DOI:

Software

- Review
- Repository
- Archive

Submitted:
Published:



# Using the `moderndive` R package for introductory linear regression

**Albert Y. Kim**[1], **Chester Ismay**[2], **and Max Kuhn**[3]

**1** Assistant Professor of Statistical and Data Sciences, Smith College, Northampton, MA, USA. **2** Data Science Evangelist, DataRobot, Portland, OR, USA. **3** Software Engineer, RStudio, USA.

## Introduction

Linear regression has long been a staple of introductory statistics courses. While the timing of when to introduce it may have changed (many argue that descriptive regression should be done earlier in the curriculum and then revisited later after statistical inference has been covered), its overall importance in the introductory statistics curriculum remains the same.

Let's consider data gathered from end of semester student evaluations for a sample of 463 courses taught by 94 professors from the University of Texas at Austin from openintro.org (Diez, Barr, and Çetinkaya-Rundel 2015). This data is included in `evals` data frame from the `moderndive` R package for tidyverse-friendly introductory linear regression, an R package designed to supplement the book "Statistical Inference via Data Science: A ModernDive into R and the Tidyverse" (Ismay and Kim 2019).

In Table **??** we present a subset of 9 of the 14 variables included for a random sample of 5 courses[1]. These include:

1. `ID` uniquely identifies the course whereas `prof_ID` identifies the professor who taught this course. This distinction is important since many professors are included more than once in this dataset.
2. `score` is the outcome variable of interest: average professor evaluation score out of 5 as given by the students in this course.
3. The remaining variables are demographic variables describing that course's instructor, including `bty_avg` average "beauty" score for that professor as given by a panel of 6 students.[2]

| ID | prof_ID | score | age | bty_avg | gender | ethnicity | language | rank |
|---|---|---|---|---|---|---|---|---|
| 129 | 23 | 3.7 | 62 | 3.000 | male | not minority | english | tenured |
| 109 | 19 | 4.7 | 46 | 4.333 | female | not minority | english | tenured |
| 28 | 6 | 4.8 | 62 | 5.500 | male | not minority | english | tenured |
| 434 | 88 | 2.8 | 62 | 2.000 | male | not minority | english | tenured |
| 330 | 66 | 4.0 | 64 | 2.333 | male | not minority | english | tenured |

### Regression analysis the "good old-fashioned" way

Let's fit a simple linear regression model of teaching `score` as a function of instructor `age` using the `lm()` function.

[1]For details on the remaining 5 variables, see the help file by running `?evals`.
[2]Note that `gender` was collected as a binary variable at the time of the study (2005).

```r
library(moderndive)
score_model <- lm(score ~ age, data = evals)
```

Let's now study the output of the fitted model `score_model` "the good old fashioned way": using `summary.lm()`.

```r
summary(score_model)
##
## Call:
## lm(formula = score ~ age, data = evals)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.9185 -0.3531  0.1172  0.4172  0.8825
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.461932   0.126778  35.195   <2e-16 ***
## age         -0.005938   0.002569  -2.311   0.0213 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5413 on 461 degrees of freedom
## Multiple R-squared:  0.01146,    Adjusted R-squared:  0.009311
## F-statistic: 5.342 on 1 and 461 DF,  p-value: 0.02125
```

Here are five common student questions we've heard over the years in our introductory statistics courses based on this output.

1. "Wow! Look at those p-value stars! Stars are good, so I should try to get many stars, right?"
2. "How do extract the values in the regression table?"
3. "Where are the fitted and predicted values and residuals?"
4. "How do I apply this model to a new set of data to make predictions?"
5. "What is all this other stuff at the bottom?"

## Regression analysis using `moderndive`

To address these comments and questions, we've included three functions in the `moderndive` package that take a fitted model object as input and return the same information as `summary.lm()`, but output in tidyverse-friendly format (Wickham, Averick, et al. 2019). As we'll discuss in Section 3.1, these three functions are merely wrappers to existing functions in the `broom` package for converting statistical objects into tidy tibbles, but with the introductory statistics student in mind (Robinson and Hayes 2019).

1. Get a tidy regression table **with confidence intervals**:

```r
get_regression_table(score_model)
## # A tibble: 2 x 7
##   term      estimate std_error statistic p_value lower_ci upper_ci
##   <chr>        <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
## 1 intercept    4.46      0.127     35.2    0         4.21     4.71
## 2 age         -0.006     0.003     -2.31   0.021    -0.011   -0.001
```

2. Get information on each point/observation in your regression, including fitted and predicted values & residuals, in a single data frame:

```r
get_regression_points(score_model)
## # A tibble: 463 x 5
##       ID score   age score_hat residual
##    <int> <dbl> <int>     <dbl>    <dbl>
##  1     1   4.7    36      4.25    0.452
##  2     2   4.1    36      4.25   -0.148
##  3     3   3.9    36      4.25   -0.348
##  4     4   4.8    36      4.25    0.552
##  5     5   4.6    59      4.11    0.488
##  6     6   4.3    59      4.11    0.188
##  7     7   2.8    59      4.11   -1.31
##  8     8   4.1    51      4.16   -0.059
##  9     9   3.4    51      4.16   -0.759
## 10    10   4.5    40      4.22    0.276
## # ... with 453 more rows
```

3. Get scalar summaries of a regression fit including $R^2$ and $R^2_{adj}$ but also the (root) mean-squared error:

```r
get_regression_summaries(score_model)
## # A tibble: 1 x 8
##   r_squared adj_r_squared   mse  rmse sigma statistic p_value    df
##       <dbl>         <dbl> <dbl> <dbl> <dbl>     <dbl>   <dbl> <dbl>
## 1     0.011         0.009 0.292 0.540 0.541      5.34   0.021     2
```

## Bonus: Visualizing parallel slopes models with `moderndive`

Furthermore, say you would like to visualize the relationship between two numerical variables and a third categorical variable with $k$ levels using a colored scatterplot using the `ggplot2` package for data visualization (Wickham, Chang, et al. 2019). Using `geom_smooth(method = "lm", se = FALSE)` yields a visualization of an *interaction model* where each of the $k$ regression lines has their own intercept and slope. For example in Figure Figure 1, we extend our previous regression model by now mapping the categorical variable `ethnicity` to the `color` aesthetic.

```r
library(ggplot2)

# Code to visualize interaction model:
ggplot(evals, aes(x = age, y = score, color = ethnicity)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  labs(x = "Age", y = "Teaching score", color = "Ethnicity")
```

However, many introductory statistics courses start with the easier to teach "common slope, different intercepts" regression model, also known as the *parallel slopes* model. However, no such method exists with `geom_smooth()`

Evgeni Chasnovski thus wrote a custom `geom_` extension to `ggplot2` called `geom_parallel_slopes()`; this extension is included in the `moderndive` package. Much like `geom_smooth()` from the `ggplot2` package, you merely add a `geom_parallel_slopes` layer to your plot as seen in Figure 2.

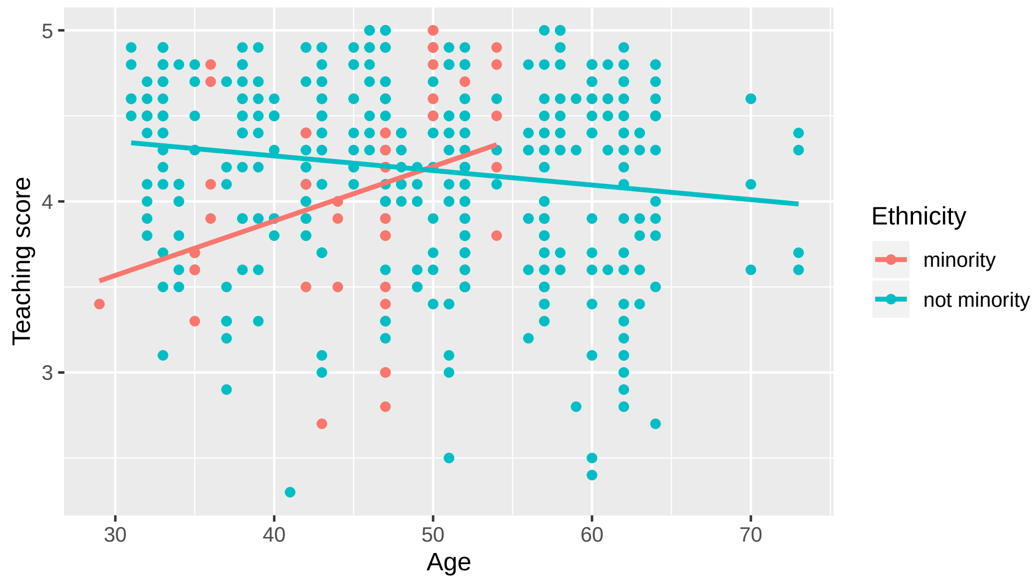


**Figure 1:** Visualization of interaction model.

```r
# Code to visualize parallel slopes model:
ggplot(evals, aes(x = age, y = score, color = ethnicity)) +
  geom_point() +
  geom_parallel_slopes(se = FALSE) +
  labs(x = "Age", y = "Teaching score", color = "Ethnicity")
```

At this point however, students will inevitably ask a sixth question: "When would you ever use a parallel slopes model?"

## Why should you use the `moderndive` package?

To recap this introduction, we believe that that the following functions included in the `moderndive` package:

1. `get_regression_table()`
2. `get_regression_points()`
3. `get_regression_summaries()`
4. `geom_parallel_slopes()`

are effective pedagogical tools that can help address the above six common student comments and questions relating to introductory linear regression performed in R:

1. "Wow! Look at those p-value stars! Stars are good, so I should try to get many stars, right?"
2. "How do extract the values in the regression table?"
3. "Where are the fitted and predicted values and residuals?"
4. "How do I apply this model to a new set of data to make predictions?"
5. "What is all this other stuff at the bottom?"
6. "When would you ever use a parallel slopes model over an interaction model?"

We now argue why.

The Journal of Open Source Software

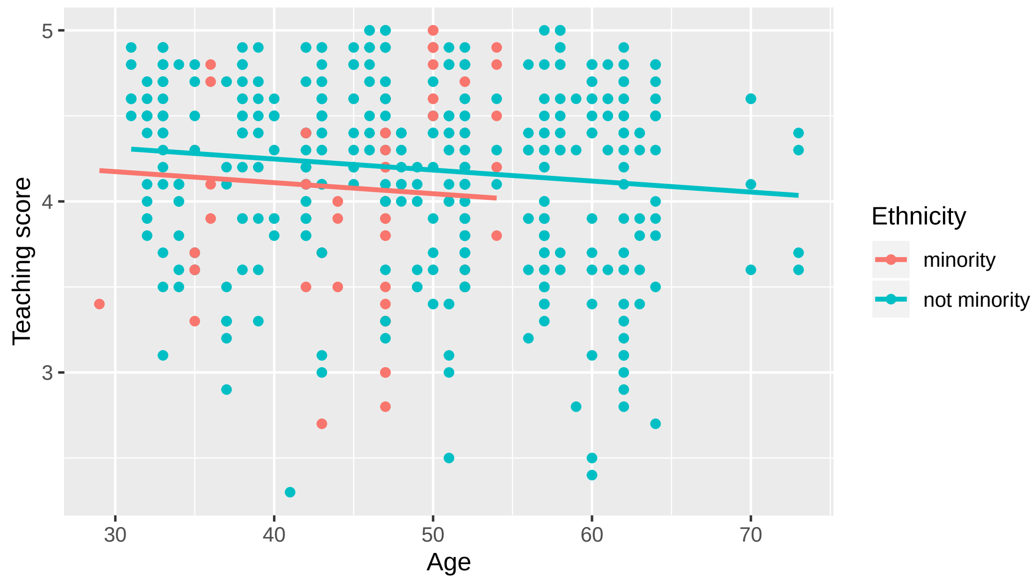


**Figure 2:** Visualization of parallel slopes model.

# Features

## 1. Less p-value stars, more confidence intervals

The first common student comment and question:

> "Wow! Look at those p-value stars! Stars are good, so I should try to get many stars, right?"

We argue that the `summary.lm()` output is deficient in an introductory statistics setting because:

1. The `Signif. codes:  0 '' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1` only encourage **p-hacking**. In case you have not yet been convinced of the perniciousness of p-hacking, perhaps comedian John Oliver can convince you.

2. While not a silver bullet for eliminating misinterpretations of statistical inference results, confidence intervals present students with a sense of the practical significance as well as the statistical significance of any results. These are not included by default in the output.

Instead of `summary()`, let's use the `get_regression_table()` function in the `moderndive` package:

```
get_regression_table(score_model)
## # A tibble: 2 x 7
##   term      estimate std_error statistic p_value lower_ci upper_ci
##   <chr>        <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
## 1 intercept    4.46      0.127     35.2    0         4.21     4.71
## 2 age         -0.006     0.003     -2.31   0.021    -0.011   -0.001
```

Observe how the p-value stars are omitted and confidence intervals for the point estimates of all regression parameters are included by default. By including them in the output, we can easily emphasize to students that they "surround" the point estimates in the `estimate` column. Note the confidence level is defaulted to 95%.

## 2. Outputs as tibbles

The second common student comment and question:

> "How do extract the values in the regression table?"

While one might argue that extracting the intercept and slope coefficients can be simply done using `coefficients(score_model)`, what about the standard errors? A Google query of "*how do I extract standard errors from lm in r*" yields results from the R mailing list and from crossvalidated suggesting we run:

```
sqrt(diag(vcov(score_model)))
## (Intercept)         age
## 0.126778499 0.002569157
```

We argue that it shouldn't be this hard, especially in an introductory statistics setting. To rectify this, the three `get_regression` functions in the `moderndive` package all return data frames in tibble format (Müller and Wickham 2019). Therefore you can easily extract columns using the `pull` from the `dplyr` package (Wickham et al. 2020):

```
get_regression_table(score_model) %>%
  pull(std_error)
## [1] 0.127 0.003
```

or equivalently you can use the `$` sign operator from base R:

```
get_regression_table(score_model)$std_error
## [1] 0.127 0.003
```

Furthermore, by piping the above `get_regression_table(score_model)` output into the `kable()` function from the `knitr` package (Xie 2020), you can obtain aesthetically pleasing regression tables in R Markdown documents, instead of jarring computer output font:

```
library(knitr)
get_regression_table(score_model) %>%
  kable()
```

| term | estimate | std_error | statistic | p_value | lower_ci | upper_ci |
|---|---|---|---|---|---|---|
| intercept | 4.462 | 0.127 | 35.195 | 0.000 | 4.213 | 4.711 |
| age | -0.006 | 0.003 | -2.311 | 0.021 | -0.011 | -0.001 |

## 3. Birds of a feather should flock together: Fitted values & residuals

The third common student comment and question:

> "Where are the fitted and predicted values and residuals?"

How can we extract point-by-point information from a regression model, such as the fitted and predicted values and the residuals? (Note we only display the first 10 out of 463 of such values for brevity's sake.)

```
fitted(score_model)
```

```
##        1        2        3        4        5        6        7        8
## 4.248156 4.248156 4.248156 4.248156 4.111577 4.111577 4.111577 4.159083
##        9       10
## 4.159083 4.224403
```

```
residuals(score_model)
```

```
##          1          2          3          4          5          6
##  0.45184376 -0.14815624 -0.34815624  0.55184376  0.48842294  0.18842294
##          7          8          9         10
## -1.31157706 -0.05908286 -0.75908286  0.27559666
```

But why have the original explanatory/predictor `age` and outcome variable `score` in `evals`, the fitted and predicted values `score_hat`, and `residual` floating around in separate vectors? Since each observation relates to the same course, we argue it makes more sense to organize them together in the same data frame using `get_regression_points()`:

```
score_model_points <- get_regression_points(score_model)
score_model_points
```

```
## # A tibble: 10 x 5
##       ID score   age score_hat residual
##    <int> <dbl> <int>     <dbl>    <dbl>
##  1     1   4.7    36      4.25    0.452
##  2     2   4.1    36      4.25   -0.148
##  3     3   3.9    36      4.25   -0.348
##  4     4   4.8    36      4.25    0.552
##  5     5   4.6    59      4.11    0.488
##  6     6   4.3    59      4.11    0.188
##  7     7   2.8    59      4.11   -1.31
##  8     8   4.1    51      4.16   -0.059
##  9     9   3.4    51      4.16   -0.759
## 10    10   4.5    40      4.22    0.276
```

Observe that the original outcome variable `score` and explanatory/predictor variable `age` are now supplemented with the fitted and predicted values `score_hat` and `residual` columns. By putting the fitted values, predicted values, and residuals next to the original data, we argue that the computation of these values is less opaque. For example in class, instructors can write out by hand how all the values in the first row corresponding to the first instructor are computed.

Furthermore, recall that since all outputs in the `moderndive` package are tibble data frames, custom residual analysis plots can be created instead of relying on the default plots yielded by `plot.lm()`. For example, we can check for the normality of residuals using the histogram of residuals shown in Figure 3.

- A *partial residual plot* of the ; in this case a scatterplot of the residuals over `age`.

```
# Code to visualize distribution of residuals:
ggplot(score_model_points, aes(x = residual)) +
  geom_histogram(bins = 20) +
  labs(x = "Residual", y = "Count")
```

As another example, we can investigate potential relationships between the residuals and all explanatory/predictor variables and the presence of heteroskedasticity using partial residual plots, like the partial residual plot over age shown in Figure 4.

```
# Code to visualize partial residual plot over age:
ggplot(score_model_points, aes(x = age, y = residual)) +
  geom_point() +
  labs(x = "Age", y = "Residual")
```

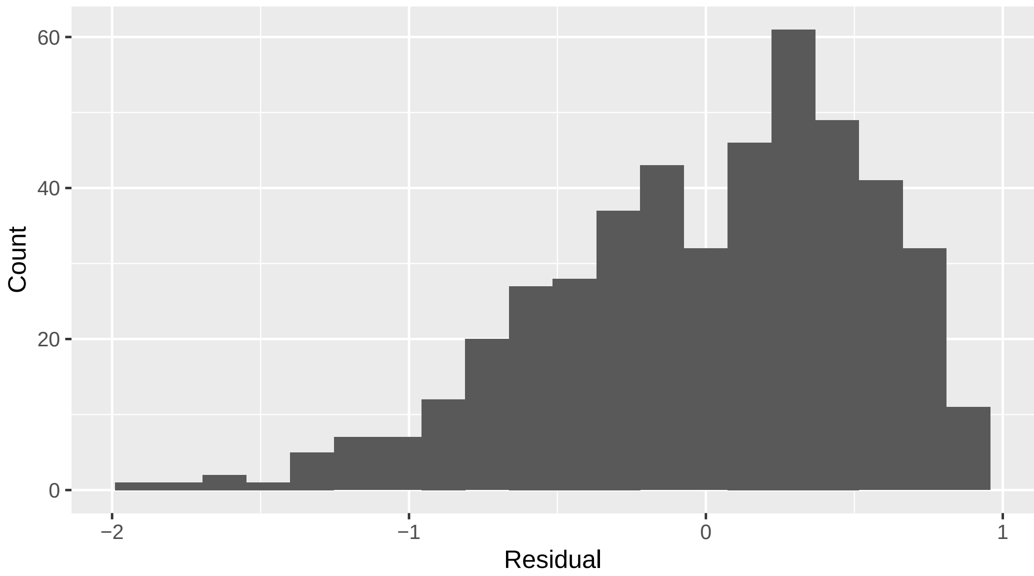


**Figure 3:** Histogram visualizing distribution of residuals.

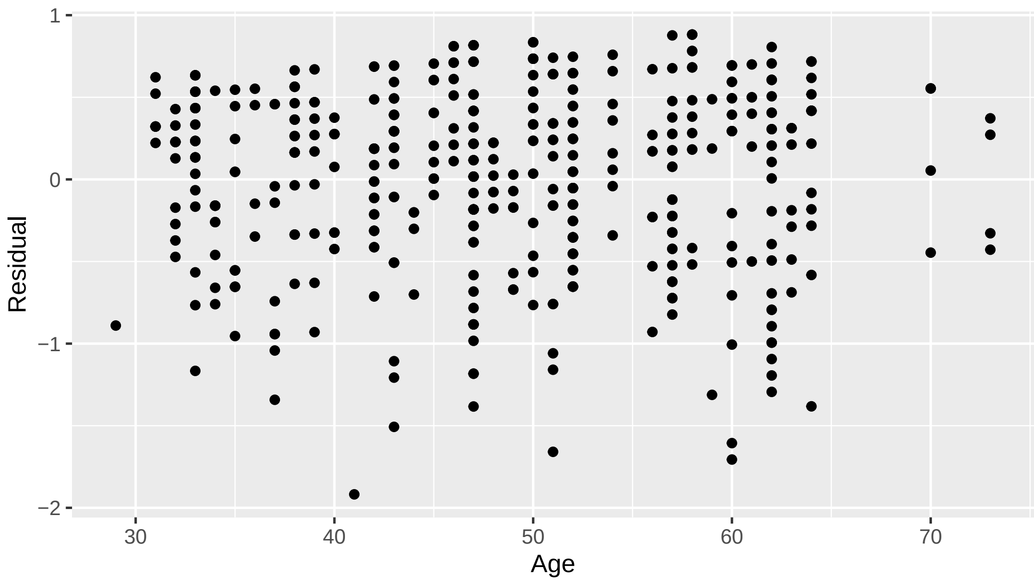


**Figure 4:** Partial residual residual plot over age.

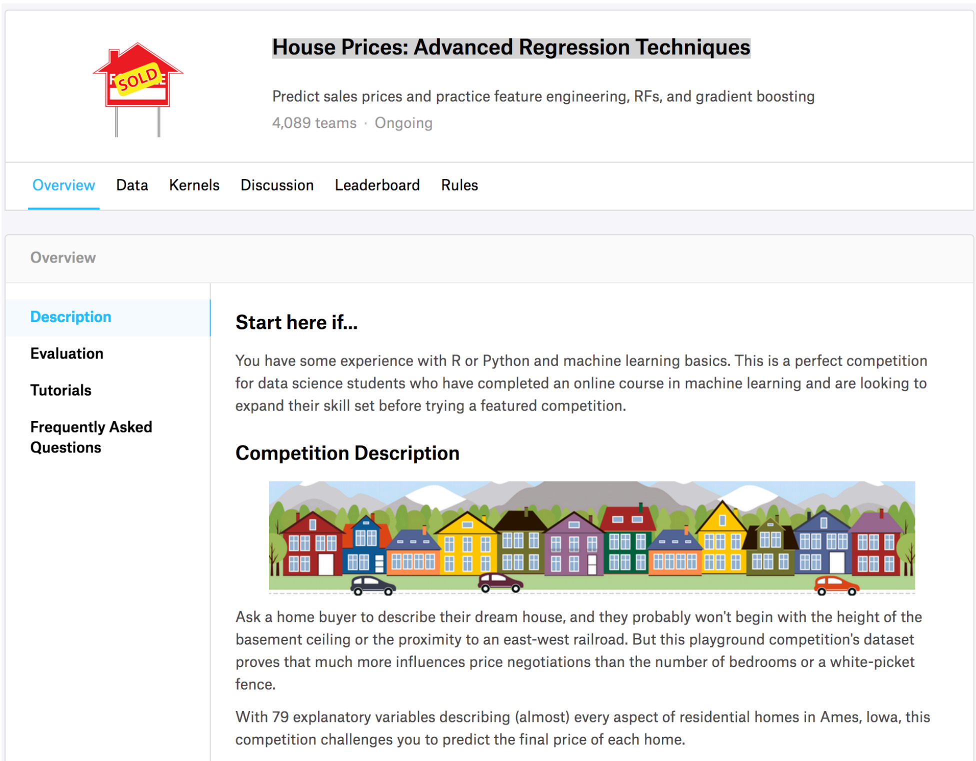


**Figure 5:** House prices Kaggle competition homepage.

## 4. A quick-and-easy Kaggle predictive modeling competition submission!

The fourth common student comment and question:

> "How do I apply this model to a new set of data to make predictions?"

With the fields of machine learning and artificial intelligence gaining prominence, the importance of predictive modeling cannot be understated. Therefore, we've designed the `get_regression_points()` function to allow for a `newdata` argument to quickly apply a previously fitted model to new observations.

Let's create an artificial "new" dataset consisting of two instructors of age 39 and 42 and save it in a data framed called `new_prof`. We then set the `newdata` argument to `get_regression_points()` to apply our previously fitted model `score_model` to this new data, where `score_hat` are the corresponding fitted/predicted values.

```
new_prof <- tibble(age = c(39, 42))
get_regression_points(score_model, newdata = new_prof)
## # A tibble: 2 x 3
##      ID   age score_hat
##   <int> <dbl>     <dbl>
## 1     1    39      4.23
## 2     2    42      4.21
```

Let's do another example, this time using the Kaggle House Prices: Advanced Regression Techniques practice competition (Figure 5 displays the homepage for this competition).

This Kaggle competition requires you to fit/train a model to the provided `train.csv` training set to make predictions of house prices in the provided `test.csv` test set. We

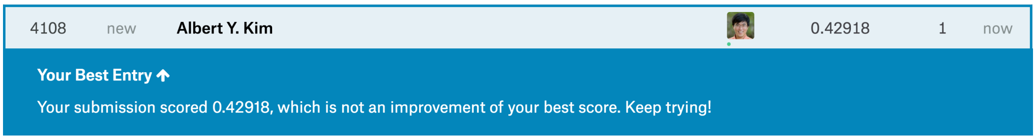


**Figure 6:** Resulting Kaggle RMSLE score.

present an application of the `get_regression_points()` function allowing students to participate in this Kaggle competition. It will:

1. Read in the training and test data.
2. Fit a naive model of house sale price as a function of year sold to the training data.
3. Make predictions on the test data and write them to a `submission.csv` file that can be submitted to Kaggle using `get_regression_points()`. Note the use of the `ID` argument to use the `id` variable in `test` to identify the rows (a requirement of Kaggle competition submissions).

```
library(tidyverse)
library(moderndive)

# Load in training and test set
train <-
  "https://github.com/moderndive/moderndive/raw/master/vignettes/train.csv" %>%
  read_csv()
test <-
  "https://github.com/moderndive/moderndive/raw/master/vignettes/test.csv"
  read_csv()

# Fit model:
house_model <- lm(SalePrice ~ YrSold, data = train)

# Make predictions and save in appropriate data frame format:
submission <- house_model %>%
  get_regression_points(newdata = test, ID = "Id") %>%
  select(Id, SalePrice = SalePrice_hat)

# Write predictions to csv:
write_csv(submission, "submission.csv")
```

After submitting `submission.csv` to the leaderboard for this Kaggle competition, we obtain a "root mean squared logarithmic error" (RMSLE) score of 0.42918 as seen in Figure 6.

```
knitr::include_graphics("leaderboard_orig.png")
```

## 5. Scalar summaries of linear regression model fits

The fifth common student comment and question:

> "What is all this other stuff at the bottom?"

Recall the output of the standard `summary.lm()` from earlier:

```
##
## Call:
## lm(formula = score ~ age, data = evals)
```

```
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.9185 -0.3531  0.1172  0.4172  0.8825
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.461932   0.126778  35.195   <2e-16 ***
## age         -0.005938   0.002569  -2.311   0.0213 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5413 on 461 degrees of freedom
## Multiple R-squared:  0.01146,    Adjusted R-squared:  0.009311
## F-statistic: 5.342 on 1 and 461 DF,  p-value: 0.02125
```

Say we wanted to extract the scalar model summaries at the bottom of this output, such as $R^2$, $R^2_{adj}$, and the $F$-statistic. We can do so using the `get_regression_summaries()` function.

```
get_regression_summaries(score_model)
## # A tibble: 1 x 8
##   r_squared adj_r_squared   mse  rmse sigma statistic p_value    df
##       <dbl>         <dbl> <dbl> <dbl> <dbl>     <dbl>   <dbl> <dbl>
## 1     0.011         0.009 0.292 0.540 0.541      5.34   0.021     2
```

We've supplemented the standard scalar summaries output yielded by `summary()` with the mean squared error `mse` and root mean squared error `rmse` given their popularity in machine learning settings.

## 6. Plot parallel slopes regression models

Finally, the last common student comment and question:

> "When would you ever use a parallel slopes model?"

For example, recall the earlier visualizations of the interaction and parallel slopes models for teaching score as a function of age and ethnicity we saw in Figures 1 and 2. Let's present both visualizations side-by-side in Figure 7.

Students might be wonder "Why would you use the parallel slopes model on the right when the data clearly form an"X" pattern as seen in the interaction model on the right?" This is an excellent opportunity to gently introduce the notion of *model selection* and *Occam's Razor*. That an interaction model should only be used over a parallel slopes model **if the additional complexity of the interaction model is warranted**. Here, we define model "complexity/simplicity" in terms of the number of parameters in the corresponding regression tables:

```
# Regression table for interaction model:
interaction_evals <- lm(score ~ age * ethnicity, data = evals)
get_regression_table(interaction_evals)
## # A tibble: 4 x 7
##   term                    estimate std_error statistic p_value lower_ci upper_c
##   <chr>                      <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl
## 1 intercept                  2.61      0.518      5.04   0        1.59      3.63
## 2 age                        0.032     0.011      2.84   0.005    0.01      0.05
## 3 ethnicitynot minority      2.00      0.534      3.74   0        0.945     3.04
```

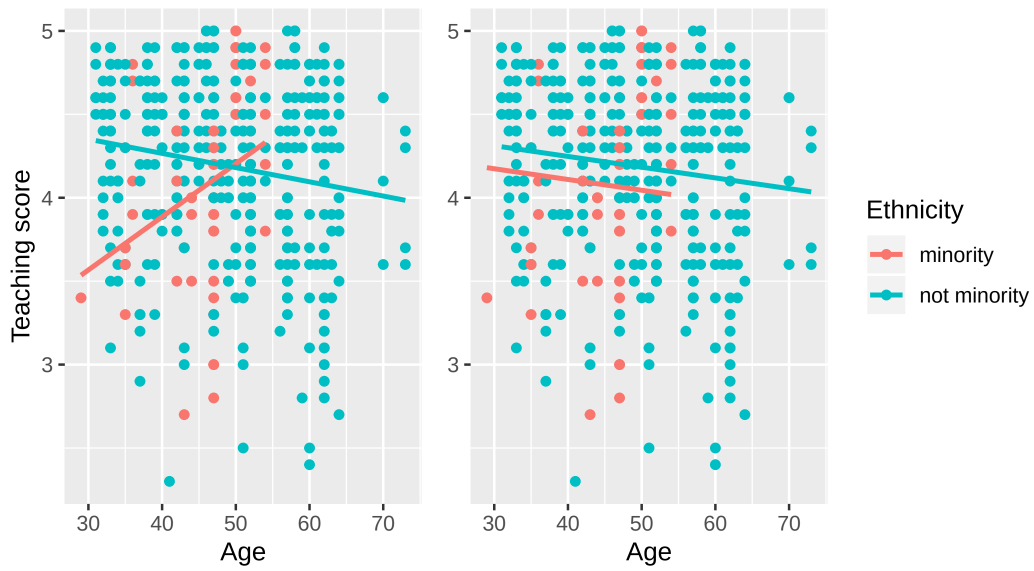


**Figure 7:** Interaction (left) and parallel slopes (right) models.

```
## 4 age:ethnicitynot minor~   -0.04      0.012     -3.51   0        -0.063   -0.01

# Regression table for parallel slopes model:
parallel_slopes_evals <- lm(score ~ age + ethnicity, data = evals)
get_regression_table(parallel_slopes_evals)
## # A tibble: 3 x 7
##   term                     estimate std_error statistic p_value lower_ci upper_ci
##   <chr>                       <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
## 1 intercept                  4.37      0.136     32.1    0         4.1      4.63
## 2 age                       -0.006     0.003     -2.5    0.013    -0.012   -0.001
## 3 ethnicitynot minority      0.138     0.073      1.89   0.059    -0.005    0.282
```

The interaction model is “more complex” as evidenced by its regression table involving 4 rows of parameter estimates whereas the parallel slopes model is “simpler” as evidenced by its regression table involving only 3 parameter estimates. In can be argued however that this additional complexity is warranted given the clearly different slopes in left-hand plot of Figure **??**.

We now present a contrasting example, this time from ModernDive 6.3.1 involving Massachusetts USA public high schools. Read the help file by running `?MA_schools` for more details. Let’s plot both the interaction and parallel slopes models in Figure 8.

```
# Code to plot interaction and parallel slopes models for MA_schools
ggplot(MA_schools, aes(x = perc_disadvan, y = average_sat_math, color = size)) +
  geom_point(alpha = 0.25) +
  labs(x = "% economically disadvantaged",
       y = "Math SAT Score",
       color = "School size") +
  geom_smooth(method = "lm", se = FALSE)

ggplot(MA_schools, aes(x = perc_disadvan, y = average_sat_math, color = size)) +
  geom_point(alpha = 0.25) +
  labs(x = "% economically disadvantaged",
       y = "Math SAT Score",
```

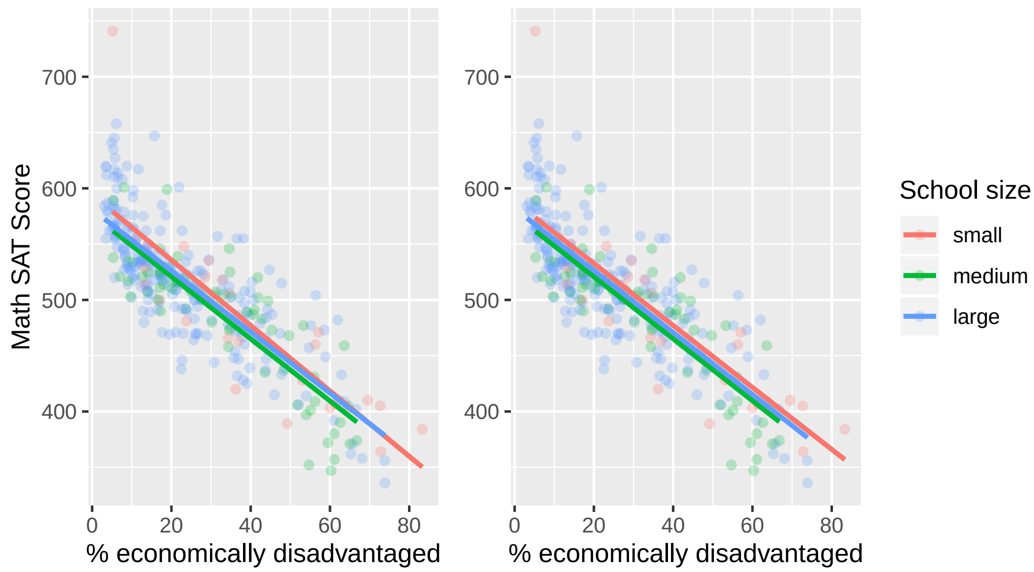


**Figure 8:** Interaction (left) and parallel slopes (right) models.

```
      color = "School size") +
  geom_parallel_slopes( se = FALSE)
```

In terms of the corresponding regression tables, observe that the corresponding regression table for the parallel slopes model has 4 rows as opposed to the 6 for the interaction model, reflecting its higher degree of "model simplicity."

```
# Regression table for interaction model:
interaction_MA <-
  lm(average_sat_math ~ perc_disadvan * size, data = MA_schools)
get_regression_table(interaction_MA)
## # A tibble: 6 x 7
##   term                      estimate std_error statistic p_value lower_ci upper_c
##   <chr>                        <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl
## 1 intercept                 594.        13.3      44.7     0       568.     620.
## 2 perc_disadvan              -2.93       0.294    -9.96    0        -3.51    -2.35
## 3 sizemedium                -17.8       15.8      -1.12    0.263  -48.9     13.4
## 4 sizelarge                 -13.3       13.8      -0.962   0.337  -40.5     13.9
## 5 perc_disadvan:sizemedi~     0.146      0.371     0.393   0.694   -0.585    0.87
## 6 perc_disadvan:sizelarge     0.189      0.323     0.586   0.559   -0.446    0.82

# Regression table for parallel slopes model:
parallel_slopes_MA <-
  lm(average_sat_math ~ perc_disadvan + size, data = MA_schools)
get_regression_table(parallel_slopes_MA)
## # A tibble: 4 x 7
##   term          estimate std_error statistic p_value lower_ci upper_ci
##   <chr>            <dbl>     <dbl>     <dbl>   <dbl>    <dbl>    <dbl>
## 1 intercept       588.        7.61     77.3    0        573.     603.
## 2 perc_disadvan    -2.78      0.106   -26.1    0         -2.99    -2.57
## 3 sizemedium      -11.9       7.54     -1.58   0.115    -26.7      2.91
## 4 sizelarge        -6.36      6.92     -0.919  0.359    -20.0      7.26
```

Unlike our earlier comparison of interaction and parallel slopes models in Figure 7, in this case it could be argued that the additional complexity of the interaction model is *not* warranted since the 3 three regression lines in the left-hand interaction are already somewhat parallel. Therefore the simpler parallel slopes model should be favored.

Going one step further, it could be argued from the visualization of the parallel slopes model in the right-hand plot of 8 that the additional model complexity induced by introducing the categorical variable school `size` is not warranted given that the intercepts are similar! Therefore, it could be argued that a simple linear regression model using only `perc_disadvan` percent of the student body that are economically disadvantaged should be favored.

While many students will inevitably find these results depressing, in our opinion it is important to additionally emphasize that such regression analyses can be used as an empowering tool to bring to light inequities in access to education and inform policy decisions.

# The Details

## Three wrappers to `broom` functions

As we mentioned earlier, the three `get_regression` functions are merely wrappers of functions from the `broom` package for converting statistical analysis objects into tidy tibbles along with a few added tweaks, but with the introductory statistics student in mind (Robinson and Hayes 2019):

1. `get_regression_table()` is a wrapper for `broom::tidy()`
2. `get_regression_points()` is a wrapper for `broom::augment()`
3. `get_regression_summaries` is a wrapper for `broom::glance()`

Why did we take this approach to address the 5 common student questions/comments at the outset of the article?

1. By writing wrappers to pre-existing functions, instead of creating new custom functions, there is minimal re-inventing the wheel necessary.
2. In our experience, novice R users had a hard time understanding the `broom` package function names `tidy()`, `augment()`, and `glance()`. The make them more user-friendly, the `moderndive` package wrappers have much more intuitively named `get_regression_table()`, `get_regression_points()`, and `get_regression_summaries()`.
3. The variables included in the outputs of the above 3 `broom` functions are not all applicable to an introductory statistics students and of those that were we found them to be unintuitively named. We therefore cut out some of the variables from the output and renamed some of the remaining variables. For example, compare the outputs of the `get_regression_points()` wrapper function and the parent `broom::augment()` function.

```
get_regression_points(score_model)
## # A tibble: 463 x 5
##        ID score   age score_hat residual
##     <int> <dbl> <int>     <dbl>    <dbl>
## 1       1   4.7    36      4.25    0.452
## 2       2   4.1    36      4.25   -0.148
## 3       3   3.9    36      4.25   -0.348
## 4       4   4.8    36      4.25    0.552
## 5       5   4.6    59      4.11    0.488
## 6       6   4.3    59      4.11    0.188
```

```
## 7      7   2.8     59       4.11    -1.31
## 8      8   4.1     51       4.16    -0.059
## 9      9   3.4     51       4.16    -0.759
## 10    10   4.5     40       4.22     0.276
## # ... with 453 more rows
broom::augment(score_model)
## # A tibble: 463 x 9
##     score   age .fitted .se.fit  .resid    .hat .sigma   .cooksd .std.resid
##     <dbl> <int>   <dbl>   <dbl>   <dbl>   <dbl>  <dbl>     <dbl>      <dbl>
##  1    4.7    36    4.25  0.0405  0.452  0.00560  0.542 0.00197        0.837
##  2    4.1    36    4.25  0.0405 -0.148  0.00560  0.542 0.000212      -0.274
##  3    3.9    36    4.25  0.0405 -0.348  0.00560  0.542 0.00117       -0.645
##  4    4.8    36    4.25  0.0405  0.552  0.00560  0.541 0.00294        1.02
##  5    4.6    59    4.11  0.0371  0.488  0.00471  0.541 0.00193        0.904
##  6    4.3    59    4.11  0.0371  0.188  0.00471  0.542 0.000288       0.349
##  7    2.8    59    4.11  0.0371 -1.31   0.00471  0.538 0.0139        -2.43
##  8    4.1    51    4.16  0.0261 -0.0591 0.00232  0.542 0.0000139     -0.109
##  9    3.4    51    4.16  0.0261 -0.759  0.00232  0.541 0.00229       -1.40
## 10    4.5    40    4.22  0.0331  0.276  0.00374  0.542 0.000488       0.510
## # ... with 453 more rows
```

The source code for these three `get_regression` functions can be found GitHub.

### Custom geometries

The `geom_parallel_slopes()` is a custom built `geom` extension to the `ggplot2` package. For example, the `ggplot2` webpage page gives instructions on how to create such extensions. The source code for `geom_parallel_slopes()` written by Evgeni Chasnovski can be found GitHub.

## Acknowledgements

Many thanks to Jenny Smetzer @smetzer180 for her helpful feedback for this vignette and to Evgeni Chasnovski @echasnovski for contributing the `geom_parallel_slopes()` function via GitHub pull request.

## References

Diez, D.M., C.D. Barr, and M. Çetinkaya-Rundel. 2015. *OpenIntro Statistics*. OpenIntro, Incorporated. https://books.google.com/books?id=xNMWswEACAAJ.

Ismay, Chester., and Albert Y. Kim. 2019. *Statistical Inference via Data Science: A Moderndive into R and the Tidyverse*. Chapman & Hall/Crc the R Series. CRC Press. https://moderndive.com/.

Müller, Kirill, and Hadley Wickham. 2019. *Tibble: Simple Data Frames*. https://CRAN.R-project.org/package=tibble.

Robinson, David, and Alex Hayes. 2019. *Broom: Convert Statistical Analysis Objects into Tidy Tibbles*. https://CRAN.R-project.org/package=broom.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, Winston Chang, Lionel Henry, Thomas Lin Pedersen, Kohske Takahashi, Claus Wilke, Kara Woo, and Hiroaki Yutani. 2019. *Ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics*. https://CRAN.R-project.org/package=ggplot2.

Wickham, Hadley, Romain François, Lionel Henry, and Kirill Müller. 2020. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Xie, Yihui. 2020. *Knitr: A General-Purpose Package for Dynamic Report Generation in R*. https://CRAN.R-project.org/package=knitr.