Master AI

Learn the AI/ML Project on:

Boombikes Share Prediction

Domain: Mobility

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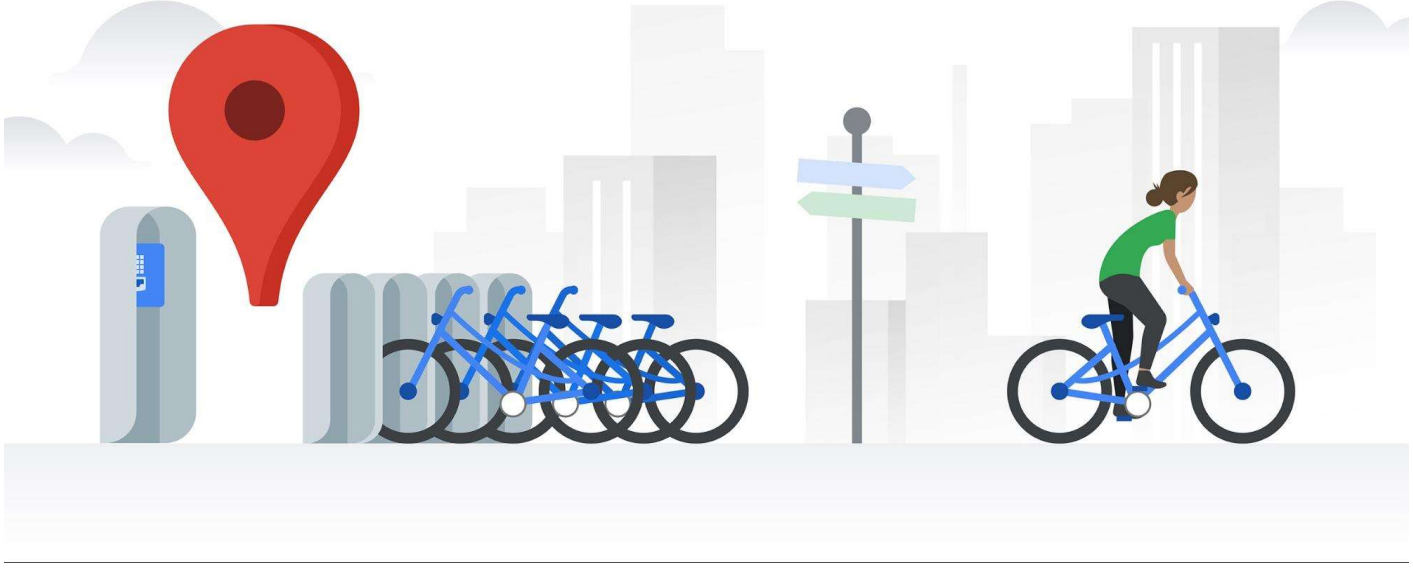
★ Machine Learning Project - Boombikes Bike Sharing Prediction ★



Description:

A US bike-sharing provider BoomBikes has recently suffered considerable dips in their revenues due to the ongoing Corona pandemic. The company is finding it very difficult to sustain in the current market scenario. So, it has decided to come up with a mindful business plan to be able to accelerate its revenue as soon as the ongoing lockdown comes to an end, and the economy restores to a healthy state.

In such an attempt, BoomBikes aspires to understand the demand for shared bikes among the people after this ongoing quarantine situation ends across the nation due to Covid-19. They have planned this to prepare themselves to cater to the people's needs once the situation gets better all around and stand out from other service providers and make huge profits.

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 variables are significant in predicting the demand for shared bikes. How well those variables describe the bike demand Based on various meteorological surveys and people's styles, the service provider firm has gathered a large dataset on daily bike demands across the American market based on some factors.

Bussiness Goal:

We are required to 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.

Acknowledgement:

The dataset is taken from Kaggle:\ https://www.kaggle.com/yasserh/bikeshare

Objective:

- Understand the Dataset & cleanup (if required).
- Build Regression models to predict the shares of bikes.
- Also evaluate the models & compare thier respective scores like R2, RMSE, etc.

Stractegic Plan of Action:

We aim to solve the problem statement by creating a plan of action, Here are some of the necessary steps:

1. Data Exploration
2. Exploratory Data Analysis (EDA)
3. Data Pre-processing
4. Data Manipulation
5. Feature Selection/Extraction
6. Predictive Modelling
7. Project Outcomes & Conclusion

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1. Data Exploration

In [1]:
```
#Importing the basic librarires

import math
import numpy as np
import pandas as pd
import seaborn as sns
from IPython.display import display

from brokenaxes import brokenaxes
from statsmodels.formula import api
from sklearn.feature_selection import RFE
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.decomposition import PCA
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [10,6]

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

In [11]:
```
#Importing the dataset

df = pd.read_csv('day.csv')

df.drop(['dteday','instant'], axis=1, inplace=True)
display(df.head())

target = 'cnt'
features = [i for i in df.columns if i not in [target]]

original_df = df.copy(deep=True)

print('\n\033[1mInference:\033[0m The Datset consists of {} features & {} samples.'.format(df.shape[1], df.shape[0]))
```

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

Inference: The Datset consists of 14 features & 730 samples.

In [12]:
```
#Checking the dtypes of all the columns

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   season      730 non-null    int64  
 1   yr          730 non-null    int64  
 2   mnth        730 non-null    int64  
 3   holiday     730 non-null    int64  
 4   weekday     730 non-null    int64  
 5   workingday  730 non-null    int64  
 6   weathersit  730 non-null    int64  
 7   temp        730 non-null    float64
 8   atemp       730 non-null    float64
 9   hum         730 non-null    float64
 10  windspeed   730 non-null    float64
 11  casual      730 non-null    int64  
 12  registered  730 non-null    int64  
 13  cnt         730 non-null    int64  
dtypes: float64(4), int64(10)
memory usage: 80.0 KB
```

In [13]:
```
#Checking number of unique rows in each feature

df.nunique().sort_values()
```

Out[13]:
```
yr             2
holiday        2
workingday     2
```

```
weathersit      3
season          4
weekday         7
mnth           12
temp          498
hum           594
casual        605
windspeed     649
registered    678
atemp         689
cnt           695
dtype: int64
```

In [14]:

```
#Checking number of unique rows in each feature

nu = df[features].nunique().sort_values()
nf = []; cf = []; nnf = 0; ncf = 0; #numerical & categorical features

for i in range(df[features].shape[1]):
    if nu.values[i]<=16:cf.append(nu.index[i])
    else: nf.append(nu.index[i])

print('\n\033[1mInference:\033[0m The Datset has {} numerical & {} categorical features.'.format(len(nf),len(cf)))
```

Inference: The Datset has 6 numerical & 7 categorical features.

In [15]:

```
#Checking the stats of all the columns

display(df.describe())
```

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual
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
mean	2.498630	0.500000	6.526027	0.028767	2.997260	0.683562	1.394521	20.319259	23.726322	62.765175	12.763620	849.249315
std	1.110184	0.500343	3.450215	0.167266	2.006161	0.465405	0.544807	7.506729	8.150308	14.237589	5.195841	686.479875
min	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.000000	2.424346	3.953480	0.000000	1.500244	2.000000
25%	2.000000	0.000000	4.000000	0.000000	1.000000	0.000000	1.000000	13.811885	16.889713	52.000000	9.041650	316.250000
50%	3.000000	0.500000	7.000000	0.000000	3.000000	1.000000	1.000000	20.465826	24.368225	62.625000	12.125325	717.000000
75%	3.000000	1.000000	10.000000	0.000000	5.000000	1.000000	2.000000	26.880615	30.445775	72.989575	15.625589	1096.500000
max	4.000000	1.000000	12.000000	1.000000	6.000000	1.000000	3.000000	35.328347	42.044800	97.250000	34.000021	3410.000000

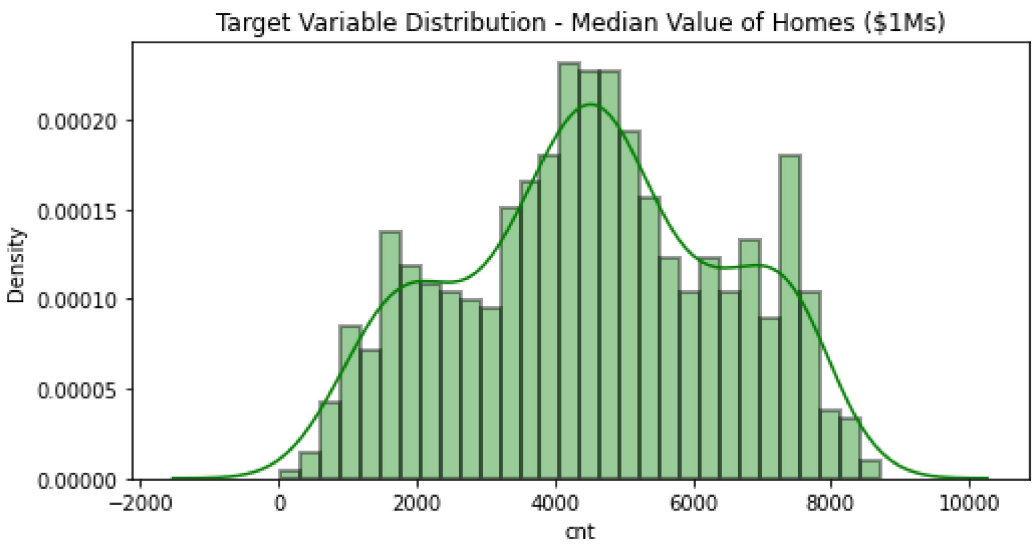
Inference: The stats seem to be fine, let us do further analysis on the Dataset

---

2. Exploratory Data Analysis (EDA)

In [16]:

```
#Let us first analyze the distribution of the target variable

plt.figure(figsize=[8,4])
sns.distplot(df[target], color='g',hist_kws=dict(edgecolor="black", linewidth=2), bins=30)
plt.title('Target Variable Distribution - Median Value of Homes ($1Ms)')
plt.show()
```

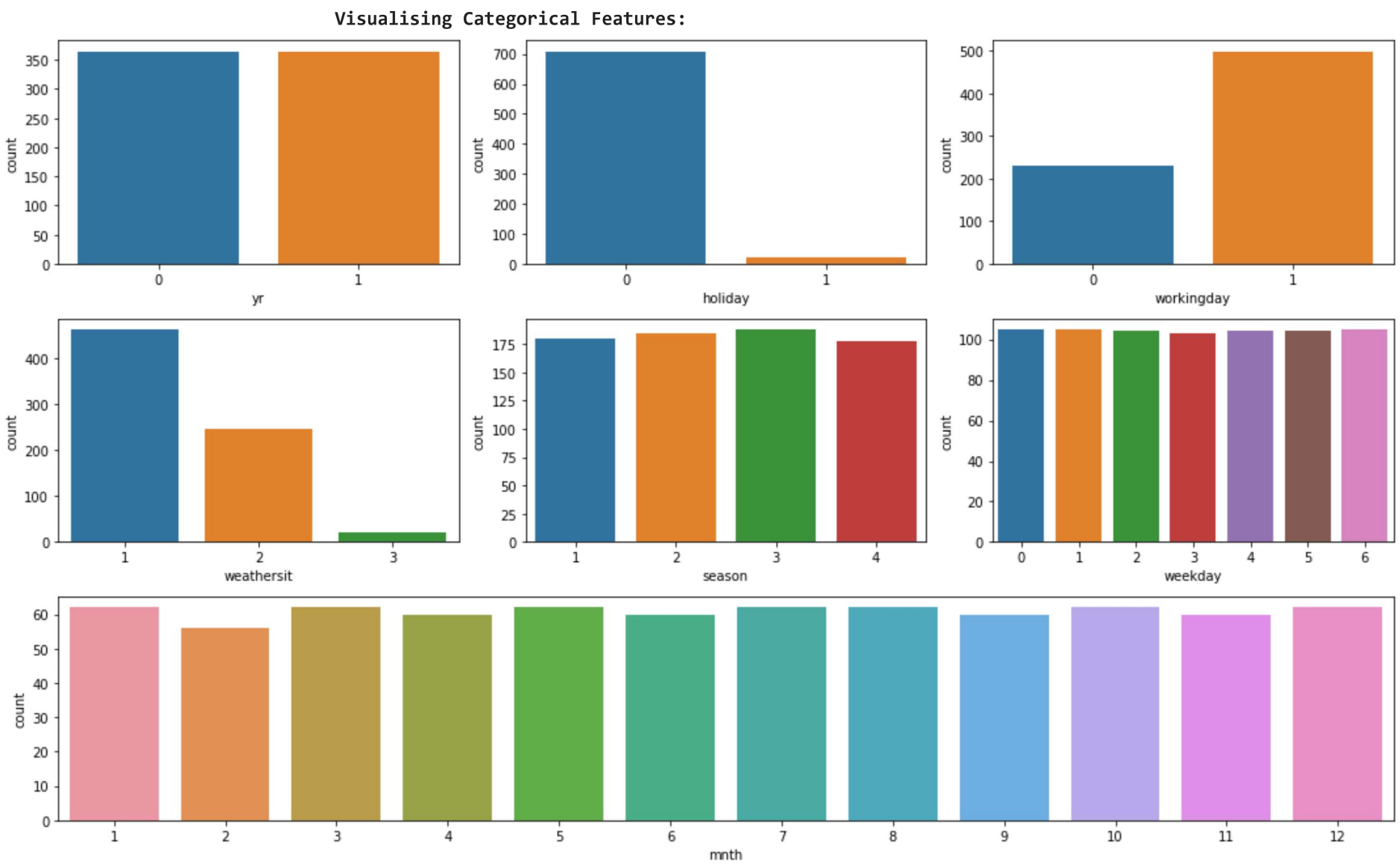


Inference: The Target Variable seems to be be normally distributed, averaging around $40000(units)

In [19]:

```
#Visualising the categorical features

print('\033[1mVisualising Categorical Features:'.center(100))

n=3
plt.figure(figsize=[15,3*math.ceil(len(cf)/n)])
```

```
# for i in range(len(cf)):
#     if df[cf[i]].nunique()<=4:
#         plt.subplot(math.ceil(len(cf)/n),n,i+1)
#         sns.countplot(df[cf[i]])
#     else:
#         plt.subplot(math.ceil(len(cf)/2),2,i)
#         sns.countplot(df[cf[i]])

for i in range(len(cf)):
    if df[cf[i]].nunique()<=8:
        plt.subplot(math.ceil(len(cf)/n),n,i+1)
        sns.countplot(df[cf[i]])
    else:
        plt.subplot(3,1,i-3)
        sns.countplot(df[cf[i]])
        #plt.subplot(4,2,8)
        #sns.countplot(df[cf[i]])

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

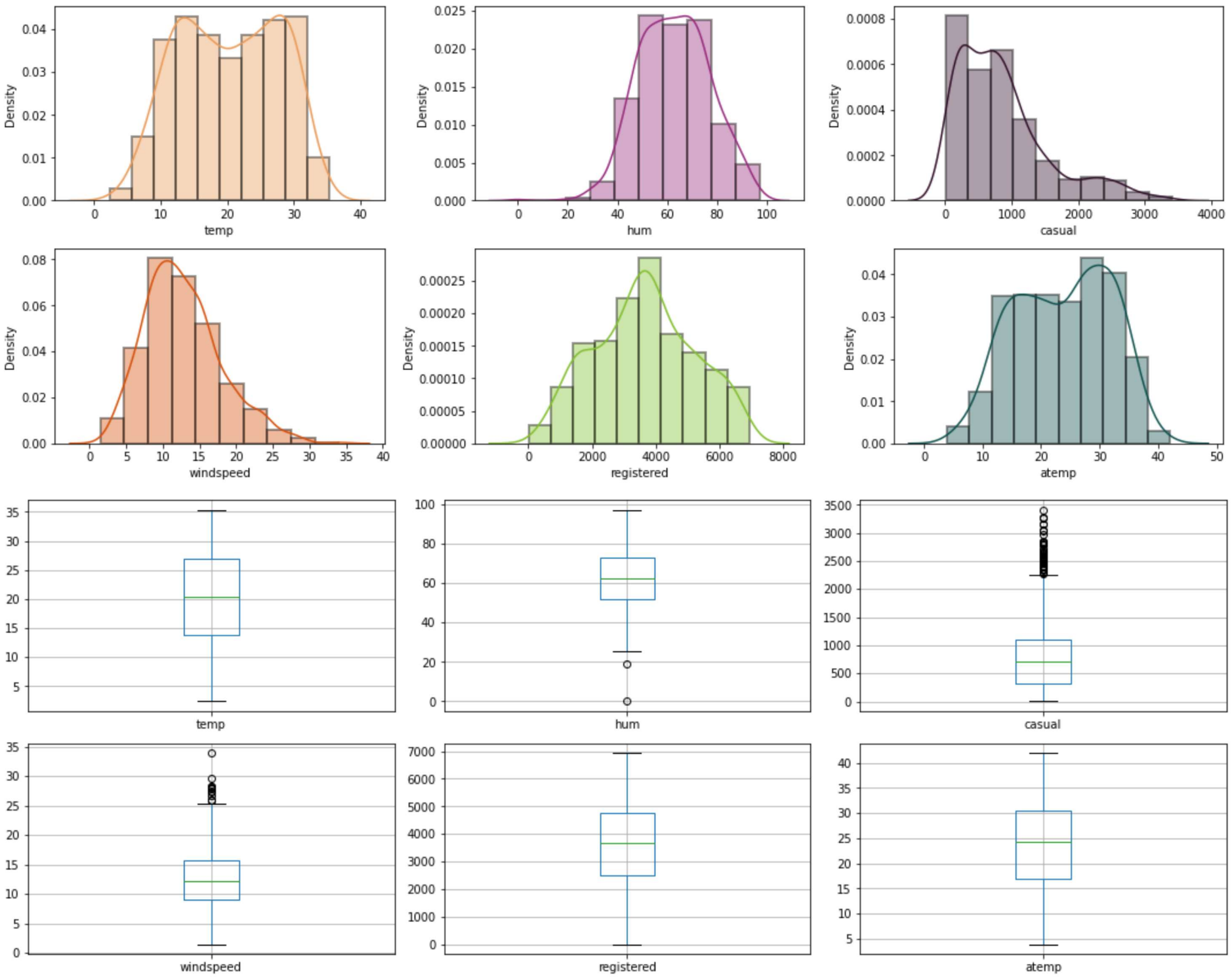


Inference: The categorical features distribution can be seen in the above plots.

In [23]:

```
#Visualising the numeric features

print('\033[1mNumeric Features Distribution'.center(130))

n=3

plt.figure(figsize=[15,3*math.ceil(len(nf)/n)])
for i in range(len(nf)):
    plt.subplot(math.ceil(len(nf)/3),n,i+1)
    sns.distplot(df[nf[i]],hist_kws=dict(edgecolor="black", linewidth=2), bins=10, color=list(np.random.randint([255,255,255])/255
plt.tight_layout()
plt.show()

plt.figure(figsize=[15,3*math.ceil(len(nf)/n)])
for i in range(len(nf)):
    plt.subplot(math.ceil(len(nf)/3),n,i+1)
    df.boxplot(nf[i])
plt.tight_layout()
plt.show()
```

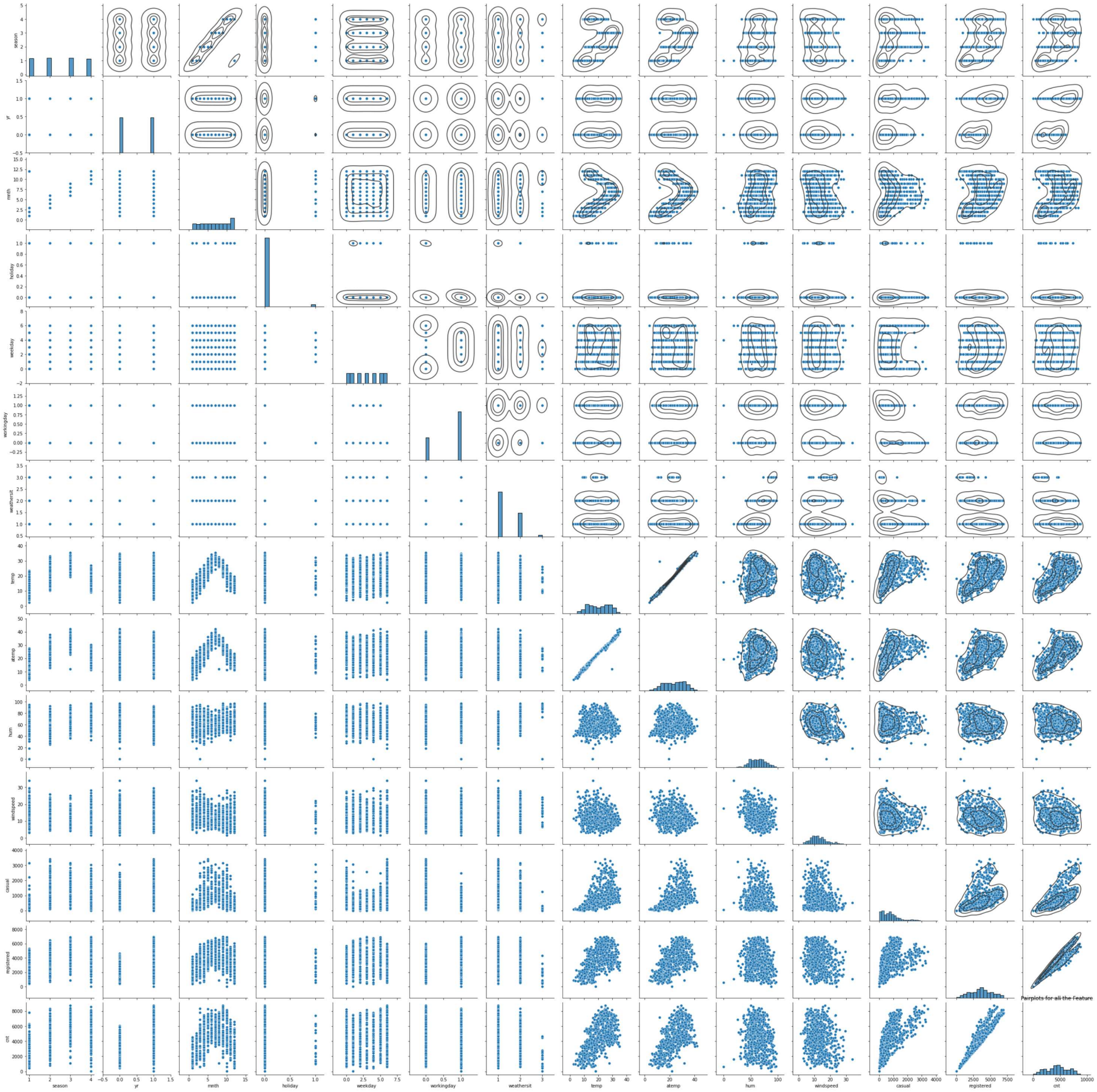
Numeric Features Distribution



Inference: There seem to be some outliers. let us fix these in the upcoming section...

In [24]:

```
#Understanding the relationship between all the features

g = sns.pairplot(df)
plt.title('Pairplots for all the Feature')
g.map_upper(sns.kdeplot, levels=4, color=".2")
plt.show()
```



Inference: We can notice that some features have linear relationship, let us futher analyze the detect multicollinearity.

---

3. Data Preprocessing

In [25]:
```
#Removal of any Duplicate rows (if any)

counter = 0
rs,cs = original_df.shape

df.drop_duplicates(inplace=True)

if df.shape==(rs,cs):
    print('\n\033[1mInference:\033[0m The dataset doesn\'t have any duplicates')
else:
    print(f'\n\033[1mInference:\033[0m Number of duplicates dropped/fixed ---> {rs-df.shape[0]}')
```

Inference: The dataset doesn't have any duplicates

In [26]:
```
#Check for empty elements

nvc = pd.DataFrame(df.isnull().sum().sort_values(), columns=['Total Null Values'])
nvc['Percentage'] = round(nvc['Total Null Values']/df.shape[0],3)*100
print(nvc)
```

```
            Total Null Values  Percentage
season                      0         0.0
yr                          0         0.0
mnth                        0         0.0
holiday                     0         0.0
```

```
weekday                 0         0.0
workingday              0         0.0
weathersit              0         0.0
temp                    0         0.0
atemp                   0         0.0
hum                     0         0.0
windspeed               0         0.0
casual                  0         0.0
registered              0         0.0
cnt                     0         0.0
```

Inference: The datset doesn't have any inconsistant values.

In [27]:
```
#Converting categorical Columns to Numeric

df1 = df.copy()
df3 = df1.copy()

ecc = nvc[nvc['Percentage']!=0].index.values
fcc = [i for i in cf if i not in ecc]
#One-Hot Binay Encoding
oh=True
dm=True
for i in fcc:
    #print(i)
    if df3[i].nunique()==2:
        if oh==True: print("\033[1mOne-Hot Encoding on features:\033[0m")
        print(i);oh=False
        df3[i]=pd.get_dummies(df3[i], drop_first=True, prefix=str(i))
    if (df3[i].nunique()>2 and df3[i].nunique()<17):
        if dm==True: print("\n\033[1mDummy Encoding on features:\033[0m")
        print(i);dm=False
        df3 = pd.concat([df3.drop([i], axis=1), pd.DataFrame(pd.get_dummies(df3[i], drop_first=True, prefix=str(i)))],axis=1)

df3.shape
```

Out[27]:
```
One-Hot Encoding on features:
yr
holiday
workingday

Dummy Encoding on features:
weathersit
season
weekday
mnth
(730, 32)
```

In [28]:
```
# for x in [i for i in ecc if i in cf]:
#     a = df3[x]
#     b=[]; c=[]

#     df4 = df3.copy()
#     df4.drop(ecc, axis=1, inplace=True)
#     df4

#     for i,e in enumerate(a):
#         if e!=e:
#             b.append(i)
#         else:
#             c.append(i)

#     RF = RandomForestClassifier()
#     RF.fit(df4.loc[c],a[c])
#     d = RF.predict(df4.loc[b])

#     f=0
#     for i,e in enumerate(df3[x]):
#         if e!=e:
#             df3.loc[i,x] = d[f]
#             f+=1
# df1 = df3.copy()
# df1
```

In [29]:
```
# #Converting categorical Columns to Numeric

# df3 = df.copy()

# gcc = nvc[nvc['Percentage']!=0].index.values
# hcc = [i for i in cf if i not in gcc]

# #One-Hot Binay Encoding
# oh=True
# dm=True
# for i in hcc:
#     #print(i)
#     if df3[i].nunique()==2:
#         if oh==True: print("\033[1mOne-Hot Encoding on features:\033[0m")
#         print(i);oh=False
```

```
#         df3[i]=pd.get_dummies(df3[i], drop_first=True, prefix=str(i))
#     if (df3[i].nunique()>2 and df3[i].nunique()<17):
#         if dm==True: print("\n\033[1mDummy Encoding on features:\033[0m")
#         print(i);dm=False
#         df3 = pd.concat([df3.drop([i], axis=1), pd.DataFrame(pd.get_dummies(df3[i], drop_first=True, prefix=str(i)))],axis=1)
# df3.shape
```

In [30]:

```
# for x in gcc:
#     a = df3[x]
#     b=[]; c=[]

#     df4 = df3.copy()
#     df4.drop([x], axis=1, inplace=True)

#     for i,e in enumerate(a):
#         if e!=e:
#             b.append(i)
#         else:
#             c.append(i)

#     LR = LinearRegression()
#     LR.fit(df4.loc[c],a[c])
#     d = LR.predict(df4.loc[b])

#     f=0
#     for i,e in enumerate(df3[x]):
#         if e!=e:
#             df3.loc[i,x] = d[f]
#             f+=1
# df3
```

In [31]:

```
#Removal of outlier:

df1 = df3.copy()

#features1 = [i for i in features if i not in ['CHAS','RAD']]
features1 = nf

for i in features1:
    Q1 = df1[i].quantile(0.25)
    Q3 = df1[i].quantile(0.75)
    IQR = Q3 - Q1
    df1 = df1[df1[i] <= (Q3+(1.5*IQR))]
    df1 = df1[df1[i] >= (Q1-(1.5*IQR))]
    df1 = df1.reset_index(drop=True)
display(df1.head())
print('\n\033[1mInference:\033[0m\nBefore removal of outliers, The dataset had {} samples.'.format(df3.shape[0]))
print('After removal of outliers, The dataset now has {} samples.'.format(df1.shape[0]))
```

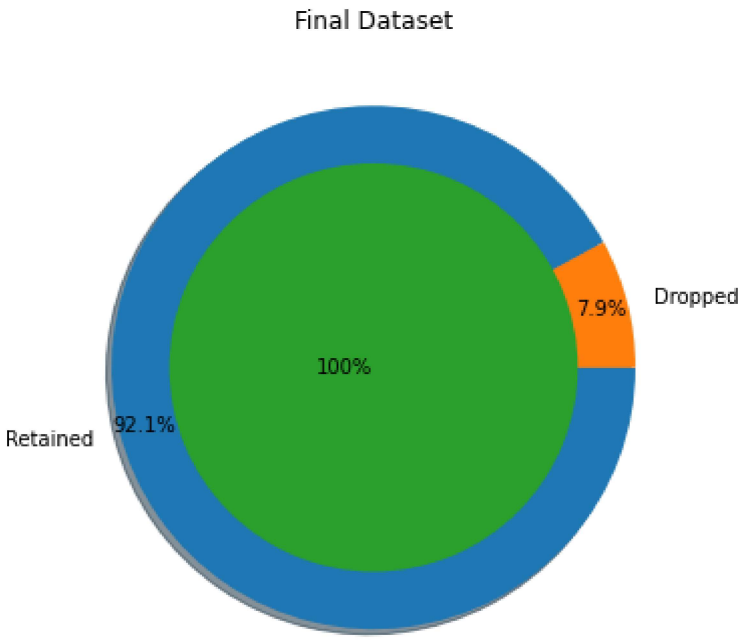
	yr	holiday	workingday	temp	atemp	hum	windspeed	casual	registered	cnt	...	mnth_3	mnth_4	mnth_5	mnth_6	mnth_7	mnth_8
0	0	0	0	14.110847	18.18125	80.5833	10.749882	331	654	985	...	0	0	0	0	0	0
1	0	0	0	14.902598	17.68695	69.6087	16.652113	131	670	801	...	0	0	0	0	0	0
2	0	0	1	8.050924	9.47025	43.7273	16.636703	120	1229	1349	...	0	0	0	0	0	0
3	0	0	1	8.200000	10.60610	59.0435	10.739832	108	1454	1562	...	0	0	0	0	0	0
4	0	0	1	9.305237	11.46350	43.6957	12.522300	82	1518	1600	...	0	0	0	0	0	0

5 rows × 32 columns

Inference:
Before removal of outliers, The dataset had 730 samples.
After removal of outliers, The dataset now has 672 samples.

In [32]:

```
#Final Dataset size after performing Preprocessing

df = df1.copy()
df.columns=[i.replace('-','_') for i in df.columns]

plt.title('Final Dataset')
plt.pie([df.shape[0], original_df.shape[0]-df.shape[0]], radius = 1, labels=['Retained','Dropped'], counterclock=False,
        autopct='%1.1f%%', pctdistance=0.9, explode=[0,0], shadow=True)
plt.pie([df.shape[0]], labels=['100%'], labeldistance=-0, radius=0.78)
plt.show()

print(f'\n\033[1mInference:\033[0m After the cleanup process, {original_df.shape[0]-df.shape[0]} samples were dropped, \
while retaining {round(100 - (df.shape[0]*100/(original_df.shape[0])),2)}% of the data.')
```



Inference: After the cleanup process, 58 samples were dropped, while retaining 7.95% of the data.

---

4. Data Manipulation

In [33]:
```
#Splitting the data intro training & testing sets

m=[]
for i in df.columns.values:
    m.append(i.replace(' ','_'))

df.columns = m
X = df.drop([target],axis=1)
Y = df[target]
Train_X, Test_X, Train_Y, Test_Y = train_test_split(X, Y, train_size=0.8, test_size=0.2, random_state=100)
Train_X.reset_index(drop=True,inplace=True)

print('Original set  ---> ',X.shape,Y.shape,'\nTraining set  ---> ',Train_X.shape,Train_Y.shape,'\nTesting set   ---> ', Test_X.sh
```

```
Original set  --->  (672, 31) (672,)
Training set  --->  (537, 31) (537,)
Testing set   --->  (135, 31)  (135,)
```

In [34]:
```
#Feature Scaling (Standardization)

std = StandardScaler()

print('\033[1mStandardardization on Training set'.center(120))
Train_X_std = std.fit_transform(Train_X)
Train_X_std = pd.DataFrame(Train_X_std, columns=X.columns)
display(Train_X_std.describe())

print('\n','\033[1mStandardardization on Testing set'.center(120))
Test_X_std = std.transform(Test_X)
Test_X_std = pd.DataFrame(Test_X_std, columns=X.columns)
display(Test_X_std.describe())
```

Standardardization on Training set

	yr	holiday	workingday	temp	atemp	hum	windspeed	casual	registered	weathersit
count	5.370000e+02	5.370000e+02	5.370000e+02	5.370000e+02	5.370000e+02	5.370000e+02	5.370000e+02	5.370000e+02	5.370000e+02	5.370000e+
mean	3.969512e-17	1.653964e-17	-3.307927e-17	3.142531e-17	-1.488567e-16	3.605641e-16	-2.646342e-17	-4.465702e-17	1.488567e-16	6.615854e-
std	1.000932e+00	1.000932e+00	1.000932e+00	1.000932e+00	1.000932e+00	1.000932e+00	1.000932e+00	1.000932e+00	1.000932e+00	1.000932e+
min	-9.263539e-01	-1.636113e-01	-1.644217e+00	-2.286119e+00	-2.323698e+00	-2.487149e+00	-2.286649e+00	-1.411974e+00	-2.269189e+00	-6.95288(
25%	-9.263539e-01	-1.636113e-01	-1.644217e+00	-8.576950e-01	-8.497981e-01	-7.718838e-01	-7.298249e-01	-8.581299e-01	-7.297237e-01	-6.95288(
50%	-9.263539e-01	-1.636113e-01	6.081924e-01	-9.448390e-02	-2.696842e-02	-3.761584e-02	-9.691080e-02	-8.739574e-02	-8.059751e-03	-6.95288(
75%	1.079501e+00	-1.636113e-01	6.081924e-01	9.008183e-01	8.527429e-01	7.172211e-01	6.128465e-01	5.768299e-01	6.781851e-01	1.438253e+
max	1.079501e+00	6.112049e+00	6.081924e-01	2.012161e+00	2.251741e+00	2.423668e+00	2.588831e+00	2.956811e+00	2.111393e+00	1.438253e+

8 rows × 31 columns

Standardardization on Testing set

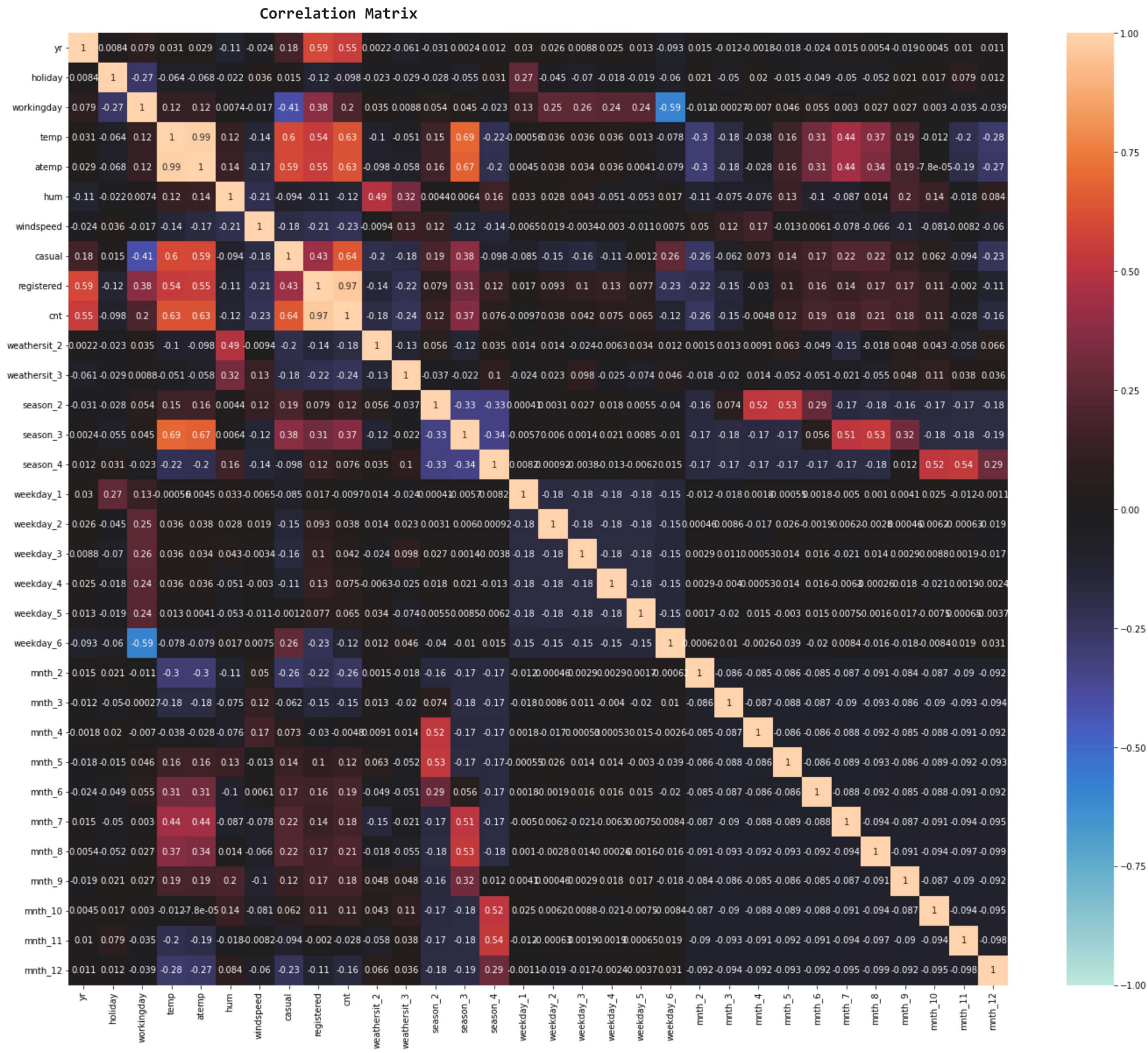
	yr	holiday	workingday	temp	atemp	hum	windspeed	casual	registered	weathersit_2	...	mnth_3	mnth

	yr	holiday	workingday	temp	atemp	hum	windspeed	casual	registered	weathersit_2	...	mnth_3	mnth
count	135.000000	135.000000	135.000000	135.000000	135.000000	135.000000	135.000000	135.000000	135.000000	135.000000	...	135.000000	135.0000
mean	0.128577	0.022334	-0.025819	0.097623	0.099003	0.137586	-0.135094	0.084897	0.074969	0.189736	...	-0.131559	0.1197
std	1.005309	1.068085	1.016730	0.953623	0.939262	0.939658	0.977444	1.057592	0.988668	1.055089	...	0.780071	1.1791
min	-0.926354	-0.163611	-1.644217	-2.085856	-2.204964	-2.237494	-1.867442	-1.342259	-1.919426	-0.695288	...	-0.313304	-0.2798
25%	-0.926354	-0.163611	-1.644217	-0.721565	-0.684823	-0.554541	-0.812458	-0.762272	-0.643073	-0.695288	...	-0.313304	-0.2798
50%	1.079501	-0.163611	0.608192	0.191166	0.253632	0.135677	-0.293537	-0.131936	0.100727	-0.695288	...	-0.313304	-0.2798
75%	1.079501	-0.163611	0.608192	0.896352	0.856560	0.778896	0.467516	0.596195	0.756929	1.438253	...	-0.313304	-0.2798
max	1.079501	6.112049	0.608192	1.864874	1.925724	2.408985	2.605845	2.935509	2.089256	1.438253	...	3.191786	3.5734

8 rows × 31 columns

5. Feature Selection/Extraction

In [35]:
```
#Checking the correlation
print('\033[1mCorrelation Matrix'.center(80))
plt.figure(figsize=[24,20])
sns.heatmap(df.corr(), annot=True, vmin=-1, vmax=1, center=0) #cmap='BuGn'
plt.show()
```



Inference: There seems to be strong multi-correlation between the features. Let us try to fix these...

In [36]:
```
#Testing a Linear Regression model with statsmodels
```

```
Train_xy = pd.concat([Train_X_std,Train_Y.reset_index(drop=True)],axis=1)
a = Train_xy.columns.values

API = api.ols(formula='{} ~ {}'.format(target,' + '.join(i for i in Train_X.columns)), data=Train_xy).fit()
#print(API.conf_int())
#print(API.pvalues)
API.summary()
```

Out[36]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	1.000
Model:	OLS	**Adj. R-squared:**	1.000
Method:	Least Squares	**F-statistic:**	3.509e+30
Date:	Mon, 20 Dec 2021	**Prob (F-statistic):**	0.00
Time:	00:50:52	**Log-Likelihood:**	13320.
No. Observations:	537	**AIC:**	-2.658e+04
Df Residuals:	506	**BIC:**	-2.645e+04
Df Model:	30		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	4338.8734	1.81e-13	2.39e+16	0.000	4338.873	4338.873
yr	-5.949e-13	3.31e-13	-1.797	0.073	-1.25e-12	5.56e-14
holiday	4.092e-13	1.97e-13	2.082	0.038	2.3e-14	7.95e-13
workingday	1.661e-13	2.83e-13	0.588	0.557	-3.89e-13	7.21e-13
temp	-1.207e-12	1.57e-12	-0.769	0.442	-4.29e-12	1.87e-12
atemp	1.655e-14	1.43e-12	0.012	0.991	-2.78e-12	2.82e-12
hum	4.716e-13	2.85e-13	1.654	0.099	-8.84e-14	1.03e-12
windspeed	-1.962e-13	2.19e-13	-0.898	0.370	-6.26e-13	2.33e-13
casual	516.3908	3.88e-13	1.33e+15	0.000	516.391	516.391
registered	1581.0683	5.18e-13	3.05e+15	0.000	1581.068	1581.068
weathersit_2	-2.98e-13	2.47e-13	-1.208	0.227	-7.83e-13	1.87e-13
weathersit_3	-2.68e-13	2.4e-13	-1.116	0.265	-7.4e-13	2.04e-13
season_2	-5.56e-13	4.72e-13	-1.177	0.240	-1.48e-12	3.72e-13
season_3	5.501e-13	6.22e-13	0.885	0.377	-6.71e-13	1.77e-12
season_4	1.724e-12	5.57e-13	3.097	0.002	6.3e-13	2.82e-12
weekday_1	-3.648e-13	1.68e-13	-2.176	0.030	-6.94e-13	-3.54e-14
weekday_2	-3.662e-13	1.75e-13	-2.094	0.037	-7.1e-13	-2.26e-14
weekday_3	-1.854e-13	1.78e-13	-1.042	0.298	-5.35e-13	1.64e-13
weekday_4	-6.229e-13	1.77e-13	-3.523	0.000	-9.7e-13	-2.76e-13
weekday_5	-5.075e-13	1.63e-13	-3.111	0.002	-8.28e-13	-1.87e-13
weekday_6	1.313e-13	2.38e-13	0.550	0.582	-3.37e-13	6e-13
mnth_2	-4.12e-13	2.41e-13	-1.711	0.088	-8.85e-13	6.11e-14
mnth_3	-1.113e-14	3e-13	-0.037	0.970	-6.01e-13	5.79e-13
mnth_4	3.384e-13	4.11e-13	0.823	0.411	-4.69e-13	1.15e-12
mnth_5	2.713e-14	4.6e-13	0.059	0.953	-8.76e-13	9.3e-13
mnth_6	-4.204e-13	4.6e-13	-0.913	0.362	-1.32e-12	4.84e-13
mnth_7	-5.065e-13	5.95e-13	-0.852	0.395	-1.67e-12	6.62e-13
mnth_8	-9.247e-13	5.76e-13	-1.604	0.109	-2.06e-12	2.08e-13
mnth_9	-8.848e-13	4.6e-13	-1.925	0.055	-1.79e-12	1.81e-14
mnth_10	-2.219e-13	4.21e-13	-0.527	0.599	-1.05e-12	6.06e-13
mnth_11	-4.79e-14	4.31e-13	-0.111	0.912	-8.95e-13	7.99e-13
mnth_12	-6.937e-13	3.4e-13	-2.041	0.042	-1.36e-12	-2.59e-14

Omnibus:	30.585	**Durbin-Watson:**	1.045
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	12.933
Skew:	-0.116	**Prob(JB):**	0.00155
Kurtosis:	2.276	**Cond. No.**	5.24e+15

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 8.63e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Inference: We can fix these multicollinearity with two techniques:

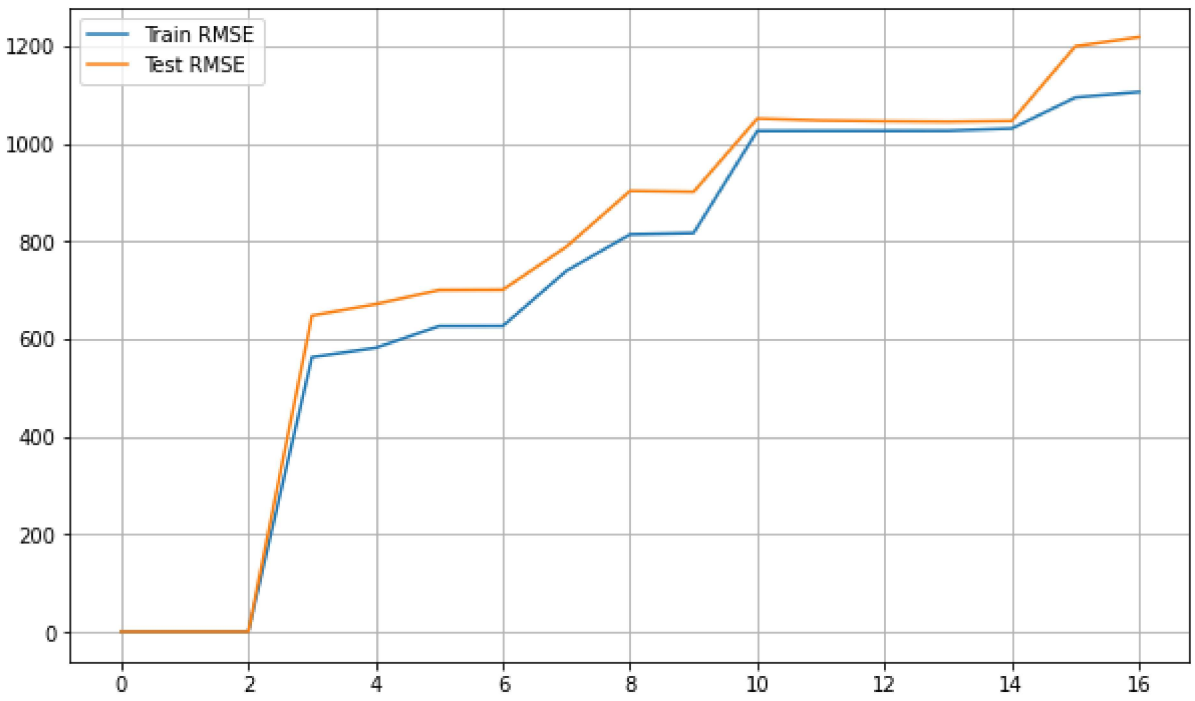
1. Manual Method - Variance Inflation Factor (VIF)
2. Automatic Method - Recursive Feature Elimination (RFE)
3. Feature Elmination using PCA Decomposition

5a. Manual Method - VIF

In [73]:

```
from sklearn.preprocessing import PolynomialFeatures
Trr=[]; Tss=[]; n=3
order=['ord-'+str(i) for i in range(2,n)]
#Trd = pd.DataFrame(np.zeros((10,n-2)), columns=order)
#Tsd = pd.DataFrame(np.zeros((10,n-2)), columns=order)

DROP=[];b=[]

for i in range(len(Train_X_std.columns)-1):
    vif = pd.DataFrame()
    X = Train_X_std.drop(DROP,axis=1)
    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)
    vif.reset_index(drop=True, inplace=True)
    if vif.loc[0][1]>=1.1:
        DROP.append(vif.loc[0][0])
        LR = LinearRegression()
        LR.fit(Train_X_std.drop(DROP,axis=1), Train_Y)

        pred1 = LR.predict(Train_X_std.drop(DROP,axis=1))
        pred2 = LR.predict(Test_X_std.drop(DROP,axis=1))

        Trr.append(np.sqrt(mean_squared_error(Train_Y, pred1)))
        Tss.append(np.sqrt(mean_squared_error(Test_Y, pred2)))

        #Trd.loc[i,'ord-'+str(k)] = round(np.sqrt(mean_squared_error(Train_Y, pred1)),2)
        #Tsd.loc[i,'ord-'+str(k)] = round(np.sqrt(mean_squared_error(Test_Y, pred2)),2)

print('Dropped Features --> ',DROP)
#plt.plot(b)
#plt.show()
#print(API.summary())

# plt.figure(figsize=[20,4])
# plt.subplot(1,3,1)
# sns.heatmap(Trd.loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max())
# plt.title('Train RMSE')
# plt.subplot(1,3,2)
# sns.heatmap(Tsd.loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max()+10)
# plt.title('Test RMSE')
# plt.subplot(1,3,3)
# sns.heatmap((Trd+Tsd).loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max()+25)
# plt.title('Total RMSE')
# plt.show()

plt.plot(Trr, label='Train RMSE')
plt.plot(Tss, label='Test RMSE')
#plt.ylim([19.75,20.75])
plt.legend()
plt.grid()
plt.show()
```

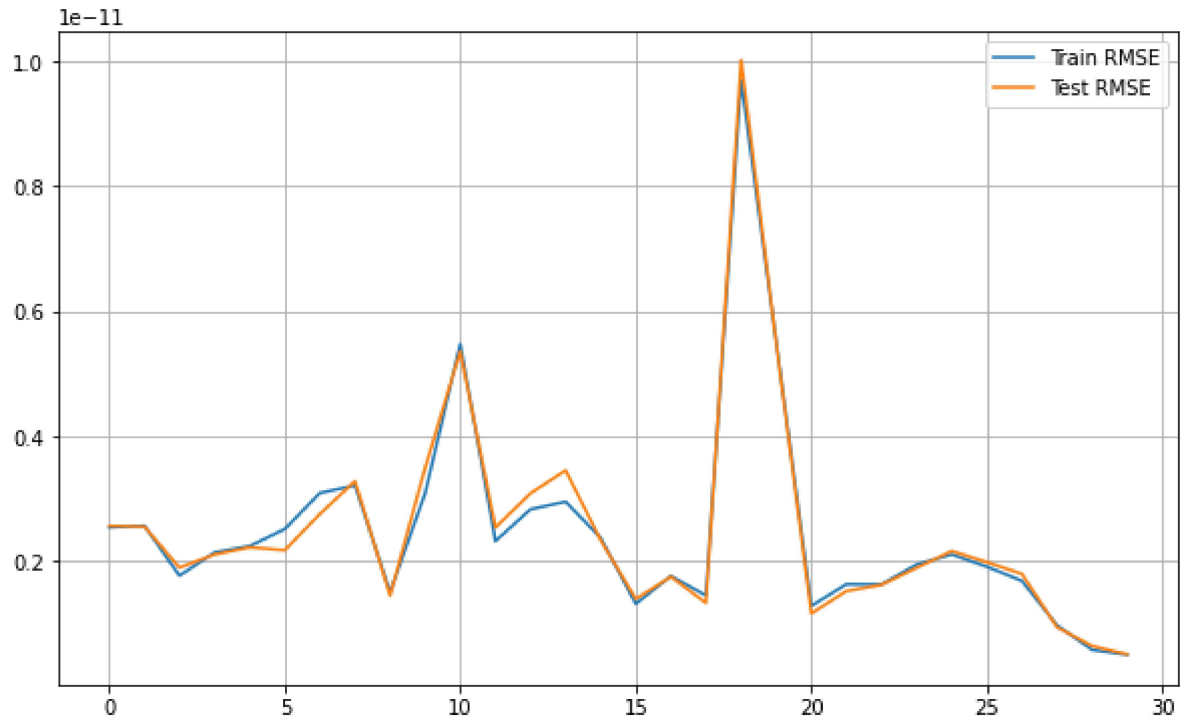
```
Dropped Features -->  ['weekday_2', 'temp', 'season_3', 'registered', 'atemp', 'season_4', 'season_2', 'workingday', 'casual', 'hu
m', 'mnth_7', 'weekday_1', 'mnth_12', 'mnth_3', 'weekday_3', 'mnth_10', 'mnth_4']
```



5b. Automatic Method - RFE

In [75]:

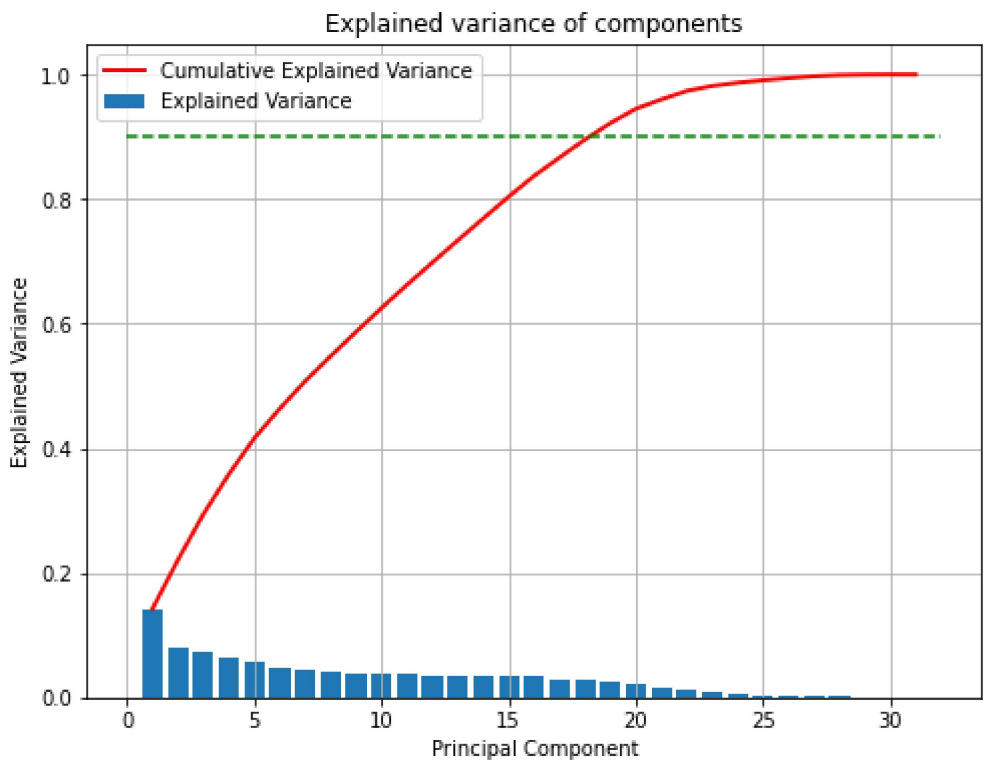
```
from sklearn.preprocessing import PolynomialFeatures
Trr=[]; Tss=[]; n=3
order=['ord-'+str(i) for i in range(2,n)]
Trd = pd.DataFrame(np.zeros((10,n-2)), columns=order)
Tsd = pd.DataFrame(np.zeros((10,n-2)), columns=order)

m=df.shape[1]-2
for i in range(m):
    lm = LinearRegression()
    #lm.fit(Train_X_std, Train_Y)

    rfe = RFE(lm,n_features_to_select=Train_X_std.shape[1]-i)             # running RFE
    rfe = rfe.fit(Train_X_std, Train_Y)

    #print(Train_X_std.shape[1]-i)

    #Train_xy = pd.concat([Train_X_std[Train_X.columns[rfe.support_]],Train_Y.reset_index(drop=True)],axis=1)
    #a = Train_xy.columns.values.tolist()
    #a.remove(target)

    #API = api.ols(formula='{} ~ {}'.format(target,' + '.join(i for i in a)), data=Train_xy).fit()
    #DROP.append(vif.loc[0][0])
    LR = LinearRegression()
    LR.fit(Train_X_std.loc[:,rfe.support_], Train_Y)

    #print(Train_X_std.loc[:,rfe.support_].columns)

    pred1 = LR.predict(Train_X_std.loc[:,rfe.support_])
    pred2 = LR.predict(Test_X_std.loc[:,rfe.support_])

    Trr.append(np.sqrt(mean_squared_error(Train_Y, pred1)))
    Tss.append(np.sqrt(mean_squared_error(Test_Y, pred2)))

# plt.figure(figsize=[20,4])
# plt.subplot(1,3,1)
# sns.heatmap(Trd.loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max())
# plt.title('Train RMSE')
# plt.subplot(1,3,2)
# sns.heatmap(Tsd.loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max()+10)
# plt.title('Test RMSE')
# plt.subplot(1,3,3)
# sns.heatmap((Trd+Tsd).loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max()+25)
# plt.title('Total RMSE')
# plt.show()

plt.plot(Trr, label='Train RMSE')
plt.plot(Tss, label='Test RMSE')
#plt.ylim([19.75,20.75])
plt.legend()
plt.grid()
plt.show()
```



5c. Feature Elmination using PCA Decomposition

In [76]:

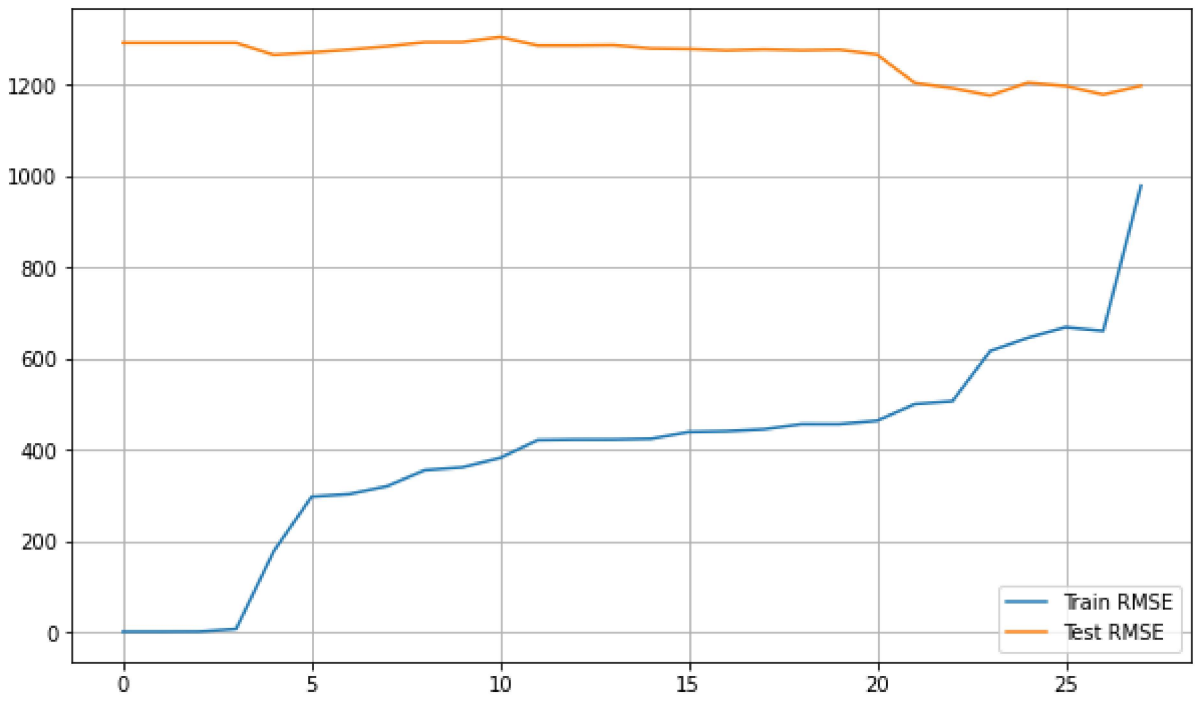
```
from sklearn.decomposition import PCA

pca = PCA().fit(Train_X_std)

fig, ax = plt.subplots(figsize=(8,6))
x_values = range(1, pca.n_components_+1)
ax.bar(x_values, pca.explained_variance_ratio_, lw=2, label='Explained Variance')
ax.plot(x_values, np.cumsum(pca.explained_variance_ratio_), lw=2, label='Cumulative Explained Variance', color='red')
plt.plot([0,pca.n_components_+1],[0.9,0.9],'g--')
ax.set_title('Explained variance of components')
ax.set_xlabel('Principal Component')
ax.set_ylabel('Explained Variance')
plt.legend()
plt.grid()
plt.show()
```



In [77]:

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import PolynomialFeatures
Trr=[]; Tss=[]; n=3
order=['ord-'+str(i) for i in range(2,n)]
Trd = pd.DataFrame(np.zeros((10,n-2)), columns=order)
Tsd = pd.DataFrame(np.zeros((10,n-2)), columns=order)
m=df.shape[1]-4

for i in range(m):
    pca = PCA(n_components=Train_X_std.shape[1]-i)
    Train_X_std_pca = pca.fit_transform(Train_X_std)
    Test_X_std_pca = pca.fit_transform(Test_X_std)

    LR = LinearRegression()
    LR.fit(Train_X_std_pca, Train_Y)

    pred1 = LR.predict(Train_X_std_pca)
    pred2 = LR.predict(Test_X_std_pca)

    Trr.append(round(np.sqrt(mean_squared_error(Train_Y, pred1)),2))
    Tss.append(round(np.sqrt(mean_squared_error(Test_Y, pred2)),2))

# plt.figure(figsize=[20,4.5])
```

```
# plt.subplot(1,3,1)
# sns.heatmap(Trd.loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max())
# plt.title('Train RMSE')
# plt.subplot(1,3,2)
# sns.heatmap(Tsd.loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max()+10)
# plt.title('Test RMSE')
# plt.subplot(1,3,3)
# sns.heatmap((Trd+Tsd).loc[:6], cmap='BuGn', annot=True, vmin=0, vmax=Trd.max().max()+25)
# plt.title('Total RMSE')
# plt.show()

plt.plot(Trr, label='Train RMSE')
plt.plot(Tss, label='Test RMSE')
#plt.ylim([19.5,20.75])
plt.legend()
plt.grid()
plt.show()
```



Inference:

It can be seen that the performance of the modelsis quiet comparable unpon dropping features using VIF, RFE & PCA Techniques. Comparing the RMSE plots, the optimal values were found for dropping most features using manual RFE Technique.

In [79]:

```
#Shortlisting the selected Features (with RFE)

lm = LinearRegression()
rfe = RFE(lm,n_features_to_select=2)             # running RFE
rfe = rfe.fit(Train_X_std, Train_Y)

LR = LinearRegression()
LR.fit(Train_X_std.loc[:,rfe.support_], Train_Y)

#print(Train_X_std.loc[:,rfe.support_].columns)

pred1 = LR.predict(Train_X_std.loc[:,rfe.support_])
pred2 = LR.predict(Test_X_std.loc[:,rfe.support_])

print(mean_squared_error(Train_Y, pred1))
print(mean_squared_error(Test_Y, pred2))

Train_X_std = Train_X_std.loc[:,rfe.support_]
Test_X_std = Test_X_std.loc[:,rfe.support_]
```

```
2.487703331979776e-25
2.5581326351176965e-25
```

---

6. Predictive Modelling

In [86]:

```
#Let us first define a function to evaluate our models

Model_Evaluation_Comparison_Matrix = pd.DataFrame(np.zeros([5,8]), columns=['Train-R2','Test-R2','Train-RSS','Test-RSS',
                                                                            'Train-MSE','Test-MSE','Train-RMSE','Test-RMSE'])
rc=np.random.choice(Train_X_std.columns,2)
def Evaluate(n, pred1,pred2):
    #Plotting predicted predicteds alongside the actual datapoints
    plt.figure(figsize=[15,6])
    for e,i in enumerate(rc):
        plt.subplot(2,3,e+1)
        plt.scatter(y=Train_Y, x=Train_X_std[i], label='Actual')
        plt.scatter(y=pred1, x=Train_X_std[i], label='Prediction')
        plt.legend()
    plt.show()

    #Evaluating the Multiple Linear Regression Model
```

```
print('\n\n{}Training Set Metrics{}'.format('-'*20, '-'*20))
print('\nR2-Score on Training set --->',round(r2_score(Train_Y, pred1),20))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Train_Y-pred1)),20))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Train_Y, pred1),20))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Train_Y, pred1)),20))

print('\n{}Testing Set Metrics{}'.format('-'*20, '-'*20))
print('\nR2-Score on Testing set --->',round(r2_score(Test_Y, pred2),20))
print('Residual Sum of Squares (RSS) on Training set  --->',round(np.sum(np.square(Test_Y-pred2)),20))
print('Mean Squared Error (MSE) on Training set       --->',round(mean_squared_error(Test_Y, pred2),20))
print('Root Mean Squared Error (RMSE) on Training set --->',round(np.sqrt(mean_squared_error(Test_Y, pred2)),20))
print('\n{}Residual Plots{}'.format('-'*20, '-'*20))

Model_Evaluation_Comparison_Matrix.loc[n,'Train-R2']  = round(r2_score(Train_Y, pred1),20)
Model_Evaluation_Comparison_Matrix.loc[n,'Test-R2']   = round(r2_score(Test_Y, pred2),20)
Model_Evaluation_Comparison_Matrix.loc[n,'Train-RSS'] = round(np.sum(np.square(Train_Y-pred1)),20)
Model_Evaluation_Comparison_Matrix.loc[n,'Test-RSS']  = round(np.sum(np.square(Test_Y-pred2)),20)
Model_Evaluation_Comparison_Matrix.loc[n,'Train-MSE'] = round(mean_squared_error(Train_Y, pred1),20)
Model_Evaluation_Comparison_Matrix.loc[n,'Test-MSE']  = round(mean_squared_error(Test_Y, pred2),20)
Model_Evaluation_Comparison_Matrix.loc[n,'Train-RMSE']= round(np.sqrt(mean_squared_error(Train_Y, pred1)),20)
Model_Evaluation_Comparison_Matrix.loc[n,'Test-RMSE'] = round(np.sqrt(mean_squared_error(Test_Y, pred2)),20)

# Plotting y_test and y_pred to understand the spread.
plt.figure(figsize=[15,4])

plt.subplot(1,2,1)
sns.distplot((Train_Y - pred1))
plt.title('Error Terms')
plt.xlabel('Errors')

    plt.subplot(1,2,2)
    plt.scatter(Train_Y,pred1)
    plt.plot([Train_Y.min(),Train_Y.max()],[Train_Y.min(),Train_Y.max()], 'r--')
    plt.title('Test vs Prediction')
    plt.xlabel('y_test')
    plt.ylabel('y_pred')
    plt.show()
```

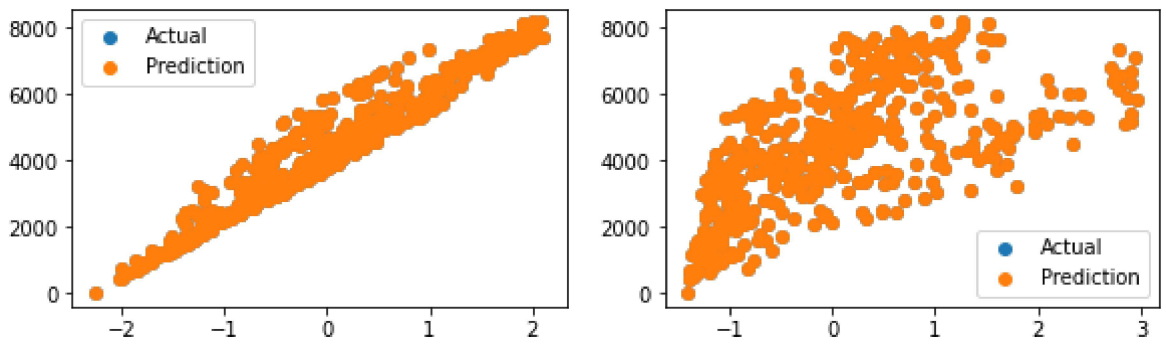
Objective: Let us now try building multiple regression models & compare their evaluation metrics to choose the best fit model both training and testing sets...

6a. Multiple Linear Regression(MLR)

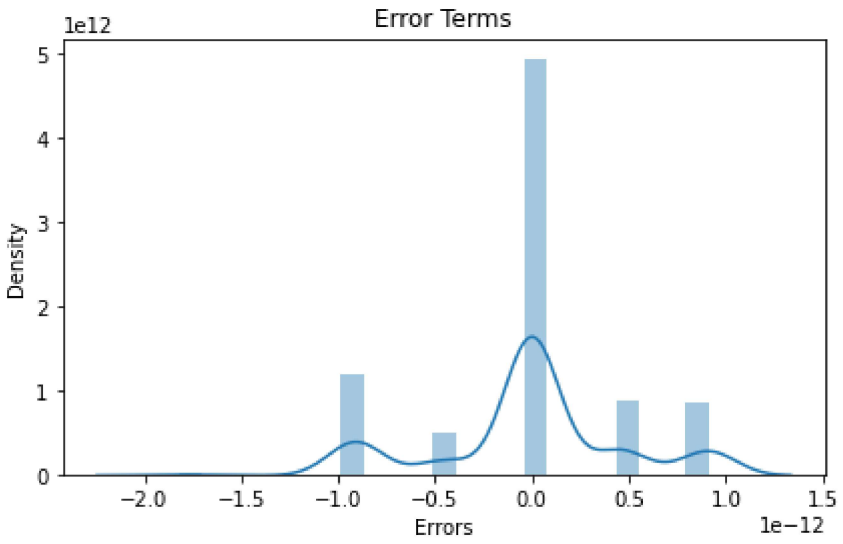
In [87]:

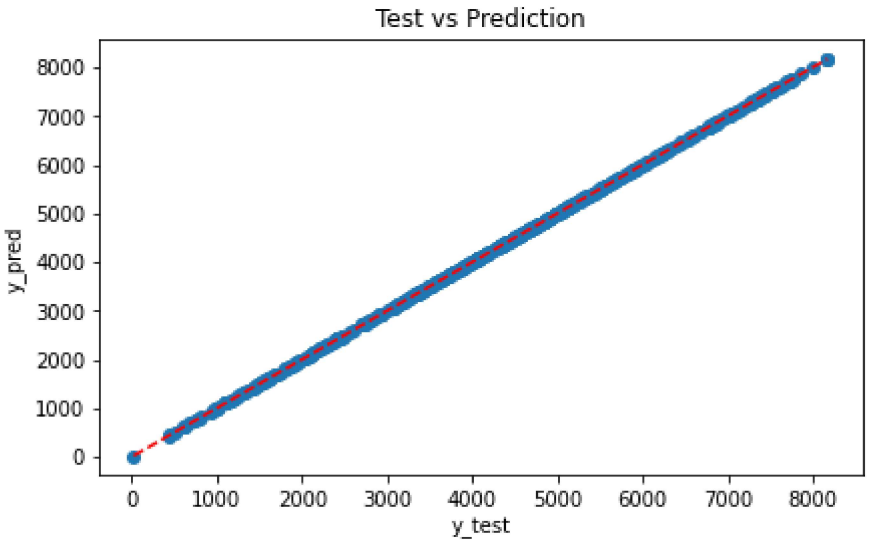
```
#Linear Regression

MLR = LinearRegression().fit(Train_X_std,Train_Y)
pred1 = MLR.predict(Train_X_std)
pred2 = MLR.predict(Test_X_std)

print('{}{}\033[1m Evaluating Multiple Linear Regression Model \033[0m{}{}\n'.format('<'*3,'-'*35 ,'-'*35,'>'*3))
print('The Coeffecient of the Regresion Model was found to be ',MLR.coef_)
print('The Intercept of the Regresion Model was found to be ',MLR.intercept_)

Evaluate(0, pred1, pred2)
```

```
<<<---------------------------------- Evaluating Multiple Linear Regression Model ----------------------------------->>>
The Coeffecient of the Regresion Model was found to be  [ 516.39075268 1581.06834478]
The Intercept of the Regresion Model was found to be  4338.873370577281
```




```
--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 0.0
Mean Squared Error (MSE) on Training set       ---> 0.0
Root Mean Squared Error (RMSE) on Training set ---> 4.9876882e-13

--------------------Testing Set Metrics--------------------

R2-Score on Testing set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 0.0
Mean Squared Error (MSE) on Training set       ---> 0.0
Root Mean Squared Error (RMSE) on Training set ---> 5.0577986e-13

--------------------Residual Plots--------------------
```

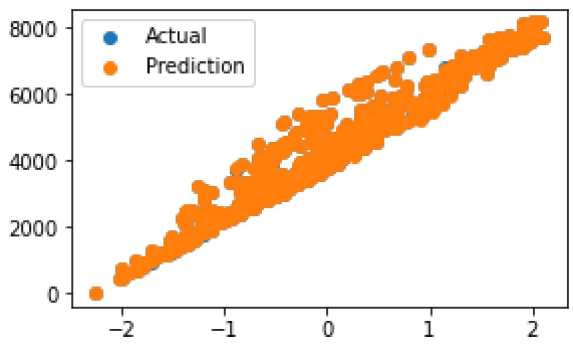


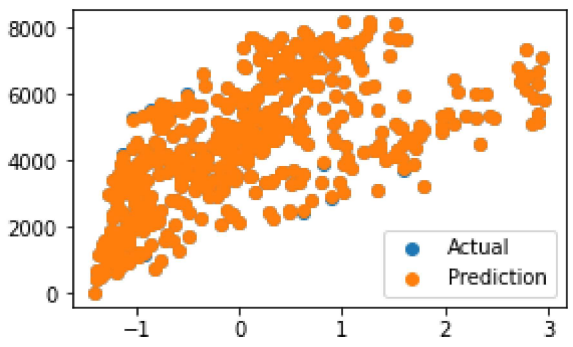


6b. Ridge Regression Model

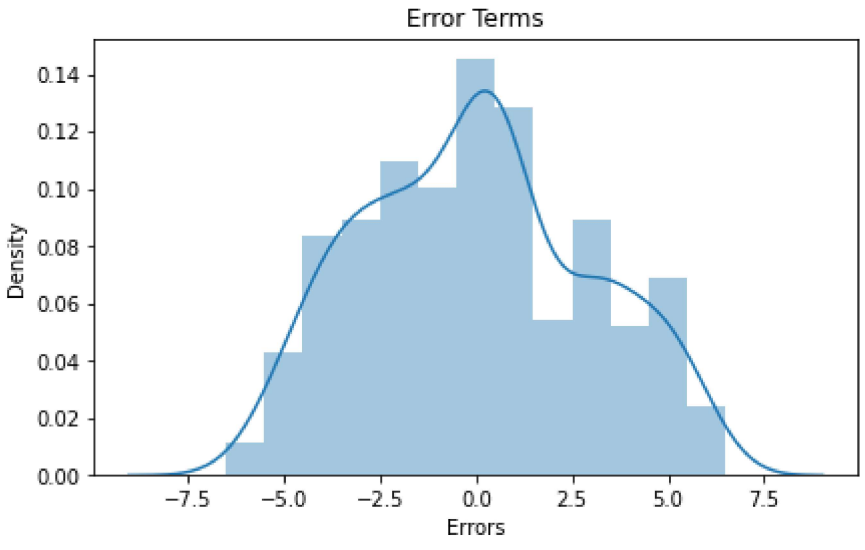
In [88]:
```
#Creating a Ridge Regression model

RLR = Ridge().fit(Train_X_std,Train_Y)
pred1 = RLR.predict(Train_X_std)
pred2 = RLR.predict(Test_X_std)

print('{}{}\033[1m Evaluating Ridge Regression Model \033[0m{}{}\n'.format('<'*3,'-'*35 ,'-'*35,'>'*3))
print('The Coeffecient of the Regresion Model was found to be ',MLR.coef_)
print('The Intercept of the Regresion Model was found to be ',MLR.intercept_)

Evaluate(1, pred1, pred2)
```

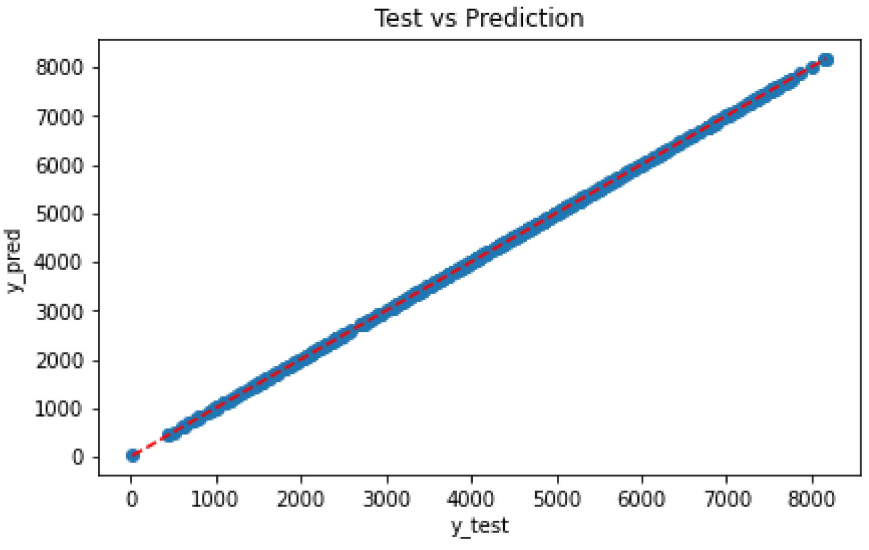
```
<<<---------------------------------- Evaluating Ridge Regression Model ----------------------------------->>>

The Coeffecient of the Regresion Model was found to be  [ 516.39075268 1581.06834478]
The Intercept of the Regresion Model was found to be  4338.873370577281
```






```
--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.9999974781597214
Residual Sum of Squares (RSS) on Training set  ---> 4695.906197264011
Mean Squared Error (MSE) on Training set       ---> 8.744704277959052
Root Mean Squared Error (RMSE) on Training set ---> 2.9571446156654315

--------------------Testing Set Metrics--------------------

R2-Score on Testing set ---> 0.999997508603511
Residual Sum of Squares (RSS) on Training set  ---> 1150.057701240193
Mean Squared Error (MSE) on Training set       ---> 8.51894593511254
Root Mean Squared Error (RMSE) on Training set ---> 2.9187233399403483

--------------------Residual Plots--------------------
```



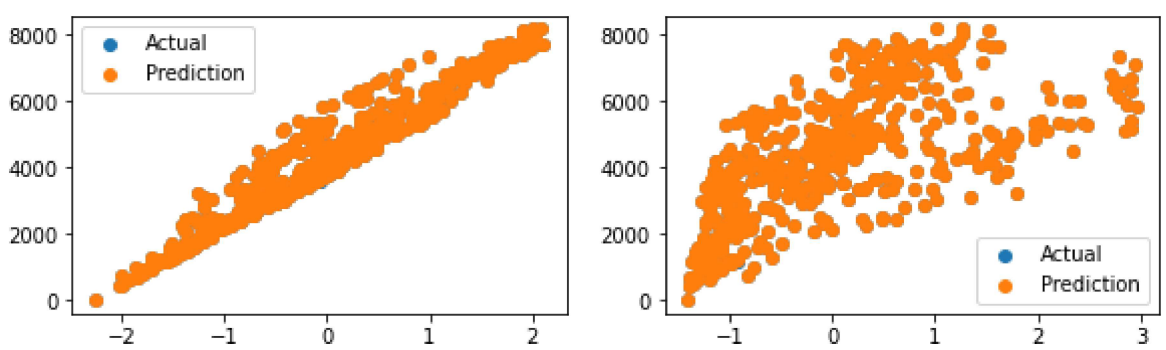


6c. Lasso Regression Model

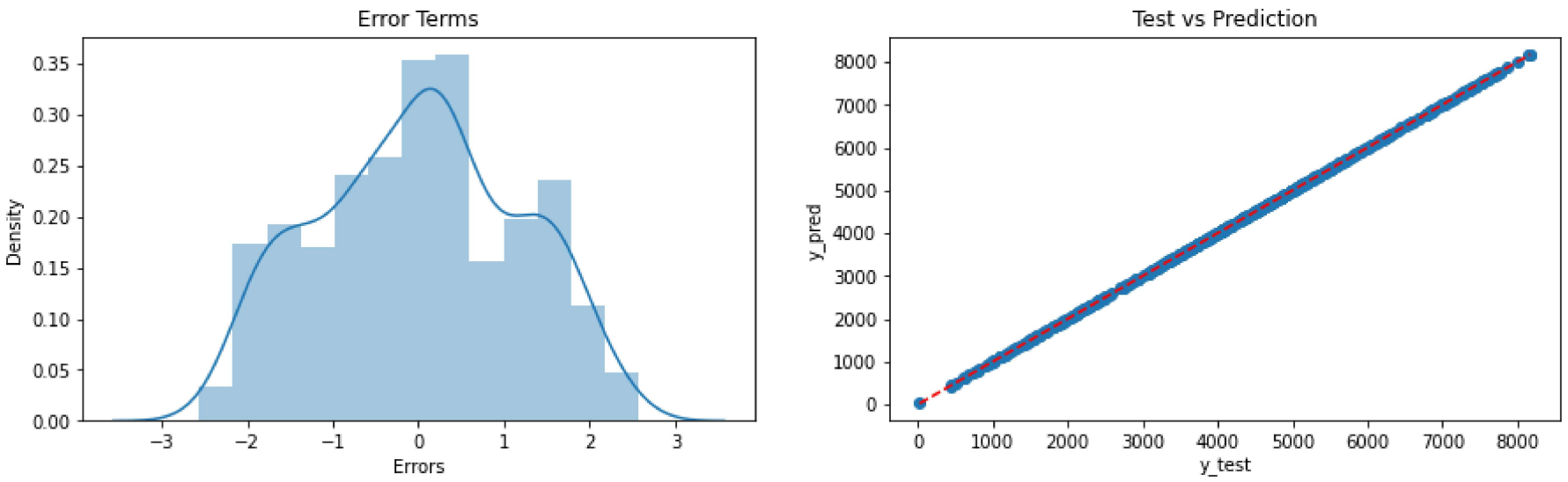
In [89]:
```
#Creating a Ridge Regression model
```

```
LLR = Lasso().fit(Train_X_std,Train_Y)
pred1 = LLR.predict(Train_X_std)
pred2 = LLR.predict(Test_X_std)

print('{}{}\033[1m Evaluating Lasso Regression Model \033[0m{}{}\n'.format('<'*3,'-'*35 ,'-'*35,'>'*3))
print('The Coeffecient of the Regresion Model was found to be ',MLR.coef_)
print('The Intercept of the Regresion Model was found to be ',MLR.intercept_)

Evaluate(2, pred1, pred2)
```

```
<<<---------------------------------- Evaluating Lasso Regression Model ----------------------------------->>>

The Coeffecient of the Regresion Model was found to be  [ 516.39075268 1581.06834478]
The Intercept of the Regresion Model was found to be  4338.873370577281
```




```
--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.9999996050993837
Residual Sum of Squares (RSS) on Training set  ---> 735.3424668634066
Mean Squared Error (MSE) on Training set       ---> 1.3693528246990812
Root Mean Squared Error (RMSE) on Training set ---> 1.1701934988278995

--------------------Testing Set Metrics--------------------

R2-Score on Testing set ---> 0.9999995863151233
Residual Sum of Squares (RSS) on Training set  ---> 190.96176802880834
Mean Squared Error (MSE) on Training set       ---> 1.41453161502821
Root Mean Squared Error (RMSE) on Training set ---> 1.1893408321537648

--------------------Residual Plots--------------------
```

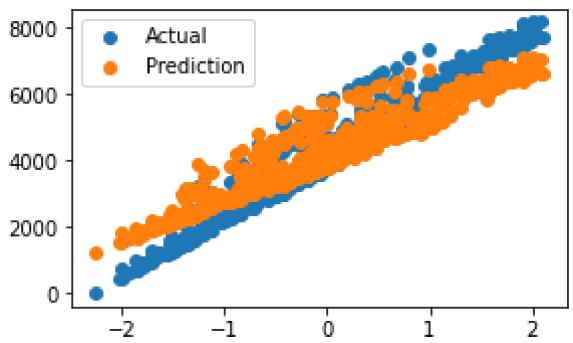


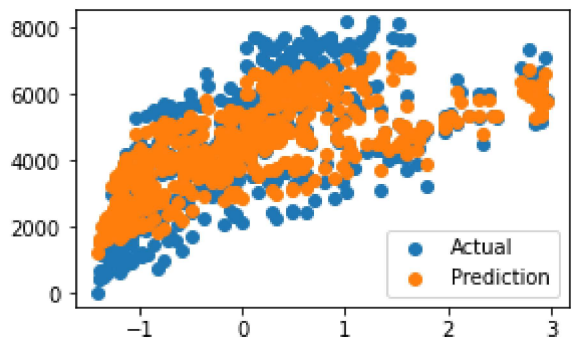
6d. Elastic-Net Regression

In [90]:

```
#Creating a ElasticNet Regression model

ENR = ElasticNet().fit(Train_X_std,Train_Y)
pred1 = ENR.predict(Train_X_std)
pred2 = ENR.predict(Test_X_std)

print('{}{}\033[1m Evaluating Elastic-Net Regression Model \033[0m{}{}\n'.format('<'*3,'-'*35 ,'-'*35,'>'*3))
print('The Coeffecient of the Regresion Model was found to be ',MLR.coef_)
print('The Intercept of the Regresion Model was found to be ',MLR.intercept_)

Evaluate(3, pred1, pred2)
```

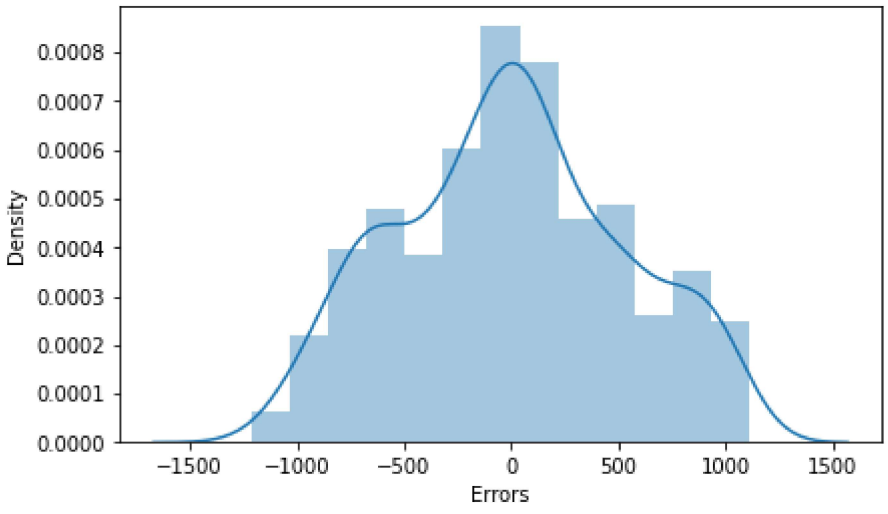
```
<<<---------------------------------- Evaluating Elastic-Net Regression Model ----------------------------------->>>

The Coeffecient of the Regresion Model was found to be  [ 516.39075268 1581.06834478]
The Intercept of the Regresion Model was found to be  4338.873370577281
```



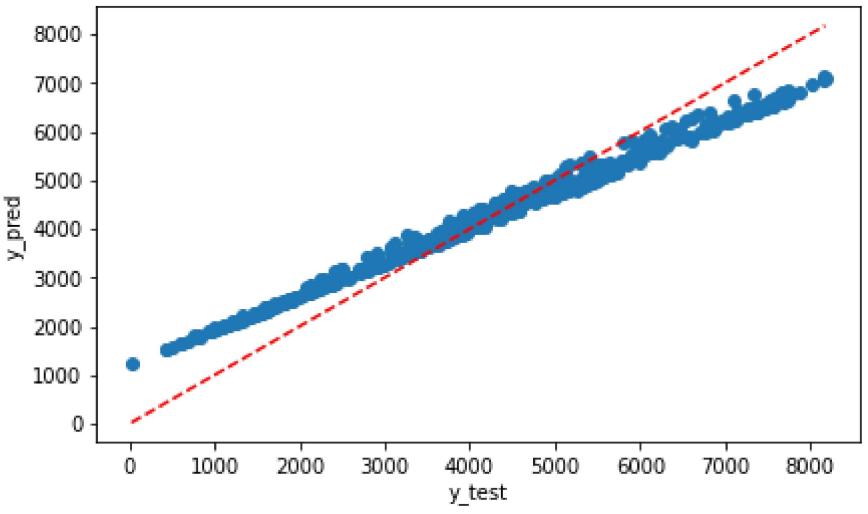



```
--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 0.9186470175174858
Residual Sum of Squares (RSS) on Training set  ---> 151486982.67961696
Mean Squared Error (MSE) on Training set       ---> 282098.6642078528
Root Mean Squared Error (RMSE) on Training set ---> 531.1296114959632

--------------------Testing Set Metrics--------------------

R2-Score on Testing set ---> 0.9193640445679679
Residual Sum of Squares (RSS) on Training set  ---> 37222498.285557985
Mean Squared Error (MSE) on Training set       ---> 275722.20952265174
Root Mean Squared Error (RMSE) on Training set ---> 525.0925723362041

--------------------Residual Plots--------------------
```

Error Terms



Test vs Prediction

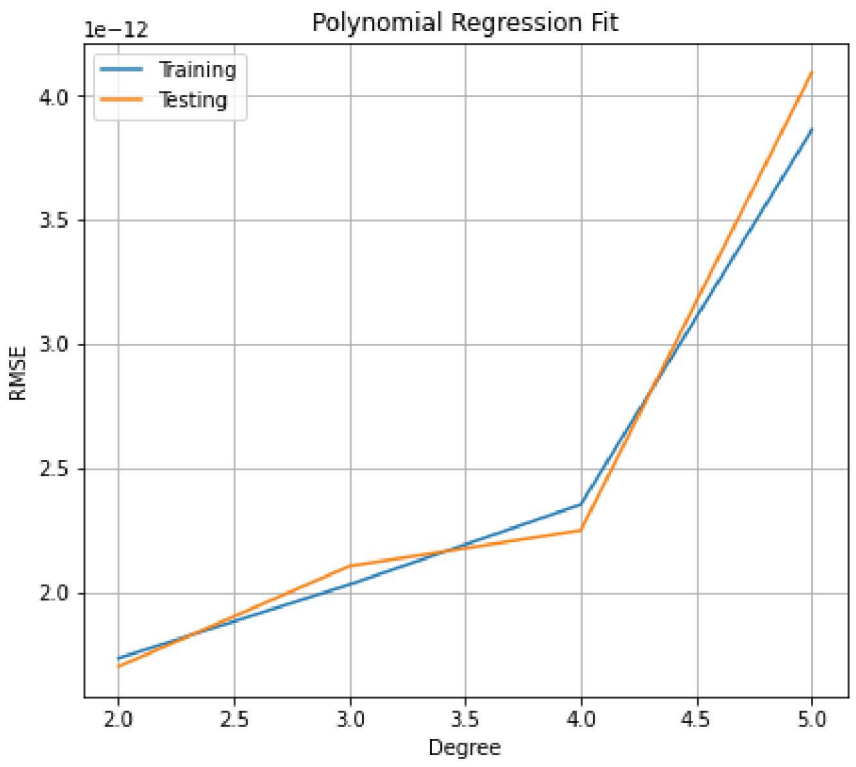


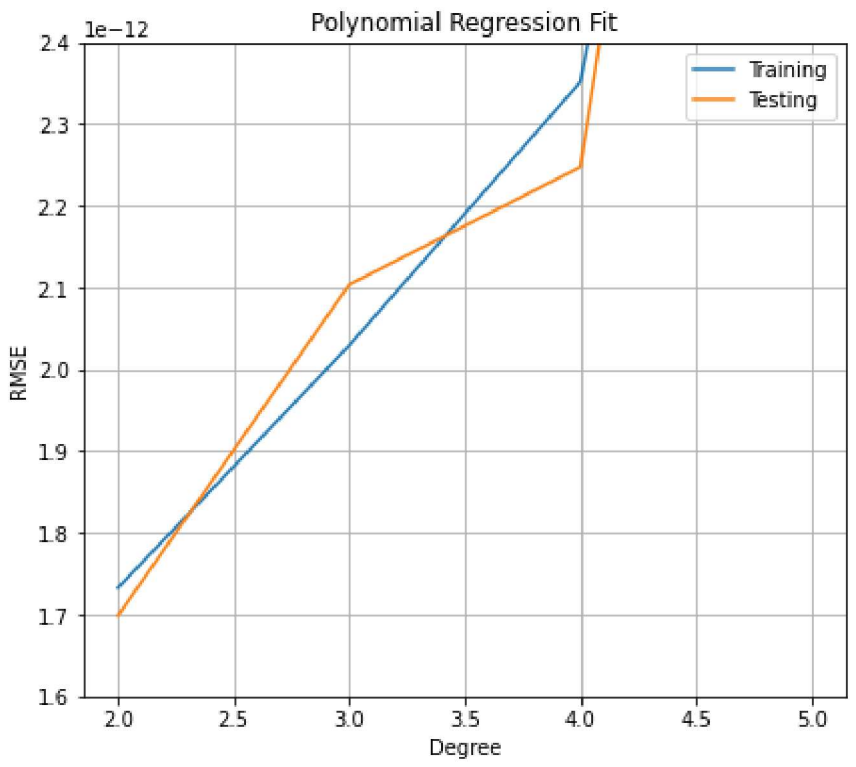
6e. Polynomial Regression Model

In [122…

```python
#Checking polynomial regression performance on various degrees

Trr=[]; Tss=[]
n_degree=6

for i in range(2,n_degree):
    #print(f'{i} Degree')
    poly_reg = PolynomialFeatures(degree=i)
    X_poly = poly_reg.fit_transform(Train_X_std)
    X_poly1 = poly_reg.fit_transform(Test_X_std)
    LR = LinearRegression()
    LR.fit(X_poly, Train_Y)

    pred1 = LR.predict(X_poly)
    Trr.append(np.sqrt(mean_squared_error(Train_Y, pred1)))

    pred2 = LR.predict(X_poly1)
    Tss.append(np.sqrt(mean_squared_error(Test_Y, pred2)))

plt.figure(figsize=[15,6])
plt.subplot(1,2,1)
plt.plot(range(2,n_degree),Trr, label='Training')
plt.plot(range(2,n_degree),Tss, label='Testing')
#plt.plot([1,4],[1,4],'b--')
plt.title('Polynomial Regression Fit')
#plt.ylim([0,5])
plt.xlabel('Degree')
plt.ylabel('RMSE')
plt.grid()
plt.legend()
#plt.xticks()

plt.subplot(1,2,2)
plt.plot(range(2,n_degree),Trr, label='Training')
plt.plot(range(2,n_degree),Tss, label='Testing')
plt.title('Polynomial Regression Fit')
plt.ylim([1.6e-12,2.4e-12])
plt.xlabel('Degree')
plt.ylabel('RMSE')
plt.grid()
plt.legend()
```

```
#plt.xticks()
plt.show()
```



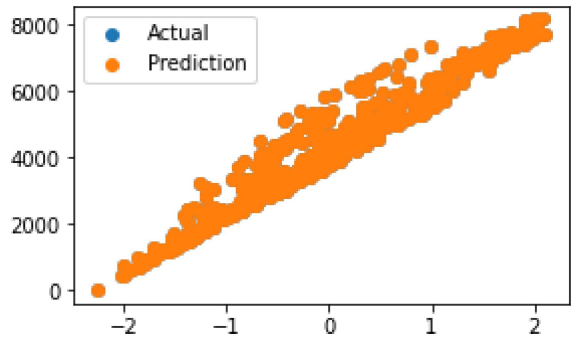


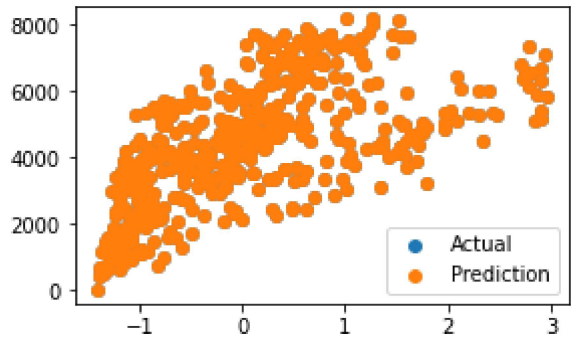
Inference: We can choose 13th order polynomial regression as it gives the optimal training & testing scores...

In [123…

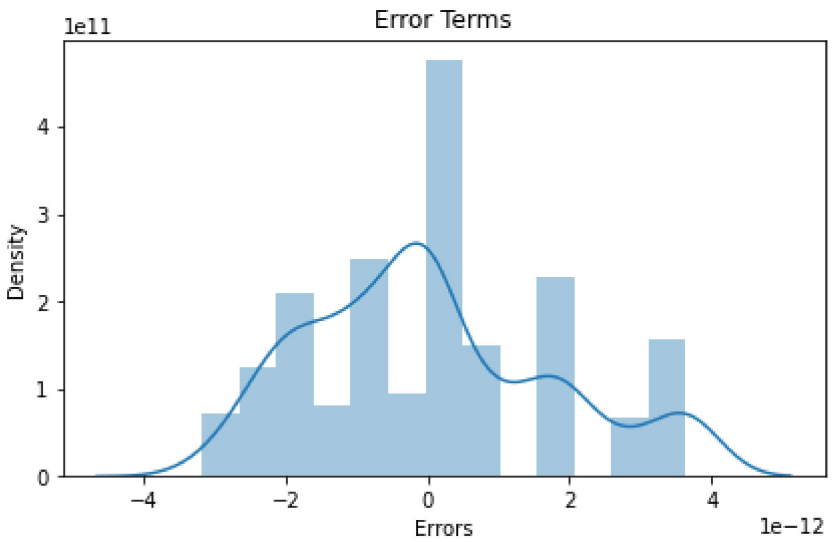
```
#Using the 4rd Order Polynomial Regression model (degree=3)

poly_reg = PolynomialFeatures(degree=2)
X_poly = poly_reg.fit_transform(Train_X_std)
X_poly1 = poly_reg.fit_transform(Test_X_std)
PR = LinearRegression()
PR.fit(X_poly, Train_Y)

pred1 = PR.predict(X_poly)
pred2 = PR.predict(X_poly1)

print('{}{}\033[1m Evaluating Polynomial Regression Model \033[0m{}{}\n'.format('<'*3,'-'*35 ,'-'*35,'>'*3))
print('The Coeffecient of the Regresion Model was found to be ',MLR.coef_)
print('The Intercept of the Regresion Model was found to be ',MLR.intercept_)

Evaluate(4, pred1, pred2)
```

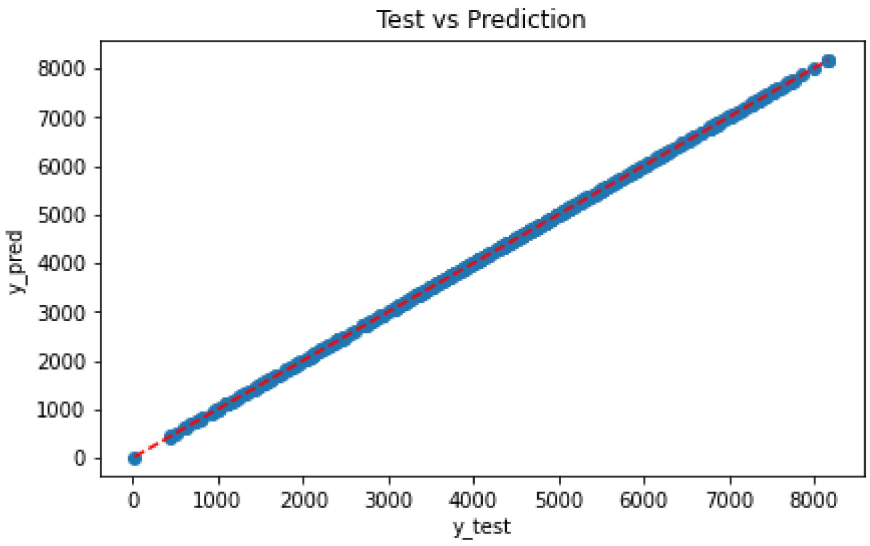
```
<<<---------------------------------- Evaluating Polynomial Regression Model ----------------------------------->>>

The Coeffecient of the Regresion Model was found to be  [ 516.39075268 1581.06834478]
The Intercept of the Regresion Model was found to be  4338.873370577281
```






```
--------------------Training Set Metrics--------------------

R2-Score on Training set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 0.0
Mean Squared Error (MSE) on Training set       ---> 0.0
Root Mean Squared Error (RMSE) on Training set ---> 1.73279347e-12

--------------------Testing Set Metrics--------------------

R2-Score on Testing set ---> 1.0
Residual Sum of Squares (RSS) on Training set  ---> 0.0
Mean Squared Error (MSE) on Training set       ---> 0.0
Root Mean Squared Error (RMSE) on Training set ---> 1.69880583e-12

--------------------Residual Plots--------------------
```





6f. Comparing the Evaluation Metics of the Models

In [124…

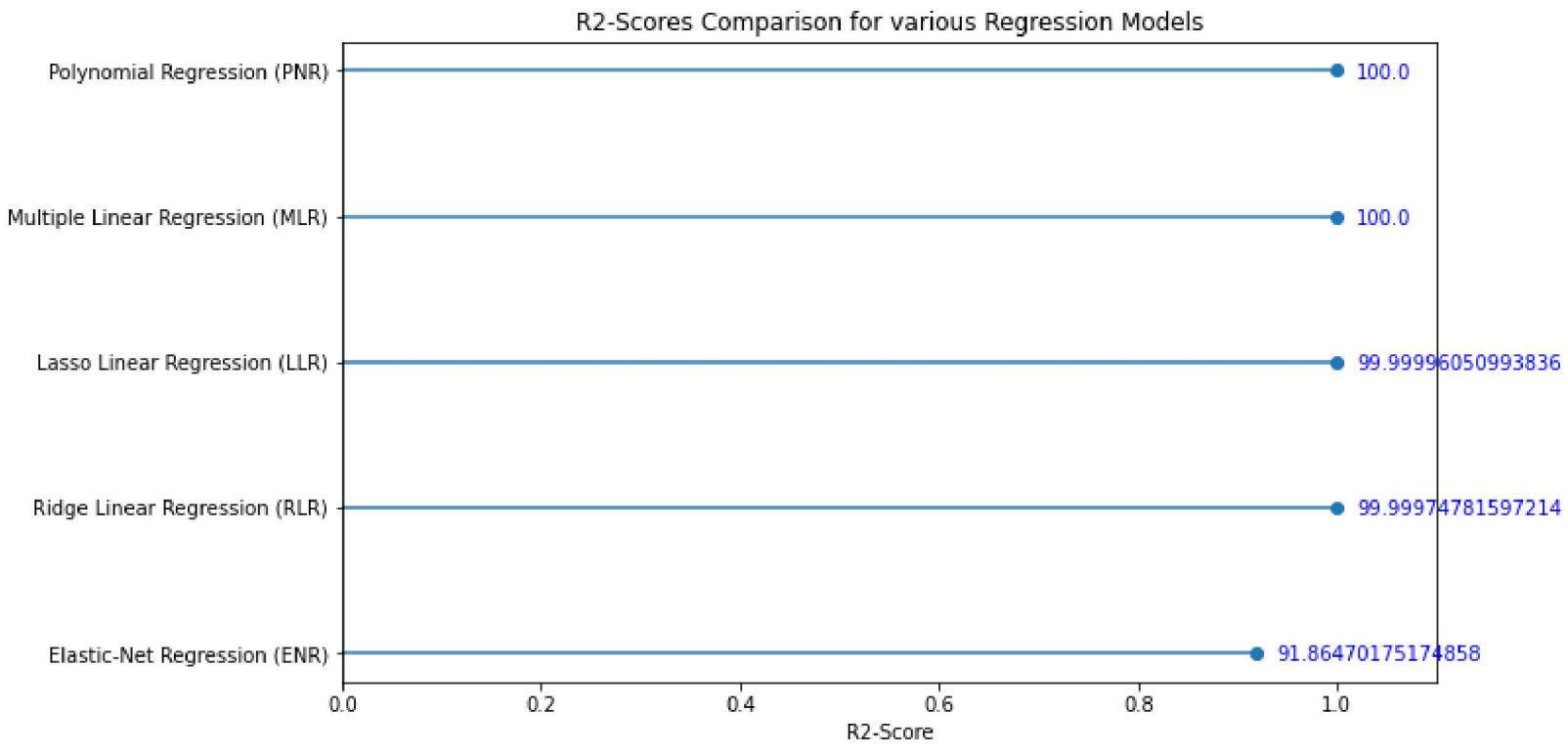
```
# Regression Models Results Evaluation

EMC = Model_Evaluation_Comparison_Matrix.copy()
EMC.index = ['Multiple Linear Regression (MLR)','Ridge Linear Regression (RLR)','Lasso Linear Regression (LLR)','Elastic-Net Regre
EMC
```

Out[124…

	Train-R2	Test-R2	Train-RSS	Test-RSS	Train-MSE	Test-MSE	Train-RMSE	Test-RMSE
Multiple Linear Regression (MLR)	1.000000	1.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	4.987688e-13	5.057799e-13
Ridge Linear Regression (RLR)	0.999997	0.999998	4.695906e+03	1.150058e+03	8.744704	8.518946	2.957145e+00	2.918723e+00
Lasso Linear Regression (LLR)	1.000000	1.000000	7.353425e+02	1.909618e+02	1.369353	1.414532	1.170193e+00	1.189341e+00
Elastic-Net Regression (ENR)	0.918647	0.919364	1.514870e+08	3.722250e+07	282098.664208	275722.209523	5.311296e+02	5.250926e+02
Polynomial Regression (PNR)	1.000000	1.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	1.732793e-12	1.698806e-12

In [125…

```
# R2-Scores Comparison for different Regression Models

R2 = EMC['Train-R2'].sort_values(ascending=True)
plt.hlines(y=R2.index, xmin=0, xmax=R2.values)
plt.plot(R2.values, R2.index,'o')
plt.title('R2-Scores Comparison for various Regression Models')
plt.xlabel('R2-Score')
#plt.ylabel('Regression Models')
for i, v in enumerate(R2):
    plt.text(v+0.02, i-0.05, str(v*100), color='blue')
plt.xlim([0,1.1])
plt.show()
```



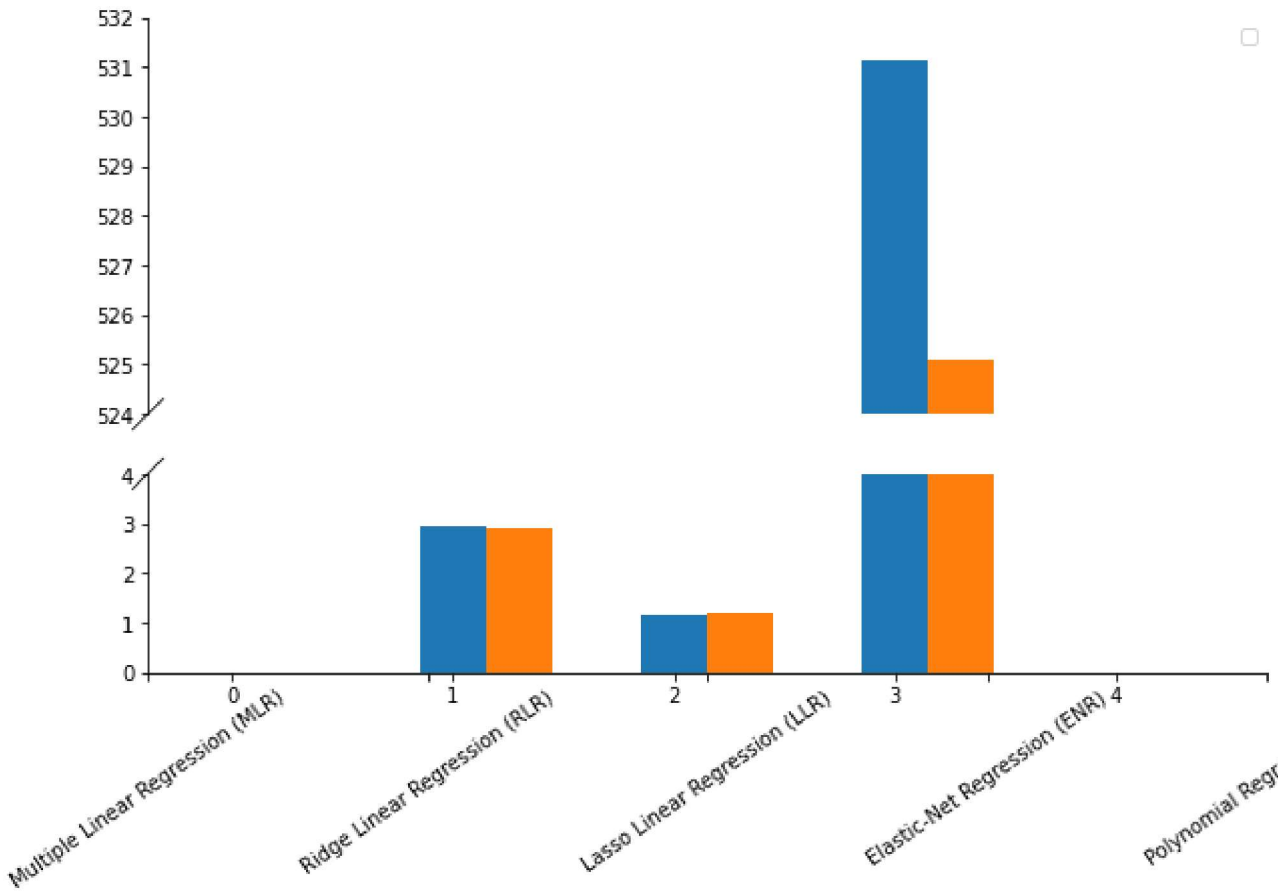
Inference: From the above plot, it is clear that the polynomial regresion models have the highest explainability power to understand the dataset.

In [146…

```
# Root Mean SquaredError Comparison for different Regression Models

cc = Model_Evaluation_Comparison_Matrix.columns.values
s=5
baxes = brokenaxes(ylims=((0,4),(524,532)))
baxes.bar(np.arange(s), Model_Evaluation_Comparison_Matrix[cc[-2]].values, width=0.3, label='RMSE (Training)')
baxes.bar(np.arange(s)+0.3, Model_Evaluation_Comparison_Matrix[cc[-1]].values, width=0.3, label='RMSE (Testing)')
# for index, value in enumerate(Model_Evaluation_Comparison_Matrix[cc[-2]].values):
#     plt.text(round(value,2), index, str(round(value,2)))
# for index, value in enumerate(Model_Evaluation_Comparison_Matrix[cc[-1]].values):
```

```
#     plt.text(round(value,2), index, str(round(value,2)))
plt.xticks(np.arange(s),EMC.index, rotation =35)
plt.legend()
#plt.ylim([0,10])
plt.show()
```

```
No artists with labels found to put in legend.  Note that artists whose label start with an underscore are ignored when legend() i
s called with no argument.
```



Inference: The complex models like polynomial & elastic-net regression overfits on the data. For this problem, it is can be said that any simple regression can be a good choice to go with...

---

10. Project Outcomes & Conclusions

Here are some of the key outcomes of the project:

- The Dataset was quiet small with just 730 samples & after preprocessing 7.9% of the datasamples were dropped.
- Visualising the distribution of data & their relationships, helped us to get some insights on the feature-set.
- The features had high multicollinearity, hence in Feature Extraction step, we shortlisted the appropriate features with VIF Technique.
- Testing multiple algorithms with default hyperparamters gave us some understanding for various models performance on this specific dataset.
- While, Polynomial Regression (Order-2) was the best choise, yet it is safe to use multiple regression algorithm, as their scores were quiet comparable & also they're more generalisable.

In [ ]:
```
<<<----------------------------------------THE END---------------------------------------------------->>>
```