In this notebook

Many college courses conclude by giving students the opportunity to evaluate the course and the instructor anonymously. In the article "Beauty in the Classroom: Professors' Pulchritude and Putative Pedagogical Productivity" (PDF), authors Daniel Hamermesh and Amy M. Parker suggest (based on a data set of teaching evaluation scores collected at UT Austin) that student evaluation scores can partially be predicted by features unrelated to teaching, such as the physical attractiveness of the instructor.

In this notebook, we will use this data to try and predict a course- and instructor-specific "baseline" score (excluding the effect of teaching quality), against which to measure instructor performance.

Attribution

Parts of this lab are based on a lab assignment from the OpenIntro textbook "Introductory Statistics with Randomization and Simulation" that is released under a Creative Commons Attribution-ShareAlike 3.0 Unported license. The book website is at https://www.openintro.org/book/isrs/.

Data

The data were gathered from end of semester student evaluations for a large sample of professors from the University of Texas at Austin. In addition, six students looked at a photograph of each professor in the sample, and rated the professors' physical appearance. More specifically:

> Each of the professors' pictures was rated by each of six undergraduate students: Three women and three men, with one of each gender being a lower-division, two upper-division students (to accord with the distribution of classes across the two levels). The raters were told to use a 10 (highest) to 1 rating scale, to concentrate on the physiognomy of the professor in the picture, to make their ratings independent of age, and to keep 5 in mind as an average.

We are using a slightly modified version of the original data set from the published paper. The dataset was released along with the textbook "Data Analysis Using Regression and Multilevel/Hierarchical Models" (Gelman and Hill, 2007).)

Setup

We will start by importing relevant libraries, setting up our notebook, reading in the data, and checking that it was loaded correctly.

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn import metrics
from sklearn import model_selection
from sklearn.linear_model import LinearRegression

from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

```
!wget 'https://www.openintro.org/stat/data/evals.csv' -O 'evals.csv'
```

```
--2022-06-16 22:03:50--  https://www.openintro.org/stat/data/evals.csv
Resolving www.openintro.org (www.openintro.org)... 192.185.65.127
Connecting to www.openintro.org (www.openintro.org)|192.185.65.127|:443... connected.
HTTP request sent, awaiting response... 200 OK
```

```
Length: 55004 (54K) [text/csv]
Saving to: ‘evals.’csv

evals.csv           100%[===================>]  53.71K  --.-KB/s    in 0.08s

2022-06-16 22:03:51 (687 KB/s) - ‘evals.’csv saved [55004/55004]
```

```
df = pd.read_csv('evals.csv')
df.head()
df.columns
df.shape
```

```
   score          rank     ethnicity  gender language  age  cls_perc_eval  \
0    4.7  tenure track      minority  female  english   36       55.81395
1    4.1  tenure track      minority  female  english   36       68.80000
2    3.9  tenure track      minority  female  english   36       60.80000
3    4.8  tenure track      minority  female  english   36       62.60163
4    4.6       tenured  not minority    male  english   59       85.00000

   cls_did_eval  cls_students cls_level  ...   cls_credits bty_f1lower  \
0            24            43     upper  ...  multi credit           5
1            86           125     upper  ...  multi credit           5
2            76           125     upper  ...  multi credit           5
3            77           123     upper  ...  multi credit           5
4            17            20     upper  ...  multi credit           4

   bty_f1upper  bty_f2upper  bty_m1lower  bty_m1upper  bty_m2upper  bty_avg  \
0            7            6            2            4            6      5.0
1            7            6            2            4            6      5.0
2            7            6            2            4            6      5.0
3            7            6            2            4            6      5.0
4            4            2            2            3            3      3.0

   pic_outfit pic_color
0  not formal     color
1  not formal     color
2  not formal     color
3  not formal     color
4  not formal     color

[5 rows x 21 columns]
```

```
Index(['score', 'rank', 'ethnicity', 'gender', 'language', 'age',
       'cls_perc_eval', 'cls_did_eval', 'cls_students', 'cls_level',
       'cls_profs', 'cls_credits', 'bty_f1lower', 'bty_f1upper', 'bty_f2upper',
       'bty_m1lower', 'bty_m1upper', 'bty_m2upper', 'bty_avg', 'pic_outfit',
       'pic_color'],
      dtype='object')
```

```
(463, 21)
```

Each row in the data frame represents a different course, and columns represent features of the courses and professors. Here’s the data dictionary:

variable	description
score	average professor evaluation score: (1) very unsatisfactory - (5) excellent.
rank	rank of professor: teaching, tenure track, tenured.
ethnicity	ethnicity of professor: not minority, minority.
gender	gender of professor: female, male.
language	language of school where professor received education: english or non-english.
age	age of professor.
cls_perc_eval	percent of students in class who completed evaluation.
cls_did_eval	number of students in class who completed evaluation.
cls_students	total number of students in class.
cls_level	class level: lower, upper.
cls_profs	number of professors teaching sections in course in sample: single, multiple.
cls_credits	number of credits of class: one credit (lab, PE, etc.), multi credit.
bty_f1lower	beauty rating of professor from lower level female: (1) lowest - (10) highest.
bty_f1upper	beauty rating of professor from upper level female: (1) lowest - (10) highest.
bty_f2upper	beauty rating of professor from second upper level female: (1) lowest - (10) highest.
bty_m1lower	beauty rating of professor from lower level male: (1) lowest - (10) highest.
bty_m1upper	beauty rating of professor from upper level male: (1) lowest - (10) highest.
bty_m2upper	beauty rating of professor from second upper level male: (1) lowest - (10) highest.
bty_avg	average beauty rating of professor.
pic_outfit	outfit of professor in picture: not formal, formal.
pic_color	color of professor's picture: color, black & white.

Source: OpenIntro book.

Note that:

- `score` is the target variable - this is what we want our model to predict. We expect that the score is a function of the teaching quality, characteristics of the course, and non-teaching related characteristics of the instructor. However, the "true" teaching quality for each course is not known.
- the variables that begin with a `cls_` prefix are features that relate to the course. These features could potentially affect student evaluations: for example, students may rank one-credit lab courses more highly than multi-credit lecture courses.
- variables such as `rank`, `ethnicity`, `gender`, `language`, `age`, and the variables with a `bty_` prefix are features that relate to the instructor. They do not necessarily to the quality of instruction! These features may also affect student evaluations: for example, students may rate instructors more highly if they are physically attractive.
- variables with the `pic_` prefix describe the photograph that was shown to the students who provided the `bty_` scores. This should have no effect on the student evaluations, since those were evaluations by students who were enrolled in the course (not the students who were shown the photograph and asked to provide an attractiveness score.) (For your reference: on the bottom of page 7 of the paper, the authors describe why they include this variable and how they used it)

Explore data

As always, start by exploring the data:

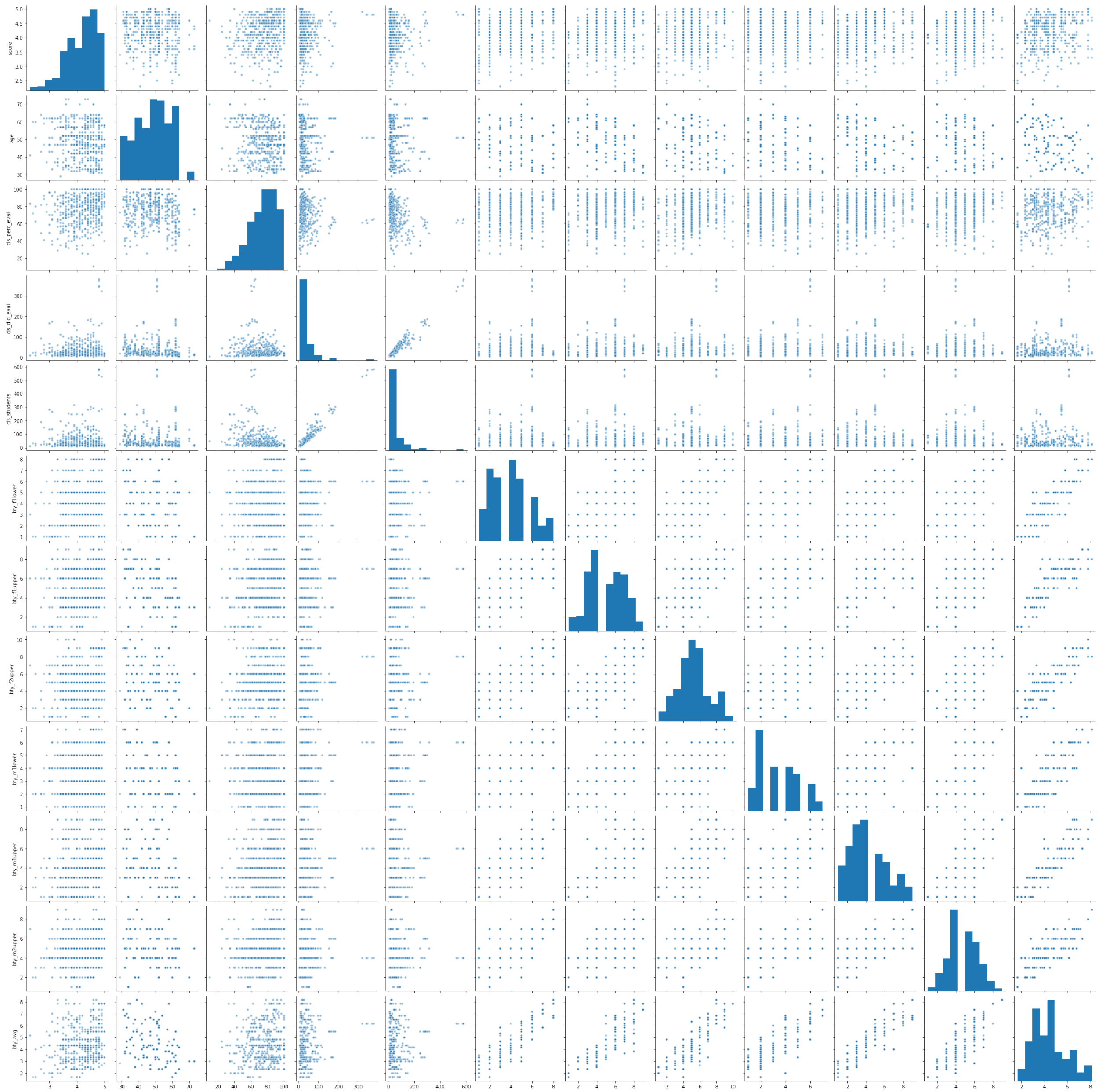
```
df.describe()
```

```
            score         age  cls_perc_eval  cls_did_eval  cls_students  \
count  463.000000  463.000000     463.000000    463.000000    463.000000
mean     4.174730   48.365011      74.427788     36.624190     55.177106
```

```
std      0.543865   9.802742    16.756311    45.018481    75.072800
min      2.300000  29.000000    10.416670     5.000000     8.000000
25%      3.800000  42.000000    62.696165    15.000000    19.000000
50%      4.300000  48.000000    76.923080    23.000000    29.000000
75%      4.600000  57.000000    87.249170    40.000000    60.000000
max      5.000000  73.000000   100.000000   380.000000   581.000000

       bty_f1lower  bty_f1upper  bty_f2upper  bty_m1lower  bty_m1upper  \
count   463.000000   463.000000   463.000000   463.000000   463.000000
mean      3.963283     5.019438     5.213823     3.412527     4.146868
std       1.873936     1.934437     2.018224     1.637102     2.110586
min       1.000000     1.000000     1.000000     1.000000     1.000000
25%       2.000000     4.000000     4.000000     2.000000     3.000000
50%       4.000000     5.000000     5.000000     3.000000     4.000000
75%       5.000000     7.000000     6.000000     5.000000     5.000000
max       8.000000     9.000000    10.000000     7.000000     9.000000

       bty_m2upper     bty_avg
count   463.000000  463.000000
mean      4.751620    4.417844
std       1.575266    1.527380
min       1.000000    1.667000
25%       4.000000    3.167000
50%       5.000000    4.333000
75%       6.000000    5.500000
max       9.000000    8.167000
```

```python
sns.pairplot(df, plot_kws={'alpha':0.5, 'size': 0.1})
```

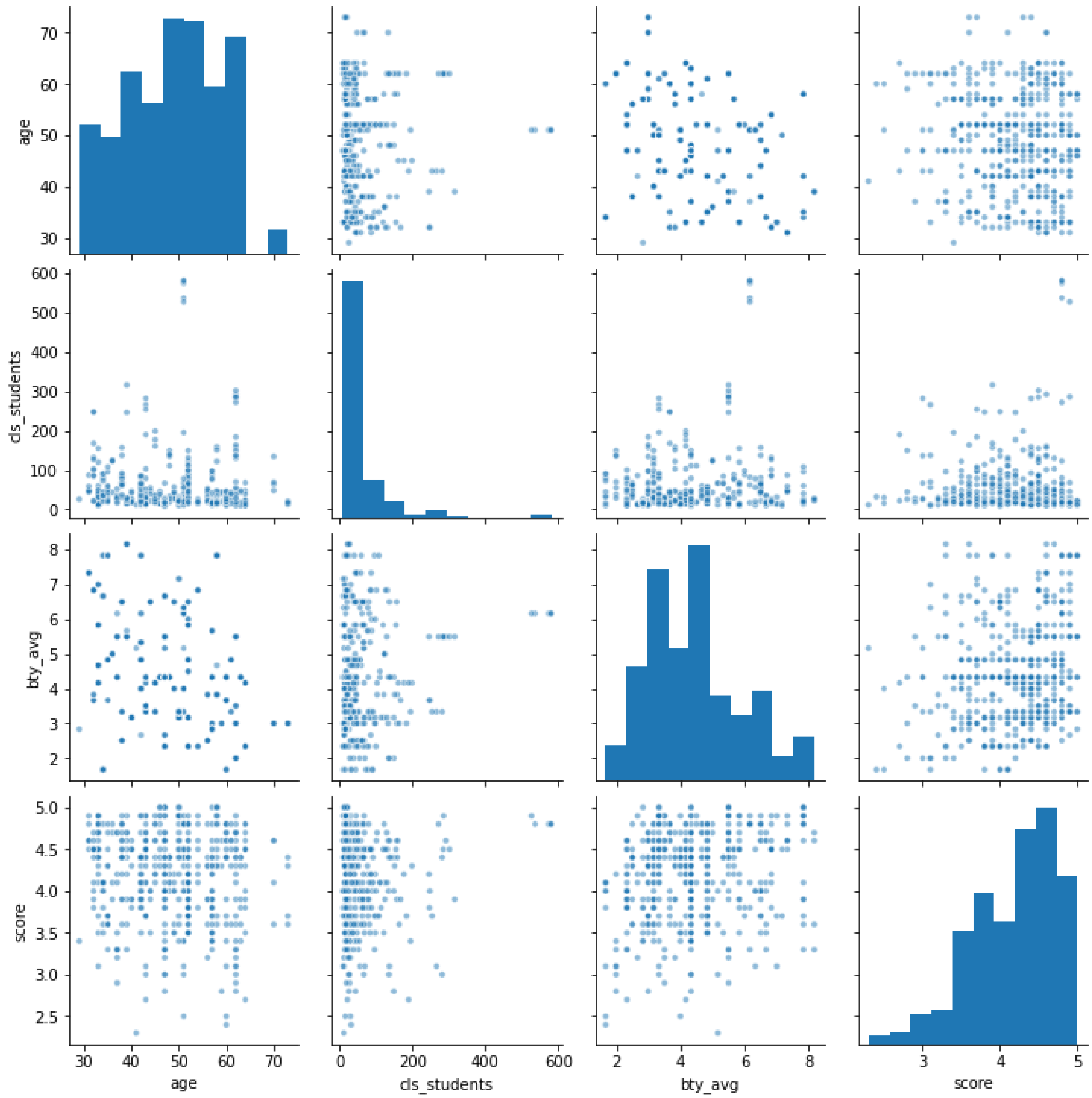
```
<seaborn.axisgrid.PairGrid at 0x7f346e0a5c40>
```



With so many numeric variables, the pair plot is hard to read. We can create a pairplot excluding some variables that we don't expect to be useful for visualization: `cls_perc_eval`, `cls_did_eval`. We will also exclude the individual attractiveness ratings `bty_f1lower`, `bty_f1upper`, `bty_f2upper`, `bty_m1lower`, `bty_m1upper`, `bty_m2upper`, since the overall attractiveness rating is still represented by `bty_avg`.

```
sns.pairplot(df, vars=['age', 'cls_students', 'bty_avg', 'score'], plot_kws={'alpha':0.5,
    'size': 0.1})
```

```
<seaborn.axisgrid.PairGrid at 0x7f341d18a5b0>
```



As part of our exploration of the data, we can also examine the effect of non-numeric variables related to the instructor and the class: `rank`, `ethnicity`, `gender`, `language`, `cls_level`, `cls_profs`, `cls_credits`.

```
for feature in ['rank', 'ethnicity', 'gender', 'language', 'cls_level', 'cls_profs',
    'cls_credits']:
    df.groupby([feature])['score'].describe()
```

```
              count      mean       std  min  25%   50%  75%  max
rank
teaching      102.0  4.284314  0.498263  3.3  3.9  4.40  4.7  5.0
tenure track  108.0  4.154630  0.561104  2.3  3.7  4.35  4.6  4.9
tenured       253.0  4.139130  0.550262  2.4  3.8  4.20  4.6  5.0
```

```
              count      mean       std  min    25%    50%    75%  max
```

```
ethnicity
minority       64.0  4.071875  0.581588  2.7  3.675  4.05  4.525  5.0
not minority  399.0  4.191228  0.536505  2.3  3.850  4.30  4.600  5.0
```

```
        count      mean       std  min  25%  50%  75%  max
gender
female  195.0  4.092821  0.563814  2.3  3.7  4.1  4.5  5.0
male    268.0  4.234328  0.521896  2.4  3.9  4.3  4.6  5.0
```

```
             count      mean       std  min  25%   50%  75%  max
language
english      435.0  4.189655  0.547183  2.3  3.9  4.30  4.6  5.0
non-english   28.0  3.942857  0.434979  3.4  3.6  3.75  4.4  4.8
```

```
           count      mean       std  min  25%  50%  75%  max
cls_level
lower      157.0  4.238217  0.592532  2.5  3.8  4.4  4.7  5.0
upper      306.0  4.142157  0.515104  2.3  3.8  4.2  4.5  5.0
```

```
           count      mean       std  min  25%  50%  75%  max
cls_profs
multiple   306.0  4.184641  0.551177  2.4  3.8  4.3  4.6  5.0
single     157.0  4.155414  0.530529  2.3  3.8  4.3  4.6  5.0
```

```
              count      mean       std  min  25%  50%  75%  max
cls_credits
multi credit  436.0  4.147018  0.542464  2.3  3.8  4.2  4.6  5.0
one credit     27.0  4.622222  0.334357  3.5  4.5  4.7  4.9  5.0
```

Discussion Question 1 Describe the relationship between `score` and the overall attractiveness rating `bty_avg`. Is there an apparent correlation? If so, is it a positive or a negative correlation? What about `age` and `cls_students`, do they appear to be correlated with `score`?

Also describe the relationship between `score` and the categorical variables you explored above that are related to characteristics of the *instructor*: `rank`, `ethnicity`, `gender`, `language`. Which of these variables have an apparent correlation with `score`? Is it a positive or a negative correlation?

Are any of the apparent relationships you observed unexpected to you? Explain.

Encoding categorical variables

To represent a categorical variable (with no inherent ordering) in a regression, we can use *one hot encoding*. It works as follows:

- For a categorical variable x with values $1, \cdots, M$
- Represent with M binary features: $\phi_1, \phi_2, \cdots, \phi_M$
- Model in regression $w1_1\phi_1 + \cdots + w_M\phi_M$

We can use the `get_dummies` function in `pandas` for one hot encoding. Create a copy of the dataframe with all categorical variables transformed into indicator ("dummy") variables, and save it in a new data frame called `df_enc`.

Compare the columns of the `df` data frame versus the `df_enc` data frame.

```python
df_enc = pd.get_dummies(df)
df_enc.columns
```

```
Index(['score', 'age', 'cls_perc_eval', 'cls_did_eval', 'cls_students',
       'bty_f1lower', 'bty_f1upper', 'bty_f2upper', 'bty_m1lower',
       'bty_m1upper', 'bty_m2upper', 'bty_avg', 'rank_teaching',
       'rank_tenure track', 'rank_tenured', 'ethnicity_minority',
       'ethnicity_not minority', 'gender_female', 'gender_male',
       'language_english', 'language_non-english', 'cls_level_lower',
       'cls_level_upper', 'cls_profs_multiple', 'cls_profs_single',
       'cls_credits_multi credit', 'cls_credits_one credit',
       'pic_outfit_formal', 'pic_outfit_not formal', 'pic_color_black&white',
       'pic_color_color'],
      dtype='object')
```

Split data

Next, we split the encoded data into a training set (70%) and test set (30%). We will be especially interested in evaluating the model performance on the test set. Since it was not used to train the model parameters (intercept and coefficients), the performance on this data gives us a better idea of how the model may perform on new data.

We'll use the `train_test_split` method in `sklearn`'s `model_selection` module. Since it randomly splits the data, we'll pass a random "state" into the function that makes the split repeatable (same split every time we run this notebook) and ensures that everyone in the class will have exactly the same split.

```python
train, test = model_selection.train_test_split(df_enc, test_size=0.3, random_state=9)
# why 9? see https://dilbert.com/strip/2001-10-25
train.shape
test.shape
```

```
(324, 31)
```

```
(139, 31)
```

Simple linear regression

Now we are finally ready to train a regression model.

Since the article is nominally abou the attractiveness of the instructor, we will train the simple linear regression on the `bty_avg` feature.

In the cell that follows, write code to

- use `sklearn` to fit a simple linear regression model on the training set, using `bty_avg` as the feature on which to train. Save your fitted model in a variable `reg_simple`.
- print the intercept and coefficient of the model.
- use `predict` on the fitted model to estimate the evaluation score on the training set, and save this array in `y_pred_train`.
- use `predict` on the fitted model to estimate the evaluation score on the test set, and save this array in `y_pred_test`.

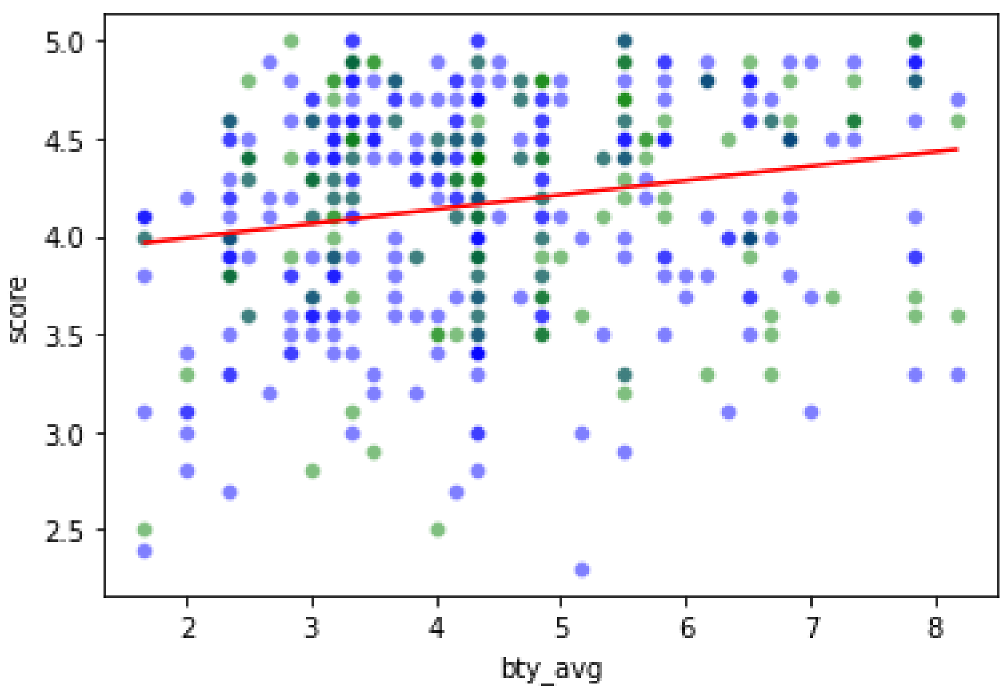
Then run the cell after that one, which will show you the training data, the test data, and your regression line.

```python
reg_simple = LinearRegression().fit(train[['bty_avg']], train['score'])
reg_simple.coef_
reg_simple.intercept_

y_pred_train = reg_simple.predict(train[['bty_avg']])
y_pred_test = reg_simple.predict(test[['bty_avg']])
```

```
array([0.07367795])
```

```
3.842544653270749
```

```python
sns.scatterplot(data=train, x="bty_avg", y="score", color='blue', alpha=0.5);
sns.scatterplot(data=test, x="bty_avg", y="score", color='green', alpha=0.5);
sns.lineplot(data=train, x="bty_avg", y=y_pred_train, color='red');
```



Evaluate simple linear regression performance

Next, we will evaluate our model performance.

In the following cell, write a *function* to compute key performance metrics for your model:

- compute the R2 score on your training data
- compute the MSE on your training data
- compute the MSE, divided by the sample variance of `score`, on your training data. Recall that this metric tells us the ratio of average error of your model to average error of prediction by mean.
- and compute the same three metrics for your test set

```python
def regression_performance(y_true_train, y_pred_train, y_true_test, y_pred_test):

    r2_train = metrics.r2_score(y_true_train, y_pred_train)
```

```
    mse_train = metrics.mean_squared_error(y_true_train, y_pred_train)
    norm_mse_train = metrics.mean_squared_error(y_true_train,
        y_pred_train)/(np.std(y_true_train)**2)

    r2_test = metrics.r2_score(y_true_test, y_pred_test)
    mse_test = metrics.mean_squared_error(y_true_test, y_pred_test)
    norm_mse_test = metrics.mean_squared_error(y_true_test,
        y_pred_test)/(np.std(y_true_test)**2)

    #print("Training:   %f %f %f" % (r2_train, mse_train, norm_mse_train))
    #print("Test:       %f %f %f" % (r2_test, mse_test, norm_mse_test))

    return [r2_train, mse_train, norm_mse_train, r2_test, mse_test, norm_mse_test]
```

Call your function to print the performance of the simple linear regression. Is a simple linear regression on `bty_avg` better than a "dumb" model that predicts the mean value of `score` for all samples?

```
vals = regression_performance(train['score'], y_pred_train, test['score'], y_pred_test)
```

Multiple linear regression

Next, we'll see if we can improve model performance using multiple linear regression, with more features included.

To start, we need to decide which features to use as input to our model. One possible approach is to use every feature in the dataset excluding the target variable, `score`.

You can build and view this list of features by running:

```
features = df_enc.columns.drop(['score'])
features
```

```
Index(['age', 'cls_perc_eval', 'cls_did_eval', 'cls_students', 'bty_f1lower',
       'bty_f1upper', 'bty_f2upper', 'bty_m1lower', 'bty_m1upper',
       'bty_m2upper', 'bty_avg', 'rank_teaching', 'rank_tenure track',
       'rank_tenured', 'ethnicity_minority', 'ethnicity_not minority',
       'gender_female', 'gender_male', 'language_english',
       'language_non-english', 'cls_level_lower', 'cls_level_upper',
       'cls_profs_multiple', 'cls_profs_single', 'cls_credits_multi credit',
       'cls_credits_one credit', 'pic_outfit_formal', 'pic_outfit_not formal',
       'pic_color_black&white', 'pic_color_color'],
      dtype='object')
```

In the following cell, write code to

- use `sklearn` to fit a linear regression model on the training set, using the `features` array as the list of features to train on. Save your fitted model in a variable `reg_multi`.
- print a table of the features used in the regression and the coefficient assigned to each. If you have saved your fitted regression in a variable named `reg_multi`, you can create and print this table with:

```
df_coef = pd.DataFrame(data =
                        {'feature': features,
                         'coefficient': reg_multi.coef_})
df_coef
```

```python
reg_multi = LinearRegression().fit(train[features], train['score'])
df_coef = pd.DataFrame(data =
                        {'feature': features,
                         'coefficient': reg_multi.coef_})
df_coef
```

```
                    feature  coefficient
0                       age    -0.009493
1             cls_perc_eval     0.004385
2              cls_did_eval     0.002983
3              cls_students    -0.001427
4               bty_f1lower     7.022264
5               bty_f1upper     7.052930
6               bty_f2upper     7.032261
7               bty_m1lower     6.959419
8               bty_m1upper     6.999172
9               bty_m2upper     6.978719
10                  bty_avg   -42.015575
11            rank_teaching     0.084572
12        rank_tenure track    -0.085993
13             rank_tenured     0.001421
14       ethnicity_minority    -0.131245
15   ethnicity_not minority     0.131245
16            gender_female    -0.121054
17              gender_male     0.121054
18         language_english     0.085742
19     language_non-english    -0.085742
20          cls_level_lower    -0.006088
21          cls_level_upper     0.006088
22       cls_profs_multiple     0.004518
23         cls_profs_single    -0.004518
24  cls_credits_multi credit    -0.283913
25    cls_credits_one credit     0.283913
26        pic_outfit_formal     0.039920
27    pic_outfit_not formal    -0.039920
28    pic_color_black&white     0.065689
29          pic_color_color    -0.065689
```

Discussion Question 2 Look at the list of features and coefficients, especially those related to the attractiveness ratings.

Are these results surprising, based on the results of the simple linear regression? Explain your answer.

Effect of collinearity

Note especially the coefficients associated with each of the individual attractiveness rankings, and the coefficient associated with the average attractiveness ranking. Each of these features separately seems to have a large effect; however, because they are strongly *collinear*, they cancel one another out.

(You should be able to see the collinearity clearly in the pairplot you created.)

In the following cell, write code to

- create a new `features` array, that drops the *individual* attractiveness rankings in addition to the `score` variable (but do *not* drop the average attractiveness ranking)
- use `sklearn` to fit a linear regression model on the training set, using the new `features` array as the list of features to train on. Save your fitted model in a variable `reg_avgbty`.
- print a table of the features used in the regression and the coefficient assigned to each.

```
features = df_enc.columns.drop(['score',
    'bty_f1lower', 'bty_f1upper', 'bty_f2upper',
    'bty_m1lower', 'bty_m1upper', 'bty_m2upper'])
reg_avgbty = LinearRegression().fit(train[features], train['score'])

df_coef = pd.DataFrame(data =
                        {'feature': features,
                         'coefficient': reg_avgbty.coef_})
df_coef
```

```
                    feature  coefficient
0                       age    -0.009297
1             cls_perc_eval     0.004900
2              cls_did_eval     0.003737
3              cls_students    -0.001740
4                   bty_avg     0.040577
5             rank_teaching     0.075283
6         rank_tenure track    -0.059429
7              rank_tenured    -0.015854
8        ethnicity_minority    -0.111830
9    ethnicity_not minority     0.111830
10            gender_female    -0.097201
11              gender_male     0.097201
12         language_english     0.083435
13     language_non-english    -0.083435
14          cls_level_lower    -0.012437
15          cls_level_upper     0.012437
16        cls_profs_multiple     0.009897
17          cls_profs_single    -0.009897
18  cls_credits_multi credit    -0.285089
19    cls_credits_one credit     0.285089
20         pic_outfit_formal     0.053104
21     pic_outfit_not formal    -0.053104
22     pic_color_black&white     0.076615
23           pic_color_color    -0.076615
```

Discussion Question 3 Given the model parameters you have found, which is associated with the strongest effect (on average) on the evaluation score:

- Instructor ethnicity
- Instructor gender

(Note that in general, we cannot use the coefficient to compare the effect of features that have a different range. But both ethnicity and gender are represented by binary one hot-encoded variables.)

Evaluate multiple regression model performance

Evaluate the performance of your `reg_avgbty` model. In the next cell, write code to:

- use the `predict` function on your fitted regression to find $\hat{y}$ for all samples in the *training* set, and save this in an array called `y_pred_train`
- use the `predict` function on your fitted regression to find $\hat{y}$ for all samples in the *test* set, and save this in an array called `y_pred_test`
- call the `regression_performance` function you wrote in a previous cell, and print the performance metrics on the training and test set.

```
y_pred_train = reg_avgbty.predict(train[features])
y_pred_test = reg_avgbty.predict(test[features])

vals = regression_performance(train['score'], y_pred_train, test['score'], y_pred_test)
```

Discussion Question 4 Based on the analysis above, what portion of the variation in instructor teaching evaluation can be explained by the factors unrelated to teaching performance, such as the physical characteristics of the instructor?

Discussion Question 5 Based on the analysis above, is your model better at predicting instructor teaching scores than a "dumb" model that just assigns the mean teaching score to every instructor? Explain.

Discussion Question 6 Suppose you are hired by the ECE department to develop a classifer that will identify high-performing faculty, who will then be awarded prizes for their efforts.

Based on the analysis above, do you think it would be fair to use scores on teaching evaluations as an input to your classifier? Explain your answer.

Exploring unexpected correlation

There are some features that we do *not* expect to be correlated with the instructor's score.

For example, consider the "features" related to the photograph used by the students who rated the instructor's attractiveness.

There is no reason that characteristics of an instructor's photograph - whether it was in black and white or color, how the instructor was dressed in the photograph - should influence the ratings of students in the instructor's class. (These students did not even see the photograph.)

In the next cell, we will write code to

- create a new `features` array that drops the `score` variable, all of the individual attractiveness rankings, and the variables related to the photograph used for attractiveness rankings.
- use it to fit a model (saved in `reg_nopic`).
- use `reg_nopic` to predict the evaluation scores on both the training and test set
- compute the same set of metrics as above.

```
features = df_enc.columns.drop(['score',
    'bty_f1lower', 'bty_f1upper', 'bty_f2upper',
    'bty_m1lower', 'bty_m1upper', 'bty_m2upper',
    'pic_outfit_formal', 'pic_outfit_not formal',
```

```
    'pic_color_black&white', 'pic_color_color'])

reg_nopic = LinearRegression().fit(train[features], train['score'])


y_pred_train = reg_nopic.predict(train[features])
y_pred_test = reg_nopic.predict(test[features])

vals = regression_performance(train['score'], y_pred_train, test['score'], y_pred_test)
```

Discussion Question 7 Is your model less predictive when features related to the instructor photograph are excluded? Explain.

When a machine learning model seems to use a feature that is not expected to be correlated with the target variable (such as the characteristics of the instructor's photograph…), this can sometimes be a signal that information is "leaking" between the training and test set.

In this dataset, each row represents a single course. However, some instructors teach more than one course, and an instructor might get similar evaluation scores on all of the courses he or she teaches.

(According to the paper for which this dataset was collected, 94 faculty members taught the 463 courses represented in the dataset, with some faculty members teaching as many as 13 courses.)

For example, consider the output of the following command, which prints all of the one credit courses in the data:

```
df.loc[df['cls_credits']=='one credit']
```

```
     score          rank     ethnicity  gender     language  age  \
124    3.5      teaching  not minority  female      english   52
179    4.4  tenure track      minority  female      english   47
185    4.6  tenure track      minority  female      english   47
245    4.2      teaching  not minority  female      english   50
246    4.7      teaching  not minority  female      english   50
339    4.8  tenure track  not minority    male      english   43
340    4.9  tenure track  not minority    male      english   43
343    4.5  tenure track  not minority    male      english   43
344    4.9  tenure track  not minority    male      english   43
345    4.4  tenure track  not minority    male      english   43
347    4.6      teaching      minority    male      english   50
348    5.0      teaching      minority    male      english   50
349    4.9      teaching      minority    male      english   50
350    4.6      teaching      minority    male      english   50
351    4.8      teaching      minority    male      english   50
352    4.9      teaching      minority    male      english   50
353    4.9      teaching      minority    male      english   50
354    4.9      teaching      minority    male      english   50
355    5.0      teaching      minority    male      english   50
356    4.5      teaching      minority    male      english   50
393    4.8      teaching  not minority    male      english   45
394    4.2      teaching  not minority    male      english   45
396    4.8      teaching  not minority    male      english   45
409    4.7      teaching  not minority  female      english   47
```

```
410    4.6      teaching  not minority  female      english   47
411    4.6      teaching  not minority  female      english   47
462    4.1  tenure track      minority  female  non-english   42

     cls_perc_eval  cls_did_eval  cls_students cls_level  ... cls_credits  \
124       89.47369            17            19     upper  ...  one credit
179      100.00000            16            16     lower  ...  one credit
185       95.23810            20            21     lower  ...  one credit
245       75.00000            24            32     lower  ...  one credit
246       66.66666            14            21     lower  ...  one credit
339       53.57143            15            28     lower  ...  one credit
340       60.00000            18            30     lower  ...  one credit
343       94.44444            17            18     lower  ...  one credit
344       84.61539            22            26     lower  ...  one credit
345       60.00000            18            30     lower  ...  one credit
347       70.83334            17            24     lower  ...  one credit
348       90.90909            20            22     lower  ...  one credit
349       84.00000            21            25     lower  ...  one credit
350       88.46154            23            26     lower  ...  one credit
351       86.36364            19            22     lower  ...  one credit
352       76.92308            20            26     lower  ...  one credit
353       85.00000            17            20     lower  ...  one credit
354       81.81818            18            22     lower  ...  one credit
355       95.23810            20            21     lower  ...  one credit
356       90.47619            19            21     lower  ...  one credit
393       70.58823            12            17     lower  ...  one credit
394       85.00000            17            20     lower  ...  one credit
396       73.07692            19            26     lower  ...  one credit
409       88.23529            15            17     lower  ...  one credit
410      100.00000            10            10     lower  ...  one credit
411       94.11765            16            17     lower  ...  one credit
462       80.00000            28            35     lower  ...  one credit

    bty_f1lower  bty_f1upper  bty_f2upper  bty_m1lower  bty_m1upper  \
124           6            6            4            2            4
179           2            6            6            3            5
185           2            6            6            3            5
245           2            3            5            2            3
246           2            3            5            2            3
339           3            4            4            2            4
340           3            4            4            2            4
343           3            4            4            2            4
344           3            4            4            2            4
345           3            4            4            2            4
347           1            5            4            1            4
348           1            5            4            1            4
349           1            5            4            1            4
350           1            5            4            1            4
351           1            5            4            1            4
352           1            5            4            1            4
353           1            5            4            1            4
354           1            5            4            1            4
355           1            5            4            1            4
356           1            5            4            1            4
```

```
393          1           4           2           5           4
394          1           4           2           5           4
396          1           4           2           5           4
409          8           6           6           4           9
410          8           6           6           4           9
411          8           6           6           4           9
462          3           8           7           4           6

     bty_m2upper  bty_avg  pic_outfit    pic_color
124            7    4.833  not formal        color
179            4    4.333  not formal        color
185            4    4.333  not formal        color
245            4    3.167  not formal        color
246            4    3.167  not formal        color
339            4    3.500  not formal        color
340            4    3.500  not formal        color
343            4    3.500  not formal        color
344            4    3.500  not formal        color
345            4    3.500  not formal        color
347            5    3.333  not formal        color
348            5    3.333  not formal        color
349            5    3.333  not formal        color
350            5    3.333  not formal        color
351            5    3.333  not formal        color
352            5    3.333  not formal        color
353            5    3.333  not formal        color
354            5    3.333  not formal        color
355            5    3.333  not formal        color
356            5    3.333  not formal        color
393            4    3.333  not formal        color
394            4    3.333  not formal        color
396            4    3.333  not formal        color
409            7    6.667  not formal  black&white
410            7    6.667  not formal  black&white
411            7    6.667  not formal  black&white
462            4    5.333  not formal        color

[27 rows x 21 columns]
```

We observe that 10 out of 27 one-credit courses are taught by what seems to be the same instructor - we don't know his name, but let's call him John. John is a teaching-track professor, minority ethnicity, male, English-language trained, 50 years old, average attractiveness 3.333, and whose photograph is in color and not formal.

This provides a clue regarding the apparent importance of the `cls_credits` variable and other "unexpected" variables in predicting the teaching score.

Certain variables may be used by the model to identify the instructor, and then learn a relationship between the *individual instructor* and his or her typical evaluation score, instead of learning a true relationship between the *variable* and the evaluation score.

In other words: the model learns "an instructor who is teaching-track, minority, male, English-language-trained, 50 years old, has average attractiveness 3.333, and whose photograph is in color and not formal typically scores X" - but it's really just learning "John typically scores X".

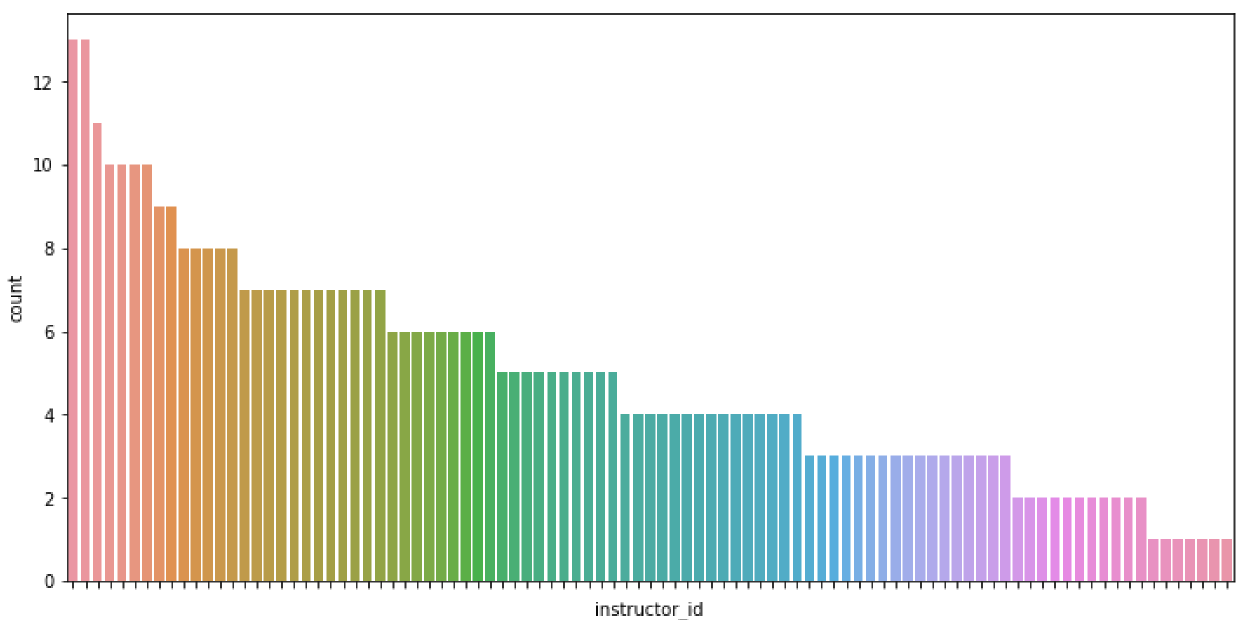
To see if this is plausible, let's add an "instructor ID" to each row in our data frame. The data set doesn't include an instructor ID column, but we can still uniquely identify every instructor by looking at the combination of rank, ethnicity, gender, language of training, age, attractiveness score, and characteristics of the photo (formal or not, black and white or color).

```
instructor_id = df[['rank', 'ethnicity', 'gender', 'language',
        'pic_outfit', 'pic_color']].agg('-'.join, axis=1)
instructor_id +=  '-' + df['age'].astype(str)
instructor_id +=  '-' + df['bty_avg'].astype(str)

df_enc = df_enc.assign(instructor_id = instructor_id)

df_enc['instructor_id'].head()
```

```
0    tenure track-minority-female-english-not forma...
1    tenure track-minority-female-english-not forma...
2    tenure track-minority-female-english-not forma...
3    tenure track-minority-female-english-not forma...
4    tenured-not minority-male-english-not formal-c...
Name: instructor_id, dtype: object
```

Let's plot the frequency with which each "instructor ID" appears in the data:

```
_  = plt.figure(figsize=(12,6))
ax = sns.countplot(x="instructor_id", data=df_enc,
    order=df_enc['instructor_id'].value_counts().index)
_  = ax.set(xticklabels=[])
```

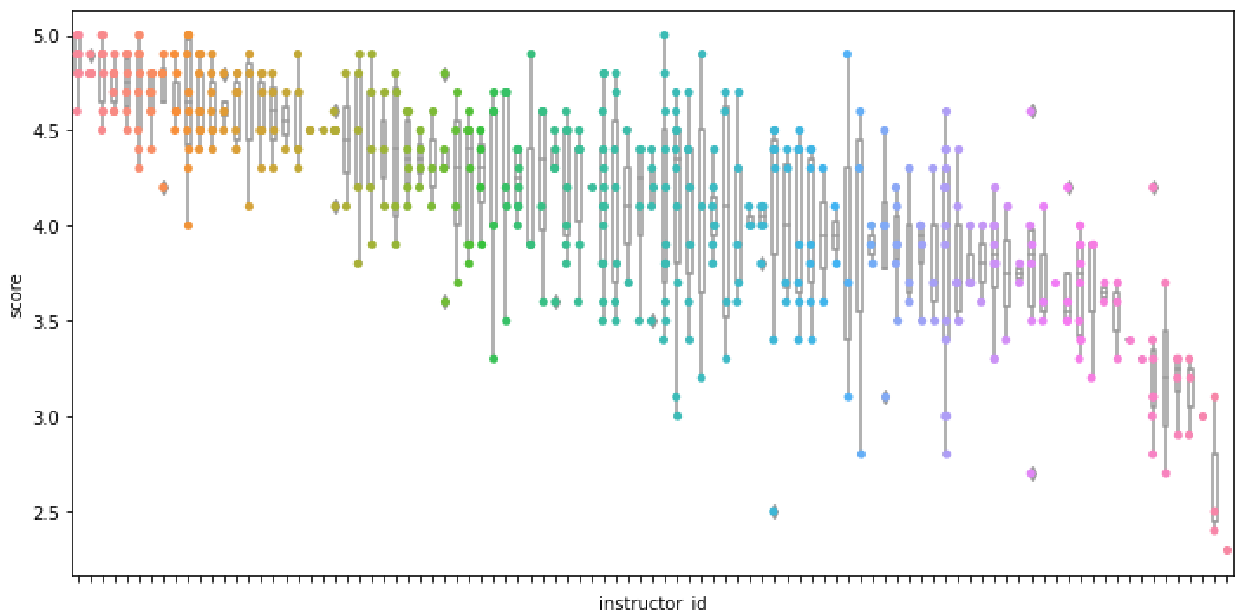


There are 95 unique instructor IDs. According to the paper, the data set includes 94 instructors. We are working with a slightly modified version of the data from the paper. It seems we've been able to uniquely identify every instructor.

Some instructors are represented as many as 13 times in the dataset. Only a handful of instructors appear only once in the data.

Furthermore, we can see that most instructors get similar scores for all of the courses they teach, with a few exceptions:

```
score_order =
    df_enc.groupby('instructor_id')['score'].agg('mean').sort_values(ascending=False).index

_  = plt.figure(figsize=(12,6))
ax = sns.boxplot(x=df_enc['instructor_id'], y=df_enc['score'],
                order=score_order,
                color='white', width=0.4)
ax = sns.stripplot(x=df_enc['instructor_id'], y=df_enc['score'],
                  order=score_order)
_  = ax.set(xticklabels=[])
```



To explore this issue further, we will repeat our analysis using two different ways of splitting the dataset:

1. **Random split**: shuffle data and split it into training and test sets. Train the model using the training data, then evaluate its performance on the test set. (This is what we have done so far.)
2. **Group split**: split data into training and test sets in a way that ensures that each individual *instructor* is represented in either the training data or the test data, but not both. Train the model using the training data, then evaluate its performance on the test set. If the model is "memorizing" individual instructors, rather than learning a general relationship between features and teaching evaluation score, it will have much worse performance on the test set, because it has to predict scores for instructors it hasn't "seen" yet.

Because the dataset is small, the performance evaluation may be influenced by the random sample of rows that happen to end up in the training vs. test set. (If a few rows more rows than usual that are very "easy" to predict are placed in the test set, we might see better performance than we would with a different test set.) So, we will also repeat the splitting procedure several times, and look at the *average* performance across different train-test splits.

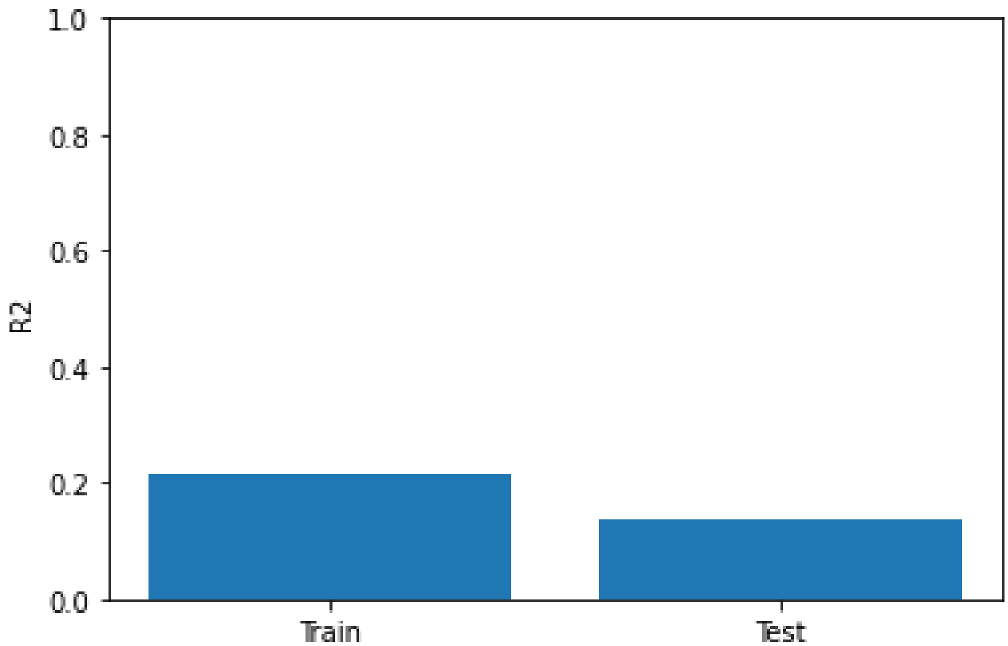
```
n_splits = 10
metrics_rs = np.zeros((n_splits, 6))
rs = model_selection.KFold(n_splits=n_splits, shuffle=True)
```

```python
for i, split in enumerate(rs.split(df_enc)):
    train_idx, test_idx = split
    train = df_enc.iloc[train_idx]
    test = df_enc.iloc[test_idx]

    features = df_enc.columns.drop(['score', 'instructor_id'])

    # train a multiple linear regression using
    # the train dataset and the list of features created above
    # save the fitted model in reg_rndsplit
    # then use the model to create y_pred_train and y_pred_test,
    # the model predictions on the training set and test set.
    # Finally, return the array of model performance metrics

    reg_rndsplit = LinearRegression().fit(train[features], train['score'])

    y_pred_train = reg_rndsplit.predict(train[features])
    y_pred_test = reg_rndsplit.predict(test[features])

    metrics_rs[i] = regression_performance(train['score'], y_pred_train, test['score'],
        y_pred_test)


np.mean(metrics_rs, axis=0)
```

```
array([0.21578756, 0.23144167, 0.78421244, 0.13535896, 0.25321174,
       0.86464104])
```

With this approach to splitting the data, the model appears to have some predictive value on the test set (which is supposed to represent performance on "new" data.)

```python
_ = plt.bar(x=['Train', 'Test'], height=np.mean(metrics_rs, axis=0)[[0,3]])
_ = plt.ylabel("R2")
_ = plt.ylim(0, 1)
```



Next, we will perform our splits, train a model, and get performance metrics according to the second scheme, in which an instructor may be present in either the training set or the test set, but not both.

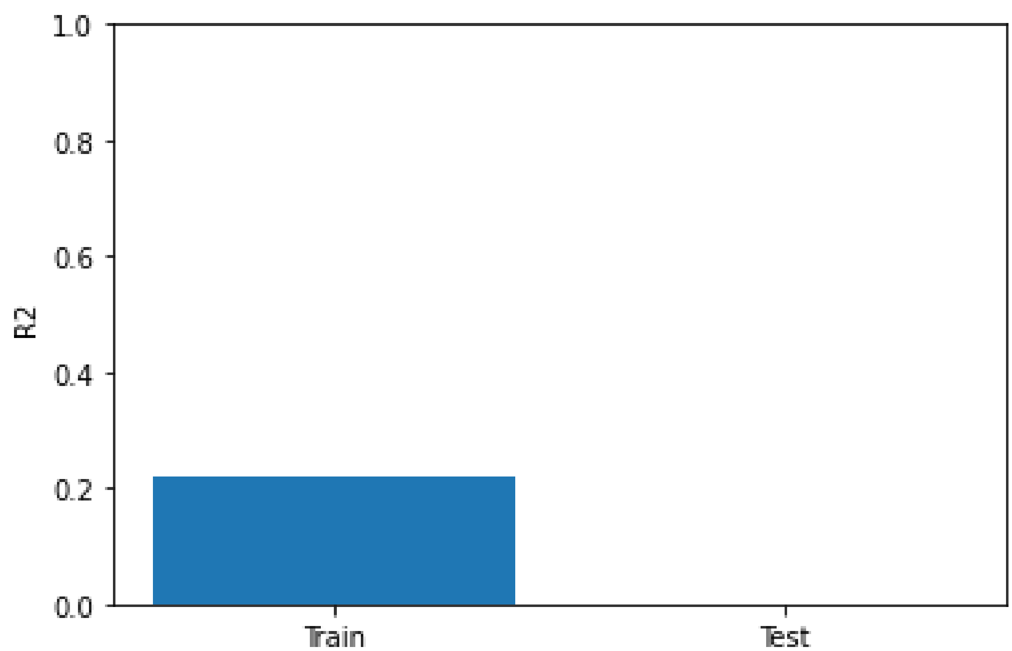
```
n_splits = 10
metrics_gs = np.zeros((n_splits, 6))
gs = model_selection.GroupKFold(n_splits=n_splits)

for i, split in enumerate(gs.split(df_enc,
                                   df_enc['score'],
                                   df_enc['instructor_id'])):

    train_idx, test_idx = split

    train = df_enc.iloc[train_idx]
    test = df_enc.iloc[test_idx]

    features = df_enc.columns.drop(['score', 'instructor_id'])

    # train a multiple linear regression using
    # the train dataset and the list of features created above
    # save the fitted model in reg_grpsplit
    # then use the model to create y_pred_train and y_pred_test,
    # the model predictions on the training set and test set.
    # Finally, return the array of model performance metrics

    reg_grpsplit = LinearRegression().fit(train[features], train['score'])

    y_pred_train = reg_grpsplit.predict(train[features])
    y_pred_test = reg_grpsplit.predict(test[features])

    metrics_gs[i] = regression_performance(train['score'], y_pred_train, test['score'],
        y_pred_test)
```

```
np.mean(metrics_gs, axis=0)
```

```
array([ 0.22092182,  0.22984319,  0.77907818, -0.03138834,  0.29278308,
        1.03138834])
```

With the second approach to splitting the data, we can see that the model has no predictive value on the test set.

```
_ = plt.bar(x=['Train', 'Test'], height=np.mean(metrics_gs, axis=0)[[0,3]])
_ = plt.ylabel("R2")
_ = plt.ylim(0, 1)
```



Discussion Question 8 Based on your analysis above, do you think your model will be useful to predict the teaching evaluation scores of a new faculty member at UT Austin, based on his or her physical characteristics and the characteristics of the course?

Review: what went wrong?

In this case study, we saw *two* problems:

The first problem is that the model was "memorizing" the individual instructors that appeared in the training data, rather than learning a general relationship between the features and the target variable. This is known as *overfitting*.

Usually, when a model is overfitting, it will be evident in the evaluation on the test set, because a model that overfits on training data will have excellent performance on training data and poor performance on test data. That's where the second problem comes in: data leakage! We expect the model to be able to predict a baseline score for instructors it has not been trained on, but our model was being trained on data from a set of instructors, then evaluated on data from the same instructors.

As a result of this data leakage, the model had overly optimistic error on the test set. The model appeared to generalize to new, unseen, data, but in fact would not generalize to different instructors.

One of the “red flags” that helped us identify the problem was that the model seemed to be learning from features that we know are not really informative - for example, the characteristics of the photo used to derive the attractiveness ratings. This is often a sign of data leakage.