Homework_1

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0.1 MSDS 593 EDA and Visualization: Homework #1

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[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

%config InlineBackend.figure_format = 'retina'
```

0.1.1 Question 1: Create a 1D ndarray of numbers from 100 to 112 (step=1) inclusively and use python to

[2]:
```
x = np.arange(100, 113, 1)
x
```

[2]:
```
array([100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112])
```

(a) Print the shape of the array

[3]:
```
print('Shape:', x.shape)
```

```
Shape: (13,)
```

(b) print the data type of the array

[4]:
```
print('Data type:', type(x))
```

```
Data type: <class 'numpy.ndarray'>
```

(c) Create a new array that is a slice of the original array with index [5 : 10] inclusively,and assign all values of the the new array to be 0.

[5]:
```
new_x = x[5:11]
print(new_x)
new_x[:] = 0
new_x
```

```
[105 106 107 108 109 110]
```

[5]:
```
array([0, 0, 0, 0, 0, 0])
```

(d) Create a boolean vector from the array to indicate if any element is greater than 105,and less than or equal to 110.

[6]:
```
boolean_x = (x >105) & (x <= 110)

boolean_x
```

[6]:
```
array([False, False, False, False, False, False, False, False, False,
       False, False, False, False])
```

(e) Replace all the elements in the array that are greater than 105 and less than or equal to 110 with 0.

[7]:
```
x[boolean_x] = 0
```

[8]:
```
x
```

[8]:
```
array([100, 101, 102, 103, 104,   0,   0,   0,   0,   0,   0, 111, 112])
```

0.1.2 Question 2: Make a Series object with year values: 1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000.

[9]:
```
year = pd.Series(range(1991,2001,1))
year
```

[9]:
```
0    1991
1    1992
2    1993
3    1994
4    1995
5    1996
6    1997
7    1998
8    1999
9    2000
dtype: int64
```

(a) Print out how many total values there are using code not manual counting

[10]:
```
print('Total number of years:', year.count())
```

```
Total number of years: 10
```

(b) Make another series with rainfall values 12.09, 12.35, 12.51, 10.25, 10.18, 10.59, 10.26, 10.48, 8.67, 10.23

```
[11]: rainfall = pd.Series([12.09, 12.35, 12.51, 10.25, 10.18, 10.59, 10.26, 10.48, 8.
      ↪67, 10.23])
      rainfall
```

```
[11]: 0    12.09
      1    12.35
      2    12.51
      3    10.25
      4    10.18
      5    10.59
      6    10.26
      7    10.48
      8     8.67
      9    10.23
      dtype: float64
```

(c) Imagine the order of rainfall values follow the order the years. Print out the years for which rainfall was less than 11.

```
[12]: # a= rainfall[rainfall < 11].index
      # print(a)
      # year[a]
      print(year[rainfall[rainfall < 11].index].values)
```

```
[1994 1995 1996 1997 1998 1999 2000]
```

(d) Normalize that rainfall series by xmean std and print it out.

```
[13]: rainfall.describe()
```

```
[13]: count    10.000000
      mean     10.761000
      std       1.200106
      min       8.670000
      25%      10.235000
      50%      10.370000
      75%      11.715000
      max      12.510000
      dtype: float64
```

```
[14]: df_mean = rainfall.describe()['mean']
      df_std = rainfall.describe()['std']

      df_mean, df_std
```

```
[14]: (10.761000000000001, 1.2001060138356296)
```

```
[15]: rainfall.index
```

```
[15]: RangeIndex(start=0, stop=10, step=1)
```

[16]:
```
for num in range(0,10):
    rainfall.iloc[num] = (rainfall.iloc[num] - df_mean)/ df_std

print(rainfall)
```

```
0    1.107402
1    1.324050
2    1.457371
3   -0.425796
4   -0.484124
5   -0.142487
6   -0.417463
7   -0.234146
8   -1.742346
9   -0.442461
dtype: float64
```

(e) Set the year starting 1996 and forward as np.nan. Count the number of missing values.

[17]:
```
year[year >= 1996] = np.nan
missing_num = year.isna().value_counts()[False]
print('Number of missing values:', missing_num)
```

```
Number of missing values: 5
```

(f) Fill all the NaNs with 0.

[18]:
```
year[year.isna()] = 0
year
```

[18]:
```
0    1991.0
1    1992.0
2    1993.0
3    1994.0
4    1995.0
5       0.0
6       0.0
7       0.0
8       0.0
9       0.0
dtype: float64
```

0.1.3 Question 3: For the cars.csv data set:

[19]:
```
cars = pd.read_csv('cars.csv')
cars.head(10)
```

[19]:

	MPG	CYL	ENG	WGT
0	18.0	8	307.0	3504
1	15.0	8	350.0	3693
2	18.0	8	318.0	3436
3	16.0	8	304.0	3433
4	17.0	8	302.0	3449
5	15.0	8	429.0	4341
6	14.0	8	454.0	4354
7	14.0	8	440.0	4312
8	14.0	8	455.0	4425
9	15.0	8	390.0	3850

(a) Use numpy's function np.corrcoe f(x, y) to compute the correlation between a car's weight and the miles per gallon; that function returns a matrix of x with x, x with y, etc... so the diagonal will always be correlation 1.0. What is the correlation between a car's weight and the MPG? What does the correlation tell us about their relationship?

The correlation between a car's weight and the miles per gallon is -*0.83224421*. This correlation is a strong negative correlation indicating that as a car's weight increases, the number of miles per gallon decreases(and vice versa).

[20]:
```
np.corrcoef(cars['MPG'], cars['WGT'])
```

[20]:
```
array([[ 1.        , -0.83224421],
       [-0.83224421,  1.        ]])
```

(b) Display the records for all 8 cylinder cars

[21]:
```
cars[cars['CYL'] == 8]
```

[21]:

	MPG	CYL	ENG	WGT
0	18.000000	8	307.0	3504
1	15.000000	8	350.0	3693
2	18.000000	8	318.0	3436
3	16.000000	8	304.0	3433
4	17.000000	8	302.0	3449
..	...	...	...	...
289	19.200001	8	267.0	3605
290	18.500000	8	360.0	3940
296	23.000000	8	350.0	3900
298	23.900000	8	260.0	3420
359	26.600000	8	350.0	3725

```
[103 rows x 4 columns]
```

(c) Create a new column called 'ENG2WGT' that has the engine to weight ratio

[22]:
```
cars['ENG2WGT'] = cars['ENG']/cars['WGT']
```

[23]:
```
cars
```

[23]:
```
      MPG  CYL    ENG   WGT   ENG2WGT
0    18.0    8  307.0  3504  0.087614
1    15.0    8  350.0  3693  0.094774
2    18.0    8  318.0  3436  0.092549
3    16.0    8  304.0  3433  0.088552
4    17.0    8  302.0  3449  0.087562
..    ...  ...    ...   ...       ...
387  27.0    4  140.0  2790  0.050179
388  44.0    4   97.0  2130  0.045540
389  32.0    4  135.0  2295  0.058824
390  28.0    4  120.0  2625  0.045714
391  31.0    4  119.0  2720  0.043750

[392 rows x 5 columns]
```

0.1.4 Question 4: For the kaggle uber other f ederal.csv data set:

[24]:
```
uber = pd.read_csv('kaggle-uber-other-federal.csv',
                   parse_dates = ['Date', 'Time'])
uber.head(2)
```

[24]:
```
        Date                Time                                 PU_Address  \
0 2014-07-01 2021-07-16 07:15:00  Brooklyn Museum, 200 Eastern Pkwy., BK NY;
1 2014-07-01 2021-07-16 07:30:00               33 Robert Dr., Short Hills NJ;

                                          DO_Address  \
0                        1 Brookdale Plaza, BK NY;
1  John F Kennedy International Airport, vitona A...

                                     Routing Details  \
0  PU: Brooklyn Museum, 200 Eastern Pkwy., BK NY;...
1  PU: 33 Robert Dr., Short Hills NJ; DO: John F ...

                                        PU_Address.1     Status
0  Brooklyn Museum, 200 Eastern Pkwy., BK NY; DO:...  Cancelled
1  33 Robert Dr., Short Hills NJ; DO: John F Kenn...    Arrived
```

(a) Create a new data frame containing 'Time', 'Status', and 'PU_Address' columns

[25]:
```python
new_uber = uber[['Time', 'Status', 'PU_Address']]
new_uber
```

[25]:
```
                   Time     Status  \
0   2021-07-16 07:15:00  Cancelled
1   2021-07-16 07:30:00    Arrived
2   2021-07-16 08:00:00   Assigned
3   2021-07-16 09:00:00   Assigned
4   2021-07-16 09:30:00   Assigned
..                  ...        ...
94  2021-07-16 06:00:00   Assigned
95  2021-07-16 08:30:00  Cancelled
96  2021-07-16 12:00:00    Arrived
97  2021-07-16 16:45:00   Assigned
98  2021-07-16 13:30:00    Arrived

                                           PU_Address
0           Brooklyn Museum, 200 Eastern Pkwy., BK NY;
1                        33 Robert Dr., Short Hills NJ;
2                              60 Glenmore Ave., BK NY;
3                              128 East 31 St., BK NY;
4                         139-39 35 Ave., Flushing NY;
..                                                  ...
94                   266 prospect park west, brooklyn NY;
95                                        42 St., BK NY;
96                              663 51st Street, BK NY;
97                     255 Fieldston Terrace, Bronx NY;
98   Columbia University, 630 W 168 St., NY NY; ST:...

[99 rows x 3 columns]
```

(b) Create a new column 'Hour' extracting hour information from 'Time'. Hint: make sure 'Time' is the correct data type and keep the date added.

[26]:
```python
df_uber = new_uber.copy()
df_uber
```

[26]:
```
                   Time     Status  \
0   2021-07-16 07:15:00  Cancelled
1   2021-07-16 07:30:00    Arrived
2   2021-07-16 08:00:00   Assigned
3   2021-07-16 09:00:00   Assigned
4   2021-07-16 09:30:00   Assigned
..                  ...        ...
94  2021-07-16 06:00:00   Assigned
95  2021-07-16 08:30:00  Cancelled
96  2021-07-16 12:00:00    Arrived
97  2021-07-16 16:45:00   Assigned
```

```
98 2021-07-16 13:30:00    Arrived

                                            PU_Address
0          Brooklyn Museum, 200 Eastern Pkwy., BK NY;
1                      33 Robert Dr., Short Hills NJ;
2                           60 Glenmore Ave., BK NY;
3                            128 East 31 St., BK NY;
4                        139-39 35 Ave., Flushing NY;
..                                               ...
94               266 prospect park west, brooklyn NY;
95                                    42 St., BK NY;
96                           663 51st Street, BK NY;
97                    255 Fieldston Terrace, Bronx NY;
98   Columbia University, 630 W 168 St., NY NY; ST:...

[99 rows x 3 columns]
```

[27]:
```
df_uber['Hour'] = df_uber['Time'].dt.hour
df_uber
```

[27]:
```
                  Time     Status  \
0  2021-07-16 07:15:00  Cancelled
1  2021-07-16 07:30:00    Arrived
2  2021-07-16 08:00:00   Assigned
3  2021-07-16 09:00:00   Assigned
4  2021-07-16 09:30:00   Assigned
..                 ...        ...
94 2021-07-16 06:00:00   Assigned
95 2021-07-16 08:30:00  Cancelled
96 2021-07-16 12:00:00    Arrived
97 2021-07-16 16:45:00   Assigned
98 2021-07-16 13:30:00    Arrived

                                            PU_Address  Hour
0          Brooklyn Museum, 200 Eastern Pkwy., BK NY;     7
1                      33 Robert Dr., Short Hills NJ;     7
2                           60 Glenmore Ave., BK NY;     8
3                            128 East 31 St., BK NY;     9
4                        139-39 35 Ave., Flushing NY;     9
..                                               ...   ...
94               266 prospect park west, brooklyn NY;     6
95                                    42 St., BK NY;     8
96                           663 51st Street, BK NY;    12
97                    255 Fieldston Terrace, Bronx NY;    16
98   Columbia University, 630 W 168 St., NY NY; ST:...    13

[99 rows x 4 columns]
```

(c) Set the index of the data frame to 'Time'.

[28]:
```
df_uber.set_index('Time', inplace = True)
df_uber
```

[28]:
```
                        Status  \
Time
2021-07-16 07:15:00  Cancelled
2021-07-16 07:30:00    Arrived
2021-07-16 08:00:00   Assigned
2021-07-16 09:00:00   Assigned
2021-07-16 09:30:00   Assigned
...                        ...
2021-07-16 06:00:00   Assigned
2021-07-16 08:30:00  Cancelled
2021-07-16 12:00:00    Arrived
2021-07-16 16:45:00   Assigned
2021-07-16 13:30:00    Arrived

                                                            PU_Address  Hour
Time
2021-07-16 07:15:00         Brooklyn Museum, 200 Eastern Pkwy., BK NY;     7
2021-07-16 07:30:00                       33 Robert Dr., Short Hills NJ;     7
2021-07-16 08:00:00                              60 Glenmore Ave., BK NY;     8
2021-07-16 09:00:00                               128 East 31 St., BK NY;     9
2021-07-16 09:30:00                         139-39 35 Ave., Flushing NY;     9
...                                                                ...   ...
2021-07-16 06:00:00                266 prospect park west, brooklyn NY;     6
2021-07-16 08:30:00                                      42 St., BK NY;     8
2021-07-16 12:00:00                               663 51st Street, BK NY;    12
2021-07-16 16:45:00                      255 Fieldston Terrace, Bronx NY;    16
2021-07-16 13:30:00  Columbia University, 630 W 168 St., NY NY; ST:...    13

[99 rows x 3 columns]
```

(d) Display records at positions between 10 and 15 inclusively

[29]:
```
df_uber.iloc[10:16]
```

[29]:
```
                       Status                    PU_Address  Hour
Time
2021-07-16 20:00:00  Assigned    35-36 32 St., Astoria NY;    20
2021-07-16 03:30:00   Arrived   862 East 21 Street, BK NY;     3
2021-07-16 14:00:00  Assigned     1539 71st Street, BK NY;    14
2021-07-16 15:00:00   Arrived       208 Elmwood ave, BK NY;    15
2021-07-16 20:45:00   Arrived              543 1 St., BK NY;    20
2021-07-16 05:00:00   Arrived  513 Montgomery StreetBK NY;     5
```

(e) Display the 'PU_Address' for records whose index is 'Today's date 20:00:00': hint: today's date depends on the day you are working on the question.

[30]:
```
df_uber.index.hour == 7
```

[30]:
```
array([ True,  True, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
        True, False, False, False, False, False, False, False, False,
       False, False, False, False,  True, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False,  True, False, False, False, False, False,  True, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False,
       False, False, False, False, False, False, False, False, False])
```

[31]:
```
df_uber[(df_uber.index.hour == 20) & (df_uber.index.minute == 0)]
```

[31]:
```
                       Status                      PU_Address  Hour
Time
2021-07-16 20:00:00  Assigned     35-36 32 St., Astoria NY;    20
2021-07-16 20:00:00   Arrived  717 President Street, BK NY;    20
```

(f) Reset the data frame so that 'Time' is a column again

[32]:
```
df_uber.reset_index('Time', inplace = True)
```

[33]:
```
df_uber
```

[33]:
```
                  Time     Status  \
0  2021-07-16 07:15:00  Cancelled
1  2021-07-16 07:30:00    Arrived
2  2021-07-16 08:00:00   Assigned
3  2021-07-16 09:00:00   Assigned
4  2021-07-16 09:30:00   Assigned
..                 ...        ...
94 2021-07-16 06:00:00   Assigned
95 2021-07-16 08:30:00  Cancelled
96 2021-07-16 12:00:00    Arrived
97 2021-07-16 16:45:00   Assigned
98 2021-07-16 13:30:00    Arrived

                                       PU_Address  Hour
0          Brooklyn Museum, 200 Eastern Pkwy., BK NY;     7
1                       33 Robert Dr., Short Hills NJ;     7
2                              60 Glenmore Ave., BK NY;     8
3                              128 East 31 St., BK NY;     9
4                           139-39 35 Ave., Flushing NY;     9
..                                                 ...   ...
```

```
94              266 prospect park west, brooklyn NY;     6
95                                    42 St., BK NY;     8
96                             663 51st Street, BK NY;    12
97                      255 Fieldston Terrace, Bronx NY;    16
98  Columbia University, 630 W 168 St., NY NY; ST:...    13

[99 rows x 4 columns]
```

0.1.5 Question 5: You work for a large school district as a data analyst. Your boss wants to purchase a large amount of cereal for school breakfasts. He needs to choose a manufacturer and product. He wants you to prepare a presentation for the executive team. You are provided with some data in cereal.csv:

(a) Initially explore the dataset by looking at the number of records, column names, column types and few record values. Through this initial look, combined with your boss's goal above, list five analytics queries or questions that you would have about this dataset in your exploratory process.

[34]:
```python
master_cereal = pd.read_csv('cereal.csv')
master_cereal.head()
```

[34]:
```
                        name mfr type  calories  protein  fat  sodium  fiber  \
0                  100% Bran   N    C        70        4    1     130   10.0
1          100% Natural Bran   Q    C       120        3    5      15    2.0
2                   All-Bran   K    C        70        4    1     260    9.0
3  All-Bran with Extra Fiber   K    C        50        4    0     140   14.0
4             Almond Delight   R    C       110        2    2     200    1.0

   carbo  sugars  potass  vitamins  shelf  weight  cups     rating
0    5.0       6     280        25      3     1.0  0.33  68.402973
1    8.0       8     135         0      3     1.0  1.00  33.983679
2    7.0       5     320        25      3     1.0  0.33  59.425505
3    8.0       0     330        25      3     1.0  0.50  93.704912
4   14.0       8      -1        25      3     1.0  0.75  34.384843
```

[35]:
```python
master_cereal.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 77 entries, 0 to 76
Data columns (total 16 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   name      77 non-null     object
 1   mfr       77 non-null     object
 2   type      77 non-null     object
 3   calories  77 non-null     int64
 4   protein   77 non-null     int64
 5   fat       77 non-null     int64
```

```
 6   sodium    77 non-null    int64
 7   fiber     77 non-null    float64
 8   carbo     77 non-null    float64
 9   sugars    77 non-null    int64
 10  potass    77 non-null    int64
 11  vitamins  77 non-null    int64
 12  shelf     77 non-null    int64
 13  weight    77 non-null    float64
 14  cups      77 non-null    float64
 15  rating    77 non-null    float64
dtypes: float64(5), int64(8), object(3)
memory usage: 9.8+ KB
```

Questions 1. Which manufacturers produce the top five highest rating cereals? 2. Which manufacturer produces healthier cereal such that it is high in vitamins and low in sugar? 3. Which type of cereal has a higher rating in average? 4. What is the average cups in a serving for a typical cereal? 5. Would more cups in a serving be more popular?

(b) To answer the questions you have listed above, what columns from this data you would need? Print some basic statistical summaries and plots for at least 5 columns you would need to check missing values, extreme values and value distributions. List three findings you have at this point. > In order to answer the questions I have listed above, I would need the columns *mfr*, *type*, *sugars*, *vitamins*, *cups*, and *rating* . > - mfr: Manufacturer of cereal: - A = American Home Food Products - G = General Mills - K = Kelloggs - N = Nabisco - P = Post - Q = Quaker Oats - R = Ralston Purina > - type: cold/hot > - sugars: grams of sugars > - vitamins: vitamins and minerals - 0, 25, or 100, indicating the typical percentage ofFDA recommended > - cups: number of cups in one serving > - rating: a rating of the cereals

[36]:
```
master_cereal.columns
```

[36]:
```
Index(['name', 'mfr', 'type', 'calories', 'protein', 'fat', 'sodium', 'fiber',
       'carbo', 'sugars', 'potass', 'vitamins', 'shelf', 'weight', 'cups',
       'rating'],
      dtype='object')
```

[37]:
```
df_cereal = master_cereal[['mfr','type', 'sugars', 'vitamins', 'cups',␣
 ↪'rating']]
```

[38]:
```
df_cereal.head()
```

[38]:

	mfr	type	sugars	vitamins	cups	rating
0	N	C	6	25	0.33	68.402973
1	Q	C	8	0	1.00	33.983679
2	K	C	5	25	0.33	59.425505
3	K	C	0	25	0.50	93.704912
4	R	C	8	25	0.75	34.384843

[39]:
```
df_cereal.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 77 entries, 0 to 76
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   mfr       77 non-null     object
 1   type      77 non-null     object
 2   sugars    77 non-null     int64
 3   vitamins  77 non-null     int64
 4   cups      77 non-null     float64
 5   rating    77 non-null     float64
dtypes: float64(2), int64(2), object(2)
memory usage: 3.7+ KB
```

[40]:
```
df_cereal.describe()
```

[40]:

	sugars	vitamins	cups	rating
count	77.000000	77.000000	77.000000	77.000000
mean	6.922078	28.246753	0.821039	42.665705
std	4.444885	22.342523	0.232716	14.047289
min	-1.000000	0.000000	0.250000	18.042851
25%	3.000000	25.000000	0.670000	33.174094
50%	7.000000	25.000000	0.750000	40.400208
75%	11.000000	25.000000	1.000000	50.828392
max	15.000000	100.000000	1.500000	93.704912

[41]:
```
df_cereal['sugars'].value_counts().loc[-1]
```

[41]: 1

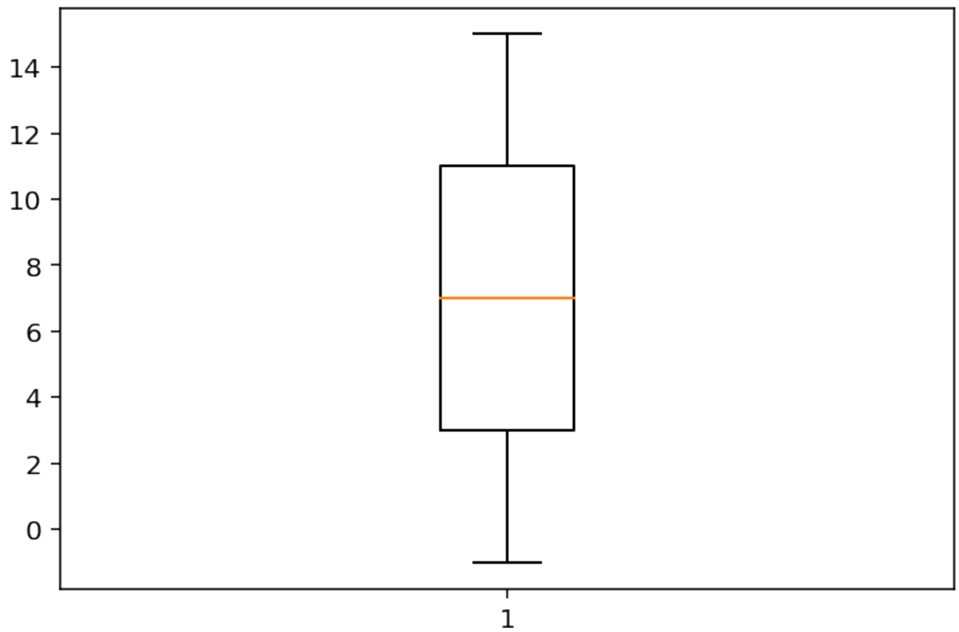
[42]:
```
df_cereal['sugars'].value_counts()
```

[42]:
```
 3     13
 0      7
 12     7
 6      7
 10     5
 5      5
 8      5
 11     5
 9      4
 7      4
 13     4
 14     3
 2      3
 15     2
 4      1
 1      1
-1      1
Name: sugars, dtype: int64
```

[43]:
```
fig, ax = plt.subplots(figsize = (6,4))

ax.boxplot(df_cereal['sugars'])
```

[43]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7fe799e14d30>,
  <matplotlib.lines.Line2D at 0x7fe799e14e10>],
 'caps': [<matplotlib.lines.Line2D at 0x7fe799e2d400>,
  <matplotlib.lines.Line2D at 0x7fe799e2d748>],
 'boxes': [<matplotlib.lines.Line2D at 0x7fe799e14940>],
 'medians': [<matplotlib.lines.Line2D at 0x7fe799e2da90>],
 'fliers': [<matplotlib.lines.Line2D at 0x7fe799e2ddd8>],
 'means': []}
```



Observations - In the *sugars* column, the minimum grams of sugar is -1 which is not logical as the least amount of sugar anything could contain is 0 gram. After delving more into this weird phenonme, I noticed there was only one element of -1 out of 77 elements. On the boxplot of df_cereal['sugars'], the one element of -1 didn't caused a big impact. It wasn't necessary to replace the element, however, it would be better to change it from -1 to 0 so the grams of sugars would make more logical sense. - The *mfr* column is currently in object dtype, however, changing the *mfr* column from object type to category dtype would help more in the later data exploration portion. - The *type* column is also currently in object dtype, however, changeing the dtype of it from object to categorical dtype would make explorating the type of cereal more efficient. - The *mfr* column contains the abbreviation of the manfacturers' names. Thus, I would need to keep referring back to above statements for clarification on the abbreviation. In order to solve that, I would subsitute back the actual names for the abbreviated names.

[44]:
```
cereal = df_cereal.copy()
```

[45]:
```
cereal[cereal['sugars']== -1].index
```

[45]:
```
Int64Index([57], dtype='int64')
```

[46]:
```
cereal['sugars'].iloc[57] = 0
```

```
/Users/amandaliluo/anaconda3/lib/python3.7/site-
packages/pandas/core/indexing.py:671: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self._setitem_with_indexer(indexer, value)
```

[47]:
```
cereal.iloc[57]
```

[47]:
```
mfr               Q
type              H
sugars            0
vitamins          0
cups           0.67
rating      50.8284
Name: 57, dtype: object
```

[48]:
```
cereal['mfr'] = cereal['mfr'].astype('category')
cereal['type'] = cereal['type'].astype('category')
```

[49]:
```
cereal.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 77 entries, 0 to 76
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   mfr       77 non-null     category
 1   type      77 non-null     category
 2   sugars    77 non-null     int64
 3   vitamins  77 non-null     int64
 4   cups      77 non-null     float64
 5   rating    77 non-null     float64
dtypes: category(2), float64(2), int64(2)
memory usage: 3.1 KB
```

[50]:
```
cereal['type'].unique()
```

[50]: [C, H]
Categories (2, object): [C, H]

[51]:
```
cereal['vitamins'].unique()
```

[51]: array([25,   0, 100])

[52]:
```
cereal['mfr'].value_counts()
```

[52]:
```
K    23
G    22
P     9
R     8
Q     8
N     6
A     1
Name: mfr, dtype: int64
```

[53]:
```
#x = {'A': 'American Home Food Products',
        #'G': 'General Mills', 'K': 'Kelloggs',
        ##Q': 'Quaker Oats', 'R': 'Ralston Purina'}
name = pd.DataFrame({'mfr': ['A', 'G', 'K', 'N', 'P', 'Q', 'R'],
                     'manfacturer': ['American Home Food Products', 'General␣
 ↪Mills',
                              'Kelloggs','Nabisco', 'Post', 'Quaker Oats',␣
 ↪'Ralston Purina']})

df = pd.merge(cereal, name, on = 'mfr')
df = df.drop('mfr', axis =1)
df = df[['manfacturer','type', 'sugars', 'vitamins','cups','rating']]
df['manfacturer'] = df['manfacturer'].astype('category')
df
```

[53]:
```
                    manfacturer type  sugars  vitamins  cups     rating
0                       Nabisco    C       6        25  0.33  68.402973
1                       Nabisco    H       0         0  1.00  64.533816
2                       Nabisco    C       0         0  1.00  68.235885
3                       Nabisco    C       0         0  0.67  74.472949
4                       Nabisco    C       0         0  0.67  72.801787
..                          ...  ...     ...       ...   ...        ...
72                         Post    C       3        25  0.25  53.371007
73                         Post    C       4        25  0.33  45.811716
74                         Post    C      11        25  1.33  28.742414
75                         Post    C      14        25  0.67  37.840594
76  American Home Food Products    H       3        25  1.00  54.850917

[77 rows x 6 columns]
```

(c) To answer the questions you have listed above, describe 5 visualizations that can help you explore this data. (Example: line graph between variable x and y.).

(d) Plot at three DIFFERENT graphs you have mentioned above. Summarise some findings from each plot. (For example, line chart of x and y and line chart of a and b doesn't count as different; line chart and box plot does.)

1. **Which manfactuers produces the top five highest rating cereals?** - Based on the histogram and the table below, Kelloggs produced the highest rating cereal of 93.70 and Nabisco produced the other 4 high rating cereals of 74.47, 72.80, 72.80, 68.40, and 68.24. Even though Kelloggs produced the highest rating cereal, however, Nabisco's productions composed majority of the top five highest rating cereals.

[54]:
```
x = df['rating'].sort_values(ascending = False).head(5).index
x
```

[54]:
```
Int64Index([15, 3, 4, 0, 2], dtype='int64')
```

[55]:
```
top5 = df.iloc[x]
top5
```

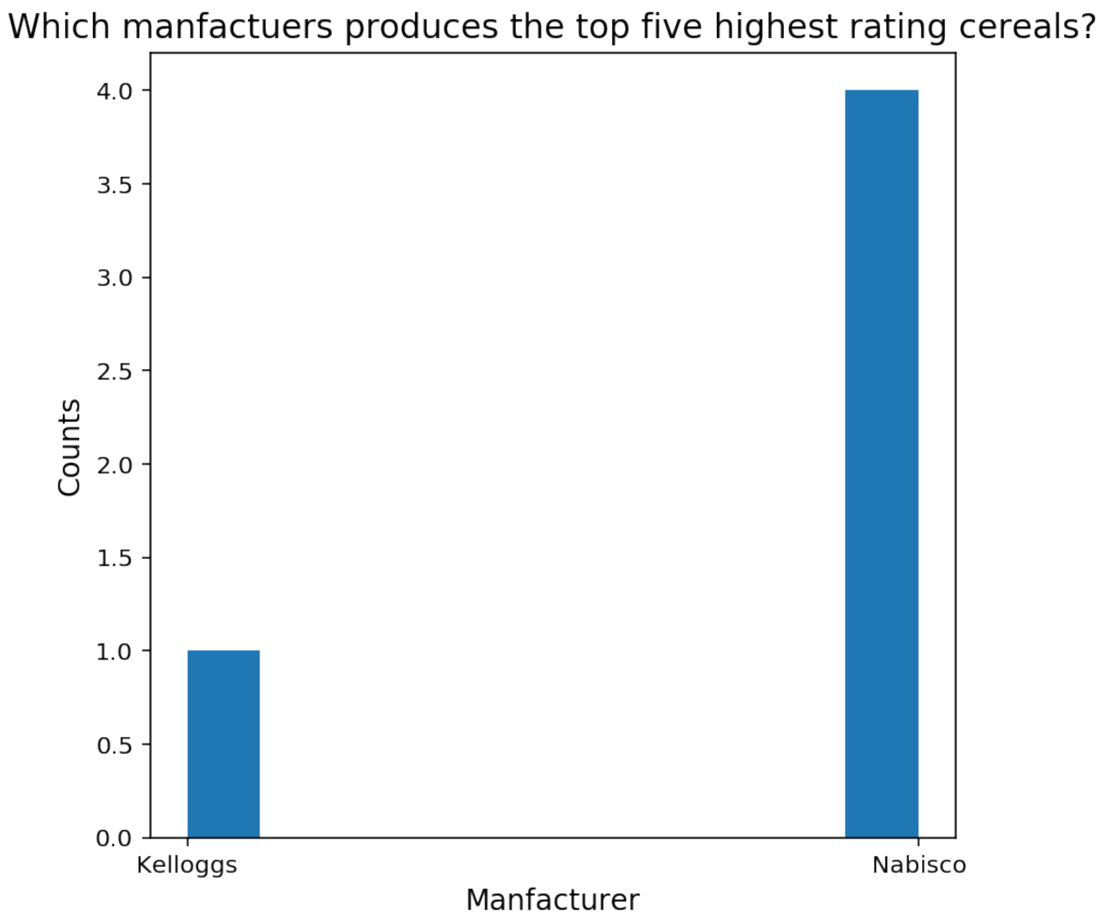
[55]:

	manfacturer	type	sugars	vitamins	cups	rating
15	Kelloggs	C	0	25	0.50	93.704912
3	Nabisco	C	0	0	0.67	74.472949
4	Nabisco	C	0	0	0.67	72.801787
0	Nabisco	C	6	25	0.33	68.402973
2	Nabisco	C	0	0	1.00	68.235885

[56]:
```
fig, ax = plt.subplots(figsize = (6,6))

ax.hist(top5.manfacturer)
ax.set_xlabel('Manfacturer', fontsize = 12)
ax.set_ylabel('Counts', fontsize = 12)
ax.set_title('Which manfactuers produces the top five highest rating cereals?',
 ↪fontsize = 14)

plt.show()
```



2. **Which manufacturer produces healthier cereal that is high in vitamins and low in sugar?** - Based on the graph below and the table, American Home Food Products produces the healthiest cereal in average compared to other manfactureres. It has the highest ratio of vitamins to sugars of around 8.33. While Kellogg whom has the highest rating claimed the third place with a ratio of around 6.79.

[57]:
```
df1 = df.copy()
df1['vitamins2sugars'] = df1['vitamins']/df1['sugars']
df1['vitamins2sugars'].unique()
# since nan means we have 0 in vitamin and 0 in grams of sugar, and inf means 0␣
↪in sugar
# I will replace nan and inf with zero
```

[57]:
```
array([ 4.16666667,         nan,  5.        ,  0.        ,  2.08333333,
        2.27272727,         inf,  1.78571429, 12.5       ,  3.57142857,
        8.33333333,  1.92307692, 16.66666667, 11.11111111,  2.77777778,
       33.33333333,  1.66666667,  3.125     ,  2.5       , 25.        ,
        7.14285714,  6.25      ])
```

[58]:
```
df1[df1['vitamins2sugars'].isnull()]
```

[58]:
```
     manfacturer type  sugars  vitamins  cups     rating  vitamins2sugars
1        Nabisco    H       0         0  1.00  64.533816              NaN
2        Nabisco    C       0         0  1.00  68.235885              NaN
3        Nabisco    C       0         0  0.67  74.472949              NaN
4        Nabisco    C       0         0  0.67  72.801787              NaN
10   Quaker Oats    C       0         0  1.00  60.756112              NaN
11   Quaker Oats    C       0         0  1.00  63.005645              NaN
13   Quaker Oats    H       0         0  0.67  50.828392              NaN
```

[59]:
```
df1['vitamins2sugars'].sort_values(ascending = False)
```

[59]:
```
15          inf
60    33.333333
31    33.333333
62    33.333333
47    25.000000
        ...
3           NaN
4           NaN
10          NaN
11          NaN
13          NaN
Name: vitamins2sugars, Length: 77, dtype: float64
```

[60]:
```
df1.iloc[15]
```

[60]:
```
manfacturer        Kelloggs
type                      C
sugars                    0
vitamins                 25
cups                    0.5
rating              93.7049
vitamins2sugars         inf
Name: 15, dtype: object
```

[61]:
```
df1 = df1.drop(index =15)
df1 = df1.dropna()
```

[62]:
```
df1
```

[62]:
```
                       manfacturer type  sugars  vitamins  cups     rating  \
0                          Nabisco    C       6        25  0.33  68.402973
5                          Nabisco    C       5        25  1.00  59.363993
6                      Quaker Oats    C       8         0  1.00  33.983679
7                      Quaker Oats    C      12        25  0.75  18.042851
8                      Quaker Oats    C      11        25  1.00  21.871292
..                             ...  ...     ...       ...   ...        ...
72                            Post    C       3        25  0.25  53.371007
73                            Post    C       4        25  0.33  45.811716
```

```
74                        Post    C      11         25  1.33  28.742414
75                        Post    C      14         25  0.67  37.840594
76  American Home Food Products    H       3         25  1.00  54.850917

    vitamins2sugars
0          4.166667
5          5.000000
6          0.000000
7          2.083333
8          2.272727
..              ...
72         8.333333
73         6.250000
74         2.272727
75         1.785714
76         8.333333

[69 rows x 7 columns]
```

[63]:
```
barh = df1.groupby('manfacturer').mean()
barh
```

[63]:
```
                               sugars   vitamins      cups     rating  \
manfacturer
American Home Food Products  3.000000  25.000000  1.000000  54.850917
General Mills                7.954545  35.227273  0.875000  34.485852
Kelloggs                     7.909091  35.227273  0.809545  41.780896
Nabisco                      5.500000  25.000000  0.665000  63.883483
Post                         8.777778  25.000000  0.714444  41.705744
Quaker Oats                  8.600000  20.000000  0.784000  33.747554
Ralston Purina               6.125000  25.000000  0.871250  41.542997

                             vitamins2sugars
manfacturer
American Home Food Products         8.333333
General Mills                       7.476863
Kelloggs                            6.799596
Nabisco                             4.583333
Post                                3.876864
Quaker Oats                         2.537879
Ralston Purina                      5.750473
```

[64]:
```
barh.index
```

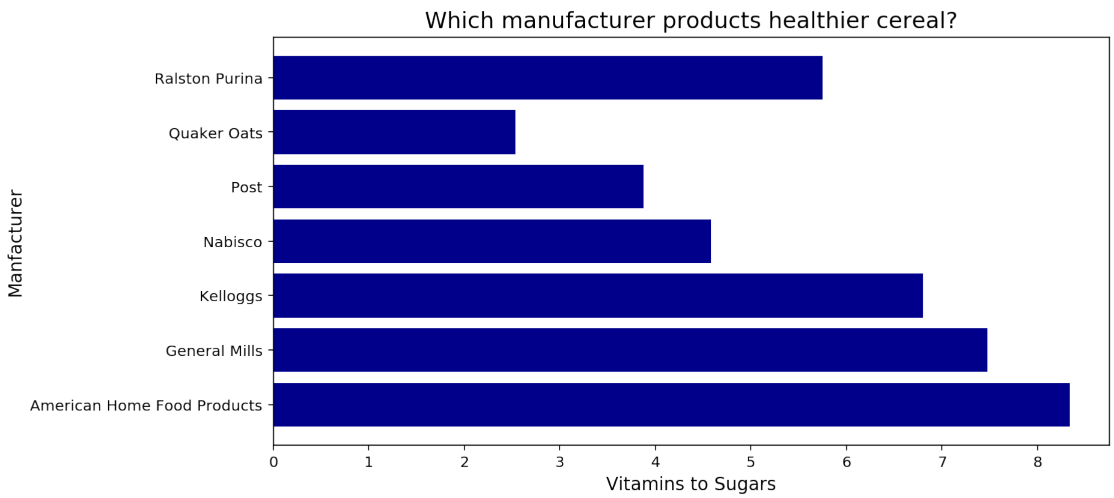
[64]:
```
CategoricalIndex(['American Home Food Products', 'General Mills', 'Kelloggs',
                  'Nabisco', 'Post', 'Quaker Oats', 'Ralston Purina'],
                 categories=['American Home Food Products', 'General Mills',
'Kelloggs', 'Nabisco', 'Post', 'Quaker Oats', 'Ralston Purina'], ordered=False,
name='manfacturer', dtype='category')
```

[65]:
```python
fig, ax = plt.subplots(figsize =(10,5))

x = barh.index
y = barh.vitamins2sugars

ax.barh(x, y, color= 'darkblue')
ax.set_ylabel('Manfacturer', fontsize = 12)
ax.set_xlabel('Vitamins to Sugars', fontsize = 12)
ax.set_title('Which manufacturer products healthier cereal?', fontsize = 15)

plt.show()
```



3. Which type of cereal has a higher rating in average? - Hot cereals have a higher rating of around 56.74 in average compared to cold cereals.

[66]:
```python
barh2 = df.groupby('type').mean()
barh2
```

[66]:

type	sugars	vitamins	cups	rating
C	7.175676	29.054054	0.818243	42.095218
H	1.000000	8.333333	0.890000	56.737708

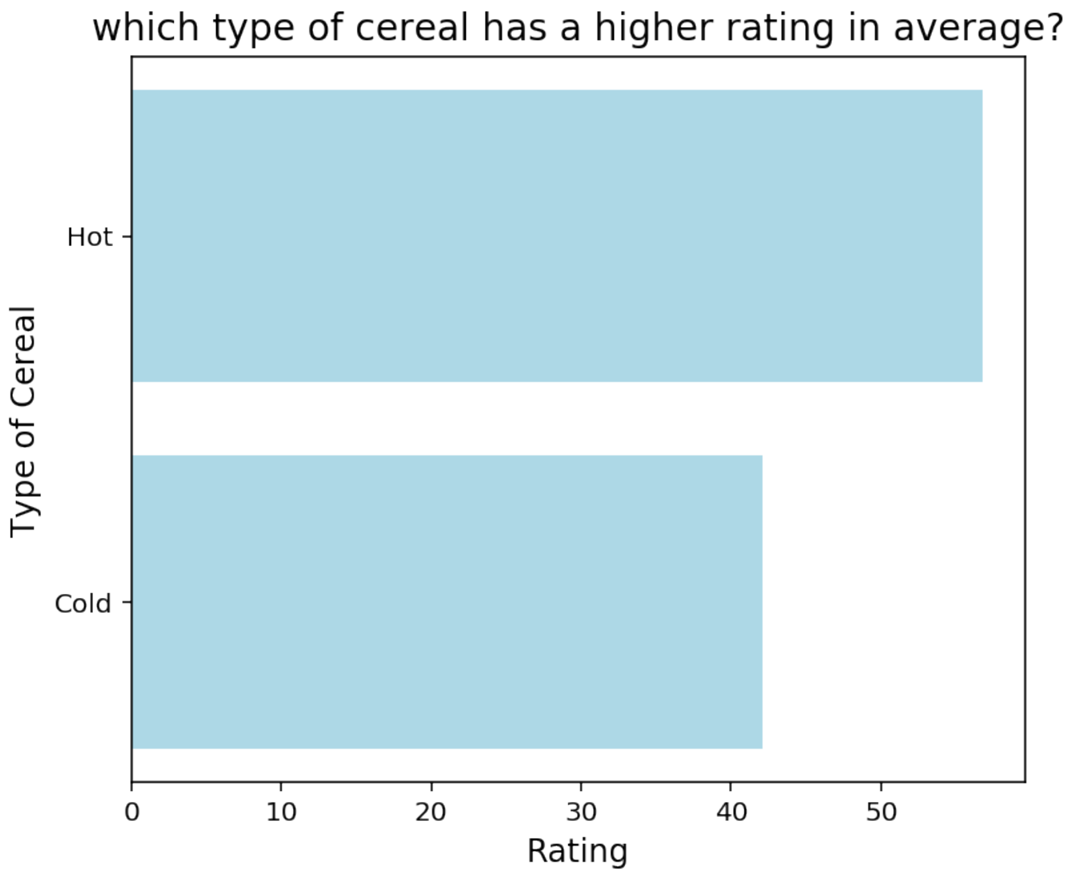
[67]:
```python
fig, ax = plt.subplots(figsize = (6,5))

x = barh2.index
y = barh2.rating

ax.barh(x, y, color = 'lightblue')
ax.set_xlabel('Rating', fontsize = 12)
ax.set_ylabel('Type of Cereal', fontsize = 12)
```

```
ax.set_title('which type of cereal has a higher rating in average?', fontsize =␣
 ↪14)
ax.set_yticklabels(['Cold', 'Hot'])

plt.show()
```



4. What is the average cups in a serving for a typical cereal? - The typical cereal have an average of around 0.82 cups of serving.

[68]:
```
df['cups'].mean()
```

[68]: 0.8210389610389613

5. Would more cups in a serving be more popular?

- From the scatterplot below, cereals that have more cups in a serving have lower ratings. However, the amount of cups in a serving and the rating of the cereal has a weak neagative correlation of around -0.20. Thus, the amount of cups in a serving have little effect on the rating of the cereal.

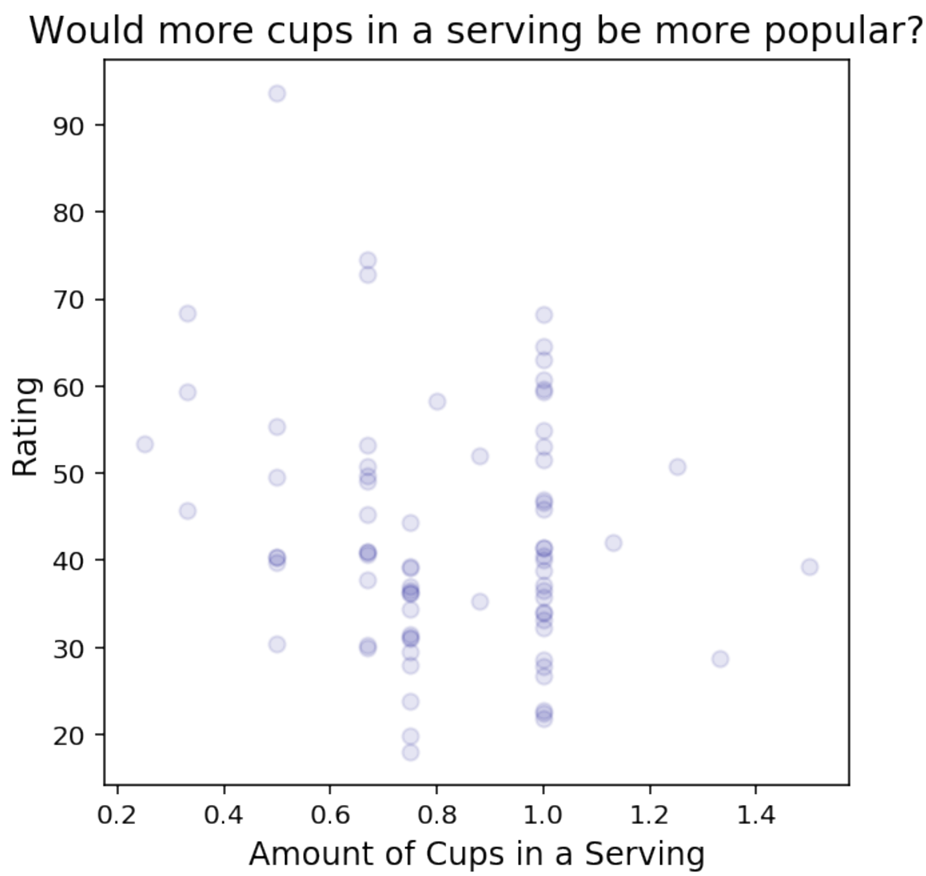
[69]:
```
f = df[['cups','rating']].corr()
f
```

[69]:
```
            cups   rating
cups     1.00000 -0.20316
rating  -0.20316  1.00000
```

[70]:
```
fig, ax = plt.subplots(figsize =(5,5))
x = df['cups']
y = df['rating']

ax.scatter(x, y, color = 'darkblue', alpha = 0.1)
ax.set_xlabel('Amount of Cups in a Serving', fontsize = 12)
ax.set_ylabel('Rating', fontsize = 12)
ax.set_title('Would more cups in a serving be more popular?', fontsize = 14)

plt.show()
```



(e) Besides the information provided in the data, what else information might be helpful to achieve your boss' goal? - Aside from the information in the data set, some additional information that would help my boss pick a manufacturer and product for school breakfasts. One additional piece of information that would be helpful is if the cereal is being used for school breakfasts before. Another one is if the cereal has received complaints before in amounts.