Assignment 1: Exploring and Visualizing Data
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https://github.com/clboetticher/practicalML/blob/master/Boetticher_MSDS%20Assignment%201.ipynb

Survey data and assumptions

The survey received 207 responses across 14 items, with mixed question types and scales for numerical responses. This report assumes those 207 respondents' perspectives represent the larger current and (at least near) future interests of MSDS students. The attached analysis makes note of any discrepancies in response completion.

Current student software preferences

This survey data reflects some notable trends in software preferences, across personal and professional scenarios and also perceptions of industry employers' expectations. As seen in Figures 4 through 6 (see Appendix), the preference distributions are quite similar for each individual software – Java, JavaScript, Python, R, and SAS – regardless of whether the scenario is personal, professional, or industry. Measures of center from descriptive statistics (see Section I: Data Preparation and Initial Inspection) favor R and Python notably across all three scenarios, with SAS, Java, and JavaScript distant followers; R is slightly more preferred than Python in professional and professional settings but the two are roughly equivalent for industry. There is greater variability in SAS preference in professional and industry scenarios, perhaps as a result of variability in that package's popularity across diverse student backgrounds (which may, in turn, reflect perceptions of future utility). All software options have outliers on the positive end for all three scenarios, with R and Python having a small selection of respondents assigning close to 100 percent value to those options personally and professionally. The lower popularity of JavaScript, Java, and to a lesser extent, SAS are further shown by the right skew of the univariate distributions (the central diagonal lines) in Figures 7 through 9. As a final visual interpretation of the correlations of all software options across all scenarios, Figure 10 shows a stronger positive correlation between individual software in one scenario with its counterpart in other (e.g., personal SAS and professional SAS), to be expected. Interestingly, Figure 10 also shows a negative correlation between Python preferences and SAS preferences, regardless of scenario, with the strongest negative correlation in the industry scenario. Exploring a bit further, the "My Python and My SAS" scatterplot from Figure 11 reinforces that trend for personal preference; Figures 12 and 13 explore Python versus SAS preferences for professional and industry scenarios. Though the scatterplot's association is not incredibly strong, the negative pattern does appear, with particularly high outliers for each on the high end (i.e., some responses with 100 percent preference for one over the other).

Software and systems planning and course recommendations

This survey's results do not definitively recommend R over Python, thus my recommendation is to continue offering a balance of courses utilizing both in the near future since both are perceived as useful. The survey notes that the current MSPA curriculum reflects a balance of 30 points for Python, 50 for R, and 20 for SAS. A more even balance between Python and R could be warranted if the trend in Python's favor grows stronger in subsequent surveys and input. The high interest in Python coursework noted in Figure 15 at least supports interest in that software to taught formally (whether or not it comes at the expense of less focus on R). A reduced focus on SAS given the variability and lower preference would be recommended, though. Enhancing this analysis with the free-text responses from questions 9 and 10 would likely provide further insight into student interests that fall outside of the choices offered in other questions.

Student coursework interests and curriculum recommendations

Figure 16 explores respondent interest in four new course offerings on a scale of 0 to 100. Interest is notably higher in Python for Data Analysis, further supporting the preferences discussed earlier in this report, with median interest just above 80 and an interquartile range (IQR) of 52 to 100. Interest in Foundations for Data Engineering and Analytics Application Development overlap almost completely, both with medians of 60 and IQR ranges of 30 to 90 and 25 to 85, respectively. Interest seems lowest in Data Science Systems Analysis, with median of 50 and IQR range of about 20 to 80. Variability is relatively high across all four courses' interest levels, though less so with Python for Data Analysis. I recommend offering each course as an elective twice over an academic year and assessing enrollment levels and CTECs for further insight. These results do not lend themselves to any recommendation on major overhauls in curriculum, though it seems advisable to continue offering courses in R and Python, particularly within the core curriculum. Both seem preferable for respondents personally and in terms of the job market's demands so equipping students with those skills is appropriate. Given Python's popularity and its results for the new course, a dedicated course offering would likely be well-received as a core offering. Additional analysis of free-text responses would likely give more insight into curriculum needs beyond these specific courses.

Recommendations for survey administration

Given the rapidly-shifting data science technology space and the increasingly-diverse needs of employers, depending on industry and analytics maturity (among other factors), I would recommend administering this survey annually.

MSDS 422 Assignment 1: Exploring and Visualizing Data

Survey background and objectives
As one of the first applied data science graduate programs, Northwestern's MSPA (now MSDS) program established an early footing in training domain experts from a variety of academic and professional backgrounds for careers in data science across a variety of industries. However, the data science field is a rapidly-evolving domain and employer hiring demands, though growing, shift regularly according to both skills demands and the relevant technology space.

This survey aims to assess current students' perception of the field's needs with respect to programming and software skills; it also provides a snapshot of course completion progress for student respondents and interest in future program offerings. In conjunction with the input of an external advisory board of 30 industry leaders who commented on their data science capability needs in a 2-5 year period, these results form part of the ongoing effort to evaluate how well the program is meeting both student and market demands, training new data scientists sufficiently for the field.

This report includes data preparation, exploration, and analysis of the survey data. Additionally, the feature for courses completed has been scaled two ways (standardization and normalization) for comparison and evaluation. The analysis below forms the basis of recommendations for future direction for the MSDS program with respect to overall curriculum and related software and systems.

I. Data Preparation and Initial Inspection

```
# Import dependencies
import pandas as pd  # data frame operations
import numpy as np  # arrays and math functions
import matplotlib.pyplot as plt  # static plotting
import seaborn as sns  # pretty plotting, including heat map
from sklearn import preprocessing  # feature transformations
%matplotlib inline
np.set_printoptions(precision=3)
# Read in comma-delimited text file, creating a pandas DataFrame object
# Note that IPAddress is formatted as an actual IP address
# But is actually a random-hash of the original IP address
survey = pd.read_csv('mspa-survey-data.csv')
# Use the RespondentID as label for the rows... the index of DataFrame
survey.set_index('RespondentID', drop = True, inplace = True)
# Show the column/variable names of the DataFrame
# Note that RespondentID is no longer present
print(survey.columns)
Index(['Personal_JavaScalaSpark', 'Personal_JavaScriptHTMLCSS',
       'Personal_Python', 'Personal_R', 'Personal_SAS',
       'Professional_JavaScalaSpark', 'Professional_JavaScriptHTMLCSS',
       'Professional_Python', 'Professional_R', 'Professional_SAS',
       'Industry_JavaScalaSpark', 'Industry_JavaScriptHTMLCSS',
       'Industry_Python', 'Industry_R', 'Industry_SAS',
       'Python_Course_Interest', 'Foundations_DE_Course_Interest',
       'Analytics_App_Course_Interest', 'Systems_Analysis_Course_Interest',
       'Courses_Completed', 'PREDICT400', 'PREDICT401', 'PREDICT410',
       'PREDICT411', 'PREDICT413', 'PREDICT420', 'PREDICT422', 'PREDICT450',
       'PREDICT451', 'PREDICT452', 'PREDICT453', 'PREDICT454', 'PREDICT455',
       'PREDICT456', 'PREDICT457', 'OtherPython', 'OtherR', 'OtherSAS',
       'Other', 'Graduate_Date'],
```

```
      dtype='object')
# Rename columns for simplicity
survey_df = survey.rename(index=str, columns={
    'Personal_JavaScalaSpark': 'My_Java',
    'Personal_JavaScriptHTMLCSS': 'My_JS',
    'Personal_Python': 'My_Python',
    'Personal_R': 'My_R',
    'Personal_SAS': 'My_SAS',
    'Professional_JavaScalaSpark': 'Prof_Java',
    'Professional_JavaScriptHTMLCSS': 'Prof_JS',
    'Professional_Python': 'Prof_Python',
    'Professional_R': 'Prof_R',
    'Professional_SAS': 'Prof_SAS',
    'Industry_JavaScalaSpark': 'Ind_Java',
    'Industry_JavaScriptHTMLCSS': 'Ind_JS',
    'Industry_Python': 'Ind_Python',
    'Industry_R': 'Ind_R',
    'Industry_SAS': 'Ind_SAS'})
# Inspect first 5 rows of data with renamed columns
survey_df.head()
```

	My_Java	**My_JS**	**My_Python**	**My_R**	**My_SAS**	**Prof_Java**	**Prof_JS**	**Prof_Python**	**Prof_R**	**Prof_SAS**	**...**	**PREDICT453**	**PREDICT454**	**PREDICT455**	**PREDICT456**	**PREDICT457**	**OtherPython**	**OtherR**	**OtherSAS**	**Other**	**Graduate_Date**
RespondentID																					
513574012 **2**	0	0	0	50	50	0	0	0	25	75	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
513330003 **7**	10	10	50	30	0	25	25	30	20	0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Spring 2018
513225330 **0**	20	0	40	40	0	0	0	40	40	20	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Fall 2018
513209663 **0**	10	10	25	35	20	10	10	25	35	20	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Fall 2017
513199036 **2**	20	0	0	70	10	20	0	0	80	0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	CS-435 with Weka	Fall 2018

5 rows × 40 columns

```
# Inspect number of samples and features
# 207 rows, 40 features
survey_df.info()
<class 'pandas.core.frame.DataFrame'>
Index: 207 entries, 5135740122 to 5109806898
Data columns (total 40 columns):
My_Java                               207 non-null int64
My_JS                                 207 non-null int64
My_Python                             207 non-null int64
My_R                                  207 non-null int64
My_SAS                                207 non-null int64
Prof_Java                             207 non-null int64
Prof_JS                               207 non-null int64
Prof_Python                           207 non-null int64
Prof_R                                207 non-null int64
Prof_SAS                              207 non-null int64
Ind_Java                              207 non-null int64
Ind_JS                                207 non-null int64
Ind_Python                            207 non-null int64
Ind_R                                 207 non-null int64
Ind_SAS                               207 non-null int64
Python_Course_Interest                206 non-null float64
Foundations_DE_Course_Interest        200 non-null float64
Analytics_App_Course_Interest         203 non-null float64
Systems_Analysis_Course_Interest      200 non-null float64
Courses_Completed                     187 non-null float64
PREDICT400                            163 non-null object
PREDICT401                            171 non-null object
PREDICT410                            145 non-null object
PREDICT411                            113 non-null object
PREDICT413                            59 non-null object
PREDICT420                            127 non-null object
PREDICT422                            48 non-null object
PREDICT450                            17 non-null object
PREDICT451                            7 non-null object
PREDICT452                            13 non-null object
PREDICT453                            11 non-null object
PREDICT454                            5 non-null object
PREDICT455                            30 non-null object
PREDICT456                            6 non-null object
PREDICT457                            4 non-null object
OtherPython                           5 non-null object
OtherR                                14 non-null object
OtherSAS                              2 non-null object
Other                                 26 non-null object
Graduate_Date                         204 non-null object
dtypes: float64(5), int64(15), object(20)
memory usage: 66.3+ KB
# Define subset of survey response data to focus on software preferences
software_df = survey_df.iloc[: , 0:15]
# Inspect first 5 rows of software DataFrame
software_df.head()
```

	My_Java	**My_JS**	**My_Python**	**My_R**	**My_SAS**	**Prof_Java**	**Prof_JS**	**Prof_Python**	**Prof_R**	**Prof_SAS**	**Ind_Java**	**Ind_JS**	**Ind_Python**	**Ind_R**	**Ind_SAS**
RespondentID															
5135740122	0	0	0	50	50	0	0	0	25	75	0	0	0	50	50

	My_Java	My_JS	My_Python	My_R	My_SAS	Prof_Java	Prof_JS	Prof_Python	Prof_R	Prof_SAS	Ind_Java	Ind_JS	Ind_Python	Ind_R	Ind_SAS
RespondentID															
5133300037	10	10	50	30	0	25	25	30	20	0	20	25	40	15	0
5132253300	20	0	40	40	0	0	0	40	40	20	30	0	30	40	0
5132096630	10	10	25	35	20	10	10	25	35	20	10	10	25	35	20
5131990362	20	0	0	70	10	20	0	0	80	0	40	0	0	60	0

```
# Define subset of survey response data to focus on course completion
courses_df = survey_df.loc[:, 'PREDICT400':'Other']
# Inspect DataFrame
courses_df.info()
<class 'pandas.core.frame.DataFrame'>
Index: 207 entries, 5135740122 to 5109806898
Data columns (total 19 columns):
PREDICT400     163 non-null object
PREDICT401     171 non-null object
PREDICT410     145 non-null object
PREDICT411     113 non-null object
PREDICT413     59 non-null object
PREDICT420     127 non-null object
PREDICT422     48 non-null object
PREDICT450     17 non-null object
PREDICT451     7 non-null object
PREDICT452     13 non-null object
PREDICT453     11 non-null object
PREDICT454     5 non-null object
PREDICT455     30 non-null object
PREDICT456     6 non-null object
PREDICT457     4 non-null object
OtherPython    5 non-null object
OtherR         14 non-null object
OtherSAS       2 non-null object
Other          26 non-null object
dtypes: object(19)
memory usage: 32.3+ KB
# Define subset of survey response data to focus on course interests
interests_df = survey_df.loc[:,
'Python_Course_Interest':'Systems_Analysis_Course_Interest']
# Inspect DataFrame
interests_df.info()
<class 'pandas.core.frame.DataFrame'>
Index: 207 entries, 5135740122 to 5109806898
Data columns (total 4 columns):
Python_Course_Interest              206 non-null float64
Foundations_DE_Course_Interest      200 non-null float64
Analytics_App_Course_Interest       203 non-null float64
Systems_Analysis_Course_Interest    200 non-null float64
dtypes: float64(4)
memory usage: 8.1+ KB
# Evaluate null values across all features
survey_df.isna().sum()
My_Java                               0
```

```
My_JS                              0
My_Python                          0
My_R                               0
My_SAS                             0
Prof_Java                          0
Prof_JS                            0
Prof_Python                        0
Prof_R                             0
Prof_SAS                           0
Ind_Java                           0
Ind_JS                             0
Ind_Python                         0
Ind_R                              0
Ind_SAS                            0
Python_Course_Interest             1
Foundations_DE_Course_Interest     7
Analytics_App_Course_Interest      4
Systems_Analysis_Course_Interest   7
Courses_Completed                 20
PREDICT400                        44
PREDICT401                        36
PREDICT410                        62
PREDICT411                        94
PREDICT413                       148
PREDICT420                        80
PREDICT422                       159
PREDICT450                       190
PREDICT451                       200
PREDICT452                       194
PREDICT453                       196
PREDICT454                       202
PREDICT455                       177
PREDICT456                       201
PREDICT457                       203
OtherPython                      202
OtherR                           193
OtherSAS                         205
Other                            181
Graduate_Date                      3
dtype: int64
# Compute descriptive statistics for numeric features for all data
survey_df.describe()
```

	My_Java	My_JS	My_Python	My_R	My_SAS	Prof_Java	Prof_JS	Prof_Python	Prof_R	Prof_SAS	Ind_Java	Ind_JS	Ind_Python	Ind_R	Ind_SAS	Python_Course_Interest	Foundations_DE_Course_Interest	Analytics_App_Course_Interest	Systems_Analysis_Course_Interest	Courses_Completed
count	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	207.000000	206.000000	200.000000	203.000000	200.000000	187.000000
mean	10.135266	4.797101	31.304348	37.125604	16.637681	9.251208	5.840580	30.028986	36.415459	18.463768	11.942029	6.966184	29.772947	32.434783	18.884058	73.529126	58.045000	55.201970	53.630000	6.342246

	My_Java	My_JS	My_Python	My_R	My_SAS	Prof_Java	Prof_JS	Prof_Python	Prof_R	Prof_SAS	Ind_Java	Ind_JS	Ind_Python	Ind_R	Ind_SAS	Python_Course_Interest	Foundations_DE_Course_Interest	Analytics_App_Course_Interest	Systems_Analysis_Course_Interest	Courses_Completed
std	11.383477	6.757764	15.570982	14.576003	13.626400	13.167505	10.812555	19.144802	20.847606	18.831841	14.706399	10.030721	17.959816	15.912209	19.137623	29.835429	32.588079	34.147954	33.539493	3.170849
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	0.000000	0.000000	20.000000	30.000000	5.000000	0.000000	0.000000	20.000000	25.000000	0.000000	0.000000	0.000000	20.000000	22.500000	0.000000	53.000000	29.500000	25.000000	21.500000	4.000000
50%	9.000000	0.000000	30.000000	35.000000	15.000000	5.000000	0.000000	30.000000	33.000000	15.000000	5.000000	0.000000	30.000000	30.000000	15.000000	82.500000	60.000000	60.000000	51.500000	6.000000
75%	20.000000	10.000000	40.000000	50.000000	25.000000	15.000000	10.000000	40.000000	50.000000	30.000000	20.000000	10.000000	40.000000	40.000000	30.000000	100.000000	89.250000	85.000000	80.250000	9.000000
max	70.000000	30.000000	90.000000	100.000000	75.000000	80.000000	100.000000	100.000000	100.000000	100.000000	70.000000	50.000000	95.000000	85.000000	100.000000	100.000000	100.000000	100.000000	100.000000	12.000000

```
# Compute descriptive statistics for software preference features
print('\nDescriptive statistics for software preferences\n------------------------------
---------')
print(software_df.describe())
Descriptive statistics for software preferences
----------------------------------------
          My_Java       My_JS   My_Python         My_R      My_SAS   Prof_Java  \
count  207.000000  207.000000  207.000000  207.000000  207.000000  207.000000
mean    10.135266    4.797101   31.304348   37.125604   16.637681    9.251208
std     11.383477    6.757764   15.570982   14.576003   13.626400   13.167505
min      0.000000    0.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000    0.000000   20.000000   30.000000    5.000000    0.000000
50%      9.000000    0.000000   30.000000   35.000000   15.000000    5.000000
75%     20.000000   10.000000   40.000000   50.000000   25.000000   15.000000
max     70.000000   30.000000   90.000000  100.000000   75.000000   80.000000

          Prof_JS  Prof_Python      Prof_R    Prof_SAS    Ind_Java  \
count  207.000000   207.000000  207.000000  207.000000  207.000000
mean     5.840580    30.028986   36.415459   18.463768   11.942029
std     10.812555    19.144802   20.847606   18.831841   14.706399
min      0.000000     0.000000    0.000000    0.000000    0.000000
```

```
25%      0.000000   20.000000   25.000000   0.000000    0.000000
50%      0.000000   30.000000   33.000000   15.000000   5.000000
75%     10.000000   40.000000   50.000000   30.000000  20.000000
max    100.000000  100.000000  100.000000  100.000000  70.000000

           Ind_JS  Ind_Python       Ind_R     Ind_SAS
count  207.000000  207.000000  207.000000  207.000000
mean     6.966184   29.772947   32.434783   18.884058
std     10.030721   17.959816   15.912209   19.137623
min      0.000000    0.000000    0.000000    0.000000
25%      0.000000   20.000000   22.500000    0.000000
50%      0.000000   30.000000   30.000000   15.000000
75%     10.000000   40.000000   40.000000   30.000000
max     50.000000   95.000000   85.000000  100.000000
# Compute descriptive statistics for course completion variable
print('\nDescriptive statistics for courses completed\n---------------------------------
------')
print(survey_df['Courses_Completed'].describe())
Descriptive statistics for courses completed
----------------------------------------
count    187.000000
mean       6.342246
std        3.170849
min        1.000000
25%        4.000000
50%        6.000000
75%        9.000000
max       12.000000
Name: Courses_Completed, dtype: float64
# Calculate counts for courses completed
# Note that the totals below do not equal the 187 courses completed from question above
print('\nCounts for individual courses completed\n---------------------------------------
-')
print(courses_df.count())
Counts for individual courses completed
----------------------------------------
PREDICT400     163
PREDICT401     171
PREDICT410     145
PREDICT411     113
PREDICT413      59
PREDICT420     127
PREDICT422      48
PREDICT450      17
PREDICT451       7
PREDICT452      13
PREDICT453      11
PREDICT454       5
PREDICT455      30
PREDICT456       6
PREDICT457       4
OtherPython      5
OtherR          14
OtherSAS         2
Other           26
dtype: int64
# Calculate counts for graduation date by quarter
print('\nCounts for expected graduation date\n----------------------------------------')
print(survey_df['Graduate_Date'].value_counts())
Counts for expected graduation date
----------------------------------------
Spring 2018      30
Winter 2017      25
```

```
Winter 2018      25
Fall 2018        20
Spring 2017      19
Fall 2017        14
Summer 2017      14
Fall 2016        13
Winter 2019      11
Summer 2018      11
Spring 2019       9
Fall 2019         5
2020 or Later     5
Summer 2019       3
Name: Graduate_Date, dtype: int64
```

II. Data Exploration: Expected Graduation Data

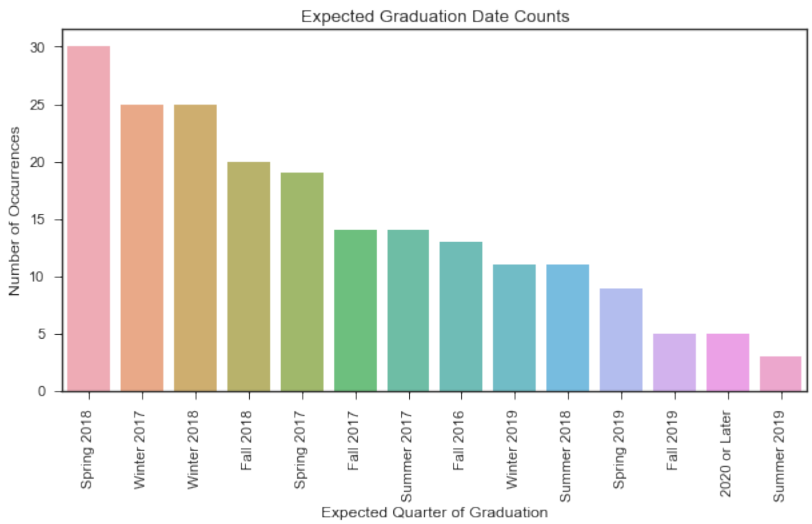
Survey respondents are split across expected graduation years as follows (with 3 null values from 207 responses):

- 2016: 13
- 2017: 72
- 2018: 86
- 2019: 28
- 2020 or later: 5

This suggests that the majority of respondents have at least a year more of coursework at the time of survey administration. Expected graduation dates do change with circumstance, but this gives an idea of the perspective on timing and opportunities remaining amongst respondents.

Figure 1: Expected Graduation Date Counts

```
# Create barplot of graduation date counts
grad_count = survey_df['Graduate_Date'].value_counts()

plt.figure(figsize=(10,5))
sns.barplot(grad_count.index, grad_count.values, alpha=0.8)
plt.title('Expected Graduation Date Counts')
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Expected Quarter of Graduation', fontsize=12)
plt.xticks(rotation='vertical')
plt.show()
```



III. Data Exploration: Course Completion Data

The survey results show a discrepancy between total courses completed across respondents (1186 total from "Courses Completed" question 13 versus 966 total across the individual courses listed in question 14). This could be a result of respondents not rigorously including any course not listed in the numerous PREDICT options and "Other" options into the final "Other" category.

Figure 2a: Completed Course Counts by Individual Courses (Question 14)

```
# Create barplot of courses completed by survey respondents by Fall 2016
# Note that totals from these values, cumulatively, do not equal the total values of
Figure 2b below
course_count = courses_df.count()

plt.figure(figsize=(10,5))
sns.barplot(course_count.index, course_count.values, alpha=0.8)
plt.title('Completed Course Counts')
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Course', fontsize=12)
plt.xticks(rotation='vertical')
plt.show()
```

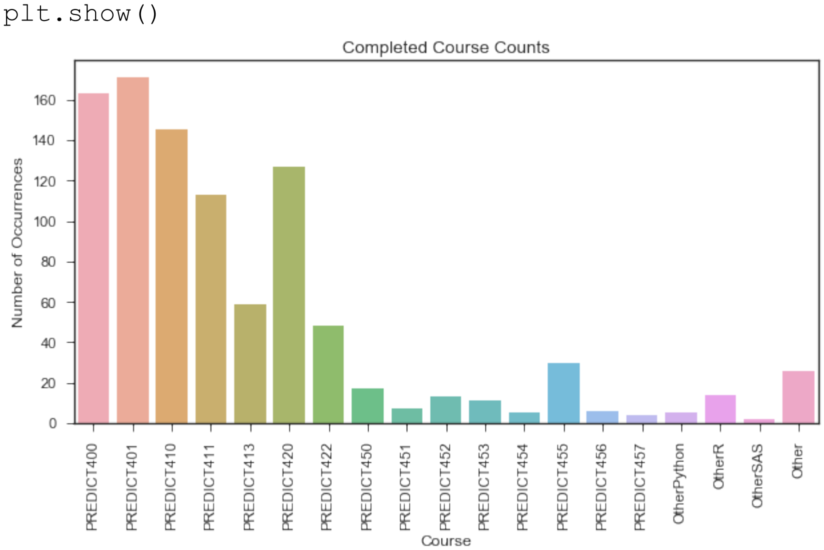
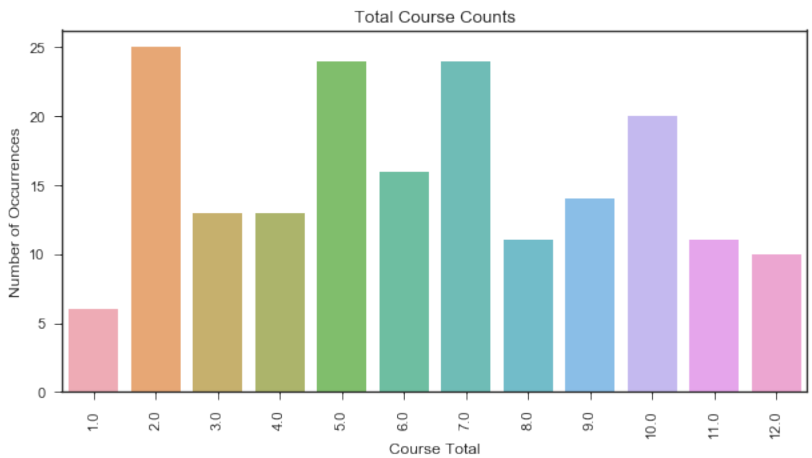


Figure 2b: Completed Course Counts by Total Courses (Question 13)

```
# Create barplot of graduation date counts
total_course_count = survey_df['Courses_Completed'].value_counts()

plt.figure(figsize=(10,5))
sns.barplot(total_course_count.index, total_course_count.values, alpha=0.8)
plt.title('Total Course Counts')
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Course Total', fontsize=12)
plt.xticks(rotation='vertical')
plt.show()
```



Data scaling and comparisons for course completion variable

Scaling methods and feature selection
Feature scaling is a useful transformation for numerical attributes having different scales, for example in a survey where one attribute may measure an interest score out of 100 and another may request a rating from 0 to 5. This transformation enables better performance with machine learning algorithms so that features can be compared more systematically. Min-Max scaling (also called normalization) and standardization and are two common methods to transform data to have the same scale. Min-Max scaling shift values so their range ends up on a 0 to 1 scale. Standardization subtracts the mean value and divides by the standard deviation to provide unit variance for the resulting distribution.

These two methods are applied to the Courses Completed feature, which asks for an integer of number of courses completed to date at time of survey response (though for further implementation of machine learning algorithms, all numeric attributes would likely be scaled to enable better comparison). Additionally, a natural log transformation with NumPy is applied to examine effects.

Figures 3a and 3b below show a visual point of comparison of the impact of transformation on this feature. Unscaled, the values range from 1 to 12. Applying the standard scaler, the values range from -1.689323 (1 class) to 1.789093 (12 classes). Applying the MinMax scaler, the values range from 0 to 1, as with all normalization. The natural log transformation results in values ranging from 0 to 2.484907. The natural log transformation, one approach for dealing with skewed data in an attempt to make values conform more closely to the normal distribution, results in a left skew with this attribute. My recommendation for this attribute would be to use the MinMax scaler since its sensitivity to outliers (not present) would not be an issue. Across all attributes for the survey data, an assessment of outliers would be needed to make the call. Additional methods, like scikit-learn's MaxAbs scaler, may also be considered.

Reference: Géron, A. (2017). Hands-on machine learning with Scikit-Learn & TensorFlow: Concepts, tools,

and techniques to build intelligent systems. Sebastopol, CA: O'Reilly.

scikit-learn preprocessing documentation:https://scikit-learn.org/stable/modules/preprocessing.html

```
# Select variable to examine, eliminating missing data codes
# Data preparation
X = survey_df['Courses_Completed'].dropna()
pd.Series(X).array
X
RespondentID
5133300037     6.0
5132253300     4.0
5132096630     7.0
5131990362     7.0
5131860849     5.0
              ...
5109972944    10.0
5109962530     6.0
5109927686     3.0
5109817376     5.0
5109806898     7.0
Name: Courses_Completed, Length: 187, dtype: float64
# Standardization of Courses Completed feature
scaler = preprocessing.StandardScaler()
X_transformed_standard = scaler.fit_transform(X[:, np.newaxis])
# Inspect transformed values
X_transformed_standard
array([[-0.108],
       [-0.741],
       [ 0.208],
       [ 0.208],
       [-0.424],
       [ 1.473],
       [-1.373],
       [-1.057],
       [-0.108],
       [-1.057],
       [-1.373],
       [ 0.208],
       [-1.057],
       [-0.741],
       [-1.373],
       [ 1.789],
       [ 0.208],
       [-0.424],
       [-0.108],
       [ 0.524],
       [ 1.789],
       [ 0.84 ],
       [ 1.789],
       [-1.373],
       [-1.057],
       [-0.424],
       [ 0.208],
       [-1.373],
       [ 0.84 ],
       [ 0.208],
       [ 0.208],
       [ 0.208],
       [-1.689],
       [-0.424],
       [-0.424],
```

```
[ 1.473],
[-0.424],
[-0.108],
[ 1.157],
[-0.108],
[ 0.84 ],
[ 1.157],
[-0.741],
[-0.741],
[ 0.208],
[-0.424],
[-1.057],
[ 0.208],
[ 1.157],
[ 0.208],
[-0.108],
[-0.424],
[-0.424],
[-1.057],
[-0.108],
[ 0.208],
[-0.108],
[ 0.524],
[ 1.157],
[-0.424],
[-1.373],
[-1.057],
[ 0.208],
[-0.424],
[-1.373],
[ 0.524],
[-0.741],
[ 0.208],
[ 0.524],
[-0.424],
[ 1.473],
[-1.689],
[-1.373],
[ 1.789],
[-1.057],
[ 0.208],
[ 1.157],
[ 0.208],
[-1.057],
[-1.373],
[ 0.84 ],
[-1.689],
[ 1.473],
[ 1.157],
[ 0.84 ],
[-1.373],
[-0.741],
[-0.108],
[-1.689],
[-0.108],
[-0.741],
[-0.424],
[-1.689],
[ 1.157],
[ 1.789],
[-0.108],
[ 1.157],
[ 1.473],
```

```
[ 0.524],
[ 0.524],
[-1.057],
[ 0.208],
[ 1.157],
[-0.108],
[ 0.524],
[-0.424],
[ 1.473],
[ 1.157],
[ 0.208],
[ 1.473],
[-1.373],
[ 0.84 ],
[-1.373],
[ 0.84 ],
[ 1.157],
[ 1.157],
[ 0.84 ],
[ 1.473],
[ 0.208],
[ 0.524],
[-1.373],
[ 1.157],
[ 0.524],
[-1.373],
[-0.741],
[-0.424],
[-1.373],
[ 0.84 ],
[-0.741],
[-0.424],
[-1.373],
[ 1.157],
[-0.424],
[-1.373],
[ 0.84 ],
[-0.424],
[ 1.157],
[-1.373],
[-1.373],
[ 1.473],
[-0.424],
[ 1.789],
[-1.373],
[ 0.84 ],
[-0.424],
[-0.741],
[ 1.789],
[-1.373],
[ 1.157],
[ 0.524],
[-0.108],
[-1.057],
[-0.424],
[ 1.157],
[-0.424],
[ 0.208],
[-1.373],
[-0.108],
[ 0.84 ],
[ 1.473],
[ 0.84 ],
```

```
       [ 1.789],
       [ 1.473],
       [ 0.208],
       [-1.057],
       [-0.741],
       [ 0.208],
       [-0.108],
       [-0.424],
       [-0.741],
       [-1.373],
       [-0.741],
       [ 1.789],
       [-1.373],
       [ 0.524],
       [ 1.157],
       [ 0.208],
       [ 1.789],
       [ 1.157],
       [ 0.84 ],
       [-1.689],
       [-1.373],
       [ 1.157],
       [-0.108],
       [-1.057],
       [-0.424],
       [ 0.208]])
# Normalization of Courses Completed feature with MinMax scaling
scaler = preprocessing.MinMaxScaler()
X_transformed_minmax = scaler.fit_transform(X[:, np.newaxis])
# Inspect transformed values
X_transformed_minmax
array([[0.455],
       [0.273],
       [0.545],
       [0.545],
       [0.364],
       [0.909],
       [0.091],
       [0.182],
       [0.455],
       [0.182],
       [0.091],
       [0.545],
       [0.182],
       [0.273],
       [0.091],
       [1.   ],
       [0.545],
       [0.364],
       [0.455],
       [0.636],
       [1.   ],
       [0.727],
       [1.   ],
       [0.091],
       [0.182],
       [0.364],
       [0.545],
       [0.091],
       [0.727],
       [0.545],
       [0.545],
       [0.545],
```

```
[0.   ],
[0.364],
[0.364],
[0.909],
[0.364],
[0.455],
[0.818],
[0.455],
[0.727],
[0.818],
[0.273],
[0.273],
[0.545],
[0.364],
[0.182],
[0.545],
[0.818],
[0.545],
[0.455],
[0.364],
[0.364],
[0.182],
[0.455],
[0.545],
[0.455],
[0.636],
[0.818],
[0.364],
[0.091],
[0.182],
[0.545],
[0.364],
[0.091],
[0.636],
[0.273],
[0.545],
[0.636],
[0.364],
[0.909],
[0.   ],
[0.091],
[1.   ],
[0.182],
[0.545],
[0.818],
[0.545],
[0.182],
[0.091],
[0.727],
[0.   ],
[0.909],
[0.818],
[0.727],
[0.091],
[0.273],
[0.455],
[0.   ],
[0.455],
[0.273],
[0.364],
[0.   ],
[0.818],
[1.   ],
```

```
       [0.455],
       [0.818],
       [0.909],
       [0.636],
       [0.636],
       [0.182],
       [0.545],
       [0.818],
       [0.455],
       [0.636],
       [0.364],
       [0.909],
       [0.818],
       [0.545],
       [0.909],
       [0.091],
       [0.727],
       [0.091],
       [0.727],
       [0.818],
       [0.818],
       [0.727],
       [0.909],
       [0.545],
       [0.636],
       [0.091],
       [0.818],
       [0.636],
       [0.091],
       [0.273],
       [0.364],
       [0.091],
       [0.727],
       [0.273],
       [0.364],
       [0.091],
       [0.818],
       [0.364],
       [0.091],
       [0.727],
       [0.364],
       [0.818],
       [0.091],
       [0.091],
       [0.909],
       [0.364],
       [1.   ],
       [0.091],
       [0.727],
       [0.364],
       [0.273],
       [1.   ],
       [0.091],
       [0.818],
       [0.636],
       [0.455],
       [0.182],
       [0.364],
       [0.818],
       [0.364],
       [0.545],
       [0.091],
       [0.455],
```

```
       [0.727],
       [0.909],
       [0.727],
       [1.   ],
       [0.909],
       [0.545],
       [0.182],
       [0.273],
       [0.545],
       [0.455],
       [0.364],
       [0.273],
       [0.091],
       [0.273],
       [1.   ],
       [0.091],
       [0.636],
       [0.818],
       [0.545],
       [1.   ],
       [0.818],
       [0.727],
       [0.   ],
       [0.091],
       [0.818],
       [0.455],
       [0.182],
       [0.364],
       [0.545]])
# Natural log transformation of X and inspection of transformed values
X_log_transformed = np.log(X)
X_log_transformed
RespondentID
5133300037    1.791759
5132253300    1.386294
5132096630    1.945910
5131990362    1.945910
5131860849    1.609438
                ...
5109972944    2.302585
5109962530    1.791759
5109927686    1.098612
5109817376    1.609438
5109806898    1.945910
Name: Courses_Completed, Length: 187, dtype: float64
# Create DatafFrame of transformed values
frame = {'Unscaled': X}
courses_feature = pd.DataFrame(frame)

# Add additional columns of transformed values
standard = X_transformed_standard.tolist()
minmax = X_transformed_minmax.tolist()
logx = X_log_transformed.tolist()

courses_feature['Standard'] = np.array(standard)
courses_feature['MinMax'] = np.array(minmax)
courses_feature['NaturalLog'] = np.array(logx)
# Inspect first 5 rows
courses_feature.head()
```

	Unscaled	Standard	MinMax	NaturalLog
RespondentID				
5133300037	6.0	-0.108225	0.454545	1.791759
5132253300	4.0	-0.740664	0.272727	1.386294
5132096630	7.0	0.207995	0.545455	1.945910
5131990362	7.0	0.207995	0.545455	1.945910
5131860849	5.0	-0.424445	0.363636	1.609438

```
# Use describe() to compare statistics across transformed values
courses_feature.describe()
```

	Unscaled	Standard	MinMax	NaturalLog
count	187.000000	1.870000e+02	187.000000	187.000000
mean	6.342246	1.335830e-16	0.485659	1.682041
std	3.170849	1.002685e+00	0.288259	0.631660
min	1.000000	-1.689323e+00	0.000000	0.000000
25%	4.000000	-7.406642e-01	0.272727	1.386294
50%	6.000000	-1.082249e-01	0.454545	1.791759
75%	9.000000	8.404340e-01	0.727273	2.197225
max	12.000000	1.789093e+00	1.000000	2.484907

Figure 3a: Scaling Comparisons

```
# Create boxplot for transformations to examine effect on distribution
boxplot = courses_feature.plot.box(grid=1, notch=1)
boxplot.set_title("Transformations")
Text(0.5,1,'Transformations')
```

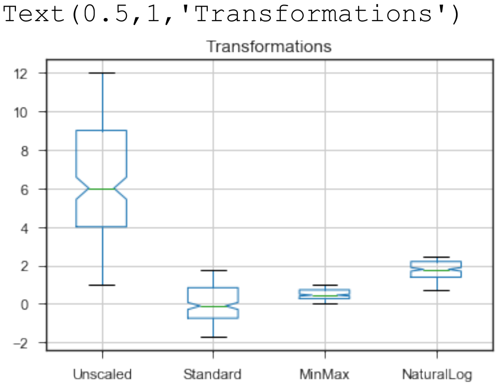
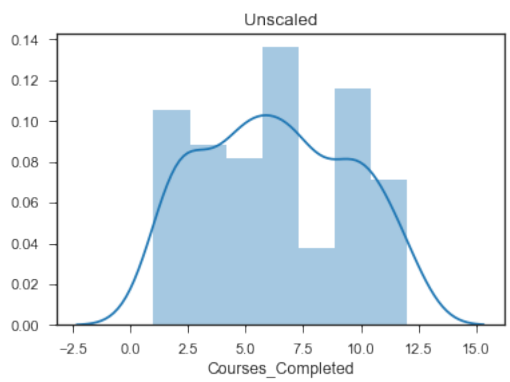
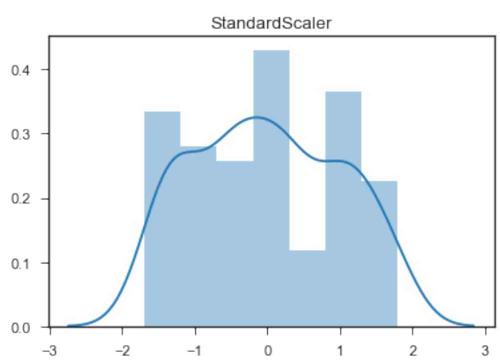


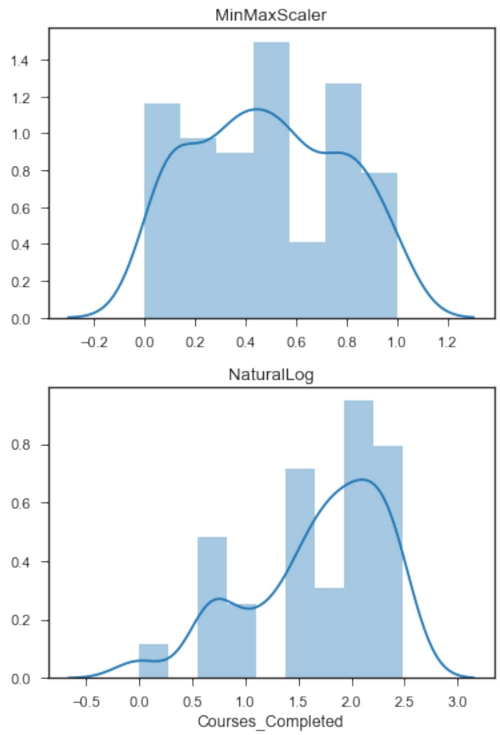
Figure 3b: Scaling Comparisons

```
# Seaborn provides a convenient way to show the effects of transformations
# on the distribution of values being transformed
# Documentation at https://seaborn.pydata.org/generated/seaborn.distplot.html

unscaled_fig, ax = plt.subplots()
sns.distplot(X).set_title('Unscaled')
unscaled_fig.savefig('Transformation-Unscaled' + '.pdf',
    bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
    orientation='portrait', papertype=None, format=None,
    transparent=True, pad_inches=0.25, frameon=None)
```

```
standard_fig, ax = plt.subplots()
sns.distplot(X_transformed_standard).set_title('StandardScaler')
standard_fig.savefig('Transformation-StandardScaler' + '.pdf',
    bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
    orientation='portrait', papertype=None, format=None,
    transparent=True, pad_inches=0.25, frameon=None)

minmax_fig, ax = plt.subplots()
sns.distplot(X_transformed_minmax).set_title('MinMaxScaler')
minmax_fig.savefig('Transformation-MinMaxScaler' + '.pdf',
    bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
    orientation='portrait', papertype=None, format=None,
    transparent=True, pad_inches=0.25, frameon=None)

log_fig, ax = plt.subplots()
sns.distplot(np.log(X)).set_title('NaturalLog')
log_fig.savefig('Transformation-NaturalLog' + '.pdf',
    bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
    orientation='portrait', papertype=None, format=None,
    transparent=True, pad_inches=0.25, frameon=None)
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
/anaconda3/lib/python3.6/site-packages/matplotlib/axes/_axes.py:6462: UserWarning: The
'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```







IV. Data Exploration: Software Preferences across Personal, Professional, and Industry Interests/Utility

Figure 4: Personal Software Preferences - Boxplot

```
# Create boxplot for personal software preferences
personal_sw = software_df[['My_Java','My_JS','My_Python','My_R','My_SAS']]
boxplot = personal_sw.plot.box(grid=1, notch=1)
boxplot.set_title("Notched Boxplots for Personal Software Preferences")
Text(0.5,1,'Notched Boxplots for Personal Software Preferences')
```

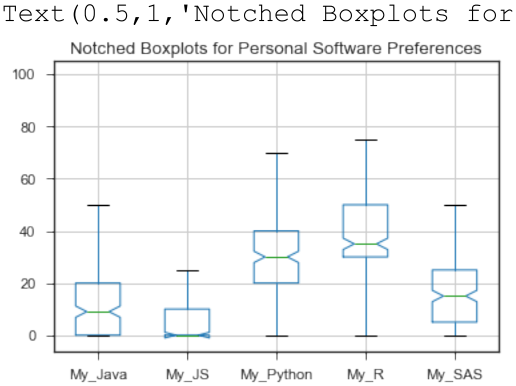


Figure 5: Professional Software Preferences - Boxplot

```
# Create boxplot for professional software preferences
professional_sw = software_df[['Prof_Java','Prof_JS','Prof_Python','Prof_R','Prof_SAS']]
boxplot = professional_sw.plot.box(grid=1, notch=1)
boxplot.set_title("Notched Boxplots for Professional Software Preferences")
Text(0.5,1,'Notched Boxplots for Professional Software Preferences')
```

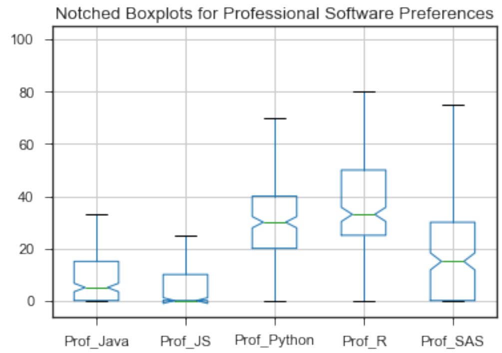


Figure 6: Industry Software Preferences - Boxplot

```
# Create boxplot for industry software preferences
industry_sw = software_df[['Ind_Java','Ind_JS','Ind_Python','Ind_R','Ind_SAS']]
boxplot = industry_sw.plot.box(grid=1, notch=1)
boxplot.set_title("Notched Boxplots for Industry Software Preferences")
Text(0.5,1,'Notched Boxplots for Industry Software Preferences')
```

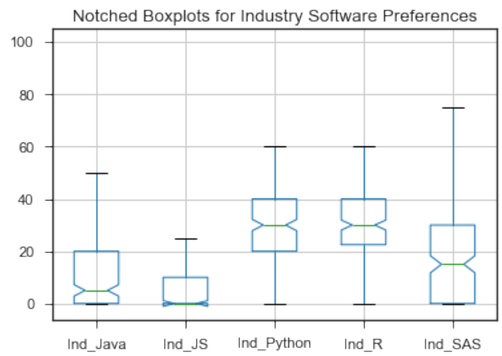


Figure 7: Personal Software Preferences - Pair Plot

```
# Create pair plot for personal software preferences
# This creates a matrix of axes and shows the relationship for each pair of columns in a
DataFrame
# By default, it also draws the univariate distribution of each variable on the diagonal
Axes
sns.pairplot(personal_sw)
<seaborn.axisgrid.PairGrid at 0x131e9d048>
```

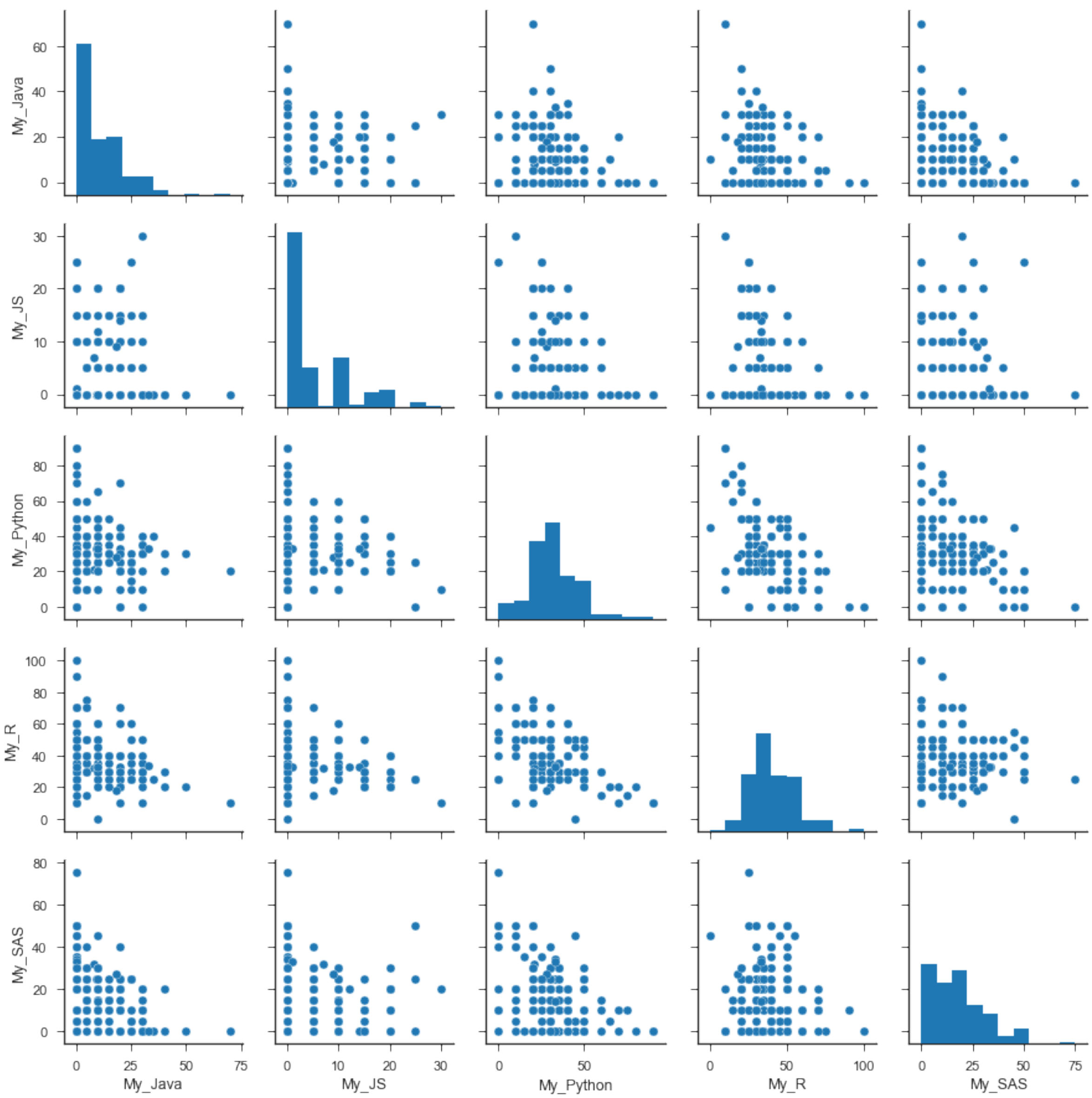


Figure 8 Professional Software Preferences - Pair Plot

```
# Create pair plot for professional software preferences
sns.pairplot(professional_sw)
<seaborn.axisgrid.PairGrid at 0x132733630>
```

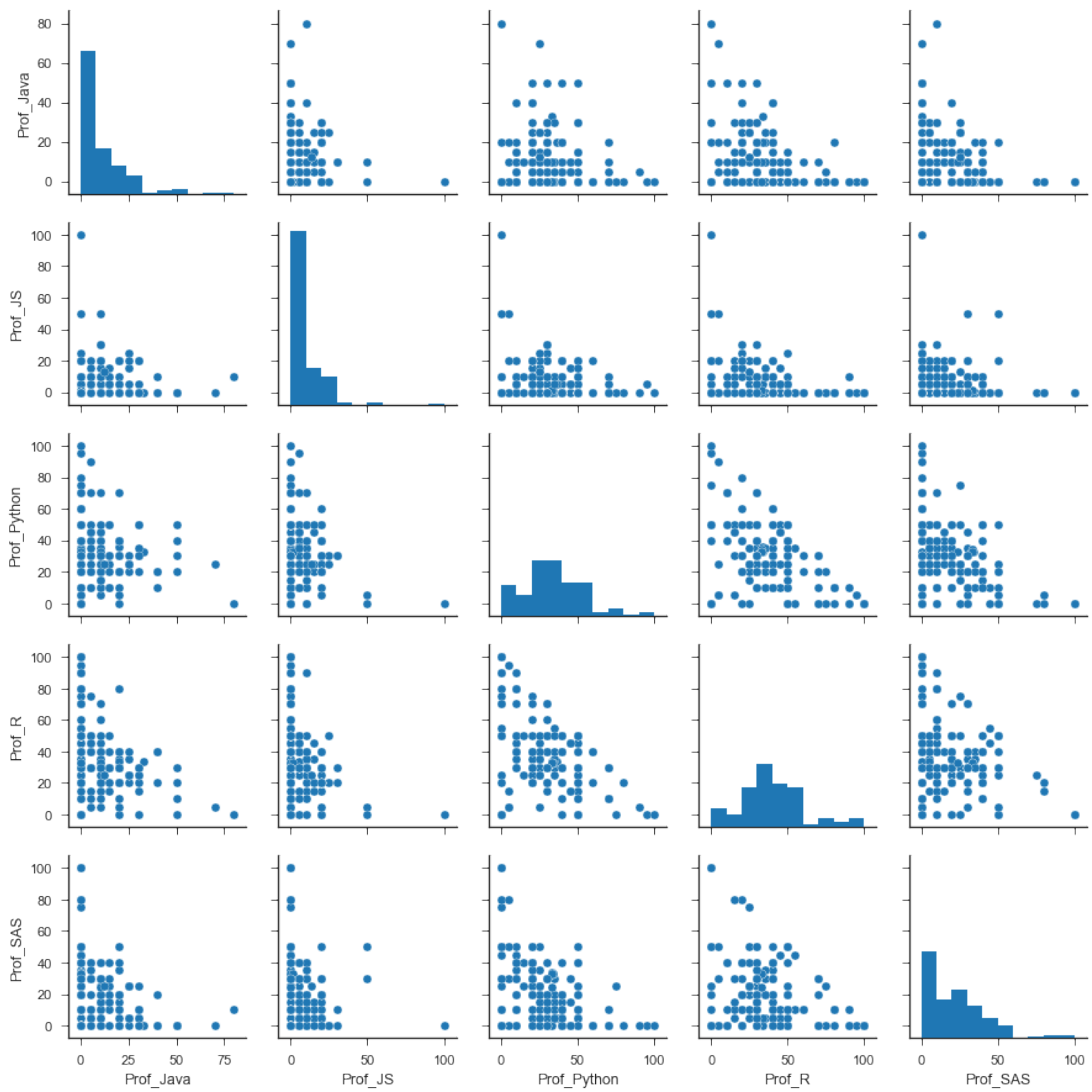
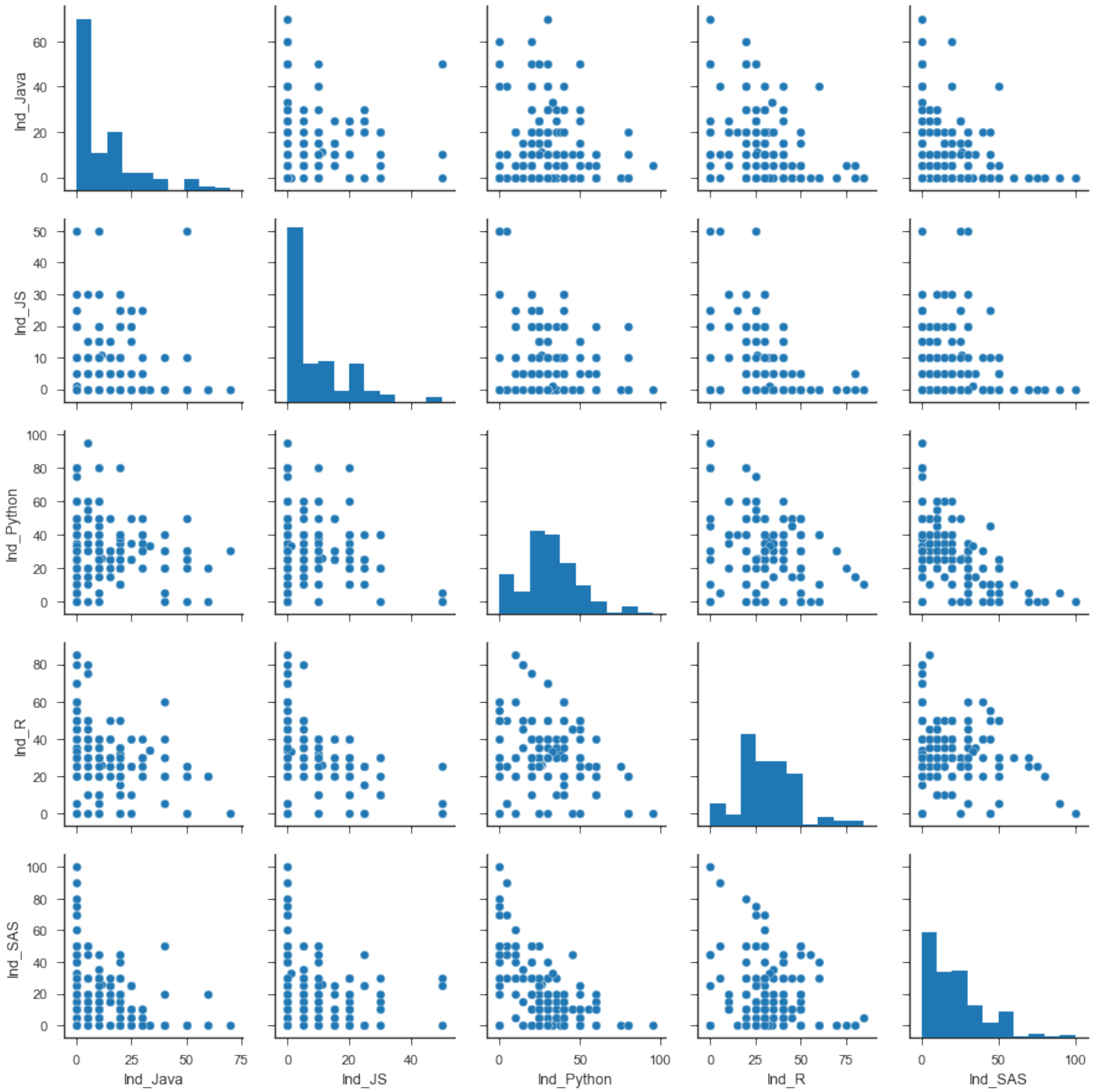


Figure 9: Industry Software Preferences - Pair Plot

```
# Create pair plot for industry software preferences
sns.pairplot(industry_sw)
<seaborn.axisgrid.PairGrid at 0x132bb3c88>
```

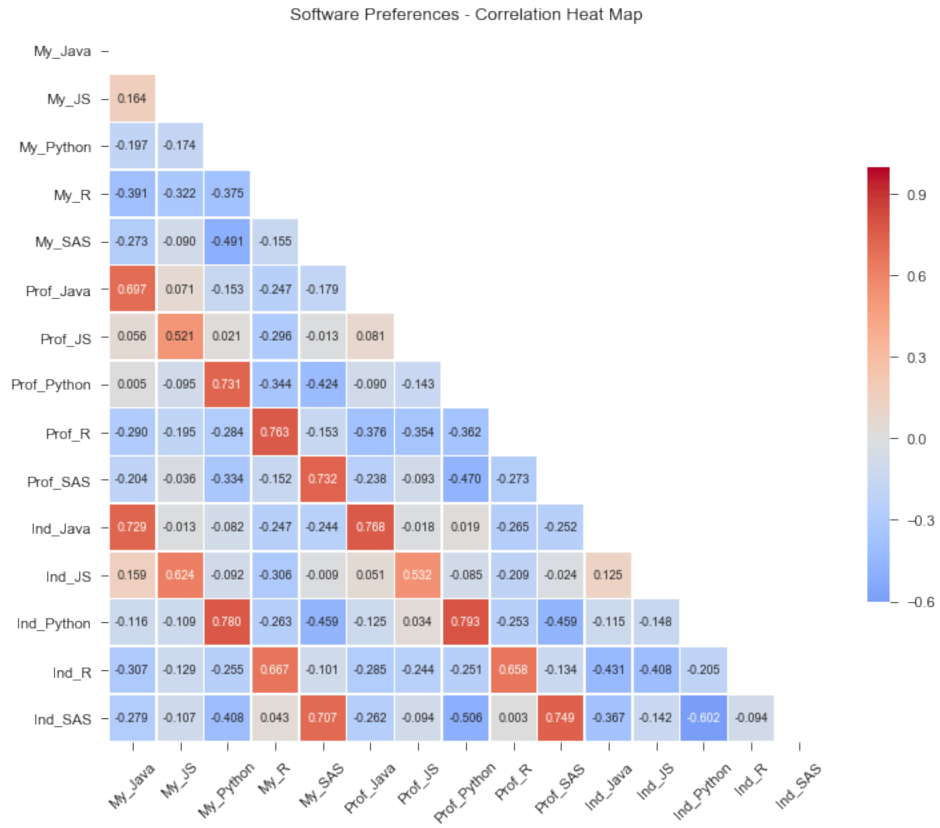



```
# Define function for correlation heat map setup for seaborn
def corr_chart(df_corr):
    corr=df_corr.corr()
    #screen top half to get a triangle
    top = np.zeros_like(corr, dtype=np.bool)
    top[np.triu_indices_from(top)] = True
    fig=plt.figure()
    fig, ax = plt.subplots(figsize=(12,12))
    sns.heatmap(corr, mask=top, cmap='coolwarm',
        center = 0, square=True,
        linewidths=.5, cbar_kws={'shrink':.5},
        annot = True, annot_kws={'size': 9}, fmt = '.3f')
    plt.xticks(rotation=45) # rotate variable labels on columns (x axis)
    plt.yticks(rotation=0) # use horizontal variable labels on rows (y axis)
    plt.title('Software Preferences - Correlation Heat Map')
    plt.savefig('plot-corr-map.pdf',
        bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
        orientation='portrait', papertype=None, format=None,
        transparent=True, pad_inches=0.25, frameon=None)
```

Figure 10: Software Preference Correlations Heatmap

```
# Examine correlations among software preference features
```

```
corr_chart(df_corr = software_df)
<Figure size 432x288 with 0 Axes>
```

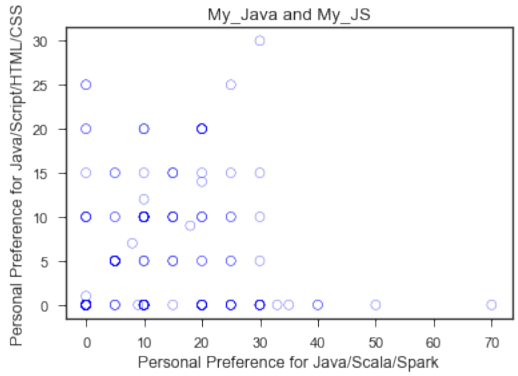


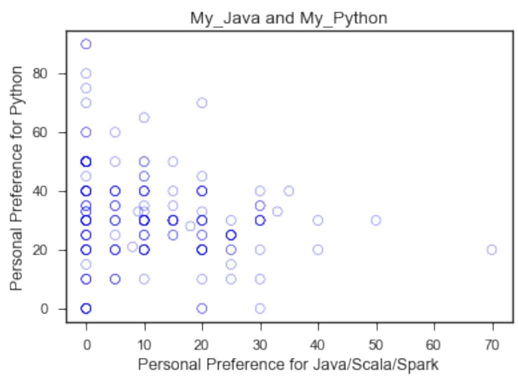

```
# Create labels for scatterplots
software_df_labels = [
    'Personal Preference for Java/Scala/Spark',
    'Personal Preference for Java/Script/HTML/CSS',
    'Personal Preference for Python',
    'Personal Preference for R',
    'Personal Preference for SAS',
    'Professional Java/Scala/Spark',
    'Professional JavaScript/HTML/CSS',
    'Professional Python',
    'Professional R',
    'Professional SAS',
    'Industry Java/Scala/Spark',
    'Industry Java/Script/HTML/CSS',
    'Industry Python',
    'Industry R',
    'Industry SAS'
]
```

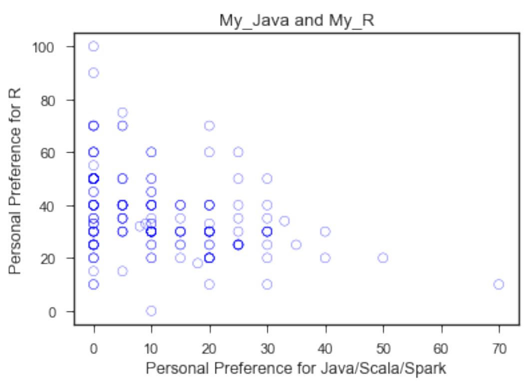
Figure 11: Software Preference Scatterplots

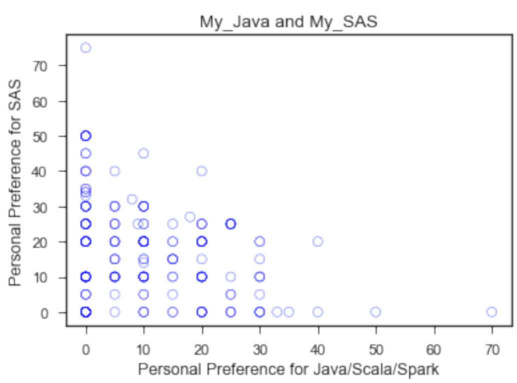
```
# Create a set of scatter plots for personal software preferences
for i in range(5):
    for j in range(5):
        if i != j:
            file_title = software_df.columns[i] + '_and_' + software_df.columns[j]
            plot_title = software_df.columns[i] + ' and ' + software_df.columns[j]
            fig, axis = plt.subplots()
            axis.set_xlabel(software_df_labels[i])
            axis.set_ylabel(software_df_labels[j])
            plt.title(plot_title)
            scatter_plot = axis.scatter(software_df[software_df.columns[i]],
            survey_df[software_df.columns[j]],
```

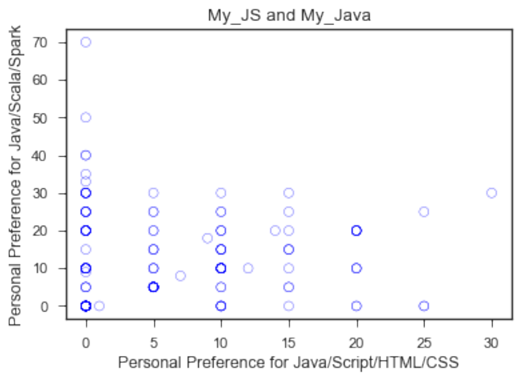
```
        facecolors = 'none',
        edgecolors = 'blue')
        plt.savefig(file_title + '.pdf',
            bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
            orientation='portrait', papertype=None, format=None,
            transparent=True, pad_inches=0.25, frameon=None)
```

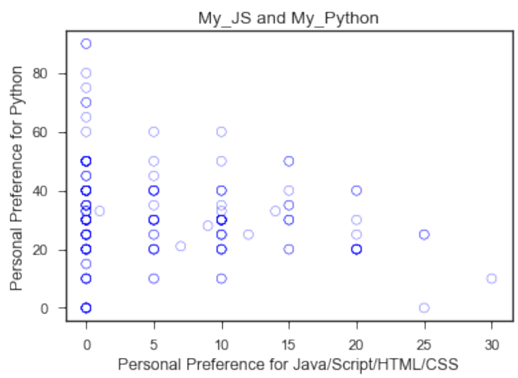


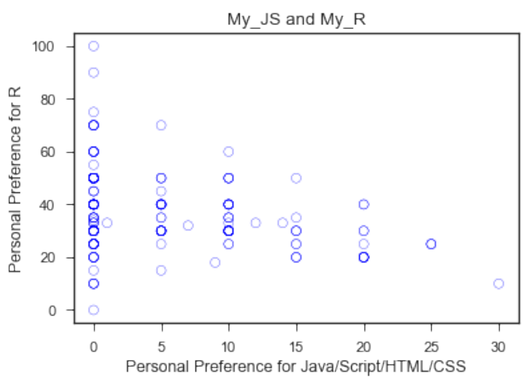


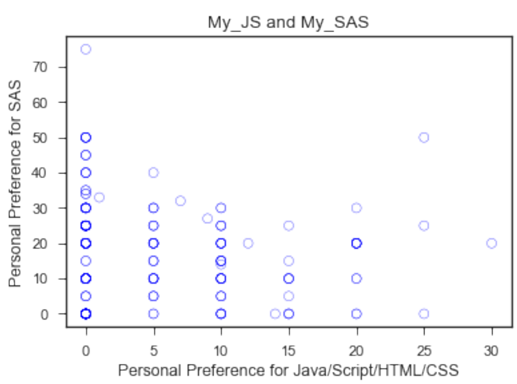


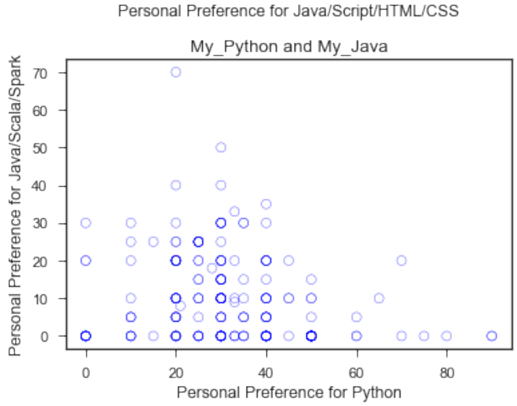


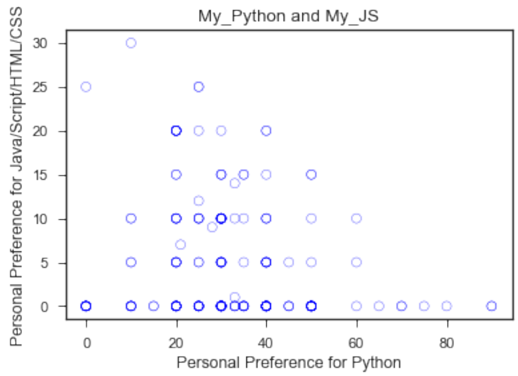

My_JS and My_Java
Personal Preference for Java/Scala/Spark
Personal Preference for Java/Script/HTML/CSS

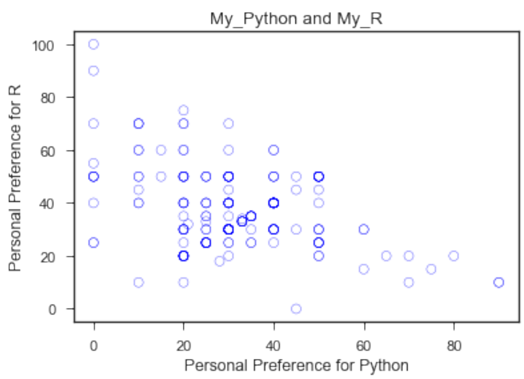

My_JS and My_Python
Personal Preference for Python
Personal Preference for Java/Script/HTML/CSS

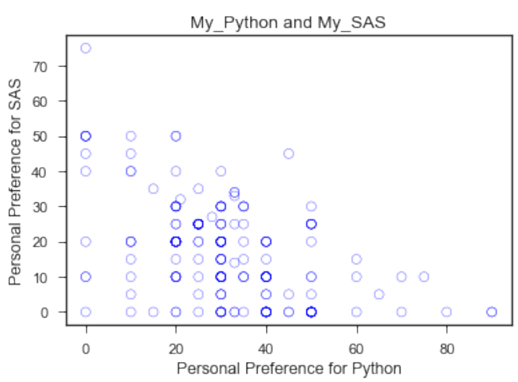

My_JS and My_R
Personal Preference for R
Personal Preference for Java/Script/HTML/CSS

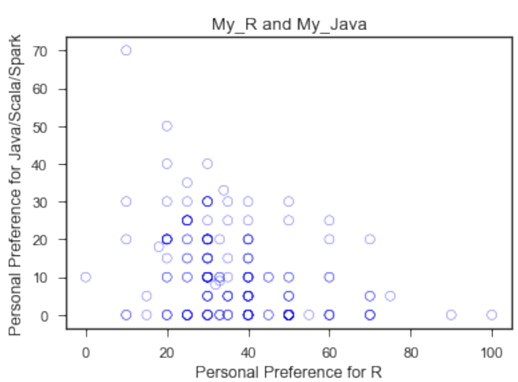

My_JS and My_SAS
Personal Preference for SAS
Personal Preference for Java/Script/HTML/CSS

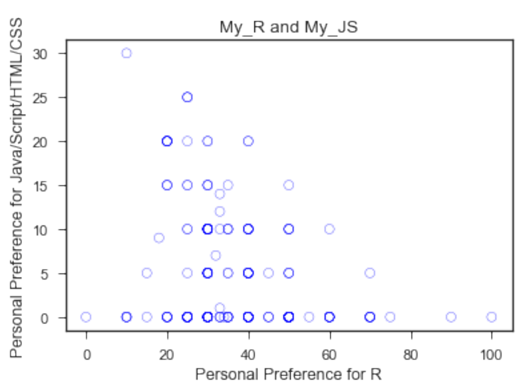

My_Python and My_Java
Personal Preference for Java/Scala/Spark
Personal Preference for Python

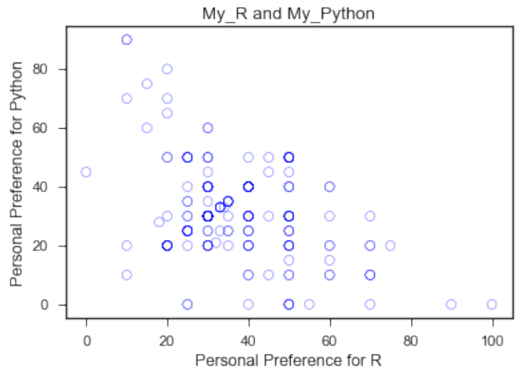

My_Python and My_JS
Personal Preference for Java/Script/HTML/CSS
Personal Preference for Python

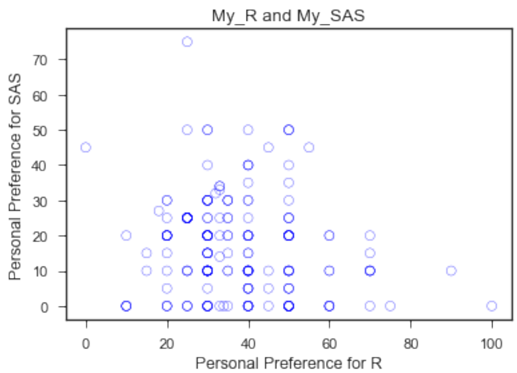

My_Python and My_R
Personal Preference for R
Personal Preference for Python

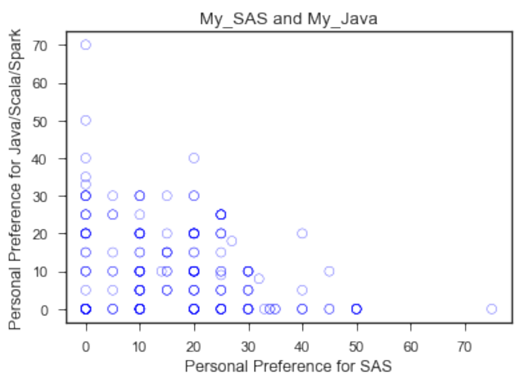

My_Python and My_SAS
Personal Preference for SAS
Personal Preference for Python

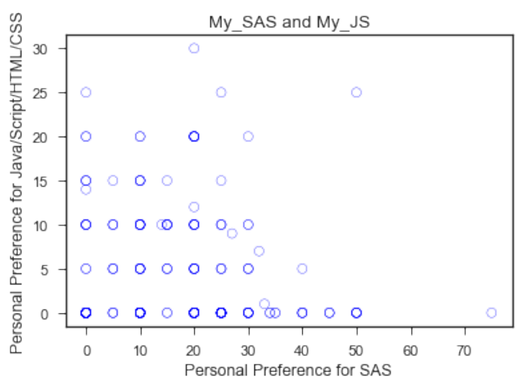

My_R and My_Java
Personal Preference for Java/Scala/Spark
Personal Preference for R

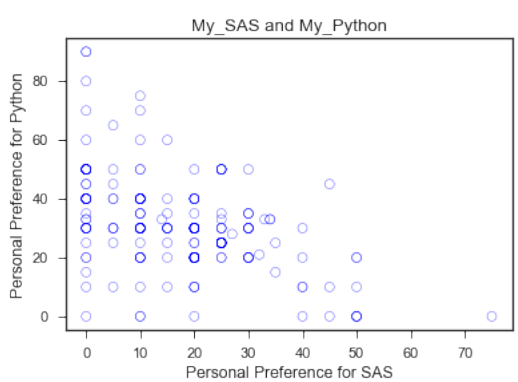

My_R and My_JS
Personal Preference for Java/Script/HTML/CSS
Personal Preference for R


My_R and My_Python
Personal Preference for Python
Personal Preference for R


My_R and My_SAS
Personal Preference for SAS
Personal Preference for R


My_SAS and My_Java
Personal Preference for Java/Scala/Spark
Personal Preference for SAS


My_SAS and My_JS
Personal Preference for Java/Script/HTML/CSS
Personal Preference for SAS


My_SAS and My_Python
Personal Preference for Python
Personal Preference for SAS

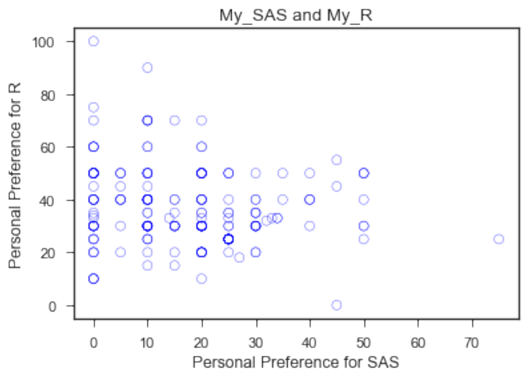


Figure 12: Professional Python and SAS Preferences

```
# Create scatterplot of professional Python versus professional SAS preference with
regression fit

# Set style of scatterplot
sns.set_context("notebook", font_scale=1.1)
sns.set_style("ticks")

# sns.regplot(x=software_df["My_R"], y=software_df["My_Python"], fit_reg=False)
sns.regplot(x=software_df["Prof_Python"], y=software_df["Prof_SAS"])

# Set title
plt.title('Professional Python and Professional SAS Preferences')

# Set x-axis label
plt.xlabel('Python')

# Set y-axis label
plt.ylabel('SAS')
Text(0,0.5,'SAS')
```

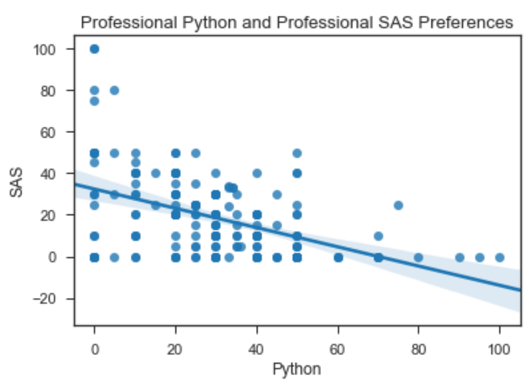


Figure 13: Industry Python and SAS Preferences

```
# Create scatterplot of industry Python versus professional SAS preference with
regression fit

# Set style of scatterplot
sns.set_context("notebook", font_scale=1.1)
sns.set_style("ticks")

# sns.regplot(x=software_df["My_R"], y=software_df["My_Python"], fit_reg=False)
sns.regplot(x=software_df["Ind_Python"], y=software_df["Ind_SAS"])

# Set title
```

```
plt.title('Industry Python and Professional SAS Preferences')

# Set x-axis label
plt.xlabel('Python')

# Set y-axis label
plt.ylabel('SAS')
Text(0,0.5,'SAS')
```

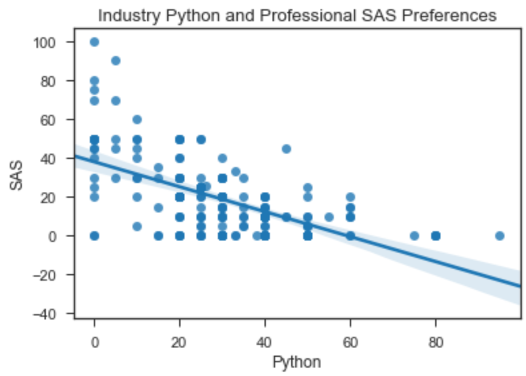
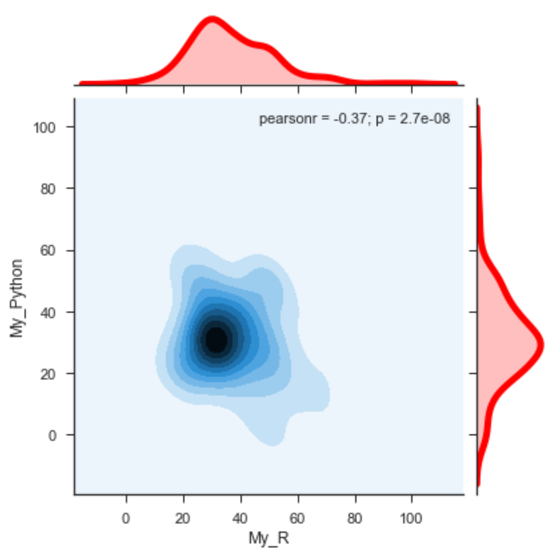


Figure 14: Joint Plot for Personal Python and R Preferences

```
# Create joint plot for Python and R preference correlation
# kde plots a kernel density estimate in the margins and converts the interior into a
shaded countour plot
# The histogram on the top shows the distribution of the variable at the x-axis and the
histogram to the
# right shows the distribution of the variable at the y-axis.
sns.jointplot(x='My_R',
              y='My_Python',
              data=software_df,
              kind="kde",
              marginal_kws={'lw':5,'color':'red'})
<seaborn.axisgrid.JointGrid at 0x136786160>
```



V. Data Exploration: Course Offering Interests

```
# Compute descriptive statistics for course interests
interests_df.describe()
```

	Python_Course_Interest	Foundations_DE_Course_Interest	Analytics_App_Course_Interest	Systems_Analysis_Course_Interest
count	206.000000	200.000000	203.000000	200.000000
mean	73.529126	58.045000	55.201970	53.630000
std	29.835429	32.588079	34.147954	33.539493
min	0.000000	0.000000	0.000000	0.000000
25%	53.000000	29.500000	25.000000	21.500000
50%	82.500000	60.000000	60.000000	51.500000
75%	100.000000	89.250000	85.000000	80.250000
max	100.000000	100.000000	100.000000	100.000000

Figure 15: Course Interests - Boxplot

```
# Create boxplot for course interest data
boxplot = interests_df.plot.box(grid=1, notch=1, rot=90)
boxplot.set_title("Notched Boxplots for Level of Interest in New Courses")
Text(0.5,1,'Notched Boxplots for Level of Interest in New Courses')
```

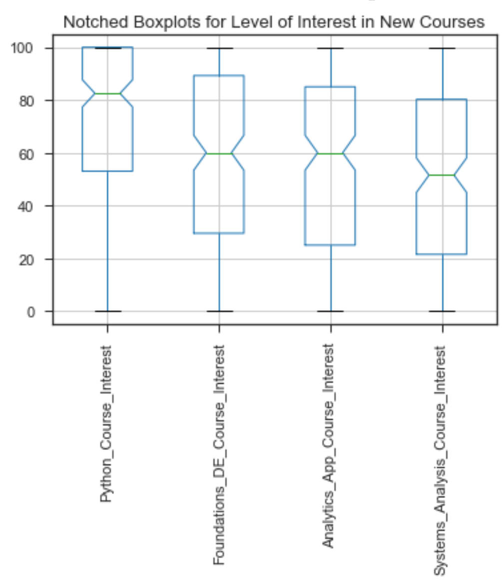
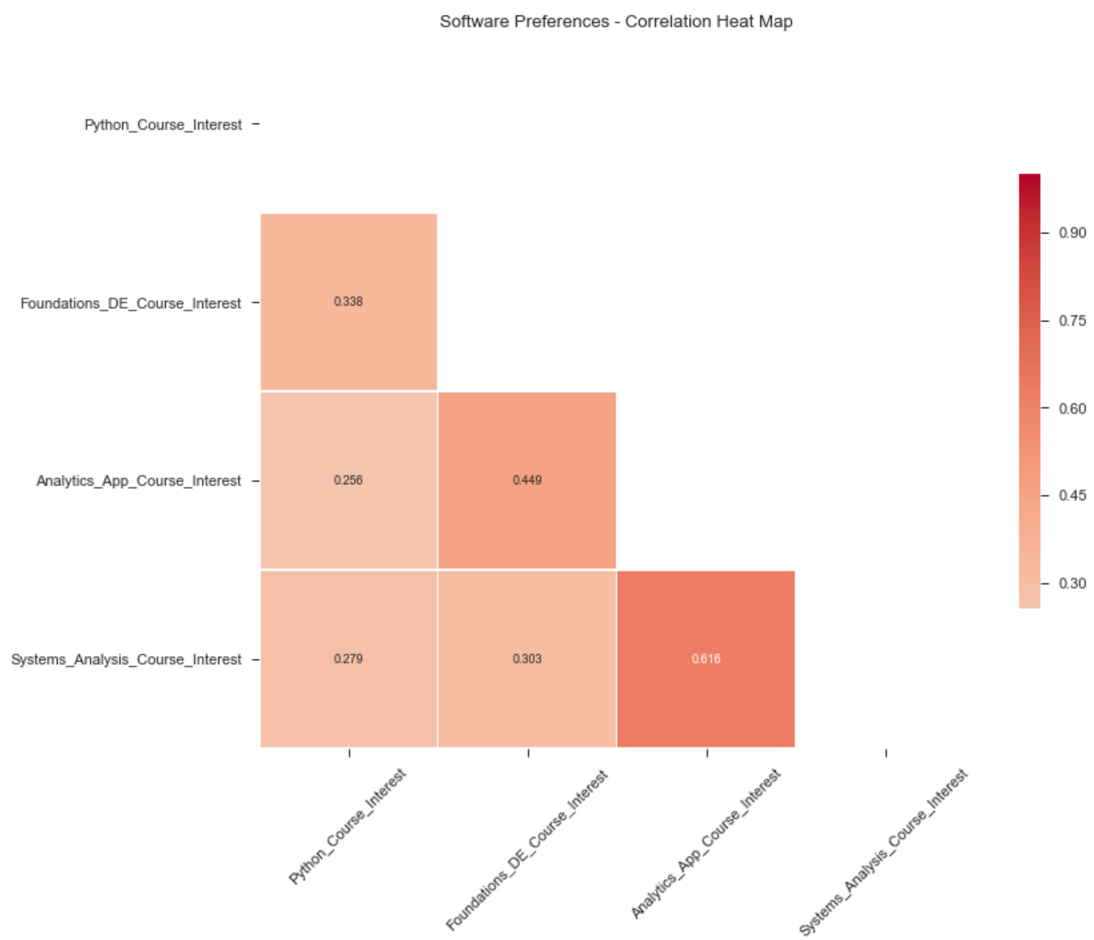


Figure 16: Course Interests - Correlation Heatmap

```
# Examine correlations among software preference features
corr_chart(df_corr = interests_df)
<Figure size 432x288 with 0 Axes>
```


Software Preferences - Correlation Heat Map
Python_Course_Interest
Foundations_DE_Course_Interest
Analytics_App_Course_Interest
Systems_Analysis_Course_Interest
0.338
0.256
0.449
0.279
0.303
0.616
Python_Course_Interest
Foundations_DE_Course_Interest
Analytics_App_Course_Interest
Systems_Analysis_Course_Interest
0.90
0.75
0.60
0.45
0.30