Project Title : Seoul Bike Sharing Demand Prediction

Problem Description

Currently Rental bikes are introduced in many urban cities for the enhancement of mobility comfort. It is important to make the rental bike available and accessible to the public at the right time as it lessens the waiting time. Eventually, providing the city with a stable supply of rental bikes becomes a major concern. The crucial part is the prediction of bike count required at each hour for the stable supply of rental bikes.

Data Description

The dataset contains weather information (Temperature, Humidity, Windspeed, Visibility, Dewpoint, Solar radiation, Snowfall, Rainfall), the number of bikes rented per hour and date information.

Features Information:

Date : year-month-day

Rented Bike count - Count of bikes rented at each hour

Hour - Hour of he day

Temperature-Temperature in Celsius

Humidity - %

Windspeed - m/s

Visibility - 10m

Dew point temperature - Celsius

Solar radiation - MJ/m2

Rainfall - mm

Snowfall - cm

Seasons - Winter, Spring, Summer, Autumn

Holiday - Holiday/No holiday

Functional Day - NoFunc(Non Functional Hours), Fun(Functional hours)

Data Prepration

Importing Libraries and dataset

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn.feature_selection import RFE
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LinearRegression
import scipy.stats as stats
from sklearn.model_selection import train_test_split, GridSearchCV,  cross_val_score
from sklearn import preprocessing, linear_model
from sklearn.preprocessing import  LabelEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from sklearn.metrics import r2_score, mean_squared_error, accuracy_score

import warnings
warnings.filterwarnings('ignore')
pd.pandas.set_option('display.max_columns',None)
%matplotlib inline
warnings.filterwarnings("ignore")
#imported different libraries where we will be working with.
```

In [2]:
```
# importing and reading the csv file
df=pd.read_csv("SeoulBikeData.csv",encoding= 'unicode_escape')
```

In [3]:
```
# Checking shape pf dataframe
df.shape
```

Out[3]: (8760, 14)

In [4]:
```
#Check all the coloumns present in our dataset
df.columns
```

Out[4]:
```
Index(['Date', 'Rented Bike Count', 'Hour', 'Temperature(°C)', 'Humidity(%)',
       'Wind speed (m/s)', 'Visibility (10m)', 'Dew point temperature(°C)',
       'Solar Radiation (MJ/m2)', 'Rainfall(mm)', 'Snowfall (cm)', 'Seasons',
       'Holiday', 'Functioning Day'],
      dtype='object')
```

In [5]:
```
# Renaming Columns for ease of usage
df.rename(columns={'Date': 'date', 'Rented Bike Count': 'bike_count', 'Hour': 'hour',
                   'Temperature(°C)': 'temp', 'Humidity(%)': 'humidity', 'Wind speed (m/s)': 'wind',
                   'Visibility (10m)': 'visibility', 'Dew point temperature(°C)': 'dew_temp',
                   'Solar Radiation (MJ/m2)': 'solar_rad', 'Rainfall(mm)': 'rain', 'Snowfall (cm)': 'snow',
                   'Seasons': 'season', 'Holiday': 'holiday', 'Functioning Day': 'functioning_day'}, inplace=Tru
```

In [6]:
```
# Checking top 5 records in dataframe
df.head()
```

Out[6]:

	date	bike_count	hour	temp	humidity	wind	visibility	dew_temp	solar_rad	rain	snow	season	holiday	functioning_day
0	01/12/2017	254	0	-5.2	37	2.2	2000	-17.6	0.0	0.0	0.0	Winter	No Holiday	Yes
1	01/12/2017	204	1	-5.5	38	0.8	2000	-17.6	0.0	0.0	0.0	Winter	No Holiday	Yes
2	01/12/2017	173	2	-6.0	39	1.0	2000	-17.7	0.0	0.0	0.0	Winter	No Holiday	Yes
3	01/12/2017	107	3	-6.2	40	0.9	2000	-17.6	0.0	0.0	0.0	Winter	No Holiday	Yes
4	01/12/2017	78	4	-6.0	36	2.3	2000	-18.6	0.0	0.0	0.0	Winter	No Holiday	Yes

In [7]:
```
# Checking bottom 5 records in dataframe
df.tail()
```

Out[7]:

	date	bike_count	hour	temp	humidity	wind	visibility	dew_temp	solar_rad	rain	snow	season	holiday	functioning_day
8755	30/11/2018	1003	19	4.2	34	2.6	1894	-10.3	0.0	0.0	0.0	Autumn	No Holiday	Yes
8756	30/11/2018	764	20	3.4	37	2.3	2000	-9.9	0.0	0.0	0.0	Autumn	No Holiday	Yes
8757	30/11/2018	694	21	2.6	39	0.3	1968	-9.9	0.0	0.0	0.0	Autumn	No Holiday	Yes
8758	30/11/2018	712	22	2.1	41	1.0	1859	-9.8	0.0	0.0	0.0	Autumn	No Holiday	Yes
8759	30/11/2018	584	23	1.9	43	1.3	1909	-9.3	0.0	0.0	0.0	Autumn	No Holiday	Yes

In [8]:
```
# checking the shape and type of the columns
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8760 entries, 0 to 8759
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   date             8760 non-null   object 
 1   bike_count       8760 non-null   int64  
 2   hour             8760 non-null   int64  
 3   temp             8760 non-null   float64
 4   humidity         8760 non-null   int64  
 5   wind             8760 non-null   float64
 6   visibility       8760 non-null   int64  
 7   dew_temp         8760 non-null   float64
 8   solar_rad        8760 non-null   float64
 9   rain             8760 non-null   float64
 10  snow             8760 non-null   float64
 11  season           8760 non-null   object 
 12  holiday          8760 non-null   object 
 13  functioning_day  8760 non-null   object 
dtypes: float64(6), int64(4), object(4)
memory usage: 958.2+ KB
```

In [9]:
```
# describing the dataset
df.describe(percentiles=[.01,.25,.5,.75,.99]).transpose()
```

Out[9]:

	count	mean	std	min	1%	25%	50%	75%	99%	max
bike_count	8760.0	704.602055	644.997468	0.0	0.000	191.00	504.50	1065.25	2526.23	3556.00
hour	8760.0	11.500000	6.922582	0.0	0.000	5.75	11.50	17.25	23.00	23.00
temp	8760.0	12.882922	11.944825	-17.8	-12.741	3.50	13.70	22.50	35.10	39.40
humidity	8760.0	58.226256	20.362413	0.0	17.000	42.00	57.00	74.00	97.00	98.00
wind	8760.0	1.724909	1.036300	0.0	0.100	0.90	1.50	2.30	4.70	7.40
visibility	8760.0	1436.825799	608.298712	27.0	173.000	940.00	1698.00	2000.00	2000.00	2000.00
dew_temp	8760.0	4.073813	13.060369	-30.6	-24.800	-4.70	5.10	14.80	24.70	27.20
solar_rad	8760.0	0.569111	0.868746	0.0	0.000	0.00	0.01	0.93	3.17	3.52
rain	8760.0	0.148687	1.128193	0.0	0.000	0.00	0.00	0.00	4.00	35.00
snow	8760.0	0.075068	0.436746	0.0	0.000	0.00	0.00	0.00	2.50	8.80

In [10]:
```
df.head(2).sort_values('date',ascending=True)
#Data is for the bikes rented between Dec 2017 and Dec 2018, one year data.

#The data is from Dec'17 to Nov'18 for a yea, 365 days
```

Out[10]:

	date	bike_count	hour	temp	humidity	wind	visibility	dew_temp	solar_rad	rain	snow	season	holiday	functioning_day
0	01/12/2017	254	0	-5.2	37	2.2	2000	-17.6	0.0	0.0	0.0	Winter	No Holiday	Yes
1	01/12/2017	204	1	-5.5	38	0.8	2000	-17.6	0.0	0.0	0.0	Winter	No Holiday	Yes

In [11]:
```
# finding unique values in the dataset
df.nunique().sort_values(ascending=True)
```

Out[11]:
```
holiday              2
functioning_day      2
season               4
hour                24
snow                51
rain                61
wind                65
humidity            90
solar_rad          345
date               365
temp               546
dew_temp           556
visibility        1789
bike_count        2166
dtype: int64
```

Insights from the dataset:

There are 14 features with 8760 rows of data.

There are 3 categorical columns, a date column (object type) and 10 numerical columns.

Object Columns: ‘Date’, ‘Seasons’ , 'Holiday' and ‘Functioning Day’ are of $object$ data type

Numerical Columns :
‘Rented Bike Count’, ‘Hour’, ‘Humidity (%)' and ‘Visibility (10m)' are of $int64$ numerical data type.

‘Temperature (°C)’, ‘Wind Speed (m/s)’, ‘Dew Point Temperature (°C)’,‘Solar Radiation ($MJ/m2$)’,‘Rainfall (mm)' and ‘Snowfall(cm) are of $float64$ numerical data type.

Unique count for categorcial columns : Seasons- 4 Holiday- 2 Functioning Day- 2

Checking for any Null Values and Duplicates

In [12]:
```
# Missing data counts
df.isnull().sum()
```

Out[12]:
```
date               0
bike_count         0
hour               0
temp               0
humidity           0
wind               0
visibility         0
dew_temp           0
solar_rad          0
rain               0
snow               0
season             0
holiday            0
functioning_day    0
dtype: int64
```

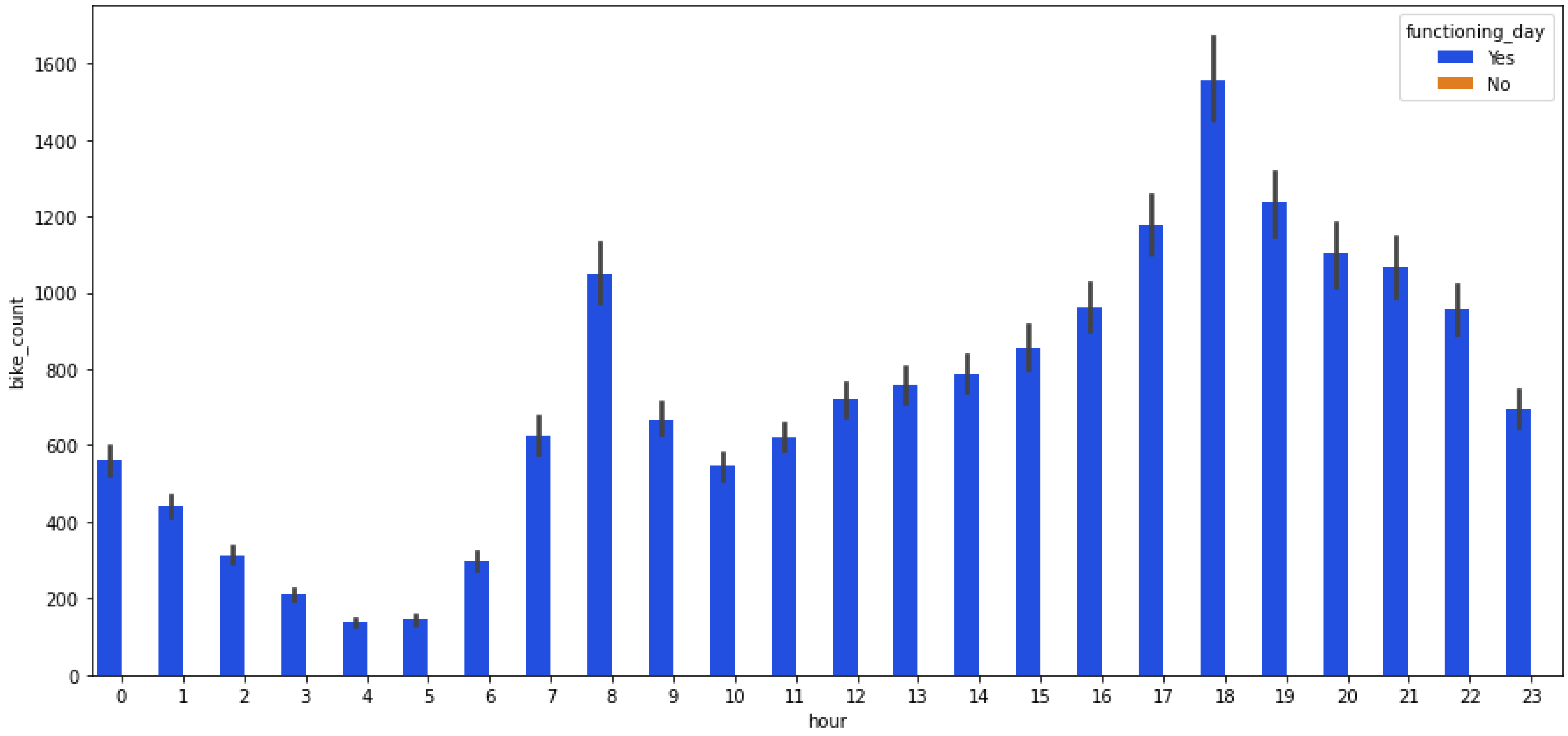
In [13]:
```
# Check for duplicated entries.
print("Duplicate entry in data:",len(df[df.duplicated()]))
```

```
Duplicate entry in data: 0
```

The ranges of values in the numerical columns seem reasonable too, so we may not have to do much data cleaning. The "Wind speed","Dew point temperature(°C)", "Solar Radiation", "Rainfall" and "Snowfall" column seems to be significantly skewed however, as the median (50 percentile) is much lower than the maximum value.

Data Filtering Rented Bike days Filtering

In [14]:
```
#for chech functioning and non functioning day ,plot (Hour Vs Rented Bike Count Graph)
def barplots(x,y,hue):
    plt.figure(figsize=(15,7))
    sns.set_palette('bright')
    sns.barplot(x=x,y=y,hue=hue,data=df);
barplots('hour','bike_count','functioning_day')
```



In [15]:
```
# Grouping by functioning day and calculating the total Rented Bike Count
df.groupby('functioning_day').sum()['bike_count'].sort_values(ascending = False).reset_index()
```

Out[15]:

	functioning_day	bike_count
0	Yes	6172314
1	No	0

As per diagnosis data found that rental bike only given on Functioning Day. So we can remove data for Non-Functioning Days and remove Functioning Day Column too.

In [16]:
```
#Removing data of non functional days (non rented days)
df=df.drop(df[df['functioning_day'] == 'No'].index)
```

In [17]:
```
#Due to not unsefull in Functioning Day Column ,remove Functioning Day Column
df=df.drop(['functioning_day'], axis = 1)
```

In [18]:
```
#Checking DataFrame Shape After Removing Non Functional Day Rows And Functional Day Column
print("Filtered Dataframe with only rented bike days :",df.shape,"\n")
```

```
Filtered Dataframe with only rented bike days : (8465, 13)
```

In [19]:
```
df1=df.copy()
```

In [20]:
```
df1.shape
```

Out[20]:
```
(8465, 13)
```

Cleaning and manipulating the data

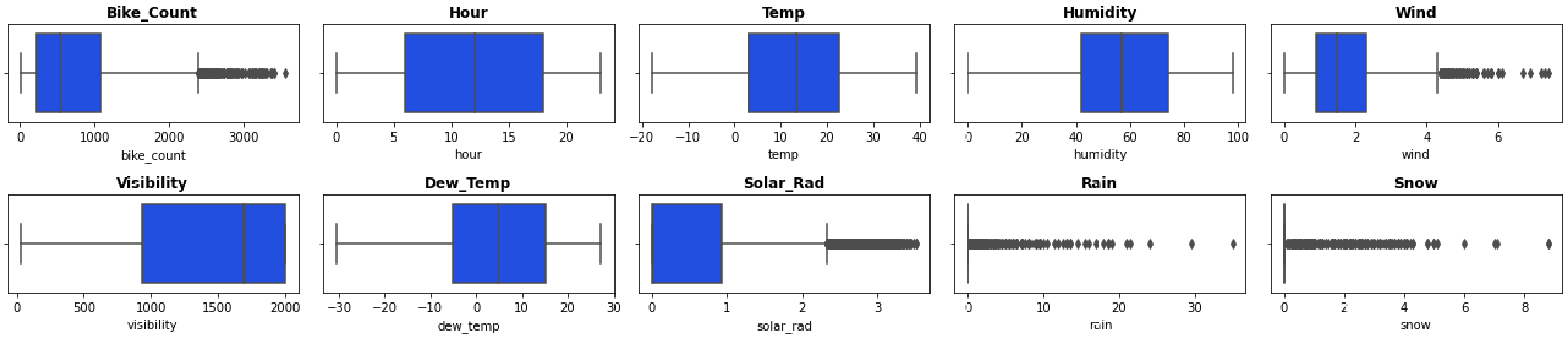
In [21]:
```
# Extracting new features from date and hour column
df1['date'] = pd.to_datetime(df1['date'])
df1['weekend'] = df1['date'].apply(lambda x : 1 if (x.day_name()=='Saturday' or x.day_name()=='Sunday') else 0
df1['timeshift'] = df1['hour'].apply(lambda x: 'Night' if 0<=x<=6 else ('Day' if 7<=x<=16 else 'Evening'))
```

In [22]:
```
df1['day']=df1['date'].dt.day
df1['month']=df1['date'].dt.month
```

In [23]:
```
# Dropping the Date column
df1.drop(columns=['date'], inplace = True)
```

Removing Outliers

In [24]:
```
# Checking for outliers
plt.figure(figsize=(18,4))
for n,column in enumerate(df.describe().columns):
  plt.subplot(2, 5, n+1)
  sns.boxplot(df[column])
  plt.title(f'{column.title()}',weight='bold')
  plt.tight_layout()
```

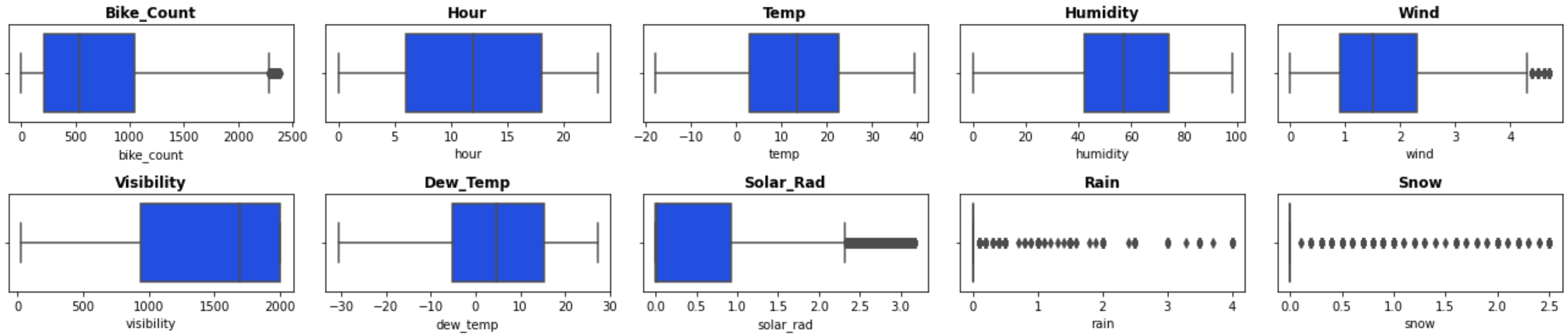


In [25]:

```
# Removing outliers by Using IQR method:
q1, q3, median = df1.bike_count.quantile([0.25,0.75,0.5])
lower_limit = q1 - 1.5*(q3-q1)
upper_limit = q3 + 1.5*(q3-q1)
df1['bike_count'] = np.where(df1['bike_count'] > upper_limit, median,
                    np.where(df1['bike_count'] < lower_limit,median,
                    df1['bike_count']))

# Removing outliers by Capping:
for col in ['wind','solar_rad','rain','snow']:
  upper_limit = df1[col].quantile(0.99)
  df1[col] = np.where(df1[col] > upper_limit, upper_limit, df1[col])
```

In [26]:
```
# Checking for outliers
plt.figure(figsize=(18,4))
for n,column in enumerate(df1.describe().columns):
  plt.subplot(2, 5, n+1)
  sns.boxplot(df1[column])
  plt.title(f'{column.title()}',weight='bold')
  plt.tight_layout()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Input In [26], in <cell line: 3>()
      2 plt.figure(figsize=(18,4))
      3 for n,column in enumerate(df1.describe().columns):
----> 4   plt.subplot(2, 5, n+1)
      5   sns.boxplot(df1[column])
      6   plt.title(f'{column.title()}',weight='bold')

File ~/opt/anaconda3/lib/python3.9/site-packages/matplotlib/pyplot.py:1268, in subplot(*args, **kwargs)
   1265 fig = gcf()
   1267 # First, search for an existing subplot with a matching spec.
-> 1268 key = SubplotSpec._from_subplot_args(fig, args)
   1270 for ax in fig.axes:
   1271     # if we found an axes at the position sort out if we can re-use it
   1272     if hasattr(ax, 'get_subplotspec') and ax.get_subplotspec() == key:
   1273         # if the user passed no kwargs, re-use

File ~/opt/anaconda3/lib/python3.9/site-packages/matplotlib/gridspec.py:608, in SubplotSpec._from_subplot_arg
s(figure, args)
    606 else:
    607     if not isinstance(num, Integral) or num < 1 or num > rows*cols:
--> 608         raise ValueError(
    609             f"num must be 1 <= num <= {rows*cols}, not {num!r}")
    610     i = j = num
    611 return gs[i-1:j]

ValueError: num must be 1 <= num <= 10, not 11
```



In [27]:
```
df1.describe(percentiles=[.01,.25,.5,.75,.99]).transpose()
```

Out[27]:

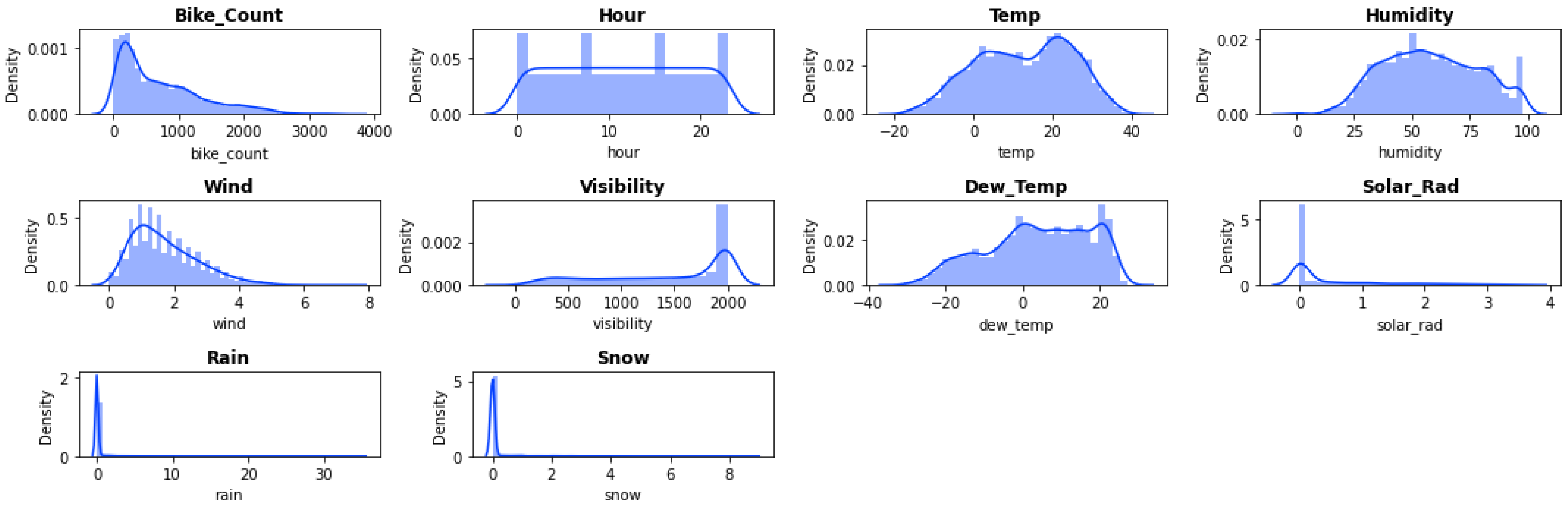
	count	mean	std	min	1%	25%	50%	75%	99%	max
bike_count	8465.0	690.201772	582.680316	2.0	17.000	214.0	542.00	1041.00	2274.720	2387.00
hour	8465.0	11.507029	6.920899	0.0	0.000	6.0	12.00	18.00	23.000	23.00
temp	8465.0	12.771057	12.104375	-17.8	-12.936	3.0	13.50	22.70	35.200	39.40
humidity	8465.0	58.147194	20.484839	0.0	17.000	42.0	57.00	74.00	97.000	98.00
wind	8465.0	1.720992	1.017240	0.0	0.100	0.9	1.50	2.30	4.700	4.70
visibility	8465.0	1433.873479	609.051229	27.0	172.640	935.0	1690.00	2000.00	2000.000	2000.00
dew_temp	8465.0	3.944997	13.242399	-30.6	-24.936	-5.1	4.70	15.20	24.736	27.20
solar_rad	8465.0	0.566737	0.864732	0.0	0.000	0.0	0.01	0.93	3.170	3.17
rain	8465.0	0.098145	0.514504	0.0	0.000	0.0	0.00	0.00	4.000	4.00
snow	8465.0	0.066533	0.340734	0.0	0.000	0.0	0.00	0.00	2.500	2.50
weekend	8465.0	0.288364	0.453028	0.0	0.000	0.0	0.00	1.00	1.000	1.00
day	8465.0	15.786651	8.821231	1.0	1.000	8.0	16.00	23.00	31.000	31.00
month	8465.0	6.493325	3.463349	1.0	1.000	4.0	6.00	10.00	12.000	12.00

Exploratory Analysis and Visualization

Let's explore the data by visualizing the distribution of values in some columns of the dataset, and the relationships between "Rented Bike count" and other columns.

We'll use libraries Matplotlib, Seaborn for visualization.

In [28]:
```
# Visualizing the distributions.
plt.figure(figsize=(15,5))
for n,column in enumerate(df.describe().columns):
  plt.subplot(3, 4, n+1)
  sns.distplot(df[column])
  plt.title(f'{column.title()}',weight='bold')
  plt.tight_layout()
```



In [29]:
```
# Lets take care of the categorical features
categorical_features = [i for i in df1.columns if i not in df1.describe().columns]
categorical_features
```

Out[29]:
```
['season', 'holiday', 'timeshift']
```

In [30]:
```
# Checking unique value with their counts in categorical features
for col in categorical_features:
  print(df1[col].value_counts(),'\n')
```

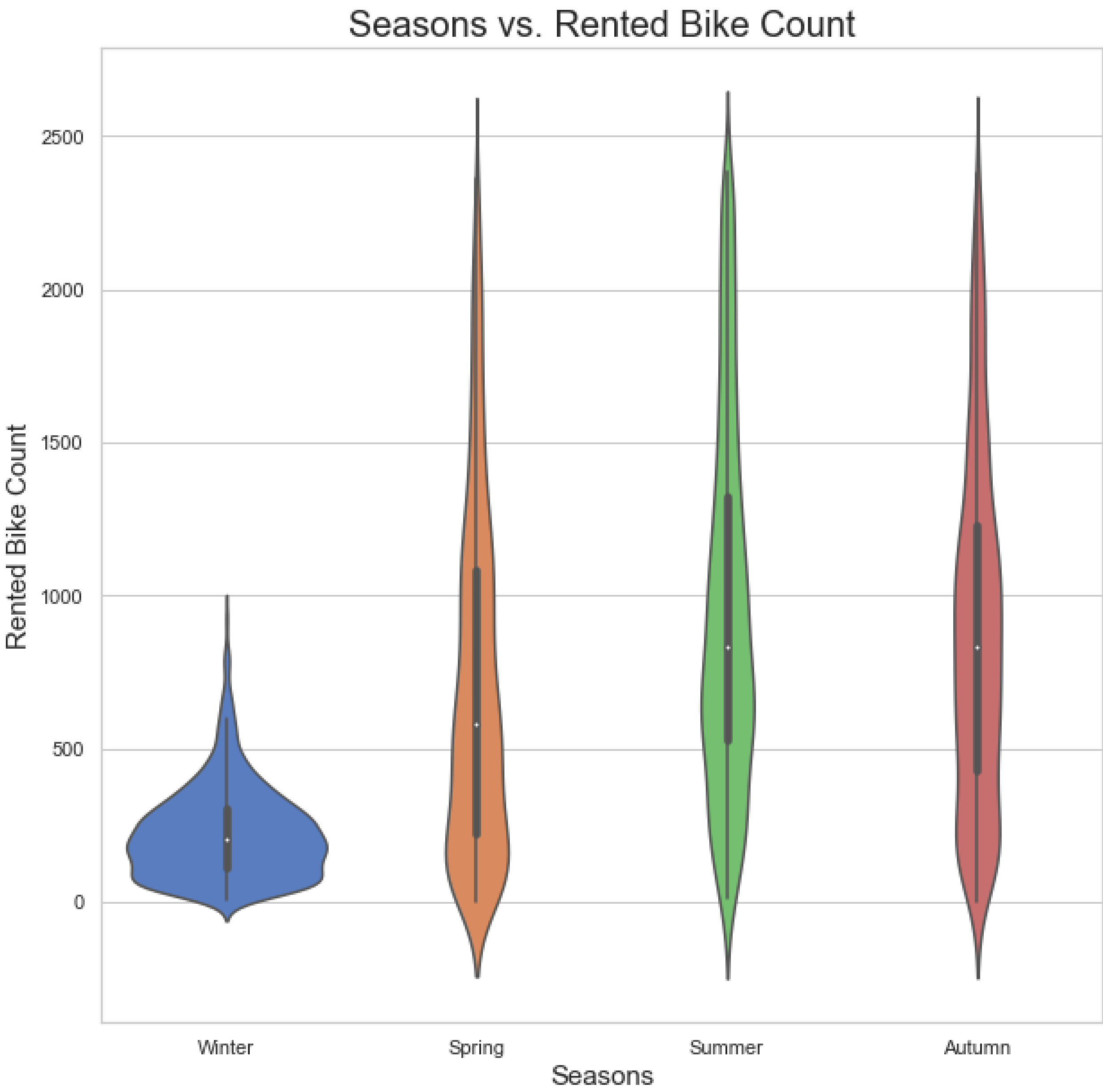
```
Summer    2208
Winter    2160
Spring    2160
Autumn    1937
Name: season, dtype: int64

No Holiday    8057
Holiday        408
Name: holiday, dtype: int64

Day        3530
Evening    2471
Night      2464
Name: timeshift, dtype: int64
```

In [31]:
```
# GROUPING BY SEASONS AND CALCULATING THE TOTAL RENTED BIKE COUNT
pd.options.display.float_format = '{:,.1f}'.format
df1.groupby('season').sum()['bike_count'].sort_values(ascending = False).reset_index()
```

Out[31]:

	season	bike_count
0	Summer	2,098,149.0
1	Autumn	1,713,936.0
2	Spring	1,543,304.0
3	Winter	487,169.0

In [32]:
```
plt.figure(figsize=(10,10))
sns.set(style="whitegrid", palette="muted", color_codes=True)
sns.violinplot(x = 'season', y = 'bike_count', data=df1)
plt.title('Seasons vs. Rented Bike Count', fontsize=20)
plt.xlabel('Seasons', fontsize=15)
plt.ylabel('Rented Bike Count', fontsize=15)
plt.show()
```


Seasons vs. Rented Bike Count
Rented Bike Count
2500
2000
1500
1000
500
0
Winter
Spring
Summer
Autumn
Seasons

In [33]:
```
# GROUPING BY HOLIDAY AND CALCULATING THE TOTAL RENTED BIKE COUNT
df1.groupby('holiday').sum()['bike_count'].sort_values(ascending = False).reset_index()
```

Out[33]:

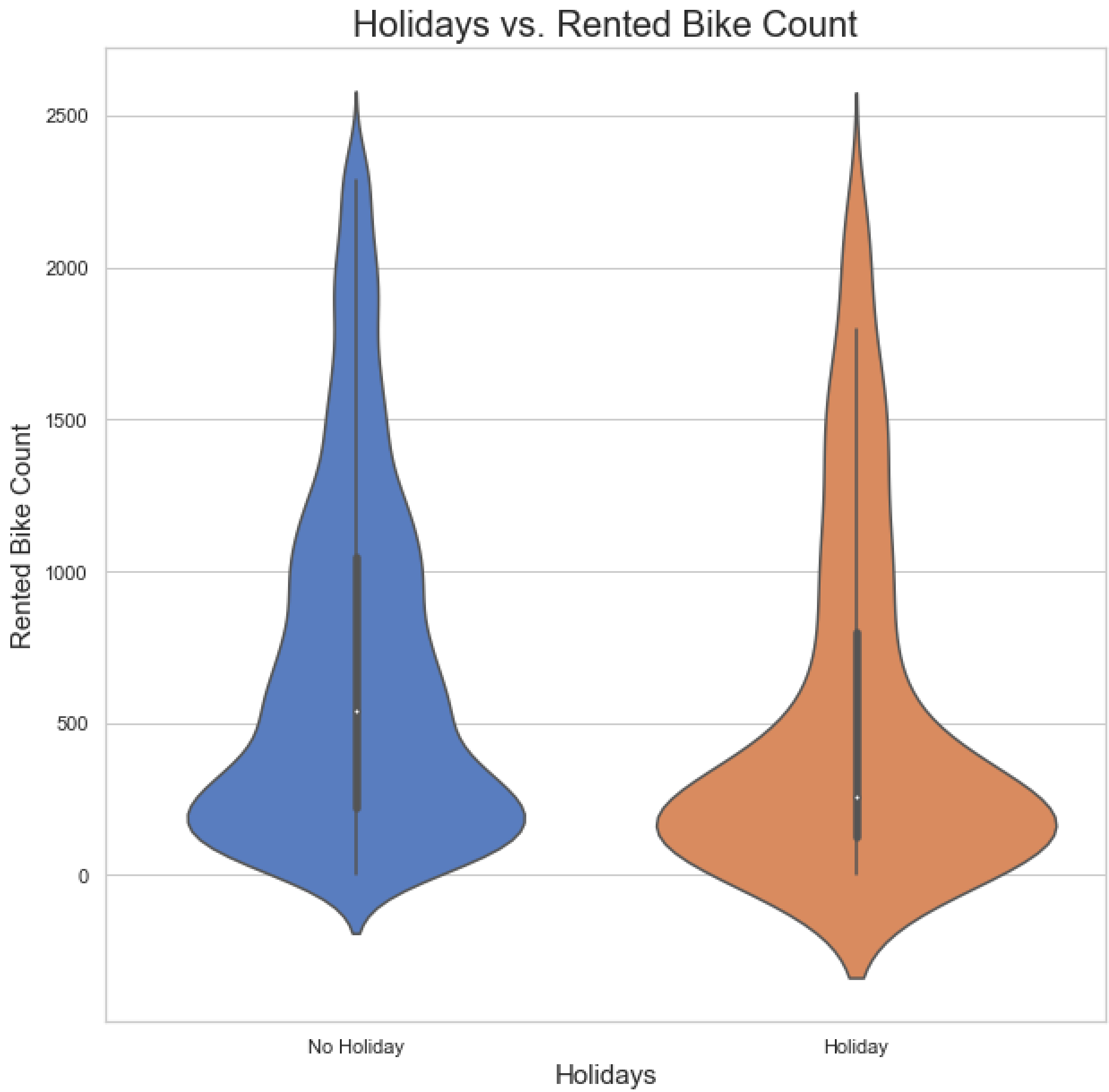
	holiday	bike_count
0	No Holiday	5,628,521.0
1	Holiday	214,037.0

In [34]:
```
# GROUPING BY HOLIDAY AND CALCULATING THE TOTAL RENTED BIKE COUNT
df1.groupby('holiday').sum()
```

Out[34]:

	bike_count	hour	temp	humidity	wind	visibility	dew_temp	solar_rad	rain	snow	weekend	day	month
holiday													
Holiday	214,037.0	4692	3,938.3	21949	760.4	609544	-14.0	228.6	25.8	22.0	120	6816	2544
No Holiday	5,628,521.0	92715	104,168.7	470267	13,807.8	11528195	33,408.4	4,568.9	805.0	541.2	2321	126818	52422

In [35]:
```
plt.figure(figsize=(10,10))
sns.set(style="whitegrid", palette="muted", color_codes=True)
sns.violinplot(x = 'holiday', y = 'bike_count', data=df1)
plt.title('Holidays vs. Rented Bike Count', fontsize=20)
plt.xlabel('Holidays', fontsize=15)
plt.ylabel('Rented Bike Count', fontsize=15)
plt.show()
```

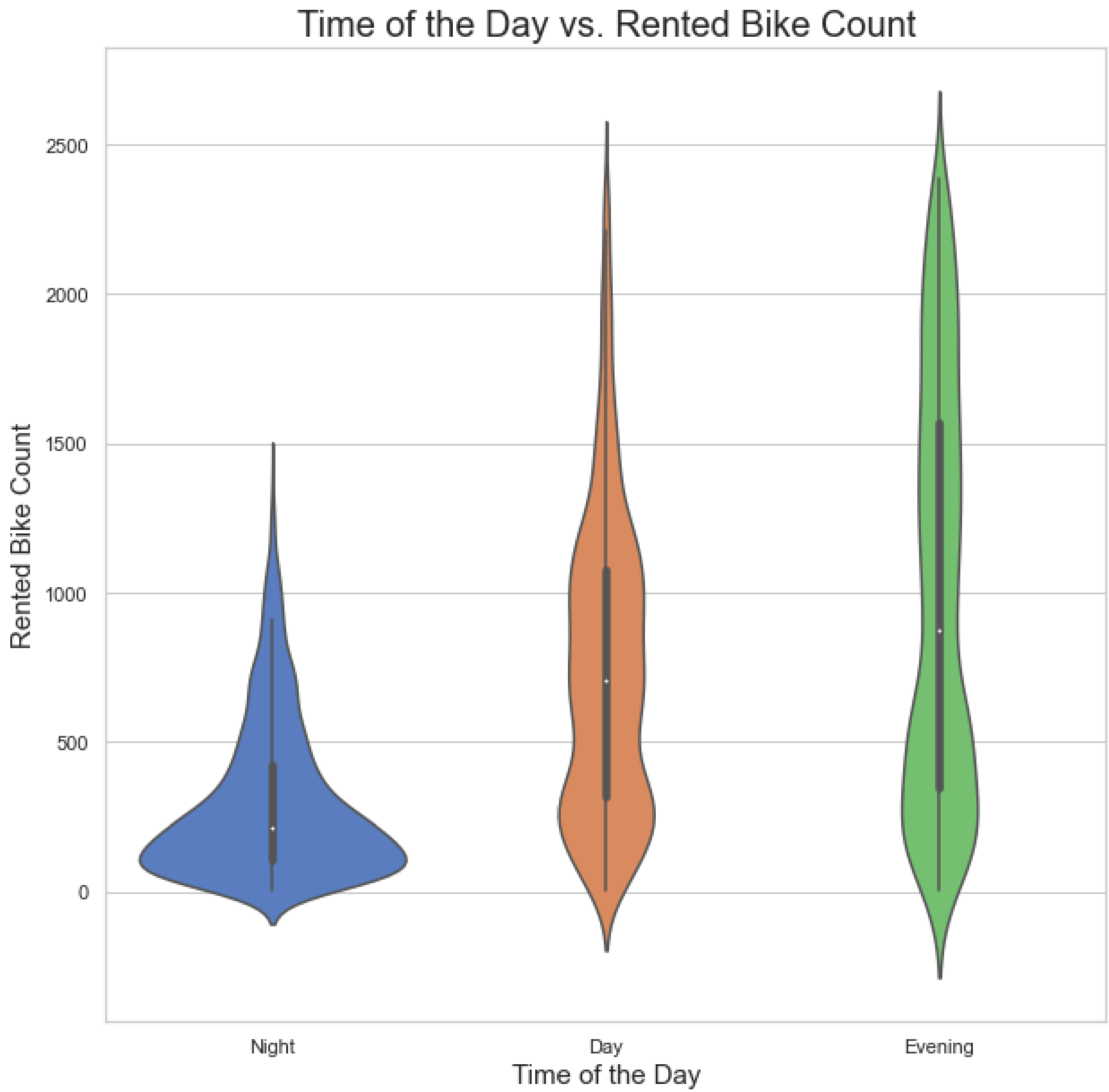

Holidays vs. Rented Bike Count
Rented Bike Count
2500
2000
1500
1000
500
0
No Holiday
Holiday
Holidays

In [36]:
```
# GROUPING BY HOLIDAY AND CALCULATING THE TOTAL RENTED BIKE COUNT
df1.groupby('timeshift').sum()['bike_count'].sort_values(ascending = False).reset_index()
```

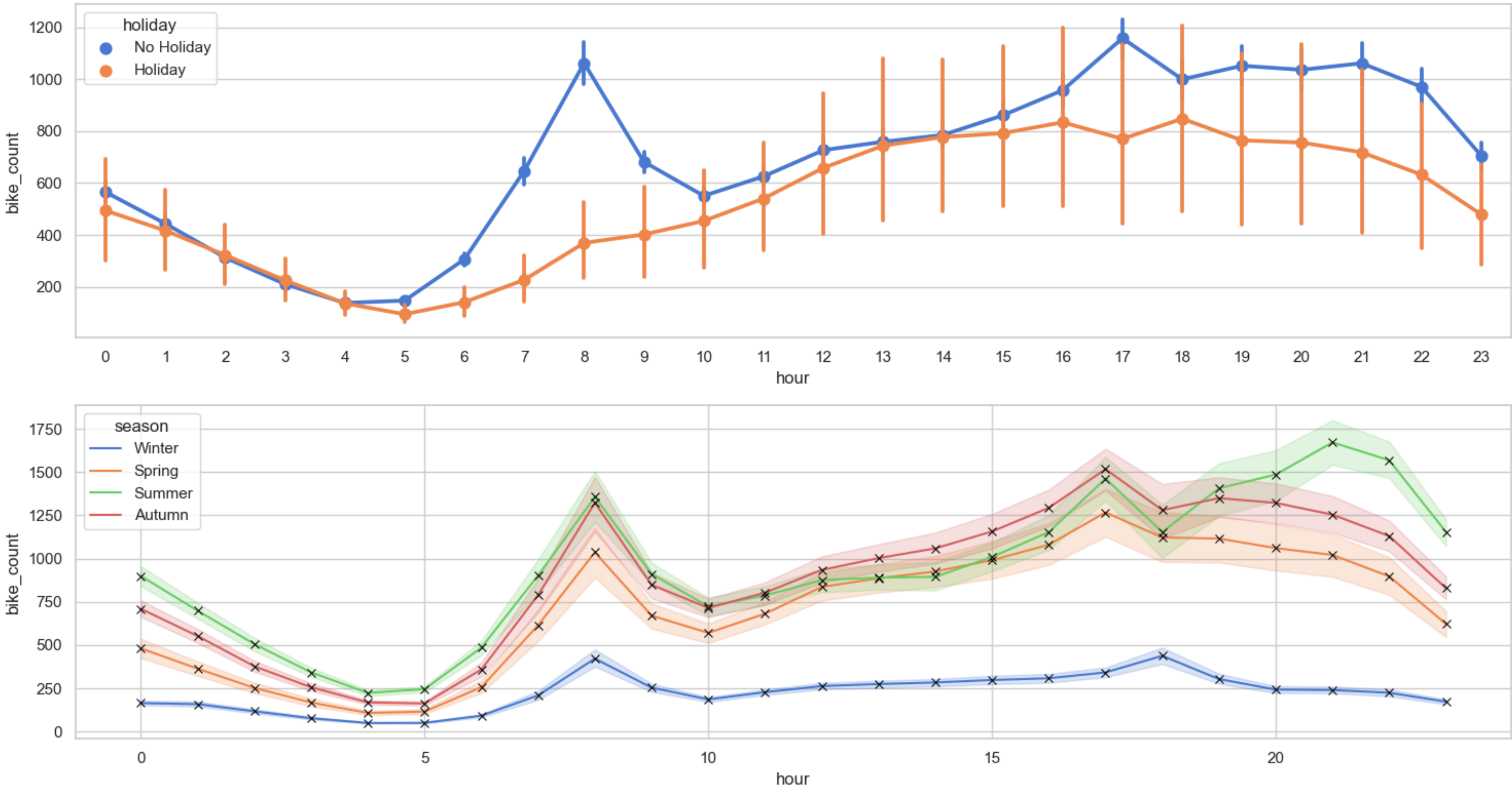
Out[36]:

	timeshift	bike_count
0	Day	2,670,448.0
1	Evening	2,430,487.0
2	Night	741,623.0

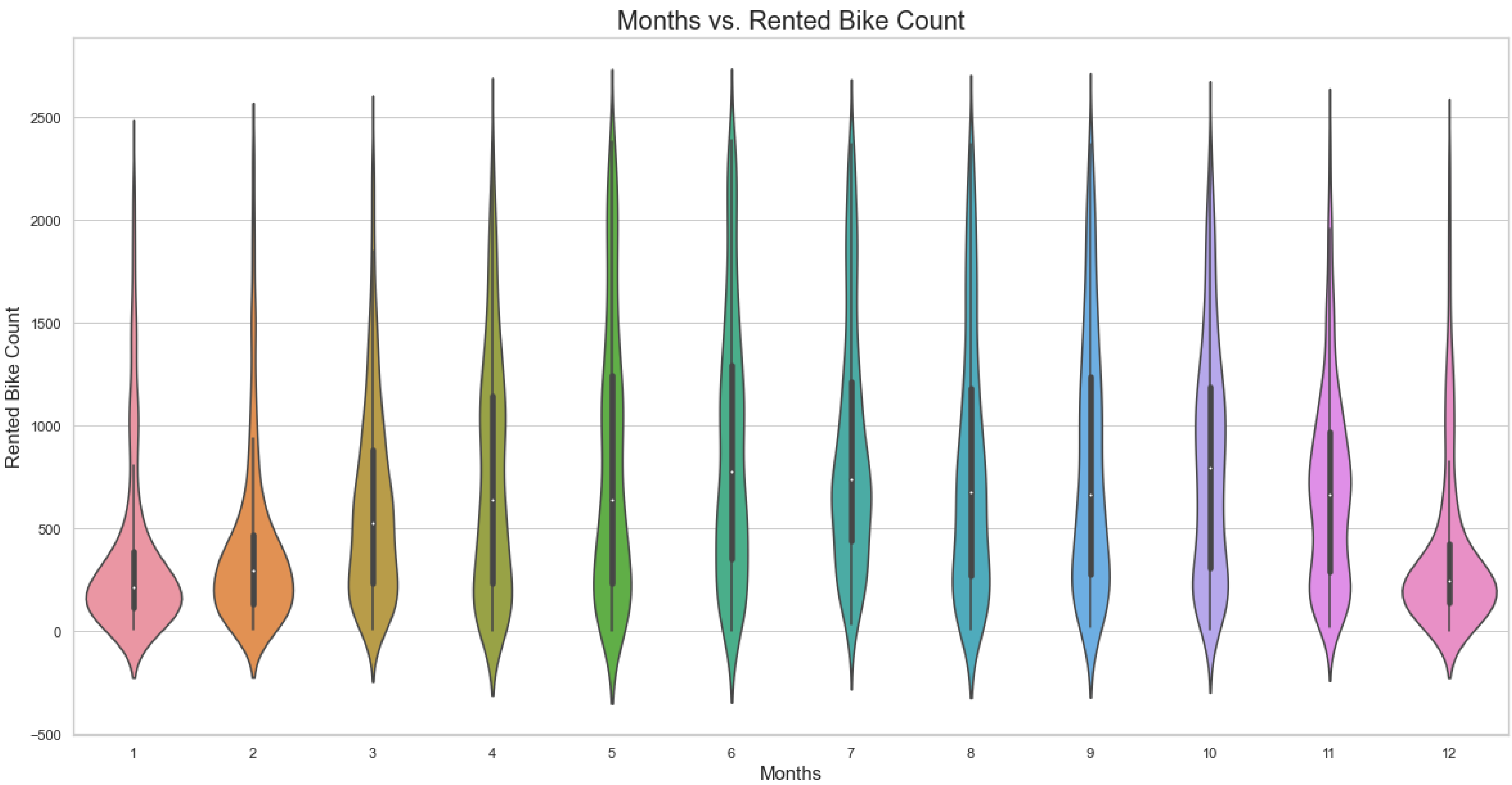
In [37]:
```
plt.figure(figsize=(10,10))
sns.set(style="whitegrid", palette="muted", color_codes=True)
sns.violinplot(x = 'timeshift', y = 'bike_count', data=df1)
plt.title('Time of the Day vs. Rented Bike Count', fontsize=20)
plt.xlabel('Time of the Day', fontsize=15)
plt.ylabel('Rented Bike Count', fontsize=15)
plt.show()
```


Time of the Day vs. Rented Bike Count
Rented Bike Count
2500
2000
1500
1000
500
0
Night
Day
Evening
Time of the Day

In [38]:
```
fig, axs = plt.subplots(nrows=2,ncols=1,figsize=(15,8), dpi=100)
sns.pointplot(data=df1, x="hour", y="bike_count", ax=axs[0],
              hue="holiday")
sns.lineplot(data=df1, x="hour", y="bike_count", ax=axs[1],
              hue="season", marker="x",markeredgecolor="black")
plt.tight_layout()
```



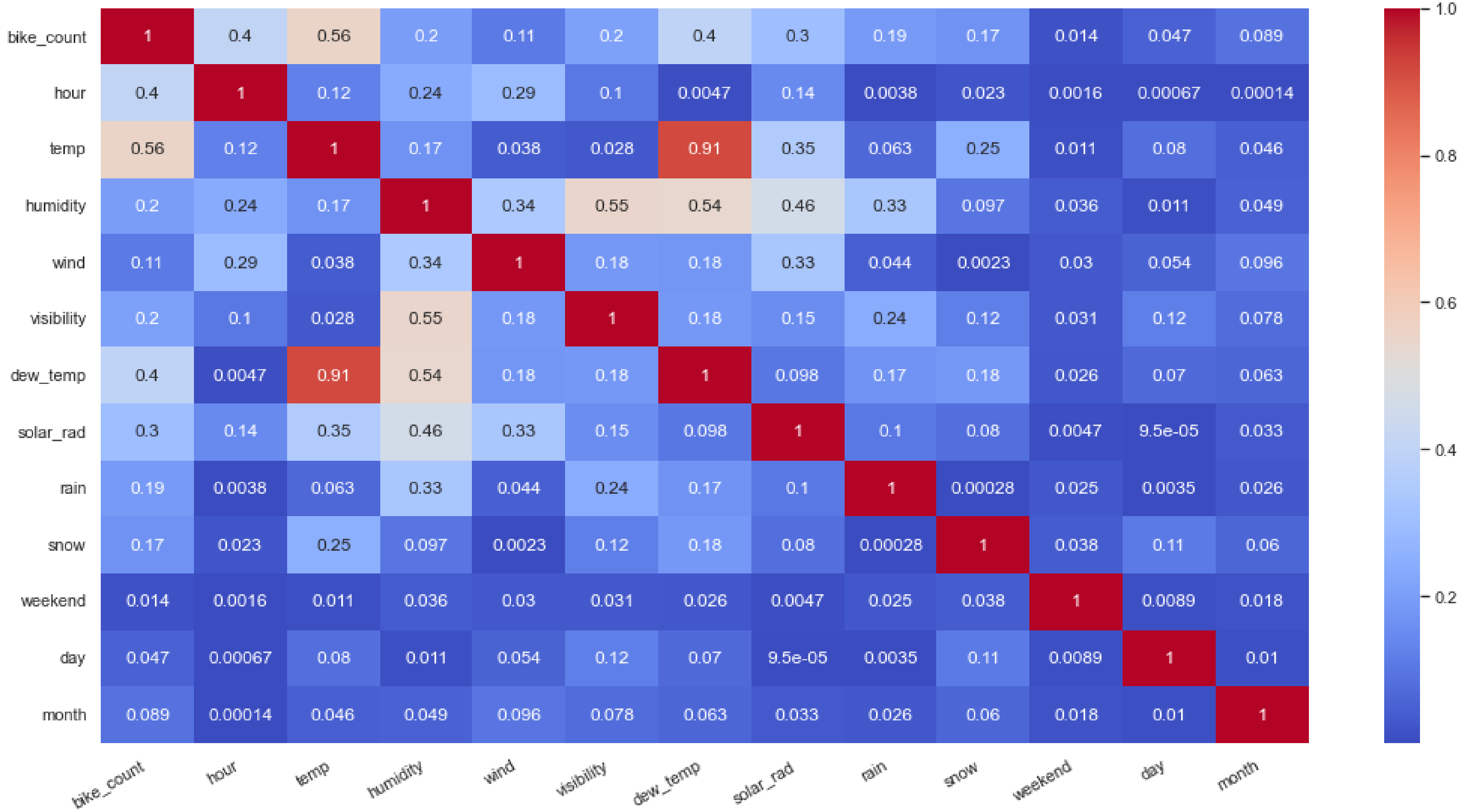
In [39]:
```
plt.figure(figsize=(20,10))
sns.set(style="whitegrid", palette="muted", color_codes=True)
sns.violinplot(x = 'month', y = 'bike_count', data=df1)
plt.title('Months vs. Rented Bike Count', fontsize=20)
plt.xlabel('Months', fontsize=15)
plt.ylabel('Rented Bike Count', fontsize=15)
plt.show()
```



Removing Multicollinearity

In [40]:
```
# Defining a function to calculate Variance Inflation factor
def calc_vif(X):

    # Calculating VIF
    vif = pd.DataFrame()
    vif["variables"] = X.columns
    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

    return(vif.sort_values(by='VIF',ascending=False).reset_index(drop=True))
```

In [41]:
```
# Checking corelations
plt.figure(figsize=(18,9))
plot=sns.heatmap(abs(df1.corr()), annot=True, cmap='coolwarm')
plot.set_xticklabels(plot.get_xticklabels(), rotation=30, horizontalalignment='right')
plt.show()
```



	bike_count	hour	temp	humidity	wind	visibility	dew_temp	solar_rad	rain	snow	weekend	day	month
bike_count	1	0.4	0.56	0.2	0.11	0.2	0.4	0.3	0.19	0.17	0.014	0.047	0.089
hour	0.4	1	0.12	0.24	0.29	0.1	0.0047	0.14	0.0038	0.023	0.0016	0.00067	0.00014
temp	0.56	0.12	1	0.17	0.038	0.028	0.91	0.35	0.063	0.25	0.011	0.08	0.046
humidity	0.2	0.24	0.17	1	0.34	0.55	0.54	0.46	0.33	0.097	0.036	0.011	0.049
wind	0.11	0.29	0.038	0.34	1	0.18	0.18	0.33	0.044	0.0023	0.03	0.054	0.096
visibility	0.2	0.1	0.028	0.55	0.18	1	0.18	0.15	0.24	0.12	0.031	0.12	0.078
dew_temp	0.4	0.0047	0.91	0.54	0.18	0.18	1	0.098	0.17	0.18	0.026	0.07	0.063
solar_rad	0.3	0.14	0.35	0.46	0.33	0.15	0.098	1	0.1	0.08	0.0047	9.5e-05	0.033
rain	0.19	0.0038	0.063	0.33	0.044	0.24	0.17	0.1	1	0.00028	0.025	0.0035	0.026
snow	0.17	0.023	0.25	0.097	0.0023	0.12	0.18	0.08	0.00028	1	0.038	0.11	0.06
weekend	0.014	0.0016	0.011	0.036	0.03	0.031	0.026	0.0047	0.025	0.038	1	0.0089	0.018
day	0.047	0.00067	0.08	0.011	0.054	0.12	0.07	9.5e-05	0.0035	0.11	0.0089	1	0.01
month	0.089	0.00014	0.046	0.049	0.096	0.078	0.063	0.033	0.026	0.06	0.018	0.01	1

In [42]:
```
# View correlation matrix
df1.corr()
```

Out[42]:

	bike_count	hour	temp	humidity	wind	visibility	dew_temp	solar_rad	rain	snow	weekend	day	month
bike_count	1.0	0.4	0.6	-0.2	0.1	0.2	0.4	0.3	-0.2	-0.2	-0.0	0.0	0.1
hour	0.4	1.0	0.1	-0.2	0.3	0.1	0.0	0.1	0.0	-0.0	0.0	-0.0	-0.0
temp	0.6	0.1	1.0	0.2	-0.0	0.0	0.9	0.4	0.1	-0.2	-0.0	0.1	0.0
humidity	-0.2	-0.2	0.2	1.0	-0.3	-0.5	0.5	-0.5	0.3	0.1	-0.0	0.0	0.0
wind	0.1	0.3	-0.0	-0.3	1.0	0.2	-0.2	0.3	-0.0	0.0	-0.0	-0.1	-0.1
visibility	0.2	0.1	0.0	-0.5	0.2	1.0	-0.2	0.2	-0.2	-0.1	0.0	-0.1	0.1
dew_temp	0.4	0.0	0.9	0.5	-0.2	-0.2	1.0	0.1	0.2	-0.2	-0.0	0.1	0.1
solar_rad	0.3	0.1	0.4	-0.5	0.3	0.2	0.1	1.0	-0.1	-0.1	0.0	-0.0	-0.0
rain	-0.2	0.0	0.1	0.3	-0.0	-0.2	0.2	-0.1	1.0	0.0	-0.0	0.0	-0.0
snow	-0.2	-0.0	-0.2	0.1	0.0	-0.1	-0.2	-0.1	0.0	1.0	-0.0	0.1	0.1
weekend	-0.0	0.0	-0.0	-0.0	-0.0	0.0	-0.0	0.0	-0.0	-0.0	1.0	-0.0	0.0
day	0.0	-0.0	0.1	0.0	-0.1	-0.1	0.1	-0.0	0.0	0.1	-0.0	1.0	0.0
month	0.1	-0.0	0.0	0.0	-0.1	0.1	0.1	-0.0	-0.0	0.1	0.0	0.0	1.0

In [43]:
```
# Return "True" for positive or negative correlations that are bigger than 0.75.
abs(df1.corr())>0.75
```

Out[43]:

	bike_count	hour	temp	humidity	wind	visibility	dew_temp	solar_rad	rain	snow	weekend	day	month
bike_count	True	False	False	False	False	False	False	False	False	False	False	False	False
hour	False	True	False	False	False	False	False	False	False	False	False	False	False
temp	False	False	True	False	False	False	True	False	False	False	False	False	False
humidity	False	False	False	True	False	False	False	False	False	False	False	False	False
wind	False	False	False	False	True	False	False	False	False	False	False	False	False
visibility	False	False	False	False	False	True	False	False	False	False	False	False	False
dew_temp	False	False	True	False	False	False	True	False	False	False	False	False	False
solar_rad	False	False	False	False	False	False	False	True	False	False	False	False	False
rain	False	False	False	False	False	False	False	False	True	False	False	False	False
snow	False	False	False	False	False	False	False	False	False	True	False	False	False
weekend	False	False	False	False	False	False	False	False	False	False	True	False	False
day	False	False	False	False	False	False	False	False	False	False	False	True	False
month	False	False	False	False	False	False	False	False	False	False	False	False	True

Since Temperature and Dew point temperature are highly correlated (0.91), so to avoid multicollinearity issue, we will drop Dew point temperature feature.

In [44]:
```
#Drop Dew point temperature(°C) from dataset df1
df1.drop(columns=['dew_temp'],inplace=True)
```

In [45]:
```
df1
```

Out[45]:

	bike_count	hour	temp	humidity	wind	visibility	solar_rad	rain	snow	season	holiday	weekend	timeshift	day	month
0	254.0	0	-5.2	37	2.2	2000	0.0	0.0	0.0	Winter	No Holiday	0	Night	12	1
1	204.0	1	-5.5	38	0.8	2000	0.0	0.0	0.0	Winter	No Holiday	0	Night	12	1
2	173.0	2	-6.0	39	1.0	2000	0.0	0.0	0.0	Winter	No Holiday	0	Night	12	1
3	107.0	3	-6.2	40	0.9	2000	0.0	0.0	0.0	Winter	No Holiday	0	Night	12	1
4	78.0	4	-6.0	36	2.3	2000	0.0	0.0	0.0	Winter	No Holiday	0	Night	12	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
8755	1,003.0	19	4.2	34	2.6	1894	0.0	0.0	0.0	Autumn	No Holiday	0	Evening	30	11
8756	764.0	20	3.4	37	2.3	2000	0.0	0.0	0.0	Autumn	No Holiday	0	Evening	30	11
8757	694.0	21	2.6	39	0.3	1968	0.0	0.0	0.0	Autumn	No Holiday	0	Evening	30	11
8758	712.0	22	2.1	41	1.0	1859	0.0	0.0	0.0	Autumn	No Holiday	0	Evening	30	11
8759	584.0	23	1.9	43	1.3	1909	0.0	0.0	0.0	Autumn	No Holiday	0	Evening	30	11

8465 rows × 15 columns

Dealing with Categorical Values

In [46]:
```
# Defining a label encoder based on above data
encoder = {'holiday':{'Holiday':1, 'No Holiday':0},'season':{'Autumn':0 , 'Spring':1,'Summer':2, 'Winter':3},
           'timeshift': {'Night':0, 'Day':1, 'Evening':2}}
```

0 : Autumn , 1 : Spring , 2 : Summer , 3 : Winter

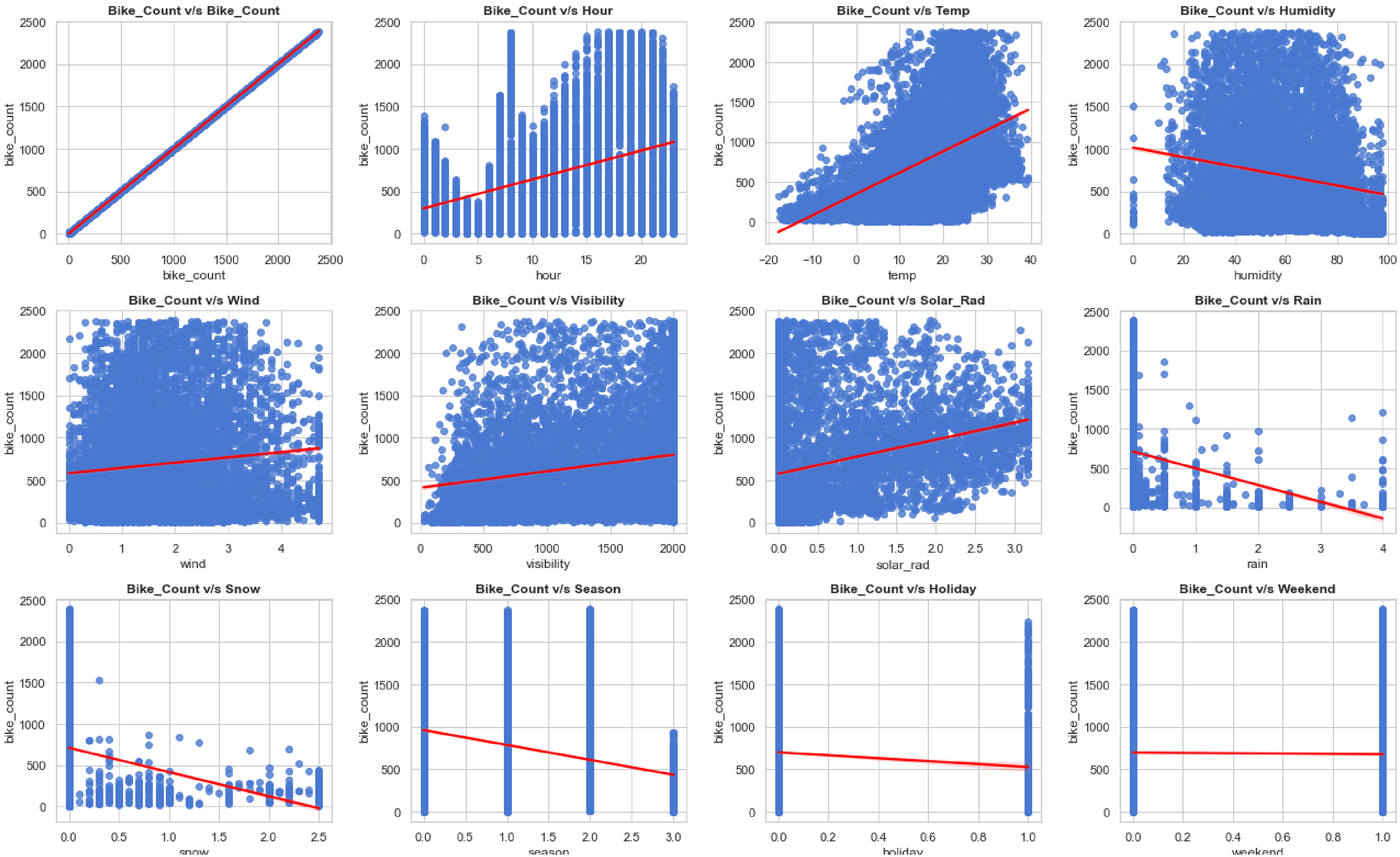
In [47]:
```
# Label Encoding
df1 = df1.replace(encoder)
```

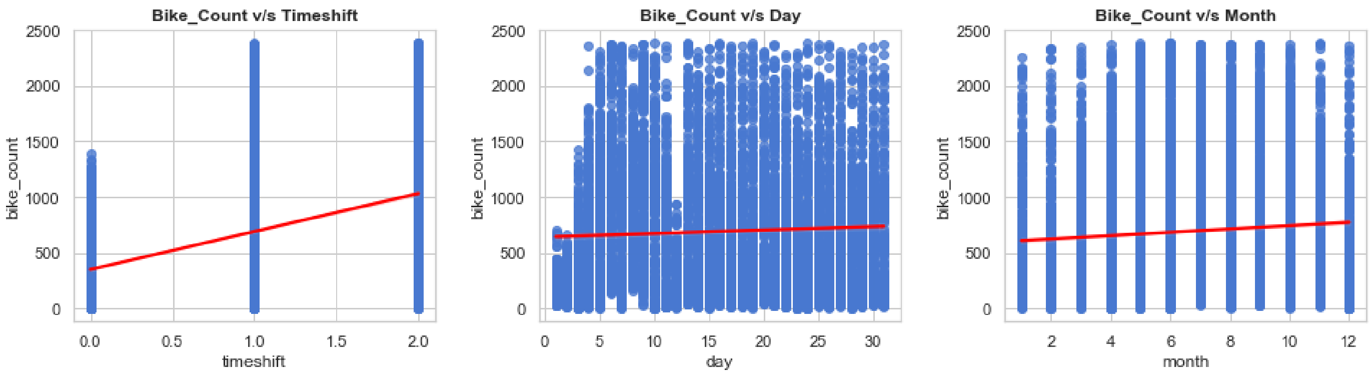
In [48]:
```
df1.head(1)
```

Out[48]:

	bike_count	hour	temp	humidity	wind	visibility	solar_rad	rain	snow	season	holiday	weekend	timeshift	day	month
0	254.0	0	-5.2	37	2.2	2000	0.0	0.0	0.0	3	0	0	0	12	1

In [49]:
```
# Checking Linearity
plt.figure(figsize=(18,18))
for n,column in enumerate(df1):
  plt.subplot(5, 4, n+1)
  sns.regplot(data = df1, x = column, y ='bike_count',line_kws={"color": "red"})
  plt.title(f'Bike_Count v/s {column.title()}',weight='bold')
  plt.tight_layout()
```

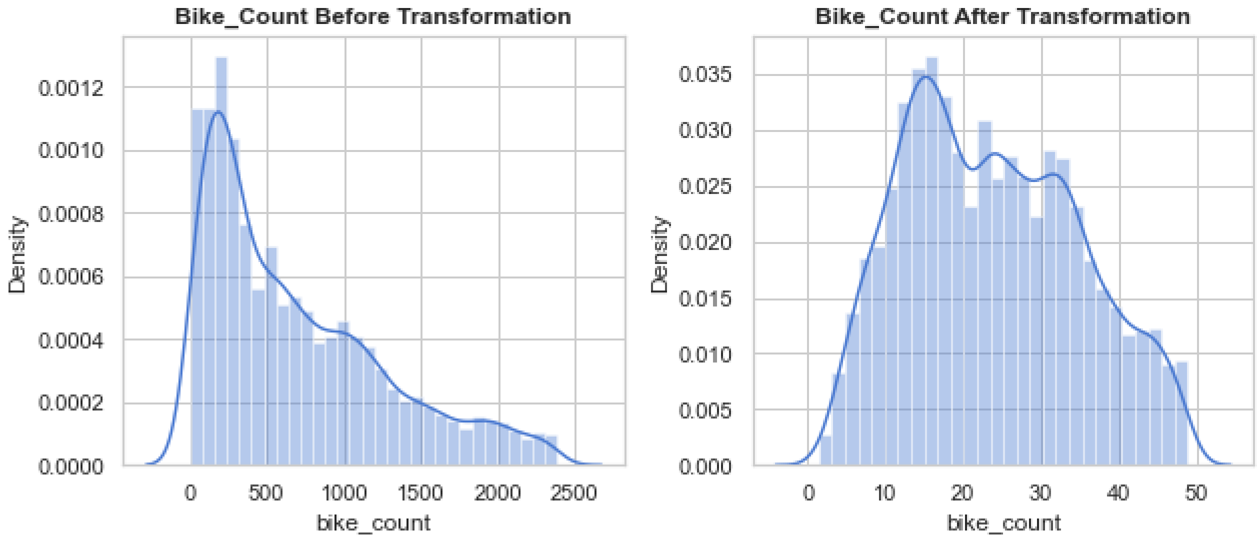




In [50]:
```python
#checking skewness of the dependend variable
print(f'Skewness of original data : {df1.bike_count.skew()}')
print(f'Skewness after log transformation : {np.log(df1.bike_count).skew()}')
print(f'Skewness after transformation : {np.sqrt(df1.bike_count).skew()}')
```

```
Skewness of original data : 0.9683253836166369
Skewness after log transformation : -0.8570855259607234
Skewness after transformation : 0.26609206416312225
```

In [51]:
```
#Since Sqrt Transformation gives skewness between -0.5 and 0.5 indicates that the distribution is fairly symmet
plt.figure(figsize=(9,4))
plot = plt.subplot(1,2,1)
sns.distplot(df1['bike_count']).set_title('Bike_Count Before Transformation',weight='bold')
plot = plt.subplot(1,2,2)
sns.distplot(np.sqrt(df1['bike_count'])).set_title('Bike_Count After Transformation',weight='bold')
plt.tight_layout()
```



In [52]:
```
df1.head(1)
```

Out[52]:

	bike_count	hour	temp	humidity	wind	visibility	solar_rad	rain	snow	season	holiday	weekend	timeshift	day	month
0	254.0	0	-5.2	37	2.2	2000	0.0	0.0	0.0	3	0	0	0	12	1

Model Building

Base Model 1

In [53]:
```
X = df1.drop('bike_count', axis=1)
y = df1['bike_count']

X_int = sm.add_constant(X)
model = sm.OLS(y,X_int).fit()
model.summary()
```

Out[53]:

OLS Regression Results

Dep. Variable:	bike_count	**R-squared:**	0.578
Model:	OLS	**Adj. R-squared:**	0.578
Method:	Least Squares	**F-statistic:**	827.5
Date:	Tue, 08 Nov 2022	**Prob (F-statistic):**	0.00
Time:	20:45:28	**Log-Likelihood:**	-62259.
No. Observations:	8465	**AIC:**	1.245e+05
Df Residuals:	8450	**BIC:**	1.247e+05
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	623.3232	34.806	17.909	0.000	555.095	691.551
hour	-24.3727	1.754	-13.895	0.000	-27.811	-20.934
temp	24.3842	0.453	53.770	0.000	23.495	25.273
humidity	-5.2903	0.330	-16.035	0.000	-5.937	-4.644
wind	-0.0638	4.615	-0.014	0.989	-9.110	8.983
visibility	0.0169	0.009	1.950	0.051	-8.43e-05	0.034
solar_rad	-6.4719	6.698	-0.966	0.334	-19.602	6.658
rain	-188.3969	8.576	-21.967	0.000	-205.209	-171.585
snow	19.0569	13.029	1.463	0.144	-6.483	44.597

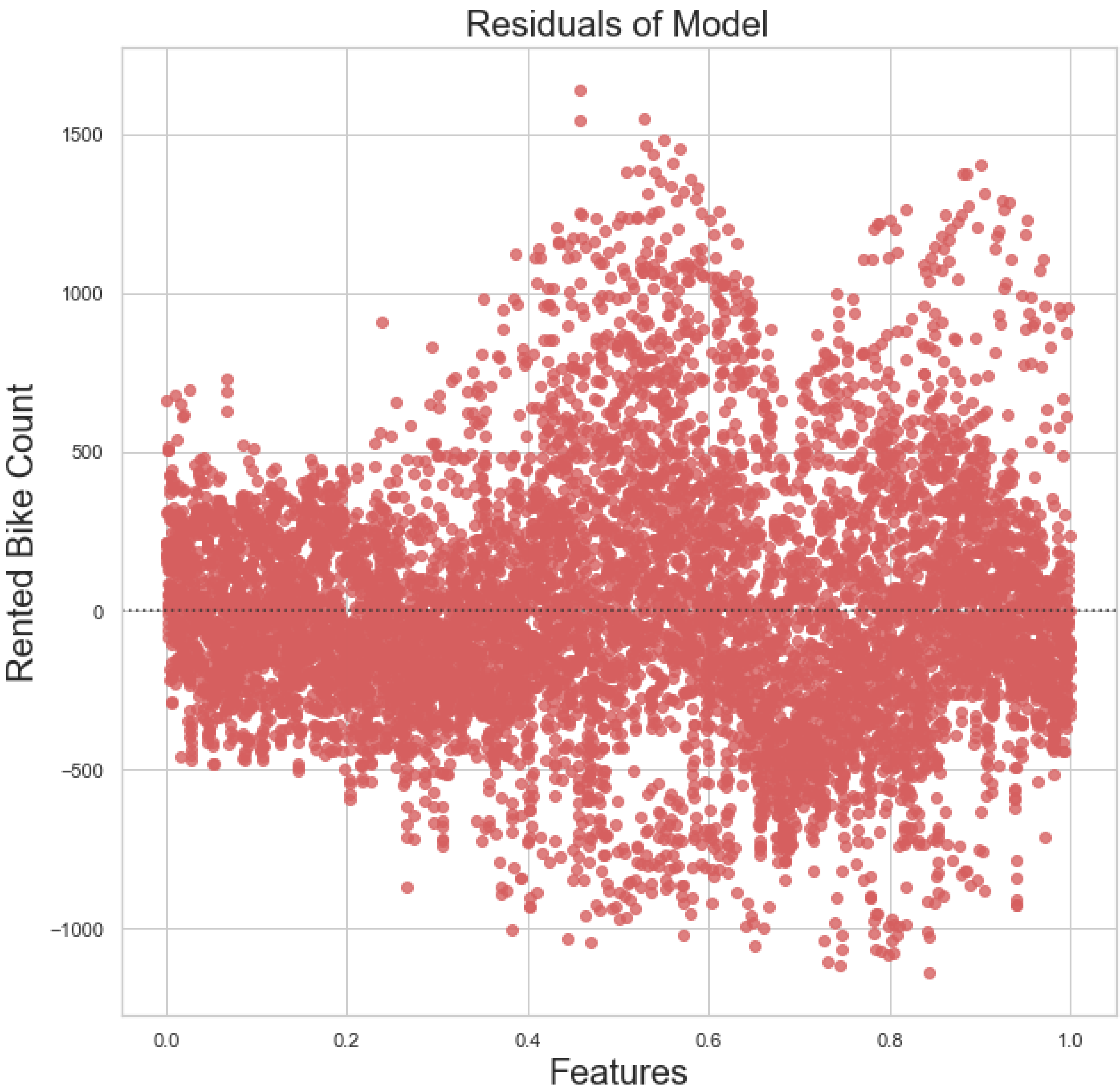
season	-98.5641	4.131	-23.860	0.000	-106.662	-90.466
holiday	-95.1938	19.299	-4.933	0.000	-133.024	-57.363
weekend	-24.4305	9.111	-2.681	0.007	-42.291	-6.570
timeshift	478.5946	15.738	30.410	0.000	447.745	509.445
day	-0.1834	0.482	-0.381	0.703	-1.128	0.761
month	4.2980	1.240	3.467	0.001	1.868	6.728

Omnibus:	605.066	**Durbin-Watson:**	0.869
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	914.840
Skew:	0.581	**Prob(JB):**	2.21e-199
Kurtosis:	4.115	**Cond. No.**	1.33e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.33e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

There are 5 features where p value > 0.05, which are wind, visibility, solar radiation, snow and day. Lets normalise the data and re-look at the P values for these features.

In [54]:
```
# Check residuals using sns.residplot
y_hat = model.predict()
residuals = df1['bike_count'] - y_hat
x_vals = np.linspace(0, 1, len(residuals))

plt.figure(figsize=(10,10))
sns.residplot(x_vals, residuals, data = df1, color='r')
plt.title('Residuals of Model', fontsize=20)
plt.xlabel('Features', fontsize=20)
plt.ylabel('Rented Bike Count', fontsize=20)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)
plt.show()
```



Model 2 - Data normalisation

In [55]:
```
df2=df1.copy()
```

In [56]:
```
# performing sqrt transformation of the target variable - Bike count, for normal distribution of this variable

df2['bike_count']=np.sqrt(df2['bike_count'])
```

In [57]:
```
df2.head(2)
```

Out[57]:

	bike_count	hour	temp	humidity	wind	visibility	solar_rad	rain	snow	season	holiday	weekend	timeshift	day	month
0	15.9	0	-5.2	37	2.2	2000	0.0	0.0	0.0	3	0	0	0	12	1
1	14.3	1	-5.5	38	0.8	2000	0.0	0.0	0.0	3	0	0	0	12	1

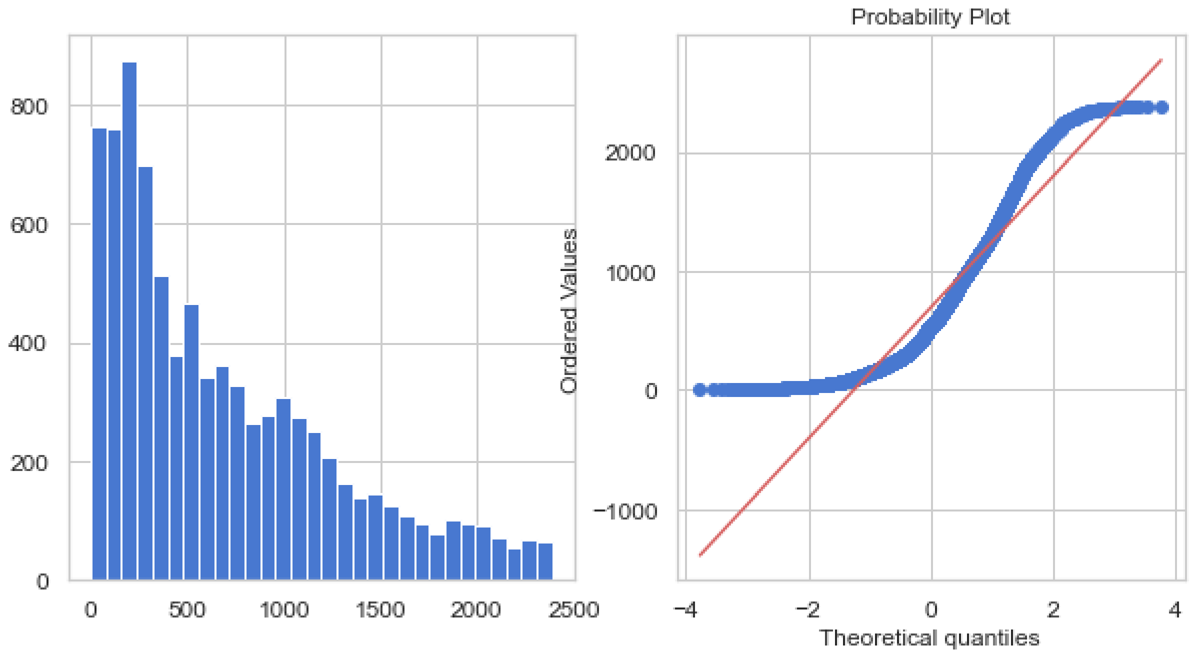
In [58]:
```
#conducting min-max scaling to normalise the whole dataset
scaler = preprocessing.MinMaxScaler()
columns = df2.columns
d = scaler.fit_transform(df2)
df3 = pd.DataFrame(d, columns=columns)
df3.head()
```

Out[58]:

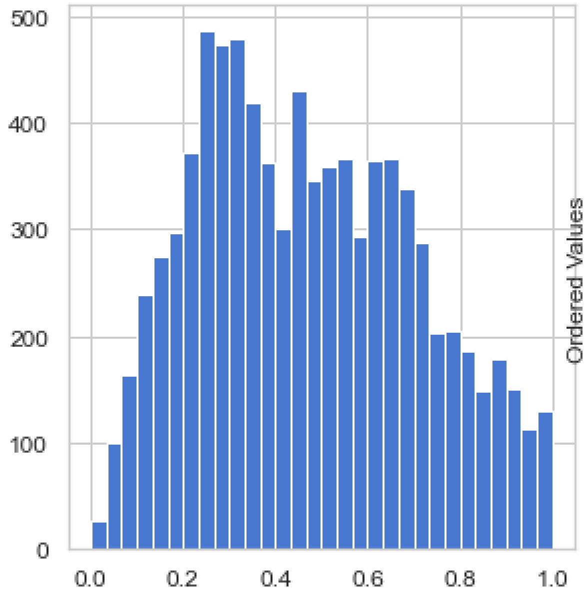
	bike_count	hour	temp	humidity	wind	visibility	solar_rad	rain	snow	season	holiday	weekend	timeshift	day	month
0	0.3	0.0	0.2	0.4	0.5	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.4	0.0
1	0.3	0.0	0.2	0.4	0.2	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.4	0.0
2	0.2	0.1	0.2	0.4	0.2	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.4	0.0
3	0.2	0.1	0.2	0.4	0.2	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.4	0.0
4	0.2	0.2	0.2	0.4	0.5	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.4	0.0

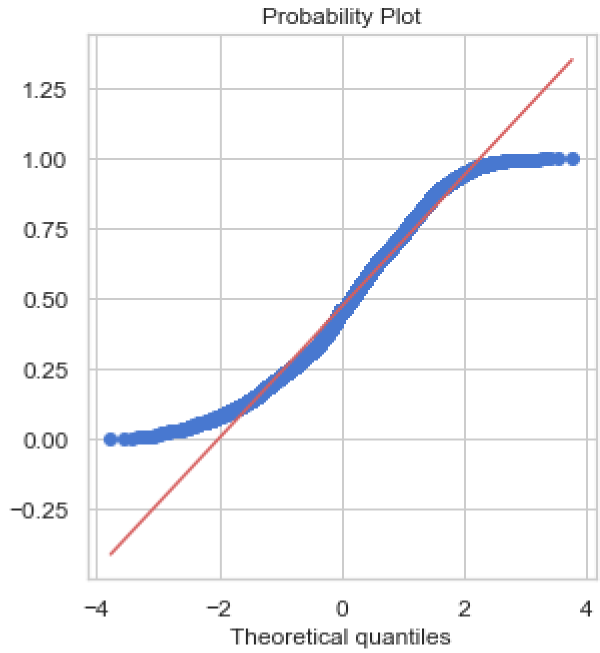
In [59]:
```
def plotvariable(df,variable):
  plt.figure(figsize=(10,5))
  plt.subplot(1,2,1)    #means 1 row, 2 Columns and 1st plot
  df[variable].hist(bins=30)

  ##QQ plot
  plt.subplot(1,2,2)
  stats.probplot(df[variable], dist='norm',plot=plt)
  plt.show()
```

In [60]:
```
plotvariable(df1,'bike_count')
```



In [61]:
```
plotvariable(df3,'bike_count')
```





In [62]:
```
X3 = df3.drop('bike_count', axis=1)
y3 = df3['bike_count']

X_int = sm.add_constant(X3)
model = sm.OLS(y3,X_int).fit()
model.summary()
```

Out[62]:

OLS Regression Results

Dep. Variable:	bike_count	**R-squared:**	0.665
Model:	OLS	**Adj. R-squared:**	0.665
Method:	Least Squares	**F-statistic:**	1200.
Date:	Tue, 08 Nov 2022	**Prob (F-statistic):**	0.00
Time:	20:45:28	**Log-Likelihood:**	4811.3
No. Observations:	8465	**AIC:**	-9593.
Df Residuals:	8450	**BIC:**	-9487.
Df Model:	14		
Covariance Type:	nonrobust		

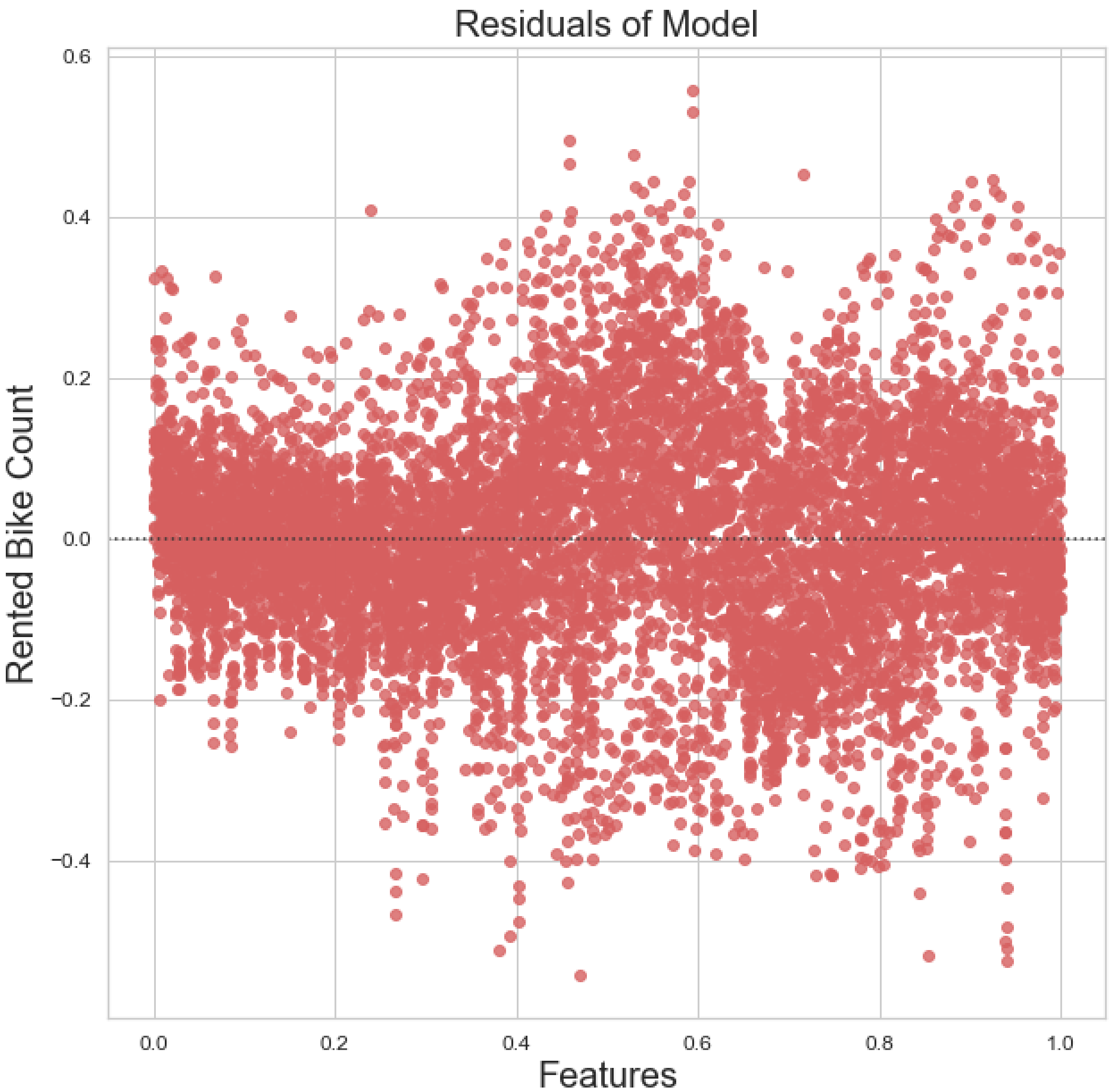
	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2798	0.012	23.162	0.000	0.256	0.304
hour	-0.2621	0.015	-17.935	0.000	-0.291	-0.233
temp	0.5795	0.009	61.671	0.000	0.561	0.598
humidity	-0.2218	0.012	-18.939	0.000	-0.245	-0.199
wind	-0.0136	0.008	-1.731	0.083	-0.029	0.002
visibility	0.0087	0.006	1.409	0.159	-0.003	0.021
solar_rad	0.0272	0.008	3.532	0.000	0.012	0.042
rain	-0.4281	0.012	-34.449	0.000	-0.452	-0.404
snow	-0.0102	0.012	-0.868	0.385	-0.033	0.013

season	-0.1304	0.004	-29.058	0.000	-0.139	-0.122
holiday	-0.0555	0.007	-7.942	0.000	-0.069	-0.042
weekend	-0.0125	0.003	-3.782	0.000	-0.019	-0.006
timeshift	0.4119	0.011	36.130	0.000	0.390	0.434
day	0.0052	0.005	0.989	0.323	-0.005	0.015
month	0.0265	0.005	5.356	0.000	0.017	0.036

Omnibus:	78.722	**Durbin-Watson:**	0.827
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	128.847
Skew:	-0.019	**Prob(JB):**	1.05e-28
Kurtosis:	3.603	**Cond. No.**	23.9

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

In [63]:
```
# Check residuals using sns.residplot
y_hat = model.predict()
residuals = df3['bike_count'] - y_hat
x_vals = np.linspace(0, 1, len(residuals))

plt.figure(figsize=(10,10))
sns.residplot(x_vals, residuals, data = df3, color='r')
plt.title('Residuals of Model', fontsize=20)
plt.xlabel('Features', fontsize=20)
plt.ylabel('Rented Bike Count', fontsize=20)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)
plt.show()
```


Residuals of Model
Rented Bike Count
Features
0.6
0.4
0.2
0.0
−0.2
−0.4
0.0
0.2
0.4
0.6
0.8
1.0

In [64]:
```
# Checking for Feature ranking with Recursive Feature Elimination
from sklearn.feature_selection import RFE

predictors = df3.drop('bike_count', axis=1)

linreg = LinearRegression()
selector = RFE(linreg, n_features_to_select = 10)
selector = selector.fit(predictors, df3['bike_count'])
```

In [65]:
```
print(list(zip(predictors, selector.support_)))
print(list(zip(predictors, selector.ranking_)))
```

```
[('hour', True), ('temp', True), ('humidity', True), ('wind', True), ('visibility', False), ('solar_rad', Tru
e), ('rain', True), ('snow', False), ('season', True), ('holiday', True), ('weekend', False), ('timeshift', T
rue), ('day', False), ('month', True)]
[('hour', 1), ('temp', 1), ('humidity', 1), ('wind', 1), ('visibility', 4), ('solar_rad', 1), ('rain', 1),
('snow', 3), ('season', 1), ('holiday', 1), ('weekend', 2), ('timeshift', 1), ('day', 5), ('month', 1)]
```

```
There have been 4 features identified which are not relevant to the model - Visibility, Snow, Weekend and
Day. Further we see the p value of Wind is more than 0.05, hence removing these 5 features from the final
model.
```

In [88]:
```
#create a df with features from RFE
df4 = df3.drop(df3[['snow', 'weekend','day','visibility','wind']], axis=1)
```

Final Model

In [110]:
```
X4 = df4.drop('bike_count', axis=1)
y4 = df4['bike_count']

X_int = sm.add_constant(X4)
model = sm.OLS(y4,X_int).fit()
model.summary()
```

Out[110]:

OLS Regression Results

Dep. Variable:	bike_count	**R-squared:**	0.665
Model:	OLS	**Adj. R-squared:**	0.664
Method:	Least Squares	**F-statistic:**	1862.
Date:	Tue, 08 Nov 2022	**Prob (F-statistic):**	0.00
Time:	20:50:01	**Log-Likelihood:**	4801.6
No. Observations:	8465	**AIC:**	-9583.
Df Residuals:	8455	**BIC:**	-9513.
Df Model:	9		
Covariance Type:	nonrobust		

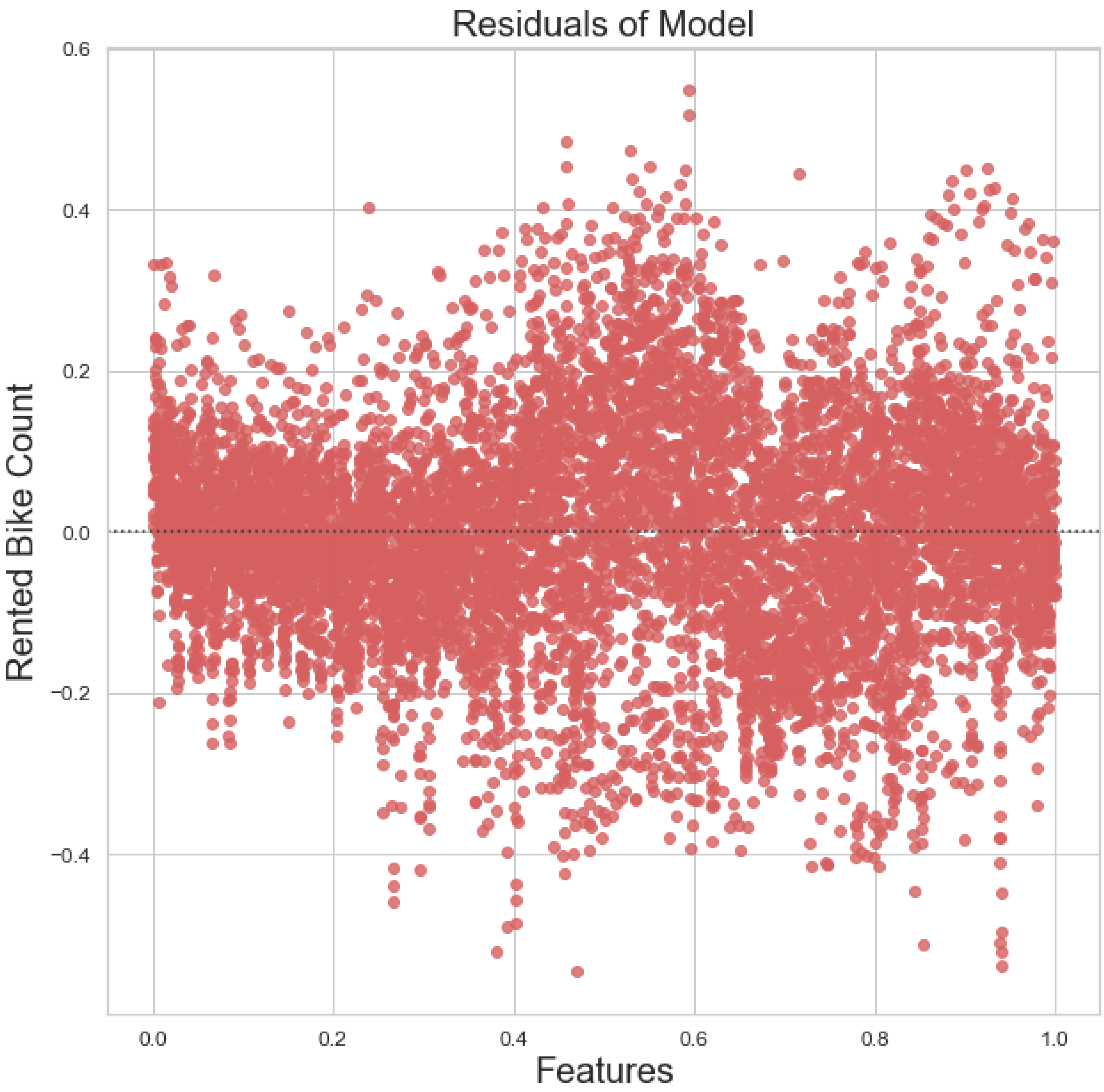
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.2837	0.008	33.821	0.000	0.267	0.300
hour	-0.2642	0.015	-18.117	0.000	-0.293	-0.236
temp	0.5868	0.009	67.350	0.000	0.570	0.604
humidity	-0.2298	0.010	-24.101	0.000	-0.249	-0.211
solar_rad	0.0208	0.007	2.904	0.004	0.007	0.035
rain	-0.4289	0.012	-34.608	0.000	-0.453	-0.405
season	-0.1319	0.004	-29.779	0.000	-0.141	-0.123
holiday	-0.0553	0.007	-7.919	0.000	-0.069	-0.042
timeshift	0.4112	0.011	36.051	0.000	0.389	0.434

month	0.0269	0.005	5.524	0.000	0.017	0.036

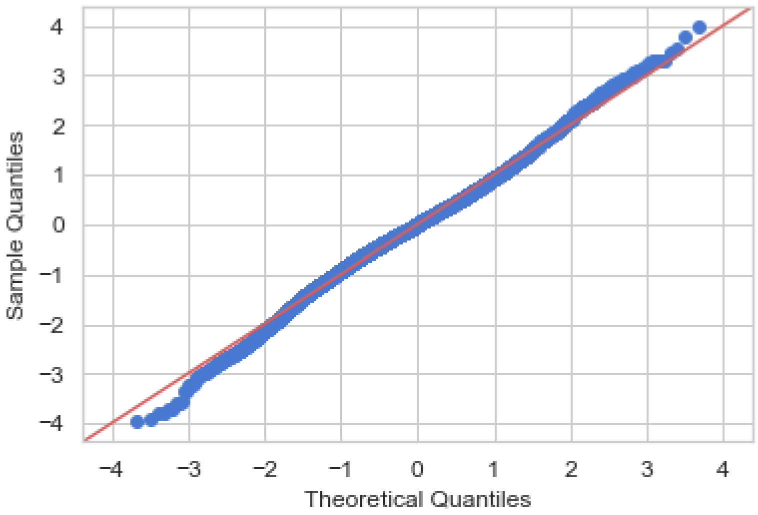
Omnibus:	79.236	**Durbin-Watson:**	0.823
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	129.830
Skew:	-0.020	**Prob(JB):**	6.42e-29
Kurtosis:	3.605	**Cond. No.**	20.4

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

In [111]:
```
# Check residuals using sns.residplot
y_hat = model.predict()
residuals = df4['bike_count'] - y_hat
x_vals = np.linspace(0, 1, len(residuals))

plt.figure(figsize=(10,10))
sns.residplot(x_vals, residuals, data = df4, color='r')
plt.title('Residuals of Model', fontsize=20)
plt.xlabel('Features', fontsize=20)
plt.ylabel('Rented Bike Count', fontsize=20)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)
# plt.show()
```


Residuals of Model
Rented Bike Count
Features
0.6
0.4
0.2
0.0
−0.2
−0.4
0.0
0.2
0.4
0.6
0.8
1.0

In [112]:
```
# QQ plot of the residuals
import scipy.stats as stats
residuals = model.resid
fig = sm.graphics.qqplot(residuals, dist=stats.norm, line='45', fit=True)
fig.show()
```



Train Test Split

In [113]:
```
X_train, X_test, y_train, y_test = train_test_split(X4, y4, test_size=0.3, random_state=42)
```

In [114]:
```
from sklearn.linear_model import LinearRegression
linreg = LinearRegression()
linreg.fit(X_train, y_train)
```

Out[114]:
```
LinearRegression()
```

In [115]:
```
#Let's check the shape of the train and test dataset

print(f'The shape of the train and test set for the independent variables are : X_train = {X_train.shape}, X_tes
print(f'The shape of the train and test set for the dependent variables are : y_train = {y_train.shape}, y_test
```

```
The shape of the train and test set for the independent variables are : X_train = (5925, 9), X_test = (2540,
9)
The shape of the train and test set for the dependent variables are : y_train = (5925,), y_test = (2540,)
```

In [116]:
```
# Fit the model and apply the model to the make test set predictions
linreg.fit(X_train, y_train)
# Test set predictions
lm_test_predictions = linreg.predict(X_test)
# Test set predictions
lm_train_predictions = linreg.predict(X_train)
```

In [117]:
```
# Calculate residuals and mean squared error
from sklearn.metrics import mean_squared_error
test_residuals = lm_test_predictions - y_test
train_mse = mean_squared_error(y_train, lm_train_predictions)
test_mse = mean_squared_error(y_test, lm_test_predictions)
print('Train Mean Squarred Error:', train_mse)
print('Test Mean Squarred Error:', test_mse)
```

```
Train Mean Squarred Error: 0.01911882854635529
Test Mean Squarred Error: 0.018182319053007902
```

Actual vs Predicted plot

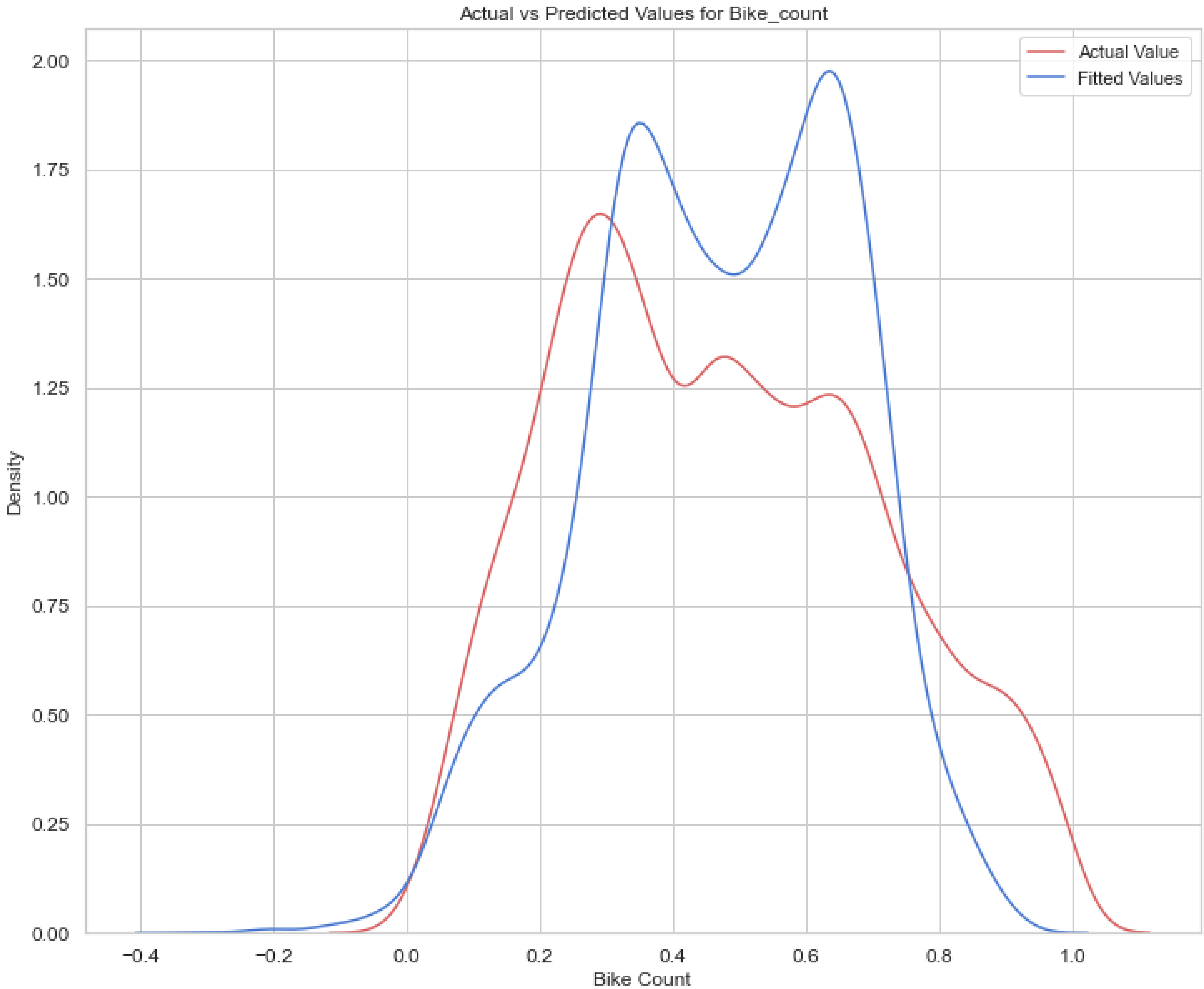
In [165]:
```
#Selecting the features im using from the j_df dataframe
z = df4[['hour','temp','humidity','solar_rad','rain','season','holiday','timeshift','month']]
target=df4['bike_count']
```

In [166]:
```
lm= LinearRegression()

lm.fit(z, target)
```

Out[166]:
```
LinearRegression()
```

In [167]:
```
#predict complete dataset
Y_hat1 = lm.predict(z)
```

In [176]:
```
#plot Actual vs Predicted plot

plt.figure(figsize=(12, 10))
ax1 = sns.distplot(df4['bike_count'], hist=False, color="r", label="Actual Value")
sns.distplot(Y_hat, hist=False, color="b", label="Fitted Values" , ax=ax1)
plt.title('Actual vs Predicted Values for Bike_count')
plt.xlabel("Bike Count")
plt.legend()
plt.show()
plt.close()
```



Calculating Bias and Variance

In [120]:
```
import numpy as np
def bias(y, y_hat):
    return np.mean(y_hat - y)
```

In [121]:
```
def variance(y_hat):
    return np.mean([yi**2 for yi in y_hat]) - np.mean(y_hat)**2
```

In [122]:
```
# Bias and variance for training set
b = bias(y_train, lm_train_predictions)
v = variance(lm_train_predictions)
print('Train bias: {} \nTrain variance: {}'.format(b, v))
```

```
Train bias: -1.0965443274441209e-16
Train variance: 0.03727077636510642
```

In [123]:
```
# Bias and variance for test set
b = bias(y_test, lm_test_predictions)
v = variance(lm_test_predictions)
print('Test bias: {} \nTest variance: {}'.format(b, v))
```

```
Test bias: 0.0007046726528165908
Test variance: 0.03700297869416366
```

Cross-Validation

In [124]:
```
#Now let's compare that single test MSE to a cross-validated test MSE.
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error, make_scorer
```

In [125]:
```
mse=make_scorer(mean_squared_error)
```

In [126]:
```
cv_10_results = cross_val_score(linreg, X4, y4, cv=10, scoring=mse)
cv_10_results
```

Out[126]:
```
array([0.00963306, 0.00703026, 0.01282022, 0.01508515, 0.02898306,
       0.03672114, 0.02763599, 0.02344549, 0.02239896, 0.01602467])
```

In [127]:
```
cv_10_results.mean()
```

Out[127]:
```
0.019977799620283 49
```

In [128]:
```
from sklearn.model_selection import cross_validate
model_simple = LinearRegression()
scores_simple = cross_validate(
                    model_simple, X_train, y_train, cv=5,
                    return_train_score=True
)
scores_simple
```

Out[128]:
```
{'fit_time': array([0.00260425, 0.00156116, 0.00138974, 0.00122619, 0.00125098]),
 'score_time': array([0.00082183, 0.00068784, 0.00071025, 0.00062609, 0.00062299]),
 'test_score': array([0.66363305, 0.64474317, 0.65923551, 0.65349027, 0.67766318]),
 'train_score': array([0.66010329, 0.66482114, 0.66122635, 0.66261511, 0.65647921])}
```

In [129]:
```
# Mean train r_2
np.mean(scores_simple['train_score']), np.std(scores_simple['train_score'])
```

Out[129]:
```
(0.66104901930952, 0.0027745480885039715)
```

In [130]:
```
# Mean test r_2
np.mean(scores_simple['test_score']), np.std(scores_simple['test_score'])
```

Out[130]:
```
(0.6597530373003423, 0.010960054582923222)
```

Conclusion

The most important feature of the model is the Temperature for our Linear model.

The demand is high during the hotter days.

Seasons and months have a strong impact on the demand for the bikes. Summer and Autumn months have higher demand.

Winter is the month with the lowest demand for the bikes.

Time of the day is also important factor to consider while planning. The demand is higher during certain times of the day during different seasons. 7am-9am and 3pm-8pm is the busiest time.

Rainy days have a negative impact on rental bikes as we could have imagined. People dont prefer to use bikes when it’s pouring.

Non holiday days are busier for rental bikes as compared to holidays.