Company Overview

Yulu is India’s leading micro-mobility service provider, which offers unique vehicles for the daily commute. Starting off as a mission to eliminate traffic congestion in India, Yulu provides the safest commute solution through a user-friendly mobile app to enable shared, solo and sustainable commuting. Yulu zones are located at all the appropriate locations (including metro stations, bus stands, office spaces, residential areas, corporate offices, etc) to make those first and last miles smooth, affordable, and convenient!

Problem Statement

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

Solution Approach

- Data Exploration
  - UVA, BVA, MVA
- Hypothesis Test
  - Z Test / T Test
  - Chi square Test
  - Anova

Detailed Breakdown

- Establishing a relation between the dependent and independent variable (Dependent “Count” & Independent: Workingday, Weather, Season etc)
- Select an appropriate test to check whether:
  - Working Day has effect on number of electric cycles rented?
  - No. of cycles rented similar or different in different seasons?
  - No. of cycles rented similar or different in different weather?
  - Weather is dependent on season?
  - Holiday has effect on number of electric cycles rented?
  - No. of cycles rented similar or different in different temperature, windspeed, humidity and actual temperature levels?
- Hypothesis Test Framework
  - Set up Null Hypothesis (H0)
  - State the alternate hypothesis (H1)

- Check assumptions of the test (Normality, Equal Variance).
- Check using Histogram, Q-Q plot, statistical methods like levene's test, Shapiro-wilk test
- Set a significance level (alpha)
- Calculate test Statistics and P value
- Decision to accept or reject null hypothesis.

- Inference from the analysis

In [197…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from scipy.stats import norm, ttest_rel, ttest_ind, kstest, chi2, chi2_contingen
from itertools import combinations
```

In [10]:

```
# data = pd.read_csv(r'F:\Muthu_2023\Personal\NextStep\DSCourse\Scaler\Business-
data = pd.read_csv(r'E:\Nextstep\Scaler\Business-Case-Study\Yulu\Dataset\bike_sh
```

EDA

In [4]:

```
data.head()
```

Out[4]:

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

Inference:

- Total: 12 Columns
- Target Variables: 'casual', 'registered', 'count'

In [5]:

```
data.info()
```

```
<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
```

Inference:

- No null values in all the columns
- datetime column is not in datetime64 format, hence conversion required
- All are numerical columns, some may be binary (holiday, working day, weather, etc.,)

In [11]:
```python
for i in ['season', 'holiday', 'workingday', 'weather']:
    print(i, ': ', data[i].unique())
```

```
season :  [1 2 3 4]
holiday :  [0 1]
workingday :  [0 1]
weather :  [1 2 3 4]
```

__Inference:__

- Holiday and Working day are binary columns
- Season and Weather are categorical with 4 categories

In [12]:
```python
data.describe()
```

Out[12]:

	season	holiday	workingday	weather	temp	ater
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.6550
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.4746
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.7600
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.6650
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.2400
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.0600
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.4550

In [15]:
```
data['datetime'].min(), data['datetime'].max()
```

Out[15]:
```
('2011-01-01 00:00:00', '2012-12-19 23:00:00')
```

Inference: Dataset contains 2 years of data

Preprocessing

In [12]:
```
data['date'] = pd.to_datetime(data['datetime']).dt.date
data['time'] = pd.to_datetime(data['datetime']).dt.time
data['day'] = pd.to_datetime(data['datetime']).dt.day_name()
data['year'] = pd.to_datetime(data['date']).dt.year
data['hour'] = pd.to_datetime(data['datetime']).dt.hour
```

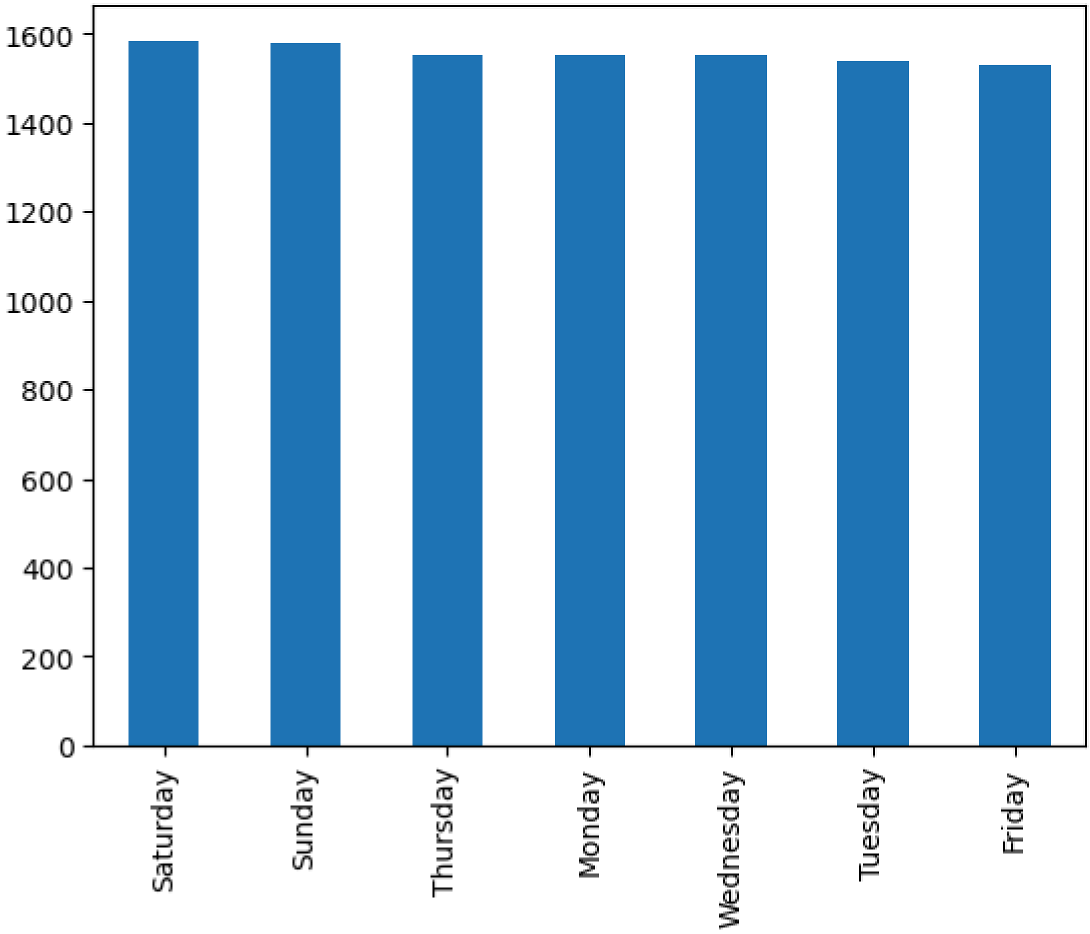
UVA

In [9]:
```
print('Total no. of days: ', data['date'].nunique())
```

```
Total no. of days:  456
```

In [17]:
```
(pd.to_datetime(data['date']).dt.day_name().value_counts()).plot(kind='bar')
```

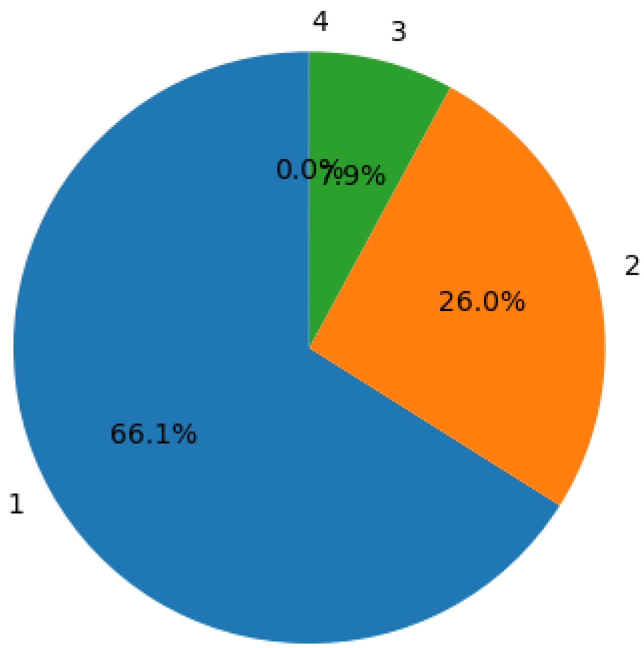
Out[17]:
```
<Axes: >
```



Inference:

- Above plot doesn't give any insight as it is a time series data from '2011-01-01 00:00:00', '2012-12-19 23:00:00' and it is recorded every 1 hour
- The univarite analysis on the given dataset gives the details about the conditions of the environment doesn't provides much insights to increase revenue

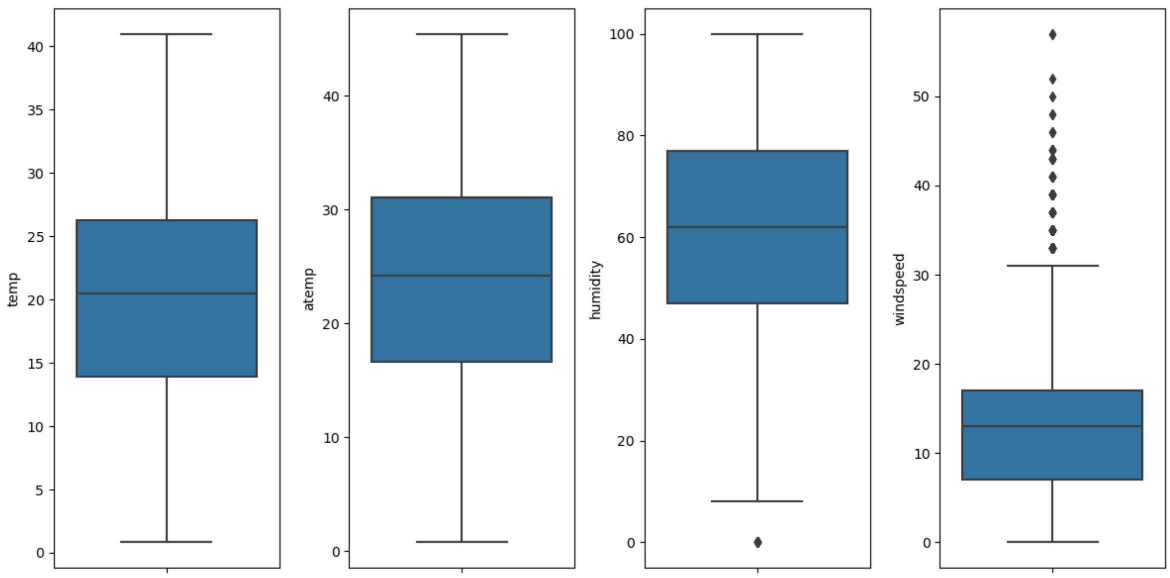
In [70]:
```
plt.pie(data['weather'].value_counts(), labels = list(data['weather'].unique()),
```



Inference:

- Weather 1 and 2 are predominant throughout the years
- Considering the strategies involving weather 1 and 2 will potentially reflect on revenue

In [119…
```
plt.figure(figsize=(12,6))
plt.subplot(1,4,1)
sns.boxplot(data=data, y = 'temp')
plt.subplot(1,4,2)
sns.boxplot(data=data, y = 'atemp')
plt.subplot(1,4,3)
sns.boxplot(data=data, y = 'humidity')
plt.subplot(1,4,4)
sns.boxplot(data=data, y = 'windspeed')
plt.tight_layout()
```



Inference:

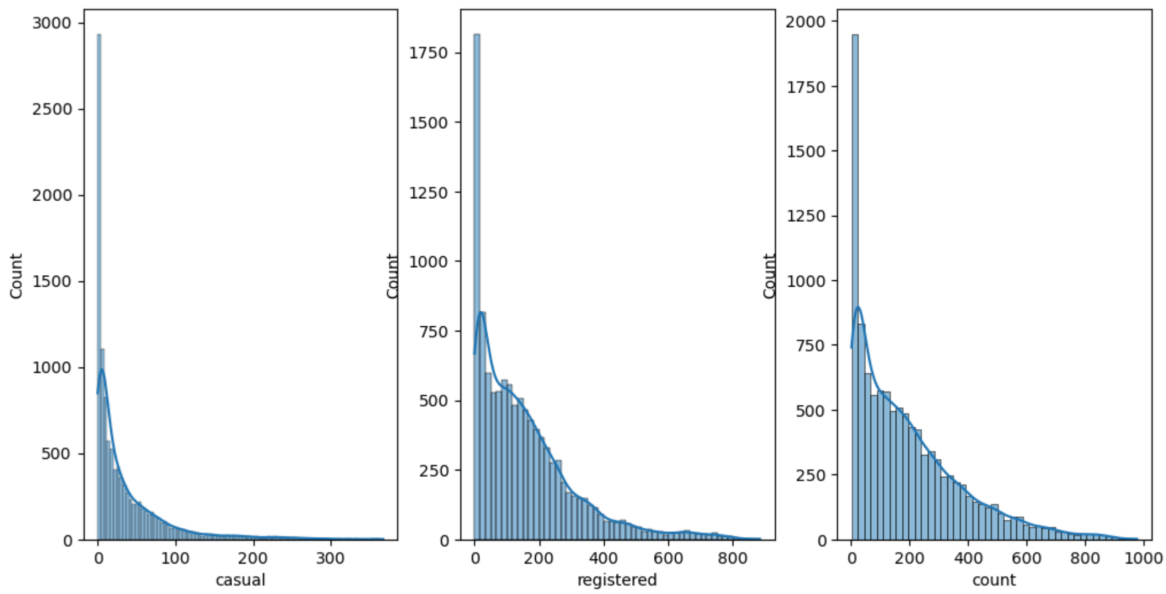
- No IQR outliers in temperature, absolute temperature and humidity columns
- IQR outlier is detected for windspeed indicating the values > 30 rarely occurs
- Range: (Excluding outliers)
    - 0 < Temp < 40
    - 0 < aTemp < 45
    - 10 < Humidity < 100
    - 0 < windspeed < 30

In [172…

```python
plt.figure(figsize=(12,6))
plt.subplot(1,3,1)
sns.histplot(data['casual'], kde=True)
plt.subplot(1,3,2)
sns.histplot(data['registered'], kde=True)
plt.subplot(1,3,3)
sns.histplot(data['count'], kde=True)
```

Out[172…

```
<Axes: xlabel='count', ylabel='Count'>
```



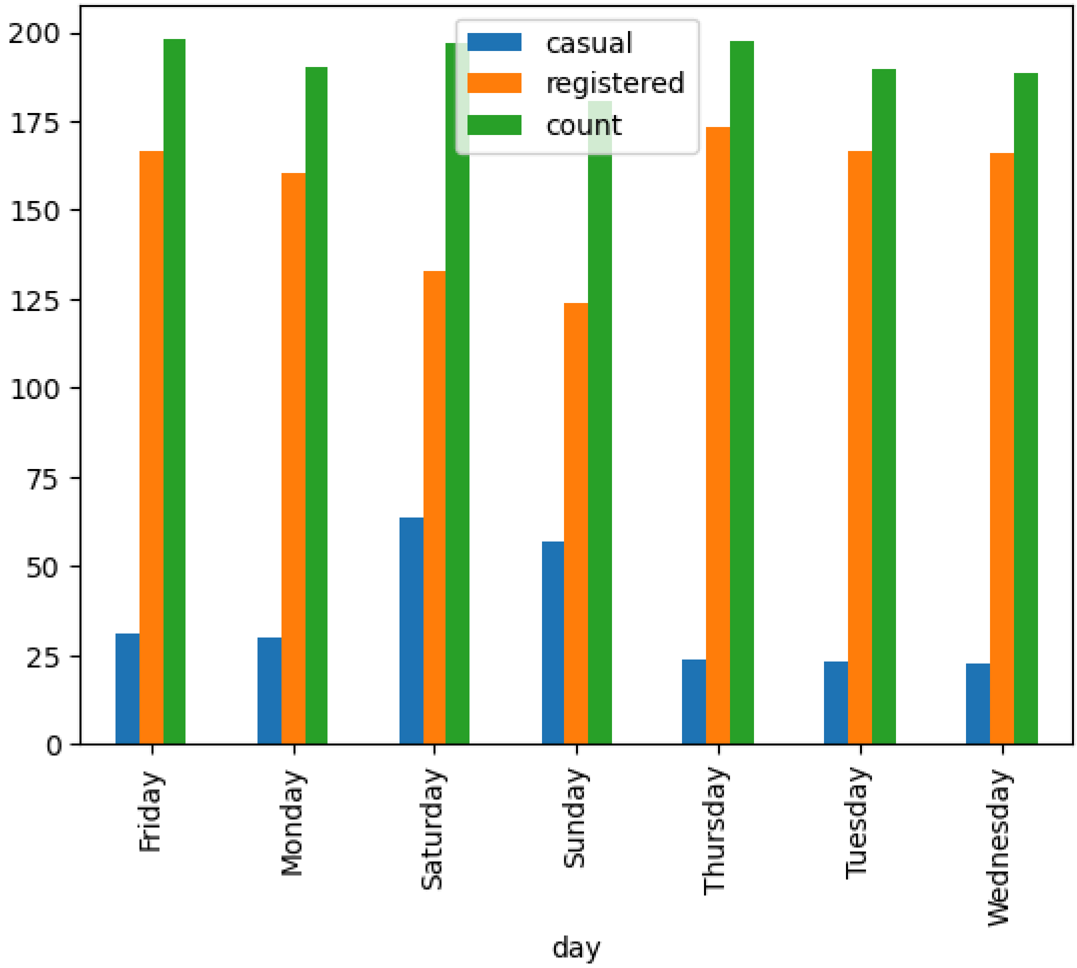
Inference:

- Distribution of usage by casual users, registered users, overall users are all right skewed

BVA

In [29]:
```
#Date Vs Count
data.groupby('day')[['casual', 'registered', 'count']].mean().plot(kind='bar')
sns.barplot(data=data, x = 'day', y='casual', estimator='mean', hue='registered'
```

Out[29]: <Axes: xlabel='day'>

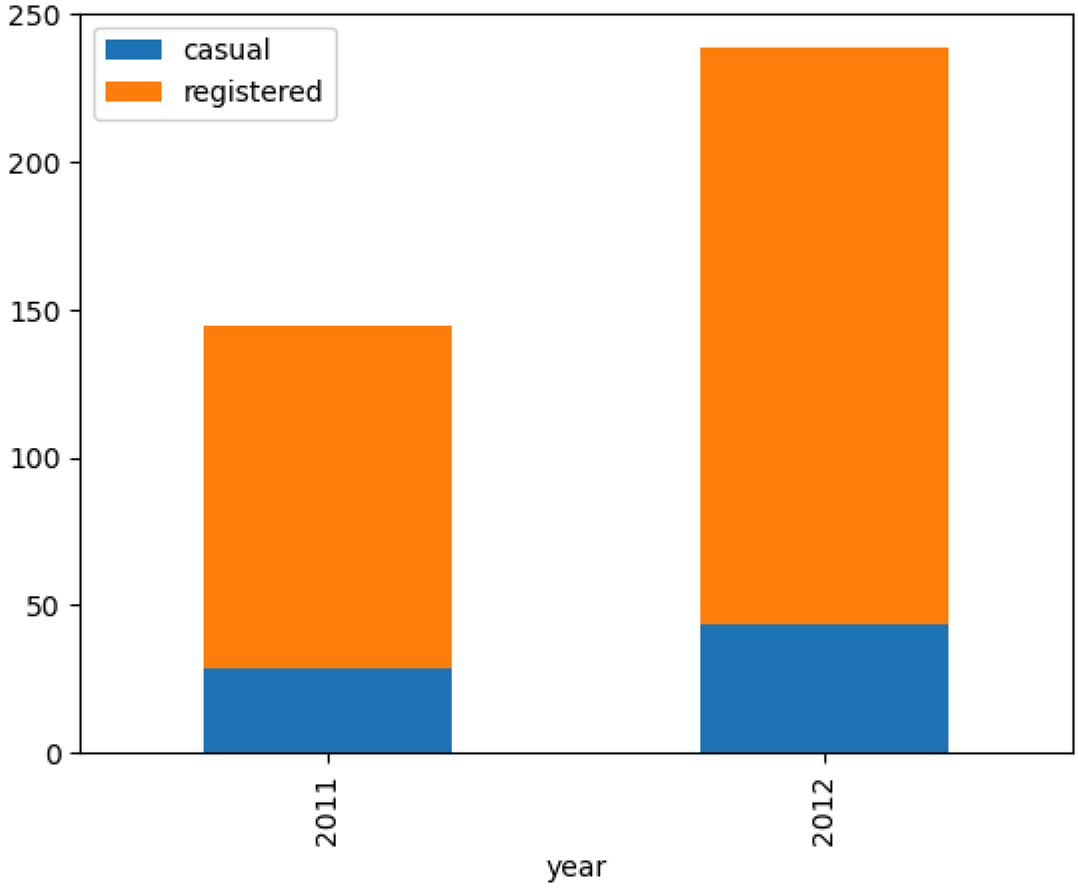


Inference:

- Casual users are comparatively very much higher on weekends and lesser on weedays
- Registered users are less during weekends
- Registered users are predominantly office goers or students
- Due to this behavior, the total count approximately remains constant throughout the days except Sunday
- It confirms the outside activity of the users are less on sunday
- Prediction of Casual users during weekends is very much required to optimize the demand and supply

In [79]:
```
data.groupby('year')[['casual', 'registered']].mean().plot(kind='bar', stacked=T
```

Out[79]: <Axes: xlabel='year'>



In [101…
```
# YoY percentage increase
df_grp = data.groupby('year')[['casual', 'registered', 'count']].sum().pct_chang
print('YoY increase of casual users: ', round(df_grp['casual'].iloc[1]), '%')
print('YoY increase of registered users: ', round(df_grp['registered'].iloc[1]),
print('YoY increase of overall users: ', round(df_grp['count'].iloc[1]), '%')
```

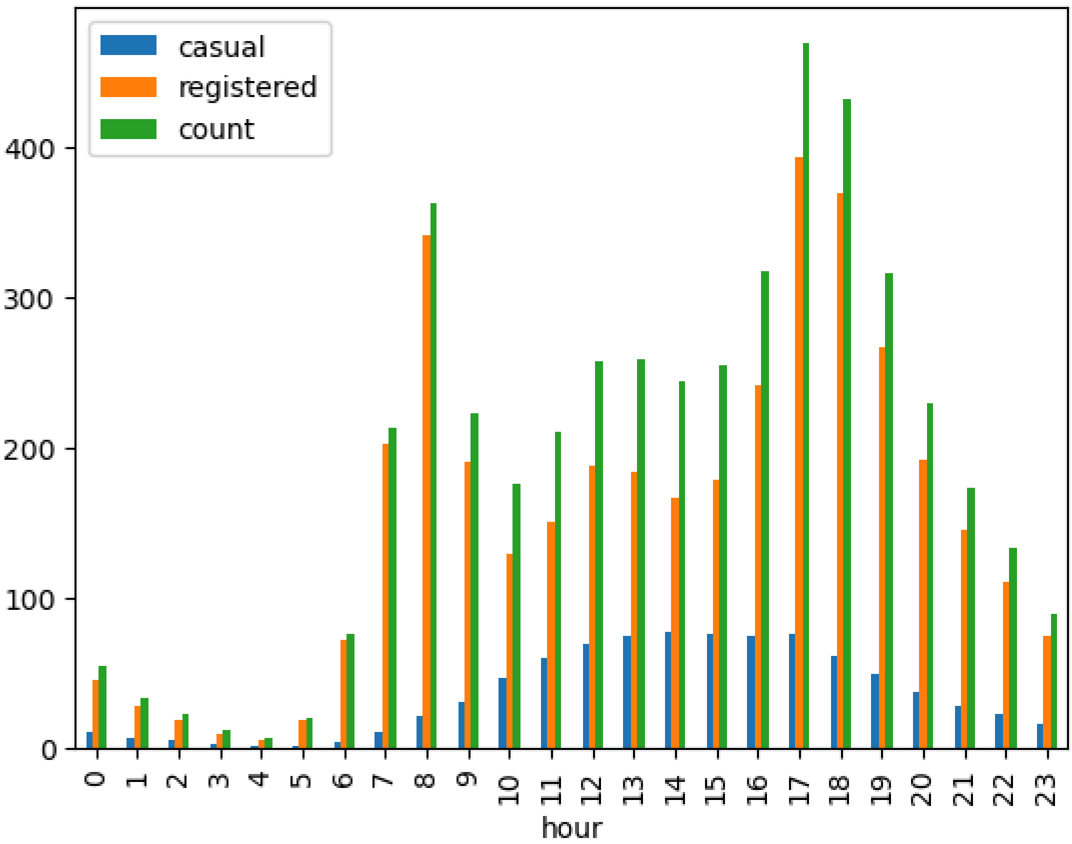
```
YoY increase of casual users:  52 %
YoY increase of registered users:  70 %
YoY increase of overall users:  67 %
```

Inference:

- Average number of casual and registered users are increased in the year 2012 compared to 2011
- The percentage increase of users is measured to be 52, 70 and 67% for casual, registerd and overall users respectively

In [163…
```
plt.figure(figsize=(12,6))
data.groupby('hour')[['casual', 'registered', 'count']].mean().plot(kind = 'bar'
plt.show()
```

```
<Figure size 2000x1600 with 0 Axes>
```

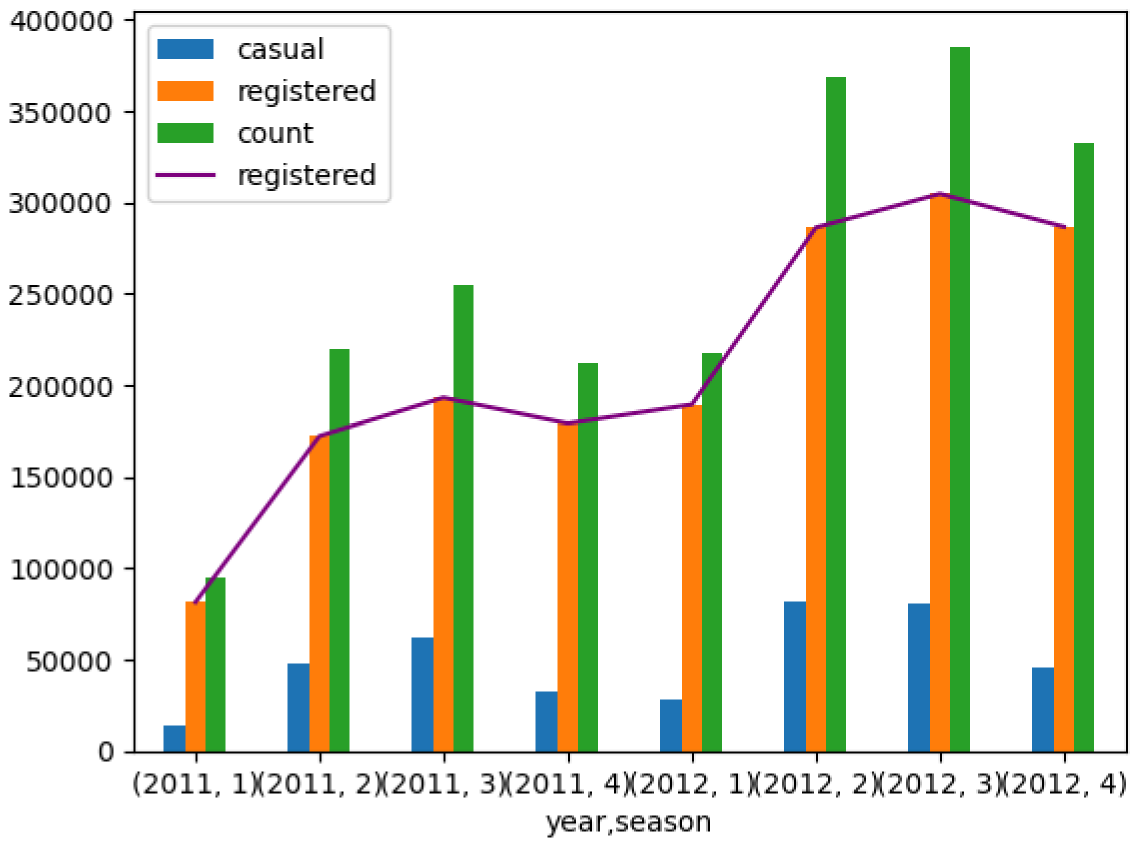


Inference:

- Bell curve pattern is observed for casual users usage with time
- Average number of Casual users peaks between 13 - 17 hrs
- Double bell curve pattern is observed for registered users with time
- Registered users peak at 7-8 hrs at morning and 17-18 hrs at evening

In [62]:
```
# Season Vs Count
ax = data.groupby(['year', 'season'])[['casual', 'registered', 'count']].sum().p
data.groupby(['year', 'season'])[['registered']].sum().plot(kind='line', ax=ax,
```

Out[62]:
```
<Axes: xlabel='year,season'>
```



Inference:

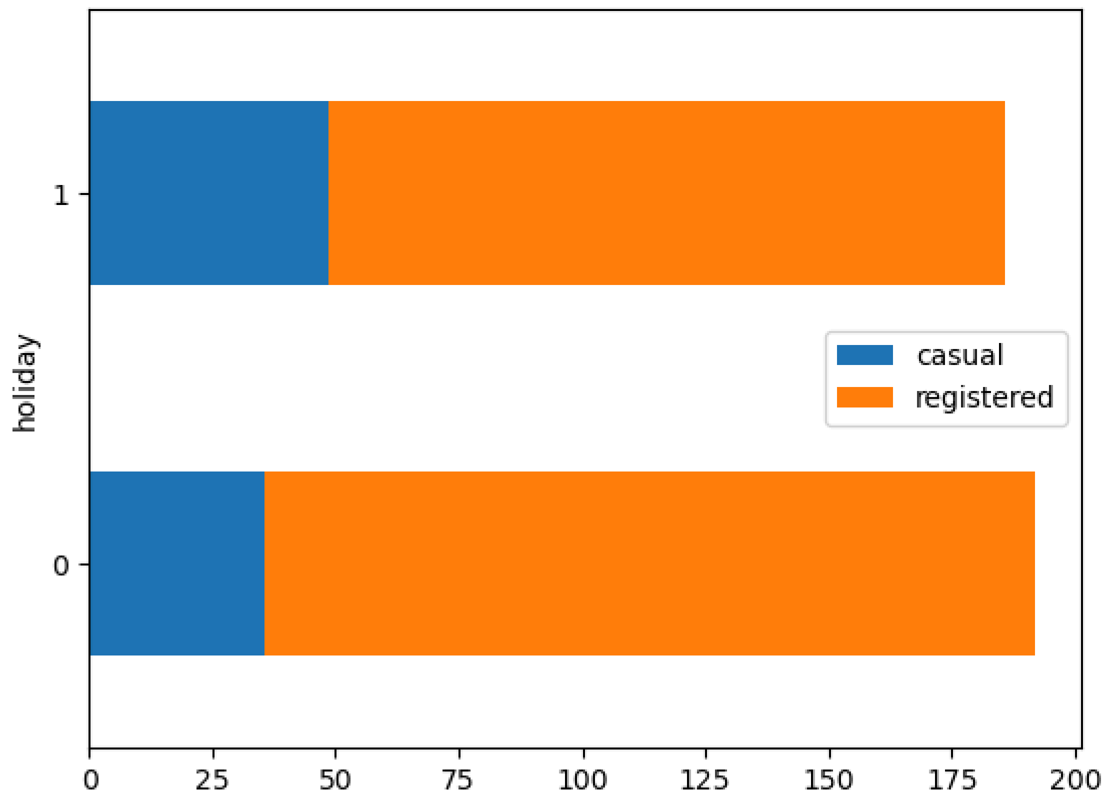
- Analysing the 2 years of data separately, both years show
    - Much higher trend in Fall followed by Summer and Winter
    - Spring shows very much lesser trend
    - YoY increasing trend for Registered users is noticed which is responsible for the YoY increase in the count
    - Concentrating on increasing the registered users would helpful to increase the revenue

In [35]:
```
data.groupby('season')['date'].nunique()
```

Out[35]:
```
season
1    114
2    114
3    114
4    114
Name: date, dtype: int64
```

In [60]:
```
# Holiday vs Count
data.groupby(['holiday'])[['casual', 'registered']].mean().plot(kind='barh', sta
```

Out[60]:
```
<Axes: ylabel='holiday'>
```

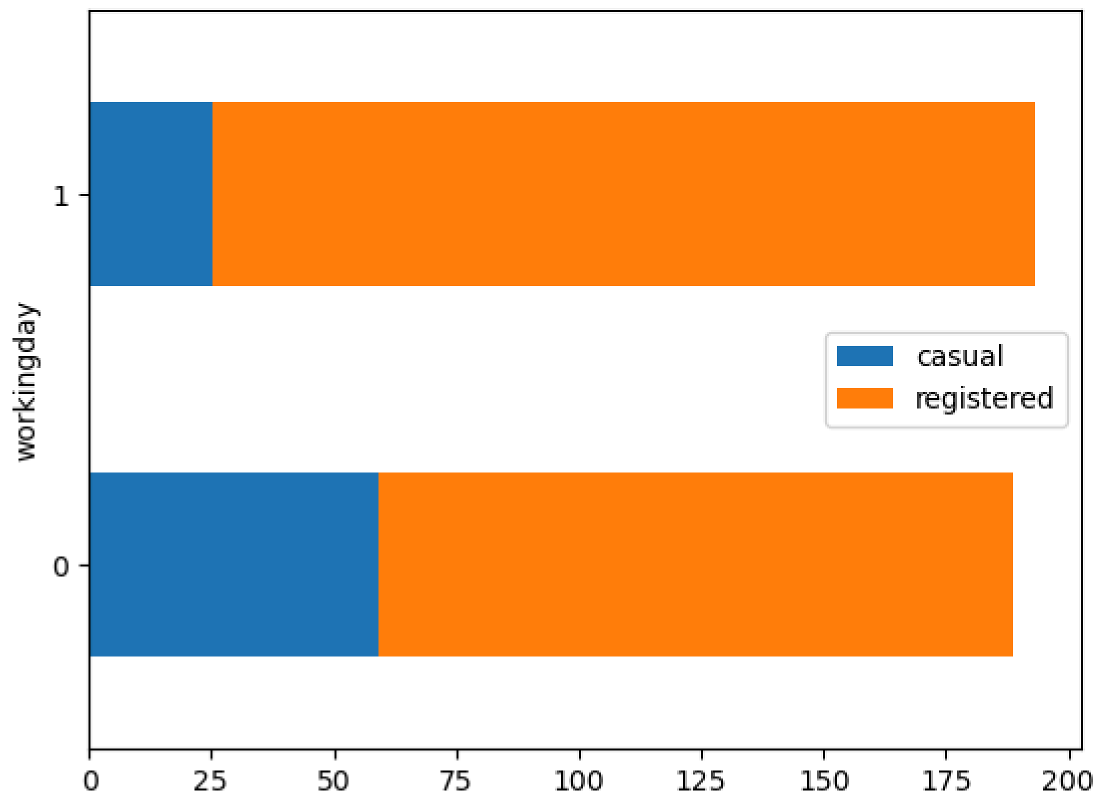


Inference:

- On Holidays, average number of casual users > average number of registered users

In [59]:
```
# Working day vs Count
data.groupby(['workingday'])[['casual', 'registered']].mean().plot(kind='barh',
```

Out[59]: <Axes: ylabel='workingday'>

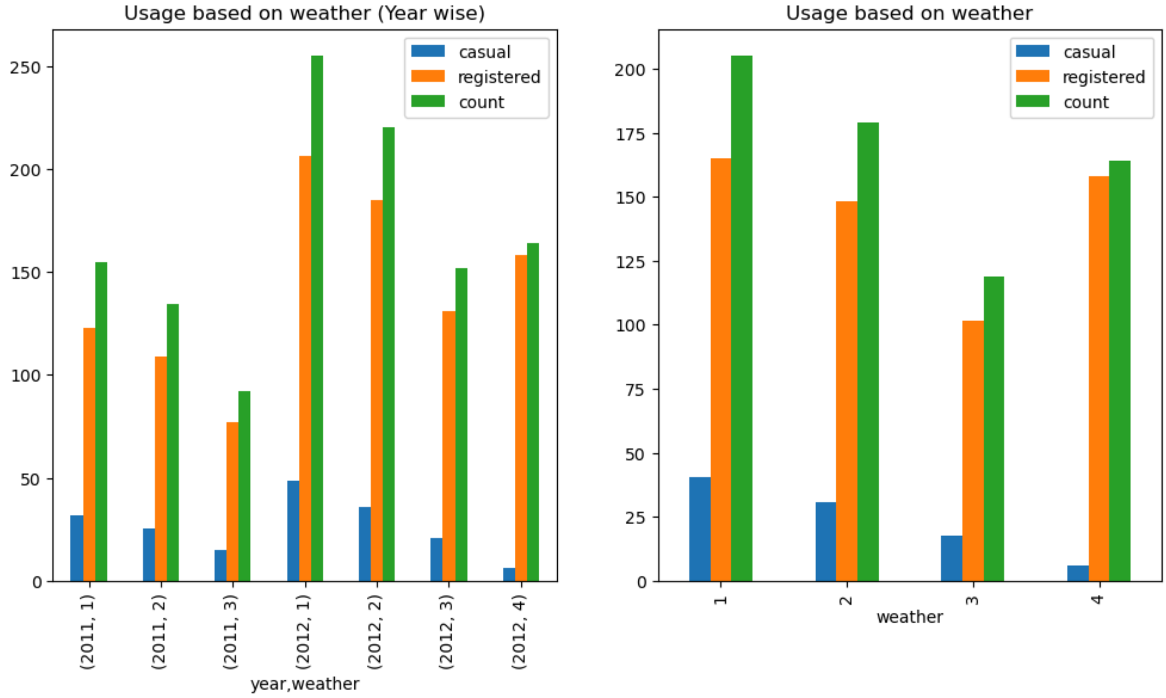


Inference:

- On Working days, average number of registered users > average number of casual users

In [76]:
```
# Weather vs Count
# Weather corresponds to time not day
plt.figure(figsize=(12,6))
ax = plt.subplot(1,2,1)
data.groupby(['year', 'weather'])[['casual', 'registered', 'count']].mean().plot
plt.title('Usage based on weather (Year wise)')
ax = plt.subplot(1,2,2)
data.groupby(['weather'])[['casual', 'registered', 'count']].mean().plot(kind='b
plt.title('Usage based on weather')
```

Out[76]:
```
Text(0.5, 1.0, 'Usage based on weather')
```



Inference:

- The usage of bikes based on weather is in the order 1 > 2 > 4 > 3
- Interestingly the usage of bikes by registered users is high during Heavy rain climate than light rain, further analysis required
- The average number of usage increases between years 2011 and 2012

In [63]:
```
data.groupby(['year', 'weather'])['date'].nunique()
```

Out[63]:
```
year  weather
2011  1          212
      2          166
      3           90
2012  1          222
      2          180
      3           97
      4            1
Name: date, dtype: int64
```

Inference:

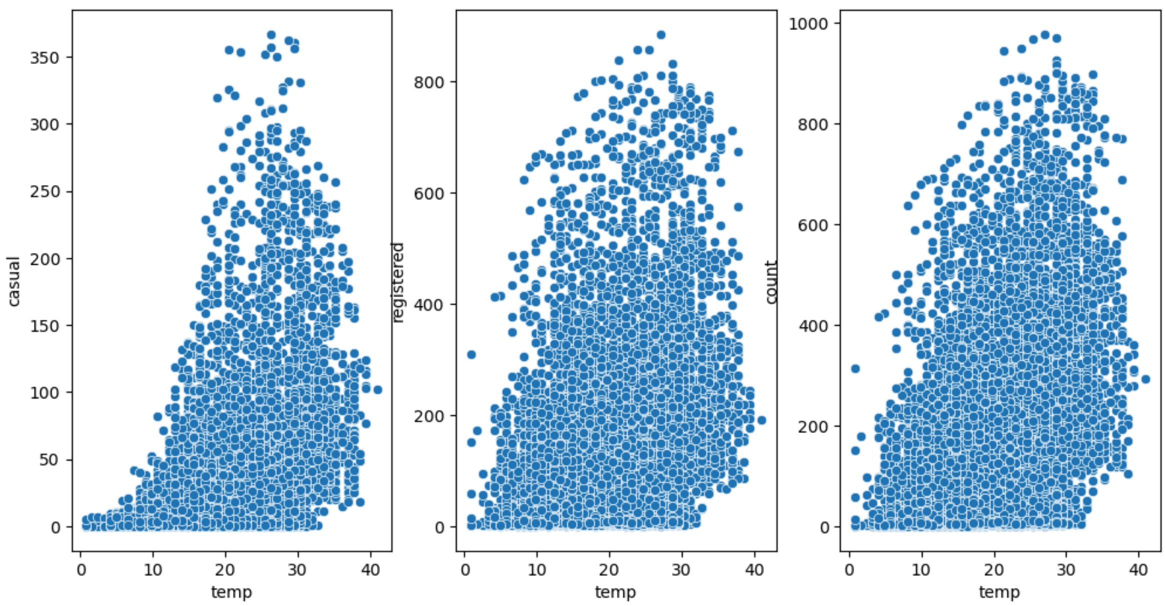
- Strategies including weather 1 and 2 makes significant impact in the revenue than weather 3
- In the dataset, Weather 4 is used in only one record, the insight due to weather 4 doesn't make significant impact
    - The insight "the average usage of bikes by registered users is high during Heavy rain climate than light rain" cannot be concluded

In [107…

```python
# Temp vs casual and registered
plt.figure(figsize=(12,6))
plt.subplot(1,3,1)
sns.scatterplot(data=data, x = 'temp', y='casual')
plt.subplot(1,3,2)
sns.scatterplot(data=data, x = 'temp', y='registered')
plt.subplot(1,3,3)
sns.scatterplot(data=data, x = 'temp', y='count')
```

Out[107…

```
<Axes: xlabel='temp', ylabel='count'>
```



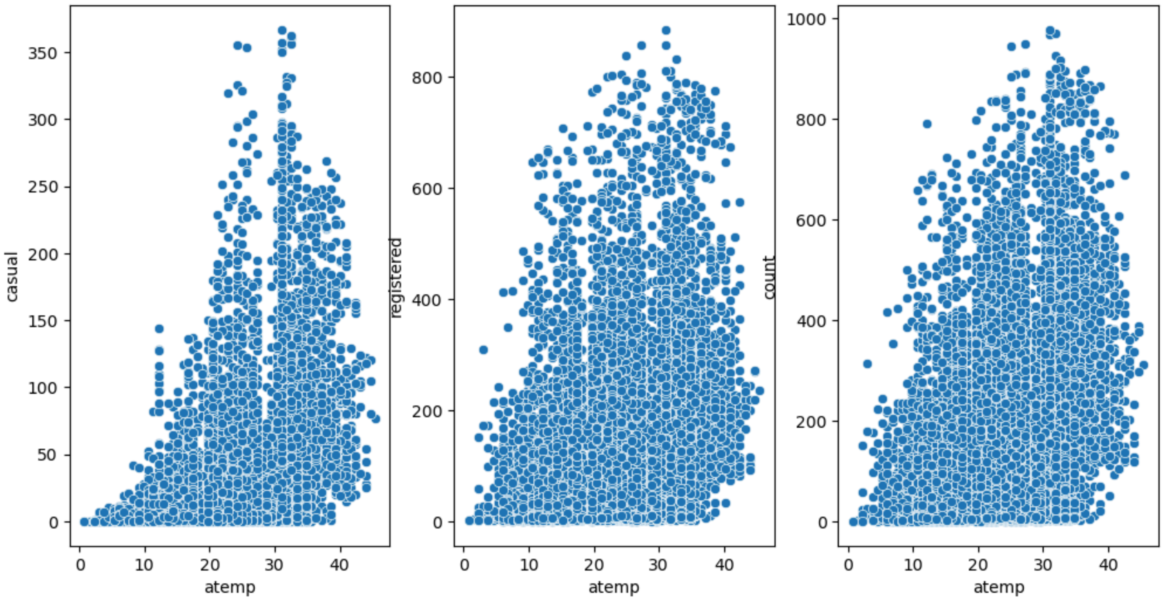
Inference:

- There is an increasing trend for the rise in temperature for casual users
- No significant pattern is observed when there is rise in temperature for registered users
- Categorizing the temperature data to different level might so show some correlation (further analysis is required)

In [114…

```python
# aTemp vs casual and registered
plt.figure(figsize=(12,6))
plt.subplot(1,3,1)
sns.scatterplot(data=data, x= 'atemp', y='casual')
plt.subplot(1,3,2)
sns.scatterplot(data=data, x = 'atemp', y='registered')
plt.subplot(1,3,3)
sns.scatterplot(data=data, x = 'atemp', y='count')
```

Out[114… <Axes: xlabel='atemp', ylabel='count'>

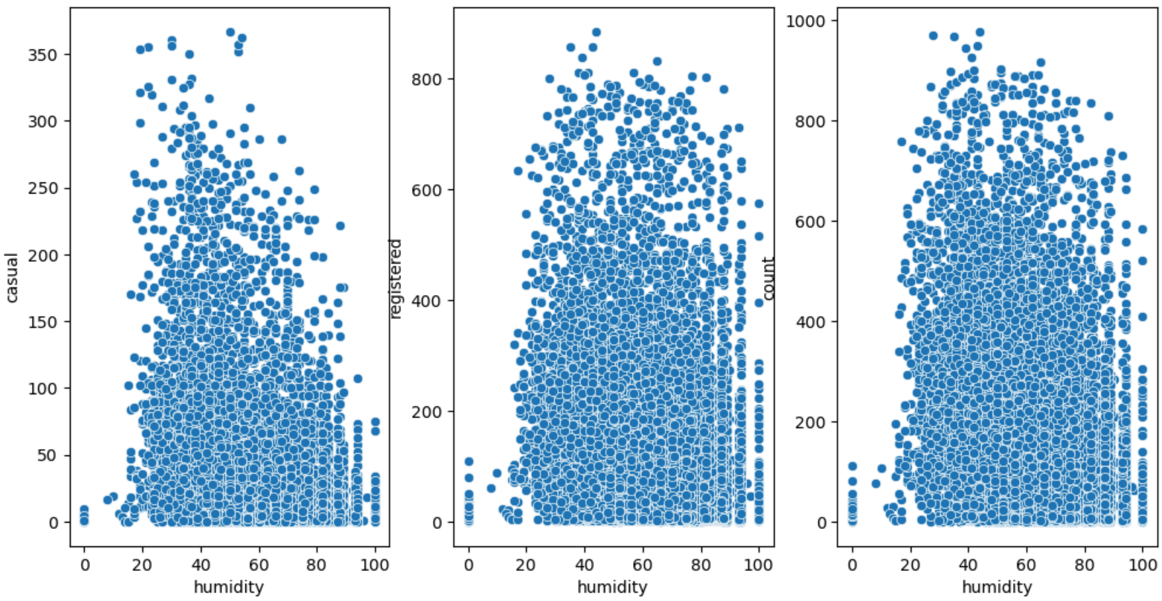


Inference:

- There is an increasing trend for the rise in actual temperature for casual users
- No significant pattern is observed when there is rise in actual temperature for registered users
- Categorizing the actual temperature data to different level might so show some correlation (further analysis is required)

In [115…
```
# Temp vs casual and registered
plt.figure(figsize=(12,6))
plt.subplot(1,3,1)
sns.scatterplot(data=data, x = 'humidity', y='casual')
plt.subplot(1,3,2)
sns.scatterplot(data=data, x = 'humidity', y='registered')
plt.subplot(1,3,3)
sns.scatterplot(data=data, x = 'humidity', y='count')
```

Out[115… <Axes: xlabel='humidity', ylabel='count'>



Inference:

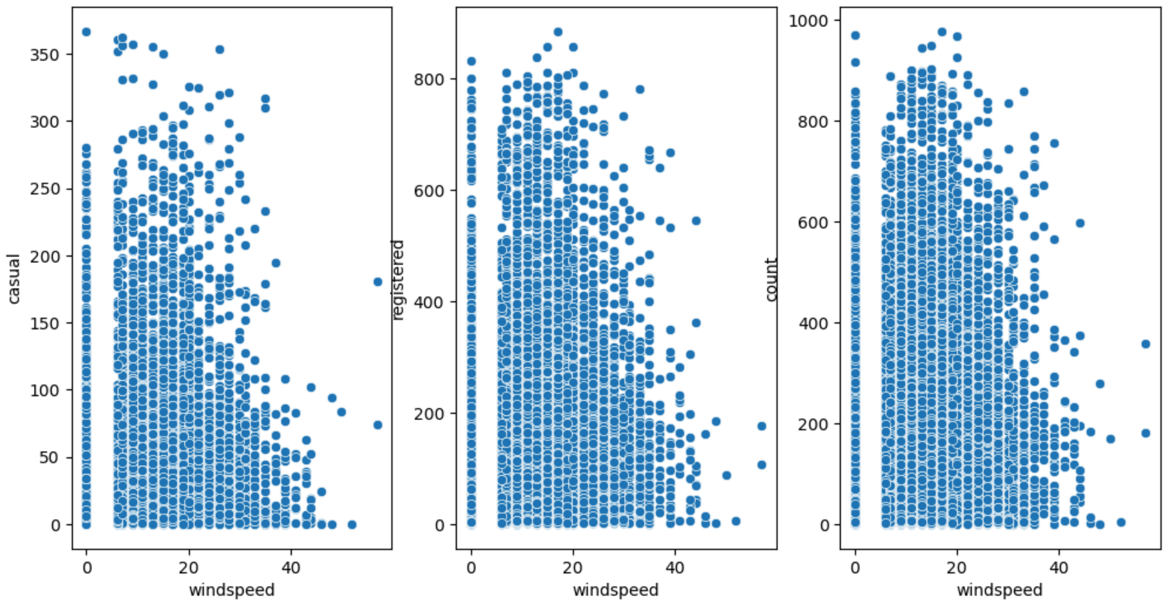
- There is an slight decreasing trend for the rise in humidity level for casual users
- No significant pattern is observed when there is rise in humidity level for registered users
- Categorizing the humidity level data to different level might so show some correlation (further analysis is required)

In [116…

```
# Temp vs casual and registered
plt.figure(figsize=(12,6))
plt.subplot(1,3,1)
sns.scatterplot(data=data, x = 'windspeed', y='casual')
plt.subplot(1,3,2)
sns.scatterplot(data=data, x = 'windspeed', y='registered')
plt.subplot(1,3,3)
sns.scatterplot(data=data, x = 'windspeed', y='count')
```

Out[116…

```
<Axes: xlabel='windspeed', ylabel='count'>
```



Inference:

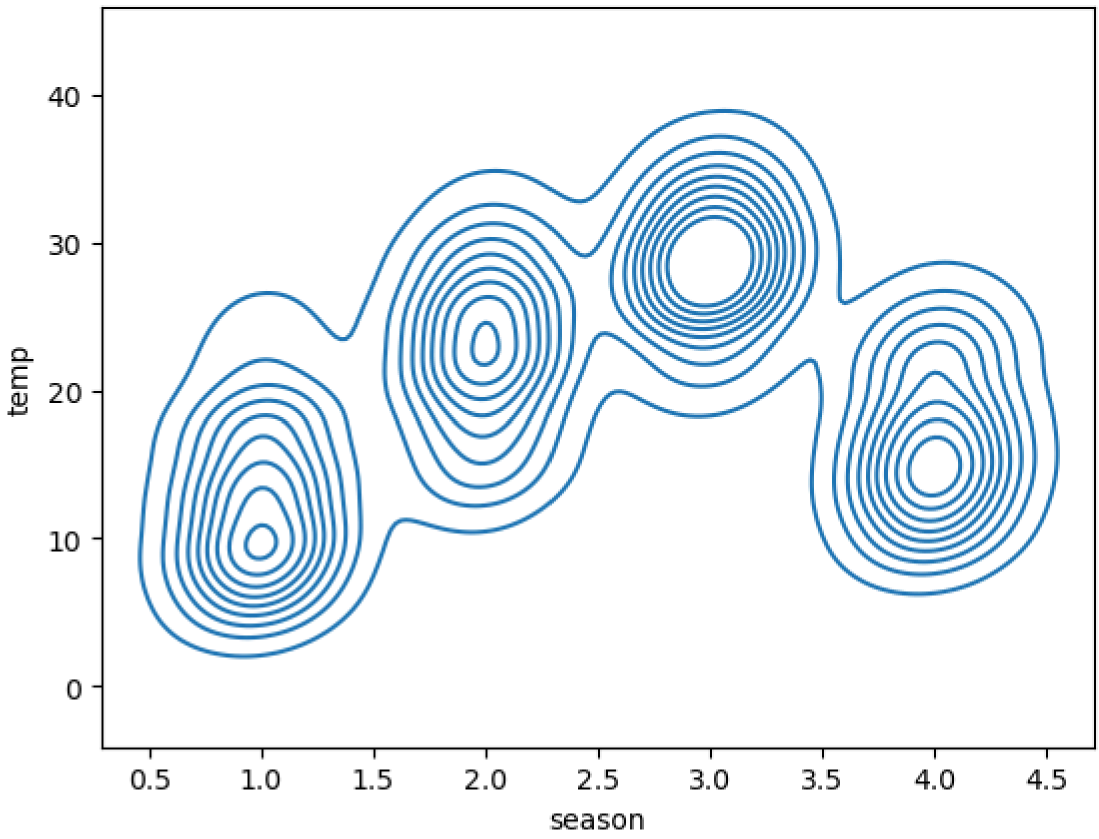
- No significant pattern is observed when there is a change in wind speed for casual and registered users
- Categorizing the wind speed data to different levels might so show some correlation (further analysis is required)

In [124…

```
# Weather vs Temp
sns.kdeplot(data = data, x = 'season', y = 'temp')
```

Out[124…

```
<Axes: xlabel='season', ylabel='temp'>
```



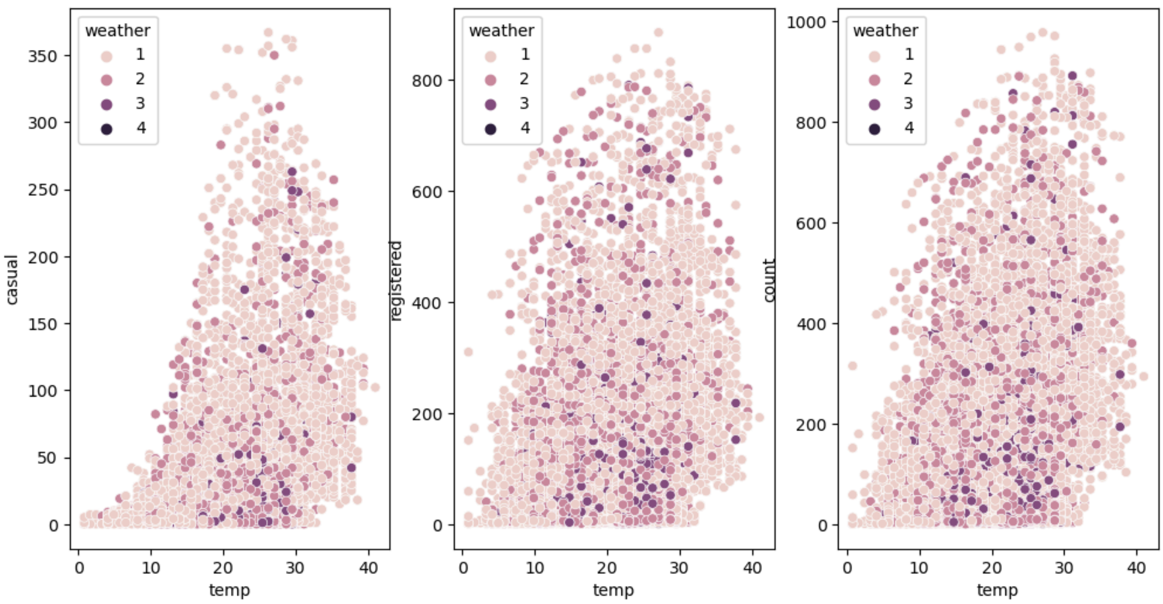
MVA

In [126…

```
# Usage, Weather,
plt.figure(figsize=(12,6))
plt.subplot(1,3,1)
sns.scatterplot(data=data, x = 'temp', y='casual', hue = 'weather')
plt.subplot(1,3,2)
sns.scatterplot(data=data, x = 'temp', y='registered', hue = 'weather')
plt.subplot(1,3,3)
sns.scatterplot(data=data, x = 'temp', y='count', hue = 'weather')
```

Out[126…

```
<Axes: xlabel='temp', ylabel='count'>
```

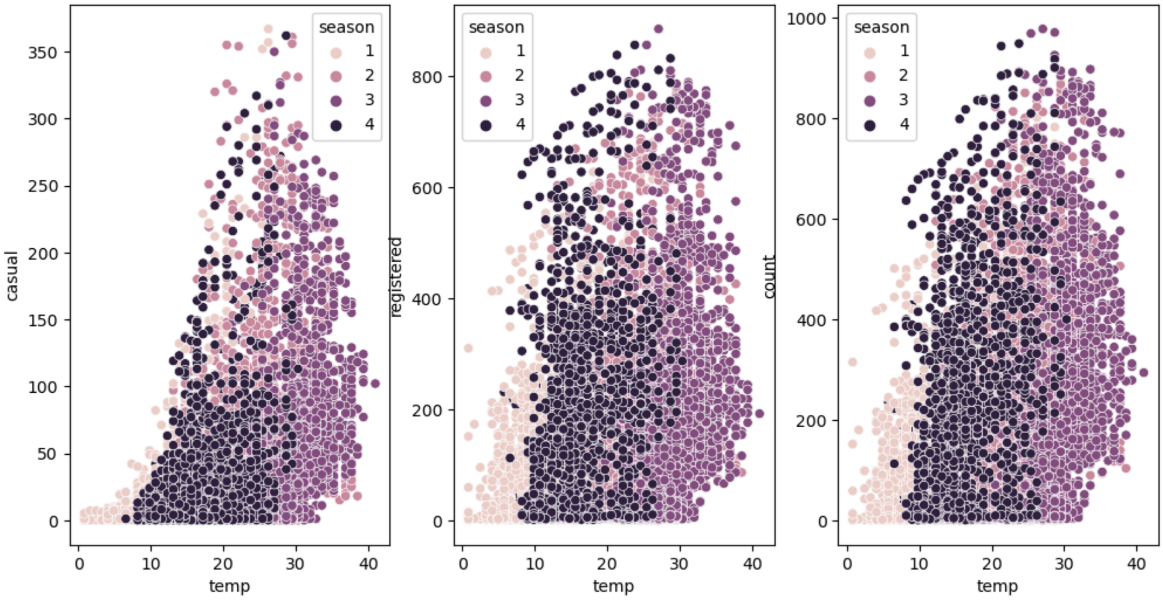


In [125…

```python
# Usage, Weather,
plt.figure(figsize=(12,6))
plt.subplot(1,3,1)
sns.scatterplot(data=data, x = 'temp', y='casual', hue = 'season')
plt.subplot(1,3,2)
sns.scatterplot(data=data, x = 'temp', y='registered', hue = 'season')
plt.subplot(1,3,3)
sns.scatterplot(data=data, x = 'temp', y='count', hue = 'season')
```

Out[125…

```
<Axes: xlabel='temp', ylabel='count'>
```

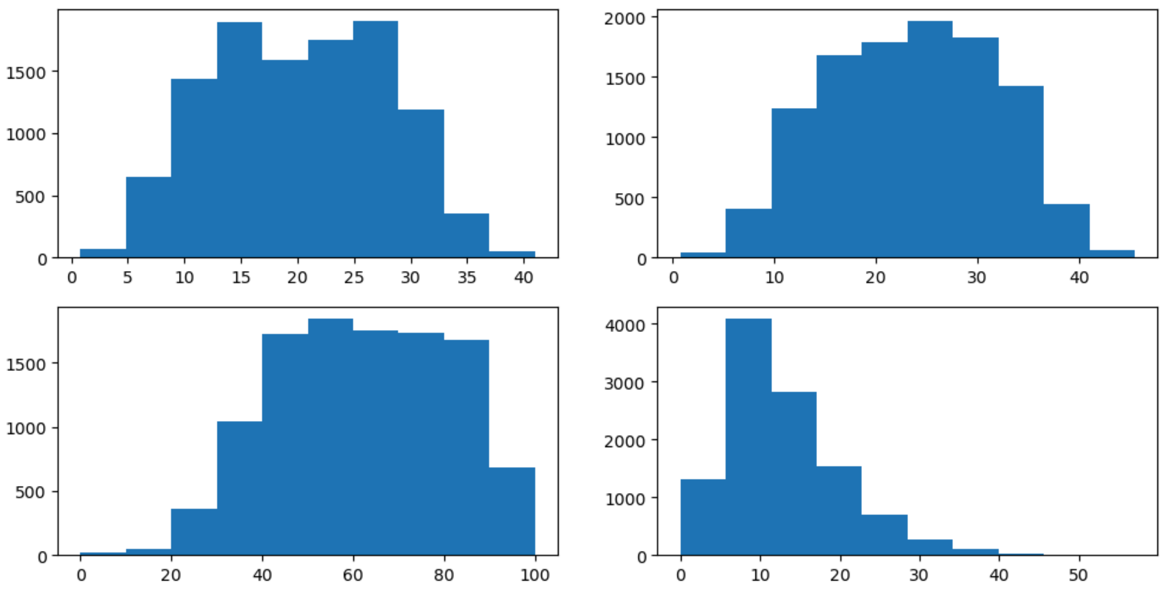


In [133…

```python
plt.figure(figsize=(12,6))
plt.subplot(2,2,1)
plt.hist(data['temp'], bins = 10)
plt.subplot(2,2,2)
plt.hist(data['atemp'], bins = 10)
plt.subplot(2,2,3)
plt.hist(data['humidity'], bins = 10)
plt.subplot(2,2,4)
plt.hist(data['windspeed'], bins = 10)
```

Out[133…

```
(array([1.313e+03, 4.083e+03, 2.827e+03, 1.540e+03, 6.960e+02, 2.800e+02,
        1.070e+02, 3.100e+01, 6.000e+00, 3.000e+00]),
 array([ 0.     ,  5.69969, 11.39938, 17.09907, 22.79876, 28.49845,
        34.19814, 39.89783, 45.59752, 51.29721, 56.9969 ]),
 <BarContainer object of 10 artists>)
```



Numerical to Categorical Features

- Temp:
  - Low: <15
  - Med: 15 - 30
  - High: >30
- aTemp:
  - Low: <15
  - Med: 15 - 30
  - High: >30
- Humidity:
  - Low: < 40
  - Med: 40 - 85
  - High: >85
- windspeed:
  - Low: 0 - 10
  - Med: 11 - 25
  - High: >25

In [13]:

```python
bins = [0, 15, 30, 50]
label = ['Low', 'Med', 'High']
data['temp_cat'] = pd.cut(data['temp'], bins=bins, labels=label)
data['temp_cat'].value_counts()
```

Out[13]:

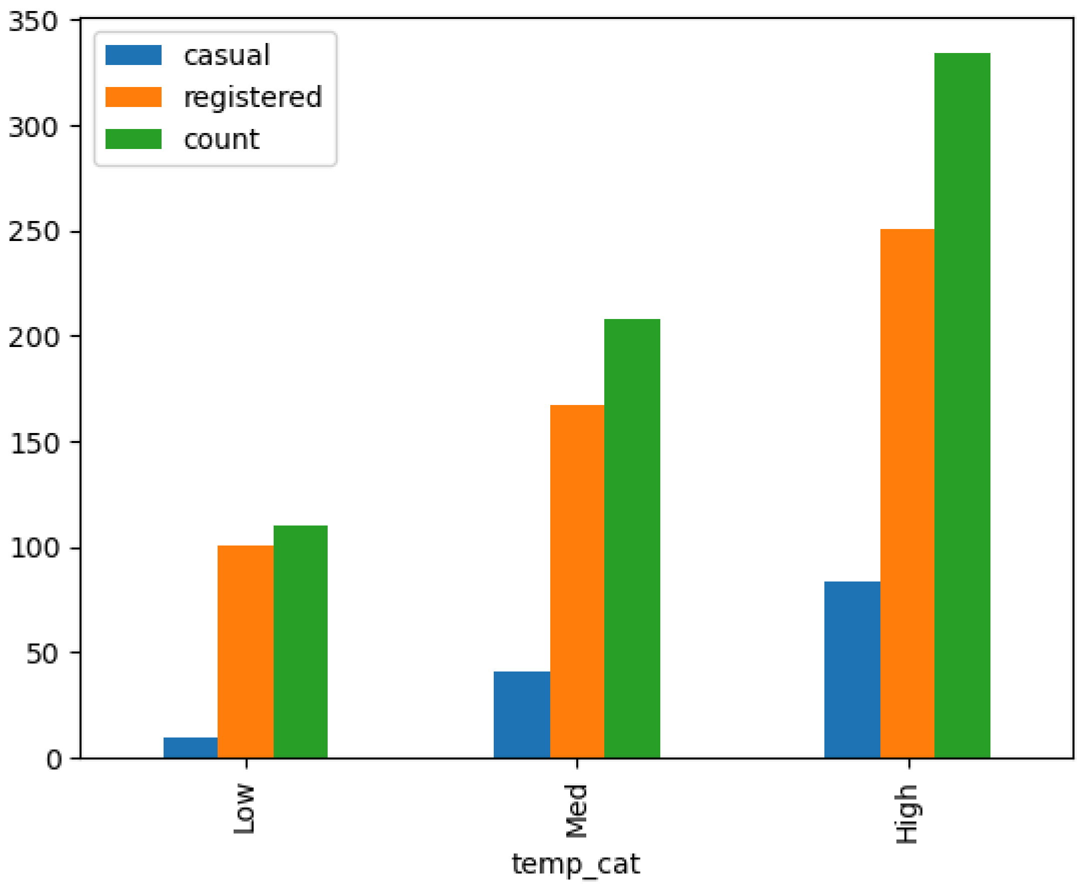
```
Med     6249
Low     3393
High    1244
Name: temp_cat, dtype: int64
```

In [136…

```python
data.groupby('temp_cat')[['casual', 'registered', 'count']].mean().plot(kind='ba
```

Out[136…

```
<Axes: xlabel='temp_cat'>
```



Inference:

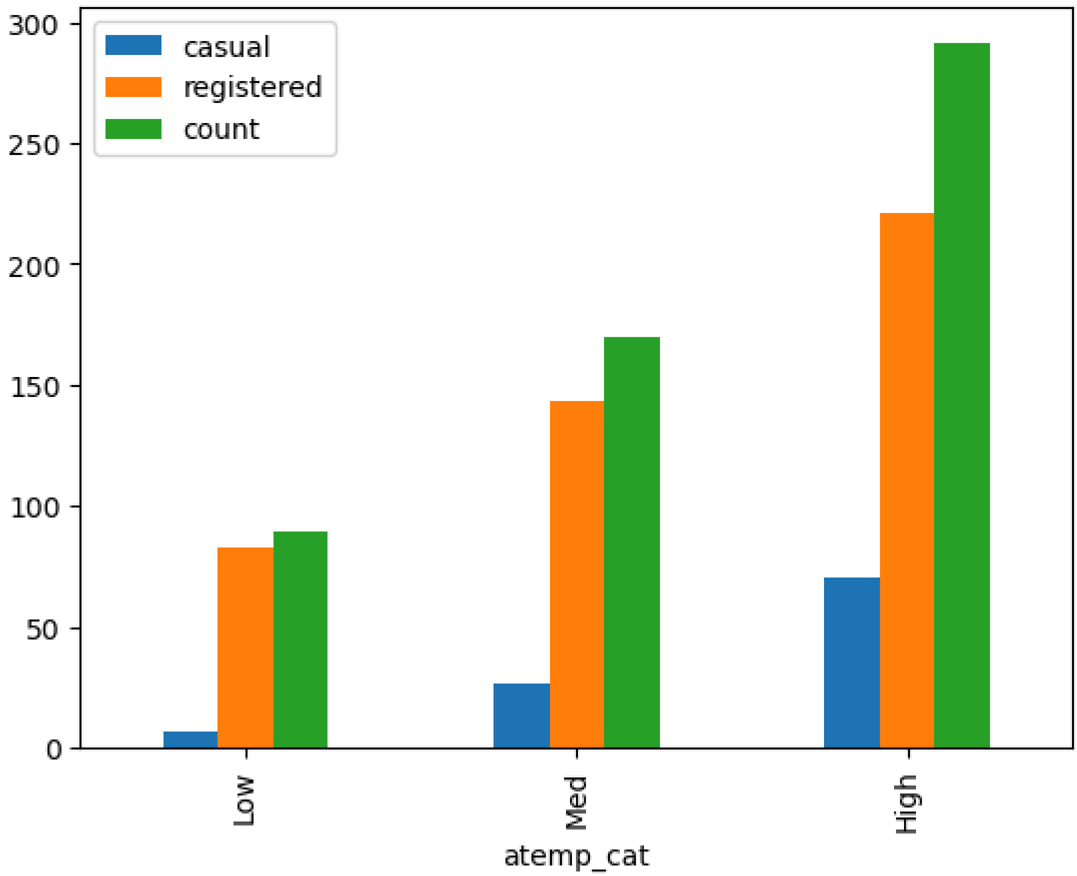
- Average number of casual and registered users increases with an increase in temperature
- It is evident that there is a linear relationship between the temperature and average number of users

In [14]:
```
bins = [0, 15, 30, 50]
label = ['Low', 'Med', 'High']
data['atemp_cat'] = pd.cut(data['atemp'], bins=bins, labels=label)
data['atemp_cat'].value_counts()
```

Out[14]:
```
Med     5674
High    3250
Low     1962
Name: atemp_cat, dtype: int64
```

In [140…
```
data.groupby('atemp_cat')[['casual', 'registered', 'count']].mean().plot(kind='b
```

Out[140…
```
<Axes: xlabel='atemp_cat'>
```



Inference:

- Average number of both casual and registered users increases with an increase in absolute temperature
- It is evident that there is a linear relationship between the absolute temperature and average number of users

In [15]:

```
bins = [0, 40, 85, 100]
label = ['Low', 'Med', 'High']
data['humidity_cat'] = pd.cut(data['humidity'], bins=bins, labels=label)
data['humidity_cat'].value_counts()
```

Out[15]:

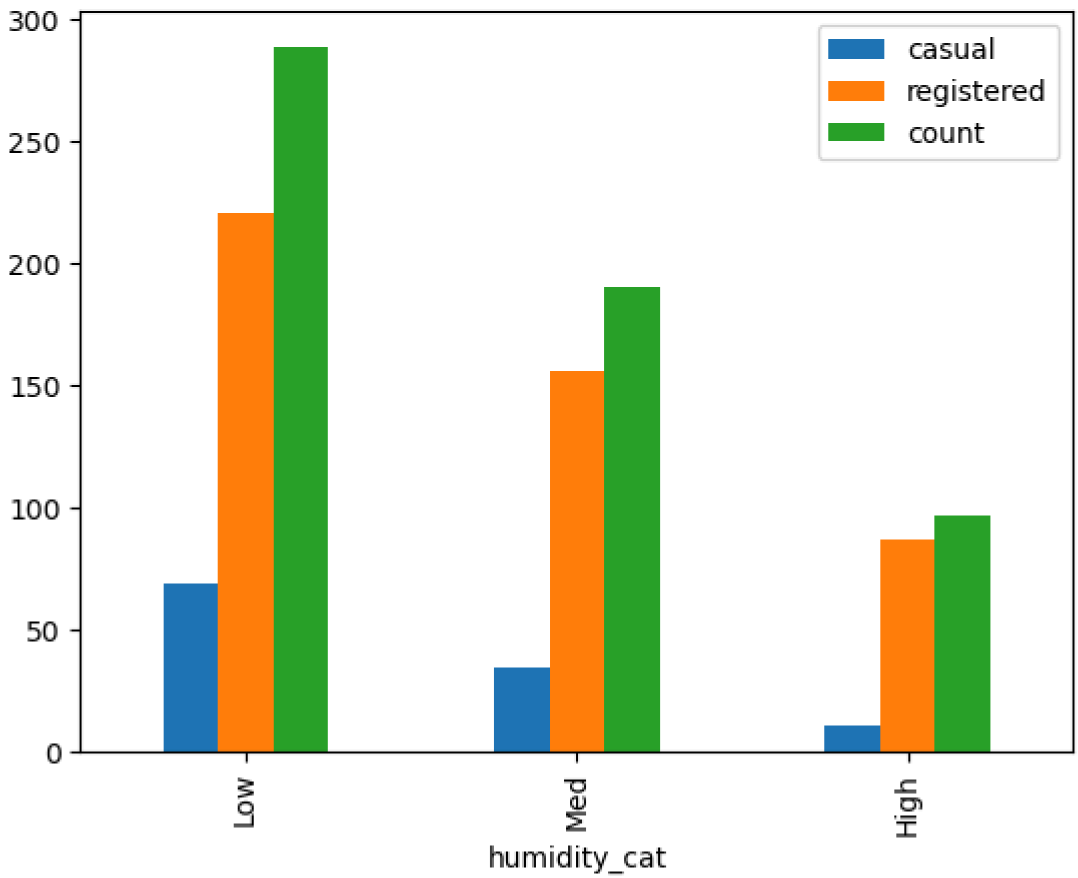
```
Med     7715
Low     1616
High    1533
Name: humidity_cat, dtype: int64
```

In [141…

```
data.groupby('humidity_cat')[['casual', 'registered', 'count']].mean().plot(kind
```

Out[141…

```
<Axes: xlabel='humidity_cat'>
```



Inference:

- Average number of both casual and registered users increases with the decrease in humidity level
- It is evident that the average number of users is negatively correlated with humidity

In [234…

```
bins = [0, 10, 25, 100]
label = ['Low', 'Med', 'High']
data['windspeed_cat'] = pd.cut(data['windspeed'], bins=bins, labels=label)
data['windspeed_cat'].value_counts()
```

Out[234…

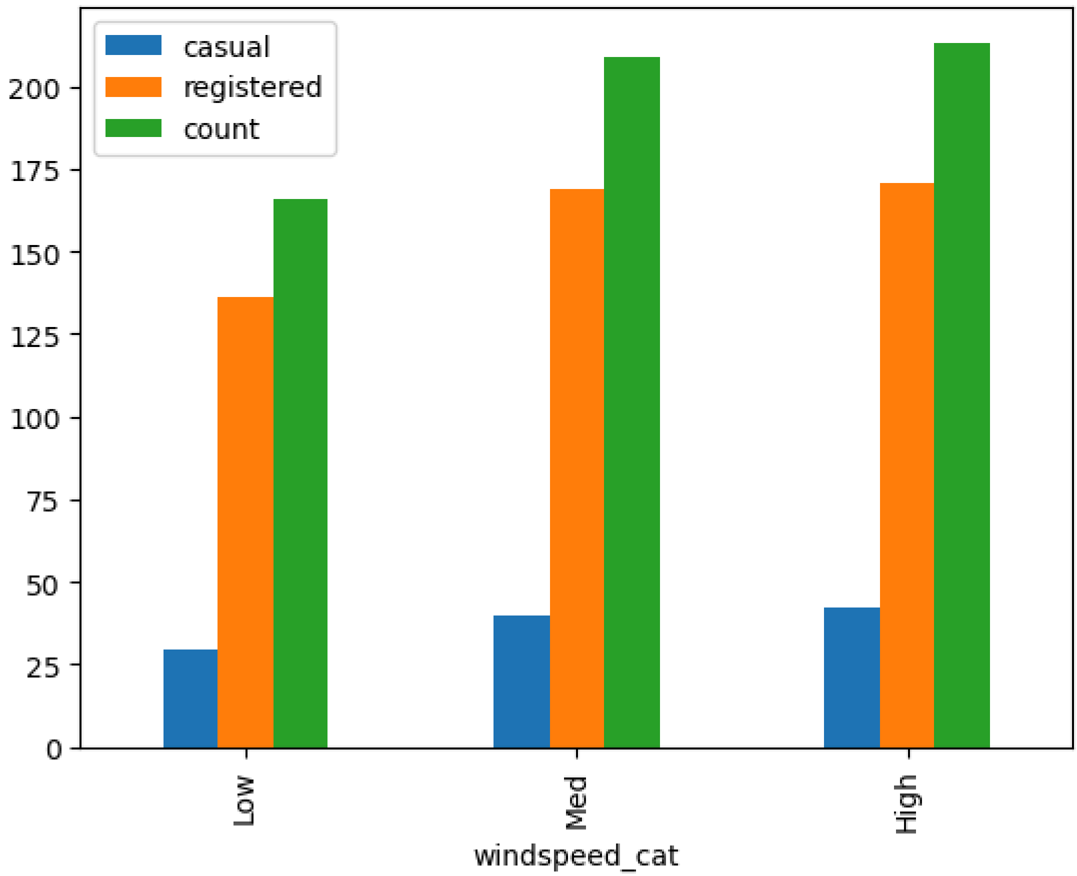
```
Med     5698
Low     3026
High     849
Name: windspeed_cat, dtype: int64
```

In [142…

```
data.groupby('windspeed_cat')[['casual', 'registered', 'count']].mean().plot(kin
```

Out[142…

```
<Axes: xlabel='windspeed_cat'>
```



Inference:

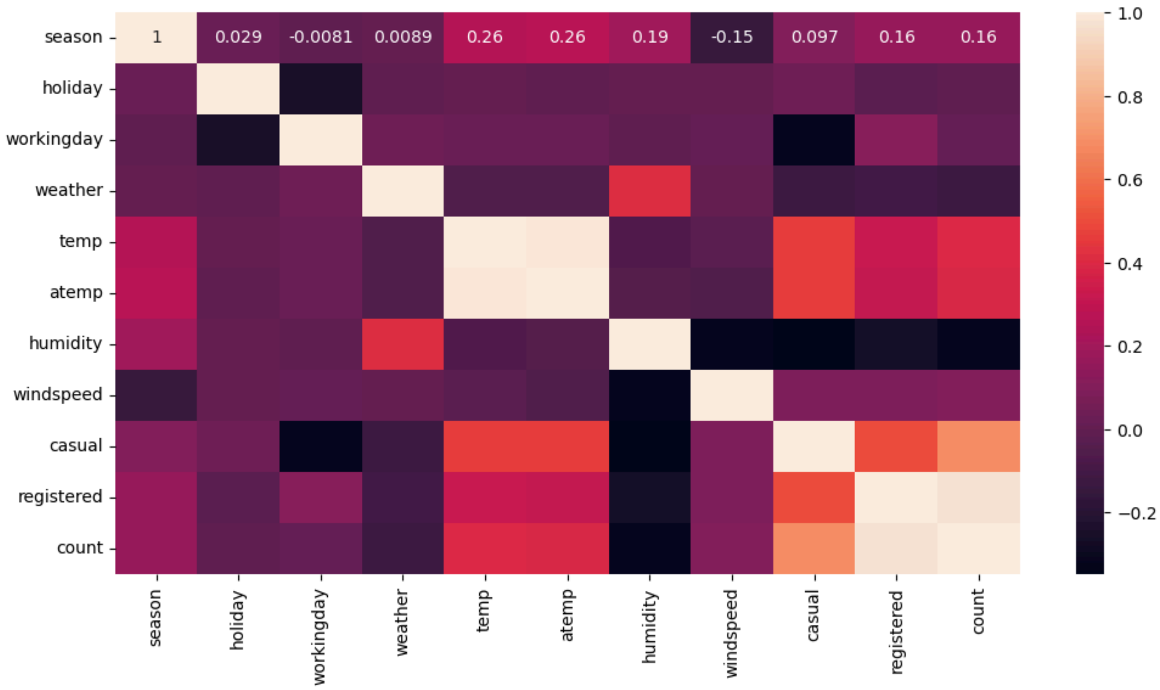
- Average number of both casual and registered users slightly increases from low to medium windspeed
- No significant change in the average number of users between medium and high windspeed conditions

In [261…

```
plt.figure(figsize=(12,6))
temp_data = data[['season', 'holiday', 'workingday', 'weather', 'temp', 'atemp',
sns.heatmap(temp_data.corr(), annot=True)
```

Out[261…

```
<Axes: >
```



Inference:

- Average number of casual and registered users are highly positively correlated with temp, atemp
- Humidity and weather are positively correlated
- Humidity and windspeed are negatively correlated
- Average number of causal users is negatively correlated with working day

Hypothesis Tests

1. Problem Statement

Working Day has effect on number of electric cycles rented

__Solution Approach:__

- Null Hypothesis: **u1=u2**
- Alternate Hypothesis: **u1>u2**
  - u1 - Average no. of cycles rented during working day
  - u2 - Average no. of cycles rented during non working day
- Significance level: 5%
- Comparison between Average no. of cycles rented (*Numerical*) and working day (*Category with 2 categories*)
- **Normality Test**
  - Check for Average no. of cycles rented follow Normal distribution
- Hence, **2 Sample T Test**

In [194…

```
def check_normality(samples):
    for i in range(len(samples)):
        stat, p_value = shapiro(samples[i])
```

```
        if p_value < 0.05:
            print("Reject Null Hypothesis. Pval is ", p_value ,". Hence, Sample"
        else:
            print("Fail to Reject Null Hypothesis. Pval is ", round(p_value,2) ,
```

In [195…

```
def plot_dist(samples):
    plt.figure(figsize=(12,6))
    for i in range(len(samples)):
        plt.subplot(1, len(samples), i+1)
        sns.kdeplot(samples[i])
        plt.title('Sample ' + str(i+1))
```

In [ ]:

```
df = data.groupby('date').agg({'workingday': 'min', 'count': 'mean'})
sample1 = df[df['workingday'] == 1]['count']
sample2 = df[df['workingday'] != 1]['count']
```

1.1 Check For Assumptions

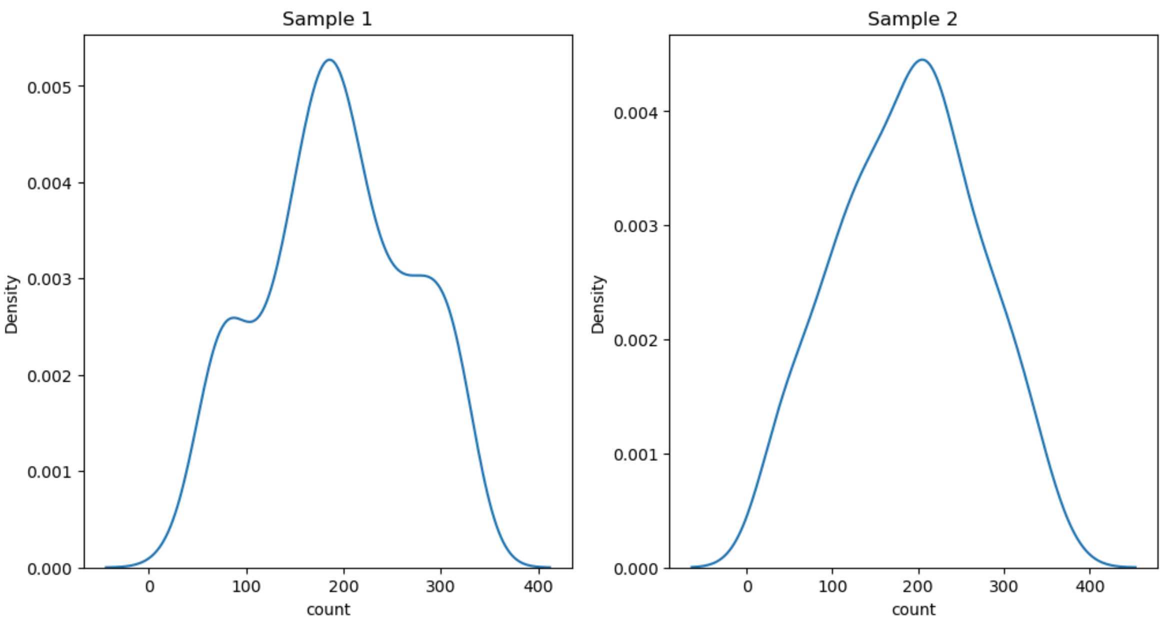
In [26]:

```
check_normality([sample1, sample2])
```

```
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 1  doesn't follow normal dis
tribution
Fail to Reject Null Hypothesis. Pval is  0.08 . Hence, Sample 2  follows normal d
istribution
```

In [60]:

```
plot_dist([sample1, sample2])
```



Inference:

- Average no. of cycles rented during non-working day follows normal distribution
- Average no. of cycles rented during working day doesn't follow normal distribution
- Distribution plot confirms the above point

1.2. Perform T-Test

In [181…

```
alpha = 0.05
print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(sampl
tstat, p_value = ttest_ind(sample1, sample2, alternative='greater')
```

```
print('T-Stat: ', round(tstat,2), 'P-Val: ', p_value)
if p_value < 0.05:
    print('Reject Null Hypothesis. Hence, Average number of cycles rented during
else:
    print('Fail to Reject Null Hypothesis. Hence, Average number of cycles rente
```

```
Sample-1 Mean:  192.28 Sample-2 Mean:  188.33
T-Stat:  0.51 P-Val:  0.31
Fail to Reject Null Hypothesis. Hence, Average number of cycles rented during wor
king day is equal to non working day
```

Inference:

- Since the test is between a numerical and categorical variable (with 2 categories), **2 sample t-test is selected**
- Alterate hypothesis is choosen as u1>u2 instead of u1<>u2
- Fail to Reject Null Hypothesis. Hence, **Average number of cycles rented during working day is equal to non working day**

2. Problem Statement

No. of cycles rented similar or different in different seasons

__Solution Approach:__

- Null Hypothesis: **Average no. of cycles rented are equal for all seasons**
- Alternate Hypothesis: **Average no. of cycles rented is different for atleast one season**
- Comparison between Average no. of cycles rented (*Numerical*) and Seasons (*Category with 4 categories*)
- **Normality Test**
  - Check for Average no. of cycles rented follow Normal distribution
  - **Shapiro Test**
- **Variance Test**
  - Check for Homogeneity of variances
  - **Levene Test**
- **One Way ANOVA Test**
- Significance level: 5%

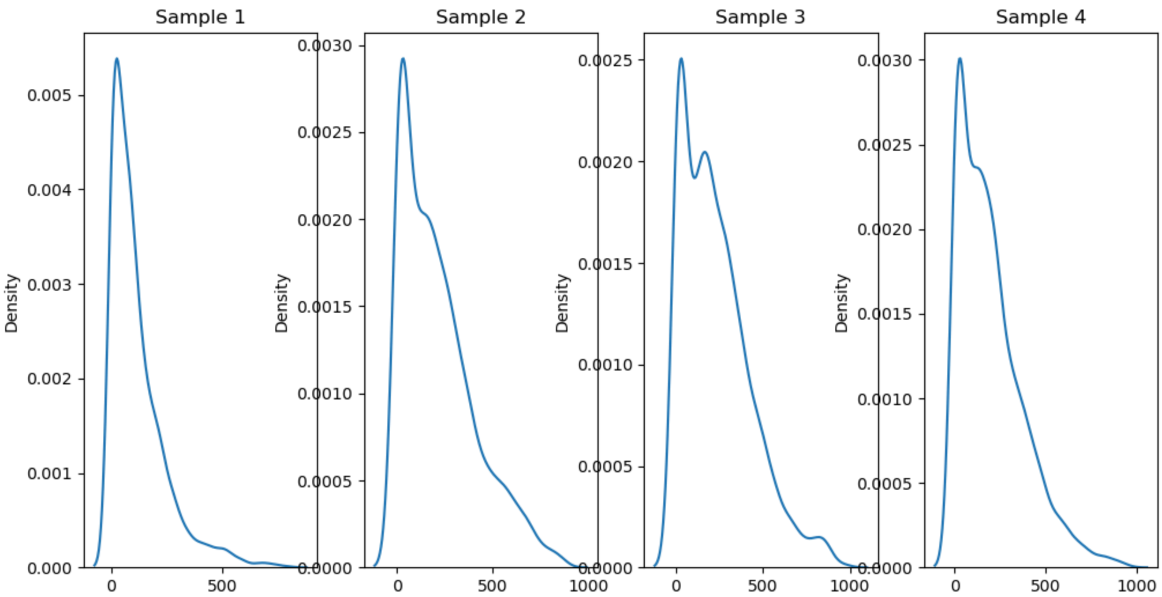
In [40]:
```
count_season = []
for i in range(1, data['season'].nunique()+1):
    count_season.append(list(data[data['season'] == i]['count']))
```

2.1. Check for Assumptions

In [44]:
```
check_normality(count_season)
```

```
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 1  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  6.039093315091269e-39 . Hence, Sample 2  doesn't
follow normal distribution
Reject Null Hypothesis. Pval is  1.0434580455873339e-36 . Hence, Sample 3  doesn't
follow normal distribution
Reject Null Hypothesis. Pval is  1.1301682309549298e-39 . Hence, Sample 4  does
n't follow normal distribution
```

In [58]:
```
plot_dist(count_season)
```



In [67]:
```
def Check_Variances(samples):
    stat, p_value = levene(samples[0], samples[1], samples[2], samples[3])
    if p_value < 0.05:
        print("Reject Null Hypothesis. Pval is ", p_value ,". Hence, the varianc
    else:
        print("Fail to Reject Null Hypothesis. Pval is ", round(p_value,2) ,". H
```

In [68]:
```
Check_Variances(count_season)
```

```
Reject Null Hypothesis. Pval is  1.0147116860043298e-118 . Hence, the variance of
atleast one sample is significantly different
```

Inference:

- For Anova, the assumptions are failed. All the samples doesn't follow normal distribution and homogeneity of variances
- Perform Anova and also Kruskal wallis test

2.2. Perform One Way Anova Test

In [86]:
```
# One Way Anova
alpha = 0.05
stat, p_value = f_oneway(count_season[0], count_season[1], count_season[2], coun
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Average no. of cycles rented is differ
```

```
else:
    print('Fail to Reject Null Hypothesis. Hence, Average no. of cycles rented i
```

```
Test Statistic:  236.95 P-Val:  6.164843386499654e-149
Reject Null Hypothesis. Hence, Average no. of cycles rented is different for atle
ast one season
```

Inference:

- One way Anova test concluded that **Average number of cycles rented is significantly different for atleast one season**
- In order the find the seasons where the Average number of cycles rented is significantly different we need to perform 2 sample t test

2.3. Perform Kruskal Wallis Test

In [73]:

```
# Kruskal Wallis Test
alpha = 0.05
stat, p_value = kruskal(count_season[0], count_season[1], count_season[2], count
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Median no. of cycles rented is differe
else:
    print('Fail to Reject Null Hypothesis. Hence, Median no. of cycles rented is
```

```
Test Statistic:  699.67 P-Val:  2.479008372608633e-151
Reject Null Hypothesis. Hence, Median no. of cycles rented is different for atlea
st one season
```

Inference:

- Since the assumptions of one way anova test is not met, the results can not concluded directly from that test
- Kruskal wallis test, concludes that the **Median no. of cycles rented is different for atleast one season**

2.4. Perform 2 Sample T Test between dependent and each independent variable

In [97]:

```
alpha = 0.05
for sample in count_season:
    print('Average no. of cycles rented in season ', str(i), ': ', np.mean(sampl

for idx1, idx2 in list(combinations(np.arange(len(count_season)),2)):
    tstat, p_value = ttest_ind(count_season[idx1], count_season[idx2], alternati
    print('T-Stat: ', round(tstat,2), 'P-Val: ', p_value)
    if p_value < 0.05:
        print('Reject Null Hypothesis. Hence, Average number of cycles rented is
    else:
        print('Fail to Reject Null Hypothesis. Hence, Average number of cycles r
```

```
Average no. of cycles rented in season  4 :  116.34326135517499
Average no. of cycles rented in season  4 :  215.25137211855105
Average no. of cycles rented in season  4 :  234.417124039517
Average no. of cycles rented in season  4 :  198.98829553767374
T-Stat:  -22.42 P-Val:  1.6578587340400098e-106
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 0  and  1
T-Stat:  -26.26 P-Val:  3.4038504355310974e-143
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 0  and  2
T-Stat:  -19.76 P-Val:  5.236417429066781e-84
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 0  and  3
T-Stat:  -3.64 P-Val:  0.00027431561172498644
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 1  and  2
T-Stat:  3.25 P-Val:  0.0011579681694131 71
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 1  and  3
T-Stat:  6.98 P-Val:  3.294359667247495e-12
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 2  and  3
```

Inference:

- Average number of cycles rented is significantly different between each seasons

3. Problem Statement

No. of cycles rented similar or different in different weather

Solution Approach:

- Null Hypothesis: **Average no. of cycles rented are equal for all weather conditions**
- Alternate Hypothesis: **Average no. of cycles rented is different for atleast one weather**
- Comparison between Average no. of cycles rented (*Numerical*) and Weather (*Category with 4 categories*)
- **Normality Test**
    - Check for Average no. of cycles rented follow Normal distribution
    - **Shapiro Test**
- **Variance Test**
    - Check for Homogeneity of variances
    - **Levene Test**
- **One Way ANOVA Test**
- Significance level: 5%

In [101…

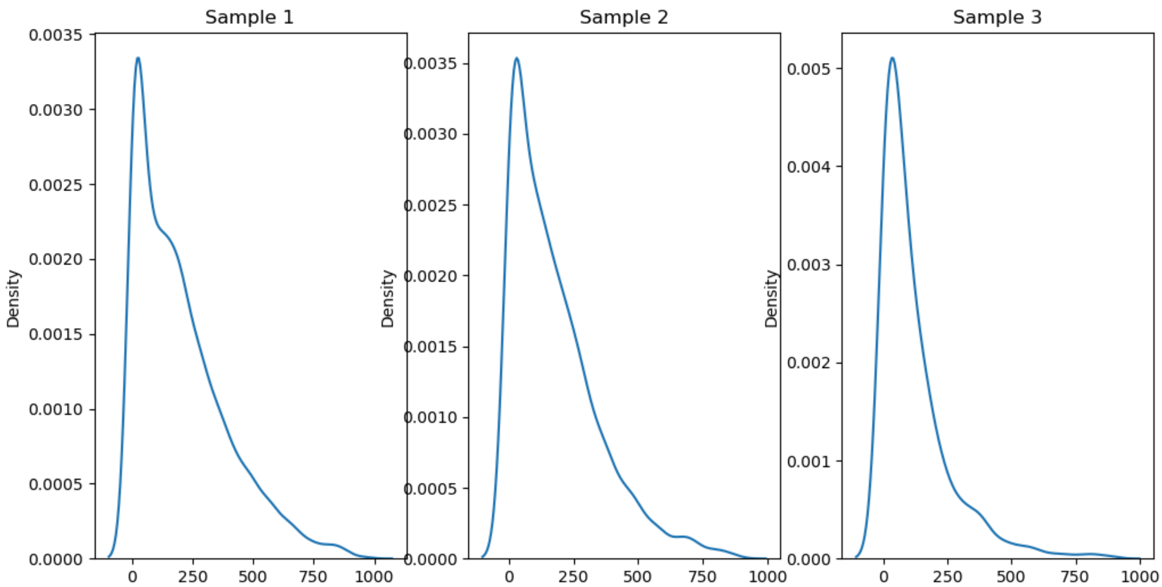
```
count_weather = []
for i in range(1, data['weather'].nunique()): # Ignoting weather 4 as it is pres
    count_weather.append(list(data[data['weather'] == i]['count']))
```

3.1. Check for Assumptions

In [102…
```
check_normality(count_weather)
```

```
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 1  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  9.781063280987223e-43 . Hence, Sample 2  doesn't
follow normal distribution
Reject Null Hypothesis. Pval is  3.876090133422781e-33 . Hence, Sample 3  doesn't
follow normal distribution
```

In [103…
```
plot_dist(count_weather)
```



In [105…
```
stat, p_value = levene(count_weather[0], count_weather[1], count_weather[2])
if p_value < 0.05:
    print("Reject Null Hypothesis. Pval is ", p_value ,". Hence, the variance of
else:
    print("Fail to Reject Null Hypothesis. Pval is ", round(p_value,2) ,". Hence
```

```
Reject Null Hypothesis. Pval is  6.198278710731511e-36 . Hence, the variance of a
tleast one sample is significantly different
```

Inference:

- For Anova, the assumptions are failed. All the samples doesn't follow normal distribution and homogeneity of variances
- Perform Anova and also Kruskal wallis test

3.2. Perform One Way Anova Test

In [107…
```
# One Way Anova
alpha = 0.05
stat, p_value = f_oneway(count_weather[0], count_weather[1], count_weather[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Average no. of cycles rented is differ
else:
    print('Fail to Reject Null Hypothesis. Hence, Average no. of cycles rented i
```

```
Test Statistic:  98.28 P-Val:  4.976448509904196e-43
Reject Null Hypothesis. Hence, Average no. of cycles rented is different for atle
ast one weather
```

Inference:

- One way Anova test concluded that **Average number of cycles rented is significantly different for atleast one weather**
- In order the find the weather condition at which the Average number of cycles rented is significantly different we need to perform 2 sample t test

3.3. Perform Kruskal Wallis Test

In [108…

```
# Kruskal Wallis Test
alpha = 0.05
stat, p_value = kruskal(count_weather[0], count_weather[1], count_weather[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Median no. of cycles rented is differe
else:
    print('Fail to Reject Null Hypothesis. Hence, Median no. of cycles rented is
```

```
Test Statistic:  204.96 P-Val:  3.122066178659941e-45
Reject Null Hypothesis. Hence, Median no. of cycles rented is different for atlea
st one weather
```

Inference:

- Since the assumptions of one way anova test is not met, the results can not concluded directly from that test
- Kruskal wallis test, concludes that the Median no. of cycles rented is different for atleast one weather conditions

3.4. Perform 2 Sample T Test between dependent and each independent variable

In [109…

```
alpha = 0.05
for sample in count_weather:
    print('Average no. of cycles rented in season ', str(i), ': ', np.mean(sampl

for idx1, idx2 in list(combinations(np.arange(len(count_weather)),2)):
    tstat, p_value = ttest_ind(count_weather[idx1], count_weather[idx2], alterna
    print('T-Stat: ', round(tstat,2), 'P-Val: ', p_value)
    if p_value < 0.05:
        print('Reject Null Hypothesis. Hence, Average number of cycles rented is
    else:
        print('Fail to Reject Null Hypothesis. Hence, Average number of cycles r
```

```
Average no. of cycles rented in season  3 :  205.23679087875416
Average no. of cycles rented in season  3 :  178.95553987297106
Average no. of cycles rented in season  3 :  118.84633294528521
T-Stat:  6.49 P-Val:  9.098916216508542e-11
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 0  and  1
T-Stat:  13.05 P-Val:  1.4918709771846279e-38
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 0  and  2
T-Stat:  9.53 P-Val:  2.7459673190273646e-21
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between seasons 1  and  2
```

Inference:

- Average number of cycles rented is significantly different between each weather conditions

4. Problem Statement

Is Weather dependent on Season ?

Solution Approach:

- Null Hypothesis: **Weather and Season are independent**
- Alternate Hypothesis: **Weather and Season are not independent**
- Comparison between Season (*Category with 4 categories*) and Weather (*Category with 4 categories*)
- **Chi Square Contingency Test**
- Significance level: 5%

In [ ]:

```python
def chi_test(ds1, ds2, alpha):
    df_conti = pd.crosstab(ds1, ds2)
    stat, p_value, dof, exp = chi2_contingency(df_conti)
    if p_value < alpha:
        print('Reject Null Hypothesis. Hence, Weather and Season are dependent')
    else:
        print('Fail to Reject Null Hypothesis. Weather and Season are independen
```

In [190…

```python
alpha = 0.05
chi_test(data[data['weather']<4]['weather'], data['season'], alpha):
```

```
Reject Null Hypothesis. Hence, Weather and Season are dependent
```

5. Problem Statement

Check the dependency of Average no. of cycles rented and all the categorical features?

5.1. Holiday Vs Average no. of cycles rented

Solution Approach:

- Null Hypothesis: **u1=u2**
- Alternate Hypothesis: **u1>u2**

- u1 - Average no. of cycles rented during Holiday
    - u2 - Average no. of cycles rented during non Holiday
- Significance level: 5%
- Comparison between Average no. of cycles rented (*Numerical*) and Holiday (*Category with 2 categories*)
- **Normality Test**
    - Check for Average no. of cycles rented follow Normal distribution
- Hence, **2 Sample T Test**

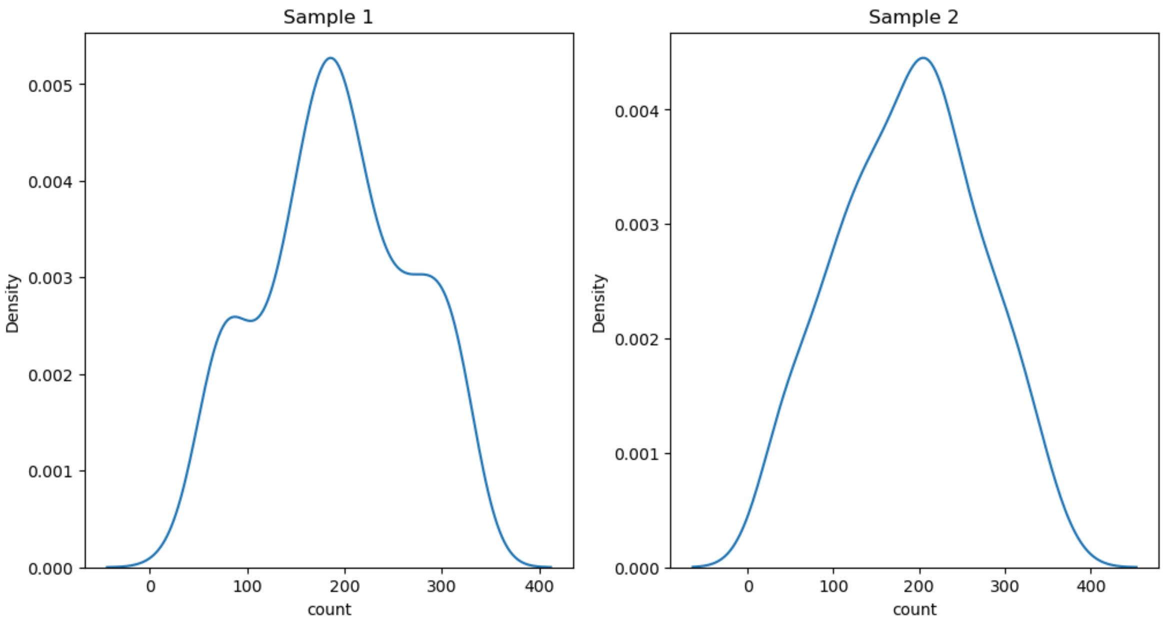
5.1.1 Check for Assumptions

In [ ]:
```
df = data.groupby('date').agg({'holiday': 'min', 'count': 'mean'})
sample1 = df[df['holiday'] == 1]['count']
sample2 = df[df['holiday'] != 1]['count']
```

In [198…
```
check_normality([sample1, sample2])
```

```
Reject Null Hypothesis. Pval is  1.3982287782710046e-05 . Hence, Sample 1  does
n't follow normal distribution
Fail to Reject Null Hypothesis. Pval is  0.08 . Hence, Sample 2  follows normal d
istribution
```

In [199…
```
plot_dist([sample1, sample2])
```



*****Inference:*****

- Average no. of cycles rented during non holiday follows normal distribution
- Average no. of cycles rented during holiday doesn't follow normal distribution
- Distribution plot confirms the above point

5.1.2 Perform T-Test

In [200…
```
alpha = 0.05
print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(sampl
tstat, p_value = ttest_ind(sample1, sample2, alternative='greater')
print('T-Stat: ', round(tstat,2), 'P-Val: ', p_value)
```

```
if p_value < 0.05:
    print('Reject Null Hypothesis. Hence, Average number of cycles rented during
else:
    print('Fail to Reject Null Hypothesis. Hence, Average number of cycles rente
```

```
Sample-1 Mean:  192.28 Sample-2 Mean:  188.33
T-Stat:  0.51 P-Val:  0.30658555817068833
Fail to Reject Null Hypothesis. Hence, Average number of cycles rented during wor
king day is equal to non working day
```

Inference:

- Since the test is between a numerical and categorical variable (with 2 categories), 2 sample t-test is selected
- Alterate hypothesis is choosen as u1>u2 instead of u1<>u2
- Fail to Reject Null Hypothesis. Hence, Average number of cycles rented during holiday day is equal to non holiday

6. Problem Statement

No. of cycles rented similar or different in different temperature bins

Solution Approach:

- Null Hypothesis: **Average no. of cycles rented are equal for all temperature bins**
- Alternate Hypothesis: **Average no. of cycles rented is different for atleast one temperature bin**
- Comparison between Average no. of cycles rented (*Numerical*) and temperature bins (*Category with 4 categories*)
- **Normality Test**
  - Check for Average no. of cycles rented follow Normal distribution
  - **Shapiro Test**
- **Variance Test**
  - Check for Homogeneity of variances
  - **Levene Test**
- **One Way ANOVA Test**
- Significance level: 5%

In [209…

```
count_temp = []
for item in list(data['temp_cat'].unique()):
    count_temp.append(list(data[data['temp_cat'] == item]['count']))
```

6.1. Check for Assumptions

In [211…

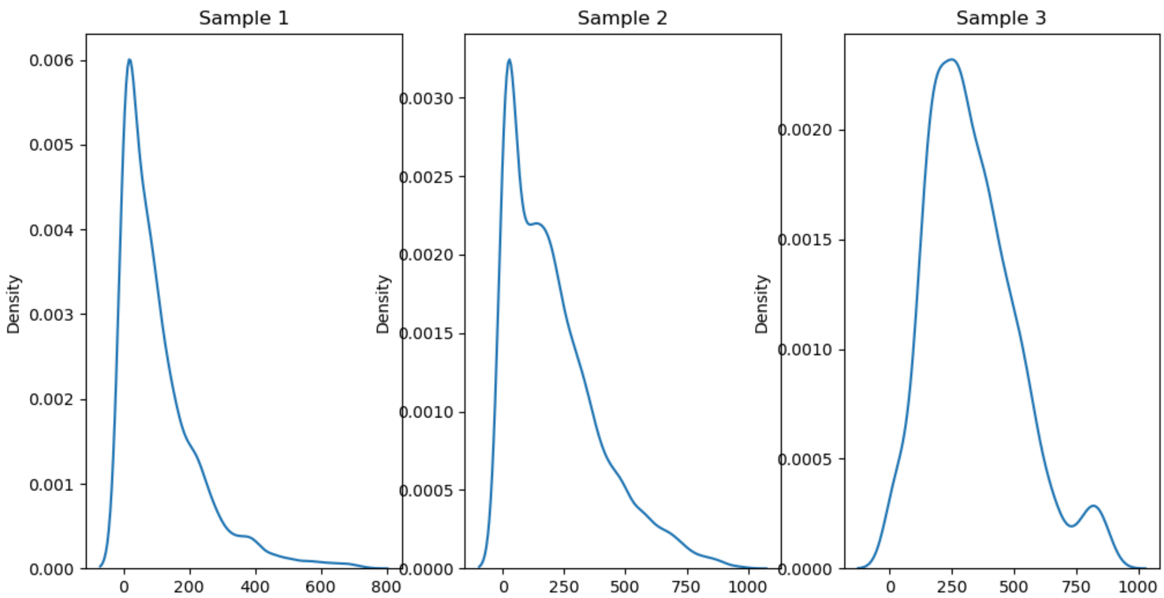
```
check_normality(count_temp)
```

```
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 1  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 2  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  2.3293470155990732e-18 . Hence, Sample 3  does
n't follow normal distribution
```

```
C:\Users\Muthukumar\AppData\Roaming\Python\Python311\site-packages\scipy\stats\_m
orestats.py:1816: UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [212…

```python
plot_dist(count_temp)
```



In [213…

```python
def Check_Variances_mod(samples):
    stat, p_value = levene(samples[0], samples[1], samples[2])
    if p_value < 0.05:
        print("Reject Null Hypothesis. Pval is ", p_value ,". Hence, the varianc
    else:
        print("Fail to Reject Null Hypothesis. Pval is ", round(p_value,2) ,". H
```

In [214…

```python
Check_Variances_mod(count_temp)
```

```
Reject Null Hypothesis. Pval is  1.3487721880363727e-133 . Hence, the variance of
atleast one sample is significantly different
```

Inference:

- For Anova, the assumptions are failed. All the samples doesn't follow normal distribution and homogeneity of variances
- Perform Anova and also Kruskal wallis test

6.2. Perform One Way Anova Test

In [215…

```python
# One Way Anova
alpha = 0.05
stat, p_value = f_oneway(count_temp[0], count_temp[1], count_temp[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Average no. of cycles rented is differ
else:
    print('Fail to Reject Null Hypothesis. Hence, Average no. of cycles rented i
```

```
Test Statistic:  874.52 P-Val:  0.0
Reject Null Hypothesis. Hence, Average no. of cycles rented is different for atle
ast one season
```

Inference:

- One way Anova test concluded that ***Average number of cycles rented is significantly different for atleast one temperature bin***
- In order the find the temperature where the Average number of cycles rented is significantly different we need to perform 2 sample t test

6.3. Perform Kruskal Wallis Test

In [217…

```
# Kruskal Wallis Test
alpha = 0.05
stat, p_value = kruskal(count_temp[0], count_temp[1], count_temp[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Median no. of cycles rented is differe
else:
    print('Fail to Reject Null Hypothesis. Hence, Median no. of cycles rented is
```

```
Test Statistic:  1650.27 P-Val:  0.0
Reject Null Hypothesis. Hence, Median no. of cycles rented is different for atlea
st one temp bin
```

Inference:

- Since the assumptions of one way anova test is not met, the results can not concluded directly from that test
- Kruskal wallis test, concludes that the Median no. of cycles rented is different for atleast one temp bin

6.4. Perform 2 Sample T Test between dependent and each independent variable

In [219…

```
alpha = 0.05
for sample in count_temp:
    print('Average no. of cycles rented in season ', str(i), ': ', np.mean(sampl

for idx1, idx2 in list(combinations(np.arange(len(count_temp)),2)):
    tstat, p_value = ttest_ind(count_temp[idx1], count_temp[idx2], alternative='
    print('T-Stat: ', round(tstat,2), 'P-Val: ', p_value)
    if p_value < 0.05:
        print('Reject Null Hypothesis. Hence, Average number of cycles rented is
    else:
        print('Fail to Reject Null Hypothesis. Hence, Average number of cycles r
```

```
Average no. of cycles rented in season  2 :  110.04892425582081
Average no. of cycles rented in season  2 :  207.43206913106096
Average no. of cycles rented in season  2 :  334.274115755627
T-Stat:  -27.46 P-Val:  6.882380020634517e-160
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between temperature bin 0  and  1
T-Stat:  -48.55 P-Val:  0.0
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between temperature bin 0  and  2
T-Stat:  -21.98 P-Val:  8.19521197158562e-104
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between temperature bin 1  and  2
```

Inference:

- Average number of cycles rented is significantly different between each temperature bins

7. Problem Statement

No. of cycles rented similar or different in different actual temperature bins

__Solution Approach:__

- Null Hypothesis: **Average no. of cycles rented are equal for all actual temperature bins**
- Alternate Hypothesis: **Average no. of cycles rented is different for atleast one actual temperature bin**
- Comparison between Average no. of cycles rented (*Numerical*) and actual temperature bins (*Category with 3 categories*)
- **Normality Test**
    - Check for Average no. of cycles rented follow Normal distribution
    - **Shapiro Test**
- **Variance Test**
    - Check for Homogeneity of variances
    - **Levene Test**
- **One Way ANOVA Test**
- Significance level: 5%

In [222…
```
count_atemp = []
for item in list(data['atemp_cat'].unique()):
    count_atemp.append(list(data[data['atemp_cat'] == item]['count']))
```

7.1. Check for Assumptions

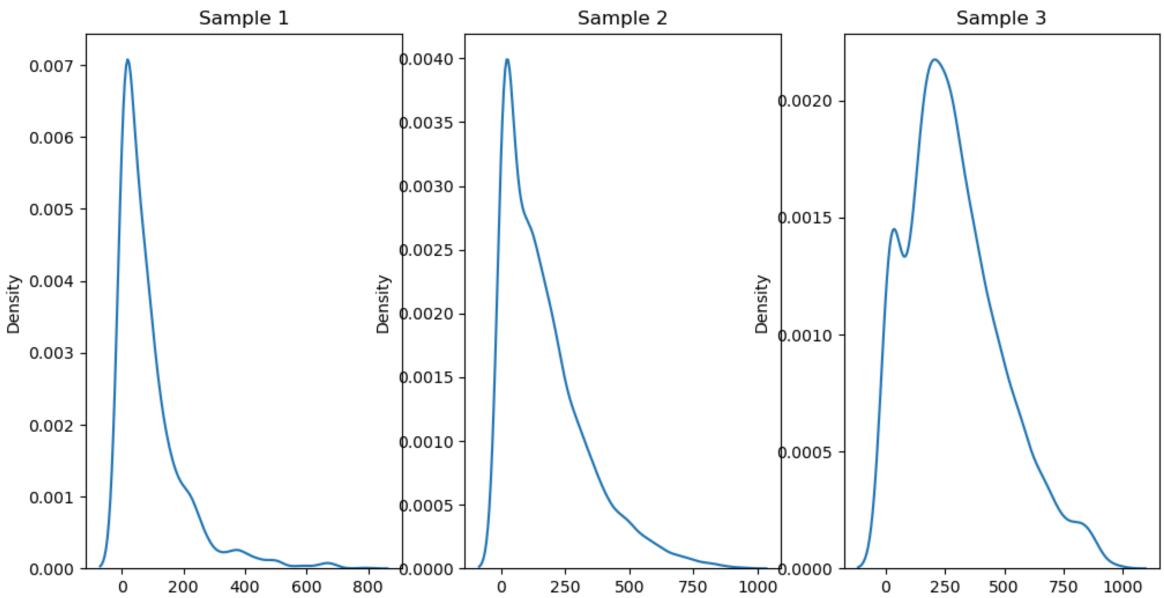
In [223…
```
check_normality(count_atemp)
```

```
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 1  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 2  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  6.537652891420251e-31 . Hence, Sample 3  doesn't
follow normal distribution
```

```
C:\Users\Muthukumar\AppData\Roaming\Python\Python311\site-packages\scipy\stats\_m
orestats.py:1816: UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [224…

```
plot_dist(count_temp)
```



In [213…

```
def Check_Variances_mod(samples):
    stat, p_value = levene(samples[0], samples[1], samples[2])
    if p_value < 0.05:
        print("Reject Null Hypothesis. Pval is ", p_value ,". Hence, the varianc
    else:
        print("Fail to Reject Null Hypothesis. Pval is ", round(p_value,2) ,". H
```

In [225…

```
Check_Variances_mod(count_atemp)
```

```
Reject Null Hypothesis. Pval is  2.2555487020783844e-150 . Hence, the variance of
atleast one sample is significantly different
```

Inference:

- For Anova, the assumptions are failed. All the samples doesn't follow normal distribution and homogeneity of variances
- Perform Anova and also Kruskal wallis test

7.2. Perform One Way Anova Test

In [226…

```
# One Way Anova
alpha = 0.05
stat, p_value = f_oneway(count_atemp[0], count_atemp[1], count_atemp[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Average no. of cycles rented is differ
else:
    print('Fail to Reject Null Hypothesis. Hence, Average no. of cycles rented i
```

```
Test Statistic:  1008.35 P-Val:  0.0
Reject Null Hypothesis. Hence, Average no. of cycles rented is different for atle
ast one temp bin
```

Inference:

- One way Anova test concluded that Average number of cycles rented is significantly different for atleast one actual temperature bin
- In order the find the temperature where the Average number of cycles rented is significantly different we need to perform 2 sample t test

7.3. Perform Kruskal Wallis Test

In [227…

```
# Kruskal Wallis Test
alpha = 0.05
stat, p_value = kruskal(count_atemp[0], count_atemp[1], count_atemp[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Median no. of cycles rented is differe
else:
    print('Fail to Reject Null Hypothesis. Hence, Median no. of cycles rented is
```

```
Test Statistic:  1846.6 P-Val:  0.0
Reject Null Hypothesis. Hence, Median no. of cycles rented is different for atlea
st one temp bin
```

Inference:

- Since the assumptions of one way anova test is not met, the results can not concluded directly from that test
- Kruskal wallis test, concludes that the Median no. of cycles rented is different for atleast one actual temperature bin

7.4. Perform 2 Sample T Test between dependent and each independent variable

In [228…

```
alpha = 0.05
for sample in count_temp:
    print('Average no. of cycles rented in season ', str(i), ': ', np.mean(sampl

for idx1, idx2 in list(combinations(np.arange(len(count_atemp)),2)):
    tstat, p_value = ttest_ind(count_atemp[idx1], count_atemp[idx2], alternative
    print('T-Stat: ', round(tstat,2), 'P-Val: ', p_value)
    if p_value < 0.05:
        print('Reject Null Hypothesis. Hence, Average number of cycles rented is
    else:
        print('Fail to Reject Null Hypothesis. Hence, Average number of cycles r
```

```
Average no. of cycles rented in season  2 :  89.24617737003058
Average no. of cycles rented in season  2 :  169.62495593937257
Average no. of cycles rented in season  2 :  291.6686153846154
T-Stat:  -20.48 P-Val:  9.160970366148517e-91
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between temperature bin 0  and  1
T-Stat:  -41.34 P-Val:  0.0
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between temperature bin 0  and  2
T-Stat:  -31.41 P-Val:  1.8596348077188179e-205
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between temperature bin 1  and  2
```

Inference:

- Average number of cycles rented is significantly different between each actual temperature bins

8. Problem Statement

No. of cycles rented similar or different in different range of windspeed

Solution Approach:

- Null Hypothesis: **Average no. of cycles rented are equal for all range of windspeed**
- Alternate Hypothesis: **Average no. of cycles rented is different for atleast one range of windspeed**
- Comparison between Average no. of cycles rented (*Numerical*) and range of windspeed (*Category with 3 categories*)
- **Normality Test**
    - Check for Average no. of cycles rented follow Normal distribution
    - **Shapiro Test**
- **Variance Test**
    - Check for Homogeneity of variances
    - **Levene Test**
- **One Way ANOVA Test**
- Significance level: 5%

In [237…
```
count_ws = []
for item in list(data['windspeed_cat'].dropna().unique()):
    count_ws.append(list(data[data['windspeed_cat'] == item]['count']))
```

In [238…
```
for i in range(len(count_ws)):
    print(len(count_ws[i]))
```

```
3026
5698
849
```

In [236…
```
data['windspeed_cat'].dropna().unique()
```

Out[236…
```
['Low', 'Med', 'High']
Categories (3, object): ['Low' < 'Med' < 'High']
```

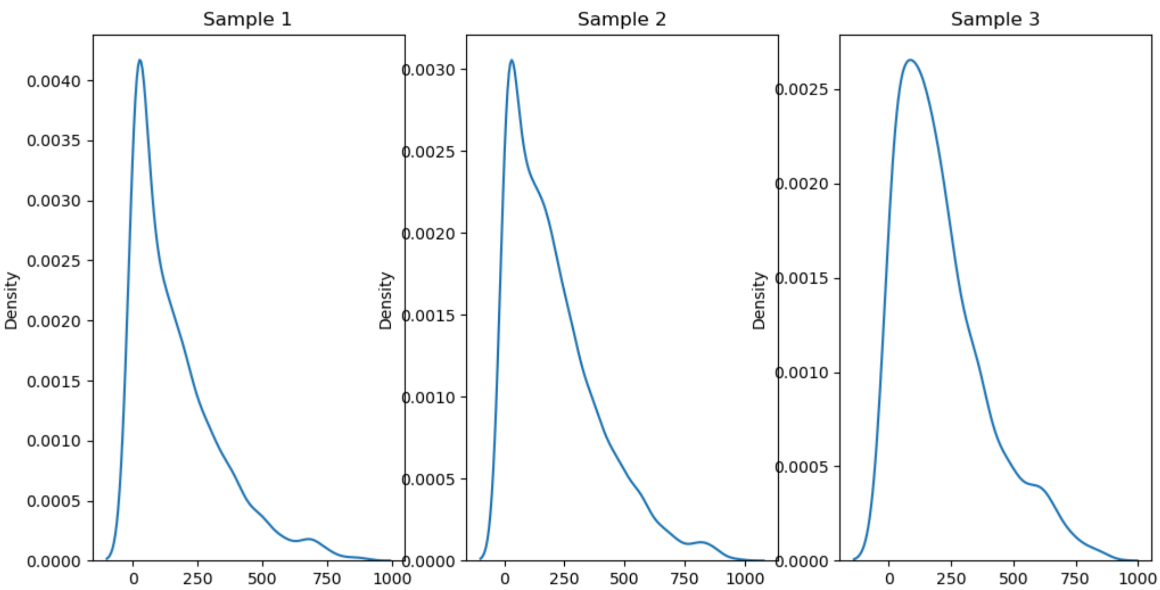
8.1. Check for Assumptions

In [239…
```python
check_normality(count_ws)
```

```
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 1  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 2  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  6.79376919669305e-23 . Hence, Sample 3  doesn't
follow normal distribution
```

```
C:\Users\Muthukumar\AppData\Roaming\Python\Python311\site-packages\scipy\stats\_m
orestats.py:1816: UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [240…
```python
plot_dist(count_ws)
```



In [241…
```python
Check_Variances_mod(count_ws)
```

```
Reject Null Hypothesis. Pval is  1.1009171815057205e-08 . Hence, the variance of
atleast one sample is significantly different
```

Inference:

- For Anova, the assumptions are failed. All the samples doesn't follow normal distribution and homogeneity of variances
- Perform Anova and also Kruskal wallis test

8.2. Perform One Way Anova Test

In [243…
```python
# One Way Anova
alpha = 0.05
stat, p_value = f_oneway(count_ws[0], count_ws[1], count_ws[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Average no. of cycles rented is differ
```

```
else:
    print('Fail to Reject Null Hypothesis. Hence, Average no. of cycles rented i
```

```
Test Statistic:  61.49 P-Val:  2.9212488566229153e-27
Reject Null Hypothesis. Hence, Average no. of cycles rented is different for atle
ast windspeed range
```

Inference:

- One way Anova test concluded that Average number of cycles rented is significantly different for atleast one windspeed range
- In order the find the windspeed range where the Average number of cycles rented is significantly different we need to perform 2 sample t test

8.3. Perform Kruskal Wallis Test

In [244…

```
# Kruskal Wallis Test
alpha = 0.05
stat, p_value = kruskal(count_ws[0], count_ws[1], count_ws[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Median no. of cycles rented is differe
else:
    print('Fail to Reject Null Hypothesis. Hence, Median no. of cycles rented is
```

```
Test Statistic:  146.64 P-Val:  1.4350374917697305e-32
Reject Null Hypothesis. Hence, Median no. of cycles rented is different for atlea
st one windspeed range
```

Inference:

- Since the assumptions of one way anova test is not met, the results can not concluded directly from that test
- Kruskal wallis test, concludes that the Median no. of cycles rented is different for atleast one windspeed range

8.4. Perform 2 Sample T Test between dependent and each independent variable

In [245…

```
alpha = 0.05
for sample in count_ws:
    print('Average no. of cycles rented in season ', str(i), ': ', np.mean(sampl

for idx1, idx2 in list(combinations(np.arange(len(count_ws)),2)):
    tstat, p_value = ttest_ind(count_ws[idx1], count_ws[idx2], alternative='two-
    print('T-Stat: ', round(tstat,2), 'P-Val: ', p_value)
    if p_value < 0.05:
        print('Reject Null Hypothesis. Hence, Average number of cycles rented is
    else:
        print('Fail to Reject Null Hypothesis. Hence, Average number of cycles r
```

```
Average no. of cycles rented in season  2 :  165.66027759418375
Average no. of cycles rented in season  2 :  209.1123201123201
Average no. of cycles rented in season  2 :  213.35689045936397
T-Stat:  -10.68 P-Val:  1.9179099323170704e-26
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between windspeed range 0  and  1
T-Stat:  -7.17 P-Val:  8.740907653897123e-13
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between windspeed range 0  and  2
T-Stat:  -0.62 P-Val:  0.5352388697851858
Fail to Reject Null Hypothesis. Hence, Average number of cycles rented is equal b
etween windspeed range 1  and  2
```

__Inference:__

- Average number of cycles rented is significantly different between windspeed range 0 and 1 & windspeed range 0 and 2
- Average number of cycles rented is significantly equal between windspeed range 1 and 2

9. Problem Statement

No. of cycles rented similar or different in different humidity levels

__Solution Approach:__

- Null Hypothesis: **Average no. of cycles rented are equal for all humidity levels**
- Alternate Hypothesis: **Average no. of cycles rented is different for atleast one humidity level**
- Comparison between Average no. of cycles rented (*Numerical*) and humidity levels (*Category with 3 categories*)
- **Normality Test**
  - Check for Average no. of cycles rented follow Normal distribution
  - **Shapiro Test**
- **Variance Test**
  - Check for Homogeneity of variances
  - **Levene Test**
- **One Way ANOVA Test**
- Significance level: 5%

In [246…

```python
count_humidity = []
for item in list(data['humidity_cat'].dropna().unique()):
    count_humidity.append(list(data[data['humidity_cat'] == item]['count']))
```

9.1. Check for Assumptions

In [249…

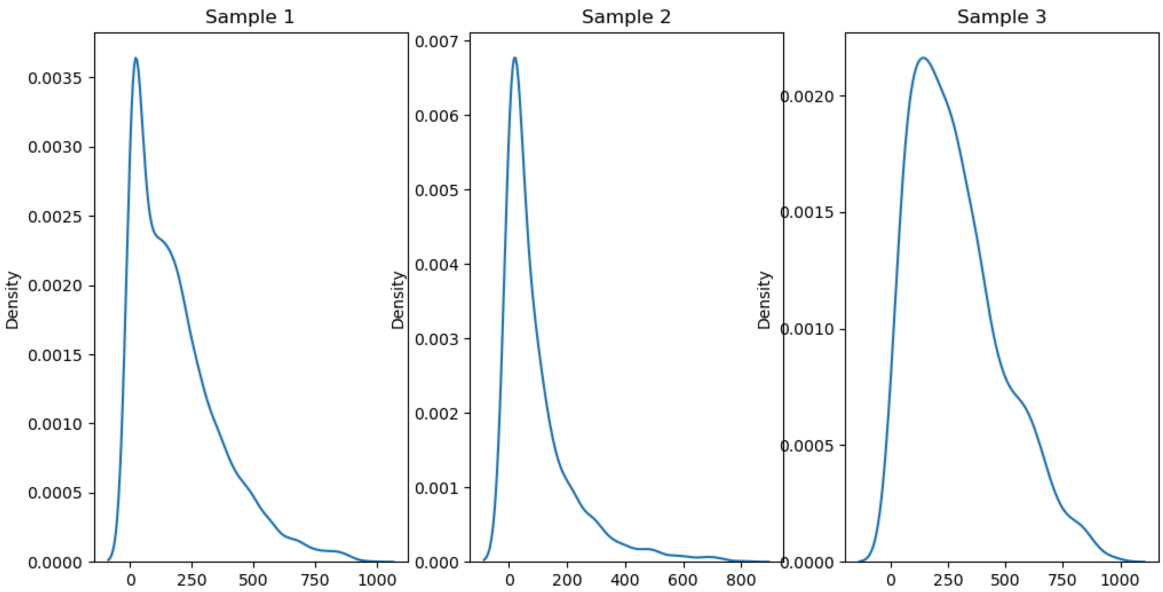
```python
check_normality(count_humidity)
```

```
Reject Null Hypothesis. Pval is  0.0 . Hence, Sample 1  doesn't follow normal dis
tribution
Reject Null Hypothesis. Pval is  4.90454462513686e-44 . Hence, Sample 2  doesn't
follow normal distribution
Reject Null Hypothesis. Pval is  1.0363253878974854e-24 . Hence, Sample 3  does
n't follow normal distribution
```

```
C:\Users\Muthukumar\AppData\Roaming\Python\Python311\site-packages\scipy\stats\_m
orestats.py:1816: UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [250…

```
plot_dist(count_humidity)
```



In [241…

```
Check_Variances_mod(count_ws)
```

```
Reject Null Hypothesis. Pval is  1.1009171815057205e-08 . Hence, the variance of
atleast one sample is significantly different
```

Inference:

- For Anova, the assumptions are failed. All the samples doesn't follow normal distribution and homogeneity of variances
- Perform Anova and also Kruskal wallis test

9.2. Perform One Way Anova Test

In [251…

```
# One Way Anova
alpha = 0.05
stat, p_value = f_oneway(count_humidity[0], count_humidity[1], count_humidity[2]
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Average no. of cycles rented is differ
else:
    print('Fail to Reject Null Hypothesis. Hence, Average no. of cycles rented i
```

```
Test Statistic:  482.02 P-Val:  2.741782831381464e-201
Reject Null Hypothesis. Hence, Average no. of cycles rented is different for atle
ast one humidity level
```

***InInferenc*e:**

- One way Anova test concluded tha*t **Average number of cycles rented is significantly different for atleast one humidity lev***el
- In order the find the humidity level where the Average number of cycles rented is significantly different we need to perform 2 sample t test

9.3. Perform Kruskal Wallis Test

In [252…

```
# Kruskal Wallis Test
alpha = 0.05
stat, p_value = kruskal(count_humidity[0], count_humidity[1], count_humidity[2])
#print('Sample-1 Mean: ', round(sample1.mean(),2), 'Sample-2 Mean: ', round(samp
print('Test Statistic: ', round(stat,2), 'P-Val: ', p_value)
if p_value < alpha:
    print('Reject Null Hypothesis. Hence, Median no. of cycles rented is differe
else:
    print('Fail to Reject Null Hypothesis. Hence, Median no. of cycles rented is
```

```
Test Statistic:  1061.6 P-Val:  2.996871369661641e-231
Reject Null Hypothesis. Hence, Median no. of cycles rented is different for atlea
st one humidity level
```

Inference:

- Since the assumptions of one way anova test is not met, the results can not concluded directly from that test
- Kruskal wallis test, concludes that the Median no. of cycles rented is different for atleast one humidity level

9.4. Perform 2 Sample T Test between dependent and each independent variable

In [253…

```
alpha = 0.05
for sample in count_humidity:
    print('Average no. of cycles rented in season ', str(i), ': ', np.mean(sampl

for idx1, idx2 in list(combinations(np.arange(len(count_humidity)),2)):
    tstat, p_value = ttest_ind(count_humidity[idx1], count_humidity[idx2], alter
    print('T-Stat: ', round(tstat,2), 'P-Val: ', p_value)
    if p_value < 0.05:
        print('Reject Null Hypothesis. Hence, Average number of cycles rented is
    else:
        print('Fail to Reject Null Hypothesis. Hence, Average number of cycles r
```

```
Average no. of cycles rented in season  2 :  190.4756966947505
Average no. of cycles rented in season  2 :  96.85192433137638
Average no. of cycles rented in season  2 :  288.89789603960395
T-Stat:  19.78 P-Val:  2.358356748074402e-85
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between humidity level 0  and  1
T-Stat:  -19.93 P-Val:  1.3306807309895657e-86
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between humidity level 0  and  2
T-Stat:  -32.53 P-Val:  2.174595591792677e-200
Reject Null Hypothesis. Hence, Average number of cycles rented is significantly d
ifferent between humidity level 1  and  2
```

Inference:

- Average number of cycles rented is significantly different between each humidity levels

10. Problem Statement

Check for dependecy between each categorical features

Solution Approach:

- Null Hypothesis: **Categorical variables are independent**
- Alternate Hypothesis: **Categorical variables are dependent**
- **Chi-square Independency Test**
- Significance level: 5%

In [270…

```
cat_features = ['season', 'workingday', 'weather', 'temp_cat', 'atemp_cat', 'hum
df = pd.DataFrame(data = np.ones((len(cat_features),len(cat_features))) * -1, co
for idx1, idx2 in list(combinations(cat_features,2)):
    contigency_table = pd.crosstab(data[idx1], data[idx2])
    stat, p_value, a, exp = chi2_contingency(contigency_table)
    print('Stat: ', round(stat,2), 'P-Val: ', p_value)
    if p_value < 0.05:
        print('Reject Null Hypothesis. Hence, ', str(idx1), ' and ', str(idx2),
    else:
        print('Fail to Reject Null Hypothesis. Hence, ', str(idx1), ' and ', str
    df.loc[idx1, idx2] = round(p_value,2)
    df.loc[idx2, idx1] = round(p_value,2)
```

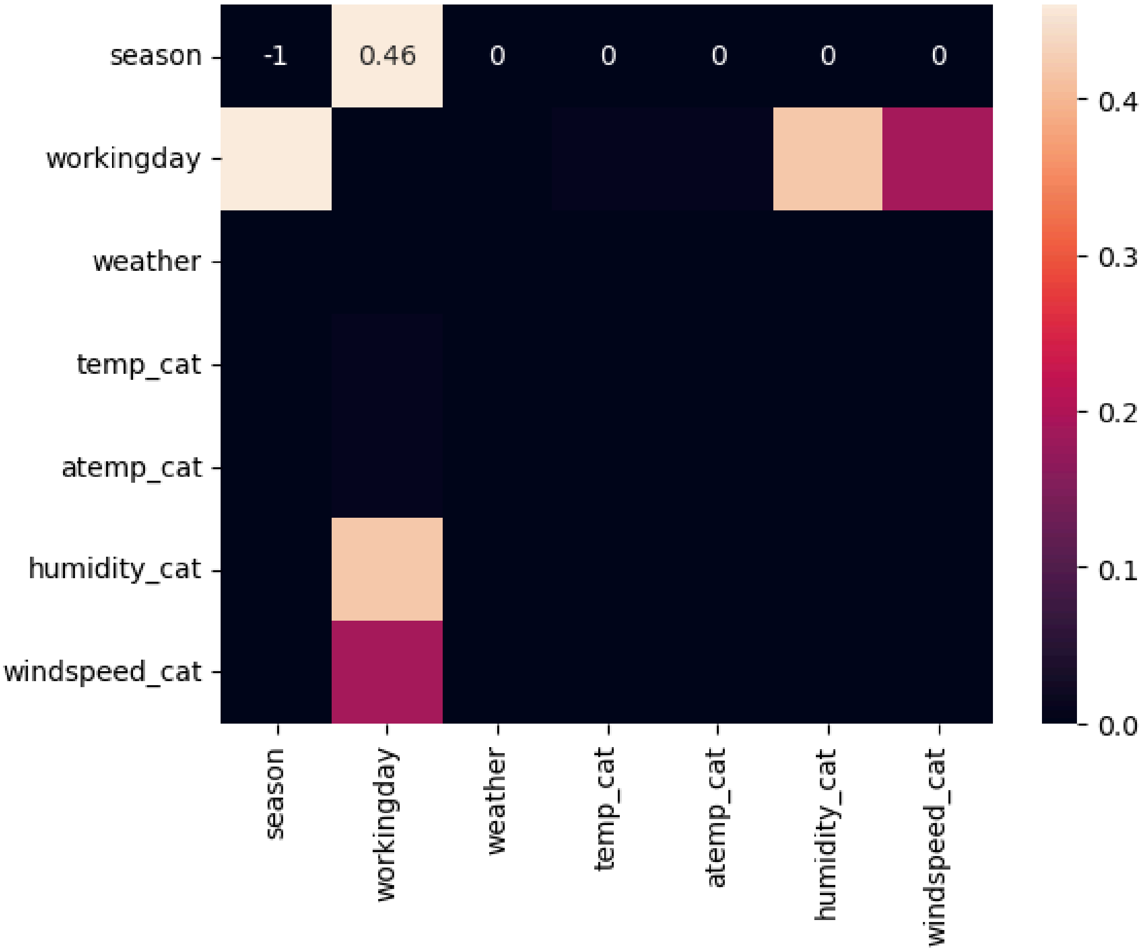
```
Stat:  2.57 P-Val:  0.4626148207703564
Fail to Reject Null Hypothesis. Hence,  season  and  workingday are independent
Stat:  49.16 P-Val:  1.549925073686492e-07
Reject Null Hypothesis. Hence,  season  and  weather are dependent
Stat:  5897.24 P-Val:  0.0
Reject Null Hypothesis. Hence,  season  and  temp_cat are dependent
Stat:  6630.76 P-Val:  0.0
Reject Null Hypothesis. Hence,  season  and  atemp_cat are dependent
Stat:  441.6 P-Val:  3.154697752402428e-92
Reject Null Hypothesis. Hence,  season  and  humidity_cat are dependent
Stat:  191.15 P-Val:  1.4477127726644647e-38
Reject Null Hypothesis. Hence,  season  and  windspeed_cat are dependent
Stat:  16.16 P-Val:  0.0010502165960627732
Reject Null Hypothesis. Hence,  workingday  and  weather are dependent
Stat:  9.57 P-Val:  0.008342423420746568
Reject Null Hypothesis. Hence,  workingday  and  temp_cat are dependent
Stat:  9.73 P-Val:  0.0077190014112448494
Reject Null Hypothesis. Hence,  workingday  and  atemp_cat are dependent
Stat:  1.74 P-Val:  0.4193926395523214
Fail to Reject Null Hypothesis. Hence,  workingday  and  humidity_cat are indepen
dent
Stat:  3.36 P-Val:  0.1865186782185527
Fail to Reject Null Hypothesis. Hence,  workingday  and  windspeed_cat are indepe
ndent
Stat:  152.29 P-Val:  2.5393088306954665e-30
Reject Null Hypothesis. Hence,  weather  and  temp_cat are dependent
Stat:  277.81 P-Val:  4.6243537419201974e-57
Reject Null Hypothesis. Hence,  weather  and  atemp_cat are dependent
Stat:  2048.43 P-Val:  0.0
Reject Null Hypothesis. Hence,  weather  and  humidity_cat are dependent
Stat:  44.31 P-Val:  6.422935286585923e-08
Reject Null Hypothesis. Hence,  weather  and  windspeed_cat are dependent
Stat:  8197.02 P-Val:  0.0
Reject Null Hypothesis. Hence,  temp_cat  and  atemp_cat are dependent
Stat:  330.26 P-Val:  3.2088658507065833e-70
Reject Null Hypothesis. Hence,  temp_cat  and  humidity_cat are dependent
Stat:  55.9 P-Val:  2.103733252175866e-11
Reject Null Hypothesis. Hence,  temp_cat  and  windspeed_cat are dependent
Stat:  808.21 P-Val:  1.2813030257313233e-173
Reject Null Hypothesis. Hence,  atemp_cat  and  humidity_cat are dependent
Stat:  82.52 P-Val:  5.1018430943325584e-17
Reject Null Hypothesis. Hence,  atemp_cat  and  windspeed_cat are dependent
Stat:  660.66 P-Val:  1.1468186720611514e-141
Reject Null Hypothesis. Hence,  humidity_cat  and  windspeed_cat are dependent
```

In [273…

```
sns.heatmap(df, vmin = 0, annot=True)
```

Out[273…

```
<Axes: >
```



__Inference:__

- In the above heatmap, dark indicates dependency (pval~0) and light color indicates independency (pval>0)
- It is evident that almost all the categorical features are dependent except working day

Business Insights and Recommendations

Weather-Based Insights:

- Obseravation:
  - Light weather conditions (Weather 1 and 2) see high usage of the cycles.
- Recommendation:
  - Focus marketing efforts and offer discounts or reduced costs during Weather 1 and 2 conditions to capitalize on high demand
  - Hypothesis test also concludes that Average number of cycles rented is significantly different for weather 1 and 2. Hence the strategies involving weather 1 and 2 will make a significant impact whereas the weather 2 doesn't.
  - Utilize dynamic pricing models that adjust costs based on real-time weather conditions, prioritizing Weather 1 for promotions to maximize revenue.

Weekly usage-Based Insights:

- Obseravation:
  - Registered users are predominant on weekdays indicates tbat they rent cycles for commuting to work/students
  - Casual users are predominant on weekends indicating that they commute for leisure
  - Users count during holiday and working day also confirms the above point
- Recommendation:
  - Increase efforts to grow the registered user base to boost weekday revenue, as they tend to have higher usage rates
  - Introduce weekday subscription plans or loyalty programs for registered users to encourage frequent use
  - On weekends, tailor promotions and offers to attract casual users with leisure-oriented marketing
  - Design weekend packages that appeal to casual users, such as group discounts or event partnerships

YoY Growth Insights:

- Obseravation:
  - Year-over-year (YoY) user growth indicates that current promotion strategies are effective.
- Recommendation:
  - Continue and refine existing promotional strategies that have proven successful.
  - Analyze which promotional channels and messages have driven the most growth and amplify those efforts.

Time-Based Insights:

- Obseravation:
  - The average number of casual users peaks between 13:00 and 17:00, indicating high demand during these hours.
- Recommendation:
  - Implement dynamic pricing during peak hours to manage demand and maximize revenue. Adjust pricing to reflect the higher value of cycles during peak usage times
  - Set up a pricing model that increases rates during peak hours (13:00-17:00) while offering discounts during off-peak times to balance demand throughout the day

Temperature-Based Insights:

- Observation:
  - Cycle usage is positively correlated with temperature
- Recommendation:
  - Hypothesis testing confirms that the average number of cycles rented varies significantly with temperature. Hence the strategies involving temperature bin will make a significant impact

- Incorporate temperature data into dynamic pricing models. Increase prices during favorable temperature conditions (higher usage) and consider lowering prices or offering incentives when conditions are less ideal.
- Utilize accurate weather prediction APIs to anticipate demand and adjust pricing accordingly.

Humidity-Based Insights:

- Observation:
  - Cycle usage is negatively correlated with humidity
- Recommendation:
  - Hypothesis testing confirms that the average number of cycles rented varies significantly with humidity. Hence the strategies involving humidity will make a significant impact
  - Incorporate humidity data into dynamic pricing models. IAdjust pricing based on humidity levels to encourage usage during less favorable conditions.
  - Utilize accurate weather prediction APIs to anticipate demand and adjust pricing accordingly.

Day-Based Insights:

- Observation:
  - The average number of cycles rented is not significantly different between working days and non-working days
- Recommendation:
  - The strategies involving working day doesn't significantly impact
  - Maintain consistent pricing across working and non-working days

Season-Based Insights:

- Observation:
  - The average number of cycles rented varies significantly between seasons
- Recommendation:
  - The strategies involving each seasons will make significantly impact
  - Increase prices during peak seasons with high demand and offer discounts or promotions during off-peak seasons to encourage usage
  - Create seasonal marketing campaigns that highlight the benefits of cycling in each season

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