Assignment Problem Statement

A US bike-sharing provider BoomBikes has recently suffered considerable dips in their revenues. They have contracted a consulting company to understand the factors on which the demand for these shared bikes depends. Specifically, they want to understand the factors affecting the demand for these shared bikes in the American market. The company wants to know:

- Which variable are significant in predicting the demand for shared bikes
- How well those variables describe the bike demands

Business Goal

Model the demand for shared bikes with the available independent variables. It will be used by the management to understand how exactly the demands vary with different features. They can accordingly manipulate the business strategy to meet the demand levels and meet the customer's expectations. Further, the model will be a good way for management to understand the demand dynamics of a new market.

Data Understanding

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr
from datetime import datetime as dt

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:
```
df = pd.read_csv("day.csv")
```

In [3]:
```
#Checking for column data types and if null values are present
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   instant     730 non-null    int64  
 1   dteday      730 non-null    object 
 2   season      730 non-null    int64  
 3   yr          730 non-null    int64  
 4   mnth        730 non-null    int64  
 5   holiday     730 non-null    int64  
 6   weekday     730 non-null    int64  
 7   workingday  730 non-null    int64  
 8   weathersit  730 non-null    int64  
 9   temp        730 non-null    float64
 10  atemp       730 non-null    float64
 11  hum         730 non-null    float64
 12  windspeed   730 non-null    float64
 13  casual      730 non-null    int64  
 14  registered  730 non-null    int64  
 15  cnt         730 non-null    int64  
dtypes: float64(4), int64(11), object(1)
memory usage: 91.4+ KB
```

In [4]:
```
#confirming that there are no null entries
df.isnull().sum()
```

Out[4]:
```
instant       0
dteday        0
season        0
yr            0
mnth          0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
cnt           0
dtype: int64
```

In [5]:
```
# Checking for number of columns and rows
df.shape
```

Out[5]:
```
(730, 16)
```

In [6]:
```
# Looking at the entries
df.head()
```

Out[6]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	1	01-01-2018	1	0	1	0	6	0	2	14.110847	18.18125	80.5833	10.749882	331	654	985
1	2	02-01-2018	1	0	1	0	0	0	2	14.902598	17.68695	69.6087	16.652113	131	670	801
2	3	03-01-2018	1	0	1	0	1	1	1	8.050924	9.47025	43.7273	16.636703	120	1229	1349
3	4	04-01-2018	1	0	1	0	2	1	1	8.200000	10.60610	59.0435	10.739832	108	1454	1562
4	5	05-01-2018	1	0	1	0	3	1	1	9.305237	11.46350	43.6957	12.522300	82	1518	1600

In [7]:
```
# Looking the statistical distribution of column
df.describe()
```

Out[7]:

	instant	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
count	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000
mean	365.500000	2.498630	0.500000	6.526027	0.028767	2.997260	0.683562	1.394521	20.319259	23.726322	62.765175	12.763620	849.249315	3658.757534	4508.006849
std	210.877136	1.110184	0.500343	3.450215	0.167266	2.006161	0.465405	0.544807	7.506729	8.150308	14.237589	5.195841	686.479875	1559.758728	1936.011647
min	1.000000	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.000000	2.424346	3.953480	0.000000	1.500244	2.000000	20.000000	22.000000
25%	183.250000	2.000000	0.000000	4.000000	0.000000	1.000000	0.000000	1.000000	13.811885	16.889713	52.000000	9.041650	316.250000	2502.250000	3169.750000
50%	365.500000	3.000000	0.500000	7.000000	0.000000	3.000000	1.000000	1.000000	20.465826	24.368225	62.625000	12.125325	717.000000	3664.500000	4548.500000
75%	547.750000	3.000000	1.000000	10.000000	0.000000	5.000000	1.000000	2.000000	26.880615	30.445775	72.989575	15.625589	1096.500000	4783.250000	5966.000000
max	730.000000	4.000000	1.000000	12.000000	1.000000	6.000000	1.000000	3.000000	35.328347	42.044800	97.250000	34.000021	3410.000000	6946.000000	8714.000000

Data Cleaning

In [8]:
```
# Looking at the column names
df.columns
```

Out[8]:
```
Index(['instant', 'dteday', 'season', 'yr', 'mnth', 'holiday', 'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum', 'windspeed',
       'casual', 'registered', 'cnt'],
      dtype='object')
```

In [9]:
```python
# Looking at the entries
df.head()
```

Out[9]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	1	01-01-2018	1	0	1	0	6	0	2	14.110847	18.18125	80.5833	10.749882	331	654	985
1	2	02-01-2018	1	0	1	0	0	0	2	14.902598	17.68695	69.6087	16.652113	131	670	801
2	3	03-01-2018	1	0	1	0	1	1	1	8.050924	9.47025	43.7273	16.636703	120	1229	1349
3	4	04-01-2018	1	0	1	0	2	1	1	8.200000	10.60610	59.0435	10.739832	108	1454	1562
4	5	05-01-2018	1	0	1	0	3	1	1	9.305237	11.46350	43.6957	12.522300	82	1518	1600

In [10]:
```python
# Dropping "instant" because it is basically the index column
df.drop("instant", axis=1, inplace=True)
```

In [11]:
```python
df.head()
```

Out[11]:

	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	01-01-2018	1	0	1	0	6	0	2	14.110847	18.18125	80.5833	10.749882	331	654	985
1	02-01-2018	1	0	1	0	0	0	2	14.902598	17.68695	69.6087	16.652113	131	670	801
2	03-01-2018	1	0	1	0	1	1	1	8.050924	9.47025	43.7273	16.636703	120	1229	1349
3	04-01-2018	1	0	1	0	2	1	1	8.200000	10.60610	59.0435	10.739832	108	1454	1562
4	05-01-2018	1	0	1	0	3	1	1	9.305237	11.46350	43.6957	12.522300	82	1518	1600

In [12]:
```python
# Dropping "casual" and "registered" as our analysis is based on the total demand and not demand category
df.drop(["casual", "registered"], axis=1, inplace=True)
```

In [13]:
```python
df.head()
```

Out[13]:

	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	cnt
0	01-01-2018	1	0	1	0	6	0	2	14.110847	18.18125	80.5833	10.749882	985
1	02-01-2018	1	0	1	0	0	0	2	14.902598	17.68695	69.6087	16.652113	801
2	03-01-2018	1	0	1	0	1	1	1	8.050924	9.47025	43.7273	16.636703	1349
3	04-01-2018	1	0	1	0	2	1	1	8.200000	10.60610	59.0435	10.739832	1562
4	05-01-2018	1	0	1	0	3	1	1	9.305237	11.46350	43.6957	12.522300	1600

In [14]:
```python
# Temp and Atemp seem to be similar. Let's investigate

df.temp.describe()
```

Out[14]:
```
count    730.000000
mean      20.319259
std        7.506729
min        2.424346
25%       13.811885
50%       20.465826
75%       26.880615
max       35.328347
Name: temp, dtype: float64
```

In [15]:
```python
df.atemp.describe()
```

Out[15]:
```
count    730.000000
mean      23.726322
std        8.150308
min        3.953480
25%       16.889713
50%       24.368225
75%       30.445775
max       42.044800
Name: atemp, dtype: float64
```

Observation

atemp seems to far more spread than temp with greater range (max - min) and greater standard deviation

In [16]:
```
# Let's find their correlation to confirm they are related
```

In [17]:
```
corr, _ = pearsonr(df.temp, df.atemp)
```

In [18]:
```
print('Pearsons correlation: %.3f' % corr)
```

```
Pearsons correlation: 0.992
```

Observation

- atemp and temp are highly correlated with 0.99 correlation. Therefore, we can drop one.
- Since Feels like temperature is what an individual experiences, we will keep atemp and drop temp.

In [19]:
```
# Dropping temp
df.drop("temp", axis=1, inplace=True)
```

In [20]:
```
df.head()
```

Out[20]:

	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	atemp	hum	windspeed	cnt
0	01-01-2018	1	0	1	0	6	0	2	18.18125	80.5833	10.749882	985
1	02-01-2018	1	0	1	0	0	0	2	17.68695	69.6087	16.652113	801
2	03-01-2018	1	0	1	0	1	1	1	9.47025	43.7273	16.636703	1349
3	04-01-2018	1	0	1	0	2	1	1	10.60610	59.0435	10.739832	1562
4	05-01-2018	1	0	1	0	3	1	1	11.46350	43.6957	12.522300	1600

In [21]:
```
# Columns "dteday", "yr", "mnth", "weekday" are all related to the date of renting the cycle.
# Let's us check for the consistency of these columns
```

In [22]:
```
# Converting dteday to datetime object
df.dteday = df.dteday.apply(lambda x: dt.strptime(x, "%d-%m-%Y"))
```

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

Out[23]:

	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	atemp	hum	windspeed	cnt
0	2018-01-01	1	0	1	0	6	0	2	18.18125	80.5833	10.749882	985
1	2018-01-02	1	0	1	0	0	0	2	17.68695	69.6087	16.652113	801
2	2018-01-03	1	0	1	0	1	1	1	9.47025	43.7273	16.636703	1349
3	2018-01-04	1	0	1	0	2	1	1	10.60610	59.0435	10.739832	1562
4	2018-01-05	1	0	1	0	3	1	1	11.46350	43.6957	12.522300	1600

In [24]:
```
df.yr.value_counts()
```

Out[24]:
```
0    365
1    365
Name: yr, dtype: int64
```

In [25]:
```
# It seems that 0 corresponds to 2018 and 1 corresponds to 2019 in yr
df.yr = df.yr.apply(lambda x: 2018 if x==0 else 2019)
```

In [26]:
```
df['yr_name'] = df.dteday.apply(lambda x: x.year)
```

In [27]:
```
df['month_name'] = df.dteday.apply(lambda x: x.month)
```

In [28]:
```
df.head()
```

Out[28]:

	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	atemp	hum	windspeed	cnt	yr_name	month_name
0	2018-01-01	1	2018	1	0	6	0	2	18.18125	80.5833	10.749882	985	2018	1
1	2018-01-02	1	2018	1	0	0	0	2	17.68695	69.6087	16.652113	801	2018	1
2	2018-01-03	1	2018	1	0	1	1	1	9.47025	43.7273	16.636703	1349	2018	1
3	2018-01-04	1	2018	1	0	2	1	1	10.60610	59.0435	10.739832	1562	2018	1
4	2018-01-05	1	2018	1	0	3	1	1	11.46350	43.6957	12.522300	1600	2018	1

In [29]:
```
# creating a function to check for the consistency of calendar columns (month, year)
def check_consistency(df):
    for i in range(0, len(df)):
        record = df.iloc[i]
        if record.month_name != record.mnth:
            print("Mismatch present at location: ",i)
            break
        elif  int(record.yr) != int(record.yr_name):
            print("Mismatch present with year at location: ", i)
            break
    print("No mismatch")
```

In [30]:
```
check_consistency(df)
```

```
No mismatch
```

Observation

- no inconsistency found with year and month
- Hence, we can delete these columns as they are redundant

In [31]:
```
df.drop(['yr_name', 'month_name'], axis=1, inplace=True)
```

In [32]:
```
# Let's Change months and yr to categorical variable and change month their names to Jan, Feb etc

df.yr = df.yr.astype("category")
```

In [33]:
```
month_map = {1: "Jan", 2: "Feb", 3: "Mar", 4: "Apr", 5: "May", 6: "Jun",
             7: "Jul", 8: "Aug", 9: "Sep", 10: "Oct", 11: "Nov", 12: "Dec"}
```

In [34]:
```
df['mnth'] = df['mnth'].map(month_map)
```

In [35]:
```
df.mnth = df.mnth.astype("category")
```

In [36]:
```
df.head()
```

Out[36]:

	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	atemp	hum	windspeed	cnt
0	2018-01-01	1	2018	Jan	0	6	0	2	18.18125	80.5833	10.749882	985
1	2018-01-02	1	2018	Jan	0	0	0	2	17.68695	69.6087	16.652113	801
2	2018-01-03	1	2018	Jan	0	1	1	1	9.47025	43.7273	16.636703	1349
3	2018-01-04	1	2018	Jan	0	2	1	1	10.60610	59.0435	10.739832	1562
4	2018-01-05	1	2018	Jan	0	3	1	1	11.46350	43.6957	12.522300	1600

In [37]:
```
# Let's see "weekday" and check its consistency with dteday
```

In [38]:
```
df['week_name'] =  df.dteday.apply(lambda x: x.strftime("%a"))
```

In [39]:
```
df[['week_name', 'weekday']]
```

Out[39]:

	week_name	weekday
0	Mon	6
1	Tue	0
2	Wed	1
3	Thu	2
4	Fri	3
...	...	...
725	Fri	4
726	Sat	5
727	Sun	6
728	Mon	0
729	Tue	1

730 rows × 2 columns

Observation

- There is discrepencies in the data.
- **Monday** maps to 6 (index 0) as well as 0 (index 728)
- **Friday** maps to 3 (index 4) as well as 4 (index 725)
- This is most likely due to mistake of not accounting for two different years
- Since the derived attribute week_name accounts for it, it is correct (verfied with calendar)
- Therefore, we will drop weekday and keep week_name

In [40]:
```
df.drop("weekday", axis=1, inplace=True)
df.rename(columns={"week_name":"weekday"}, inplace=True)
```

In [41]:
```
df['weekday'] = df.weekday.astype("category")
df.head()
```

Out[41]:

	dteday	season	yr	mnth	holiday	workingday	weathersit	atemp	hum	windspeed	cnt	weekday
0	2018-01-01	1	2018	Jan	0	0	2	18.18125	80.5833	10.749882	985	Mon
1	2018-01-02	1	2018	Jan	0	0	2	17.68695	69.6087	16.652113	801	Tue
2	2018-01-03	1	2018	Jan	0	1	1	9.47025	43.7273	16.636703	1349	Wed
3	2018-01-04	1	2018	Jan	0	1	1	10.60610	59.0435	10.739832	1562	Thu
4	2018-01-05	1	2018	Jan	0	1	1	11.46350	43.6957	12.522300	1600	Fri

In [42]:
```
# since we have extrated all the important data from "dteday" we can now drop it
df.drop("dteday", axis=1, inplace=True)
```

In [43]:
```
# It seems that Monday and Tuesday are labelled as Non-Working Days. Let's check for consistency

df.loc[(df.weekday == "Tue") & (df.workingday == 1)].head(3)
```

Out[43]:

	season	yr	mnth	holiday	workingday	weathersit	atemp	hum	windspeed	cnt	weekday
428	1	2019	Mar	0	1	1	12.05855	50.6250	15.333486	3333	Tue
435	1	2019	Mar	0	1	1	22.97960	48.9167	13.916771	5298	Tue
442	1	2019	Mar	0	1	1	26.64105	72.8750	10.875239	6153	Tue

In [44]:
```
df.loc[(df.weekday == "Tue") & (df.workingday == 0)].head(3)
```

Out[44]:

	season	yr	mnth	holiday	workingday	weathersit	atemp	hum	windspeed	cnt	weekday
1	1	2018	Jan	0	0	2	17.68695	69.6087	16.652113	801	Tue
8	1	2018	Jan	0	0	1	5.80875	43.4167	24.250650	822	Tue
15	1	2018	Jan	0	0	1	11.71085	48.3750	12.625011	1204	Tue

In [45]:
```
# Working day column has inconsistency. Tuesday is marked as working day for 2019 but non-working day for 2018
# Deleting workingday column

df.drop("workingday", axis=1,inplace=True)
```

Mapping with Data Dictionary

- Mapping categorical columns with numeric values with their right labels

In [46]:
```
df.season.value_counts()
```

Out[46]:
```
3    188
2    184
1    180
4    178
Name: season, dtype: int64
```

In [47]:
```
# Data Dictionary ---> (1:spring, 2:summer, 3:fall, 4:winter)
df.season = df.season.map({1: "Spring", 2: "Summer", 3: "Fall", 4: "Winter"})
```

In [48]:
```
df.season.value_counts()
```

Out[48]:
```
Fall      188
Summer    184
Spring    180
Winter    178
Name: season, dtype: int64
```

weathersit :

- 1: Clear, Few clouds, Partly cloudy, Partly cloudy
- 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
- 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
- 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog

In [49]:
```
df.weathersit.value_counts()
```

Out[49]:
```
1    463
2    246
3     21
Name: weathersit, dtype: int64
```

Observation

- No heavy rain present in actual dataset

In [50]:
```
df.weathersit = df.weathersit.map({1: "Clear", 2: "Mist", 3: "Snow/Rain"})

df.weathersit.value_counts()
```

Out[50]:
```
Clear        463
Mist         246
Snow/Rain     21
Name: weathersit, dtype: int64
```

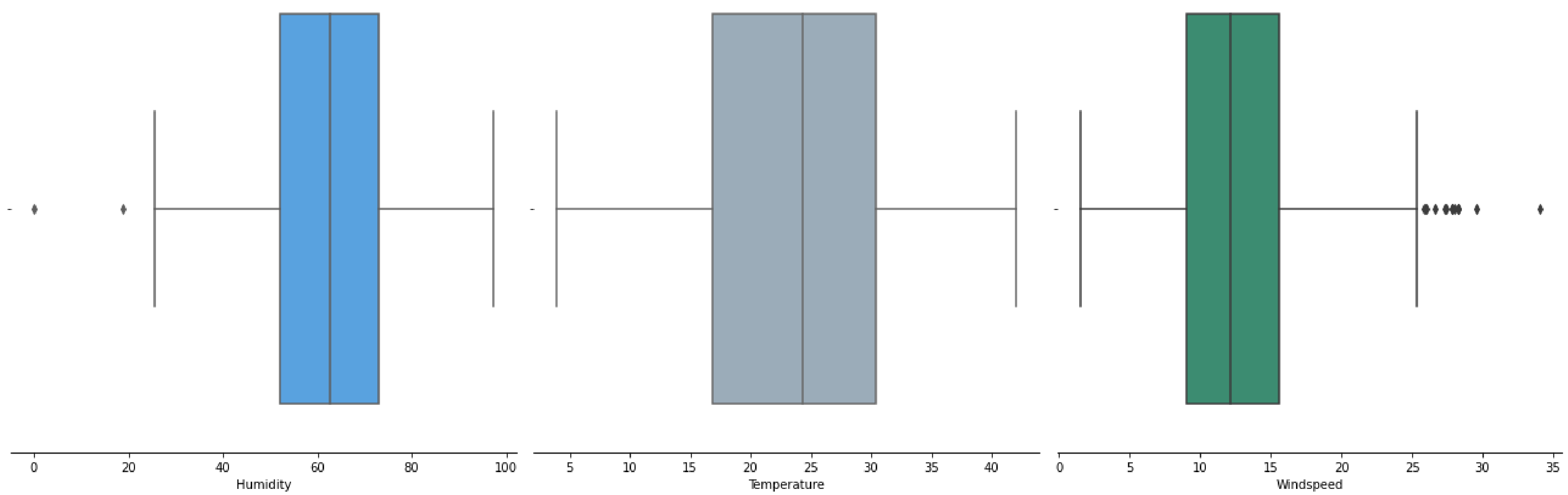
In [51]:
```
df.head()
```

Out[51]:

	season	yr	mnth	holiday	weathersit	atemp	hum	windspeed	cnt	weekday
0	Spring	2018	Jan	0	Mist	18.18125	80.5833	10.749882	985	Mon
1	Spring	2018	Jan	0	Mist	17.68695	69.6087	16.652113	801	Tue
2	Spring	2018	Jan	0	Clear	9.47025	43.7273	16.636703	1349	Wed
3	Spring	2018	Jan	0	Clear	10.60610	59.0435	10.739832	1562	Thu
4	Spring	2018	Jan	0	Clear	11.46350	43.6957	12.522300	1600	Fri

Outlier Handling

In [52]:
```
# fig, axes = plt.subplots(2, 2, figsize=(18, 5), sharey=False)
fig = plt.figure(figsize=(18, 12))
ax1 = fig.add_subplot(2,3,1)
ax2 = fig.add_subplot(2,3,2)
ax3 = fig.add_subplot(2,3,3)



sns.boxplot(df.hum, ax=ax1, color = "#43A4F5")
ax1.set_xlabel('Humidity')


sns.boxplot(df.atemp, ax=ax2, color= "#96ADBE")
ax2.set_xlabel('Temperature')

sns.boxplot(df.windspeed, ax=ax3, color = "#2F9975")
ax3.set_xlabel('Windspeed')



sns.despine(left=True)

plt.tight_layout()

plt.show()
```



Observation:

- Humidity has outliers on the lower side
- Windspeed has outliers on the higher side
- Tempearture does not seem to have outliers

In [53]:
```
df.shape
```
Out[53]:
```
(730, 10)
```

Observation:

- With only 730 rows, which will be further broken down to Training and Testing set, removing outliers will remove data points from our dataset
- Therefore, no outlier handling will be done

Exploratory Data Analysis

Univariate Analysis

Creating Bins

Creating bins for the analysis of continuous variables

In [54]:
```
eda = df.copy()
```
In [55]:
```
pd.qcut(eda.atemp, 4, labels=["low", "medium", "high", "very high"]).value_counts()
```
Out[55]:
```
low          183
very high    183
medium       182
high         182
Name: atemp, dtype: int64
```
In [56]:
```
eda['temp_bins'] = pd.qcut(eda.atemp, 4, labels=["low", "medium", "high", "very high"])
```
In [57]:
```
# Looking into humidity
```
In [58]:
```
pd.qcut(eda.hum, 4, labels=["low", "medium", "high", "very high"]).value_counts()
```
Out[58]:
```
low          184
very high    183
high         182
medium       181
Name: hum, dtype: int64
```
In [59]:
```
eda['hum_bins'] = pd.qcut(eda.hum, 4, labels=["low", "medium", "high", "very high"])
```
In [60]:
```
# Looking into windspeed
```
In [61]:
```
pd.qcut(eda.windspeed, 4, labels=["low", "medium", "high", "very high"]).value_counts()
```
Out[61]:
```
low          184
very high    183
medium       182
high         181
Name: windspeed, dtype: int64
```
In [62]:
```
eda['windspeed_bins'] = pd.qcut(eda.windspeed, 4, labels=["low", "medium", "high", "very high"])
```

In [63]:
```
eda.head()
```

Out[63]:

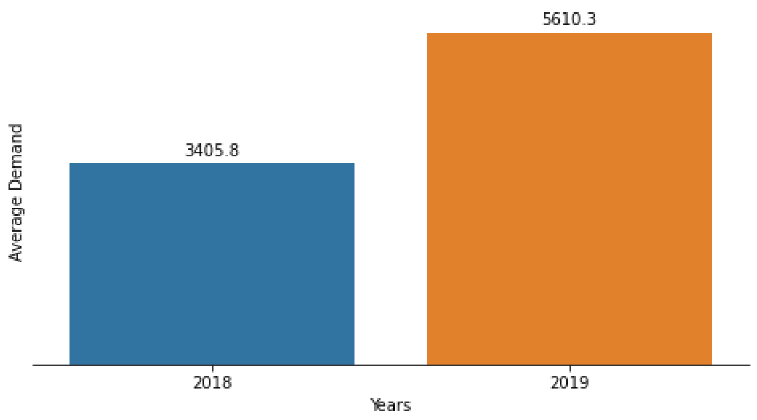
	season	yr	mnth	holiday	weathersit	atemp	hum	windspeed	cnt	weekday	temp_bins	hum_bins	windspeed_bins
0	Spring	2018	Jan	0	Mist	18.18125	80.5833	10.749882	985	Mon	medium	very high	medium
1	Spring	2018	Jan	0	Mist	17.68695	69.6087	16.652113	801	Tue	medium	high	very high
2	Spring	2018	Jan	0	Clear	9.47025	43.7273	16.636703	1349	Wed	low	low	very high
3	Spring	2018	Jan	0	Clear	10.60610	59.0435	10.739832	1562	Thu	low	medium	medium
4	Spring	2018	Jan	0	Clear	11.46350	43.6957	12.522300	1600	Fri	low	low	high

In [64]:
```
#--------------------------------Defining a function to annotate bar graphs----------------------------------------#
```

In [65]:
```
def annotate_graph(ax):

    for bar in ax.patches:
        ax.annotate(format((bar.get_height()), '.1f'),
                   (bar.get_x() + bar.get_width() / 2,  bar.get_height()),
                   ha='center', va='center',
                   size=10, xytext=(0, 8),
                   textcoords='offset points')
    return ax
```

Data Visualisation

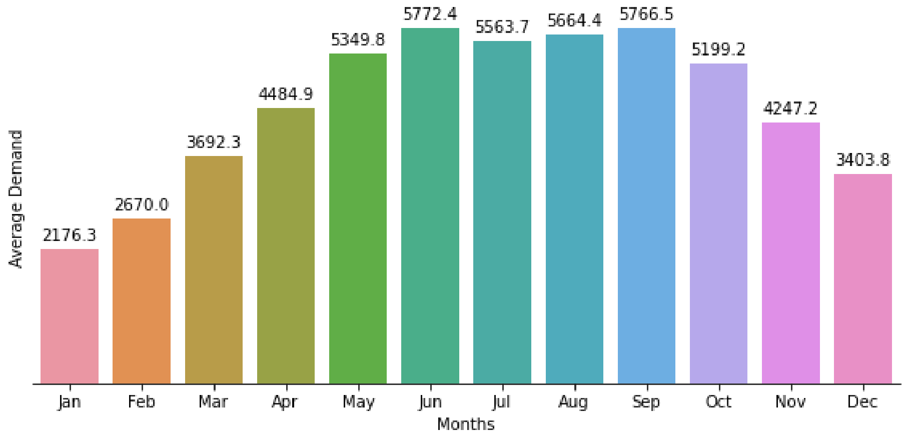
In [66]:
```
plt.figure(figsize=(8,4))
ax = sns.barplot(x = eda.yr, y=eda.cnt, estimator=np.mean, ci=None)

ax = annotate_graph(ax)

plt.ylabel('Average Demand')
plt.xlabel('Years')
plt.yticks([], [])
sns.despine(left=True)

plt.show()
```



Observation

- 2019 shows more than 60% growth in demand

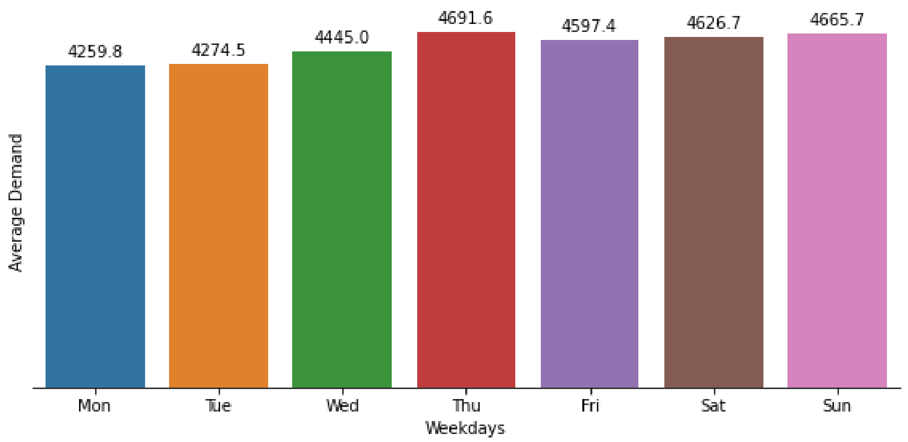
In [67]:
```
plt.figure(figsize=(8,4))
myOrder = ["Jan", "Feb", "Mar","Apr", "May", "Jun", "Jul" , "Aug" , "Sep" , "Oct" , "Nov" , "Dec"]
ax = sns.barplot(x = eda.mnth, y=eda.cnt, estimator=np.mean, ci=None, order=myOrder)

ax = annotate_graph(ax)

plt.ylabel('Average Demand')
plt.xlabel('Months')
plt.yticks([], [])
sns.despine(left=True)

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



Observation

- Demands steady rises till Fall Season and then slowly declines.

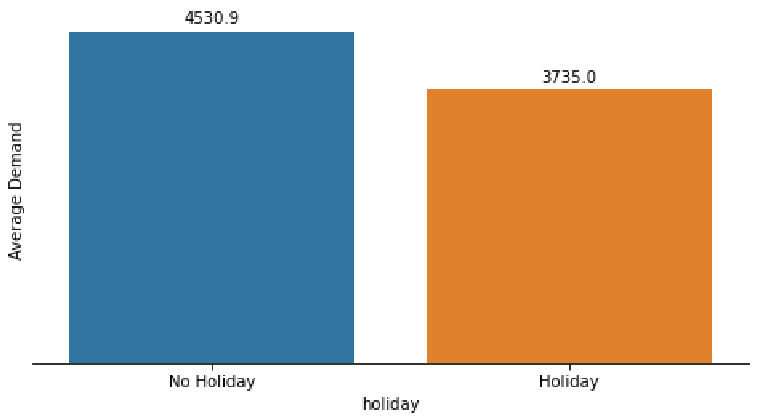
In [68]:
```
plt.figure(figsize=(8,4))
myOrder = ["Mon", "Tue", "Wed","Thu", "Fri", "Sat", "Sun"]
ax = sns.barplot(x = eda.weekday, y=eda.cnt, estimator=np.mean, ci=None, order=myOrder)

ax = annotate_graph(ax)

plt.ylabel('Average Demand')
plt.xlabel('Weekdays')
plt.yticks([], [])
sns.despine(left=True)

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



Observation

- There is not much one can say from days of the week.
- People do demand for bikes more at the later half of the week but the trend is not strong

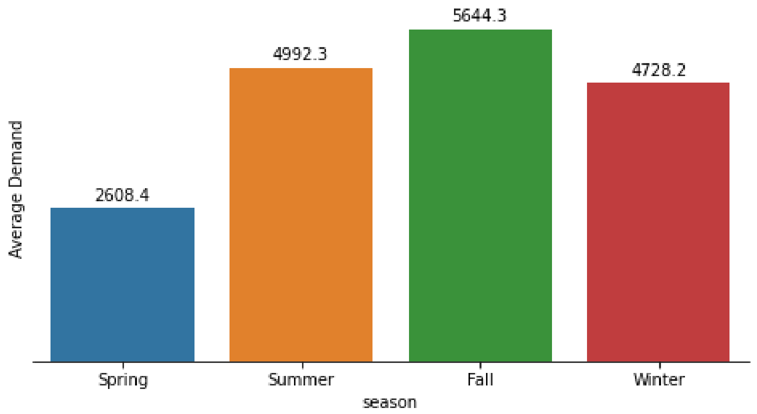
In [69]:
```
plt.figure(figsize=(8,4))
ax = sns.barplot(x = eda.holiday, y=eda.cnt, estimator=np.mean, ci=None, order=[0,1])

ax = annotate_graph(ax)

plt.ylabel('Holidays')
plt.ylabel('Average Demand')
plt.yticks([])
ax.set_xticklabels(['No Holiday','Holiday'])
sns.despine(left=True)

plt.show()
```



Observation

- Demand for bikes is more on working days. Most likely, office commutes increases demand

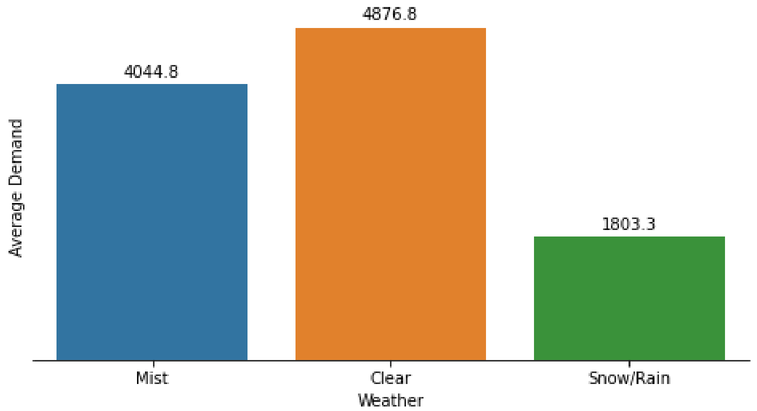
In [70]:
```
plt.figure(figsize=(8,4))
ax = sns.barplot(x = eda.season, y=eda.cnt, estimator=np.mean, ci=None)

ax = annotate_graph(ax)

plt.ylabel('Average Demand')
plt.yticks([])
sns.despine(left=True)

plt.show()
```



Observation

- Fall season has the highest average bike demand
- Spring sees the biggest dip
- Summer and Winter have similar demands

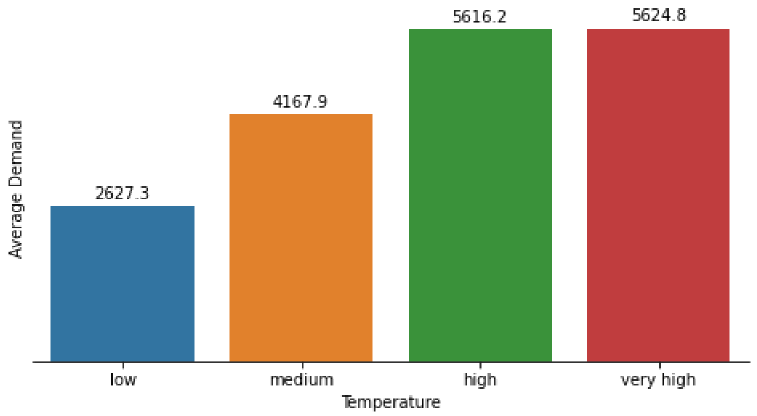
In [71]:
```
plt.figure(figsize=(8,4))
ax = sns.barplot(x = eda.weathersit, y=eda.cnt, estimator=np.mean, ci=None)

ax = annotate_graph(ax)

plt.ylabel('Average Demand')
plt.xlabel('Weather')
plt.yticks([])
sns.despine(left=True)

plt.show()
```



Observation

- It is not surprising to see demands for bikes rise in clear weather and be very low in snowy or rainy condition

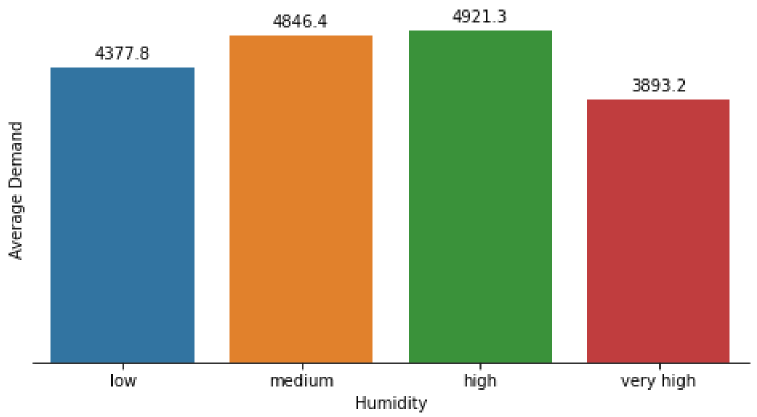
In [72]:
```
plt.figure(figsize=(8,4))
ax = sns.barplot(x = eda.temp_bins, y=eda.cnt, estimator=np.mean, ci=None)

ax = annotate_graph(ax)

plt.ylabel('Average Demand')
plt.xlabel('Temperature')
plt.yticks([])
sns.despine(left=True)

plt.show()
```



Observation

- Demands rise in warm and hot condition

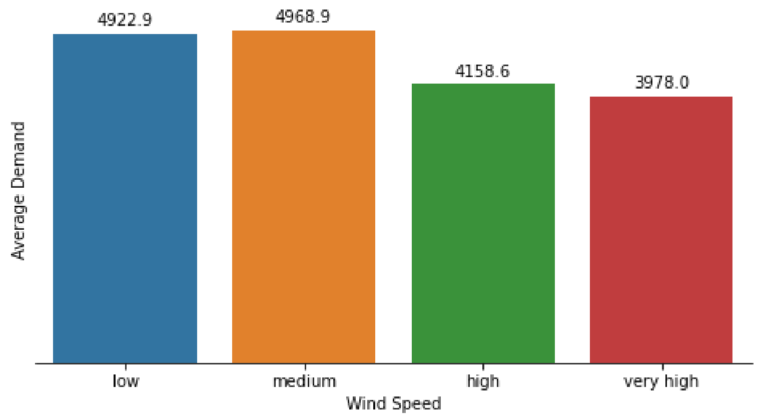
In [73]:
```
plt.figure(figsize=(8,4))
ax = sns.barplot(x = eda.hum_bins, y=eda.cnt, estimator=np.mean, ci=None)

ax = annotate_graph(ax)

plt.ylabel('Average Demand')
plt.xlabel('Humidity')
plt.yticks([])
sns.despine(left=True)

plt.show()
```



Observation

- As expected, people don't prefer bikes on very humid days

In [74]:
```
plt.figure(figsize=(8,4))
ax = sns.barplot(x = eda.windspeed_bins, y=eda.cnt, estimator=np.mean, ci=None)

ax = annotate_graph(ax)

plt.ylabel('Average Demand')
plt.xlabel('Wind Speed')
plt.yticks([])
sns.despine(left=True)

plt.show()
```



Observation

- As expected, people prefer biking in less windy condition when it is easier to ride a bike

Bivariate Analysis

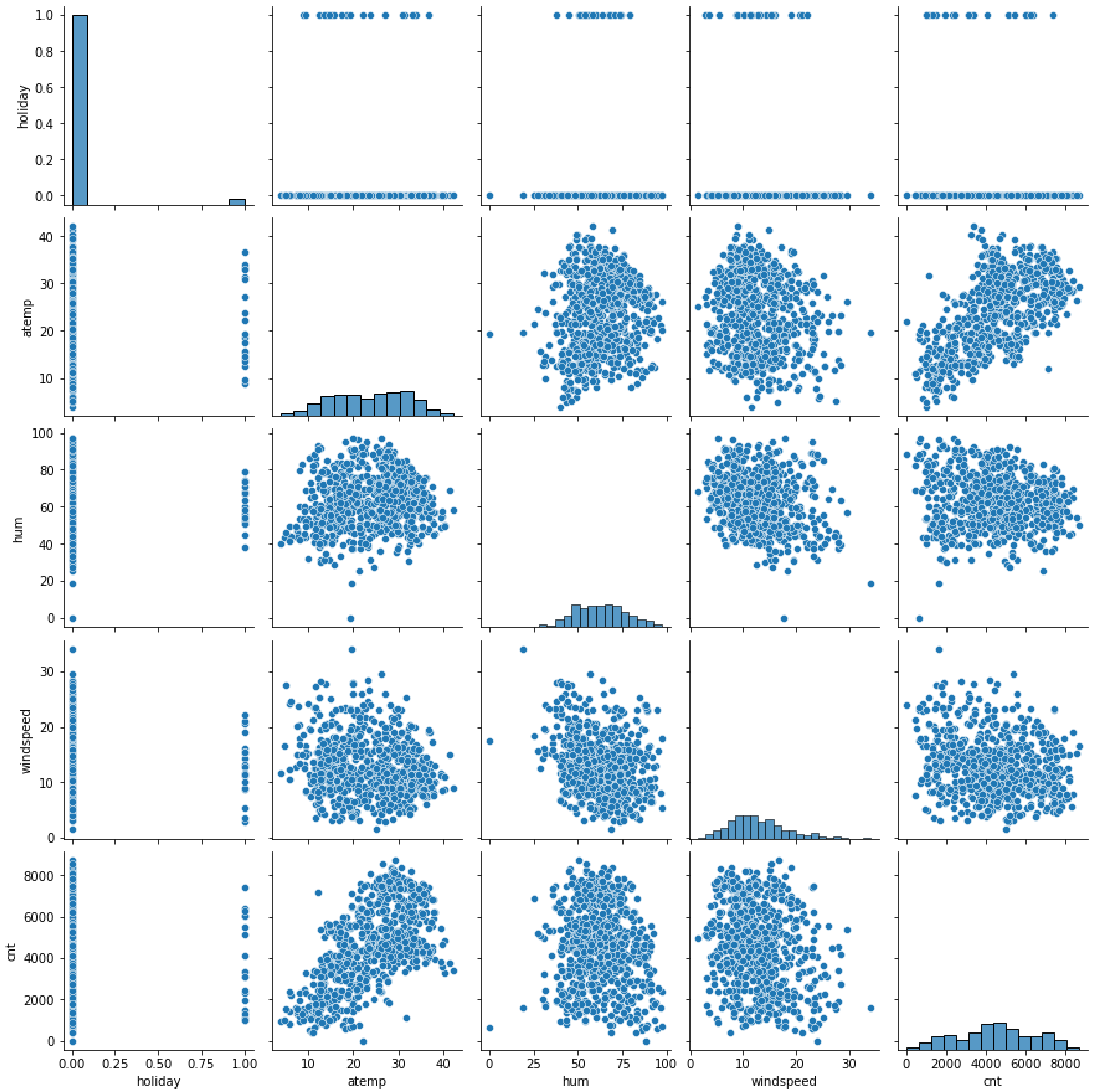
In [75]:
```
eda.head()
```

Out[75]:

	season	yr	mnth	holiday	weathersit	atemp	hum	windspeed	cnt	weekday	temp_bins	hum_bins	windspeed_bins
0	Spring	2018	Jan	0	Mist	18.18125	80.5833	10.749882	985	Mon	medium	very high	medium
1	Spring	2018	Jan	0	Mist	17.68695	69.6087	16.652113	801	Tue	medium	high	very high
2	Spring	2018	Jan	0	Clear	9.47025	43.7273	16.636703	1349	Wed	low	low	very high
3	Spring	2018	Jan	0	Clear	10.60610	59.0435	10.739832	1562	Thu	low	medium	medium
4	Spring	2018	Jan	0	Clear	11.46350	43.6957	12.522300	1600	Fri	low	low	high

In [76]:
```
sns.pairplot(eda)
plt.plot()
```

Out[76]: []



Observation

- Bike demand has positive correlation with Temperature
- Humidity and Demand follow a normal Distribution with centre somewhere close to 60 unit humidity
- Lower windspeeds see higher demand

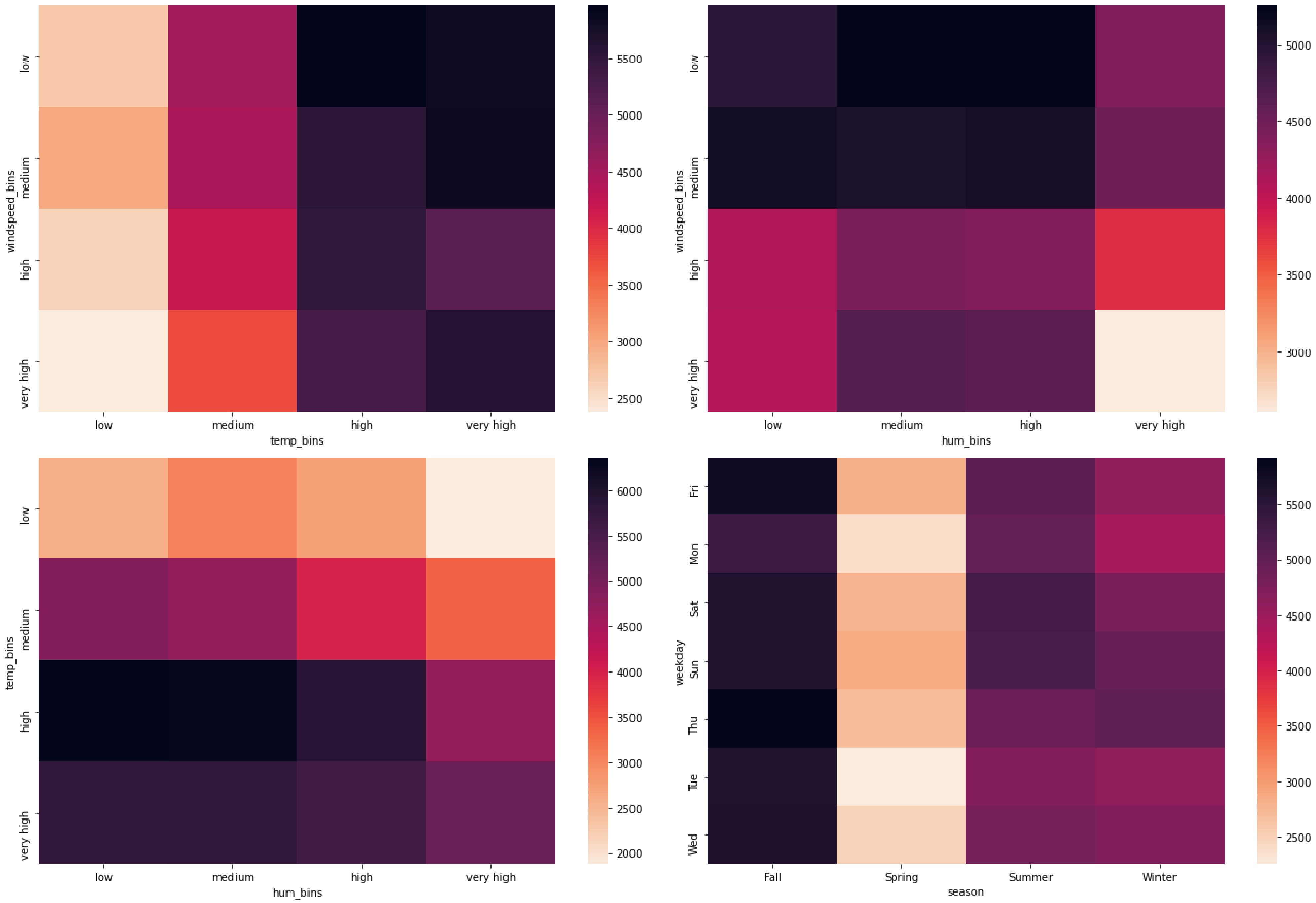
In [77]:
```
ba1 = pd.pivot_table(data=eda, index="windspeed_bins", columns="temp_bins", values="cnt")
```

In [78]:
```
ba2 = pd.pivot_table(data=eda, index="windspeed_bins", columns="hum_bins", values="cnt")
```

In [79]:
```
ba3 = pd.pivot_table(data=eda, index="temp_bins", columns="hum_bins", values="cnt")
```

In [80]:
```
ba4 = pd.pivot_table(data=eda, index="weekday", columns="season", values="cnt")
```

In [81]:
```
# fig, axes = plt.subplots(2, 2, figsize=(18, 5), sharey=False)
fig = plt.figure(figsize=(18, 12))
ax1 = fig.add_subplot(2,2,1)
ax2 = fig.add_subplot(2,2,2)
ax3 = fig.add_subplot(2,2,3)
ax4 = fig.add_subplot(2,2,4)



sns.heatmap(ax=ax1,data=ba1, annot=False, cmap=sns.cm.rocket_r)
sns.heatmap(ax=ax2,data=ba2, annot=False, cmap=sns.cm.rocket_r)
sns.heatmap(ax=ax3,data=ba3, annot=False, cmap=sns.cm.rocket_r)
sns.heatmap(ax=ax4,data=ba4, annot=False, cmap=sns.cm.rocket_r)


plt.tight_layout()

plt.show()
```



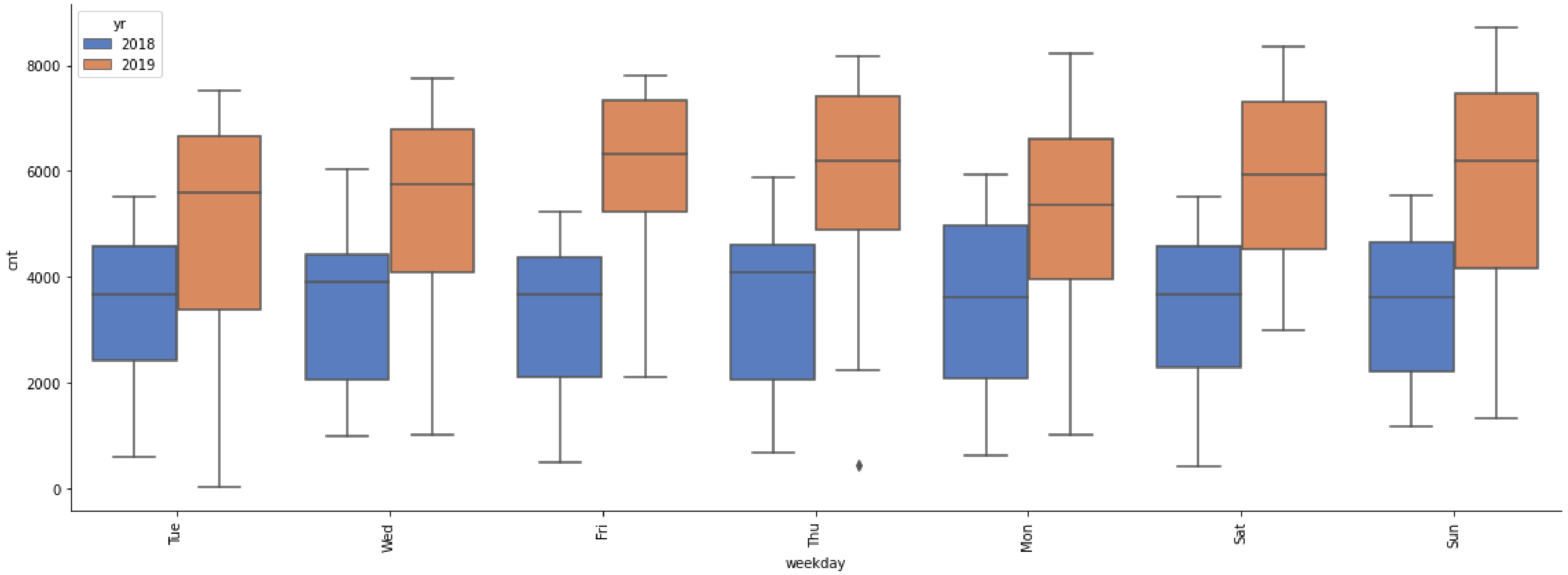
Observation

- Demands are high for Low windspeed and high temperature. Even at high wind speed, if temperature is high, demand stays high
- People demand for bikes more if windspeed and humidity is low

- People demand for bikes more if temperature is high and and humidity is low. But if temperature is high or very high, then humidity does not have a severe negative affect on demand
- Spring sees a dip in demand. In Fall, Thursday and Fri are the most popular days for bike demands

In [82]:
```
grouped = eda.loc[:,['weekday', 'cnt']].groupby(['weekday']).max().sort_values(by='cnt')
```

In [83]:
```
fig = plt.figure(figsize=(16, 6))

sns.boxplot(x="weekday", y="cnt", data=eda, hue="yr" ,palette="muted", order=grouped.index)

plt.xticks(rotation="vertical")
plt.tight_layout()
sns.despine()
plt.show()
```



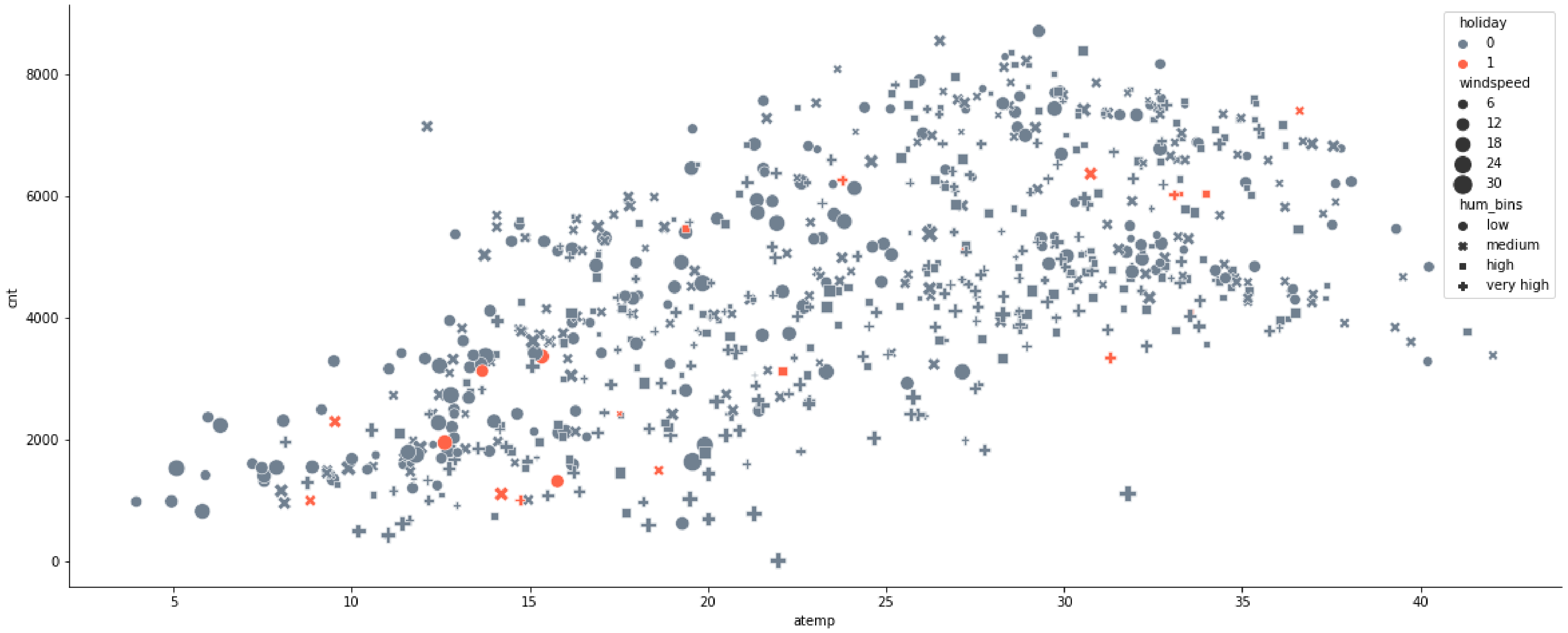
Observation:

- Though Sunday has the highest maximum demand but the medians all are identical for 2019
- For 2018, the medians vary. Thursday enjoyed the highest demand back in 2018

Multivariate Analysis

In [84]:
```
fig = plt.figure(figsize=(20, 8))

sns.scatterplot(x="atemp", y="cnt", hue="holiday",
                data=eda, style="hum_bins",size="windspeed", sizes=(15, 200),
                palette=["slategrey","tomato"] )

sns.despine()

plt.plot()
```

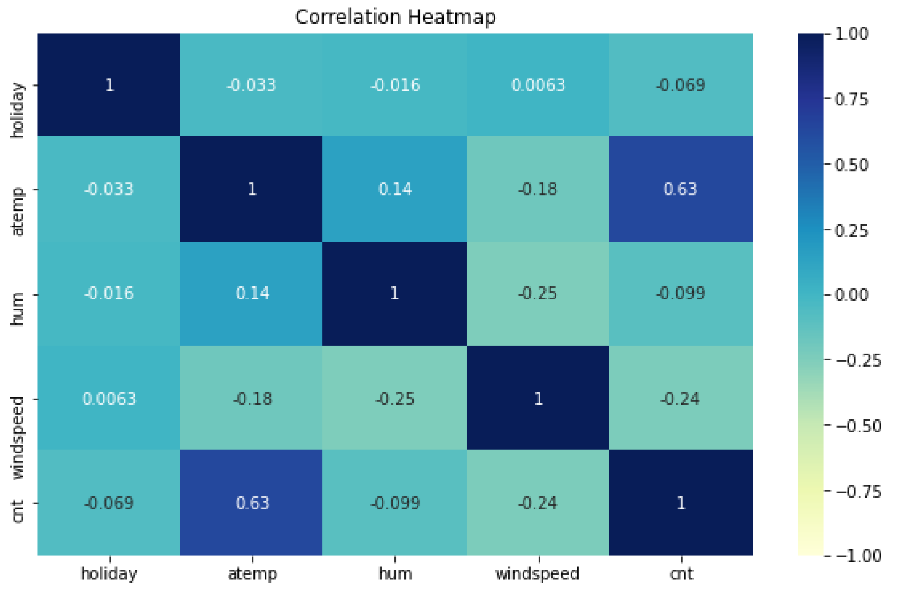
Out[84]: []



Observation

- Temperature between 25C to 33C is favorable
- No Holidays is favorable
- Low windspeed is favourable
- low and medium humidity is favourable

In [85]:
```
# plot heat map to see correlation between features
plt.figure(figsize=(10,6))
myData = eda.corr()

sns.heatmap(myData,vmin=-1.0,vmax=1.0,annot=True, cmap="YlGnBu")
plt.title("Correlation Heatmap")
plt.show()
```



Observation

- Temperature has the highest influence on bike demand

Regression Modelling

Data Preparation

Dummy Variables

In [86]:
```
df.head()
```

Out[86]:

	season	yr	mnth	holiday	weathersit	atemp	hum	windspeed	cnt	weekday
0	Spring	2018	Jan	0	Mist	18.18125	80.5833	10.749882	985	Mon
1	Spring	2018	Jan	0	Mist	17.68695	69.6087	16.652113	801	Tue
2	Spring	2018	Jan	0	Clear	9.47025	43.7273	16.636703	1349	Wed
3	Spring	2018	Jan	0	Clear	10.60610	59.0435	10.739832	1562	Thu
4	Spring	2018	Jan	0	Clear	11.46350	43.6957	12.522300	1600	Fri

Season

In [87]:
```
df.season.value_counts()
```

Out[87]:
```
Fall      188
Summer    184
Spring    180
Winter    178
Name: season, dtype: int64
```

In [88]:
```
# Season has Four Levels
pd.get_dummies(df.season, drop_first=True)
```

Out[88]:

	Spring	Summer	Winter
0	1	0	0
1	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0
...	...	...	...
725	1	0	0
726	1	0	0
727	1	0	0
728	1	0	0
729	1	0	0

730 rows × 3 columns

In [89]:
```
season_status = pd.get_dummies(df.season, drop_first=True)

#Adding the results to the original housing dataframe
df = pd.concat([df, season_status], axis=1)

# Now let's see the head of dataframe
df.head()
```

Out[89]:

	season	yr	mnth	holiday	weathersit	atemp	hum	windspeed	cnt	weekday	Spring	Summer	Winter
0	Spring	2018	Jan	0	Mist	18.18125	80.5833	10.749882	985	Mon	1	0	0
1	Spring	2018	Jan	0	Mist	17.68695	69.6087	16.652113	801	Tue	1	0	0
2	Spring	2018	Jan	0	Clear	9.47025	43.7273	16.636703	1349	Wed	1	0	0
3	Spring	2018	Jan	0	Clear	10.60610	59.0435	10.739832	1562	Thu	1	0	0
4	Spring	2018	Jan	0	Clear	11.46350	43.6957	12.522300	1600	Fri	1	0	0

In [90]:
```
# confirming Winter and Summer has true values as well
df.Winter.value_counts()
```

Out[90]:
```
0    552
1    178
Name: Winter, dtype: int64
```

In [91]:
```
df.Summer.value_counts()
```

Out[91]:
```
0    546
1    184
Name: Summer, dtype: int64
```

In [92]:
```
# Dropping Season as dummy variable is already created
df.drop("season", axis=1, inplace=True)
```

In [93]:
```
# Now let's see the head of dataframe
df.head()
```

Out[93]:

	yr	mnth	holiday	weathersit	atemp	hum	windspeed	cnt	weekday	Spring	Summer	Winter
0	2018	Jan	0	Mist	18.18125	80.5833	10.749882	985	Mon	1	0	0
1	2018	Jan	0	Mist	17.68695	69.6087	16.652113	801	Tue	1	0	0
2	2018	Jan	0	Clear	9.47025	43.7273	16.636703	1349	Wed	1	0	0
3	2018	Jan	0	Clear	10.60610	59.0435	10.739832	1562	Thu	1	0	0
4	2018	Jan	0	Clear	11.46350	43.6957	12.522300	1600	Fri	1	0	0

Month

In [94]:
```
df.mnth.value_counts()
```

Out[94]:
```
Aug    62
Dec    62
Jan    62
Jul    62
Mar    62
May    62
Oct    62
Apr    60
Jun    60
Nov    60
Sep    60
Feb    56
Name: mnth, dtype: int64
```

In [95]:
```
# Month has 12 Levels
pd.get_dummies(df.mnth, drop_first=True)
```

Out[95]:

	Aug	Dec	Feb	Jan	Jul	Jun	Mar	May	Nov	Oct	Sep
0	0	0	0	1	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0	0	0	0	0
2	0	0	0	1	0	0	0	0	0	0	0
3	0	0	0	1	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
725	0	1	0	0	0	0	0	0	0	0	0
726	0	1	0	0	0	0	0	0	0	0	0
727	0	1	0	0	0	0	0	0	0	0	0
728	0	1	0	0	0	0	0	0	0	0	0
729	0	1	0	0	0	0	0	0	0	0	0

730 rows × 11 columns

In [96]:
```
month_status = pd.get_dummies(df.mnth, drop_first=True)

#Adding the results to the original housing dataframe
df = pd.concat([df, month_status], axis=1)

# Now let's see the head of dataframe
df.head()
```

Out[96]:

	yr	mnth	holiday	weathersit	atemp	hum	windspeed	cnt	weekday	Spring	...	Dec	Feb	Jan	Jul	Jun	Mar	May	Nov	Oct	Sep
0	2018	Jan	0	Mist	18.18125	80.5833	10.749882	985	Mon	1	...	0	0	1	0	0	0	0	0	0	0
1	2018	Jan	0	Mist	17.68695	69.6087	16.652113	801	Tue	1	...	0	0	1	0	0	0	0	0	0	0
2	2018	Jan	0	Clear	9.47025	43.7273	16.636703	1349	Wed	1	...	0	0	1	0	0	0	0	0	0	0
3	2018	Jan	0	Clear	10.60610	59.0435	10.739832	1562	Thu	1	...	0	0	1	0	0	0	0	0	0	0
4	2018	Jan	0	Clear	11.46350	43.6957	12.522300	1600	Fri	1	...	0	0	1	0	0	0	0	0	0	0

5 rows × 23 columns

In [97]:
```
#Let's drop month column since it's already converted into dummy variable
df.drop("mnth", axis=1, inplace=True)
```

Year

In [98]:
```
df.yr.value_counts()
```

Out[98]:
```
2018    365
2019    365
Name: yr, dtype: int64
```

In [99]:
```
#Turning year to binary where 0--> "2018" and 1 --> "2019"
df['yr'] = df.yr.apply(lambda x: 0 if x==2018 else 1)
```

Weather Situation

In [100]:
```
#Weather Situation has Three Levels
df.weathersit.value_counts()
```

Out[100]:
```
Clear        463
Mist         246
Snow/Rain     21
Name: weathersit, dtype: int64
```

In [101]:
```
weather_status = pd.get_dummies(df.weathersit, drop_first=True)

#Adding the results to the original housing dataframe
df = pd.concat([df, weather_status], axis=1)

# Now let's see the head of dataframe
df.head()
```

Out[101]:

	yr	holiday	weathersit	atemp	hum	windspeed	cnt	weekday	Spring	Summer	...	Jan	Jul	Jun	Mar	May	Nov	Oct	Sep	Mist	Snow/Rain
0	0	0	Mist	18.18125	80.5833	10.749882	985	Mon	1	0	...	1	0	0	0	0	0	0	0	1	0
1	0	0	Mist	17.68695	69.6087	16.652113	801	Tue	1	0	...	1	0	0	0	0	0	0	0	1	0
2	0	0	Clear	9.47025	43.7273	16.636703	1349	Wed	1	0	...	1	0	0	0	0	0	0	0	0	0
3	0	0	Clear	10.60610	59.0435	10.739832	1562	Thu	1	0	...	1	0	0	0	0	0	0	0	0	0
4	0	0	Clear	11.46350	43.6957	12.522300	1600	Fri	1	0	...	1	0	0	0	0	0	0	0	0	0

5 rows × 24 columns

In [102]:
```
# Dropping Weather Situation as dummy variable is already created
df.drop("weathersit", axis=1, inplace=True)
```

In [103]:
```
# Making sure Clear, Mist and Snow/Rain have columns
df.Mist.value_counts()
```

Out[103]:
```
0    484
1    246
Name: Mist, dtype: int64
```

In [104]:
```
df['Snow/Rain'].value_counts()
```

Out[104]:
```
0    709
1     21
Name: Snow/Rain, dtype: int64
```

Weekday

In [105]:
```
#WeekDay should have 7 levels. Confirming
df.weekday.value_counts().shape[0]
```

Out[105]:
```
7
```

In [106]:
```
df.weekday.value_counts()
```

Out[106]:
```
Mon    105
Tue    105
Fri    104
Sat    104
Sun    104
Thu    104
Wed    104
Name: weekday, dtype: int64
```

In [107]:
```
weekday_status = pd.get_dummies(df.weekday, drop_first=True)

#Adding the results to the original housing dataframe
df = pd.concat([df, weekday_status], axis=1)
```

In [108]:
```
# Dropping Weekday since dummy columns have been created
df.drop("weekday", axis=1, inplace=True)
```

DataFrame after Dummy Variable Creation

In [109]:
```
# Now let's see the head of dataframe
df.head()
```

Out[109]:

	yr	holiday	atemp	hum	windspeed	cnt	Spring	Summer	Winter	Aug	...	Oct	Sep	Mist	Snow/Rain	Mon	Sat	Sun	Thu	Tue	Wed
0	0	0	18.18125	80.5833	10.749882	985	1	0	0	0	...	0	0	1	0	1	0	0	0	0	0
1	0	0	17.68695	69.6087	16.652113	801	1	0	0	0	...	0	0	1	0	0	0	0	0	1	0
2	0	0	9.47025	43.7273	16.636703	1349	1	0	0	0	...	0	0	0	0	0	0	0	0	0	1
3	0	0	10.60610	59.0435	10.739832	1562	1	0	0	0	...	0	0	0	0	0	0	0	1	0	0
4	0	0	11.46350	43.6957	12.522300	1600	1	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 28 columns

In [110]:
```
df.shape
```

Out[110]:
```
(730, 28)
```

Splitting the Data into trainning and testing split

In [111]:
```
from sklearn.model_selection import train_test_split

# Random State is mentioned so that consistent result is obtained every time
df_train, df_test = train_test_split(df, train_size=0.7, test_size=0.3, random_state = 747)
```

Rescaling the Features

In [112]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
```

In [113]:
```
# Now let's see the head of dataframe
df.head(2)
```

Out[113]:

	yr	holiday	atemp	hum	windspeed	cnt	Spring	Summer	Winter	Aug	...	Oct	Sep	Mist	Snow/Rain	Mon	Sat	Sun	Thu	Tue	Wed
0	0	0	18.18125	80.5833	10.749882	985	1	0	0	0	...	0	0	1	0	1	0	0	0	0	0
1	0	0	17.68695	69.6087	16.652113	801	1	0	0	0	...	0	0	1	0	0	0	0	0	1	0

2 rows × 28 columns

In [114]:
```
df.columns
```

Out[114]:
```
Index(['yr', 'holiday', 'atemp', 'hum', 'windspeed', 'cnt', 'Spring', 'Summer',
       'Winter', 'Aug', 'Dec', 'Feb', 'Jan', 'Jul', 'Jun', 'Mar', 'May', 'Nov',
       'Oct', 'Sep', 'Mist', 'Snow/Rain', 'Mon', 'Sat', 'Sun', 'Thu', 'Tue',
       'Wed'],
      dtype='object')
```

In [115]:
```
continuous_var = ["atemp", "hum", "windspeed"]
df_train[continuous_var] = scaler.fit_transform(df_train[continuous_var])
df_train.head()
```

Out[115]:

	yr	holiday	atemp	hum	windspeed	cnt	Spring	Summer	Winter	Aug	...	Oct	Sep	Mist	Snow/Rain	Mon	Sat	Sun	Thu	Tue	Wed
62	0	0	0.231824	0.627678	0.431695	1944	1	0	0	0	...	0	0	1	0	0	0	1	0	0	0
246	0	0	0.769676	0.763067	0.439141	4940	0	0	0	0	...	0	1	0	0	0	0	0	0	1	0
132	0	0	0.545046	0.887746	0.375344	4105	0	1	0	0	...	0	0	1	0	0	0	1	0	0	0
128	0	0	0.585667	0.605398	0.366457	4362	0	1	0	0	...	0	0	0	0	0	0	0	0	0	1
248	0	0	0.572480	0.912038	0.767112	2710	0	0	0	0	...	0	1	0	1	0	0	0	1	0	0

5 rows × 28 columns

Observation

Our three continuous variables: "atemp", "hum", "windspeed" have been scaled between 0 to 1

Dividing trainning dataset to X and Y for the model building

In [116]:
```
#pop will remove the column and return it to y_train
y_train = df_train.pop("cnt")
X_train = df_train
```

In [117]:
```
y_train.head()
```

Out[117]:
```
62     1944
246    4940
132    4105
128    4362
248    2710
Name: cnt, dtype: int64
```

In [118]:
```
X_train.head()
```

Out[118]:

	yr	holiday	atemp	hum	windspeed	Spring	Summer	Winter	Aug	Dec	...	Oct	Sep	Mist	Snow/Rain	Mon	Sat	Sun	Thu	Tue	Wed
62	0	0	0.231824	0.627678	0.431695	1	0	0	0	0	...	0	0	1	0	0	0	1	0	0	0
246	0	0	0.769676	0.763067	0.439141	0	0	0	0	0	...	0	1	0	0	0	0	0	0	1	0
132	0	0	0.545046	0.887746	0.375344	0	1	0	0	0	...	0	0	1	0	0	0	1	0	0	0
128	0	0	0.585667	0.605398	0.366457	0	1	0	0	0	...	0	0	0	0	0	0	0	0	0	1
248	0	0	0.572480	0.912038	0.767112	0	0	0	0	0	...	0	1	0	1	0	0	0	1	0	0

5 rows × 27 columns

Data Modelling

Recursive Feature Elimination

- We will use RFE to get **top 20 columns**

In [119]:
```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
```

In [120]:
```
# Creating the Linear Regression Model and running RFE to get top 20 columns

lm = LinearRegression()
lm.fit(X_train, y_train)

rfe = RFE(lm, 20)
ref = rfe.fit(X_train, y_train)
```

In [121]:
```
# Checking out the selected columns

top20 = X_train.columns[rfe.support_]
top20
```

Out[121]:
```
Index(['yr', 'holiday', 'atemp', 'hum', 'windspeed', 'Spring', 'Summer',
       'Winter', 'Dec', 'Feb', 'Jan', 'Jul', 'Mar', 'May', 'Nov', 'Sep',
       'Mist', 'Snow/Rain', 'Mon', 'Tue'],
      dtype='object')
```

Observation

- As we had also seen our Exploratory Data Analysis, weekdays did not have much impact on demand
- We can see that none of the weekday dummy variables could make it into top15 columns

Building StatsModel

In [122]:
```
# creating X_train dataframe with RFE selected top20 variables

X_train_rfe = X_train[top20]
```

In [123]:
```
import statsmodels.api as sm

#Adding constant
X_train_rfe = sm.add_constant(X_train_rfe)
```

In [124]:
```
#Running the model
lm = sm.OLS(y_train, X_train_rfe).fit()
```

In [125]:
```
lm.summary()
```

Out[125]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.849
Model:	OLS	**Adj. R-squared:**	0.843
Method:	Least Squares	**F-statistic:**	137.6
Date:	Mon, 08 Mar 2021	**Prob (F-statistic):**	3.48e-186
Time:	07:39:48	**Log-Likelihood:**	-4098.7
No. Observations:	510	**AIC:**	8239.
Df Residuals:	489	**BIC:**	8328.
Df Model:	20		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3698.5187	321.844	11.492	0.000	3066.150	4330.887
yr	1999.3302	68.770	29.073	0.000	1864.209	2134.451
holiday	-713.7103	217.255	-3.285	0.001	-1140.578	-286.842
atemp	3292.6774	348.211	9.456	0.000	2608.504	3976.851
hum	-1386.8793	324.534	-4.273	0.000	-2024.532	-749.227
windspeed	-923.2572	199.331	-4.632	0.000	-1314.908	-531.606
Spring	-903.3886	215.350	-4.195	0.000	-1326.514	-480.264
Summer	-143.9084	142.070	-1.013	0.312	-423.052	135.235
Winter	627.7866	148.076	4.240	0.000	336.842	918.731
Dec	-703.7793	177.686	-3.961	0.000	-1052.901	-354.658
Feb	-519.0783	242.035	-2.145	0.032	-994.635	-43.522
Jan	-722.8937	244.685	-2.954	0.003	-1203.658	-242.129
Jul	-472.9602	152.081	-3.110	0.002	-771.773	-174.148
Mar	-132.0992	183.392	-0.720	0.472	-492.434	228.235
May	329.0880	146.350	2.249	0.025	41.535	616.641
Nov	-769.8973	174.922	-4.401	0.000	-1113.588	-426.206
Sep	331.9179	149.827	2.215	0.027	37.533	626.302
Mist	-464.4928	90.669	-5.123	0.000	-642.642	-286.344
Snow/Rain	-2100.2763	215.113	-9.764	0.000	-2522.935	-1677.617
Mon	-306.3700	98.776	-3.102	0.002	-500.447	-112.293
Tue	-311.8787	101.173	-3.083	0.002	-510.666	-113.091

Omnibus:	63.265	**Durbin-Watson:**	1.977
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	145.581
Skew:	-0.665	**Prob(JB):**	2.44e-32
Kurtosis:	5.255	**Cond. No.**	23.6

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Observation

- Mar and Summer have a p-value more than 0.05. With Mar having the highest p-value of 0.472
- Model is able to explain 84.9% variance. (r-squared value: 0.849)
- Adjusted r-squared value: 0.843
- The model is overall significant as the prob(F-stat) is low
- Coeff of constant shows the demand when all columns are zero. ie:

- year = 0: 2018
- winter, spring, summer = 0 0 0 : Fall
- Mist, Snow/Rain = 0 0: Clear
- and so on...

In [126]:
```
# Calculating VIF
from statsmodels.stats.outliers_influence import variance_inflation_factor


# Defining a function to give VIF value
def vif_cal(X):
    vif = pd.DataFrame()
    vif['Features'] = X.columns
    vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
    vif['VIF'] = round(vif['VIF'], 2)

    vif = vif.sort_values(by="VIF", ascending=False)

    return vif
```

In [127]:
```
vif = vif_cal(X_train_rfe)
vif
```

Out[127]:

	Features	VIF
0	const	90.47
6	Spring	7.69
3	atemp	4.91
11	Jan	4.62
10	Feb	3.53
8	Winter	3.43
7	Summer	3.37
13	Mar	2.27
9	Dec	2.22
4	hum	2.00
15	Nov	1.89
17	Mist	1.60
14	May	1.59
12	Jul	1.56
18	Snow/Rain	1.38
16	Sep	1.32
5	windspeed	1.18
19	Mon	1.05
20	Tue	1.05
1	yr	1.03
2	holiday	1.02

Observation

- Mar: High p-value, Low VIF
- Summer: High p-value, Low VIF
- Spring: Low p-value, High VIF

By Rule of thumb, we will remove Mar first becase VIF can decrease then

Dropping Mar (p-value=0.472)

In [128]:
```
X_train_rfe.head()
```

Out[128]:

	const	yr	holiday	atemp	hum	windspeed	Spring	Summer	Winter	Dec	...	Jan	Jul	Mar	May	Nov	Sep	Mist	Snow/Rain	Mon	Tue
62	1.0	0	0	0.231824	0.627678	0.431695	1	0	0	0	...	0	0	1	0	0	0	1	0	0	0
246	1.0	0	0	0.769676	0.763067	0.439141	0	0	0	0	...	0	0	0	0	0	1	0	0	0	1
132	1.0	0	0	0.545046	0.887746	0.375344	0	1	0	0	...	0	0	0	1	0	0	1	0	0	0
128	1.0	0	0	0.585667	0.605398	0.366457	0	1	0	0	...	0	0	0	1	0	0	0	0	0	0
248	1.0	0	0	0.572480	0.912038	0.767112	0	0	0	0	...	0	0	0	0	0	1	0	1	0	0

5 rows × 21 columns

In [129]:
```
X_train_rfe.shape
```

Out[129]:
```
(510, 21)
```

In [130]:
```
X_train_rfe.columns
```

Out[130]:
```
Index(['const', 'yr', 'holiday', 'atemp', 'hum', 'windspeed', 'Spring',
       'Summer', 'Winter', 'Dec', 'Feb', 'Jan', 'Jul', 'Mar', 'May', 'Nov',
       'Sep', 'Mist', 'Snow/Rain', 'Mon', 'Tue'],
      dtype='object')
```

In [131]:
```
# Dropping Mar and recreating model
X_train_rfe.drop("Mar", axis=1, inplace=True)
```

In [132]:
```
lm = sm.OLS(y_train, X_train_rfe ).fit()
```

In [133]:
```
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.849
Model:                            OLS   Adj. R-squared:                  0.843
Method:                 Least Squares   F-statistic:                     145.0
Date:                Mon, 08 Mar 2021   Prob (F-statistic):          3.69e-187
Time:                        07:39:48   Log-Likelihood:                -4099.0
No. Observations:                 510   AIC:                             8238.
Df Residuals:                     490   BIC:                             8323.
Df Model:                          19
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       3647.1208    313.680     11.627      0.000    3030.796    4263.445
yr          1998.1258     68.716     29.078      0.000    1863.112    2133.140
holiday     -703.9591    216.726     -3.248      0.001   -1129.786    -278.132
atemp       3368.0513    331.953     10.146      0.000    2715.825    4020.278
hum        -1398.4828    323.974     -4.317      0.000   -2035.033    -761.933
windspeed   -922.5299    199.231     -4.630      0.000   -1313.981    -531.078
Spring      -980.0432    187.126     -5.237      0.000   -1347.711    -612.375
Summer      -153.0886    141.428     -1.082      0.280    -430.969     124.791
Winter       626.3651    147.991      4.232      0.000     335.591     917.139
Dec         -644.9959    157.759     -4.088      0.000    -954.963    -335.029
Feb         -407.2488    185.590     -2.194      0.029    -771.900     -42.598
Jan         -606.2894    183.391     -3.306      0.001    -966.620    -245.959
Jul         -477.4191    151.880     -3.143      0.002    -775.836    -179.002
May          347.9598    143.915      2.418      0.016      65.193     630.727
Nov         -740.8981    170.142     -4.355      0.000   -1075.196    -406.600
Sep          340.4159    149.289      2.280      0.023      47.091     633.741
Mist        -462.1777     90.568     -5.103      0.000    -640.127    -284.229
Snow/Rain  -2093.6445    214.810     -9.746      0.000   -2515.707   -1671.582
Mon         -303.9781     98.671     -3.081      0.002    -497.849    -110.107
Tue         -308.2830    101.000     -3.052      0.002    -506.730    -109.836
==============================================================================
Omnibus:                       62.302   Durbin-Watson:                   1.975
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              140.047
Skew:                          -0.663   Prob(JB):                     3.88e-31
Kurtosis:                       5.198   Cond. No.                         21.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [134]:
```
vif = vif_cal(X_train_rfe)

vif
```

Out[134]:

	Features	VIF
0	const	86.02
6	Spring	5.81
3	atemp	4.47
8	Winter	3.43
7	Summer	3.34
11	Jan	2.60
10	Feb	2.08
4	hum	1.99
14	Nov	1.79
9	Dec	1.75
16	Mist	1.59
12	Jul	1.56
13	May	1.54
17	Snow/Rain	1.37
15	Sep	1.31
5	windspeed	1.18
18	Mon	1.04
19	Tue	1.04
1	yr	1.03
2	holiday	1.02

Observation

- Summer has High P-value, Low VIF
- Spring has Low P-value, high VIF

Dropping Summer (p-value=0.280)

In [135]:
```
# Dropping Mar and recreating model
X_train_rfe.drop("Summer", axis=1, inplace=True)

lm = sm.OLS(y_train, X_train_rfe).fit()
```

In [136]:
```
lm.summary()
```

Out[136]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.849
Model:	OLS	**Adj. R-squared:**	0.843
Method:	Least Squares	**F-statistic:**	152.9
Date:	Mon, 08 Mar 2021	**Prob (F-statistic):**	5.26e-188
Time:	07:39:48	**Log-Likelihood:**	-4099.6
No. Observations:	510	**AIC:**	8237.
Df Residuals:	491	**BIC:**	8318.
Df Model:	18		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	3485.9653	276.146	12.624	0.000	2943.391	4028.539
yr	1996.4443	68.710	29.056	0.000	1861.442	2131.447
holiday	-710.5062	216.680	-3.279	0.001	-1136.240	-284.773
atemp	3528.1336	297.241	11.870	0.000	2944.112	4112.155
hum	-1423.9599	323.175	-4.406	0.000	-2058.936	-788.984
windspeed	-938.9098	198.690	-4.726	0.000	-1329.297	-548.523
Spring	-865.4614	154.335	-5.608	0.000	-1168.700	-562.223
Winter	716.0827	122.624	5.840	0.000	475.149	957.016
Dec	-611.0538	154.638	-3.952	0.000	-914.888	-307.220
Feb	-382.5443	184.214	-2.077	0.038	-744.489	-20.600
Jan	-571.1530	180.527	-3.164	0.002	-925.855	-216.451
Jul	-425.4846	144.128	-2.952	0.003	-708.668	-142.301
May	278.3520	128.772	2.162	0.031	25.340	531.364
Nov	-708.1785	167.465	-4.229	0.000	-1037.215	-379.142
Sep	394.0927	140.837	2.798	0.005	117.375	670.810
Mist	-461.5510	90.582	-5.095	0.000	-639.526	-283.575
Snow/Rain	-2083.7453	214.653	-9.708	0.000	-2505.497	-1661.994
Mon	-302.1265	98.674	-3.062	0.002	-496.002	-108.251
Tue	-311.8281	100.965	-3.088	0.002	-510.204	-113.452

Omnibus:	62.009	**Durbin-Watson:**	1.981
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	138.914
Skew:	-0.661	**Prob(JB):**	6.84e-31
Kurtosis:	5.188	**Cond. No.**	19.0

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [137]:
```
vif = vif_cal(X_train_rfe)
```

In [138]:
```
vif
```

Out[138]:

	Features	VIF
0	const	66.65
6	Spring	3.95
3	atemp	3.58
10	Jan	2.52
7	Winter	2.35
9	Feb	2.05
4	hum	1.98
13	Nov	1.73
8	Dec	1.68
15	Mist	1.59
11	Jul	1.40
16	Snow/Rain	1.37
12	May	1.24
5	windspeed	1.18
14	Sep	1.17
17	Mon	1.04
18	Tue	1.04
1	yr	1.03
2	holiday	1.02

Observation:

- All columns are significant with p-value less than 0.05
- There is no problem of multicollinearity with predictor columns less than 5

Constant is significant. But has high VIF

- Conceptually it doesn't matter if we add or remove the constant from the VIF calculation.
- Overall it doesn't make a difference for the model, **because the constant is not a predictor.**
- A constant has irrational VIF values as it is not supposed to be calculated/factored.
- **Therefore, not dropping the constant.**
- Coeff of constant shows the demand when all columns are zero. ie:
  - year => 0---> "2018"
  - winter, spring, summer => 0 0 0 : "Fall"
  - Mist, Snow/Rain => 0 0: "Clear"
  - and so on...
  - Therefore, with all them zero, our model assumes that the demand will be 3485.9 ie 3486

In [139]:
```
lm.summary()
```

Out[139]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.849
Model:	OLS	**Adj. R-squared:**	0.843
Method:	Least Squares	**F-statistic:**	152.9
Date:	Mon, 08 Mar 2021	**Prob (F-statistic):**	5.26e-188
Time:	07:39:49	**Log-Likelihood:**	-4099.6
No. Observations:	510	**AIC:**	8237.
Df Residuals:	491	**BIC:**	8318.
Df Model:	18		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3485.9653	276.146	12.624	0.000	2943.391	4028.539
yr	1996.4443	68.710	29.056	0.000	1861.442	2131.447
holiday	-710.5062	216.680	-3.279	0.001	-1136.240	-284.773
atemp	3528.1336	297.241	11.870	0.000	2944.112	4112.155
hum	-1423.9599	323.175	-4.406	0.000	-2058.936	-788.984
windspeed	-938.9098	198.690	-4.726	0.000	-1329.297	-548.523
Spring	-865.4614	154.335	-5.608	0.000	-1168.700	-562.223
Winter	716.0827	122.624	5.840	0.000	475.149	957.016
Dec	-611.0538	154.638	-3.952	0.000	-914.888	-307.220
Feb	-382.5443	184.214	-2.077	0.038	-744.489	-20.600
Jan	-571.1530	180.527	-3.164	0.002	-925.855	-216.451
Jul	-425.4846	144.128	-2.952	0.003	-708.668	-142.301
May	278.3520	128.772	2.162	0.031	25.340	531.364
Nov	-708.1785	167.465	-4.229	0.000	-1037.215	-379.142
Sep	394.0927	140.837	2.798	0.005	117.375	670.810
Mist	-461.5510	90.582	-5.095	0.000	-639.526	-283.575
Snow/Rain	-2083.7453	214.653	-9.708	0.000	-2505.497	-1661.994
Mon	-302.1265	98.674	-3.062	0.002	-496.002	-108.251
Tue	-311.8281	100.965	-3.088	0.002	-510.204	-113.452

Omnibus:	62.009	**Durbin-Watson:**	1.981
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	138.914
Skew:	-0.661	**Prob(JB):**	6.84e-31
Kurtosis:	5.188	**Cond. No.**	19.0

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Observation

- **R-squared**: The model is able to explain 84.9% of variance in data.
- **Adj-R-squared**: The model is able to explain 84.3% of variance in data.
- **Prob (F-statistic**: Is very low, signifying that the model is overall statiscally significant
- **Important Features**: Temperature, Snow/Rain Conditions, and year are the top features based on coeff.

Residual Analysis

In [140]:
```
X_train_rfe.head()
```

Out[140]:

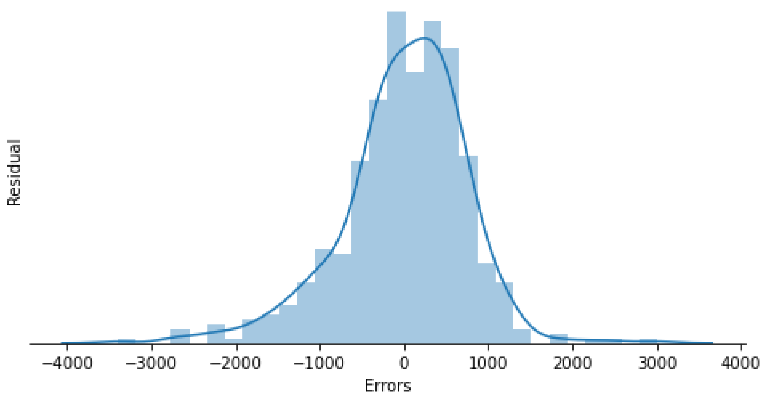
	const	yr	holiday	atemp	hum	windspeed	Spring	Winter	Dec	Feb	Jan	Jul	May	Nov	Sep	Mist	Snow/Rain	Mon	Tue
62	1.0	0	0	0.231824	0.627678	0.431695	1	0	0	0	0	0	0	0	0	1	0	0	0
246	1.0	0	0	0.769676	0.763067	0.439141	0	0	0	0	0	0	0	0	1	0	0	0	1
132	1.0	0	0	0.545046	0.887746	0.375344	0	0	0	0	0	0	1	0	0	1	0	0	0
128	1.0	0	0	0.585667	0.605398	0.366457	0	0	0	0	0	0	1	0	0	0	0	0	0
248	1.0	0	0	0.572480	0.912038	0.767112	0	0	0	0	0	0	0	0	1	0	1	0	0

In [141]:
```
y_train_pred = lm.predict(X_train_rfe)
```

In [142]:
```
residual = y_train - y_train_pred
```

Normal Distribution of errors

In [143]:
```
plt.figure(figsize=(8,4))
ax = sns.distplot(residual)


plt.ylabel('Residual')
plt.xlabel('Errors')
plt.yticks([])
sns.despine(left=True)

plt.show()
```

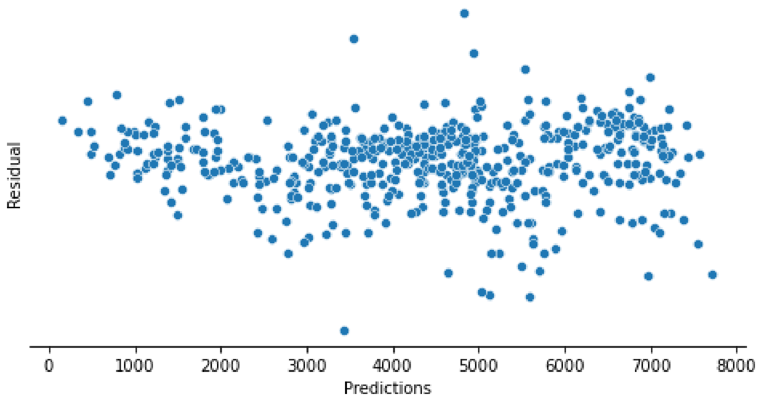


Observation:

- Errors are normally distributed
- Mean of error is qualitatively zero

Scatterplot of Predictions v/s Residuals

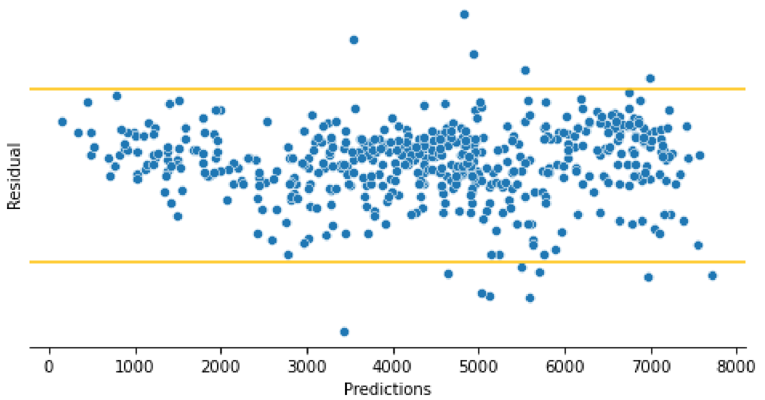
In [144]:
```
plt.figure(figsize=(8,4))
ax = sns.scatterplot(x=y_train_pred, y=residual)


plt.ylabel('Residual')
plt.xlabel('Predictions')
plt.yticks([])
# plt.xticks([])
sns.despine(left=True)

plt.show()
```



Observation:

- Error Terms have no pattern and therefore, are independent.
- Apart from few outliers, variance is consistent. Error terms equal variance.

In [145]:
```
plt.figure(figsize=(8,4))
ax = sns.scatterplot(x=y_train_pred, y=residual)

plt.axhline(y=1500, color='#FFBF00', linestyle='-')
plt.axhline(y=-2000, color='#FFBF00', linestyle='-')

plt.ylabel('Residual')
plt.xlabel('Predictions')
plt.yticks([])
# plt.xticks([])
sns.despine(left=True)

plt.show()
```



Observation:

- Apart from few outliers, variance is consistent. Error terms have equal variance.
- Since we did not perform outlier handling, we can expect few points to be outside our imaginary parallel lines but almost all data points do lie within the lines

Making Predictions

In [146]:
```
df.columns
```

Out[146]:
```
Index(['yr', 'holiday', 'atemp', 'hum', 'windspeed', 'cnt', 'Spring', 'Summer',
       'Winter', 'Aug', 'Dec', 'Feb', 'Jan', 'Jul', 'Jun', 'Mar', 'May', 'Nov',
       'Oct', 'Sep', 'Mist', 'Snow/Rain', 'Mon', 'Sat', 'Sun', 'Thu', 'Tue',
       'Wed'],
      dtype='object')
```

In [147]:
```
df.head(2)
```

Out[147]:

	yr	holiday	atemp	hum	windspeed	cnt	Spring	Summer	Winter	Aug	...	Oct	Sep	Mist	Snow/Rain	Mon	Sat	Sun	Thu	Tue	Wed
0	0	0	18.18125	80.5833	10.749882	985	1	0	0	0	...	0	0	1	0	1	0	0	0	0	0
1	0	0	17.68695	69.6087	16.652113	801	1	0	0	0	...	0	0	1	0	0	0	0	0	1	0

2 rows × 28 columns

In [148]:
```
const_var = ["atemp", "hum", "windspeed"]
```

In [149]:
```
df_test[const_var] = scaler.transform(df_test[const_var])
```

Dividing into Testing DataFrame into X and Y

In [150]:
```
y_test = df_test.pop("cnt")
X_test = df_test
```

Making Predictions with our model

In [151]:
```
X_train_rfe.columns
```

Out[151]:
```
Index(['const', 'yr', 'holiday', 'atemp', 'hum', 'windspeed', 'Spring',
       'Winter', 'Dec', 'Feb', 'Jan', 'Jul', 'May', 'Nov', 'Sep', 'Mist',
       'Snow/Rain', 'Mon', 'Tue'],
      dtype='object')
```

In [152]:
```
# since constant term is added by us, it is not present in X_Test
X_train_rfe.columns[1:]
```

Out[152]:
```
Index(['yr', 'holiday', 'atemp', 'hum', 'windspeed', 'Spring', 'Winter', 'Dec',
       'Feb', 'Jan', 'Jul', 'May', 'Nov', 'Sep', 'Mist', 'Snow/Rain', 'Mon',
       'Tue'],
      dtype='object')
```

In [153]:
```
X_test = X_test[X_train_rfe.columns[1:]]
```

In [154]:
```
X_test = sm.add_constant(X_test)
```

In [155]:
```
X_test.head(1)
```

Out[155]:

	const	yr	holiday	atemp	hum	windspeed	Spring	Winter	Dec	Feb	Jan	Jul	May	Nov	Sep	Mist	Snow/Rain	Mon	Tue
61	1.0	0	0	0.158912	0.327335	0.485153	1	0	0	0	0	0	0	0	0	0	0	0	0

In [156]:
```
y_test_pred = lm.predict(X_test)
```

Model Evaluation

In [157]:
```
from sklearn.metrics import r2_score
```

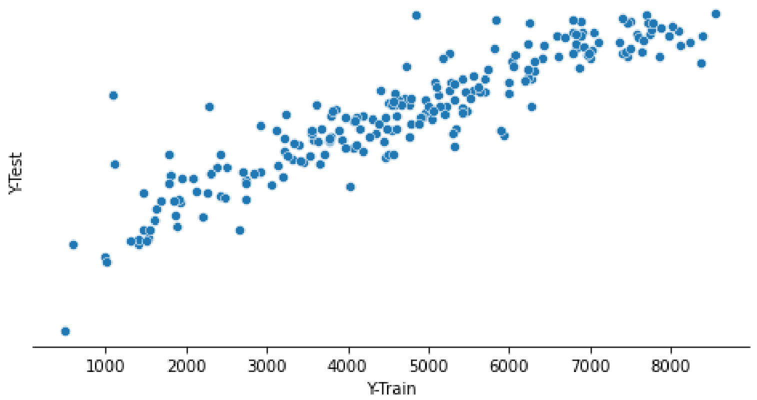
In [158]:
```
r2_score(y_true = y_test, y_pred = y_test_pred)
```

Out[158]:
```
0.8317417208092988
```

Observation:

- We got 84.9% in Training Dataset
- We got 83.1% in Testing Dataste
- (84.9-83.1)/(84.9) * 100 = 2.1%
- Therefore, difference between R2 score of train and test dataset is less than 5%

In [159]:
```
plt.figure(figsize=(8,4))
sns.scatterplot(x=y_test, y=y_test_pred)


plt.ylabel('Y-Test')
plt.xlabel('Y-Train')
plt.yticks([])
# plt.xticks([])
sns.despine(left=True)

plt.show()
```



Observation:

- Strong correlation

Analysing R-Squared and Adjusted R-Squared

R-Squared

In [160]:
```
#Test Set
r2_score(y_true = y_test, y_pred = y_test_pred)
```

Out[160]: 0.8317417208092988

In [161]:
```
# Training Set
r2_score(y_true = y_train, y_pred = y_train_pred)
```

Out[161]: 0.8486139204011544

Observation:

- **R-squared Train DataSet**: The model is able to explain 84% of variance in data.
- **R-squared Test DataSet**: The model is able to explain 83% of variance in data.

Adjusted R-Squared

In [162]:
```
# Adj. RSquared for Train
1-(1-r2_score(y_train, y_train_pred))*((len(X_train)-1)/(len(X_train)-len(X_train.columns)-1))
```

Out[162]: 0.8401337873115925

In [163]:
```
# Adj. RSquared for Test
1-(1-r2_score(y_test, y_test_pred))*((len(X_test)-1)/(len(X_test)-len(X_test.columns)-1))
```

Out[163]: 0.8156768599820459

Observation:

- **Adj-R-squared Train DataSet**: The model is able to explain 84% of variance in data.
- **Adj-R-squared Test DataSet**: The model is able to explain 81% of variance in data.

Final Model

In [164]:
```
lm.summary()
```

Sep	394.0927	140.837	2.798	0.005	117.375	670.810
Mist	-461.5510	90.582	-5.095	0.000	-639.526	-283.575
Snow/Rain	-2083.7453	214.653	-9.708	0.000	-2505.497	-1661.994
Mon	-302.1265	98.674	-3.062	0.002	-496.002	-108.251
Tue	-311.8281	100.965	-3.088	0.002	-510.204	-113.452

Omnibus:	62.009	**Durbin-Watson:**	1.981
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	138.914
Skew:	-0.661	**Prob(JB):**	6.84e-31
Kurtosis:	5.188	**Cond. No.**	19.0

Coefficients are rounded for presentation purpose

Demand = 3486 + (yr x 1996) - (holiday x 710) + (atemp x 3528) - (hum x 1424) - (windspeed x 939) - (Spring x 864) + (winter x 716) - (Dec x 611) - (Feb x 382) - (Jan x 571) - (Jul x 425) + (May x 278) - (Nov x 708) + (Sep x 394) - (Mist x 461) - (Snow/Rain x 2083) - (Mon x 302)

In [ ]: