DA1

March 11, 2025

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2.1 DA1

3 EDA on Automobile dataset

3.0.1 Importing necessary libraries

[10]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
```

3.0.2 Loading the dataset

[15]:
```
df = pd.read_csv(r'D:\study material\VIT_Data_Science\Winter_Sem\Exploratory␣
↪Data Analysis Lab\24_jan\automobile.csv')
df
```

[15]:
```
     symboling normalized-losses         make fuel-type aspiration  \
0            3                 ?  alfa-romero       gas        std
1            3                 ?  alfa-romero       gas        std
2            1                 ?  alfa-romero       gas        std
3            2               164         audi       gas        std
4            2               164         audi       gas        std
..         …               …          …       …        …
200         -1                95        volvo       gas        std
201         -1                95        volvo       gas      turbo
202         -1                95        volvo       gas        std
203         -1                95        volvo    diesel      turbo
204         -1                95        volvo       gas      turbo

    num-of-doors   body-style drive-wheels engine-location  wheel-base  …  \
0            two  convertible          rwd           front        88.6  …
1            two  convertible          rwd           front        88.6  …
2            two    hatchback          rwd           front        94.5  …
```

```
3           four        sedan         fwd          front        99.8  …
4           four        sedan         4wd          front        99.4  …
..            …           …         …            …          …   …
200         four        sedan         rwd          front       109.1  …
201         four        sedan         rwd          front       109.1  …
202         four        sedan         rwd          front       109.1  …
203         four        sedan         rwd          front       109.1  …
204         four        sedan         rwd          front       109.1  …

     engine-size  fuel-system  bore  stroke compression-ratio horsepower  \
0            130         mpfi  3.47    2.68               9.0        111
1            130         mpfi  3.47    2.68               9.0        111
2            152         mpfi  2.68    3.47               9.0        154
3            109         mpfi  3.19     3.4              10.0        102
4            136         mpfi  3.19     3.4               8.0        115
..             …           …   …     …              …          …
200          141         mpfi  3.78    3.15               9.5        114
201          141         mpfi  3.78    3.15               8.7        160
202          173         mpfi  3.58    2.87               8.8        134
203          145          idi  3.01     3.4              23.0        106
204          141         mpfi  3.78    3.15               9.5        114

     peak-rpm city-mpg highway-mpg  price
0        5000       21          27  13495
1        5000       21          27  16500
2        5000       19          26  16500
3        5500       24          30  13950
4        5500       18          22  17450
..         …        …           …     …
200      5400       23          28  16845
201      5300       19          25  19045
202      5500       18          23  21485
203      4800       26          27  22470
204      5400       19          25  22625

[205 rows x 26 columns]
```

[17]:
```python
df.dtypes
```

[17]:
```
symboling              int64
normalized-losses     object
make                  object
fuel-type             object
aspiration            object
num-of-doors          object
body-style            object
drive-wheels          object
```

```
engine-location       object
wheel-base           float64
length               float64
width                float64
height               float64
curb-weight            int64
engine-type           object
num-of-cylinders      object
engine-size            int64
fuel-system           object
bore                  object
stroke                object
compression-ratio    float64
horsepower            object
peak-rpm              object
city-mpg               int64
highway-mpg            int64
price                 object
dtype: object
```

3.1 Data cleaning

[22]:
```
# Find out the number of values which are not numeric
df['price'].str.isnumeric().value_counts()
```

[22]:
```
price
True     201
False      4
Name: count, dtype: int64
```

[24]:
```
df['price'].loc[df['price'].str.isnumeric()== False]
```

[24]:
```
9      ?
44     ?
45     ?
129    ?
Name: price, dtype: object
```

[26]:
```
## setting the missing value to mean of price and convert the datatype to␣
↪integer
price = df['price'].loc[df['price'] != '?']
pmean = price.astype(int).mean()
df['price'] = df['price'].replace('?',pmean).astype(int)
df['price']
```

[26]:
```
0      13495
1      16500
```

```
2       16500
3       13950
4       17450
        …
200     16845
201     19045
202     21485
203     22470
204     22625
Name: price, Length: 205, dtype: int32
```

- 4 values in the price column were non numeric we replaced them by the mean value of the column
-

3.1.1 cleaning the horsepower feild

[30]:
```python
df['horsepower'].str.isnumeric().value_counts()
```

[30]:
```
horsepower
True     203
False      2
Name: count, dtype: int64
```

[32]:
```python
horsepower = df['horsepower'].loc[df['horsepower'] != '?']
hpmean = horsepower.astype(int).mean()
df['horsepower'] = df['horsepower'].replace('?',hpmean).astype(int)
df['horsepower']
```

[32]:
```
0       111
1       111
2       154
3       102
4       115
       …
200     114
201     160
202     134
203     106
204     114
Name: horsepower, Length: 205, dtype: int32
```

-

3.1.2 Cleaning normalized losses feild

[35]:
```
df['normalized-losses'].str.isnumeric().value_counts()
```

[35]:
```
normalized-losses
True     164
False     41
Name: count, dtype: int64
```

[37]:
```
nl = df['normalized-losses'].loc[df['normalized-losses'] != '?']
nlmean = nl.astype(int).mean()
df['normalized-losses'] = df['normalized-losses'].replace('?',nlmean).
 ↪astype(int)
df['normalized-losses']
```

[37]:
```
0      122
1      122
2      122
3      164
4      164
      …
200     95
201     95
202     95
203     95
204     95
Name: normalized-losses, Length: 205, dtype: int32
```

[39]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   symboling          205 non-null    int64
 1   normalized-losses  205 non-null    int32
 2   make               205 non-null    object
 3   fuel-type          205 non-null    object
 4   aspiration         205 non-null    object
 5   num-of-doors       205 non-null    object
 6   body-style         205 non-null    object
 7   drive-wheels       205 non-null    object
 8   engine-location    205 non-null    object
 9   wheel-base         205 non-null    float64
 10  length             205 non-null    float64
 11  width              205 non-null    float64
 12  height             205 non-null    float64
```

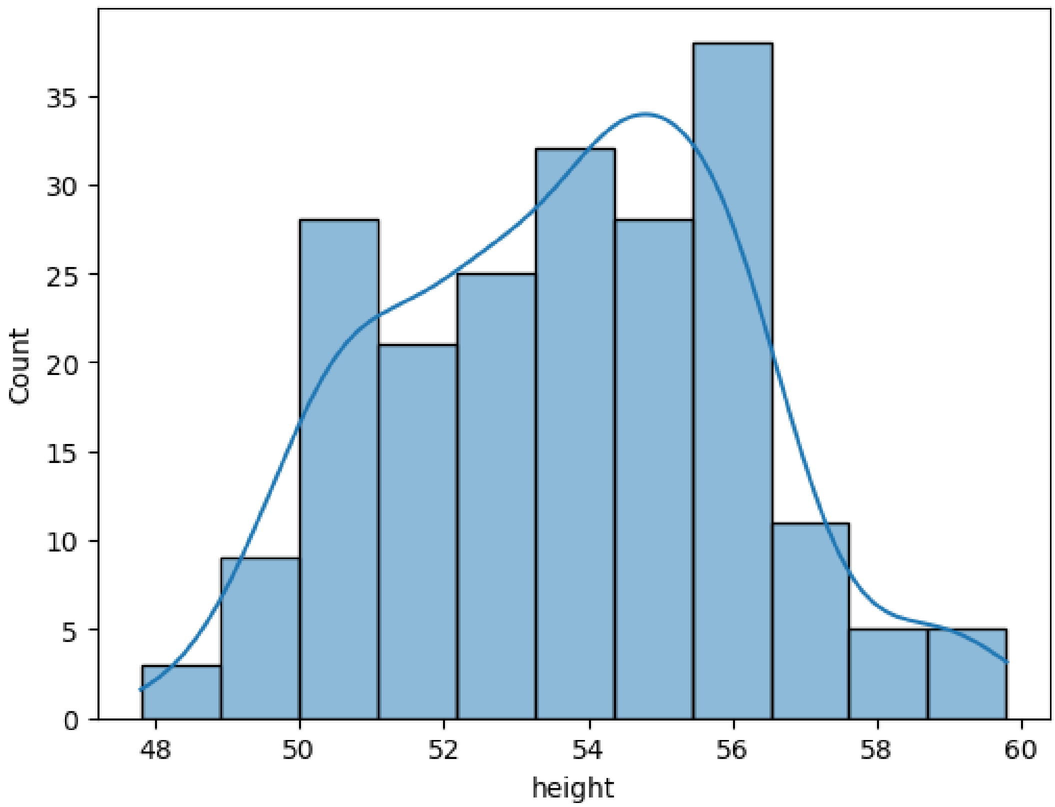
```
 13   curb-weight        205 non-null    int64
 14   engine-type        205 non-null    object
 15   num-of-cylinders   205 non-null    object
 16   engine-size        205 non-null    int64
 17   fuel-system        205 non-null    object
 18   bore               205 non-null    object
 19   stroke             205 non-null    object
 20   compression-ratio  205 non-null    float64
 21   horsepower         205 non-null    int32
 22   peak-rpm           205 non-null    object
 23   city-mpg           205 non-null    int64
 24   highway-mpg        205 non-null    int64
 25   price              205 non-null    int32
dtypes: float64(5), int32(3), int64(5), object(13)
memory usage: 39.4+ KB
```

[43]:
```
#calculate mean, median and mode of dataset height
mean = df["height"].mean()
median =df["height"].median()
mode = df["height"].mode()
print(mean , median, mode)
```

```
53.72487804878049 54.1 0    50.8
Name: height, dtype: float64
```

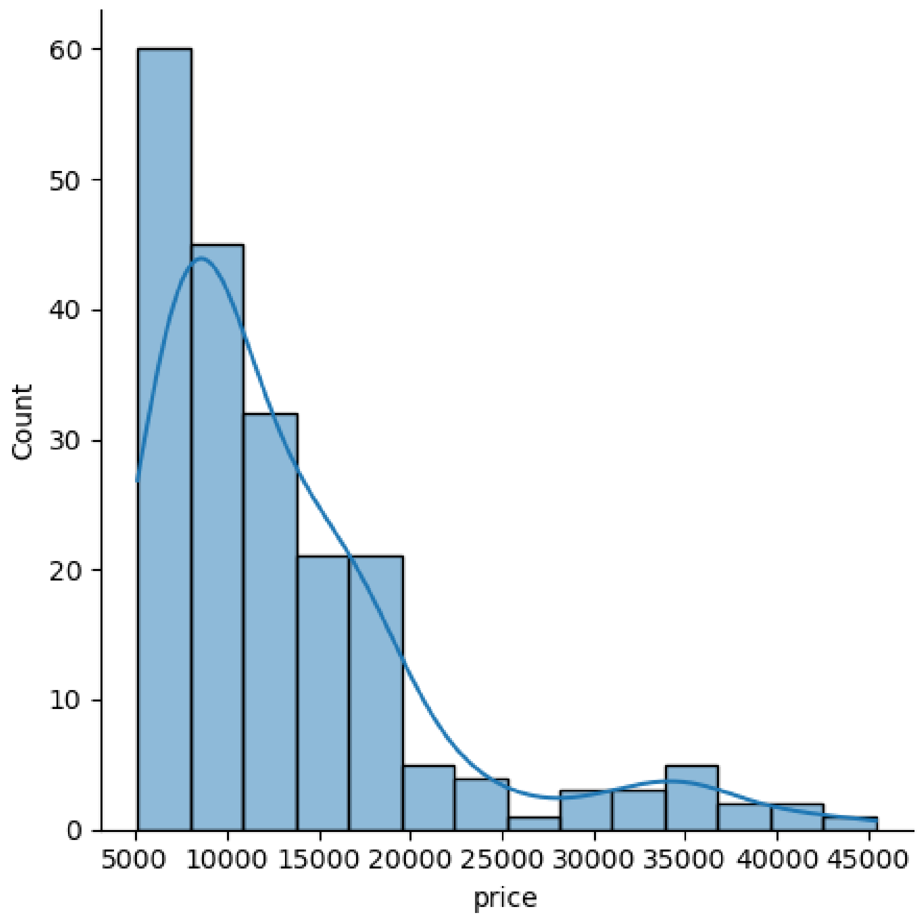
4 Visualization

[53]:
```
sns.histplot(df['height'],kde=True)
plt.show()
```



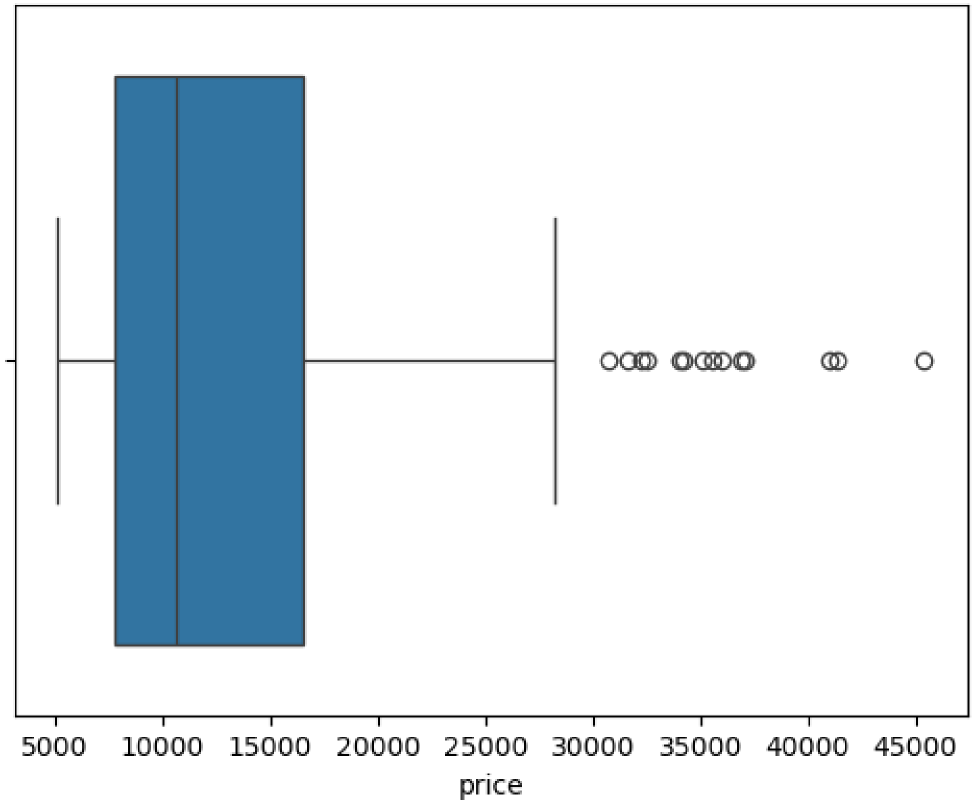
4.1 Height column is right skewed

```
[56]: sns.displot(df['price'],kde=True)
plt.tight_layout()
plt.show()
```



4.2 Price is left skewed

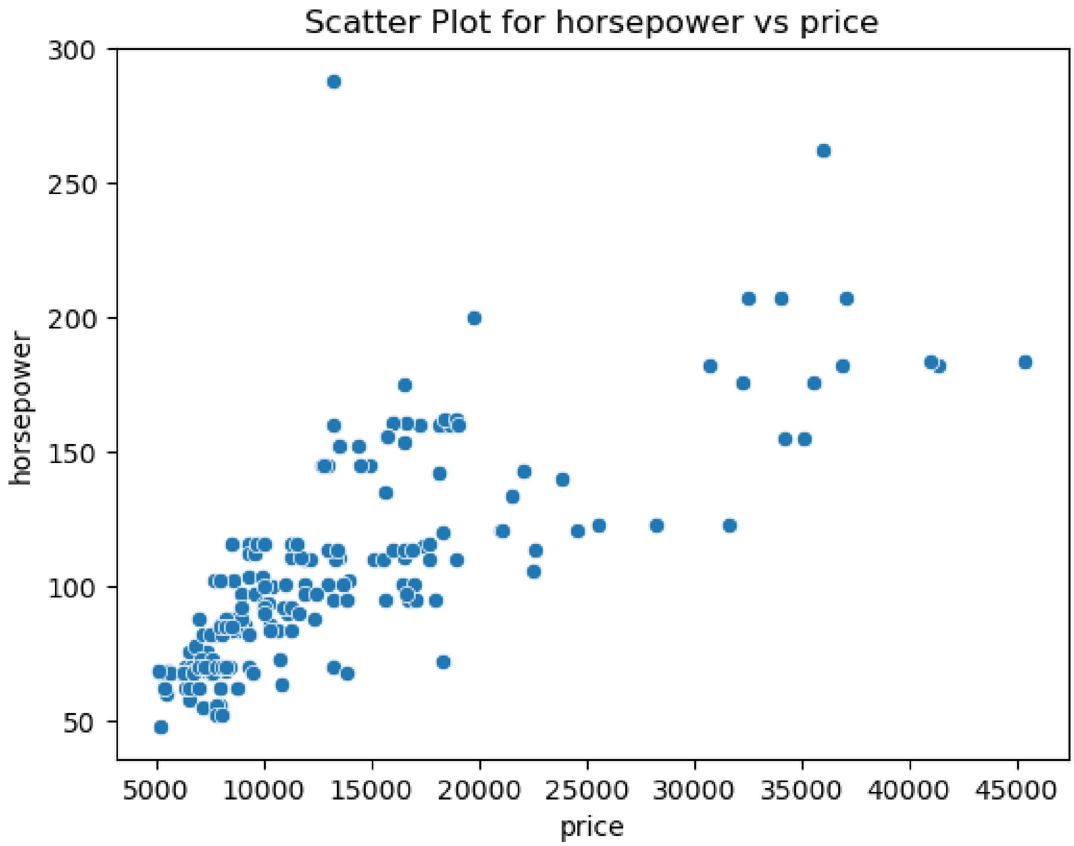
[61]:
```
#boxplot for price of cars
sns.boxplot(x="price",data=df)
plt.show()
```



4.3 Bivariate analysis

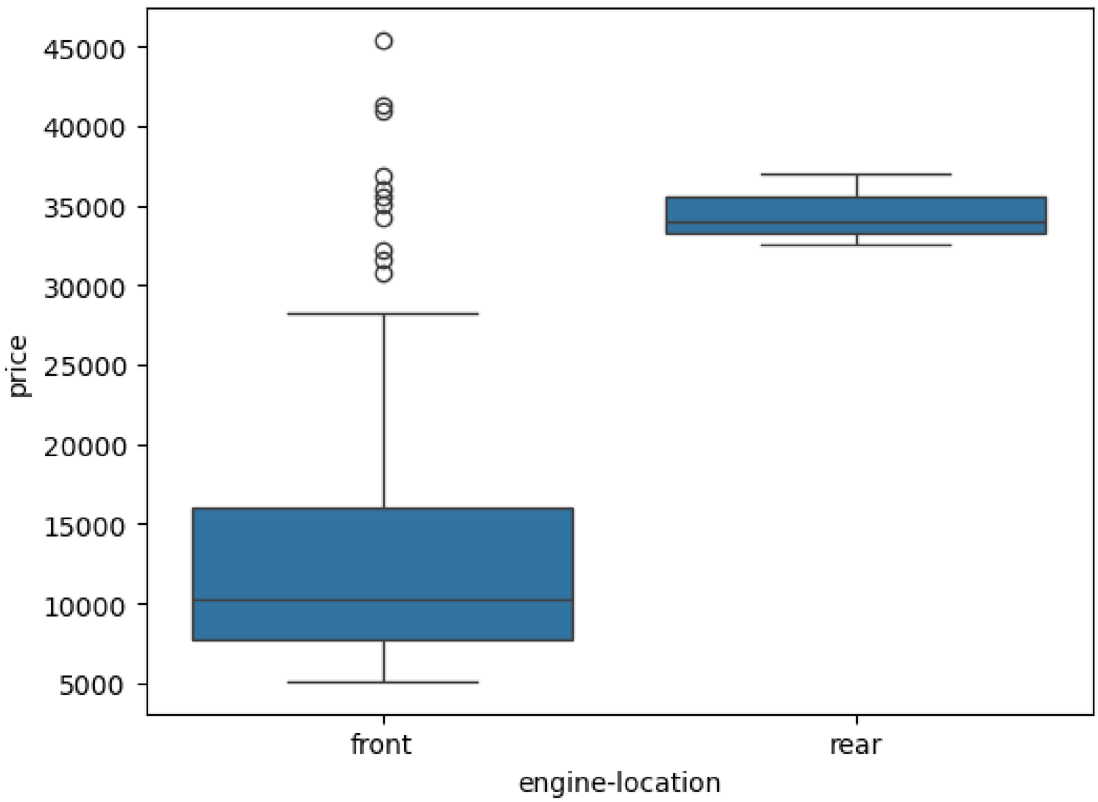
[66]:
```
# plot the relationship between "horsepower" and "price"
sns.scatterplot(x = df["price"],y = df["horsepower"])
plt.title("Scatter Plot for horsepower vs price")
plt.xlabel("price")
plt.ylabel("horsepower")
```

[66]: Text(0, 0.5, 'horsepower')



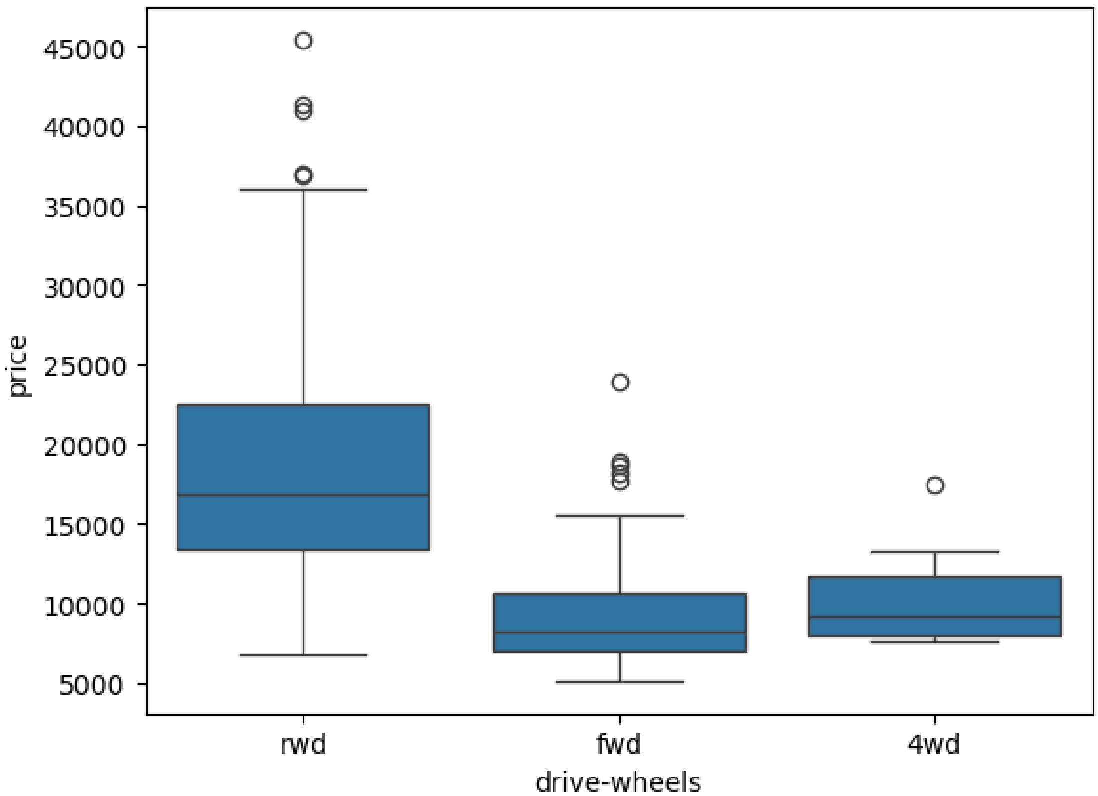
4.4 As the horse power of the car increases, price also increases

[73]:
```
#boxplot
sns.boxplot(x="engine-location",y="price",data=df)
plt.show()
```



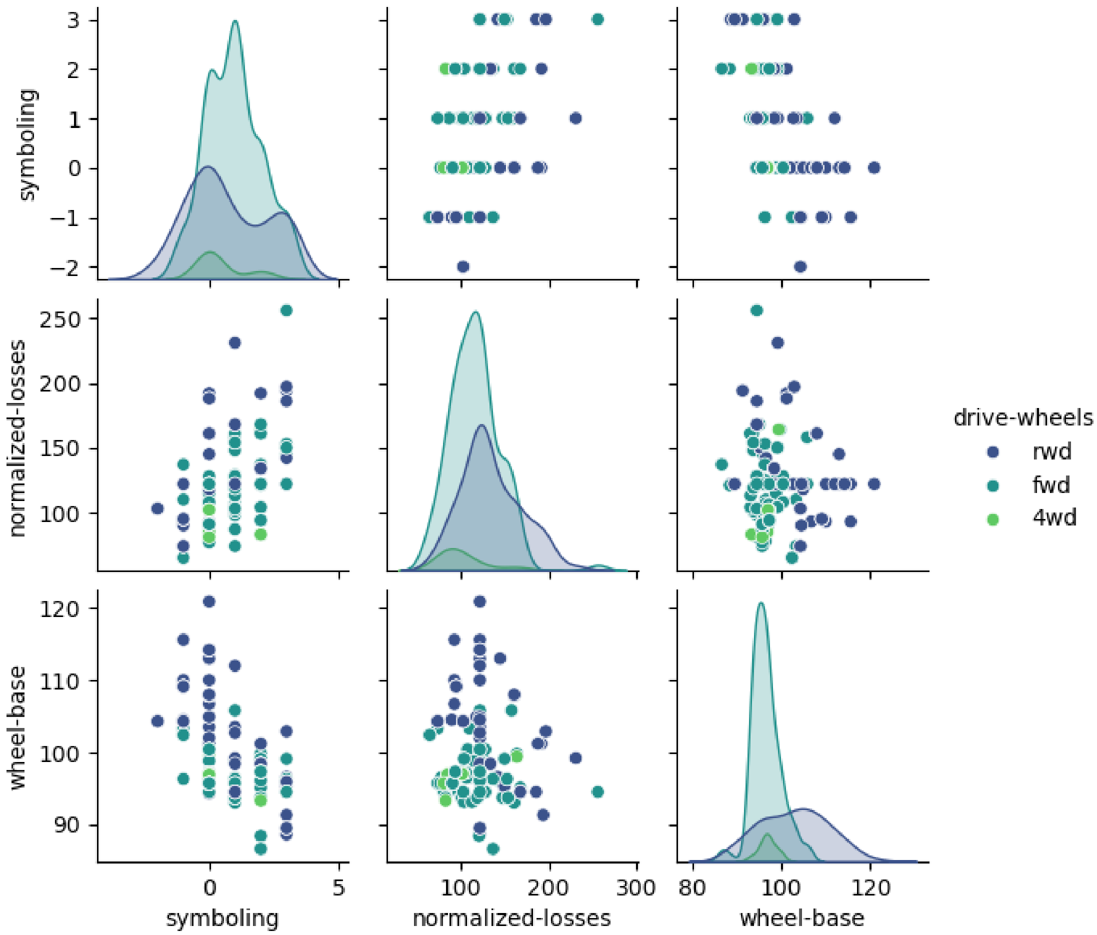
4.5 Price of car with engine in the front are higher

[76]:
```
#boxplot to visualize the distribution of "price" with types of "drive-wheels"
sns.boxplot(x="drive-wheels", y="price",data=df)
plt.show()
```



4.6 Multivariate analysis

[81]:
```
sns.pairplot(df,height=2,vars = ['symboling',␣
↪'normalized-losses','wheel-base'], hue="drive-wheels",palette='viridis')
plt.show()
```




```
[83]: from scipy import stats

corr = stats.pearsonr(df["price"], df["horsepower"])
print("p-value:\t", corr[1])
print("cor:\t\t", corr[0])
```

```
p-value:         1.5910332446595850e-39
cor:             0.7579456217935241
```

Here the correlation of these two variable is 0.80957 which is close to +1 thus we can make sure that price and horsepower are highly positively correlated. Using pandas corr() function correlation between entire numerical record can be calculated.

```
[86]: correlation = df.corr(method='pearson',numeric_only=True)
correlation
```

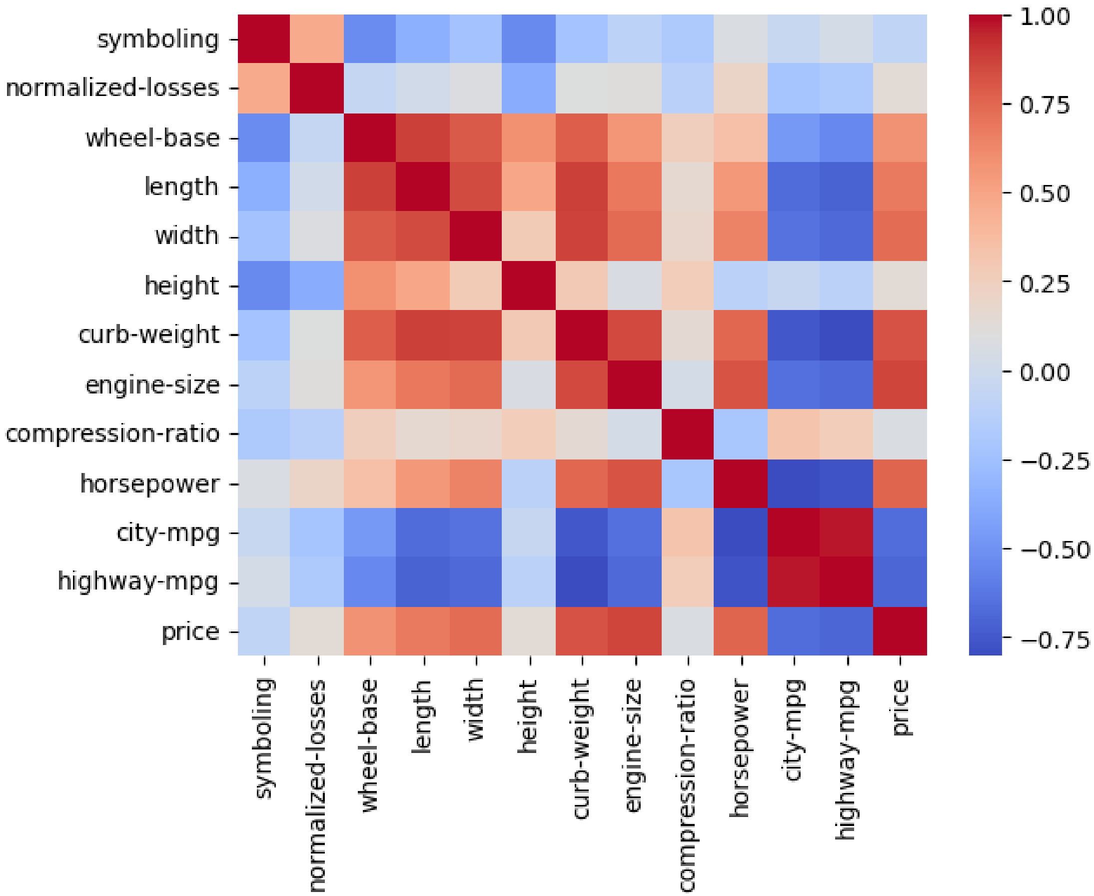
```
[86]:                    symboling  normalized-losses  wheel-base    length  \
symboling             1.000000           0.465190   -0.531954 -0.357612
```

```
normalized-losses   0.465190           1.000000   -0.056518  0.019209
wheel-base         -0.531954          -0.056518    1.000000  0.874587
length             -0.357612           0.019209    0.874587  1.000000
width              -0.232919           0.084195    0.795144  0.841118
height             -0.541038          -0.370706    0.589435  0.491029
curb-weight        -0.227691           0.097785    0.776386  0.877728
engine-size        -0.105790           0.110997    0.569329  0.683360
compression-ratio  -0.178515          -0.114525    0.249786  0.158414
horsepower          0.071380           0.203434    0.351985  0.554408
city-mpg           -0.035823          -0.218749   -0.470414 -0.670909
highway-mpg         0.034606          -0.178221   -0.544082 -0.704662
price              -0.082201           0.133999    0.583168  0.682986

                      width    height  curb-weight  engine-size  \
symboling         -0.232919 -0.541038    -0.227691    -0.105790
normalized-losses  0.084195 -0.370706     0.097785     0.110997
wheel-base         0.795144  0.589435     0.776386     0.569329
length             0.841118  0.491029     0.877728     0.683360
width              1.000000  0.279210     0.867032     0.735433
height             0.279210  1.000000     0.295572     0.067149
curb-weight        0.867032  0.295572     1.000000     0.850594
engine-size        0.735433  0.067149     0.850594     1.000000
compression-ratio  0.181129  0.261214     0.151362     0.028971
horsepower         0.642176 -0.110114     0.750973     0.810705
city-mpg          -0.642704 -0.048640    -0.757414    -0.653658
highway-mpg       -0.677218 -0.107358    -0.797465    -0.677470
price              0.728699  0.134388     0.820825     0.861752

                   compression-ratio  horsepower  city-mpg  highway-mpg  \
symboling                  -0.178515    0.071380 -0.035823     0.034606
normalized-losses          -0.114525    0.203434 -0.218749    -0.178221
wheel-base                  0.249786    0.351985 -0.470414    -0.544082
length                      0.158414    0.554408 -0.670909    -0.704662
width                       0.181129    0.642176 -0.642704    -0.677218
height                      0.261214   -0.110114 -0.048640    -0.107358
curb-weight                 0.151362    0.750973 -0.757414    -0.797465
engine-size                 0.028971    0.810705 -0.653658    -0.677470
compression-ratio           1.000000   -0.205717  0.324701     0.265201
horsepower                 -0.205717    1.000000 -0.803140    -0.770905
city-mpg                    0.324701   -0.803140  1.000000     0.971337
highway-mpg                 0.265201   -0.770905  0.971337     1.000000
price                       0.070990    0.757946 -0.667449    -0.690526

                      price
symboling         -0.082201
normalized-losses  0.133999
wheel-base         0.583168
```

```
length               0.682986
width                0.728699
height               0.134388
curb-weight          0.820825
engine-size          0.861752
compression-ratio    0.070990
horsepower           0.757946
city-mpg            -0.667449
highway-mpg         -0.690526
price                1.000000
```

[92]:

```
sns.heatmap(correlation,xticklabels=correlation.columns,
            yticklabels=correlation.columns,cmap='coolwarm')
plt.show()
```



5 EDA on mtcars dataset

5.1 Loading the dataset

[100]:
```
df1 = pd.read_csv(r"D:\study material\VIT_Data_Science\Winter_Sem\Exploratory␣
↪Data Analysis Lab\24_jan\mtcars.csv")
df1.head()
```

[100]:
```
              model   mpg  cyl   disp   hp  drat     wt   qsec  vs  am  gear  \
0         Mazda RX4  21.0    6  160.0  110  3.90  2.620  16.46   0   1     4
1     Mazda RX4 Wag  21.0    6  160.0  110  3.90  2.875  17.02   0   1     4
2        Datsun 710  22.8    4  108.0   93  3.85  2.320  18.61   1   1     4
3    Hornet 4 Drive  21.4    6  258.0  110  3.08  3.215  19.44   1   0     3
4 Hornet Sportabout  18.7    8  360.0  175  3.15  3.440  17.02   0   0     3

   carb
0     4
1     4
2     1
3     1
4     2
```

[102]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32 entries, 0 to 31
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   model   32 non-null     object
 1   mpg     32 non-null     float64
 2   cyl     32 non-null     int64
 3   disp    32 non-null     float64
 4   hp      32 non-null     int64
 5   drat    32 non-null     float64
 6   wt      32 non-null     float64
 7   qsec    32 non-null     float64
 8   vs      32 non-null     int64
 9   am      32 non-null     int64
 10  gear    32 non-null     int64
 11  carb    32 non-null     int64
dtypes: float64(5), int64(6), object(1)
memory usage: 3.1+ KB
```

5.2 checking for null values

[105]:
```
df1.isnull().sum()
```

[105]:
```
model    0
mpg      0
cyl      0
disp     0
hp       0
drat     0
wt       0
qsec     0
vs       0
am       0
gear     0
carb     0
dtype: int64
```

5.2.1 no missing values

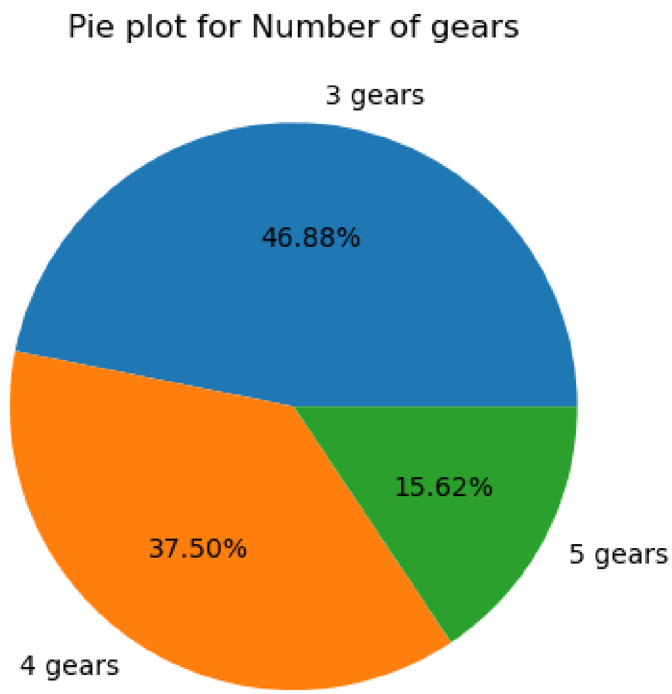
5.3 checking for duplicates values

[111]:
```
df1.duplicated().sum()
```

[111]:
```
0
```

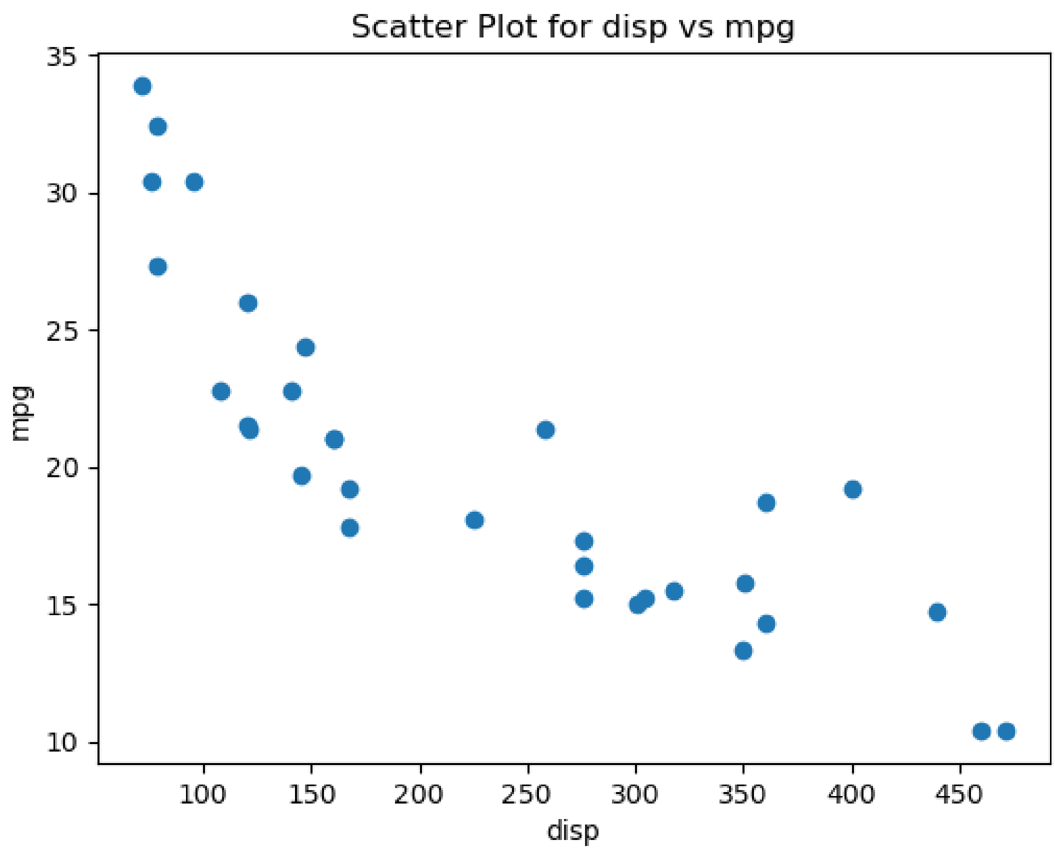
5.3.1 No duplicate values

[116]:
```
gear = df1['gear'].value_counts()
plt.pie(gear,labels=['3 gears','4 gears','5 gears'],autopct='%.2f%%')
plt.title("Pie plot for Number of gears")
plt.show()
```



5.3.2 Majority of cars have 3 gears

[123]:
```
plt.scatter(df1["disp"], df1["mpg"])
plt.title("Scatter Plot for disp vs mpg")
plt.xlabel("disp")
plt.ylabel("mpg")
plt.show()
```



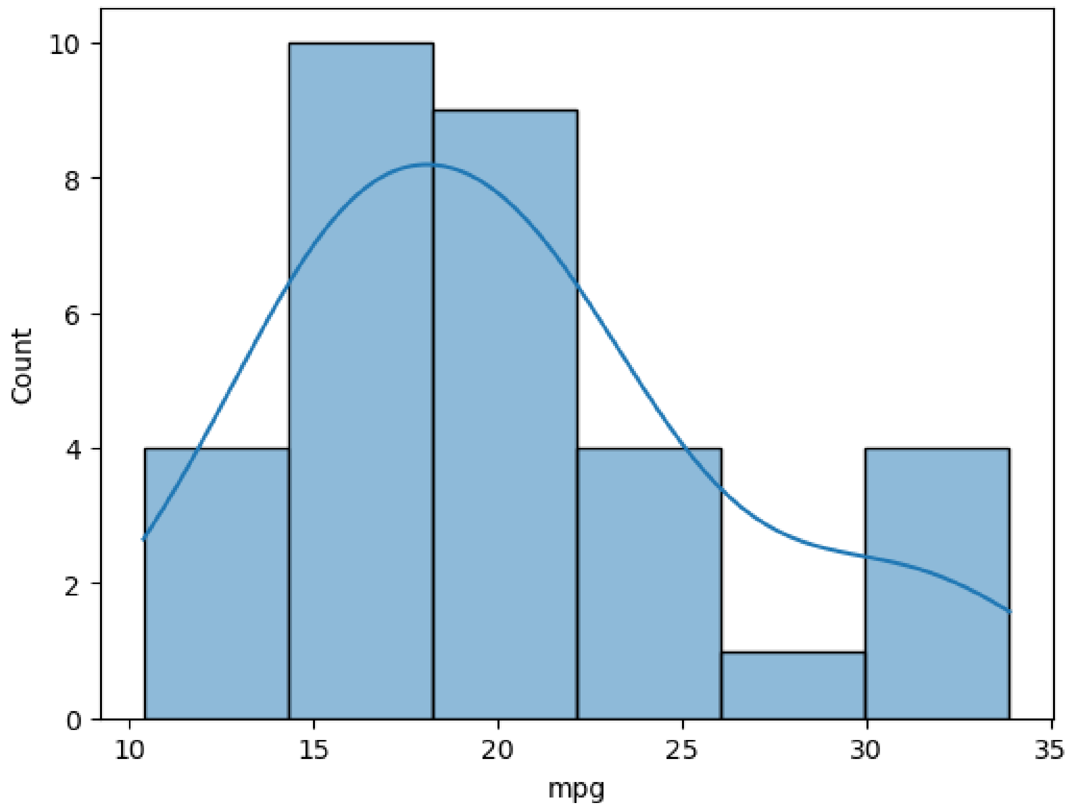
- as the displacemnt of the car increases the mileage decreases

[126]:
```
df1.groupby(['gear','cyl'])['mpg'].agg([np.sum, np.mean])
```

[126]:

gear	cyl	sum	mean
3	4	21.5	21.500
	6	39.5	19.750
	8	180.6	15.050
4	4	215.4	26.925
	6	79.0	19.750
5	4	56.4	28.200
	6	19.7	19.700
	8	30.8	15.400

[128]:
```
sns.histplot(df1['mpg'],kde=True)
plt.show()
```



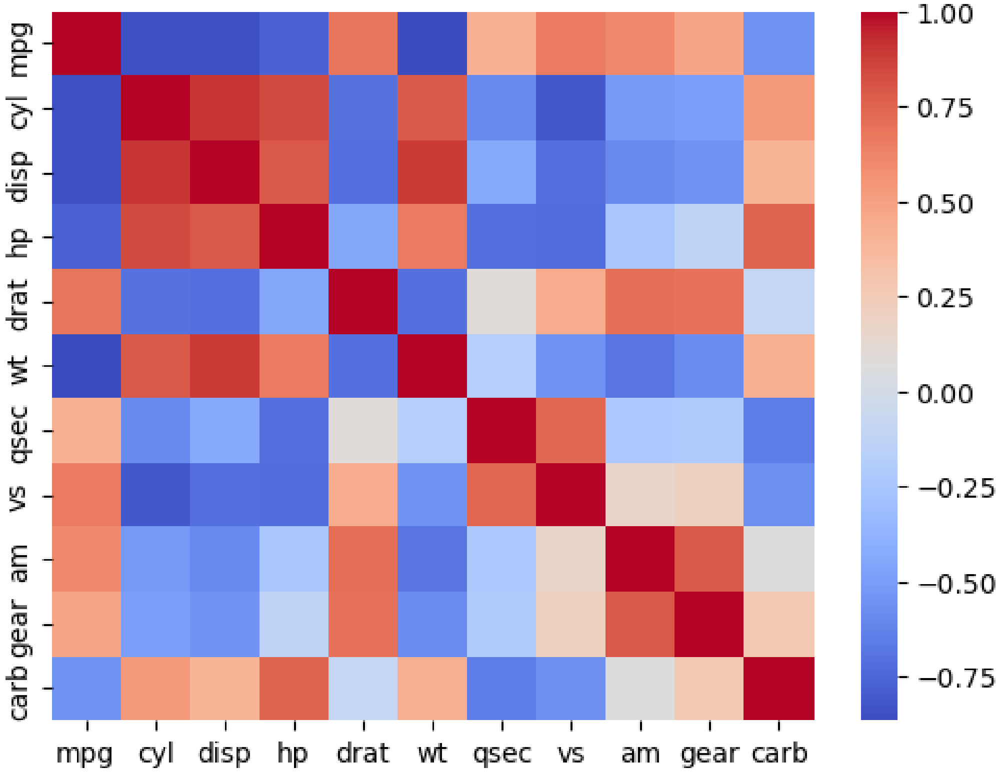
- most cars have mpg in the range 13-23

[131]:
```
correlation = df1.corr(method='pearson',numeric_only=True)
correlation
```

[131]:
```
           mpg       cyl      disp        hp      drat        wt      qsec  \
mpg   1.000000 -0.852162 -0.847551 -0.776168  0.681172 -0.867659  0.418684
cyl  -0.852162  1.000000  0.902033  0.832447 -0.699938  0.782496 -0.591242
disp -0.847551  0.902033  1.000000  0.790949 -0.710214  0.887980 -0.433698
hp   -0.776168  0.832447  0.790949  1.000000 -0.448759  0.658748 -0.708223
drat  0.681172 -0.699938 -0.710214 -0.448759  1.000000 -0.712441  0.091205
wt   -0.867659  0.782496  0.887980  0.658748 -0.712441  1.000000 -0.174716
qsec  0.418684 -0.591242 -0.433698 -0.708223  0.091205 -0.174716  1.000000
vs    0.664039 -0.810812 -0.710416 -0.723097  0.440278 -0.554916  0.744535
am    0.599832 -0.522607 -0.591227 -0.243204  0.712711 -0.692495 -0.229861
gear  0.480285 -0.492687 -0.555569 -0.125704  0.699610 -0.583287 -0.212682
carb -0.550925  0.526988  0.394977  0.749812 -0.090790  0.427606 -0.656249

            vs        am      gear      carb
mpg   0.664039  0.599832  0.480285 -0.550925
cyl  -0.810812 -0.522607 -0.492687  0.526988
```

```
disp -0.710416 -0.591227 -0.555569  0.394977
hp   -0.723097 -0.243204 -0.125704  0.749812
drat  0.440278  0.712711  0.699610 -0.090790
wt   -0.554916 -0.692495 -0.583287  0.427606
qsec  0.744535 -0.229861 -0.212682 -0.656249
vs    1.000000  0.168345  0.206023 -0.569607
am    0.168345  1.000000  0.794059  0.057534
gear  0.206023  0.794059  1.000000  0.274073
carb -0.569607  0.057534  0.274073  1.000000
```

[133]:
```
sns.heatmap(correlation,xticklabels=correlation.columns,
            yticklabels=correlation.columns,cmap='coolwarm')
plt.show()
```



6 EDA on titanic dataset

[136]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
titanic = pd.read_csv(r"D:\study␣
↪material\VIT_Data_Science\Winter_Sem\Exploratory Data Analysis␣
↪Lab\7_Feb\titanic_new.csv")
```

[138]:
```
titanic.head()
```

[138]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

[140]:
```
titanic.shape
```

[140]:
```
(891, 12)
```

6.1 Checking for missing values

[143]:
```
titanic.isnull().sum().sort_values(ascending=False)
```

[143]:
```
Cabin          687
Age            177
Embarked         2
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
SibSp            0
Parch            0
Ticket           0
Fare             0
```

```
dtype: int64
```

6.1.1 Inference:

- cabin column has the most missing values followed by Age and Embarked

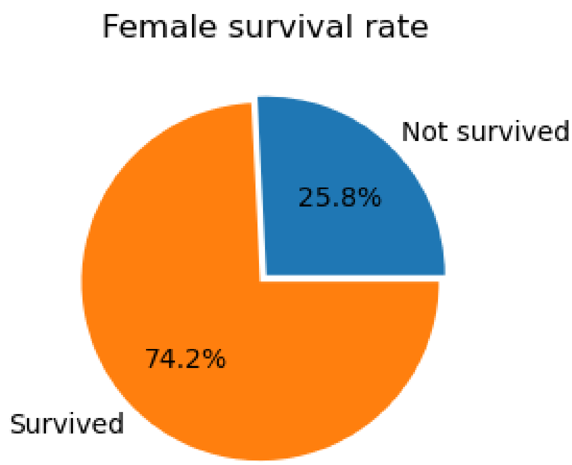
[148]:
```
## Percentage of women survived

women = titanic.loc[titanic.Sex == 'female']['Survived']
rate_women = sum(women)/len(women)
rate_women

## percentage of men survived

men = titanic.loc[titanic.Sex == 'male']['Survived']
rate_men = sum(men)/len(men)

print(f"{round(rate_women,3)*100}% women survived")
print(f"{round(rate_men,3)*100}% men survived")
```

```
74.2% women survived
18.9% men survived
```

6.1.2 Inference:

- Women had a significantly higher chance of survival due to the "women and children first" policy.

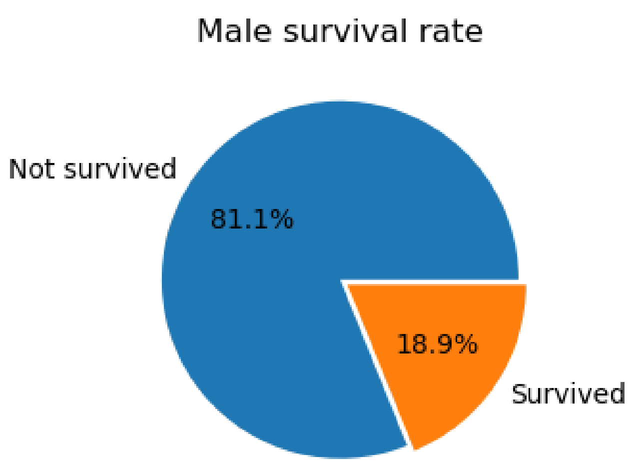
[151]:
```
titanic[titanic['Sex'] == 'female'].Survived.groupby(titanic.Survived).count().
 ↪plot(kind='pie',
figsize=(3, 6),explode=[0,0.05],autopct='%1.1f%%',labels=["Not␣
 ↪survived","Survived"])
plt.title("Female survival rate")
plt.ylabel("")
plt.show()
```



6.1.3 Inference:

- 74.2% of women survived, indicating majority of women survived.

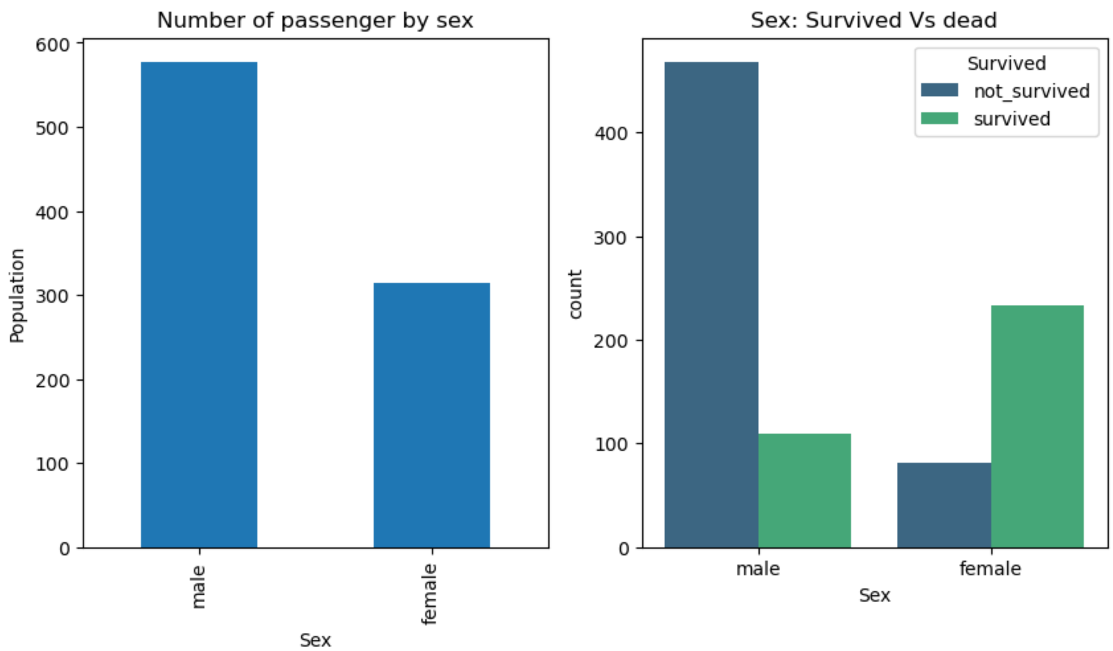
[154]:
```
titanic[titanic['Sex'] == 'male'].Survived.groupby(titanic.Survived).count().
 ↪plot(kind='pie',
figsize=(3, 6),explode=[0,0.05],autopct='%1.1f%%',labels=["Not␣
 ↪survived","Survived"])
plt.title("Male survival rate")
plt.ylabel("")
plt.show()
```



6.1.4 Inference:

- only 18.9% of men survived, indicating majority of men could not survive.

[159]:
```
titanic['Survived'] = titanic['Survived'].map({0:"not_survived",1:"survived"})
plt.figure(figsize = (10,5))
plt.subplot(1,2,1)
titanic['Sex'].value_counts().plot.bar()
plt.title("Number of passenger by sex")
plt.ylabel("Population")
plt.subplot(1,2,2)
sns.countplot(x ="Sex",data = titanic, hue="Survived",palette='viridis')
plt.title("Sex: Survived Vs dead")
plt.show()
```

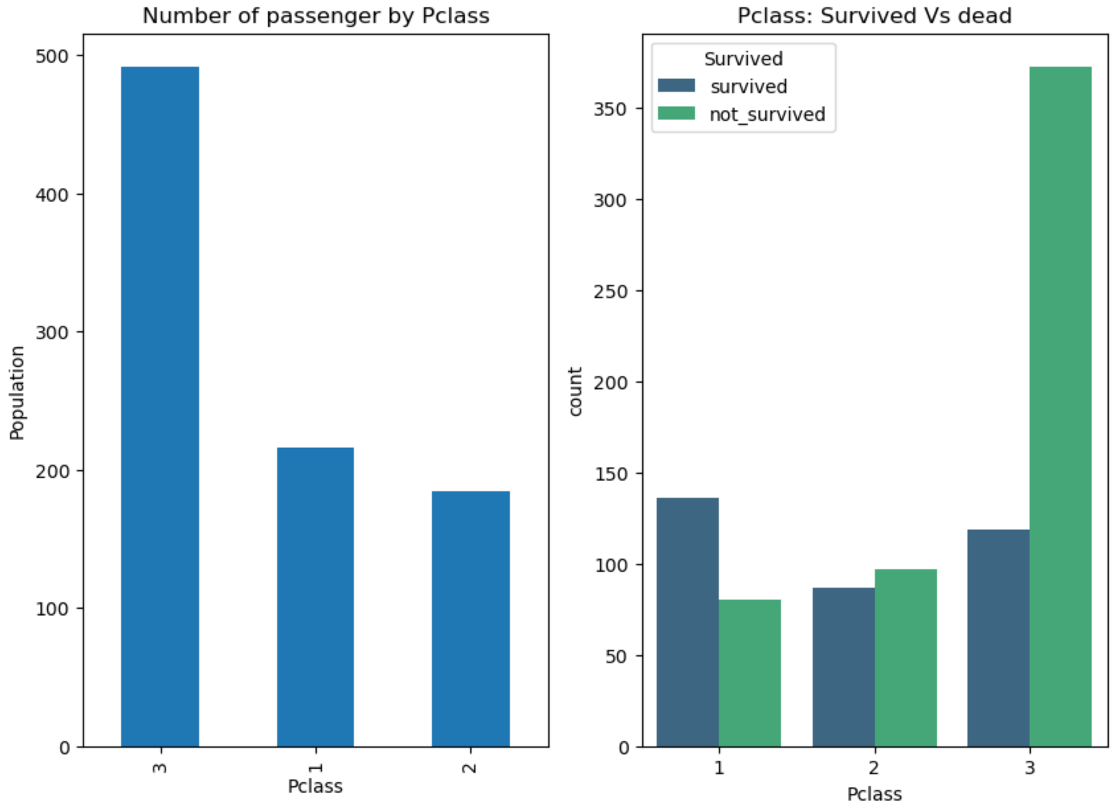


6.1.5 Inference:

- Though more males than females onboarded, still majority of males did not survive.

[162]:
```
plt.figure(figsize = (10,7))
plt.subplot(1,2,1)
titanic['Pclass'].value_counts().plot.bar()
plt.title("Number of passenger by Pclass")
plt.ylabel("Population")
plt.subplot(1,2,2)
sns.countplot(x ="Pclass",data = titanic, hue="Survived",palette='viridis')
plt.title("Pclass: Survived Vs dead")
```

```
plt.show()
```



6.1.6 Inference:

- Most people were from pclass 3
- Survival rate was the lowest in Pclass 3
- Pclass 1 had the highest survival rate (higher-class passengers had better access to lifeboats).

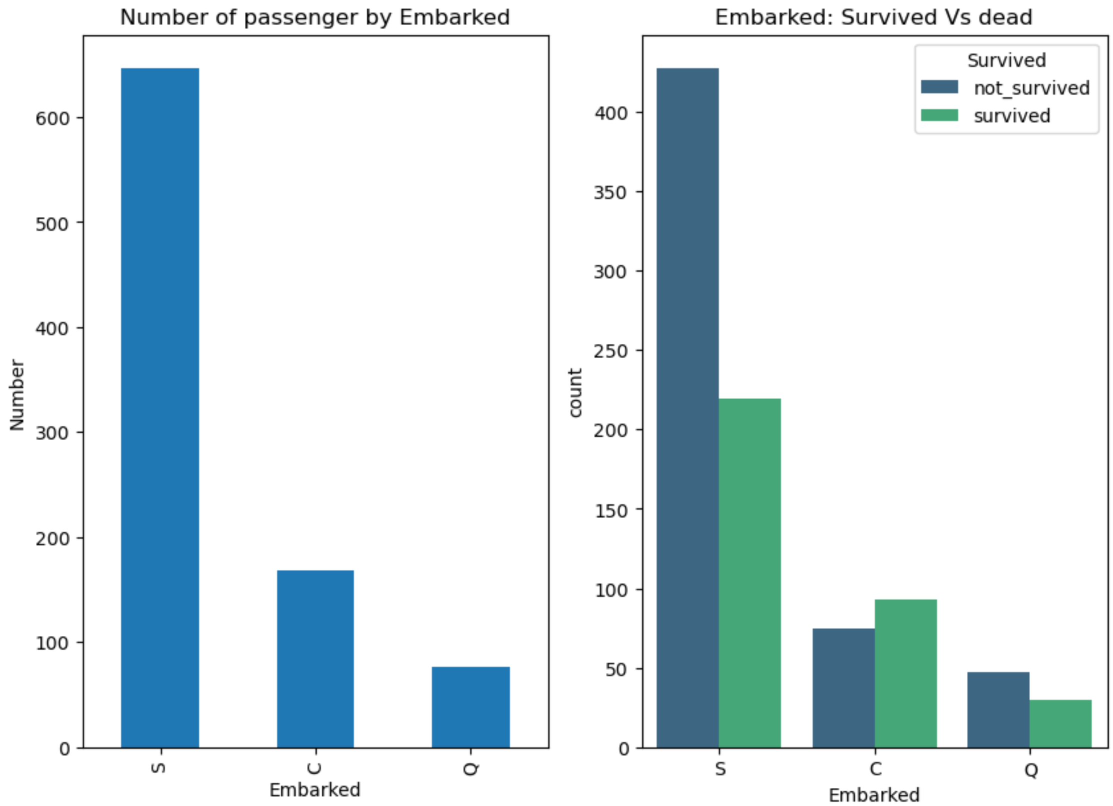
[165]:
```
titanic["Embarked"] = titanic["Embarked"].fillna("S")
titanic
```

[165]:
```
     PassengerId      Survived  Pclass  \
0              1  not_survived       3
1              2      survived       1
2              3      survived       3
3              4      survived       1
4              5  not_survived       3
..           …            …       …
886          887  not_survived       2
887          888      survived       1
888          889  not_survived       3
```

```
889          890      survived       1
890          891  not_survived       3

                                                 Name     Sex   Age  SibSp  \
0                             Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                              Heikkinen, Miss. Laina  female  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                            Allen, Mr. William Henry    male  35.0      0
..                                                 …     …    …    …
886                             Montvila, Rev. Juozas    male  27.0      0
887                      Graham, Miss. Margaret Edith  female  19.0      0
888          Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                             Behr, Mr. Karl Howell    male  26.0      0
890                               Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …               …      …   …       …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

[169]:

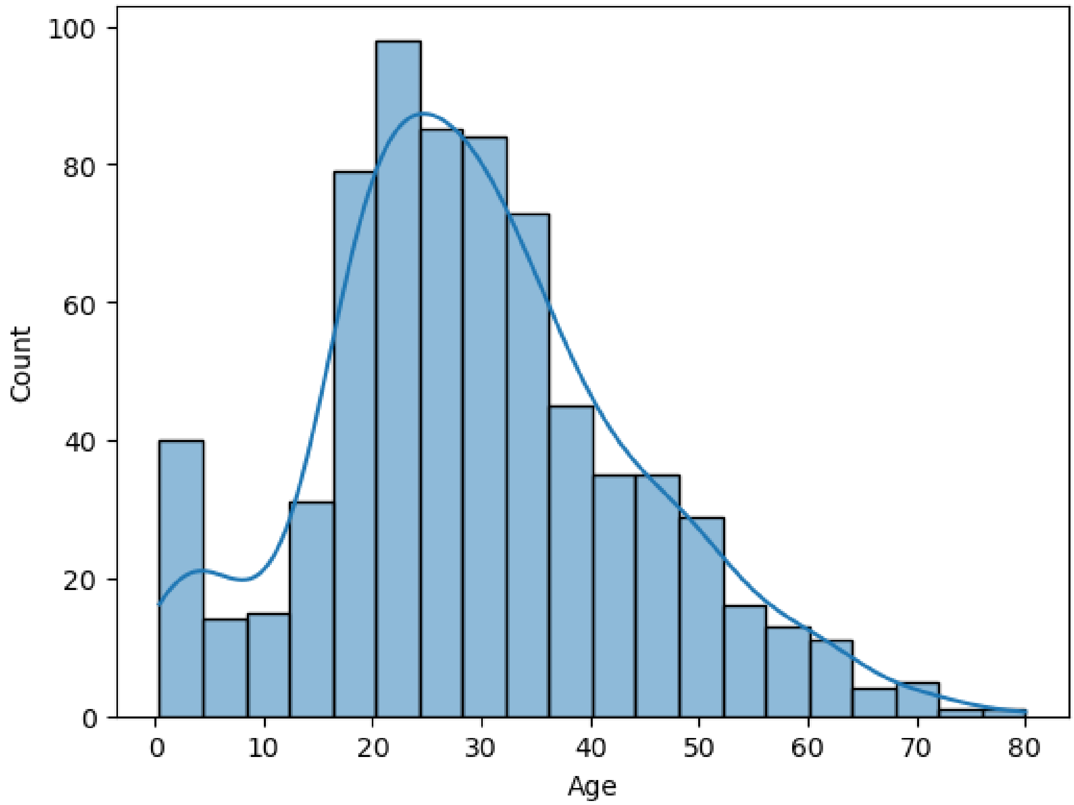
```
plt.figure(figsize = (10,7))
plt.subplot(1,2,1)
titanic['Embarked'].value_counts().plot.bar()
plt.title("Number of passenger by Embarked")
plt.ylabel("Number")
plt.subplot(1,2,2)
sns.countplot(x ="Embarked",data = titanic, hue="Survived",palette='viridis')
plt.title("Embarked: Survived Vs dead")
plt.show()
```



6.1.7 Inference:

- Most passengers embarked from Southampton (S).
- Embarked from "C" (Cherbourg) had a higher survival rate (possibly more first-class passengers).
- Embarked from "S" (Southampton) had the lowest survival rate (many third-class passengers).

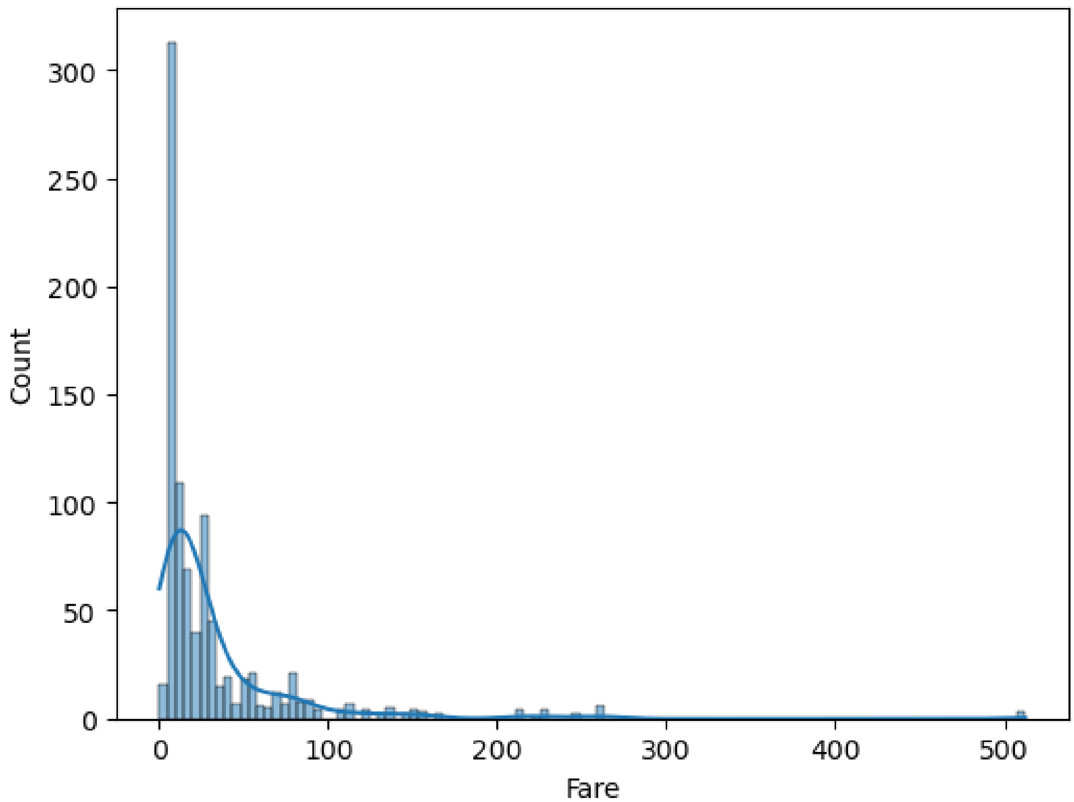
[172]:
```
sns.histplot(titanic['Age'].dropna(), kde = True)
plt.show()
```



6.1.8 Inference:

- Most passengers were between 20-40 years old.

[175]:
```
sns.histplot(titanic['Fare'], kde=True)
plt.show()
```

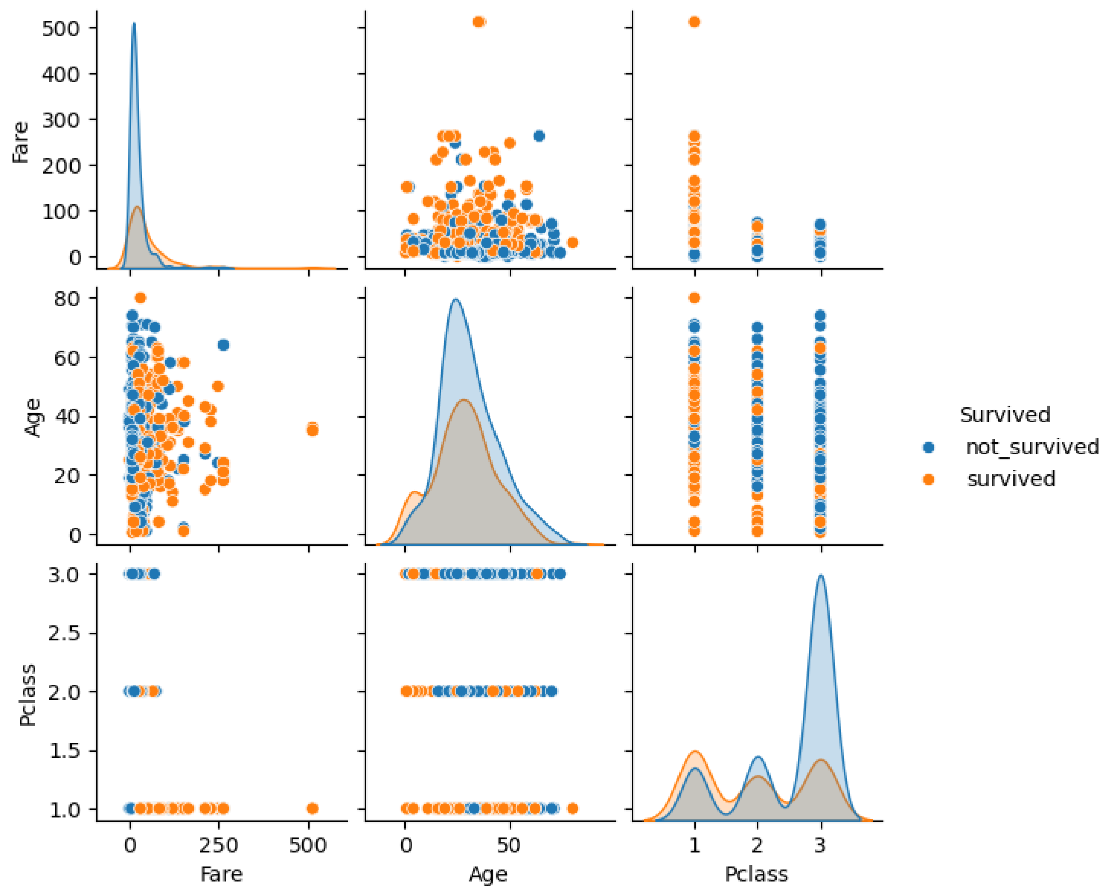


6.1.9 `Inference:`

- Right-skewed distribution → Most fares were low, but a few passengers paid very high fares.
- Indicates wealthier passengers in first-class paid significantly more.

6.1.10 Multivariate analysis

[179]:
```
sns.pairplot(titanic,height=2,vars = [ 'Fare','Age','Pclass'], hue="Survived")
plt.show()
```



6.1.11 Inference:

- Higher fares were associated with higher survival rates

6.2 Correlation table with heatmap

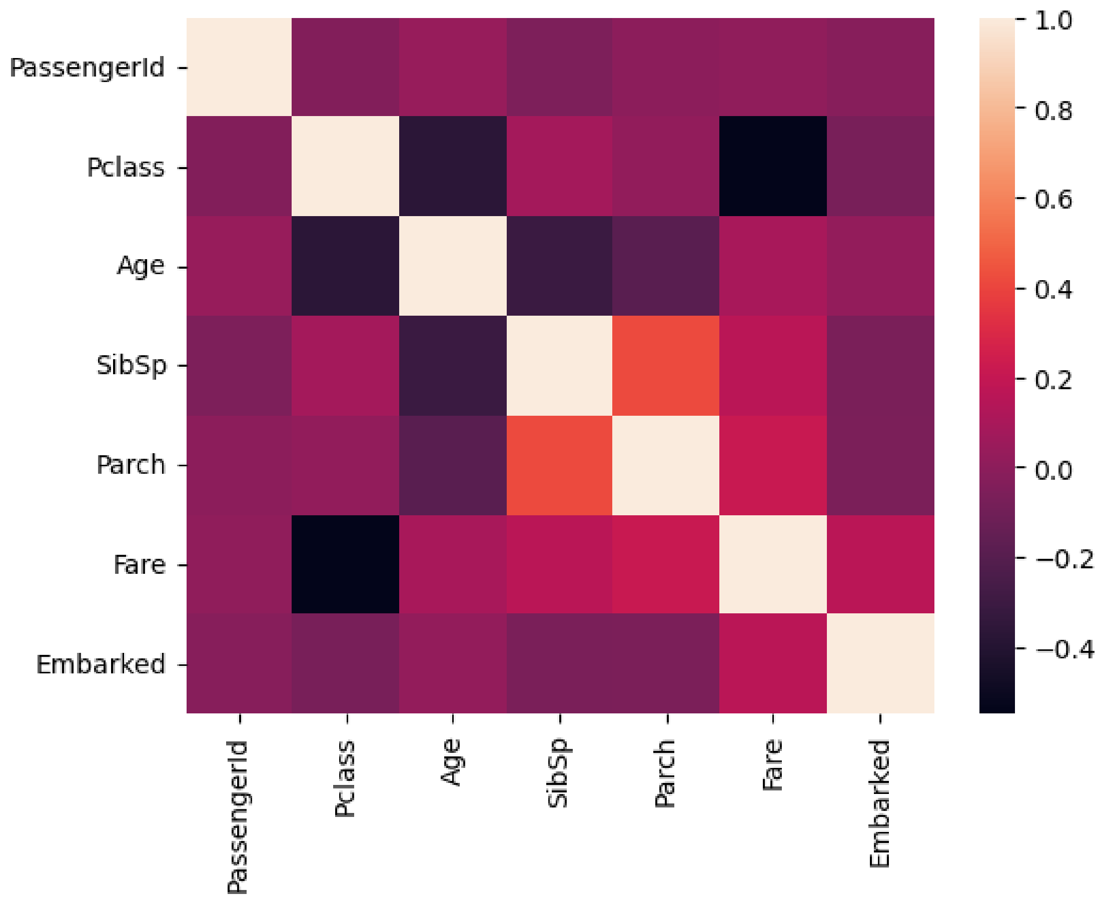
[183]:
```
titanic['Embarked'] = titanic['Embarked'].map({"S":1, "C":2,"Q":2,"NaN":0})
Tcorrelation = titanic.corr(method='pearson', numeric_only=True)
Tcorrelation
```

[183]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare	\
PassengerId	1.000000	-0.035144	0.036847	-0.057527	-0.001652	0.012658	
Pclass	-0.035144	1.000000	-0.369226	0.083081	0.018443	-0.549500	
Age	0.036847	-0.369226	1.000000	-0.308247	-0.189119	0.096067	
SibSp	-0.057527	0.083081	-0.308247	1.000000	0.414838	0.159651	
Parch	-0.001652	0.018443	-0.189119	0.414838	1.000000	0.216225	
Fare	0.012658	-0.549500	0.096067	0.159651	0.216225	1.000000	
Embarked	-0.022204	-0.074053	0.023233	-0.068734	-0.060814	0.162184	

```
             Embarked
PassengerId -0.022204
Pclass      -0.074053
Age          0.023233
SibSp       -0.068734
Parch       -0.060814
Fare         0.162184
Embarked     1.000000
```

[187]:
```python
sns.heatmap(Tcorrelation,xticklabels=Tcorrelation.columns,
            yticklabels=Tcorrelation.columns)
plt.show()
```



6.2.1 Inference:

- Fare and Pclass has strongest negative correlation
- Age had little correlation with survival

7 Time series analysis on OPSD dataset

7.1 loading a dataset

[192]:
```
df = pd.read_csv(r"D:\study material\VIT_Data_Science\Winter_Sem\Exploratory␣
↪Data Analysis Lab\7_Feb\opsd_germany_daily.csv")
df
```

[192]:
```
            Date  Consumption     Wind   Solar  Wind+Solar
0     2006-01-01   1069.18400      NaN     NaN         NaN
1     2006-01-02   1380.52100      NaN     NaN         NaN
2     2006-01-03   1442.53300      NaN     NaN         NaN
3     2006-01-04   1457.21700      NaN     NaN         NaN
4     2006-01-05   1477.13100      NaN     NaN         NaN
…            …            …        …       …           …
4378  2017-12-27   1263.94091  394.507  16.530     411.037
4379  2017-12-28   1299.86398  506.424  14.162     520.586
4380  2017-12-29   1295.08753  584.277  29.854     614.131
4381  2017-12-30   1215.44897  721.247   7.467     728.714
4382  2017-12-31   1107.11488  721.176  19.980     741.156

[4383 rows x 5 columns]
```

[194]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4383 entries, 0 to 4382
Data columns (total 5 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Date         4383 non-null   object
 1   Consumption  4383 non-null   float64
 2   Wind         2920 non-null   float64
 3   Solar        2188 non-null   float64
 4   Wind+Solar   2187 non-null   float64
dtypes: float64(4), object(1)
memory usage: 171.3+ KB
```

[196]:
```
#convert object to datetime format
df['Date'] = pd.to_datetime(df['Date'])
df
```

[196]:
```
           Date  Consumption     Wind   Solar  Wind+Solar
0    2006-01-01   1069.18400      NaN     NaN         NaN
1    2006-01-02   1380.52100      NaN     NaN         NaN
2    2006-01-03   1442.53300      NaN     NaN         NaN
3    2006-01-04   1457.21700      NaN     NaN         NaN
4    2006-01-05   1477.13100      NaN     NaN         NaN
```

```
…          …            …         …       …           …
4378 2017-12-27   1263.94091  394.507  16.530     411.037
4379 2017-12-28   1299.86398  506.424  14.162     520.586
4380 2017-12-29   1295.08753  584.277  29.854     614.131
4381 2017-12-30   1215.44897  721.247   7.467     728.714
4382 2017-12-31   1107.11488  721.176  19.980     741.156

[4383 rows x 5 columns]
```

Now that the Date column is in correct datatype, let's set it as the DataFrame's index because in time series analysis the index column is always datetime column.

[199]:
```
df = df.set_index('Date')
```

[201]:
```
df.tail()
```

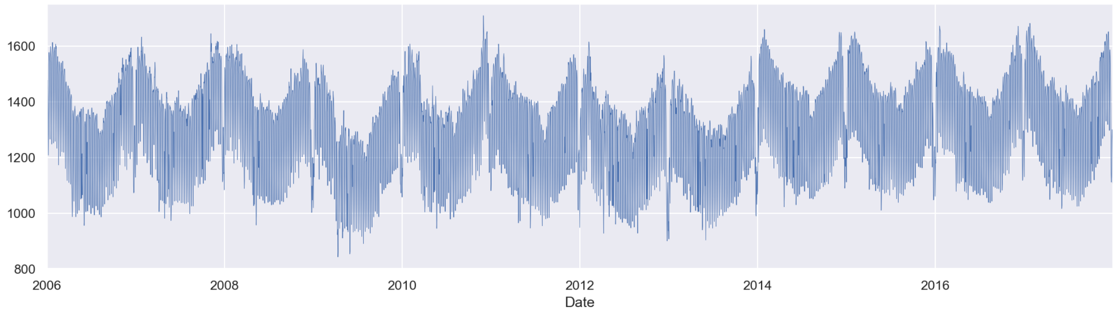
[201]:
```
            Consumption     Wind   Solar  Wind+Solar
Date
2017-12-27   1263.94091  394.507  16.530     411.037
2017-12-28   1299.86398  506.424  14.162     520.586
2017-12-29   1295.08753  584.277  29.854     614.131
2017-12-30   1215.44897  721.247   7.467     728.714
2017-12-31   1107.11488  721.176  19.980     741.156
```

[203]:
```
## Adding columns with year, month and weekday name
df['Year'] = df.index.year
df['Month'] = df.index.month
df['Weekday Name'] = df.index.day_name()
```

[205]:
```
## displaying a random sample of 5 rows

df.sample(5,random_state=42)
```

[205]:
```
            Consumption    Wind    Solar  Wind+Solar  Year  Month Weekday Name
Date
2007-11-02     1408.209     NaN      NaN         NaN  2007     11       Friday
2012-08-14     1269.779  64.136  153.658     217.794  2012      8      Tuesday
2007-08-20     1373.403     NaN      NaN         NaN  2007      8       Monday
2013-03-14     1420.149  28.595   62.718      91.313  2013      3     Thursday
2009-10-27     1405.611     NaN      NaN         NaN  2009     10      Tuesday
```

[207]:
```
# Visualization for Time series analysis
sns.set_theme(rc={'figure.figsize':(16, 4)})
plt.rcParams['figure.dpi'] = 150
df['Consumption'].plot(linewidth = 0.4)
plt.show()
```



7.1.1 Inference:

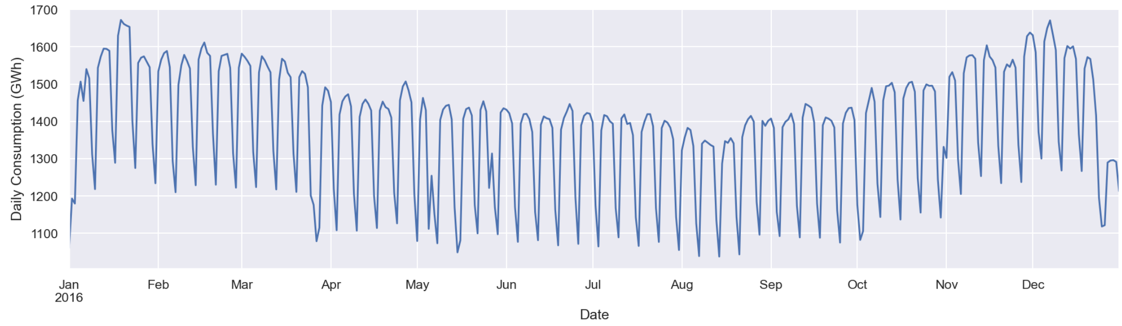
- Electricity consumption varies over time.
- Periodic spikes suggest seasonal trends.

[212]:
```
cols_to_plot = ['Consumption', 'Solar', 'Wind']
axes = df[cols_to_plot].plot(marker='.', alpha=0.5,␣
↪linestyle='None',figsize=(14, 7), subplots=True,grid=True)
for ax in axes:
    ax.set_ylabel('Daily Totals (GWh)')
```

7.1.2 Inference:

- Solar power peaks in summer (more sunshine).

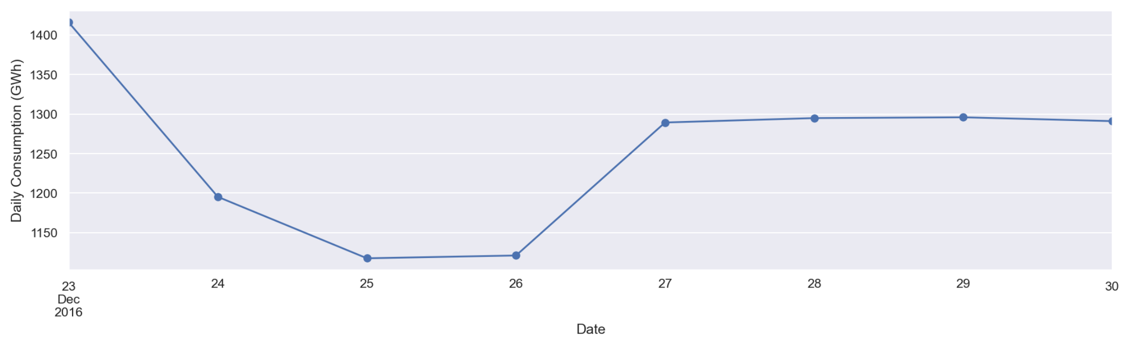
[215]:
```
df.loc['2016', 'Consumption'].plot()
plt.ylabel('Daily Consumption (GWh)')
plt.show()
```



7.1.3 Inference:

- Consumption of electricity is the most in winter

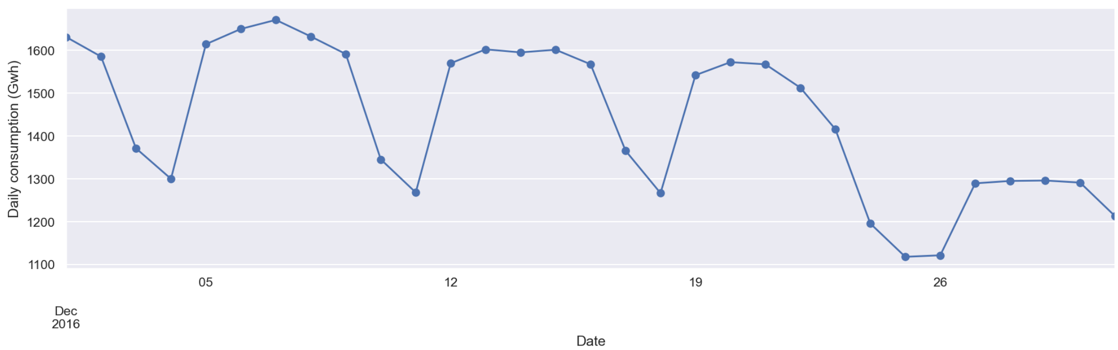
[218]:
```
df.loc['2016-12-23':'2016-12-30', 'Consumption'].plot(marker='o', linestyle='-')
plt.ylabel('Daily Consumption (GWh)')
plt.show()
```



7.1.4 Inference:

- shows the consumption pattern of electricity from '2016-12-23' to '2016-12-30'

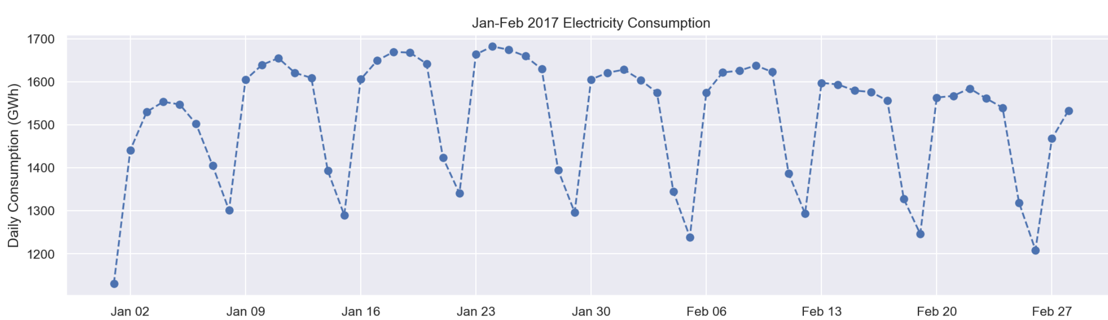
[221]:
```
df.loc['2016-12','Consumption'].plot(marker = 'o', linestyle = '-')
plt.ylabel("Daily consumption (Gwh)")
plt.show()
```



7.1.5 Inference:

- shows the weekly pattern of electricity consumption, indicating consumption decreases in the weekends

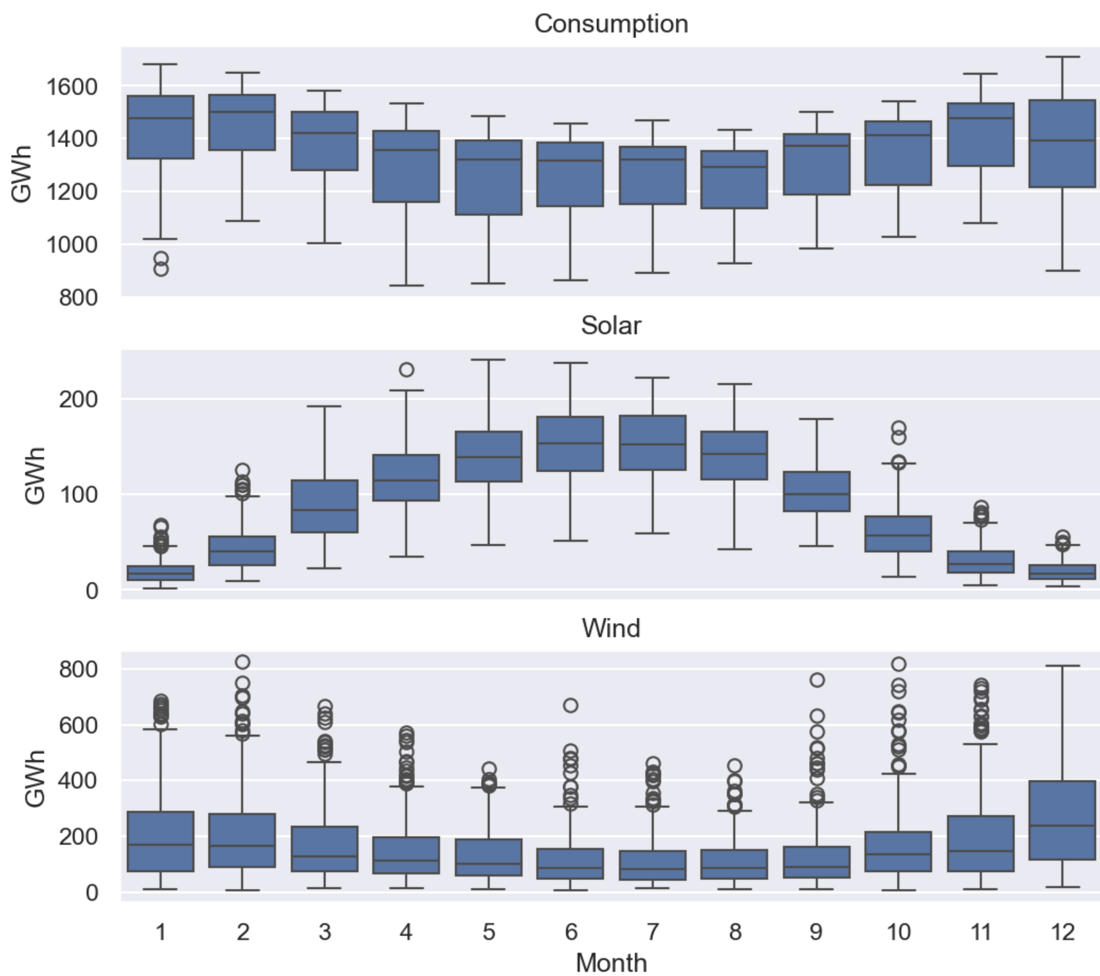
[224]:
```
# import dates module from matplotlib
import matplotlib.dates as mdates

# plot graph
fig, ax = plt.subplots()

ax.plot(df.loc['2017-01':'2017-02', 'Consumption'], marker='o', linestyle='--')
ax.set_ylabel('Daily Consumption (GWh)')
ax.set_title('Jan-Feb 2017 Electricity Consumption')

# to set x-axis major ticks to weekly interval, on Mondays
ax.xaxis.set_major_locator(mdates.WeekdayLocator(byweekday=mdates.MONDAY))
# to set format for x-tick labels as 3-letter month name and day number
ax.xaxis.set_major_formatter(mdates.DateFormatter('%b %d'))
```



7.1.6 Inference:

- Shows a smoother version of the trends by removing daily fluctuations.

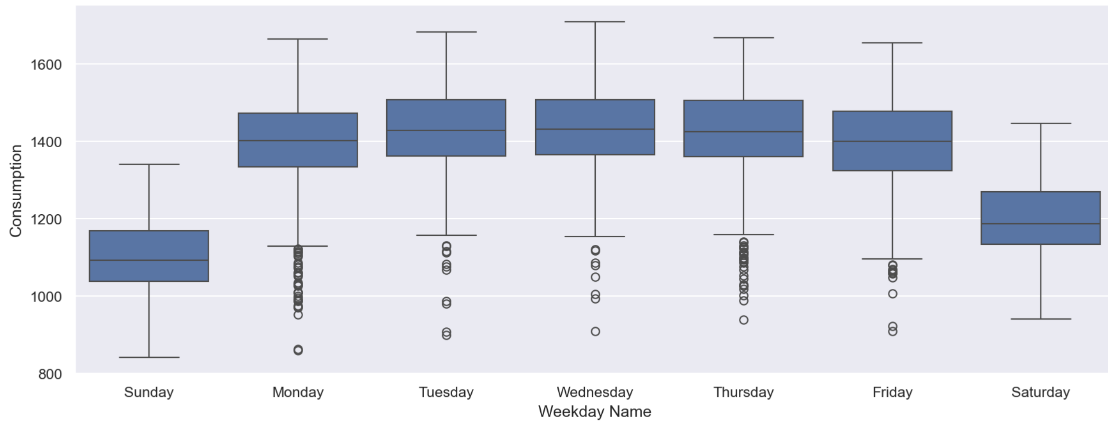
[229]:
```
fig, axes = plt.subplots(3, 1, figsize=(8, 7), sharex=True)
for name, ax in zip(['Consumption', 'Solar', 'Wind'], axes):
  sns.boxplot(data=df, x='Month', y=name, ax=ax)
  ax.set_ylabel('GWh')
  ax.set_title(name)
  if ax != axes[-1]:
    ax.set_xlabel('')
```



7.1.7 Inference:

- Higher consumption in winter months (possibly due to heating).
- Lower consumption in summer months.

[232]:
```
plt.figure(figsize=(14,5))
sns.boxplot(data=df, x='Weekday Name', y='Consumption')
plt.show()
```



7.1.8 Inference:

- Consumption is lowest on the weekends

[235]:
```
columns = ['Consumption', 'Wind', 'Solar', 'Wind+Solar']

power_weekly_mean = df[columns].resample('W').mean()
power_weekly_mean.head(10)
```

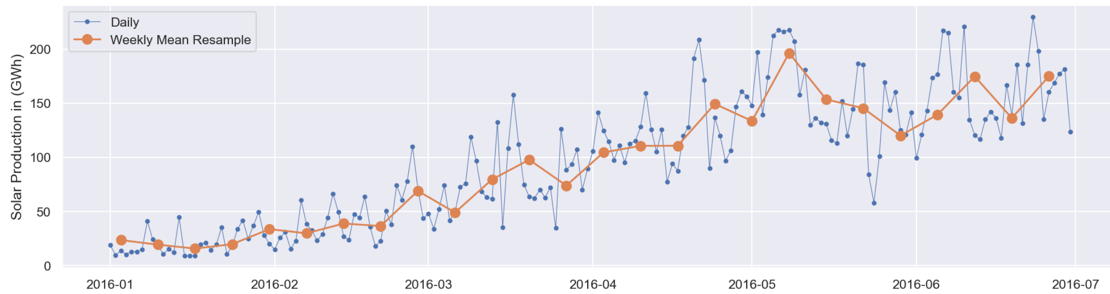
[235]:

Date	Consumption	Wind	Solar	Wind+Solar
2006-01-01	1069.184000	NaN	NaN	NaN
2006-01-08	1381.300143	NaN	NaN	NaN
2006-01-15	1486.730286	NaN	NaN	NaN
2006-01-22	1490.031143	NaN	NaN	NaN
2006-01-29	1514.176857	NaN	NaN	NaN
2006-02-05	1501.403286	NaN	NaN	NaN
2006-02-12	1498.217143	NaN	NaN	NaN
2006-02-19	1446.507429	NaN	NaN	NaN
2006-02-26	1447.651429	NaN	NaN	NaN
2006-03-05	1439.727857	NaN	NaN	NaN

[237]:
```
start, end = '2016-01', '2016-06'
```

[239]:
```
fig, ax = plt.subplots()

ax.plot(df.loc[start:end, 'Solar'],
marker='.', linestyle='-', linewidth=0.5, label='Daily')
ax.plot(power_weekly_mean.loc[start:end, 'Solar'],
marker='o', markersize=8, linestyle='-', label='Weekly Mean Resample')
ax.set_ylabel('Solar Production in (GWh)')
ax.legend()
```

```
plt.show()
```



7.1.9 Inference:

- Helps in identifying trends across weeks.
- Shows that consumption has increased on an average over the weeks

8 Time Series analysis on Weather Data

8.1 Importing the dataset

[245]:
```
df = pd.read_csv(r"D:\study material\VIT_Data_Science\Winter_Sem\Exploratory␣
↪Data Analysis Lab\8_feb\Weather Data.csv")
df
```

[245]:
```
                Date/Time  Temp_C  Dew Point Temp_C  Rel Hum_%  Wind Speed_km/h  \
0          1/1/2012 0:00    -1.8              -3.9         86                4
1          1/1/2012 1:00    -1.8              -3.7         87                4
2          1/1/2012 2:00    -1.8              -3.4         89                7
3          1/1/2012 3:00    -1.5              -3.2         88                6
4          1/1/2012 4:00    -1.5              -3.3         88                7
…                     …       …                …          …                …
8779  12/31/2012 19:00     0.1              -2.7         81               30
8780  12/31/2012 20:00     0.2              -2.4         83               24
8781  12/31/2012 21:00    -0.5              -1.5         93               28
8782  12/31/2012 22:00    -0.2              -1.8         89               28
8783  12/31/2012 23:00     0.0              -2.1         86               30

      Visibility_km  Press_kPa                Weather
0               8.0     101.24                    Fog
1               8.0     101.24                    Fog
2               4.0     101.26  Freezing Drizzle,Fog
3               4.0     101.27  Freezing Drizzle,Fog
4               4.8     101.23                    Fog
…                …          …                     …
```

```
8779            9.7    100.13                Snow
8780            9.7    100.03                Snow
8781            4.8     99.95                Snow
8782            9.7     99.91                Snow
8783           11.3     99.89                Snow

[8784 rows x 8 columns]
```

[247]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8784 entries, 0 to 8783
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Date/Time         8784 non-null   object
 1   Temp_C            8784 non-null   float64
 2   Dew Point Temp_C  8784 non-null   float64
 3   Rel Hum_%         8784 non-null   int64
 4   Wind Speed_km/h   8784 non-null   int64
 5   Visibility_km     8784 non-null   float64
 6   Press_kPa         8784 non-null   float64
 7   Weather           8784 non-null   object
dtypes: float64(4), int64(2), object(2)
memory usage: 549.1+ KB
```

8.2 Checking for the missing values

[250]:
```
df.isna().sum()
```

[250]:
```
Date/Time           0
Temp_C              0
Dew Point Temp_C    0
Rel Hum_%           0
Wind Speed_km/h     0
Visibility_km       0
Press_kPa           0
Weather             0
dtype: int64
```

`Inference:` - No missing values present in the dataset

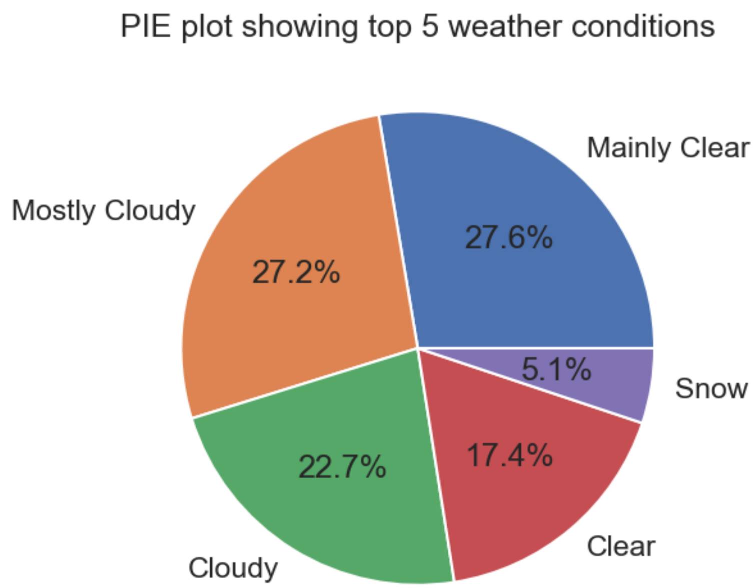
8.3 Checking for duplicates

[254]:
```
df.duplicated().sum()
```

[254]:
```
0
```

`Inference:` - No duplicate values present in the dataset

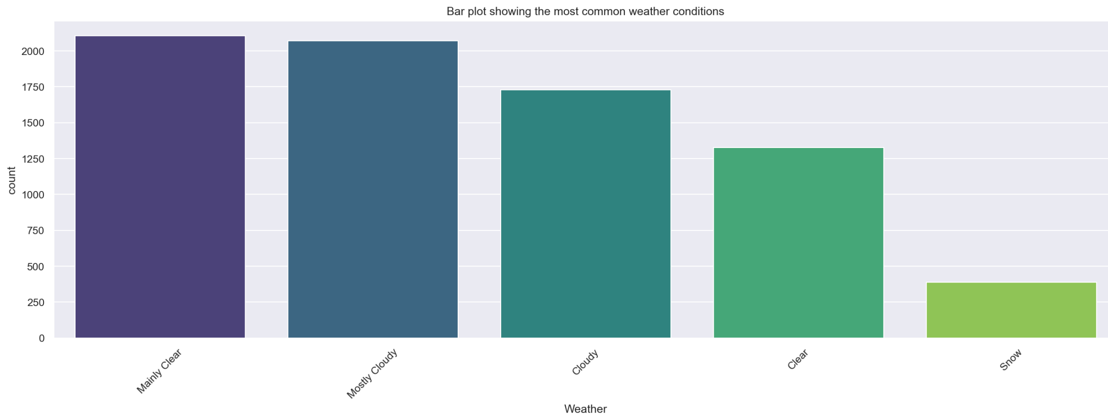
[257]:
```
df['Weather'].value_counts().nlargest(5).plot(kind = 'pie',autopct='%1.1f%%')
plt.title("PIE plot showing top 5 weather conditions")
plt.ylabel("")
plt.show()
```



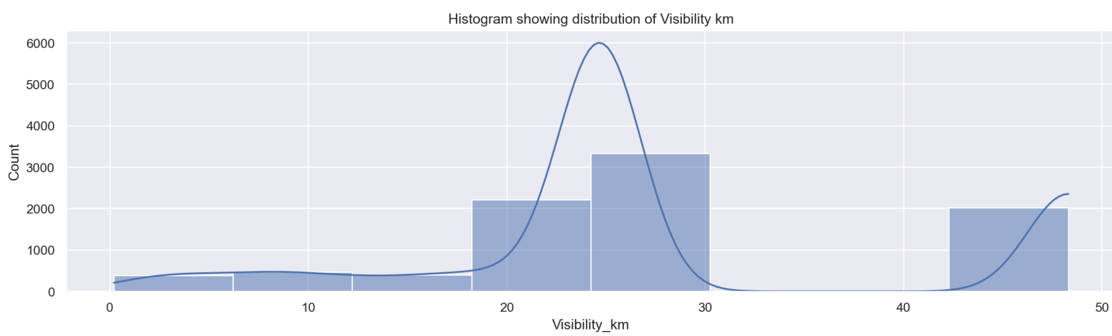
Inference: - The weather is mostly either clear or cloudy followed by 5% snowy weather

[260]:
```
plt.figure(figsize=(20,6))
k = df['Weather'].value_counts().nlargest(5)
sns.barplot(data = k,palette='viridis')
plt.xticks(rotation = 45)
plt.title("Bar plot showing the most common weather conditions")
plt.show()
```

```
C:\Users\TUFAN\AppData\Local\Temp\ipykernel_12868\2648648754.py:3:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.barplot(data = k,palette='viridis')
```

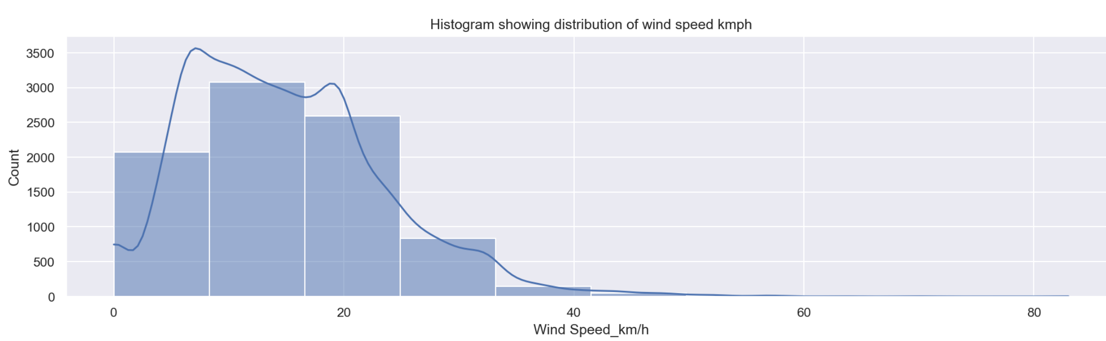


[262]:
```
sns.histplot(df['Visibility_km'],kde=True,bins=8)
plt.title("Histogram showing distribution of Visibility km")
plt.show()
```



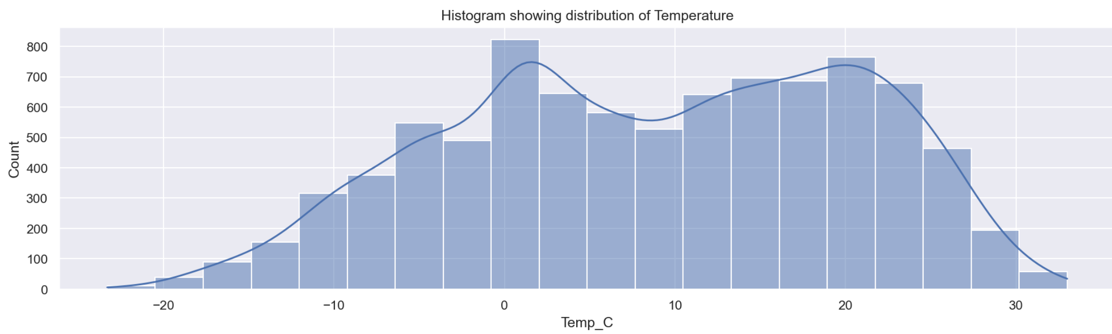
Inference: - Most visible range is between 20-30 km

[265]:
```
sns.histplot(df['Wind Speed_km/h'],kde=True,bins=10)
plt.title("Histogram showing distribution of wind speed kmph")
plt.show()
```



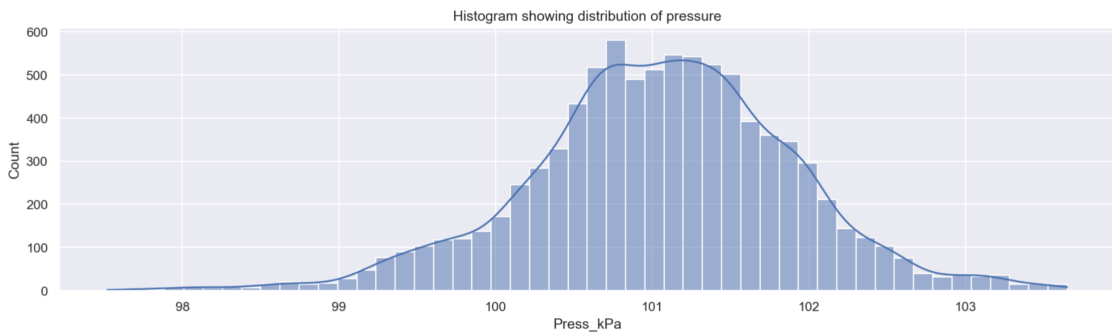
Inference: - Mostly windspeed is around 8-20 kmph

[268]:
```python
sns.histplot(df['Temp_C'],kde=True,bins=20)
plt.title("Histogram showing distribution of Temperature")
plt.show()
```



Inference: - the temperature is mostly in the cooler side, -1 to 2 degree Celcius

[271]:
```python
sns.histplot(df['Press_kPa'],kde=True,bins=50)
plt.title("Histogram showing distribution of pressure")
plt.show()
```



Inference: - Average pressure ranges between 100-102 K pascal

[274]:
```python
df.corr(numeric_only='True')
```

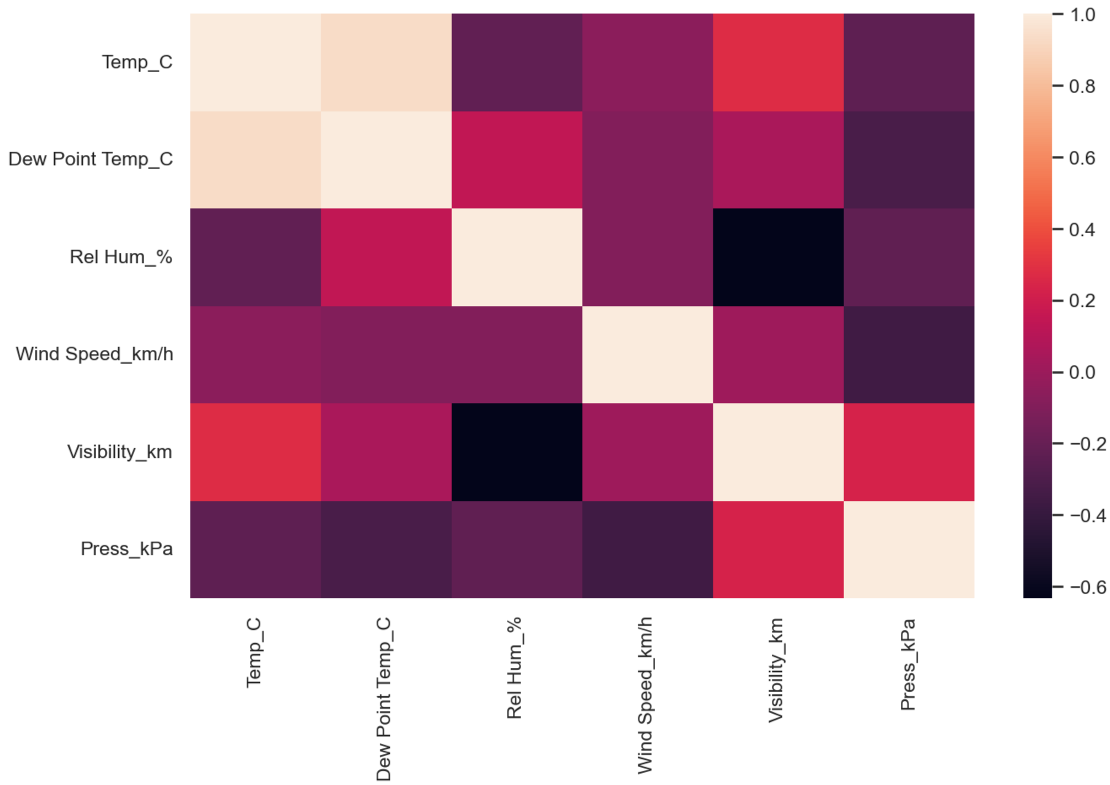
[274]:

	Temp_C	Dew Point Temp_C	Rel Hum_%	Wind Speed_km/h	\
Temp_C	1.000000	0.932714	-0.220182	-0.061876	
Dew Point Temp_C	0.932714	1.000000	0.139494	-0.095685	
Rel Hum_%	-0.220182	0.139494	1.000000	-0.092743	
Wind Speed_km/h	-0.061876	-0.095685	-0.092743	1.000000	

```
Visibility_km     0.273455          0.050813  -0.633683          0.004883
Press_kPa        -0.236389         -0.320616  -0.231424         -0.356613

                  Visibility_km  Press_kPa
Temp_C                 0.273455  -0.236389
Dew Point Temp_C       0.050813  -0.320616
Rel Hum_%             -0.633683  -0.231424
Wind Speed_km/h        0.004883  -0.356613
Visibility_km          1.000000   0.231847
Press_kPa              0.231847   1.000000
```

[278]:

```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(numeric_only='True'))
plt.show()
```



`Inference:` - Dew Point and temperature has a very high positive correlation - relative humidity and visibility has very high negative correlation

[281]:

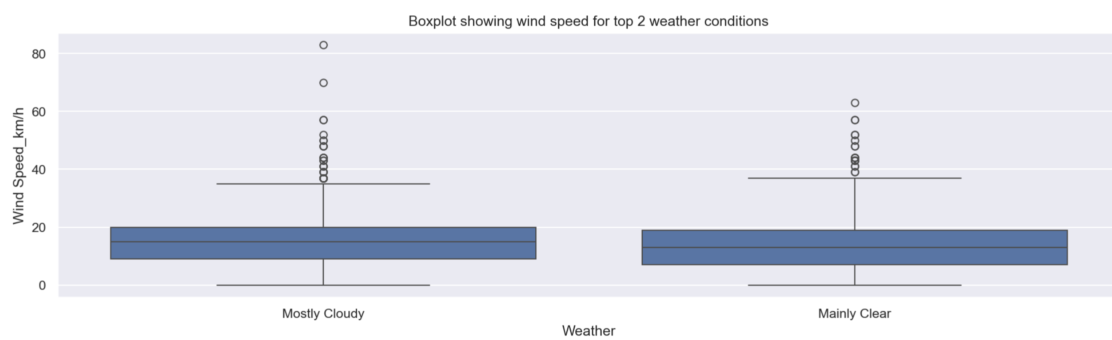
```
top_2_weather = df['Weather'].value_counts().nlargest(2).index
df_filtered = df[df['Weather'].isin(top_2_weather)]
df_filtered
```

[281]:

```
                Date/Time  Temp_C  Dew Point Temp_C  Rel Hum_%  Wind Speed_km/h  \
16       1/1/2012 16:00     2.6              -0.2         82               13
26        1/2/2012 2:00     3.9              -0.9         71               32
27        1/2/2012 3:00     3.7              -1.5         69               33
28        1/2/2012 4:00     2.9              -2.3         69               32
29        1/2/2012 5:00     2.6              -2.3         70               32
…                   …     …               …        …              …
8755  12/30/2012 19:00   -13.4             -16.5         77               26
8757  12/30/2012 21:00   -13.8             -16.5         80               20
8758  12/30/2012 22:00   -13.7             -16.3         81               19
8759  12/30/2012 23:00   -12.1             -15.1         78               28
8763   12/31/2012 3:00   -11.8             -14.4         81                6

      Visibility_km  Press_kPa        Weather
16             12.9      99.93  Mostly Cloudy
26             25.0      99.26  Mostly Cloudy
27             25.0      99.30  Mostly Cloudy
28             25.0      99.26  Mostly Cloudy
29             25.0      99.21  Mostly Cloudy
…               …        …            …
8755           25.0     101.47   Mainly Clear
8757           25.0     101.50   Mainly Clear
8758           25.0     101.54   Mainly Clear
8759           25.0     101.52  Mostly Cloudy
8763           25.0     101.42  Mostly Cloudy

[4175 rows x 8 columns]
```

[283]:

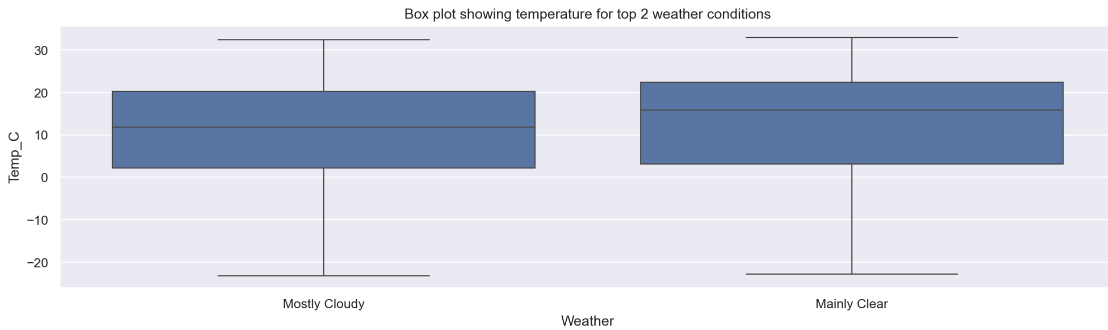
```python
sns.boxplot(x='Weather', y = 'Wind Speed_km/h', data = df_filtered)
plt.title("Boxplot showing wind speed for top 2 weather conditions")
plt.show()
```



8.4 Inference:

- average windspeed ins around 10-20 kmph with some outliers in both the weather

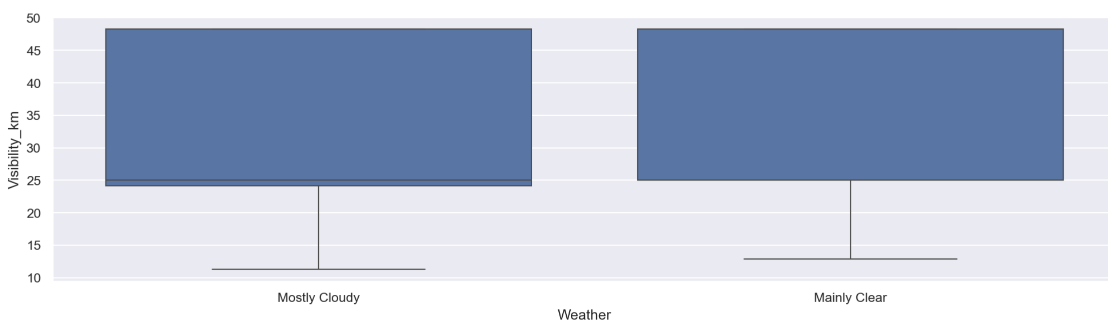
[286]:
```python
sns.boxplot(x='Weather', y = 'Temp_C', data = df_filtered)
plt.title("Box plot showing temperature for top 2 weather conditions")
plt.show()
```



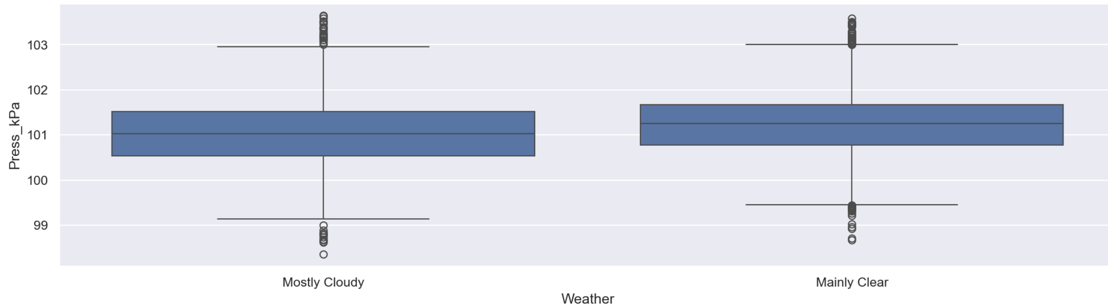
8.5 Inference:

This box plot shows average weather in both the weather condition ranges between 1 to 20 degrees celsius

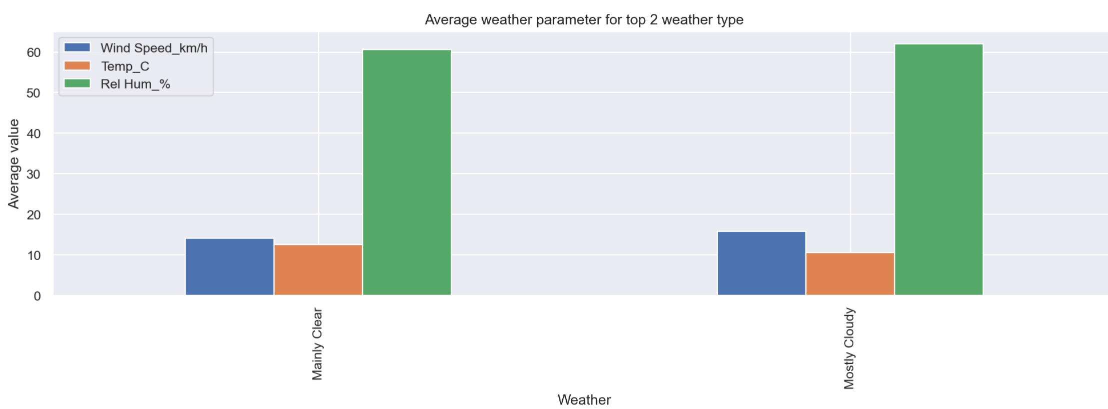
[289]:
```python
sns.boxplot(x='Weather', y = 'Visibility_km', data = df_filtered)
plt.show()
```



[291]:
```python
sns.boxplot(x='Weather', y = 'Press_kPa', data = df_filtered)
plt.show()
```



[293]:
```
df_grouped = df_filtered.groupby('Weather')[['Wind Speed_km/h','Temp_C','Rel␣
↪Hum_%']].mean()
df_grouped.plot(kind = 'bar')
plt.title("Average weather parameter for top 2 weather type")
plt.ylabel("Average value")
plt.show()
```



8.6 Inference:

- on a cloudy day the temperature is lesser and the wind speed is more

8.6.1 Grouping by Weather Condition & Computing Summary Statistics

[297]:
```
df.groupby('Weather')[['Temp_C', 'Wind Speed_km/h', 'Rel Hum_%', 'Press_kPa']].
↪agg(['mean', 'median', 'std'])
```

[297]:
```
                                          Temp_C                    \
                                            mean median        std
Weather
Clear                                   6.825716   7.50  12.132015
```

Cloudy	7.970544	7.35	11.000283
Drizzle	7.353659	5.40	5.297126
Drizzle,Fog	8.067500	9.15	4.970286
Drizzle,Ice Pellets,Fog	0.400000	0.40	NaN
Drizzle,Snow	1.050000	1.05	0.212132
Drizzle,Snow,Fog	0.693333	0.60	0.317280
Fog	4.303333	2.65	8.038802
Freezing Drizzle	-5.657143	-5.50	2.024728
Freezing Drizzle,Fog	-2.533333	-1.85	2.122891
Freezing Drizzle,Haze	-5.433333	-5.50	0.404145
Freezing Drizzle,Snow	-5.109091	-4.40	1.705552
Freezing Fog	-7.575000	-5.60	9.214255
Freezing Rain	-3.885714	-4.80	2.112183
Freezing Rain,Fog	-2.225000	-1.45	2.772935
Freezing Rain,Haze	-4.900000	-4.90	0.000000
Freezing Rain,Ice Pellets,Fog	-2.600000	-2.60	NaN
Freezing Rain,Snow Grains	-5.000000	-5.00	NaN
Haze	-0.200000	-0.25	6.292535
Mainly Clear	12.558927	15.80	12.348807
Moderate Rain,Fog	1.700000	1.70	NaN
Moderate Snow	-5.525000	-5.45	0.613052
Moderate Snow,Blowing Snow	-5.450000	-5.45	0.070711
Mostly Cloudy	10.574287	11.80	11.312839
Rain	9.786275	8.90	6.404164
Rain Showers	13.722340	14.95	6.977575
Rain Showers,Fog	12.800000	12.80	NaN
Rain Showers,Snow Showers	2.150000	2.15	0.070711
Rain,Fog	8.273276	7.90	6.037209
Rain,Haze	4.633333	4.40	0.776745
Rain,Ice Pellets	0.600000	0.60	NaN
Rain,Snow	1.055556	1.05	0.279121
Rain,Snow Grains	1.900000	1.90	NaN
Rain,Snow,Fog	0.800000	0.80	NaN
Rain,Snow,Ice Pellets	1.100000	1.10	0.163299
Snow	-4.524103	-4.80	4.155435
Snow Pellets	0.700000	0.70	NaN
Snow Showers	-3.506667	-3.70	4.322776
Snow Showers,Fog	-10.675000	-10.70	0.556028
Snow,Blowing Snow	-5.410526	-5.00	2.854995
Snow,Fog	-5.075676	-7.40	4.668714
Snow,Haze	-4.020000	-4.00	0.294958
Snow,Ice Pellets	-1.883333	-2.55	2.017341
Thunderstorms	24.150000	24.15	3.606245
Thunderstorms,Heavy Rain Showers	10.900000	10.90	NaN
Thunderstorms,Moderate Rain Showers,Fog	19.600000	19.60	NaN
Thunderstorms,Rain	20.433333	20.60	0.960902
Thunderstorms,Rain Showers	20.037500	20.85	4.203947

```
Thunderstorms,Rain Showers,Fog            21.600000  22.40   1.835756
Thunderstorms,Rain,Fog                    20.600000  20.60        NaN

                                         Wind Speed_km/h                    \
                                                    mean median        std
Weather
Clear                                          10.557315    9.0   6.725291
Cloudy                                         16.127315   15.0   8.416282
Drizzle                                        16.097561   17.0   6.456798
Drizzle,Fog                                    11.862500   11.0   6.289923
Drizzle,Ice Pellets,Fog                        20.000000   20.0        NaN
Drizzle,Snow                                   14.000000   14.0   7.071068
Drizzle,Snow,Fog                               15.533333   11.0   9.287985
Fog                                             7.946667    7.0   4.572733
Freezing Drizzle                               16.571429   19.0   7.502381
Freezing Drizzle,Fog                           17.000000   14.0  11.541230
Freezing Drizzle,Haze                          10.333333   11.0   1.154701
Freezing Drizzle,Snow                          16.272727   19.0   6.574054
Freezing Fog                                    4.750000    5.0   3.774917
Freezing Rain                                  19.214286   18.5   6.040613
Freezing Rain,Fog                              15.500000   14.5   9.949874
Freezing Rain,Haze                              7.500000    7.5   2.121320
Freezing Rain,Ice Pellets,Fog                  28.000000   28.0        NaN
Freezing Rain,Snow Grains                      32.000000   32.0        NaN
Haze                                           10.437500   10.0   4.486554
Mainly Clear                                   14.144824   13.0   8.359296
Moderate Rain,Fog                              17.000000   17.0        NaN
Moderate Snow                                  33.750000   35.0   5.737305
Moderate Snow,Blowing Snow                     40.000000   40.0   1.414214
Mostly Cloudy                                  15.813920   15.0   8.403605
Rain                                           19.254902   19.0   9.667949
Rain Showers                                   17.132979   17.0   8.376717
Rain Showers,Fog                               13.000000   13.0        NaN
Rain Showers,Snow Showers                      22.500000   22.5   7.778175
Rain,Fog                                       14.793103   15.0   6.794521
Rain,Haze                                      11.666667   11.0   5.033223
Rain,Ice Pellets                               24.000000   24.0        NaN
Rain,Snow                                      28.388889   24.0  12.476514
Rain,Snow Grains                               26.000000   26.0        NaN
Rain,Snow,Fog                                   9.000000    9.0        NaN
Rain,Snow,Ice Pellets                          23.250000   24.0   4.856267
Snow                                           20.038462   20.0  10.282441
Snow Pellets                                   35.000000   35.0        NaN
Snow Showers                                   19.233333   20.0   9.388718
Snow Showers,Fog                               13.750000   13.0   6.396614
Snow,Blowing Snow                              34.842105   35.0   6.256225
Snow,Fog                                       17.324324   19.0   8.107110
```

Snow,Haze	5.000000	4.0	6.164414
Snow,Ice Pellets	23.833333	24.0	5.115336
Thunderstorms	7.500000	7.5	10.606602
Thunderstorms,Heavy Rain Showers	9.000000	9.0	NaN
Thunderstorms,Moderate Rain Showers,Fog	15.000000	15.0	NaN
Thunderstorms,Rain	15.666667	13.0	13.203535
Thunderstorms,Rain Showers	18.312500	17.0	7.002083
Thunderstorms,Rain Showers,Fog	19.666667	17.0	14.189198
Thunderstorms,Rain,Fog	19.000000	19.0	NaN

	Rel Hum_%		\
	mean	median	std
Weather			
Clear	64.497738	65.0	16.171895
Cloudy	69.592593	71.0	14.915147
Drizzle	88.243902	90.0	4.978858
Drizzle,Fog	93.275000	94.0	4.047112
Drizzle,Ice Pellets,Fog	92.000000	92.0	NaN
Drizzle,Snow	93.500000	93.5	2.121320
Drizzle,Snow,Fog	95.866667	97.0	2.166850
Fog	92.286667	92.0	4.501061
Freezing Drizzle	83.571429	83.0	4.649629
Freezing Drizzle,Fog	88.500000	88.5	4.277850
Freezing Drizzle,Haze	82.000000	82.0	1.000000
Freezing Drizzle,Snow	86.090909	85.0	4.206056
Freezing Fog	87.750000	90.5	13.351030
Freezing Rain	84.642857	83.5	3.002746
Freezing Rain,Fog	89.500000	91.5	5.196152
Freezing Rain,Haze	82.500000	82.5	0.707107
Freezing Rain,Ice Pellets,Fog	92.000000	92.0	NaN
Freezing Rain,Snow Grains	84.000000	84.0	NaN
Haze	81.625000	83.0	4.716991
Mainly Clear	60.667142	60.0	15.773872
Moderate Rain,Fog	94.000000	94.0	NaN
Moderate Snow	87.750000	87.5	5.500000
Moderate Snow,Blowing Snow	92.500000	92.5	0.707107
Mostly Cloudy	62.102465	62.0	15.424275
Rain	83.624183	86.0	9.784528
Rain Showers	75.159574	77.0	12.310426
Rain Showers,Fog	96.000000	96.0	NaN
Rain Showers,Snow Showers	76.500000	76.5	2.121320
Rain,Fog	93.189655	94.0	4.434869
Rain,Haze	83.333333	83.0	2.516611
Rain,Ice Pellets	92.000000	92.0	NaN
Rain,Snow	89.000000	89.5	4.325030
Rain,Snow Grains	75.000000	75.0	NaN
Rain,Snow,Fog	96.000000	96.0	NaN

Rain,Snow,Ice Pellets	91.500000	92.0	2.516611
Snow	79.307692	81.0	9.311391
Snow Pellets	59.000000	59.0	NaN
Snow Showers	72.350000	72.5	10.616305
Snow Showers,Fog	90.750000	91.0	1.500000
Snow,Blowing Snow	84.473684	88.0	7.290545
Snow,Fog	90.675676	90.0	4.307965
Snow,Haze	80.600000	81.0	0.547723
Snow,Ice Pellets	87.666667	90.0	6.153590
Thunderstorms	77.000000	77.0	14.142136
Thunderstorms,Heavy Rain Showers	88.000000	88.0	NaN
Thunderstorms,Moderate Rain Showers,Fog	93.000000	93.0	NaN
Thunderstorms,Rain	89.000000	91.0	5.291503
Thunderstorms,Rain Showers	86.375000	87.5	8.562515
Thunderstorms,Rain Showers,Fog	84.000000	81.0	6.082763
Thunderstorms,Rain,Fog	88.000000	88.0	NaN

	Press_kPa		
	mean	median	std
Weather			
Clear	101.587443	101.560	0.668658
Cloudy	100.911441	100.900	0.813979
Drizzle	100.435366	100.610	0.710785
Drizzle,Fog	100.786625	100.765	0.803076
Drizzle,Ice Pellets,Fog	100.790000	100.790	NaN
Drizzle,Snow	100.890000	100.890	0.367696
Drizzle,Snow,Fog	99.281333	99.650	0.905056
Fog	101.184067	101.245	0.877428
Freezing Drizzle	100.202857	100.420	0.854726
Freezing Drizzle,Fog	100.441667	100.640	0.944784
Freezing Drizzle,Haze	100.316667	100.310	0.040415
Freezing Drizzle,Snow	100.520909	100.750	0.667959
Freezing Fog	102.320000	102.230	0.374789
Freezing Rain	99.647143	99.840	0.894861
Freezing Rain,Fog	99.945000	100.225	1.146429
Freezing Rain,Haze	100.375000	100.375	0.049497
Freezing Rain,Ice Pellets,Fog	100.950000	100.950	NaN
Freezing Rain,Snow Grains	98.560000	98.560	NaN
Haze	101.482500	101.120	0.907160
Mainly Clear	101.248832	101.250	0.701775
Moderate Rain,Fog	99.980000	99.980	NaN
Moderate Snow	100.275000	100.275	0.444710
Moderate Snow,Blowing Snow	100.570000	100.570	0.098995
Mostly Cloudy	101.025288	101.030	0.786758
Rain	100.233333	100.330	0.788261
Rain Showers	100.404043	100.495	0.766391
Rain Showers,Fog	99.830000	99.830	NaN

```
Rain Showers,Snow Showers                  101.100000  101.100  0.014142
Rain,Fog                                   100.500862  100.555  0.618777
Rain,Haze                                  100.540000  100.510  0.060828
Rain,Ice Pellets                           100.120000  100.120       NaN
Rain,Snow                                   99.951111   99.820  0.724292
Rain,Snow Grains                           100.600000  100.600       NaN
Rain,Snow,Fog                              100.730000  100.730       NaN
Rain,Snow,Ice Pellets                      100.105000  100.050  0.267145
Snow                                       100.536103  100.625  1.002490
Snow Pellets                                99.700000   99.700       NaN
Snow Showers                               100.963500  100.980  0.825917
Snow Showers,Fog                           101.292500  101.010  0.840253
Snow,Blowing Snow                           99.704737  100.010  0.838871
Snow,Fog                                   100.688649  100.600  0.584476
Snow,Haze                                  100.782000  100.780  0.148223
Snow,Ice Pellets                           100.548333  100.885  0.622042
Thunderstorms                              100.230000  100.230  0.551543
Thunderstorms,Heavy Rain Showers           100.260000  100.260       NaN
Thunderstorms,Moderate Rain Showers,Fog    100.010000  100.010       NaN
Thunderstorms,Rain                         100.420000  100.240  0.355949
Thunderstorms,Rain Showers                 100.233750  100.205  0.424576
Thunderstorms,Rain Showers,Fog             100.063333   99.840  0.503620
Thunderstorms,Rain,Fog                     100.080000  100.080       NaN
```

8.7 Converting Date/Time column to DateTime format

[300]:
```python
df['Date/Time'] = pd.to_datetime(df['Date/Time'])
```

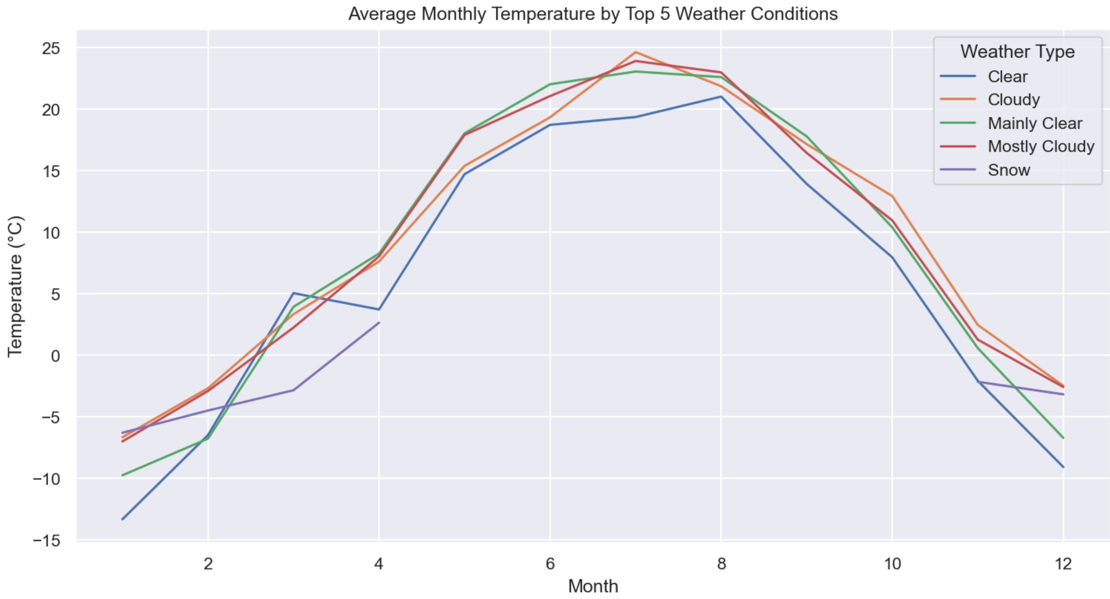
[302]:
```python
df['Year'] = df['Date/Time'].dt.year
df['Month'] = df['Date/Time'].dt.month
df['Day'] = df['Date/Time'].dt.day
df['Weekday'] = df['Date/Time'].dt.day_name()
df['Hour'] = df['Date/Time'].dt.hour
df['Minute'] = df['Date/Time'].dt.minute
df['Second'] = df['Date/Time'].dt.second

df
```

[302]:
```
               Date/Time  Temp_C  Dew Point Temp_C  Rel Hum_%  \
0    2012-01-01 00:00:00    -1.8              -3.9         86
1    2012-01-01 01:00:00    -1.8              -3.7         87
2    2012-01-01 02:00:00    -1.8              -3.4         89
3    2012-01-01 03:00:00    -1.5              -3.2         88
4    2012-01-01 04:00:00    -1.5              -3.3         88
…                      …       …                 …          …
8779 2012-12-31 19:00:00     0.1              -2.7         81
8780 2012-12-31 20:00:00     0.2              -2.4         83
```

```
8781 2012-12-31 21:00:00    -0.5             -1.5         93
8782 2012-12-31 22:00:00    -0.2             -1.8         89
8783 2012-12-31 23:00:00     0.0             -2.1         86

      Wind Speed_km/h  Visibility_km  Press_kPa               Weather  Year  \
0                   4            8.0     101.24                   Fog  2012
1                   4            8.0     101.24                   Fog  2012
2                   7            4.0     101.26  Freezing Drizzle,Fog  2012
3                   6            4.0     101.27  Freezing Drizzle,Fog  2012
4                   7            4.8     101.23                   Fog  2012
…                 …            …        …                    …   …
8779               30            9.7     100.13                  Snow  2012
8780               24            9.7     100.03                  Snow  2012
8781               28            4.8      99.95                  Snow  2012
8782               28            9.7      99.91                  Snow  2012
8783               30           11.3      99.89                  Snow  2012

      Month  Day Weekday  Hour  Minute  Second
0         1    1  Sunday     0       0       0
1         1    1  Sunday     1       0       0
2         1    1  Sunday     2       0       0
3         1    1  Sunday     3       0       0
4         1    1  Sunday     4       0       0
…       …  …     …   …    …    …
8779     12   31  Monday    19       0       0
8780     12   31  Monday    20       0       0
8781     12   31  Monday    21       0       0
8782     12   31  Monday    22       0       0
8783     12   31  Monday    23       0       0

[8784 rows x 15 columns]
```

[304]:

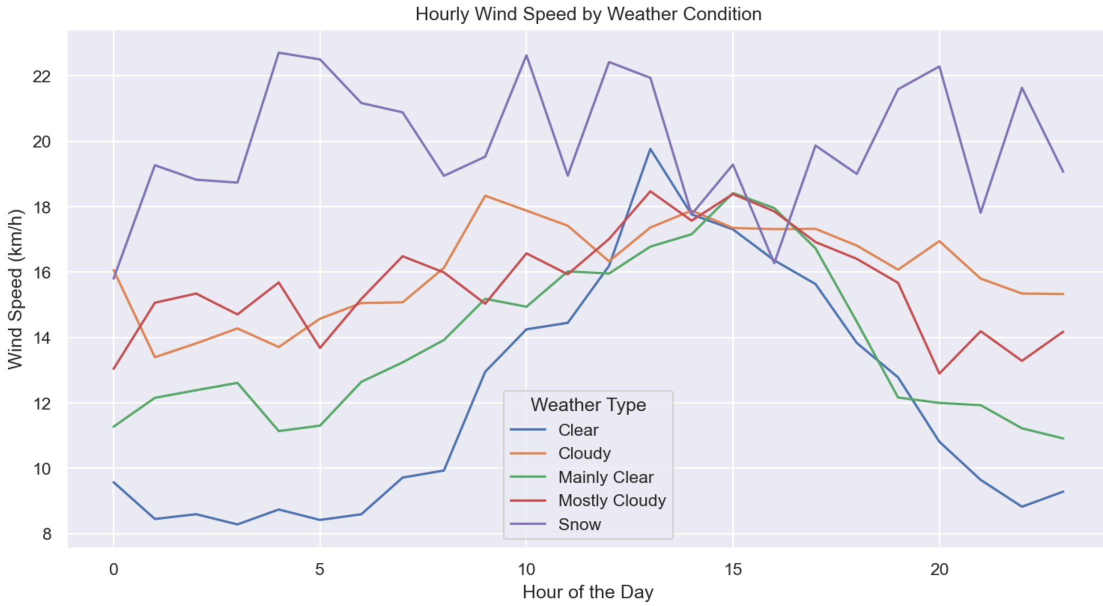
```
# Selecting the top 5 most common weather conditions
top_5_weather = df['Weather'].value_counts().nlargest(5).index

# Filtering dataset for only these top 5 weather types
df_top5 = df[df['Weather'].isin(top_5_weather)]

# Group by Month and Weather for temperature analysis
df_top5.groupby(['Month', 'Weather'])['Temp_C'].mean().unstack().
 ↪plot(figsize=(12,6))

plt.title("Average Monthly Temperature by Top 5 Weather Conditions")
plt.xlabel("Month")
plt.ylabel("Temperature (°C)")
plt.legend(title="Weather Type")
plt.show()
```



8.7.1 Interpretation:

- Helps understand how weather change month to month

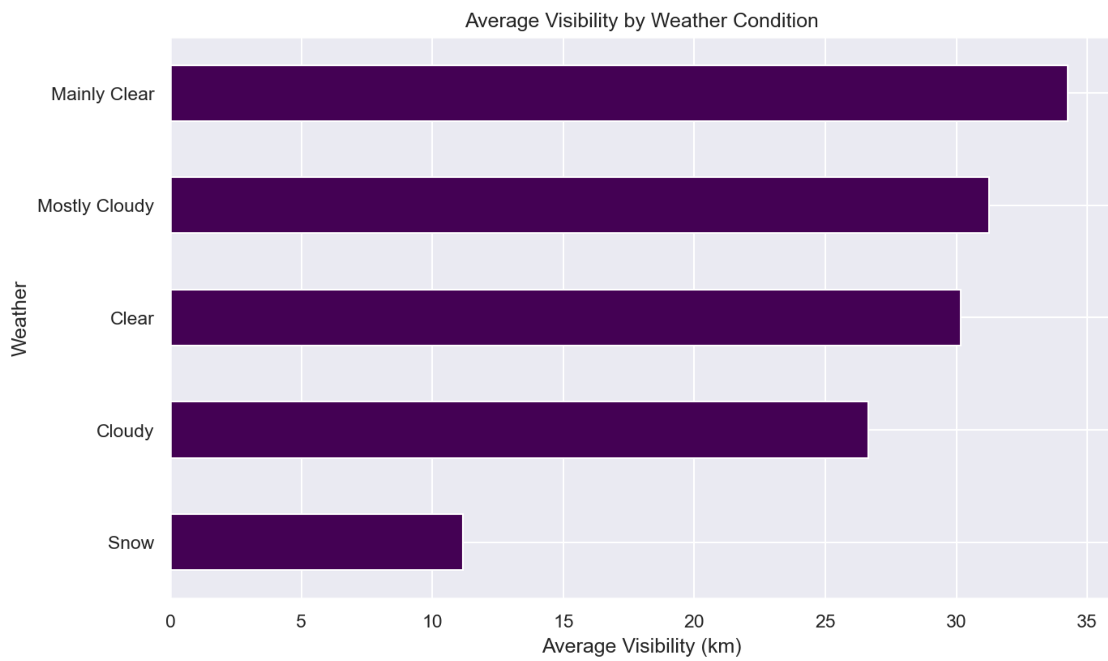
[307]:
```
df_top5.groupby(['Hour', 'Weather'])['Wind Speed_km/h'].mean().unstack().
    ↪plot(figsize=(12,6))
plt.title("Hourly Wind Speed by Weather Condition")
plt.xlabel("Hour of the Day")
plt.ylabel("Wind Speed (km/h)")
plt.legend(title="Weather Type")
plt.show()
```



8.7.2 Inference:

- snowy weather has the highest windspeed

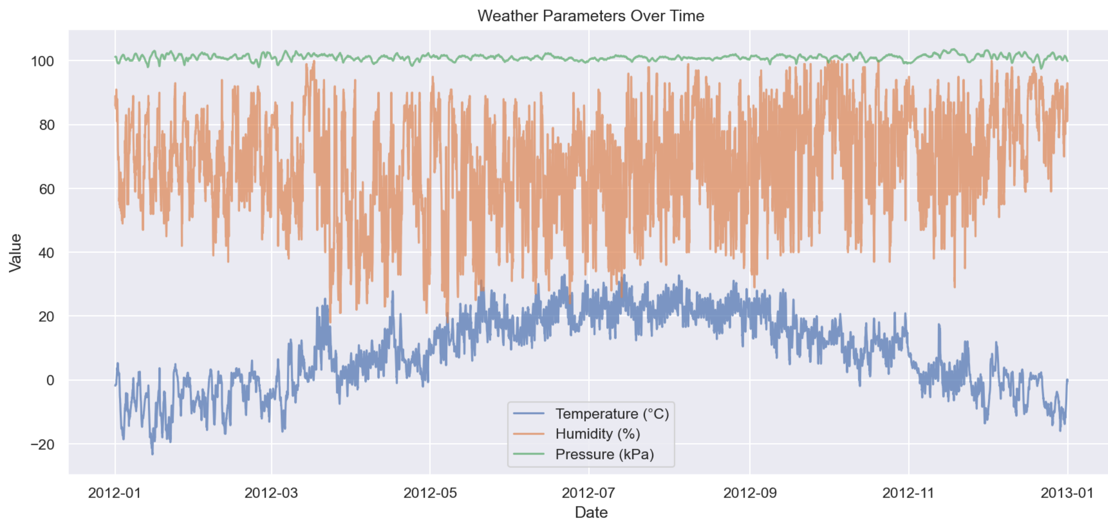
[310]:
```
df_top5.groupby('Weather')['Visibility_km'].mean().sort_values().
 ↪plot(kind='barh', figsize=(10,6), colormap='viridis')
plt.title("Average Visibility by Weather Condition")
plt.xlabel("Average Visibility (km)")
plt.show()
```



8.7.3 Inference:

- snowy weather has the lowest visibility

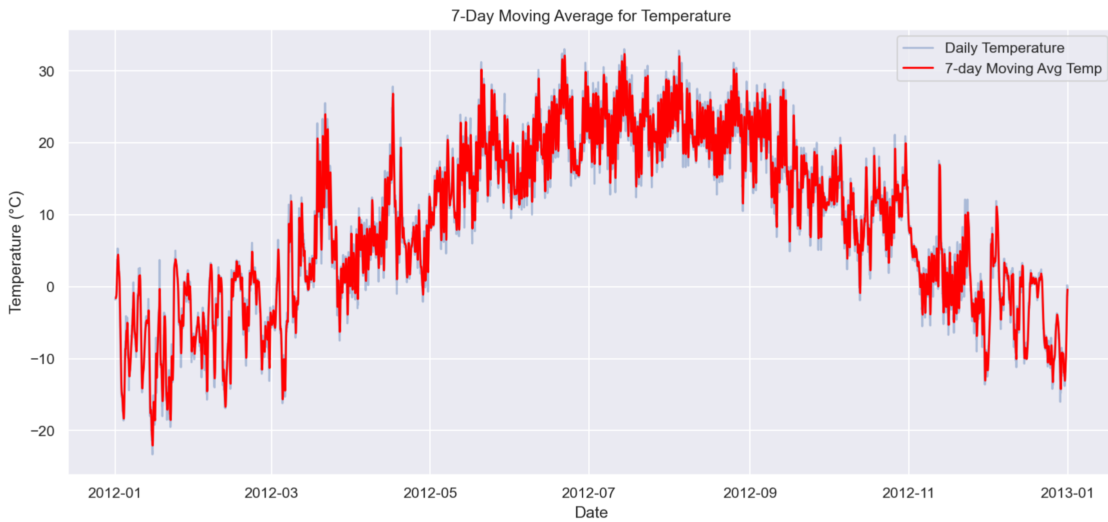
[313]:
```
plt.figure(figsize=(14,6))
plt.plot(df['Date/Time'], df['Temp_C'], label='Temperature (°C)', alpha=0.7)
plt.plot(df['Date/Time'], df['Rel Hum_%'], label='Humidity (%)', alpha=0.7)
plt.plot(df['Date/Time'], df['Press_kPa'], label='Pressure (kPa)', alpha=0.7)
plt.legend()
plt.xlabel("Date")
plt.ylabel("Value")
plt.title("Weather Parameters Over Time")
plt.show()
```



8.7.4 Inference:

- shows how weather parameters have changed over time
- helps identifying seasonal patterns

[316]:
```
df['Temp_MA7'] = df['Temp_C'].rolling(window=7).mean()

plt.figure(figsize=(14,6))
plt.plot(df['Date/Time'], df['Temp_C'], alpha=0.4, label="Daily Temperature")
plt.plot(df['Date/Time'], df['Temp_MA7'], label="7-day Moving Avg Temp",␣
    ↪color='red')
plt.legend()
plt.xlabel("Date")
plt.ylabel("Temperature (°C)")
plt.title("7-Day Moving Average for Temperature")
plt.show()
```

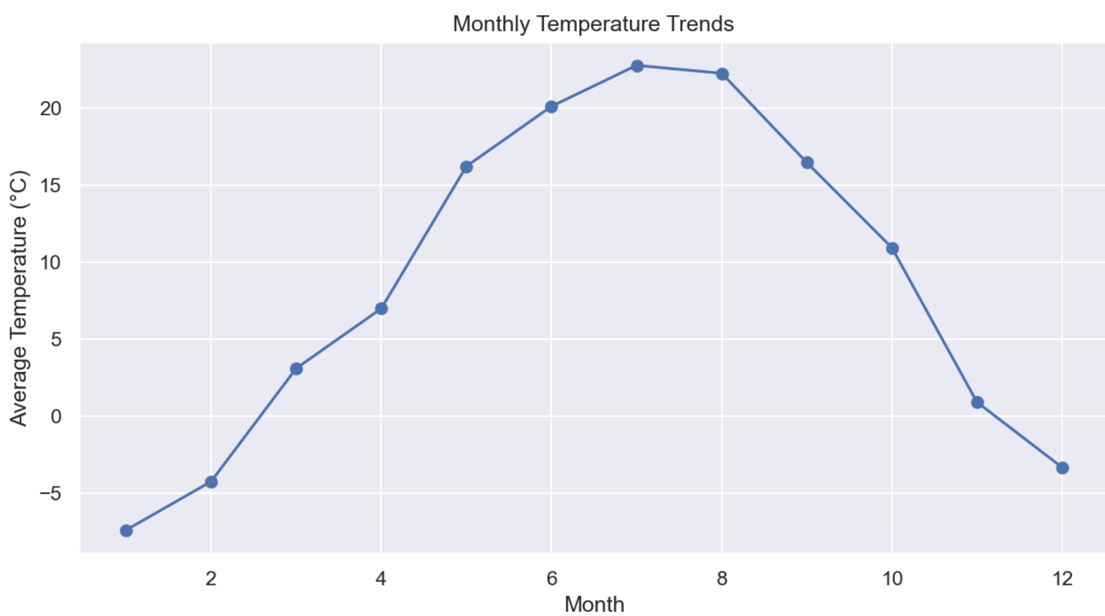


8.7.5 Interpretation:

- Helps smooth out short-term fluctuations and highlight long-term trends.

[319]:

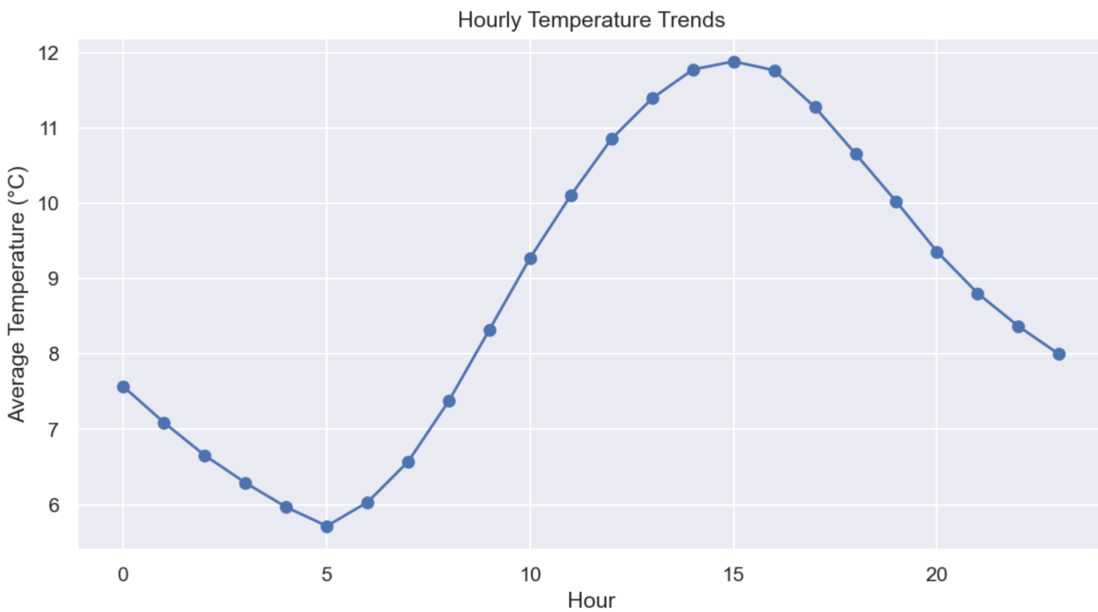
```
df.groupby('Month')['Temp_C'].mean().plot(kind='line', marker='o',␣
 ↪figsize=(10,5))
plt.xlabel("Month")
plt.ylabel("Average Temperature (°C)")
plt.title("Monthly Temperature Trends")
plt.show()
```



8.7.6 Inference:

- In the month of june july august the temperature reaches maximum

[322]:
```
df.groupby('Hour')['Temp_C'].mean().plot(kind='line', marker='o',␣
↪figsize=(10,5))
plt.xlabel("Hour")
plt.ylabel("Average Temperature (°C)")
plt.title("Hourly Temperature Trends")
plt.show()
```



8.7.7 Inference:

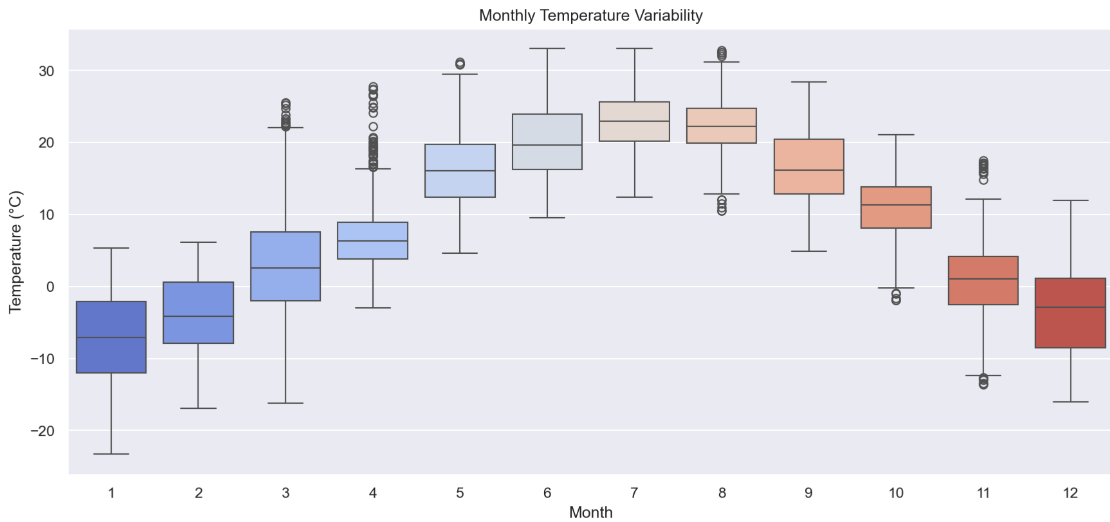
- Shows how the average temperature changes in a day

[325]:
```
plt.figure(figsize=(14,6))
sns.boxplot(x='Month', y='Temp_C', data=df, palette="coolwarm")
plt.xlabel("Month")
plt.ylabel("Temperature (°C)")
plt.title("Monthly Temperature Variability")
plt.show()
```

```
C:\Users\TUFAN\AppData\Local\Temp\ipykernel_12868\165339793.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
```

effect.

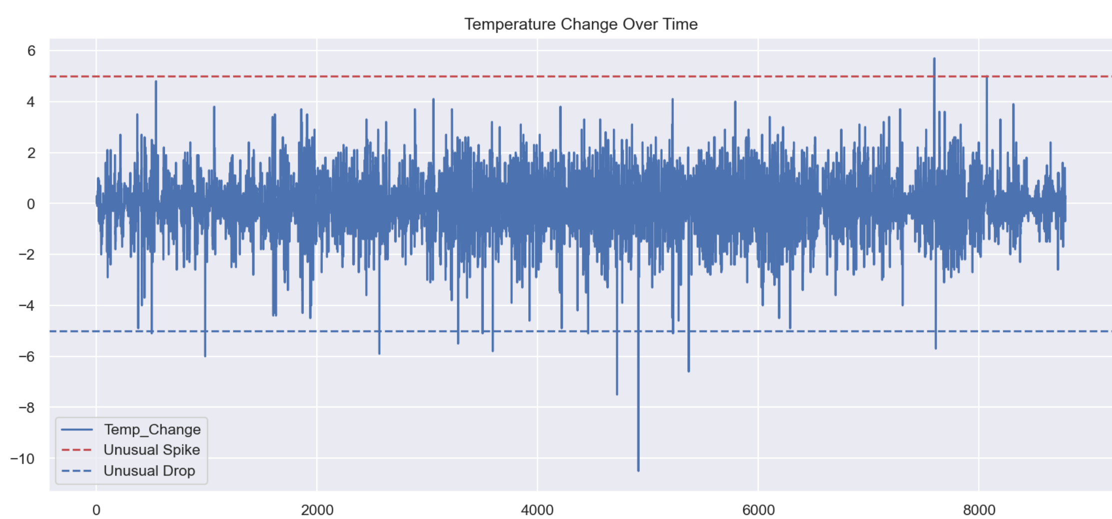
```
sns.boxplot(x='Month', y='Temp_C', data=df, palette="coolwarm")
```



8.7.8 Inference:

- Shows temperature variations within each month

[328]:
```
df['Temp_Change'] = df['Temp_C'].diff() # Calculate the change in temperature␣
↪from the previous row
df['Temp_Change'].plot(figsize=(14,6), title="Temperature Change Over Time")
plt.axhline(y=5, color='r', linestyle='--', label='Unusual Spike')
plt.axhline(y=-5, color='b', linestyle='--', label='Unusual Drop')
plt.legend()
plt.show()
```



8.7.9 `Inference:`

- In the month of july and august there is huge temperature fluctuations