

Introduction to Data Science – DS GA 1001

Capstone project

Assessing Professor Effectiveness (APE)

The purpose of this capstone project is to tie everything we learned in this class together. This might be challenging in the short term, but is consistently rated by students as being extremely valuable and useful in the long run. **Please read these instructions carefully.**

It is widely recognized that academia is in severe crisis and dire need for fundamental reform. Armed with your domain knowledge as a student and your technical skills as a data scientist, you heed the call of duty and come to the rescue in support of this noble cause. **In this capstone project, you will focus on the assessment of professors from a sufficiently large dataset and the insights you can glean from that.**

As a data source for this undertaking, the professor has **scraped the website ratemyprofessor.com** ("RMP", from now on). Students enjoy RMP as a source of information to inform their course choices and also contribute ratings to RMP to help out their fellow students by giving back to the community. Whereas **overall response rates are low and potentially affected by response bias (the students who do provide a rating might do so in a complimentary or retaliatory fashion)**, Research shows that this data source is **not entirely invalid**, as the correlation between RMP ratings and student evaluations of teaching obtained at the end of a class are on the order of 0.7. In contrast to student evaluations of teaching, RMP data is considerably larger and publicly available, which is why this is the dataset we use for this project.

As this is not a data engineering class, almost all the necessary data munging and scaffolding (e.g. scraping the actual site, converting the html to data, collating the information from individual ratings, anonymization, etc.) has already been done by the professor (you are welcome). **The remaining pre-processing steps are data science relevant (e.g. how to identify and handle missing data) and are thus left for you to implement.**

Mission command preamble: As usual, we won't tell you *how* to do something. That is up to you and allows you to showcase your creative problem-solving skills. However, we will pose the questions that you should answer by interrogating the data. We might also give hints.

Format: The project consist of your answers to 10 (equally-weighted, grade-wise) questions. Each answer ***must*** include some **text** (describing both what you *did* and what you *found*, i.e. the answer to the question), a **figure** that illustrates the findings and some **numbers** (e.g. test statistics, confidence intervals, p-values or the like). Please save it as a pdf document. This document should be 5-7 pages long (arbitrary font size and margins). About $\frac{1}{2}$ a page/question is reasonable. In addition, open your document with a title page where you introduce your group (and group name), state author contributions as well as statements as to how you handled preprocessing (e.g. data cleaning), as this will apply to all answers.

Deliverables: Upload two files to the Brightspace portal by the due date in the sittyba:

*A pdf (the "project report") that contains your answers to the questions, as well as an introductory paragraph about preprocessing, how you seeded the RNG, etc.

*A .py file with the code that performed the data analysis and created the figures.

Academic integrity: You are expected to do this project as a group. So make sure this works reflects your intellectual contribution – not that of third parties. You can use generative AI like chatGPT to aid you in this task. There are enough degrees of freedom (e.g. how to clean the data, what variables to compare, aesthetic choices in the figures, etc.) that no two reports will be alike. We'll be on the lookout for suspicious similarities, so please refrain from collaborating.

To prevent cheating (please don't do this – it is easily detected), it is very important that you – at the beginning of the code file – **seed the random number generator with the N-number of one of your team members (specify which one)**. That way, the correct answers will be keyed to your own solution (as this matters, e.g. for the specific train/test split or bootstrapping). As N-numbers are unique, this will also protect your work from plagiarism.

Failure to seed the RNG in this way will also result in the loss of grade points.

We do wish you all the best in executing on these instructions. We aimed at an optimal balance between specificity and implementation leeway, while still allowing us to grade the projects in a **fast, fair** and faithful (=consistent and accurate) manner (FFF).

Everything we ask for should be doable from what was covered in this course.

If you take this project seriously and do a quality job, you can easily use it as an item in your DS portfolio. Former students told us that they secured internships and even jobs by well executed capstone projects that impressed recruiters and interviewers.

Considerations: *There is some **missing data**, you'll have to handle it somehow.

*Note that the ***average*** rating is more meaningful if it is based on more ratings, as discussed in class. You have to handle this somehow. Either you can accept all data (which will likely yield extreme average ratings of 1 or 5, based on a single rating), set a threshold (only accept data with more than k ratings as valid) or weigh the average somehow. This is a judgment call. Argue how you make it.

*As we are concerned about false positives, as you have sufficient power and as we have to correct for multiple comparisons, consider an **alpha level of 0.005 as the threshold for statistical significance** for all of your results (Button et al., 2018).

*One of the data files (rmpCapStoneTags.csv) contains the **raw number of how many “tags”** of that kind a professor received. A student can award up to 3 to a professor in a given rating. This means that you likely can't just use the raw number of tags for anything meaningful, as a professor with more ratings will have received more tags, everything else being equal. You will have to **normalize these numbers somehow. And explain how and why you did it the way you did**. Or you can use the raw numbers, but then need to also explain why and why that makes sense.

Description of dataset: The datafile **rmpCapstoneNum.csv** contains 89893 records. Each of these records (rows) corresponds to **information about one professor**.

The columns represent the following information, in order:

- 1: Average Rating (the arithmetic mean of all individual quality ratings of this professor)
- 2: Average Difficulty (the arithmetic mean of all individual difficulty ratings of this professor)
- 3: Number of ratings (simply the total number of ratings these averages are based on)
- 4: Received a “pepper”? (Boolean - was this professor judged as “hot” by the students?)
- 5: The proportion of students that said they would take the class again
- 6: The number of ratings coming from online classes
- 7: Male gender (Boolean – 1: determined with high confidence that professor is male)
- 8: Female (Boolean – 1: determined with high confidence that professor is female)

There is a second datafile `rmpCapstoneQual.csv` that has the same number of 89893 records in the same order, but only 3 columns containing qualitative information:

Column 1: Major/Field

Column 2: University

Column 3: US State (2 letter abbreviation)

There is a third datafile `rmpCapstoneTags.csv` that has the same number of 89893 records in the same order. It also has 20 columns. The numbers in these columns correspond to the raw number of “tags” a professor has received. A student can award up to 3 such tags, but doesn’t have to award any. These tags are supposed to characterize the teaching style of the professor qualitatively, beyond ratings. Here is what the columns in this dataset represent:

Column 1: “Tough grader”

Column 2: “Good feedback”

Column 3: “Respected”

Column 4: “Lots to read”

Column 5: “Participation matters”

Column 6: “Don’t skip class or you will not pass”

Column 7: “Lots of homework”

Column 8: “Inspirational”

Column 9: “Pop quizzes!”

Column 10: “Accessible”

Column 11: “So many papers”

Column 12: “Clear grading”

Column 13: “Hilarious”

Column 14: “Test heavy”

Column 15: “Graded by few things”

Column 16: “Amazing lectures”

Column 17: “Caring”

Column 18: “Extra credit”

Column 19: “Group projects”

Column 20: “Lecture heavy”

References:

Benjamin, D. J., Berger, J. O., Johannesson, M., Nosek, B. A., Wagenmakers, E. J., Berk, R., ... & Johnson, V. E. (2018). Redefine statistical significance. *Nature human behaviour*, 2(1), 6-10.

Centra, J. A., & Gaubatz, N. B. (2000). Is there gender bias in student evaluations of teaching?. *The journal of higher education*, 71(1), 17-33.

MacNell, L., Driscoll, A., & Hunt, A. N. (2015). What’s in a name: Exposing gender bias in student ratings of teaching. *Innovative Higher Education*, 40(4), 291-303.

Mitchell, K. M., & Martin, J. (2018). Gender bias in student evaluations. *PS: Political Science & Politics*, 51(3), 648-652.

With this dataset in hand, we would like you to answer the following questions:

1. Activists have asserted that there is a strong gender bias in student evaluations of professors, with male professors enjoying a boost in rating from this bias. While this has been celebrated by ideologues, skeptics have pointed out that this research is of technically poor quality, either due to a low sample size – as small as $n = 1$ (Mitchell & Martin, 2018), failure to control for confounders such as teaching experience (Centra & Gaubatz, 2000) or obvious p-hacking (MacNell et al., 2015). We would like you to answer the question whether there is evidence of a pro-male gender bias in this dataset.

Hint: A significance test is probably required.

2. Is there a gender difference in the spread (variance/dispersion) of the ratings distribution? Again, it is advisable to consider the statistical significance of any observed gender differences in this spread.

3. What is the likely size of both of these effects (gender bias in average rating, gender bias in spread of average rating), as estimated from this dataset? Please use 95% confidence and make sure to report each/both.

4. Is there a gender difference in the tags awarded by students? Make sure to teach each of the 20 tags for a potential gender difference and report which of them exhibit a statistically significant different. Comment on the 3 most gendered (lowest p-value) and least gendered (highest p-value) tags.

5. Is there a gender difference in terms of average difficulty? Again, a significance test is indicated.

6. Please quantify the likely size of this effect at 95% confidence.

7. Build a regression model predicting average rating from all numerical predictors (the ones in the rmpCapstoneNum.csv) file. Make sure to include the R^2 and RMSE of this model. Which of these factors is most strongly predictive of average rating? Hint: Make sure to address collinearity concerns.

8. Build a regression model predicting average ratings from all tags (the ones in the rmpCapstoneTags.csv) file. Make sure to include the R^2 and RMSE of this model. Which of these tags is most strongly predictive of average rating? Hint: Make sure to address collinearity concerns. Also comment on how this model compares to the previous one.

9. Build a regression model predicting average difficulty from all tags (the ones in the rmpCapstoneTags.csv) file. Make sure to include the R^2 and RMSE of this model. Which of these tags is most strongly predictive of average difficulty? Hint: Make sure to address collinearity concerns.

10. Build a classification model that predicts whether a professor receives a “pepper” from all available factors (both tags and numerical). Make sure to include model quality metrics such as AU(ROC) and also address class imbalance concerns.

Extra credit: Tell us something interesting about this dataset that is not trivial and not already part of an answer (implied or explicitly) to these enumerated questions [Suggestion: Do something with the qualitative data, e.g. major, university or state by linking the qualitative data to the two other data files (tags and numerical)].