DISPLAYING TABLE (CSV)

We chose the drinks.csv dataset which is a dataset with beverage consumption per country split by different types of beverages. In this section, we are making sure that we have access to the table and storing it to a variable called Drink_data. Our dataset is from the Canvas files provided to us on the assignment, the LabHelp/Labs/data/drinks.csv.

What the below code does is it reads the drinks.csv file from our data folder and displays the head of the dataframe.

In [1]:

```
# DISPLAYING TABLE (CSV)
import os
import numpy as np
import pandas as pd
from scipy.stats import zscore
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
%matplotlib inline

path = "./data/"

filename_read = os.path.join(path,"drinks.csv")
drink_Data = pd.read_csv(filename_read, na_values=['NA','?'])
drink_Data.head(10)
```

Out[1]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent
0	Afghanistan	0	0	0	0.0	Asia
1	Albania	89	132	54	4.9	Europe
2	Algeria	25	0	14	0.7	Africa
3	Andorra	245	138	312	12.4	Europe
4	Angola	217	57	45	5.9	Africa
5	Antigua & Barbuda	102	128	45	4.9	North America
6	Argentina	193	25	221	8.3	South America
7	Armenia	21	179	11	3.8	Europe
8	Australia	261	72	212	10.4	Oceania
9	Austria	279	75	191	9.7	Europe

MISSING VALUE

In this portion, we are looking for the amount of missing values in each column. In here, since we have previously read and store the drinks.csv we can use the variable: drink_Data. The first code portion is checking to see where all empty value are and replacing them with pandas NaN so that we can see where all the missing values are based off the column they are in. As seen below, we found that there are no missing values in the drinks.csv dataset.

In [2]:
```
# MISSING INPUTS

import numpy as np

drink_Data = drink_Data.replace('', np.NaN)

print('Number of instances = %d' % (drink_Data.shape[0]))
print('Number of attributes = %d' % (drink_Data.shape[1]))

print('Number of missing values:')
for col in drink_Data.columns:
    print('\t%s: %d' % (col,drink_Data[col].isna().sum()))
```

```
Number of instances = 193
Number of attributes = 6
Number of missing values:
	country: 0
	beer_servings: 0
	spirit_servings: 0
	wine_servings: 0
	total_litres_of_pure_alcohol: 0
	continent: 0
```

In [3]:
```
drink_Data_missing = drink_Data.copy()
drink_Data_missing.iloc[3, 0] = None
drink_Data_missing.iloc[0, 3] = np.NaN

# Now we should see 2 missing values
print('Number of missing values:')
for col in drink_Data_missing.columns:
    print('\t%s: %d' % (col,drink_Data_missing[col].isna().sum()))
```

```
Number of missing values:
	country: 1
	beer_servings: 0
	spirit_servings: 0
	wine_servings: 1
	total_litres_of_pure_alcohol: 0
	continent: 0
```

We can replace the missing numerical values with their column median.

In [4]:
```
missing_values_column = drink_Data_missing['wine_servings']

print('Before replacing missing values:')
print(missing_values_column[:4])

missing_values_column=missing_values_column.fillna(missing_values_column.median())
print('\nAfter replacing missing values:')
print(missing_values_column[:4])

drink_Data_missing['wine_servings'] = missing_values_column
```

```
print('Number of missing values:')
for col in drink_Data_missing.columns:
    print('\t%s: %d' % (col,drink_Data_missing[col].isna().sum()))
```

```
Before replacing missing values:
0      NaN
1     54.0
2     14.0
3    312.0
Name: wine_servings, dtype: float64

After replacing missing values:
0      8.5
1     54.0
2     14.0
3    312.0
Name: wine_servings, dtype: float64
Number of missing values:
	country: 1
	beer_servings: 0
	spirit_servings: 0
	wine_servings: 0
	total_litres_of_pure_alcohol: 0
	continent: 0
```

We decided to drop the rows that have missing categorical values (country name) since we could not find a good way to replace it. The resulted clean dataframe is drink_Data_clean.

In [5]:
```
print('Before replacing missing values:')
print('Number of rows before discarding missing values = %d' % (drink_Data.shape[0]))
drink_Data_clean = drink_Data_missing.dropna()
print('Number of rows after discarding missing values = %d' % (drink_Data_clean.shape[
```

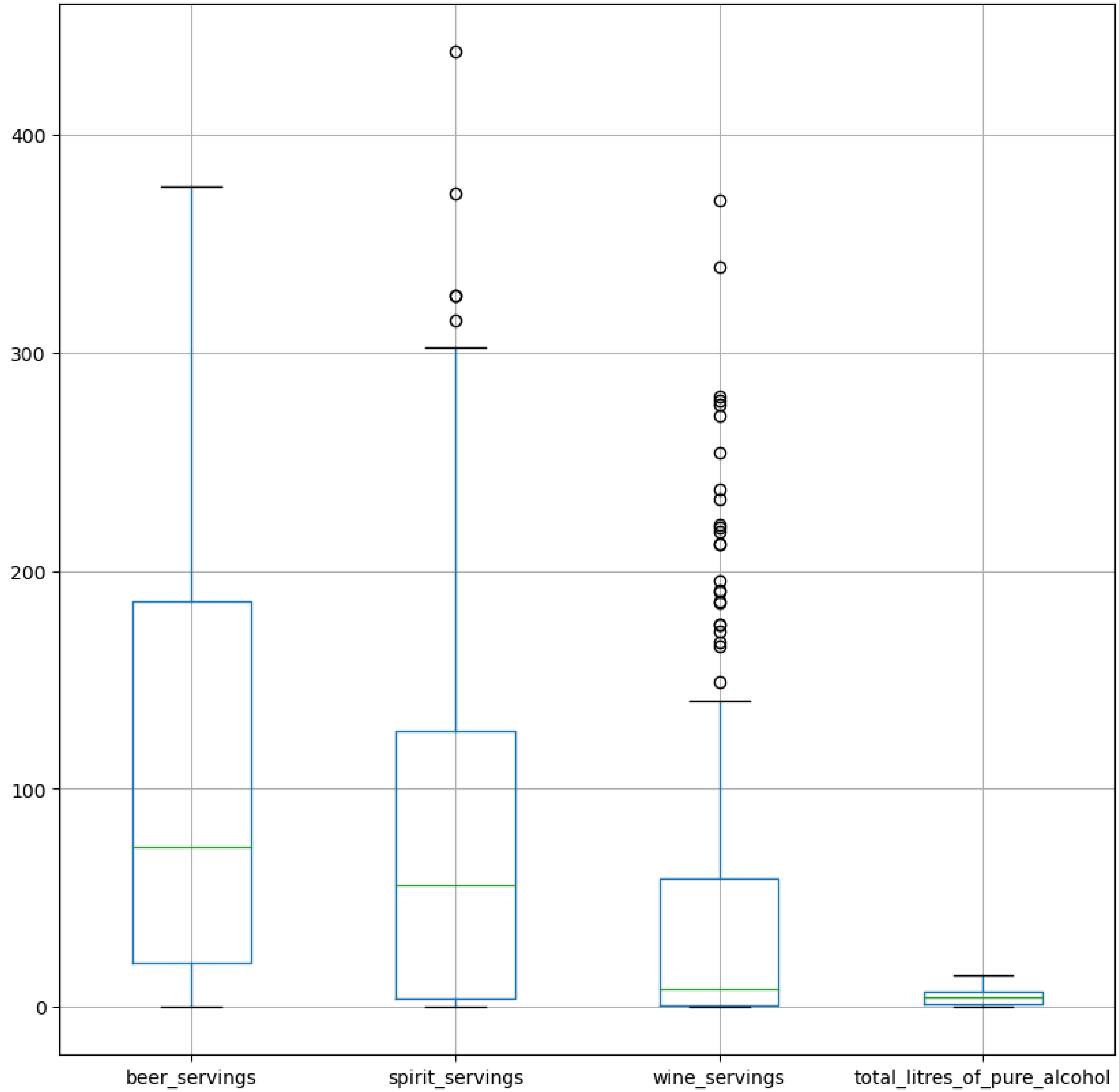
```
Before replacing missing values:
Number of rows before discarding missing values = 193
Number of rows after discarding missing values = 192
```

OUTLIERS

We start with a boxplot of the dataframe after we drop the categorical columns (country and continent). Visually outliers will show up at the extremities of the boxplot.

In [6]:
```
%matplotlib inline

# Drop categorical values and boxplot
data2 = drink_Data_clean.drop(['country', 'continent'],axis=1)
data2.boxplot(figsize=(10,10))
```

Out[6]: <Axes: >



To detect outliers we are going to compute the Z-score of each column. In the code below, we are finding the standardization of each row. Note that because we are still using the variable data2, it does not have the column 'country' and 'continent'. We apply the formula for standardizing and then print out each row standardization.

In [7]:
```
Z = (data2-data2.mean())/data2.std()
Z
```

Out[7]:

	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol
0	-1.044907	-0.912682	-0.510813	-1.249929
1	-0.162899	0.580219	0.075697	0.059573
2	-0.797152	-0.912682	-0.439916	-1.062857
4	1.105607	-0.268020	-0.040316	0.326819
5	-0.034066	0.534980	-0.040316	0.059573
...	...	...	...	...
188	2.255191	0.218304	-0.581709	0.807860
189	0.055126	-0.890062	-0.607490	-0.715438
190	-0.985446	-0.912682	-0.620380	-1.223204
191	-0.727781	-0.697794	-0.568819	-0.581815
192	-0.410654	-0.709104	-0.568819	0.006124

192 rows × 4 columns

We decided to use the outside of the interval of -3 to 3 on the Z-Scores to exclude outliers. We also print what were the outlier candidates for removal.

In [8]:

```
print('Number of rows before discarding outliers = %d' % (Z.shape[0]))
Z2 = Z.loc[((Z > -3).sum(axis=1)==4) & ((Z <= 3).sum(axis=1)==4)]
print('Number of rows after discarding outliers = %d' % (Z2.shape[0]))
zDrop = Z.loc[((Z <= -3).sum(axis=1)>=1) | ((Z > 3).sum(axis=1)>=1)]
zDrop
```

```
Number of rows before discarding outliers = 192
Number of rows after discarding outliers = 188
```

Out[8]:

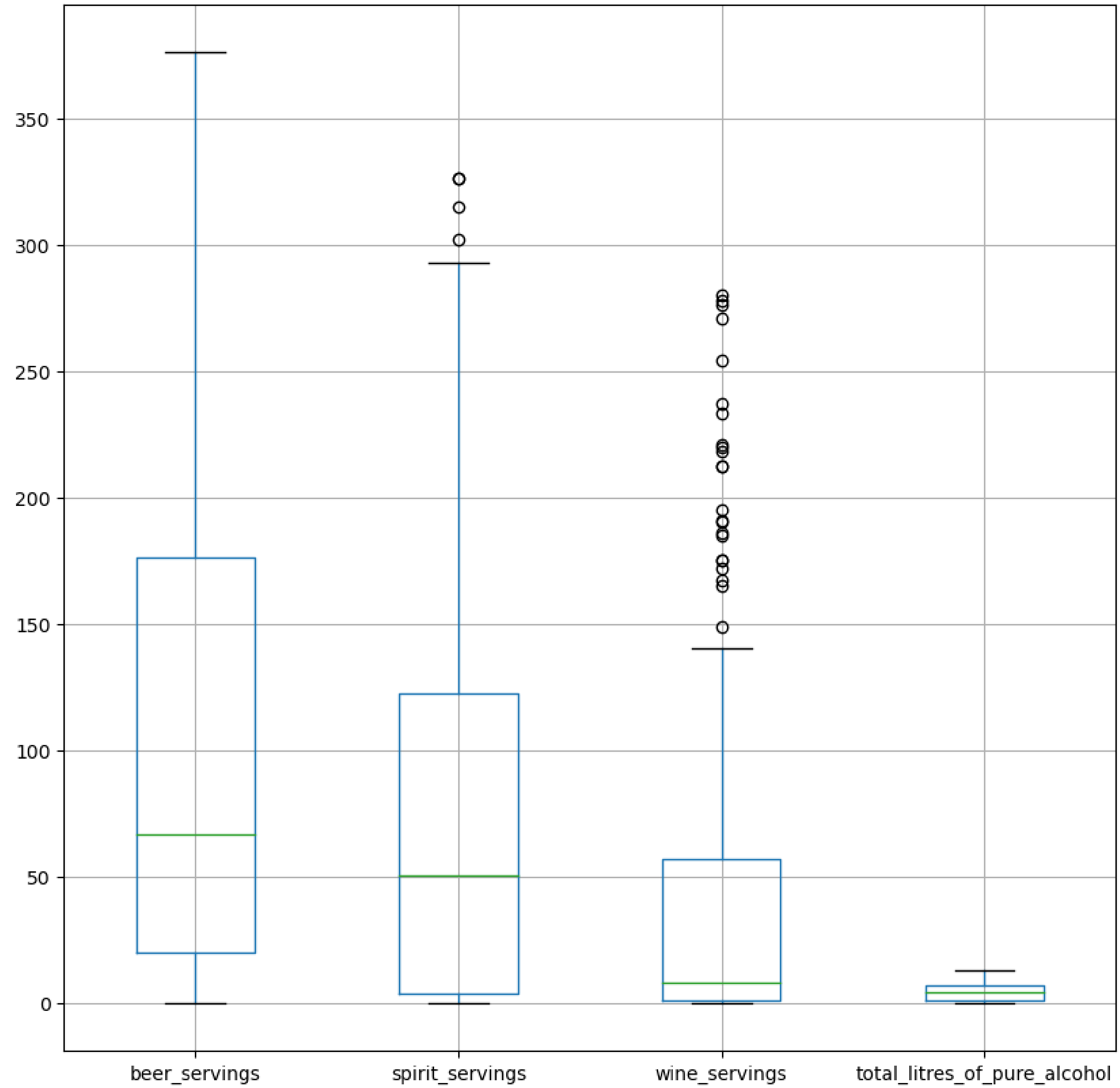
	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol
15	0.362342	3.305894	-0.078987	2.598404
61	0.213689	0.795106	4.149040	1.903566
68	0.927224	4.041035	-0.259451	1.930290
136	0.877673	-0.154921	3.749440	1.689770

In [9]:

```
# Box plot after removing outliers
data2_outremoved = data2.loc[((Z > -3).sum(axis=1)==4) & ((Z <= 3).sum(axis=1)==4)]
drink_Data_clean_outremoved = drink_Data_clean.loc[((Z > -3).sum(axis=1)==4) & ((Z <=
data2_outremoved.boxplot(figsize=(10,10))
```

Out[9]:

```
<Axes: >
```



Sorting Dataframes

The code below is showing what sorting by a column is like. Let's sort descending on total litres of alcohol.

In [10]:
```
# SORTING BY total_litres_of_pure_alcohol
sorted_drink_Data = drink_Data_clean_outremoved.sort_values(by='total_litres_of_pure_a
sorted_drink_Data[:20]
```

Out[10]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent
98	Lithuania	343	244	56.0	12.9	Europe
45	Czech Republic	361	170	134.0	11.8	Europe
141	Russian Federation	247	326	73.0	11.5	Asia
99	Luxembourg	236	133	271.0	11.4	Europe
81	Ireland	313	118	165.0	11.4	Europe
155	Slovakia	196	293	116.0	11.4	Europe
75	Hungary	234	215	185.0	11.3	Europe
65	Germany	346	117	175.0	11.3	Europe
135	Poland	343	215	56.0	10.9	Europe
156	Slovenia	270	51	276.0	10.6	Europe
16	Belgium	295	84	212.0	10.5	Europe
93	Latvia	281	216	62.0	10.5	Europe
182	United Kingdom	219	126	195.0	10.4	Europe
48	Denmark	224	81	278.0	10.4	Europe
8	Australia	261	72	212.0	10.4	Oceania
140	Romania	297	122	167.0	10.4	Europe
25	Bulgaria	231	252	94.0	10.3	Europe
42	Croatia	230	87	254.0	10.2	Europe
166	Switzerland	185	100	280.0	10.2	Europe
144	St. Lucia	171	315	71.0	10.1	North America

In [11]:

```
# SORTING BY beer_servings
sorted_drink_Data = drink_Data_clean_outremoved.sort_values(by='total_litres_of_pure_a
sorted_drink_Data[:20]
```

Out[11]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent
98	Lithuania	343	244	56.0	12.9	Europe
45	Czech Republic	361	170	134.0	11.8	Europe
141	Russian Federation	247	326	73.0	11.5	Asia
99	Luxembourg	236	133	271.0	11.4	Europe
81	Ireland	313	118	165.0	11.4	Europe
155	Slovakia	196	293	116.0	11.4	Europe
75	Hungary	234	215	185.0	11.3	Europe
65	Germany	346	117	175.0	11.3	Europe
135	Poland	343	215	56.0	10.9	Europe
156	Slovenia	270	51	276.0	10.6	Europe
16	Belgium	295	84	212.0	10.5	Europe
93	Latvia	281	216	62.0	10.5	Europe
182	United Kingdom	219	126	195.0	10.4	Europe
48	Denmark	224	81	278.0	10.4	Europe
8	Australia	261	72	212.0	10.4	Oceania
140	Romania	297	122	167.0	10.4	Europe
25	Bulgaria	231	252	94.0	10.3	Europe
42	Croatia	230	87	254.0	10.2	Europe
166	Switzerland	185	100	280.0	10.2	Europe
144	St. Lucia	171	315	71.0	10.1	North America

Duplicate Data

In this section, we are looking for duplicate samples in the dataset.We can use the function duplicated() to figure out all of the duplicated rows. If we ignore the 'country' column, the drinks.csv dataset has 13 duplicated rows with the convention of keeping count of all of them, duplicated(keep=False). With convention duplicated(keep='first') the dataset has 9 duplicated rows.

NOTE: we had to make sure to ignore the 'country' column since this dataset would not provide us with any duplicates as each row has a different country value.

In [12]:
```
# Look for duplicated rows in drinks.csv

dups = drink_Data_clean_outremoved.loc[:, drink_Data_clean_outremoved.columns != 'cour
print('Number of duplicate rows = %d' % (dups.sum()))
drink_Data_clean_outremoved.loc[dups==True]
```

```
Number of duplicate rows = 13
```

Out[12]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent
13	Bangladesh	0	0	0.0	0.0	Asia
46	North Korea	0	0	0.0	0.0	Asia
78	Indonesia	5	1	0.0	0.1	Asia
79	Iran	0	0	0.0	0.0	Asia
90	Kuwait	0	0	0.0	0.0	Asia
97	Libya	0	0	0.0	0.0	Africa
103	Maldives	0	0	0.0	0.0	Asia
107	Mauritania	0	0	0.0	0.0	Africa
111	Monaco	0	0	0.0	0.0	Europe
116	Myanmar	5	1	0.0	0.1	Asia
128	Pakistan	0	0	0.0	0.0	Asia
147	San Marino	0	0	0.0	0.0	Europe
158	Somalia	0	0	0.0	0.0	Africa

The below code outputs the total amount of rows before we discard the duplicates rows. We can easily drop our duplicates with the function drop_duplicates().

In [13]:
```
print('Number of rows before discarding duplicates = %d' % (drink_Data_clean_outremove
data2 = drink_Data_clean_outremoved.loc[:, drink_Data_clean_outremoved.columns != 'cou
print('Number of rows after discarding duplicates = %d' % (data2.shape[0]))
```

```
Number of rows before discarding duplicates = 188
Number of rows after discarding duplicates = 179
```

Shuffling Dataframes

To shuffle a dataframe we use reindex() method with a random index.

In [14]:
```
# Shuffling Dataframe

drink_Data_clean_outremoved = drink_Data_clean_outremoved.reindex(np.random.permutatic
drink_Data_clean_outremoved.reset_index(inplace=True, drop=True)

drink_Data_clean_outremoved
```

Out[14]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent
0	Suriname	128	178	7.0	5.6	South America
1	Uganda	45	9	0.0	8.3	Africa
2	Argentina	193	25	221.0	8.3	South America
3	Jamaica	82	97	9.0	3.4	North America
4	Tajikistan	2	15	0.0	0.3	Asia
...	...	...	...	...	...	...
183	Kyrgyzstan	31	97	6.0	2.4	Asia
184	Egypt	6	4	1.0	0.2	Africa
185	Spain	284	157	112.0	10.0	Europe
186	Japan	77	202	16.0	7.0	Asia
187	Malaysia	13	4	0.0	0.3	Asia

188 rows × 6 columns

Saving a Dataframe

Now that we have a clean, shuffled dataset with no missing values and no outliers we want to save it to disk. We use to_csv() to do this.

In [15]:

```
#SAVING A DATAFRAME
filename_write = os.path.join(path,"drinks_clean_outremoved_shuffle.csv")
drink_Data_clean_outremoved.to_csv(filename_write,index=False)   # Specify index = fal
print("Done")
```

Done

Dropping Fields

As an example of dropping fields from a dataframe, we can choose the 'continent' column and drop it.

In [16]:

```
#DROPPING FIELDS

print("Before drop: {}".format(drink_Data_clean_outremoved.columns))
dataTemp = drink_Data_clean_outremoved.drop('continent', axis=1, inplace=False)
print("After drop: {}".format(dataTemp.columns))
dataTemp[0:5]
```

```
Before drop: Index(['country', 'beer_servings', 'spirit_servings', 'wine_servings',
       'total_litres_of_pure_alcohol', 'continent'],
      dtype='object')
After drop: Index(['country', 'beer_servings', 'spirit_servings', 'wine_servings',
       'total_litres_of_pure_alcohol'],
      dtype='object')
```

Out[16]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol
0	Suriname	128	178	7.0	5.6
1	Uganda	45	9	0.0	8.3
2	Argentina	193	25	221.0	8.3
3	Jamaica	82	97	9.0	3.4
4	Tajikistan	2	15	0.0	0.3

Calculate Fields

A Total Servings column is added to drink_Data, by drink_Data.insert(), and then each row is filled by the result of summing (beer_servings + spirit_servings + wine_servings).

In [17]:

```
#CALCULATED FIELDS USING DRINKS.csv
drink_Data.insert(1,'Total Servings',(drink_Data['beer_servings']+drink_Data['spirit_s
drink_Data
```

Out[17]:

	country	Total Servings	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	c
0	Afghanistan	0	0	0	0	0.0	
1	Albania	275	89	132	54	4.9	
2	Algeria	39	25	0	14	0.7	
3	Andorra	695	245	138	312	12.4	
4	Angola	319	217	57	45	5.9	
...	...	...	...	...	...	...	
188	Venezuela	436	333	100	3	7.7	
189	Vietnam	114	111	2	1	2.0	
190	Yemen	6	6	0	0	0.1	
191	Zambia	55	32	19	4	2.5	
192	Zimbabwe	86	64	18	4	4.7	

193 rows × 7 columns

Feature Normalization

The z-score is used to find how close to the average an item is. We select total_litres_of_pure_alcohol because it provides the best description for the z-score. The column 'total_litres_of_pure_alcohol' changes it's values to it's z-score via the function zscore().

In [18]:
```
#FEATURE NORMALIZATION

drink_Data['total_litres_of_pure_alcohol'] = zscore(drink_Data['total_litres_of_pure_a
drink_Data.head(10)
```

Out[18]:

	country	Total Servings	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	con
0	Afghanistan	0	0	0	0	-1.253377	
1	Albania	275	89	132	54	0.048599	E
2	Algeria	39	25	0	14	-1.067381	
3	Andorra	695	245	138	312	2.041419	E
4	Angola	319	217	57	45	0.314308	
5	Antigua & Barbuda	275	102	128	45	0.048599	A
6	Argentina	439	193	25	221	0.952011	A
7	Armenia	211	21	179	11	-0.243682	E
8	Australia	545	261	72	212	1.510000	O
9	Austria	545	279	75	191	1.324004	E

Concatenating Rows and Columns

To create a new dataframe from an existing dataframe we can use pandas concat() method.

In [19]:
```
# Create a new dataframe from 'country' and the standardized 'total_litres_of_pure_alc

col_country = drink_Data['country']
col_total = drink_Data['total_litres_of_pure_alcohol']
result = pd.concat([col_country,col_total],axis=1)
result
```

Out[19]:

	country	total_litres_of_pure_alcohol
0	Afghanistan	-1.253377
1	Albania	0.048599
2	Algeria	-1.067381
3	Andorra	2.041419
4	Angola	0.314308
...	...	...
188	Venezuela	0.792585
189	Vietnam	-0.721959
190	Yemen	-1.226806
191	Zambia	-0.589104
192	Zimbabwe	-0.004543

193 rows × 2 columns

Like the above section, except when concatenating country and continent from 'Drinks.csv,' we can use the panda concat() method to to create a new dataframe by row instead.

In [20]:
```
# Create a new dataframe from country and continent, but this time by row

col_country = drink_Data['country']
col_continent = drink_Data['continent']
result = pd.concat([col_country,col_continent])
result
```

Out[20]:
```
0        Afghanistan
1            Albania
2            Algeria
3            Andorra
4             Angola
            ...
188    South America
189             Asia
190             Asia
191           Africa
192           Africa
Length: 386, dtype: object
```

Helpful Functions for Tensorflow (Little Gems)

Rather than generating any specific output, these are all helper functions for specific preprocessing tasks used later. In order:

encode_text_dummy function takes text values and inputs them into dummy data in columns.

encode_text_index function also takes text values but inserts them into an index.

encode_numeric_zscore function encodes a zscore using the data and calculating it by subtracting it by the mean and dividing that value by the standard deviation.

missing_median function takes missing values in the data and fills them using the median of that data.

missing_default function also takes missing values but instead fills them with whatever the default value is.

to_xy function takes the data and converts them into an x y matrix format that is readable by Tensorflow.

hms_string function calculates time setting them respectively to hms; hour, minute, second before returning it as a string.

chart_regression function creates a regression chart using expected and predicted values.

remove_outliers function uses the data index to calculate the absolute value minus the mean and comparing it to the standard deviation in order to remove rows which are larger than or equal to the standard deviation.

encode_numeric_range function encodes a column which ranges between either normalized low or normalizd high.

In [21]:

```
import collections
from sklearn import preprocessing
import matplotlib.pyplot as plt
import shutil

# Encode text values to dummy variables(i.e. [1,0,0],[0,1,0],[0,0,1] for red,green,blu
def encode_text_dummy(data, name):
    dummies = pd.get_dummies(data[name])
    for x in dummies.columns:
        dummy_name = "{}-{}".format(name, x)
        data[dummy_name] = dummies[x]
    data.drop(name, axis=1, inplace=True)


# Encode text values to indexes(i.e. [1],[2],[3] for red,green,blue).
def encode_text_index(data, name):
    le = preprocessing.LabelEncoder()
    data[name] = le.fit_transform(data[name])
    return le.classes_


# Encode a numeric column as zscores
def encode_numeric_zscore(data, name, mean=None, sd=None):
    if mean is None:
        mean = data[name].mean()

    if sd is None:
        sd = data[name].std()
```

```
    data[name] = (data[name] - mean) / sd


# Convert all missing values in the specified column to the median
def missing_median(data, name):
    med = data[name].median()
    data[name] = data[name].fillna(med)


# Convert all missing values in the specified column to the default
def missing_default(data, name, default_value):
    data[name] = data[name].fillna(default_value)


# Convert a Pandas dataframe to the x,y inputs that TensorFlow needs
def to_xy(data, target):
    result = []
    for x in data.columns:
        if x != target:
            result.append(x)
    # find out the type of the target column.
    target_type = data[target].dtypes
    target_type = target_type[0] if isinstance(target_type, collections.abc.Sequence)
    # Encode to int for classification, float otherwise. TensorFlow likes 32 bits.
    if target_type in (np.int64, np.int32):
        # Classification
        dummies = pd.get_dummies(data[target])
        return data[result].values.astype(np.float32), dummies.values.astype(np.float3
    else:
        # Regression
        return data[result].values.astype(np.float32), data[target].values.astype(np.f

# Nicely formatted time string
def hms_string(sec_elapsed):
    h = int(sec_elapsed / (60 * 60))
    m = int((sec_elapsed % (60 * 60)) / 60)
    s = sec_elapsed % 60
    return "{}:{:>02}:{:>05.2f}".format(h, m, s)


# Regression chart.
def chart_regression(pred,y,sort=True):
    t = pd.DataFrame({'pred' : pred, 'y' : y.flatten()})
    if sort:
        t.sort_values(by=['y'],inplace=True)
    a = plt.plot(t['y'].tolist(),label='expected')
    b = plt.plot(t['pred'].tolist(),label='prediction')
    plt.ylabel('output')
    plt.legend()
    plt.show()

# Remove all rows where the specified column is +/- sd standard deviations
def remove_outliers(data, name, sd):
    drop_rows = data.index[(np.abs(data[name] - data[name].mean()) >= (sd * data[name]
    data.drop(drop_rows, axis=0, inplace=True)


# Encode a column to a range between normalized_low and normalized_high.
def encode_numeric_range(data, name, normalized_low=-1, normalized_high=1,
```

```
                              data_low=None, data_high=None):
    if data_low is None:
        data_low = min(data[name])
        data_high = max(data[name])

    data[name] = ((data[name] - data_low) / (data_high - data_low)) * (normalized_high
```

Examples of label encoding, one hot encoding, and creating X/Y for TensorFlow

To represent the differences between encoding, this section like much earlier sections simply reads from the 'LaqnData.csv' dataset and specifies missing values with NaN.

In [22]:
```
air_Data = pd.read_csv("data/LaqnData.csv", na_values=['NaN', '?'])
air_Data
```

Out[22]:

	Site	Species	ReadingDateTime	Value	Units	Provisional or Ratified
0	HI0	CO	01/01/2018 00:00	NaN	mg m-3	P
1	HI0	CO	01/01/2018 00:15	NaN	mg m-3	P
2	HI0	CO	01/01/2018 00:30	NaN	mg m-3	P
3	HI0	CO	01/01/2018 00:45	NaN	mg m-3	P
4	HI0	CO	01/01/2018 01:00	NaN	mg m-3	P
...	...	...	...	...	...	...
175195	HI0	O3	31/12/2018 22:45	57.0	ug m-3	R
175196	HI0	O3	31/12/2018 23:00	61.1	ug m-3	R
175197	HI0	O3	31/12/2018 23:15	61.1	ug m-3	R
175198	HI0	O3	31/12/2018 23:30	61.1	ug m-3	R
175199	HI0	O3	31/12/2018 23:45	61.1	ug m-3	R

175200 rows × 6 columns

Moving on to encoding, we call the encode_text_index helper function in order to preprocess the data using the Species column from air_Data to generate an index value for each unique value.

In [23]:
```
encode_text_index(air_Data, "Species") # Label encoding
air_Data
```

Out[23]:

	Site	Species	ReadingDateTime	Value	Units	Provisional or Ratified
0	HI0	0	01/01/2018 00:00	NaN	mg m-3	P
1	HI0	0	01/01/2018 00:15	NaN	mg m-3	P
2	HI0	0	01/01/2018 00:30	NaN	mg m-3	P
3	HI0	0	01/01/2018 00:45	NaN	mg m-3	P
4	HI0	0	01/01/2018 01:00	NaN	mg m-3	P
...	...	...	...	...	...	...
175195	HI0	4	31/12/2018 22:45	57.0	ug m-3	R
175196	HI0	4	31/12/2018 23:00	61.1	ug m-3	R
175197	HI0	4	31/12/2018 23:15	61.1	ug m-3	R
175198	HI0	4	31/12/2018 23:30	61.1	ug m-3	R
175199	HI0	4	31/12/2018 23:45	61.1	ug m-3	R

175200 rows × 6 columns

Similarly, this also encodes the same data from Species in air_Data by when we call the helper function encode_text_dummy. However, we generate a new column for each unique dataset rather than with an index value.

In [24]:
```
air_Data = pd.read_csv("data/LaqnData.csv", na_values=['NaN', '?'])

encode_text_dummy(air_Data, "Species") # One hot encoding
air_Data
```

Out[24]:

	Site	ReadingDateTime	Value	Units	Provisional or Ratified	Species-CO	Species-NO	Species-NO2	Species-NOX	Spe
0	HI0	01/01/2018 00:00	NaN	mg m-3	P	1	0	0	0	
1	HI0	01/01/2018 00:15	NaN	mg m-3	P	1	0	0	0	
2	HI0	01/01/2018 00:30	NaN	mg m-3	P	1	0	0	0	
3	HI0	01/01/2018 00:45	NaN	mg m-3	P	1	0	0	0	
4	HI0	01/01/2018 01:00	NaN	mg m-3	P	1	0	0	0	
...	...	...	...	...	...	...	...	...	...	
175195	HI0	31/12/2018 22:45	57.0	ug m-3	R	0	0	0	0	
175196	HI0	31/12/2018 23:00	61.1	ug m-3	R	0	0	0	0	
175197	HI0	31/12/2018 23:15	61.1	ug m-3	R	0	0	0	0	
175198	HI0	31/12/2018 23:30	61.1	ug m-3	R	0	0	0	0	
175199	HI0	31/12/2018 23:45	61.1	ug m-3	R	0	0	0	0	

175200 rows × 10 columns

Make sure you encode the lables first before you call to_xy()

We use this block of code to preprocess the data by encoding the column labels "country" and "continent" in order to allow it to be used with the to_xy() funciton. Once called they generate an index value for those columns which we can then use in order to generate the matrix using to_xy(). It would not be able to read otherwise.

In [25]:
```
drink_Data = pd.read_csv("data/drinks.csv", na_values=['NaN', '?'])

encode_text_index(drink_Data, "country") # encoding first before you call to_xy()
encode_text_index(drink_Data, "continent")

drink_Data
```

Out[25]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent
0	0	0	0	0	0.0	1
1	1	89	132	54	4.9	2
2	2	25	0	14	0.7	0
3	3	245	138	312	12.4	2
4	4	217	57	45	5.9	0
...	...	...	...	...	...	...
188	188	333	100	3	7.7	5
189	189	111	2	1	2.0	1
190	190	6	0	0	0.1	1
191	191	32	19	4	2.5	0
192	192	64	18	4	4.7	0

193 rows × 6 columns

After converting by encoding, we call to_xy() using "continent" from drink_Data to create values in an x and y matrix format.

In [26]:
```
x,y = to_xy(drink_Data, "continent")
```

x is then called to print the x matrix values created from to_xy.

In [27]:
```
x
```

Out[27]:
```
array([[0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
       [1.00e+00, 8.90e+01, 1.32e+02, 5.40e+01, 4.90e+00],
       [2.00e+00, 2.50e+01, 0.00e+00, 1.40e+01, 7.00e-01],
       [3.00e+00, 2.45e+02, 1.38e+02, 3.12e+02, 1.24e+01],
       [4.00e+00, 2.17e+02, 5.70e+01, 4.50e+01, 5.90e+00],
       [5.00e+00, 1.02e+02, 1.28e+02, 4.50e+01, 4.90e+00],
       [6.00e+00, 1.93e+02, 2.50e+01, 2.21e+02, 8.30e+00],
       [7.00e+00, 2.10e+01, 1.79e+02, 1.10e+01, 3.80e+00],
       [8.00e+00, 2.61e+02, 7.20e+01, 2.12e+02, 1.04e+01],
       [9.00e+00, 2.79e+02, 7.50e+01, 1.91e+02, 9.70e+00],
       [1.00e+01, 2.10e+01, 4.60e+01, 5.00e+00, 1.30e+00],
       [1.10e+01, 1.22e+02, 1.76e+02, 5.10e+01, 6.30e+00],
       [1.20e+01, 4.20e+01, 6.30e+01, 7.00e+00, 2.00e+00],
       [1.30e+01, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
       [1.40e+01, 1.43e+02, 1.73e+02, 3.60e+01, 6.30e+00],
       [1.50e+01, 1.42e+02, 3.73e+02, 4.20e+01, 1.44e+01],
       [1.60e+01, 2.95e+02, 8.40e+01, 2.12e+02, 1.05e+01],
       [1.70e+01, 2.63e+02, 1.14e+02, 8.00e+00, 6.80e+00],
       [1.80e+01, 3.40e+01, 4.00e+00, 1.30e+01, 1.10e+00],
       [1.90e+01, 2.30e+01, 0.00e+00, 0.00e+00, 4.00e-01],
       [2.00e+01, 1.67e+02, 4.10e+01, 8.00e+00, 3.80e+00],
       [2.10e+01, 7.60e+01, 1.73e+02, 8.00e+00, 4.60e+00],
       [2.20e+01, 1.73e+02, 3.50e+01, 3.50e+01, 5.40e+00],
       [2.30e+01, 2.45e+02, 1.45e+02, 1.60e+01, 7.20e+00],
       [2.40e+01, 3.10e+01, 2.00e+00, 1.00e+00, 6.00e-01],
       [2.50e+01, 2.31e+02, 2.52e+02, 9.40e+01, 1.03e+01],
       [2.60e+01, 2.50e+01, 7.00e+00, 7.00e+00, 4.30e+00],
       [2.70e+01, 8.80e+01, 0.00e+00, 0.00e+00, 6.30e+00],
       [4.10e+01, 3.70e+01, 1.00e+00, 7.00e+00, 4.00e+00],
       [2.80e+01, 1.44e+02, 5.60e+01, 1.60e+01, 4.00e+00],
       [2.90e+01, 5.70e+01, 6.50e+01, 1.00e+00, 2.20e+00],
       [3.00e+01, 1.47e+02, 1.00e+00, 4.00e+00, 5.80e+00],
       [3.10e+01, 2.40e+02, 1.22e+02, 1.00e+02, 8.20e+00],
       [3.20e+01, 1.70e+01, 2.00e+00, 1.00e+00, 1.80e+00],
       [3.30e+01, 1.50e+01, 1.00e+00, 1.00e+00, 4.00e-01],
       [3.40e+01, 1.30e+02, 1.24e+02, 1.72e+02, 7.60e+00],
       [3.50e+01, 7.90e+01, 1.92e+02, 8.00e+00, 5.00e+00],
       [3.60e+01, 1.59e+02, 7.60e+01, 3.00e+00, 4.20e+00],
       [3.70e+01, 1.00e+00, 3.00e+00, 1.00e+00, 1.00e-01],
       [3.80e+01, 7.60e+01, 1.00e+00, 9.00e+00, 1.70e+00],
       [3.90e+01, 0.00e+00, 2.54e+02, 7.40e+01, 5.90e+00],
       [4.00e+01, 1.49e+02, 8.70e+01, 1.10e+01, 4.40e+00],
       [4.20e+01, 2.30e+02, 8.70e+01, 2.54e+02, 1.02e+01],
       [4.30e+01, 9.30e+01, 1.37e+02, 5.00e+00, 4.20e+00],
       [4.40e+01, 1.92e+02, 1.54e+02, 1.13e+02, 8.20e+00],
       [4.50e+01, 3.61e+02, 1.70e+02, 1.34e+02, 1.18e+01],
       [1.27e+02, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
       [4.60e+01, 3.20e+01, 3.00e+00, 1.00e+00, 2.30e+00],
       [4.70e+01, 2.24e+02, 8.10e+01, 2.78e+02, 1.04e+01],
       [4.80e+01, 1.50e+01, 4.40e+01, 3.00e+00, 1.10e+00],
       [4.90e+01, 5.20e+01, 2.86e+02, 2.60e+01, 6.60e+00],
       [5.00e+01, 1.93e+02, 1.47e+02, 9.00e+00, 6.20e+00],
       [5.10e+01, 1.62e+02, 7.40e+01, 3.00e+00, 4.20e+00],
       [5.20e+01, 6.00e+00, 4.00e+00, 1.00e+00, 2.00e-01],
       [5.30e+01, 5.20e+01, 6.90e+01, 2.00e+00, 2.20e+00],
       [5.40e+01, 9.20e+01, 0.00e+00, 2.33e+02, 5.80e+00],
       [5.50e+01, 1.80e+01, 0.00e+00, 0.00e+00, 5.00e-01],
       [5.60e+01, 2.24e+02, 1.94e+02, 5.90e+01, 9.50e+00],
       [5.70e+01, 2.00e+01, 3.00e+00, 0.00e+00, 7.00e-01],
       [5.80e+01, 7.70e+01, 3.50e+01, 1.00e+00, 2.00e+00],
```

```
[5.90e+01, 2.63e+02, 1.33e+02, 9.70e+01, 1.00e+01],
[6.00e+01, 1.27e+02, 1.51e+02, 3.70e+02, 1.18e+01],
[6.10e+01, 3.47e+02, 9.80e+01, 5.90e+01, 8.90e+00],
[6.20e+01, 8.00e+00, 0.00e+00, 1.00e+00, 2.40e+00],
[6.30e+01, 5.20e+01, 1.00e+02, 1.49e+02, 5.40e+00],
[6.40e+01, 3.46e+02, 1.17e+02, 1.75e+02, 1.13e+01],
[6.50e+01, 3.10e+01, 3.00e+00, 1.00e+01, 1.80e+00],
[6.60e+01, 1.33e+02, 1.12e+02, 2.18e+02, 8.30e+00],
[6.70e+01, 1.99e+02, 4.38e+02, 2.80e+01, 1.19e+01],
[6.80e+01, 5.30e+01, 6.90e+01, 2.00e+00, 2.20e+00],
[6.90e+01, 9.00e+00, 0.00e+00, 2.00e+00, 2.00e-01],
[7.00e+01, 2.80e+01, 3.10e+01, 2.10e+01, 2.50e+00],
[7.10e+01, 9.30e+01, 3.02e+02, 1.00e+00, 7.10e+00],
[7.20e+01, 1.00e+00, 3.26e+02, 1.00e+00, 5.90e+00],
[7.30e+01, 6.90e+01, 9.80e+01, 2.00e+00, 3.00e+00],
[7.40e+01, 2.34e+02, 2.15e+02, 1.85e+02, 1.13e+01],
[7.50e+01, 2.33e+02, 6.10e+01, 7.80e+01, 6.60e+00],
[7.60e+01, 9.00e+00, 1.14e+02, 0.00e+00, 2.20e+00],
[7.70e+01, 5.00e+00, 1.00e+00, 0.00e+00, 1.00e-01],
[7.80e+01, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[7.90e+01, 9.00e+00, 3.00e+00, 0.00e+00, 2.00e-01],
[8.00e+01, 3.13e+02, 1.18e+02, 1.65e+02, 1.14e+01],
[8.10e+01, 6.30e+01, 6.90e+01, 9.00e+00, 2.50e+00],
[8.20e+01, 8.50e+01, 4.20e+01, 2.37e+02, 6.50e+00],
[8.30e+01, 8.20e+01, 9.70e+01, 9.00e+00, 3.40e+00],
[8.40e+01, 7.70e+01, 2.02e+02, 1.60e+01, 7.00e+00],
[8.50e+01, 6.00e+00, 2.10e+01, 1.00e+00, 5.00e-01],
[8.60e+01, 1.24e+02, 2.46e+02, 1.20e+01, 6.80e+00],
[8.70e+01, 5.80e+01, 2.20e+01, 2.00e+00, 1.80e+00],
[8.80e+01, 2.10e+01, 3.40e+01, 1.00e+00, 1.00e+00],
[8.90e+01, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[9.00e+01, 3.10e+01, 9.70e+01, 6.00e+00, 2.40e+00],
[9.10e+01, 6.20e+01, 0.00e+00, 1.23e+02, 6.20e+00],
[9.20e+01, 2.81e+02, 2.16e+02, 6.20e+01, 1.05e+01],
[9.30e+01, 2.00e+01, 5.50e+01, 3.10e+01, 1.90e+00],
[9.40e+01, 8.20e+01, 2.90e+01, 0.00e+00, 2.80e+00],
[9.50e+01, 1.90e+01, 1.52e+02, 2.00e+00, 3.10e+00],
[9.60e+01, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[9.70e+01, 3.43e+02, 2.44e+02, 5.60e+01, 1.29e+01],
[9.80e+01, 2.36e+02, 1.33e+02, 2.71e+02, 1.14e+01],
[1.00e+02, 2.60e+01, 1.50e+01, 4.00e+00, 8.00e-01],
[1.01e+02, 8.00e+00, 1.10e+01, 1.00e+00, 1.50e+00],
[1.02e+02, 1.30e+01, 4.00e+00, 0.00e+00, 3.00e-01],
[1.03e+02, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[1.04e+02, 5.00e+00, 1.00e+00, 1.00e+00, 6.00e-01],
[1.05e+02, 1.49e+02, 1.00e+02, 1.20e+02, 6.60e+00],
[1.06e+02, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[1.07e+02, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[1.08e+02, 9.80e+01, 3.10e+01, 1.80e+01, 2.60e+00],
[1.09e+02, 2.38e+02, 6.80e+01, 5.00e+00, 5.50e+00],
[1.10e+02, 6.20e+01, 5.00e+01, 1.80e+01, 2.30e+00],
[1.12e+02, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[1.13e+02, 7.70e+01, 1.89e+02, 8.00e+00, 4.90e+00],
[1.14e+02, 3.10e+01, 1.14e+02, 1.28e+02, 4.90e+00],
[1.15e+02, 1.20e+01, 6.00e+00, 1.00e+01, 5.00e-01],
[1.16e+02, 4.70e+01, 1.80e+01, 5.00e+00, 1.30e+00],
[1.17e+02, 5.00e+00, 1.00e+00, 0.00e+00, 1.00e-01],
[1.18e+02, 3.76e+02, 3.00e+00, 1.00e+00, 6.80e+00],
[1.19e+02, 4.90e+01, 0.00e+00, 8.00e+00, 1.00e+00],
[1.20e+02, 5.00e+00, 6.00e+00, 0.00e+00, 2.00e-01],
```

```
[1.21e+02, 2.51e+02, 8.80e+01, 1.90e+02, 9.40e+00],
[1.22e+02, 2.03e+02, 7.90e+01, 1.75e+02, 9.30e+00],
[1.23e+02, 7.80e+01, 1.18e+02, 1.00e+00, 3.50e+00],
[1.24e+02, 3.00e+00, 2.00e+00, 1.00e+00, 1.00e-01],
[1.25e+02, 4.20e+01, 5.00e+00, 2.00e+00, 9.10e+00],
[1.26e+02, 1.88e+02, 2.00e+02, 7.00e+00, 7.00e+00],
[1.28e+02, 1.69e+02, 7.10e+01, 1.29e+02, 6.70e+00],
[1.29e+02, 2.20e+01, 1.60e+01, 1.00e+00, 7.00e-01],
[1.30e+02, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[1.31e+02, 3.06e+02, 6.30e+01, 2.30e+01, 6.90e+00],
[1.32e+02, 2.85e+02, 1.04e+02, 1.80e+01, 7.20e+00],
[1.33e+02, 4.40e+01, 3.90e+01, 1.00e+00, 1.50e+00],
[1.34e+02, 2.13e+02, 1.17e+02, 7.40e+01, 7.30e+00],
[1.35e+02, 1.63e+02, 1.60e+02, 2.10e+01, 6.10e+00],
[1.36e+02, 7.10e+01, 1.86e+02, 1.00e+00, 4.60e+00],
[1.37e+02, 3.43e+02, 2.15e+02, 5.60e+01, 1.09e+01],
[1.38e+02, 1.94e+02, 6.70e+01, 3.39e+02, 1.10e+01],
[1.39e+02, 1.00e+00, 4.20e+01, 7.00e+00, 9.00e-01],
[1.57e+02, 1.40e+02, 1.60e+01, 9.00e+00, 9.80e+00],
[1.11e+02, 1.09e+02, 2.26e+02, 1.80e+01, 6.30e+00],
[1.40e+02, 2.97e+02, 1.22e+02, 1.67e+02, 1.04e+01],
[1.41e+02, 2.47e+02, 3.26e+02, 7.30e+01, 1.15e+01],
[1.42e+02, 4.30e+01, 2.00e+00, 0.00e+00, 6.80e+00],
[1.60e+02, 1.94e+02, 2.05e+02, 3.20e+01, 7.70e+00],
[1.61e+02, 1.71e+02, 3.15e+02, 7.10e+01, 1.01e+01],
[1.62e+02, 1.20e+02, 2.21e+02, 1.10e+01, 6.30e+00],
[1.43e+02, 1.05e+02, 1.80e+01, 2.40e+01, 2.60e+00],
[1.44e+02, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[1.45e+02, 5.60e+01, 3.80e+01, 1.40e+02, 4.20e+00],
[1.46e+02, 0.00e+00, 5.00e+00, 0.00e+00, 1.00e-01],
[1.47e+02, 9.00e+00, 1.00e+00, 7.00e+00, 3.00e-01],
[1.48e+02, 2.83e+02, 1.31e+02, 1.27e+02, 9.60e+00],
[1.49e+02, 1.57e+02, 2.50e+01, 5.10e+01, 4.10e+00],
[1.50e+02, 2.50e+01, 3.00e+00, 2.00e+00, 6.70e+00],
[1.51e+02, 6.00e+01, 1.20e+01, 1.10e+01, 1.50e+00],
[1.52e+02, 1.96e+02, 2.93e+02, 1.16e+02, 1.14e+01],
[1.53e+02, 2.70e+02, 5.10e+01, 2.76e+02, 1.06e+01],
[1.54e+02, 5.60e+01, 1.10e+01, 1.00e+00, 1.20e+00],
[1.55e+02, 0.00e+00, 0.00e+00, 0.00e+00, 0.00e+00],
[1.56e+02, 2.25e+02, 7.60e+01, 8.10e+01, 8.20e+00],
[1.58e+02, 2.84e+02, 1.57e+02, 1.12e+02, 1.00e+01],
[1.59e+02, 1.60e+01, 1.04e+02, 0.00e+00, 2.20e+00],
[1.63e+02, 8.00e+00, 1.30e+01, 0.00e+00, 1.70e+00],
[1.64e+02, 1.28e+02, 1.78e+02, 7.00e+00, 5.60e+00],
[1.65e+02, 9.00e+01, 2.00e+00, 2.00e+00, 4.70e+00],
[1.66e+02, 1.52e+02, 6.00e+01, 1.86e+02, 7.20e+00],
[1.67e+02, 1.85e+02, 1.00e+02, 2.80e+02, 1.02e+01],
[1.68e+02, 5.00e+00, 3.50e+01, 1.60e+01, 1.00e+00],
[1.69e+02, 2.00e+00, 1.50e+01, 0.00e+00, 3.00e-01],
[1.71e+02, 9.90e+01, 2.58e+02, 1.00e+00, 6.40e+00],
[9.90e+01, 1.06e+02, 2.70e+01, 8.60e+01, 3.90e+00],
[1.72e+02, 1.00e+00, 1.00e+00, 4.00e+00, 1.00e-01],
[1.73e+02, 3.60e+01, 2.00e+00, 1.90e+01, 1.30e+00],
[1.74e+02, 3.60e+01, 2.10e+01, 5.00e+00, 1.10e+00],
[1.75e+02, 1.97e+02, 1.56e+02, 7.00e+00, 6.40e+00],
[1.76e+02, 5.10e+01, 3.00e+00, 2.00e+01, 1.30e+00],
[1.77e+02, 5.10e+01, 2.20e+01, 7.00e+00, 1.40e+00],
[1.78e+02, 1.90e+01, 7.10e+01, 3.20e+01, 2.20e+00],
[1.79e+02, 6.00e+00, 4.10e+01, 9.00e+00, 1.00e+00],
[1.81e+02, 4.50e+01, 9.00e+00, 0.00e+00, 8.30e+00],
```

```
       [1.82e+02, 2.06e+02, 2.37e+02, 4.50e+01, 8.90e+00],
       [1.83e+02, 1.60e+01, 1.35e+02, 5.00e+00, 2.80e+00],
       [1.84e+02, 2.19e+02, 1.26e+02, 1.95e+02, 1.04e+01],
       [1.70e+02, 3.60e+01, 6.00e+00, 1.00e+00, 5.70e+00],
       [1.80e+02, 2.49e+02, 1.58e+02, 8.40e+01, 8.70e+00],
       [1.85e+02, 1.15e+02, 3.50e+01, 2.20e+02, 6.60e+00],
       [1.86e+02, 2.50e+01, 1.01e+02, 8.00e+00, 2.40e+00],
       [1.87e+02, 2.10e+01, 1.80e+01, 1.10e+01, 9.00e-01],
       [1.88e+02, 3.33e+02, 1.00e+02, 3.00e+00, 7.70e+00],
       [1.89e+02, 1.11e+02, 2.00e+00, 1.00e+00, 2.00e+00],
       [1.90e+02, 6.00e+00, 0.00e+00, 0.00e+00, 1.00e-01],
       [1.91e+02, 3.20e+01, 1.90e+01, 4.00e+00, 2.50e+00],
       [1.92e+02, 6.40e+01, 1.80e+01, 4.00e+00, 4.70e+00]], dtype=float32)
```

Likewise, y is called to print the y matrix variables created from to_xy.

In [28]:
```
y
```

Out[28]:
```
array([[0., 1., 0., 0., 0., 0.],
       [0., 0., 1., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0.],
       ...,
       [0., 1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0.]], dtype=float32)
```

Example of Deal with Missing Values and Outliers

The code block below reads the data from the CSV file specified in filename_read into a DataFrame called drink_Data. It also specifies that the values 'NaN' and '?' should be treated as missing values in the dataset. The missing_median function is called to replace missing values in the 'total_litres_of_pure_alcohol' column of the drink_Data DataFrame with the median value of that column. A function called remove_outliers is called to remove outliers from the 'beer_servings' column of the drink_Data DataFrame. The function removes data points that are more than 2 standard deviations away from the mean. The number 2 passed as the second argument suggests this. The code then prints the number of rows in the DataFrame before and after removing outliers to show how many outliers were dropped.

In [29]:
```
path = "./data/"

filename_read = os.path.join(path,"drinks.csv")
drink_Data = pd.read_csv(filename_read,na_values=['NaN','?'])
# Handle mising values in total_litres_of_pure_alcohol
missing_median(drink_Data, 'total_litres_of_pure_alcohol')
#drink_Data.drop('name', 1,inplace=True)

# Drop outliers in Total_litres_of_pure_alcohol
print("Value before value outliers dropped: {}".format(len(drink_Data)))
remove_outliers(drink_Data,'beer_servings',2)
print("Value after value outliers dropped: {}".format(len(drink_Data)))
```

```
Value before value outliers dropped: 193
Value after value outliers dropped: 185
```

Training and Validation

The code below reads the data from the CSV file specified in the filename_read, into a dataframe called drink_Data, displays the first 5 rows of the DataFrame, showing the data read from the CSV file, creates a label encoder object, encodes the 'country' column of the DataFrame using label encoding and assigns the encoded values to a new column named 'encoded_country' in the same DataFrame, again displays the first 5 rows of the DataFrame, now including the 'encoded_country' column, which contains numeric labels instead of country names. Then scikit-learn is used to split the dataset into training and testing sets. It takes three main arguments: drink_Data[['beer_servings', 'spirit_servings', 'wine_servings']] selects the features (independent variables) for the input to the model, drink_Data['encoded_country'] selects the target variable (dependent variable) that the model will predict, test_size=0.25 specifies that 25% of the data will be used for testing, and 75% will be used for training. Finally random_state=42 is used to set a seed for the random number generator. This ensures that the data split is reproducible, meaning that if you run this code multiple times with the same dataset, you'll get the same data split. The number 42 is an arbitrary choice and can be any non-negative integer.

In [30]:
```
from sklearn.model_selection import train_test_split
from sklearn import preprocessing

path = "./data/"

filename = os.path.join(path,"drinks.csv")
drink_Data = pd.read_csv(filename,na_values=['NA','?'])

le = preprocessing.LabelEncoder()
drink_Data['encoded_country'] = le.fit_transform(drink_Data['country'])

drink_Data[0:5]
```

Out[30]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent	en
0	Afghanistan	0	0	0	0.0	Asia	
1	Albania	89	132	54	4.9	Europe	
2	Algeria	25	0	14	0.7	Africa	
3	Andorra	245	138	312	12.4	Europe	
4	Angola	217	57	45	5.9	Africa	

The x_train will contain the features 'beer_servings', 'spirit_servings', 'wine_servings' and 'total_litres_of_pure_alcohol' for 75% of the dataset used for training an ML model. The y_train will contain the target variable 'encoded_country' corresponding to the training data. The x_test will contain the same features but for testing your model's performance and it is one quarter -

25% - of the dataset. The y_test will contain the target variable 'encoded_country' corresponding to the testing data.

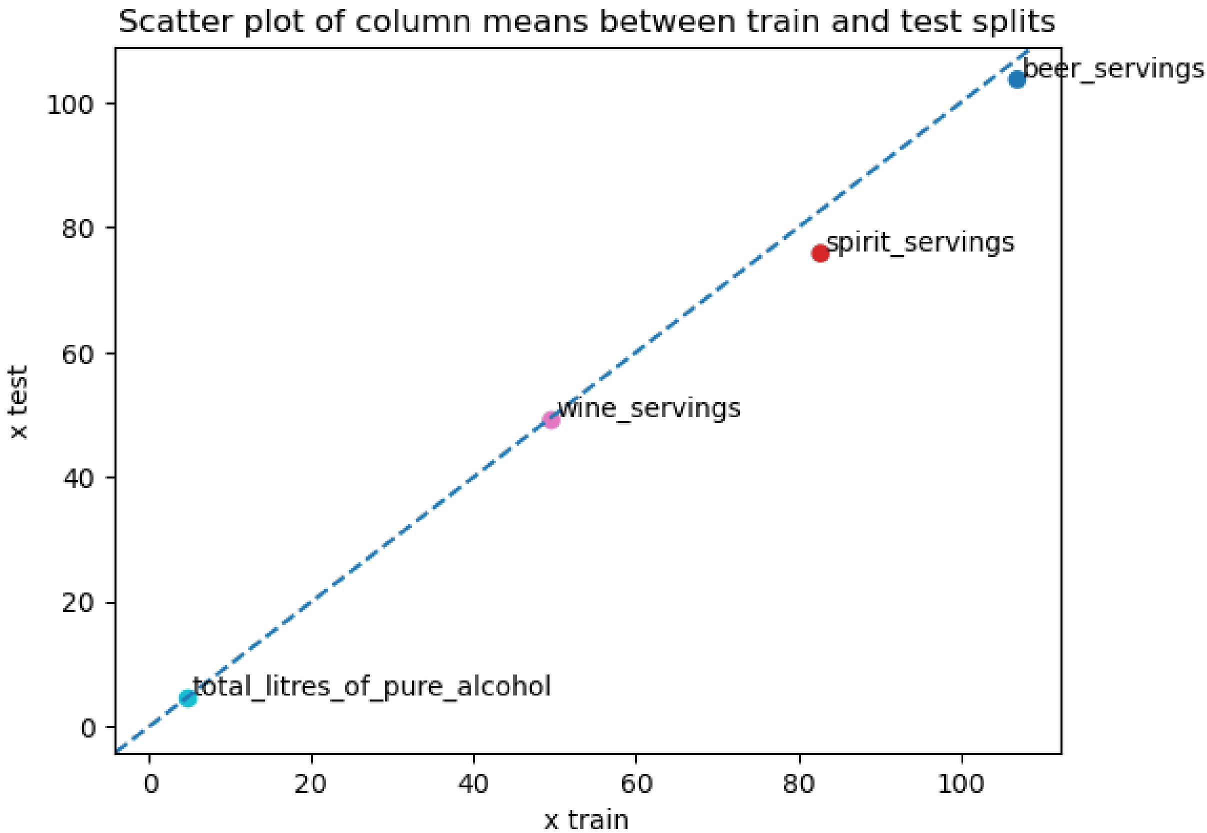
In [31]:
```
# Split into train/test
x_train, x_test, y_train, y_test = train_test_split(
  drink_Data[['beer_servings', 'spirit_servings', 'wine_servings', 'total_litres_of_pu
  drink_Data['encoded_country'],
  test_size=0.25,
  random_state=99)
print("x_train shape: ", x_train.shape)
print("y_train shape: ", y_train.shape)

print("x_test shape: ", x_test.shape)
print("y_test shape: ", y_test.shape)
```

```
x_train shape:  (144, 4)
y_train shape:  (144,)
x_test shape:  (49, 4)
y_test shape:  (49,)
```

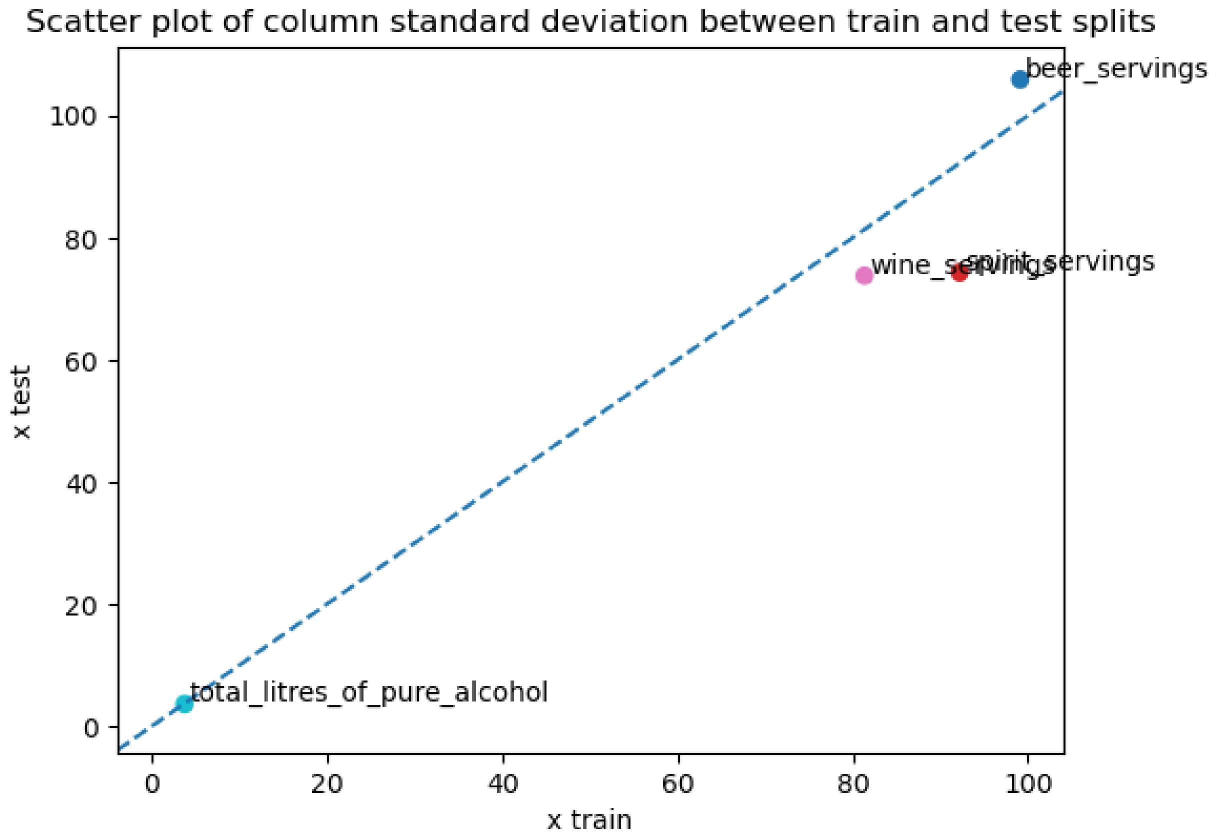
Calculate Means and Standard Deviations on both partitions of the dataset.

In [32]:
```
# Statistics for training set
x_train_mean = np.mean(x_train)
x_train_std = np.std(x_train)

# Statistics for test set
x_test_mean = np.mean(x_test)
x_test_std = np.std(x_test)

column_names = ['beer_servings', 'spirit_servings', 'wine_servings', 'total_litres_of_
plt.scatter(x_train_mean, x_test_mean, cmap='tab10', c=range(len(column_names)))
plt.axline((1, 1), slope=1, linestyle="--")
plt.title("Scatter plot of column means between train and test splits")
plt.xlabel("x train")
plt.ylabel("x test")
for i, txt in enumerate(column_names):
    plt.annotate(txt, (x_train_mean[i], x_test_mean[i]), xytext=(x_train_mean[i]+0.5,

plt.show()
```

```
C:\Users\sho85\anaconda3\Lib\site-packages\numpy\core\fromnumeric.py:3462: FutureWarn
ing: In a future version, DataFrame.mean(axis=None) will return a scalar mean over th
e entire DataFrame. To retain the old behavior, use 'frame.mean(axis=0)' or just 'fra
me.mean()'
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
C:\Users\sho85\anaconda3\Lib\site-packages\numpy\core\fromnumeric.py:3462: FutureWarn
ing: In a future version, DataFrame.mean(axis=None) will return a scalar mean over th
e entire DataFrame. To retain the old behavior, use 'frame.mean(axis=0)' or just 'fra
me.mean()'
  return mean(axis=axis, dtype=dtype, out=out, **kwargs)
```



In [33]:
```
plt.scatter(x_train_std, x_test_std, cmap='tab10', c=range(len(column_names)))
plt.axline((1, 1), slope=1, linestyle="--")
plt.title("Scatter plot of column standard deviation between train and test splits")
plt.xlabel("x train")
plt.ylabel("x test")
for i, txt in enumerate(column_names):
    plt.annotate(txt, (x_train_std[i], x_test_std[i]), xytext=(x_train_std[i]+0.5, x_t

plt.show()
```

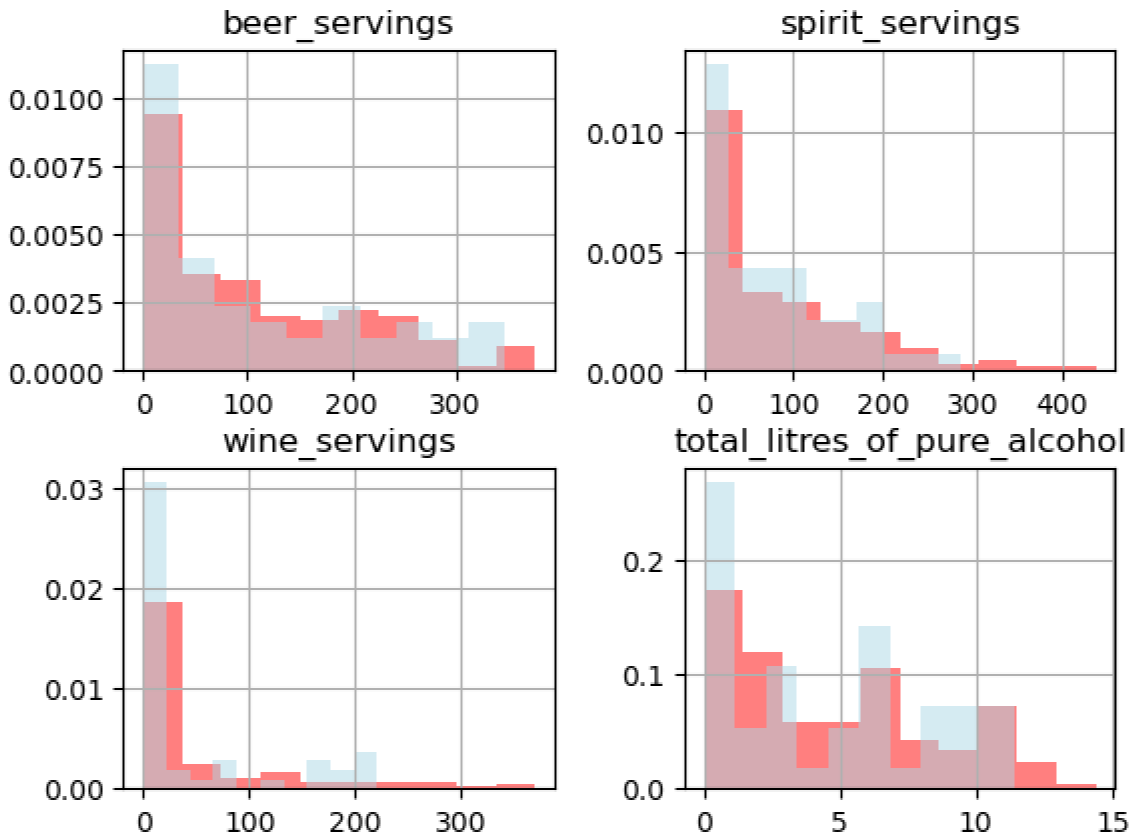


Comparing training and test sets

Distribuitons of data per column look similar enough between training split and test split.

In [34]:
```
# drink_Data[['beer_servings', 'spirit_servings', 'wine_servings', 'total_litres_of_pu
x_train_df = pd.DataFrame(x_train)
x_train_df.columns = column_names

x_test_df = pd.DataFrame(x_test)
x_test_df.columns = column_names

print("Normalized histogram of train and test values per column")
axs = x_train_df.hist(alpha=0.5, color='red', density=True)
for ax, (colname, values) in zip(axs.flat, x_test_df.iteritems()):
  values.hist(ax=ax, bins=10, alpha=0.5, color='lightblue', density=True)

plt.show()
```

```
Normalized histogram of train and test values per column
C:\Users\sho85\AppData\Local\Temp\ipykernel_19972\1345280957.py:10: FutureWarning: it
eritems is deprecated and will be removed in a future version. Use .items instead.
  for ax, (colname, values) in zip(axs.flat, x_test_df.iteritems()):
```

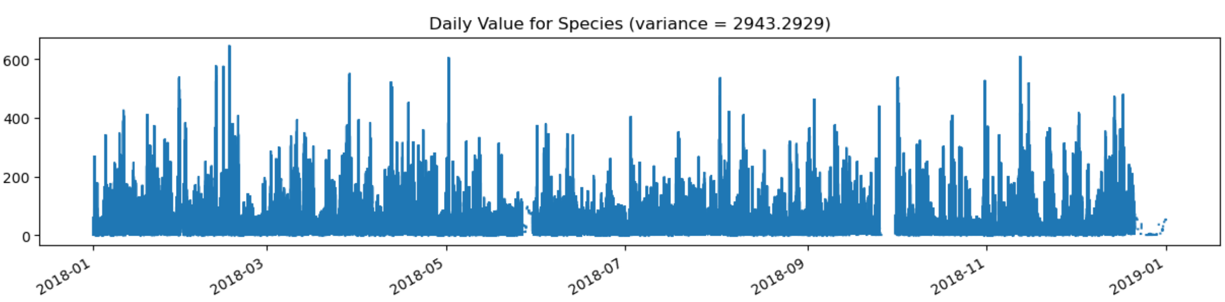


Aggregation

Reads from a CSV and assigns it to a variable called 'daily'. Assumes first row of CSV contains column headers. It then sets the index of the 'daily' DataFrame to a datetime object from the 'ReadingDateTime' column using pd.to_datetime function. It then plots the variance throughout the years.

In [35]:
```
daily = pd.read_csv('./Data/LaqnData.csv', header='infer')
daily.index = pd.to_datetime(daily['ReadingDateTime'])
daily = daily['Value']
ax = daily.plot(kind='line',figsize=(15,3))
ax.set_title('Daily Value for Species (variance = %.4f)' % (daily.var()))
```

Out[35]:
```
Text(0.5, 1.0, 'Daily Value for Species (variance = 2943.2929)')
```

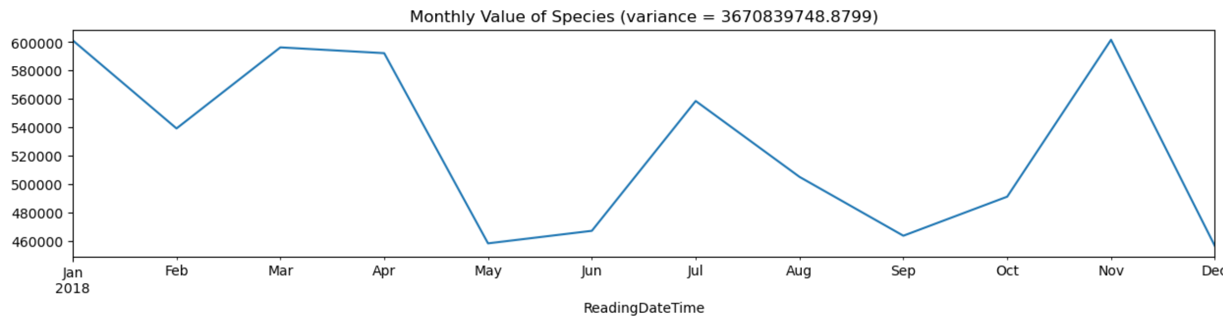


In [36]:
```
daily
```

Out[36]:
```
ReadingDateTime
2018-01-01 00:00:00     NaN
2018-01-01 00:15:00     NaN
2018-01-01 00:30:00     NaN
2018-01-01 00:45:00     NaN
2018-01-01 01:00:00     NaN
                       ...
2018-12-31 22:45:00    57.0
2018-12-31 23:00:00    61.1
2018-12-31 23:15:00    61.1
2018-12-31 23:30:00    61.1
2018-12-31 23:45:00    61.1
Name: Value, Length: 175200, dtype: float64
```

In [37]:
```
monthly = daily.groupby(pd.Grouper(freq='M')).sum()
ax = monthly.plot(kind='line',figsize=(15,3))
ax.set_title('Monthly Value of Species (variance = %.4f)' % (monthly.var()))
```

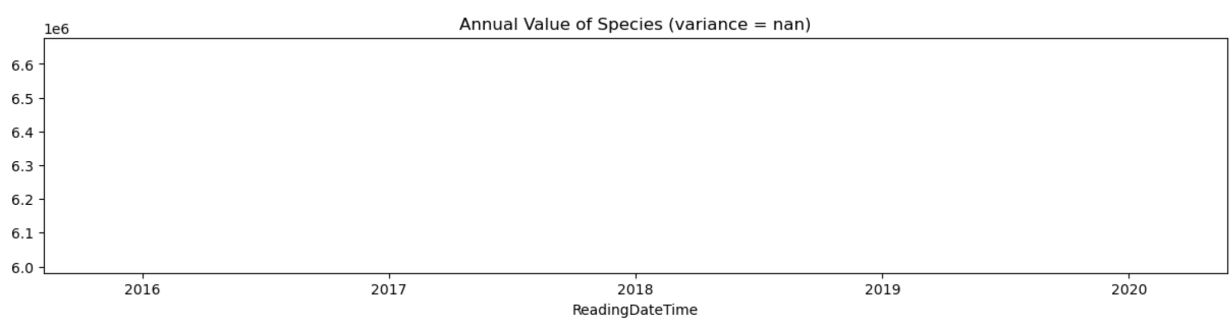
Out[37]:
```
Text(0.5, 1.0, 'Monthly Value of Species (variance = 3670839748.8799)')
```



In [38]:
```
# WILL NOT USE SINCE OUR CSV ONLY HAS 1 YEAR (2018)
annual = daily.groupby(pd.Grouper(freq='Y')).sum()
ax = annual.plot(kind='line',figsize=(15,3))
ax.set_title('Annual Value of Species (variance = %.4f)' % (annual.var()))
```

```
C:\Users\sho85\anaconda3\Lib\site-packages\pandas\plotting\_matplotlib\core.py:1400:
UserWarning: Attempting to set identical low and high xlims makes transformation sing
ular; automatically expanding.
  ax.set_xlim(left, right)
```

Out[38]:
```
Text(0.5, 1.0, 'Annual Value of Species (variance = nan)')
```



Sampling

Sampling is a technique used in data analysis to make large datasets more manageable. Imagine you have a massive dataset with millions or billions of data points. Performing analyses and visualizations on such a vast dataset can be computationally intensive and time-consuming. Here's where sampling comes into play.

Sampling without Replacement: In this method, you randomly select a subset of data points from the original dataset. Each data point can be chosen only once, and once selected, it's removed from the dataset. This way, you obtain a smaller but representative sample of the original data. EDA can then be performed on this sample, giving you insights and patterns that can be extrapolated to the entire dataset with some degree of confidence.

Sampling with Replacement: In contrast, when you use sampling with replacement, each data point you select is not removed from the dataset. This means that the same data point can be selected multiple times. Sampling with replacement can be useful if you want to create bootstrap samples for statistical analysis or if you're dealing with imbalanced datasets where some classes are underrepresented.

In [39]:
```
drink_Data.head()
```

Out[39]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent	en
0	Afghanistan	0	0	0	0.0	Asia	
1	Albania	89	132	54	4.9	Europe	
2	Algeria	25	0	14	0.7	Africa	
3	Andorra	245	138	312	12.4	Europe	
4	Angola	217	57	45	5.9	Africa	

In [40]:
```
sample = drink_Data.sample(n=3)
sample
```

Out[40]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent	enc
92	Laos	62	0	123	6.2	Asia	
14	Barbados	143	173	36	6.3	North America	
19	Bhutan	23	0	0	0.4	Asia	

In [41]:
```
sample = drink_Data.sample(frac=0.01, random_state=1)
sample
```

Out[41]:

	country	beer_servings	spirit_servings	wine_servings	total_litres_of_pure_alcohol	continent	en
44	Cyprus	192	154	113	8.2	Europe	
69	Guatemala	53	69	2	2.2	North America	

In [42]:
```
sample = air_Data.sample(frac=0.1, replace=True, random_state=1)
sample
```

Out[42]:

	Site	ReadingDateTime	Value	Units	Provisional or Ratified	Species-CO	Species-NO	Species-NO2	Species-NOX	Spe
128037	HI0	27/08/2018 17:15	49.2	ug m-3 as NO2	R	0	0	0	1	
5192	HI0	24/02/2018 02:00	NaN	mg m-3	P	1	0	0	0	
50057	HI0	06/06/2018 10:15	5.4	ug m-3	R	0	1	0	0	
109259	HI0	13/02/2018 02:45	21.2	ug m-3 as NO2	R	0	0	0	1	
73349	HI0	04/02/2018 01:15	15.0	ug m-3	R	0	0	1	0	
...	...	...	...	...	...	...	...	...	...	
38124	HI0	02/02/2018 03:00	0.2	ug m-3	R	0	1	0	0	
61423	HI0	02/10/2018 19:45	1.7	ug m-3	R	0	1	0	0	
16011	HI0	16/06/2018 18:45	NaN	mg m-3	P	1	0	0	0	
144902	HI0	19/02/2018 09:30	1.7	ug m-3	R	0	0	0	0	
56757	HI0	15/08/2018 05:15	13.3	ug m-3	R	0	1	0	0	

17520 rows × 10 columns

Discretization

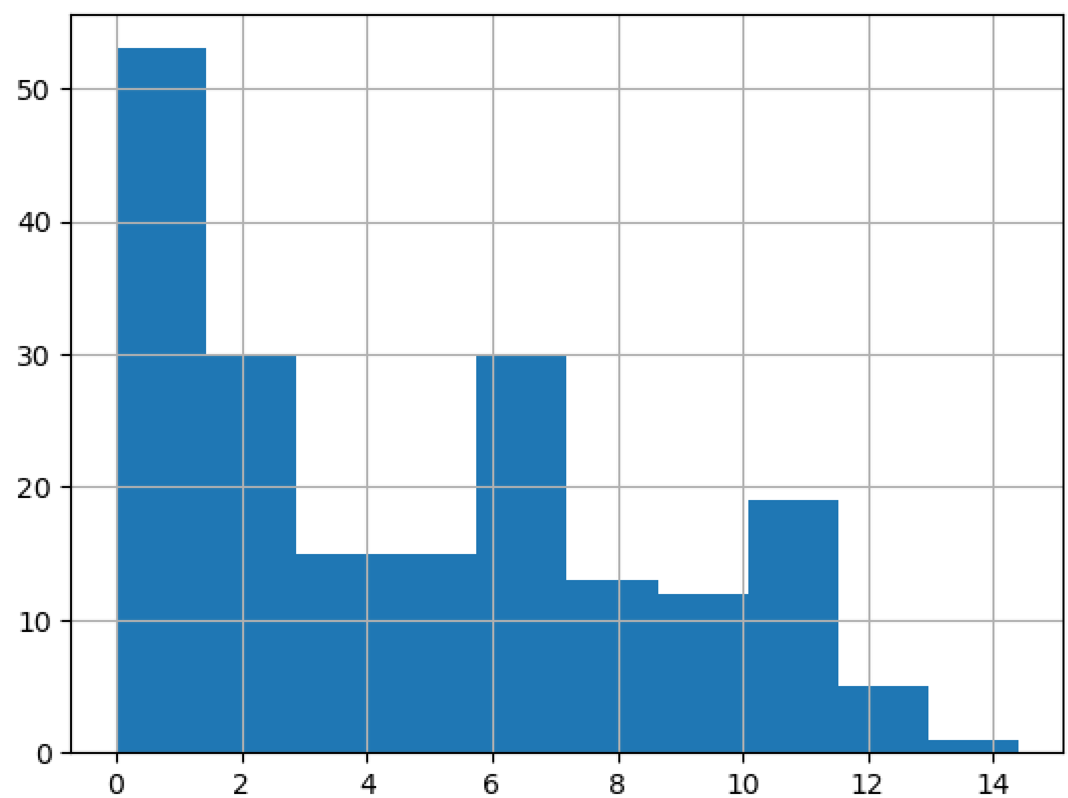
Discretization is a data preprocessing technique used to convert these continuous-valued attributes into categorical attributes. It, involves dividing the range of possible values into discrete intervals or bins and then assigning each data point to one of these bins. This process turns the continuous attribute into a categorical one, making it easier to work with in certain types of analyses or machine learning algorithms.

Equal width discretization is one of the more common methods for discretization. It involves dividing the range of values into equally sized intervals. For example, if you have values ranging from 1 to 10, you could create bins like [1-3], [4-6], and [7-10], each of which has the same width of 3 units. Any data point falling within a specific bin is assigned to that bin. So, if 'Clump Thickness' had values like 2.5 or 4.7, they might be categorized into the appropriate bins.t

Equal depth discretization, also known as quantile-based discretization, divides the data into bins in a way that ensures each bin contains approximately the same number of data points. It takes into account the distribution of data, so if you have outliers or unevenly distributed data, this method can be more robust. In the context of 'Clump Thickness,' equal depth discretization would group values into bins so that each bin contains roughly the same number of patients' data.

In [43]:
```
drink_Data['total_litres_of_pure_alcohol'].hist(bins=10)
drink_Data['total_litres_of_pure_alcohol'].value_counts(sort=False)
```

Out[43]:
```
0.0     13
4.9      4
0.7      3
12.4     1
5.9      3
        ..
6.4      2
3.9      1
1.4      1
5.7      1
8.7      1
Name: total_litres_of_pure_alcohol, Length: 90, dtype: int64
```



In [44]:
```
bins = pd.cut(drink_Data['total_litres_of_pure_alcohol'],4)
bins.value_counts(sort=False)
```

Out[44]:
```
(-0.0144, 3.6]    87
(3.6, 7.2]        59
(7.2, 10.8]       33
(10.8, 14.4]      14
Name: total_litres_of_pure_alcohol, dtype: int64
```

In [45]:
```
bins = pd.qcut(drink_Data['total_litres_of_pure_alcohol'],4)
bins.value_counts(sort=False)
```

Out[45]:
```
(-0.001, 1.3]    52
(1.3, 4.2]       45
(4.2, 7.2]       49
(7.2, 14.4]      47
Name: total_litres_of_pure_alcohol, dtype: int64
```

Principal Component Analysis

The code below loads six images, displays them in a 4x4 grid within a Matplotlib figure, and also stores the flattened pixel data of each image in the imgData NumPy array for further processing or analysis. The images are assumed to be 256x256 pixels each, and the code assumes a specific naming convention for the image files.

In [46]:
```
# PICTURES IS 256 x 256
numImages = 6
fig = plt.figure(figsize=(7,7))
imgData = np.zeros(shape=(numImages,196608))

for i in range(1,numImages+1):
    filename = 'data_Pic/Picture'+str(i)+'.jpg'
    img = mpimg.imread(filename)
    ax = fig.add_subplot(4,4,i)
    plt.imshow(img)
    plt.axis('off')
    ax.set_title(str(i))
    imgData[i-1] = np.array(img.flatten()).reshape(1,img.shape[0]*img.shape[1]*img.sha
```

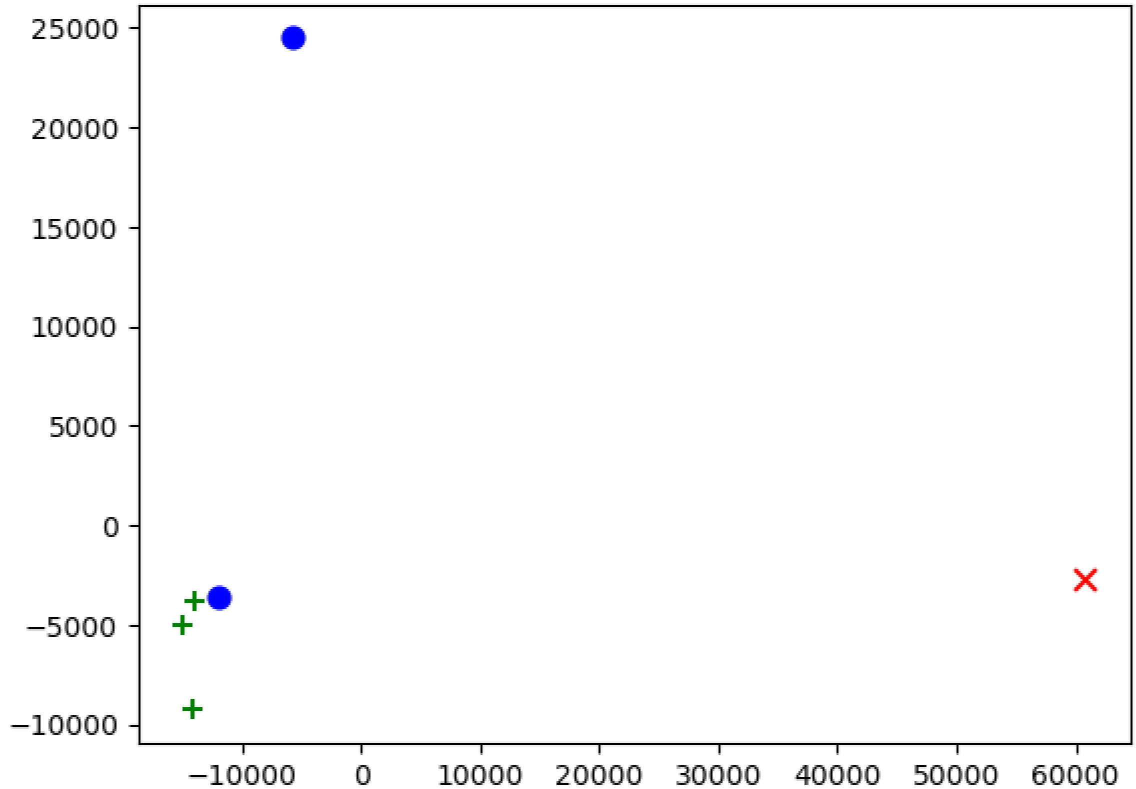
The code below performs PCA to reduce the dimensionality of the image data to two principal components and then creates a DataFrame to visualize the reduced data along with the drink labels for each image. This can be useful for visualizing the relationships or clusters among the images based on their reduced-dimensional representations.

In [47]:
```
import pandas as pd
from sklearn.decomposition import PCA

numComponents = 2
pca = PCA(n_components=numComponents)
pca.fit(imgData)

projected = pca.transform(imgData)
projected = pd.DataFrame(projected,columns=['pc1','pc2'],index=range(1,numImages+1))
projected['drink'] = ['energy drink', 'alcohol','energy drink','energy drink', 'juice'
projected
```

Out[47]:

	pc1	pc2	drink
1	-13888.266845	-3824.372095	energy drink
2	60778.894246	-2701.257537	alcohol
3	-14213.624857	-9285.123620	energy drink
4	-14931.018828	-5056.830314	energy drink
5	-5714.527126	24482.476841	juice
6	-12031.456590	-3614.893275	juice

In [48]:
```
import matplotlib.pyplot as plt

colors = {'energy drink':'g', 'alcohol':'r', 'juice':'b'}
markerTypes = {'energy drink':'+', 'alcohol':'x', 'juice':'o'}

for drinkType in markerTypes:
    d = projected[projected['drink']==drinkType]
    plt.scatter(d['pc1'],d['pc2'],c=colors[drinkType],s=60,marker=markerTypes[drinkTyp
```

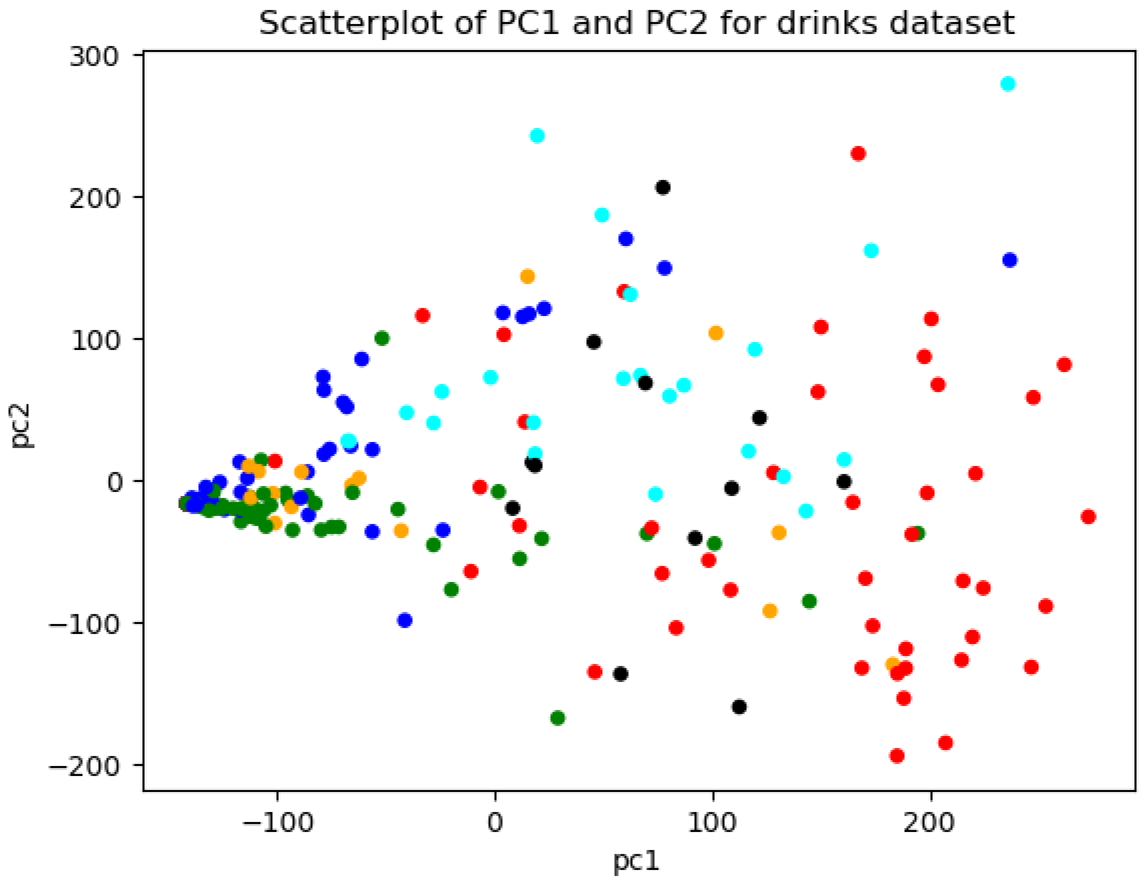


PCA Analysis on drink dataset.

Using all four numerical features that were used for extracting x_train/x_test and projecting them on their 2 principal components.

In [49]:
```
# Map continents to colors
colors = {'Africa':'g', 'Europe':'r', 'Asia':'b', 'North America': 'cyan', 'Oceania':'

numComponents = 2
pca = PCA(n_components=numComponents)
numerical_drink_Data = drink_Data[['beer_servings', 'spirit_servings', 'wine_servings'
pca.fit(numerical_drink_Data)

projected = pca.transform(numerical_drink_Data)
projected = pd.DataFrame(projected,columns=['pc1','pc2'])

projected.plot.scatter(x='pc1',y='pc2',c=drink_Data.continent.map(colors),
                       s=20, title='Scatterplot of PC1 and PC2 for drinks dataset')
```

Out[49]:
```
<Axes: title={'center': 'Scatterplot of PC1 and PC2 for drinks dataset'}, xlabel='pc
1', ylabel='pc2'>
```


Scatterplot of PC1 and PC2 for drinks dataset
300
200
100
0
−100
−200
pc2
−100
0
100
200
pc1