1. IMPORTING THE DATASET AND NECESSARY LIBRARIES

DATASET SOURCE: https://data.gov.in/catalog/variety-wise-daily-market-prices-data-wheat

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

In [2]: data=pd.read_excel(r"C:\Users\Aditi Ravi\Downloads\Wheat_2023.xlsx")
   #Importing the dataset as a dataframe and storing it as data
```

2. UNDERSTANDING THE DATA

In	[3]:	data.head()									
Out[3]:			state	district	market	commodity	variety	arrival_date	min_price	max_price	modal
		0	Bihar	Muzaffarpur	Muzaffarpur	Wheat	147 Average	2023-01-03	1950.0	2800.0	:
		1	Bihar	Muzaffarpur	Muzaffarpur	Wheat	147 Average	2023-01-04	2000.0	2800.0	;
		2	Bihar	Muzaffarpur	Muzaffarpur	Wheat	147 Average	2023-01-05	1950.0	2800.0	;
		3	Bihar	Muzaffarpur	Muzaffarpur	Wheat	147 Average	2023-01-09	2000.0	2900.0	;
		4	Bihar	Muzaffarpur	Muzaffarpur	Wheat	147 Average	2023-01-10	2000.0	2900.0	ï
◀											•
In	[4]:	: data.tail()									

Out[4]:		state	district	market	commodity	variety	arrival_date	min_price	max_price	modal_pri
	7630	West Bengal	Uttar Dinajpur	Raiganj	Wheat	Local	2023-01-12	2700.0	2800.0	275(
	7631	West Bengal	Uttar Dinajpur	Raiganj	Wheat	Local	2023-01-13	2700.0	2800.0	2750
	7632	West Bengal	Uttar Dinajpur	Raiganj	Wheat	Local	2023-01-14	2700.0	2800.0	275(
	7633	West Bengal	Uttar Dinajpur	Raiganj	Wheat	Local	2023-01-15	2700.0	2800.0	2750
	7634	West Bengal	Uttar Dinajpur	Raiganj	Wheat	Local	2023-01-16	2700.0	2800.0	275(
4										•

In [5]: data.describe()

Out[5]:		min_price	max_price	modal_price
	count	7619.000000	7612.000000	7634.000000
	mean	2536.964694	2763.356280	2652.908174
	std	445.122096	679.814203	479.184000
	min	245.000000	680.000000	660.000000
	25%	2450.000000	2605.000000	2550.000000
	50%	2550.000000	2725.000000	2650.000000
	75%	2660.000000	2850.000000	2750.000000

In [6]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7635 entries, 0 to 7634
Data columns (total 10 columns):

max 34000.000000 38000.000000 38000.000000

	(, -	
#	Column	Non-Null Count	Dtype
0	state	7635 non-null	object
1	district	7635 non-null	object
2	market	7635 non-null	object
3	commodity	7635 non-null	object
4	variety	7635 non-null	object
5	arrival_date	7635 non-null	<pre>datetime64[ns]</pre>
6	min_price	7619 non-null	float64
7	max_price	7612 non-null	float64
8	modal_price	7634 non-null	float64
9	update_date	7635 non-null	<pre>datetime64[ns]</pre>
dtype	es: datetime64	[ns](2), float64	(3), object(5)

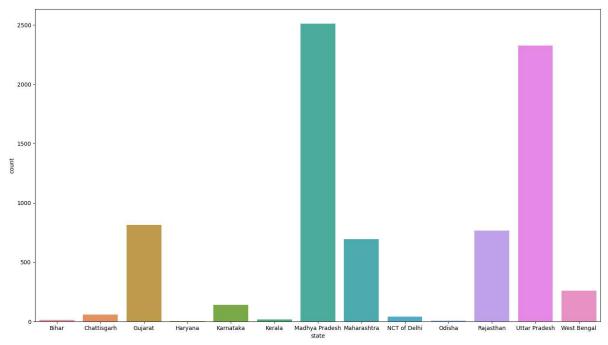
memory usage: 596.6+ KB

```
In [7]: #total number of null values in each column
         data.isnull().sum()
 Out[7]: state
         district
                          0
         market
                          0
         commodity
                          0
         variety
                          0
         arrival_date
                         0
         min price
                         16
         max price
                         23
         modal_price
                          1
         update_date
                          0
         dtype: int64
           3. CLEANING THE DATA
 In [8]: #filling in null values
         data = data.fillna(data.mode().iloc[0])
 In [9]: #checking to see if the total number of null values in each column is zero
         data.isnull().sum()
 Out[9]: state
                         0
         district
                         0
         market
                         0
         commodity
                         0
         variety
                         0
         arrival_date
                         0
         min_price
         max_price
                         0
         modal_price
                         0
         update_date
                         0
         dtype: int64
In [10]: #checking to see if there are duplicated values
         data.duplicated().sum()
Out[10]: 0
           4. EXPLORATORY DATA ANALYSIS
In [11]: #Generating a count plot for the states
         print(data['state'].value_counts())
         plt.figure(figsize=(18,10))
         sns.countplot(x='state', data=data)
```

Madhya Pradesh 2	2510
Uttar Pradesh 2	325
Gujarat	812
Rajasthan	766
Maharashtra	694
West Bengal	260
Karnataka	138
Chattisgarh	56
NCT of Delhi	39
Kerala	15
Bihar	14
Odisha	5
Haryana	1
Name: state, dtvpe:	inte

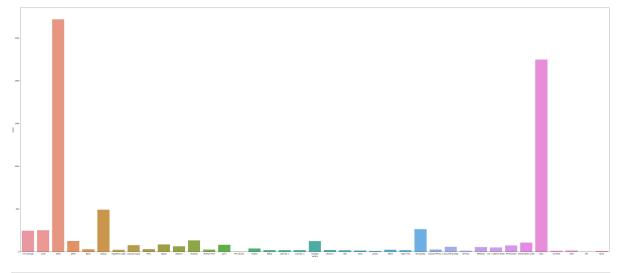
Name: state, dtype: int64

Out[11]: <AxesSubplot: xlabel='state', ylabel='count'>



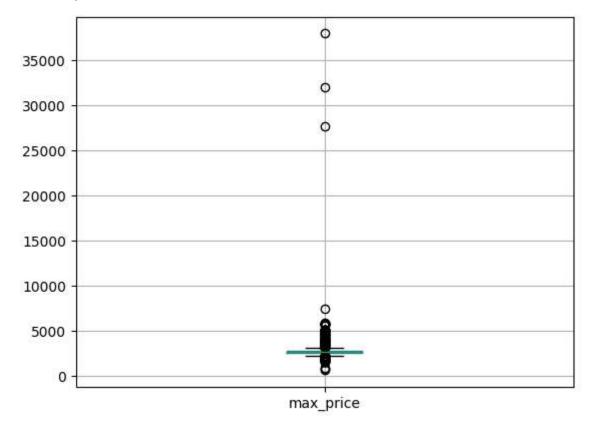
```
In [12]: #Generating a count plot for the districts
   plt.figure(figsize=(60,25))
   sns.countplot(x='variety', data=data)
```

Out[12]: <AxesSubplot: xlabel='variety', ylabel='count'>



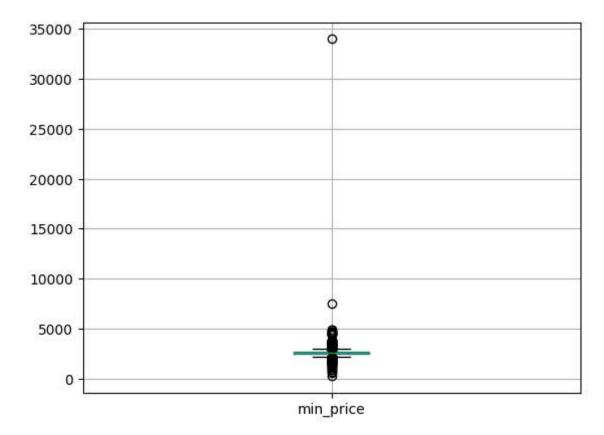
```
In [54]: #Boxplot for maximum price
  data[['max_price']].boxplot()
```

Out[54]: <AxesSubplot: >



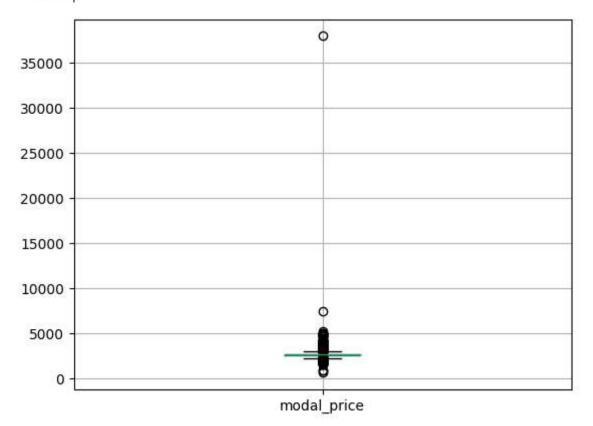
```
In [13]: #Boxplot for minimum price
  data[['min_price']].boxplot()
```

Out[13]: <AxesSubplot: >



```
In [56]: #Boxplot for modal price
data[['modal_price']].boxplot()
```

Out[56]: <AxesSubplot: >



```
In [14]:
           #The scatter plot for maximum price
           data.plot.scatter(x = 'state', y = 'max price', s = 20, c='red', figsize=(18,5));
            30000
            25000
            20000
            15000
            10000
                  Bihai
                        Chattisgarh
                               Gujarat
                                      Haryana
                                             Karnataka
                                                     Kerala
                                                         Madhya Pradesh Maharashtra NCT of Delhi
                                                                                Odisha
                                                                                      Rajasthan
                                                                                            Uttar Pradesh
                                                                                                   West Bengal
In [15]: #The scatter plot for minimum price
           data.plot.scatter(x = 'state', y = 'min_price', s = 20, c='blue', figsize=(18,5));
           ₹ 15000
            10000
                                                     Kerala
                                                         Madhya Pradesh Maharashtra NCT of Delhi
                                      Haryana
In [16]: #The scatter plot for modal price
           data.plot.scatter(x = 'state', y = 'modal_price', s = 20, c='green', figsize=(18,5)
            35000
            30000
           를 20000
            15000
            5000
                                                         Madhya Pradesh Maharashtra
In [17]: #To find the state with highest price
           costly_state = data[data['max_price'] == data['max_price'].max()]
           print("Inference: The state with highest wheat price is: ",costly_state state value
           Inference: The state with highest wheat price is: Karnataka and it is Rs. 38000.0
In [18]:
          #To find the Market with Lowest price
           least_price = data[data['min_price'] == data['min_price'].min()]
           print("Inference: The state with lowest wheat price is: ",least_price.market.values
           Inference: The state with lowest wheat price is: Dewas and it is Rs. 245.0
```

In [19]: #To find the variety with highest price
 var = data[data['max_price'] == data['max_price'].max()]
 print("Inference: The variety of wheat which is the the most priced is ",var.variet")

Inference: The variety of wheat which is the the most priced is Local and it is R s. 38000.0

```
In [20]: #To find the variety with lowest price
  var = data[data['min_price'] == data['min_price'].min()]
  print("Inference: The variety of wheat which is the least priced is ",var.varie")
```

Inference: The variety of wheat which is the least priced is Lokwan and it is Rs. 245.0

CONCLUSION: We see that the Wheat sales in Madhya Pradesh is the highest and Karnataka sells it at the highest price. We conclude that our data is not normally distributed and it has outliers. We can further predict the evrage wheat price for the entire year.