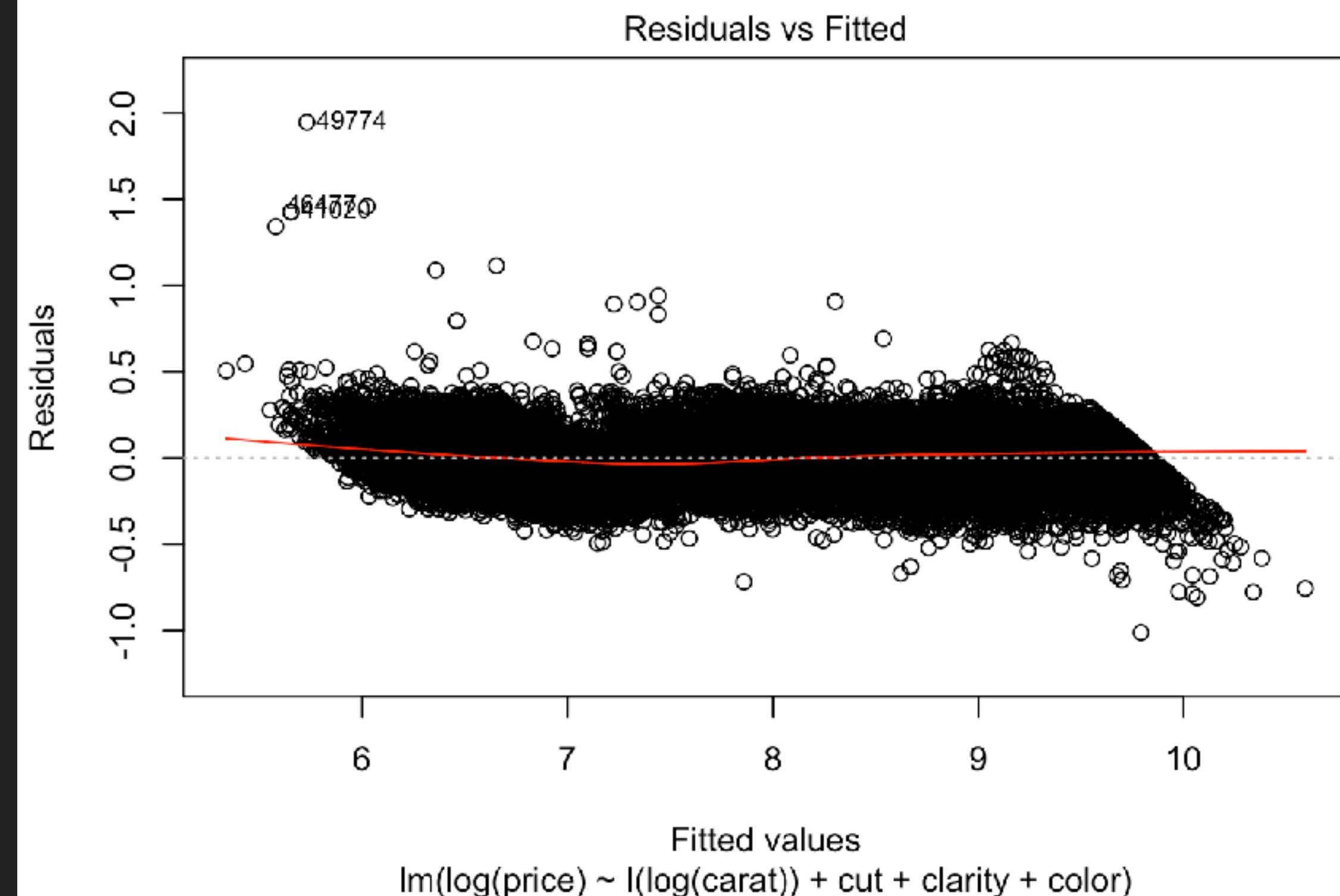


# Regression Diagnostics on the Diamonds Example

```
diamonds.lm <- lm(price ~ carat  
+ cut  
+ clarity  
+ color,  
data = diamonds)
```

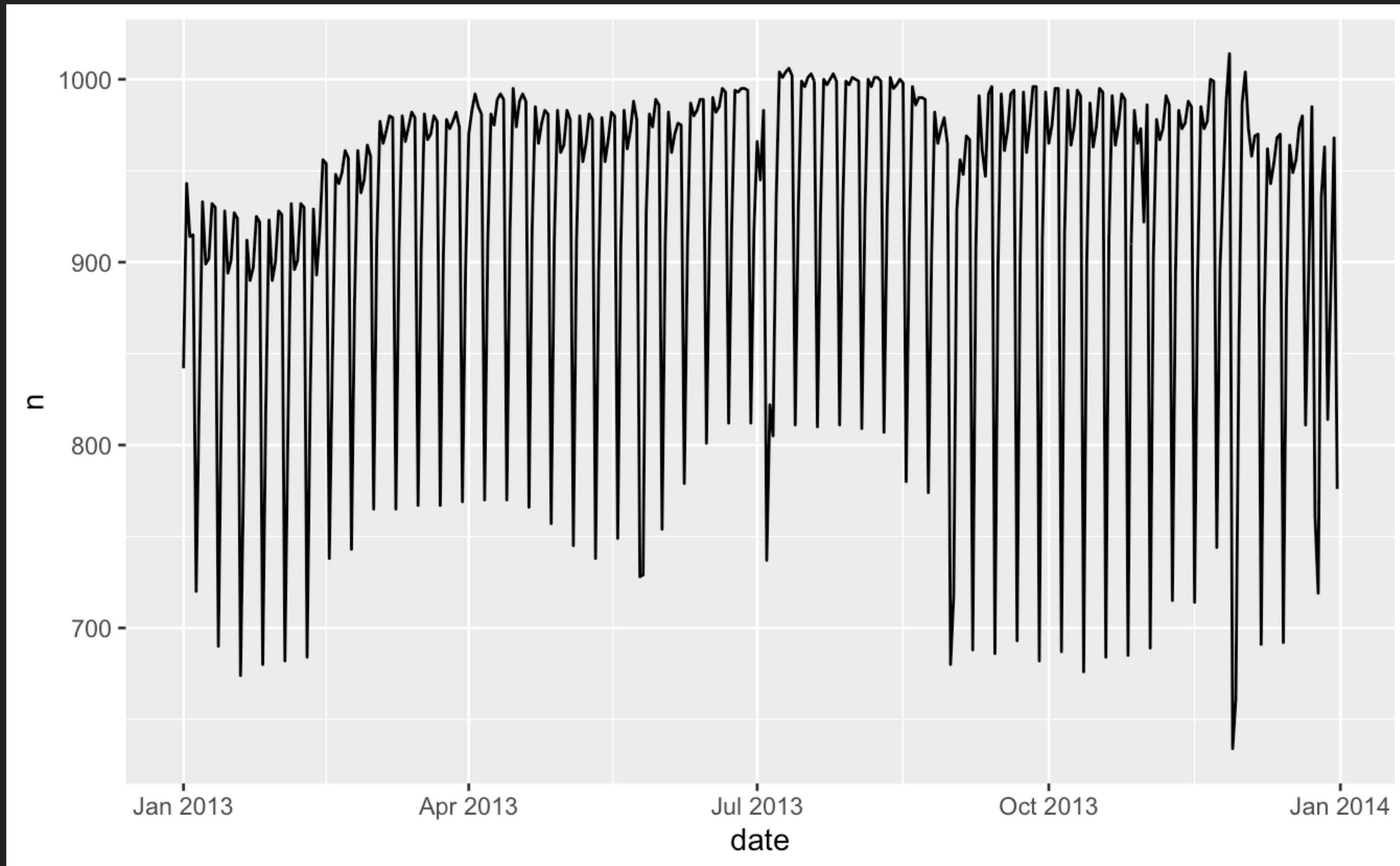


```
diamonds.lm2 <- lm(log(price) ~ I(log(carat))  
+ cut  
+ clarity  
+ color,  
data = diamonds)
```

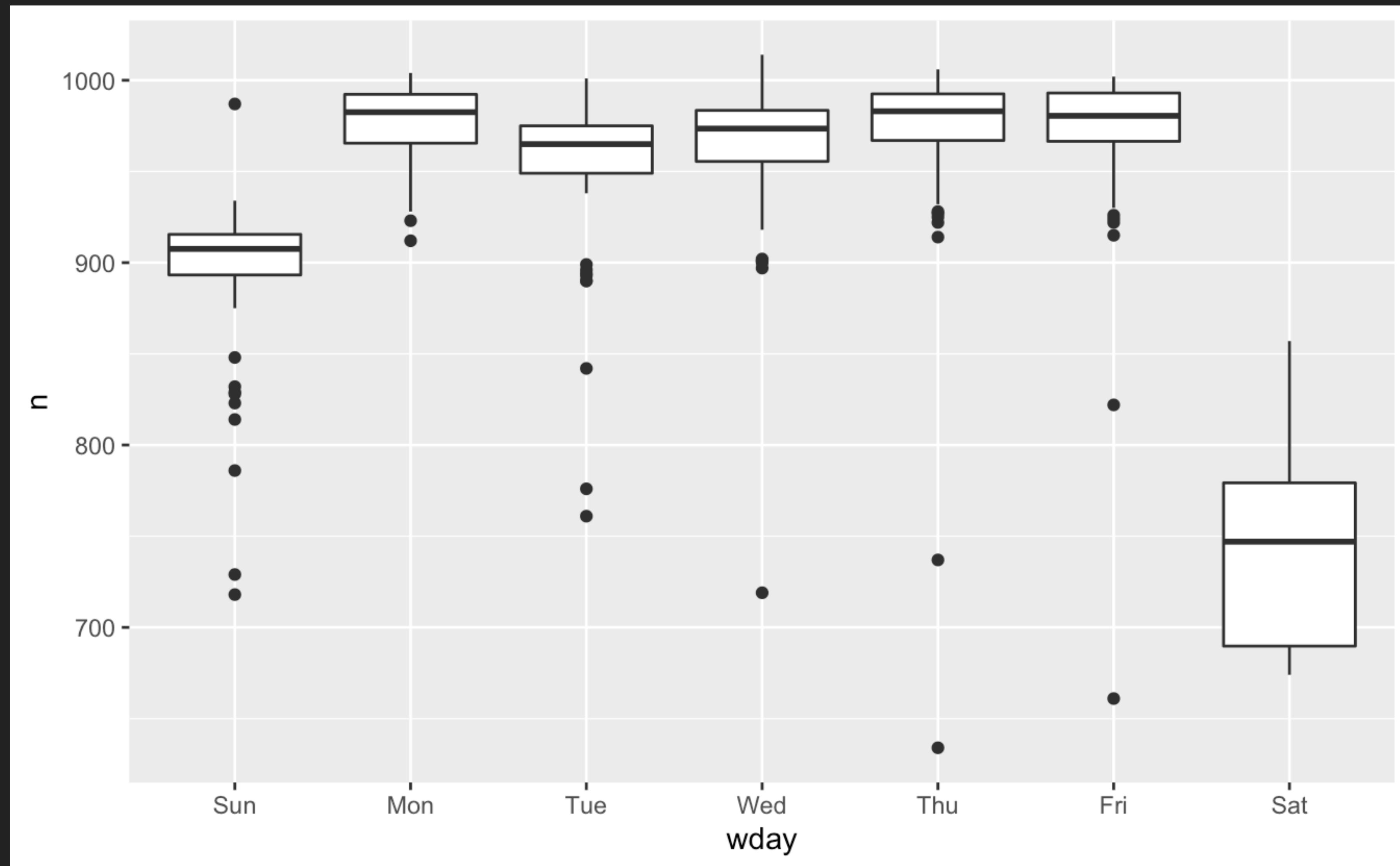


# Another example

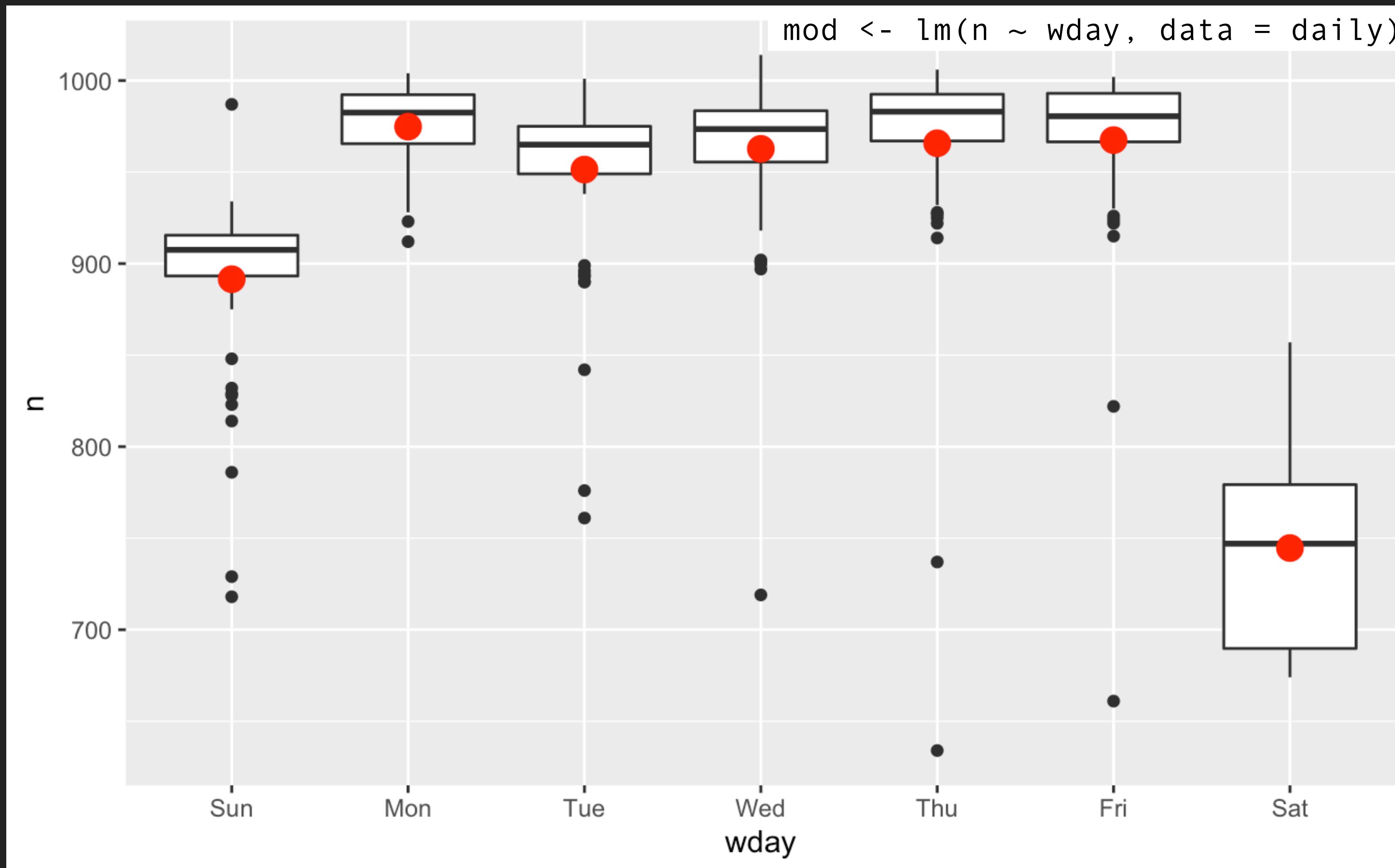
# The number of flights that leave NYC per day



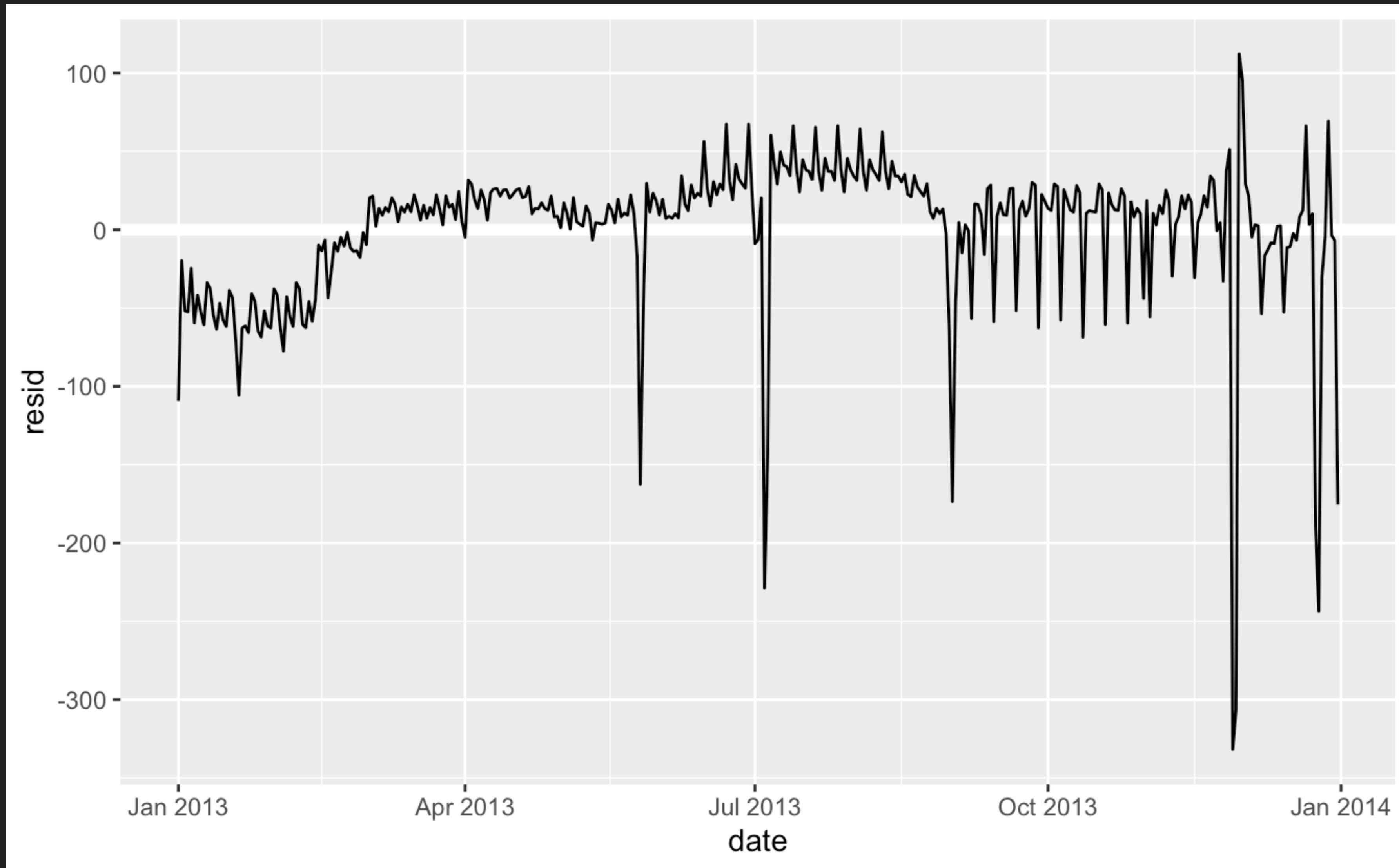
# A very strong day-of-week effect dominates the subtler patterns



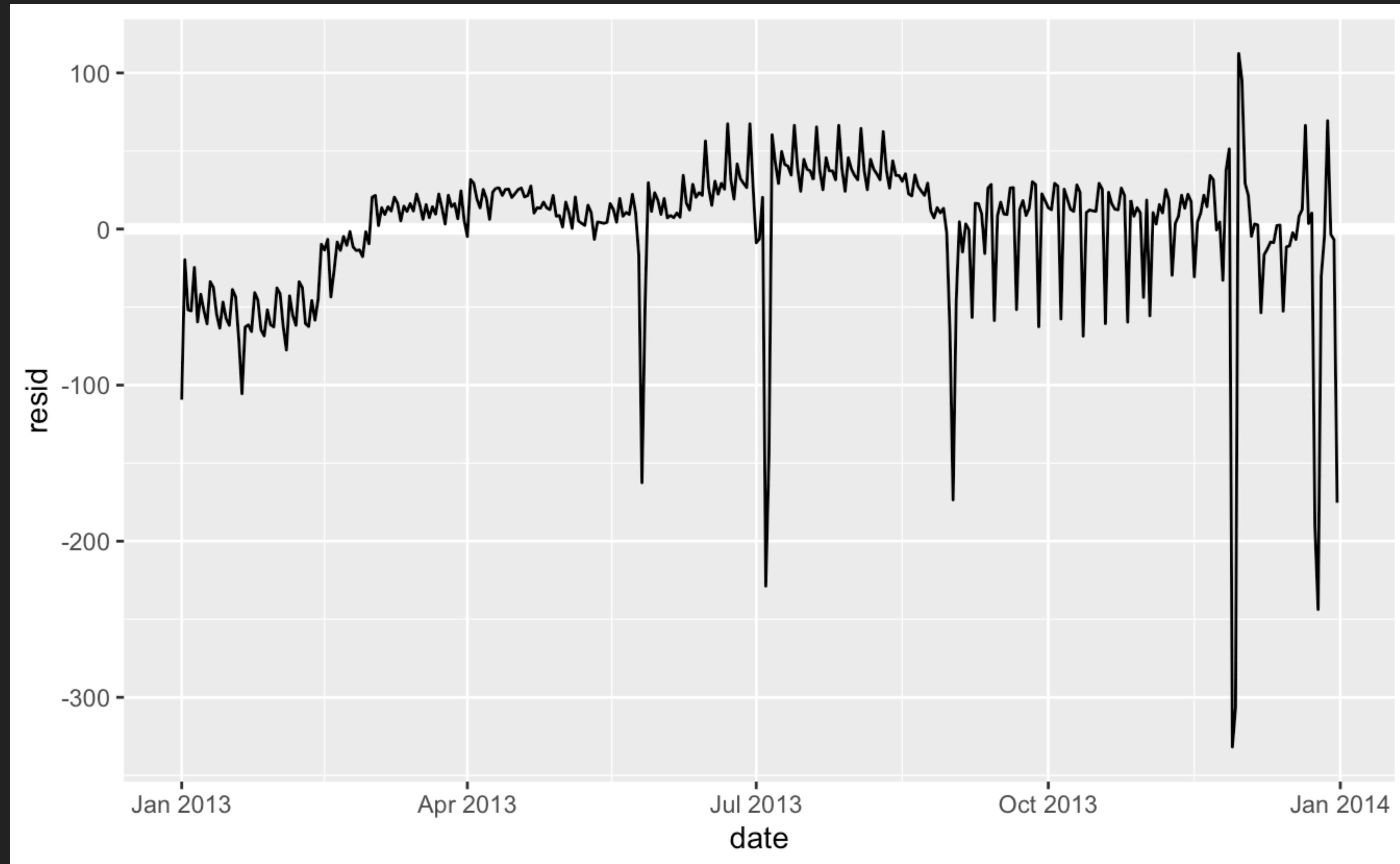
# Modeling the week day effect



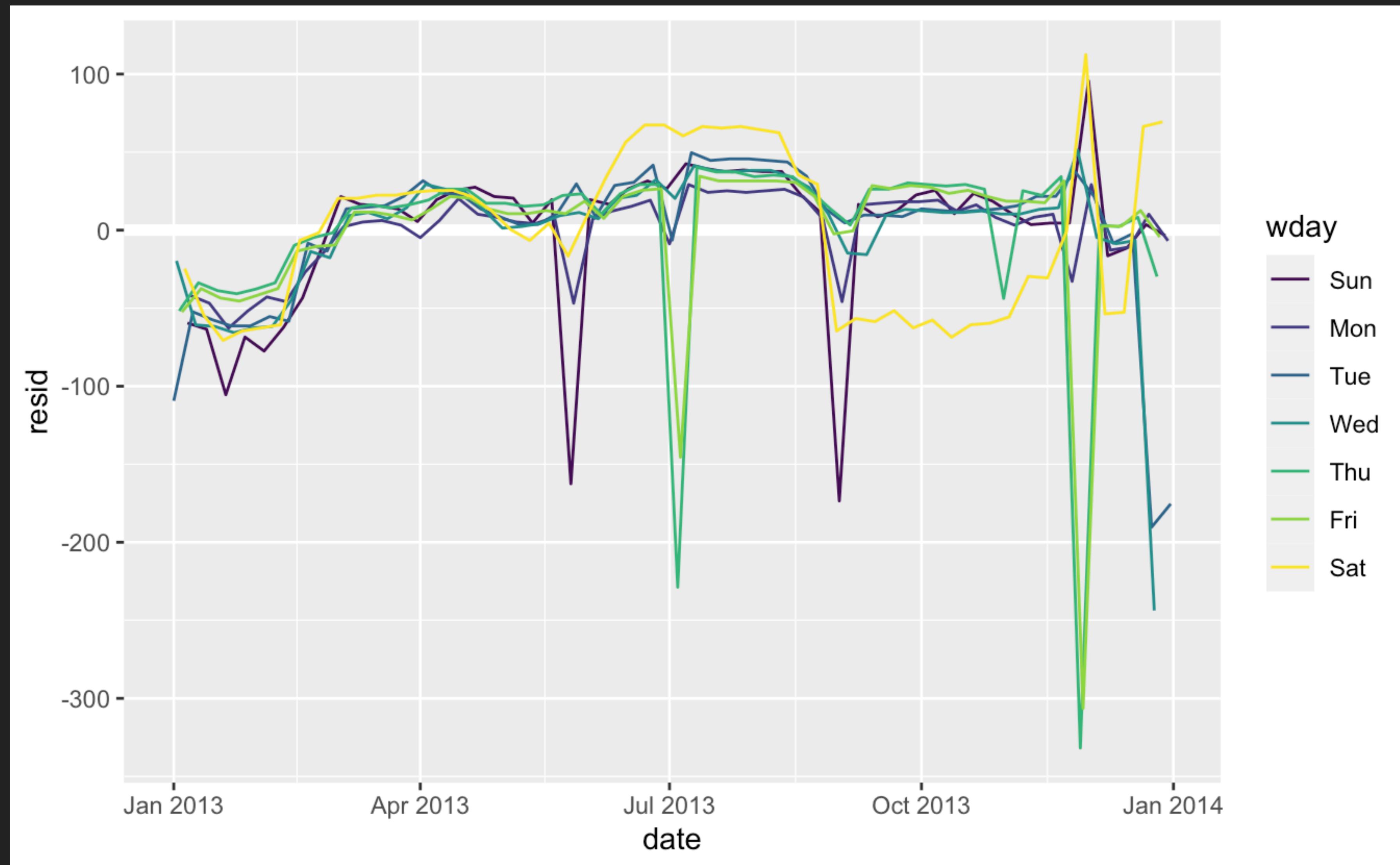
# Visualizing the residuals



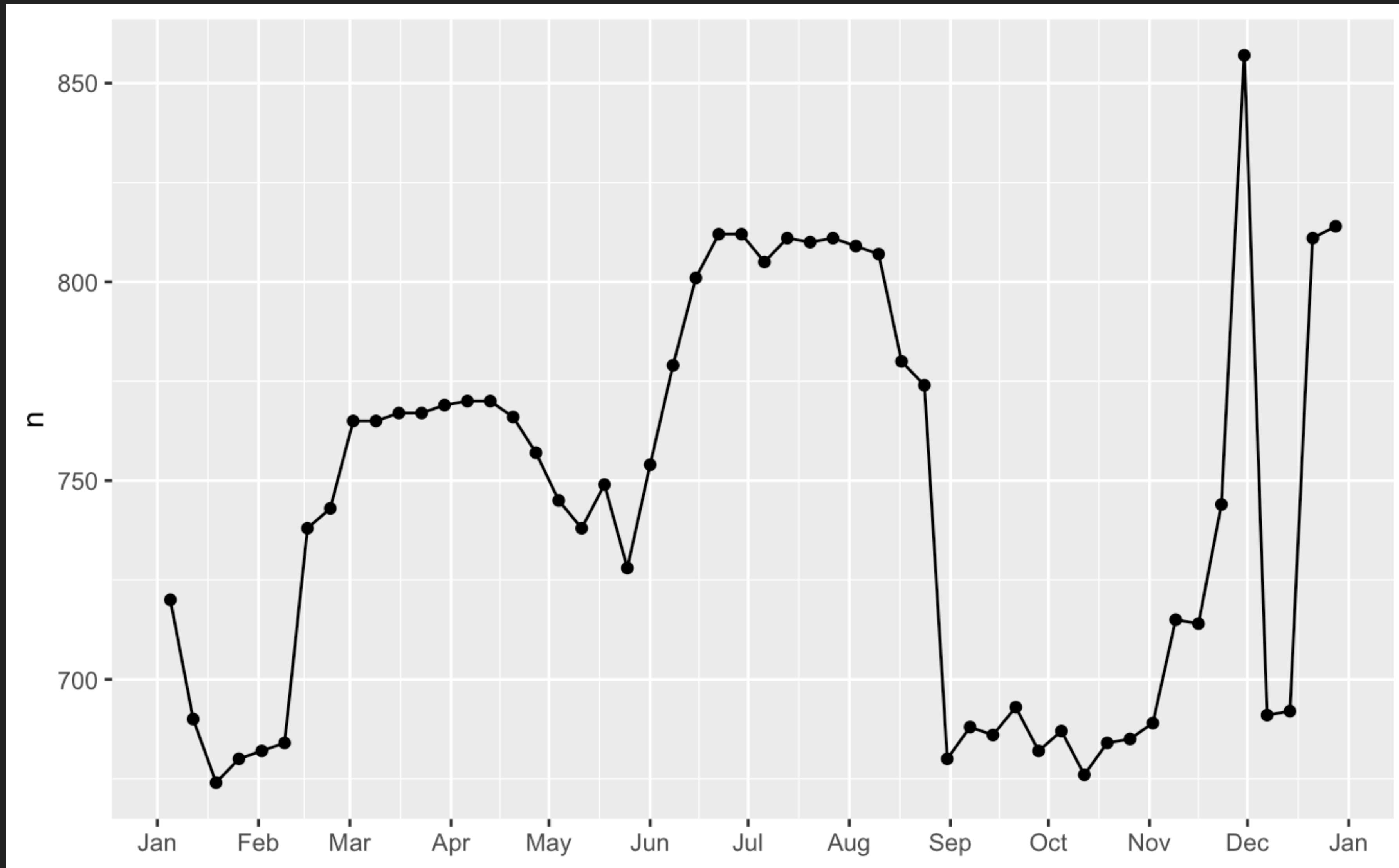
# Our model seems to fail starting in June



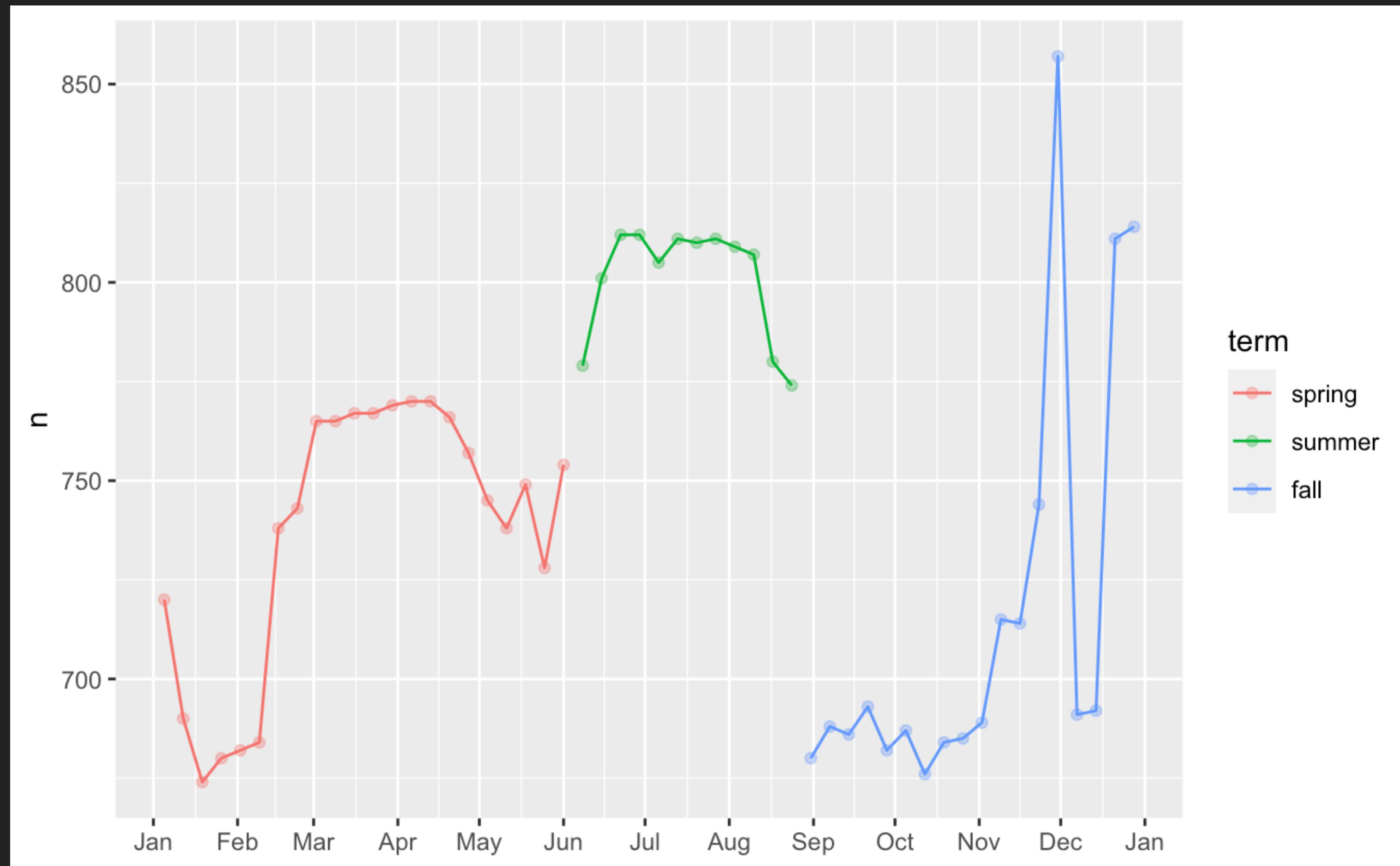
# ... especially when looking at weekend days



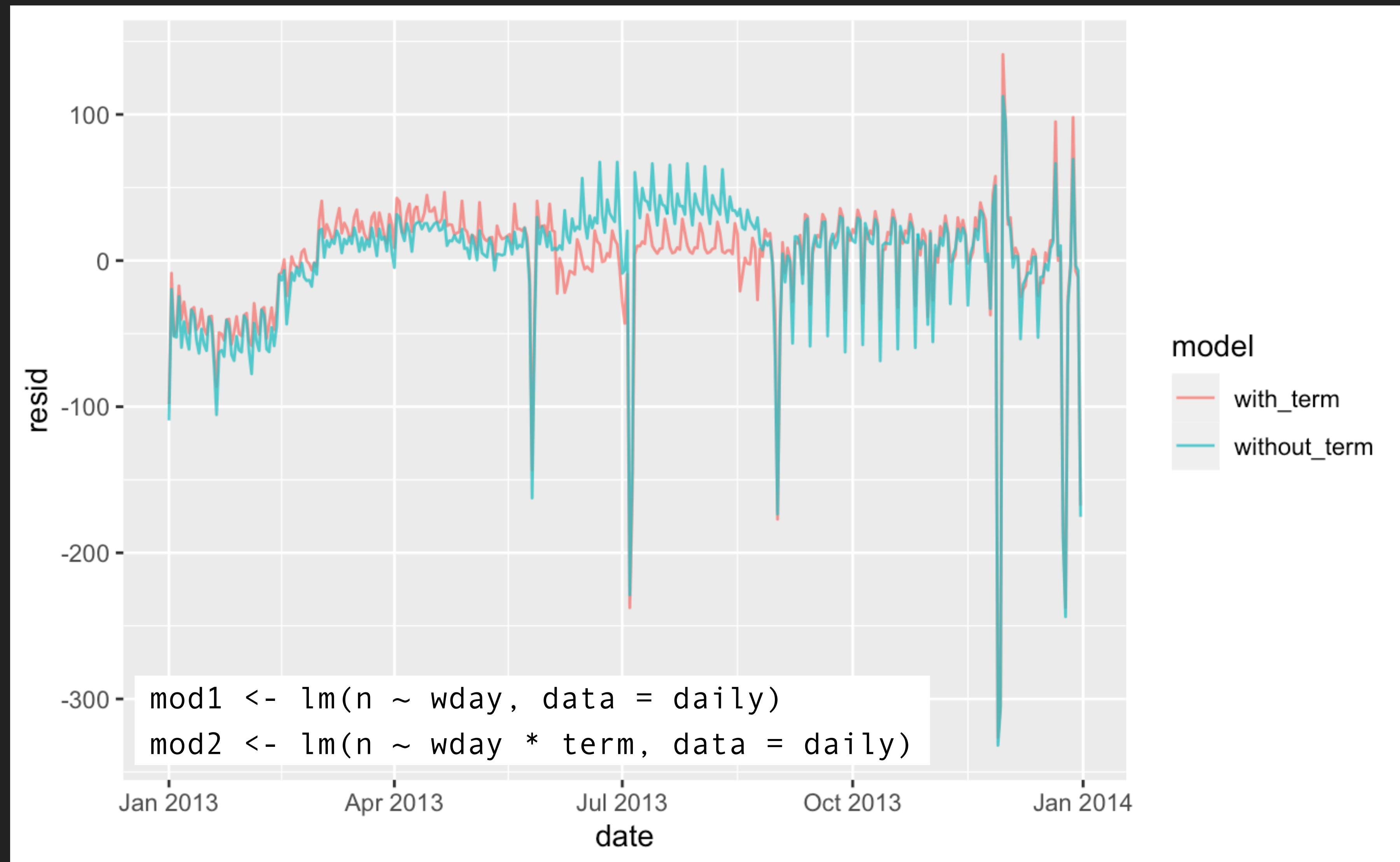
# The model fails to accurately predict the number of flights on Saturday



# Let's create a “term” variable that roughly captures the three school terms



# Fitting a separate day of week effect for each term improves our model



# Credits

- ▶ Graphics: Dave DiCello photography (cover)
- ▶ Bruce, P., Bruce, A., & Gedeck, P. (2020). Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python. O'Reilly Media.
- ▶ Goodman, S. (2008). A dirty dozen: Twelve p-value misconceptions. In Seminars in Hematology (Vol. 45, No. 3, pp. 135-140). WB Saunders.
- ▶ James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, p. 18). New York: springer.
- ▶ Grolemund, G., & Wickham, H. (2018). R for data science.