Analysis Overview

Here we will look at three interesting questions pertaining to the 2017 Stack Overflow Survery Data

The questions on which we will focus are:

- Question 1: How likely is someone to program as a hobby or contribute to open source projects, based on their current professional status?
- Question 2: If someone responded that they don't care what they work on as long as they are paid well, what is their reported salary?
- Question 3: For respondents who have finished college, how does job satisfaction depend on level of formal education?

Let's begin by importing the necessary libraries and creating the dataframe

In [279…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
#import HowToBreakIntoTheField as t
%matplotlib inline

df = pd.read_csv('./survey_results_public.csv')
schema = pd.read_csv('./survey_results_schema.csv')
df.head()
```

Out[279]:

	Respondent	Professional	ProgramHobby	Country	University	EmploymentStatus	Forma
0	1	Student	Yes, both	United States	No	Not employed, and not looking for work	Secon
1	2	Student	Yes, both	United Kingdom	Yes, full-time	Employed part-time	colleg st
2	3	Professional developer	Yes, both	United Kingdom	No	Employed full-time	
3	4	Professional non-developer who sometimes write...	Yes, both	United States	No	Employed full-time	Doc
4	5	Professional developer	Yes, I program as a hobby	Switzerland	No	Employed full-time	Mas

5 rows × 154 columns

Next, determined which columns have no missing values:

In [280…

```
no_nulls = set(df.columns[df.isnull().mean()==0])
no_nulls
```

Out[280]:

```
{'Country',
 'EmploymentStatus',
 'FormalEducation',
 'Professional',
 'ProgramHobby',
 'Respondent',
 'University'}
```

==================================

Analysis for Question 1

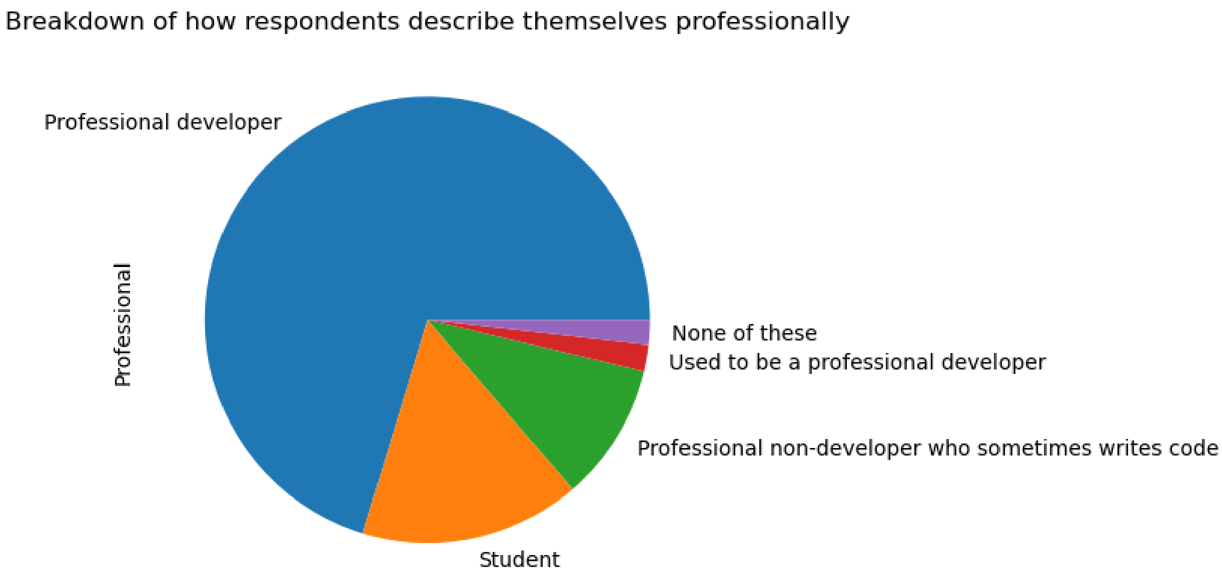
- Question 1 statement: How likely is someone to program as a hobby or contribute to open source projects, based on their current professional status?

To begin, let's get a feeling for the types of responses to the survey question "Which of the following best describes you?", in

the "Professional" column of the dataframe. From above, we can see that the "Professional" column has no missing values.

In [281…
```
# Breaking down values in the "Professional" column by response
Professional_vals = df.Professional.value_counts()
```

In [282…
```
# Normalizing by the total number of respondents, given the the number of rows
(Professional_vals/df.shape[0]).plot(kind="pie");
plt.title("Breakdown of how respondents describe themselves professionally");
```



From the pie chart breakdown above, one can see that most responded as "Professional developer", followed by "Student" and "Professional non-developer who sometimes writes code". The remaining responses had very few participants.

Here are the normalized breakdown probabilities by response:

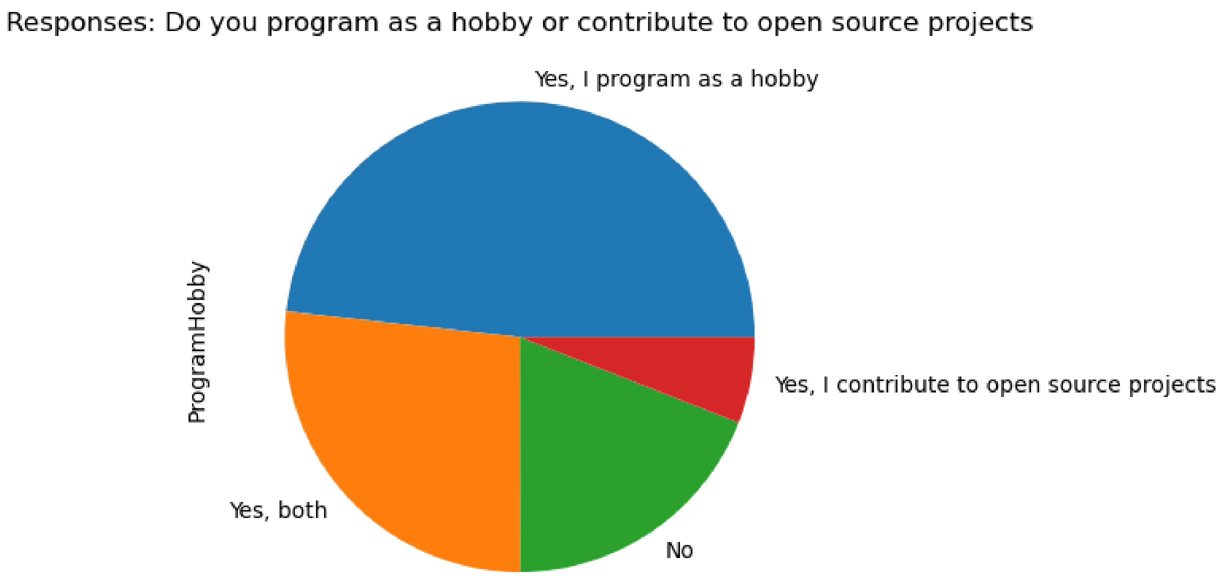
In [283…
```
# Output normalized responses
print(Professional_vals/df.shape[0])
```

```
Professional developer                                  0.703047
Student                                                 0.160025
Professional non-developer who sometimes writes code    0.100016
Used to be a professional developer                     0.019127
None of these                                           0.017785
Name: Professional, dtype: float64
```

Here we see that the majority of respondents identify as professional developers, at 70.3%. Next, let's do a similar analysis on the breakdown of responses to the question "Do you program as a hobby or contribute to open source projects?" for the column "ProgramHobby". We know that "ProgramHobby" does have missing values, but we will continue with the analysis to compare which responses were give.

In [284…
```
# Breaking down values in the "ProgramHobby" column by response
Hobby_vals = df.ProgramHobby.value_counts()
```

In [285…
```
# Normalizing by the total number of respondents, given the the number of rows
(Hobby_vals/df.shape[0]).plot(kind="pie");
plt.title("Responses: Do you program as a hobby or contribute to open source pr
```



In [286…
```
# Output normalized responses
print(Hobby_vals/df.shape[0])
```

```
Yes, I program as a hobby                    0.482585
Yes, both                                    0.267668
No                                           0.190438
Yes, I contribute to open source projects    0.059309
Name: ProgramHobby, dtype: float64
```

Now let's determine how people responded based on their profession in the survey.

In [287…
```
# Filter the main dataframe to include only respondents filtered by their profe
df_pro_dev = df[df['Professional'] == 'Professional developer']
df_student = df[df['Professional'] == 'Student']
df_pro_nondev = df[df['Professional'] == 'Professional non-developer who someti
df_used = df[df['Professional'] == 'Used to be a professional developer']

# Now break down values based on profession
Hobby_vals_pro_dev = df_pro_dev.ProgramHobby.value_counts()
Hobby_vals_student = df_student.ProgramHobby.value_counts()
Hobby_vals_pro_nondev = df_pro_nondev.ProgramHobby.value_counts()
Hobby_vals_used = df_used.ProgramHobby.value_counts()

# And see how the normalized responses here look
# And see how the normalized responses here look
print('Professional developer:')
print(Hobby_vals_pro_dev/df_pro_dev.shape[0])
print('\nStudent:')
print(Hobby_vals_student/df_student.shape[0])
```

```
print('\nProfessional non-developer who sometimes writes code:')
print(Hobby_vals_pro_nondev/df_pro_nondev.shape[0])
print('\nUsed to be a professional developer:')
print(Hobby_vals_used/df_used.shape[0])
```

```
Professional developer:
Yes, I program as a hobby                    0.452105
Yes, both                                    0.277352
No                                           0.208464
Yes, I contribute to open source projects    0.062080
Name: ProgramHobby, dtype: float64

Student:
Yes, I program as a hobby                    0.588886
Yes, both                                    0.246960
No                                           0.123906
Yes, I contribute to open source projects    0.040248
Name: ProgramHobby, dtype: float64

Professional non-developer who sometimes writes code:
Yes, I program as a hobby                    0.499805
Yes, both                                    0.227821
No                                           0.202724
Yes, I contribute to open source projects    0.069650
Name: ProgramHobby, dtype: float64

Used to be a professional developer:
Yes, I program as a hobby                    0.472024
Yes, both                                    0.261445
No                                           0.197355
Yes, I contribute to open source projects    0.069176
Name: ProgramHobby, dtype: float64
```

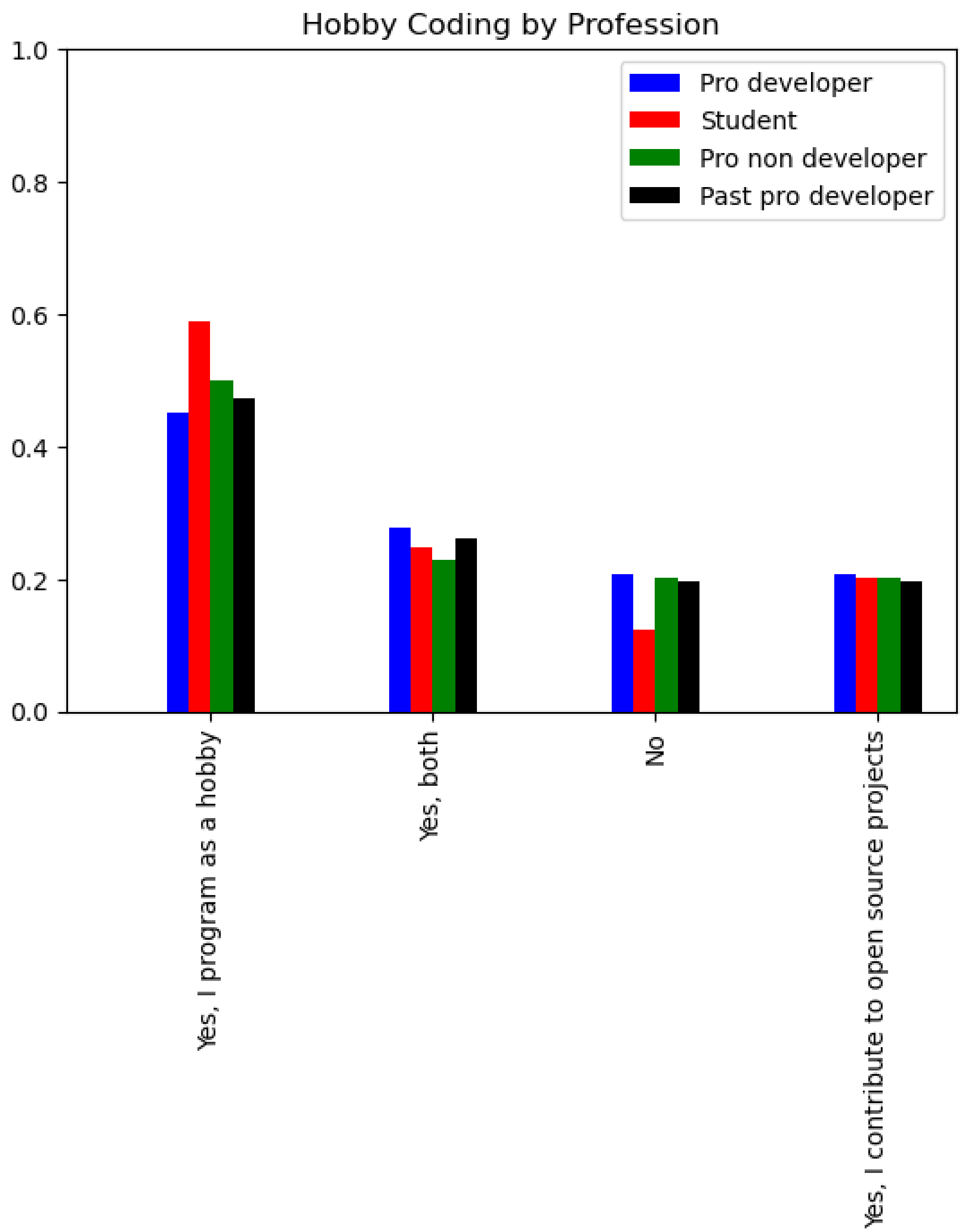
Plotting these results allows us to see how likely people are to spend time coding as a hobby, based on their reported professional status. Here, we can use a bar graph because it is easy to display the normalized results.

In [288…

```
# And plotting these results together on a bar graph:
#(Hobby_vals/df.shape[0])[0].plot(kind="box");
#(Hobby_vals_pro_dev/df_pro_dev.shape).plot(kind="box");
#plt.title("Do you program as a hobby or contribute to open source projects");
plt.figure(1)
plt.xticks([1.15,2.15,3.15,4.15],
           ['Yes, I program as a hobby','Yes, both','No','Yes, I contribute to
plt.title('Hobby Coding by Profession')
plt.bar(1,(Hobby_vals_pro_dev/df_pro_dev.shape[0])[0], width = 0.1, color = 'b'
plt.bar(2,(Hobby_vals_pro_dev/df_pro_dev.shape[0])[1], width = 0.1, color = 'b'
plt.bar(3,(Hobby_vals_pro_dev/df_pro_dev.shape[0])[2], width = 0.1, color = 'b'
plt.bar(4,(Hobby_vals_pro_dev/df_pro_dev.shape[0])[2], width = 0.1, color = 'b'
plt.bar(1.1,(Hobby_vals_student/df_student.shape[0])[0], width = 0.1, color = '
plt.bar(2.1,(Hobby_vals_student/df_student.shape[0])[1], width = 0.1, color = '
plt.bar(3.1,(Hobby_vals_student/df_student.shape[0])[2], width = 0.1, color = '
plt.bar(4.1,(Hobby_vals_pro_nondev/df_pro_nondev.shape[0])[2], width = 0.1, col
plt.bar(1.2,(Hobby_vals_pro_nondev/df_pro_nondev.shape[0])[0], width = 0.1, col
plt.bar(2.2,(Hobby_vals_pro_nondev/df_pro_nondev.shape[0])[1], width = 0.1, col
plt.bar(3.2,(Hobby_vals_pro_nondev/df_pro_nondev.shape[0])[2], width = 0.1, col
plt.bar(4.2,(Hobby_vals_pro_nondev/df_pro_nondev.shape[0])[2], width = 0.1, col
```

```
plt.bar(1.3,(Hobby_vals_used/df_used.shape[0])[0], width = 0.1, color = 'k',lab
plt.bar(2.3,(Hobby_vals_used/df_used.shape[0])[1], width = 0.1, color = 'k')
plt.bar(3.3,(Hobby_vals_used/df_used.shape[0])[2], width = 0.1, color = 'k')
plt.bar(4.3,(Hobby_vals_used/df_used.shape[0])[2], width = 0.1, color = 'k')
plt.legend()
plt.ylim(0,1)
plt.xlim(0.5,4.5)
```

Out[288]: (0.5, 4.5)



Summary for Question 1:

Finally, we can see from the above graph how many respondents spend time coding as a hobby, broken out by their professional

status. A prominent feature of this plot is how students spend more time coding compared to other professions for those who answered "Yes, I program as a hobby". One can speculate that perhaps this is because student's may have more free time, or they are contributing to coding outside of their required work to gain more experience in the field.

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Analysis for Question 2

- Question 2 statement: If someone responded that they don't care what they work on as long as they are paid well, what is their reported salary?

By filtering, we can build a dataframe from the main one, containing only values where people responded to the question "I don't really care what I work on, so long as I'm paid well". This is one method of dealing with missing data points from the WorkPayCare data set.

In [289…
```
df_workpaycare = df[df['WorkPayCare'].isnull() == False]
df_workpaycare.head()
```

Out[289]:

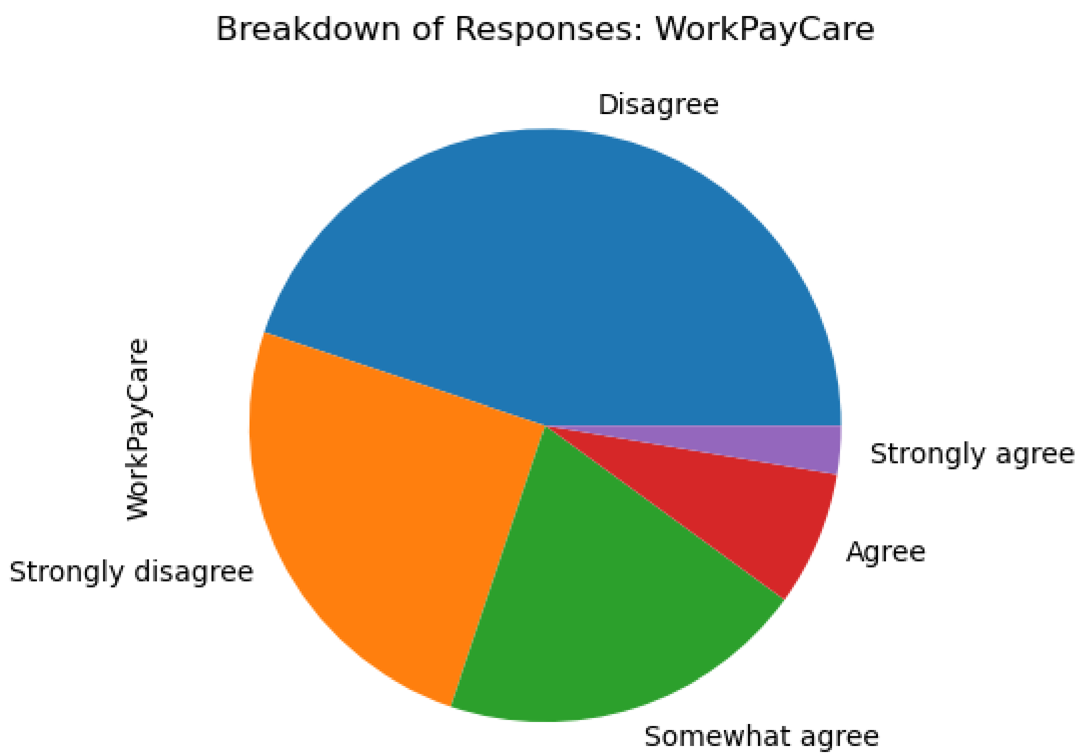
	Respondent	Professional	ProgramHobby	Country	University	EmploymentStatus	Formal
0	1	Student	Yes, both	United States	No	Not employed, and not looking for work	Seconc
2	3	Professional developer	Yes, both	United Kingdom	No	Employed full-time	
3	4	Professional non-developer who sometimes write...	Yes, both	United States	No	Employed full-time	Doctc
8	9	Professional developer	Yes, I program as a hobby	Colombia	Yes, part-time	Employed full-time	
14	15	Professional developer	Yes, I program as a hobby	United Kingdom	No	Employed full-time	P

5 rows × 154 columns

Now let's see a breakdown of these responses from this filtered data set:

In [290…

```
workpaycare_vals = df_workpaycare.WorkPayCare.value_counts()
# Plotting as a pie chare
(workpaycare_vals/df_workpaycare.shape[0]).plot(kind="pie");
plt.title('Breakdown of Responses: WorkPayCare');
```



In [291…

```
# Output normalized responses
print(workpaycare_vals/df_workpaycare.shape[0])
```

```
Disagree             0.449120
Strongly disagree    0.249281
Somewhat agree       0.201453
Agree                0.073761
Strongly agree       0.026385
Name: WorkPayCare, dtype: float64
```

One can see from the above that in response to the question "I don't really care what I work on, so long as I'm paid well"; 44.9% disagree, 24.9% strongly disagree, 20.1% somewhat agree, 7.3% agree, and 2.6% strongly agree.

Next, within this filtered dataset, let's get a feeling for how many of those who responded entered salary data. This is yet again, another technique for dealing with missing data.

In [292…

```
df_salary = df_workpaycare[df_workpaycare['Salary'].isnull() == False]
df_salary.head()
```

Out[292]:

	Respondent	Professional	ProgramHobby	Country	University	EmploymentStatus	FormalI
2	3	Professional developer	Yes, both	United Kingdom	No	Employed full-time	
14	15	Professional developer	Yes, I program as a hobby	United Kingdom	No	Employed full-time	Pr
17	18	Professional developer	Yes, both	United States	Yes, part-time	Employed full-time	
18	19	Professional developer	Yes, I program as a hobby	United States	No	Employed full-time	
25	26	Professional developer	Yes, I program as a hobby	United States	No	Employed full-time	Maste

5 rows × 154 columns

In [293…

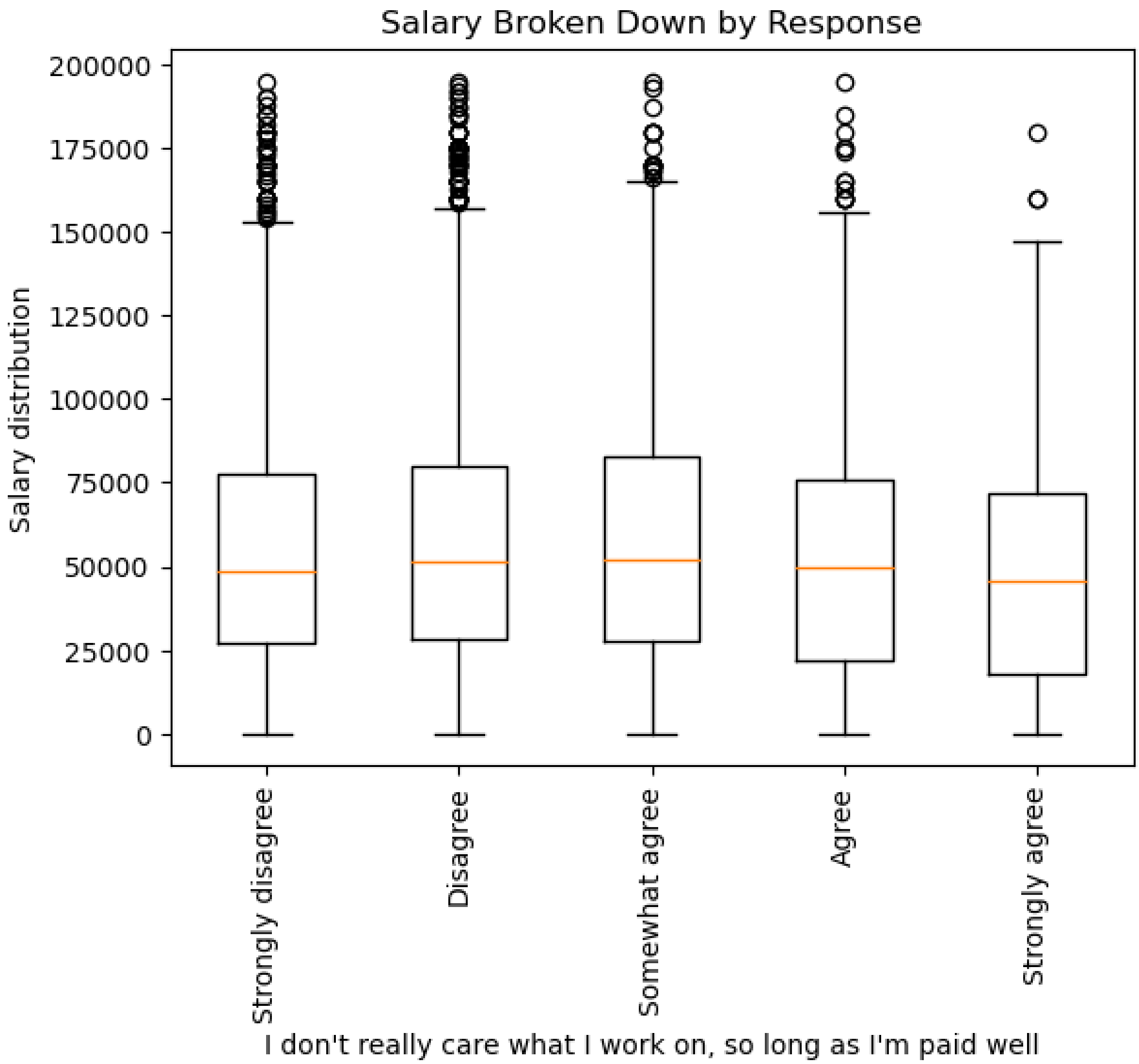
```
df_stronglydisagree = df_salary[df_salary['WorkPayCare'] == 'Strongly disagree'
df_disagree = df_salary[df_salary['WorkPayCare'] == 'Disagree']
df_somewhatagree = df_salary[df_salary['WorkPayCare'] == 'Somewhat agree']
df_agree = df_salary[df_salary['WorkPayCare'] == 'Agree']
df_stronglyagree = df_salary[df_salary['WorkPayCare'] == 'Strongly agree']
data = [df_stronglydisagree['Salary'],
        df_disagree['Salary'],
        df_somewhatagree['Salary'],
        df_agree['Salary'],
        df_stronglyagree['Salary']
       ]
```

In [294…

```
fig, ax = plt.subplots()
ax.boxplot(data)
plt.xticks([1,2,3,4,5],['Strongly disagree','Disagree','Somewhat agree','Agree'
plt.xlabel('I don\'t really care what I work on, so long as I\'m paid well')
plt.ylabel('Salary distribution')
plt.title('Salary Broken Down by Response')
```

Out[294]:

```
Text(0.5, 1.0, 'Salary Broken Down by Response')
```



And finally we can compare the numerical values from the above plot for the medians in each case, where we see there are very small differences between them:

In [307…

```
print(df_stronglydisagree['Salary'].median())
print(df_disagree['Salary'].median())
print(df_somewhatagree['Salary'].median())
print(df_agree['Salary'].median())
print(df_stronglyagree['Salary'].median())
```

```
48387.0967741935
51583.7104072398
52000.0
50000.0
45469.5340501792
```

Summary for Question 2:

Surprisingly, the above figure suggests that the respondent's reported salary is esssentially independent of their responses to

the questions "I don't really care what I work on, so long as I'm paid well". One might have expected those who make the highest salary might care the least about their work, but this does not seem to be the case.

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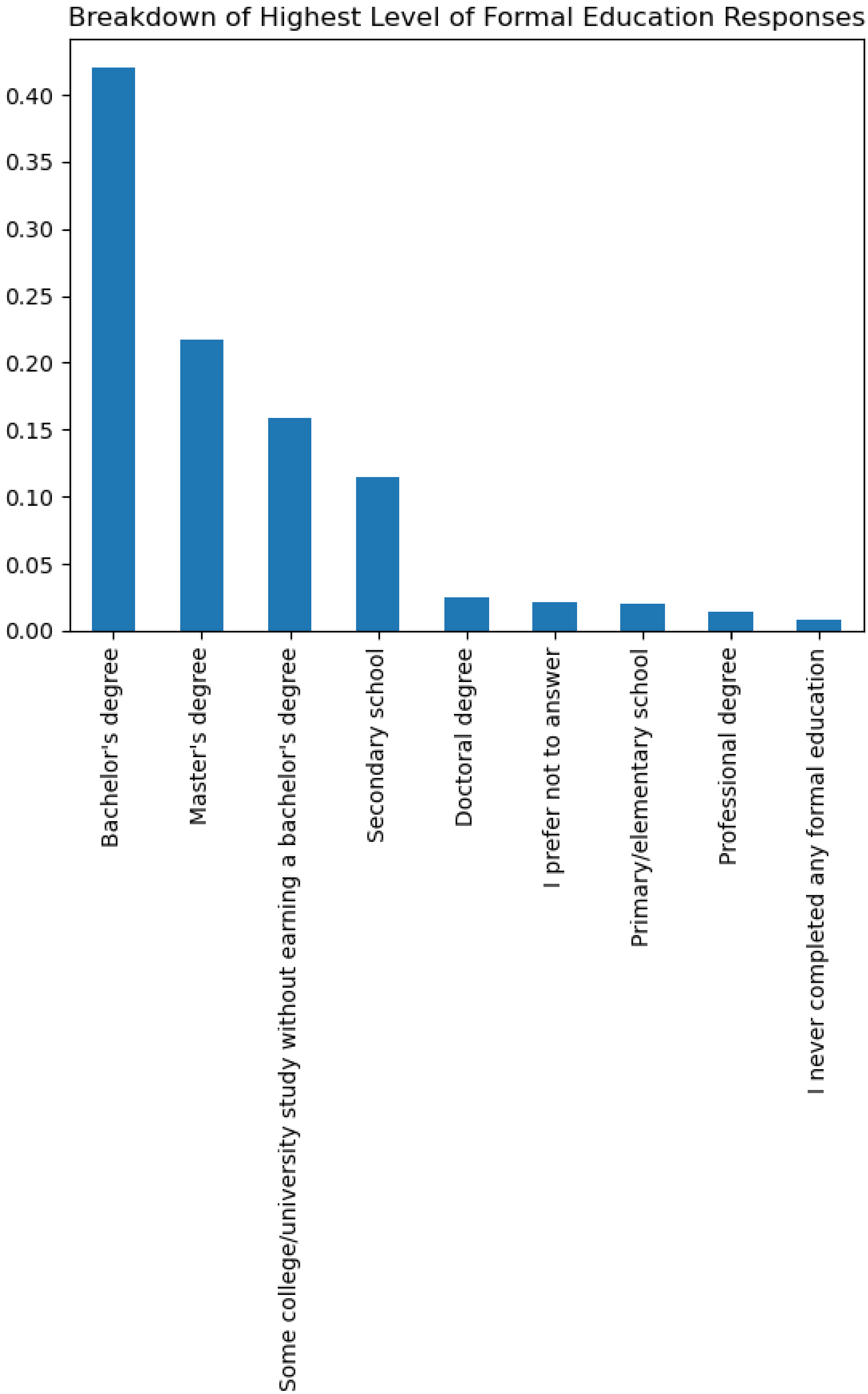
Analysis for Question 3

- Question 3 statement: For respondents who have finished college, how does job satisfaction depend on level of formal education?

To begin, look at the values reported for the question "Which of the following best describes the highest level of formal education that you've completed?" from the main dataframe that is not filtered. By plotting this on a bar chart, we can easily see all responses and the relative number of respondents who selected each one.

In [382…

```
# Values reported for formal education; recall that this column has no missing
ed_vals = df['FormalEducation'].value_counts()
(ed_vals/df.shape[0]).plot(kind="bar");
plt.title("Breakdown of Highest Level of Formal Education Responses");
```

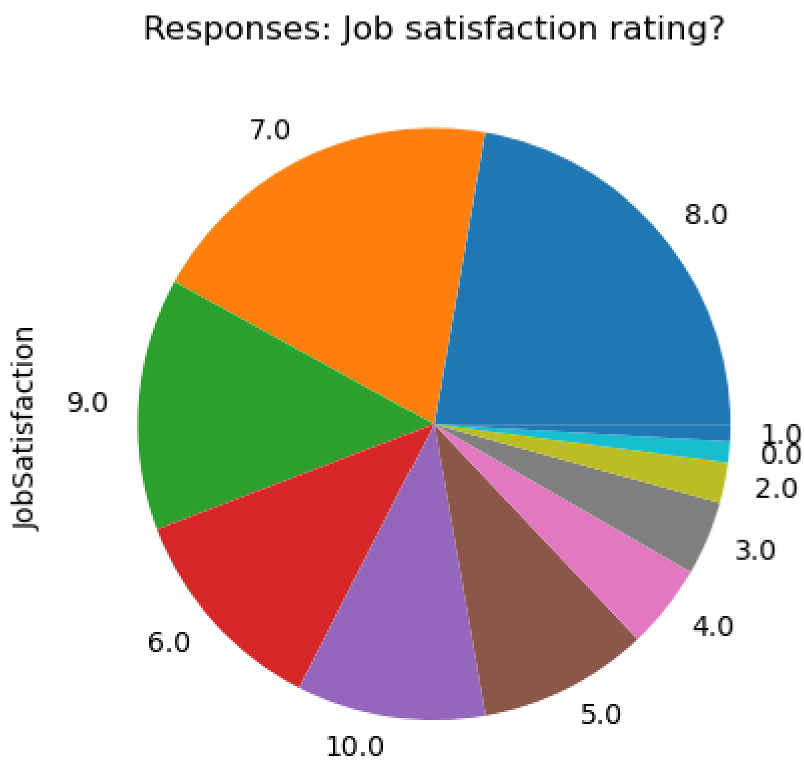


Next, let's separate these data into the categories by focusing only on those respondents who reported 1) Bachelor's degree, 2) Master's degree, and 3) Doctoral degree. Once again, note that there are no missing values from these subsets of df['FormalEducation'].

In [317…
```
df_bach = df[df['FormalEducation'] == 'Bachelor\'s degree']
df_mast = df[df['FormalEducation'] == 'Master\'s degree']
df_doc = df[df['FormalEducation'] == 'Doctoral degree']
```

Now let's see how the values look for reported job satisfaction. A pie plot is useful here, just for looking at the relative number of responses for each value reported.

In [326…
```
satisfaction_vals = df['JobSatisfaction'].value_counts()
(satisfaction_vals).plot(kind="pie");
plt.title("Responses: Job satisfaction rating?");
```



Let's further pare down the formal education data to exclude entries that are blank for the job satisfaction data:

In [341…
```
df_bach_nonulls = df_bach[df_bach['JobSatisfaction'].isnull() == False]
df_mast_nonulls = df_mast[df_mast['JobSatisfaction'].isnull() == False]
df_doc_nonulls = df_doc[df_doc['JobSatisfaction'].isnull() == False]
```

And then plot these data separated by number of responses for each score on a bar graph, where a semi-log scale has been used to allow the reader to more easily view all data displayed.

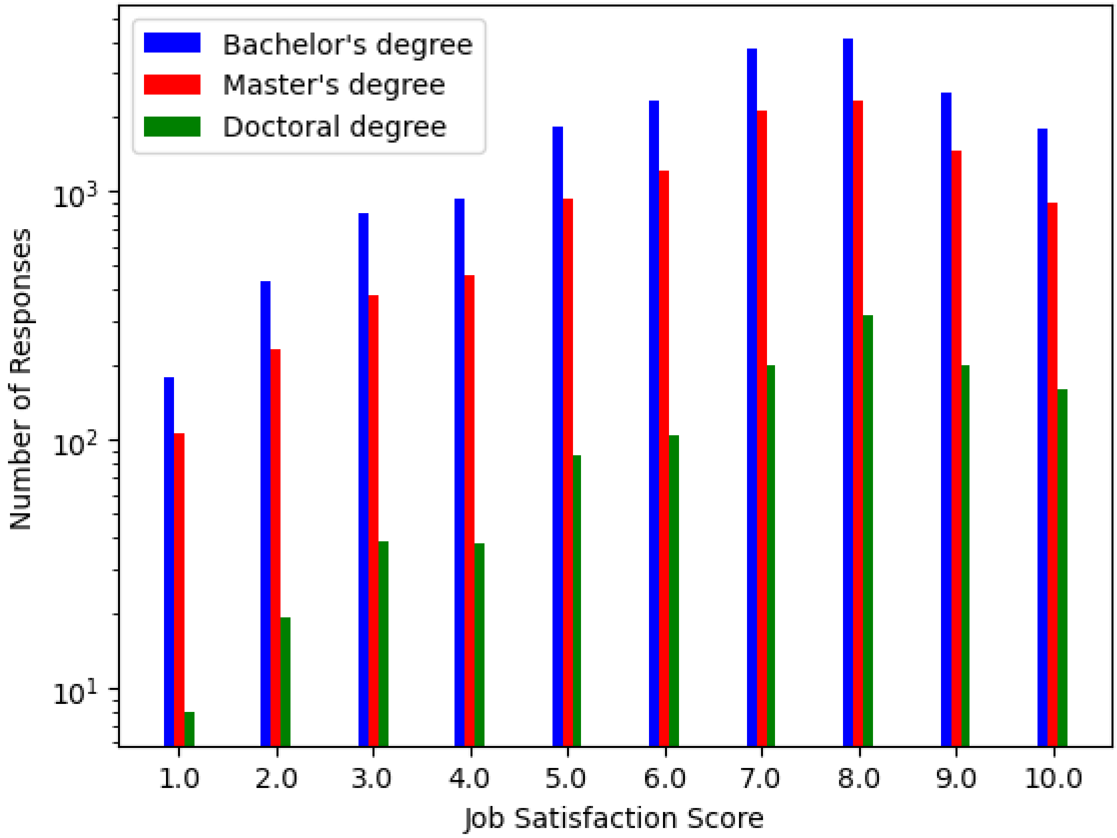
In [381…
```
plt.figure()
# Bachelor's degree
```

```
plt.bar(1, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 1.0]), wic
plt.bar(2, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 2.0]), wic
plt.bar(3, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 3.0]), wic
plt.bar(4, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 4.0]), wic
plt.bar(5, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 5.0]), wic
plt.bar(6, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 6.0]), wic
plt.bar(7, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 7.0]), wic
plt.bar(8, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 8.0]), wic
plt.bar(9, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 9.0]), wic
plt.bar(10, len(df_bach_nonulls[df_bach_nonulls['JobSatisfaction'] == 10.0]), v

# Master's degree
plt.bar(1.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 1.0]), v
plt.bar(2.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 2.0]), v
plt.bar(3.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 3.0]), v
plt.bar(4.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 4.0]), v
plt.bar(5.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 5.0]), v
plt.bar(6.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 6.0]), v
plt.bar(7.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 7.0]), v
plt.bar(8.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 8.0]), v
plt.bar(9.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 9.0]), v
plt.bar(10.1, len(df_mast_nonulls[df_mast_nonulls['JobSatisfaction'] == 10.0]),

# Doctoral degree
plt.bar(1.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 1.0]), wic
plt.bar(2.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 2.0]), wic
plt.bar(3.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 3.0]), wic
plt.bar(4.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 4.0]), wic
plt.bar(5.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 5.0]), wic
plt.bar(6.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 6.0]), wic
plt.bar(7.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 7.0]), wic
plt.bar(8.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 8.0]), wic
plt.bar(9.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 9.0]), wic
plt.bar(10.2, len(df_doc_nonulls[df_doc_nonulls['JobSatisfaction'] == 10.0]), v

plt.xticks([1.1,2.1,3.1,4.1,5.1,6.1,7.1,8.1,9.1,10.1], ['1.0','2.0','3.0','4.0'
plt.xlabel('Job Satisfaction Score')
plt.ylabel('Number of Responses')
plt.legend(loc = 'best')
plt.yscale('log')
```



Summary for Question 3:

From the above plot, one can conclude that the most commonly reported job satisfaction score from 1.0 to 10.0 for respondents who have at least finished college is 8.0, independent of their level of formal education. The relative differences in height displayed here arise from the difference in the number of respondents in each formal education category. There are far more respondents who have as their formal education level as "Bachelor's degree", with the number having "Mater's degree" following that, and the least number of respondents having "Doctoral degree" as their level of formal education.