Untitled7

June 24, 2020

```
In [1]: %matplotlib inline
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        import pandas as pd
In [2]: #reading csv file using pandas
        da = pd.read_csv("nhanes_2015_2016.csv")
In [3]: #value_counts is used to determine the number of time each dat has appeared distinctly
        da.DMDEDUC2.value_counts()
Out[3]: 4.0
               1621
        5.0
               1366
        3.0
               1186
        1.0
                655
        2.0
                643
        9.0
        Name: DMDEDUC2, dtype: int64
In [5]: #use of sum function, manually summing and determining the shape
        print(da.DMDEDUC2.value_counts().sum())
        print(1621+ 1366+ 1186+ 655+ 643+3)
        print(da.shape)
5474
5474
(5735, 28)
In [6]: #isnull function used to locate all the null values and later determine how many null
        pd.isnull(da.DMDEDUC2).sum()
Out[6]: 261
In [7]: # replacing the values and then countiing the results using replace
        da["DMDEDUC2x"] = da.DMDEDUC2.replace({1: "<9", 2: "9-11", 3: "HS/GED", 4: "Some college"
                                                7: "Refused", 9: "Don't know"})
        da.DMDEDUC2x.value_counts()
```

```
Out[7]: Some college/AA
                           1621
        College
                           1366
        HS/GED
                           1186
        <9
                            655
        9-11
                            643
        Don't know
        Name: DMDEDUC2x, dtype: int64
In [9]: da["RIAGENDRx"] = da.RIAGENDR.replace({1:"Male", 2:"Female" })
        da.RIAGENDRx.value counts()
Out[9]: Female
                  2976
        Male
                  2759
        Name: RIAGENDRx, dtype: int64
In [13]: # using proportions in x
         x = da.DMDEDUC2x.value_counts()
         (x / x.sum())
Out[13]: Some college/AA
                            0.296127
         College
                            0.249543
         HS/GED
                            0.216661
         <9
                            0.119657
         9-11
                            0.117464
                            0.000548
         Don't know
         Name: DMDEDUC2x, dtype: float64
In [14]: # using percentage in x
         x = da.DMDEDUC2x.value_counts()
         (x / x.sum())*100
Out[14]: Some college/AA
                            29.612715
                            24.954330
         College
         HS/GED
                            21.666058
         <9
                            11.965656
         9-11
                            11.746438
         Don't know
                             0.054805
         Name: DMDEDUC2x, dtype: float64
In [15]: # missing is now created as another category and is renamed using "fillna"
         # the result shows that "missing" is 4.6%
         da["DMDEDUC2x"] = da.DMDEDUC2.fillna("Missing")
         x = da.DMDEDUC2x.value_counts()
         (x / x.sum())*100
Out[15]: 4.0
                    28.265039
        5.0
                    23.818657
         3.0
                    20.680035
         1.0
                   11.421099
```

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Missing
                     4.551003
         9.0
                     0.052310
         Name: DMDEDUC2x, dtype: float64
In [17]: #quick way of getting numerical summaries in quantitative data using describe an drop
         #you can interchange describe and dropna they will yield similar results
         da.BMXWT.describe().dropna()
Out[17]: count
                  5666.000000
                    81.342676
         mean
         std
                    21.764409
         min
                    32.400000
         25%
                    65.900000
         50%
                    78.200000
         75%
                    92,700000
         max
                   198.900000
         Name: BMXWT, dtype: float64
In [25]: #individual summary statistics for one dataset using pandas and numpy
         x = da.BMXWT.dropna() # extract all the missing data in dropna
         print(x.mean()) #pandas method
         print(np.mean(x)) # using numpy(put the 'x' in bracket as it can lead to error)
         print(x.median()) #pandas method to get median
         print(np.median(x)) #numpy method to get median
         print(np.percentile(x, 50)) # same as median(numpy)
         print(np.percentile(x, 75)) # to get 75 percentile(numpy)
         print(x.quantile(0.75)) #here quantile is used to get 75 percentile(pandas)
81.34267560889516
81.34267560889516
78.2
78.2
78.2
92.7
92.7
In [26]: #frequencies for a systolic blood pressure measurement (BPXSY1).
         #"BPX" here is the NHANES prefix for blood pressure measurements.
         #"SY" stands for "systolic" blood pressure (blood pressure at the peak of a heartbeat
         #"1" indicates that this is the first of three systolic blood presure measurements ta
         #A person is generally considered to have pre-hypertension when their systolic blood
         #Considering only the systolic condition, we can calculate the proprotion of the NHAN.
         np.mean((da.BPXSY1 >= 120) & (da.BPXSY2 <= 139))
Out[26]: 0.3741935483870968
```

2.0

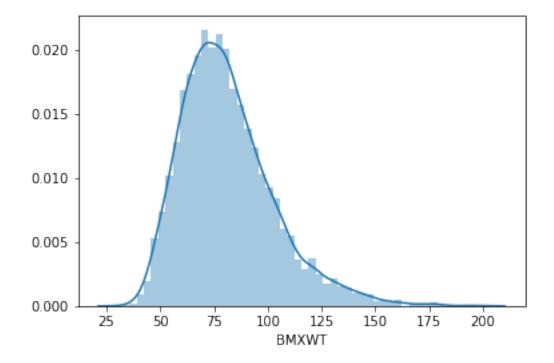
11.211857

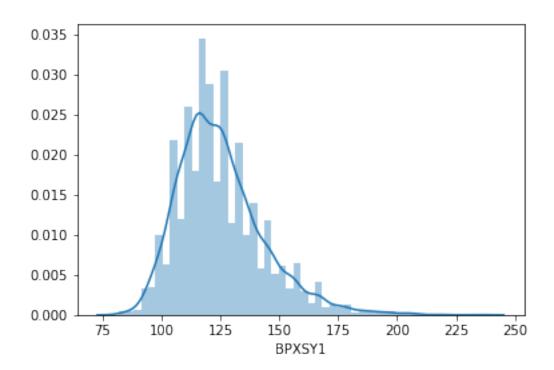
In [31]: #Graphical summaries

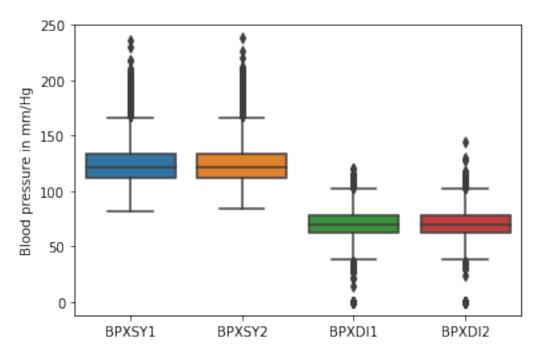
#distribution of body weight (in kg)

sns.distplot(da.BMXWT.dropna())

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7f32952a3da0>



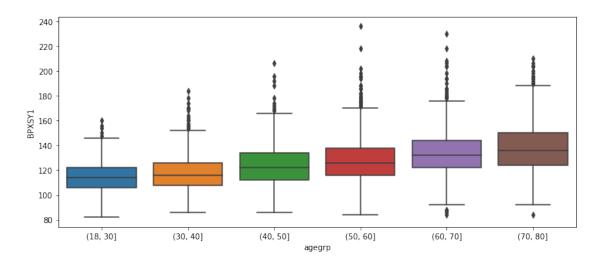




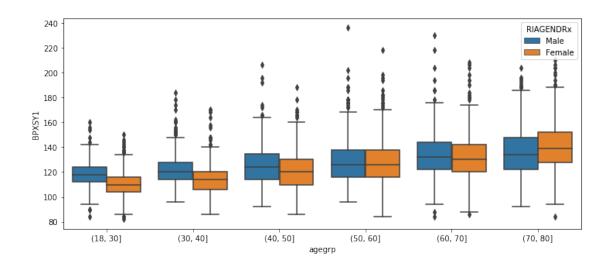
0.0.1 Stratification

One of the most effective ways to get more information out of a dataset is to divide it into smaller, more uniform subsets, and analyze each of these "strata" on its own. We can then formally or informally compare the findings in the different strata. When working with human subjects, it is very common to stratify on demographic factors such as age, sex, and race.

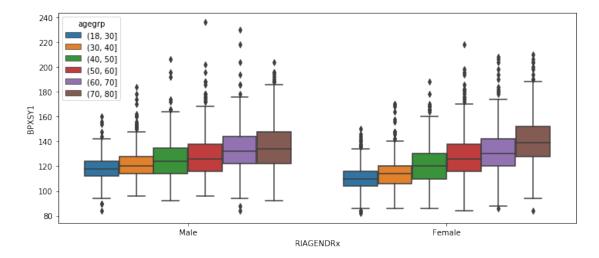
To illustrate this technique, consider blood pressure, which is a value that tends to increase with age. To see this trend in the NHANES data, we can partition the data into age strata, and construct side-by-side boxplots of the systolic blood pressure (SBP) distribution within each stratum. Since age is a quantitative variable, we need to create a series of "bins" of similar SBP values in order to stratify the data. Each box in the figure below is a summary of univariate data within a specific population stratum (here defined by age).



In [43]: a["agegrp"] = pd.cut(da.RIDAGEYR, [18, 30, 40, 50, 60, 70, 80]) # Create age strata b
 plt.figure(figsize=(12, 5)) # Make the figure wider than default (12cm wide by 5cm t
 sns.boxplot(x="agegrp", y="BPXSY1",hue = "RIAGENDRx", data=da) # Make boxplot of BPX
 plt.show()



In [44]: a["agegrp"] = pd.cut(da.RIDAGEYR, [18, 30, 40, 50, 60, 70, 80]) # Create age strata b
 plt.figure(figsize=(12, 5)) # Make the figure wider than default (12cm wide by 5cm t
 sns.boxplot(x="RIAGENDRx", y="BPXSY1", hue = "agegrp", data=da) # Make boxplot of BPX
 plt.show()



Out[48]: agegrp DMDEDUC2x
(18, 30] Some college/AA 364
College 278
HS/GED 237

```
<9
                                        47
         (30, 40]
                   Some college/AA
                                       282
                   College
                                       264
                   HS/GED
                                       182
                   9-11
                                       111
                   <9
                                        93
         (40, 50]
                   Some college/AA
                                       262
                   College
                                       260
                   HS/GED
                                       171
                   9-11
                                       112
                   <9
                                        98
         (50, 60]
                   Some college/AA
                                       258
                   College
                                       220
                   HS/GED
                                       220
                   9-11
                                       122
                   <9
                                       104
         (60, 70]
                   Some college/AA
                                       238
                   HS/GED
                                       192
                   College
                                       188
                   <9
                                       149
                   9-11
                                       111
         (70, 80]
                   Some college/AA
                                       217
                   HS/GED
                                       184
                   <9
                                       164
                   College
                                       156
                   9-11
                                        88
                   Don't know
                                         3
         Name: DMDEDUC2x, dtype: int64
In [49]: dx = da.loc[~da.DMDEDUC2x.isin(["Don't know", "Missing"]), :] # Eliminate rare/missi
         dx = dx.groupby(["agegrp", "RIAGENDRx"])["DMDEDUC2x"]
         dx = dx.value_counts()
         dx = dx.unstack() # Restructure the results from 'long' to 'wide'
         dx = dx.apply(lambda x: x/x.sum(), axis=1) # Normalize within each stratum to get pro
         print(dx.to_string(float_format="%.3f")) # Limit display to 3 decimal places
DMDEDUC2x
                                 College HS/GED Some college/AA
                    9-11
agegrp
         RIAGENDRx
(18, 30] Female
                   0.080 0.049
                                   0.282
                                           0.215
                                                             0.374
         Male
                   0.117 0.042
                                   0.258
                                           0.250
                                                             0.333
(30, 40] Female
                   0.089 0.097
                                   0.314
                                           0.165
                                                             0.335
                                   0.251
         Male
                   0.151 0.103
                                           0.227
                                                             0.269
(40, 50] Female
                                   0.299
                   0.110 0.106
                                           0.173
                                                             0.313
         Male
                   0.142 0.112
                                   0.274
                                           0.209
                                                             0.262
(50, 60] Female
                   0.117 0.102
                                   0.245
                                           0.234
                                                             0.302
         Male
                   0.148 0.123
                                   0.231
                                           0.242
                                                             0.256
```

99

9-11

0.206

0.293

0.195

(60, 70] Female

0.118 0.188

	Male	0.135 0.151	0.233	0.231	0.249
(70, 80]	Female	0.105 0.225	0.149	0.240	0.281
	Male	0.113 0.180	0.237	0.215	0.255