Importing Libraries

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
```

Importing Data and analysing data

In [3]:
```
data=pd.read_csv('day.csv')
```

In [4]:
```
data.head()
```

Out[4]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	regis
0	1	01-01-2018	1	0	1	0	1	1	2	14.110847	18.18125	80.5833	10.749882	331	
1	2	02-01-2018	1	0	1	0	2	1	2	14.902598	17.68695	69.6087	16.652113	131	
2	3	03-01-2018	1	0	1	0	3	1	1	8.050924	9.47025	43.7273	16.636703	120	
3	4	04-01-2018	1	0	1	0	4	1	1	8.200000	10.60610	59.0435	10.739832	108	
4	5	05-01-2018	1	0	1	0	5	1	1	9.305237	11.46350	43.6957	12.522300	82	

In [5]:
```
data.columns
```

Out[5]:
```
Index(['instant', 'dteday', 'season', 'yr', 'mnth', 'holiday', 'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum', 'windspeed',
       'casual', 'registered', 'cnt'],
      dtype='object')
```

In [6]:
```
data.describe()
```

Out[6]:

	instant	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	h
count	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000
mean	365.500000	2.498630	0.500000	6.526027	0.028767	2.995890	0.690411	1.394521	20.319259	23.726322	62.765
std	210.877136	1.110184	0.500343	3.450215	0.167266	2.000339	0.462641	0.544807	7.506729	8.150308	14.237
min	1.000000	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.000000	2.424346	3.953480	0.000
25%	183.250000	2.000000	0.000000	4.000000	0.000000	1.000000	0.000000	1.000000	13.811885	16.889713	52.000
50%	365.500000	3.000000	0.500000	7.000000	0.000000	3.000000	1.000000	1.000000	20.465826	24.368225	62.625
75%	547.750000	3.000000	1.000000	10.000000	0.000000	5.000000	1.000000	2.000000	26.880615	30.445775	72.989
max	730.000000	4.000000	1.000000	12.000000	1.000000	6.000000	1.000000	3.000000	35.328347	42.044800	97.250

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 16 columns):
instant       730 non-null int64
dteday        730 non-null object
season        730 non-null int64
yr            730 non-null int64
mnth          730 non-null int64
holiday       730 non-null int64
weekday       730 non-null int64
workingday    730 non-null int64
weathersit    730 non-null int64
temp          730 non-null float64
atemp         730 non-null float64
hum           730 non-null float64
windspeed     730 non-null float64
casual        730 non-null int64
registered    730 non-null int64
cnt           730 non-null int64
dtypes: float64(4), int64(11), object(1)
memory usage: 91.4+ KB
```

Data Preparation

In [8]:
```
## Our aim is to find significant features from the dataset which add value to the target
## Here registered and casual column indicates number of bike rentals in appropriate way
## As cnt=registered + casual
## In order to get the significant variables to find the demand, let's drop these two columns first
```

In [9]:
```
data.drop(['registered','casual'],axis=1,inplace=True)
```

In [10]:
```
pd.unique(data['season'])
```

Out[10]:
```
array([1, 2, 3, 4], dtype=int64)
```

In [11]:
```
pd.unique(data['weathersit'])
```

Out[11]:
```
array([2, 1, 3], dtype=int64)
```

In [12]:
```
## Convert season and weathersit features into appropriate categories
```

In [13]:
```
def season(x):
    return x.map({1:'spring',2:'summer',3:'fall',4:'winter'})
def weathersit(x):
    return x.map({1:'Clear_Few clouds',2:'Mist_Cloudy',3:'Light Snow_Rain_Thunderstorm',4:'Heavy Rain_I
ce Pallets'})
```

In [14]:
```
data[['season']]=data[['season']].apply(season)
data[['weathersit']]=data[['weathersit']].apply(weathersit)
```

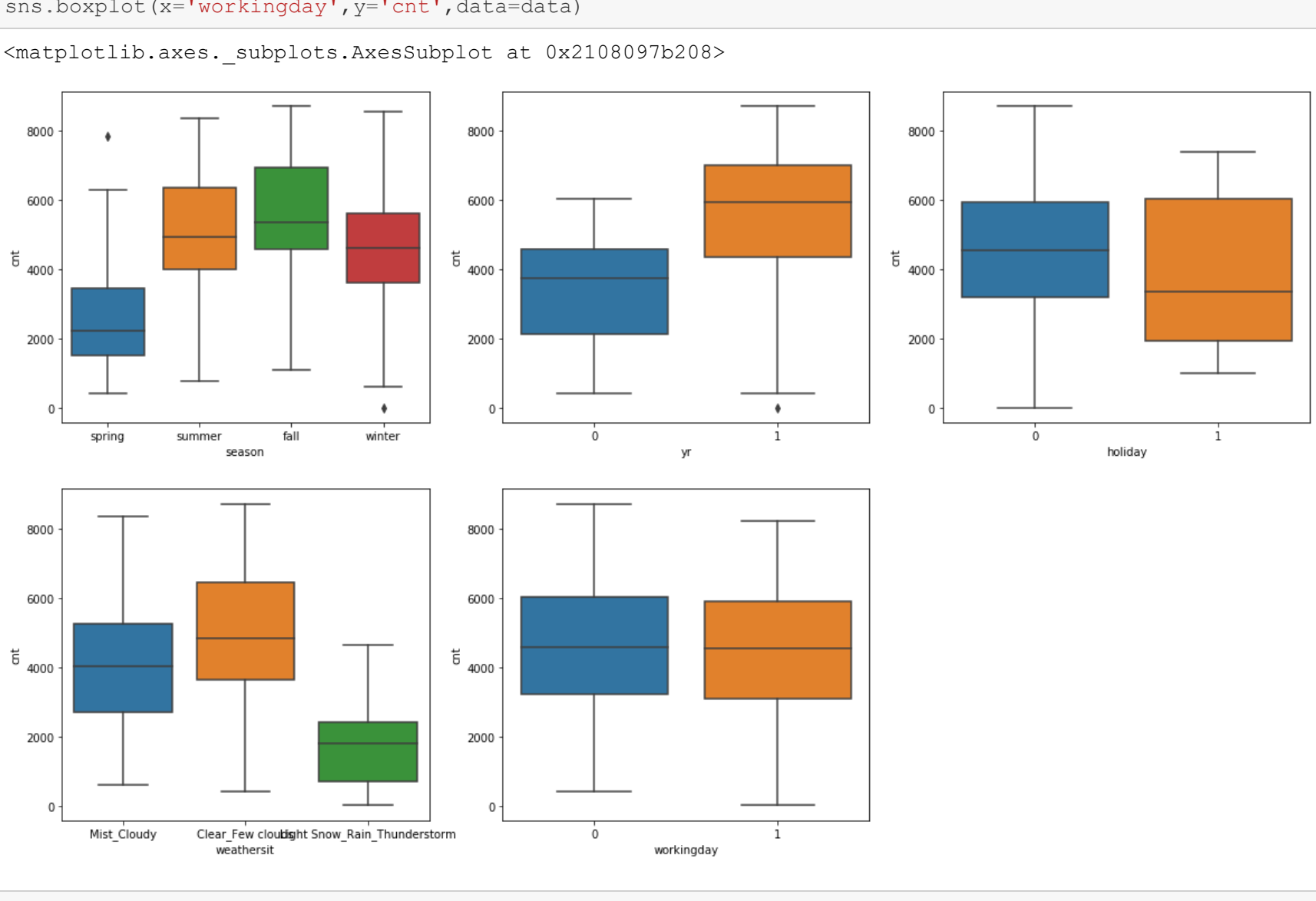
Visualizing Data

In [15]:
```
data.columns
```

Out[15]:
```
Index(['instant', 'dteday', 'season', 'yr', 'mnth', 'holiday', 'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'cnt'],
      dtype='object')
```

In [16]:
```
plt.figure(figsize=[20,12])
plt.subplot(2,3,1)
sns.boxplot(x='season',y='cnt',data=data)
plt.subplot(2,3,2)
sns.boxplot(x='yr',y='cnt',data=data)
plt.subplot(2,3,3)
sns.boxplot(x='holiday',y='cnt',data=data)
plt.subplot(2,3,4)
sns.boxplot(x='weathersit',y='cnt',data=data)
plt.subplot(2,3,5)
sns.boxplot(x='workingday',y='cnt',data=data)
```

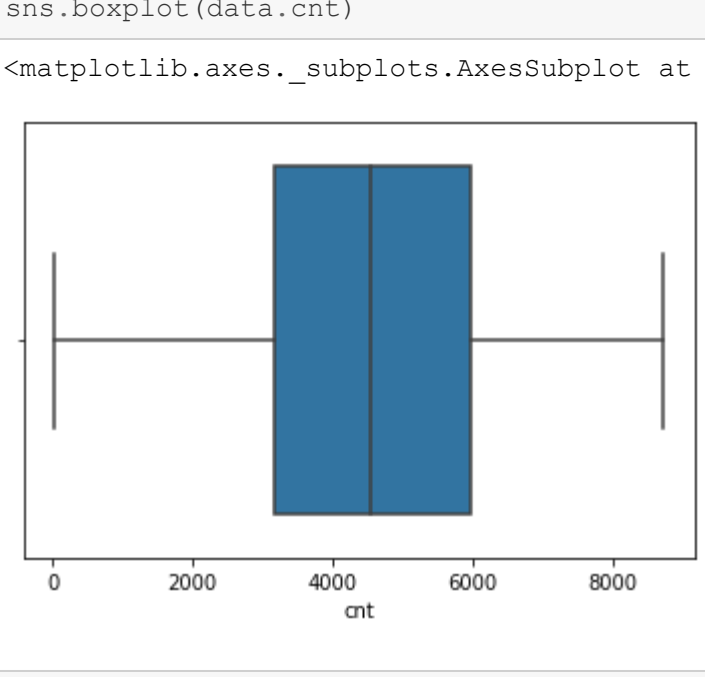
Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2108097b208>
```



In [17]:
```
## We can observe that there are no outliers in the categorical data
```

In [18]:
```
sns.boxplot(data.cnt)
```

Out[18]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x21080fbe5c8>
```



In [19]:
```
## We can also observe that there are no outliers in target variable
# So we can proceed with data preparation
```

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

Out[20]:
```
(730, 14)
```

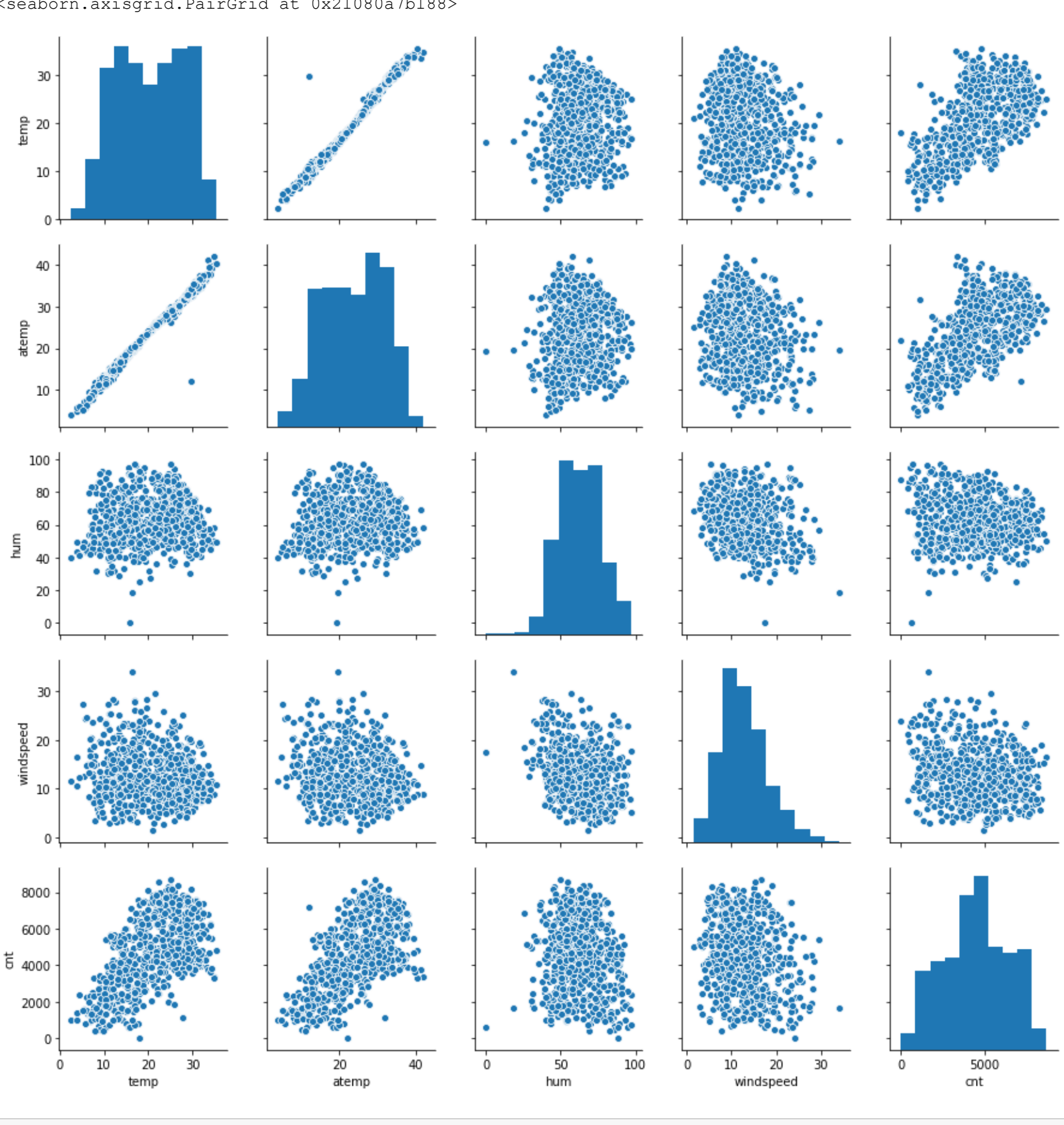
In [21]:
```
data.columns
```

Out[21]:
```
Index(['instant', 'dteday', 'season', 'yr', 'mnth', 'holiday', 'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'cnt'],
      dtype='object')
```

In [22]:
```
# Let's plot a pair plot for numerical analysis
pair_plot=['temp','atemp','hum','windspeed','cnt']
```

In [23]:
```
sns.pairplot(data[pair_plot])
```

Out[23]:
```
<seaborn.axisgrid.PairGrid at 0x21080a7b188>
```



In [24]:
```
## We can observe that temp and atemp are highly correlated, so we might need to drop either of them to
 avoid multicollinearity
## Also temp and atemp are correlated with target variable
```

In [25]:
```
data.head()
```

Out[25]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	cnt
0	1	01-01-2018	spring	0	1	0	1	1	Mist_Cloudy	14.110847	18.18125	80.5833	10.749882	985
1	2	02-01-2018	spring	0	1	0	2	1	Mist_Cloudy	14.902598	17.68695	69.6087	16.652113	801
2	3	03-01-2018	spring	0	1	0	3	1	Clear_Few clouds	8.050924	9.47025	43.7273	16.636703	1349
3	4	04-01-2018	spring	0	1	0	4	1	Clear_Few clouds	8.200000	10.60610	59.0435	10.739832	1562
4	5	05-01-2018	spring	0	1	0	5	1	Clear_Few clouds	9.305237	11.46350	43.6957	12.522300	1600

Adding Dummies

In [26]:
```
temp=pd.get_dummies(data['season'])
```

In [27]:
```
temp.head()
```

Out[27]:

	fall	spring	summer	winter
0	0	1	0	0
1	0	1	0	0
2	0	1	0	0
3	0	1	0	0
4	0	1	0	0

In [28]:
```
temp=pd.get_dummies(data['season'],drop_first=True)
```

In [29]:
```
temp.head()
```

Out[29]:

	spring	summer	winter
0	1	0	0
1	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0

In [30]:
```
data=pd.concat([data,temp],axis=1)
```

In [31]:
```
data.head()
```

Out[31]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	cnt	spring
0	1	01-01-2018	spring	0	1	0	1	1	Mist_Cloudy	14.110847	18.18125	80.5833	10.749882	985	1
1	2	02-01-2018	spring	0	1	0	2	1	Mist_Cloudy	14.902598	17.68695	69.6087	16.652113	801	1
2	3	03-01-2018	spring	0	1	0	3	1	Clear_Few clouds	8.050924	9.47025	43.7273	16.636703	1349	1
3	4	04-01-2018	spring	0	1	0	4	1	Clear_Few clouds	8.200000	10.60610	59.0435	10.739832	1562	1
4	5	05-01-2018	spring	0	1	0	5	1	Clear_Few clouds	9.305237	11.46350	43.6957	12.522300	1600	1

In [32]:
```
data=data.drop('season',axis=1)
```

In [33]:
```
temp=pd.get_dummies(data['weathersit'])
```

In [34]:
```
temp.head()
```

Out[34]:

	Clear_Few clouds	Light Snow_Rain_Thunderstorm	Mist_Cloudy
0	0	0	1
1	0	0	1
2	1	0	0
3	1	0	0
4	1	0	0

In [35]:
```
pd.unique(data['weathersit'])
```

Out[35]:
```
array(['Mist_Cloudy', 'Clear_Few clouds', 'Light Snow_Rain_Thunderstorm'],
      dtype=object)
```

In [36]:
```
# Since we have only 3 columns in temp no need to drop first row
## This means in this data only three weathersits are listed which means
## we don't have data related to other weathersit as there might not be any users in that weathersit: H
eavy rain-ThunderStrom
## Which is obvious that a person wouldn't like to travel with bike during heavy, so there aren't any d
ata in heavy rain
```

In [37]:
```
data=pd.concat([data,temp],axis=1)
```

In [38]:
```
data=data.drop('weathersit',axis=1)
```

In [39]:
```
data.head()
```

Out[39]:

	instant	dteday	yr	mnth	holiday	weekday	workingday	temp	atemp	hum	windspeed	cnt	spring	summer	winter	Cl
0	1	01-01-2018	0	1	0	1	1	14.110847	18.18125	80.5833	10.749882	985	1	0	0	
1	2	02-01-2018	0	1	0	2	1	14.902598	17.68695	69.6087	16.652113	801	1	0	0	
2	3	03-01-2018	0	1	0	3	1	8.050924	9.47025	43.7273	16.636703	1349	1	0	0	
3	4	04-01-2018	0	1	0	4	1	8.200000	10.60610	59.0435	10.739832	1562	1	0	0	
4	5	05-01-2018	0	1	0	5	1	9.305237	11.46350	43.6957	12.522300	1600	1	0	0	

In [40]:
```
temp=pd.get_dummies(data['mnth'],prefix='month',drop_first=True)
```

In [41]:
```
temp.head()
```

Out[41]:

	month_2	month_3	month_4	month_5	month_6	month_7	month_8	month_9	month_10	month_11	month_12
0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0

In [42]:
```
data=pd.concat([data,temp],axis=1)
```

In [43]:
```
data.drop('mnth',axis=1,inplace=True)
```

In [44]:
```
# create a weekend variable to indicate the weekend status
```

In [45]:
```
data['weekend']=data['weekday'].map(lambda x: 1 if x==6 or x==7 else 0)
```

In [46]:
```
data.columns
```

Out[46]:
```
Index(['instant', 'dteday', 'yr', 'holiday', 'weekday', 'workingday', 'temp',
       'atemp', 'hum', 'windspeed', 'cnt', 'spring', 'summer', 'winter',
       'Clear_Few clouds', 'Light Snow_Rain_Thunderstorm', 'Mist_Cloudy',
       'month_2', 'month_3', 'month_4', 'month_5', 'month_6', 'month_7',
       'month_8', 'month_9', 'month_10', 'month_11', 'month_12', 'weekend'],
      dtype='object')
```

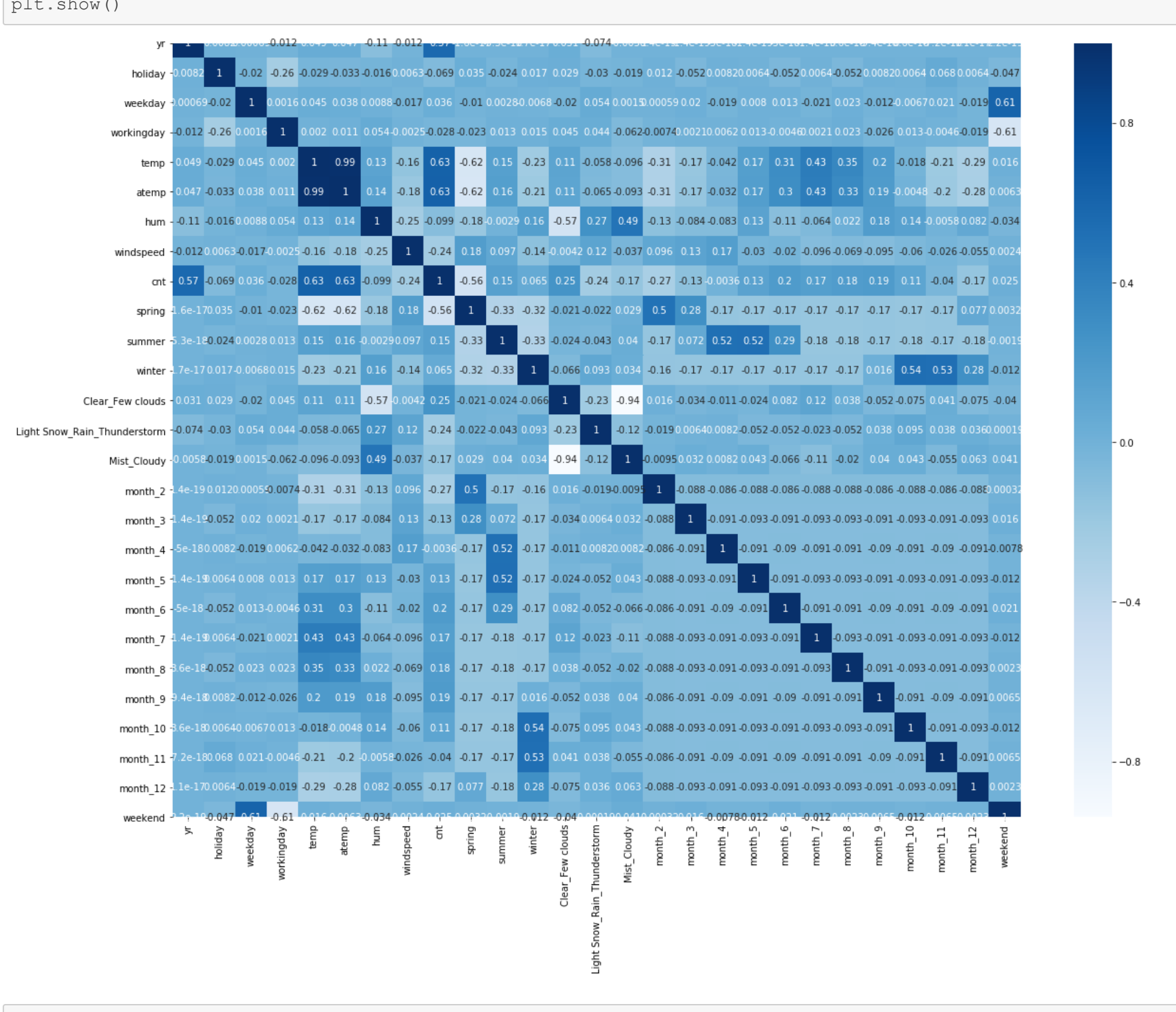
In [47]:
```
data['weekend'].head()
```

Out[47]:
```
0    0
1    0
2    0
3    0
4    0
Name: weekend, dtype: int64
```

In [48]:
```
# We can drop 'instant variable as it is the unique row'
```

In [49]:
```
data.drop('instant',inplace=True,axis=1)
```

In [50]:
```
plt.figure(figsize = (20, 15))
sns.heatmap(data.corr(),cmap='Blues',annot=True)
plt.show()
```



In [51]:
```
## This is difficult to observe collinearity with heatmap of complete data
## So we can go for pairplot with limited columns for better data understanding
```

In [52]:
```
## We can give a quick insight of temp, atemp related to cnt
## cnt is correlated with year to, this may mean that people using this sharing scheme might have incre
ased over year
## Also we can observe that target variable is negatively correlated to spring season
## Consequently people might not have preferred bikes during spring
## For now with this we can get to a thought that we need to drop temp or atemp from the data to avoid
 multicollinearity
## as no of users may also depend upon temp
## Let's just not drop them directly as we can also get better insight once we build a basic model and
 go for VIF
```

In [53]:
```
data.columns
```

Out[53]:
```
Index(['dteday', 'yr', 'holiday', 'weekday', 'workingday', 'temp', 'atemp',
       'hum', 'windspeed', 'cnt', 'spring', 'summer', 'winter',
       'Clear_Few clouds', 'Light Snow_Rain_Thunderstorm', 'Mist_Cloudy',
       'month_2', 'month_3', 'month_4', 'month_5', 'month_6', 'month_7',
       'month_8', 'month_9', 'month_10', 'month_11', 'month_12', 'weekend'],
      dtype='object')
```

In [54]:
```
data.head()
```

Out[54]:

	dteday	yr	holiday	weekday	workingday	temp	atemp	hum	windspeed	cnt	...	month_4	month_5	month_6	month_7
0	01-01-2018	0	0	1	1	14.110847	18.18125	80.5833	10.749882	985	...	0	0	0	0
1	02-01-2018	0	0	2	1	14.902598	17.68695	69.6087	16.652113	801	...	0	0	0	0
2	03-01-2018	0	0	3	1	8.050924	9.47025	43.7273	16.636703	1349	...	0	0	0	0
3	04-01-2018	0	0	4	1	8.200000	10.60610	59.0435	10.739832	1562	...	0	0	0	0
4	05-01-2018	0	0	5	1	9.305237	11.46350	43.6957	12.522300	1600	...	0	0	0	0

5 rows × 28 columns

In [55]:
```
## We can drop dteday as it just indicates the date of booking and not have much correlation with cnt
## We can drop weekday column as we have added weekend column to indicate further details
```

In [56]:
```
data.drop('dteday',axis=1,inplace=True)
```

In [57]:
```
data.drop('weekday',axis=1,inplace=True)
```

In [58]:
```
data.shape
```

Out[58]:
```
(730, 26)
```

Model Building

In [59]:
```
## Splitting train and test datasets
## Let's try for the mostly used splitting range 7:3 for training and testing dataset
```

In [60]:
```
train_df,test_df=train_test_split(data,train_size=0.7,test_size=0.3,random_state=100)
```

In [61]:
```
## I am using MinMaxScaler and not for StandardScaler
## for this dataset as the data seems to have a variation in numeric range in each column
## Also I would like to avoid negative values in this dataset which may make be clumsy for observation
```

In [62]:
```
Scaler=MinMaxScaler()
num_data=['temp','atemp','hum','windspeed','cnt']
train_df[num_data]=Scaler.fit_transform(train_df[num_data])
```

In [63]:
```
y_train=train_df.pop('cnt')
X_train=train_df
```

In [64]:
```
## Training model using statsmodels.api
```

In [65]:
```
from sklearn.feature_selection import RFE
lm=LinearRegression()
lm.fit(X_train,y_train)
rfe=RFE(lm,15)
rfe = rfe.fit(X_train,y_train)
```

In [66]:
```
col=X_train.columns[rfe.support_]
```

In [67]:
```
col
```

Out[67]:
```
Index(['yr', 'holiday', 'temp', 'hum', 'windspeed', 'spring', 'summer',
       'winter', 'Clear_Few clouds', 'Light Snow_Rain_Thunderstorm',
       'Mist_Cloudy', 'month_3', 'month_8', 'month_9', 'month_10'],
      dtype='object')
```

In [68]:
```
lm.score(X_train,y_train)
```

Out[68]:
```
0.848665878657833
```

In [69]:
```
X_train=X_train[col]
```

In [70]:
```
X_train_sm=sm.add_constant(X_train)
lr=sm.OLS(y_train,X_train).fit()
```

In [71]:
```
lr.params
```

Out[71]:
```
yr                              0.229702
holiday                        -0.090301
temp                            0.495171
hum                            -0.170179
windspeed                      -0.185711
spring                         -0.036642
summer                          0.085070
winter                          0.113720
Clear_Few clouds                0.268696
Light Snow_Rain_Thunderstorm    0.021999
Mist_Cloudy                     0.212762
month_3                         0.028540
month_8                         0.050642
month_9                         0.120374
month_10                        0.042113
dtype: float64
```

In [72]:
```
lr.summary()
```

Out[72]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.845
Model:	OLS	Adj. R-squared:	0.840
Method:	Least Squares	F-statistic:	192.2
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	9.02e-190
Time:	17:17:52	Log-Likelihood:	513.33
No. Observations:	510	AIC:	-996.7
Df Residuals:	495	BIC:	-933.1
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
yr	0.2297	0.008	28.400	0.000	0.214	0.246
holiday	-0.0903	0.025	-3.543	0.000	-0.140	-0.040
temp	0.4952	0.034	14.582	0.000	0.428	0.562
hum	-0.1702	0.038	-4.519	0.000	-0.244	-0.096
windspeed	-0.1857	0.026	-7.241	0.000	-0.236	-0.135
spring	-0.0366	0.023	-1.618	0.106	-0.081	0.008
summer	0.0851	0.016	5.202	0.000	0.053	0.117
winter	0.1137	0.020	5.675	0.000	0.074	0.153
Clear_Few clouds	0.2687	0.035	7.622	0.000	0.199	0.338
Light Snow_Rain_Thunderstorm	0.0220	0.047	0.468	0.640	-0.070	0.114
Mist_Cloudy	0.2128	0.039	5.496	0.000	0.137	0.289
month_3	0.0285	0.014	1.975	0.049	0.000	0.057
month_8	0.0506	0.017	2.897	0.004	0.016	0.085
month_9	0.1204	0.017	6.966	0.000	0.086	0.154
month_10	0.0421	0.017	2.414	0.016	0.008	0.076

Omnibus:	72.046	Durbin-Watson:	2.030
Prob(Omnibus):	0.000	Jarque-Bera (JB):	169.620
Skew:	-0.742	Prob(JB):	1.47e-37
Kurtosis:	5.404	Cond. No.	26.1

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

In [73]:
```
## By looking at the summary it seems good with Rsquared and Adjusted Rsquared as 0.84
## But pvalues are high for few features, we can still reduce no of features
## Let's try predicting the test set
```

In [74]:
```
## Use transform with the same scaler object used for the numerical columns as in train data for proper
 analysis
num_data=['temp','atemp','hum','windspeed','cnt']
test_df[num_data]=Scaler.transform(test_df[num_data])
```

In [75]:
```
y_test=test_df.pop('cnt')
X_test=test_df
```

In [76]:
```
X_test=X_test[col]
```

In [77]:
```
X_test_sm=sm.add_constant(X_test)
y_pred=lr.predict(X_test)
```

In [78]:
```
from sklearn.metrics import mean_squared_error, r2_score
```

In [79]:
```
mse = mean_squared_error(y_test, y_pred)

r_squared = r2_score(y_test, y_pred)
```

In [80]:
```
rmse= mse**(1/2)
```

In [81]:
```
rmse
```

Out[81]:
```
0.09262048821533898
```

In [82]:
```
mse
```

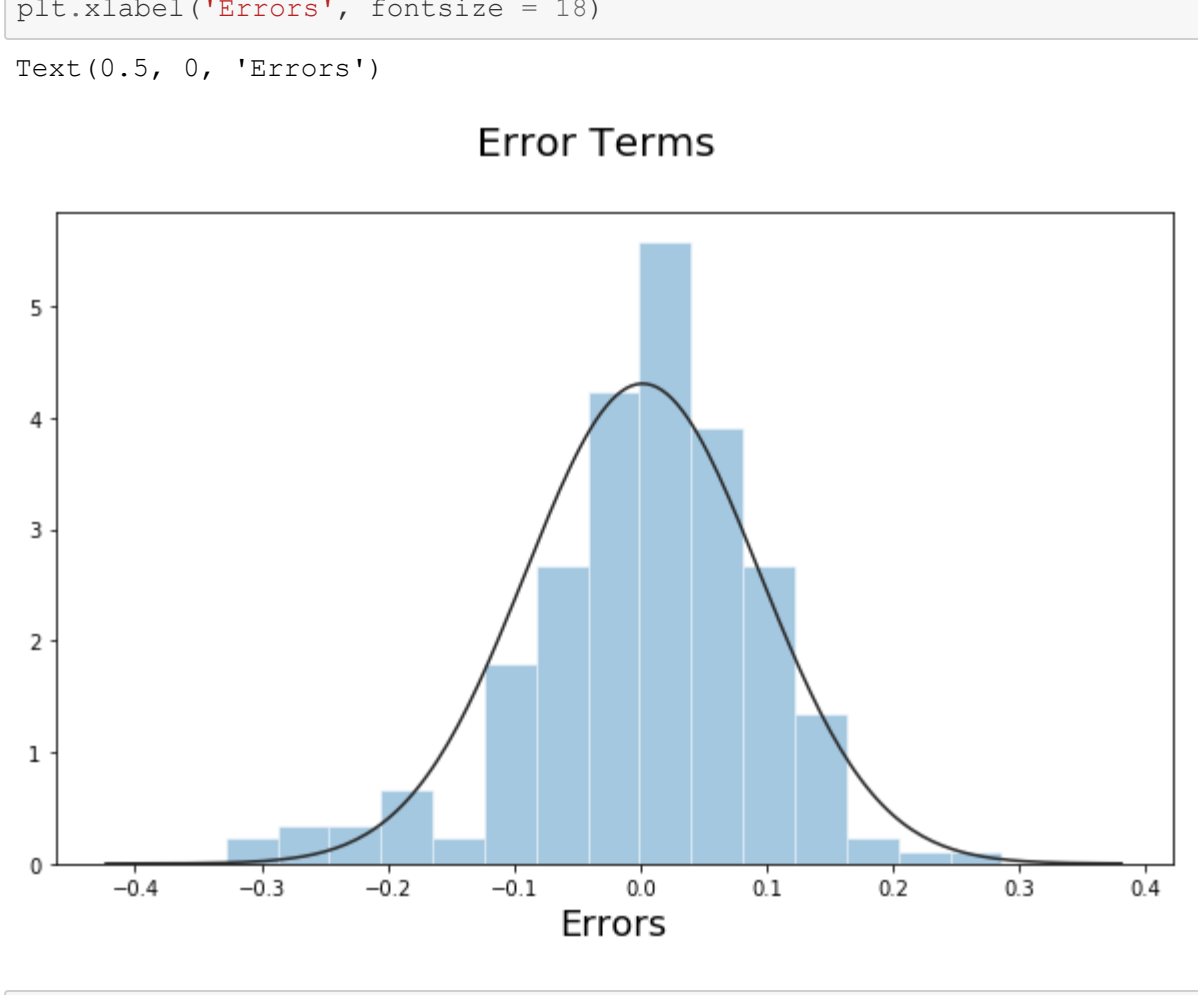
Out[82]:
```
0.008578554837247747
```

In [83]:
```
r_squared
```

Out[83]:
```
0.8193829061692349
```

In [84]:
```
from scipy.stats import norm
fig = plt.figure(figsize=[10,6])
sns.distplot((y_test - y_pred), bins = 15,fit=norm,kde=False,hist_kws=dict(edgecolor='w'))
fig.suptitle('Error Terms', fontsize = 20)                  # Plot heading
plt.xlabel('Errors', fontsize = 18)
```

Out[84]:
```
Text(0.5, 0, 'Errors')
```



In [85]:
```
## we can observe that r2_score for the test is also 0.81 which is quite good also rmse is low 0.09
## But we still need to make sure if this model is good
```

In [86]:
```
## Let's check VIF to check if there is any multicollinearity in the data
```

In [87]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train.columns
vif['VIF'] = [variance_inflation_factor(X_train.values, i) for i in range(X_train.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[87]:

	Features	VIF
8	Clear_Few clouds	49.36
10	Mist_Cloudy	32.54
5	spring	5.97
7	winter	4.75
9	Light Snow_Rain_Thunderstorm	4.12
2	temp	3.72
6	summer	3.13
3	hum	1.91
12	month_8	1.68
14	month_10	1.52
13	month_9	1.40
4	windspeed	1.20
11	month_3	1.17
0	yr	1.03
1	holiday	1.02

In [88]:
```
## We can observe that there is high collinearity between the predictors
## We have 2 predictors above 10 VIF which can make this model unstable in further datasets
```

In [89]:
```
# Clear_Few clouds and Mist_Cloudy have high vif but pvalue for both is 0
## Let's try dropping Clear_Few clouds
```

In [90]:
```
X_train_1=X_train.copy()
```

In [91]:
```
X_train_1.drop('Clear_Few clouds',axis=1,inplace=True)
```

In [92]:
```
X_train_sm=sm.add_constant(X_train_1)
lr_2=sm.OLS(y_train,X_train_sm).fit()
lr_2.summary()
```
Out[92]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.845
Model:	OLS	Adj. R-squared:	0.840
Method:	Least Squares	F-statistic:	192.2
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	9.02e-190
Time:	17:17:58	Log-Likelihood:	513.33
No. Observations:	510	AIC:	-996.7
Df Residuals:	495	BIC:	-933.1
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2687	0.035	7.622	0.000	0.199	0.338
yr	0.2297	0.008	28.400	0.000	0.214	0.246
holiday	-0.0903	0.025	-3.543	0.000	-0.140	-0.040
temp	0.4952	0.034	14.582	0.000	0.428	0.562
hum	-0.1702	0.038	-4.519	0.000	-0.244	-0.096
windspeed	-0.1857	0.026	-7.241	0.000	-0.236	-0.135
spring	-0.0366	0.023	-1.618	0.106	-0.081	0.008
summer	0.0851	0.016	5.202	0.000	0.053	0.117
winter	0.1137	0.020	5.675	0.000	0.074	0.153
Light Snow_Rain_Thunderstorm	-0.2467	0.026	-9.338	0.000	-0.299	-0.195
Mist_Cloudy	-0.0559	0.010	-5.342	0.000	-0.077	-0.035
month_3	0.0285	0.014	1.975	0.049	0.000	0.057
month_8	0.0506	0.017	2.897	0.004	0.016	0.085
month_9	0.1204	0.017	6.966	0.000	0.086	0.154
month_10	0.0421	0.017	2.414	0.016	0.008	0.076

Omnibus:	72.046	Durbin-Watson:	2.030
Prob(Omnibus):	0.000	Jarque-Bera (JB):	169.620
Skew:	-0.742	Prob(JB):	1.47e-37
Kurtosis:	5.404	Cond. No.	20.5

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

In [93]:
```
## We can see that still after removing 'atemp' we have rsquared value unchanged
## Let's check the VIF again
```
In [94]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_1.columns
vif['VIF'] = [variance_inflation_factor(X_train_1.values, i) for i in range(X_train_1.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```
Out[94]:

	Features	VIF
3	hum	29.49
2	temp	15.32
5	spring	4.70
4	windspeed	4.69
7	winter	4.33
6	summer	3.26
9	Mist_Cloudy	2.29
0	yr	2.09
11	month_8	1.80
13	month_10	1.61
12	month_9	1.49
10	month_3	1.29
8	Light Snow_Rain_Thunderstorm	1.27
1	holiday	1.05

In [95]:
```
## Let's drop the other feature 'hum' which have next high vif
```
In [96]:
```
X_train_2=X_train_1.copy()
```
In [97]:
```
X_train_2.drop('hum',axis=1,inplace=True)
```
In [98]:
```
X_train_sm=sm.add_constant(X_train_2)
lr_3=sm.OLS(y_train,X_train_sm).fit()
lr_3.summary()
```
Out[98]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.838
Model:	OLS	Adj. R-squared:	0.834
Method:	Least Squares	F-statistic:	197.7
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	1.33e-186
Time:	17:17:59	Log-Likelihood:	503.02
No. Observations:	510	AIC:	-978.0
Df Residuals:	496	BIC:	-918.8
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1874	0.031	6.063	0.000	0.127	0.248
yr	0.2338	0.008	28.539	0.000	0.218	0.250
holiday	-0.0909	0.026	-3.497	0.001	-0.142	-0.040
temp	0.4589	0.034	13.643	0.000	0.393	0.525
windspeed	-0.1522	0.025	-6.081	0.000	-0.201	-0.103
spring	-0.0514	0.023	-2.252	0.025	-0.096	-0.007
summer	0.0741	0.016	4.493	0.000	0.042	0.106
winter	0.0956	0.020	4.778	0.000	0.056	0.135
Light Snow_Rain_Thunderstorm	-0.2933	0.025	-11.829	0.000	-0.342	-0.245
Mist_Cloudy	-0.0830	0.009	-9.476	0.000	-0.100	-0.066
month_3	0.0318	0.015	2.161	0.031	0.003	0.061
month_8	0.0452	0.018	2.541	0.011	0.010	0.080
month_9	0.1104	0.017	6.321	0.000	0.076	0.145
month_10	0.0395	0.018	2.225	0.027	0.005	0.074

Omnibus:	72.205	Durbin-Watson:	2.035
Prob(Omnibus):	0.000	Jarque-Bera (JB):	171.532
Skew:	-0.741	Prob(JB):	5.65e-38
Kurtosis:	5.424	Cond. No.	18.6

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

In [99]:
```
## After dropping hum column, rsquared is affected a little
## Let's check VIF again
```
In [100]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_2.columns
vif['VIF'] = [variance_inflation_factor(X_train_2.values, i) for i in range(X_train_2.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```
Out[100]:

	Features	VIF
2	temp	5.11
3	windspeed	4.62
5	summer	2.43
4	spring	2.35
6	winter	2.31
0	yr	2.07
10	month_8	1.73
12	month_10	1.60
8	Mist_Cloudy	1.57
11	month_9	1.41
9	month_3	1.29
7	Light Snow_Rain_Thunderstorm	1.10
1	holiday	1.05

In [101]:
```
## Now vif for the features is less than 10
## Even pvalues seems to be less for all the features listed
## We are using 13 features here, let's to reduce these features
## Since we have temp, seasons,weather all listed here,
## So it's try dropping one of the month column as this data would be covered in the other features lis
ted
## Let's check if our assumption is right
## Let's drop month_10 which has high vif comparatively, also with some pvalue
```
In [102]:
```
X_train_3=X_train_2.copy()
```
In [103]:
```
X_train_3.drop('month_10',axis=1,inplace=True)
```
In [104]:
```
X_train_sm=sm.add_constant(X_train_3)
lr_4=sm.OLS(y_train,X_train_sm).fit()
lr_4.summary()
```
Out[104]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.837
Model:	OLS	Adj. R-squared:	0.833
Method:	Least Squares	F-statistic:	212.1
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	1.04e-186
Time:	17:18:01	Log-Likelihood:	500.49
No. Observations:	510	AIC:	-975.0
Df Residuals:	497	BIC:	-919.9
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1743	0.030	5.723	0.000	0.114	0.234
yr	0.2333	0.008	28.376	0.000	0.217	0.249
holiday	-0.0925	0.026	-3.547	0.000	-0.144	-0.041
temp	0.4762	0.033	14.494	0.000	0.412	0.541
windspeed	-0.1502	0.025	-5.979	0.000	-0.199	-0.101
spring	-0.0442	0.023	-1.949	0.052	-0.089	0.000
summer	0.0761	0.017	4.608	0.000	0.044	0.109
winter	0.1139	0.018	6.216	0.000	0.078	0.150
Light Snow_Rain_Thunderstorm	-0.2866	0.025	-11.599	0.000	-0.335	-0.238
Mist_Cloudy	-0.0821	0.009	-9.345	0.000	-0.099	-0.065
month_3	0.0312	0.015	2.112	0.035	0.002	0.060
month_8	0.0437	0.018	2.451	0.015	0.009	0.079
month_9	0.1066	0.017	6.105	0.000	0.072	0.141

Omnibus:	61.437	Durbin-Watson:	2.048
Prob(Omnibus):	0.000	Jarque-Bera (JB):	134.121
Skew:	-0.664	Prob(JB):	7.51e-30
Kurtosis:	5.132	Cond. No.	18.0

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

In [105]:
```
## There isn't much change in rsquared
## Let's check VIF again
```
In [106]:
```
vif=pd.DataFrame()
vif['features']=X_train_3.columns
vif['VIF']=[variance_inflation_factor(X_train_3.values,i) for i in range(X_train_3.shape[1])]
vif['VIF']=round(vif['VIF'],2)
vif=vif.sort_values(by='VIF',ascending=False)
vif
```
Out[106]:

	features	VIF
2	temp	5.02
3	windspeed	4.62
5	summer	2.41
4	spring	2.35
0	yr	2.07
6	winter	1.88
10	month_8	1.72
8	Mist_Cloudy	1.57
11	month_9	1.37
9	month_3	1.29
7	Light Snow_Rain_Thunderstorm	1.08
1	holiday	1.05

In [107]:
```
## Let's drop month_3 which has high pval
## Even spring seems to have high pvalue
## But as per our previous analysis in heatmap, spring seems to be negatively correlated with target,
## It means target has more impact with spring than month_3
## So let's not drop this right way
```
In [108]:
```
X_train_4=X_train_3.copy()
```
In [109]:
```
X_train_4.drop('month_3',axis=1,inplace=True)
```
In [110]:
```
X_train_sm=sm.add_constant(X_train_4)
lr_5=sm.OLS(y_train,X_train_sm).fit()
lr_5.summary()
```
Out[110]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.835
Model:	OLS	Adj. R-squared:	0.832
Method:	Least Squares	F-statistic:	229.4
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	6.11e-187
Time:	17:18:02	Log-Likelihood:	498.21
No. Observations:	510	AIC:	-972.4
Df Residuals:	498	BIC:	-921.6
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1712	0.031	5.606	0.000	0.111	0.231
yr	0.2334	0.008	28.283	0.000	0.217	0.250
holiday	-0.0960	0.026	-3.677	0.000	-0.147	-0.045
temp	0.4790	0.033	14.543	0.000	0.414	0.544
windspeed	-0.1472	0.025	-5.850	0.000	-0.197	-0.098
spring	-0.0348	0.022	-1.560	0.120	-0.079	0.009
summer	0.0811	0.016	4.942	0.000	0.049	0.113
winter	0.1150	0.018	6.254	0.000	0.079	0.151
Light Snow_Rain_Thunderstorm	-0.2844	0.025	-11.481	0.000	-0.333	-0.236
Mist_Cloudy	-0.0822	0.009	-9.332	0.000	-0.100	-0.065
month_8	0.0438	0.018	2.450	0.015	0.009	0.079
month_9	0.1069	0.018	6.103	0.000	0.072	0.141

Omnibus:	59.763	Durbin-Watson:	2.050
Prob(Omnibus):	0.000	Jarque-Bera (JB):	137.610
Skew:	-0.630	Prob(JB):	1.31e-30
Kurtosis:	5.211	Cond. No.	17.9

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

In [111]:
```
## There isn't much change in rsquared and adjusted rsquared
## Let's check VIF again
```
In [112]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_4.columns
vif['VIF'] = [variance_inflation_factor(X_train_4.values, i) for i in range(X_train_4.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```
Out[112]:

	Features	VIF
2	temp	5.02
3	windspeed	4.61
5	summer	2.36
4	spring	2.17
0	yr	2.07
6	winter	1.88
9	month_8	1.72
8	Mist_Cloudy	1.57
10	month_9	1.37
7	Light Snow_Rain_Thunderstorm	1.08
1	holiday	1.04

In [113]:
```
## Let's drop month_8 now
```
In [114]:
```
X_train_5=X_train_4.copy()
```
In [115]:
```
X_train_5.drop('month_8',axis=1,inplace=True)
```
In [116]:
```
X_train_sm=sm.add_constant(X_train_5)
lr_6=sm.OLS(y_train,X_train_sm).fit()
lr_6.summary()
```
Out[116]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.833
Model:	OLS	Adj. R-squared:	0.830
Method:	Least Squares	F-statistic:	249.2
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	7.36e-187
Time:	17:18:04	Log-Likelihood:	495.16
No. Observations:	510	AIC:	-968.3
Df Residuals:	499	BIC:	-921.7
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1910	0.030	6.456	0.000	0.133	0.249
yr	0.2341	0.008	28.246	0.000	0.218	0.250
holiday	-0.0969	0.026	-3.691	0.000	-0.148	-0.045
temp	0.4782	0.033	14.446	0.000	0.413	0.543
windspeed	-0.1482	0.025	-5.860	0.000	-0.198	-0.098
spring	-0.0551	0.021	-2.641	0.009	-0.096	-0.014
summer	0.0610	0.014	4.271	0.000	0.033	0.089
winter	0.0959	0.017	5.730	0.000	0.063	0.129
Light Snow_Rain_Thunderstorm	-0.2860	0.025	-11.492	0.000	-0.335	-0.237
Mist_Cloudy	-0.0801	0.009	-9.090	0.000	-0.097	-0.063
month_9	0.0909	0.016	5.565	0.000	0.059	0.123

Omnibus:	63.599	Durbin-Watson:	2.076
Prob(Omnibus):	0.000	Jarque-Bera (JB):	143.759
Skew:	-0.674	Prob(JB):	6.07e-32
Kurtosis:	5.225	Cond. No.	17.2

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

In [117]:
```
## There isn't much change in rsquared and adjusted rsquared
## Now we can see all the features have close to 0 pvalue
## Let's check VIF again
```
In [118]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_5.columns
vif['VIF'] = [variance_inflation_factor(X_train_5.values, i) for i in range(X_train_5.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```
Out[118]:

	Features	VIF
3	windspeed	4.59
2	temp	3.84
0	yr	2.07
4	spring	1.99
5	summer	1.89
6	winter	1.63
8	Mist_Cloudy	1.54
9	month_9	1.23
7	Light Snow_Rain_Thunderstorm	1.08
1	holiday	1.04

In [119]:
```
## Let's drop spring as it has some pvalue
```
In [120]:
```
X_train_6=X_train_5.copy()
```
In [121]:
```
X_train_6.drop('spring',axis=1,inplace=True)
```
In [122]:
```
X_train_sm=sm.add_constant(X_train_6)
lr_7=sm.OLS(y_train,X_train_sm).fit()
lr_7.summary()
```
Out[122]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.831
Model:	OLS	Adj. R-squared:	0.828
Method:	Least Squares	F-statistic:	272.9
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	1.37e-186
Time:	17:18:05	Log-Likelihood:	491.62
No. Observations:	510	AIC:	-963.2
Df Residuals:	500	BIC:	-920.9
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1264	0.017	7.541	0.000	0.093	0.159
yr	0.2328	0.008	27.973	0.000	0.216	0.249
holiday	-0.0992	0.026	-3.761	0.000	-0.151	-0.047
temp	0.5480	0.020	27.381	0.000	0.509	0.587
windspeed	-0.1533	0.025	-6.045	0.000	-0.203	-0.103
summer	0.0868	0.010	8.307	0.000	0.066	0.107
winter	0.1306	0.010	12.476	0.000	0.110	0.151
Light Snow_Rain_Thunderstorm	-0.2838	0.025	-11.344	0.000	-0.333	-0.235
Mist_Cloudy	-0.0797	0.009	-8.995	0.000	-0.097	-0.062
month_9	0.1011	0.016	6.327	0.000	0.070	0.132

Omnibus:	57.277	Durbin-Watson:	2.088
Prob(Omnibus):	0.000	Jarque-Bera (JB):	116.021
Skew:	-0.648	Prob(JB):	6.40e-26
Kurtosis:	4.945	Cond. No.	10.2

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

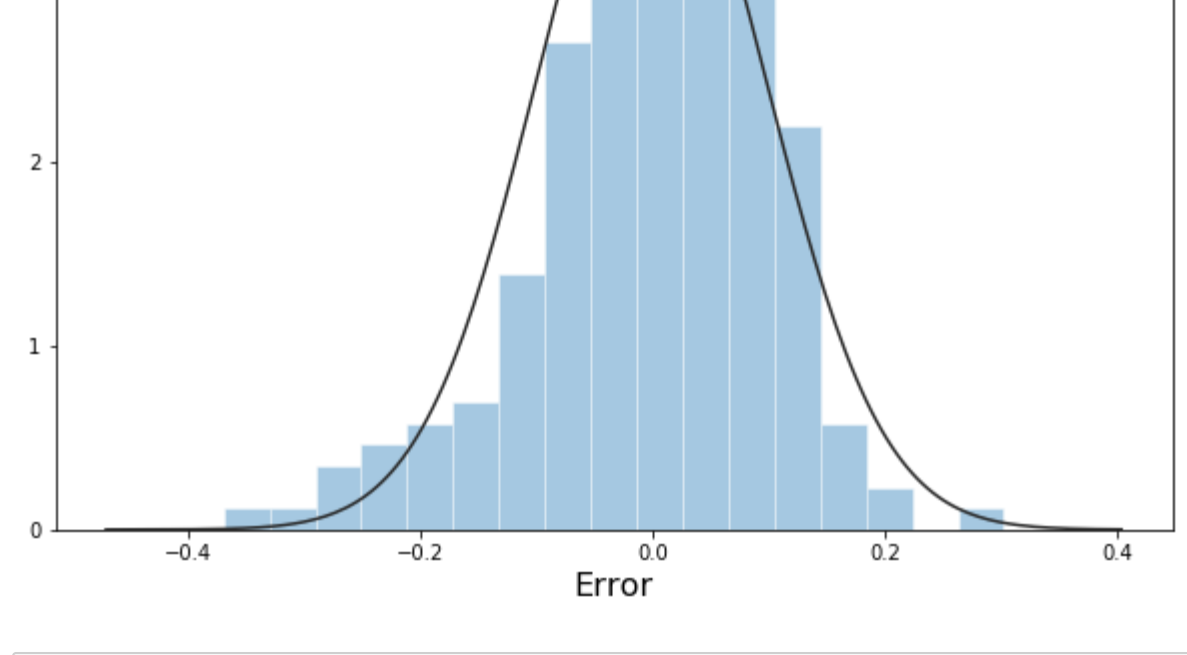
In [123]:
```
## There is small change in adjusted rsquared but now pvalues are 0 for all the features listed
## Let's check VIF again
```
In [124]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_6.columns
vif['VIF'] = [variance_inflation_factor(X_train_6.values, i) for i in range(X_train_6.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```
Out[124]:

	Features	VIF
2	temp	3.68
3	windspeed	3.05
0	yr	2.00
4	summer	1.56
7	Mist_Cloudy	1.48
5	winter	1.38
8	month_9	1.20
6	Light Snow_Rain_Thunderstorm	1.08
1	holiday	1.03

In [125]:
```
## Even VIF for all has dropped a little
```
In [126]:
```
## Before proceeding for dropping another variable, let's try to predict with this model, and evaluate
 this
## So that we can make sure if we drop more variables it doesn't get to overfit
```
In [127]:
```
X_test=X_test[X_train_6.columns]
```
In [128]:
```
X_test_sm=sm.add_constant(X_test)
y_pred=lr_7.predict(X_test_sm)
```
In [129]:
```
mean_squared_error(y_test,y_pred)
```
Out[129]: 0.009792258183115958

In [130]:
```
r2_score(y_test,y_pred)
```
Out[130]: 0.793829001664065

In [131]:
```
plt.figure(figsize=[10,8])
sns.distplot((y_test-y_pred),fit=norm,kde=False,hist_kws=dict(edgecolor='w'))
plt.xlabel('Error',fontsize=16)
plt.title('Residual Analysis',fontsize=18)
```
Out[131]: Text(0.5, 1.0, 'Residual Analysis')



In [132]:
```
lr_7.summary()
```
Out[132]:

OLS Regression Results

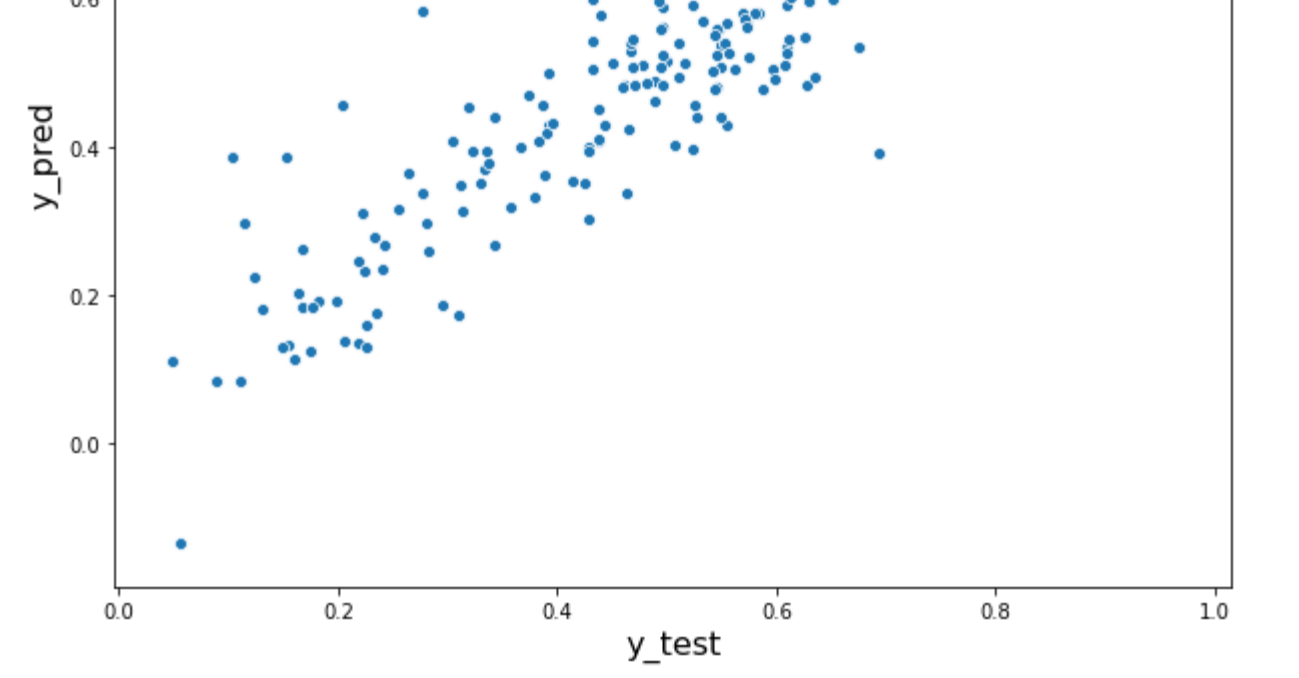
Dep. Variable:	cnt	R-squared:	0.831
Model:	OLS	Adj. R-squared:	0.828
Method:	Least Squares	F-statistic:	272.9
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	1.37e-186
Time:	17:18:08	Log-Likelihood:	491.62
No. Observations:	510	AIC:	-963.2
Df Residuals:	500	BIC:	-920.9
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1264	0.017	7.541	0.000	0.093	0.159
yr	0.2328	0.008	27.973	0.000	0.216	0.249
holiday	-0.0992	0.026	-3.761	0.000	-0.151	-0.047
temp	0.5480	0.020	27.381	0.000	0.509	0.587
windspeed	-0.1533	0.025	-6.045	0.000	-0.203	-0.103
summer	0.0868	0.010	8.307	0.000	0.066	0.107
winter	0.1306	0.010	12.476	0.000	0.110	0.151
Light Snow_Rain_Thunderstorm	-0.2838	0.025	-11.344	0.000	-0.333	-0.235
Mist_Cloudy	-0.0797	0.009	-8.995	0.000	-0.097	-0.062
month_9	0.1011	0.016	6.327	0.000	0.070	0.132

Omnibus:	57.277	Durbin-Watson:	2.088
Prob(Omnibus):	0.000	Jarque-Bera (JB):	116.021
Skew:	-0.648	Prob(JB):	6.40e-26
Kurtosis:	4.945	Cond. No.	10.2

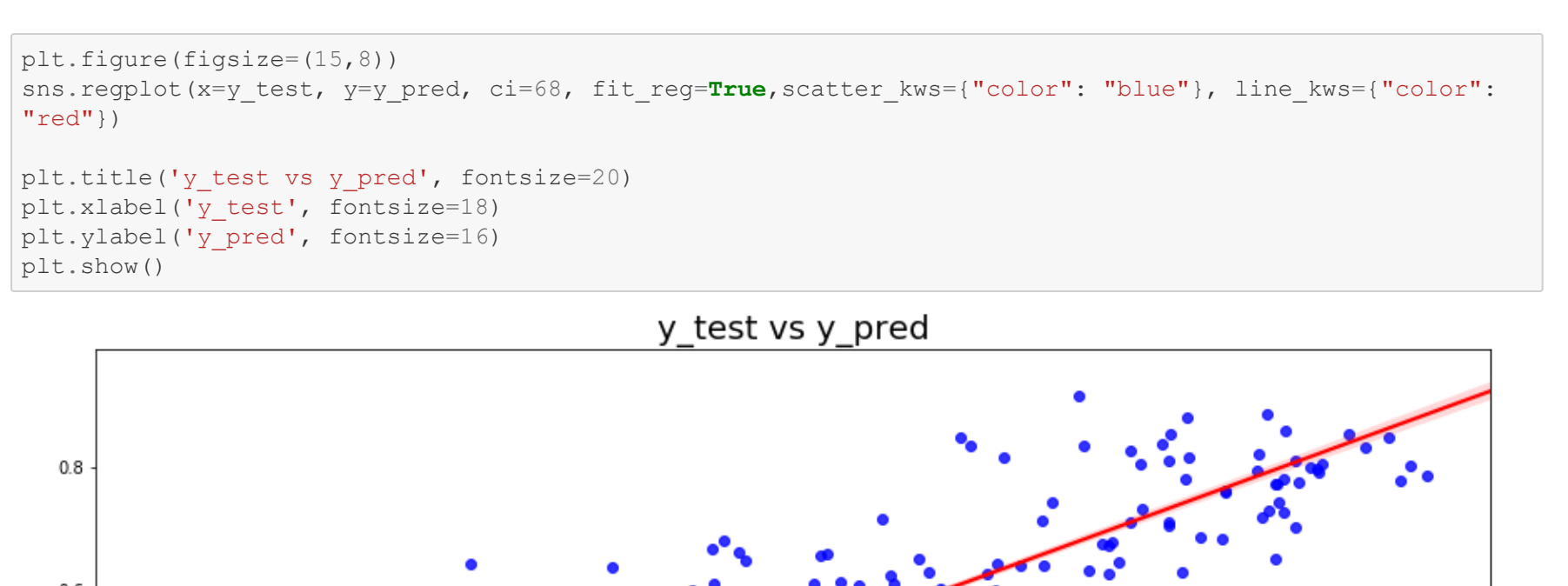
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [133]:
```
X_train_6.columns
```
Out[133]:
```
Index(['yr', 'holiday', 'temp', 'windspeed', 'summer', 'winter',
       'Light Snow_Rain_Thunderstorm', 'Mist_Cloudy', 'month_9'],
      dtype='object')
```
In [134]:
```
y_p=0.1264+0.2328*X_train_6.iloc[:,0]-0.0992*X_train_6.iloc[:,1]+0.5480*X_train_6.iloc[:,2]-0.1533*X_tr
ain_6.iloc[:,3]+0.868*X_train_6.iloc[:,4]+0.1306*X_train_6.iloc[:,5]-0.2838*X_train_6.iloc[:,6]-0.0797*
X_train_6.iloc[:,7]+0.1011*X_train_6.iloc[:,8]
```
In [135]:
```
plt.figure(figsize=[10,8])
sns.scatterplot(y_test,y_pred)
plt.xlabel('y_test',fontsize=16)
plt.ylabel('y_pred',fontsize=16)
plt.title('y_test vs y_pred',fontsize=18)
```
Out[135]: Text(0.5, 1.0, 'y_test vs y_pred')



In [136]:
```
plt.figure(figsize=(15,8))
sns.regplot(x=y_test, y=y_pred, ci=68, fit_reg=True,scatter_kws={"color": "blue"}, line_kws={"color":
"red"})

plt.title('y_test vs y_pred', fontsize=20)
plt.xlabel('y_test', fontsize=18)
plt.ylabel('y_pred', fontsize=16)
plt.show()
```



In [137]:
```
## This model looks good
## with r2=0.79 for test, 0.82 for training set
## mse= 0.009
## Residual analysis is normally distributed
```
In [138]:
```
## Now since we already have seasons, weather listed, only a month's data might not be very significant
 enough
## Let's check if our assumption is right by dropping the month_9 column
```
In [139]:
```
X_train_7=X_train_6.copy()
```
In [140]:
```
X_train_7.drop('month_9',axis=1,inplace=True)
```
In [141]:
```
X_train_sm=sm.add_constant(X_train_7)
lr_8=sm.OLS(y_train,X_train_sm).fit()
lr_8.summary()
```
Out[141]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.817
Model:	OLS	Adj. R-squared:	0.814
Method:	Least Squares	F-statistic:	280.1
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	1.72e-179
Time:	17:18:12	Log-Likelihood:	471.98
No. Observations:	510	AIC:	-926.0
Df Residuals:	501	BIC:	-887.9
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1257	0.017	7.221	0.000	0.091	0.160
yr	0.2320	0.009	26.855	0.000	0.215	0.249
holiday	-0.0898	0.027	-3.285	0.001	-0.144	-0.036
temp	0.5752	0.020	28.339	0.000	0.535	0.615
windspeed	-0.1639	0.026	-6.239	0.000	-0.216	-0.112
summer	0.0739	0.011	6.939	0.000	0.053	0.095
winter	0.1273	0.011	11.727	0.000	0.106	0.149
Light Snow_Rain_Thunderstorm	-0.2749	0.026	-10.598	0.000	-0.326	-0.224
Mist_Cloudy	-0.0751	0.009	-8.185	0.000	-0.093	-0.057

Omnibus:	51.763	Durbin-Watson:	2.018
Prob(Omnibus):	0.000	Jarque-Bera (JB):	120.606
Skew:	-0.545	Prob(JB):	6.47e-27
Kurtosis:	5.119	Cond. No.	10.2

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

In [142]:
```
## Adjusted rsquared is affected a little but still this is good
## Let's try dropping holiday too, as it has little pvalue,
## Also we need to make sure if our model is not overfit as we dropping many columns
```

In [143]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_7.columns
vif['VIF'] = [variance_inflation_factor(X_train_7.values, i) for i in range(X_train_7.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[143]:

	Features	VIF
2	temp	3.33
3	windspeed	3.03
0	yr	2.00
4	summer	1.50
7	Mist_Cloudy	1.47
5	winter	1.37
6	Light Snow_Rain_Thunderstorm	1.08
1	holiday	1.03

In [144]:
```
X_test=X_test[X_train_7.columns]
```

In [145]:
```
X_test_sm=sm.add_constant(X_test)
y_pred=lr_8.predict(X_test_sm)
```

In [146]:
```
mean_squared_error(y_test,y_pred)
```

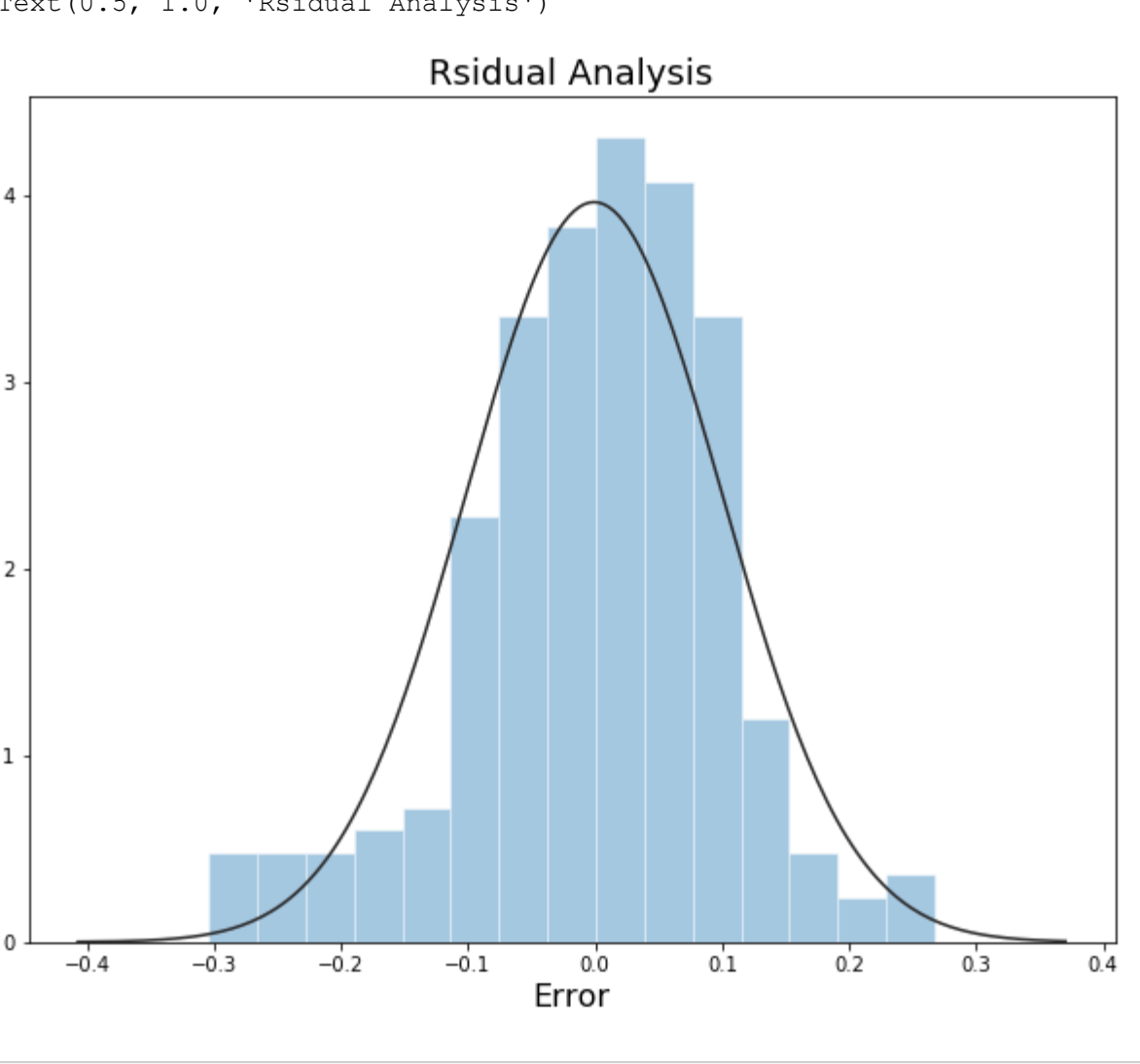
Out[146]: 0.010139057332758243

In [147]:
```
r2_score(y_test,y_pred)
```

Out[147]: 0.7865273225654599

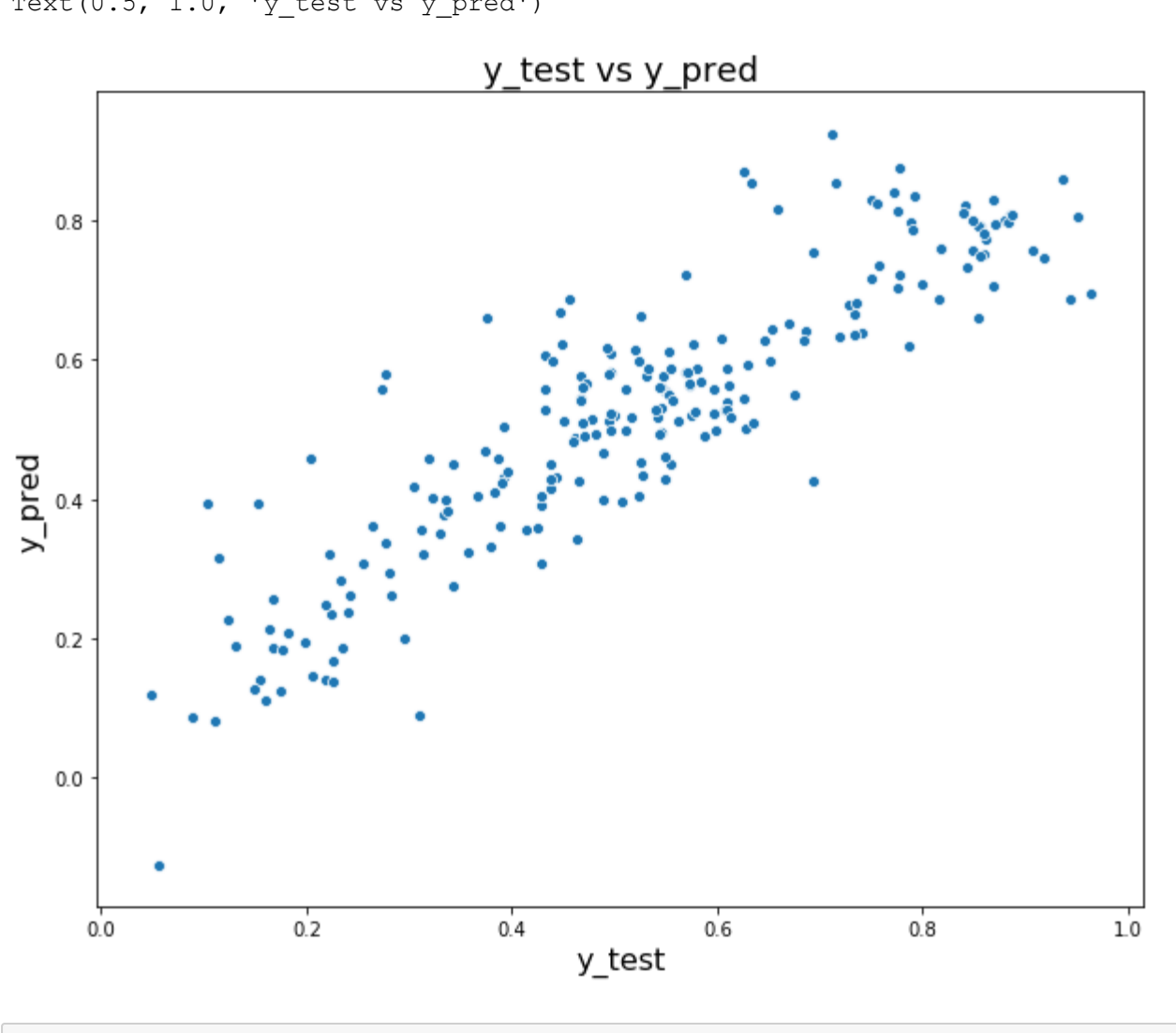
In [148]:
```
plt.figure(figsize=[10,8])
sns.distplot((y_test-y_pred),hist_kws=dict(edgecolor='w'),fit=norm,kde=False)
plt.xlabel('Error',fontsize=16)
plt.title('Rsidual Analysis',fontsize=18)
```

Out[148]: Text(0.5, 1.0, 'Rsidual Analysis')



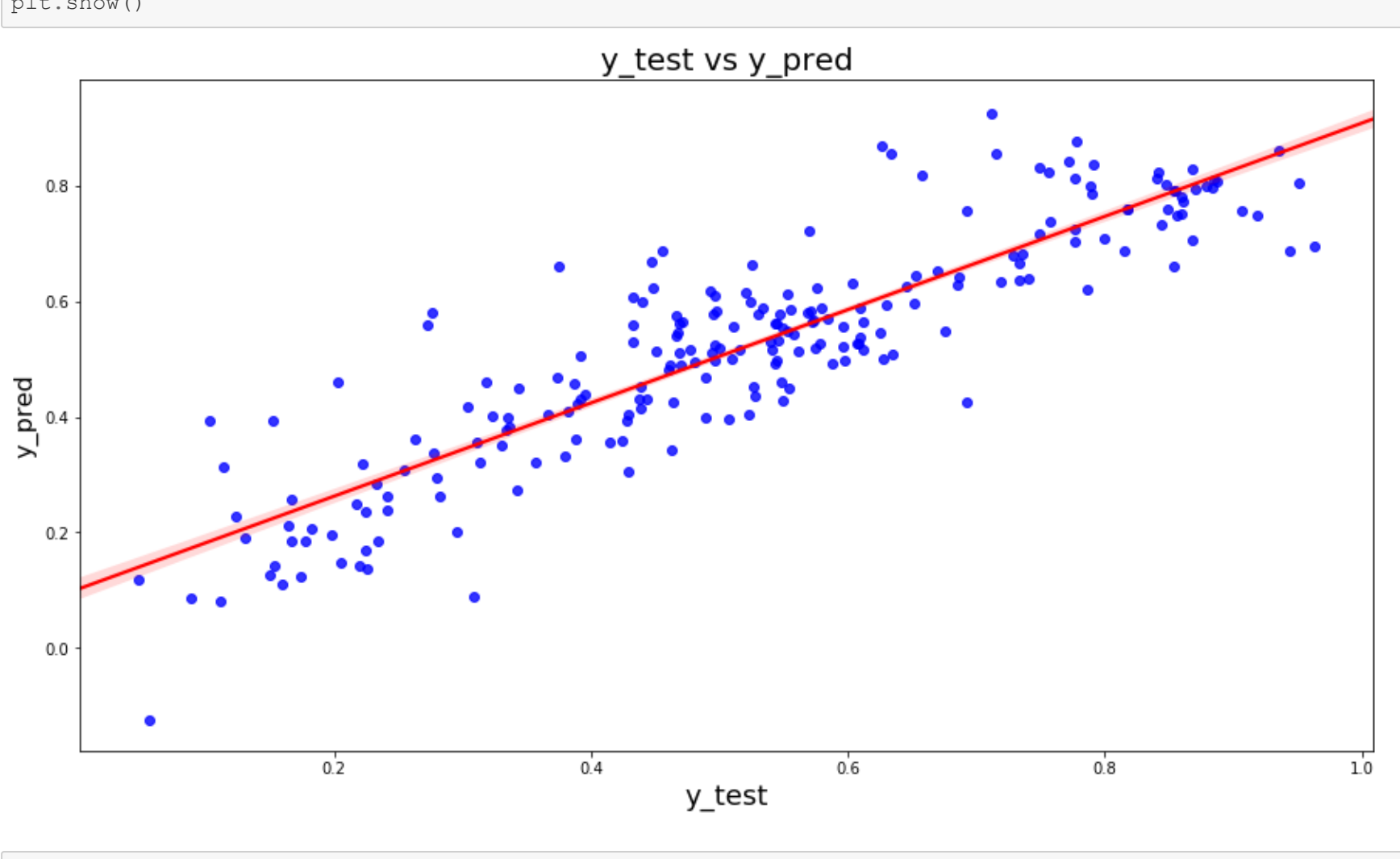
In [149]:
```
plt.figure(figsize=[10,8])
sns.scatterplot(y_test,y_pred)
plt.xlabel('y_test',fontsize=16)
plt.ylabel('y_pred',fontsize=16)
plt.title('y_test vs y_pred',fontsize=18)
```

Out[149]: Text(0.5, 1.0, 'y_test vs y_pred')



In [150]:
```
plt.figure(figsize=(15,8))
sns.regplot(x=y_test, y=y_pred, ci=68, fit_reg=True,scatter_kws={"color": "blue"}, line_kws={"color":
"red"})

plt.title('y_test vs y_pred', fontsize=20)
plt.xlabel('y_test', fontsize=18)
plt.ylabel('y_pred', fontsize=16)
plt.show()
```



In [151]:
```
X_train_8=X_train_7.copy()
```

In [152]:
```
X_train_8.drop('holiday',axis=1,inplace=True)
```

In [153]:
```
X_train_sm=sm.add_constant(X_train_8)
lr_9=sm.OLS(y_train,X_train_sm).fit()
lr_9.summary()
```

Out[153]:

OLS Regression Results

Dep. Variable:	cnt	R-squared:	0.813
Model:	OLS	Adj. R-squared:	0.811
Method:	Least Squares	F-statistic:	312.5
Date:	Wed, 07 Jul 2021	Prob (F-statistic):	1.92e-178
Time:	17:18:15	Log-Likelihood:	466.55
No. Observations:	510	AIC:	-917.1
Df Residuals:	502	BIC:	-883.2
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1211	0.018	6.914	0.000	0.087	0.156
yr	0.2323	0.009	26.635	0.000	0.215	0.249
temp	0.5786	0.020	28.272	0.000	0.538	0.619
windspeed	-0.1654	0.027	-6.236	0.000	-0.217	-0.113
summer	0.0755	0.011	7.029	0.000	0.054	0.097
winter	0.1263	0.011	11.530	0.000	0.105	0.148
Light Snow_Rain_Thunderstorm	-0.2712	0.026	-10.365	0.000	-0.323	-0.220
Mist_Cloudy	-0.0737	0.009	-7.963	0.000	-0.092	-0.055

Omnibus:	58.136	Durbin-Watson:	1.976
Prob(Omnibus):	0.000	Jarque-Bera (JB):	143.406
Skew:	-0.591	Prob(JB):	7.24e-32
Kurtosis:	5.313	Cond. No.	10.1

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

In [154]:
```
## Let's check VIF again
```

In [155]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif = pd.DataFrame()
vif['Features'] = X_train_8.columns
vif['VIF'] = [variance_inflation_factor(X_train_8.values, i) for i in range(X_train_8.shape[1])]
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[155]:

	Features	VIF
1	temp	3.33
2	windspeed	3.01
0	yr	2.00
3	summer	1.50
6	Mist_Cloudy	1.46
4	winter	1.37
5	Light Snow_Rain_Thunderstorm	1.08

Model Evaluation

In [156]:
```
X_test=X_test[X_train_8.columns]
```

In [157]:
```
X_test_sm=sm.add_constant(X_test)
y_pred=lr_9.predict(X_test_sm)
```

In [158]:
```
mean_squared_error(y_test,y_pred)
```

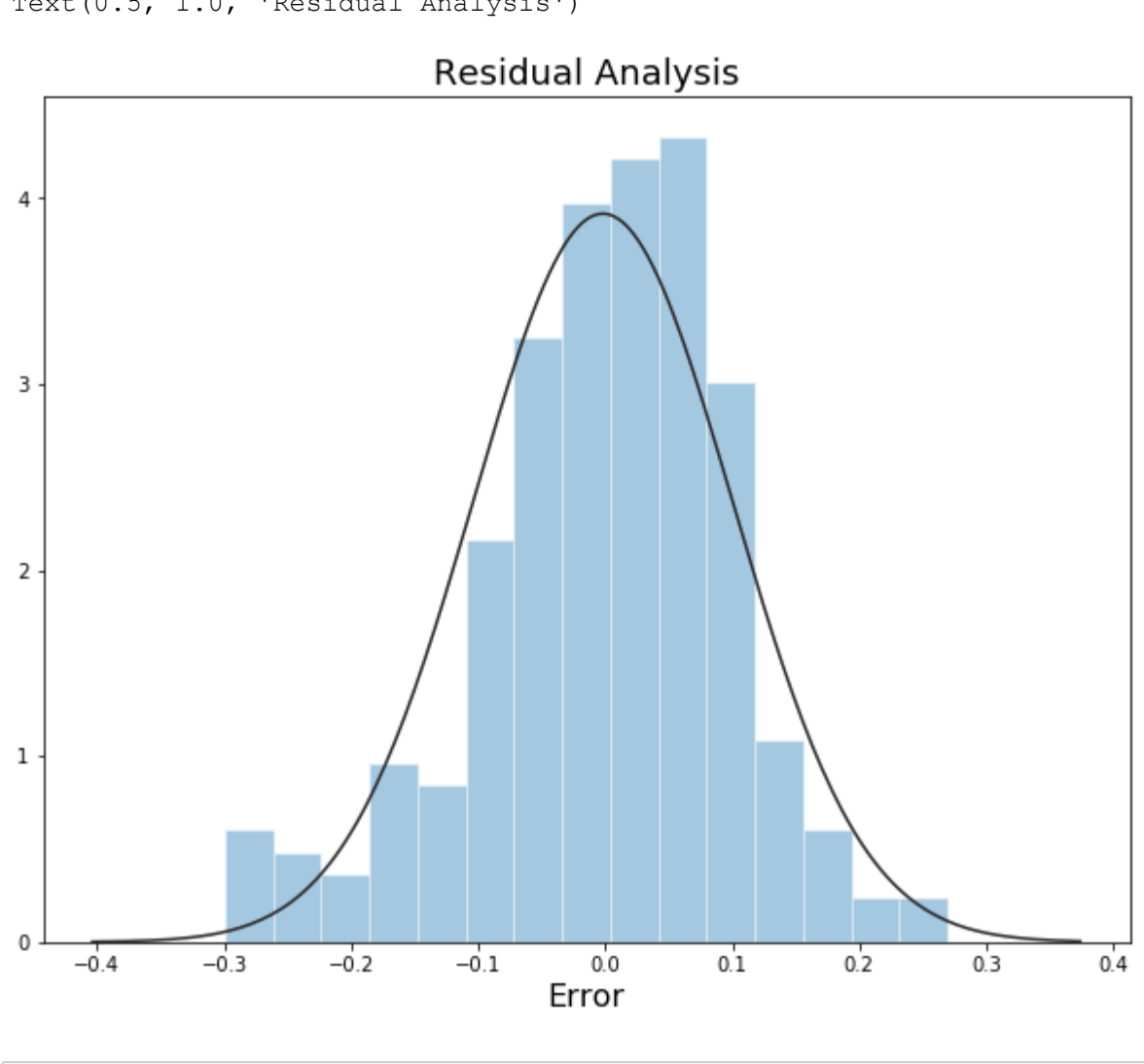
Out[158]: 0.010377676044333185

In [159]:
```
r2_score(y_test,y_pred)
```

Out[159]: 0.7815033273779284

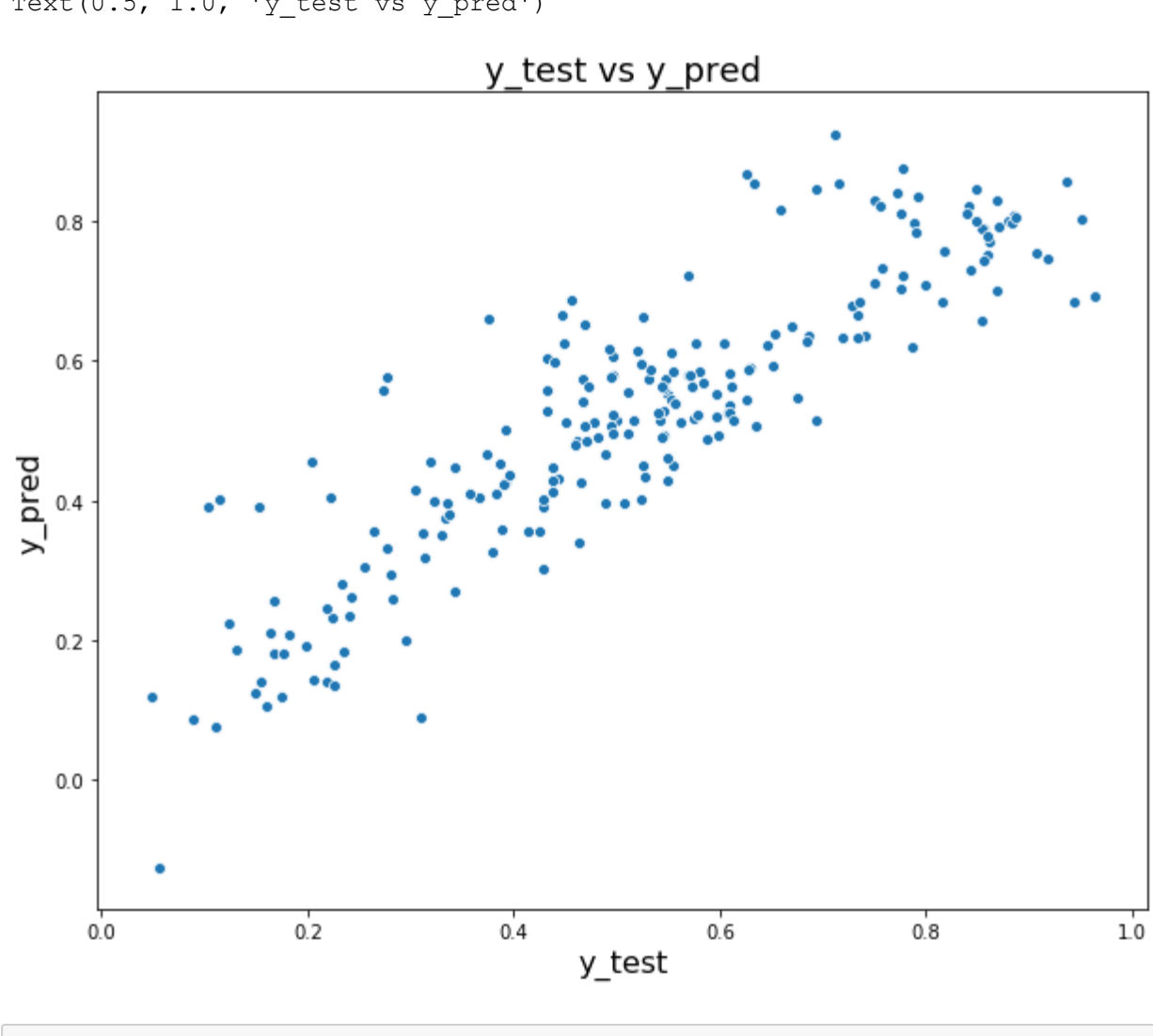
In [160]:
```
plt.figure(figsize=[10,8])
sns.distplot((y_test-y_pred),hist_kws=dict(edgecolor='w'),fit=norm,kde=False,bins=15)
plt.xlabel('Error',fontsize=16)
plt.title('Residual Analysis',fontsize=18)
```

Out[160]: Text(0.5, 1.0, 'Residual Analysis')



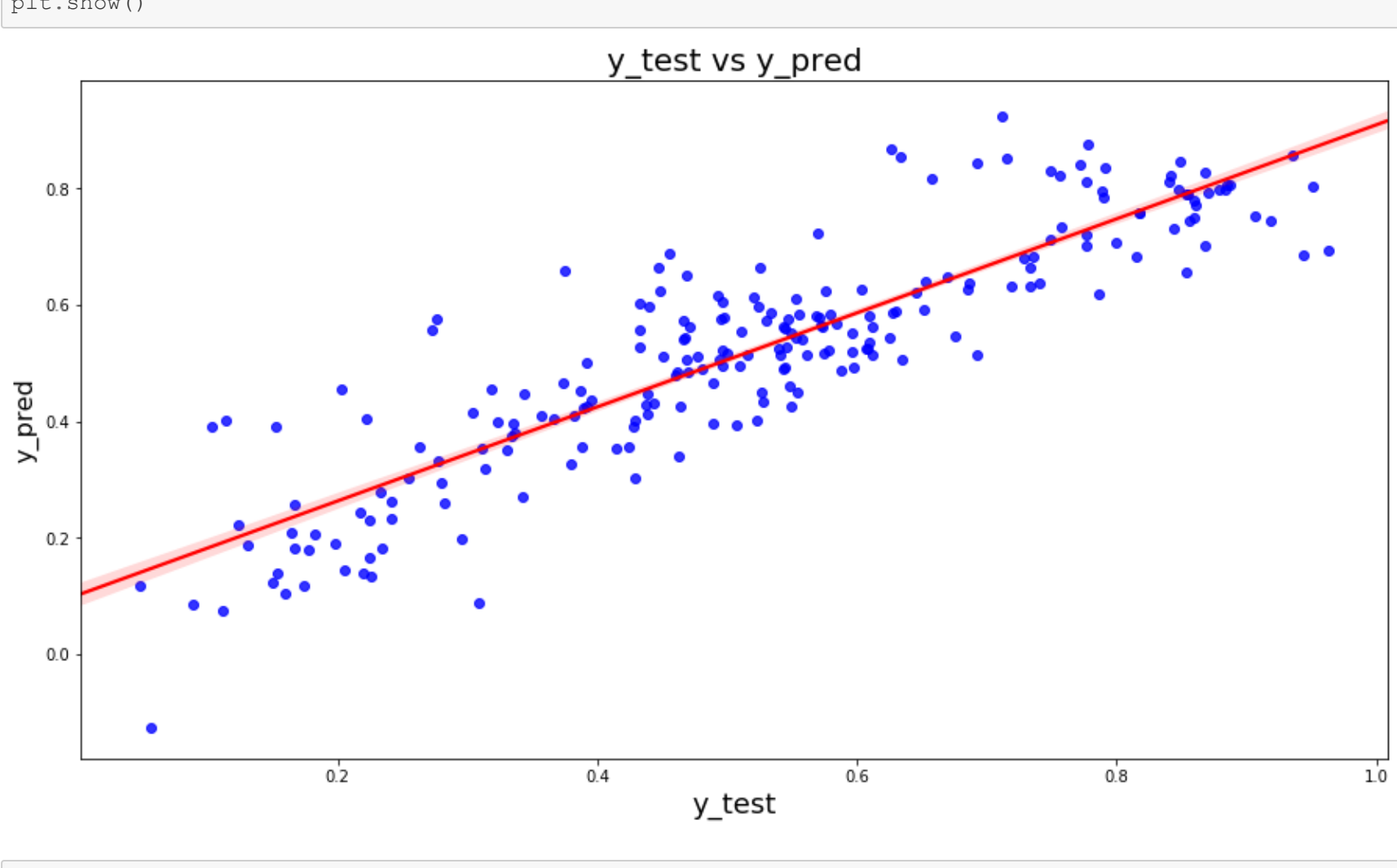
In [161]:
```
plt.figure(figsize=[10,8])
sns.scatterplot(y_test,y_pred)
plt.xlabel('y_test',fontsize=16)
plt.ylabel('y_pred',fontsize=16)
plt.title('y_test vs y_pred',fontsize=18)
```

Out[161]: Text(0.5, 1.0, 'y_test vs y_pred')



In [162]:
```
plt.figure(figsize=(15,8))
sns.regplot(x=y_test, y=y_pred, ci=68, fit_reg=True,scatter_kws={"color": "blue"}, line_kws={"color":
"red"})

plt.title('y_test vs y_pred', fontsize=20)
plt.xlabel('y_test', fontsize=18)
plt.ylabel('y_pred', fontsize=16)
plt.show()
```



In [163]:
```
residuals = y_test-y_pred
mean_residuals = np.mean(residuals)
print("Mean of Residuals {}".format(mean_residuals))
```

Mean of Residuals -0.0019315920640096747

Observations

In [164]:
```
## The 7 features used for this model are
## 'yr', 'temp', 'windspeed', 'summer', 'winter','Light Snow_Rain_Thunderstorm', 'Mist_Cloudy'
## Within given temperature range, demand is directly proportional to the temperature and
## inversely proportional to rain or thunderstorm which states no rain is preferred more.
## This means that a major portion of people using this retal scheme depends upon season and weather
## Also we can say less windspeed, no rain and no mist conditions are preferred as they have negative c
oefficients
## Both summer and winter are preferred but mainly depending on temperature
## However if we wish to choose to have more accuracy then we could choose the above linear models with
 2 more features added.
```