# What is the relationship between professor ratings and grades?

December 20, 2021

## 1 Do the grades students receive influence the ratings they leave on professor reviews?

Among people who design course review websites, there is a common concern that the reviews of the professors paint a misleading picture. The idea is that if a professor is teaching a difficult course, then the average grades they give out will likely be lower. As a result, students will be more likely to negatively rate their experience with that professor, and if someone reads their reviews, they may get the wrong impression that the professor is bad when in reality, it's just that the course they teach is more difficult.

In this analysis, I will use grade and review data from PlanetTerp to look at the relationship between a professor's ratings and the grades they give out. According to the PlanetTerp website, the review data comes in part from OurUMD.com. Professor and course information comes from umd.io. Grade data comes from the UMD Office of Institutional Research, Planning & Assessment (IRPA) and through a request under the state of Maryland's Public Information Act (PIA) (grade data initially from VAgrades.com).

The null hypothesis will be that there is a positive correlation between a professor's ratings and the grades they give out in their courses.

## 2 Average Rating vs. Average GPA

Our first task will be to gather some data. There are two things that we need to start out. The average rating of each professor and their average GPA over all the courses they teach. The first of these is really easy. The PlanetTerp API provides the average rating for a requested professor when you hit a certain endpoint.

First, we need to get all of the professors. We will use this code below to build a dataframe object that contains the following properties: - name: name of professor - slug - type: professor or TA - courses: list of courses taught - average_rating

[205]:
```
import requests
import pandas as pd
import io
import time
from bs4 import BeautifulSoup
import matplotlib.pyplot as plt

cur_offset = 0
```

```
professor_df = None
while cur_offset < 11039:
    time.sleep(3)
    # print(f"Requesting data. Offset is {cur_offset}")
    req = requests.get(f"https://api.planetterp.com/v1/professors?
 ↪limit=1000&offset={cur_offset}").content
    df = pd.read_json(io.StringIO(req.decode('utf-8')))
    cur_offset += 1000
    if professor_df is None:
        professor_df = df
    else:
        professor_df = professor_df.append(df)
```

[206]:
```
professor_df = professor_df.loc[professor_df["type"] == "professor"] # Filter␣
 ↪out all the TA's
professor_df = professor_df[professor_df["average_rating"].notna()] # Drop␣
 ↪anyone who doesn't have any ratings
professor_df
```

[206]:
```
               name            slug       type  \
1         A Anthony         anthony  professor
2      A Kruglanski      kruglanski  professor
4           A Sharma        sharma_a  professor
6      A.U. Shankar    shankar_a.u.  professor
8       Aaron Allen     allen_aaron  professor
..              ...             ...        ...
4     Zhengguo Xiao  xiao_zhengguo  professor
20     Zhongchi Liu    liu_zhongchi  professor
29       Zita Nunes      nunes_zita  professor
32   Zohreh Davoudi         davoudi  professor
34     Zsuzsa Daczo           daczo  professor

                                              courses  average_rating
1                           [AMST202, AMST203, AMST101]            1.00
2    [PSYC743, PSYC748M, PSYC489H, PSYC489T, PSYC78…           2.00
4                                             [ASTR300]            1.80
6        [CMSC412, CMSC414, CMSC712, CMSC216, CMSC798]            2.10
8                                    [HHUM205, HHUM206]            5.00
..                                                  …               …
4    [ANSC460, ANSC214, GEMS296, ANSC212, GEMS297, …           4.00
20             [BSCI378H, BSCI410, CBMG699Y, MOCB899]            4.50
29   [ENGL234, ENGL749B, ENGL448B, ENGL300, ENGL301…           3.75
32                          [PHYS604, PHYS411, PHYS624]            2.50
34               [SOCY105, SOCY227, SOCY325, WMST325]            4.50

[2481 rows x 5 columns]
```

Now that we have a table for our professors, we need to figure out the average GPA they give out for their courses. We'll do this by navigating to their page on PlanetTerp and scraping the content using BeautifulSoup.

[207]:
```python
import re

base_url = "https://planetterp.com/professor/"
matches = []
for idx, row in professor_df.iterrows():
    time.sleep(0.1)
    r = requests.get(base_url + row["slug"])
    root = BeautifulSoup(r.content, "html")
    s = root.find("strong", id="grade-statistics")
    # print(s)
    search_res = re.search(r"\d\.\d{2}", str(s))
    if search_res is None:
        # print(row["slug"])
        matches.append(float("NaN"))
    else:
        matches.append(search_res.group(0))
matches
```

[207]:
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 '3.83',
 '2.90',
 '2.81',
 '2.86',
 '2.85',
 '3.28',
 '3.17',
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 '3.51',
 '3.59',
 '3.37',
 '3.33',
 '2.88',
 '3.54',
 '3.52',
 nan,
 '3.58',
 '3.53',
 '3.61',
 '3.67',
 '2.59',
 …]
```

[208]:

```
professor_df["average_gpa"] = matches
old_professor_df = professor_df
professor_df = professor_df[professor_df["average_gpa"].notna()] # Drop anyone␣
↪who doesn't have an average gpa
professor_df
```

[208]:

```
             name          slug       type  \
1       A Anthony       anthony  professor
2    A Kruglanski    kruglanski  professor
4        A Sharma      sharma_a  professor
```

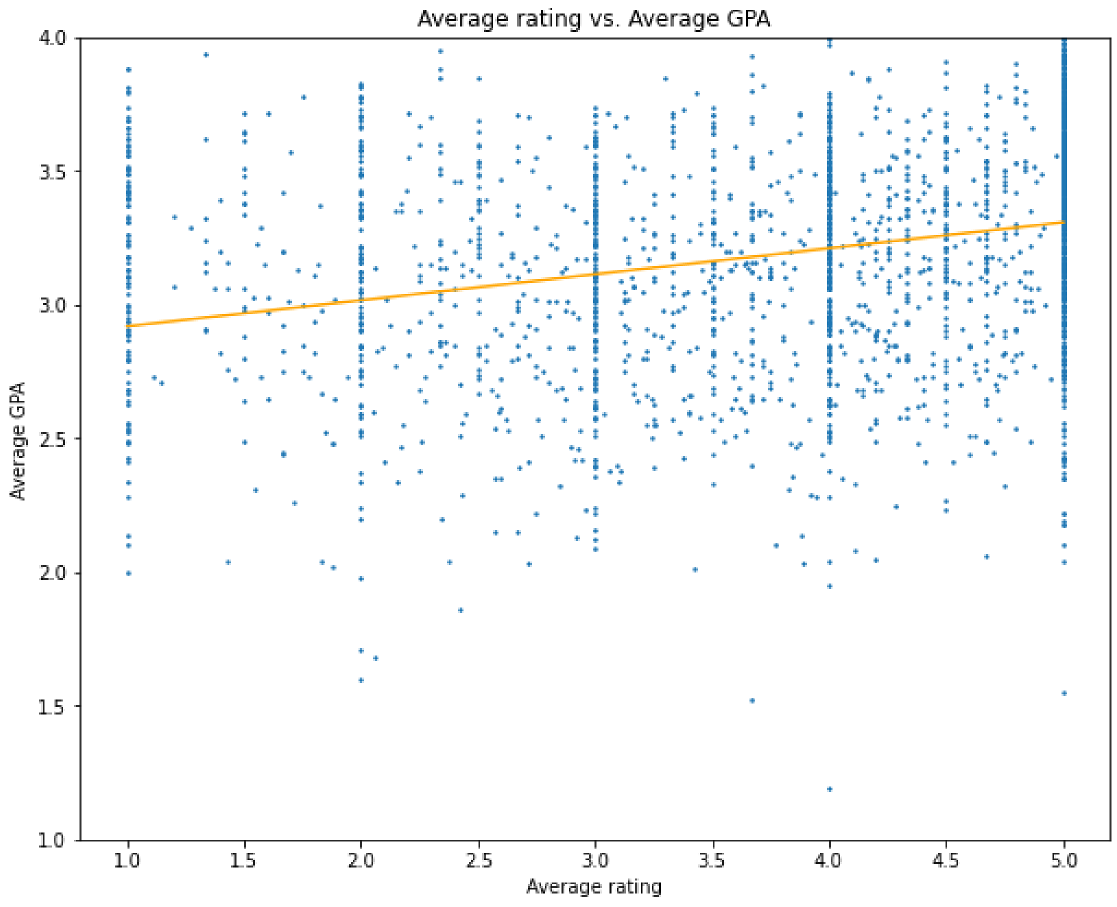
```
6     A.U. Shankar   shankar_a.u.  professor
8      Aaron Allen    allen_aaron  professor
..             …             …        …
4    Zhengguo Xiao  xiao_zhengguo  professor
20    Zhongchi Liu   liu_zhongchi  professor
29      Zita Nunes     nunes_zita  professor
32  Zohreh Davoudi        davoudi  professor
34    Zsuzsa Daczo          daczo  professor

                                                  courses  average_rating  \
1                            [AMST202, AMST203, AMST101]            1.00
2   [PSYC743, PSYC748M, PSYC489H, PSYC489T, PSYC78…           2.00
4                                              [ASTR300]            1.80
6       [CMSC412, CMSC414, CMSC712, CMSC216, CMSC798]            2.10
8                                     [HHUM205, HHUM206]            5.00
..                                                    …              …
4   [ANSC460, ANSC214, GEMS296, ANSC212, GEMS297, …           4.00
20             [BSCI378H, BSCI410, CBMG699Y, MOCB899]            4.50
29  [ENGL234, ENGL749B, ENGL448B, ENGL300, ENGL301…           3.75
32                           [PHYS604, PHYS411, PHYS624]            2.50
34                 [SOCY105, SOCY227, SOCY325, WMST325]            4.50

   average_gpa
1         2.48
2         3.49
4         2.82
6         2.41
8         3.61
..          …
4         2.95
20        3.37
29        2.75
32        3.38
34        3.62

[2363 rows x 6 columns]
```

[209]:
```python
import matplotlib.pyplot as plt
import numpy as np
plt.rcParams['figure.figsize'] = [10, 8]
average_rating = [float(x) for x in professor_df["average_rating"]]
average_gpa = [float(x) for x in professor_df["average_gpa"]]
# print(average_gpa)
plt.scatter(x=average_rating, y=average_gpa, s=2)
plt.title("Average rating vs. Average GPA")
plt.xlabel("Average rating")
plt.ylabel("Average GPA")
plt.ylim([1,4])
plt.plot(np.unique(average_rating), np.poly1d(np.polyfit(average_rating,␣
↪average_gpa, 1))(np.unique(average_rating)), c = "orange")
plt.show()
```



Due to the volume of data, I've made each point rather small so that we can better distinguish between the different data points. As expected, there are a lot of points concentrated on ratings that are whole numbers (1.0, 2.0, 3.0, 4.0, 5.0). This is likely because not every professor has multiple reviews and even the ones who do may have just a few reviews that are all of the same rating. However, despite the volume of data points, we can see that there seems to be a large density of points around the 5.0 rating and they seem to be skewed towards high GPA. Furthermore, the line of best fit seems to show that there is some positive relationship between the two measures. Let's calculate the R squared value to be sure.

[210]:
```
import statsmodels.formula.api as smf
res = smf.ols(formula="average_rating ~ average_gpa", data=professor_df).fit()
print('R squared: {}'.format(res.rsquared))
```

```
R squared: 0.15051243926885027
```

While an R squared value of 0.15 is not huge, it does seem appropriate given what we are measuring. There are a lot of factors that students take into consideration when rating a professor, such as how organized the class was, the professor's lecture style, how good the TA's were, etc. Furthermore, even if a student receives a low grade, it could be the case that they received that grade just because the class was difficult, and it had nothing to do with the quality of the professor. When you consider the multitude of factors that influence the reviews students give, anything more than a modest relationship between the professor's rating and their average GPA would seem suspicious.

## 3 Another Approach

There may be a better, more direct way to go about measuring this relationship. On PlanetTerp, when you leave a review, there is an option to leave what grade you are expecting in the class. Instead of just measuring the average GPA of a professor across all the courses that he/she teaches, we could instead look at the individual reviews for each professor and see if there is a relationship between the grade that the reviewer is expecting to get and the rating they give the professor.

In the code below, I've marked down the grades as A, B, C, D, F, Pass (P), Withdrawn (W), and Not Reported (NR). The expectation is that those who received high grades (A's and B's) are likely going to leave higher ratings than those who recieved low grades. We also expect that people who withdrew from the class, passed the class (which was likely a lot of people during the COVID semesters), or simply didn't report the grade they got will give lower ratings to the professors.

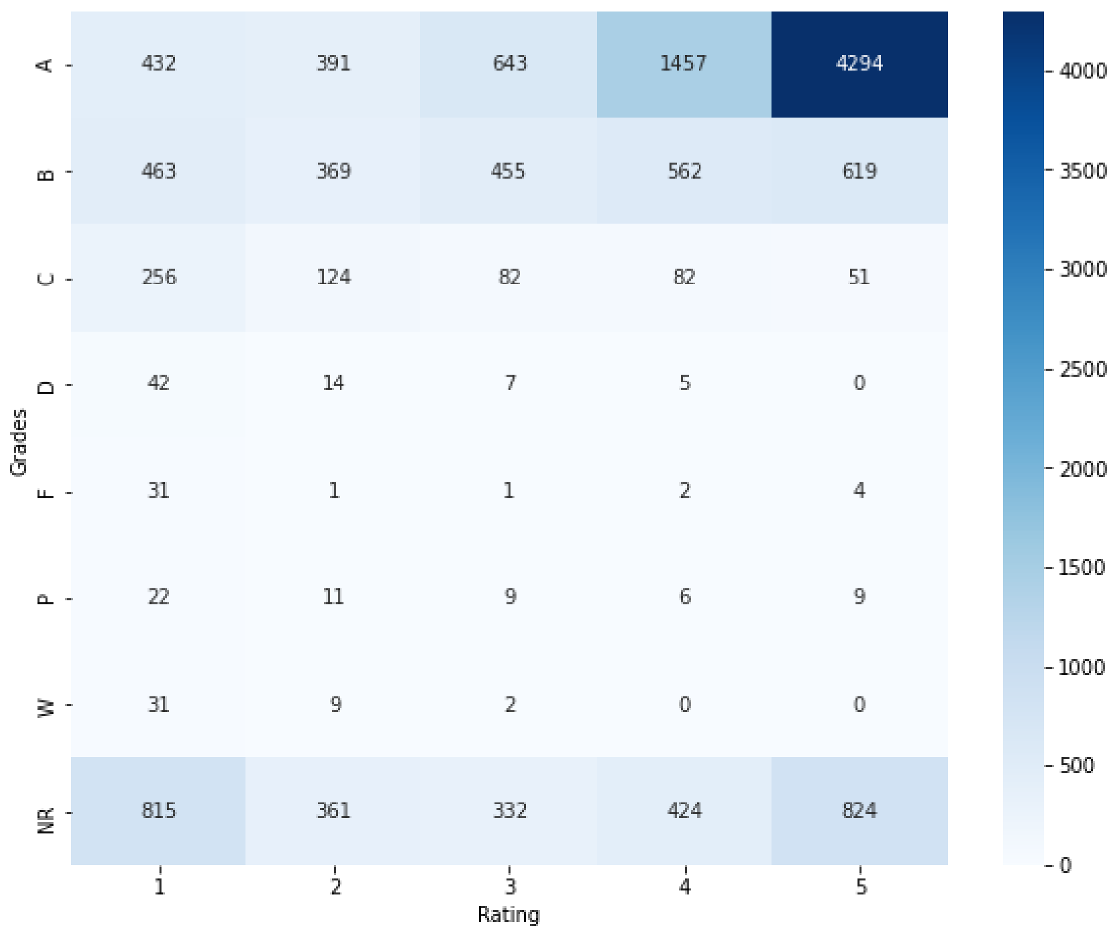
This next block of code takes a long time to run, so you might want to go for a walk or put on a TV show if you are going to try and run this snippet yourself.

[211]:
```
grades = {
    "A": {"1": 0, "2": 0, "3": 0, "4": 0, "5": 0},
    "B": {"1": 0, "2": 0, "3": 0, "4": 0, "5": 0},
    "C": {"1": 0, "2": 0, "3": 0, "4": 0, "5": 0},
    "D": {"1": 0, "2": 0, "3": 0, "4": 0, "5": 0},
    "F": {"1": 0, "2": 0, "3": 0, "4": 0, "5": 0},
    "P": {"1": 0, "2": 0, "3": 0, "4": 0, "5": 0},
    "W": {"1": 0, "2": 0, "3": 0, "4": 0, "5": 0},
    "NR": {"1": 0, "2": 0, "3": 0, "4": 0, "5": 0}
}
g = ["A", "B", "C", "D", "F", "P", "W"]
for idx, row in professor_df.iterrows():
    # print(idx)
    reviews = requests.get(f"https://api.planetterp.com/v1/professor?
 ↪name={row['name']}&reviews=true").json()
    if reviews is None or "reviews" not in reviews:
        # print(reviews)
        continue
    reviews = reviews["reviews"]
    for rev in reviews:
        if rev["expected_grade"] == "" or rev["expected_grade"] is None:
            # print(rev["course"])
            grades["NR"][str(rev["rating"])] += 1
            continue
        grade = rev["expected_grade"][0].upper()
        if grade not in g:
            # print(f"Continuing, {grade}")
            continue
        # print(grade)
        grades[grade][str(rev["rating"])] += 1
print(grades)
```

```
{'A': {'1': 432, '2': 391, '3': 643, '4': 1457, '5': 4294}, 'B': {'1': 463, '2':
369, '3': 455, '4': 562, '5': 619}, 'C': {'1': 256, '2': 124, '3': 82, '4': 82,
'5': 51}, 'D': {'1': 42, '2': 14, '3': 7, '4': 5, '5': 0}, 'F': {'1': 31, '2':
1, '3': 1, '4': 2, '5': 4}, 'P': {'1': 22, '2': 11, '3': 9, '4': 6, '5': 9},
'W': {'1': 31, '2': 9, '3': 2, '4': 0, '5': 0}, 'NR': {'1': 815, '2': 361, '3':
332, '4': 424, '5': 824}}
```

[212]:
```
data = [np.array(list(d.values())) for d in grades.values()]
import seaborn as sb
sb.heatmap(data, xticklabels="12345", yticklabels=["A", "B", "C", "D", "F",␣
 ↪"P", "W", "NR"], cmap="Blues", annot=True, fmt="g");
plt.xlabel("Rating")
plt.ylabel("Grades")
```

[212]:
```
Text(69.0, 0.5, 'Grades')
```



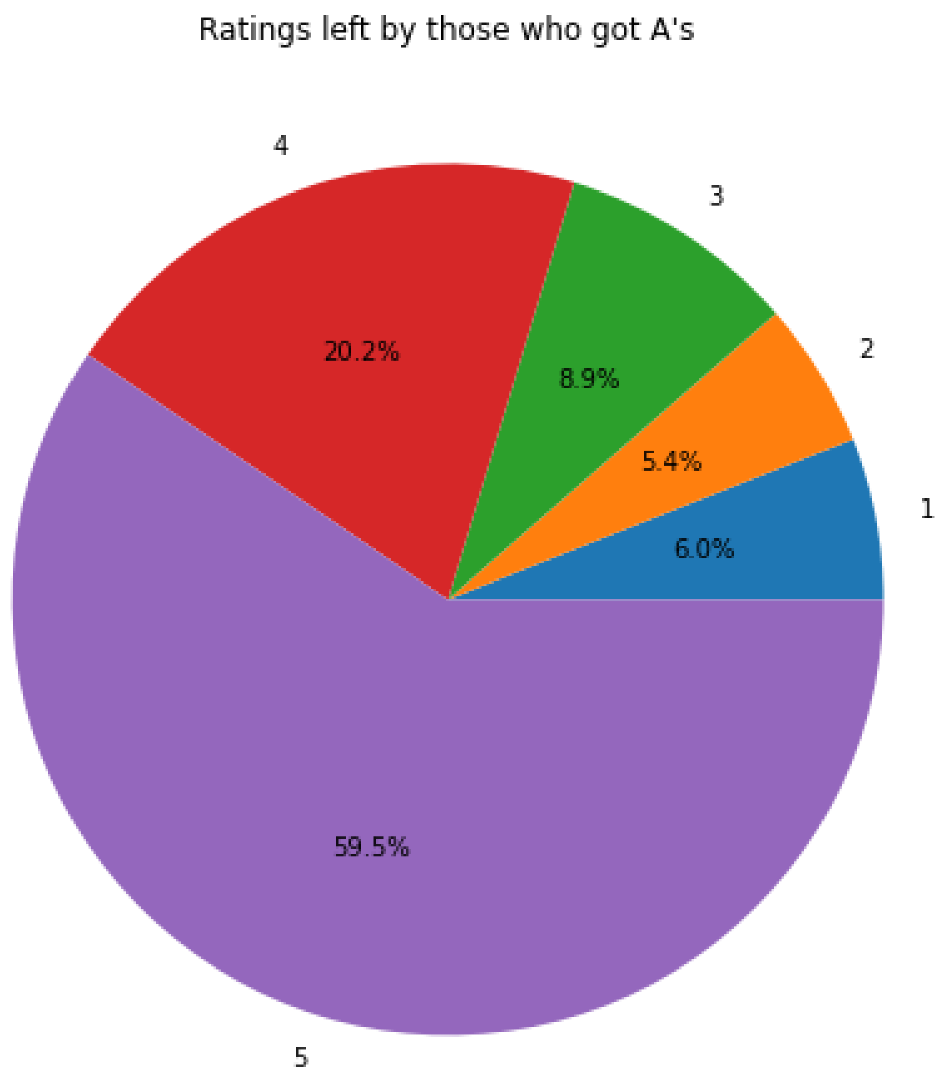
Wow. That certainly tells us something about the kinds of people who are leaving reviews on PlanetTerp. It's not even a contest. People who gave their professor 5-star ratings and also got A's in the class make up the grand majority of the reviews on the site. The group that comes in second place (people who got A's and left 4-star reviews) has less than half the number of people in this majority group. All other groups look absolutely tiny by comparison, as evidenced by the fact that they are all colored a very pale blue.

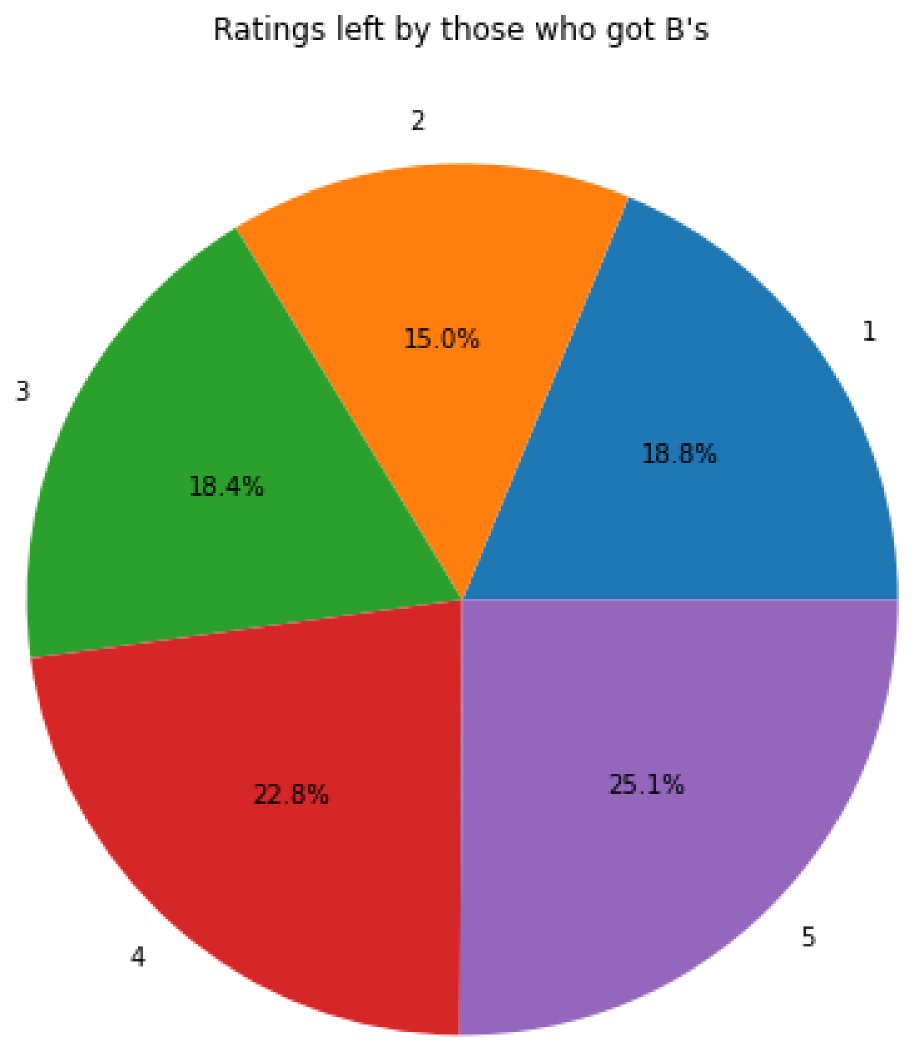
It is worth noting that all of the trends that we anticipated seem to be born out in this heat map. If we look at each of the different grade categories, we can see that people who got A's are overwhelmingly more likely to leave high reviews. The people who got B's, on the other hand, seem to have a more mixed relationship with a pretty even spread among the different ratings. People who got C's or lower were skewed in the opposite direction as those who got A's, with more people leaving low ratings. This is also true of those who passed or withdrew from the class.

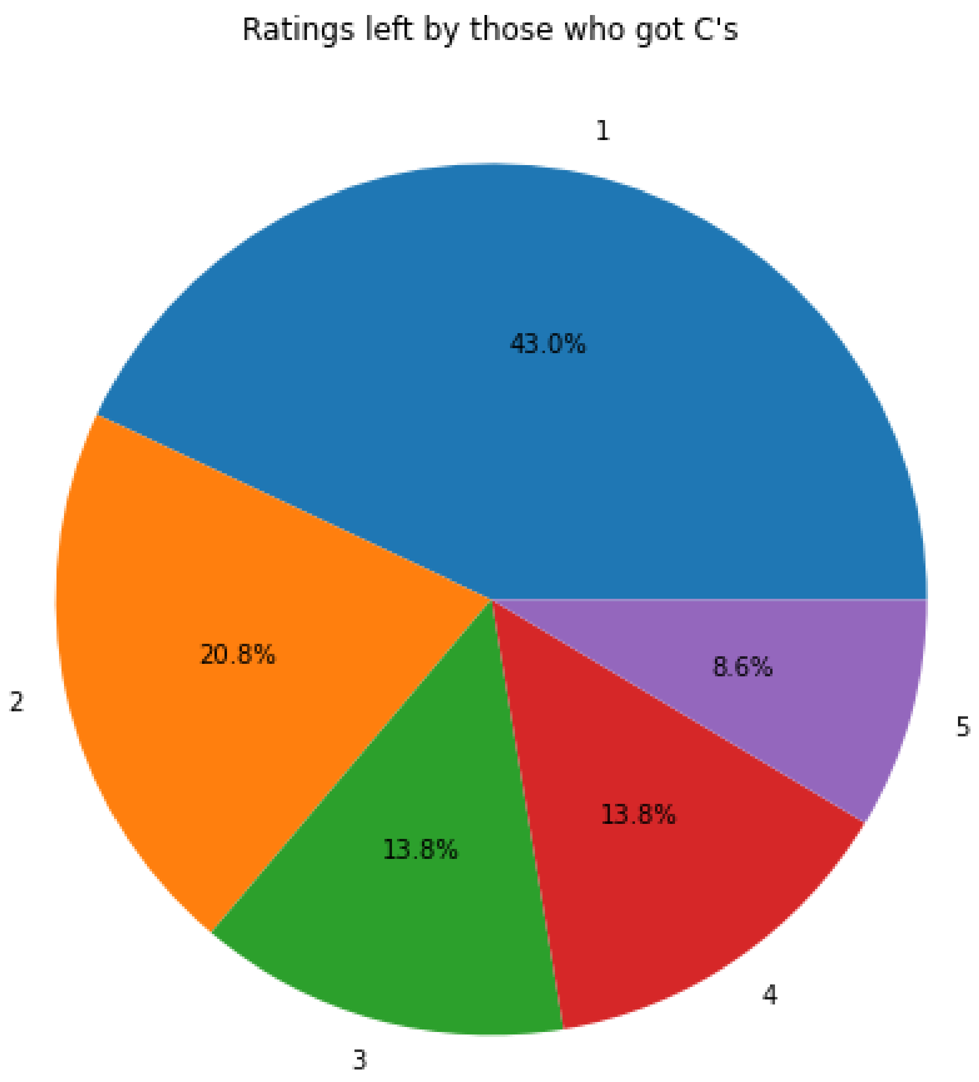
It is also interesting to observe that there doesn't seem to be a clear relationship between not reporting one's grade and the rating. In the group of people who didn't report their grades, we see that about the same number of people of people left 1-star and 5-star ratings, with the rest pretty evenly spread among 2 to 4-star ratings.

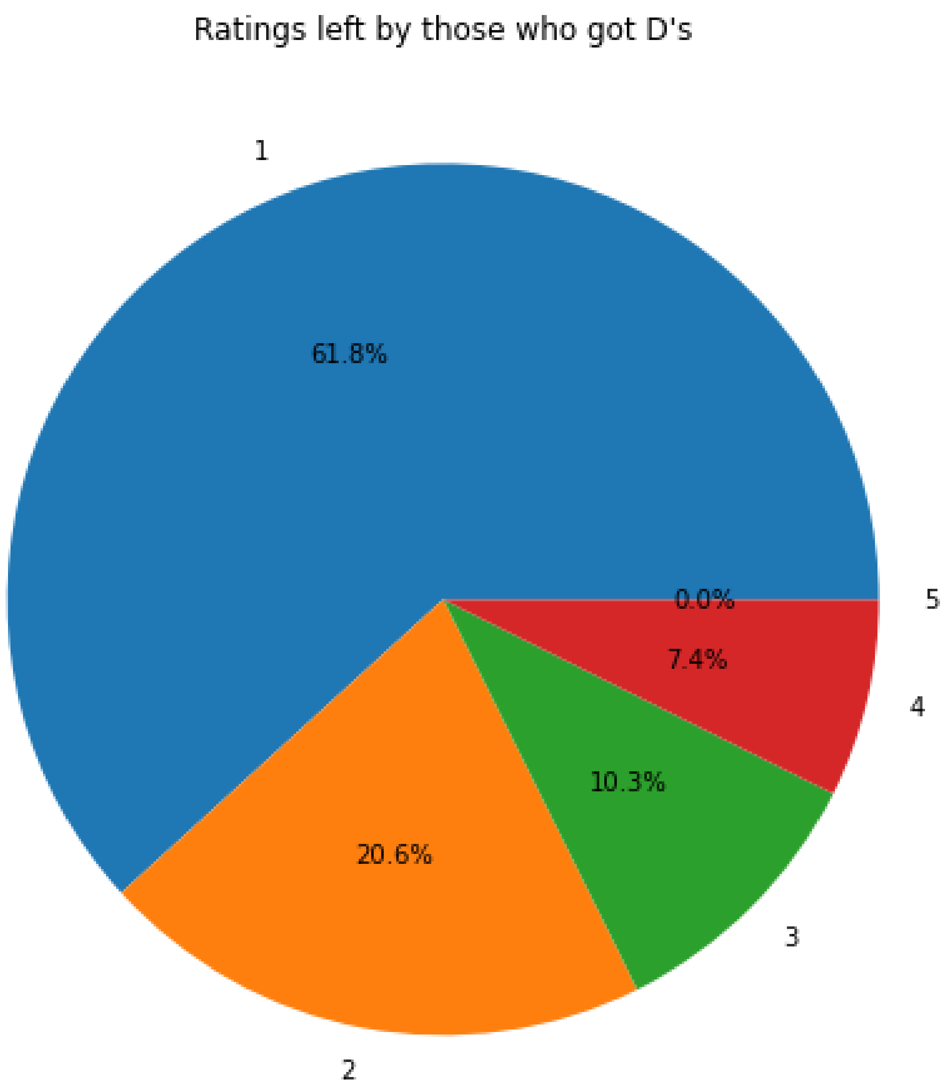
You might find the pie charts below to be helpful in seeing these proportions among the different grade categories more clearly.

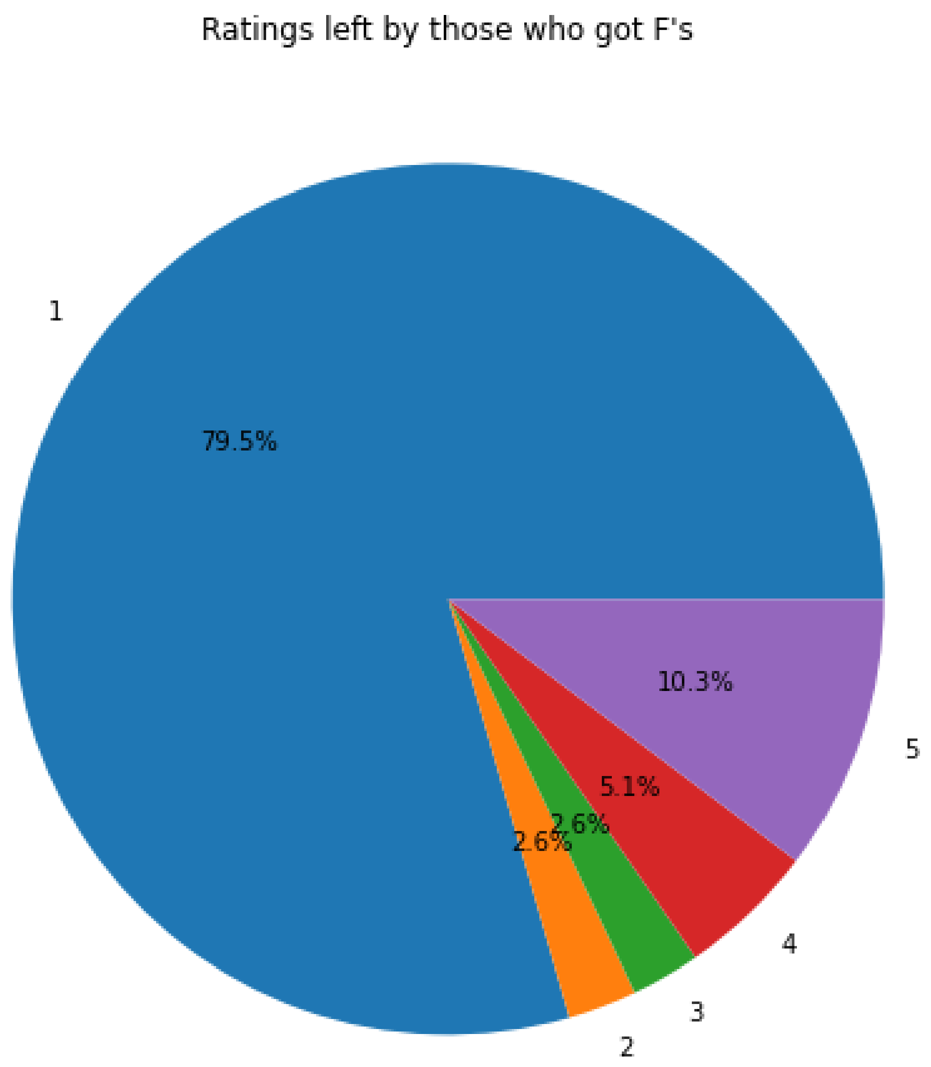
[213]:
```
def get_title(grade):
    switcher={
        "A": "those who got A's",
        "B": "those who got B's",
        "C": "those who got C's",
        "D": "those who got D's",
        "F": "those who got F's",
        "P": "those who passed",
        "W": "those who withdrew",
        "NR": "those who didn't report their grade"
    }
    return switcher.get(grade)

for grade in grades.keys():
    title = f"Ratings left by {get_title(grade)}"
    ratings = grades[grade]
    rate_vals = []
    for rating in ratings.values():
        rate_vals.append(rating)
    labels = ["1", "2", "3", "4", "5"]
    plt.pie(rate_vals,labels=labels, autopct='%1.1f%%')
    plt.title(title)
    plt.show()
```

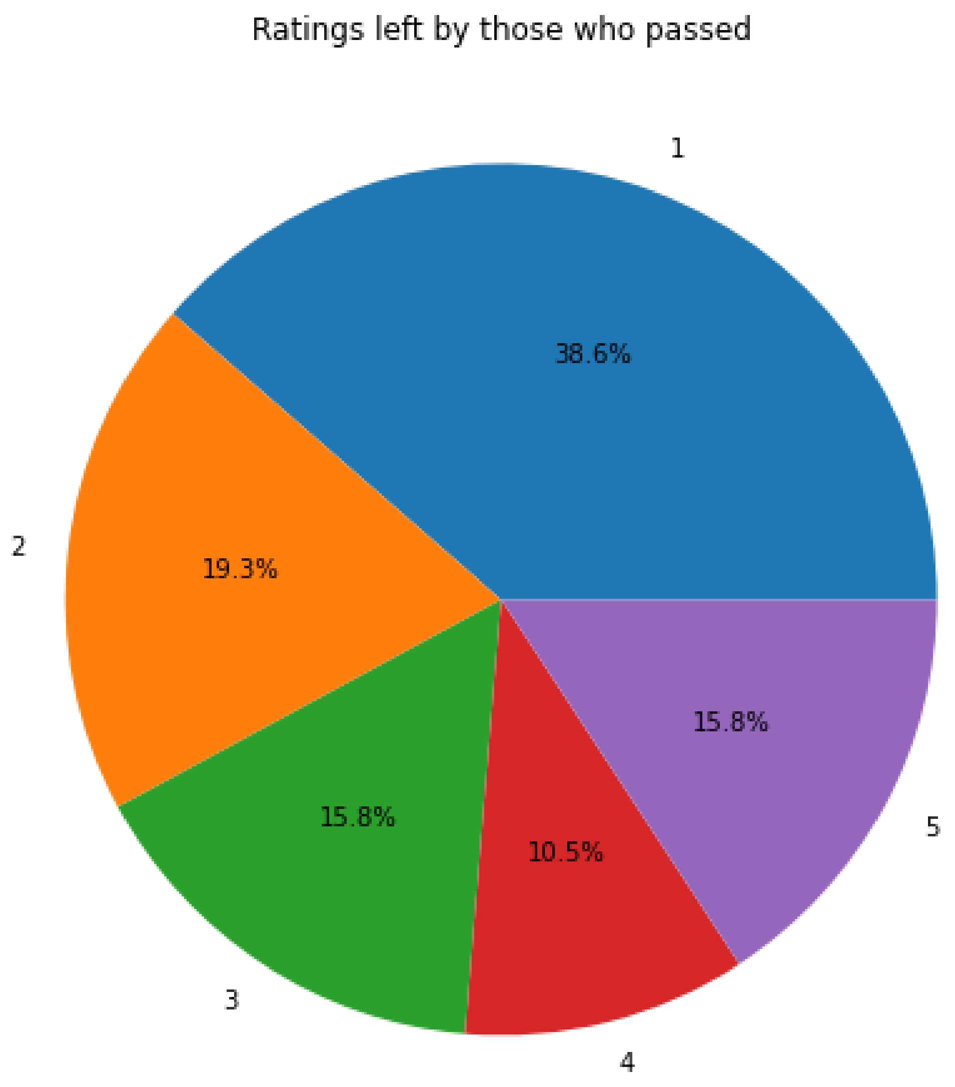

Ratings left by those who got A's
1
6.0%
2
5.4%
3
8.9%
4
20.2%
5
59.5%

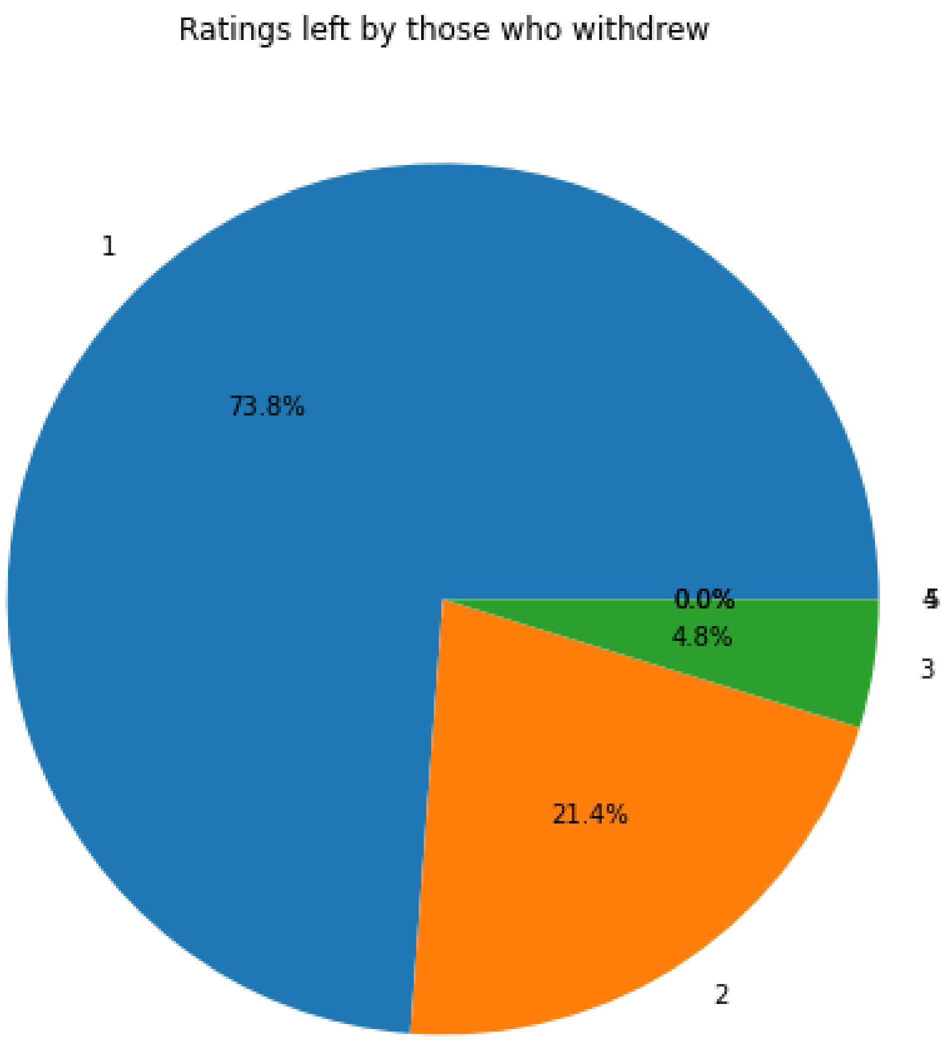

Ratings left by those who got B's
1
18.8%
2
15.0%
3
18.4%
4
22.8%
5
25.1%

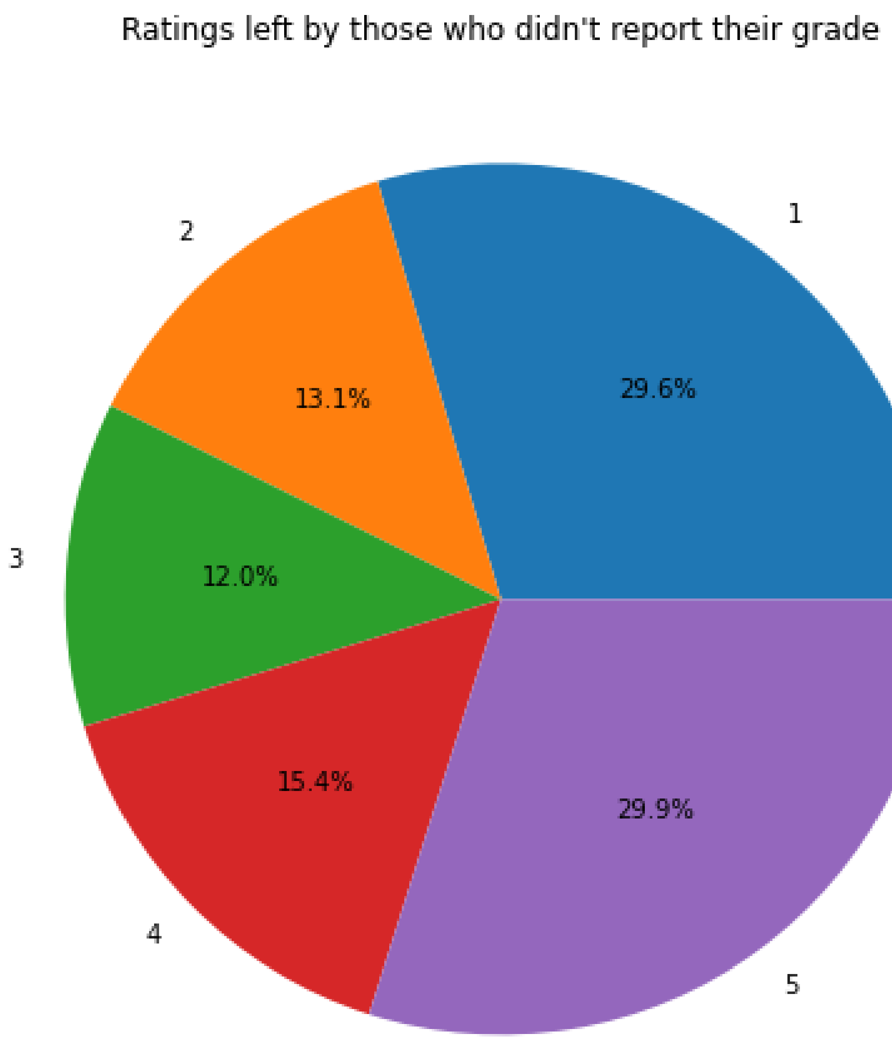

Ratings left by those who got C's
1
43.0%
2
20.8%
3
13.8%
4
13.8%
5
8.6%


Ratings left by those who got D's
1
61.8%
2
20.6%
3
10.3%
4
7.4%
5
0.0%


Ratings left by those who got F's
1
79.5%
2
2.6%
3
2.6%
4
5.1%
5
10.3%


Ratings left by those who passed
1
38.6%
2
19.3%
3
15.8%
4
10.5%
5
15.8%


Ratings left by those who withdrew
1
73.8%
2
21.4%
3
4.8%
4
5
0.0%



## 4 A new measure?

Given our analysis so far, it seems fair to conclude that people who leave reviews on PlanetTerp are more likely to be people who received high grades in the courses they are reviewing. This presents a problem for those who are relying on PlanetTerp reviews and rating data to determine the quality of a professor, as these ratings might be biased towards professors who simply teach easy classes or grade easily. In this last part of the analysis, let's try and see if we can devise a way to measure the quality of a professor that doesn't suffer from the issues we face with the current information. I think that it's fair to say that if a student receives a high grade in a class, but rates the professor very low, then that indicates that the professor might not be very good. Similarly, if a student receives a low grade, but still rates the professor very highly, that would be a strong indication that the professor is very good. Obviously, it's not perfect. For example, some professors might still be very bad, but have cool personalities that cause students to still leave high ratings and vice versa. However, analyzing the review data in this way might yield some interesting results.

I'm going to only create this score for professors that have more than 20 ratings, as it likely wouldn't be very meaningful otherwise.

[214]:
```
def get_number_ratings(prof_df):
    ratings_count = []
    for idx, row in prof_df.iterrows():
        print(idx)
        reviews = requests.get(f"https://api.planetterp.com/v1/professor?
↪name={row['name']}&reviews=true").json()
        if reviews is None or "reviews" not in reviews:
            ratings_count.append(float("NaN"))
            continue
        reviews = reviews["reviews"]
        ratings_count.append(len(reviews))
    return ratings_count

num_ratings = get_number_ratings(professor_df)
professor_df["num_ratings"] = num_ratings
professor_df
```

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```
<ipython-input-214-ac9bd26733b1>:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  professor_df["num_ratings"] = num_ratings
```

[214]:
```
              name         slug       type  \
1        A Anthony      anthony  professor
2     A Kruglanski   kruglanski  professor
4         A Sharma     sharma_a  professor
```

```
6     A.U. Shankar   shankar_a.u.  professor
8      Aaron Allen    allen_aaron  professor
..             …              …          …
4    Zhengguo Xiao  xiao_zhengguo  professor
20    Zhongchi Liu   liu_zhongchi  professor
29      Zita Nunes     nunes_zita  professor
32  Zohreh Davoudi        davoudi  professor
34    Zsuzsa Daczo          daczo  professor

                                               courses  average_rating  \
1                            [AMST202, AMST203, AMST101]            1.00
2   [PSYC743, PSYC748M, PSYC489H, PSYC489T, PSYC78…            2.00
4                                            [ASTR300]            1.80
6       [CMSC412, CMSC414, CMSC712, CMSC216, CMSC798]            2.10
8                                   [HHUM205, HHUM206]            5.00
..                                                 …              …
4   [ANSC460, ANSC214, GEMS296, ANSC212, GEMS297, …            4.00
20              [BSCI378H, BSCI410, CBMG699Y, MOCB899]            4.50
29  [ENGL234, ENGL749B, ENGL448B, ENGL300, ENGL301…            3.75
32                           [PHYS604, PHYS411, PHYS624]            2.50
34                  [SOCY105, SOCY227, SOCY325, WMST325]            4.50

   average_gpa  num_ratings
1         2.48          1.0
2         3.49          1.0
4         2.82          5.0
6         2.41         20.0
8         3.61          1.0
..         …          …
4         2.95          1.0
20        3.37          6.0
29        2.75          4.0
32        3.38          2.0
34        3.62          4.0

[2363 rows x 7 columns]
```

[215]:
```
more_than_20 = professor_df.loc[professor_df["num_ratings"] >= 20]
more_than_20
```

[215]:
```
                    name          slug       type  \
6           A.U. Shankar  shankar_a.u.  professor
124  Adrianos Papamarcou    papamarcou  professor
331       Alice Mignerey     mignerey  professor
362          Alka Gandhi        gandhi  professor
369      Allan Yashinski     yashinski  professor
..                     …             …          …
```

```
605        Wesley Lawson    lawson_wesley  professor
649      William Higgins  higgins_william  professor
676   William McClenahan       mcclenahan  professor
727         Wiseley Wong     wong_wiseley  professor
729       Wojciech Czaja            czaja  professor

                                                  courses  average_rating  \
6        [CMSC412, CMSC414, CMSC712, CMSC216, CMSC798]          2.1000
124  [ENEE222, ENEE324, ENEE620, ENEE322, ENEE322H,…        4.2400
331  [CHEM271, CHEM705, CHEM889A, CHEM403, CHEM131,…        2.4444
362               [ECON312, ECON422, ECON321, ECON325]          3.8788
369  [MATH240, MATH401, MATH406, MATH461, MATH141H,…        4.6400
..                                                  …             …
605  [ENEE131, ENEE132, ENEE200, ENEE205, ENEE381, …        3.7027
649  [BIOL608F, BSCI440, BSCI105, BSCI207, CLFS510,…        3.4082
676  [BMGT380H, BMGT381, BMGT380, BUSI764, BMGT496,…        4.1250
727  [MATH141, MATH241H, MATH401, MATH241, MATH475,…        4.8621
729  [MATH648I, MATH141H, MATH411, MATH648Q, MATH14…        3.8929

    average_gpa  num_ratings
6          2.41         20.0
124        2.87         25.0
331        2.59         36.0
362        2.14         33.0
369        2.72         25.0
..          …            …
605        3.10         37.0
649        2.66         49.0
676        3.10         24.0
727        2.49         29.0
729        2.03         28.0

[126 rows x 7 columns]
```

[216]:
```
def get_grade_point(grade):
    switcher={
        "A": 5,
        "B": 4,
        "C": 3,
        "D": 2,
        "F": 1,
        "P": 1,
        "W": 1
    }
    return switcher.get(grade)

g = ["A", "B", "C", "D", "F", "P", "W"]
```

```
scores = []
for idx, row in more_than_20.iterrows():
    reviews = requests.get(f"https://api.planetterp.com/v1/professor?
↪name={row['name']}&reviews=true").json()
    reviews = reviews["reviews"]
    cur_score = 0
    for rev in reviews:
        if rev["expected_grade"] == "" or rev["expected_grade"] is None:
            continue
        grade = rev["expected_grade"][0].upper()
        if grade not in g:
            continue
        # print(grade)
        rating = rev["rating"]
        cur_score += rating - get_grade_point(grade) # High rating, low grade␣
↪-> high score. Low rating, high grade -> low score
    scores.append(cur_score)
print(scores)
```

```
[-35, -3, -27, -13, 6, -14, -24, 1, -16, -15, -34, -16, -6, -57, -8, -23, -30,
-40, -49, -18, -65, -32, -51, 2, -3, -8, -1, -41, -10, -33, 3, -1, -62, -6, -10,
-46, -41, -24, 0, -23, -22, -13, -8, -8, -29, -75, -26, -36, -9, -21, -7, 5,
-31, -13, -36, -27, -7, -12, -16, -47, -8, -10, 21, -5, -21, -25, -4, -5, -42,
-103, 0, -22, -29, -7, -15, -53, -11, -38, -24, -22, -28, -30, -34, 3, -21, -15,
-8, 2, -99, -14, -7, 0, -13, -10, -28, -42, -25, -7, -39, -45, -5, -19, -17, -2,
-13, -42, -27, -26, -5, -55, 7, 3, -1, -36, -20, -4, -13, -12, -43, -60, -24,
-27, -40, -6, 0, -8]
```

[217]:
```
more_than_20["score"] = scores
```

```
<ipython-input-217-76e9b4c5cf59>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  more_than_20["score"] = scores
```

[218]:
```
sorted_by_score = more_than_20.sort_values(by=["score"],ascending=False)
sorted_by_score.head(40)
```

[218]:
```
                      name            slug       type  \
386   Justin Wyss-Gallifent    wyss-gallifent  professor
724       Stefan Doboszczak        doboszczak  professor
369         Allan Yashinski         yashinski  professor
467           Jeffery Davis     davis_jeffery  professor
352      Michael Galczynski        galczynski  professor
```

```
997      Elizabeth Griffith            griffith  professor
823         Steven Chadwick            chadwick  professor
434            Michael Ross        ross_michael  professor
513           David Straney             straney  professor
803              Anne Simon          simon_anne  professor
503            Gary Pertmer             pertmer  professor
822            Naveen Sarna               sarna  professor
207     Lawrence Washington  washington_lawrence  professor
727            Wiseley Wong        wong_wiseley  professor
209      Erich Studer-Ellis        studer-ellis  professor
939          Susan Mazzullo            mazzullo  professor
706      Dionisios Margetis            margetis  professor
774      Robert Bonenberger         bonenberger  professor
124     Adrianos Papamarcou          papamarcou  professor
527             David Yager               yager  professor
84             Terence Long        long_terence  professor
756         Kendall Williams     williams_kendall  professor
496          Kasso Okoudjou            okoudjou  professor
829           Kevin Calabro             calabro  professor
711            Richard King        king_richard  professor
50              Ryan Curtis              curtis  professor
416          Bryan Eichhorn            eichhorn  professor
355              Fawzi Emad          emad_fawzi  professor
676      William McClenahan           mcclenahan  professor
495               Louisa Wu           wu_louisa  professor
804          Nathan Manning      manning_nathan  professor
411            Progyan Basu                basu  professor
982              John Pease               pease  professor
465             Jeff Miller         miller_jeff  professor
403  Michael Montague-Smith      montague-smith  professor
258             Judd Nelson         nelson_judd  professor
25             Ibrahim Ades        ades_ibrahim  professor
985             Hugh Turner         turner_hugh  professor
729          Wojciech Czaja               czaja  professor
684   Chandrasekhar Thamire             thamire  professor

                                                courses  average_rating  \
386  [MATH206, MATH241, MATH410, MATH695, HONR219O,…          4.9149
724  [AMSC460, CMSC460, MATH140, MATH410, MATH120, …          4.9500
369  [MATH240, MATH401, MATH406, MATH461, MATH141H,…          4.6400
467  [CHEM241, CHEM611, CHEM889D, CHEM648F, CHEM640…          4.7407
352  [ENES100, ENES100A, ENES113, ENES102, ENES102H…          4.9677
997  [CHEM135, CHEM482, CHEM177, CHEM271, CHEM131, …          4.4167
823  [MATH140, MATH140H, STAT410, MATH141, MATH401,…          4.2000
434  [HIST289K, HIST455, HIST454, HIST619R, HIST131…          4.4286
513            [BSCI222, CPSP219L, BSCI348R, BSCI415]          4.8621
803  [BSCI105C, BSCI105S, CBMG688B, CBMG688X, BSCI1…          3.2245
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503  [ENES102, ENES102H, ENME489V, ENME472, ENME201…          4.6000
822                              [ECON201, ECON317]           4.4444
207  [MATH456, MATH620, MATH406, MATH808N, MATH220,…          4.8571
727  [MATH141, MATH241H, MATH401, MATH241, MATH475,…          4.8621
209                             [BMGT230, BMGT230B]           4.2973
939  [STAT100, STAT400, STAT430, STAT401, STAT440, …          4.8696
706  [MATH648M, MATH241, MATH424, MATH463, MATH858M…          4.5581
774                              [ENES102, ENES220]           4.3810
124  [ENEE222, ENEE324, ENEE620, ENEE322, ENEE322H,…          4.2400
527  [NACS728Q, PSYC301, HONR209O, PSYC407, PSYC606…          3.8333
84   [MATH213, MATH140, MATH113, MATH115, MATH246, …          4.4000
756  [MATH241, MATH241H, MATH310, MATH274, MATH402,…          2.8929
496  [MATH141, MATH140, MATH630, MATH631, MATH858G,…          3.8400
829  [ENES100, ENES221, ENES100A, ENES232, ENES499,…          4.2917
711  [MUSC205, MUSC230, HONR209Z, MUSC639H, MUSC320…          4.4286
50   [PSYC100, PSYC420, PSYC334, PSYC798B, HONR219E…          4.1613
416  [CHEM131, CHEM608B, CHEM602, CHEM401, CHEM271,…          3.9231
355     [CMSC122, CMSC131, CMSC132, CMSC131H, CMSC250]        4.4086
676  [BMGT380H, BMGT381, BMGT380, BUSI764, BMGT496,…          4.1250
495  [BSCI378H, BSCI416, BSCI410, MOCB899, HLSC322,…          4.3333
804  [MATH220, MATH445, MATH140, MATH401, MATH140H,…          3.4231
411  [BMGT313, BMGT220, BMGT398C, BUAC743, BUSI610,…          3.9697
982  [SOCY441, SOCY200, SOCY200H, SOCY699T, SOCY653…          4.1500
465  [BMGT110, BMGT289I, BMGT372, BMGT110S, BMGT466…          4.1064
403  [CHEM241, CHEM395, CHEM231, CPSP218L, CHEM399X…          4.1081
258             [BSCI105, ENTM788C, BSCI105M, TOXI609]        4.2424
25    [BSCI338P, BSCI433, BSCI330, BSCI338G, BSCI339Q]        4.1892
985  [BMGT198F, BMGT372, BMGT110F, BULM758G, BMGT37…          4.4400
729  [MATH648I, MATH141H, MATH411, MATH648Q, MATH14…          3.8929
684  [ENES221, ENME371, ENME632, ENPM620, ENES232, …          4.2727

     average_gpa  num_ratings  score
386         3.29        141.0     21
724         2.72         20.0      7
369         2.72         25.0      6
467         2.81         27.0      5
352         3.56         31.0      3
997         2.57         24.0      3
823         2.57         20.0      3
434         3.14         21.0      2
513         3.01         29.0      2
803         3.17         49.0      1
503         3.08         20.0      0
822         2.73         27.0      0
207         3.12         28.0      0
727         2.49         29.0      0
209         2.58         37.0     -1
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939         2.98        23.0     -1
706         2.70        43.0     -1
774         2.62        21.0     -2
124         2.87        25.0     -3
527         2.48        30.0     -3
84          2.73        20.0     -4
756         2.47        28.0     -4
496         2.36        25.0     -5
829         2.80        24.0     -5
711         3.08        21.0     -5
50          2.74        31.0     -5
416         2.29        26.0     -6
355         2.41        93.0     -6
676         3.10        24.0     -6
495         3.69        21.0     -7
804         2.01        26.0     -7
411         2.44        66.0     -7
982         3.00        20.0     -7
465         2.90        47.0     -7
403         2.33        37.0     -8
258         2.83        33.0     -8
25          2.80        37.0     -8
985         3.35        25.0     -8
729         2.03        28.0     -8
684         2.93        22.0     -8
```

Ok so it looks like my new measure might be a little bit too harsh, as the mean is -21. On the other hand, it has also reaffirmed to me that at the top of all things teaching at UMD is always Justin Wyss-Gallifent. His score is triple the next-highest score. Looking at the data in this table, it's really interesting to see where different teachers land. As a student who has taken classes with a number of these professors, I notice certain ones that appear lower than I would have thought, and others that appear higher than I would have thought.

## 5 Conclusion

Students lead stressful lives, and trying to determine which professors will give the best learning experience is a very tricky task. Consulting different sources of data, such as ratings on PlanetTerp, is one approach to tackling this task. However, as we've seen through this analysis, there are problems with the kind of data that you see on PlanetTerp ratings (and likely with other similar review sites). It does seem to be the case that these sites are dominated by students who receive high marks in the courses they are reviewing, which could lead to biased data that paints an inaccurate picture of which professors will be best. However, it does still seem to be possible to harness the ratings data in a way that combats these biases.

For future research, I believe there is a lot of potential for using grade and rating data to help students. One possibility would be some way for students to see how well they are likely to do in future courses based on their past performance. A big issue that I've encountered as a student is knowing how difficult a courseload will likely be. For example, I might be planning out my schedule for next semester and go on the UMD subreddit to ask if my schedule is manageable. I may get wildly different answers. Moreover, because everyone has different levels of ability, what might be an unmanageable workload for me might be a cakewalk for someone on Reddit responding to my proposed schedule. One way you could combat this would be to have some sort of resource where each student would have their grades uploaded to an account. Then you would have some sort of machine-learning model that predicts future performance based on past performance. So as a CMSC student, if I got an A in CMSC131, a B in CMSC132, and a B- in CMSC216, the model would be able to take in that data and predict how well I'm likely to do in CMSC330 and CMSC351 based on the grades of upperclassmen who also got those same grades in CMSC 131, 132, and 216. This could help give students a better idea of how difficult certain courses and workloads will be. Currently, I don't believe this is possible since grade data would have to be associated with individual student accounts, and that sort of thing would only be available if students voluntarily give it up. But if these kinds of barriers could be overcome, I believe this kind of tool would be very helpful in helping students plan out their academic roadmap.

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