

```
In [1]: # The first data set (avocado) was download from :Link to dataset: https://www.kaggle.com/neuromusic/avocado-prices.
# The second data set Link :https://www.downloadexcelfiles.com/us\_en/download-excel-file-list-state-capitals-united-states#.Xc4z61dKjIV
# Columns
# index
# Date          The date of the observation
# AveragePrice  the average price of a single avocado
# Total Volume  Total number of avocados sold
# 4046          Total number of avocados with PLU 4046 sold
# 4225          Total number of avocados with PLU 4225 sold
# 4770          Total number of avocados with PLU 4770 sold
# Total Bags
# Small Bags
# Large Bags
# XLarge Bags
# type          conventional or organic
# year          the year
# region        the city or region of the observation
```

```
In [ ]:
```

```
In [ ]: #import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.pyplot as pl
import seaborn as sns
```

```
In [2]: # Load a file and print the head of our data
df1 = pd.read_csv('avocado-prices/state_capitals_us.csv', index_col=0)
df1.head()
```

Out[2]:

	State	Abr.	Date of statehood	Capital	Capital since	Land area (mi <sup>2</sup> )	Most populous city?	Municipal population	Metropolitan population	Notes
<b>SNo</b>										
1	Alabama	AL	1819.0	Montgomery	1846.0	155.4	No	205764.0	374536.0	Birmingham is the state's largest city
2	Alaska	AK	1959.0	Juneau	1906.0	2716.7	No	31275.0	NaN	Juneau is the largest capital by land area. An...
3	Arizona	AZ	1912.0	Phoenix	1889.0	474.9	Yes	1445632.0	4192887.0	Phoenix is the most populous U.S. state capita...
4	Arkansas	AR	1836.0	Little Rock	1821.0	116.2	Yes	193524.0	877091.0	NaN
5	California	CA	1850.0	Sacramento	1854.0	97.2	No	466488.0	2527123.0	The Supreme Court of California is headquarter...

```
In [3]: # Load a file and print the head of our data
df2 = pd.read_csv('avocado-prices/avocado.csv', index_col=0)
df2.head()
```

Out[3]:

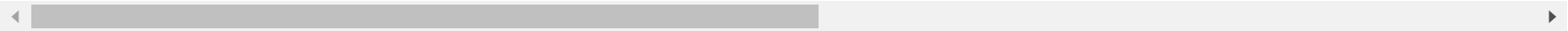
	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags	XLarge Bags	type	year	region
0	2015-12-27	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.25	0.0	conventional	2015	Albany
1	2015-12-20	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.49	0.0	conventional	2015	Albany
2	2015-12-13	0.93	118220.22	794.70	109149.67	130.50	8145.35	8042.21	103.14	0.0	conventional	2015	Albany
3	2015-12-06	1.08	78992.15	1132.00	71976.41	72.58	5811.16	5677.40	133.76	0.0	conventional	2015	Albany
4	2015-11-29	1.28	51039.60	941.48	43838.39	75.78	6183.95	5986.26	197.69	0.0	conventional	2015	Albany

```
In [4]: # Load both df1 and df2 merge using sql and print the head of our data  
df = pd.read_csv('avocado-prices/merge_df.csv', index_col=0)  
df.head()
```

Out[4]:

	Date	AveragePrice	TotalVolume	4046	4225	4770	TotalBags	SmallBags	LargeBags	XLargeBags	...	State	Abr.	I
field1														
0	2015-12-27	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.25	0.0	...	New York	NY	
1	2015-12-20	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.49	0.0	...	New York	NY	
2	2015-12-13	0.93	118220.22	794.70	109149.67	130.50	8145.35	8042.21	103.14	0.0	...	New York	NY	
3	2015-12-06	1.08	78992.15	1132.00	71976.41	72.58	5811.16	5677.40	133.76	0.0	...	New York	NY	
4	2015-11-29	1.28	51039.60	941.48	43838.39	75.78	6183.95	5986.26	197.69	0.0	...	New York	NY	

5 rows × 24 columns



```
In [5]: # Print the shape of our df
print(df.shape)
```

(18249, 24)

```
In [6]: #drop columns( Metropolitan, population Notes and Capital since)
df = df.drop(columns=['Metropolitanpopulation', 'Notes', 'Capitalsince'])
df.head()
```

Out[6]:

	Date	AveragePrice	TotalVolume	4046	4225	4770	TotalBags	SmallBags	LargeBags	XLargeBags	...	year	region
field1													
0	2015-12-27	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.25	0.0	...	2015	Albany
1	2015-12-20	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.49	0.0	...	2015	Albany
2	2015-12-13	0.93	118220.22	794.70	109149.67	130.50	8145.35	8042.21	103.14	0.0	...	2015	Albany
3	2015-12-06	1.08	78992.15	1132.00	71976.41	72.58	5811.16	5677.40	133.76	0.0	...	2015	Albany
4	2015-11-29	1.28	51039.60	941.48	43838.39	75.78	6183.95	5986.26	197.69	0.0	...	2015	Albany

5 rows × 21 columns



```
In [7]: # convert date to datetime
df['Date']=pd.to_datetime(df.Date)
```

```
In [8]: # check the table to see if any nna and the check all data types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18249 entries, 0 to 11
Data columns (total 21 columns):
Date                18249 non-null datetime64[ns]
AveragePrice        18249 non-null float64
TotalVolume         18249 non-null float64
4046                18249 non-null float64
4225                18249 non-null float64
4770                18249 non-null float64
TotalBags           18249 non-null float64
SmallBags           18249 non-null float64
LargeBags           18249 non-null float64
XLargeBags          18249 non-null float64
type                18249 non-null object
year                18249 non-null int64
region              18249 non-null object
SNo                 3042 non-null float64
State               3042 non-null object
Abr.                3042 non-null object
Dateofstatehood     3042 non-null float64
Capital             3042 non-null object
Landarea(mi²)       3042 non-null float64
Mostpopulouscity?   3042 non-null object
Municipalpopulation 3042 non-null float64
dtypes: datetime64[ns](1), float64(13), int64(1), object(6)
memory usage: 3.1+ MB
```

```
In [9]: #inspect our df by printing the head() and the tail()  
print(df.head())  
print(df.tail())
```

	Date	AveragePrice	TotalVolume	4046	4225	4770	\
field1							
0	2015-12-27	1.33	64236.62	1036.74	54454.85	48.16	
1	2015-12-20	1.35	54876.98	674.28	44638.81	58.33	
2	2015-12-13	0.93	118220.22	794.70	109149.67	130.50	
3	2015-12-06	1.08	78992.15	1132.00	71976.41	72.58	
4	2015-11-29	1.28	51039.60	941.48	43838.39	75.78	

	TotalBags	SmallBags	LargeBags	XLargeBags	...	year	\
field1					...		
0	8696.87	8603.62	93.25	0.0	...	2015	
1	9505.56	9408.07	97.49	0.0	...	2015	
2	8145.35	8042.21	103.14	0.0	...	2015	
3	5811.16	5677.40	133.76	0.0	...	2015	
4	6183.95	5986.26	197.69	0.0	...	2015	

	region	SNo	State	Abr.	Dateofstatehood	Capital	Landarea(mi²)	\
field1								
0	Albany	32.0	New York	NY	1788.0	Albany	21.4	
1	Albany	32.0	New York	NY	1788.0	Albany	21.4	
2	Albany	32.0	New York	NY	1788.0	Albany	21.4	
3	Albany	32.0	New York	NY	1788.0	Albany	21.4	
4	Albany	32.0	New York	NY	1788.0	Albany	21.4	

	Mostpopulouscity?	Municipalpopulation
field1		
0	No	97856.0
1	No	97856.0
2	No	97856.0
3	No	97856.0
4	No	97856.0

[5 rows x 21 columns]

	Date	AveragePrice	TotalVolume	4046	4225	4770	\
field1							
7	2018-02-04	1.63	17074.83	2046.96	1529.20	0.00	
8	2018-01-28	1.71	13888.04	1191.70	3431.50	0.00	
9	2018-01-21	1.87	13766.76	1191.92	2452.79	727.94	
10	2018-01-14	1.93	16205.22	1527.63	2981.04	727.01	
11	2018-01-07	1.62	17489.58	2894.77	2356.13	224.53	

	TotalBags	SmallBags	LargeBags	XLargeBags	...	year	\
field1					...		



7	13498.67	13066.82	431.85	0.0	...	2018
8	9264.84	8940.04	324.80	0.0	...	2018
9	9394.11	9351.80	42.31	0.0	...	2018
10	10969.54	10919.54	50.00	0.0	...	2018
11	12014.15	11988.14	26.01	0.0	...	2018

	region	SNo	State	Abr.	Dateofstatehood	Capital	\
field1							
7	WestTexNewMexico	NaN	NaN	NaN	NaN	NaN	
8	WestTexNewMexico	NaN	NaN	NaN	NaN	NaN	
9	WestTexNewMexico	NaN	NaN	NaN	NaN	NaN	
10	WestTexNewMexico	NaN	NaN	NaN	NaN	NaN	
11	WestTexNewMexico	NaN	NaN	NaN	NaN	NaN	

	Landarea(mi²)	Mostpopulouscity?	Municipalpopulation
field1			
7	NaN	NaN	NaN
8	NaN	NaN	NaN
9	NaN	NaN	NaN
10	NaN	NaN	NaN
11	NaN	NaN	NaN

[5 rows x 21 columns]

```
In [10]: # use the describe() method to calculate summary statistics of your data
df.describe()
```

Out[10]:

	AveragePrice	TotalVolume	4046	4225	4770	TotalBags	SmallBags	LargeBags	XLargeBags
<b>count</b>	18249.000000	1.824900e+04	1.824900e+04	1.824900e+04	1.824900e+04	1.824900e+04	1.824900e+04	1.824900e+04	18249.000000
<b>mean</b>	1.405978	8.506440e+05	2.930084e+05	2.951546e+05	2.283974e+04	2.396392e+05	1.821947e+05	5.433809e+04	3106.426500
<b>std</b>	0.402677	3.453545e+06	1.264989e+06	1.204120e+06	1.074641e+05	9.862424e+05	7.461785e+05	2.439660e+05	17692.894600
<b>min</b>	0.440000	8.456000e+01	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000
<b>25%</b>	1.100000	1.083858e+04	8.540700e+02	3.008780e+03	0.000000e+00	5.088640e+03	2.849420e+03	1.274700e+02	0.000000
<b>50%</b>	1.370000	1.073768e+05	8.645300e+03	2.906102e+04	1.849900e+02	3.974383e+04	2.636282e+04	2.647710e+03	0.000000
<b>75%</b>	1.660000	4.329623e+05	1.110202e+05	1.502069e+05	6.243420e+03	1.107834e+05	8.333767e+04	2.202925e+04	132.500000
<b>max</b>	3.250000	6.250565e+07	2.274362e+07	2.047057e+07	2.546439e+06	1.937313e+07	1.338459e+07	5.719097e+06	551693.650000

```
In [11]: # There are two types of avocado, firstly we analyse the conventional ones:  
df_conventional = df[df.type == 'conventional']
```

```
In [12]: # count type of conventional avocado by region
print (len(df.groupby('region')))
df_conventional['region'].value_counts()
```



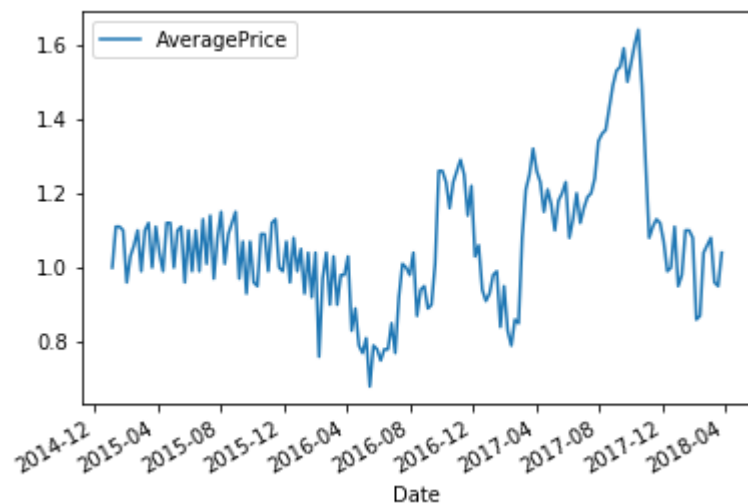
```
Out[12]: GrandRapids      169
         Detroit          169
         Spokane          169
         Houston          169
         Boise            169
         Albany           169
         HartfordSpringfield 169
         GreatLakes       169
         Pittsburgh       169
         LosAngeles       169
         NorthernNewEngland 169
         Tampa            169
         NewYork           169
         Southeast        169
         Northeast        169
         SouthCarolina    169
         Chicago          169
         Roanoke          169
         WestTexNewMexico 169
         SanDiego         169
         HarrisburgScranton 169
         Portland         169
         NewOrleansMobile 169
         Boston           169
         Syracuse         169
         Columbus         169
         Seattle          169
         StLouis          169
         TotalUS          169
         RaleighGreensboro 169
         Philadelphia     169
         PhoenixTucson    169
         Plains           169
         BuffaloRochester 169
         SouthCentral     169
         Jacksonville     169
         Louisville       169
         RichmondNorfolk  169
         SanFrancisco     169
         Charlotte        169
         DallasFtWorth    169
         West             169
         Denver           169
```

```
Midsouth          169
LasVegas          169
Sacramento        169
MiamiFtLauderdale 169
California         169
Indianapolis       169
BaltimoreWashington 169
Atlanta           169
Orlando           169
CincinnatiDayton  169
Nashville          169
Name: region, dtype: int64
```

```
In [13]: # plot the AveragePrice of conventional avocado
regions_conventional = df_conventional.groupby(df_conventional.region)
date_conventional = regions_conventional.get_group('Atlanta')[['Date', 'AveragePrice']].reset_index(drop=True)
```

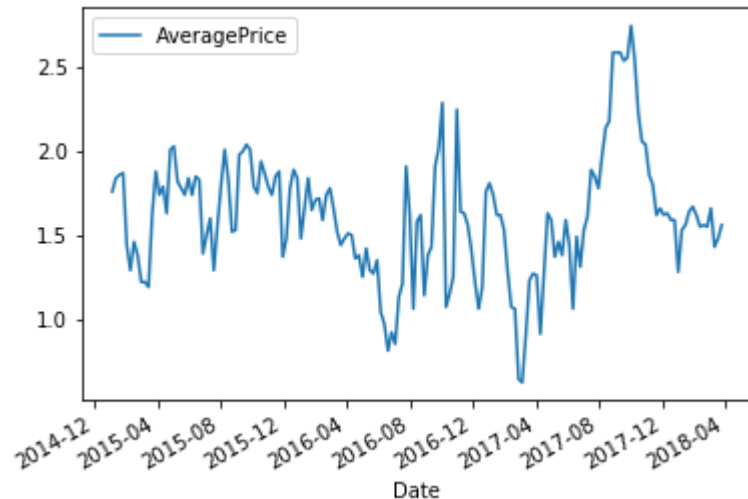
```
In [14]: date_conventional.plot(x='Date', y='AveragePrice', kind="line")
```

```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x19a87b9e2e8>
```



```
In [15]: ## plot the AveragePrice of organic avocado  
df_organic = df[df.type == 'organic']  
regions_organic = df_organic.groupby(df_organic.region)  
date_organic = regions_organic.get_group('Atlanta')[['Date', 'AveragePrice']].reset_index(drop=True)  
date_organic.plot(x='Date', y='AveragePrice', kind="line")
```

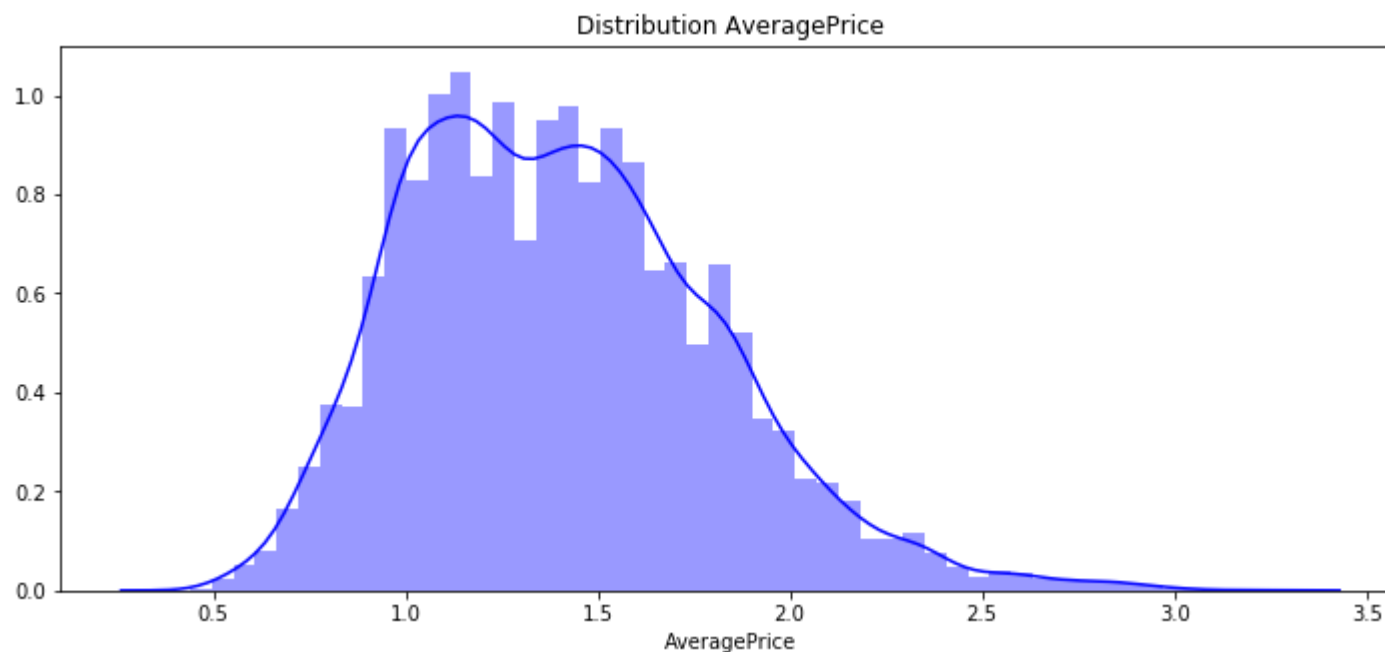
Out[15]: <matplotlib.axes.\_subplots.AxesSubplot at 0x19a8824ae10>



```
In [16]: # plot the Distribution of AveragePrice
plt.figure(figsize=(12,5))
plt.title("Distribution AveragePrice")
ax = sns.distplot(df["AveragePrice"], color = 'b')
```

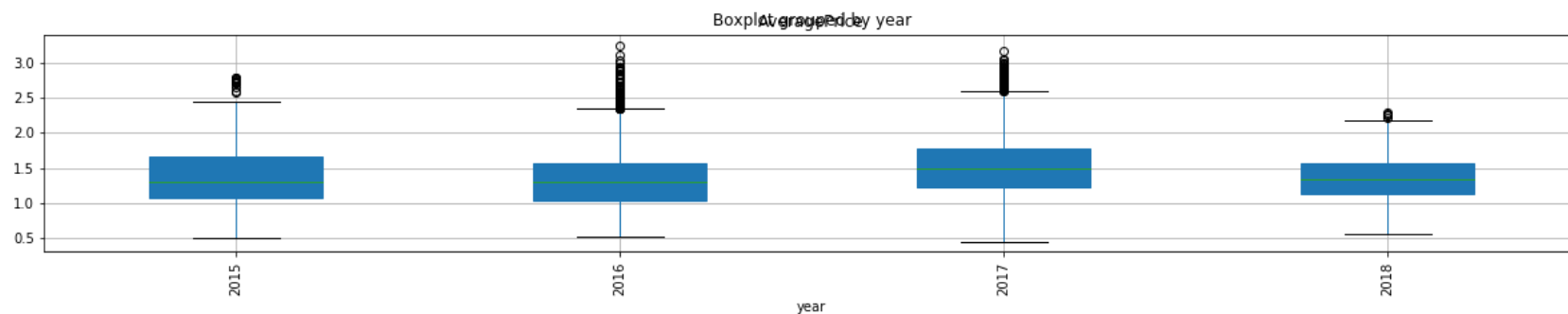
C:\Users\fcheb\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimensional indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as an array index, `arr[np.array(seq)]`, which will result either in an error or a different result.

```
return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



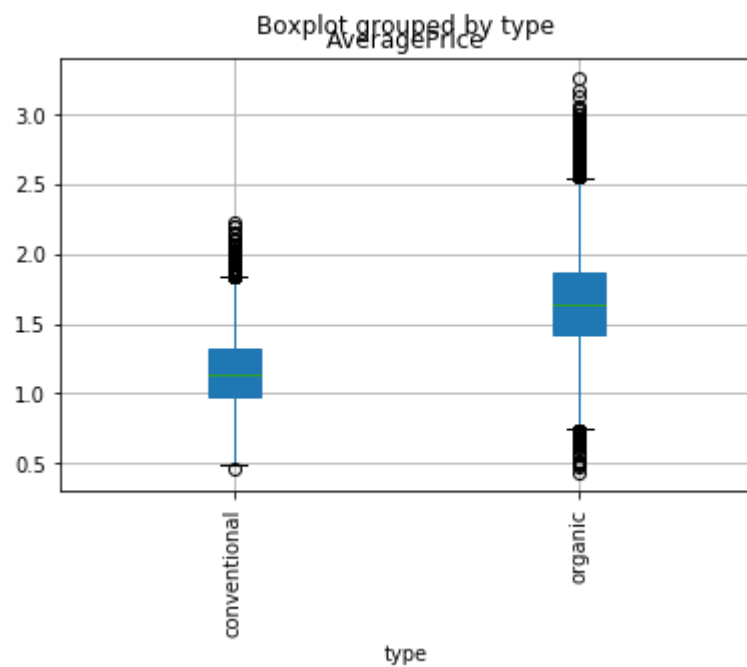


```
In [17]: # Create the boxplot to show average price by year
df.boxplot(column='AveragePrice', by='year', figsize=(20,3), rot=90, patch_artist = True)
# Display the plot
plt.show()
```



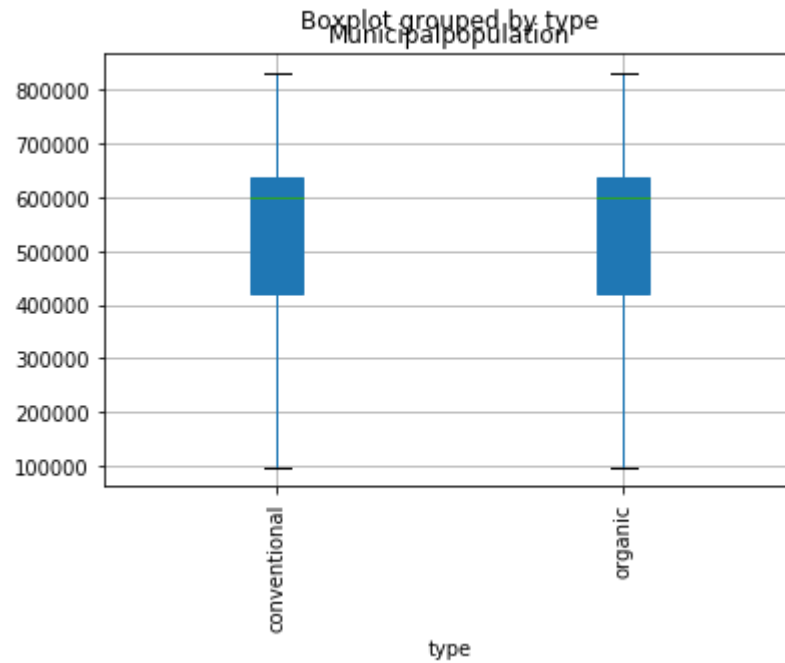
```
In [18]: # Create the boxplot to show average price by type
df.boxplot(column='AveragePrice', by='type', rot=90, patch_artist = True)

# Display the plot
plt.show()
```



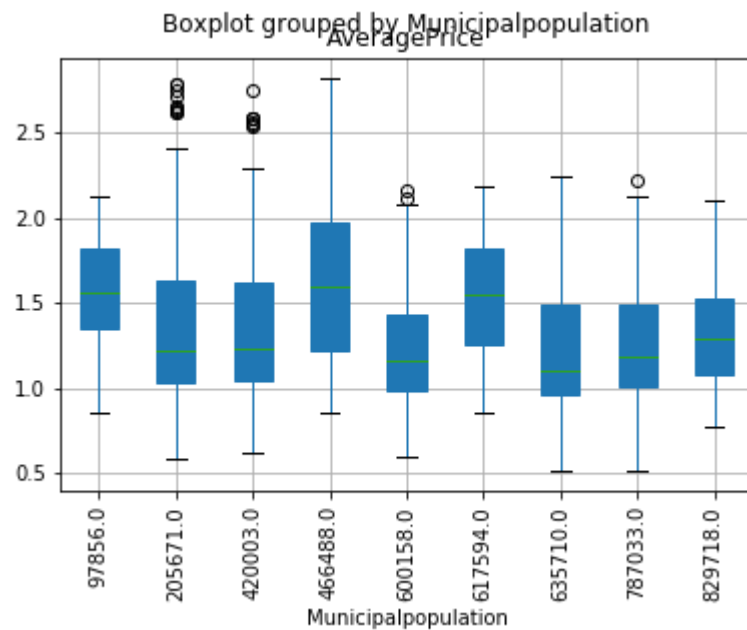
```
In [19]: # Create the boxplot to show population type
df.boxplot(column='Municipalpopulation', by='type', rot=90, patch_artist = True)

# Display the plot
plt.show()
```



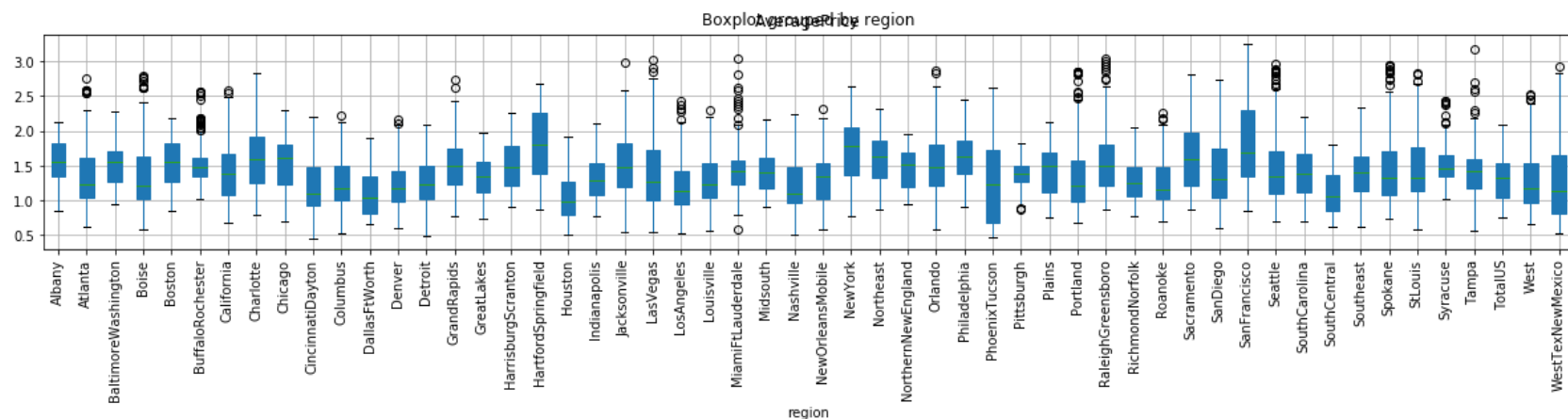
```
In [20]: # Create the boxplot to compare average price and Municipal population
df.boxplot(column='AveragePrice', by='Municipalpopulation', rot=90, patch_artist = True)

# Display the plot
plt.show()
```



```
In [21]: # Create the boxplot to show average price by region
df.boxplot(column='AveragePrice', by='region', figsize=(20,3), rot=90, patch_artist = True)

# Display the plot
plt.show()
```



```
In [22]: # print the 10 1st region where the AveragePrice <= min(AveragePrice)
# top_place_to_leave = df[df.AveragePrice < 1.40]
top_place_to_leave = df.sort_values(["AveragePrice"], ascending=True)
top_place_to_leave.head()
```

Out[22]:

	Date	AveragePrice	TotalVolume	4046	4225	4770	TotalBags	SmallBags	LargeBags	XLargeBags	...	year	
field1													
43	2017-03-05	0.44	64057.04	223.84	4748.88	0.00	59084.32	638.68	58445.64	0.00	...	2017	C
47	2017-02-05	0.46	2200550.27	1200632.86	531226.65	18324.93	450365.83	113752.17	330583.10	6030.56	...	2017	
43	2017-03-05	0.48	50890.73	717.57	4138.84	0.00	46034.32	1385.06	44649.26	0.00	...	2017	
44	2017-02-26	0.49	44024.03	252.79	4472.68	0.00	39298.56	600.00	38698.56	0.00	...	2017	C
0	2015-12-27	0.49	1137707.43	738314.80	286858.37	11642.46	100891.80	70749.02	30142.78	0.00	...	2015	

5 rows × 21 columns



```
In [23]: # Best 10 place to leave
print(top_place_to_leave['region'].unique())
```

```
['CincinnatiDayton' 'PhoenixTucson' 'Detroit' 'Nashville' 'Houston'
'WestTexNewMexico' 'Columbus' 'LosAngeles' 'Jacksonville' 'LasVegas'
'Louisville' 'Tampa' 'StLouis' 'NewOrleansMobile' 'Boise' 'Orlando'
'MiamiFtLauderdale' 'Denver' 'SanDiego' 'SouthCentral' 'Southeast'
'Atlanta' 'DallasFtWorth' 'West' 'California' 'Portland' 'SouthCarolina'
'Roanoke' 'Seattle' 'Chicago' 'GreatLakes' 'Spokane' 'TotalUS' 'Plains'
'NewYork' 'GrandRapids' 'Indianapolis' 'RichmondNorfolk' 'Charlotte'
'SanFrancisco' 'Albany' 'Boston' 'Sacramento' 'RaleighGreensboro'
'HartfordSpringfield' 'Pittsburgh' 'Northeast' 'HarrisburgScranton'
'Philadelphia' 'Midsouth' 'NorthernNewEngland' 'BaltimoreWashington'
'BuffaloRochester' 'Syracuse']
```

**Best top place to leave and continue have enough avocados base on our analysis in 2017 was:**

**CincinnatiDayton**

```
In [24]: # Filter the DataFrame down only to those columns to chart  
top_place_to_leave = top_place_to_leave[["region", "AveragePrice"]]  
  
# Set the index to be "State" so they will be used as labels  
top_place_to_leave = top_place_to_leave.set_index("region").head(30)  
  
top_place_to_leave
```

Out[24]:

AveragePrice	
region	
CincinnatiDayton	0.44
PhoenixTucson	0.46
Detroit	0.48
CincinnatiDayton	0.49
PhoenixTucson	0.49
PhoenixTucson	0.51
Nashville	0.51
Houston	0.51
CincinnatiDayton	0.51
PhoenixTucson	0.51
PhoenixTucson	0.52
WestTexNewMexico	0.52
Columbus	0.52
LosAngeles	0.53
PhoenixTucson	0.53
Houston	0.53
Houston	0.53
PhoenixTucson	0.53
PhoenixTucson	0.53
Jacksonville	0.54
LasVegas	0.54
PhoenixTucson	0.54
PhoenixTucson	0.54
PhoenixTucson	0.54
PhoenixTucson	0.54

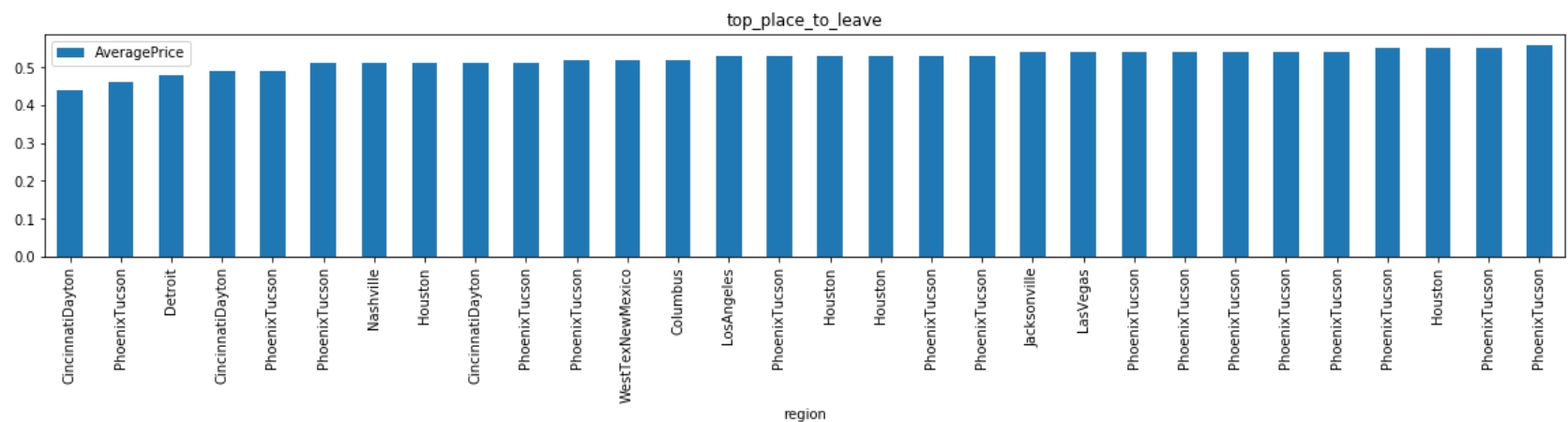


AveragePrice	
region	
PhoenixTucson	0.54
PhoenixTucson	0.55
Houston	0.55
PhoenixTucson	0.55
PhoenixTucson	0.56

```
In [25]: # Use DataFrame.plot() in order to create a bar chart of the data
top_place_to_leave.plot(kind="bar", figsize=(20,3))

# Set a title for the chart
plt.title("top_place_to_leave")

plt.show()
plt.tight_layout()
```



<Figure size 432x288 with 0 Axes>

In [ ]: