Fruit_and_Veg

January 23, 2025

1 Fruit and Veggie price analysis

1.1 Data Source

The data comes from the USDA Economic Eesearch Service estimates of average costs of fruits and vegetables. The datasets can be found on the USDA website.

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

1.2 Importing and Exploring the Datasets

First we will import the two datasets we will be working with. The USDA stores the information for fruit and vegetables seperatley, so we read both datasets into pandas dataframes here.

[2]:
```
justFruit = pd.read_csv('Fruit-Prices-2022.csv')
justVeggies = pd.read_csv('Vegetable-Prices-2022.csv')
```

Then we move to initial exploration into our datasets.

[3]:
```
justFruit.head()
```

[3]:

	Fruit	Form	RetailPrice	RetailPriceUnit	Yield	\
0	Apples	Fresh	1.8541	per pound	0.90	
1	Apples, applesauce	Canned	1.1705	per pound	1.00	
2	Apples, ready-to-drink	Juice	0.8699	per pint	1.00	
3	Apples, frozen concentrate	Juice	0.6086	per pint	1.00	
4	Apricots	Fresh	3.6162	per pound	0.93	

	CupEquivalentSize	CupEquivalentUnit	CupEquivalentPrice
0	0.2425	pounds	0.4996
1	0.5401	pounds	0.6323
2	8.0000	fluid ounces	0.4349
3	8.0000	fluid ounces	0.3043
4	0.3638	pounds	1.4145

[4]:
```
justVeggies.head()
```

[4]:
```
       Vegetable    Form  RetailPrice RetailPriceUnit   Yield  \
0  Acorn squash   Fresh       1.2136       per pound  0.4586
1     Artichoke   Fresh       2.4703       per pound  0.3750
2     Artichoke  Canned       3.4498       per pound  0.6500
3     Asparagus   Fresh       2.9531       per pound  0.4938
4     Asparagus  Canned       3.4328       per pound  0.6500

   CupEquivalentSize CupEquivalentUnit  CupEquivalentPrice
0             0.4519            pounds              1.1961
1             0.3858            pounds              2.5415
2             0.3858            pounds              2.0476
3             0.3968            pounds              2.3731
4             0.3968            pounds              2.0958
```

We can see our datasets for both fruits and vegetables contain the same information for each entry, which will make working with and comparing the two datsets easy for us. We have the name, form, price, and price unit for each item. Yield means the proportion of the item that is edible, for example: apples have an inedible core and so the yield is less than 1 (0.9), whereas there is no part of applesauce that is inedible so it is assigned a yield of 1. CupEquivalentSize and CupEquivalentUnit together tell us how much of a food item it takes to make a cup, and the CupEquivalentPrice is the price for that cup. This is especially useful because the retail price is determined by different things for each item (pounds, pints, etc.), so a cup equivalent price gives us a standard unit to compare between items.

1.3 Data Shaping

Since our two tables contain all the same information it will be useful to combine them into a larger dataframe. That being said, it is stil useful to know if an item is classified as a fruit or a vegetable, so we add this column here as well as rename the fruit column in preperation for merging.

[5]:
```
renamedFruit = justFruit.rename(columns={'Fruit':'Name'}, inplace=False)
renamedFruit['Type'] = 'Fruit'
renamedFruit.head()
```

[5]:
```
                         Name    Form  RetailPrice RetailPriceUnit  Yield  \
0                      Apples   Fresh       1.8541       per pound   0.90
1          Apples, applesauce  Canned       1.1705       per pound   1.00
2      Apples, ready-to-drink   Juice       0.8699        per pint   1.00
3  Apples, frozen concentrate   Juice       0.6086        per pint   1.00
4                     Apricots   Fresh       3.6162       per pound   0.93

   CupEquivalentSize CupEquivalentUnit  CupEquivalentPrice   Type
0             0.2425            pounds              0.4996  Fruit
1             0.5401            pounds              0.6323  Fruit
2             8.0000      fluid ounces              0.4349  Fruit
3             8.0000      fluid ounces              0.3043  Fruit
4             0.3638            pounds              1.4145  Fruit
```

[6]:
```
renamedVeggies = justVeggies.rename(columns={'Vegetable':'Name'}, inplace=False)
renamedVeggies['Type'] = 'Vegetable'
renamedVeggies.head()
```

[6]:

	Name	Form	RetailPrice	RetailPriceUnit	Yield	CupEquivalentSize	CupEquivalentUnit	CupEquivalentPrice	Type
0	Acorn squash	Fresh	1.2136	per pound	0.4586	0.4519	pounds	1.1961	Vegetable
1	Artichoke	Fresh	2.4703	per pound	0.3750	0.3858	pounds	2.5415	Vegetable
2	Artichoke	Canned	3.4498	per pound	0.6500	0.3858	pounds	2.0476	Vegetable
3	Asparagus	Fresh	2.9531	per pound	0.4938	0.3968	pounds	2.3731	Vegetable
4	Asparagus	Canned	3.4328	per pound	0.6500	0.3968	pounds	2.0958	Vegetable

Now the data is prepared to merge into a larger dataframe.

[7]:
```
allPriceData = pd.merge(renamedFruit,renamedVeggies, how='outer')
allPriceData.head()
```

[7]:

	Name	Form	RetailPrice	RetailPriceUnit	Yield	CupEquivalentSize	CupEquivalentUnit	CupEquivalentPrice	Type
0	Acorn squash	Fresh	1.2136	per pound	0.4586	0.4519	pounds	1.1961	Vegetable
1	Apples	Fresh	1.8541	per pound	0.9000	0.2425	pounds	0.4996	Fruit
2	Apples, applesauce	Canned	1.1705	per pound	1.0000	0.5401	pounds	0.6323	Fruit
3	Apples, frozen concentrate	Juice	0.6086	per pint	1.0000	8.0000	fluid ounces	0.3043	Fruit
4	Apples, ready-to-drink	Juice	0.8699	per pint	1.0000	8.0000	fluid ounces	0.4349	Fruit

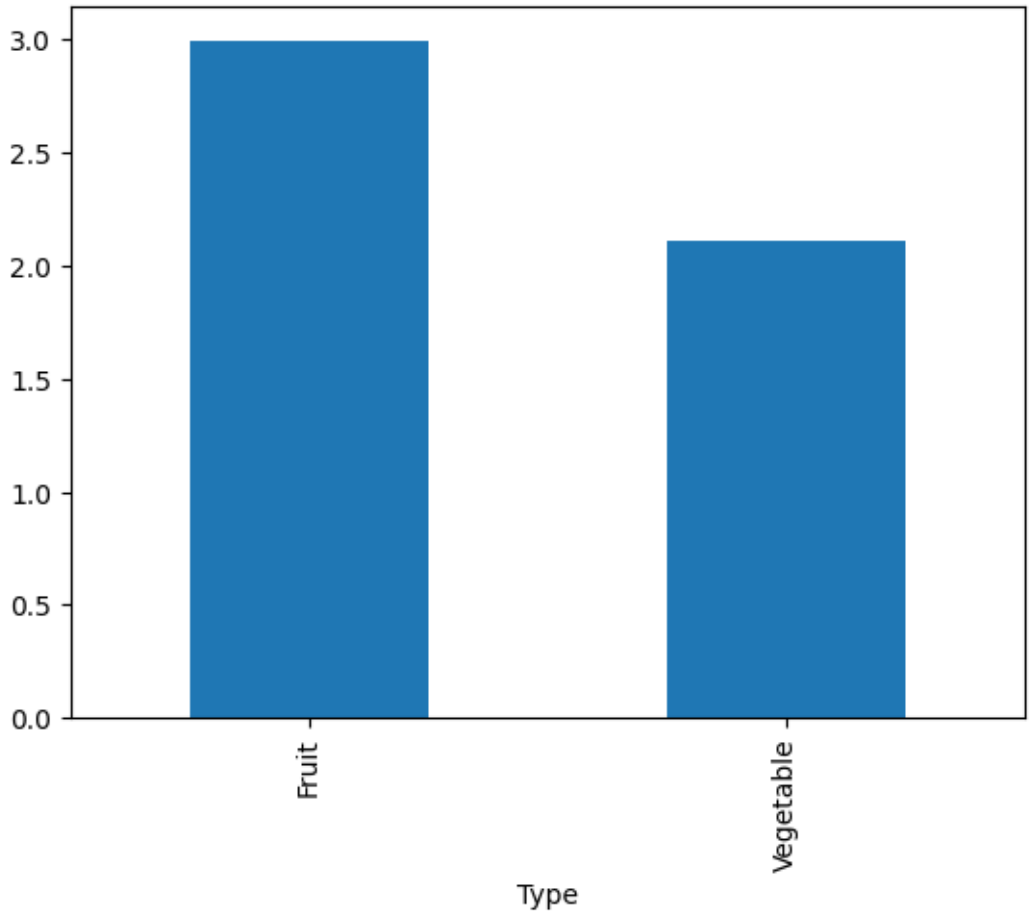
1.4 Basic Plots

Now we can use some basic plots to get some ideas about what the data tells us.

1.4.1 Fruits vs. Vegetables

[8]:
```
bar1 = allPriceData.groupby(['Type'])['RetailPrice'].mean()
bar1.plot.bar()
```

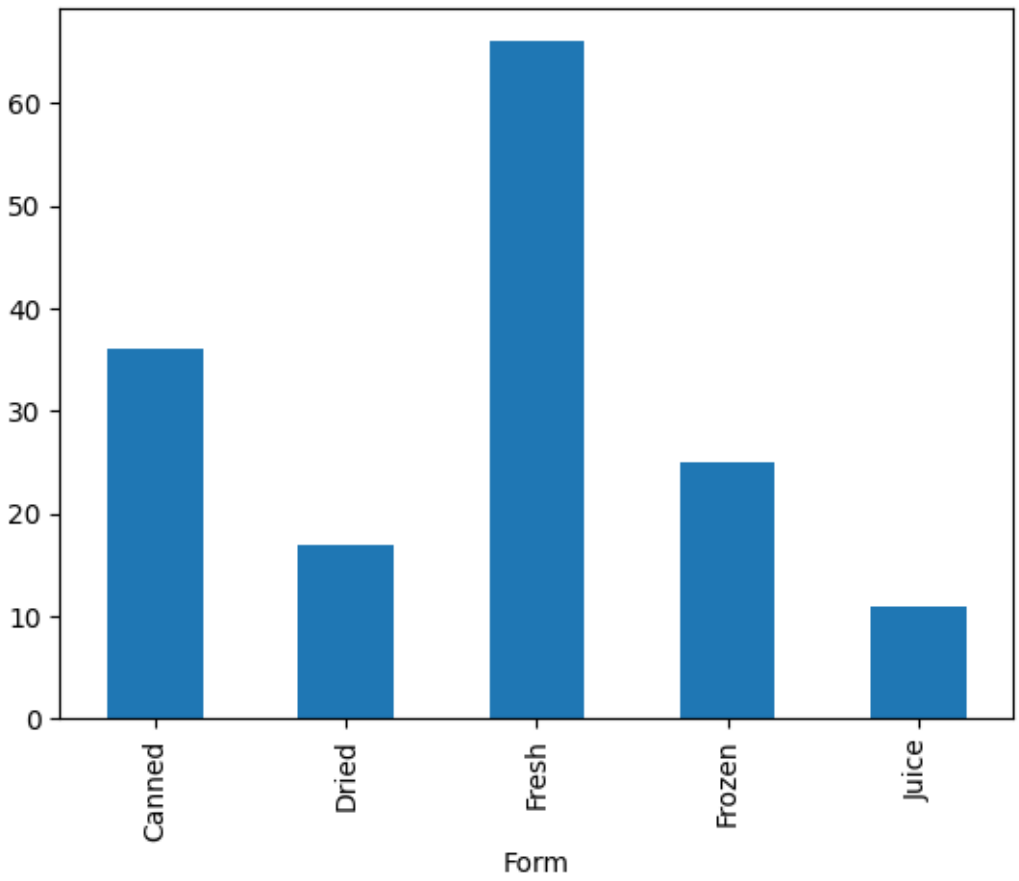
[8]:
```
<Axes: xlabel='Type'>
```



1.4.2 Representaion of Each Type

[9]:
```
allPriceData.groupby(['Form'])['Type'].count().plot.bar()
```

[9]:
```
<Axes: xlabel='Form'>
```



1.4.3 Retail Price by Type

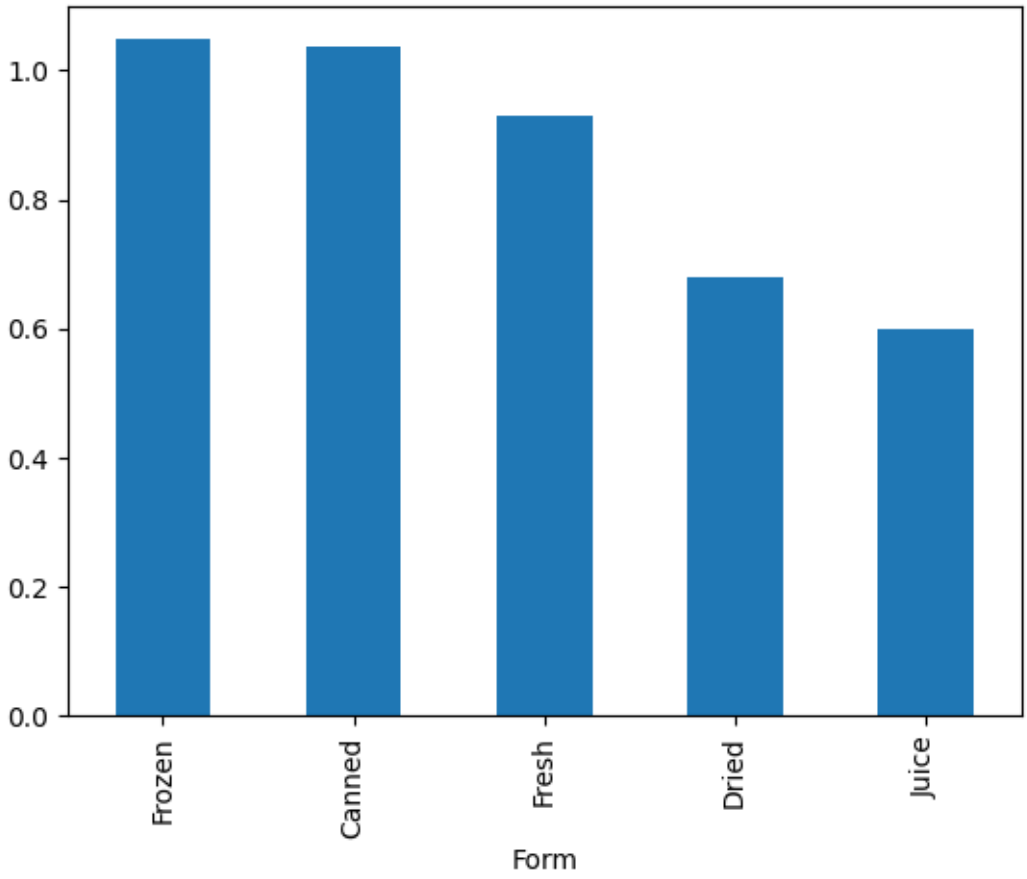
[10]:
```
bar2 = allPriceData.groupby(['Form'])['RetailPrice'].mean()
pd.Series.sort_values(bar2, ascending=False ,inplace=True)
bar2
```

[10]:
```
Form
Dried     4.428729
Frozen    2.873968
Fresh     2.350041
Canned    1.840772
Juice     1.199436
Name: RetailPrice, dtype: float64
```

1.4.4 Cup Price by Type

[11]:
```
bar3 = allPriceData.groupby(['Form'])['CupEquivalentPrice'].mean()
pd.Series.sort_values(bar3, ascending=False ,inplace=True)
bar3.plot.bar()
```

[11]: <Axes: xlabel='Form'>



[12]:
```
allPriceData.groupby(['Type','Form'])['Name'].count()
```

[12]:
```
Type       Form
Fruit      Canned    12
           Dried      9
           Fresh     24
           Frozen     6
           Juice     11
Vegetable  Canned    24
           Dried      8
           Fresh     42
```

```
            Frozen    19
Name: Name, dtype: int64
```

[ ]: