Problem Statement:

Avocado is a fruit consumed by people heavily in the United States.

Content :
This data was downloaded from the Hass Avocado Board website in May of 2018 & compiled into a single CSV.

The table below represents weekly 2018 retail scan data for National retail volume (units) and price. Retail scan data comes directly from retailers' cash registers based on actual retail sales of Hass avocados.

Starting in 2013, the table below reflects an expanded, multi-outlet retail data set. Multi-outlet reporting includes an aggregation of the following channels: grocery, mass, club, drug, dollar and military. The Average Price (of avocados) in the table reflects a per unit (per avocado) cost, even when multiple units (avocados) are sold in bags.

The Product Lookup codes (PLU's) in the table are only for Hass avocados. Other varieties of avocados (e.g. greenskins) are not included in this table.

Some relevant columns in the dataset:

Date - The date of the observation AveragePrice - the average price of a single avocado type - conventional or organic year - the year Region - the city or region of the observation 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

Inspiration /Label

Your task is to make a mode that can consider the data provided and predict the Average Price.

Importing Required Library

```
In [45]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pickle
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
import xgboost as xgb
from sklearn.metrics import r2_score, mean_squared_error
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Reading Data

```
In [2]: df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\csv file\avocado.csv")
df.head()
```

Out[2]:

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

Check no of row and column

```
In [3]: print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (18249, 14)
```

Checking for Null values

In [4]:
```
print('----------------------\n')
print(df.isnull().sum())
print('\n----------------------')
```

```
----------------------

Unnamed: 0      0
Date            0
AveragePrice    0
Total Volume    0
4046            0
4225            0
4770            0
Total Bags      0
Small Bags      0
Large Bags      0
XLarge Bags     0
type            0
year            0
region          0
dtype: int64

----------------------
```

There is no null value

Information about dataset

In [5]:
```
print('---------------------------------------------------\n')
print(df.info())
print('\n---------------------------------------------------')
```

```
----------------------------------------------------

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18249 entries, 0 to 18248
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Unnamed: 0    18249 non-null  int64  
 1   Date          18249 non-null  object 
 2   AveragePrice  18249 non-null  float64
 3   Total Volume  18249 non-null  float64
 4   4046          18249 non-null  float64
 5   4225          18249 non-null  float64
 6   4770          18249 non-null  float64
 7   Total Bags    18249 non-null  float64
 8   Small Bags    18249 non-null  float64
 9   Large Bags    18249 non-null  float64
 10  XLarge Bags   18249 non-null  float64
 11  type          18249 non-null  object 
 12  year          18249 non-null  int64  
 13  region        18249 non-null  object 
dtypes: float64(9), int64(2), object(3)
memory usage: 1.9+ MB
None

----------------------------------------------------
```

Categorical data present in our data set

Statistics of Data

In [6]:
```
df.describe()
```

Out[6]:

	Unnamed: 0	AveragePrice	Total Volume	4046	4225	4770	To
count	18249.000000	18249.000000	1.824900e+04	1.824900e+04	1.824900e+04	1.824900e+04	1.824
mean	24.232232	1.405978	8.506440e+05	2.930084e+05	2.951546e+05	2.283974e+04	2.396
std	15.481045	0.402677	3.453545e+06	1.264989e+06	1.204120e+06	1.074641e+05	9.862
min	0.000000	0.440000	8.456000e+01	0.000000e+00	0.000000e+00	0.000000e+00	0.000
25%	10.000000	1.100000	1.083858e+04	8.540700e+02	3.008780e+03	0.000000e+00	5.088
50%	24.000000	1.370000	1.073768e+05	8.645300e+03	2.906102e+04	1.849900e+02	3.974
75%	38.000000	1.660000	4.329623e+05	1.110202e+05	1.502069e+05	6.243420e+03	1.107
max	52.000000	3.250000	6.250565e+07	2.274362e+07	2.047057e+07	2.546439e+06	1.937

Outliers are present in data

Features engineering

Add Months Column

In [7]:
```
df['Months'] = df['Date'].str[5:7]
df['Months'] = df['Months'].astype('int32')
df.head(2)
```

Out[7]:

	Unnamed: 0	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags	XI
0	0	2015-12-27	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.25	
1	1	2015-12-20	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.49	

Month column added and convert into int32

In [8]:
```
print('---------------------------------------------------\n')
print(df.info())
print('\n---------------------------------------------------')
```

```
---------------------------------------------------

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18249 entries, 0 to 18248
Data columns (total 15 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Unnamed: 0    18249 non-null  int64  
 1   Date          18249 non-null  object 
 2   AveragePrice  18249 non-null  float64
 3   Total Volume  18249 non-null  float64
 4   4046          18249 non-null  float64
 5   4225          18249 non-null  float64
 6   4770          18249 non-null  float64
 7   Total Bags    18249 non-null  float64
 8   Small Bags    18249 non-null  float64
 9   Large Bags    18249 non-null  float64
 10  XLarge Bags   18249 non-null  float64
 11  type          18249 non-null  object 
 12  year          18249 non-null  int64  
 13  region        18249 non-null  object 
 14  Months        18249 non-null  int32  
dtypes: float64(9), int32(1), int64(2), object(3)
memory usage: 2.0+ MB
None

---------------------------------------------------
```

Months column is converted into int32

Add Sales column

In [9]:
```
df['Sales']= df['Total Volume'] * df['AveragePrice']
df.head(2)
```

Out[9]:

	Unnamed: 0	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags	XI
0	0	2015-12-27	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.25	
1	1	2015-12-20	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.49	

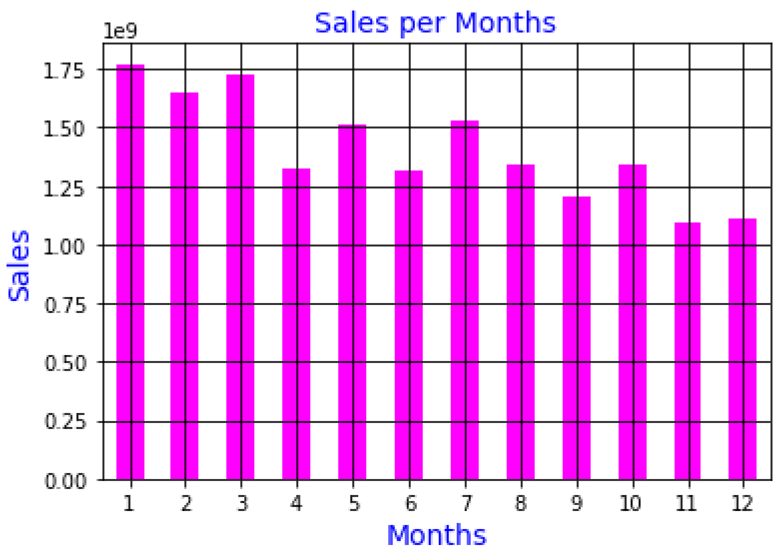
Sales column added in our dataset

To know highest month for sales

In [10]:
```
s = df.groupby('Months')['Sales'].sum()
s
```

Out[10]:
```
Months
1     1.771539e+09
2     1.648614e+09
3     1.730009e+09
4     1.327835e+09
5     1.515673e+09
6     1.312736e+09
7     1.529586e+09
8     1.343889e+09
9     1.207088e+09
10    1.342014e+09
11    1.097177e+09
12    1.107970e+09
Name: Sales, dtype: float64
```

In [11]:
```
s.plot.bar(x = 'Months', y = 'Sales', rot = 360,color = 'magenta')
plt.grid(c = 'black')
plt.ylabel('Sales',fontsize = 14, color = 'b')
plt.xlabel('Months',fontsize = 14, color = 'b')
plt.title('Sales per Months',fontsize = 14, color = 'b')
plt.show()
```



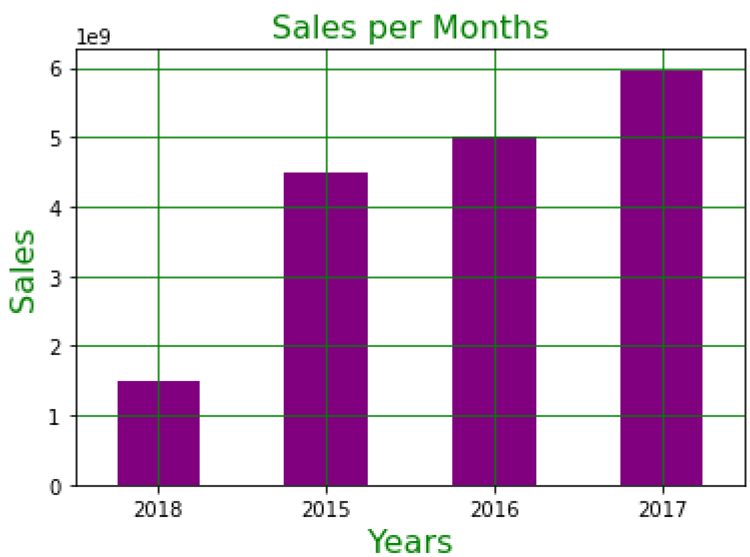
January is best month for sales

To know highest year of sales

In [12]:
```
y = df.groupby('year')['Sales'].sum().sort_values()
y
```

Out[12]:
```
year
2018    1.482343e+09
2015    4.488448e+09
2016    4.997590e+09
2017    5.965750e+09
Name: Sales, dtype: float64
```

In [13]:
```
y.plot.bar(x = 'year', y = 'Sales', rot = 360,color = 'purple')
plt.grid(c = 'g')
plt.ylabel('Sales',fontsize = 16, color = 'g')
plt.xlabel('Years',fontsize = 16, color = 'g')
plt.title('Sales per Months',fontsize = 16, color = 'g')
plt.show()
```



In 2017 highest sales are done

In [14]:
```
df['XLarge Bags'].value_counts()
```

Out[14]:
```
0.00        12048
3.33           29
6.67           16
1.11           15
5.00           12
            ...
9.95            1
3.47            1
59.32           1
16090.51        1
4920.17         1
Name: XLarge Bags, Length: 5588, dtype: int64
```

Above we check 'XLarge Bags' column we have doubt it is zero value but it is not

To know which type of avacado highest sales

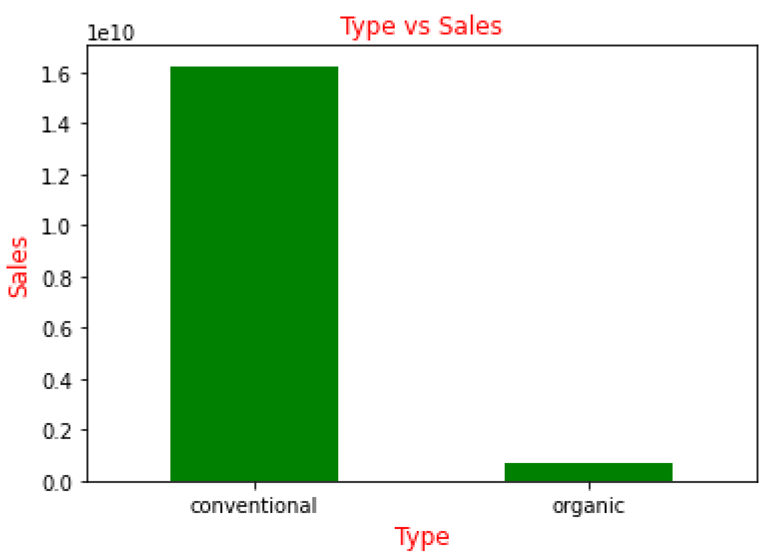
In [15]:
```python
df['type'].value_counts()
```

Out[15]:
```
conventional    9126
organic         9123
Name: type, dtype: int64
```

In [16]:
```python
t = df.groupby('type')['Sales'].sum()
t
```

Out[16]:
```
type
conventional    1.625352e+10
organic         6.806085e+08
Name: Sales, dtype: float64
```

In [17]:
```python
t.plot.bar(x = 'type', y = 'Sales', rot = 360, color = 'g')
plt.ylabel('Sales',fontsize = 12, color = 'r')
plt.xlabel('Type',fontsize = 12, color = 'r')
plt.title('Type vs Sales',fontsize = 12, color = 'r')
plt.show()
```



Conventional type has highest sales

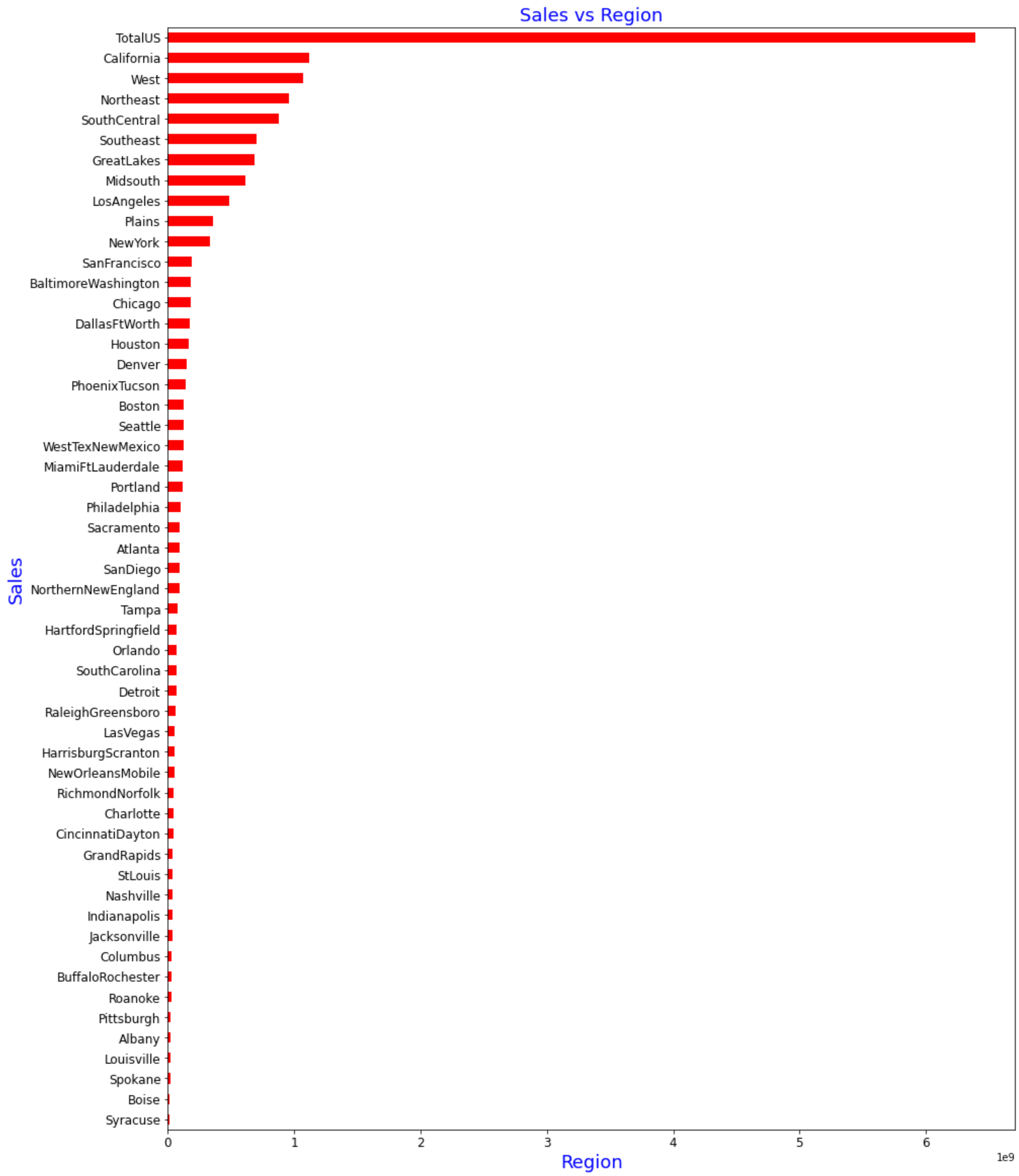
To know which region has highest sales

In [18]:
```
r = df.groupby('region')['Sales'].sum().sort_values()
r
```

Out[18]:
```
region
Syracuse               1.520519e+07
Boise                  1.534667e+07
Spokane                1.715649e+07
Louisville             1.749555e+07
Albany                 2.176672e+07
Pittsburgh             2.319481e+07
Roanoke                2.740928e+07
BuffaloRochester       3.154509e+07
Columbus               3.156295e+07
Jacksonville           3.348396e+07
Indianapolis           3.402474e+07
Nashville              3.572664e+07
StLouis                3.743946e+07
GrandRapids            3.785124e+07
CincinnatiDayton       4.498958e+07
Charlotte              4.574304e+07
RichmondNorfolk        4.734482e+07
NewOrleansMobile       4.867626e+07
HarrisburgScranton     5.295472e+07
LasVegas               5.480905e+07
RaleighGreensboro      5.983780e+07
Detroit                6.912624e+07
SouthCarolina          6.952808e+07
Orlando                6.961121e+07
HartfordSpringfield    7.118645e+07
Tampa                  7.695906e+07
NorthernNewEngland     8.962525e+07
SanDiego               9.352710e+07
Atlanta                9.379337e+07
Sacramento             9.480870e+07
Philadelphia           9.981583e+07
Portland               1.128646e+08
MiamiFtLauderdale      1.185815e+08
WestTexNewMexico       1.215654e+08
Seattle                1.251791e+08
Boston                 1.265429e+08
PhoenixTucson          1.384515e+08
Denver                 1.459828e+08
Houston                1.655713e+08
DallasFtWorth          1.756093e+08
Chicago                1.791106e+08
BaltimoreWashington    1.799084e+08
SanFrancisco           1.858341e+08
NewYork                3.351955e+08
Plains                 3.600366e+08
LosAngeles             4.842276e+08
Midsouth               6.157238e+08
GreatLakes             6.886618e+08
Southeast              7.036306e+08
SouthCentral           8.740593e+08
Northeast              9.600079e+08
West                   1.066834e+09
```

```
California              1.121414e+09
TotalUS                 6.387593e+09
Name: Sales, dtype: float64
```

In [19]:
```
r.plot.barh(x = 'region', y = 'Sales', rot = 360, figsize = (15,20), color = 'r',
plt.ylabel('Sales',fontsize = 18, color = 'b')
plt.xlabel('Region',fontsize = 18, color = 'b')
plt.title('Sales vs Region', fontsize = 18, color = 'b')
plt.show()
```



US region has highest sales

Label Encoder

In [20]:
```
le = LabelEncoder()
```

In [21]:
```
df['type'] = le.fit_transform(df['type'])
```

In [22]:
```
df['region'] = le.fit_transform(df['region'])
```

In [23]:
```
df.head(2)
```

Out[23]:

	Unnamed: 0	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags	XI
0	0	2015-12-27	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.25	
1	1	2015-12-20	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.49	

In [24]:
```
print('----------------------------------------------------\n')
print(df.info())
print('\n----------------------------------------------------')
```

```
----------------------------------------------------

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18249 entries, 0 to 18248
Data columns (total 16 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Unnamed: 0    18249 non-null  int64  
 1   Date          18249 non-null  object 
 2   AveragePrice  18249 non-null  float64
 3   Total Volume  18249 non-null  float64
 4   4046          18249 non-null  float64
 5   4225          18249 non-null  float64
 6   4770          18249 non-null  float64
 7   Total Bags    18249 non-null  float64
 8   Small Bags    18249 non-null  float64
 9   Large Bags    18249 non-null  float64
 10  XLarge Bags   18249 non-null  float64
 11  type          18249 non-null  int32  
 12  year          18249 non-null  int64  
 13  region        18249 non-null  int32  
 14  Months        18249 non-null  int32  
 15  Sales         18249 non-null  float64
dtypes: float64(10), int32(3), int64(2), object(1)
memory usage: 2.0+ MB
None

----------------------------------------------------
```

Columns are encoded

Delete Unwanted Columns

In [25]:
```
col = ['Unnamed: 0', 'Date']
```

In [26]:
```
df = df.drop(col, axis = 1)
df.head()
```

Out[26]:

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

In [27]:
```
print('No of Rows and Columns ----->', df.shape )
```

```
No of Rows and Columns -----> (18249, 14)
```

Columns has been deleted

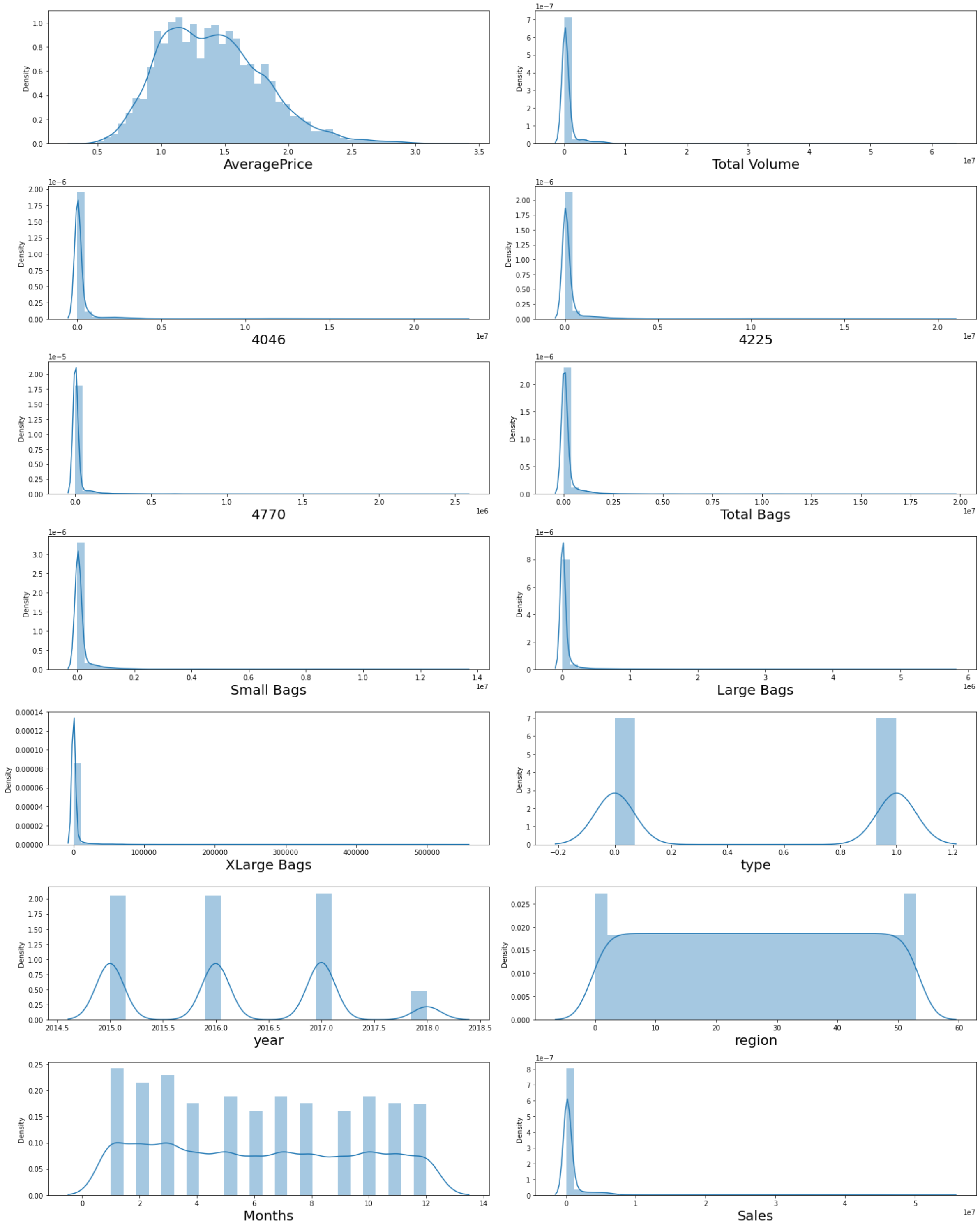
Data distribution and checking outliers

```
In [28]: print('---------------------')
         print('Distribution Plot :- ')
         print('---------------------')

         plt.figure(figsize = (20,25))
         plotnumber = 1

         for column in df:
             if plotnumber <=14:
                 ax = plt.subplot(7,2, plotnumber)
                 sns.distplot(df[column])
                 plt.xlabel(column, fontsize = 20)
             plotnumber +=1
         plt.tight_layout()
```

```
---------------------
Distribution Plot :-
---------------------
```


AveragePrice
Total Volume
4046
4225
4770
Total Bags
Small Bags
Large Bags
XLarge Bags
type
year
region
Months
Sales
Density

In [29]:
```
df.skew()
```

Out[29]:
```
AveragePrice     0.580303
Total Volume     9.007687
4046             8.648220
4225             8.942466
4770            10.159396
Total Bags       9.756072
Small Bags       9.540660
Large Bags       9.796455
XLarge Bags     13.139751
type             0.000329
year             0.215339
region           0.000030
Months           0.106617
Sales            8.915413
dtype: float64
```

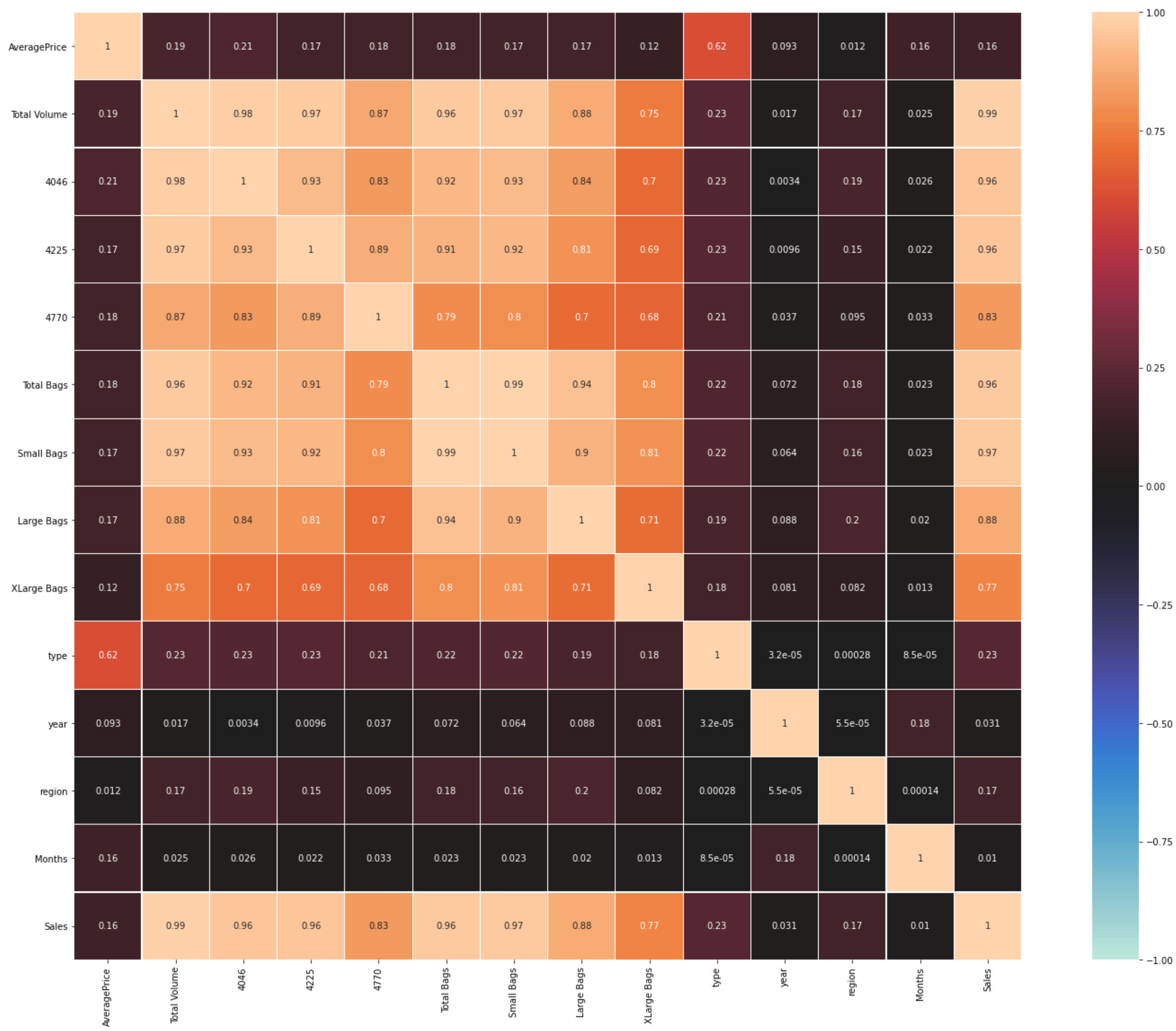
Data has outliers and skewed

Corelation of Feature vs Label using Heat map

In [30]:
```
print('-----------')
print('Heat Map :-')
print('-----------')
df_corr = df.corr().abs()

plt.figure(figsize = (22,16))
sns.heatmap(df_corr, vmin = -1, annot = True, square = True, center = 0, fmt = '.
plt.tight_layout()
```

```
-----------
Heat Map :-
-----------
```



Total Volume has highest and months has lowest relation with label

Checking class imbalence

In [31]:
```
df['AveragePrice'].value_counts()
```

Out[31]:
```
1.15    202
1.18    199
1.08    194
1.26    193
1.13    192
       ... 
2.91      1
2.68      1
3.04      1
3.17      1
3.03      1
Name: AveragePrice, Length: 259, dtype: int64
```

Class is not balanced

Quntile metthod to removing outliers and skewness.

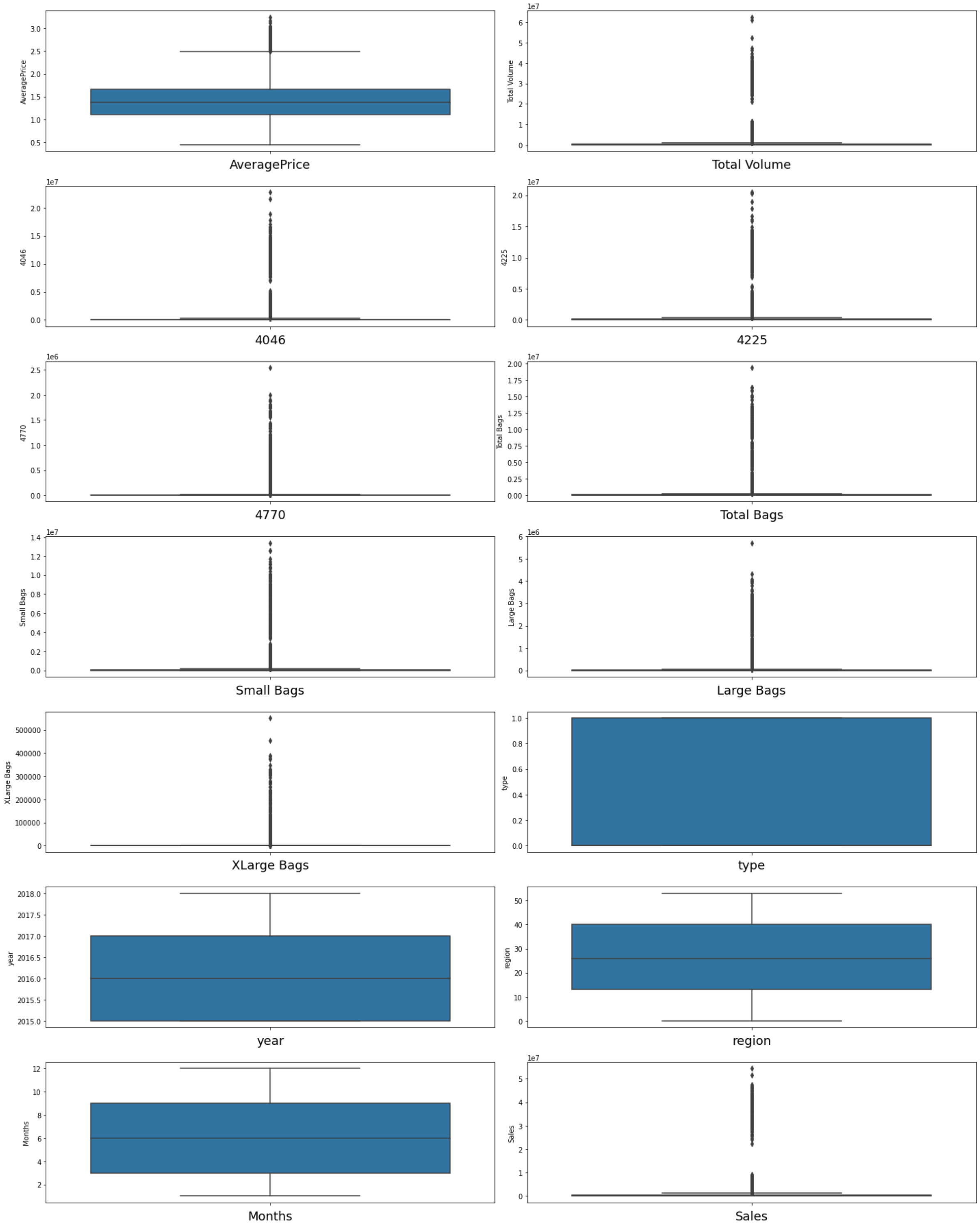
In [32]:
```
# we are removing the top 2% data from the Total Volume column
q = df['Total Volume'].quantile(0.98)
data_cleaned = df[df['Total Volume']<q]
# we are removing the top 2% data from the 4046 column
q = df['4046'].quantile(0.98)
data_cleaned = data_cleaned[data_cleaned['4046']<q]
# we are removing the top 2% data from the 4225 column
q = df['4225'].quantile(0.98)
data_cleaned = data_cleaned[data_cleaned['4225']<q]
# we are removing the top 2% data from the 4770 column
q = df['4770'].quantile(0.98)
data_cleaned = data_cleaned[data_cleaned['4770']<q]
# we are removing the top 2% data from the free Total Bags column
q = df['Total Bags'].quantile(0.98)
data_cleaned = data_cleaned[data_cleaned['Total Bags']<q]
# we are removing the top 2% data from the Small Bags column
q = df['Small Bags'].quantile(0.98)
data_cleaned = data_cleaned[data_cleaned['Small Bags']<q]
# we are removing the top 2% data from the Large Bags column
q = df['Large Bags'].quantile(0.98)
data_cleaned = data_cleaned[data_cleaned['Large Bags']<q]
# we are removing the top 2% data from the XLarge Bags column
q = df['XLarge Bags'].quantile(0.98)
data_cleaned = data_cleaned[data_cleaned['XLarge Bags']<q]
# we are removing the top 2% data from the Sales column
q = df['Sales'].quantile(0.98)
data_cleaned = data_cleaned[data_cleaned['Sales']<q]
```

Checking Outliers and skewness removed or not

In [33]:
```
# Let' see outliers are removed in columns or not.
print('\nDistribution Plot :-\n')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in df:
    if plotnumber <=14:
        ax = plt.subplot(7,2, plotnumber)
        sns.boxplot(y=df[column]) # It is the axis for vertical set as y
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
Distribution Plot :-
```



Outliers are removed

Spliting Dataset into features and labels

In [34]:

```
x = df.drop('AveragePrice', axis = 1)
y = df. AveragePrice
print('Data has been splited')
```

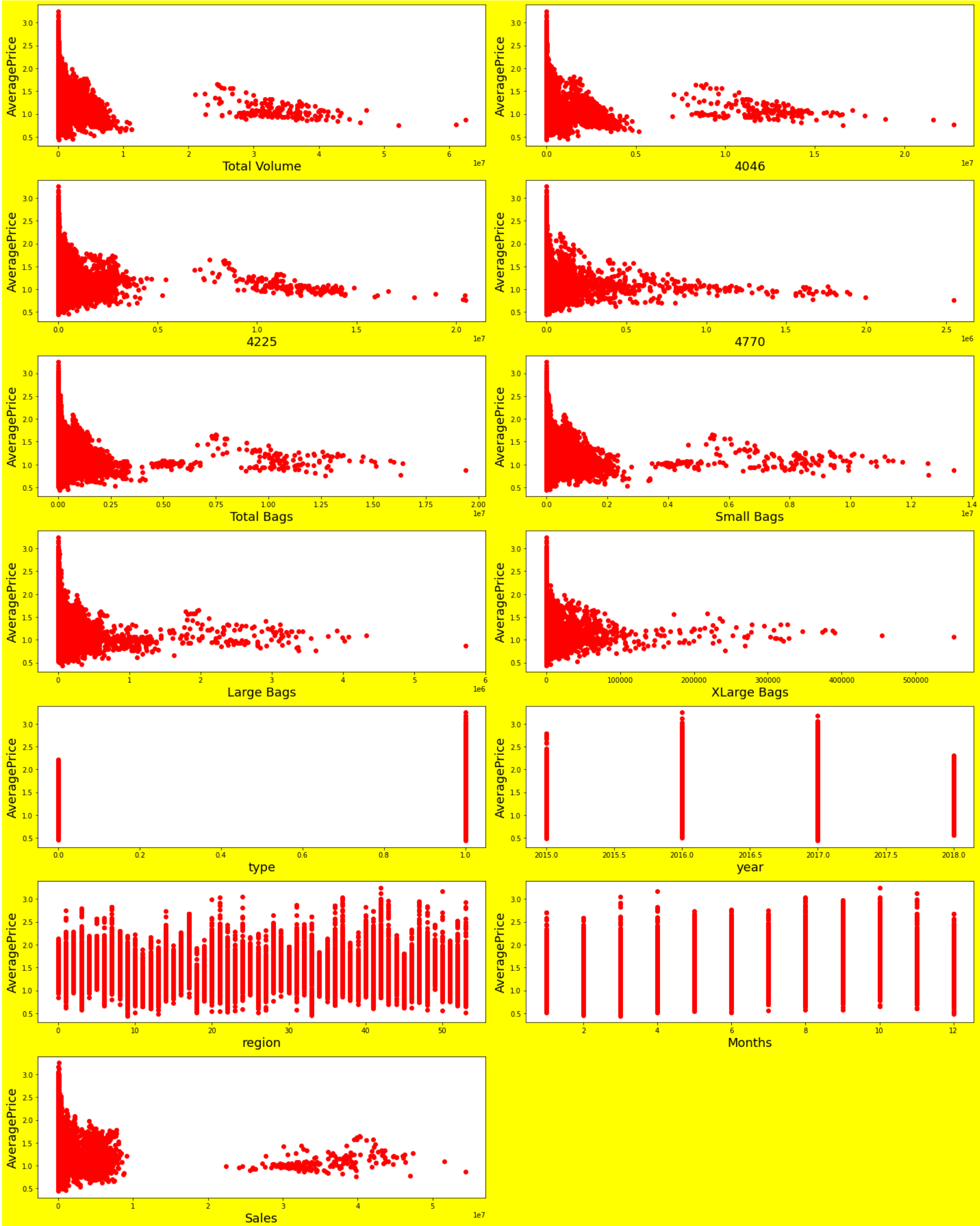
```
Data has been splited
```

In [40]:

```
# Let' see relation between features and labels.
print('------------------------')
print('Distribution Plot :-')
print('------------------------')

plt.figure(figsize = (20,25), facecolor = 'yellow')
plotnumber = 1
for column in x:
    if plotnumber <=14:
        ax = plt.subplot(7,2, plotnumber)
        plt.scatter(x[column],y, c = 'r')
        plt.xlabel(column, fontsize = 18)
        plt.ylabel('AveragePrice', fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
------------------------
Distribution Plot :-
------------------------
```



Features are related to label

Data Scaling

In [41]:
```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
x_scaled
```

Out[41]:
```
array([[-0.22771641, -0.23081597, -0.1999022 , ..., -1.7002522 ,
         1.64763162, -0.22857453],
       [-0.23042664, -0.23110251, -0.20805446, ..., -1.7002522 ,
         1.64763162, -0.23165401],
       [-0.21208462, -0.23100731, -0.1544779 , ..., -1.7002522 ,
         1.64763162, -0.22192493],
       ...,
       [-0.24233073, -0.2306933 , -0.24309014, ...,  1.70081131,
        -1.46495942, -0.24476871],
       [-0.24162464, -0.2304279 , -0.24265143, ...,  1.70081131,
        -1.46495942, -0.24326781],
       [-0.24125273, -0.22934712, -0.24317042, ...,  1.70081131,
        -1.46495942, -0.24406623]])
```

Split data into train and test. Model will be bulit on training data and tested on test data

In [42]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.25, rando
print('Data has been splited.')
```

```
Data has been splited.
```

Model Building

Logistic Regression model instantiaing, training and evaluating

In [46]:
```
Lr = LinearRegression()
Lr.fit(x_train, y_train)
y_pred = Lr.predict(x_test)
```

In [47]:
```python
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', Lr.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.4528681041347923
=========================================================
RMSE of Model -------> 0.29939625971037953
=========================================================
MSE of Model -------> 0.08963812032856502
=========================================================
Score of test data ----> 0.4528681041347923
=========================================================
```

Conclusion : Linear Regression model has 45% score

Knn model instantiaing, training and evaluating

In [49]:
```python
Knn = KNeighborsRegressor()
Knn.fit(x_train, y_train)
y_pred = Knn.predict(x_test)
```

In [50]:
```python
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', Knn.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.9642415902557608
=========================================================
RMSE of Model -------> 0.07654017521596569
=========================================================
MSE of Model -------> 0.0058583984220907295
=========================================================
Score of test data ----> 0.9642415902557608
=========================================================
```

Conclusion : Knn model has 96% score

Decision Tree model instantiaing, training and evaluating

In [52]:
```
DT = DecisionTreeRegressor()
DT.fit(x_train, y_train)
y_pred = DT.predict(x_test)
```

In [53]:
```
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', DT.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.8217825605874876
=========================================================
RMSE of Model -------> 0.17087379053020385
=========================================================
MSE of Model -------> 0.029197852290159986
=========================================================
Score of test data ----> 0.8217825605874876
=========================================================
```

Conclusion : Decision Tree model has 82% score

Random Forest model instantiaing, training and evaluating

In [55]:
```
Rn = RandomForestRegressor()
Rn.fit(x_train, y_train)
y_pred = Rn.predict(x_test)
```

In [56]:
```python
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', Rn.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.9252366407800727
=========================================================
RMSE of Model -------> 0.11067378352550787
=========================================================
MSE of Model -------> 0.012248686359850977
=========================================================
Score of test data ----> 0.9252366407800727
=========================================================
```

Conclusion : Random Forest model has 92% score

XGBoost model instantiaing, training and evaluating

In [57]:
```python
xgb = xgb.XGBRegressor(eval_metric='mlogloss')
xgb.fit(x_train, y_train)
y_pred = xgb.predict(x_test)
```

In [58]:
```python
print('=========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('=========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('=========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('=========================================================')
print('Score of test data ---->', xgb.score(x_test, y_test))
print('=========================================================')
```

```
=========================================================
R2 Score -----> 0.9632619783377186
=========================================================
RMSE of Model -------> 0.07758151153188628
=========================================================
MSE of Model -------> 0.006018890931572203
=========================================================
Score of test data ----> 0.9632619783377186
=========================================================
```

Conclusion : XGBoost model has 96% score

Looking R2 score we found KNN has best model so we do Hyperparameter Tuning on it.

In [63]:
```
grid_param = {'leaf_size' : [1,3,5], 'n_neighbors': [3],
              'p':[1,2,3,4]}
```

In [64]:
```
grid_search = GridSearchCV(estimator = Knn, param_grid = grid_param, cv = 5 , n_j
```

In [65]:
```
grid_search.fit(x_train, y_train)
```

Out[65]:
```
GridSearchCV(cv=5, estimator=KNeighborsRegressor(), n_jobs=-1,
             param_grid={'leaf_size': [1, 3, 5], 'n_neighbors': [3],
                         'p': [1, 2, 3, 4]})
```

In [66]:
```
best_parameters = grid_search.best_params_
print(best_parameters)
```

```
{'leaf_size': 1, 'n_neighbors': 3, 'p': 3}
```

In [68]:
```
hknn = KNeighborsRegressor(leaf_size = 1, n_neighbors = 3, p = 3)
hknn.fit(x_train, y_train)
hknn.score(x_test, y_test)
```

Out[68]:
```
0.9663003004702655
```

In [69]:
```
print('==========================================================')
print('R2 Score ----->', r2_score(y_test, y_pred))
print('==========================================================')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('==========================================================')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('==========================================================')
print('Score of test data ---->', hknn.score(x_test, y_test))
print('==========================================================')
```

```
==========================================================
R2 Score -----> 0.9632619783377186
==========================================================
RMSE of Model -------> 0.07758151153188628
==========================================================
MSE of Model -------> 0.006018890931572203
==========================================================
Score of test data ----> 0.9663003004702655
==========================================================
```

After Hyperparameter Tuning model accuracy score increase to 96%.

Saving The Model

In [70]:
```
# saving the model to the Local file system
filename = 'Avacado Project.pickle'
pickle.dump(hknn, open(filename, 'wb'))
```

Model has been saved.

Final Conclusion : Knn is our best model.

In [ ]:
```
```