Business Case: Yulu - Hypothesis Testing

1.Define Problem Statement and perform Exploratory Data Analysis (10 points)

```
1.Definition of problem (as per given problem statement with additional vie
ws)

2. Observations on shape of data, data types of all the attributes, convers
ion of categorical attributes to 'category' (If required) , missing value d
etection, statistical summary.

3. Univariate Analysis (distribution plots of all the continuous variable
(s) barplots/countplots of all the categorical variables)

4. Bivariate Analysis (Relationships between important variables such as wo
rkday and count, season and count, weather and count.

5. Illustrate the insights based on EDA
    1. Comments on range of attributes, outliers of various attributes
    2. Comments on the distribution of the variables and relationship betwe
en them
    3. Comments for each univariate and bivariate plots
```

Problem Statement:

```
Yulu is India’s leading micro-mobility service provider, which offers uniqu
e vehicles for the daily commute. Starting off as a mission to eliminate tr
affic congestion in India, Yulu provides the safest commute solution throug
h a user-friendly mobile app to enable shared, solo and sustainable commuti
ng.

Yulu zones are located at all the appropriate locations (including metro st
ations, bus stands, office spaces, residential areas, corporate offices, et
c) to make those first and last miles smooth, affordable, and convenient!

Yulu has recently suffered considerable dips in its revenues. They have con
tracted a consulting company to understand the factors on which the demand
 for these shared electric cycles depends. Specifically, they want to under
stand the factors affecting the demand for these shared electric cycles in
 the Indian market.

Which variables are significant in predicting the demand for shared electri
c cycles in the Indian market?
How well those variables describe the electric cycle demands?

Let's find out...
```

In [ ]:

User defined helper functions which helps for hypothesis testing and their assumptions

In [255]:

```
def shapiro_test(series):
    print("Mean : ", round(series.mean(),2),", Standard deviation : ",round(series.

    # calling function for shapiro test
    test_stat, p_value = shapiro(series)

    print("p-value : ", p_value)
    if p_value < 0.05:
        print("Reject H0")
        print("Data is not Gaussian")
    else:
        print("Fail to reject H0")
        print("Data is Gaussian")
```

In [256]:

```
def levene_test(series1,series2):
    print("Series1 metrics : ")
    print("Mean : ", round(series1.mean(),2),", Standard deviation : ",round(series
    print("Series2 metrics : ")
    print("Mean : ", round(series2.mean(),2),", Standard deviation : ",round(series

    # calling function for levene test
    test_stat, p_value = levene(series1,series2)

    print("p-value : ", p_value)
    if p_value < 0.05:
        print("Reject H0")
        print("Variances are different")
    else:
        print("Fail to reject H0")
        print("Variances are the same")
    print()
```

In [257]:

```
def kstest_test(series):
    mu = series.mean()
    sigma = series.std()
    print("Mean : ", round(series.mean(),2),", Standard deviation : ",round(series.

    # calling function for ks-test
    test_stat, p_value = kstest(
        series,
        norm.cdf,
        args=(mu, sigma)
    )

    print("p-value : ", p_value)
    if p_value < 0.05:
        print("Reject H0")
        print("Data is not Gaussian")
    else:
        print("Fail to reject H0")
        print("Data is Gaussian")
```

In [258]:

```
def ttest_ind_test(series1,series2,alternative='two-sided'):
    print("Series1 metrics : ")
    print("Mean : ", round(series1.mean(),2),", Standard deviation : ",round(series
    print("Series2 metrics : ")
    print("Mean : ", round(series2.mean(),2),", Standard deviation : ",round(series

    # calling function for t-test for 2 independent samples
    t_stat, p_value = ttest_ind(series1,series2,alternative=alternative)
    print("p-value : ", p_value)
    if p_value < 0.05:
        print("Reject H0")
    else:
        print("Fail to reject H0")
```

In [ ]:

```

```

In [259]:

```
def anova_test(series1,series2,series3,series4=None):
    print("Series1 metrics : ")
    print("Mean : ", round(series1.mean(),2),", Standard deviation : ",round(series
    print("Series2 metrics : ")
    print("Mean : ", round(series2.mean(),2),", Standard deviation : ",round(series
    print("Series3 metrics : ")
    print("Mean : ", round(series3.mean(),2),", Standard deviation : ",round(series
    if series4 is not None:
        print("Series4 metrics : ")
        print("Mean : ", round(series4.mean(),2),", Standard deviation : ",round(se

        f_stat, p_value = f_oneway(series1,series2,series3,series4)
    else:
        f_stat, p_value = f_oneway(series1,series2,series3)
    print("p-value : ", p_value)
    if p_value < 0.05:
        print("Reject H0")
    else:
        print("Fail to reject H0")
```

In [ ]:

```

```

Libraries needed for this project

In [199]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(style='whitegrid')
from statsmodels.graphics.gofplots import qqplot

from scipy.stats import norm
from scipy.stats import ttest_ind
from scipy.stats import levene
from scipy.stats import shapiro, kstest
from scipy.stats import f_oneway
from scipy.stats import chi2_contingency
```

In [3]:

```
df = pd.read_csv("bike_sharing.csv") # read the tabular data file
```

In [5]:

```
df.shape  # the data hase 10886 rows and 12 columns
```

Out[5]:

```
(10886, 12)
```

In [6]:

```
df.head()  # first 5 rows of the data, just to have a brief view
```

Out[6]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casua
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	

In [7]:

```
df.info()   # displays the number of non nulls and data types of each column, we ca
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   datetime    10886 non-null  object 
 1   season      10886 non-null  int64  
 2   holiday     10886 non-null  int64  
 3   workingday  10886 non-null  int64  
 4   weather     10886 non-null  int64  
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64  
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64  
 10  registered  10886 non-null  int64  
 11  count       10886 non-null  int64  
dtypes: float64(3), int64(8), object(1)
memory usage: 1020.7+ KB
```

In [4]:

```
df['datetime'] = pd.to_datetime(df['datetime'])  # convert string to datetime datat
```

In [221]:

```
# extracting the necessary field from the datetime datatype
df['day'] = df['datetime'].dt.day.apply(str)
df['month'] = df['datetime'].dt.month.apply(str)
df['dayofyear'] = df['datetime'].dt.dayofyear.apply(str)
df['week'] = df['datetime'].dt.week.apply(str)
df['hour'] = df['datetime'].dt.hour
df['dayofweek'] = df['datetime'].dt.dayofweek
```

```
/tmp/ipykernel_6116/43653281.py:4: FutureWarning: Series.dt.weekofyear
and Series.dt.week have been deprecated.  Please use Series.dt.isocale
ndar().week instead.
  df['week'] = df['datetime'].dt.week.apply(str)
```

In [6]:

```
# converting the int datatypes to the categorical datatypes which are actually cate
df['season'] = df['season'].apply(str)
df['holiday'] = df['holiday'].apply(str)
df['weather'] = df['weather'].apply(str)
df['workingday'] = df['workingday'].apply(str)
```

In [8]:

```
df.info() # these are the modified datatypes, which will be appropriate to do furth
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 17 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  datetime64[ns]
 1   season      10886 non-null  object
 2   holiday     10886 non-null  object
 3   workingday  10886 non-null  object
 4   weather     10886 non-null  object
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
 12  day         10886 non-null  object
 13  month       10886 non-null  object
 14  dayofyear   10886 non-null  object
 15  week        10886 non-null  object
 16  hour        10886 non-null  int64
dtypes: datetime64[ns](1), float64(3), int64(5), object(8)
memory usage: 1.4+ MB
```

In [37]:

```
df.describe().T
```

Out[37]:

	count	mean	std	min	25%	50%	75%	max
weather	10886.0	1.418427	0.633839	1.00	1.0000	1.000	2.0000	4.0000
temp	10886.0	20.230860	7.791590	0.82	13.9400	20.500	26.2400	41.0000
atemp	10886.0	23.655084	8.474601	0.76	16.6650	24.240	31.0600	45.4550
humidity	10886.0	61.886460	19.245033	0.00	47.0000	62.000	77.0000	100.0000
windspeed	10886.0	12.799395	8.164537	0.00	7.0015	12.998	16.9979	56.9969
casual	10886.0	36.021955	49.960477	0.00	4.0000	17.000	49.0000	367.0000
registered	10886.0	155.552177	151.039033	0.00	36.0000	118.000	222.0000	886.0000
count	10886.0	191.574132	181.144454	1.00	42.0000	145.000	284.0000	977.0000
day	10886.0	9.992559	5.476608	1.00	5.0000	10.000	15.0000	19.0000
month	10886.0	6.521495	3.444373	1.00	4.0000	7.000	10.0000	12.0000
dayofyear	10886.0	177.562466	105.055551	1.00	92.0000	182.500	274.0000	354.0000
week	10886.0	25.917784	15.017269	1.00	14.0000	26.000	40.0000	52.0000

In [38]:

```
df.describe(include='object').T
```

Out[38]:

	count	unique	top	freq
season	10886	4	4	2734
holiday	10886	2	0	10575
workingday	10886	2	1	7412

Here we can observe that for each month there is only data for 19 days i.e from 1st day of the month to 19th day

In [23]:

```
# grouping the data monthly and getting the min and max of each month
df.groupby(['month'])['datetime'].agg(['min','max'])
```

Out[23]:

	min	max
month		
1	2011-01-01	2012-01-19 23:00:00
2	2011-02-01	2012-02-19 23:00:00
3	2011-03-01	2012-03-19 23:00:00
4	2011-04-01	2012-04-19 23:00:00
5	2011-05-01	2012-05-19 23:00:00
6	2011-06-01	2012-06-19 23:00:00
7	2011-07-01	2012-07-19 23:00:00
8	2011-08-01	2012-08-19 23:00:00
9	2011-09-01	2012-09-19 23:00:00
10	2011-10-01	2012-10-19 23:00:00
11	2011-11-01	2012-11-19 23:00:00
12	2011-12-01	2012-12-19 23:00:00

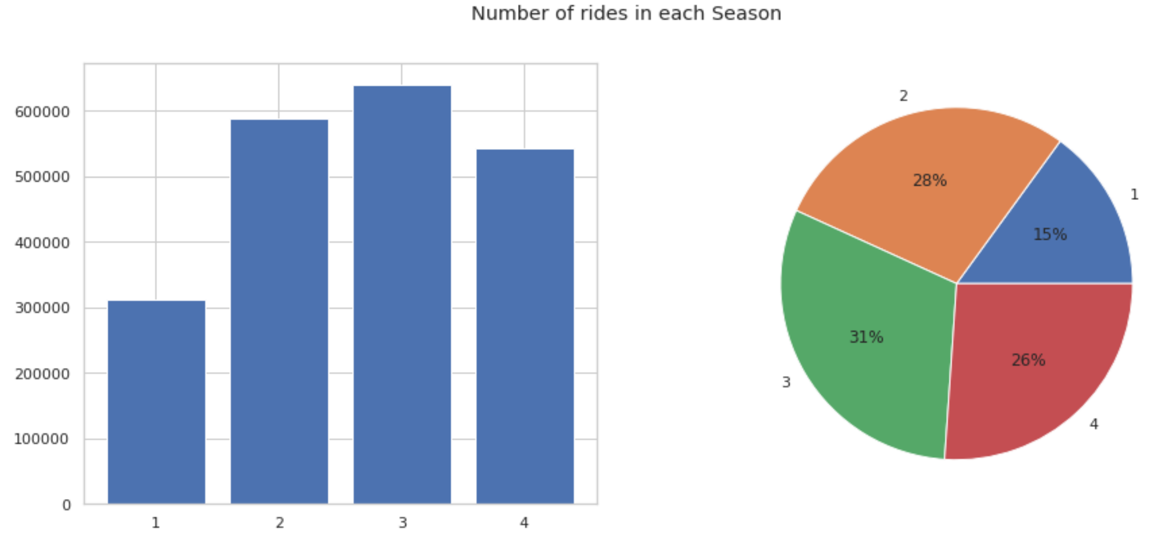
In [ ]:

```

```

The graph below says, ride bookings grew in summer and fall, but have degrew in the winter

In [78]:

```
s_vc = df.groupby(['season'])['count'].sum()
fig, axs = plt.subplots(1, 2 , figsize =(15, 6))
fig.suptitle('Number of rides in each Season ')
axs[0].bar(s_vc.index,s_vc.values)
axs[1].pie(s_vc.values,labels=s_vc.index, autopct='%1.0f%%')
plt.show()
```

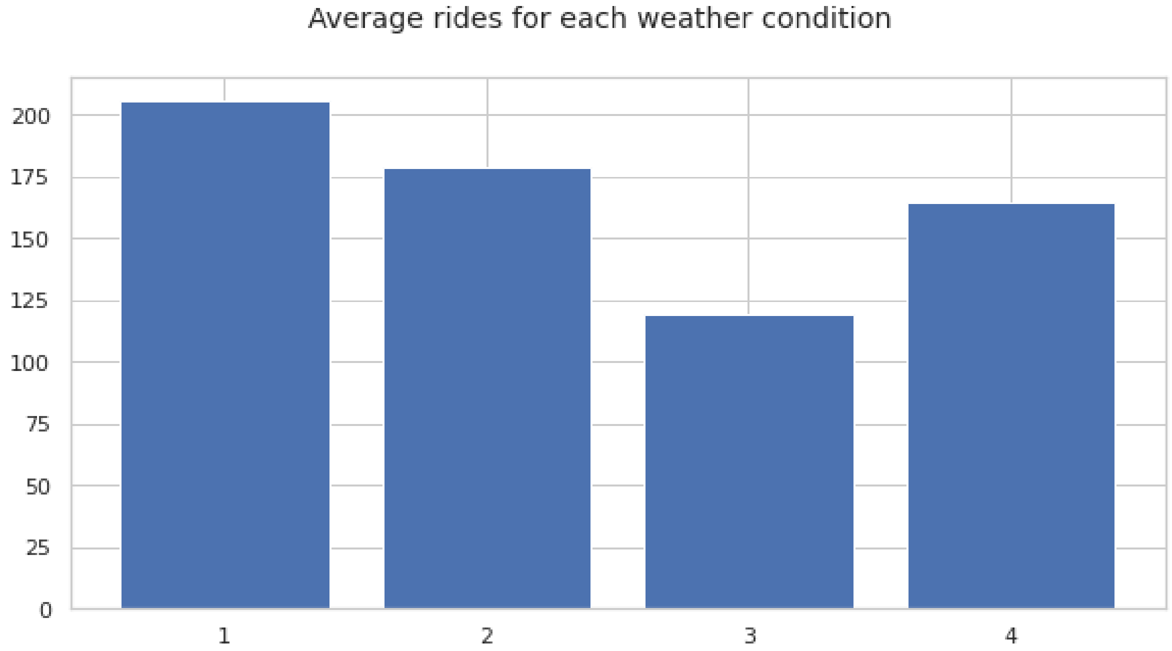


In [ ]:

Ride bookings decreases as the weather condition deteriotes

In [247]:

```
s_vc = df.groupby(['weather'])['count'].mean()
fig, axs = plt.subplots(1, 1 , figsize =(10, 5))
fig.suptitle('Average rides for each weather condition')
axs.bar(s_vc.index,s_vc.values)
plt.show()
```



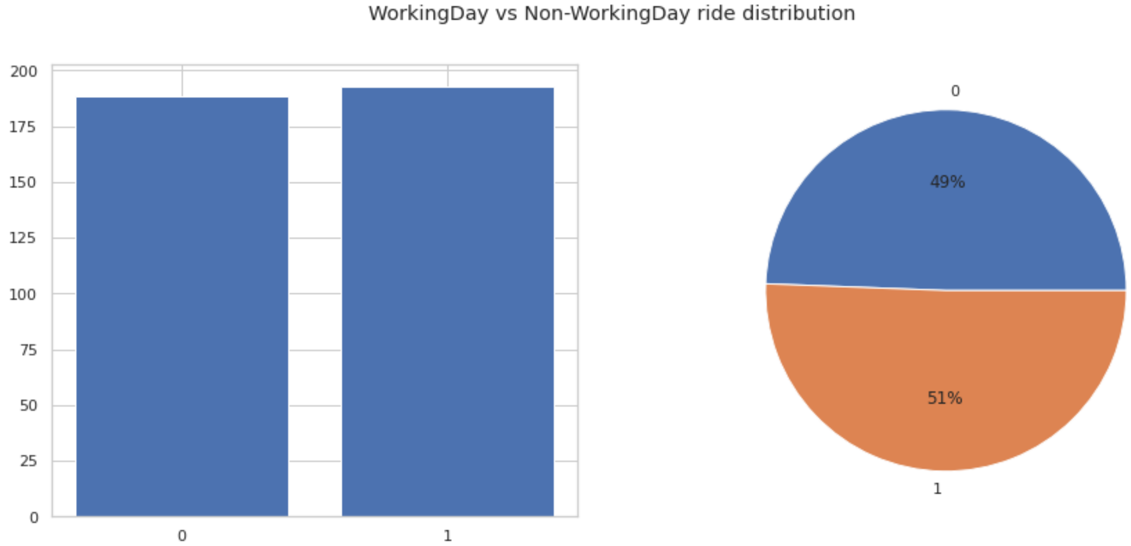
In [ ]:

In [ ]:

Ride bookings doesnt change much comparing working and nonworking day both are almost same

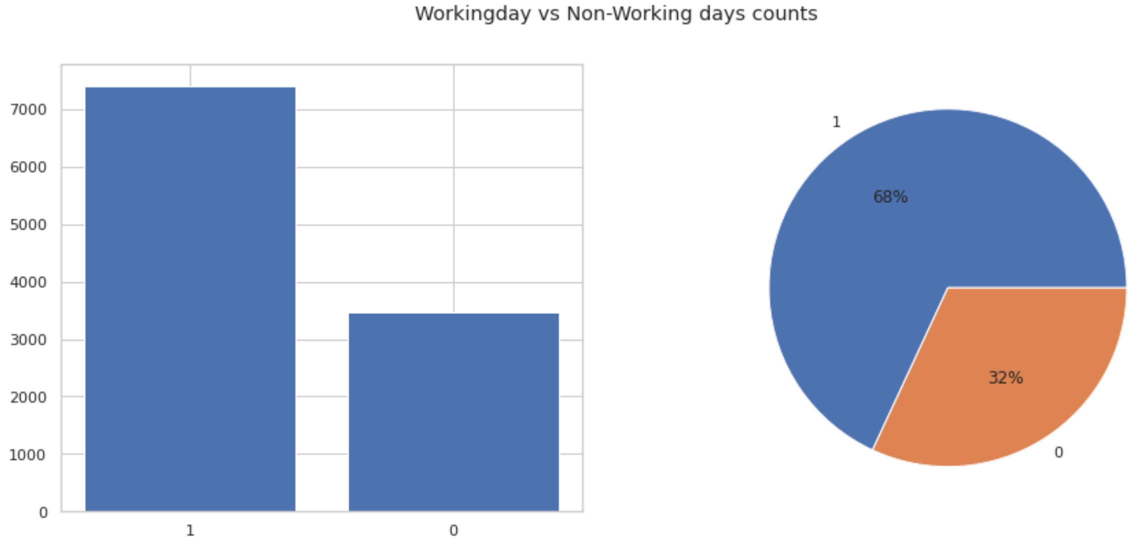
In [250]:

```
s_vc = df.groupby(['workingday'])['count'].mean()
fig, axs = plt.subplots(1, 2 , figsize =(15, 6))
fig.suptitle('WorkingDay vs Non-WorkingDay ride distribution')
axs[0].bar(s_vc.index,s_vc.values)
axs[1].pie(s_vc.values,labels=s_vc.index, autopct='%1.0f%%')
plt.show()
```



In [249]:

```
s_vc = df['workingday'].value_counts()
fig, axs = plt.subplots(1, 2 , figsize =(15, 6))
fig.suptitle('Workingday vs Non-Working days counts')
axs[0].bar(s_vc.index,s_vc.values)
axs[1].pie(s_vc.values,labels=s_vc.index, autopct='%1.0f%%')
plt.show()
```



In [ ]:

In [80]:

```
df.head()
```

Out[80]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casua
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0

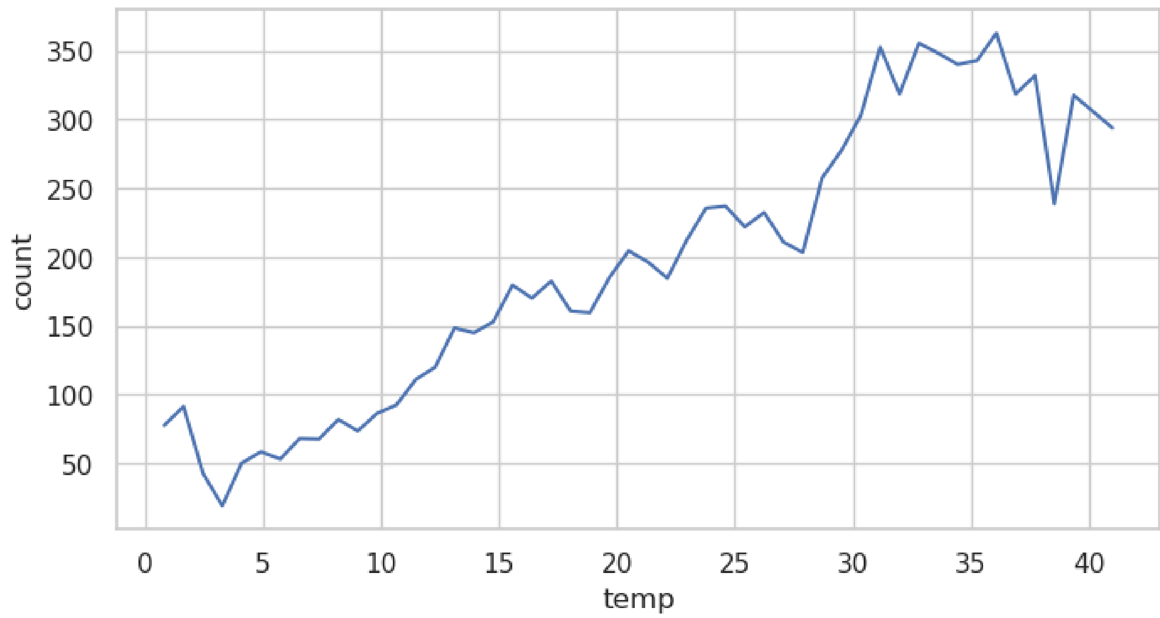
In [ ]:

In [129]:

```
plt.figure(figsize = (8, 4))
sns.lineplot(x='temp',y='count',data=df,estimator=np.mean,ci=None)
```

Out[129]:

<AxesSubplot:xlabel='temp', ylabel='count'>



Observations:

1. As the temperature increases the average bookings increases almostly linearly.
2. People prefer to travel through this bikes at temperatures between 30 and 37,as the data suggests it has highest bookings average.

In [ ]:

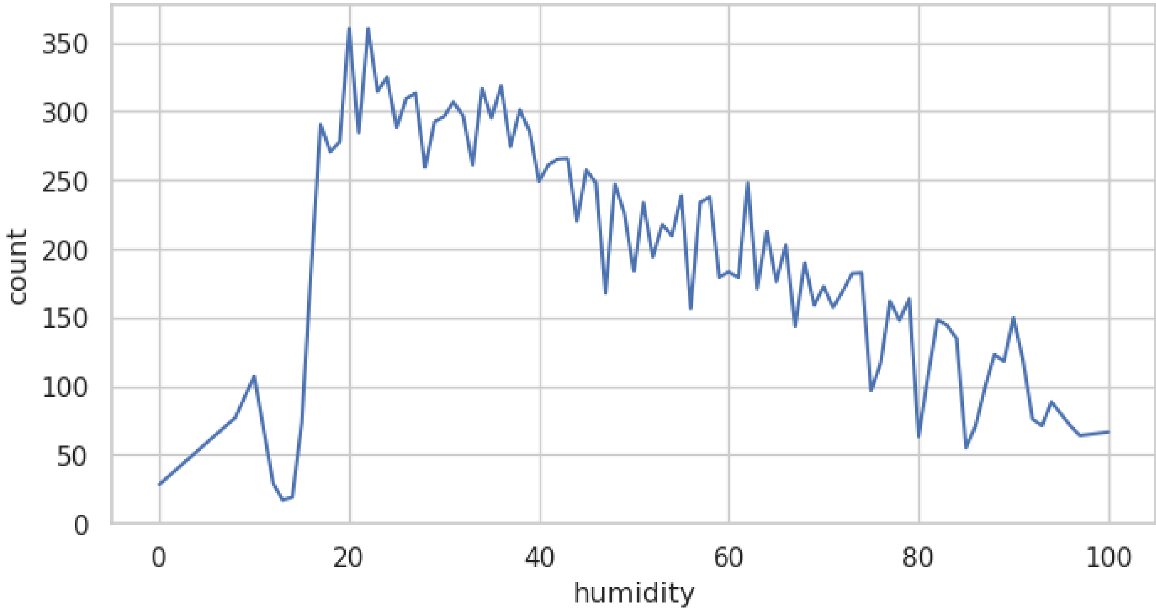
```

```

In [130]:

```
plt.figure(figsize = (8, 4))
sns.lineplot(x='humidity',y='count',data=df,estimator=np.mean,ci=None)
```

Out[130]:

<AxesSubplot:xlabel='humidity', ylabel='count'>



Observations:

1. The graph shows as the humidity increases the average rides degrease, says an inverse relationship.
2. We can ignore the values below 20, because the available data is very less to show the projections

In [ ]:

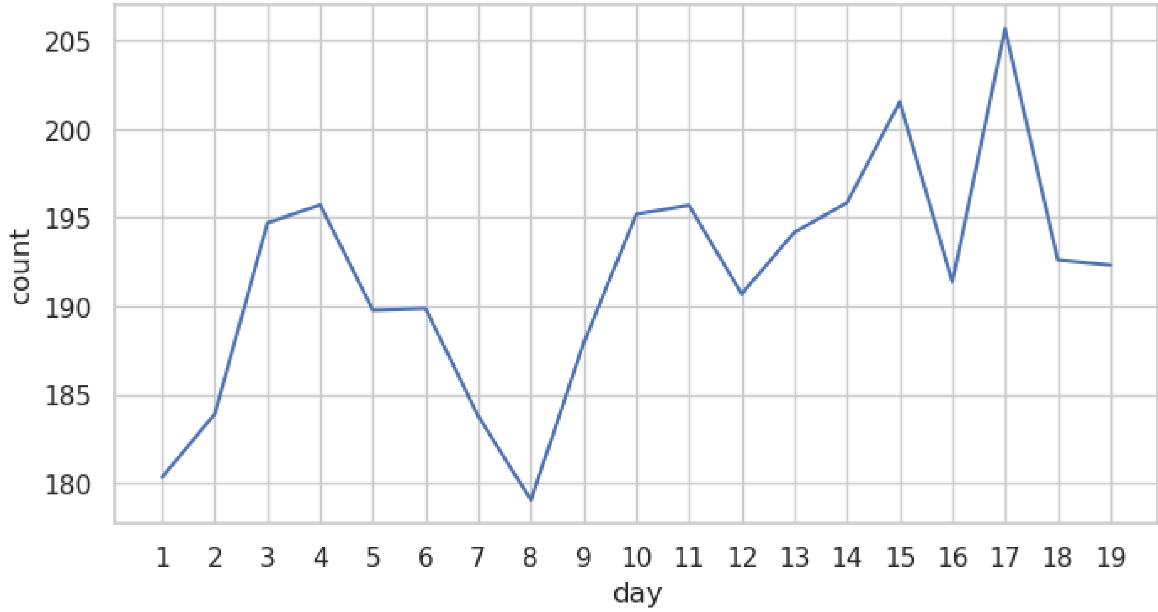
```

```

In [137]:

```
plt.figure(figsize = (8, 4))
sns.lineplot(x='day',y='count',data=df,estimator=np.mean,ci=None)
```

Out[137]:

```
<AxesSubplot:xlabel='day', ylabel='count'>
```



Observations:

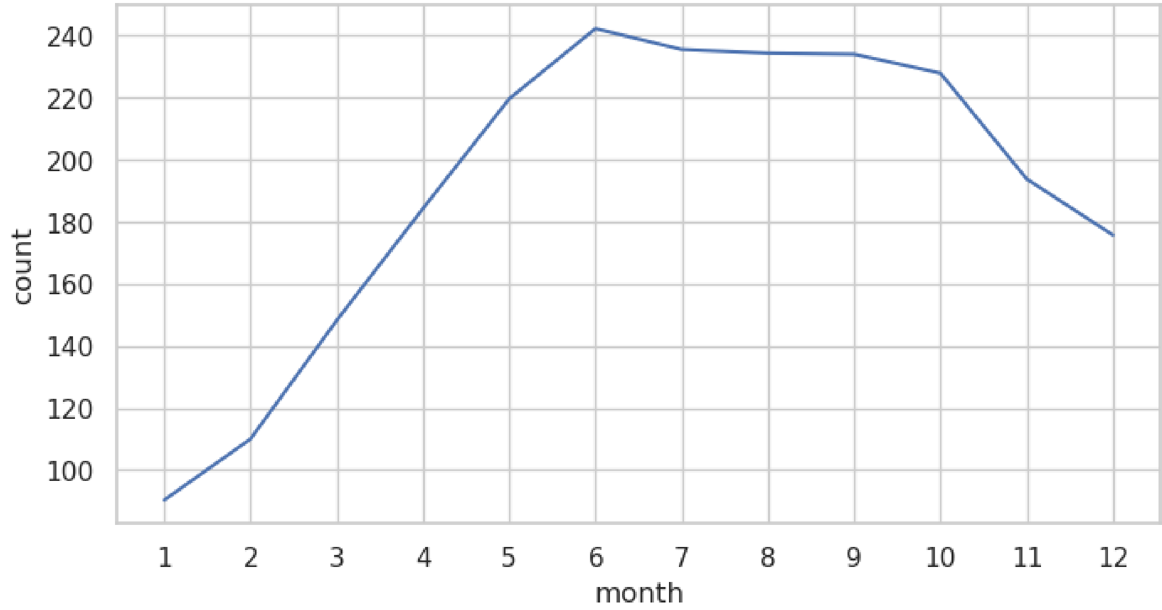
1. 8th day of the month has an unusual trend of very low ride bookings
2. First 2 weeks bookings are comparitively less than the 3rd week sales

In [138]:

```
plt.figure(figsize = (8, 4))
sns.lineplot(x='month',y='count',data=df,estimator=np.mean,ci=None)
```

Out[138]:

<AxesSubplot:xlabel='month', ylabel='count'>



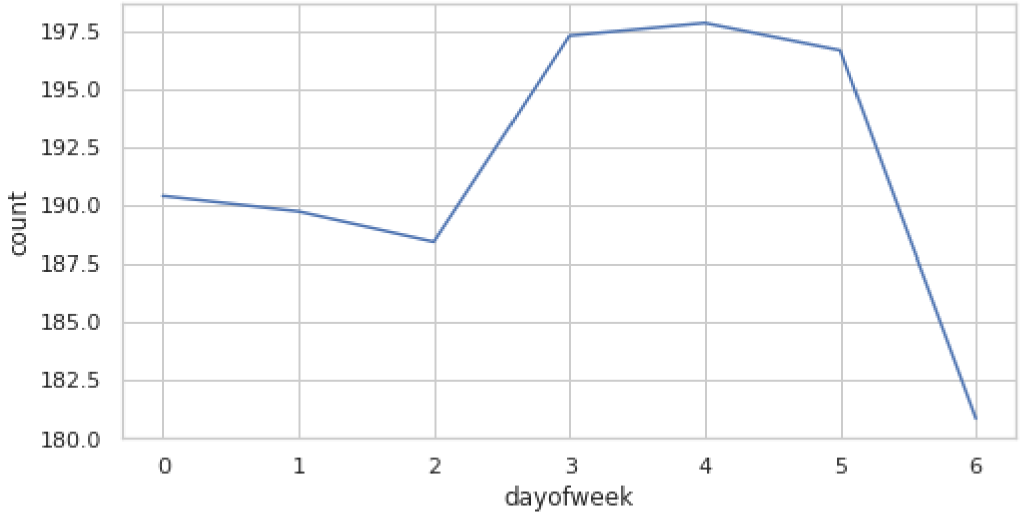
Type *Markdown* and LaTeX: α^2

In [225]:

```
plt.figure(figsize = (8, 4))
sns.lineplot(x='dayofweek',y='count',data=df,estimator=np.mean,ci=None)
```

Out[225]:

```
<AxesSubplot:xlabel='dayofweek', ylabel='count'>
```



Observations:

```
Here 0-6 represents from Monday - Sunday
1. Sundays have very low average bookings
2. Most tend to travel mostly in the days between Thursday to Saturday
```

In [ ]:

In [146]:

```
df.head()
```

Out[146]:

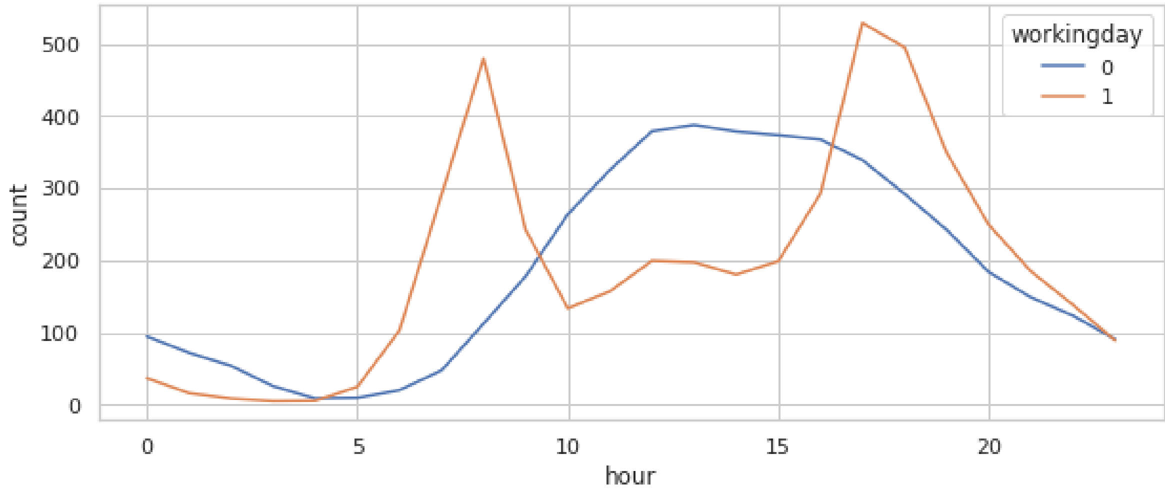
	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casua
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0

In [26]:

```
plt.figure(figsize = (10, 4))
sns.lineplot(x='hour',y='count',hue='workingday',data=df,estimator=np.mean,ci=None)
```

Out[26]:

<AxesSubplot:xlabel='hour', ylabel='count'>



Observations:

1. Peek rides on week days are between 7-9am and 5-7pm as these are the pea k office hours
2. On weekendsthe peak ride bookings are in between 10am-5pm.
3. We can clearly see the riders behaviour in comparision with working days and holidays

In [ ]:

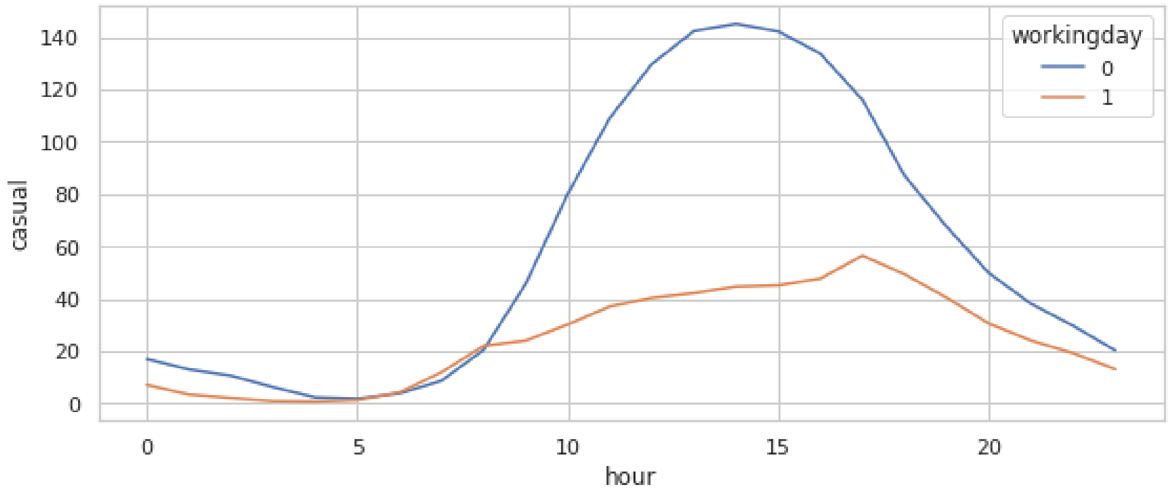
```

```

In [23]:

```
plt.figure(figsize = (10, 4))
sns.lineplot(x='hour',y='casual',hue='workingday',data=df,estimator=np.mean,ci=None
```

Out[23]:

```
<AxesSubplot:xlabel='hour', ylabel='casual'>
```



Observations:

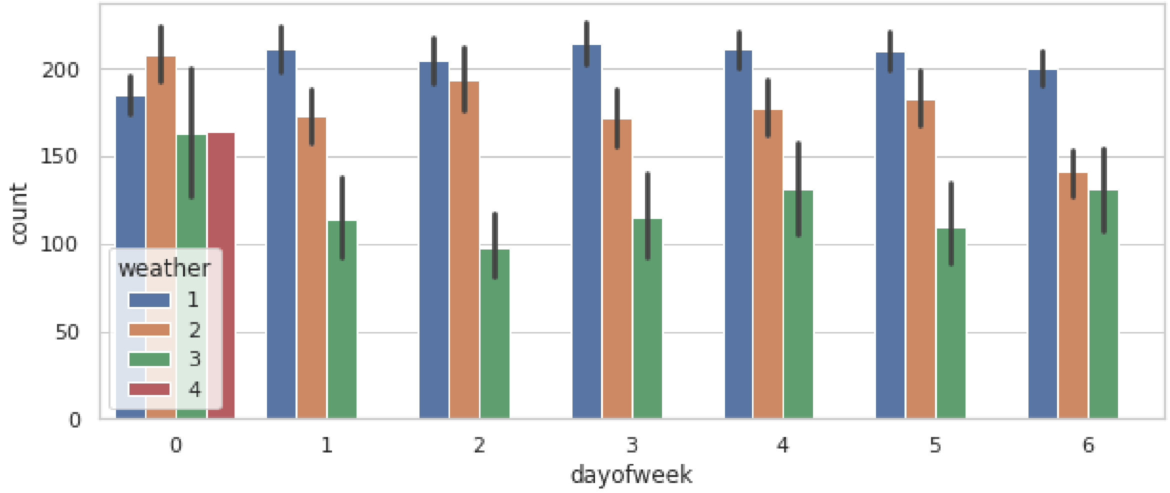
```
Most of the people who book on weekends are casual riders, they might not b
e our repeated customers, so people who use on weekdays are more loyal cust
omers and repeated customers.
```

In [241]:

```
plt.figure(figsize = (10, 4))
sns.barplot(x='dayofweek',y='count',hue='weather',data=df)
```

Out[241]:

```
<AxesSubplot:xlabel='dayofweek', ylabel='count'>
```

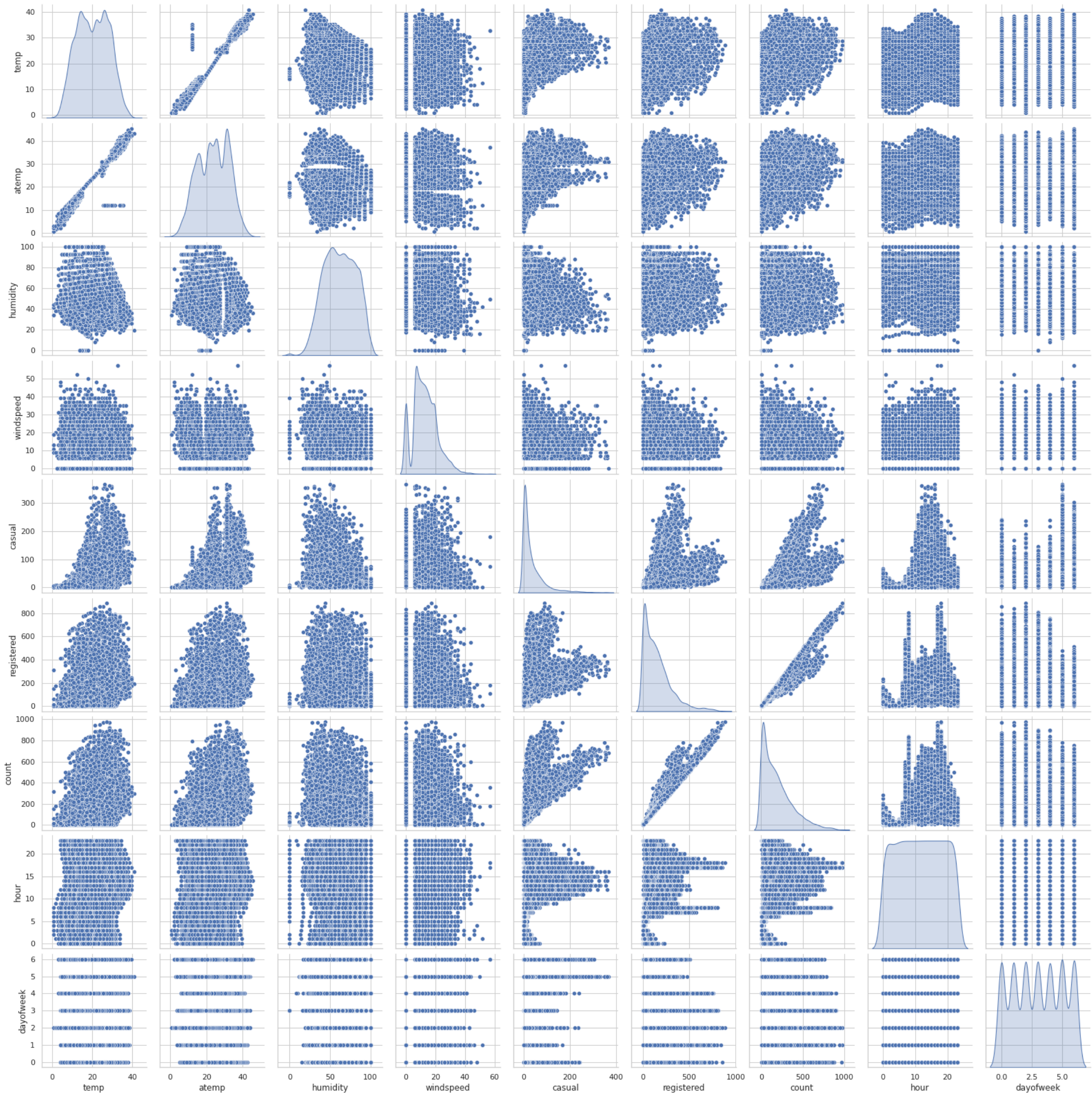


In [246]:

```
sns.pairplot(data=df,diag_kind='kde')
```

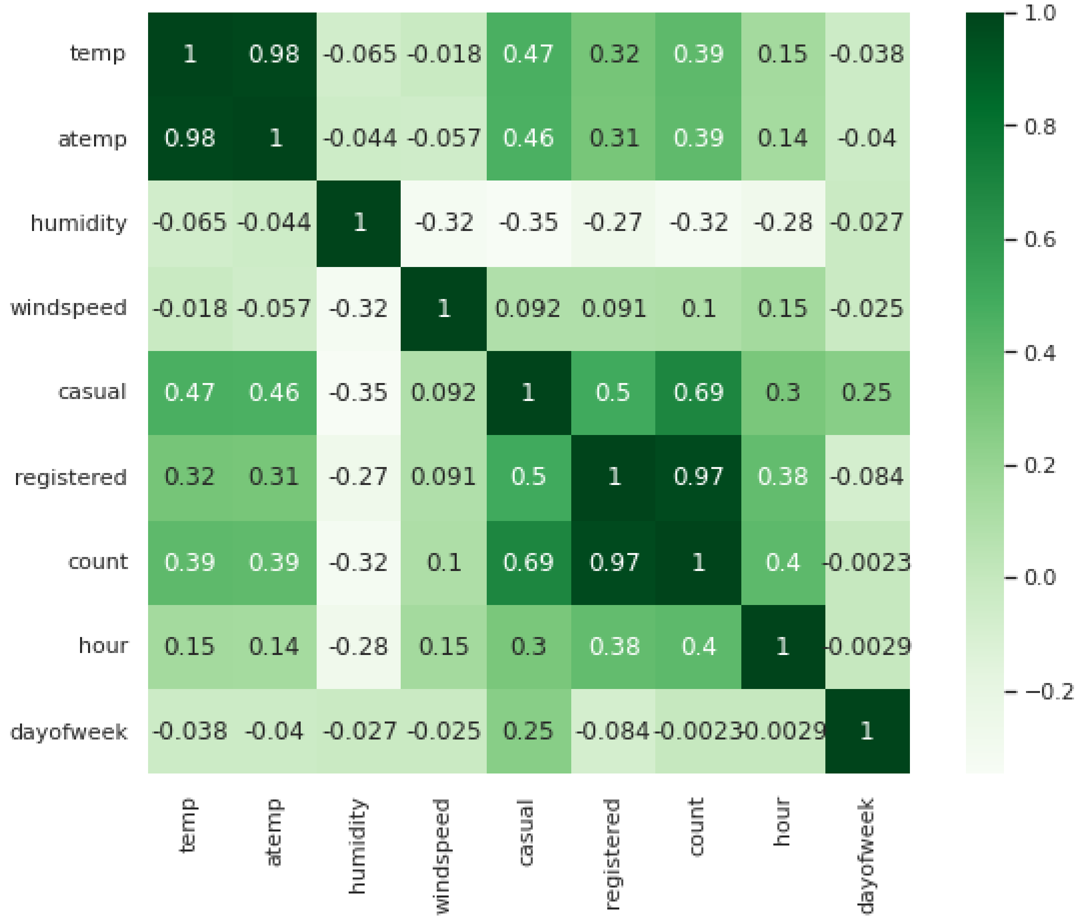
Out[246]:

```
<seaborn.axisgrid.PairGrid at 0x7fa0c5e5dd30>
```



In [244]:

```
plt.figure(figsize = (10, 7))
ax = sns.heatmap(df.corr(),
            annot=True,cmap='Greens',square=True)
```



Observations:

```
1. Temperature is more correlated with casual riders compared to registered
riders.
2. Humidity has negative correlation with windspeed, ride counts, hour
3. Registered users have high correlation with total rides,than casual user
s with total rides
4. total ride bookings have good correlation with hour of booking
5. day of week has correlation with casual riders, so people who travel cas
ually have correlation with the day of the week they travel
```

2. Hypothesis Testing (30 Points):

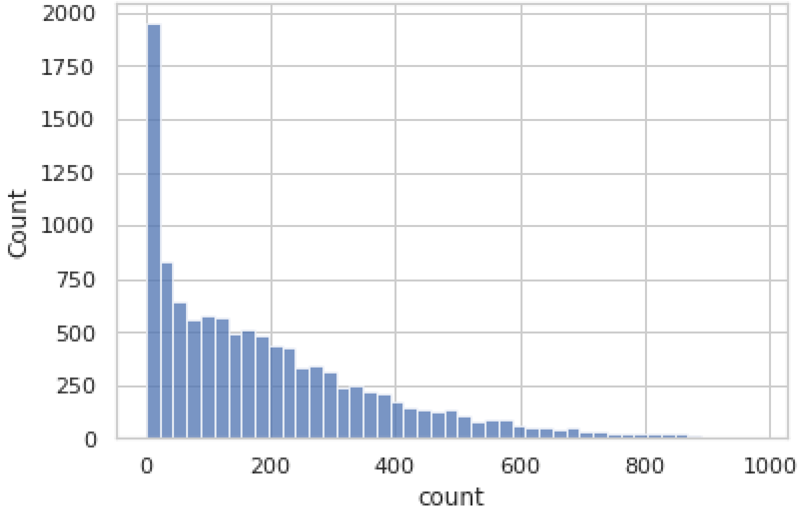
In [ ]:

In [32]:

```
sns.histplot(df['count'])
```

Out[32]:

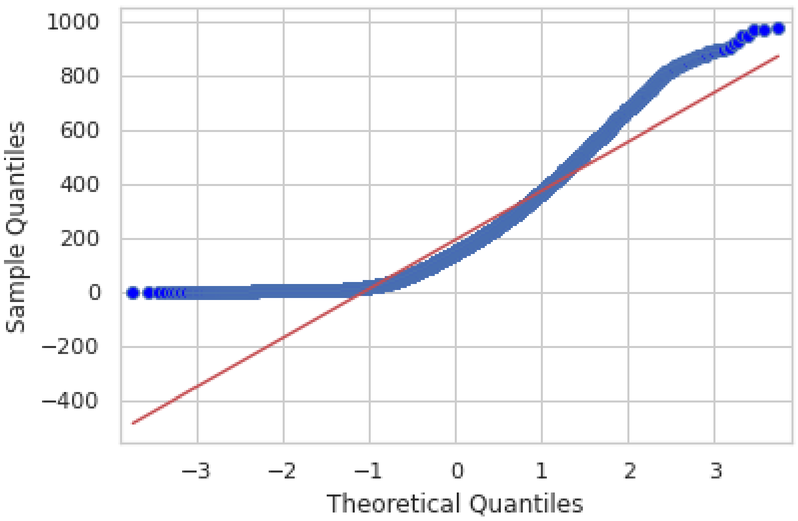
<AxesSubplot:xlabel='count', ylabel='Count'>



In [12]:

```
# QQ plot - visual way of confirming gaussian distribution
qqplot(df['count'], line="s")
plt.show()
```

```
/home/bharath/anaconda3/lib/python3.9/site-packages/statsmodels/graphi
cs/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The
keyword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
```



Observations:

```
1. From the qqplot we can interpret that data in the middle part follows th
e normal distribution, but the tails doesnt.
```

In [41]:

```
df['workingday'].unique()
```

Out[41]:

```
array(['0', '1'], dtype=object)
```

H0: Data is Gaussian
Ha: Data is not Gaussian

test : shapiro, kstest

p-value : 0.05

In [102]:

```
shapiro_test(df['count'].sample(400))
```

```
Mean :  187.91 , Standard deviation :  187.74
8.829537823422984e-19
Reject H0
Data is not Gaussian
```

According to the Shapiro test the probability to be gaussian is way too less we reject the null hypothesis and hence the ride booking data isnt gaussian

In [104]:

```
kstest_test(df['count'].sample(1000))
```

```
Mean :  192.35 , Standard deviation :  185.28
2.4740725155571976e-20
Reject H0
Data is not Gaussian
```

According to the KS test the probability to be gaussian is way too less we reject the null hypothesis and hence the ride booking data isnt gaussian

In [ ]:

```

```

H0: Data has same variance within groups of workingday and holiday
Ha: Data has different variance within groups of workingday and holiday

test : levene

p-value : 0.05

In [105]:

```
df_wkday = df.loc[df['workingday']=='1']
df_holiday = df.loc[df['workingday']=='0']
```

In [106]:

```
levene_test(df_wkday['count'],df_wkday['count'])
```

```
Series1 metrics :
Mean :  193.01 , Standard deviation :  184.51
Series2 metrics :
Mean :  193.01 , Standard deviation :  184.51
1.0
Fail to reject H0
Variances are the same
```

According to the Levene test the probability having the same variance is way too high, so we fail to reject the null hypothesis and hence the ride booking data for working day and non-working day has same same spread in the distribution

In [ ]:

```

```

H0: Data has same variance within groups of workingday and holiday
Ha: Data has different variance within groups of workingday and holiday

test : levene

p-value : 0.05

In [108]:

```
df['season'].unique()
```

Out[108]:

```
array(['1', '2', '3', '4'], dtype=object)
```

In [109]:

```
df_weather1 = df.loc[df['weather']=='1','count']
df_weather2 = df.loc[df['weather']=='2','count']
df_weather3 = df.loc[df['weather']=='3','count']
df_weather4 = df.loc[df['weather']=='4','count']
```

In [110]:

```
print("Variance test for weather data : 1 and 2")
levene_test(df_weather1,df_weather2)
print("Variance test for weather data : 1 and 3")
levene_test(df_weather1,df_weather3)
print("Variance test for weather data : 1 and 4")
levene_test(df_weather1,df_weather4)
print("Variance test for weather data : 2 and 3")
levene_test(df_weather2,df_weather3)
print("Variance test for weather data : 2 and 4")
levene_test(df_weather2,df_weather4)
print("Variance test for weather data : 3 and 4")
levene_test(df_weather3,df_weather4)
```

```
Variance test for weather data : 1 and 2
Series1 metrics :
Mean :  205.24 , Standard deviation :  187.96
Series2 metrics :
Mean :  178.96 , Standard deviation :  168.37
3.49541909725777e-10
Reject H0
Variances are different

Variance test for weather data : 1 and 3
Series1 metrics :
Mean :  205.24 , Standard deviation :  187.96
Series2 metrics :
Mean :  118.85 , Standard deviation :  138.58
3.766646059363359e-32
Reject H0
Variances are different

Variance test for weather data : 1 and 4
Series1 metrics :
Mean :  205.24 , Standard deviation :  187.96
Series2 metrics :
Mean :  164.0 , Standard deviation :  nan
0.2552894702604411
Fail to reject H0
Variances are the same

Variance test for weather data : 2 and 3
Series1 metrics :
Mean :  178.96 , Standard deviation :  168.37
Series2 metrics :
Mean :  118.85 , Standard deviation :  138.58
2.031067178520127e-15
Reject H0
Variances are different

Variance test for weather data : 2 and 4
Series1 metrics :
Mean :  178.96 , Standard deviation :  168.37
Series2 metrics :
Mean :  164.0 , Standard deviation :  nan
0.2823235008702964
Fail to reject H0
Variances are the same
```

```
Variance test for weather data : 3 and 4
Series1 metrics :
Mean :  118.85 , Standard deviation :  138.58
Series2 metrics :
Mean :  164.0 , Standard deviation :  nan
0.42868270048569357
Fail to reject H0
Variances are the same
```

According to the Levene test from the above we see that variances of 1, 4 and 3,4 and 2,4 fail to reject the null hypothesis and the variances of 1,2 and 1,3 and 2,3 rejects the null hypothesis

In [ ]:

```

```

In [111]:

```
df_season1 = df.loc[df['season']=='1','count']
df_season2 = df.loc[df['season']=='2','count']
df_season3 = df.loc[df['season']=='3','count']
df_season4 = df.loc[df['season']=='4','count']
```

In [112]:

```
print("Variance test for season data : 1 and 2")
levene_test(df_season1,df_season2)
print("Variance test for season data : 1 and 3")
levene_test(df_season1,df_season3)
print("Variance test for season data : 1 and 4")
levene_test(df_season1,df_season4)
print("Variance test for season data : 2 and 3")
levene_test(df_season2,df_season3)
print("Variance test for season data : 2 and 4")
levene_test(df_season2,df_season4)
print("Variance test for season data : 3 and 4")
levene_test(df_season3,df_season4)
```

```
Variance test for season data : 1 and 2
Series1 metrics :
Mean :  116.34 , Standard deviation :  125.27
Series2 metrics :
Mean :  215.25 , Standard deviation :  192.01
9.72630153046414e-93
Reject H0
Variances are different

Variance test for season data : 1 and 3
Series1 metrics :
Mean :  116.34 , Standard deviation :  125.27
Series2 metrics :
Mean :  234.42 , Standard deviation :  197.15
4.930332866006357e-102
Reject H0
Variances are different

Variance test for season data : 1 and 4
Series1 metrics :
Mean :  116.34 , Standard deviation :  125.27
Series2 metrics :
Mean :  198.99 , Standard deviation :  177.62
2.542187031248091e-61
Reject H0
Variances are different

Variance test for season data : 2 and 3
Series1 metrics :
Mean :  215.25 , Standard deviation :  192.01
Series2 metrics :
Mean :  234.42 , Standard deviation :  197.15
0.2505258503598953
Fail to reject H0
Variances are the same

Variance test for season data : 2 and 4
Series1 metrics :
Mean :  215.25 , Standard deviation :  192.01
Series2 metrics :
Mean :  198.99 , Standard deviation :  177.62
1.825507161361946e-05
Reject H0
Variances are different
```

```
Variance test for season data : 3 and 4
Series1 metrics :
Mean :  234.42 , Standard deviation :  197.15
Series2 metrics :
Mean :  198.99 , Standard deviation :  177.62
5.704158850509495e-08
Reject H0
Variances are different
```

According to the Levene test from the above we see that variances of 2,3 fail to reject the null hypothesis and the variances of rest of the hypothesis rejects the null hypothesis

2- Sample T-Test to check if Working Day has an effect on the number of electric cycles rented (10 points)

t-test for 2 independent samples comparision

H0: mean bike rentals on working days is equal to mean bike rentals of holidays
Ha: mean bike rentals on working days is not-equal to mean bike rentals of holidays

hypothesis test : T-test for independent samples
p-value : 0.05 (two-tailed)

In [121]:

```
df['workingday'].value_counts()
```

Out[121]:

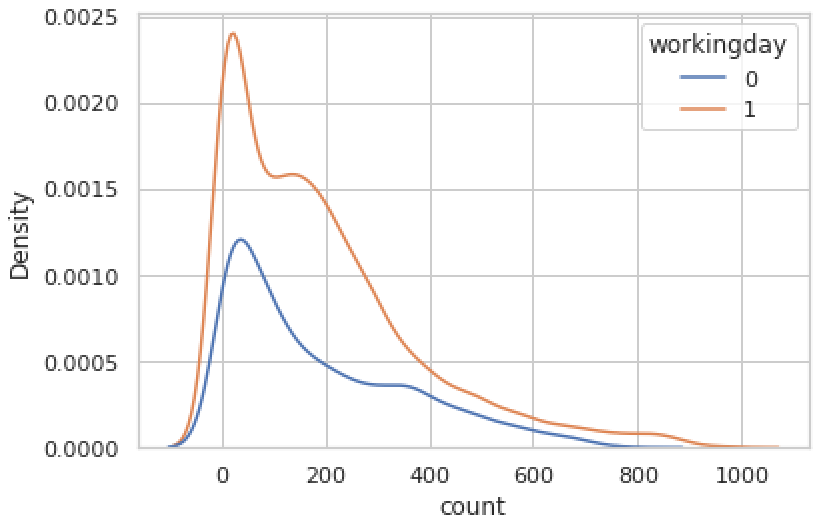
```
1    7412
0    3474
Name: workingday, dtype: int64
```

In [148]:

```
sns.kdeplot(x='count',data=df,hue='workingday')
```

Out[148]:

```
<AxesSubplot:xlabel='count', ylabel='Density'>
```



In [113]:

```
wkday = df.loc[df['workingday']=='1','count']
holiday = df.loc[df['workingday']=='0','count']
```

In [150]:

```
ttest_ind_test(wkday.sample(500),holiday.sample(500),alternative='two-sided')
```

```
Series1 metrics :
Mean :  201.0 , Standard deviation :  190.35
Series2 metrics :
Mean :  193.14 , Standard deviation :  175.17
p-value :  0.4974719510201552
Fail to reject H0
```

The t-test for the 2 samples of the working and non-working day fail to reject the null hypothesis, from the above graph also we can interpret that both the distributions of working and non-working days falls in the same range, hence there is no any significant difference in ride bookings, weather its a working day or non-working day.

In [ ]:

```

```

ANNOVA to check if No. of cycles rented is similar or different in different 1. weather 2. season (10 points)

ANOVA 4 samples comparision for Weather with count of bike rentals

H0: mean bike rentals for different weather are same
Ha: mean bike rentals for different weather are not same

hypothesis test : Anova
p-value : 0.05

In [163]:

```
df['weather'].value_counts()
```

Out[163]:

```
1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64
```

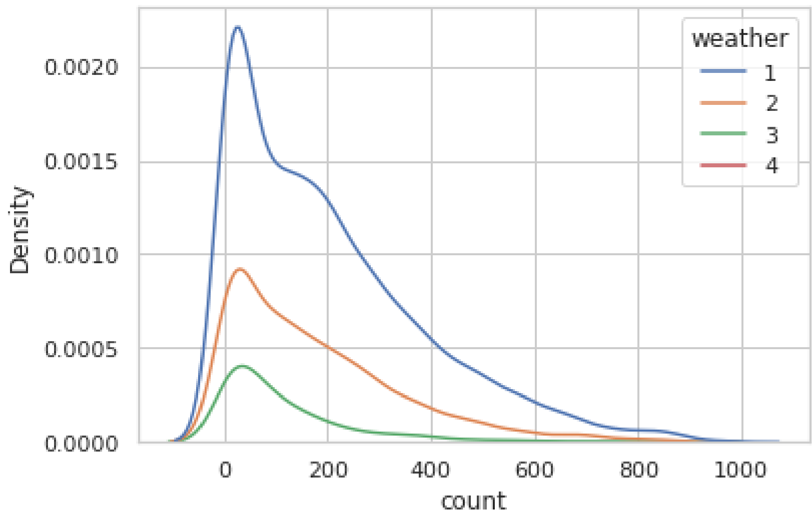
In [172]:

```
sns.kdeplot(x='count',data=df,hue='weather')
```

```
/home/bharath/anaconda3/lib/python3.9/site-packages/seaborn/distributi
ons.py:316: UserWarning: Dataset has 0 variance; skipping density esti
mate. Pass `warn_singular=False` to disable this warning.
  warnings.warn(msg, UserWarning)
```

Out[172]:

```
<AxesSubplot:xlabel='count', ylabel='Density'>
```



In [159]:

```
weather1 = df.loc[df['weather']=='1','count']
weather2 = df.loc[df['weather']=='2','count']
weather3 = df.loc[df['weather']=='3','count']
weather4 = df.loc[df['weather']=='4','count']
```

In [168]:

```
anova_test(weather1,weather2,weather3)
```

```
Series1 metrics :
Mean :  205.24 , Standard deviation :  187.96
Series2 metrics :
Mean :  178.96 , Standard deviation :  168.37
Series3 metrics :
Mean :  118.85 , Standard deviation :  138.58
p-value :  4.976448509904196e-43
Reject H0
```

Annova test rejects the null hypothesis for the different weather samples, so we can say that weather have significant impact on the bike ride bookings

In [ ]:

```

```

ANOVA 4 samples comparision for Season with count of bike rentals

H0: mean bike rentals for different seasons are same
Ha: mean bike rentals for different seasons are not same

hypothesis test : Anova
p-value : 0.05

In [169]:

```
df['season'].value_counts()
```

Out[169]:

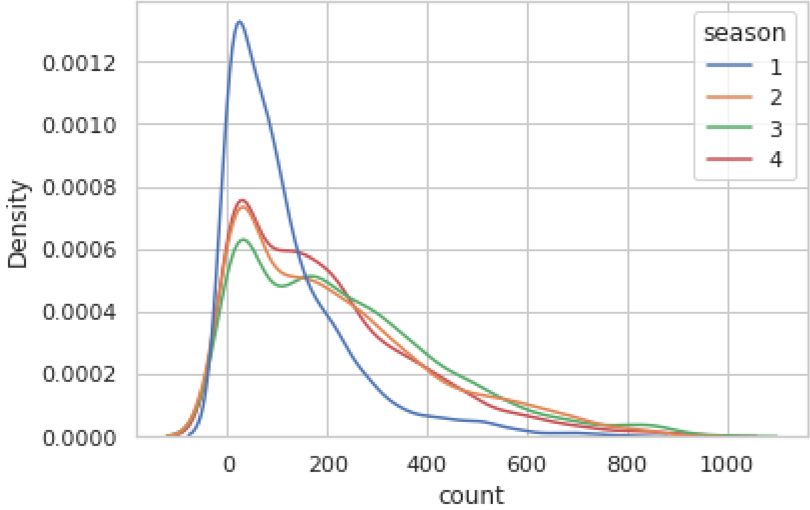
```
4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64
```

In [173]:

```
sns.kdeplot(x='count',data=df,hue='season')
```

Out[173]:

```
<AxesSubplot:xlabel='count', ylabel='Density'>
```



In [161]:

```
season1 = df.loc[df['season']=='1','count']
season2 = df.loc[df['season']=='2','count']
season3 = df.loc[df['season']=='3','count']
season4 = df.loc[df['season']=='4','count']
```

In [170]:

```
anova_test(season1,season2,season3,season4)
```

```
Series1 metrics :
Mean :  116.34 , Standard deviation :  125.27
Series2 metrics :
Mean :  215.25 , Standard deviation :  192.01
Series3 metrics :
Mean :  234.42 , Standard deviation :  197.15
Series4 metrics :
Mean :  198.99 , Standard deviation :  177.62
p-value :  6.164843386499654e-149
Reject H0
```

Annova test rejects the null hypothesis for the different season samples, so we can say that season have significant impact on the bike ride bookings

In [ ]:

```

```

In [ ]:

```

```

Till now we have done hypothesis testing for the data that is at the granular level of hour, now lets convert the data to daily granular level and do the analysis, we are doing this because, day level granularity might provide better analysis when comparing with seasons,weather, working day

In [174]:

```
df['date'] = df['datetime'].dt.date
```

In [175]:

```
df_season = df[['date','season']].drop_duplicates()
df_workingday = df[['date','workingday']].drop_duplicates()
df_weather = df[['date','weather']].drop_duplicates()
```

In [176]:

```
df_ = df.groupby(['date'])['count'].sum().reset_index()
```

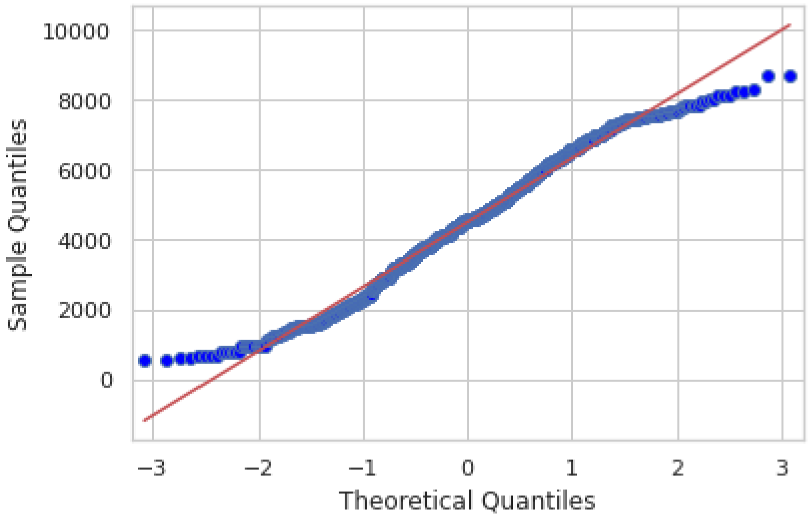
In [177]:

```
df_ = df_.merge(df_season,on='date')
df_ = df_.merge(df_workingday,on='date')
df_ = df_.merge(df_weather,on='date')
```

In [251]:

```
# QQ plot - visual way of confirming gaussian distribution
qqplot(df_['count'], line="s")
plt.show()
```

```
/home/bharath/anaconda3/lib/python3.9/site-packages/statsmodels/graphi
cs/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The
keyword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
```



We can observe from the above graph that this graph is more normally distributed compared to the hourly granular data

In [ ]:

H0: Data is Gaussian
Ha: Data is not Gaussian

test : shapiro, kstest

p-value : 0.05

In [253]:

```
shapiro_test(df_['count'].sample(200))
print()
kstest_test(df_['count'].sample(200))
```

```
Mean :  4385.41 , Standard deviation :  1836.51
p-value :  0.000882214168086648
Reject H0
Data is not Gaussian

Mean :  4559.15 , Standard deviation :  1802.44
p-value :  0.8635154491455485
Fail to reject H0
Data is Gaussian
```

Shapiro test says that data isnt gaussian, but KS test says that data is gaussian with high probability

In [ ]:

```

```

t-test for 2 independent samples comparision

H0: mean bike rentals on working days is equal to mean bike rentals of holidays
Ha: mean bike rentals on working days is not-equal to mean bike rentals of holidays

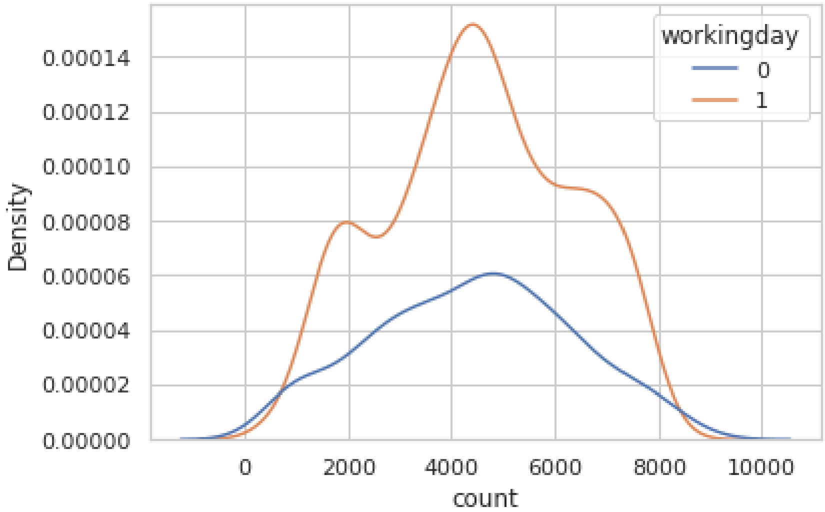
hypothesis test : T-test for independent samples
p-value : 0.05 (two-tailed)

In [178]:

```
sns.kdeplot(x='count',data=df_,hue='workingday')
```

Out[178]:

<AxesSubplot:xlabel='count', ylabel='Density'>



Type *Markdown* and LaTeX: α^2

In [ ]:

```

```

In [179]:

```
wkday = df_.loc[df['workingday']=='1','count']
holiday = df_.loc[df['workingday']=='0','count']
```

In [254]:

```
ttest_ind_test(wkday.sample(200),holiday.sample(200),alternative='greater')
```

```
Series1 metrics :
Mean :  4643.28 , Standard deviation :  1805.65
Series2 metrics :
Mean :  4142.3 , Standard deviation :  1930.62
p-value :  0.00383100481107288
Reject H0
```

The t-test for the 2 samples of the working and non-working day reject the null hypothesis, hence there is significant difference in ride bookings between working day and holiday, so when tested with the hour granularity we rejected the null hypothesis, but with the more meaningfull daily data, we reject the null hypothesis

In [ ]:

```

```

ANOVA 4 samples comparision for Season and Weather categories with count of bike rentals

H0: mean bike rentals for different weather are same
Ha: mean bike rentals for different weather are not same

hypothesis test : Anova
p-value : 0.05

In [183]:

```
df_['weather'].value_counts()
```

Out[183]:

```
1    434
2    346
3    187
4      1
Name: weather, dtype: int64
```

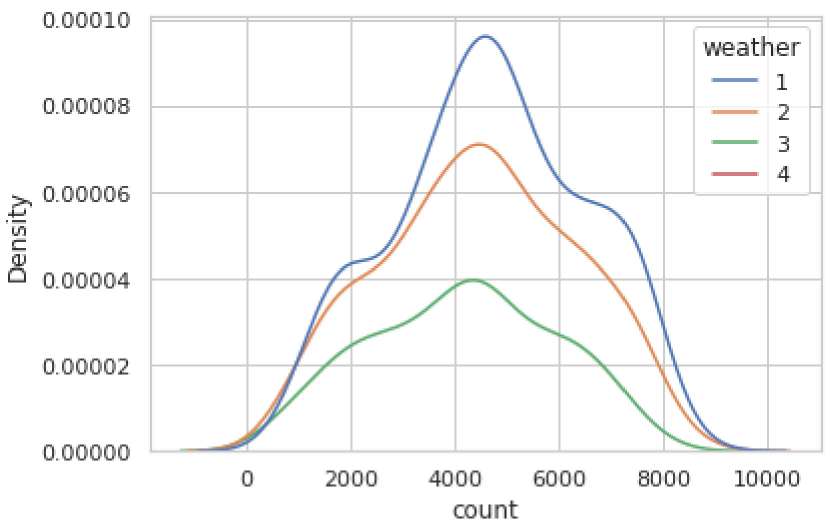
In [184]:

```
sns.kdeplot(x='count',data=df_,hue='weather')
```

```
/home/bharath/anaconda3/lib/python3.9/site-packages/seaborn/distributi
ons.py:316: UserWarning: Dataset has 0 variance; skipping density esti
mate. Pass `warn_singular=False` to disable this warning.
  warnings.warn(msg, UserWarning)
```

Out[184]:

```
<AxesSubplot:xlabel='count', ylabel='Density'>
```



In [194]:

```
weather1 = df_.loc[df_['weather']=='1','count']
weather2 = df_.loc[df_['weather']=='2','count']
weather3 = df_.loc[df_['weather']=='3','count']
weather4 = df_.loc[df_['weather']=='4','count']
```

In [195]:

```
anova_test(weather1,weather2,weather3)
```

```
Series1 metrics :
Mean :  4673.6 , Standard deviation :  1834.22
Series2 metrics :
Mean :  4457.73 , Standard deviation :  1853.27
Series3 metrics :
Mean :  4158.45 , Standard deviation :  1771.03
p-value :  0.005107881061067 82
Reject H0
```

In [ ]:

```

```

H0: mean bike rentals for different seasons are same
Ha: mean bike rentals for different seasons are not same

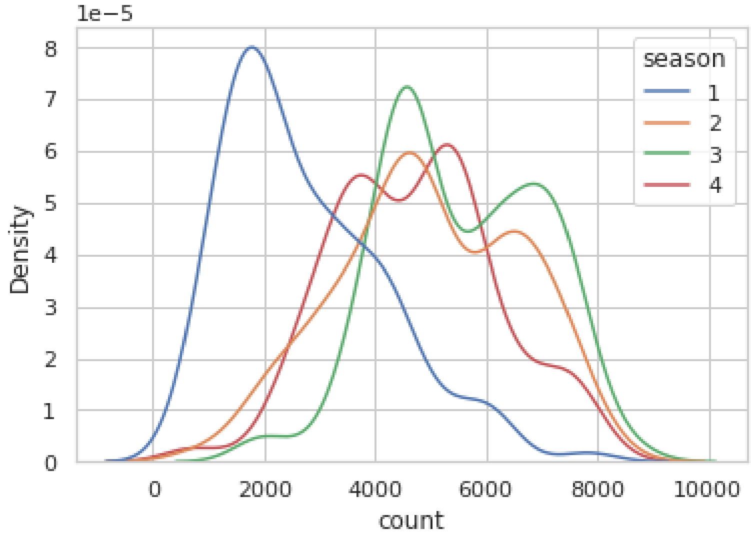
hypothesis test : Anova
p-value : 0.05

In [198]:

```
sns.kdeplot(x='count',data=df_,hue='season')
```

Out[198]:

```
<AxesSubplot:xlabel='count', ylabel='Density'>
```



In [196]:

```
season1 = df_.loc[df_['season']=='1','count']
season2 = df_.loc[df_['season']=='2','count']
season3 = df_.loc[df_['season']=='3','count']
season4 = df_.loc[df_['season']=='4','count']
```

In [197]:

```
anova_test(season1,season2,season3,season4)
```

```
Series1 metrics :
Mean :  2754.77 , Standard deviation :  1450.68
Series2 metrics :
Mean :  4963.92 , Standard deviation :  1640.56
Series3 metrics :
Mean :  5553.77 , Standard deviation :  1426.92
Series4 metrics :
Mean :  4718.94 , Standard deviation :  1485.44
p-value :  2.5221443728393988e-84
Reject H0
```

Both season and weather have significant impact on ride bookings

In [ ]:

In [ ]:

Chi-square test to check if Weather is dependent on the season (10 points)

In [210]:

```
s_h  = pd.crosstab(df['season'],df.loc[df['weather']!='4','weather'])
```

In [211]:

```
s_h
```

Out[211]:

weather	1	2	3
season			
1	1759	715	211
2	1801	708	224
3	1930	604	199
4	1702	807	225

In [ ]:

H0: Gender and product are not related
Ha: Gender impacts which product

hypothesis test : Chi-square test

p-value : 0.05

In [213]:

```
chi_stat, p_value, dof, expected = chi2_contingency(s_h)

print(p_value)
print(dof)
if p_value < 0.05:
    print("Reject H0")
else:
    print("Fail to reject H0")
```

```
2.8260014509929343e-08
6
Reject H0
```

According to the chi-square test we can conclude that weather is dependent on season

In [ ]: