Wanat_Assignment_1_Python

June 30, 2019

```
In [1]: # Jump-Start Example: Python analysis of MSPA Software Survey
        # Update 2017-09-21 by Tom Miller and Kelsey O'Neill
        # Update 2018-06-30 by Tom Miller v005 transformation code added
        # tested under Python 3.6.1 :: Anaconda custom (x86_64)
        # on Windows 10.0 and Mac OS Sierra 10.12.2
        # shows how to read in data from a comma-delimited text file
        # manipuate data, create new count variables, define categorical variables,
        # work with dictionaries and lambda mapping functions for recoding data
        # visualizations in this program are routed to external pdf files
        # so they may be included in printed or electronic reports
        # prepare for Python version 3x features and functions
        # these two lines of code are needed for Python 2.7 only
        # commented out for Python 3.x versions
        # from __future__ import division, print_function
        # from future_builtins import ascii, filter, hex, map, oct, zip
In [2]: # external libraries for visualizations and data manipulation
        # ensure that these packages have been installed prior to calls
        import pandas as pd # data frame operations
        import numpy as np # arrays and math functions
        import pandas_profiling
        import matplotlib
        import matplotlib.pyplot as plt # static plotting
        import seaborn as sns # pretty plotting, including heat map
In [3]: # 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()
```

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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('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)
       np.set_printoptions(precision=3)
In [4]: # 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
       valid_survey_input = pd.read_csv('mspa-survey-data.csv')
        # use the RespondentID as label for the rows... the index of DataFrame
       valid_survey_input.set_index('RespondentID', drop = True, inplace = True)
        # examine the structure of the DataFrame object
       print('\nContents of initial survey data -----')
        # could use len() or first index of shape() to get number of rows/observations
       print('\nNumber of Respondents =', len(valid_survey_input))
Contents of initial survey data -----
Number of Respondents = 207
In [5]: #The shape attribute tells us the numbers of rows and columns in the data frame
       print('\nThe shape of the dataframe (rows, columns):')
       valid_survey_input.shape
The shape of the dataframe (rows, columns):
Out[5]: (207, 40)
In [6]: # provide the number of columns in data frame
       print('\nNumber of columns in data frame = ', valid_survey_input.shape[1])
Number of columns in data frame = 40
```

```
In [7]: # show the column/variable names of the DataFrame
        # note that RespondentID is no longer present
       print(valid_survey_input.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')
```

Personal_JavaScalaSpark	int64
Personal_JavaScriptHTMLCSS	int64
Personal_Python	int64
Personal_R	int64
Personal_SAS	int64
Professional_JavaScalaSpark	int64
Professional_JavaScriptHTMLCSS	int64
Professional_Python	int64
Professional_R	int64
Professional_SAS	int64
Industry_JavaScalaSpark	int64
Industry_JavaScriptHTMLCSS	int64
Industry_Python	int64
Industry_R	int64
Industry_SAS	int64
Python_Course_Interest	float64
Foundations_DE_Course_Interest	float64
Analytics_App_Course_Interest	float64
Systems_Analysis_Course_Interest	float64
Courses_Completed	float64
PREDICT400	object
PREDICT401	object
PREDICT410	object
PREDICT411	object
PREDICT413	object

PREDICT420	object
PREDICT422	object
PREDICT450	object
PREDICT451	object
PREDICT452	object
PREDICT453	object
PREDICT454	object
PREDICT455	object
PREDICT456	object
PREDICT457	object
OtherPython	object
OtherR	object
OtherSAS	object
Other	object
Graduate_Date	object
dtype: object	

Out[9]:	Personal_JavaScalaSpark	0
	Personal_JavaScriptHTMLCSS	0
	Personal_Python	0
	Personal_R	0
	Personal_SAS	0
	Professional_JavaScalaSpark	0
	Professional_JavaScriptHTMLCSS	0
	Professional_Python	0
	Professional_R	0
	Professional_SAS	0
	${\tt Industry_JavaScalaSpark}$	0
	${\tt Industry_JavaScriptHTMLCSS}$	0
	Industry_Python	0
	Industry_R	0
	Industry_SAS	0
	Python_Course_Interest	1
	${\tt Foundations_DE_Course_Interest}$	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
                                        3
Graduate_Date
dtype: int64
```

0.1 Profile Analysis of Data Set

0.2 Analysis of Course Completion

profile.to_file()

```
In [12]: # Analysis of Course Completion
         # shorten the variable/column names for software preference variables
         survey_df = valid_survey_input.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'})
```

profile = pandas_profiling.ProfileReport(valid_survey_input)

print(pd.DataFrame.head(survey_df))

	My_Java	My_	JS 1	Му_Р	ython	My_I	R My	y_SAS	Prof_J	ava	Prof_	JS	\
${\tt RespondentID}$													
5135740122	0		0		0	50)	50		0		0	
5133300037	10		10		50	30)	0		25		25	
5132253300	20		0		40	40)	0		0		0	
5132096630	10		10		25	35	5	20		10		10	
5131990362	20		0		0	70)	10		20		0	
		_	_			~ . ~			_		~		
	Prof_Pyt	hon	Pro	t_R	Prof	_SAS		• • •	Р	REDI	CT453	\	
RespondentID		_						• • •					
5135740122		0		25		75		• • •			NaN		
5133300037		30		20		0		• • •			NaN		
5132253300		40		40		20		• • •			NaN		
5132096630		25		35		20		• • •			NaN		
5131990362		0		80		0		• • •			NaN		
	PREDICT4	54	PRED	ICT4	55 P	REDIC:	Г456	PRED	ICT457	Oth	erPyth	on	\
RespondentID	PREDICT4	54	PRED:	ICT4	55 P	REDIC	Γ456	PRED	ICT457	Oth	erPyth.	ion	\
RespondentID 5135740122		154 JaN	PRED:		55 P aN	REDIC'	Γ456 NaN	PRED	OICT457 NaN	Oth	·	ion IaN	\
•	N		PRED	N		REDIC:		PRED		Oth	N		\
5135740122	N N	IaN	PRED:	N N	aN	REDICT	NaN	PRED	NaN	Oth	N N	IaN	\
5135740122 5133300037	N N	IaN IaN	PRED	N N N	aN aN	REDICT	NaN NaN	PRED	NaN NaN	Oth	n N	IaN IaN	\
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5135740122 5133300037 5132253300 5132096630 5131990362 RespondentID	N N N N OtherR	JaN JaN JaN JaN	erSAS	N N N	aN aN aN aN		NaN NaN NaN NaN NaN		NaN NaN NaN NaN NaN	ıte	n n n	IaN IaN IaN IaN	\
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5135740122 5133300037 5132253300 5132096630 5131990362 RespondentID 5135740122 5133300037	N N OtherR NaN NaN	JaN JaN JaN JaN	erSAS NaN NaN	N N N	aN aN aN aN		NaN NaN NaN NaN ther	Grad Sp	NaN NaN NaN NaN Wate_Da	ite Jan 918	n n n	IaN IaN IaN IaN	\
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[5 rows x 40 columns]

Descriptive statistics for courses completed -----count 187.000000

```
6.342246
mean
           3.170849
std
           1.000000
min
25%
           4.000000
50%
           6.000000
           9.000000
75%
max
          12.000000
Name: Courses_Completed, dtype: float64
In [15]: #Summarize courses completed by displaying the number of students in each category
         courses_completed_counts = survey_df['Courses_Completed'].value_counts()
         print('\nThe number of courses completed by students: ')
         courses_completed_counts.sort_index()
The number of courses completed by students:
Out[15]: 1.0
                  6
         2.0
                 25
         3.0
                 13
         4.0
                 13
         5.0
                 24
         6.0
                 16
         7.0
                 24
         8.0
                 11
         9.0
                 14
         10.0
                 20
         11.0
                 11
         12.0
                 10
         Name: Courses_Completed, dtype: int64
In [16]: #Display the percentages of each course completed category
         print('\nPercentage of the Number of Courses Completed: ')
         ((courses_completed_counts/sum(courses_completed_counts))*100)
Percentage of the Number of Courses Completed:
Out[16]: 2.0
                 13.368984
         5.0
                 12.834225
         7.0
                 12.834225
         10.0
                 10.695187
         6.0
                  8.556150
         9.0
                  7.486631
         3.0
                  6.951872
```

4.0

6.951872

```
8.0
                  5.882353
         11.0
                  5.882353
         12.0
                  5.347594
         1.0
                  3.208556
         Name: Courses Completed, dtype: float64
In [17]: # Display the percentages of each course completed category
         # Another way to calculate
         print('\nPercentage of the Number of Courses Completed: ')
         survey df['Courses Completed'].value counts(normalize=True)*100
Percentage of the Number of Courses Completed:
Out[17]: 2.0
                 13.368984
         5.0
                 12.834225
         7.0
                 12.834225
         10.0
                10.695187
         6.0
                 8.556150
         9.0
                 7.486631
         3.0
                  6.951872
         4.0
                  6.951872
         8.0
                 5.882353
         11.0
                 5.882353
         12.0
                  5.347594
         1.0
                  3.208556
         Name: Courses_Completed, dtype: float64
In [18]: # Examine the number of courses completed by student with a bar graph
         %matplotlib inline
         course_completed_date_fig, ax = plt.subplots()
         sns.barplot(y = courses_completed_counts.values,
                      x = courses_completed_counts.index, alpha=0.8,
                      palette="Blues_d").set_title('Number of Courses Completed')
         ax.set_xlabel('Number of Courses', fontsize=12)
         ax.set_ylabel('Number of Students', fontsize=12)
         course_completed_date_fig.savefig('CourseCompleted' + '.pdf',
             bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
             orientation='portrait', papertype=None, format=None,
             transparent=True, pad inches=0.25, frameon=None)
```



25

20

15

10

5

2.0

class_completed_df.head()

RespondentID 5135740122

5133300037

5132253300 5132096630

5131990362

Out [20]:

3.0

4.0

1.0

Number of Students

6.0

Number of Courses

7.0

8.0

9.0

PREDICT400 \

NaN

NaN

10.0

11.0

PREDICT 400 Math for Modelers (Python)
PREDICT 400 Math for Modelers (Python)

PREDICT 400 Math for Modelers (Python)

		PREDIC	CT401 \
${\tt RespondentID}$			
5135740122	DD DD T GE 40.		NaN
5133300037		Introduction to Statistical Analy	
5132253300 5132096630		Introduction to Statistical Analy	
5131990362		Introduction to Statistical Analy Introduction to Statistical Analy	
0101930002	TILDIOT 40.	introduction to beatistical analy	, 5
		PREDIC	CT410 \
RespondentID			
5135740122	DD DD T GE 444		NaN
5133300037	PREDICT 410	Regression and Multivariate Analy	
5132253300 5132096630	DDEDICT 410	Pograggian and Multivariate Analy	NaN
5131990362		Regression and Multivariate Analy Regression and Multivariate Analy	
3131990302	TILEDICI 410	negression and Multivariate analy	, s
		PREDICT411 F	PREDICT413 \
${\tt RespondentID}$			
5135740122		NaN	NaN
5133300037	PREDICT 41:	Generalized Linear Models (SAS)	NaN
5132253300	DD IID T (III) 1.1.1	NaN (AAA)	NaN
5132096630		Generalized Linear Models (SAS)	NaN N-N
5131990362	PREDICT 41.	Generalized Linear Models (SAS)	NaN
		PREDIC	CT420 PREDICT422 \
RespondentID		PREDIC	CT420 PREDICT422 \
5135740122			NaN NaN
5135740122 5133300037		Database Systems and Data Prepara	NaN NaN at NaN
5135740122 5133300037 5132253300	PREDICT 420	Database Systems and Data Prepara Database Systems and Data Prepara	NaN NaN at NaN
5135740122 5133300037 5132253300 5132096630	PREDICT 420	Database Systems and Data Prepara	NaN NaN at NaN at NaN
5135740122 5133300037 5132253300	PREDICT 420	Database Systems and Data Prepara Database Systems and Data Prepara	NaN NaN at NaN
5135740122 5133300037 5132253300 5132096630	PREDICT 420 PREDICT 420	Database Systems and Data Prepara Database Systems and Data Prepara	NaN NaN at NaN at NaN at NaN NaN NaN
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5135740122 5133300037 5132253300 5132096630 5131990362 RespondentID 5135740122 5133300037 5132253300 5132096630 5131990362 RespondentID	PREDICT 420 PREDICT 420 PREDICT450 I NaN NaN NaN NaN NaN PREDICT455 I	Database Systems and Data Prepara Database Systems and Data Prepara Database Systems and Data Prepara REDICT451 PREDICT452 PREDICT453 PR NaN NaN NaN NaN NaN NaN NaN NaN NaN Na	NaN NaN at NaN at NaN nat NaN
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5135740122 5133300037 5132253300 5132096630 5131990362 RespondentID 5135740122 5133300037 5132253300 5132096630 5131990362 RespondentID 5135740122 5133300037	PREDICT 420 PREDICT 420 PREDICT450 I NaN NaN NaN NaN NaN PREDICT455 I NaN NaN	Database Systems and Data Prepara Database Systems and Data Prepara Database Systems and Data Prepara REDICT451 PREDICT452 PREDICT453 PR NaN NaN NaN NaN NaN NaN NaN NaN NaN Na	NaN NaN at NaN at NaN nat NaN

The number of respondents that have completed the following courses:

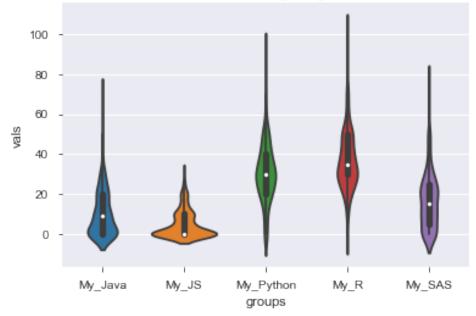
```
Out[21]: PREDICT401
                       171
         PREDICT400
                       163
         PREDICT410
                       145
         PREDICT420
                       127
         PREDICT411
                       113
         PREDICT413
                       59
         PREDICT422
                        48
         PREDICT455
                        30
         PREDICT450
                        17
         PREDICT452
                        13
         PREDICT453
                        11
         PREDICT451
                         7
         PREDICT456
                         6
         PREDICT454
                         5
         PREDICT457
                         4
         dtype: int64
```

0.3 Analysis of Software Preference, Part I

Out[22]:		${ t My_Java}$	My_JS	My_Python	My_R	My_SAS
	count	207.000000	207.000000	207.000000	207.000000	207.000000
	mean	10.135266	4.797101	31.304348	37.125604	16.637681
	std	11.383477	6.757764	15.570982	14.576003	13.626400
	min	0.000000	0.000000	0.000000	0.000000	0.000000
	25%	0.000000	0.000000	20.000000	30.000000	5.000000
	50%	9.000000	0.000000	30.000000	35.000000	15.000000
	75%	20.000000	10.000000	40.000000	50.000000	25.000000
	max	70.000000	30.000000	90.000000	100.000000	75.000000

```
In [23]: # Place the columns for respondent desire to learn for each
         # of the five language/software options into a new data frame.
         # The dataframe columns are 'melted' together in order to examine in
         # a type of boxplot called a violinplot.
         # The shape in a violinplot demonstrates the distribution of the data.
         # The columns for respondent desire to learn each of the
         # five language/software options were examined.
         personal_df = survey_df.iloc[:,0:5]
         personal melted df = personal_df.melt(var_name='groups', value name='vals')
         personal_desire_learn_fig, ax = plt.subplots()
         sns.violinplot(x="groups", y="vals", data=personal_melted_df)
         ax.set_title('Personal Desire to Learn Language or Software System', fontsize=18)
         personal_desire_learn_fig.savefig('PersonalDesireToLearn' + '.pdf',
             bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
             orientation='portrait', papertype=None, format=None,
             transparent=True, pad inches=0.25, frameon=None)
```

Personal Desire to Learn Language or Software System



```
207.000000
                            207.000000
                                         207.000000
                                                      207.000000
                                                                  207.000000
         count
                  9.251208
                              5.840580
                                          30.028986
                                                       36.415459
                                                                   18.463768
         mean
         std
                 13.167505
                             10.812555
                                          19.144802
                                                       20.847606
                                                                   18.831841
                                           0.000000
                                                       0.000000
         min
                  0.000000
                              0.000000
                                                                    0.000000
         25%
                  0.000000
                              0.000000
                                          20.000000
                                                       25.000000
                                                                    0.00000
         50%
                  5.000000
                              0.000000
                                          30.000000
                                                       33.000000
                                                                   15.000000
         75%
                 15.000000
                             10.000000
                                          40.000000
                                                       50.000000
                                                                   30.000000
                 80.000000 100.000000
                                         100.000000
                                                      100.000000 100.000000
         max
In [25]: # Place the columns for respondent professional need to learn for each
         # of the five language/software options into a new data frame.
         # The dataframe columns are 'melted' together in order to examine in
         # a type of boxplot called a violinplot.
         # The shape in a violinplot demonstrates the distribution of the data.
         # The columns for respondent professional need to learn each of the
         # five language/software options were examined.
         professional_df = survey_df.iloc[:,5:10]
         professional melted df = professional df.melt(var name='groups', value name='vals')
         professional_need_learn_fig, ax = plt.subplots()
         sns.violinplot(x="groups", y="vals", data=professional melted df)
         ax.set_title('Professional Need to Learn Language or Software System', fontsize=18)
         professional need learn fig.savefig('ProfessionalNeedToLearn' + '.pdf',
             bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
             orientation='portrait', papertype=None, format=None,
             transparent=True, pad inches=0.25, frameon=None)
```

Prof_JS Prof_Python

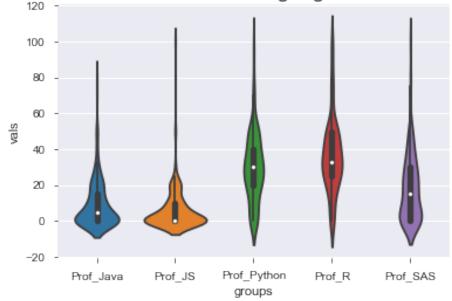
Prof R

Prof_SAS

Out [24]:

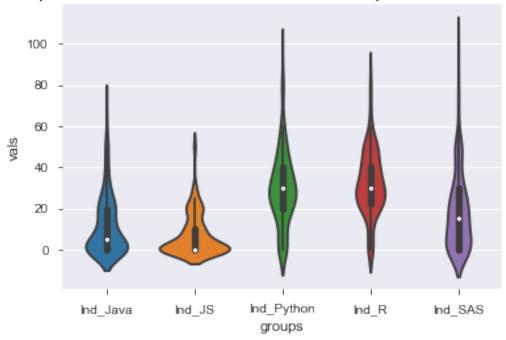
Prof_Java

Professional Need to Learn Language or Software System



```
In [26]: # Examine the columns for respondent industry importance and prevalence to learn
         # for each of the five language/software options.
         # The describe function provides a basic statistical analysis.
        survey_df.iloc[:,10:15].describe()
Out [26]:
                 Ind_Java
                               Ind_JS Ind_Python
                                                        Ind_R
                                                                  Ind_SAS
        count 207.000000 207.000000 207.000000 207.000000 207.000000
                11.942029
                             6.966184
                                        29.772947
                                                    32.434783
                                                                18.884058
        mean
        std
                14.706399 10.030721 17.959816
                                                    15.912209
                                                               19.137623
        min
                0.000000
                           0.000000
                                        0.000000
                                                     0.000000
                                                               0.000000
        25%
                 0.000000
                           0.000000
                                        20.000000
                                                    22.500000
                                                               0.000000
        50%
                                                    30.000000
                 5.000000
                            0.000000
                                        30.000000
                                                                15.000000
        75%
                20.000000
                            10.000000
                                        40.000000
                                                    40.000000
                                                                30.000000
        max
                70.000000
                            50.000000
                                        95.000000
                                                    85.000000 100.000000
In [27]: # Place the columns for respondent industry importance and prevalence to learn for ea
         # of the five language/software options into a new data frame.
         # The dataframe columns are 'melted' together in order to examine in
         # a type of boxplot called a violinplot.
         # The shape in a violinplot demonstrates the distribution of the data.
        # The columns for respondent industry importance and prevalence to learn
        # each of the five language/software options were examined.
        industry_df = survey_df.iloc[:,10:15]
        industry_melted_df = industry_df.melt(var_name='groups', value_name='vals')
        industry_importance_fig, ax = plt.subplots()
        sns.violinplot(x="groups", y="vals", data=industry_melted_df)
        ax.set_title('Importance and Prevalence in Respondent Industry', fontsize=18)
        industry_importance_fig.savefig('IndustryImportance' + '.pdf',
            bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
             orientation='portrait', papertype=None, format=None,
            transparent=True, pad_inches=0.25, frameon=None)
```

Importance and Prevalence in Respondent Industry

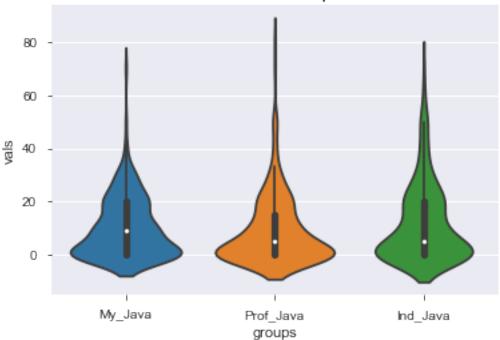


In [28]: # Examining the Java/Scala/Spark responses

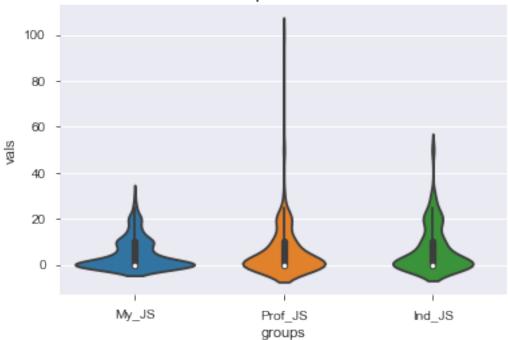
```
java_df = survey_df.iloc[:,[0,5,10]]
java_melted_df = java_df.melt(var_name='groups', value_name='vals')

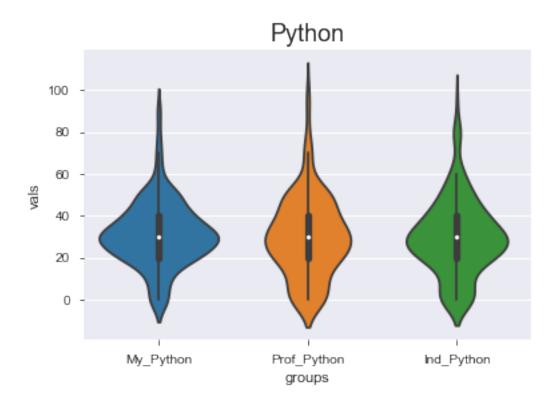
java_scala_spark_fig, ax = plt.subplots()
sns.violinplot(x="groups", y="vals", data=java_melted_df)
ax.set_title('Java/Scala/Spark', fontsize=18)
java_scala_spark_fig.savefig('JavaScalaSpark' + '.pdf',
    bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
    orientation='portrait', papertype=None, format=None,
    transparent=True, pad_inches=0.25, frameon=None)
```

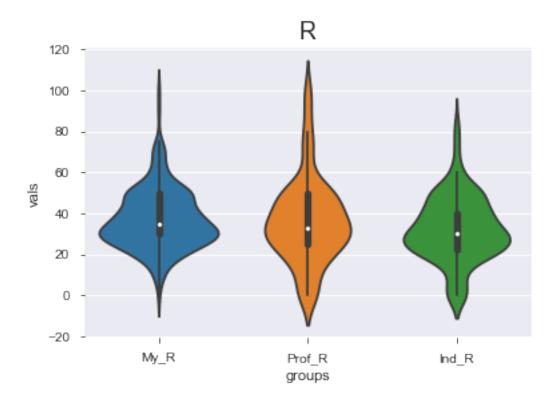
Java/Scala/Spark

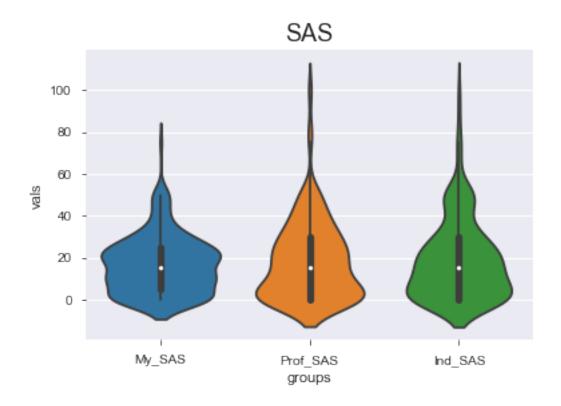


JavaScript/HTML/CSS









0.4 Analysis of Software Preference, Part II

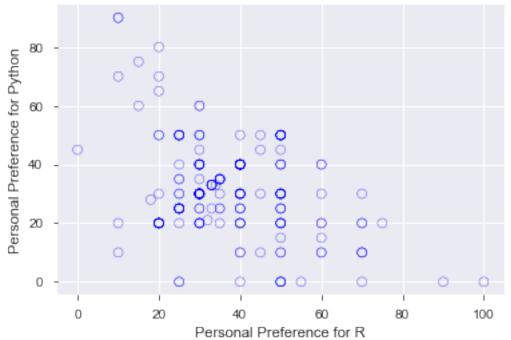
	My_Java	My_JS	My_P	ython	My_F	R My_SAS	Prof_Ja	va	Prof_JS	\
${\tt RespondentID}$										
5135740122	0	0		0	50	50		0	0	
5133300037	10	10		50	30	0		25	25	
5132253300	20	0		40	40	0		0	0	
5132096630	10	10		25	35	5 20		10	10	
5131990362	20	0		0	70	10		20	0	
	Prof_Pyt	hon Pr	of_R	Prof_	SAS	${\tt Ind_Java}$	${\tt Ind_JS}$	In	d_Python	\
${\tt RespondentID}$										
5135740122		0	25		75	0	0		0	
5133300037		30	20		0	20	25		40	
5132253300		40	40		20	30	0		30	
5132096630		25	35		20	10	10		25	

513199	0362	0	80	0 40	0	0	
	Ind	D Ind CAC					
Pognon	Ind_ dentID	R Ind_SAS					
513574		50 50					
513330		.5 0					
513225		.0 0					
513209		5 20					
513199		50 0					
010100	0002	.0					
In [35	_	tive statist					
	_	Descriptive :		or survey da	ta	')	
	print(sof	tware_df.des	cribe())				
Descri	ntive statis	tics for surv	vev data				
DCBCII	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		
	10.812555	19.144802	20.847606	18.831841	14.706399		
std				0.000000			
min	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		30.000000	20.000000		
max	100.000000	100.000000	100.000000	100.000000	70.000000		
	T J TC	To d Dooth on	T J. D.	T 3 CAC			
	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			

In [36]: # single scatter plot example

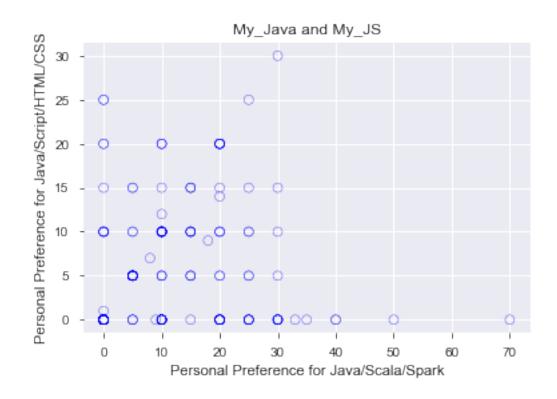
```
fig, axis = plt.subplots()
axis.set_xlabel('Personal Preference for R')
axis.set_ylabel('Personal Preference for Python')
plt.title('R and Python Perferences')
scatter_plot = axis.scatter(survey_df['My_R'],
    survey_df['My_Python'],
    facecolors = 'none',
    edgecolors = 'blue')
plt.savefig('plot-scatter-r-python.pdf',
    bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
    orientation='portrait', papertype=None, format=None,
    transparent=True, pad_inches=0.25, frameon=None)
```

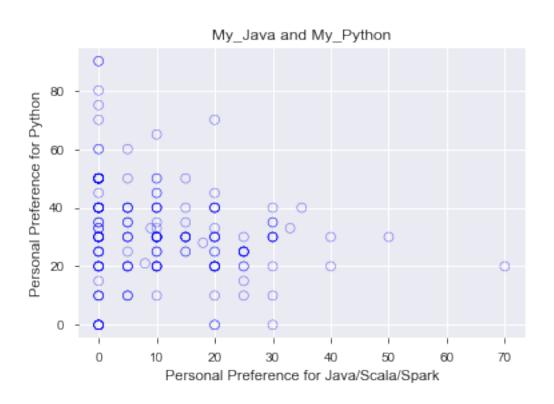
R and Python Perferences

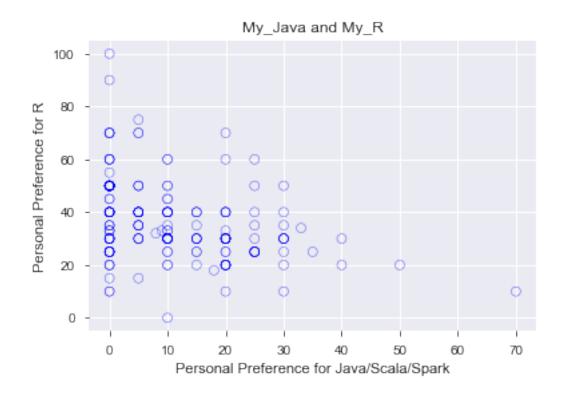


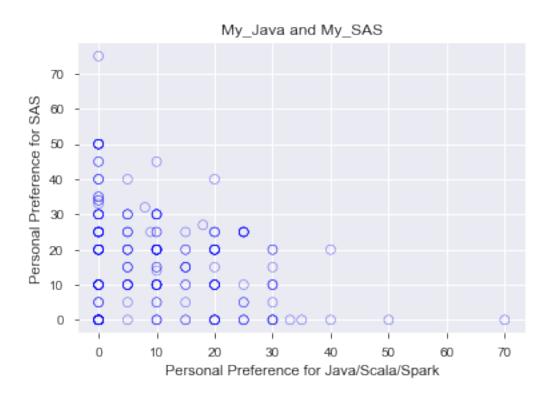
```
survey_df_labels = [
    'Personal Preference for Java/Scala/Spark',
    'Personal Preference for Java/Script/HTML/CSS',
    'Personal Preference for Python',
    'Personal Preference for R',
    'Personal Preference for SAS',
    'Professional Java/Scala/Spark',
    'Professional JavaScript/HTML/CSS',
```

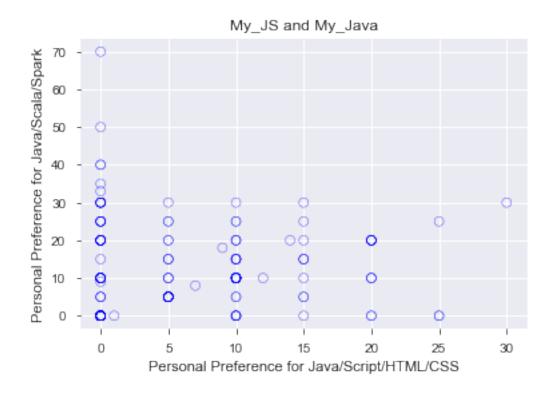
```
'Professional Python',
             'Professional R',
             'Professional SAS',
             'Industry Java/Scala/Spark',
             'Industry Java/Script/HTML/CSS',
             'Industry Python',
             'Industry R',
             'Industry SAS'
         ]
In [38]: # create a set of scatter plots for personal preferences
         for i in range(5):
             for j in range(5):
                 if i != j:
                     file_title = survey_df.columns[i] + '_and_' + survey_df.columns[j]
                     plot_title = survey_df.columns[i] + ' and ' + survey_df.columns[j]
                     fig, axis = plt.subplots()
                     axis.set_xlabel(survey_df_labels[i])
                     axis.set_ylabel(survey_df_labels[j])
                     plt.title(plot_title)
                     scatter_plot = axis.scatter(survey_df[survey_df.columns[i]],
                     survey_df[survey_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)
```

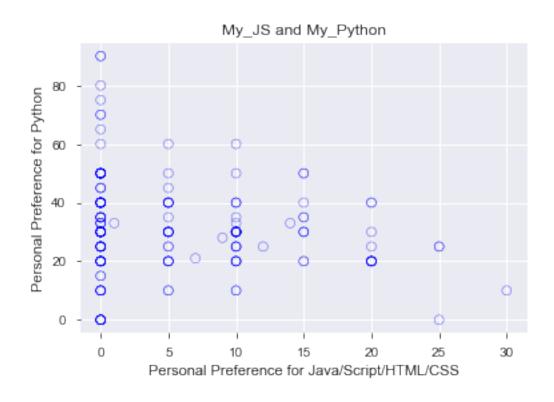


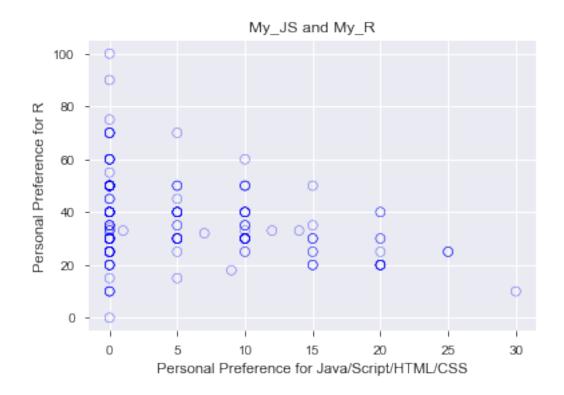


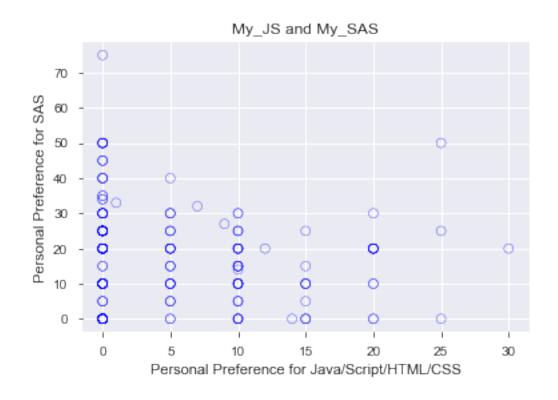


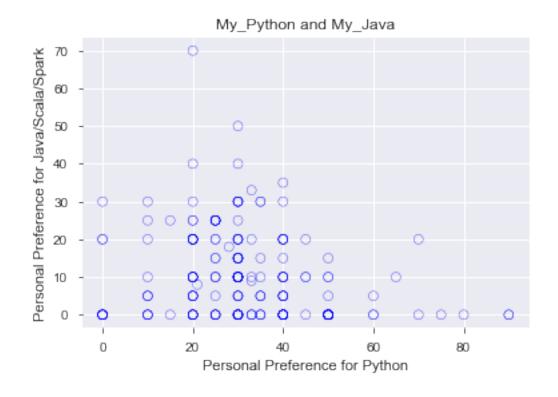


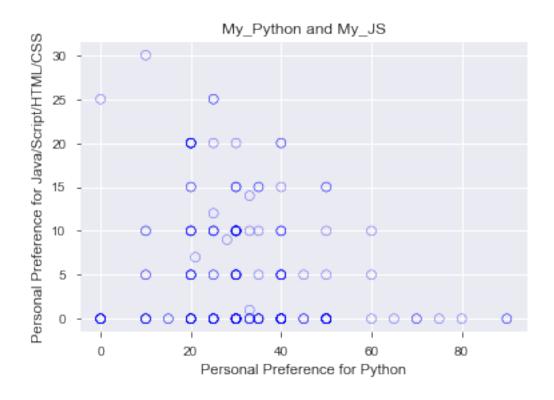


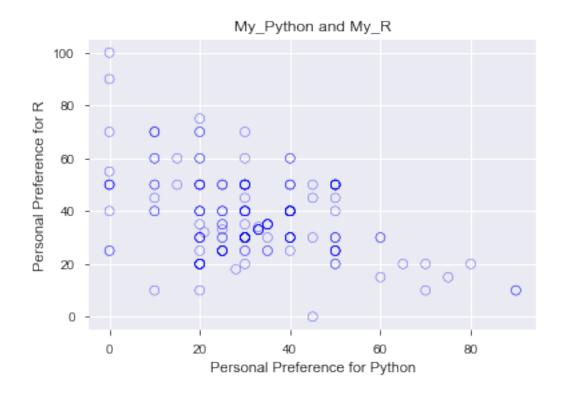


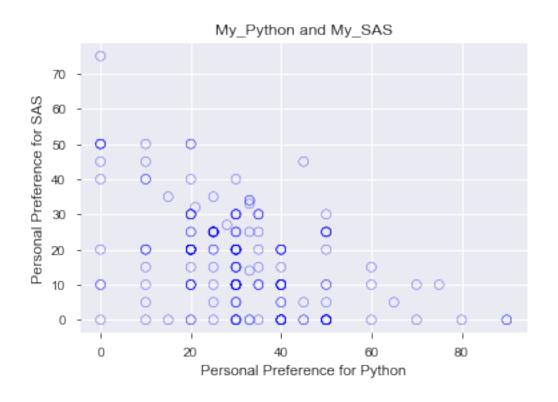


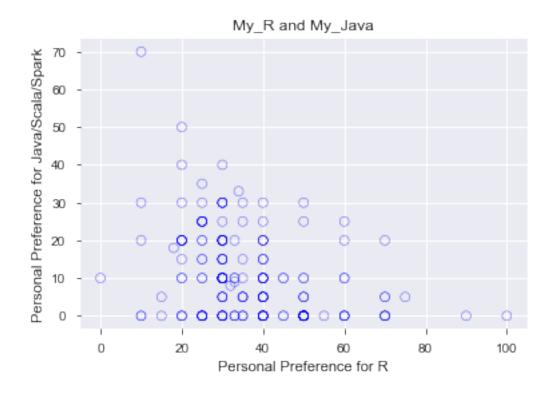


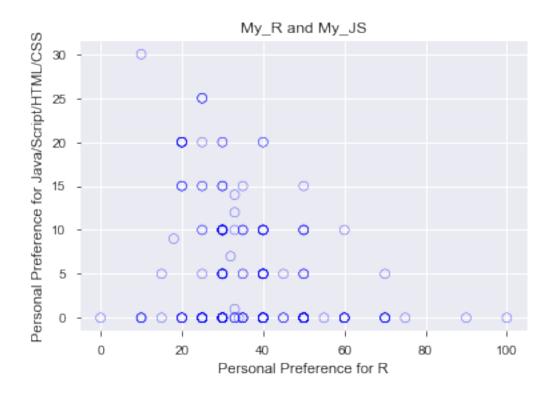


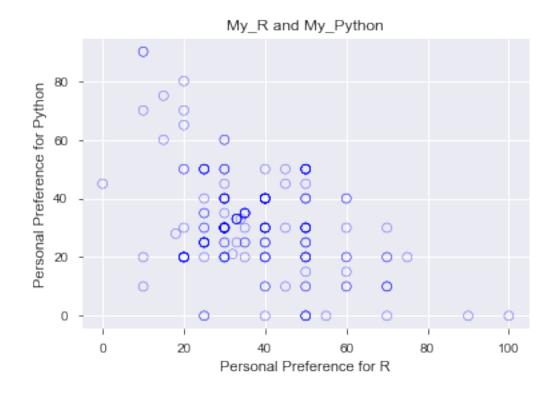


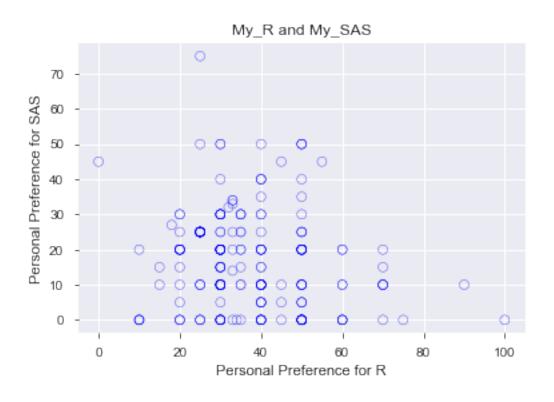


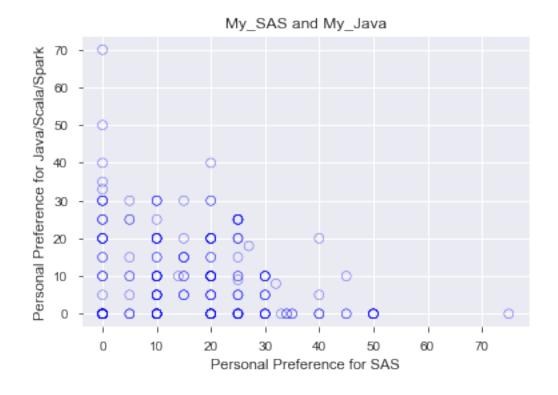


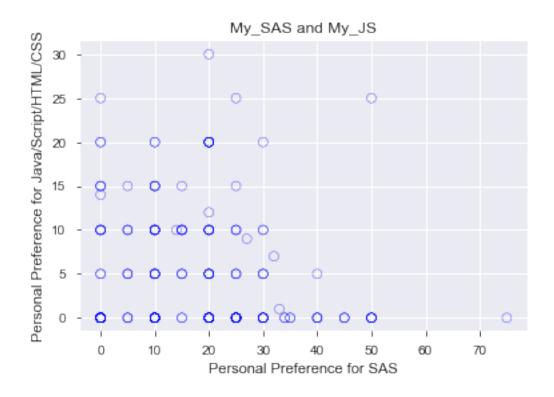


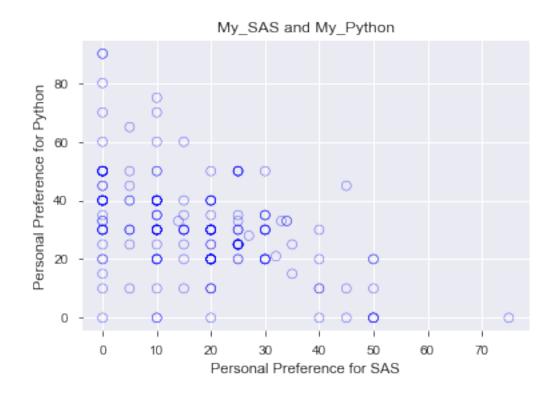


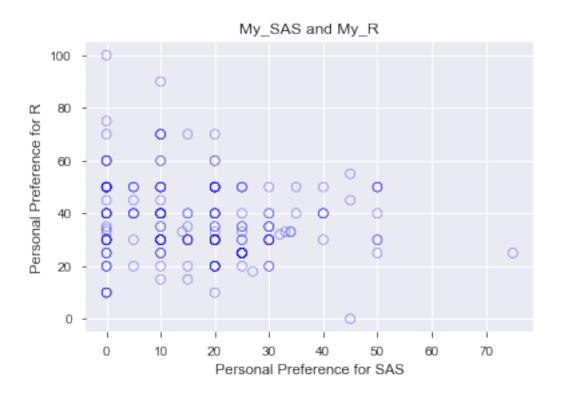




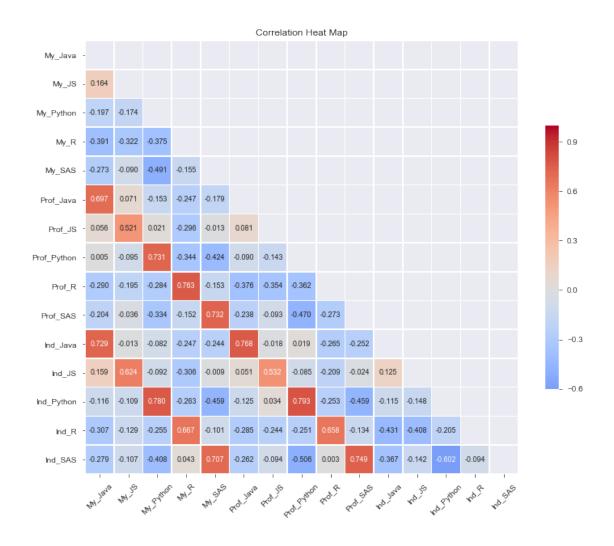








<Figure size 432x288 with 0 Axes>



Out[40]:	My_Java	1.000000
	Ind_Java	0.728855
	Prof_Java	0.697135
	My_JS	0.164302
	Ind_JS	0.158573
	Prof_JS	0.056456
	Prof_Python	0.004771

```
Ind_Python
              -0.115839
My_Python
              -0.197282
Prof_SAS
              -0.203620
My_SAS
              -0.273014
Ind SAS
              -0.278953
Prof R
              -0.290046
Ind R
              -0.307342
My_R
              -0.391172
Name: My_Java, dtype: float64
```

0.5 Analysis of New Course Interest and Graduation Date

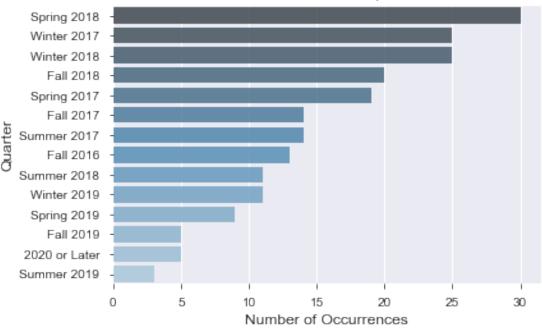
```
In [41]: # A new dataframe will be created to examine the relationship between
         # course interest and expected graduation date.
         # Select the graduation date column
         example = survey_df.Graduate_Date
         # Select the columns for course interest
         example_2 = survey_df.iloc[:,15:19]
         # Combine the two into a new dataframe and show the first five rows
         interest_grad_date_df = pd.concat([example_2, example], axis=1, sort=False)
         print(interest_grad_date_df.head())
              Python_Course_Interest Foundations_DE_Course_Interest \
RespondentID
5135740122
                                50.0
                                                                 90.0
                                20.0
                                                                 50.0
5133300037
5132253300
                               100.0
                                                                 70.0
5132096630
                                85.0
                                                                 60.0
                                60.0
5131990362
                                                                 10.0
              Analytics_App_Course_Interest Systems_Analysis_Course_Interest \
RespondentID
5135740122
                                        51.0
                                                                           50.0
                                        90.0
                                                                           50.0
5133300037
                                       100.0
                                                                           60.0
5132253300
5132096630
                                        90.0
                                                                           82.0
5131990362
                                        40.0
                                                                          80.0
             Graduate_Date
RespondentID
5135740122
                       NaN
5133300037
               Spring 2018
5132253300
                 Fall 2018
                 Fall 2017
5132096630
```

5131990362

Fall 2018

```
In [42]: # Examing the dataframe by grouping by graduation date
         # and checking that this works.
         interest_grad_date_df.groupby(['Graduate_Date']).groups.keys()
         # Out: dict_keys(['2020 or Later', 'Fall 2016', 'Fall 2017', 'Fall 2018',
         # 'Fall 2019', 'Spring 2017', 'Spring 2018', 'Spring 2019', 'Summer 2017', 'Summer 20
         # 'Summer 2019', 'Winter 2017', 'Winter 2018', 'Winter 2019'])
Out[42]: dict_keys(['2020 or Later', 'Fall 2016', 'Fall 2017', 'Fall 2018', 'Fall 2019', 'Spri:
In [43]: # Examing the dataframe by grouping by graduation date
         # and checking that this works.
         len(interest_grad_date_df.groupby(['Graduate_Date']).groups['Fall 2018'])
         #Out: 20
Out[43]: 20
In [44]: # Examine the number of respondents by graduation date
         graduate_date_counts = survey_df.Graduate_Date.value_counts()
         print('\nCount of students by graduation date: ')
         graduate_date_counts
Count of students by graduation date:
Out [44]: Spring 2018
                          30
         Winter 2017
                          25
         Winter 2018
                          25
        Fall 2018
                          20
         Spring 2017
                          19
         Fall 2017
                          14
         Summer 2017
                          14
         Fall 2016
                          13
         Summer 2018
                          11
         Winter 2019
                          11
         Spring 2019
                           9
         Fall 2019
                           5
         2020 or Later
                           5
         Summer 2019
                           3
         Name: Graduate_Date, dtype: int64
In [45]: # Examine the number of respondents by graduation date in bar chart
         graduation_date_fig, ax = plt.subplots()
```

Graduation Date of Respondents



```
In [46]: # Examing the dataframe by grouping by graduation date.
         # The count (number of respondents), min, max, and mean
         # for each course interest question was evaluated.
         interest_grad_date_df.groupby(['Graduate_Date']).agg(
             {# find the count min, max, and mean of each course interest column
                 'Python_Course_Interest': ['count', min, max, 'mean'],
                 'Foundations DE Course Interest': ['count', min, max, 'mean'],
                 'Analytics_App_Course_Interest': ['count', min, max, 'mean'],
                 'Systems_Analysis_Course_Interest': ['count', min, max, 'mean']})
Out [46]:
                       Python_Course_Interest
                                        count
                                                 min
                                                                    mean
                                                        max
         Graduate_Date
         2020 or Later
                                                35.0 100.0
                                                               82.400000
```

Fall 2016 Fall 2017 Fall 2018 Fall 2019 Spring 2017 Spring 2018 Spring 2019 Summer 2017 Summer 2018 Summer 2019 Winter 2017 Winter 2018 Winter 2019	1: 3: 1: 1:	4 30.0 0 15.0 5 83.0 8 12.0 0 0.0 9 30.0 4 0.0 1 0.0 3 100.0 5 0.0 5 5.0	100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0	76.92 85.00 76.80 91.80 70.16 70.20 77.00 74.64 73.36 100.00 63.52 68.60 73.90	0000 0000 0000 6667 0000 0000 2857 3636 0000 0000	
	Foundations_DE_Course	Interest				\
		count	min	max	mean	`
Graduate_Date 2020 or Later Fall 2016 Fall 2017 Fall 2018 Fall 2019 Spring 2017 Spring 2018 Spring 2019 Summer 2017 Summer 2018 Summer 2019 Winter 2017 Winter 2018 Winter 2019		4 12 14 19 5 18 30 9 14 9 3 25 24	10.0 51.0 18.0 0.0 25.0 0.0 0.0 64.0	95.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0	61.250000 70.250000 49.142857 58.894737 80.600000 70.444444 55.200000 62.666667 57.500000 53.666667 88.000000 49.920000 50.833333 56.636364	
	Analytics_App_Course_	Interest count	min	max	mean	\
Graduate_Date 2020 or Later Fall 2016 Fall 2017 Fall 2018 Fall 2019 Spring 2017 Spring 2018 Spring 2019 Summer 2017 Summer 2018 Summer 2019 Winter 2017		5 13 14 19 5 17 30 9 14 10 3 25	50.0 0.0 0.0 10.0 20.0 20.0 0.0 30.0 0.0 100.0	90.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0 100.0	72.200000 52.307692 60.714286 58.210526 60.200000 59.058824 49.133333 66.666667 59.214286 50.500000 100.000000 43.120000	
Winter 2018		25	0.0	100.0	61.800000	

Systems_Analysis_Course_Interest

count	min	max	mean
5	10.0	70.0	32.000000
13	3.0	100.0	59.307692
14	0.0	100.0	61.785714
18	0.0	100.0	56.611111
5	10.0	100.0	55.400000
18	4.0	100.0	55.111111
29	0.0	100.0	48.689655
9	30.0	100.0	77.333333
14	0.0	100.0	52.857143
9	0.0	100.0	45.555556
3	90.0	100.0	96.666667
25	0.0	100.0	40.400000
25	0.0	100.0	54.280000
10	0.0	100.0	55.700000
	5 13 14 18 5 18 29 9 14 9 3 25	5 10.0 13 3.0 14 0.0 18 0.0 5 10.0 18 4.0 29 0.0 9 30.0 14 0.0 9 0.0 3 90.0 25 0.0	5 10.0 70.0 13 3.0 100.0 14 0.0 100.0 18 0.0 100.0 5 10.0 100.0 29 0.0 100.0 9 30.0 100.0 9 0.0 100.0 9 0.0 100.0 3 90.0 100.0 25 0.0 100.0 25 0.0 100.0

Out[47]: Python_Course_Interest Foundations_DE_Course_Interest \

	mean	mean
<pre>Graduate_Date</pre>		
2020 or Later	82.400000	61.250000
Fall 2016	76.923077	70.250000
Fall 2017	85.000000	49.142857
Fall 2018	76.800000	58.894737
Fall 2019	91.800000	80.600000
Spring 2017	70.166667	70.44444
Spring 2018	70.200000	55.200000
Spring 2019	77.000000	62.666667
Summer 2017	74.642857	57.500000
Summer 2018	73.363636	53.666667
Summer 2019	100.000000	88.00000
Winter 2017	63.520000	49.920000
Winter 2018	68.600000	50.833333
Winter 2019	73.909091	56.636364

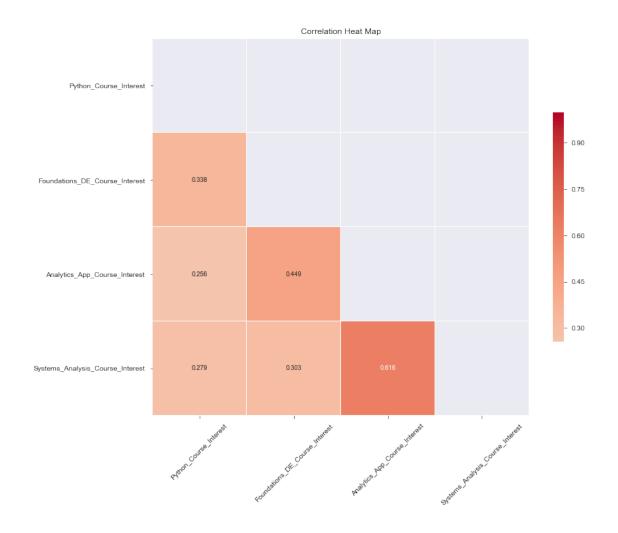
Analytics_App_Course_Interest Systems_Analysis_Course_Interest mean mean Graduate_Date 2020 or Later 72.200000 32.000000 Fall 2016 52.307692 59.307692 Fall 2017 60.714286 61.785714 Fall 2018 58.210526 56.611111 Fall 2019 60.200000 55.400000 Spring 2017 59.058824 55.111111 Spring 2018 49.133333 48.689655 Spring 2019 66.66667 77.333333 Summer 2017 59.214286 52.857143 Summer 2018 50.500000 45.55556 Summer 2019 100.000000 96.666667 Winter 2017 43.120000 40.400000 Winter 2018 61.800000 54.280000 Winter 2019 55.700000

43.818182

0.6 Analysis of Course Interest

```
In [48]: # Is there any correlation between interest in classes
         corr_chart(df_corr = interest_grad_date_df)
```

<Figure size 432x288 with 0 Axes>



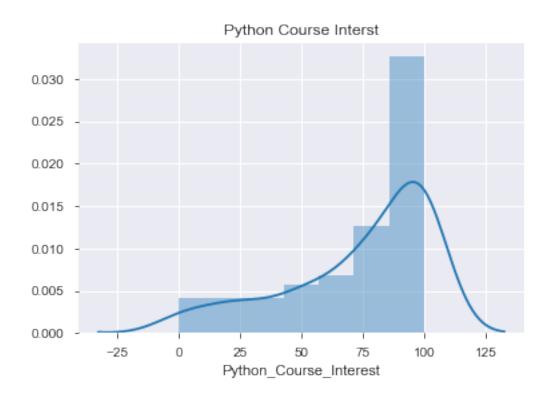
Out[49]:	Python_Course_Interest	Foundations_DE_Course_Interest \
count	206.000000	200.000000
mean	73.529126	58.045000
std	29.835429	32.588079
min	0.00000	0.000000
25%	53.000000	29.500000
50%	82.500000	60.000000
75%	100.000000	89.250000
max	100.000000	100.000000

Analytics_App_Course_Interest Systems_Analysis_Course_Interest count 203.000000 200.000000

mean	55.201970	53.630000
std	34.147954	33.539493
min	0.00000	0.000000
25%	25.000000	21.500000
50%	60.000000	51.500000
75%	85.000000	80.250000
max	100.000000	100.000000

In [50]: # $\it Examining the python course interest distribution$

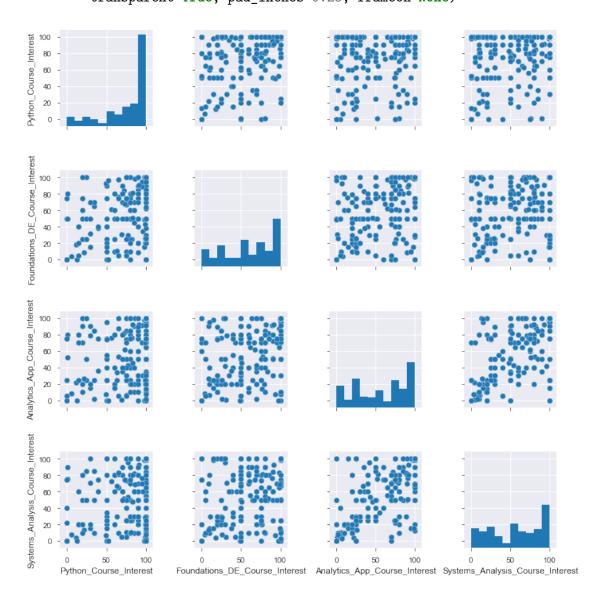
```
python_course_interst_fig, ax = plt.subplots()
sns.distplot(what_df.Python_Course_Interest.dropna()).set_title('Python Course Inters'
python_course_interst_fig.savefig('PythonCourseInterest' + '.pdf',
    bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
    orientation='portrait', papertype=None, format=None,
    transparent=True, pad_inches=0.25, frameon=None)
```



In [51]: # Examining the course interest between the four courses via pairplot

```
course_interest_pairplot_fig = sns.pairplot(what_df.dropna())
course_interest_pairplot_fig.savefig('CourseInterestPairplot' + '.pdf',
```

```
bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
orientation='portrait', papertype=None, format=None,
transparent=True, pad_inches=0.25, frameon=None)
```



0.7 Transformations

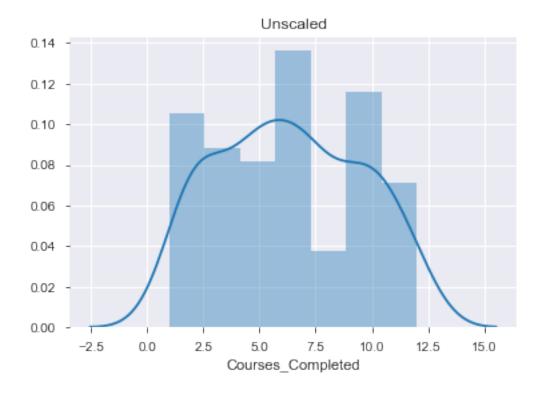
```
In [52]: # ------
    # transformation code added with version v005
    # -------
    # transformations a la Scikit Learn
    # documentation at http://scikit-learn.org/stable/auto_examples/
    # preprocessing/plot_all_scaling.html#sphx-glr-auto-
    # examples-preprocessing-plot-all-scaling-py
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

# transformations a la Scikit Learn
# select variable to examine, eliminating missing data codes
X = survey_df['Courses_Completed'].dropna()

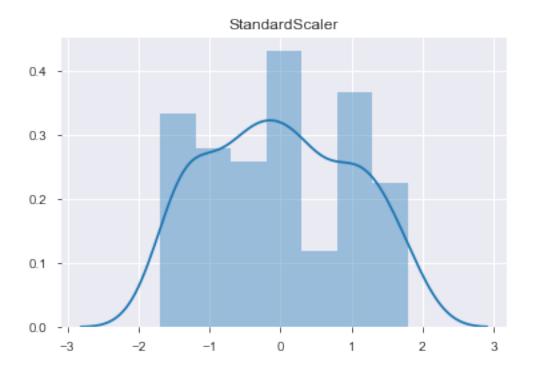
# Seaborn provides a convenient way to show the effects of transformations
# on the distribution of values being transformed
# Documentation at https://seaborn.pydata.org/generated/seaborn.distplot.html

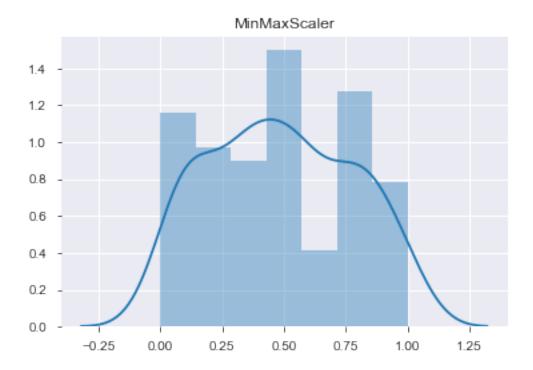
unscaled_fig, ax = plt.subplots()
sns.distplot(X).set_title('Unscaled')
unscaled_fig.savefig('Transformation-Unscaled' + '.pdf',
    bbox_inches = 'tight', dpi=None, facecolor='w', edgecolor='b',
    orientation='portrait', papertype=None, format=None,
    transparent=True, pad_inches=0.25, frameon=None)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

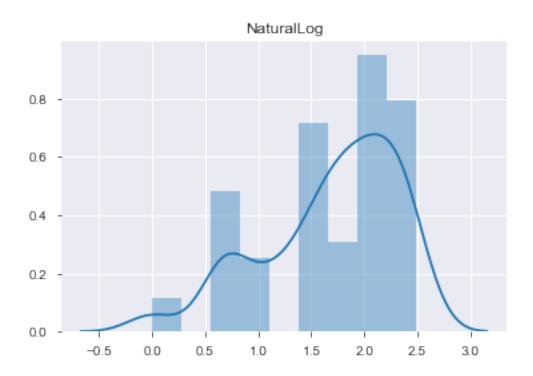


In [53]: # Reshape your data either using array.reshape(-1, 1) if your data has a single featu # or array.reshape(1, -1) if it contains a single sample.

```
X = X.values.reshape(-1, 1)
standard_fig, ax = plt.subplots()
sns.distplot(StandardScaler().fit_transform(X)).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)
```







0.8 Transformation of Selected Variable

```
In [56]: # Get rid of NaN values
    P = survey_df['Python_Course_Interest'].dropna()
    # Change zero to 1 so in transformation will work
    P[P == 0] = 1

# 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

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

