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          DSC 540
          Project_Milestone2
In [1]: import pandas as pd
          import numpy as np
          # import and read data
          data = 'Table_10_Offenses_Known_to_Law_Enforcement_by_State_by_Metropolitan_and_Nonmetropoli
          tan_Counties_2018.xls'
          df = pd.read_excel(data, header=0, index_col=False, keep_default_na=True)
          df.head()
Out[1]:
                                                                Murder
                 State County Violent\ncrime
                                                                       Rape Robbery Aggravated\nassault Property\ncrime
                                           and\nnonnegligent\nmanslaughter
           0 ALABAMA Autauga
                                                                                                  40.0
                                                                                                               372.0
                                      51.0
                                                                   0.0
                                                                         6.0
                                                                                 5.0
                                      223.0
                                                                                37.0
                                                                                                 177.0
                                                                                                               615.0
           1 ALABAMA Baldwin
                                                                   0.0
                                                                         9.0
           2 ALABAMA
                        Blount
                                     375.0
                                                                   1.0
                                                                       19.0
                                                                                 5.0
                                                                                                 350.0
                                                                                                               796.0
           3 ALABAMA Calhoun
                                      14.0
                                                                   0.0
                                                                        5.0
                                                                                 7.0
                                                                                                   2.0
                                                                                                               144.0
           4 ALABAMA
                       Elmore
                                      68.0
                                                                   4.0 30.0
                                                                                12.0
                                                                                                  22.0
                                                                                                               669.0
In [2]: # data frame shape
          df.shape
Out[2]: (2356, 12)
 In [3]: #get column names
          list(df.columns)
 Out[3]: ['State',
            'County'
            'Violent\ncrime',
           'Murder and\nnonnegligent\nmanslaughter',
           'Rape',
           'Robbery',
           'Aggravated\nassault',
           'Property\ncrime',
           'Burglary',
           'Larceny-\ntheft',
            'Motor\nvehicle\ntheft',
           'Arson']
          #rename column headers
          df.columns = ['State', 'County', 'Violent_crime', 'Murder',
                          'Rape', 'Robbery', 'Aggravated_assault', 'Property_crime',
                          'Burglary','Larceny_theft','Motor_vehicle_theft','Arson']
          df.head()
Out[4]:
                 State County Violent_crime Murder Rape Robbery Aggravated_assault Property_crime Burglary Larceny_theft M
                                                            5.0
                                                                            40.0
                                                                                        372.0
                                                                                                  92.0
                                                                                                              240
           0 ALABAMA Autauga
                                      51.0
                                              0.0
                                                   6.0
           1 ALABAMA Baldwin
                                     223.0
                                              0.0
                                                           37.0
                                                                           177.0
                                                                                         615.0
                                                                                                 173.0
                                                                                                              397
           2 ALABAMA
                        Blount
                                     375.0
                                                            5.0
                                                                           350.0
                                                                                         796.0
                                                                                                 191.0
                                                                                                              492
                                              1.0
                                                  19.0
           3 ALABAMA Calhoun
                                      14.0
                                              0.0
                                                   5.0
                                                            7.0
                                                                             2.0
                                                                                        144.0
                                                                                                  49.0
                                                                                                               95
           4 ALABAMA Elmore
In [5]: #Check the data type
          df.dtypes
 Out[5]: State
                                     object
          County
                                     object
          Violent_crime
                                    float64
                                    float64
          Murder
          Rape
                                    float64
                                    float64
          Robbery
          Aggravated_assault
                                    float64
          Property_crime
                                    float64
                                    float64
          Burglary
                                      int64
          Larceny_theft
          Motor_vehicle_theft
                                    float64
          Arson
                                    float64
          dtype: object
In [6]: #remove whitespace from the beginning and end
          df.columns = [x.strip() for x in df.columns]
 In [7]: # get a statistical summary of the data
          df.describe()
 Out[7]:
                 Violent_crime
                                                      Robbery Aggravated_assault Property_crime
                                                                                                Burglary Larceny_theft
                                 Murder
                                              Rape
                  2296.000000
                             2355.000000 2301.000000
                                                   2355.000000
                                                                     2353.000000
                                                                                  2348.000000 2349.000000
                                                                                                         2356.000000
           count
           mean
                    83.155052
                                1.179618
                                          11.398522
                                                     12.633121
                                                                       59.467063
                                                                                   502.102215
                                                                                              108.122605
                                                                                                          343.252971
                   297.490125
                                4.676039
                                          32.092133
                                                     85.625454
                                                                     198.717364
                                                                                  1800.823555
                                                                                              307.080632
                                                                                                         1311.923551
             std
             min
                     0.000000
                                0.000000
                                           0.000000
                                                      0.000000
                                                                       0.000000
                                                                                     0.000000
                                                                                                0.000000
                                                                                                            0.000000
            25%
                     5.000000
                                0.000000
                                           0.000000
                                                      0.000000
                                                                       4.000000
                                                                                    39.000000
                                                                                               11.000000
                                                                                                           22.000000
            50%
                    18.500000
                                0.000000
                                           3.000000
                                                      1.000000
                                                                       14.000000
                                                                                   123.000000
                                                                                               33.000000
                                                                                                           76.000000
            75%
                    54.000000
                                1.000000
                                                                       42.000000
                                                                                               93.000000
                                                                                                          209.250000
                                           9.000000
                                                      3.000000
                                                                                   332.250000
                  5790.000000
                               86.000000
                                         591.000000 2271.000000
                                                                     3969.000000
                                                                                 41708.000000 7640.000000 28113.000000
          #Checking for missing values
          df.isnull().sum()
 Out[8]: State
                                      0
          County
                                      0
          Violent_crime
                                     60
          Murder
                                      1
          Rape
                                     55
          Robbery
                                      1
          Aggravated_assault
                                      3
          Property_crime
          Burglary
                                      7
          Larceny_theft
          Motor_vehicle_theft
                                      1
                                    123
          Arson
          dtype: int64
 In [9]: #dealing with missing data using mean
          df=df.fillna(df.mean().apply(np.floor))
 Out[9]:
                    State
                             County Violent_crime Murder Rape Robbery Aggravated_assault Property_crime Burglary Larceny_tl
              0 ALABAMA
                                                                                                       92.0
                            Autauga
                                           51.0
                                                   0.0
                                                         6.0
                                                                 5.0
                                                                                 40.0
                                                                                              372.0
              1 ALABAMA
                             Baldwin
                                          223.0
                                                   0.0
                                                         9.0
                                                                37.0
                                                                                177.0
                                                                                              615.0
                                                                                                      173.0
              2 ALABAMA
                                          375.0
                                                   1.0 19.0
                                                                                350.0
                                                                                              796.0
                                                                                                      191.0
                              Blount
                                                                 5.0
                ALABAMA
                            Calhoun
                                                                                                      178.0
              4 ALABAMA
                                           68.0
                                                       30.0
                                                                12.0
                                                                                 22.0
                                                                                              669.0
                             Elmore
                                                   4.0
           2351 WYOMING
                                                         0.0
                                                                 0.0
                                                                                  4.0
                                                                                               49.0
                                                                                                       11.0
                            Sublette
                                            4.0
                                                   0.0
           2352 WYOMING Sweetwater
                                                                 0.0
                                                                                               77.0
                                                                                                       17.0
                                           22.0
                                                   0.0
                                                         8.0
                                                                                 14.0
           2353 WYOMING
                                                                                               53.0
                                                                                                       12.0
                              Uinta
                                            7.0
                                                   1.0
                                                         1.0
                                                                 1.0
                                                                                  4.0
           2354 WYOMING
                                                         0.0
                                                                 0.0
                                                                                                        4.0
                           Washakie
                                            0.0
                                                   0.0
                                                                                  0.0
                                                                                               17.0
                                                                                                0.0
           2355 WYOMING
                             Weston
                                            5.0
                                                   0.0
                                                        1.0
                                                                 0.0
                                                                                  4.0
                                                                                                        0.0
          2356 rows × 12 columns
In [10]: | ##Checking again for missing values
          df.isnull().sum()
Out[10]: State
          County
                                    0
          Violent_crime
                                    0
          Murder
          Rape
          Robbery
          Aggravated_assault
          Property_crime
                                    0
          Burglary
          Larceny_theft
          Motor_vehicle_theft
          Arson
          dtype: int64
In [11]: #check outliers for Violent_crime col.
          outliers_Violent_crime = df[df['Violent_crime'] > df['Violent_crime'].mean() + 3 * df['Viole
          nt_crime'].std()]
          outliers_Violent_crime.shape
Out[11]: (32, 12)
In [12]: #check outlier for Murder col.
          outliers_Murder = df[df['Murder'] > df['Murder'].mean() + 3 * df['Murder'].std()]
          outliers_Murder.shape
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Out[12]: (28, 12) In [13]: #check outlier for Rape col.

outliers_Rape = df[df['Rape'] > df['Rape'].mean() + 3 * df['Rape'].std()] outliers_Rape.shape

Out[13]: (46, 12) In [14]: #check outlier for Robbery col. outliers_Robbery = df[df['Robbery'] > df['Robbery'].mean() + 3 * df['Robbery'].std()]

outliers_Robbery.shape

Out[14]: (23, 12) In [15]: #check outlier for Aggravated_assault col. outliers_Aggravated_assault = df[df['Aggravated_assault'] > df['Aggravated_assault'].mean() + 3 * df['Aggravated_assault'].std()]

outliers_Aggravated_assault.shape Out[15]: (31, 12)

In [16]: #check outlier for Property_crime col. outliers_Property_crime = df[df['Property_crime'] > df['Property_crime'].mean() + 3 * df['Pr operty_crime'].std()]

outliers_Property_crime.shape

Out[16]: (31, 12) In [17]: #check outlier for Burglary col. outliers_Burglary = df[df['Burglary'] > df['Burglary'].mean() + 3 * df['Burglary'].std()] outliers_Burglary.shape

Out[17]: (35, 12)

In [18]: #check outlier for Larceny_theft col. outliers_Larceny_theft = df[df['Larceny_theft'] > df['Larceny_theft'].mean() + 3 * df['Larceny_theft'] ny_theft'].std()]

outliers_Larceny_theft.shape

Out[18]: (32, 12) In [19]: #check outlier for Motor_vehicle_theft col. outliers_Motor_vehicle_theft = df[df['Motor_vehicle_theft'] > df['Motor_vehicle_theft'].mean

In [20]: #check outlier for Arson col.

() + 3 * df['Motor_vehicle_theft'].std()] outliers_Motor_vehicle_theft.shape Out[19]: (26, 12)

outliers_Arson = df[df['Arson'] > df['Arson'].mean() + 3 * df['Arson'].std()] outliers_Arson.shape Out[20]: (27, 12)